Millimeter-Wave Precipitation Retrievals and Observed-versus-Simulated Radiance Distributions: Sensitivity to Assumptions

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ABSTRACT

Brightness temperature histograms observed at 50–191 GHz by the Advanced Microwave Sounding Unit (AMSU) on operational NOAA satellites are shown to be consistent with predictions made using a mesoscale NWP model [the fifth-generation Pennsylvania State University–National Center for Atmospheric Research Mesoscale Model (MM5)] and a radiative transfer model [TBSCAT/F(λ)] for a global set of 122 storms coincident with the AMSU observations. Observable discrepancies between the observed and modeled histograms occurred when 1) snow and graupel mixing ratios were increased more than 15% and 25%, respectively, or their altitudes increased more than ~25 mb; 2) the density, F(λ), of equivalent Mie-scattering ice spheres increased more than 0.03 g cm$^{-3}$; and 3) the two-stream ice scattering increased more than ~1%. Using the same MM5/TBSCAT/F(λ) model, neural networks were developed to retrieve the following from AMSU and geostationary microwave satellites: hydrometeor water paths, 15-min average surface-precipitation rates, and cell-top altitudes, all with 15-km resolution. Simulated AMSU rms precipitation-rate retrieval accuracies ranged from 0.4 to 21 mm h$^{-1}$ when grouped by octaves of MM5 precipitation rate between 0.1 and 64 mm h$^{-1}$, and were ~3.8 mm h$^{-1}$ for the octave 4–8 mm h$^{-1}$. AMSU and geostationary microwave (GEM) precipitation-rate retrieval accuracies for random 50–50 mixtures of profiles simulated with either the baseline or a modified-physics model were largely insensitive to changes in model physics that would be clearly evident in AMSU observations if real. This insensitivity of retrieval accuracies to model assumptions implies that MM5/TBSCAT/F(λ) simulations offer a useful test bed for evaluating alternative millimeter-wave satellite designs and methods for retrieval and assimilation, to the extent that surface effects are limited.

1. Introduction

To assimilate passive microwave precipitation observations or retrievals into numerical weather prediction (NWP) models, the modeled radiances must be consistent with those observed. This paper tests the sensitivity of that consistency to assumptions in a particular radiative transfer model (RTM), and in a cloud-resolving NWP model that predicts hydrometeor habits and profiles. The precipitation and water path retrieval accuracies are shown to be less sensitive to the physical models than are the radiances, provided that the retrieval method is tuned to reality.

These model-sensitivity results are most relevant to imaging microwave spectrometers such as the Advanced Microwave Sounding Unit (AMSU) on the National Oceanic and Atmospheric Administration (NOAA) polar orbiting satellites NOAA-15, NOAA-16, NOAA-17, and NOAA-18 (Hewison and Saunders 1996; Mo 1999; Chen and Staelin 2003; Ferraro et al. 2005), and its planned successor, the Advanced Technology Microwave Sounder (ATMS; Muth et al. 2004). These instruments observe frequencies above 23 GHz with a spatial resolution of approximately 15–50 km. Retrieval accuracies at nadir are also predicted for proposed geosynchronous microwave sounders that could monitor precipitation at intervals as short as approximately 5–15 min (Solman et al. 1998; Bizzarri et al. 2002). Development and analysis of AMSU precipitation retrieval algorithms for use at all angles is deferred to future papers.

The use of cloud-resolving NWP model-based simulations for developing and evaluating microwave precipitation retrieval methods is motivated by the lack of trustworthy ground truth coincident with microwave observations. For example, there is no practical method...
for accurately observing the three-dimensional density, size, and habit distributions of various hydrometeor species at the same time their microwave emission spectrum is being continuously mapped from above. Although multifrequency Doppler radar systems offer some hope for accurate three-dimensional imaging of hydrometeors, such studies are rare and require simultaneous microwave spectrometers operating overhead to complete the experiment. Even rain gauge measurements of surface rainfall are suspect because of the influence of local winds and because arrays of gauges are seldom sufficiently extensive to compensate for the nonuniformity of rain, particularly convective rain. Moreover, because the character of precipitation varies substantially over the globe, high-quality ground-truth instrumentation must be mobile or replicated.

One way to obtain more precise precipitation retrieval training data is to use cloud-resolving NWP models in combination with RTMs, which together match satellite observations with acceptable fidelity over a global set of collocated test cases. For example, simulated cloud radiation databases linking meteorological parameters to emergent microwave spectra have long been used to train “physically based” retrieval algorithms designed for Tropical Rainfall Measuring Mission (TRMM) data (e.g., Smith et al. 1994; Grecu and Anagnostou 2001). Another model-based approach to precipitation retrievals involves Bayesian schemes based on Gaussian assumptions, as demonstrated by Bauer et al. (2005) for a hypothetical sensor with five window channels between 18 and 150 GHz plus 8 channels in the 54- and 118-GHz oxygen absorption bands.

A simpler approach is to evaluate the separate impacts of various modifications to the NWP and RTM models. This was done, for example, by Tassa et al. (2006) for the TRMM frequencies and in a limited way by Surussavadee and Staelin (2006) for AMSU frequencies between 23 and 191 GHz. In the latter work, observed AMSU radiance histograms agreed within approximately ±10 K at all frequencies with those predicted by the NWP fifth-generation Pennsylvania State University–National Center for Atmospheric Research (NCAR) Mesoscale Model (MM5) followed by the RTM model TBSCAT/F(λ), not only for global averages over 122 diverse storms observed between 83°N and 73°S over a year, but also for subsets of convective, stratiform, rainy, and other types of precipitation. This paper extends this initial sensitivity analysis to several additional model assumptions and to their impact upon predicted retrieval accuracies.

Section 2 of this paper reviews briefly the approach taken and the data and models used, including 1) the physical basis for the link between millimeter-wave spectra and surface-precipitation rates, 2) the satellite and model observations, 3) the MM5 configuration, and 4) the radiative transfer algorithm. Section 3 explores the sensitivity of the brightness temperature histograms to various assumptions in the RTM and MM5. Section 4 then presents analyses of 1) precipitation retrieval accuracies for AMSU and a proposed geostationary microwave sounder using frequencies 150–430 GHz, and 2) the sensitivity of those predicted accuracies to model assumptions and meteorological conditions. Section 5 summarizes the prospects for assimilation of millimeter-wave precipitation-sensitive radiances and retrievals into numerical models, and the conclusions to be drawn from these studies.

2. Approach

a. Physical basis

Most prior centimeter-wave precipitation observations from satellites have used dual-polarized window channels below 90 GHz viewed at large constant zenith angles that permit surface emissivity and temperature to be partially distinguished, thus permitting atmospheric absorption and water paths to be estimated (Kummerow et al. 1996). In contrast, millimeter-wave spectrometers rely more on scattering signatures deduced as a function of altitude and wavelength for wavelengths that span the transition between Rayleigh and geometric scattering for typical hydrometeors. Thus, millimeter-wave spectra reveal information about hydrometeor size and altitude distributions, both of which are correlated with precipitation intensity. Millimeter-wave observations in window channels over ocean also yield water path information, but multiple channels are required to help distinguish the effects of water vapor and ocean roughness from absorption by water droplets. The instrument of primary interest in this paper, AMSU, scans cross track with only a single angle-dependent polarization.

