Identifying the Uncertainty in Determining Satellite-Derived Atmospheric Motion Vector Height Attribution

CHRISTOPHER S. VELDEN AND KRISTOPHER M. BEDKA
Cooperative Institute for Meteorological Satellite Studies, University of Wisconsin—Madison, Madison, Wisconsin

(Manuscript received 28 January 2008, in final form 11 June 2008)

ABSTRACT

This study investigates the assignment of pressure heights to satellite-derived atmospheric motion vectors (AMVs), commonly known as cloud-drift and water vapor–motion winds. Large volumes of multispectral AMV datasets are compared with collocated rawinsonde wind profiles collected by the U.S. Department of Energy Atmospheric Radiation Measurement Program at three geographically disparate sites: the southern Great Plains, the North Slope of Alaska, and the tropical western Pacific Ocean. From a careful analysis of these comparisons, the authors estimate that mean AMV observation errors are \( \pm 5 \text{ to } 5.5 \text{ m s}^{-1} \) and that vector height assignment is the dominant factor in AMV uncertainty, contributing up to 70% of the error. These comparisons also reveal that in most cases the RMS differences between matched AMVs and rawinsonde wind values are minimized if the rawinsonde values are averaged over specified layers. In other words, on average, the AMV values better correlate to a motion over a mean tropospheric layer rather than to a traditionally assigned discrete level. The height assignment behavioral characteristics are specifically identified according to AMV height (high cloud vs low cloud), type (spectral bands; clear vs cloudy), geolocation, height assignment method, and amount of environmental vertical wind shear present. The findings have potentially important implications for data assimilation of AMVs, and these are discussed.

1. Introduction

It is well known that accurate numerical weather prediction (NWP) requires upper-air observations for representing the initial state of the atmosphere and for updating the model analyses through data assimilation. In particular, the proper specification of tropospheric winds is an important prerequisite to accurate numerical model forecasts. Over oceanic regions, where significant weather is common, conventional data sources are especially scarce. Thus, atmospheric motions vectors (AMVs) derived from satellites are useful for NWP because they can provide wind information in these important regions.

The retrieval of AMVs from satellites has been evolving since the early 1970s (Schmetz et al. 1993; LeMarshall et al. 1994; Menzel 2001). Most of the major meteorological geostationary satellite data centers around the globe are now producing cloud- and water vapor–tracked winds with automated algorithms using imagery from operational geostationary satellites. Contemporary AMV processing methods are continuously being updated and advanced through the exploitation of new sensor technologies and innovative new approaches (Velden et al. 2005). Advances in data assimilation and NWP in recent years have placed an increasing demand on observation quality. With remotely sensed observations dominating the initialization of NWP models over regions of the globe that are traditionally data sparse, the motivation is clear: the importance of providing high-quality AMVs becomes crucial to their relevance and contributions toward realizing superior model predictability.

AMVs are derived by tracking either cloud or water vapor (WV) features (sharp radiance gradients) in sequential images of multispectral satellite imagery. AMVs derived from infrared (IR) window images typically capture flow features in both the upper and lower troposphere, whereas AMVs derived from visible (VIS) images generally track cumuliform cloud motions in the lower troposphere. Mid- to upper-tropospheric WV features are tracked in cloud-free scenes using imagery derived from WV-sensitive spectral bands that are present on most of the
current operational environmental satellites (Holmlund 1993; Velden et al. 1997). The full complement of multispectral AMVs produced routinely from satellites can provide wind data coverage over most of the globe, most of the time.

Many studies have shown the positive impact that AMVs can have on NWP. For example, Geostationary Operational Environmental Satellite (GOES) AMVs were assimilated into the Geophysical Fluid Dynamics Laboratory (GFDL) hurricane prediction system to determine their impact on simulations of Atlantic Ocean hurricanes (Soden et al. 2001). In over 100 cases, the GOES AMVs dramatically reduced a persistent westward track bias common in the GFDL model at the time. Furthermore, the AMVs were able to depict more accurately the vorticity gyres in the environmental flow, which led to significant improvements in track predictions at all forecast times. A study using the European Centre for Medium-Range Weather Forecasts system showed that AMVs are also beneficial to simulations of systems other than hurricanes (Kelly 2004). In the Australian region, LeMarshall et al. (1994) has demonstrated a positive impact on local regional model forecasts. In another study, the Navy Operational Global Atmospheric Prediction System was used to investigate the impact of targeted aircraft dropsondes and satellite-derived winds on model analyses and forecasts of North Pacific Ocean weather events (Langland et al. 1999). It was found that the satellite data had a more positive impact on the forecast errors than did the dropsonde data. This was a result of the large area covered by the satellite data and the high temporal resolution. The generally positive impact of AMVs has led to routine assimilation, to varying degrees, in operational global forecast models.

