The Effect of Hydrometeors on MSU/AMSU Temperature Observations over the Tropical Ocean

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ABSTRACT

The temperature of Earth's atmosphere has been monitored continuously since late 1978 by the Microwave Sounding Unit (MSU) and the Advanced Microwave Sounding Unit (AMSU) flown on polar-orbiting weather satellites. It is well known that these measurements are affected by the scattering and emission from hydrometeors, including cloud water, precipitation, and ice particles. In this study the hydrometeor effects on MSU/AMSU temperature observations are investigated by comparing satellite-observed temperature of the middle troposphere (TMT) with synthetic TMT constructed using temperature fields from ECMWF Interim [ERA-Interim (ERA-I)]. Precipitation data have been used to estimate how much of the difference between these two TMT fields is due to hydrometeor contamination effects. It is shown that there exists a robust linear proportionality between TMT deficit (i.e., the measured TMT minus the synthetic TMT) and precipitation at individual grid points in monthly mean fields. The linear correlation is even stronger in the annual mean and seasonally varying climatology and also in the spatial pattern of ENSO-related anomalies. The linear regression coefficient obtained in all of these analyses is virtually identical: $-0.042 \text{ K (mm day}^{-1})^{-1}$. The channel that senses lower-tropospheric temperature (TLT) is more sensitive to precipitation than the TMT channel: the regression coefficient is $-0.059 \text{ K (mm day}^{-1})^{-1}$. It is shown that correcting the TMT or TLT monthly anomalies by removing the hydrometeor contamination does not significantly influence estimates of tropical mean temperature trends, but it could affect the pattern of temperature trend over the tropical oceans.

1. Introduction

Measurements made by the Microwave Sounding Unit (MSU) and the Advanced Microwave Sounding Unit (AMSU) flown on the polar-orbiting weather satellites provide a record of global atmospheric temperature from late 1978 onward. Each of the MSU/AMSU channels provides measurements of a vertically weighted average of microwave radiation emitted from a deep atmospheric layer. The respective vertical weighting functions describe the relative contribution of the radiation emitted by different atmospheric layers to the total radiance

measured by the satellite (e.g., Fu et al. 2004; Fu and Johanson 2005). Hence, the measured microwave radiation is most sensitive to the temperature at the altitude where the weighting function reaches its maximum value. This altitude ranges from the lower troposphere to the lower stratosphere in different channels. The up-to-date homogenized datasets for the MSU/AMSU channels from various teams include the lower- and middle-tropospheric temperatures (TLT and TMT, respectively) and the lower-stratospheric temperature (TLS) (e.g., Christy et al. 2003; Mears et al. 2003; Zou et al. 2006; Po-Chedley et al. 2015; Mears and Wentz 2016; Spencer et al. 2017).

Microwave sounders are designed to measure the thermal emission by molecular oxygen in the atmosphere at various frequencies near a complex of oxygen absorption lines around 60 GHz. The spatial uniformity of oxygen concentration in Earth's atmosphere makes it an ideal tracer for remote sensing of atmospheric temperature. However, one of the concerns in using MSU/AMSU temperature products is the presence of signals in the measurements other than thermal emission by

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molecular oxygen. These include emission and scattering by cloud water, precipitation, large ice particles, and surface emissivity (Spencer et al. 1990). Based on an examination of MSU channel-2 (i.e., TMT) measurements, Spencer et al. (1990) concluded that precipitation-sized ice particles in deep moist convection can depress the brightness temperature by as much as several kelvins. To remove ice particle contamination, which occurs in only a small percentage of the total number of observations, they filtered the MSU data by screening out the pixels in regions of deep convection (Spencer et al. 1990).