The altitude distributions of hydrometeors can be inferred, for example, using the opaque oxygen band channels near 54, 118, and 425 GHz. Only frequencies penetrating down to cell-top levels can sense their scattering signature (Gasiewski and Staelin 1989; Spina et al. 1998), and these penetration depths are frequency dependent, ranging from the surface to the mesosphere. The observable cell tops are defined by hydrometeors of approximately 1–5-mm diameter, which generally dominate millimeter-wave scattering, and these tops can lie well below the visible cloud top. The signature of an icy cell top can be strong because its albedo can exceed 50% and yield local perturbations over 100 K, large compared with nominal satellite receiver sensitiv-
ties of ~0.2 K. This “altitude slicing” phenomenon associated with frequency-dependent penetration depths is also evident in 183-GHz water vapor observations because, for example, only the highest cell tops rise to the dry altitudes observable from space near 183.7 GHz (Chen and Staelin 2003; Leslie and Staelin 2004). Hydrometeor size distributions are revealed by the frequency dependence of scattering signatures between 50 and 200 GHz because the transition between Rayleigh and geometric scattering for most hydrometeors lies within this band. The larger hydrometeors are more evident in the 50–100-GHz region, while smaller ones dominate above 100 GHz (Gasiewski and Staelin 1989; Blackwell et al. 2001; Leslie and Staelin 2004). Because hydrometeor size and weight are related to the vertical wind necessary to maintain them aloft, there is significant correlation between the presence of larger hydrometeors, higher vertical winds, and stronger convective rain.

The information content in the millimeter-wave brightness temperature spectrum relevant to icy hydrometeor distributions can be estimated from the variances of the eigenvectors characterizing the millimeter-wave spectral difference between atmospheric columns with and without such icy hydrometeors. Studies of ~1.6 million 15-km resolution differential microwave emission spectra between 21 and 190 GHz computed for 122 storms distributed over the globe and year, as described in more detail in section 2b, yielded normalized variances for the first three differential spectral eigenvectors of 95.7%, 3.2%, and 0.7%. Millimeter-wave aircraft and satellite data have shown that both cell-top altitudes and particle size distributions are separately revealed by such spectra (Spina et al. 1998; Blackwell et al. 2001; Leslie and Staelin 2004). These parameters are correlated to some degree, however, and are also correlated with precipitation rate.

b. Observations

The most extensive observations of millimeter-wave spectral images of the earth have been made by AMSU on the operational satellites NOAA-15, NOAA-16, NOAA-17, and NOAA-18, beginning in May 1998. AMSU comprises AMSU-A with ~50-km resolution near nadir at 15 frequency bands centered between 50.3 and 89 GHz, and AMSU-B with ~15-km resolution in five channels distributed between approximately 88 and 191 GHz (Hewison and Saunders 1996; Mo 1999). AMSU-A and AMSU-B scan through nadir 48.33° and 48.95° from nadir, respectively. Each scan maps a swath beneath the spacecraft 2200 km wide with 30 AMSU-A views and 90 AMSU-B views; the scan periods for AMSU-A and AMSU-B are 8 and 2.67 s, respectively. Similar microwave-sounding instruments include ASMU/Humidity Sounder for Brazil (HSB) on the National Aeronautics and Space Administration (NASA) Aqua satellite, AMSU/European Microwave Humidity Sounder (MHS) on NOAA-18, the future ATMS on the National Polar-orbiting Operational Environmental Satellite System, and others (Lambrightsen 2003; Mo 2006; Muth et al. 2004). This paper utilizes only data from AMSU-A/B, which observes the frequencies listed in Table 1; the pressures at which the temperature weighting function for each channel peaks for the U.S. standard atmosphere are also listed together with the geophysical parameters to which each channel is most sensitive.

### Table 1. Frequencies and weighting function peak heights for AMSU-A/B and GEM, as computed using the U.S. Standard Atmosphere, 1976, viewed at nadir over a nonreflective surface.

<table>
<thead>
<tr>
<th>Channel</th>
<th>Center frequency (GHz)</th>
<th>Weighting function peak height (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>23.8 ± 0.07</td>
<td>0</td>
</tr>
<tr>
<td>A2</td>
<td>31.4 ± 0.05</td>
<td>0</td>
</tr>
<tr>
<td>A3</td>
<td>50.3 ± 0.05</td>
<td>0</td>
</tr>
<tr>
<td>A4</td>
<td>52.8 ± 0.11</td>
<td>0</td>
</tr>
<tr>
<td>A5</td>
<td>53.6 ± 0.12</td>
<td>4</td>
</tr>
<tr>
<td>A6</td>
<td>54.4 ± 0.11</td>
<td>8</td>
</tr>
<tr>
<td>A7</td>
<td>54.9 ± 0.11</td>
<td>9.5</td>
</tr>
<tr>
<td>A8</td>
<td>55.5 ± 0.09</td>
<td>12.5</td>
</tr>
<tr>
<td>B1</td>
<td>89 ± 0.9</td>
<td>0</td>
</tr>
<tr>
<td>B2</td>
<td>150 ± 0.9</td>
<td>0</td>
</tr>
<tr>
<td>B3</td>
<td>183.31 ± 1</td>
<td>6.1</td>
</tr>
<tr>
<td>B4</td>
<td>183.31 ± 3</td>
<td>4.0</td>
</tr>
<tr>
<td>B5</td>
<td>183.31 ± 7</td>
<td>1.8</td>
</tr>
<tr>
<td>B1</td>
<td>150 ± 0.9</td>
<td>0</td>
</tr>
<tr>
<td>B2</td>
<td>183.31 ± 1</td>
<td>6.1</td>
</tr>
<tr>
<td>B3</td>
<td>183.31 ± 3</td>
<td>4.0</td>
</tr>
<tr>
<td>B4</td>
<td>183.31 ± 7</td>
<td>1.8</td>
</tr>
</tbody>
</table>
c. Mesoscale model

MM5 is a nonhydrostatic primitive equation limited-area nested-grid model with a terrain-following vertical coordinate. We used 34 levels and the 3 cocentered domains characterized in Table 2. The reasons for selecting these options were described earlier (Surussavadee and Staelin 2006). Planetary boundary layer parameterization for the Medium-Range Forecast model was used for all 3 domains (Hong and Pan 1996). Precipitation was treated using the implicit Kain–Fritsch 2 model (Kain 2004) and the explicit Goddard model (Tao and Simpson 1993), which uses a parameterized Kessler-type two-category liquid water scheme that includes cloud water and rain, and three ice-phase schemes for hail/graupel, snow, and cloud ice (Lin et al. 1983). The Goddard model also assumes that hydrometeors have size distributions that are inverse-exponential functions of diameter $D$:

$$N(D) = N_0 \exp(-\lambda D),$$  (1)

where $N(D)$ (cm$^{-3}$) is the number of drops per cubic centimeter per centimeter of diameter $D$. The intercept values, $N_0 = N(0)$, for rain, snow, and graupel are assumed to be 0.08, 0.04, and 0.04 cm$^{-4}$, respectively. By assumption, the decay rate $\lambda = (\pi \rho N_0 / \rho_o g)^{0.25}$ (cm$^{-1}$), where the densities $\rho$ for rain, snow, and graupel are 1, 0.1, and 0.4 g cm$^{-3}$, respectively. Here, $q$ is the mass mixing ratio (kg kg$^{-1}$) given by MM5 for each species as a function of altitude, and $\rho_o$ is the local air density. All cloud ice is assumed to have a single diameter $D = 2 \times 10^{-3}$ cm and a density of 0.917 g cm$^{-3}$.

