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On the importance of Vaisala RS92 radiosonde humidity corrections for a better agreement between measured and modeled satellite radiances

AJIL KOTTAYIL *

SRT-RY, Luleå University of Technology, Space Campus 1, SE-98128 Kiruna, Sweden

STEFAN. A. BUEHLER

SRT-RY, Luleå University of Technology, Space Campus 1, SE-98128 Kiruna, Sweden

VIJU. O. JOHN

Met Office Hadley Centre, Exeter, UK

LARRY M. MILOSHEVICH

Milo Scientific LLC, Lafayette, Colorado, USA

M. MILZ

SRT-RY, Luleå University of Technology, Space Campus 1, SE-98128 Kiruna, Sweden

G. HOLL

SRT-RY, Luleå University of Technology, Space Campus 1, SE-98128 Kiruna, Sweden

*Corresponding author address: Ajil Kottayil, Division of Space Technology, Department of Computer Science, Electrical and Space Engineering, Lule University of Technology, Box 812, SE-98128 Kiruna, Sweden

ABSTRACT

A study has been carried out to assess the importance of radiosonde corrections in improving the agreement between satellite and radiosonde measurements of upper tropospheric humidity. Infrared (HIRS_12) and microwave (AMSU_18) measurements from the NOAA-17 satellite were used for this purpose. The agreement was assessed by comparing the satellite measurements against simulated measurements using collocated radiosonde profiles of the Atmospheric Radiation Measurement program (ARM) undertaken at tropical and mid-latitude sites. The radiative transfer model ARTS was used to simulate the satellite radiances. The comparisons have been done under clear sky conditions, separately for daytime and nighttime soundings. Only Vaisala RS92 radiosonde sensors were used and an empirical correction (EC) was applied to the radiosonde measurements. The EC includes correction for mean calibration bias and for solar radiation error, and it removes radiosonde bias relative to three instruments of known accuracy. For the night time dataset, the EC significantly reduces the bias from 0.63 K to -0.10 K in AMSU_18 and from 1.26 K to 0.35 K in HIRS_12. The EC has an even greater impact on the daytime dataset with a bias reduction from 2.38 K to 0.28 K in AMSU_18 and from 2.51 K to 0.59 K in HIRS_12. The present study promises a more accurate approach in future radiosonde based studies in the upper troposphere.

1. Introduction

The vertical distribution of water vapour in the troposphere is quite inhomogeneous ranging from concentrations of few percent near the surface to only a few parts per million near the tropopause. Despite the fact that the upper tropospheric water vapour constitutes only a small fraction of the total water vapour, it still has a large effect on the outgoing longwave radiation (Kiehl and Briegleb 1992). Model studies suggest that nearly two thirds of the total radiative feedback from water vapour occurs in the upper troposphere (Held and Soden 2000). These studies confirm the need for an accurate monitoring of the upper tropospheric humidity (UTH) which is not very well simulated in current climate models (John and Soden 2007). One of the sources of UTH measurements is radiosonde data since the mid 20th century. These observations however, are limited mainly to land areas and are known to have data quality issues (Elliott and Gaffen 1991; Miloshevich et al. 2009; Soden and Lanzante 1996).

The satellite era has offered us the advantage of measuring UTH globally along with a wealth of other information to understand the earth's atmospheric system better. In the microwave and infrared spectral range, certain frequency ranges are dominated by water vapour emission from a broad range of pressure levels approximately between 200 and 500 hPa. These frequency ranges are suitable for deriving UTH. The typical frequencies used for this application are $6.7\text{ }\mu\text{m}$ for infrared and $183 \pm 1\text{ GHz}$ for microwave. The term UTH was first used by Soden and Bretherton in early 1990s, to describe relative humidity regressed from satellite observed brightness temperatures obtained by broadband infrared instruments. A similar approach was followed by Buehler and John (2005) to derive UTH from microwave measurements near the 183 GHz water vapour emission line.

Though there have been studies on both infrared and microwave measurements (Buehler et al. 2004; Soden and Lanzante 1996), none of the studies so far have looked into both instrument types simultaneously to judge their consistency. For this purpose, the satellite infrared and microwave measurements have been collocated with radiosonde profiles of

the Atmospheric Radiation Measurements (ARM) program undertaken at mid-latitude and tropical locations. The comparisons were performed in radiance space by simulating the infrared and microwave channel radiance from the radiosonde data using the radiative transfer model, ARTS (Atmospheric Radiative Transfer Simulator) (Eriksson et al. 2011).