Prabhakara et al. (1995, 1996) used the tropical oceanic MSU channel-1 data to estimate the hydrometeor effects on MSU channel-2. They concluded that there is a significant residual contamination in the temperature time series produced by Spencer et al. (1990) from MSU channel-2 that could potentially influence the long-term trend, because the concentration of hydrometeors varies with time. This conclusion was challenged by Spencer et al. (1996), who used a combination of theoretical arguments, MSU data, and radiosonde measurements to show that the analysis by Prabhakara et al. (1995, 1996) greatly exaggerates the residual hydrometeor contamination effects.

Weng et al. (2014) recently assessed the effects of the emission and scattering by clouds and precipitation on AMSU-A brightness temperature, using the information from AMSU-A window channels. They concluded that the global mean temperature trends in the lower and middle troposphere for 1998–2010 become $\sim 20\%$ – 30% higher when cloud-affected brightness temperature measurements are removed from the AMSU data.

The significance of hydrometeor contamination in satellite-observed temperatures and the corresponding long-term tropospheric trend is still under debate. In this paper we investigate the impact of cloud water, precipitation, and ice particles on MSU/AMSU TMT and TLT observations by comparing them with the synthetic TMT and TLT based on the temperature data from the European Centre for Medium-Range Forecasts interim reanalysis [ERA-Interim (ERA-I)] (Dee et al. 2011). We will show the *temperature deficit* fields (observed TMT and TLT minus synthetic TMT and TLT) (i) in individual months, (ii) in the annual mean climatology, (iii) in the spatial signature of ENSO, and (iv) in the climatological mean annual cycle. In each of these cases we use precipitation as a measure to determine how much of the temperature deficit can be attributed to the hydrometeor emission and scattering. We will focus on the TMT results but show some of the important TLT results. Section 2 describes the data used in this study and the method of computing the synthetic brightness temperature from data at discrete pressure levels. The

results are presented in section 3. Section 4 presents the conclusions and discussion.

2. Data and methodology

The MSU/AMSU TMT and TLT brightness temperature observations used in this study are from Remote Sensing Systems (RSS) version 4.0 datasets (Mears and Wentz 2016, 2017), which are available online (at <http://www.remss.com>). These monthly datasets are interpolated onto a latitude–longitude grid with a horizontal resolution of 2.5° . TMT is a product based on MSU (AMSU) channel-2 (–5) near-nadir observations, while TLT is the MSU (AMSU) channel-2 (–5) angular scanning retrieval. Uncertainties arise wherever the satellite-scan path crosses the land–ocean boundary. Hence, in this study the coastline grid points are not considered. It should be emphasized that the RSS team has not applied any precipitation screening to the MSU/AMSU TMT and TLT observations.

A simple and effective way to investigate the effects of precipitation on MSU/AMSU temperature observations is to compare these deep-layer measurements with other sources of atmospheric temperature data, such as in situ radiosonde measurements or gridded temperature fields from reanalysis datasets. To make such comparisons, it is necessary to compute a synthetic microwave brightness temperature from the discrete-level data. This synthetic temperature is then compared with the brightness temperature measured by the satelliteborne instruments. In this paper we will “primarily” use monthly averaged, gridded data from ERA-I to calculate the synthetic microwave brightness temperature. ERA-I covers the period from January 1979 to the present, and is available at 37 levels between the surface and the top of the atmosphere (Dee et al. 2011).

There are algorithms of varying sophistication for computing synthetic microwave brightness temperatures from discrete-level data. In practice, a simple weighting function approach has often been used that employs fixed global-mean weights at each level. This computationally fast and efficient method requires information only about the temperature on various pressure levels and the temperature and pressure at Earth’s surface.

RSS provides temperature weighting functions at various heights above sea level for each MSU/AMSU channel. These weighting functions are based on the *U.S. Standard Atmosphere 1976* (COESA 1976), assuming a surface relative humidity of 70%, and a scale height of 1500 m for estimating the partial pressure of water vapor. It is assumed that no liquid or solid water is present.