The MM5 experiments reported here were initialized using the National Centers for Environmental Prediction (NCEP) 1° 6-h global final (FNL) analysis fields extending to 10 mbar (NCAR 2006). Based on AMSU images, 255 diverse storms distributed over the globe between latitudes 90°N and 80°S were selected from the period July 2002–June 2003, and tested for consistency between the 15-km resolution MM5 predictions (domain 2) and AMSU observations near 183 ± 7 GHz. Of these storms, 128 were eliminated from further consideration because of gross subjective differences between the MM5 and AMSU locations of precipitation, or because they included a geographic pole or extremely high mountains. Each precipitating MM5 15-km pixel in the set of 122 storms selected for further study was categorized by type, as presented in Table 3. For simplicity the seasons were defined as starting on the first of a month, so “spring” begins April 1, for example. The reduced latitude range was 83°N to 73°S. Figure 1 shows two examples of MM5/AMSU comparisons of storms at 183 ± 7 GHz; one was observed over Florida at 2344 UTC 31 December 2002, and the other was observed over Europe at 1003 UTC 2 January 2003.

To minimize computer time the brightness temperatures analyzed in section 3 were based on the 15-km resolution MM5 domain 2 output, whereas the brightness temperatures analyzed in sections 4 and 5 were based on blurred versions of the 5-km resolution domain 3 MM5/RTM output and therefore represent only one-ninth of the total storm area. The blurring was accomplished for AMSU retrieval simulations by convolving the 5-km resolution brightness temperatures with Gaussian functions having full width at half maximum (FWHM) of 15 and 33 km were used to blur the 380/425- and 183-GHz bands, respectively, corresponding to their relative diffraction limits.

d. Radiative transfer

AMSU radiances were computed using a two-stream Mie-scattering variant of P. W. Rosenkranz’s efficient radiative transfer algorithm TBSCAT (Rosenkranz 2002) that incorporated improved transmittance models (Liebe et al. 1992; Rosenkranz 1998), and the complex permittivities for water and ice given by Liebe et al.

### Table 2. MM5 domain configurations.

<table>
<thead>
<tr>
<th>Domain</th>
<th>No. of cells</th>
<th>Cell size (km)</th>
<th>Implicit scheme</th>
<th>Explicit scheme</th>
<th>Time step (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>100 × 100</td>
<td>45</td>
<td>Kain–Fritsch 2</td>
<td>Goddard</td>
<td>40</td>
</tr>
<tr>
<td>2</td>
<td>190 × 190</td>
<td>15</td>
<td>Kain–Fritsch 2</td>
<td>Goddard</td>
<td>13.33</td>
</tr>
<tr>
<td>3</td>
<td>190 × 190</td>
<td>5</td>
<td>None</td>
<td>Goddard</td>
<td>4.44</td>
</tr>
</tbody>
</table>

### Table 3. Numbers of MM5 precipitating pixels (in thousands) in various precipitation categories.

<table>
<thead>
<tr>
<th>Category</th>
<th>Pixels (×1000)</th>
<th>Category</th>
<th>Pixels (×1000)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>latitude</td>
<td></td>
<td></td>
</tr>
<tr>
<td>⩾ 25°</td>
<td>112</td>
<td>Winter</td>
<td>115</td>
</tr>
<tr>
<td>25° &lt;</td>
<td>latitude</td>
<td></td>
<td>⩾ 55°</td>
</tr>
<tr>
<td>55° &lt;</td>
<td>latitude</td>
<td></td>
<td>⩾ 90°</td>
</tr>
<tr>
<td>Convective</td>
<td>10</td>
<td>Autumn</td>
<td>221</td>
</tr>
<tr>
<td>Stratiform</td>
<td>631</td>
<td>Rain only</td>
<td>558</td>
</tr>
<tr>
<td>Nonglaciated (land)</td>
<td>37</td>
<td>Mixed rain, snow</td>
<td>39</td>
</tr>
<tr>
<td>Nonglaciated (ocean)</td>
<td>35</td>
<td>Snow only</td>
<td>44</td>
</tr>
<tr>
<td>Snow only (per MM5)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>Snow only (surface T &lt; 266 K)</td>
<td></td>
</tr>
</tbody>
</table>

November 2007, Surussavadee and Staelin, 3811
al. (1991) and Hufford (1991), respectively. Sea surface emissivity was computed using FASTEM (English and Hewison 1998), which incorporates geometric optics, Bragg scattering, and foam effects. Sea surface temperatures and 10-m winds were provided by MM5, and land emissivities were assumed to be uniformly distributed over the typical range of 0.91–0.97 (Karbou et al. 2005). Although multistream scattering models would perform better, Tassa et al. (2006) reported that the maximum brightness difference found at 85 GHz between two-stream and multistream models was only 13 K in the presence of strong cloud inhomogeneities; this difference is modest compared with the impact of minor changes in front-to-backscattering ratios presented later.

Icy hydrometeors were modeled as homogeneous spheres having wavelength-dependent densities $F(\lambda)$ deduced from electromagnetic computations for various ice shapes, as demonstrated by Surussavadee and Staelin (2006). The densities $F(\lambda)$ were chosen so as to yield total Mie-scattering cross sections identical to those computed for equal-mass hexagonal plates (snow), 6-point bullet rosettes (graupel), and spheres (cloud ice) using the Discrete Dipole Approximation for Scattering and Absorption of Light by Irregular Particles (DDSCAT), version 6.1, program (Draine and Flatau 2004). The hydrometeors studied using DDSCAT were defined to have observed ice-habit dimensions and densities (Heymsfield 1972; Hobbs et al. 1974; Davis 1974). The hydrometeor lengths varied from 0.2 to 5 mm, and the scattering cross sections were averaged over many orientations. The resulting $F(\lambda)$ values for snow, graupel, and cloud ice were found to be nearly independent of hydrometeor size below 200 GHz and were defined as shown in Table 4. All liquid hydrometeors were also assumed to be spherical. Note that the only physical significance of $F(\lambda)$ is that it

\[ F(\lambda) = \frac{\text{frequency in units of THz}}{H} \]

TABLE 4. Ice factors for snow, graupel, and cloud ice based on DDSCAT.

<table>
<thead>
<tr>
<th>Ice species</th>
<th>Ice factors [$F(\lambda)$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Snow</td>
<td>0.863 $f_{\text{THz}}$ + 0.115</td>
</tr>
<tr>
<td>Graupel</td>
<td>0.815 $f_{\text{THz}}$ + 0.0112</td>
</tr>
<tr>
<td>Cloud ice</td>
<td>0.917</td>
</tr>
</tbody>
</table>

$f_{\text{THz}}$ = frequency in units of THz.
yields at each wavelength $\lambda$ the same total scattering cross section as would a hexagonal plate (snow) or rosette (graupel) averaged over all orientations; therefore it cannot easily be related to other physical models.

3. Sensitivity of radiance histograms

a. Sensitivity to the radiative transfer model

Successful assimilation of observed radiances into NWP models requires that simulated radiances match the observations, and therefore both the NWP and RTM models must be correct. The same is true if precipitation retrievals are assimilated instead of radiances, because retrievals are trained and tested using such models.

