Global Precipitation Retrievals Using the NOAA AMSU Millimeter-Wave Channels: Comparisons with Rain Gauges

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ABSTRACT

A surface-precipitation-rate retrieval algorithm for 13-channel Advanced Microwave Sounding Unit (AMSU) millimeter-wave spectral observations from 23 to 191 GHz is described. It was trained using cloud-resolving fifth-generation Pennsylvania State University–National Center for Atmospheric Research Mesoscale Model (MM5) simulations over 106 global storms. The resulting retrievals from the U.S. NOAA-15 and NOAA-16 operational weather satellites are compared with average annual accumulations (mm yr\(^{-1}\)) for 2006–07 observed by 787 rain gauges globally distributed across 11 surface classifications defined using Advanced Very High Resolution Radiometer infrared spectral images and two classifications defined geographically. Most surface classifications had bias ratios for AMSU/gauges that ranged from 0.88 to 1.59, although higher systematic AMSU overestimates by factors of 2.4, 3.1, and 9 were found for grassland, shrubs over bare ground, and pure bare ground, respectively. The retrievals were then empirically corrected using these observed biases for each surface type. Global images of corrected average annual accumulations of rain, snow, and convective and stratiform precipitation are presented for the period 2002–07. Most results are consistent with Global Precipitation Climatology Project estimates. Evidence based on MM5 simulations suggests that near-surface evaporation of precipitation may have necessitated most of the corrections for undervegetated surfaces. A new correction for radio-frequency interference affecting AMSU is also presented for the same two NOAA satellites and improves retrieval accuracies.

1. Introduction

Although the sensitivity of satelliteborne passive millimeter-wave spectrometers to precipitation was quickly demonstrated by several researchers (Staelin and Chen 2000; Kummerow et al. 2001; McCollum and Ferraro 2003; Weng et al. 2005), the resulting precipitation retrieval accuracy has evolved more slowly as we learn more about the physical and stochastic relationship between hydrometeors aloft and those that reach the ground. The physical relationship is fourfold. First, storms are usually topped by frozen hydrometeors that scatter millimeter waves to produce a distinct cold radiometric spectral signature; second, hydrometeor profile information that further improves retrieval accuracy is provided by channels seeing to different depths in the atmosphere near the 53-GHz oxygen and 183-GHz water vapor resonances (Spina et al. 1998). Third, both strongly and weakly scattering storms over water usually produce strong warming signatures against the cold radiometric background provided by oceanic reflections of cosmic radio waves originally near 3 K; fourth, emission from colder nonscattering precipitating hydrometeor layers (e.g., warm rain) can often be seen against the warmer background of microwave-opaque air below.

The stochastic link between hydrometeors aloft and those reaching the ground varies with climate and terrain. This relationship can be revealed by faithful cloud-resolving numerical weather prediction models such as the fifth-generation Pennsylvania State University–National Center for Atmospheric Research Mesoscale Model (MM5; Dudhia et al. 2005) and then independently...
validated by large experiments over a wide range of geographic and meteorological conditions. Both modeling and observational approaches are explored in this paper, in which data from 787 global rain gauges for 2006 and 2007 in less hilly regions are compared with Advanced Microwave Sounding Unit (AMSU) surface precipitation retrievals to determine systematic biases and clues to their physical origin.

The retrieval algorithm used in this study (Surussavadee and Staelin 2008c) is summarized here in section 3 after presentation in section 2 of a new correction for radio-frequency interference on the National Oceanic and Atmospheric Administration NOAA-15 (N15) and NOAA-16 (N16) satellites that contaminates the two 183-GHz water vapor channels most sensitive to lower-tropospheric water vapor and midtropospheric hydrometeors. This interference arises from onboard data transmitters located near AMSU and is modulated as the sizes of openings into the instrument vary with scan angle.

Section 4 compares the 2006–07 N15 and N16 average annual precipitation estimates (mm yr\(^{-1}\)) with reliable rain gauges distributed around the globe and identifies systematic differences as a function of nation and land classification. Although numerous studies have compared satellite precipitation retrievals with rain gauges (Adler et al. 2001), this is the first to relate retrieval discrepancies to land classification and thereby to possible terrain-related explanations. The corrections related to land classification were then implemented and used in the subsequent analyses. These differences suggest that virga, surface emissivity, storm structure, or other factors result in overestimation by AMSU over deserts, grassland, and certain other terrain.

These hypotheses are then explored in a preliminary way in section 5, in which similar effects are sought in MM5 cloud-resolving-model simulations of comparable situations. The evidence favors rain evaporation as the primary cause of AMSU precipitation overestimates over desert and grassland. Such near-surface evaporation would affect all microwave remote sensing techniques to varying degrees and would require careful field experiments to determine appropriate bias corrections for each retrieval method.