Thus, in this study the synthetic microwave brightness temperatures for TMT and TLT are calculated by

FIG. 1. One month (November 2016) as an example of the effect of precipitation on MSU/AMSU temperature observations. (a) TMT^*_{Obs} , (b) TMT^*_{Syn} , and (c) $TMT^*_{Obs} - TMT^*_{Syn}$, superimposed by GPCP precipitation (colored shading); TMT^* is the departure from the tropical 20°N–20°S mean. The contour interval in (a) and (b) is 0.2 K, and the zero contour is marked (heavy black line). The contour interval in (c) is 0.1 K, and negative contours are marked (gray).

applying the RSS weighting functions to the ERA-I temperature data using the following equation:

$$T_b = \int_0^{P_{surf}} T(P)W(P)dP + T_{surf}W_{surf} + T_{space}W_{space}, \quad (1)$$

where P_{surf} is the surface pressure, $T(P)$ is the atmospheric temperature, $W(P)$ is the weighting function, T_{surf} is the surface temperature, W_{surf} is the surface weighting, T_{space} is the brightness temperature of space (2.73 K), and W_{space} is the associated weight. In the RSS weighting functions, it is assumed that the surface pressure is constant and equal to 1013.25 hPa. In reality, $W(P)$, W_{surf} , and W_{space} depend on the thickness of the atmosphere and so are dependent upon the surface pressure. In this study we use the updated version of RSS weighting functions (C. A. Mears 2017, private communication), which accounts for variations in the surface pressure.

We compare the field of the observed MSU/AMSU TMT and TLT with the synthetic ones in individual monthly means, in the annual mean climatology, in the spatial signature of ENSO, and in the climatological annual cycle. The spatial signature of ENSO is inferred by regressing the TMT and TLT fields upon the Niño-3.4 index, obtained from the NOAA Climate Prediction Center website (<http://www.cpc.ncep.noaa.gov/data/indices/>). To assess how much of the difference between the observed and the synthetic temperatures is due to and explained by hydrometeor contamination, we use precipitation data that can be viewed as a proxy for the hydrometeor concentration of cloud water, precipitation,

and ice particles. The monthly precipitation data are from Global Precipitation Climatology Project (GPCP), version 2.3, dataset. The GPCP data are generated by merging information from rain gauge stations, satellites, and sounding observations (Adler et al. 2003). The GPCP data are provided on a 2.5° global grid from 1979 to the present by the NOAA/OAR/ESRL/Physical Sciences Division (<http://www.esrl.noaa.gov/psd>).

3. Results

Figures 1a and 1b show the satellite-observed TMT^* and synthetic TMT^* fields, respectively, for a single month (November 2016), where TMT^* is the departure from the tropical 20°N–20°S mean. Differences are evident, but they are difficult to interpret. However, the temperature deficit field (i.e., observed TMT^* minus synthetic TMT^*) shown in Fig. 1c strongly resembles the precipitation field from which the tropical mean has been removed. Apparently, hydrometeor contamination, as represented by the precipitation field, noticeably depresses the observed brightness temperature. Figure 2a shows the data in Fig. 1c formatted as a scatterplot, which suggests a linear relationship between TMT^* deficit and precipitation: the correlation coefficient between TMT^* deficit and precipitation is -0.75 . Regression and correlation coefficients for other months are similar: the regression coefficient averaged over all months is $-0.042 \text{ K (mm day}^{-1})^{-1}$ with a month-to-month standard deviation of 0.004; the corresponding correlation coefficient is -0.76 (see Table 1).

FIG. 2. Temperature deficit ($TMT_{Obs} - TMT_{Syn}$) vs precipitation for (a) one month (November 2016) as an example, (b) climatological annual mean, (c) the ENSO signature as inferred by regressing monthly anomaly fields upon the normalized Niño-3.4 index, and (d) climatological mean annual cycle (DJF – JJA). Each point represents one grid box. The period of record is 1979–2016. In (a) and (b) the tropical mean has been removed from temperature and precipitation fields.