This section characterizes the effects of radiative transfer assumptions on the quality of brightness temperature histogram matches between NWP models and AMSU observations for 122 global storms. Histograms are matched instead of values at individual pixels because the precise locations and strengths of simulated convective instabilities are partially determined by chaotic processes within MM5 that are not resolved or predicted by available NWP initialization fields. Even pixel-to-pixel radiance comparisons for stratiform systems would be problematic, as suggested in Fig. 1 where AMSU and NCEP/MM5/RTM radiances at 183 ± 7 GHz are compared for two storms. Surussavadee and Staelin (2006) demonstrated earlier that histogram comparisons are sensitive to modest changes in MM5 and AMSU radiative transfer models.

Modeling radiative transfer in precipitation at millimeter wavelengths is problematic because ice habits are diverse and have unknown three-dimensional distributions in form, size, and density, all of which affect microwave scattering and absorption. Both complex (Voronovich et al. 2004) and simpler approximations (e.g., Smith et al. 2002) have been used to model radiative transfer in these cases. The related simple RTM used here (Rosenkranz 2002; Surussavadee and Staelin 2006) is generally consistent with AMSU observations, as demonstrated below, and is designated the TBSCAT/$F(\lambda)$ model, which identifies its two most significant components.

The sensitivity of computed brightness temperature histograms to RTM assumptions was tested by comparing radiance histograms computing using a baseline RTM versus RTMs with alternative ice factors, loss tangents, backscattering fraction, and hydrometeor size distributions. Figure 2 presents the brightness temperature histograms observed by AMSU at 6 frequencies for the 122 global storms characterized in Table 3, and the corresponding histograms for simulated NCEP/MM5/TBSCAT/$F(\lambda)$ brightnesses for the same storms. The worst-case discrepancy in these histograms between observed and modeled brightness temperatures is roughly 10 K, and this is used as the nominal threshold for detecting possible failures in the MM5 and RTM models as their parameters are varied. Because these observed and modeled storms overlap almost exactly in time and space for a very large number of pixels, these histogram comparisons are more sensitive to model deficiencies than are comparisons lacking concurrence or scale.

Figure 3 presents the same data as in Fig. 2, but subdivided by precipitation type; only those 3 frequencies most sensitive to icy hydrometeors are illustrated; that is, 89, 150, and 183 ± 7 GHz. The six types include convective, stratiform, snow only, rain only, tropical (|latitude| ≤ 25°), and nonglaciated (warm) rain, as classified for each pixel using its observed or simulated brightness spectrum (Surussavadee and Staelin, 2006). The baseline RTM generally matches the AMSU brightness temperature histograms for these diverse types of precipitation, suggesting its ability to match reality despite its simplicity. The strong exception is snow-only pixels, for which the window channels at 89 and 150 GHz respond to the frozen surface and possible deep snow, which is not consistent with the current assumption of 0.91–0.97 surface emissivity. Although existing frozen-surface emissivity models could be used, these two window channels would remain problematic for hydrometeor retrievals over ice or snow fields. Fortunately the more opaque bands near 183 GHz are insensitive to the surface, but are sensitive to snow and graupel (as suggested here and later in Fig. 7). The next
largest type of discrepancy in Fig. 3 involves a few of the very coldest pixels observed by AMSU, but some of these are located over water misclassified as land.

The first change made to the RTM was an arbitrary increase in the ice factor $F$ by 0.1 for snow alone and graupel alone, as shown in Figs. 4a and 4b, respectively. These perturbations to $F(\lambda)$ are generally small compared with its possible range between 0 and 1, but nonetheless produce a noticeable change in the MM5/TBSCAT/F(\lambda) brightness temperature distributions. This sensitivity of radiance to $F(\lambda)$ is consistent with the difficulty encountered in some earlier studies that effectively used larger values, leading to conjectures that modeled ice densities should be lowered (Tassa et al. 2006). Note that 183 GHz responds more strongly
to graupel than to snow, and therefore senses strong convection. Figure 4c compares the histograms for all 122 storms for the case where the ice loss tangent has been decreased by reducing the imaginary part of the permittivity \( \varepsilon^* \) by a nonphysical factor of 10. Figure 4 implies that only reasonably apt RTMs will produce agreement across all precipitation types. Changes of \( \sim 0.1 \) in \( F(\lambda) \) for snow and graupel produce worst-case discrepancies of \( \sim 40 \) K in the Fig. 4 histograms, suggesting that changes or errors in \( F(\lambda) \) of \( \sim 0.025 \) might be detectable, and certainly changes of \( \sim 0.05 \), which are small fractions of the possible range from 0 to 1. It should be noted that the baseline MM5 and RTM models incorporated no tuning other than the model architecture itself, and they nonetheless yield few discrepancies in Fig. 2 beyond 10 K for the benchmark 122 storms.

This conclusion is reinforced by Figs. 5a and 5b, which respectively illustrate for 122 storms the effects of increasing the backward scattering slightly, and the particle size distribution by a significant factor. The Mie backscattering fraction was increased by 0.02. The Mie backscattering fraction is the fraction of radiance scattering backward and equals \((1 - G)/2\), where \( G \) is the scattering asymmetry factor from the Mie calculation for the assumed particle size distribution, which is defined here by (1). The worst-case brightness discrepancies for a 0.02 increase in the Mie backscattering (BS) fraction in the two-stream Mie-scattering model are \( \sim 30 \) K in Fig. 5a, so a change of \( \sim 0.01 \) would produce a noticeable discrepancy with the AMSU histograms. This sensitivity is high because it is \( \sim 10\%–20\% \) of the nominal BS ratio for typical particle sizes (approximately 0.05–0.1), and is therefore equivalent to an approximately 10%–20% change in scattering cross section in the two-stream radiative transfer limit. Because scattering can cool brightness temperatures approximately 50–100 K, this high sensitivity is not unexpected.

The exponentially distributed particle sizes assumed in (1) were decreased by increasing the zero-diameter intercept \( N_o \) for snow \((N_s)\) and graupel \((N_g)\) from 0.04 to 3; this increases the numbers of particles because the mass mixing ratio was held constant. Because the volume of a sphere varies as \( D^3 \) and its scattering cross section in the Rayleigh and geometric limits varies as \( D^4 \) and \( D^2 \), respectively, scattering for constant mass will decrease in the Rayleigh limit and increase in the geometric limit as a result of increasing \( N_o \), depending on wavelength \( \lambda \) and the initial value of \( N_o \). The warmer MM5/TBSCAT brightness temperatures in Fig. 5b are generally increased for a given histogram pixel count, consistent with reduced scattering by smaller hydrometeors in the Rayleigh limit. The colder temperatures remain unchanged, however, which is consistent with the coldest pixels scattering more strongly and being characterized by hydrometeors somewhat closer to the geometric scattering limit. The worst-case brightness discrepancies are no more than 10 K, however, so the histogram comparisons do not strongly constrain \( N_o \).

b. Sensitivity to MM5/RTM assumptions

Successful assimilation of observed radiances into NWP models also requires that the NWP model produce hydrometeor profiles faithful to the true atmosphere. The potential NWP benefits from assimilated radiance information increases with the sensitivity of radiances and their histograms to hydrometeor profiles. Figures 6a and 6b illustrate for 122 storms the sensitivity of radiance histograms to increases in MM5-predicted mass profiles of snow and graupel. The worst-case brightness temperature discrepancies resulting when snow and graupel mass distributions are increased by 50% and 75%, respectively, are both \( \sim 25 \) K.
corresponding to detectable 10-K excursions of ~20% and ~30% in MM5 snow and graupel production, respectively. Only snow and graupel significantly affect these millimeter wavelengths, while the impacts of cloud ice and liquid water were usually found to be negligible in comparison.