Section 6 then presents representative global averages of retrieved precipitation based on averages of N15 and N16 data for the years 2002–07. These results should facilitate comparisons with other sensors and datasets, and they include retrievals of annual accumulations of rain, snow, and convective and stratiform precipitation as well as two seasonal examples. Strong interannual variations are evident—in particular, in the Arctic where this algorithm successfully maps precipitation events for over four warm months each year despite extensive ice cover.

### Table 1. AMSU channels utilized. Here WF indicates weighting-function peak heights (km) for channels A1–A8 and indicates water vapor burden (mm) at approximately one optical depth for channels B1–B5 assuming the U.S. Standard Atmosphere, 1976 at nadir over a nonreflecting surface.

| Channel | Frequency (MHz) | WF (km) | Channel | Frequency (GHz) | WF (mm) |
|---------|-----------------|---------|---------|-----------------|---------|
| A1      | 23 800 ± 72.5   | 0       | B1      | 89 ± 0.9        | >70     |
| A2      | 31 400 ± 50     | 0       | B2      | 150 ± 0.9       | 41      |
| A3      | 50 300 ± 50     | 0       | B3      | 183 ± 1         | 0.75    |
| A4      | 52 800 ± 105    | 0       | B4      | 183.3 ± 3       | 3       |
| A5      | 53 596 ± 115    | 4       | B5      | 183.3 ± 7       | 9       |
| A6      | 54 400 ± 105    | 8       |         |                 |         |
| A7      | 54 940 ± 105    | 9.5     |         |                 |         |
| A8      | 55 500 ± 87.5   | 12.5    |         |                 |         |

Comparisons with Global Precipitation Climatology Project (GPCP) data are also presented.

### 2. AMSU characteristics and interference

Table 1 characterizes those AMSU channels used for precipitation retrievals by listing their approximate frequency bands and altitudes to which they penetrate the U.S. Standard Atmosphere, 1976 at nadir over a nonreflecting surface. The channel abbreviations A1–A8 indicate channels 1–8 of AMSU-A, and B1–B5 indicate channels 1–5 of AMSU-B, respectively. The listed weighting-function (WF) values correspond to the altitudes of the peaks (km) of the temperature-sounding weighting functions near 53 GHz for channels A1–A8 and to the water vapor burden (mm) at approximately 1 optical depth (zenith transmittance = 1/e) for channels B1–B5. The AMSU-B WF peak altitudes are very sensitive to absolute humidity, and even the most transparent channel, B1, does not fully see the surface at extreme humidity whereas under extreme dryness even the most opaque channel, B3, can.

Although AMSU receiver frequencies are far above those of the NOAA spacecraft transmissions, when those transmissions penetrate the interior of the instrument the AMSU intermediate-frequency amplifiers pick up traces of them through the instrument radio-frequency shielding. These telecommunications signals enter AMSU-B through a scan-angle-dependent gap and are sufficiently stable that the resulting brightness temperature offsets can be evaluated using on-orbit data. Although initial corrections (NOAA 2009) for residual uncorrected radio-frequency interference (RFI) were made to the AMSU datasets now available from the NOAA/National Environmental Satellite, Data, and Information Service (NESDIS) Internet site (http://www.class.ncdc.noaa.gov), small adjustments now appear to be warranted.
Our RFI study began after our initial retrievals yielded unexplained differences between NOAA-15 and NOAA-16 precipitation statistics. First, the N16 RFI was deduced from the left–right asymmetry of globally averaged brightness temperatures; 1-month averages were computed over the entire 2002–07 time period. These small additive interference effects were restricted to one edge of the scan. The N16 corrections were then used to correct the more extensive N15 interference by comparing average brightness temperatures observed by the two satellites over full days spaced at 2-week intervals over the same 6 yr. These N15/N16 comparisons were based only on pixels observed at the same scan angle by both N15 and N16 within 40 min and 100 km for |lat| > 65°. The corrections and comparisons were computed separately for land and sea, for which the geophysical perturbations were slightly different.

Although small RFI effects of less than 1 K were observed on several AMSU channels, only the interference to channels 4 and 5 of AMSU-B clearly warranted correction. Figure 1 shows the deduced interference to channels B4 (183 ± 3 GHz) and B5 (183 ± 7 GHz) in units of kelvins as a function of scan angle over the 6-yr period analyzed here. Since public AMSU data are subject to recalibration, these residual interference levels may be reduced in the future. AMSU data prior to 4 January 2007 were obtained from NOAA in December of 2007, and the remainder was obtained in August of 2008. The scan positions 1–90 correspond to scan angles of ±48.95°, from left to right across the swath.

