

Comparison of Tropospheric Temperatures from Radiosondes and Satellites: 1979–98



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ABSTRACT

A comprehensive comparison is made between two tropospheric temperature datasets over the period 1979–98: the most recent and substantially revised (version d) microwave sounding unit (MSU) channel 2 data retrievals, and a gridded radiosonde analysis provided by the Hadley Centre of the U.K. Meteorological Office. The latter is vertically weighted to approximate the deep layer temperatures measured by the satellite data. At individual grid points, there is good overall agreement among monthly anomalies, especially over the Northern Hemisphere continents where the climate signal is large, although monthly root-mean-square (rms) differences typically exceed 0.6°C . Over the Tropics, correlations are lower and rms differences can be as large as the standard deviations of monthly anomalies. Differences in the gridpoint variances are significant at many locations, which presumably reflects sources of noise in one or both measurement systems.

It is often argued for climate purposes that temperature anomalies are large in scale so that averaging over larger areas better serves to define the anomalies while reducing sampling error. This is the case for the Tropics (20°S – 20°N) where the large signal associated with El Niño–Southern Oscillation events is well captured in both datasets. Over the extratropics, however, the results indicate that it is essential to subsample the satellite data with the radiosonde coverage in both space and time in any evaluation. For collocated global average monthly anomalies, correlations are ~ 0.9 with rms differences $\sim 0.10^{\circ}\text{C}$ for both lower- (MSU_{2LT}) and mid- (MSU_2) tropospheric anomalies.

The agreement between the satellite and radiosonde data is slightly better for the latest version of MSU_{2LT} than it is for MSU_2 , in spite of the higher noise levels of the former. This is primarily attributable to a strong warming trend in the MSU_2 data relative to the radiosonde data toward the end of the record. Given the global nature of this discrepancy, it is suspected that it primarily reflects problems in the MSU analysis. As radiosonde records almost universally contain temporal inhomogeneities as well, caution is required when interpreting trends, which are not known to within $0.1^{\circ}\text{C decade}^{-1}$. However, the evidence suggests that global surface air temperatures are indeed warming at a significantly faster rate than tropospheric temperatures over the past 20 yr, and this is primarily attributable to physical differences in these two quantities.

1. Introduction

The possibility of inadvertent climate change induced by continuing emissions of greenhouse gases

has prompted many recent analyses of historical weather data. Observations of surface temperature and precipitation have received the most attention, largely because long records of these variables exist. Globally averaged surface air temperature, for instance, has increased 0.4° – 0.8°C this century with the most rapid warming ($\sim 0.2^{\circ}\text{C decade}^{-1}$) observed over the past 20 yr. Upper-air data, although available only for the last few decades, have also received increased scrutiny. Knowledge of changes in the vertical temperature structure of the atmosphere, for instance, may be a useful indicator of anthropogenic change (e.g., Karoly et al. 1994; Santer et al. 1996; Tett et al. 1996; Folland et al. 1998). Radiosonde records indicate global warming throughout the troposphere and cooling in the lower stratosphere since the late 1950s (Gaffen

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et al. 2000a), consistent with computer projections of the temperature change expected from enhanced greenhouse-gas forcing. Over the last 20 yr, however, very little change has been noted in the global lower to midtropospheric temperature (e.g., Parker et al. 1997), in contrast to the strong warming trend in surface air temperature.

This apparent discrepancy has motivated much recent research. While linear trends calculated over such short periods are simplistic and unreliable measures of temperature change (Karl et al. 1994; Santer et al. 2000a), several studies have shown that important physical differences in the quantities measured help to explain the trend difference. In particular, volcanic eruptions, the El Niño–Southern Oscillation (ENSO) phenomenon, decadal variations in extratropical patterns of circulation variability, stratospheric ozone depletion, and anthropogenic forcings have all been shown to have differential effects on global surface and tropospheric air temperature variability (Trenberth et al. 1992; Christy and McNider 1994; Jones 1994a; Hansen et al. 1995; Hurrell and Trenberth 1996; Tett et al. 1996; Santer et al. 2000b; Shah et al. 2000), although the extent to which such variations may produce decade-long changes in lower-tropospheric lapse rates (Brown et al. 2000; Gaffen et al. 2000b) is not clear. Another contributing factor could be that the rise in surface air temperature has resulted, in part, from the daily minimum temperature increasing at a faster rate than the daily maximum, resulting in a decrease in the diurnal temperature range over many parts of the world (Easterling et al. 1997; Dai et al. 1999). Because of nighttime temperature inversions, the increase in daily minimum temperatures likely involves only a shallow layer of the atmosphere that would not be well sampled in upper-air radiosonde or satellite records.

However, questions remain as to whether the observed differences point to problems in both the surface and upper-air records because of data uncertainties, as well as inadequacies and differences in the spatial coverage of datasets (Jones et al. 1997; Hurrell and Trenberth 1998; Santer et al. 1999). Because of recent improvements in the upper-air datasets, this aspect is pursued here.

The homogeneity of the surface air temperature database has been extensively reviewed in many previous studies (e.g., Jones et al. 1999). Uncertainties arise through changes in instrumentation, exposure, and measurement technique; influences such as urban heat-island effects; and coverage changes and deficien-

cies. Upper-air radiosonde data have been subject to serious discontinuities as well, including both random errors and time-varying biases resulting from changes of instrumentation and operating or processing procedures. For temperature, the latter can be large, ranging from several tenths to as much as several degrees Celsius in individual radiosonde records (Gaffen 1994). Correcting such errors in the radiosonde records is very difficult, and this problem is exacerbated by inadequate station history metadata throughout much of the world (Gaffen 1996). Moreover, different correction methods can lead to quite different results, especially for trend estimation (Gaffen et al. 2000a).