Figure 7 shows that increasing and decreasing the MM5-predicted altitudes of snow and graupel by 75 and 50 mb, respectively, does not always produce comparable histogram effects, where the MM5 pressure levels are equally spaced at 25 mb. This figure also indicates the substantial sensitivity of the 183-GHz band to the altitudes of icy hydrometeors as a result of the water vapor altitude-slicing effect. The worst-case brightness temperature discrepancies shown in Fig. 7 are ~35 K for 75-mb altitude changes, so systematic errors in MM5 snow/graupel altitudes of ~20 mb would be marginally detectable using the AMSU brightness histograms.

The sensitivity of radiance histograms to MM5 and the RTM was also evaluated by computing the rms difference between simulated radiances for the baseline case and the same radiances computed using different MM5/RTM variations. The measure for the difference is defined as

$$
\Delta T_B = \sqrt{\frac{1}{Q} \sum_{i=1}^{Q} \sigma_i^2} \text{ (K),} \quad \text{with (2)}
$$

$$
\sigma_i^2 = \frac{1}{N_i} \sum_{j=1}^{N_i} (y_j - x_i)^2, \quad \text{(3)}
$$

where $Q$ is the number of brightness temperature histogram bins; $N_i$ is the number of baseline pixels that fall in brightness bin $i$; $x_i$ and $y_j$ are brightness temperatures from the baseline case and the perturbed case, respectively, for a given pixel $j$ and bin $i$; $\bar{x}$ is the sample mean of $x_i$ for bin $i$; and the variance within bin $i$ is $\sigma_i^2$. This rms $\Delta T_B$ sensitivity metric is presented in Table 5 for the same 122 storms and the 6 AMSU frequencies 50.3–183 ± 1 GHz used before: AMSU-A channel 3 (A3) at 50.3 GHz, and AMSU-B channels 1–5 (B1–B5) at the frequencies 89, 150, 183 ± 1, 183 ± 3, and 183 ± 7 GHz, respectively.

The model-sensitivity results presented in Table 5 are
Table 1. The $\Delta T_{b}$ (K) (rms) for different variants of RTM and MM5; S, G, I, and W signify snow, graupel, cloud ice, and rainwater, respectively.

<table>
<thead>
<tr>
<th>Variations</th>
<th>A3</th>
<th>B1</th>
<th>B2</th>
<th>B3</th>
<th>B4</th>
<th>B5</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F_3 + 0.1$</td>
<td>1.57</td>
<td>9.82</td>
<td>11.86</td>
<td>2.28</td>
<td>6.54</td>
<td>10.16</td>
</tr>
<tr>
<td>$F_6 + 0.1$</td>
<td>2.76</td>
<td>16.24</td>
<td>11.81</td>
<td>15.36</td>
<td>15.18</td>
<td>13.05</td>
</tr>
<tr>
<td>$F_1 = 0.1$</td>
<td>0.50</td>
<td>2.12</td>
<td>1.27</td>
<td>0.36</td>
<td>0.28</td>
<td>0.87</td>
</tr>
<tr>
<td>BS + 0.02</td>
<td>0.75</td>
<td>6.53</td>
<td>10.92</td>
<td>10.39</td>
<td>12.61</td>
<td>13.41</td>
</tr>
<tr>
<td>$e_{\text{ice}}^s \times 6$</td>
<td>0.67</td>
<td>12.74</td>
<td>22.43</td>
<td>8.80</td>
<td>16.80</td>
<td>21.46</td>
</tr>
<tr>
<td>$e_{\text{water}}^s \times 2$</td>
<td>0.84</td>
<td>2.18</td>
<td>1.39</td>
<td>0.47</td>
<td>0.46</td>
<td>0.73</td>
</tr>
<tr>
<td>$N_s = N_w = 3$</td>
<td>2.58</td>
<td>12.68</td>
<td>7.25</td>
<td>2.99</td>
<td>4.22</td>
<td>4.72</td>
</tr>
<tr>
<td>$S \times 1.5$</td>
<td>1.48</td>
<td>7.44</td>
<td>9.61</td>
<td>2.33</td>
<td>6.15</td>
<td>9.30</td>
</tr>
<tr>
<td>$G \times 1.75$</td>
<td>1.20</td>
<td>6.85</td>
<td>5.70</td>
<td>11.31</td>
<td>10.16</td>
<td>8.13</td>
</tr>
<tr>
<td>$I \times 20$</td>
<td>0.51</td>
<td>6.24</td>
<td>14.13</td>
<td>6.17</td>
<td>11.66</td>
<td>14.70</td>
</tr>
<tr>
<td>$W \times 20$</td>
<td>5.69</td>
<td>14.94</td>
<td>15.99</td>
<td>3.54</td>
<td>9.04</td>
<td>11.84</td>
</tr>
<tr>
<td>$S/G \downarrow 50$</td>
<td>0.72</td>
<td>6.62</td>
<td>9.75</td>
<td>18.47</td>
<td>17.68</td>
<td>13.00</td>
</tr>
</tbody>
</table>

$F_1 = F(\lambda)$ for cloud ice.

$e_{\text{ice}}^s$ and $e_{\text{water}}^s$ = imaginary parts of ice and water permittivity, respectively.

$\downarrow$ = movement to lower altitude.

generally consistent with those inferred from Figs. 4–7, but also reveal the insensitivity of the brightness temperature histograms to three parameters: $F(\lambda)$ for cloud ice, $e^s$ for water (related to the loss tangent for water), and the abundances of cloud ice and rainwater. The table suggests a modest sensitivity to $e^s$ for ice, however, to within a factor of $\approx 3$, where $e^s$ is highly sensitive to ice temperature, particularly near the melting point. The table also shows that AMSU-B channels are usually at least 3 times more sensitive than the 50.3-GHz window channel to changes in hydrometeor distributions or propagation physics. Thus with respect to snow and graupel mixing ratios and altitudes, $F(\lambda)$, and ice scattering, the baseline MM5/RTM cannot depart from physical truth very far before yielding clearly observable differences of $\approx 10$ K between simulated and observed brightness temperatures.

4. Retrievals of hydrometeor profiles and precipitation rates

a. Retrieval accuracies

Retrievals of precipitation rates and hydrometeor profiles can also be assimilated into NWP models. Two different instruments are analyzed here: the operational instrument AMSU, characterized in Table 1, and a proposed GEM spectrometer, also characterized in Table 1, that could map and assimilate precipitation for important storms at $\approx 15$-min intervals with $\approx 15$-km resolution. The GEM frequencies were selected for their abilities to sense individual convective cells larger than $\approx 10$ km, and the 183-GHz water vapor band was selected because it can sense to the surface except in the Tropics. For simplicity the sensitivity of all channels is assumed to be 0.2-K rms, although for precipitation retrievals this specification is not critical because hydrometeor perturbations can exceed 100 K. For GEM simulations $F(\lambda)$ was defined as the average of the values given by Table 4 and $F(200$ GHz), which was generally consistent with preliminary DDSCAT calculations at these higher frequencies; section 4b demonstrates that estimated retrieval accuracies are reasonably insensitive to errors in $F(\lambda)$. The assumed zenith angle was $40^\circ$.