AMVs are typically treated as single-level data, that is, the AMV displacements (wind speed and direction) are assigned by automated processing algorithms to a determined/estimated pressure height, and these are used by the NWP data assimilation systems. Although, as noted above, AMVs have had positive impacts on NWP, the representative vector heights have proven to be a relatively large source of observation uncertainty (Schmetz and Holmlund 1992; Nieman et al. 1993; EUMETSAT 2006) because in most cases the satellite imagers actually sense radiation emitted from a finite layer of the troposphere rather than just one specific level. Thus, problems in data assimilation can arise from the difficulty in accurately placing the height of the tracer and/or representing the measured motion of a layer by a single-level value. This latter type of discrepancy is especially prevalent in clear-air WV winds for which the radiometric gradient signal (tracking feature) may result from a deep layer of advecting moisture (Velden et al. 1997; Soden et al. 2001; Rao et al. 2002).

The height-assignment issues discussed above, and the potential impact on NWP when assimilating AMVs, are the primary motivation for this research. Various approaches to minimize the height-assignment problems in data assimilation have been investigated, such as spreading the information over more than one level (Rao et al. 2002). However, an optimal forward operator for AMVs has remained elusive because the height assignment uncertainties and the vertical representativeness of the AMVs have not been examined thoroughly. To this end, we investigate a large and diverse sample of AMVs by comparing them with colocated rawinsondes in an attempt to begin identifying these qualities. This information may then be exploited in numerical model simulations to determine the potential forecast impact.

The data and methods used in this study are described in section 2. Section 3 presents results of the comparisons with rawinsonde observations. Section 4 summarizes the findings and offers potential application directions. Although the findings presented here are directly applicable only to the current National Oceanic and Atmospheric Administration/National Environmental Satellite, Data, and Information Service (NOAA/NESDIS) processed AMV datasets, they are likely also relevant to other AMV data processing centers as well, because the derivation methods are similar.

2. Data and analysis method

a. Datasets

The AMV datasets analyzed in this study are derived by the University of Wisconsin—Madison Cooperative Institute for Meteorological Satellite Studies (CIMSS) automated algorithm that is nearly identical to the code used to produce operational AMVs at NOAA/NESDIS (Daniels et al. 2002). All of the AMVs have passed the routine quality-control and postprocessing steps and are considered to be the vectors that would be made operationally available by NESDIS to its users. Therefore, the results are robust in terms of their representative-ness of NESDIS AMV datasets and are consistent with regard to the regional comparisons discussed in the next section. The AMV processing algorithm employs successive image triplets using VIS, shortwave IR (SWIR), WV, and IR window (IRW) spectral channels. The basic algorithm method is described in Velden et al. (1998). The AMV pressure-altitude assignments are derived from first passing the targeted features through a series of height-assignment routines based on the radiative
properties of the cloud or WV features being tracked (Niemann et al. 1993; Schmetz and Holmlund 1992) to produce an initial set of estimated height values. Once the vector displacements are calculated, the AMVs are then passed through an automated quality-control procedure (Velden et al. 1998) that can adjust the initially assigned heights based on a best fit of each vector to a local three-dimensional analysis of all AMVs in the immediate vicinity (and with some influence of a model-based background analysis) and the minimization of a prescribed penalty function. In the investigations reported on in the next section, both the initial and adjusted heights are considered.