It is with such biases in mind that there has been an increasing emphasis on the use of satellites for climate monitoring. For upper-air temperature, satellite microwave sounding unit (MSU) measurements are available since 1979 (Christy et al. 1998, 2000). These data, which represent temperatures averaged over deep layers of the atmosphere, provide the truly global coverage that the historical instrumental records lack. Like the radiosonde records, the MSU data indicate little change in global tropospheric temperature over the last two decades. A difficulty in creating a continuous, consistent climate record from satellite observations alone, however, is that satellites and instruments have a finite lifetime of a few years and have to be replaced, and their orbits are not stable. Nine satellites compose the current operational MSU record, and the methods of merging the data from these different satellites are complex (Christy et al. 1998). Moreover, the satellite data record is continually evolving as newly discovered problems are accounted for and corrected (Christy et al. 2000).

The above issues limit our ability to quantify and understand the reasons for changes in upper-air temperatures, whether measured by radiosondes or satellite instruments, and how those changes relate to variations in the surface climate. One way to make progress is through comparisons of datasets. Trenberth et al. (1992), for instance, evaluated the reproducibility of surface temperature anomalies from several different analyses and made assessments of the sources and levels of noise in the data (see also Folland et al. 1993; Hurrell and Trenberth 1999). Fewer studies, however, have rigorously compared different upper-air temperature datasets. One exception is the recent study by Santer et al. (1999). They compared atmospheric temperatures from several different radiosonde datasets, different versions of MSU data, and two atmospheric reanalysis datasets (see also Christy 1995; Parker et al. 1997; Hurrell and Trenberth 1998; Stendel

et al. 2000, manuscript submitted to *Climate Dyn.*). They showed that considerable differences existed among the different analyses, especially in global mean trends, and they concluded that our knowledge of recent changes in the thermal structure of the free atmosphere is far from certain.

It is important, therefore, to continue critical evaluations and comparisons of upper-air datasets, especially as the datasets evolve. Here we compare two widely used tropospheric temperature datasets: the latest substantially revised MSU product (version d; Christy et al. 2000) and a radiosonde dataset updated from Parker et al. (1997). Since most previous studies have focused on the change in temperature over some period of time, their emphasis has been on the level of trend agreement among different datasets. We provide a more comprehensive comparison to assess how well monthly anomalies in deep-layer tropospheric temperatures agree at the gridbox, hemispheric, and global scales. In particular, cross correlations, autocorrelations, standard deviations, and root-mean-square (rms) differences, in addition to linear trends, are evaluated in order to appraise the reproducibility of tropospheric temperatures between the MSU and radiosonde datasets.

2. Tropospheric temperature data

The technical aspects of the MSU data retrievals have been described by Spencer et al. (1990), and the data used in our analysis have been described by Christy et al. (2000). Two deep-layer tropospheric temperature products exist. The vertical weighting function for MSU channel 2 (MSU_2) is quite broad: it peaks near 500 hPa but extends from the surface into the lower stratosphere. Removal of the small, but non-trivial, stratospheric influence is obtained through a linear combination of channel 2 data from different view angles. The adjusted vertical weighting function peaks lower in the troposphere near 700 hPa, and these data are referred to as MSU channel 2 lower troposphere (MSU_{2LT}).

The MSU products have evolved over time. Updates are principally related to changes in the procedure employed to correct and merge information from individual satellite records. In the most recent data, version d, significant adjustments were incorporated for orbit decay and orbit drift. The former refers to the loss of satellite altitude over time due to atmospheric drag, and it contributed to a spurious cooling

in previous MSU_{2LT} data of roughly $0.10^\circ\text{C decade}^{-1}$ but with little impact on MSU_2 (Wentz and Schabel 1998). The net diurnal effect of east–west satellite drift was to produce a spurious warming trend in MSU_{2LT} of $0.03^\circ\text{C decade}^{-1}$. In addition, Christy et al. (2000) describe two other sources of error that were adjusted in version d: variations in the instrument body temperature on each of the satellites (a consequence of orbit drift) and erroneous calibration coefficients for the *NOAA-12* satellite (Mo 1995). The combined effect of these two errors was to induce a spurious warming trend of $0.04^\circ\text{C decade}^{-1}$, so that after adjustment global trends in version d were quite close to those in the previous data release (version c; Christy et al. 1998). Later we illustrate the effects of these revisions on the satellite record. Monthly MSU temperatures from January 1979 onward are available on a 2.5° latitude and longitude grid.

The gridded radiosonde data, described by Parker et al. (1997), are produced at the Hadley Centre of the U.K. Meteorological Office (UKMO). Several different versions exist. Parker et al. (1997) and Santer et al. (1999) used versions that relied on collocated MSU observations to adjust inhomogeneous radiosonde data from stations in Australia and New Zealand. They did not, therefore, compare completely independent data.¹ Those studies also made use of an eigenvector-reconstructed version of the radiosonde data, which retained about 76%–80% of the original variance in the station records. This technique was employed to fill in temporal gaps and minimize noise in the data. Results were made available on a very coarse 10° latitude by 20° longitude grid, so that the implied fractional coverage of the globe was much greater.

Here we use a more basic version of the radiosonde data, hereafter referred to as HADRT 2.0. Quality controls including hydrostatic checks were applied (Parker and Cox 1995), but no attempt was made to adjust for time-varying biases. The dataset is based on monthly CLIMAT TEMP messages, data in national publications, and digitized data from some national meteorological services. About 400 stations worldwide make up the database. The HADRT 2.0 data are given at nine standard levels, from 850 up to 30 hPa, and are interpolated onto a 5° latitude by 10° longitude grid using the techniques described by Parker et al. (1997). To facilitate comparisons to other

¹Santer et al. (1999) did, however, also perform comparisons excluding Australian and New Zealand data.

gridded datasets, however, the radiosonde data are then duplicated onto a 5° latitude by longitude grid. Information on surface temperature variations was obtained from an updated version of the dataset employed by IPCC (1996). It consists of near-surface air temperature anomalies over land from Jones (1994b) merged with sea surface temperature anomalies over marine areas from the UKMO (Parker et al. 1995). The development of this dataset has been documented in many papers, the most recent being Jones et al. (1999). Monthly HADRT 2.0 anomalies are available beginning in January 1958.