The potential consequences of residual uncorrected RFI (expected to be less than 1 K) were determined by increasing the brightness temperatures 3 K one channel at a time to simulate the increase in the retrieved surface precipitation rate when averaged over the same 106 global storms used for training (Surussavadee and Staelin 2008a,b). The expected values of these increases, denoted by \( E[\hat{P}] \), are summarized in Table 2. Note that the average increase due to an unexpectedly large 3-K single-channel residual error (after the RFI corrections) is always less than 0.2 mm h⁻¹, with an increase in rms deviation of less than 0.46 mm h⁻¹ for those channels with nonnegligible RFI: B4 and B5. The percentage increases in average retrieved rates shown in the rightmost column are similarly acceptable because all channels should have residual rms RFI errors of less or much less than 1-K.

### 3. Retrieval algorithm

The retrieval algorithm is summarized in Table 3 and is explained more fully elsewhere (Surussavadee and Staelin 2009). The algorithm is preceded by the RFI corrections illustrated in Fig. 1. The algorithm was trained using the MM5 cloud-resolving numerical weather prediction model incorporating the Goddard cloud-physics model with 5-km resolution (Surussavadee and Staelin 2006). Hydrometeor scattering was based on discrete-dipole electromagnetic calculations for hexagonal plates (snow) and six-pointed rosettes (graupel).

The retrieval algorithm has six steps: 1) rejection of out-of-bounds brightness temperatures \( T_B \) and surface elevations \( h_{surf} \) that are too high, and zeroing of retrievals when the air is so cold that surface effects could invalidate the retrieval and precipitation should be

![Figure 1](https://via.placeholder.com/150)

**Table 2.** Average increase and standard deviation in surface precipitation retrieval (mm h⁻¹) due to 3-K increases in AMSU brightness temperatures. Here, \( P \) and \( P' \) are the original and RFI-perturbed surface precipitation rate retrievals, respectively; \( E[\hat{P}] = 0.85 \).

| AMSU Channel | \( E[\hat{P} - \hat{P}] \) (mm h⁻¹) | RMS (mm h⁻¹) | \( \frac{100}{E[\hat{P}] - \hat{P}} \) (%) |
|--------------|----------------------------------|--------------|-------------------------------------|
| A1           | -0.02                            | 0.40         | -2.16                               |
| A2           | 0.01                             | 0.34         | 1.42                                |
| A3           | -0.00                            | 0.35         | -0.04                               |
| A4           | 0.06                             | 1.10         | 6.76                                |
| A5           | 0.01                             | 0.65         | 0.69                                |
| A6           | 0.03                             | 0.83         | 3.34                                |
| A7           | 0.03                             | 0.62         | 3.95                                |
| A8           | -0.01                            | 0.75         | -1.53                               |
| B1           | -0.00                            | 0.13         | -0.49                               |
| B2           | -0.01                            | 0.21         | -1.29                               |
| B3           | 0.19                             | 0.47         | 22.48                               |
| B4           | -0.07                            | 0.40         | -8.34                               |
| B5           | -0.11                            | 0.46         | -13.25                              |
Table 3. AMSU precipitation rate retrieval algorithm. Here PCA indicates PC analysis and $P$ here is surface precipitation rate.

| No. | Action |
|-----|--------|
| 1   | Flag pixel (omit) if $T_B < 50$ K or $T_B > 400$ K or 2 km < $h_{surf}$; | Land, A4–A8 Land, 122 orbits | PC1, B3–B4 106 MM5, land |
|     | $|\text{lat}| < 60^\circ$ and 1.5 km < $h_{surf}$; $60^\circ < |\text{lat}| < 70^\circ$ and 0.5 km < $h_{surf}$; $|\text{lat}| > 70^\circ$. Retrieval = 0 if A5 < 242 K | Ice-free sea, 122 orbits | PC2–5 106 MM5, ice-free sea |
| 2   | Remove biases relative to MM5 simulations for A5–A8. Neural nets (NN) correct $T_B$ to nadir values (trained using 106 MM5 storms). Classify surface: land vs water using coordinates; ice/snow vs other (Grody algorithm) | A1–A8, B1–B5 Ice-free sea, 122 orbits | PC2–5 106 MM5, ice-free sea |
| 3   | Bound scattering areas (convective cells) using [B5 < 0.667(A5 - 248) + 258] if A5 ≥ 248 or (B4 < 247.5) if A5 < 248 K, then evaluate boundary value $T_B$. Compute $\Delta T_B$ relative to interpolated boundary values for A4–A8. Compute scores for those PCs (see step 4) that correlate well globally with rain but not with surface emissivity or humidity. Feed $\Delta T_B$, secant of zenith angle, PCs and other inputs to NNs | A4–A8 A5 < 248 K, 122 orbits | PC1–2, B3–B4 106 MM5, 53.6 GHz < 248 K |
| 4   | 4. Comparisons with rain gauges |