To investigate regional variations, we examine AMVs produced from both geostationary and polar-orbiting platforms (Velden et al. 2005; Key et al. 2003) in diverse atmospheric conditions. The AMV datasets are compared to rawinsonde wind observations collected by the U.S. Department of Energy Atmospheric Radiation Measurement (ARM) Program at three supersites located in the southern Great Plains (SGP), the North Slope of Alaska (NSA), and the tropical western Pacific Ocean area (TWP). The advantage in using ARM rawinsonde data is that wind observations are collected at a very high vertical resolution, every 2 s during the balloon flight, allowing for extra precision in the height assignment analyses described in the next section. For informational purposes, the measurement errors in these rawinsonde winds are estimated to be \(\pm 0.5 \text{ m s}^{-1}\) (Loran method at SGP) and \(0.2 \text{ m s}^{-1}\) (GPS method at TWP and NSA). The primary rawinsonde launch locations associated with these ARM sites are summarized in Table 1, in addition to the satellite instrumentation used to acquire AMVs over the three regions, the time period for the comparisons, and the total number of available AMV–rawinsonde matches. The NSA comparison period differs from that of SGP and TWP because an insufficient number of rawinsondes were launched before June of 2006 and therefore the period was extended until November of 2006.

### b. Comparison method

Each AMV data record contains the originally assigned vector altitude and the postprocessed readjusted height if an adjustment was performed. We examine both of these values against collocated rawinsondes to assess the impact of the readjustments. The values are matched against a collocated rawinsonde at the respective AMV height assignment levels (to assess absolute accuracy) and then also at the level of best rawinsonde match, or “fit” (to interrogate the accuracy possible if the height assignment error is minimized). A final component to our analysis is to examine the AMVs against layer-averaged rawinsonde values to assess the vertical representativeness of the vectors at their assigned heights and as a further potential indicator of height uncertainty spread.

For this study, an AMV is considered for a comparison with a rawinsonde when it is matched within 50 km and 1 h from the location and time of the rawinsonde launch. For each match, the AMV speed and direction are compared with the nearest (in pressure altitude) rawinsonde value at 1) the originally assigned AMV height, 2) the postprocessed adjusted height, and 3) the level of best fit (minimum vector difference within \(\pm 100 \text{ hPa}\) of the assigned AMV height) and with 4) layer-mean rawinsonde wind values derived for layers ranging from 10 to 300 hPa in thickness, starting from the assigned AMV heights. In method 4, rawinsonde winds are accumulated within the layer of a specified thickness, the \(u\) and \(v\) components are averaged, and then the vector difference between the layer-mean rawinsonde and AMV is computed. AMV–rawinsonde vector differences are further separated into categories: spectral (satellite imaging channel), height assignment level (lower tropospheric vs upper), height assignment technique, geographic location (ARM site), local wind shear...
magnitude, and clear-sky versus cloudy target type (for WV AMVs). Vector root-mean-square (VRMS) difference statistics are computed for each of these categories.

The computations of the layer means for method 4 are done differently depending on the target type from which the AMV was derived. For clear-sky WV AMVs, the AMV height assignment represents the center of the layer-mean computations, because the signal detected by the WV channel originates from a deep atmospheric layer (broad spectral response function; Weldon and Holmes 1991; Velden et al. 1997). Thus, the layer means are computed for up to 300 hPa from the assigned AMV heights. For vectors derived by cloud tracking, the AMV height assignment most closely represents the top of the cloud. Therefore, this value is used for the upper limit of the layer-mean computations. For lower-tropospheric cloud-drift AMVs (i.e., below 700 hPa), the layer mean cannot include winds over the full 300-hPa thickness range because of the earth’s surface, and therefore the rawinsonde near-surface wind represents the lower limit of the layer-mean computations.

c. Comparison interpretations

The results presented in the next section are focused on the VRMS differences between the collocated AMV–rawinsonde matches. These differences should not be strictly interpreted as AMV observational error. As mentioned previously, the rawinsonde instrument measurement error is on the order of 0.2–0.5 m s$^{-1}$. In addition, there are errors introduced through the matching process. Although our match requirements are fairly strict, any offsets in space and time can introduce an increase in the comparison differences.