For our comparisons, the MSU data were first averaged onto the coarser radiosonde grid. The monthly surface and standard-level radiosonde data were then vertically averaged with weights matching the relevant MSU profile. If a standard-level temperature was missing, an equivalent MSU deep-layer temperature was not computed for that grid box. Incomplete data records are most common at stratospheric pressure levels (Gaffen et al. 2000a), so comparisons to MSU₂ are based on fewer observations than are those to MSU_{2LT}. Radiosonde data from India were found to be especially temporally and spatially incoherent (Parker et al. 1997), so these data were excluded from the comparisons. The mean annual cycle for 1979–98 was subtracted from each upper-air dataset, with 10 years required to define the annual cycle, thereby removing possible systematic biases.

3. Results

a. Local reproducibility of tropospheric temperatures

Gridpoint correlations and rms differences between the 240 monthly MSU_{2LT} and equivalently weighted HADRT 2.0 temperature anomalies for 1979–98 show relatively good agreement over most of the globe (Figs. 1a,b). The highest correlations (> 0.9) are evident over the mid- and high latitudes of Europe, Asia, and North America where rms differences are roughly 0.8°C. Generally, correlations are slightly less (~0.8) over the subtropical latitudes of the Northern Hemisphere (NH) as well as over Australia, New Zealand, and South America. In these regions, rms differences are typically around 0.5°C. The lowest correlations (~0.5–0.7) and rms differences (~0.4°C) are found within the Tropics. Very similar results are evident for comparisons between the radiosonde data and MSU₂ (not shown).

The spatial pattern evident in the map of correlation coefficients arises from spatial variations in the size and persistence of the signal of actual climate variability relative to the noise in the datasets. A map of standard deviations of monthly mean lower-tropospheric anomalies from HADRT 2.0 (Fig. 1c) reveals a mostly zonally symmetric structure, with the highest values at mid- and high latitudes of both hemispheres. The largest variability is over the NH continents, where month-to-month anomaly variations are generally between 1° and 2°C. Such a large signal is hard to miss and the high correlation coefficients reflect this, although local rms differences are typically as large as 50%–60% of the standard deviations. The lowest correlation coefficients tend to occur where the standard deviations are small, implying that noise from errors in measurements and spatial and temporal sampling might account for a substantial part of the total variance in these regions. At most grid points within the Tropics, for instance, standard deviations are less than 0.6°C, so that the rms differences between MSU_{2LT} and HADRT 2.0 (Fig. 1b) are roughly as large as the variability. It is also noteworthy that, at many grid points, the monthly HADRT 2.0 variances differ significantly from those in the MSU_{2LT} data (Fig. 1c). Over the Tropics, the radiosonde data generally exhibit greater variability than the satellite data, while the reverse is true over mid- and high latitudes, especially over the NH. The factors that most likely contribute to this result are discussed later.

b. Impact of spatial sampling

The radiosonde coverage is incomplete in space and time (Fig. 1d). There is a clear bias toward land areas with relatively few observations over the Tropics and at high latitudes. There is also a strong hemispheric asymmetry in coverage, with nearly twice the fractional coverage over the NH than over the Southern Hemisphere (SH). Over the globe, the maximum implied fractional coverage in HADRT 2.0 is around 30%–40%, with declining coverage after about 1986 (Santer et al. 1999). The result is that there is always a component of the global or hemispheric mean temperature that is missing in radiosonde records (Trenberth and Olson 1991), so that it is essential to compare the MSU and HADRT 2.0 datasets over areas of common data coverage. Most previous studies have not done this, although Santer et al. (1999) found that coverage differences among datasets could have considerable effects on linear trends, sometimes substantially degrading initial trend agreement. Christy

et al. (1998, 2000) also performed collocated comparisons in their assessment of the MSU data, but for only 97 stations in the western NH.

A related issue is the sensitivity of results to the averaging procedure employed to create regionally averaged temperature anomalies. We have explored the differences between two straightforward and common techniques. The first, hereafter referred to as GRDPT, is to sum the temperatures at all available grid points over a region, after appropriately weighting each gridpoint temperature by the cosine of the latitude. The second method, hereafter referred to as ZONAL, is to first compute the average temperature for a given latitude band, then sum each cosine-weighted zonal-mean temperature anomaly within the desired region. For full coverage data, obviously, the two averaging techniques yield identical results.

The impact of subsampling (masking) the MSU data with the HADRT 2.0 coverage, and the sensitivity to the averaging method, are shown in Table 1 for monthly, regional temperature anomalies over the period 1979–98. The influence of masking is significant, especially over the data-sparse SH. For MSU₂, for instance, the variance in the extratropical SH (90°–20°S) masked data is nearly three times larger than with full coverage, the correlation coefficient between the two series is only about 0.6, and the rms difference is larger than the standard deviation of the full coverage time series by a factor of ~1.5. Differences are smallest over the Tropics (20°S–20°N), where there are roughly five (eight) spatially independent estimates of tropical temperature for MSU₂ (MSU_{2LT}) (Hurrell and Trenberth 1998). The result is that the relatively sparse radiosonde network is capable of capturing much of the ENSO-dominated tropical signal, although the lack of stations throughout the central and eastern tropical Pacific results in a systematic bias during both warm and cold events of roughly 0.15°C relative to the full coverage data (not shown). The agreement is also good over the relatively data rich extratropical NH (20°–90°N), although rms differences are as large as 50%–70% of the signal, depending on the layer of the troposphere sampled and the averaging technique employed. For global-average temperatures, monthly differences on the order of 0.2°C are common between the masked and full coverage datasets (not shown). These differences do not show any systematic biases, however, even though the global time series of both the full coverage and masked MSU data are dominated by the tropical signal (Hurrell and Trenberth 1996). This occurs because the much