The relative humidity (RH) measurements from Vaisala radiosondes are known to have a dry bias in the upper troposphere (Vömel et al. 2007b; Moradi et al. 2010). Recently, Miloshevich et al. (2009) have implemented an empirical correction procedure to remove the mean bias error in RS92 radiosonde sensors by characterizing their accuracy relative to three reference instruments of known accuracy. We have applied this correction to the RS92 radiosonde profiles. The correction is applied for mean calibration bias as a function of RH and temperature. A correction for solar radiation error caused due to solar heating of the RH sensor is also applied for daytime soundings. In addition, a non-bias correction for sensor time lag error caused by slow response at low temperature is also examined. The time lag correction recovers vertical structure in the RH profile that was "smoothed" by slow sensor response (Miloshevich et al. 2004). Although the time lag correction is not directly a bias correction, it may remove some parts of a bias, in particular in regions with strong gradients. An important objective of this study is to assess whether the various corrections improves the agreement between radiosonde and satellite data in both infrared and microwave band.

The paper is structured as follows.: Section 2 focuses on the details of measurements and the models and methods used. Section 3 presents results and discussions on the impact of radiosonde correction procedure in satellite–radiosonde comparison. Finally, Section 4 presents the summary and conclusions.

2. Measurements, Models and Methods Used

a. Satellite Data

The NOAA-17 (National Oceanic and Atmospheric Administration) satellite carries the Advanced Microwave Sounding Unit (AMSU) and the High Resolution Infrared Sounder (HIRS)/3. AMSU consists of AMSU-A and AMSU-B sensors with a total of 20 channels. The primary function of the 15-channel AMSU-A (channels 1–15) is to provide temperature sounding of the atmosphere. The five channels of AMSU-B (channels 16–20) mainly measure water vapour and liquid precipitation over land and sea. Three channels (18–20) are situated around the strong water vapour spectral line at 183.31 GHz with different offsets from the line center. AMSU-B is a cross track, continuous line scanning, total power radiometer with an instantaneous field of view of 1.18° (at the half-power points), equivalent to a nominal spatial resolution of 16 km at nadir. The antenna provides a cross-track scan, scanning $\pm 49.5^\circ$ from nadir with a total of 90 earth fields of view per scan line.

HIRS/3 on-board NOAA-17 is a 20 channel instrument with an instantaneous field of view of 1.38° providing a nominal spatial resolution of 18.9 km at nadir. The antenna provides a cross-track stepped scan covering $\pm 49.58^\circ$ from nadir with a total of 56 fields of view per scan. The spectral characteristics of the HIRS/3 channels are available at <http://www.ncdc.noaa.gov/oa/pod-guide/ncdc/docs/klm/index.htm>. The spectral characteristics differ between different satellites. Hereafter, the two channels used in inferring UTH measurements viz., HIRS Channel 12 and AMSU Channel 18 will be referred to as HIRS_12 ($6.7 \mu\text{m}$) and AMSU_18 ($183 \pm 1 \text{ GHz}$) (Soden and Bretherton 1993; Buehler and John 2005; Buehler et al. 2008). We have used measurements of HIRS_12 and AMSU_18 for the period 2005–2008 on NOAA-17.

100 The ARM programme operated by the United States Department of Energy launches
 101 radiosondes from several dedicated sites. We have used radiosonde data from 2005–2008 of
 102 two stations: one in the Southern Great Plains (SGP) at 36.61°N, 97.49°W in the USA, and
 103 one in the tropical western Pacific, located at 12.42°S, 130.88°E near Darwin, on the north-
 104 western coast of Australia. We have taken day and nighttime radiosonde data measured
 105 using Vaisala RS92 sensors. The number of profiles used for nighttime analysis is 624 out of
 106 which 457 belongs to SGP and 167 belongs to Darwin. All the 419 profiles used for daytime
 107 analysis belong to SGP. The profiles used to study the impact of the time lag correction also
 108 belong to SGP.

109 The accuracy of radiosonde RH measurements in the upper troposphere is known to be
 110 poor. A number of studies have shown that RS92 radiosonde sensors exhibit a dry bias in
 111 the upper troposphere (Vömel et al. 2007b; Moradi et al. 2010). Miloshevich et al. (2009)
 112 have characterized the accuracy of RS92 RH sensors relative to three water vapor reference
 113 instruments of known accuracy. The reference instruments are a cryogenic frostpoint hy-
 114 grometer (CFH; Vömel et al. (2007a)), which quantifies the accuracy of RS92 above 700
 115 mb, a microwave radiometer that mainly senses water vapor in the lower troposphere, and
 116 a system of 6 calibrated RH probes at the surface. The RS92 mean calibration bias was
 117 determined by comparing RS92 measurements with simultaneous measurements from these
 118 instruments, and an empirical correction (EC) procedure was described that removes the
 119 RS92 mean bias as a function of RH and pressure:

$$\text{RH}_{\text{corr}} = G(P, \text{RH}) \times \text{RH} \quad (1)$$

120 where $G(P, \text{RH})$ is the correction factor. The correction factor is determined from pressure-
 121 dependent curve fits for several RH intervals (Figure 9 in Miloshevich et al. (2009)), with
 122 different curve fits for nighttime and daytime soundings. The bias error that is corrected
 123 for nighttime soundings is the mean sensor calibration bias. The daytime soundings, are