To estimate this effect in our study, two sets of comparisons were performed using ARM SGP datasets to evaluate the natural spatial and temporal variability of the local wind field. The first comparison involves the combined use of rawinsonde and 6-min-resolution wind profiler data to examine spatial variability. The wind profiler collects observations from a fixed location whereas the rawinsonde drifts away from the nearby profiler during ascent. Because the wind profiler actually observes motions within a layer of the
atmosphere [320-m (900 m) depth for low (high) mode], rawinsonde data are averaged over the layer and vector differences between the layer-averaged rawinsonde and wind profiler data are computed. Because the balloon ascends over time, incremental profiler scans are used to remove most of the temporal variability from the comparisons. A time match criteria of ±3 min is imposed for these comparisons. Vector differences are grouped into 25-km bins based on the distance between the drifting rawinsonde and the fixed profiler locations. VRMS statistics are computed from these vector differences for each of the profiler levels at five distance ranges. Figure 1 presents the results of this analysis for a 1-yr period, April 2005–06, for which data from 1626 rawinsonde ascents are included. If we assume that the 0–25-km bin is a “perfect” match, the VRMS from this bin can be subtracted from the VRMS at greater bin distances at a given height to estimate the match error due to the natural spatial wind variability. For example, the effects of spatial wind

![Figure 2](image-url)

**FIG. 2.** An analysis of temporal wind variability from April 2005 to April 2006 using sequences of fixed-location 404-MHz wind profiler observations at the SGP ARM site. The VRMS value at a 6-min time interval can be subtracted from the VRMS at longer time separations to estimate local temporal wind variability.

**Table 2.** Mean statistical comparisons between collocated AMVs and rawinsondes at SGP, TWP, and NSA.

<table>
<thead>
<tr>
<th>AMV speed</th>
<th>Rawinsonde speed</th>
<th>AMV–rawinsonde speed bias</th>
<th>AMV–sonde VRMS</th>
<th>AMV height (hPa)</th>
<th>Match distance (km)</th>
<th>Time separation (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SGP</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Original AMV height</td>
<td>21.50</td>
<td>21.91</td>
<td>-0.41</td>
<td>6.31</td>
<td>358</td>
<td>48.2</td>
</tr>
<tr>
<td>Adjusted AMV height</td>
<td>22.87</td>
<td>23.00</td>
<td>-0.13</td>
<td>5.75</td>
<td>349</td>
<td>48.9</td>
</tr>
<tr>
<td>Rawinsonde LBF height</td>
<td>22.87</td>
<td>22.73</td>
<td>0.14</td>
<td>2.53</td>
<td>352</td>
<td>49.1</td>
</tr>
<tr>
<td>TWP</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Original AMV height</td>
<td>10.21</td>
<td>10.68</td>
<td>-0.47</td>
<td>5.62</td>
<td>271</td>
<td>35.1</td>
</tr>
<tr>
<td>Adjusted AMV height</td>
<td>10.27</td>
<td>10.91</td>
<td>-0.64</td>
<td>5.27</td>
<td>265</td>
<td>35.2</td>
</tr>
<tr>
<td>Rawinsonde LBF height</td>
<td>10.27</td>
<td>10.09</td>
<td>0.18</td>
<td>1.96</td>
<td>280</td>
<td>35.0</td>
</tr>
<tr>
<td>NSA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Original AMV height</td>
<td>16.29</td>
<td>17.17</td>
<td>-0.88</td>
<td>5.49</td>
<td>430</td>
<td>52.5</td>
</tr>
<tr>
<td>Adjusted AMV height</td>
<td>16.30</td>
<td>17.19</td>
<td>-0.89</td>
<td>5.36</td>
<td>430</td>
<td>52.5</td>
</tr>
<tr>
<td>Rawinsonde LBF height</td>
<td>16.30</td>
<td>16.19</td>
<td>0.12</td>
<td>2.77</td>
<td>444</td>
<td>52.2</td>
</tr>
</tbody>
</table>
variability are at a maximum in the range of 10–12 km in altitude, where the highest tropospheric wind speeds are usually found.