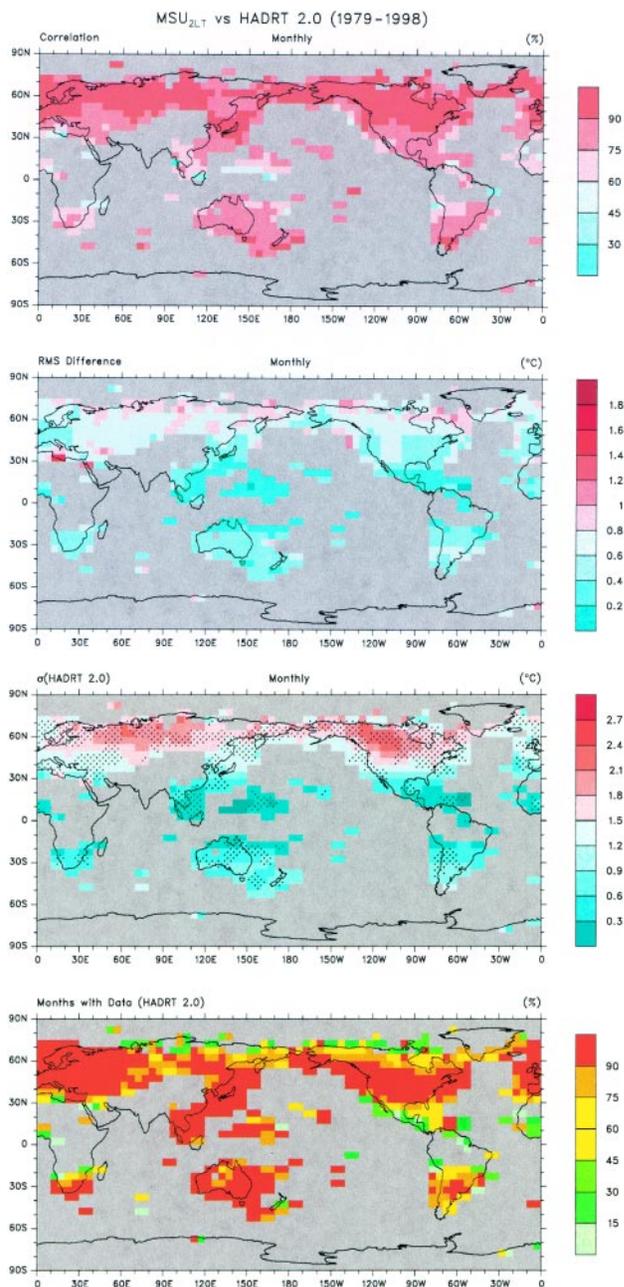


FIG. 1. Correlation coefficients (%) (top panel) and rms differences (°C, second panel) between monthly temperature anomalies from MSU_{2LT} and HADRT 2.0 for 1979–98. Standard deviations (°C) of the lower-tropospheric HADRT 2.0 monthly anomalies are shown in the third panel. The stippling indicates where the HADRT 2.0 variances differ at the 5% level from MSU_{2LT} variances using their ratio and the *F* distribution (third panel). The percentage of months with gridded HADRT 2.0 data is shown in the bottom panel.

larger differences from masking over the extratropics dominate the global differences, as shown by the regional rms values in Table 1. Also note that, in general, the agreement between the masked and the full

TABLE 1. Comparison of monthly MSU tropospheric temperature anomalies with and without masking of the radiosonde (HADRT 2.0) coverage in both space and time. Regional anomalies were computed using the GRDPT (ZONAL) averaging technique (see text for details). Correlation coefficients (r), standard deviations (σ , °C), rms differences (°C), lag-1 month autocorrelations (ar1), and linear trends (T) with 95% confidence intervals (°C decade⁻¹) were computed from monthly anomalies over the period 1979–98 ($n = 240$). The confidence intervals were estimated accounting for the correlation in the monthly residuals from the linear trend fit following Cryer (1986, p. 38).

	90°S–90°N	90°–20°S	20°S –20°N	20°–90°N
MSU_{2LT}				
r	0.81 (0.92)	0.64 (0.71)	0.95 (0.96)	0.86 (0.91)
σ	0.20	0.21	0.29	0.29
$\sigma_{(\text{Mask})}$	0.27 (0.21)	0.34 (0.30)	0.26 (0.27)	0.37 (0.31)
rms	0.16 (0.08)	0.26 (0.21)	0.09 (0.08)	0.19 (0.13)
ar1	0.80	0.45	0.88	0.64
ar1 _(Mask)	0.62 (0.71)	0.35 (0.35)	0.82 (0.82)	0.50 (0.57)
T	0.06 ± 0.11	−0.01 ± 0.08	0.01 ± 0.15	0.17 ± 0.11
$T_{(\text{Mask})}$	0.14 ± 0.10 (0.06 ± 0.11)	0.07 ± 0.12 (−0.02 ± 0.11)	−0.01 ± 0.13 (−0.00 ± 0.14)	0.22 ± 0.10 (0.17 ± 0.10)
MSU₂				
r	0.80 (0.88)	0.56 (0.60)	0.96 (0.96)	0.82 (0.85)
σ	0.18	0.20	0.31	0.24
$\sigma_{(\text{Mask})}$	0.24 (0.22)	0.35 (0.33)	0.27 (0.28)	0.30 (0.28)
rms	0.14 (0.11)	0.29 (0.26)	0.09 (0.09)	0.17 (0.14)
ar1	0.78	0.50	0.86	0.60
ar1 _(Mask)	0.56 (0.58)	0.47 (0.28)	0.77 (0.76)	0.47 (0.49)
T	0.03 ± 0.10	−0.07 ± 0.06	0.09 ± 0.16	0.08 ± 0.10
$T_{(\text{Mask})}$	0.09 ± 0.10 (0.06 ± 0.11)	0.04 ± 0.09 (0.00 ± 0.13)	0.06 ± 0.13 (0.06 ± 0.13)	0.11 ± 0.09 (0.10 ± 0.09)

coverage MSU data is worse for MSU₂. This most likely occurs because of more missing data at stratospheric pressure levels in HADRT 2.0: the masked MSU₂ data contain about 30% fewer grid points than the masked MSU_{2LT} data.