124 additionally affected by an error caused by solar heating of the RH sensor. Therefore, in
125 addition to the mean sensor calibration bias correction, the daytime soundings also require
126 a correction to remove the bias due to the so called solar radiation error (SRE). Hence the
127 bias and the correction for daytime soundings would be higher than the nighttime soundings.
128 In presence of clouds the daytime corrections could in fact overcorrect the radiation bias.
129 However this is not a factor in this study because only clear conditions were used. We have
130 applied these corrections on RS92 radiosonde data and quantified their effect by comparing
131 the corrected data to satellite measurements.

132 This study uses a modified version of the published correction for mean calibration bias
133 that improves the accuracy for very dry conditions, and extends the upper limit of validity of
134 the correction to encompass the tropical UT/LS (Upper troposphere/Lower stratosphere).
135 The primary difference is that the correction was converted from a function of pressure to
136 a function of temperature based on the mean $T(P)$ relationship for the soundings used to
137 derive the correction. A temperature dependence is more consistent with the actual sensor
138 calibration, and generalizes the correction to atmospheric profiles substantially different from
139 the mid-latitude soundings used to derive the correction. Further details of the modified
140 correction for mean calibration bias, and associated IDL code, can be found at [http://](http://milo-scientific.com/prof/radiosonde.php)
141 milo-scientific.com/prof/radiosonde.php.

142 The correction procedure described by Miloshevich et al. (2009) also includes a correc-
143 tion for sensor time-lag error that causes "smoothing" of the measured RH profile due to
144 slow sensor response at low temperatures. To see whether the time-lag correction has a sig-
145 nificant role in reducing the brightness temperature bias, a subset of RS92 profiles were also
146 corrected for time-lag error as described by Miloshevich et al. (2004). A subset of soundings
147 is used because older ARM data (and most operational RS92 data) have integer RH values,
148 which results in a less accurate time-lag correction because much of the detailed information
149 important for a time-lag correction is lost due to "rounding off" of the data. For this and
150 other reasons, it is recommended that users of the Vaisala Digicora III data system output

the higher-resolution RH data in so-called FLEDT files rather than the integer RH values in standard EDT data files.

It should be noted here that in December 2010, Vaisala updated their data processing algorithm to include time-lag and solar radiation corrections that differ from those of Miloshevich et al. (2009), but this does not include the correction for mean calibration bias used in this study. This change affects only new Digicora III data systems or older systems updated with software version 3.64, and the effect on soundings is described in Vaisala's "RS92 Data Continuity" webpage.

c. Radiative Transfer Model

The Atmospheric Radiative Transfer Simulator (ARTS) is a line by line radiative transfer model which simulates radiances from the infrared to the microwave spectral range (Buehler et al. 2005; Eriksson et al. 2011). The model uses pre-calculated absorption data to speed up the calculation, as described in Eriksson et al. (2011).

The code is flexible from the user point of view and is freely available along with comprehensive documentation (<http://www.sat.ltu.se/arts/>). The ARTS model has been validated against other models and satellite measurements (John and Buehler 2005; Melsheimer et al. 2005; Saunders et al. 2007). The model has been used for a wide range of atmospheric studies including applications from the infrared to the microwave wavelength range (Deuber et al. 2005; Fiorucci et al. 2008; Eriksson et al. 2003).

Buehler et al. (2010) recently implemented a fast setup to reduce the computational cost of the broadband radiance simulations of HIRS channels through representative frequency selection by simulated annealing. The computational cost has been reduced significantly while keeping the accuracy of the radiance calculations the same as conventional line by line calculations. They have shown that the HIRS channel radiances on NOAA-14 can be simulated with only 133 frequencies. For comparison, a full line-by-line calculation would require 72717 frequencies. The accuracy of this method is of the order of 0.03 K. This

modified setup has been used for the present study.