A second comparison utilizes time sequences of fixed-location 6-min wind profiler observations to estimate the local temporal wind variability. For this analysis, a given wind profile is compared with those from 6 to 120 min into the future, over the same 1-yr period that is described above. Because the profiler is in a fixed location, the vector differences between current and future wind observations are primarily related to the local temporal wind variability. For the dataset as a whole, vector differences for each successive time interval are grouped together to compute VRMS. Figure 2 shows an example of this analysis for the profiler high mode. It is assumed that the VRMS difference for the initial 6-min interval is primarily caused by instrument effects and can be used as a baseline to estimate temporal wind variability at longer time intervals. For example, Fig. 2 shows that the average temporal variability between two wind observations spaced 60 min apart in time is \(\sim 1.6 \text{ m s}^{-1}\) at a 10-km height (yellow curve). For a 120-min time interval, temporal variability increases to \(3.2 \text{ m s}^{-1}\) at this same height.

These analyses show that the combined spatial and temporal effects on collocation “matching” statistics can be significant. These errors need to be taken into account to estimate a true AMV observation error or in the development of a forward operator for AMVs in data assimilation. Pertinent to this study, the results presented below will estimate these errors.

3. Results

a. Assigned AMV height level versus rawinsonde level of best fit

To gauge the uncertainty in AMV height assignments, it is of interest to examine the characteristics of the assigned single-level AMV heights against what we will refer to as the collocated rawinsonde level of best fit (LBF). The LBF is the level of minimum AMV–rawinsonde vector difference, limited to \(\pm 100 \text{ hPa}\) from the AMV height assignment (constrained to limit spurious results from rawinsonde winds far from the actual tracer height that just happen to match up the best). If we assume that the rawinsonde LBF is the best possible single-level wind that the AMV represents, this method can be used to isolate the part of AMV error that is associated with the uncertainty in assigning vector heights. The residual error can then be attributed to the aforementioned instrument and matching noise and to target tracking errors.

![Fig. 3. The distribution of assigned AMV height deviations from the corresponding rawinsonde LBF for the three regions: (top) SGP, (middle) TWP, and (bottom) NSA. Negative height differences correspond to vectors being assigned higher than the LBF.](image-url)
Table 2 shows the mean statistics for the collocated matches at the three ARM sites. As discussed earlier, optimal numerical data assimilation requires a good estimate of observation error. Although the VRMS statistics shown in Table 2 are not a true representation of AMV observation error, we can use this information and that gleaned in section 2c to make a concerted estimate of this quantity, at least in terms of a mean value, as follows [after Kitchen (1989) and Schmetz et al. (1993)]:

\[
\text{observation error (VRMS; m s}^{-1}\text{)} = \left[\text{adjusted-height VRMS}^2 - (\sigma_T^2 + \sigma_S^2 + \sigma_R^2)\right]^{1/2},
\]

where \(\sigma_T\) is temporal wind variability (VRMS), \(\sigma_S\) is spatial wind variability (VRMS), and \(\sigma_R\) is rawinsonde error (VRMS).

Thus, for example, at SGP the mean VRMS is 5.7 m s\(^{-1}\) for the adjusted AMV height assignments and the mean vector height is \(-350\) hPa (\(-8300\) m) from Table 2. From Fig. 2 we get 1.3 m s\(^{-1}\) for the average comparison time offset, and from Fig. 1 we get 0.3 m s\(^{-1}\) for the average spatial offset and 0.5 m s\(^{-1}\) for rawinsonde instrument error at the SGP site. Applying the equation above yields an observation error (VRMS) of 5.57 m s\(^{-1}\). The analysis in section 2c was based on data only from SGP, but we can use it to estimate the mean AMV observational errors at the other two sites as well. The results are VRMS\(_{SGP}\) = 5.57 m s\(^{-1}\), VRMS\(_{TWP}\) = 5.12 m s\(^{-1}\), and VRMS\(_{NSA}\) = 5.32 m s\(^{-1}\). These values are corrected for matching errors, and, although the adjustments are relatively small in comparison with the values listed in Table 2, they better represent the true bulk AMV observation errors for the three data samples.