It is also worthwhile to note the differences that arise as a result of the averaging method. In general, the agreement between the masked and full coverage

data is worse using the GRDPT method, especially when estimating the linear change in temperature over the short 20-yr period. The GRDPT technique strongly biases the results toward the extratropical NH landmasses where the number of observations is largest (Fig. 1d). Since the late 1970s, changes in atmospheric circulation have resulted in surface warming over the northern continents (e.g., Hurrell 1996), and this is

reflected in the warmer global temperature trends relative to the full coverage MSU data using the GRDPT method. The ZONAL averaging technique, on the other hand, gives much more weight to the Tropics and portions of the SH relative to the GRDPT method. Because the large tropical (ENSO) signal dominates the full coverage MSU data and the masked data if the ZONAL technique is employed, there is a significant reduction in the rms errors due to sampling, for instance from 0.16° to 0.08°C for global $\text{MSU}_{2\text{LT}}$ temperatures. For the ZONAL results, the requirement was that a minimum of only one grid point ($n \geq 1$) was needed to define a zonal-mean temperature. As this is increased to about $n = 12$, the ZONAL and GRDPT results converge. Given the results in Table 1, the subsequent comparisons to radiosonde data employ the ZONAL averaging method with $n \geq 1$. This method was employed in many previous comparisons as well, including IPCC (1996).

c. Area-averaged and zonal-mean tropospheric temperatures

As expected from Table 1, the agreement between the monthly mean satellite and radiosonde deep-layer tropospheric temperatures is markedly improved by subsampling the MSU data with the HADRT 2.0 data coverage. For instance, the correlation coefficient and rms difference for global anomalies over the 240-month period 1979–98 is 0.93 and 0.08°C , respectively, for masked $\text{MSU}_{2\text{LT}}$ anomalies, compared with values of 0.75 and 0.17°C for the full coverage satellite data.

Comparisons of the HADRT 2.0 and masked MSU datasets for different regions are shown in Table 2, and time series of global anomalies and their differences are illustrated in Fig. 2. Overall, there is quite good agreement in all statistical measures. Correlations for all regions for both measures of tropospheric temperature are near 0.9, and the satellite and radiosonde standard deviations are nearly equal. Root-mean-square differences can be substantial, however. Over the SH extratropics, for instance, rms differences are half the size of the signal, and the same is true for the MSU_2 comparison over the Tropics and for the global average. Lag-1 month autocorrelations are slightly less in the HADRT 2.0 equivalent $\text{MSU}_{2\text{LT}}$ data in all regions, indicating less temporal persistence of anomalies in the radiosonde data, but for MSU_2 they are nearly the same in all regions excluding the extratropical SH.

In terms of linear trends in lower-tropospheric temperature data over the last 20 yr, only the warming over the extratropical NH is significantly differ-

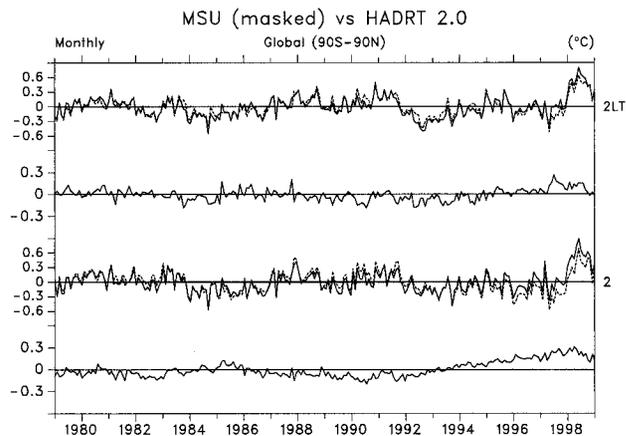


FIG. 2. Monthly time series of global anomalies from the MSU and HADRT 2.0 datasets over 1979–98. The MSU data were masked by the radiosonde coverage in both space and time. The top curves are time series for $\text{MSU}_{2\text{LT}}$ (solid) and equivalent anomalies from HADRT 2.0 (dashed), and the second curve shows their difference (MSU–HADRT 2.0). The bottom two curves are the same, but for MSU_2 . Note the difference in scaling for the difference curves.

ent from zero in both datasets. In all regions, the trends are very close, and the trends of the monthly mean differences (MSU minus HADRT 2.0) are not significantly different from zero. The same is not true of the midtroposphere, however, as represented by the channel 2 comparisons. As is evident from Fig. 2, the trend difference arises mostly from a warming in MSU_2 relative to the radiosonde data beginning around 1992. Although global in extent, the Tropics contribute the most to this trend difference. Within this region, MSU_2 warms relative to the equivalent deep-layer temperatures from HADRT 2.0 at a rate of $0.17^\circ\text{C decade}^{-1}$, and this difference is significant at the 99% level (not shown). Figure 2 shows that this recent warming is also evident in the $\text{MSU}_{2\text{LT}}$ comparisons; however, since the satellite data exhibit a slight warm bias relative to the radiosonde data at the beginning of the record as well, the 20-yr trend differences in regional lower-tropospheric anomalies are minimal.

These aspects are more clearly illustrated in Fig. 3, which shows the time evolution of monthly differences in zonal-mean tropospheric temperature anomalies between the radiosonde and masked satellite datasets. The largest differences ($\sim 1^\circ\text{C}$) are typically found at high latitudes, especially in the $\text{MSU}_{2\text{LT}}$ comparison where differences in all latitude bands are larger in general. It is also clear that, during many months, the cancellation of errors of opposite sign improves the agreement evident in large-scale regional averages

TABLE 2. Comparison of monthly tropospheric temperature anomalies from MSU and HADRT 2.0. The MSU data were masked by the radiosonde coverage in both space and time, and regional anomalies in both datasets were computed using the ZONAL averaging technique (see text for details). The variables and units are as in Table 1.