Different continuum models have to be used for the infrared and the microwave spectral range. The absorption model setups for the two different spectral ranges are as follows. In the microwave, we have used PWR98 (Rosenkranz 1998) for H₂O lines and continuum and PWR93 (Rosenkranz 1993) for N₂ and O₂ lines and their respective continuum. Furthermore, line data of O₃ was taken from HITRAN 2004 (Rothman et al. 2003). In the infrared, line data were taken from HITRAN 2004 while the continua of H₂O, CH₄, N₂, O₂ and CO₂ were taken from MT_CKD_1.0 (Mlawer et al. 2003). A model inter-comparison study between ARTS and the Line-Line Radiative Transfer model (LBLRTM), an established reference model for the infrared spectral range was carried out for HIRS_12 on NOAA satellites 14, 15, 16 and 17. The model comparison approach is described in Appendix A. The two radiative transfer (RT) models were found to agree within a brightness temperature difference of 0.22 K. ARTS includes various algorithms to simulate the influence of clouds (Davis et al. 2005; Emde et al. 2004). However, for the present study only clear sky simulations were performed.

d. Collocations and Cloud Detection Approach

The collocations between NOAA-17 measurements and ARM radiosondes are based on spatial and temporal constraints. The spatial constraint is implemented by a target area of radius 50 km around the radiosonde location as in Buehler et al. (2004). This approximately takes into account the drift of the radiosonde as it ascends through the atmosphere. The number of collocated pixels in a target area varies from 2–8 for HIRS_12 and from 10–30 for AMSU_18 respectively. The time constraint imposed on the collocated dataset is ± 2 hours. This should accommodate the time taken for the radiosonde to reach the satellite measuring altitude peak (300 hPa) which is approximately 25 minutes. Hence, the radiosonde time in the collocated dataset is the sum of the radiosonde launch time and 25 minutes. Radiances are simulated from radiosonde profiles using ARTS to match with the satellite viewing geometry.

A meaningful comparison between satellite measurements and clear sky RT model simulations is possible only if the measurements are free of cloud contamination. Therefore we use the cloud detection tests developed by McMillin and Dean (1982) to filter out contaminated HIRS pixels from our analysis. Details of this procedure are as follows.

Each pixel from satellite measurements is subjected to the following cloud detection tests. The first two tests are based on the long-wave window channel ($11 \mu\text{m}$) brightness temperature and is applicable to all the measurements.

i. A pixel is classified as cloudy if its window channel brightness temperature is too cold ($< 210 \text{ K}$).

ii. A pixel is classified as cloudy, if the long-wave window channel brightness temperature is 4 K cooler than that of the warmest pixel from the target area.

iii. If any one of the followings conditions fail for night time measurements, then the pixel is classified as cloudy.

$$-4.0 \text{ K} \leq \text{TB}(18) - \text{TB}(8) \leq 2.0 \text{ K}$$

$$-4.0 \text{ K} \leq \text{TB}(19) - \text{TB}(18) \leq 2.0 \text{ K}$$

iv. During the day a pixel is clear if

$$|\text{TB}(18) - \text{TB}(8)| < 10 \text{ K}$$

where $\text{TB}(i)$ is the brightness temperature for a given HIRS channel i . If there is more than one clear pixel in the target area, the average over all the clear pixels are used otherwise it is classified as cloudy. This very stringent clear scene requirement condition satisfies 25 to 100 % of the target area for HIRS depending on the cloud cover. We assume that the AMSU_18 pixels coincident to the clear HIRS_12 pixels are not cloud contaminated. This could even result in the removal of the AMSU_18 pixel which are unaffected by clouds due to the much higher sensitivity of HIRS measurements to thin clouds.

e. Relation between UTH and Brightness temperature

The relationship between UTH and brightness temperature T_b is given by,

$$\ln(\text{UTH}) = a + b \times T_b \quad (2)$$

where a and b can be determined by linear regression. The derivative yields

$$\frac{\Delta \text{UTH}}{\text{UTH}} = b \times \Delta T \quad (3)$$

In other words, absolute changes in brightness temperature map to relative changes in UTH. To ensure complete consistency here, we have re-determined the parameters $b_{\text{HIRS}_{12}}$ and $b_{\text{AMSU}_{18}}$ using linear regression on the simulated measurements for the Chevallier et al. (2006) data set. The values obtained for $b_{\text{HIRS}_{12}}$ and $b_{\text{AMSU}_{18}}$ are 0.110 and 0.070 for the nadir viewing direction. For the extreme off-nadir viewing direction the $b_{\text{HIRS}_{12}}$ and $b_{\text{AMSU}_{18}}$ values are 0.118 and 0.076. These values are in good agreement with Soden and Bretherton (1993) and Buehler and John (2005). The regression coefficients a and b for different viewing angles of HIRS_12 are summarised in Table 1.