It is interesting to compare the estimated AMV observation errors for the three sites. It is certain that the geographic location will have some influence on the statistical performance because of the local characteristics of the atmospheric conditions and trackable cloud/moisture features. However, we must also remember that in this study the AMVs derived over the SGP and TWP sites were derived from geostationary satellite imagery, whereas at NSA they were derived from polar-orbiter imagery. Although the processing algorithm employed was identical in all cases, there do exist some differences in the tracking metrics. For example, geostationary satellite imagery is available at 15–30-min intervals, whereas the polar-orbiting Moderate Resolution Imaging Spectroradiometer (MODIS) imagery is available at \(-100\)-min intervals. The geostationary spatial resolution is 4–5 km, whereas the MODIS is 1–2 km. So it is not surprising that there are subtle differences in the observed errors between the comparison sites.

Of course, in practical applications of the AMV observation error such as data assimilation, the regional mean values would not be sufficient. A proper forward operator should take into account the observational error as a function of parameters such as vector altitude, type, location, target cloud properties, height assignment method, etc. This study is intended only as a starting point in that regard, and future work should address the AMV observational error characteristics in further detail.

Of particular interest to our study is the uncertainty in the AMV height assignment. This can be estimated by examining the differences in VRMS between the
assigned AMV heights and the associated LBF in Table 2. In each of the three disparate regions, there is a significant reduction in the VRMS when the LBF altitude is considered as the AMV height assignment. To estimate the height attribution uncertainty, we use the following formula:

\[
\text{Fraction of error from height assignment} = \frac{1}{\sqrt{C_0}} \left( \frac{\text{VRMS}_{LBF}^2}{\text{VRMS}_{\text{Adjusted-height}}^2} \right)^{1/2}
\]

Thus, after adjusting for the matching errors noted above, the height assignment uncertainty accounts for a remarkable 70% of the VRMS differences at TWP, 58% at SGP, and 49% at NSA. The reverse correlation with latitude is not surprising given the increase in tropopause height and the greater occurrence of semitransparent cirrus as AMV tracers in the tropics (TWP). The latter issue has been a long-identified AMV height-assignment problem area (Schmetz and Holmlund 1992; Menzel 2001; Nieman et al. 1993).

It is notable that the adjusted AMV heights (by the CIMSS/NESDIS postprocessing method) are generally an improvement (lower VRMS) over the original height assignments. This is particularly true in the SGP and TWP comparisons, with the largest impacts at the SGP site. The height reassignments result in improved VRMS
values in about 60% of the cases. Although the reassignments are constrained by the postprocessing algorithm and are typically not huge (as also supported by a comparison of the mean AMV height values in Table 2), they appear to be in the right direction in most cases.

Figure 3 shows the distribution of assigned (in this case, the adjusted heights) AMV height deviations from the corresponding LBFs. Negative height differences correspond to vectors being assigned to higher than the level of best fit. The results show a "normal" distribution over the SGP site but a tendency for the TWP AMVs to be assigned higher heights relative to the best-fit level. NSA results show a relatively even distribution, with a slight tendency toward high assignment. Furthermore, 47% of the AMVs at SGP assigned > 90 hPa from their LBF were assigned to heights above 300 hPa, which coincides with the mean vertical location of the jet stream over the central United States. This underscores the challenge in accurate tracer height assignment in high-vertical-shear regions near and within upper-tropospheric jets. This will be further emphasized in section 3c.

Another way to view the significance of height assignment on the AMV observation error is evident from Fig. 4. The improvement in AMV–rawinsonde vector difference yielded by theoretically reassigning the AMV heights to the LBFs is that ~50% of AMV–rawinsonde vector differences at SGP and TWP would improve by at least 2.5 m s⁻¹ and ~20% would improve by at least 5 m s⁻¹. Improvements yielded by an LBF assignment at NSA are slightly less than those from SGP and TWP.

Having considered the height assignment uncertainty, and taken out the estimated matching error, the residual values are an indication of the error involved in the
AMV targeting/tracking process. In our analysis above, these residual errors are 30%, 42%, and 51% of the total observation error for the AMVs analyzed at TWP, SGP, and NSA, respectively. The larger fraction at NSA makes sense, because the MODIS AMVs at NSA employ successive images at much greater time intervals. At SGP and TWP, the target tracking is superior because of the higher frequency of available images (Velden et al. 2005), as noted earlier.