Many of the points in Fig. 2a are concentrated along the left edge of the plot, which correspond to the regions with little or no observed precipitation. It turns out that most of these grid points are located off the west coasts of continents, where marine stratocumulus clouds are frequently present. Hence, it can be concluded that this cluster of points is associated with nonprecipitating

water clouds. Evidently, these clouds do not contribute to the observed linear relation between TMT^* deficit and rainfall.

Figures 3a and 3b compare the annual means of TMT^*_{Obs} and TMT^*_{Syn} based on the 1979–2016 climatology. Differences between the two fields are subtle but clearly discernible. The synthetic pattern is slightly

TABLE 1. Regression [$K (mm day^{-1})^{-1}$] and correlation coefficients (parentheses) for the effect of precipitation on TMT and TLT for the period 1979–2016.

	Monthly ^a	Annual	ENSO	DJF – JJA
TMT	–0.042 (–0.76)	–0.042 (–0.86)	–0.043 (–0.91)	–0.041 (–0.85)
TLT	–0.059 (–0.65)	–0.059 (–0.81)	–0.059 (–0.91)	–0.059 (–0.73)

^a Monthly values are averaged over all months.

FIG. 3. Climatological annual mean for the period 1979–2016. (a) TMT^*_{Obs} , (b) TMT^*_{Syn} , (c) $TMT^*_{Obs} - TMT^*_{Syn}$, superimposed by GPCP precipitation (colored shading), and (d) residual after removing the precipitation effect using GPCP data; TMT^* is the departure from the tropical 20°N–20°S mean. The contour interval in (a) and (b) is 0.1 K, and the zero contour is marked (heavy black line). The contour interval in (c) and (d) is 0.05 K, and negative contours are marked (gray).

simpler and more dominated by the planetary-scale wave structure. Figure 3c shows the temperature deficit field superimposed upon the field of annual mean precipitation from which the tropical mean has been removed. The correspondence between the TMT^* deficit and precipitation is even stronger than in Fig. 1. The stronger correspondence is also reflected in the scatterplot (cf. Figs. 2a and 2b). The slopes $[-0.042 \text{ K (mm day}^{-1})^{-1}]$ are virtually identical, but the correlation for the climatological mean distribution is substantially stronger (-0.86 vs -0.75). Regressing out the spatial pattern of precipitation from the TMT^* deficit pattern yields the much weaker residual pattern shown in Fig. 3d. Summary statistics presented in Table 1 verify that 74% of the spatial variance of the annual mean TMT^* deficit field is explained by the climatological mean precipitation field.

ENSO is the primary source of interannual climate variability, and its atmospheric signature is robust and well defined (Adames and Wallace 2017). Hence, Figs. 4a and 4b are generated by linearly regressing the observed and synthetic TMT anomaly fields (departures from the 1979–2016 mean for each calendar month) upon the monthly time series of the standardized ENSO Niño-3.4 index (SST averaged over the region 5°N–5°S and 170°–120°W) for the period of 1979–2016. The patterns are very similar to the ones in Plates 7a and 8a of

Wallace et al. (1998), respectively, in which the ENSO signature in MSU channel-2 is compared with the ENSO signature in the 1000–200-hPa layer-mean temperature derived from an early version of the NCEP–NCAR reanalysis. Here, as in their analysis, the tropospheric temperature signature of ENSO is dominated by an equatorially symmetric dumbbell pattern centered near 140°W, and the pattern in the reanalysis is simpler and more equatorially symmetric than its MSU/AMSU counterpart. The precipitation signature of ENSO is shown in Fig. 4c with superimposed contours of the TMT deficit, demonstrating their strong correspondence. The corresponding scatterplot is shown in Fig. 2c. The regression coefficient of $-0.043 \text{ K (mm day}^{-1})^{-1}$ is virtually identical to those inferred from the individual monthly fields and the annual mean climatology (see Table 1). A correlation coefficient of -0.91 means that 82% of spatial variance of the ENSO signature in the TMT deficit is explained by precipitation. These findings again confirm the existence of a robust linear relationship between precipitation and the MSU/AMSU TMT deficit.