f. Ozone Impact on AMSU_18 Radiances

The impact of ozone lines on AMSU-B radiances was investigated by John and Buehler (2004). They found that the ozone impact is largest for AMSU_18. This can reduce its brightness temperature, with a reduction that can reach a maximum of 0.5 K. It was also reported that zonal, monthly mean climatological values of ozone profiles are sufficient to account for the ozone impact on AMSU_18 radiances. With the above work as a base, temperature and humidity profiles from ARM radiosondes were taken up to 100 hPa and the rest of the pressure levels up to 0.2 hPa were filled in with climatological ozone and temperature profiles, for AMSU_18 simulations. A water vapor concentration of 5 ppmv was assumed above 100 hPa. It is to be noted that the temperature and humidity profiles above

100 hPa have negligible impact on AMSU_18 radiance. So, it is the presence of ozone that contributes to the impact. Climatological ozone and temperature profiles from Total Ozone Mapping Spectrometer (TOMS v8) which are given for each 10 degree latitude bin and month were used to fill in the radiosondes above 100 hPa. In the case of the HIRS_12 simulations, we have restricted the temperature and humidity profiles from ARM radiosondes to 90 hPa as the profiles above this level have negligible impact on HIRS_12 radiances. Ozone has no influence on HIRS_12 simulations.

3. Results and Discussion

The radiosonde-satellite comparison results in terms of bias for AMSU_18 and HIRS_12 are discussed in this section. The results of daytime and nighttime comparisons are presented separately. The bias is calculated as the mean of the difference between the simulated and measured brightness temperature, so a positive bias means that the radiosonde measurements are dry and vice versa. The same convention is followed throughout the discussion that follows.

The bias value can be used to determine the relative difference in the UTH measurements between satellite and radiosonde. Applying the transformation coefficients (b_{HIRS_12} (0.114) and b_{AMSU_18} (0.073)) in equation 3, it can be inferred that a 1 K bias in AMSU_18 corresponds to a relative error of 7% in UTH where as for HIRS_12, it corresponds to a relative difference of 11%. Even though both AMSU_18 and HIRS_12 measure UTH, their sensitivity lies at slightly different altitudes. As shown in Figure 1, the peak of HIRS_12 sensitivity lies approximately 2 km higher in altitude than for AMSU_18. These differences in sensing height will lead to a bias rather than a random error. Knowing the fact that radiosonde bias is altitude dependent (Miloshevich et al. 2009), the bias for HIRS_12 and AMSU_18 could be different as the sounding altitudes of the two instruments are not the same.

As a separate study to show the impact of ozone in AMSU_18 simulations, we have

calculated the bias with and without the inclusion of ozone. The nighttime uncorrected radiosonde datasets were alone chosen for this study. The results reveal that the inclusion of ozone improved the bias to 0.63 K from a bias of 0.99 K. Obviously, here the inclusion of ozone reduces the AMSU_18 brightness temperature by 0.35 K. This is a clear confirmation that inclusion of ozone leads to a better agreement between satellite and radiosonde measured UTH as argued by John and Buehler (2004).

The nighttime comparison results for AMSU_18 and HIRS_12 are summarised in Table 2. Also Figure 2 shows a scatter plot of simulated versus observed brightness temperatures for AMSU_18 and HIRS_12 before and after correction. The empirical correction reduces the bias from 0.63 to -0.1 K for AMSU_18 and from 1.26 K to 0.35 K for HIRS_12. The reduction in the bias is higher for HIRS_12 (0.91 K) in comparison to AMSU_18 (0.73 K). The results of daytime analysis are presented in Table 3. In contrast to the night time biases, the daytime biases in the uncorrected datasets are much higher (2.38 K in AMSU_18 and 2.51 K in HIRS_12). As a result, the empirical correction on daytime datasets has a profound influence in reducing the bias in AMSU_18 and HIRS_12. Accordingly, the bias reduction is of the order of 2.1 K for AMSU_18 and 1.92 K for HIRS_12. This clearly is an indication that the corrections are especially required for all daytime radiosonde observations which are subject to solar radiation error. Recall that in addition to the mean bias correction as applied in nighttime dataset, the daytime correction also includes a correction for solar radiation error which is most significant here.

The bias as a function of brightness temperature binned at 5 K intervals for day and nighttime dataset is shown in Figure 3 . The reduction in bias due to correction is evident in all brightness temperature ranges which represent varying humidity conditions in the upper troposphere from wet (low brightness temperature) to dry (high brightness temperature). The impact of empirical correction on the radiosonde profiles themselves can be inferred from Figure 4, showing the mean RH of all the profiles before and after correction. The magnitude of correction is much higher for the daytime data as compared to nighttime. It is the solar

radiation correction rather than the mean calibration bias correction which accounts for this large difference in the daytime dataset. The bias correction for SRE accounts for more than 50% of the bias reduction in the daytime dataset. It is also worthwhile to mention that the magnitude of the correction is dependent on different humidity conditions in the upper troposphere and is higher under drier conditions for the nighttime dataset while in the daytime dataset it is higher under moist conditions with the exception of some parts of the upper troposphere (Figure 5). These results highlight the importance of corrected radiosonde profiles for satellite validation. In addition, the results also reveal that the empirical correction is quite effective in reducing the dry bias of radiosondes in the upper troposphere and leads to a better agreement between HIRS_12 and AMSU_18.