In summary, the major point to be made is that the AMV targeting, tracking, and quality-control algorithms have been refined and improved to a much greater degree than the height-assignment algorithms have (which have proven to be a more difficult task). For these reasons, the above results make intuitive sense, and height-assignment uncertainty contributes in an important way to the AMV observation error.

b. Assigned AMV height level versus rawinsonde layer of best fit

Having established the importance of proper height attribution to AMVs, we now turn our attention to mitigation strategies. It is obvious that improving the processing methods for accurately determining the cloud/water vapor target heights is a continuing research path. However, we can also challenge the long-standing constraint that AMVs need to be associated/assigned to a discrete tropospheric level. In fact, it is intuitive that they do not represent a single level; rather, they best represent a finite tropospheric layer of motion. Combine with this the large uncertainty noted above in assigning AMVs to discrete level heights. Therefore, we next examine the tropospheric layer motion that best correlates with the AMVs.
AMV–rawinsonde comparisons are plotted as VRMS differences for rawinsonde winds averaged over varying layer thickness categories (10–300 hPa, in 10-hPa increments, as described in section 2b), and are represented by the curves in Figs. 5–7. These analyses use AMVs from the adjusted height, with the corresponding single-level-based VRMS values plotted on the y-axis. In general, the results using originally assigned AMV heights (before postprocessing adjustments) are similar (not shown), except for the fact the y intercept starting points are higher VRMS values. The major findings are summarized as follows:

- The results presented in Figs. 5–7 consistently indicate that better AMV–rawinsonde agreement exists when a layer-averaged rawinsonde wind is considered versus just the single-level value at the assigned AMV height. The VRMS curve minima (best agreements) are on the order of 0.5–1 m s⁻¹ lower than the corresponding single-level values. These results indicate that AMVs (at least the current NOAA/NESDIS product) are better correlated with tropospheric layer-average winds, and the optimal layer depths can be specifically identified in terms of selected AMV qualities (Figs. 5–7). As mentioned previously, this result is likely a combination of AMV representativeness and height-assignment uncertainty.

- Upper-level (100–600 hPa) cloud-tracked AMVs generally correlate with a shallower layer (~30–60 hPa) than that from low-level tracers. Most of the upper-level
Tracers are cirrus clouds, which are often thin/shallow “sheets” advected by higher-wind environments. Thus, these AMVs correlate best with a shallower layer flow. TWP AMVs agree with a slightly deeper layer than those over SGP, which is likely related to differing shear characteristics, coupled with the tracking of thicker cirrus plumes associated with higher WV amounts over the tropics. The depth of the best-fit layer appears to be independent of the tracer height-assignment technique employed. The exception to the above generalizations is apparent in the NSA domain, where again the results are less clear. The characteristics of Arctic clouds, together with the extreme variability in flow regimes at higher latitudes, may be washing out definitive signals in this region.

- Lower-level (600–1000 hPa) AMVs over land (SGP) best correlate to a layer depth of ~70–100 hPa. Over marine regions (TWP), these vectors better correspond to a depth of ~150–200 hPa, although the curve minima are less defined. This general finding relates well with previous studies that showed that the wind at or near marine cumulus cloud base (rather than the cloud tops usually assumed as the AMV heights) best corresponds to the overall cloud motion (Hasler et al. 1979; Spinoso 1997). In high latitudes (NSA), the results are less conclusive but suggest a slight tendency toward a layer thickness similar to TWP. The results for lower-level AMVs are not as robust when compared with upper-level vector results, partially due to the effects of near-surface flow being included in the layer-mean calculations. Such flow can be vastly different than the flow just above the planetary boundary layer.

- Upper-level clear-sky WV AMVs over all three domains agree closest with a thicker layer (~150–250 hPa) than their cloud tracer counterparts. This is not...
unexpected, because the signal from advecting WV features in cloud-free regions results from emittance over a thicker layer, and tracers represent a broader layer-mean flow. As Rao et al. (2002) show, the precise depth of this layer is likely modulated by upper-tropospheric moisture content. It also is evident that the profiles are relatively flat near the level of minimum VRMS. In other words, the increase of error both above and below the minimum value is gradual rather than abrupt. This result confirms that the winds represent a broad layer rather than just a single level of the troposphere.

c. Effects of vertical wind shear

The uncertainty in AMV single-level height assignments is magnified in high-vertical-shear environments, because even small errors can result in large misrepresentations. The term “wind shear” here refers to the vector difference between two selected rawinsonde levels, for which we vary the depth between them. The most substantial impact will occur when there exists a high vertical shear over a relatively shallow depth (i.e., 50 hPa), usually found in upper-tropospheric levels.