	90°S–90°N	90°–20°S	20°S–20°N	20°–90°N
MSU_{2LT}				
r	0.93	0.87	0.94	0.94
$\sigma_{(\text{MSU})}$	0.21	0.30	0.27	0.31
$\sigma_{(\text{HAD})}$	0.20	0.29	0.24	0.30
rms	0.08	0.15	0.10	0.11
$\text{ar1}_{(\text{MSU})}$	0.71	0.35	0.82	0.57
$\text{ar1}_{(\text{HAD})}$	0.63	0.29	0.70	0.54
$T_{(\text{MSU})}$	0.06 ± 0.11	-0.02 ± 0.11	-0.00 ± 0.14	0.17 ± 0.10
$T_{(\text{HAD})}$	0.04 ± 0.07	0.00 ± 0.08	-0.01 ± 0.09	0.13 ± 0.09
$T_{(\text{MSU-HAD})}$	0.01 ± 0.06	-0.02 ± 0.09	0.01 ± 0.05	0.04 ± 0.05
MSU₂				
r	0.88	0.89	0.89	0.93
$\sigma_{(\text{MSU})}$	0.22	0.33	0.28	0.28
$\sigma_{(\text{HAD})}$	0.22	0.33	0.29	0.28
rms	0.11	0.15	0.14	0.10
$\text{ar1}_{(\text{MSU})}$	0.58	0.28	0.76	0.49
$\text{ar1}_{(\text{HAD})}$	0.58	0.37	0.74	0.49
$T_{(\text{MSU})}$	0.06 ± 0.11	0.00 ± 0.13	0.06 ± 0.13	0.10 ± 0.09
$T_{(\text{HAD})}$	-0.05 ± 0.08	-0.06 ± 0.11	-0.10 ± 0.10	-0.00 ± 0.08
$T_{(\text{MSU-HAD})}$	0.11 ± 0.10	0.06 ± 0.16	0.17 ± 0.07	0.10 ± 0.07

(Table 2). The most notable exception to this generalization is the channel 2 comparison, where the satellite data tend to be systematically colder than the radiosonde data at most latitudes and times from about 1986 until about 1993, then are systematically warmer thereafter.

The reasons for the recent warming in the satellite data relative to the radiosonde anomalies (Figs. 2 and 3) are not fully understood. Radiosonde data may be

partly responsible. For instance, the switch from VIZ to Vaisala instrumentation at many U.S. controlled stations beginning in December 1995 resulted in a shift to cooler tropospheric temperatures, and this effect is especially noticeable at stations in the western tropical Pacific (not shown; see Luers and Eskridge 1995). The nearly global nature of this discrepancy suggests, however, that the differences may also relate to remaining problems with the NOAA-12 time series. Al-

though the new *NOAA-12* calibration coefficients incorporated into the version d MSU data considerably reduce both spurious intra- and interannual noise relative to other satellites, the corrections also introduce a strong warming trend relative to the version c data, especially after about 1994; see Fig. 4 (Christy et al. 2000). The warming coincides with the east–west orbital drift of *NOAA-12* in which the instrument body temperature experienced a fairly dramatic shift. Unfortunately, this shift was during a period when *NOAA-12* was the only satellite in operation (*NOAA-13* failed after one week in orbit), so there are no independent satellite data from which to corroborate the *NOAA-12* adjustments from late 1994 to early 1995.

Differences between the two most recent versions of the MSU data (Fig. 4) also illustrate the impact of the new corrections for orbital decay and orbital drift in both MSU_2 and MSU_{2LT} . The magnitude of these corrections is large. In addition, a substantial difference is also notable in the treatment of *NOAA-9* data, so that a strong cooling exists in version d relative to version c from about 1985–86. Christy et al. (1998) note especially the sensitivity of trends to how the inadequate overlap of *NOAA-9* with other satellites is handled. In fact, it is this cooling during the *NOAA-9* period that largely compensates the relative warming in version d during the *NOAA-7* (1981–84) and *NOAA-12* (1991–98) periods in MSU_{2LT} . The spikes in the difference time series after 1991 are related to the instrument body temperature effect and the erroneous calibration coefficients for *NOAA-12* in version c (Christy et al. 2000). Given the magnitude of these adjustments, one must be cautious drawing conclusions about trends in spite of overall good agreement between the MSU and HADRT 2.0 anomalies over 1979–97 yield results quite similar to those in Table 2 in most statistical measures, including trends (not shown). Metrics such as correlation coefficients, standard deviations, and rms differences are dominated by variations on interannual and shorter timescales, which are not as

(MSU masked) - (HADRT 2.0)

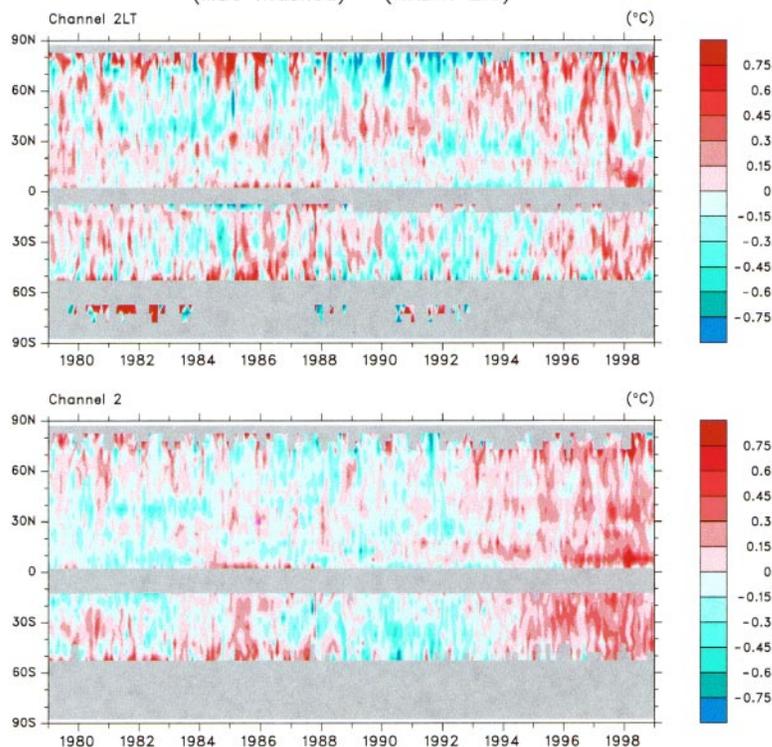


FIG. 3. Zonally averaged temperature anomaly differences ($^{\circ}\text{C}$, MSU – HADRT 2.0) for MSU_{2LT} (top) and MSU_2 (bottom). The MSU data were masked by the radiosonde coverage in both space and time. No latitudinal cosine weighting has been applied so that values near the poles represent small areas.