Because the RTM is nonlinear and the statistics of precipitation are non-Gaussian, the optimum estimator is nonlinear. For that reason neural networks were used to estimate, for both AMSU and GEM, the 15-min average surface-precipitation rates for rain and snow, and also the water paths for graupel, snow, cloud ice, rainwater, and the sum of graupel, snow, and rainwater. The neural networks were trained using 5-km-resolution MM5/RTM brightness temperatures blurred to 15-km resolution. The pixels used for training were distributed uniformly over the blurred 4.4 million 5-km pixels in the 122 globally distributed MM5/TBSCAT/AMSU-$S$ storms that were selected from a larger set of 255 storms to best match concurrent AMSU observations (Surussavadee and Staelin 2006). Only large sets of representative cloud-resolved physical model data permit neural networks to yield realistic retrievals in the absence of precise in situ ground truth. It is reassuring that this MM5/TBSCAT/F(\lambda) physical model data yields brightness temperature distributions that reasonably match those observed by AMSU over the same set of storms (see Figs. 2 and 3).

All neural networks had 3 layers with 10, 5, and 1 neurons, respectively, where the first 2 layers employed tangent sigmoid operators, and the final layer was linear. Limited experimentation with network architectures did not reveal significant opportunities for improvement, probably because the 10–5–1 networks were more complex than needed, but were sufficiently simple that the extensive training data was adequate. These networks were trained using MM5/TBSCAT/F(\lambda) simulations of nadir radiances for 122 globally representative storms. The first 2 layers employed tangent sigmoid operators, and the final layer was linear.
Other network architectures did not offer noticeable improvement. The Levenberg–Marquardt (Hagan and Menhaj 1994) training algorithm was used and the net weights were initialized using the Nguyen–Widrow method (Nguyen and Widrow 1990). Each of the 122 MM5 storms has 190 × 190 15-km pixels, and altogether 293,000 pixels were used for training and validating, and all 4.4 million were used for testing. The same neural network was used for both land and sea without introducing significant coastal artifacts (as illustrated later in Fig. 12a).

The retrieval architectures used for AMSU and GEM are illustrated in Figs. 8a and 8b, respectively. The simulated AMSU data included 18 numbers: the brightness temperatures for channels 1–8 of AMSU-A and all AMSU-B channels, plus the 5 estimated brightness perturbations due to icy hydrometeors for AMSU-A channels 4–8. The perturbations were estimated using the method described by Chen and Staelin (2003), but were left at 50-km resolution. Such perturbations are the difference between simulated AMSU-A icy signatures at locations detected using 183 ± 7 GHz data, and brightness temperatures determined by Laplacian interpolation of AMSU-A brightness temperatures surrounding the icy patch.

The architecture for estimating surface-precipitation rates using GEM has two stages, the first of which merely determines which of the following two neural networks should be used. This two-stage complexity was not necessary for the water path estimates, which were extracted at point A in Fig. 8b. Each estimated parameter was produced by its own neural network, independent of others. The input data for GEM simulations included only the 15- and 33-km resolution brightness temperatures at the frequencies listed in Table 1; no perturbations were estimated.

Because millions of globally and seasonally representative pixels were used, the size of the dataset is believed to be adequate for the purposes of this study. The simulated radiances are believed to be relevant and adequate because MM5 models the altitude distributions of snow, ice, rainwater, graupel, and cloud ice, all of which are uniquely handled by the radiative transfer model with 5-km resolution. Any residual biases relative to reality are believed to have minor consequences in view of 1) the similarity between observed and simulated radiances histograms, despite the sensitivity of these histograms to several critical assumptions, as demonstrated in this paper; 2) the agreement shown in Fig. 3 between observed and simulated radiances histograms for five precipitation types (convective, stratiform, tropical, rain only, and warm rain), and in similar comparisons for three latitude bands (tropical, midlatitude, and beyond ±55°; Surussavadee and Staelin 2006); and 3) the insensitivity of the predicted rms retrieval accuracies to changes in many key model param-
eters, as demonstrated later in section 4b and Tables 6 and 7.

Scatterplots characterizing retrieval accuracies are presented for AMSU and GEM in Figs. 9a and 9b, respectively; water paths of snow, graupel, other ice, and rainwater (mm) are evaluated. Because surface precipitation is shielded by overlying opacity at most millimeter wavelengths and because precipitation that evaporates before reaching the ground (virga) is difficult to detect, better retrieval accuracies are obtained for ice water paths near the cell tops than for rainwater at lower altitudes.

Figure 10 illustrates the simulated 15-min surface-precipitation-rate retrieval accuracy of AMSU and GEM relative to MM5 truth for 15-km resolution. AMSU estimates are based on one look at the end of the 15-min averaging period. It was found that a small improvement was obtained when the GEM estimates were based on 2 looks 15-min apart (before and after), partially accounting for the effect of virga; this doubled the number of inputs to the GEM neural network from 12 to 24. The scatterplots suggest useful accuracy for precipitation rates greater than $1 \text{mm h}^{-1}$.

Figure 11 presents the accuracy with which cell-top altitudes can be estimated using GEM, where cloud-top altitude is defined as the highest altitude for which the summed rain, snow, and graupel water paths to space exceed 0.05 mm. The mean and rms altitude errors for GEM are approximately 0 and 0.7 km, respectively, above 5-km altitude and 0.5 and 0.9–1.2 km, respectively, below 5-km altitude. The accuracy degradation in the low troposphere is consistent with the limited penetration depths above 140 GHz for tropical humidity. Similar simulations of cell-top altitude retrievals using AMSU yielded mean errors near zero at all altitudes and rms errors of approximately 0.9–1.2 km, consistent with the results from earlier airborne 118-GHz spectrometers observing oxygen absorption bands (Spina et al. 1998).

The accuracies for surface rain and snowfall rates are determined largely by their statistical correlation with the abundance and altitudes of snow and graupel, which at millimeter wavelengths can be estimated more accurately than precipitation rates. Although this statistical relationship is climate-dependent, climate information is provided by the temperature and humidity profiles sensed by the same millimeter-wave sounding channels. The accuracy of the resulting surface-precipitation retrievals is suggested in Fig. 12, which presents MM5 ground-truth precipitation rates and the corresponding rates derived for simulated AMSU and GEM observations of a midlatitude front over France at 1003 UTC 2 January 2003 (Fig. 12a), the ITCZ at
threshold, and only a few smaller convective cells contribute to the precipitation.

The largest errors occur when warm rain is observed by GEM, which usually cannot penetrate the lowest 1–2 km of the atmosphere where warm rain may reside, and therefore may fail to register some or all of it.