As mentioned earlier, we have used a different algorithm than the published algorithm for mean calibration bias correction. In the night time dataset, the correction with the new algorithm results in a bias of 0.35 K in HIRS_12 whereas with the published algorithm it is 0.38 K, but for AMSU_18 these values are -0.07 K and -0.10 K respectively. For the daytime dataset, correction with the new algorithm yields a bias of 1.71 K in HIRS_12 and a bias of 1.75 K with the published algorithm, while in AMSU_18 these values are 1.76 K and 1.78 K respectively. Though these differences are small the use of the new algorithm is recommended for mean calibration correction since the temperature dependence is more consistent with actual sensor calibration than the pressure dependence as used in the published algorithm.

The impact of the time lag (TL) correction is shown in Table 4. This result reveals that the TL correction has a negligible impact in reducing the bias in AMSU_18 and HIRS_12 because the bias reduction is of the order of only 0.03 K. Since TL correction needs profiles of higher resolution, it is applied here only to a subset of RS92 profiles. A noteworthy observation is that the bias reduction in AMSU_18 and HIRS_12 due to empirical correction on this subset is the same as that for all the RS92 profiles (not shown).

Though the agreement between HIRS_12 and AMSU_18 has been improved due to correction, a small discrepancy of the order of 0.45 K for nighttime and 0.31 K for daytime

data still remains. One of the major reasons for the discrepancy can be attributed to the uncertainty in the corrected RS92 measurements. Miloshevich et al. (2009) have shown that the bias uncertainty is $\pm(4\% + 0.5\% \text{ RH})$, which implies 4% of the measured value plus a 0.5 %RH offset component that is increasingly important for drier conditions. For example, the relative uncertainty in the corrected RS92 data is $\pm 5\%$ for conditions of 50 %RH, $\pm 6.5\%$ at 20 %RH, $\pm 9\%$ at 10 %RH, and $\pm 20\%$ at 3 %RH. Therefore, there could be a larger uncertainty in the correction occurring at the HIRS_12 sensing altitude than at the AMSU_18 sensing altitude as it senses a drier atmosphere. A part of the difference could also be attributed to error in the radiative transfer modeling. However, based on the comparison to LBLRTM described in Appendix A, we expect this error to be smaller than 0.3 K. Systematic error in the satellite measurements which is of the order of 0.5 K in AMSU_18 and HIRS_12 on NOAA-17 could also play a role (Shi and Bates 2011; John et al. submitted 2011). It is difficult to attribute the remaining discrepancy between AMSU_18 and HIRS_12 to any single cause as it is a very small bias. Therefore, it is only fair to say that the radiosonde, radiative transfer modelling and systematic error in AMSU/HIRS measurements are equally plausible contributors to the bias.

Coming back to the subject of radiosonde correction, one can state that in addition to significantly reducing the bias between satellite and radiosonde measurements, empirical correction also brings forth a better agreement between AMSU_18 and HIRS_12. The discrepancy in the apparent radiosonde bias between HIRS_12 and AMSU_18 before correction in nighttime dataset was around 10% and it was lowered to approximately 5% after correction. Similarly, the discrepancy in the uncorrected daytime dataset was 12% which reduces to 4.7% after correction. These results show that the radiosonde correction is very important in bringing about a better agreement between satellite and radiosonde measurements of UTH.

There have been a number of earlier correction methods for improving the accuracy of RS80 radiosonde sensors (Turner et al. 2003; Miloshevich et al. 2001). However, Soden et al.

(2004) showed that these correction procedures offer only a small improvement in the upper troposphere, though they are effective in the lower troposphere. In contrast to this, our work for the RS92 sensors and Miloshevich et al. (2009) correction method, shows a significant improvement, particularly, in the upper troposphere. The present study therefore may open up the possibility of applying a similar correction approach to other radiosonde sensors.