strongly affected by the revisions and updates to the datasets as are trends. This is why Christy et al. (1998, 2000) use trends as a metric to evaluate changes in merging procedures.

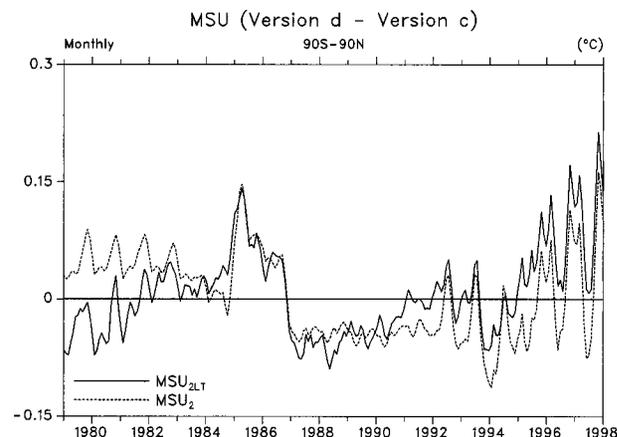


FIG. 4. Monthly differences ($^{\circ}\text{C}$), smoothed with a 1–1–1 filter, between the two most recent versions (d–c) of the MSU data over 1979–97. Differences for MSU_{2LT} (MSU_2) are given by the solid (dashed) line.

4. Discussion and conclusions

Information on atmospheric temperatures is available from several sources. Radiosonde releases provide the longest record of upper-air measurements. Temperature records of equal length are or soon will be available from the reanalysis projects at the National Centers for Environmental Prediction (Kalnay et al. 1996) and European Centre for Medium-Range Weather Forecasts (Gibson et al. 1996). These analyses do not represent direct observations, however, as they are influenced by data assimilation strategies and the numerical models employed. On the other hand, they do benefit from a physically consistent framework and multivariate input data, which includes satellite data. Satellites provide a third source of information on atmospheric temperatures, especially the records provided by the MSU instruments over the past two decades.

Given the importance of upper-air data to our ability to monitor and understand climate variability and change, it is critical that efforts to evaluate and compare datasets continue. In this paper we have compared two widely cited tropospheric temperature datasets: the latest version of the MSU data retrievals (version d) and an updated, gridded radiosonde analysis from the Hadley Centre. Overall, the two datasets exhibit good agreement, especially in terms of monitoring temperature variability on interannual and shorter timescales over large regions. At individual grid points, the agreement is best where the climate signal is large, and it is worst over the Tropics, where mostly the signal is small. Differences in the gridpoint variances are substantial at many locations (Fig. 1c), and these differences provide insight into the sources of noise in one or both measurement systems. Differences between versions c and d of the MSU dataset similarly provide insights into the uncertainties in the satellite record.

Over the Tropics, where the variances in the gridpoint radiosonde data are typically greater than those in the satellite data, inhomogeneities in the radiosonde records are most common (Gaffen 1994; Parker and Cox 1995; Hurrell and Trenberth 1998). Moreover, the relatively low number of monthly reports from tropical stations (Fig. 1d), and the fact that monthly mean statistics are computed from relatively few daily reports, are additional factors that contribute to spurious variance in the monthly mean radiosonde data. The latter source of error is often underappreciated. For stations between 30°S and 30°N, for instance, the average number of reports that

go into estimating a monthly mean temperature is around 25 (D. J. Gaffen 1999, personal communication). Moreover, the missing observations are often consecutive, not randomly or equally spaced. As shown by Kidson and Trenberth (1988, hereafter KT), the standard error of a monthly mean depends on the standard deviation of the daily values and the effective number of independent observations each month. For tropospheric temperature, a reasonable value for the 12-h lag correlation is ~ 0.8 (Fig. 10 of KT), while the standard deviation of daily values ranges from less than 1°C near the equator to just over 2°C in the subtropics (Figs. A31 and A69 of Trenberth 1992). Using Table 5 of KT, therefore, yields typical monthly standard errors of $\sim 0.4^\circ\text{C}$ for a near-equatorial station and up to 0.8°C for a subtropical station, which is as large as the standard deviation of monthly tropospheric temperatures throughout these latitudes (Fig. 1c).

While such issues are also a factor for higher-latitude stations, the problems are less severe, especially over the relatively data-rich regions of the NH (Parker and Cox 1995), and the climate signal is much larger. Moreover, at midlatitudes records from several stations are more likely to contribute to the gridbox average temperature (especially over North America and Europe), which effectively reduces the noise level in the gridded data. In addition, the higher variances in the satellite data relative to HADRT 2.0 at mid- and high latitudes (Fig. 1c) may reflect the greater noise and the greater influence of surface emissions in $\text{MSU}_{2\text{LT}}$ relative to MSU_2 . The standard errors of monthly mean $\text{MSU}_{2\text{LT}}$ temperatures are approximately 0.15°C over tropical oceans but $0.3^\circ\text{--}0.5^\circ\text{C}$ over tropical land and higher latitudes, which are about a factor of 3 larger than the standard errors in MSU_2 (Spencer and Christy 1992). Indeed, variances in gridpoint MSU_2 temperatures are generally not significantly different from HADRT 2.0 gridpoint variances in mid- and high latitudes while, as for $\text{MSU}_{2\text{LT}}$, they exhibit less variability than the radiosonde data at many grid points throughout the Tropics (not shown). The coarse vertical resolution of the HADRT 2.0 product is another factor that may contribute to the observed differences. Deep-layer variations in temperature directly observed by the MSUs were only approximated from the radiosonde data through the application of coarse, static weighting functions. Thus, variations not well sampled by the mandatory pressure level data in HADRT 2.0 may contribute to spurious variability in the radiosonde-simulated values.