Performing the same analysis on the climatological mean annual cycle, as represented by the DJF-minus-JJA climatological means for the period 1979–2016, yields quite similar results, as shown in Figs. 5 and 2d with the summary statistics in Table 1. The estimated

FIG. 4. The ENSO signature as inferred by regressing anomaly fields upon the standardized Niño-3.4 index for the period 1979–2016. (a) TMT_{Obs} , (b) TMT_{Syn} , (c) $TMT_{Obs} - TMT_{Syn}$, superimposed by GPCP precipitation (colored shading), and (d) residual after removing the precipitation effect using GPCP data. The contour interval in (a) and (b) is 0.05 K, and the zero contour is marked (heavy black line). The counter interval in (c) and (d) is 0.03 K, and negative contours are marked (gray).

regression coefficient is again approximately the same as that obtained in previous analysis, and 73% of the variance of the spatial pattern of the TMT deficit is explained by precipitation.

That the same regression coefficient is obtained from the analysis of monthly mean data for individual months and for data that have been aggregated in various ways supports the notion that the MSU/AMSU TMT data can

FIG. 5. Climatological mean annual cycle (DJF - JJA) for the period 1979–2016. (a) TMT_{Obs} , (b) TMT_{Syn} , (c) $TMT_{Obs} - TMT_{Syn}$, superimposed by GPCP precipitation (colored shading), and (d) residual after removing the precipitation effect using GPCP data. The contour interval in (a) and (b) is 0.2 K, and the zero contour is marked (heavy black line). The counter interval in (c) and (d) is 0.1 K, and negative contours are marked (gray).

FIG. 6. Monthly anomalies of observed TMT averaged in the tropical ocean (20°S – 20°N) along with the precipitation effect ($\text{TMT}_{\text{Obs}} - \text{TMT}_{\text{Corrected}}$), where $\text{TMT}_{\text{Corrected}}$ is obtained by removing the precipitation effect using the GPCP data.

be corrected by regressing out the precipitation pattern from each individual month of the period 1976–2016. On average 58% of the variance of the TMT deficit is explained by precipitation alone in means for individual months.

Thus far, we have shown that heavy precipitation causes a significant depression in satellite-observed brightness temperature that can be corrected by simple linear regression. Does this correction have a significant impact on the long-term trends in tropical atmospheric temperature? [Spencer et al. \(1996\)](#) showed that the hydrometeor effects on the long-term trend from MSU channel-2 is negligible. On the contrary, [Weng et al. \(2014\)](#) argued that screening out grid points with hydrometeor contamination significantly alters estimates of the trends, and they reported that when cloud-affected data are removed, the global ocean (between 60°S and 60°N) tropospheric temperature trends from the AMSU data increase by $\sim 20\%$ – 30% . [Figure 6](#) shows monthly anomaly time series of TMT_{Obs} and also $\text{TMT}_{\text{Obs}} - \text{TMT}_{\text{Corrected}}$, averaged over the tropical oceans (between 20°S and 20°N) for the period 1979–2016. $\text{TMT}_{\text{Corrected}}$ was obtained by removing the precipitation effect from TMT_{Obs} in each individual month using the linear relationship developed in this study with the GPCP data. It is clear from [Fig. 6](#) that the effect of the correction upon the long-term trend in tropical mean is negligible. The correction does have a small but discernible impact on estimated regional temperature trends by as much as 15%, and then on the spatial pattern of the temperature trend over the tropical oceans, as evidenced by the results shown in [Fig. 7](#).