- Minimal, 2) removal of biases, conversion of $T_B$ to equivalent nadir values, and surface classification, 3) detection of local cold spots $\Delta T_B$ near 53 GHz associated with scattering from larger icy hydrometeors, and computation of window-channel principal components (PC) sensitive to precipitation but nearly blind to surface and humidity effects, 4) neural network retrievals of multiple estimates of surface precipitation rate depending on surface type, 5) combination of the multiple estimates from step 4 into a single estimate, and 6) rejection (flagging) of precipitation values over snow and ice that are excessively high, along with those for nearby pixels.

Of 255 MM5-simulated storms, 122 were morphologically consistent with concurrent AMSU images; each storm was 2835 km square, and they were chosen from all seasons and latitudes (Surussavadee and Staelin 2006). The algorithm was trained by a random subset of 106 of these, each being 945 km square with 5-km resolution, where the reduction from 122 to 106 storms was due to lack of data storage capacity (Surussavadee and Staelin 2008a). There are no empirical retrieval adjustment factors based on ground truth beyond those embedded in MM5 itself.

Perhaps the most significant geographic limitations of this algorithm are its exclusion of high altitudes and cold air temperatures in step 1. High altitudes are excluded because they are more likely to be excessively dry, which permits the most-opaque channels to see the surface and introduce retrieval errors. Excessively cold air temperatures sensed at 53.6 GHz similarly indicate a risk of excessively dry air and retrieval errors. Both of these limitations can easily be overcome in future satellite designs by including channels near a more nearly opaque water vapor resonance such as 380 GHz that still see through the thin cirrus that can obscure such cold zones.

### 4. Comparisons with rain gauges

Monthly rain gauge data assembled by NOAA (NOAA 2007) were used for comparison and correction purposes. Only gauges that reported entries for all 24 months in 2006 and 2007 were utilized, and sites deemed less reliable because they were too hilly were deleted. Hilly sites were arbitrarily defined as those for which the surface elevation varied by more than 500 m within a box of ±0.2° of longitude and latitude.

For each gauge, the corresponding annual precipitation (mm yr$^{-1}$) retrieved from all passes by N15 and N16 in 2006–07 was averaged within a box centered on that gauge and bounded by ±0.4° of longitude and latitude. Only pixels centered within a box were averaged. Smaller boxes had more sample noise, and larger boxes often introduced biases; this box size empirically balanced these effects. Even though each spot on Earth was observed by AMSU on N15 and N16 roughly 4 times daily, there is considerable interannual variation in the ratios between each gauge and AMSU because annual accumulations at single locations are typically dominated by a few large storms that last only a few hours and
may be missed by AMSU during gaps of up to about 8 h between satellite overpasses. This AMSU “sampling noise” for 1-yr averages appears to be significant for roughly one-half of all sites, based on comparison of the variances of such 1- and 2-yr average ratios within homogeneous regions containing multiple gauges. For this reason 2 yr of monthly accumulation data were averaged before computing the ratio; this variance is smaller for regions experiencing primarily stratiform precipitation of long duration.

Table 4 shows this comparison between 1) uncorrected AMSU retrievals based on the algorithm of Table 3 and 2) gauges for all sampled regions having at least 14 sites that are not hilly, desert, or coastal. Desert gauges were defined as those averaging less than 300 mm yr\(^{-1}\) of precipitation, and coastal gauges were on large landmasses within 55 km of a coastline. Desert, coastal, and >75°N sites that are not hilly are presented as separate regions. To reflect climate differences, the Former Soviet Union (FSU) was divided into east and west at 60°E longitude (the Ural Mountains) and the contiguous United States was divided at 100°W longitude. The regions in the table are ordered by their ratio of the mean satellite retrieval to that of the gauges. These precipitation ratios \(R\) vary from 0.99 in France to 1.31 in the eastern United States, with higher ratios in the more desertlike regions of Australia (1.59) and the western United States (2.27).