It is interesting to note that it took ~22 min to train a neural network to retrieve precipitation using AMSU data and $2.9 \times 10^5$ MM5 training pixels. Once trained, it retrieved ~$2 \times 10^5$ pixels per second with a conventional 2.8-GHz personal computer (PC) and the (MATLAB) neural network toolbox operating in its computationally inefficient interpretive mode; it could therefore reduce one satellite year of data in a couple of hours. The most time-consuming step was the generation of the $2.9 \times 10^5$ brightness temperature and MM5 training pixels. To predict a single storm for 1 h using the MM5 configurations shown in Table 2 took ~254 min using a conventional 2.4-GHz PC. To simulate AMSU-A and -B brightness temperatures for a single MM5 output with 190×190 pixels in the inner domain required ~1 h with a 2.4-GHz PC. Clusters of 20 PCs were typically used for the 255 storms analyzed.

One important metric involves the ability of retrieval algorithms to distinguish precipitating from nonprecipitating pixels. Such errors commonly occur near true precipitation, as suggested in Fig. 12, and depend upon the threshold definition for precipitation. For example, MM5 pixels with surface-precipitation rates above 0.3 mm h$^{-1}$ and retrievals less than 0.3 mm h$^{-1}$ contribute ~3.2% and 3.0% of MM5 total surface-precipitation rates for AMSU and GEM, respectively. On the other hand, MM5 pixels with surface-precipitation rates below 0.3 mm h$^{-1}$ and retrievals above 0.3 mm h$^{-1}$ contribute ~7.9% and 11.8% of AMSU and GEM total surface-precipitation rates, respectively. Both AMSU and GEM retrieve some excess precipitation when heavy cirrus spreads beyond convective cores.

b. Sensitivity of predicted accuracies to model imperfections

Retrieval accuracies determined using only simulations rather than field observations are suspect because they depend on how well the simulations model reality, which is often unknown. This section examines the de-
gree to which the deduced retrieval accuracy depends upon the fidelity of the simulated world, designated "planet MM5," to earth. The approach involves computation of retrieval accuracies for an ensemble of planets MM5 for which the physics has been varied over a dynamic range that arguably approximates or exceeds the unknown true differences between planet MM5 and earth. Because the deduced retrieval accuracies are surprisingly independent of these large simulated physical variations, it can be inferred that the retrieval accuracies deduced from these simulations are reasonably reliable and probably would be achievable in practice.

Table 6 presents MM5-simulated AMSU rms surface-precipitation-rate retrieval accuracies for the baseline NCEP/MM5/TBSCAT/F(λ) model discussed in sections 2 and 3, and for a variety of altered physical assumptions involving the ice factors, abundances, altitudes, backscattering, loss tangent, and size distributions for snow and graupel. The table also presents the rms water path accuracies listed for AMSU in Table 6 correspond to the scatterplots presented in Fig. 9a. The derived rms accuracies are less than the corresponding mean values in any octave range of interest, suggesting that all water path retrievals are useful, although rainwater path estimates are less accurate than those for icy hydrometeors. They also suggest that retrievals of the total water path for S + G + R are more accurate than are sums of the estimated components, and sometimes more accurate than single contributors (S, G, or R).

The baseline AMSU surface-precipitation-rate accuracies tabulated in Table 6 correspond to the scatterplot in Fig. 10a, and suggest that surface-precipitation-rate retrievals are useful primarily above 1 mm h⁻¹. The baseline case, however, assumed a fixed 1) set of F(λ)s;
2) mixing ratio–dependent hydrometeor size distribution function \( N(D) \) given by (1); 3) MM5 strategy for determining hydrometeor altitudes and abundances; 4) backscattering dependence on particle diameter, permittivity, and wavelength; and 5) temperature-dependent ice loss tangent. In fact, these assumptions represent averages of behaviors that vary, even within a single storm. For example 1) hydrometeor habits and \( F \) values vary far more than assumed here in the DDSCAT computations for simple hexagonal plates, 6-pointed rosettes, and spheres; 2) the backscattering ratio depends on those ice shapes; 3) the size distribution \( N(D) \) can vary with electrification, storm age, turbulence, and other variables; and 4) hydrometeor loss tangents and \( \varepsilon_{\text{ice}}^r \) can depend on temperature and impurities. Therefore it is not sufficient simply to evaluate rms retrieval accuracies under different fixed sets of assumptions. Instead the simulated retrievals must reflect uncertainties and variations that can occur within a single test ensemble of storms. How best to accomplish this is the “randomization problem.”

The retrieval system was randomized here by assuming that half the time MM5/RTM physics was governed by the baseline assumptions, and half the time by a relatively extreme modification of one of those assumptions. For example, the third column in Table 6 corresponds to a planet MM5 for which, at random, half the time the physics is that of the baseline, and half the time the ice factors \( F_S \) and \( F_G \) for snow and graupel are both increased by 0.1, a change that produced clear disagreement with AMSU observations in Figs. 4a and 4b. The neural network retrieval system was both trained and tested with the same 50% ratio. The fourth column of the table similarly mixes the baseline with cases for which all ice is doubled, while columns 5, 6, and 7 present the rms retrieval errors for which the nonbaseline cases involve lifting the snow and graupel by 100 mbar in altitude, increasing the backscattering ratio by 0.1, and increasing \( \varepsilon_{\text{ice}}^r \) by a factor of 6, respectively.

Table 7 corresponds to Table 6, but for the geostationary sounder GEM. The results are similar, although the rms retrieval accuracies for GEM are \( ~20\% \) worse than for AMSU because of the lack of GEM observations below \( \sim 140 \) GHz. Random doubling of snow and graupel abundances degrades the rms retrieval accuracy only \( ~11\% \). For all physical assumptions, all estimated retrieval accuracies for each octave range are below the octave maximum for rain rates above 1 mm h\(^{-1}\), and below the octave minimum for AMSU rates above 4 mm h\(^{-1}\), and for GEM rates above 8 mm h\(^{-1}\).

The important result derived from Tables 6 and 7 is that the predicted rms retrieval accuracies for all surface-precipitation rates are surprisingly independent of the changes in physical assumptions, provided the statistics of the randomization are known. For example, for MM5 precipitation rates of 2–4 mm h\(^{-1}\), the rms retrieval error varied no more than \( \pm 7\% \) over all assumptions tested, the worst case being a reduction when the snow-to-graupel ratio increased an average of 50%. For rates of 32–64 mm h\(^{-1}\) the maximum departure from baseline was only \( \pm 4\% \) in predicted rms retrieval errors. When the percentage increases in predicted rms retrieval errors are averaged over all rain-

![Fig. 10. Scatter diagrams for retrieved surface-precipitation rates (mm h\(^{-1}\), 15-min averages) for (a) AMSU and (b) GEM.](image)

![Fig. 11. Scatter diagram for cloud-top altitudes (km) retrieved using GEM.](image)
rate octaves, they changed by approximately 1.3%, 9.0%, 4.6%, 2.2%, 1.0%, and 0.8% for detectably different $F(\lambda)$, snow/graupel abundances, snow/graupel altitudes, backscattering, ice loss tangents, and snow/graupel size distributions, respectively. The largest increase in simulated retrieval errors is only 9% and corresponds to an average increase in snow and graupel mixing ratios of 50%, approximately twice the increase that would make the modeled brightness temperature histograms inconsistent with those observed by AMSU. The second largest increase, 4.6%, corresponds to increases in snow/graupel altitudes averaging 50 mb, also approximately twice the changes that could be detected using AMSU brightness histograms. That is, the retrieval accuracies estimated using MM5 vary less than a few percent for changes in the tested assumptions that would produce noticeable degradation in the demonstrated agreement (Fig. 2) between MM5 and observed AMSU brightness temperature distributions for 122 storms. The reason for this surprising insensitivity of predicted retrieval accuracies to physical uncertainties is still unclear.