The same analysis has been performed upon the TLT channel dataset and some of the important results are presented in [Table 1](#) and in the supplementary

information. The algorithm for generating TLT, which involves differencing measurements from near-limb views and views closer to the nadir, tends to amplify any noise that may be present, increasing the uncertainty in the final results ([Fu and Johanson 2005](#), [Mears and Wentz 2009](#)). Hence, there is a higher noise level in the TLT results after regressing out the precipitation pattern than TMT, as evidenced by the slightly weaker correlation coefficients in [Table 1](#), except for ENSO ([Fig. S1](#)). However, we still see a robust linear relationship between temperature deficit and precipitation, with a regression coefficient of $-0.059 \text{ K (mm day}^{-1})^{-1}$, compared to $-0.042 \text{ K (mm day}^{-1})^{-1}$ for TMT. The larger regression coefficient (in terms of absolute value) implies that TLT is more strongly influenced by the emission and scattering from hydrometeors than the TMT is. As is the case for TMT, the effect of the correction upon the long-term trend in tropical mean TLT is negligible, although the regional TLT trend can differ by as much as 30% ([Fig. S2](#)).

4. Discussion

We have compared MSU/AMSU temperature observations with synthetic microwave brightness temperature to examine the effect of hydrometeors on satellite-observed tropospheric temperature, including both TMT and TLT. The synthetic temperatures are calculated by applying RSS weighting functions to the ERA-I temperature data [see [Eq. \(1\)](#)]. We have demonstrated that the differences between observed and synthetic temperatures correspond closely to the precipitation patterns in fields for individual months (as shown in [Fig. 1](#)), in the annual mean climatology (see

FIG. 7. Trend map of TMT for the period 1979–2016. (a) TMT_{Obs} , (b) $TMT_{Corrected}$, and (c) the relative change in trend after correction of precipitation effects for each individual month at each grid. The contour interval in (c) is 5%, and negative contours are marked (gray).

Fig. 3), in ENSO as the dominant pattern of interannual variability (see Fig. 4), and in the climatological mean annual cycle as represented by DJF-minus-JJA averages (see Fig. 5). In addition, we have shown that there is a robust linear relationship between temperature deficit and precipitation (see Fig. 2; Table 1). These findings are a strong confirmation of the cooling effect of hydrometeors on MSU/AMSU brightness temperature as reported in previous studies (e.g., Spencer et al. 1990; Weng et al. 2014). The results presented here also confirm that scattering and emission by hydrometeors are relatively unimportant at the frequencies used in microwave sounding of temperatures except when heavy precipitation is present. We further show that the cooling effect of hydrometeors appears to have a negligible influence on the long-term trend of tropical mean tropospheric temperature (see the red line in Fig. 6), which is in accordance with the study by Spencer et al. (1996), but that could change local trends by as much as 15% for TMT and 30% for TLT (see Fig. 7; Fig. S2).

We have tested the sensitivity of our results to the choice of reanalysis and precipitation datasets. To this end, we repeated the abovementioned analysis using two other reanalysis datasets: NCEP/NCAR (Kalnay et al. 1996) and MERRA-2 (Gelaro et al. 2017) to calculate the synthetic microwave brightness temperatures.

We also repeated all these analyses using data from the Tropical Rainfall Measurement Mission (TRMM) for the period of 1998–2016 (Huffman et al. 2007). For the sake of brevity, we show in Table 2 just the spatial regression and correlation coefficients for individual months averaged over all the months of the dataset (456 months for GPCP and 228 months for TRMM) for TMT. Note that the results using the three reanalyses along with the GPCP data are the same for the period of 1979–2016 versus 1998–2016. That the regression coefficients based on TRMM tend to be lower by as much as 20% than those based on GPCP while the correlation coefficients are just as high suggests that the amplitude of the TRMM monthly rainfall is slightly higher than that of GPCP monthly rainfall, and we have verified that this is in fact the case. The GPCP dataset, being a statistical blend of the data from different sensors, tends to be more conservative than estimates based on data from individual sensors. The different reanalysis products yield quite similar regression and correlation coefficients (Table 2) and the regression patterns (not shown) are also similar. We have also verified that the correction of temperature (i.e., removing the precipitation effect) using GPCP or TRMM datasets leads to the similar results and has similar impacts on the pattern of temperature trends (e.g., see Fig. S3).