Table 4 shows how the variance of the ratio \(R\) between AMSU and the gauge readings within each region varies among regions. In particular, “sat rms,” which is defined for each land classification as the standard deviation of (satellite – gauge) divided by its mean gauge value, increases almost monotonically with \(R\), from 18% to 64% of the regional mean gauge value. The inferred rms reliability of the average region ratio, “region rms,” is listed in the rightmost column and is equal to sat rms divided by the square root of \((N – 1)\), where \(N\) is the number of gauges that were averaged. The observed overestimation by the unadjusted AMSU retrieval algorithm is statistically significant at the 3-sigma level if \(R – 1\) exceeds 3 times the region rms; this is true for classifications where \(1.25 \leq R \leq 2.5\). The even larger \(R\) values involving bare ground are also significant, but those \(Rs\) are noisy because of occasional very small rain gauge values. The high ratios \(R\) over coastline are probably due to some combination of coastal meteorology and antenna side-lobes that straddle the land–sea boundary, particularly indented boundaries, although the algorithm assumes pure land. The reasons for the high ratios for the seven gauges north of 75°N are unknown.

To understand further the possible reasons for these regional overestimates, including coastline and desert, the entire set of 787 gauges in nonhilly sites was then grouped instead by land surface classification as defined by a 1° global land-cover map derived from Advanced Very High Resolution Radiometer (AVHRR) data (Hansen et al. 2000). Table 5 lists these surface classes in order of the degree of satellite overestimation, as in Table 4. In this table each site within 55 km of a coastline was included only once as “coastline” instead of its original AVHRR surface category because some combination of convoluted coastlines, small pixel location errors, and coastal meteorological effects appears to dominate other surface-classification effects in the global precipitation maps. The main conclusion drawn from Table 5 is that AMSU overestimation ranges from 0.88 for tundra to 1.25 for wooded grassland and then increases monotonically with the approximate average annual fraction of barren or exposed land, going from 1.37 to 2.4, 3.06, and 9.08 in going from cultivated crops to grassland, shrubs over bare ground, and bare ground, respectively; land covered by evergreens has ratios \(R\) near unity. The bare-ground cases are mostly North African, Middle Eastern, and Gobi deserts. Tundra and high-latitude deciduous forest exhibit the lowest ratios

### Table 4. AMSU surface precipitation retrievals vs reliable rain gauges 2006–07.

| Region                  | Satellite (mm yr\(^{-1}\)) | Gauge (mm yr\(^{-1}\)) | Ratio | Sat rms (%) | No. sites | Region rms (%) |
|-------------------------|-----------------------------|------------------------|-------|-------------|-----------|----------------|
| France                  | 776                         | 783                    | 0.99  | 18.2        | 17        | 4.6            |
| FSU west                | 596                         | 579                    | 1.03  | 22.2        | 70        | 2.7            |
| Germany                 | 776                         | 737                    | 1.05  | 15.2        | 49        | 2.2            |
| FSU east                | 540                         | 495                    | 1.09  | 27.0        | 54        | 3.7            |
| Canada                  | 849                         | 679                    | 1.25  | 25.1        | 19        | 5.9            |
| Brazil                  | 1612                        | 1270                   | 1.27  | 28.8        | 14        | 8.0            |
| Eastern United States   | 1310                        | 998                    | 1.31  | 25.7        | 60        | 3.4            |
| Australia               | 1000                        | 630                    | 1.59  | 56.7        | 20        | 13.0           |
| Western United States   | 1157                        | 509                    | 2.27  | 63.7        | 14        | 17.6           |
| Coastal                 | 1439                        | 928                    | 1.55  | 57.82       | 260       | 3.59           |
| >75°N                   | 366                         | 230                    | 1.59  | 44.15       | 7         | 18.03          |
| Desert                  | 558                         | 141                    | 3.94  | 146.9       | 94        | 15.24          |

TABLE 4. AMSU surface precipitation retrievals vs reliable rain gauges 2006–07.
perhaps because they seldom experience high surface temperatures or low relative humidity that could promote virga, whereas barren land often does.

5. Possible physical explanations of AMSU overestimates

Both Tables 4 and 5 suggest that barren or grassy land is systematically associated with overestimation. There are at least three possible explanations for why MM5 and the present AMSU algorithm might not anticipate this overestimation: 1) the surface emissivity spectrum of barren terrain was not specifically identified in the AMSU training datasets, 2) hydrometeor habits and cloud drop size distributions aloft are affected by barren terrain in ways that promote overestimation, and 3) AMSU is insensitive to terrain-correlated evaporation near the surface (virga).