The comparisons presented in Tables 1 and 2 show that subsampling the MSU data with the radiosonde coverage greatly improves the level of agreement. Typically, this has not been done (e.g., IPCC 1996), and most previous studies have focused on the level of trend agreement between different datasets (see Santer et al. 1999). The impact of masking on linear trends over 1979–98 is small, however, if the ZONAL averaging method is employed. This is because the global average MSU temperatures are most strongly correlated with grid points throughout the Tropics (Fig. 7 of Hurrell and Trenberth 1996), and tropical average temperatures are well approximated by the radiosonde network (Table 1). The impact on temperature trends over the NH extratropics is also small, due to relatively good radiosonde coverage, but the impact is larger over the data-sparse SH. For instance, the trend difference between masked and full coverage MSU₂ data over the SH extratropics is 0.07°C decade⁻¹ (Table 1).

Estimates of the change in temperature over some period of time can also be sensitive to the fitting method (Santer et al. 2000a; Gaffen et al. 2000a). Here we have used a simple least squares estimator of the trend, but we also examined alternative linear trend estimators that are less sensitive to outliers, such as the resistant method of Velleman and Hoaglin (1981). Due primarily to the strong 1998 El Niño warming near the end of the time series (Fig. 2), this technique yielded lower trends in both datasets over all regions. For instance, the trend in monthly, global, masked MSU_{2LT} and MSU₂ data changed from 0.06° to -0.04°C decade⁻¹ over 1979–98, while the global HADRT 2.0 trend was reduced by 0.07°C decade⁻¹ (0.08°C decade⁻¹) for equivalent MSU_{2LT} (MSU₂) anomalies. Because differencing the radiosonde and masked satellite anomalies reduces noise levels by subtracting variability common to both datasets (such as the ENSO signal), however, the trends of the difference time series (Table 2) were not sensitive to the fitting method employed.

Another result evident from Table 2 is that the agreement between MSU₂ and HADRT 2.0 is slightly worse than it is for MSU_{2LT}. Differences in data coverage between the MSU_{2LT} and MSU₂ comparisons do not explain this result. The slightly degraded agreement for MSU₂ is surprising in view of the fact that the retrieval process, used to remove the small stratospheric influence from channel 2 data, amplifies errors and results in a greater influence of surface emissions (Spencer and Christy 1992). On the other

hand, errors in radiosonde data tend to amplify at higher altitudes (Gaffen et al. 2000a), which would have a greater influence on the MSU₂ comparisons. Comparisons between MSU₂ and HADRT 2.1s, which incorporates corrections for time-varying biases at stratospheric pressure levels only through the use of collocated MSU channel 4 data, yield results almost identical to those in Table 2. It is possible that part of the channel 2 disagreement may relate from small MSU errors still embedded in the new NOAA-12 calibration coefficients, which may have a larger effect on MSU₂ than MSU_{2LT}. If the impact of the strong, relative global warming trend evident in the MSU₂ data near the end of the record is lessened through detrending, correlations and rms differences between MSU₂ and HADRT 2.0 are as good or better than those for MSU_{2LT} in Table 2 (not shown).

The results of this evaluation show that MSU trends for 1979–98 are positive but small, and they are not significantly different from zero. Nor do they differ significantly from trends in the HADRT 2.0 data, except for over the Tropics in MSU₂ data. Radiosonde data almost universally contain temporal inhomogeneities arising from changes in instruments or sensors, and the net effect of such problems on trends is difficult to assess as discontinuities do not always act in the same sense. Similarly, creating a homogeneous temperature record from the nine different satellites that compose the current MSU record is a difficult task because of changes in instruments, platforms, equator-crossing times, and algorithms. As a result, the MSU products are evolving, and the latest adjustments each have large, yet nearly compensating, effects on trends over 1979–98 (Fig. 4). Based on the comparisons presented here, such uncertainties in both records suggest that trends in tropospheric temperatures over the past 20 yr are known to an accuracy of ~0.1°C decade⁻¹. Ongoing efforts, such as the quality-controlled Comprehensive Aerological Reference Data Set (Eskridge et al. 1995), continual evaluation and reprocessing of the satellite data, and improvements in the ongoing atmospheric reanalyses projects should help reduce, but not eliminate, this uncertainty. Clearly, as these different analyses evolve and improve, it will be important to continue critical evaluations and comparisons of the datasets.

Although both the surface and tropospheric records are imperfect, current evidence suggests that the surface is warming significantly relative to the troposphere since 1979. It is important to remember that surface and upper-air records are of physically differ-

ent quantities. Stratospheric ozone depletion, volcanic eruptions, and ENSO, among other factors, influence tropospheric temperatures differently than surface temperatures (Santer et al. 2000b). Moreover, changes in temperature over a very shallow layer of the atmosphere associated with increases in daily minimum temperatures and cloudiness (Dai et al. 1999), and the fact that the global surface temperatures mostly reflect changes over the extratropical NH continents while the Tropics dominate global average upper-air records (Hurrell and Trenberth 1996), suggest that most of the difference between surface and upper-air trends over the past 20 yr is real. Over the longer 1958–1998 record, it is noteworthy that the two trends are much closer. The equivalent MSU_{2LT} trend from HADRT 2.0 is 0.13°C decade⁻¹ compared to 0.12°C decade⁻¹ from the global (land plus marine) surface temperature of Jones et al. (1999).

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