4. Summary and Conclusions

The present study evaluates the importance of radiosonde correction in improving the agreement between satellite and radiosonde measured UTH. The satellite measurements from infrared (HIRS_12) and microwave (AMSU_18) instruments were used for this purpose. The satellite measurements were collocated with ARM radiosonde profiles. The satellite-radiosonde comparison was performed by simulating the radiances from collocated radiosonde profiles using the radiative transfer model ARTS. The comparisons were performed only for clear sky conditions. The empirical correction procedure applied to RS92 radiosonde sensors was found to have a significant impact in reducing the bias in AMSU_18 and HIRS_12. The nighttime bias in AMSU_18 (from 0.63 K to -0.10 K) was reduced by 0.73 K and by 0.91 K in HIRS_12 (from 1.26 K to 0.35 K). During daytime, the decrease in bias is significantly higher with a reduction of 2.1 K (from 2.38 K to 0.28 K) in AMSU_18 and 1.92 K (from 2.51 K to 0.59 K) in HIRS_12. This is on account of the bias removal associated with the solar radiation error. The correction also improved the consistency between AMSU_18 and HIRS_12 and reduced the difference between them by 5% in nighttime and by 7% in daytime datasets.

Besides showing the importance of radiosonde correction for satellite validation, this study also cautions against the use of uncorrected radiosonde profiles for various water vapour related studies in the upper troposphere. The need for such corrections is especially due to the imperfect characterization and calibration of the sensor output by the manufacturer. The

occurrence of a similar or worse type of imperfection as addressed here for Vaisala radiosondes cannot be ruled out for many other operational radiosondes. In any case, accuracy is one aspect that cannot be ignored or compromised in climate related studies. The correction method developed by Miloshevich et al. (2009) and implemented in this study is an example as to how these errors can be reduced to a significant extent.

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Model-Inter Comparison

This is a comparison of results from the ARTS and LBLRTM forward radiance models. LBLRTM is a line by line radiative transfer model (Clough et al. 2005). It has been validated against atmospheric radiance spectra from the ultraviolet to the sub-millimeter wavelength range (Turner et al. 2004). In this study infrared radiances were simulated using LBLRTM version 11.6 which uses the modified water vapour continuum model MT_CKD.2.4. We verified that continuum changes are negligible in the frequency range where HIRS_12 is located, since ARTS uses MT_CKD.1.0 as the continuum model. The line parameters are the same as for ARTS (HITRAN 2004).

Model inter-comparisons were performed for the HIRS water vapour channel (HIRS_12) of NOAA satellites 14, 15, 16 and 17. The simulations were based on a subset of the diverse set of atmospheric profiles from European Centre for Medium-Range Weather Forecasts (ECMWF) re-analysis data (Chevallier et al. 2006). The number of used profiles is 4700.

Each channel in HIRS has an individual sensor response function (SRF), specifying the weight as a function of frequency within the spectral range of the channel. The H₂O zenith opacity and the SRF for HIRS_12 is shown in Figure 6. In the normal line by line calculation mode, ARTS simulates the radiances within the pass band of the sensor with a high spectral resolution. These radiances are convolved with the SRF to obtain the radiance of the HIRS channel. For n frequency grid points within the passband of the j_{th} HIRS channel, the convolved radiance $R(j)$ is given by

$$R(j) = \frac{\sum_{i=1}^n w_i r_i}{\sum_{i=1}^n w_i} \quad (\text{A1})$$

where r_i is the radiance for the i_{th} frequency grid point and w_i is the associated weight. The weights for the high resolution frequency grids are obtained through interpolation from

the sensor specified weights defined for the frequencies within the SRF. However, the fast set up for HIRS in ARTS uses only a few frequencies to simulate the entire HIRS channel radiance. These representative frequencies are selected using a simulated annealing method (Buehler et al. 2010). In the fast setup for HIRS simulations, the weights for $R(j)$ are derived using multiple linear regression over a set of line by line calculations using an ensemble of atmospheric conditions.

LBLRTM generates monochromatic infrared radiances with high spectral resolution for a user specified frequency range. It has no built-in option to consider the SRF or other instrumental properties. Thus to allow comparison with ARTS, the HIRS channel radiances have been generated by convolving the high resolution spectra with the respective SRF. The Planck function is used for the conversion of convolved radiance to brightness temperature. During the conversions, care was taken to ensure that the transformations were applied to both the models in the same manner. Simulations were performed assuming clear sky conditions and nadir viewing geometry with a surface emissivity of 1. The statistics of comparison for different NOAA satellites sensors are summarised in Table 5.

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TABLE 1. The regression coefficients a and b used to derive UTH from HIRS_12 for its different viewing angles. The UTH is defined with respect to liquid water. The angle θ is in degrees, a is dimensionless, and b is in K^{-1} .