The first hypothesis would require very large systematic surface emissivity differences over barren terrain because only channels A1, A2, A3, B1, B2, and sometimes B5 sense the surface in a nonnegligible way. The rightmost column of Table 2, however, suggests that the influence of these channels, except B5, has been reduced by the algorithm to such a degree that factor-of-2 retrieval errors would require brightness temperature errors greater than 100 K that are correlated with land classification, which is inconceivable. Table 2 suggests that, on average, the surface would have to appear roughly 20 K hotter in channel B5 (7 times the 3-K perturbation that produced the 13% increase reported in the table); this too is inconceivable because it would require surface physical temperatures that were unexpectedly several times hotter still in order to overcome the limited transmittance of the atmosphere. Even in dry atmospheres, channel B5 sees the surface weakly if at all; it sees it strongly only in very dry winter conditions.

The second potential mechanism links terrain type with size distributions and involves, for example, terrain-dependent nucleating agents such as dust that might promote larger numbers of smaller hydrometeors. However, smaller hydrometeors should generally reduce AMSU-retrieved precipitation values over land where large-hydrometeor scattering is the principal signature used to infer precipitation rates. This aerosol effect therefore appears to have the wrong sign. Moreover, maps of global aerosol optical depth produced by MODIS at 550 nm show little correlation with those regions and land classifications exhibiting the greatest AMSU retrieval overestimations (NASA 2009). Deserts and other hot surfaces could alternatively increase the population of large hydrometeors aloft when superheated surfaces promote strong convection, but a wide variety of convective strengths were included in the MM5 simulations, and therefore this possibility also seems remote.

The third possibility involves significant terrain-dependent reductions in hydrometeor populations aloft before they impact the surface. To characterize this effect we arbitrarily define a “virga metric” (V metric) for a given 15-km field-of-view (FOV) as the ratio V between the highest MM5 layer-average hydrometeor density H (kg m\(^{-3}\)) in air and H in the lowest MM5 atmospheric layer. For example, large values of V could arise from partial or total evaporation of precipitation before it reaches the ground (virga). This phenomenon is commonly observed over western U.S. prairies and similar terrain where warm dry air increases evaporation rates. Alternatively, hydrometeor mass densities H aloft can also be relatively larger if those hydrometeors fall slowly because of strong updrafts or because of their large aerodynamic drag coefficients (e.g., snowflakes), whereas the same melted mass flux (kg m\(^{-2}\) s\(^{-1}\)) falls more swiftly at lower values of H nearer the surface. However, there is no evidence in the MM5 simulations
that snow production aloft is significantly higher over grassland or desert than it is elsewhere.

The V-metric hypothesis is tested in Fig. 2, where the vertical axis represents the mean ratio $R$ of simulated AMSU retrievals relative to MM5 “truth” over 106 globally distributed MM5 storms, and where MM5 truth of less than 1 mm h$^{-1}$ was omitted to avoid overemphasis of less significant storms. The horizontal axis is the V metric. The dashed curve represents the mean plus 1 standard deviation over the entire ensemble of storms, and the gray curve is the probability distribution of the MM5 V metric for the 106 global storms used for training; the a priori standard deviation of the V metric is 0.45. The high degree of correlation between the MM5 virga metric and the corresponding overestimates of precipitation by AMSU for the same FOVs strongly suggests that terrain-related evaporation of rain is the principal explanation for AMSU overestimates relative to rain gauges, as presented in Tables 4 and 5. Although timing delays between events aloft and near the surface could contribute to the observed high correlation between the V metric and $R$, they would not explain high time-average values of $R$ because delays alone would decrease $R$ as often as they increase it.

Because AMSU can retrieve both tropospheric temperature and humidity profiles, it can also retrieve V. This is shown in Fig. 3, which depicts MM5 values of V for two typical storms, together with the corresponding simulated AMSU-retrieved images of V. The corresponding simulated AMSU retrieval accuracies for V are presented in Table 6. Although the nominal rms accuracies of 0.27–1.98 are a fraction of the range of V, preliminary experiments incorporating these retrieved Vs in the precipitation estimator produced no significant improvement; stratiform retrievals improved most, but less than 10% and with uncertain statistical significance. Such a null result is expected if the existing neural network precipitation retrievals already extract all relevant V-metric information from AMSU.

Thus the virga problem apparently arises because the MM5 training did not include surface classification. These biases in $R$ can fortunately be greatly reduced within each terrain class by using the terrain-dependent correction factors of Table 5, which are based on statistically significant rain gauge data. The resulting accuracies for regional annual averages should approach the regional rms values presented in Table 5. Such corrections were generally incorporated in the data presented in the next section.

6. Global observations of precipitation

This surface-classification-corrected precipitation-rate retrieval algorithm was evaluated by comparisons with known meteorological phenomena and other global datasets. For example, Fig. 4 presents retrievals over the North Pole for two consecutive days in 2004 as observed from N16. Light pink indicates sea ice detected by
AMSU, and dark pink indicates altitudes that were too high to permit reliable retrievals. Such retrieved precipitation rates are consistent with MM5 cloud-resolving models, and the observed storm morphology is consistent with enhanced polar geostrophic effects.