TABLE 2. Regression [$K (mm day^{-1})^{-1}$] and correlation coefficients (parentheses) for the effect of precipitation on TMT by using different reanalysis and precipitation datasets. The values are derived for individual months averaged over all months.

	ERA	NCEP	MERRA-2
GPCP (1979–2016) ^a	−0.042 (−0.76)	−0.043 (−0.68)	−0.047 (−0.74)
TRMM (1998–2016)	−0.035 (−0.75)	−0.036 (−0.69)	−0.039 (−0.74)

^a The coefficients using the GPCP data along with the three reanalyses are the same for the periods of 1979–2016 and 1998–2016.

FIG. 8. Time series of the (a) correlation coefficient and (b) regression coefficient between TMT deficit and GPCP precipitation for each individual month. Each point is averaged over 12 months of each calendar year.

The period of our reanalysis, starting in 1979, has seen a gradual increase in the number of observations, including those from satellite MSU/AMSU, that are assimilated in ERA-I. Consistent with this increase, the spatial correlation coefficient between the monthly mean fields of temperature deficit and rainfall has increased over this period, as shown in Fig. 8a. The flatness of the curve for the regression coefficient (Fig. 8b) despite the increase in the correlation coefficient attests to the robustness of the linear relationship between them.

In our analysis we have used the synthetic temperature fields as “ground truth.” However, it is conceivable that the reanalysis dataset itself might be contaminated by hydrometeor effects because MSU/AMSU observations are also assimilated into the reanalysis data. To address this concern, we repeated the analysis of the ENSO signature using the NCEP reanalysis for the period of 1950–1978, which predates the MSU, and compared the regression pattern in the synthetic TMT with that for the 1979–2016 period of record. If the reanalysis from 1979 onward were contaminated by hydrometeor effects, then the pure pre-1979 signature and the contaminated post-1979 signatures should be discernibly different, and the difference between them should bear a strong relationship to the pattern of rainfall anomalies associated with ENSO. In fact, we found that the ENSO regression patterns based on the two periods of record (not shown) are remarkably similar and that the difference between them bears no recognizable relation to the rainfall pattern (the scatterplot similar to Fig. 2 shows a correlation coefficient of zero). On the basis of this analysis, we conclude that little, if any, of the spurious precipitation signal in the MSU/AMSU measurements is assimilated into the temperature fields in the reanalysis products.

In view of the use of filtering (i.e., screening out) grid points with heavy precipitation in the MSU/AMSU tropospheric temperature products from the National Oceanic and Atmospheric Administration (NOAA), its efficacy has been examined by applying the same analyses to its TMT, version 3.0, dataset (Zou et al. 2015). The results (not shown) demonstrate that the regression coefficient between the monthly mean fields of temperature deficit and precipitation starts from $-0.023\ K\ (mm\ day^{-1})^{-1}$ for the year 1979 and decreases over time (in terms of absolute value). Hence, it can be concluded that the precipitation filtering 1) is unable to completely remove the cooling effect of hydrometeors on the brightness temperature and 2) leads to an inconsistency in the linear relationship between temperature deficit and precipitation for different periods. Although further investigation is needed for a better understanding of this finding, the results suggest that precipitation filtering might do more harm than good by introducing an inconsistency into the dataset. It should be mentioned that in the latest version of MSU/AMSU tropospheric temperature products from the University of Alabama at Huntsville (UAH) (Spencer et al. 2017), precipitation filtering is no longer used. Hence, applying the same analyses to its TMT, version 6.0, dataset yields results quite similar to those obtained by analyzing the RSS TMT dataset.

In this study we have used precipitation data as a measure of the amount of emission and scattering by hydrometeors because of the availability of a long, continuous, complete record of high-quality data that extend over the tropical oceans. It might be informative to repeat the analysis using datasets that discriminate between water droplets and ice particles.

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