As a result of this insensitivity to physical model uncertainties, quantified in Table 6, NCEP/MM5/TBSCAT/$(\text{Fig. } 12)$ simulations should yield reasonably reliable predictions of precipitation-rate retrieval performance for a variety of millimeter-wave instruments and algorithms, and these accuracies should be reasonably achievable in practice.

c. Characterization of retrieval errors

Improved understanding of the origins of retrieval errors can facilitate future retrieval improvements and understanding of limits to performance potentially available from cloud-scale precipitation assimilation methods. This understanding was sought by computing correlation coefficients between various storm-characterization parameters and “fractional surface precipitation rate error” $\Delta$, where for each 15-km pixel $\Delta$ is defined as $\Delta = (\hat{R} - R)/(R + 1)$, where $\hat{R}$ and $R$ are
the estimated and MM5 true surface-precipitation rates, respectively. The additive constant 1 mm h\(^{-1}\) in the denominator of the \(\Delta\) definition was empirically selected to yield reasonable results; values much less than \(\sim 1\) unduly exaggerated the error contributions of low rain rates, while much larger values excessively muted them.

The single most highly correlated explanatory variable for fractional error \(\Delta\) is the dimensionless “virga parameter,” which is defined here for each 15-km pixel as
\[
V = \frac{(\rho_{\text{max}} + 0.2)}{\rho_{\text{ground}}}.
\]
In this expression \(\rho_{\text{max}}\) is the maximum sum of rain, snow, and graupel densities (g m\(^{-3}\)) for any MM5 level, and \(\rho_{\text{ground}}\) is the corresponding summed density at 1000 mb. The correlation coefficient between virga \(V\) and fractional error \(\Delta\) over 122 storms was found to be 34\% for AMSU and 50\% for GEM, as listed in Table 8. The additive constant 0.2 in the expression for \(V\) was empirically found to yield a reasonable compromise between excessive emphasis of low surface densities and excessive muting of low precipitation rates. Another way to characterize typical values of virga is by the ratios: \(\langle \rho_{\text{max}} \rangle / \rho_{\text{ground}} = 2.54\) and \(\langle (\rho_{\text{max}} + 0.05) / \rho_{\text{ground}} \rangle = 1.79\), where \(\langle x \rangle\) is the sample mean for \(x\). Thus, very roughly, only half of all MM5 precipitation reaches the surface, and most microwave sensors have difficulty detecting virga. The standard deviation associated with the second ratio is 1.35 for 15-km pixels. Corrections for descent velocity would refine these ratios. GEM retrievals are more sensitive to virga than are AMSU retrievals because AMSU has window, water vapor, and temperature-sounding channels that penetrate to the surface, whereas GEM usually does not.

On the other hand, by assimilating GEM data directly into cloud-scale convective models at \(\sim 15\)-min intervals there is hope that virga might be predicted by MM5 with sufficient fidelity that GEM-assimilated retrievals of surface-precipitation rates could be noticeably improved. In addition, such assimilation success would also more properly account for the tendency of snow to spread laterally away from strong convective regions, mimicking stronger rain in millimeter-wave spectra. Thus there is substantial opportunity for improvement in the retrieval accuracies presented in Table 7. Success with precipitation assimilation on such spatial and time scales remains a grand challenge, however. Table 8 also presents correlation coefficients between fractional error \(\Delta\) and the MM5 snow/graupel integrated mass ratio, cell-top altitude, and surface-precipitation rate, none of which are strongly correlated.

<table>
<thead>
<tr>
<th>MM5 parameter</th>
<th>AMSU fractional error (\Delta)</th>
<th>GEM fractional error (\Delta)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Virga</td>
<td>0.34</td>
<td>0.50</td>
</tr>
<tr>
<td>Cloud-top altitude</td>
<td>0.13</td>
<td>0.21</td>
</tr>
<tr>
<td>Snow/graupel ratio</td>
<td>(-0.04)</td>
<td>0.005</td>
</tr>
<tr>
<td>Precipitation rate</td>
<td>(-0.12)</td>
<td>(-0.13)</td>
</tr>
</tbody>
</table>

5. Summary and conclusions

This paper makes four technical points. First, there is an observable increase in the differences between NCEP/MM5/TBSCAT/\(F(\lambda)\) simulated radiance histograms and those observed by AMSU over coincident storm systems as certain properties of MM5 and the RTM are varied modestly. That is, changes in the equivalent Mie ice sphere density \([F(\lambda)]\) of more than \(\sim 0.03\) produced observable discrepancies with observations, as did increases in two-stream ice scattering of greater than \(\sim 1\%\), snow production greater than \(\sim 15\%\), graupel production greater than 25\%, and the altitudes of snow and graupel greater than \(\sim 25\) mb. Less sensitive were ice loss tangents characterized by \(e^x\) and particle size distributions characterized by their zero intercept \(N_o\); increases in \(e^x\) and \(N_o\) by factors of 4 and 7, respectively, were detectable. However, physically plausible changes in cloud ice and rainwater mixing ratios and water loss tangents were largely undetectable.

The second point is that the rms retrieval accuracies inferred from MM5 simulations are relatively insensitive to MM5 and RTM variations that are sufficient to cause the MM5 simulations to differ from the AMSU radiance histogram observations. When the model changes were randomly inserted half the time, and the changes were at least twice those detectable by the observed AMSU radiance histograms for 122 storms, the predicted rms retrieval errors for surface-precipitation rate typically increased less than 5\%, and sometimes declined. This result suggests that retrieval accuracies predicted using physical models comparable to MMS/TBSCAT/\(F(\lambda)\) should be achievable by satellites in orbit once the model physics is tuned to the actual observations. The AMSU retrievals tested here emphasized opaque frequencies and therefore these conclusions may not apply to retrievals for sensors relying more on surface channels because variations of the sea and land models described earlier were not tested.

Third, the simulated retrieved precipitation-rate images (Fig. 12), scatterplots for surface-precipitation rate and water paths versus model truth (Figs. 9 and 10), and predicted rms retrieval errors for each rate and water
path octave (Tables 6 and 7) suggest the utility of operational NOAA satellites carrying AMSU and successor instruments such as ATMS. The 2 or 3 such satellites now typically in orbit each map most of the earth in wide swaths twice daily, yielding repeat sampling by the constellation approximately every 4–8 h.

Finally, it was shown in Table 7 that geostationary satellites could approach AMSU precipitation retrieval performance with a 2-m-diameter filled-aperture antenna that could be integrated on current operational polar satellites. Such geostationary microwave precipitation sounders could observe significant storms on the spatial and time scales at which they evolve by making ~15-min repeat observations with ~15-km resolution.

One implication of these results is that simulated assimilation experiments using appropriate NWP/RTM models should predict with reasonable accuracy the performance of actual systems for which the NWP and RTM models are fine-tuned before operational use. Therefore it may not be necessary to place more experimental millimeter-wave systems in orbit before estimating their potential retrieval performance and contributions to NWP; rather accurate performance predictions can arguably now be made using proper simulations alone.

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