Arctic precipitation generally remains observable between 20 May and 20 September, after which further observations are precluded by excessively cold air indicated by 53.6-GHz brightness temperatures below 242 K. Approximately 10 yr of AMSU precipitation data have now been collected over the Arctic by one–four AMSU satellites simultaneously, providing a unique way to observe Arctic precipitation morphology and decadal changes. Moreover AMSU polar orbits pass over the pole every 100 min per satellite, and multiple satellites often reduce observing time gaps to less than 1 h.

To facilitate comparisons with meteorological expectations and other global precipitation retrievals, Fig. 5 presents eight different global maps of annual surface precipitation retrievals (mm yr\(^{-1}\)) for either single years or annual averages for 2002–07. In all cases retrievals from \(N15\) and \(N16\) were averaged together to reduce diurnal effects. Figures 5a and 5b present, respectively, the average rates (mm yr\(^{-1}\)) for 2002–07 estimated by AMSU (corrected for surface classification) and by the GPCP (Huffman et al. 2001). They are encouragingly similar. Evident differences include GPCP’s wetter estimates near the Antarctic coast, over desert, and between 60° and 75°N; dryer estimates near the North Pole; and sharp discontinuities near 60°N and 60°S latitudes. AMSU exhibits a sharp discontinuity near 75°N that is due to the Arctic correction discussed in section 4, and higher extreme values in the ITCZ. No correction has been made for the fact that all AMSU retrievals are set to zero when the 53.6-GHz brightness temperature is below 242 K; such a correction would slightly increase AMSU polar accumulation estimates. Because most of these areas have little reliable ground truth, resolving these differences will require careful study.

Figures 5c and 5d exhibit 6-yr averages for convective and stratiform precipitation, respectively, where the existence of convection is inferred from AMSU spectral signatures associated with vertical velocities above 0.45 m s\(^{-1}\) in that MM5 layer exhibiting maximum values. Peak vertical velocities are retrieved using the same retrieval algorithm architecture illustrated in Table 3, where these neural networks are trained instead using 15-km resolution MM5-predicted peak vertical wind. The physical basis for velocity estimation relies largely on the sensitivity of millimeter-wave spectra to hydrometeor size distributions, abundance, and altitudes (Surussavadee and Staelin 2008a,b). Figures 5c and 5d also suggest that the coastal discontinuities evident in Figs. 5a and 5b are due mostly to oceanic stratiform precipitation.

The large retrieved stratiform rates over midlatitude ocean may be partly due to winter snow over warm sea, as suggested by Figs. 5c and 5f, which present retrievals of average rain and snow accumulations for the same 6-yr period. Oceanic snowfall peaks near 800 mm yr\(^{-1}\), which is roughly one-half of the totals shown in Fig. 5d near 50° latitude. Snowfall also exhibits land–sea discontinuities similar to those noted earlier for stratiform precipitation. AMSU distinguishes between rain and snow by using a tropospheric temperature threshold (248 K) sensed at 53.6 GHz and chosen using MM5 global truth (Surussavadee and Staelin 2009). Because this threshold was determined globally, it classifies too much precipitation as rain versus snow when the lapse rates are small, particularly in polar regions; a more accurate classifier is under development.

Figures 5g and 5h illustrate seasonal variations, where Fig. 5g portrays total precipitation (mm) from December through February, averaged over 2002–07, and Fig. 5h portrays precipitation from June through August. This annual cycle is much more pronounced in the Northern Hemisphere than in the more oceanic south. The low
retrieved precipitation values over Siberia and elsewhere in winter are probably partly due to low air temperatures that preclude retrievals in step 1 of the algorithm (A5 < 242 K).

Figure 6 presents similar data in a format that more clearly reveals interannual variations as a function of latitude for the driest and wettest years in this set, 2003 and 2006. All forms of precipitation increased by
approximately 5%–20% in 2006 relative to 2003 with a few small exceptions, including a large increase by a factor of 2–3 north of 85°N. Although the factor of 2–3 is dramatic, the polar geographic area is relatively small and therefore the regional rms interannual variation is correspondingly larger. Because the Arctic is very sensitive to global warming and polar ice and tundra are sensitive to precipitation, this new ability to monitor Arctic precipitation trends during the summer months should prove useful. As noted earlier, the ratio of rain to snow is overestimated near the Pole. Much of the increase between 2003 and 2006 appears to be related to corresponding increases in the probability of precipitation at rates that are above 0.5 mm h$^{-1}$.