θ	a	b
0.900	29.554	-0.110
2.700	29.556	-0.110
4.500	29.560	-0.110
6.300	29.566	-0.110
8.100	29.574	-0.110
9.900	29.584	-0.110
11.700	29.596	-0.110
13.500	29.610	-0.110
15.300	29.626	-0.111
17.100	29.645	-0.111
18.900	29.667	-0.111
20.700	29.691	-0.111
22.500	29.718	-0.111
24.300	29.748	-0.111
26.100	29.781	-0.112
27.900	29.818	-0.112
29.700	29.859	-0.112
31.500	29.904	-0.112
33.300	29.955	-0.113
35.100	30.011	-0.113
36.900	30.073	-0.113
38.700	30.143	-0.114
40.500	30.222	-0.114
42.300	30.311	-0.115
44.100	30.412	-0.116
45.900	30.529	-0.116
47.700	30.666	-0.117
49.500	30.828	-0.118

TABLE 2. Statistics comparing satellite radiance and simulated radiance in brightness temperature units for the nighttime dataset. The bias is defined as the mean of simulated minus measured data. SD refers to the standard deviation. The number of profiles used is 624. Suffix *bc* and *ac* refers to before and after empirical correction.

Channel	Bias (K)	Bias in UTH (%)	SD (K)	SD UTH (%)
AMSU_18 _{bc}	0.63	-4.5	1.66	11.62
AMSU_18 _{ac}	-0.10	0.7	1.68	11.76
HIRS_12 _{bc}	1.26	-14.3	1.40	16
HIRS_12 _{ac}	0.35	-3.9	1.42	16.18

TABLE 3. Statistics comparing satellite radiance and simulated radiance in brightness temperature units for the daytime dataset. The bias is defined as the mean of simulated minus measured data. SD refers to the standard deviation. The number of profiles used is 419. Suffix *bc* and *ac* refers to before and after empirical correction.

Channel	Bias (K)	Bias in UTH (%)	SD (K)	SD UTH (%)
AMSU_18 _{bc}	2.38	-16.6	1.31	9.17
AMSU_18 _{ac}	0.28	-1.96	1.39	9.73
HIRS_12 _{bc}	2.51	-28.61	1.19	13.57
HIRS_12 _{ac}	0.59	- 6.73	1.27	14.48

TABLE 4. Statistics comparing satellite radiance and simulated radiance in brightness temperature units for RS92 sensors. The bias is defined as the mean of simulated minus measured data. SD refers to the standard deviation. The number of profiles used is 85. Suffix *btl* and *atl* refers to before and after time lag correction.

Channel	Bias (K)	Bias in UTH (%)	SD (K)	SD UTH (%)
AMSU_18 _{btl}	0.14	-0.9	1.52	10.64
AMSU_18 _{atl}	0.17	-1.2	1.51	10.57
HIRS_12 _{btl}	0.94	-10.7	1.21	13.80
HIRS_12 _{atl}	0.91	-10.4	1.19	13.56

TABLE 5. Statistics comparing ARTS and LBLRTM simulations. The bias is defined as the mean of the difference ARTS minus LBLRTM. SD refers to the standard deviation.

Satellite	Channel	Bias (K)	SD (K)
NOAA-14	HIRS_12	-0.07	0.15
NOAA-15	HIRS_12	-0.21	0.23
NOAA-16	HIRS_12	-0.17	0.22
NOAA-17	HIRS_12	-0.21	0.22

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FIG. 1. Jacobian of AMSU_18 and HIRS_12 UTH channels for the standard tropical atmosphere (Garand et al. 2001) with a nadir viewing geometry. Jacobian values are divided by their sum.

FIG. 2. Scatter plots of simulated versus observed brightness temperature for AMSU_18 and HIRS_12 before (upper panels) and after empirical correction (lower panels, corrected RS92) for the nighttime data. The black and red lines are diagonal and regression lines respectively. The number of datapoints is 624 for each plot.

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FIG. 4. Left: The mean RH of RS92 radiosonde sensors before (black) and after Empirical correction. Right: The thick line represents mean of the percentage difference between the corrected and the original profiles. The horizontal bars represent the standard deviation. For the figure RH profiles from ARM radiosondes before and after the corrections were interpolated to specific pressure levels (53) ranging from 980 to 100 hPa. The Percentage difference is defined as $\left(\frac{\text{corrected}-\text{original}}{\text{original}}\right) \times 100\%$. Upper panels are for nighttime data, lower panels are for daytime data.

FIG. 5. The percentage difference between the corrected and original profiles classified in terms of different humidity conditions in the upper troposphere (dry, moist and moderate). Classification is based on the percentiles of the observed brightness temperature in HIRS_12 such that values ≥ 75 percentile are considered as dry, ≤ 25 percentile moist and values ranging between these as moderate. Left plot is for nighttime data and the right plot is for daytime data.

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