Analyses of AMV–rawinsonde differences with respect to varying shear regimes are shown in Figs. 8–10. At SGP, for 15–20 m s\(^{-1}\) of shear over 50 hPa in both IR and WV, assignment to a shallow layer of \(\sim 30\) hPa in depth can improve the AMV–rawinsonde agreement by up to 2.5 m s\(^{-1}\) over single-level height assignment. At TWP, for a high shear within a low-depth situation, layer-mean assignment improves agreement by up to 2–4 m s\(^{-1}\). For the NSA region, layer-assigned AMVs also show significant improvement in high-shear situations for cloudy IR AMVs. In higher-shear situations, the rate of VRMS increases dramatically, confirming the importance of an accurate AMV height assignment in high-shear situations. These regimes appear to be the leading candidate for mitigating AMV height assignment uncertainties through layer approximations.

4. Discussion

The results found in this study strongly suggest that the uncertainty associated with height attribution is a very important contributor to AMV observation errors. Evaluation of level-based AMV height assignments indicates that significant improvements in AMV–rawinsonde vector agreements are achieved by reassignment to a collocated rawinsonde level of “best fit.” Because this is impractical in terms of operational applications, it is also shown that some of this height-assignment uncertainty can be overcome by treating the AMVs as representing finite tropospheric layers rather than single discrete levels as is currently done. Attribution of AMV information to a specified layer improves upon AMV–rawinsonde agreement by \(\sim 0.5–1\) m s\(^{-1}\) over traditional level-based assignment, with significantly greater improvement (\(\sim 2–4\) m s\(^{-1}\)) in strong-wind-shear regimes. The uncertainty is likely due to a combination of vector representativeness as a finite tropospheric layer rather than discrete level and current height-assignment-method inadequacies. The results of this study only directly apply to NESDIS operational AMVs, but they are likely applicable to other global data processing centers as well because of the similarities in AMV processing methods and quality statistics.

In terms of practical applications, the AMVs have traditionally not been optimally represented in numerical model analyses via single-level data assimilation. Data assimilation procedures create analyses of atmospheric

Fig. 10. As in Fig. 8, but for AMVs derived from MODIS over the NSA ARM site and only for IR.
fields by blending information from the model background with observations. An observation’s influence on the analysis is determined largely by the ratio of the assumed error of that observation with the assumed error of the model background at the observation location. Observations that are believed to be more accurate (e.g., smaller observation error) receive more weight than do less accurate observations. In most contemporary data assimilation systems, precise knowledge of the true AMV observation errors and their representativeness is unknown, resulting in a large fraction of AMV observations being used in a suboptimal manner. In addition, while the current more-sophisticated objective analysis systems (i.e., variational approaches) include vertical spread functions of various data inputs, for AMVs these are not well known or understood. Therefore, AMV data are typically constrained in the vertical direction and have less chance of making an impact on the initial analysis.

So how can these results be applied in numerical weather prediction? Data assimilation of AMV observations could benefit by utilizing height uncertainty information and ancillary information such as the optimal representative layer thickness relative to the original AMV assigned height. Future data assimilation studies should test a new AMV forward operator based on the results presented here. It is likely that the most significant impact potential will be realized from regions with high shear, which would be fortuitous, because these regimes are often associated with meteorological conditions that lead to rapid model forecast error growth.

Acknowledgments. The AMV datasets used in this study were postprocessed by Dave Stettner of CIMSS, and the special rawinsondes were provided through the courtesy of the ARM Program. Ralph Petersen of CIMSS helped in determining atmospheric wind variability parameters. Useful comments were provided by Ken Holmlund and Jo Schmetz of EUMETSAT and Mary Forsythe of the Met Office.

REFERENCES