Figure 7 compares the average surface-classification-corrected and -uncorrected AMSU annual latitudinal retrievals (mm yr$^{-1}$) with GPCP for 2002–07. In general the surface-classification-corrected AMSU retrievals are consistent with GPCP with the notable exceptions of modest AMSU shortfalls below 55°S and AMSU excesses above 82°N and in the latitude band 45°–55°N over ocean. Because reliable gauges in these regions are scarce, additional gauge data are needed to apportion these discrepancies reliably between AMSU and GPCP. The higher GPCP values over high-latitude land may be partly due to wind-loss adjustments applied to the Global Precipitation Climatology Centre gauge analysis observations incorporated in GPCP analyses but not to the gauges used to correct AMSU. The land-classification corrections to AMSU are generally smaller in the tropics, very small at latitudes of 50°–70°, and greater at mid-latitudes 20°–50°N, because that is where much desert is located. Because of reliability concerns, the surface-classification corrections for water were defined as unity because of the lack of reliable rain gauge data there; the “water” gauges reside mostly on small islands with uncertain local effects. Because water surfaces generally promote less virga than does hot land, this assumption that $R \equiv 1$ is also plausible on physical grounds. The difference between the surface-classification-corrected

FIG. 6. Average annual retrievals as a function of latitude using NOAA-15 and NOAA-16 AMSU data for 2003 (dashed lines) and 2006 (solid lines). (left)–(right) Average precipitation $P$ (mm yr$^{-1}$), $P$ for land only, $P$ for ocean only, probability of precipitation rates (RR) above 0.5 mm h$^{-1}$, stratiform precipitation (mm yr$^{-1}$), and snowfall (mm yr$^{-1}$).
and -uncorrected ocean AMSU retrievals is because the land/sea flag data used to separate land and sea are at finer resolution than the 1° resolution of the land classification data that were used to define land and sea for the corrections; therefore some land pixels were inadvertently included in the corrected-sea set, particularly along convoluted coastlines. Retrievals north of 75°N latitude yielded high values inconsistent with MM5, so these retrievals were reduced by a correction factor of 1.59 based on seven northern rain gauges near the coasts, despite the uncertainties involved.

7. Summary and conclusions

These comparisons between annual averages of surface-classification-corrected N15 and N16 AMSU precipitation retrievals, rain gauge data averaged for two years, and comparable global GPCP estimates suggest that AMSU data collected since 1999 can usefully augment other global precipitation datasets when MM5-trained neural networks are employed using 13 microwave channels. When AMSU is corrected for surface classification, the ratios AMSU/GPCP for 6-yr average latitudinal plots of precipitation over land and sea typically vary between 0.6 and 1.4 for latitudes between 55°S and 55°N. Below 55°S this ratio drops below 0.5, partly because of cold temperatures that result in zero-value AMSU estimates, and above 82°N the ratio climbs past 1.4 to values near 2.2. Current AMSU retrievals are not computed for high surface elevations (latitude dependent) and very cold weather (53.6-GHz nadir-corrected brightness temperatures below 242 K) because of excessive surface emissivity effects.

Evaporation of precipitation near the surface may contribute significantly to the observed AMSU overestimates over bare ground and grassland and may affect other retrieval methods as well. This conjecture is largely based upon 1) the observed correlation between simulated AMSU overestimates and MM5-predicted ratios between hydrometeor densities aloft and near the surface and 2) the physical plausibility that superheated desert and grassland surfaces could facilitate evaporation of rain near the surface. Hot surfaces and rain evaporation can diminish gauge readings without alerting AMSU since AMSU retrievals primarily use frequencies for which the atmosphere is nearly opaque so as to reduce the influence of variable surface emission spectra. The more dramatic correction factors observed for bare ground (9.08) and grassland (2.40) suggest those retrievals are likely to be less accurate; they are echoed by milder but statistically significant surface-dependent differences between 1) wooded grassland and cultivated crops (correction factors of 1.25–1.37) and 2) more intensely vegetated broadleaf and coniferous evergreen forests (correction factors of 1.03–1.11).

Retrievals yet to be validated with trustworthy rain gauges include those over the summertime North Pole and most of those over ocean. Based on these results it seems that the retrieval algorithm could be improved further by incorporating the surface classification and local time information in the neural network retrievals instead of using a constant multiplier for each surface class. Local time would differentiate between hot solar-heated afternoon surfaces that could promote virga and cooler surfaces at other times of day that would have little such effect. In addition, the evidence presented for strong interannual precipitation variations near the North Pole warrants further study of their continued evolution, potential effects, and relation to El Niño and other global oscillations and trends.
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