Precipitation Observations Near 54 and 183 GHz Using the NOAA-15 Satellite

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Abstract—Promising agreement over land and sea has been obtained between NEXRAD 3-GHz radar observations of precipitation rate and retrievals based on simultaneous passive observations at 50–191 GHz from the Advanced Microwave Sounding Unit (AMSU) on the NOAA-15 meteorological satellite. A neural network with three hidden nodes and one linear output node operated on 15 km resolution data at 183 ± 1 and 183 ± 7 GHz, plus the cosine of scan angle, to produce estimates that match well the morphology of NEXRAD hurricane and frontal precipitation data smoothed to 15-km resolution. A second neural network operated on the same three parameters used in the first network, but smoothed to 50-km resolution, plus spatially-filtered cold perturbations detected in three AMSU tropospheric temperature-sounding channels (channels 4–6), which also have 50-km resolution. Comparison with the same NEXRAD data smoothed to 50-km resolution yielded root mean square (rms) discrepancies for two frontal systems and two passes over Hurricane Georges of ~ 1.1 mm/h, and ± 1.4 dB for those precipitation events over 4 mm/h. Only 8.9% of the total AMSU-derived rainfall was in areas where AMSU saw more than 1-mm/h and NEXRAD saw less than 1-mm/h, and only 6.2% of the total NEXRAD-derived rainfall was in areas where NEXRAD saw more than 1-mm/h and AMSU saw less than 1-mm/h.

Index Terms—Measurement, microwave propagation, microwave radiometry, microwave spectroscopy, precipitation, remote sensing.

I. INTRODUCTION

LOCAL and global monitoring of precipitation is important for both scientific purposes and applications. Long established observation methods utilizing rain gauges [1], [2] have been supplemented by increasingly extensive networks of ground-based radar systems [3], [4] and by visible and infrared sensors in polar and geostationary orbits [5]. Satelliteborne radars and passive microwave sensors operating in atmospheric windows currently provide additional precipitation information [6]–[12].

The present paper introduces a new technique based on observations made simultaneously in the opaque water vapor and oxygen microwave absorption bands. These initial results are based on data from the U.S. Advanced Microwave Sounding Unit (AMSU) on the National Oceanic and Atmospheric Administration, NOAA-15 satellite. AMSU observes from polar orbit 20 channels distributed from ~ 1.6 - to 13-mm wavelength.

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Potential advantages of AMSU relative to ground-based precipitation monitoring systems include uniform global coverage, and advantages relative to satelliteborne visible or infrared systems include its ability to penetrate most nonprecipitating clouds. Its principal advantage relative to orbiting passive microwave sensors viewing window frequencies is the increased ability of AMSU's opaque bands to sense precipitation over land without strong surface emissivity effects. Advantages relative to current satellite-borne radars include AMSU's wider swath width, permitting full Earth coverage twice per day from a single satellite. The performance of these new frequencies for precipitation retrievals is estimated by comparison of AMSU and nearly simultaneous NEXRAD precipitation images for four orbital passes over the eastern United States, where NEXRAD coverage is nearly complete.

II. DESCRIPTION OF THE ADVANCED MICROWAVE SOUNDING UNIT (AMSU)

The AMSU consists of two largely independent units: AMSU-A, which observes at 15 frequencies up to 90 GHz with ~ 50 -km spatial resolution and AMSU-B, which observes at five frequencies 88–191 GHz with ~ 15 -km resolution. These resolutions degrade at large scan angles. AMSU-A and AMSU-B images cover the same swath width of ~ 2200 km and are 30 and 90 spots wide, respectively. The center frequencies and bandwidths of the AMSU channels are listed in Table I [13]. Each channel has two (or more) sidebands centered at the listed frequencies. The table lists the number of sidebands and their individual bandwidths. The symbol f_{LO} represents the local oscillator frequency of channel 7 (57 290.344 MHz). The opaque channels used for precipitation estimation can be characterized by temperature weighting functions near the 54-GHz wing of the oxygen absorption band, and by water-vapor-burden weighting functions near the 183-GHz water vapor resonance. The water vapor burden is the integrated abundance of water above the indicated atmospheric level. These weighting functions are shown in Figs. 1 and 2 for the US standard atmosphere viewed at nadir over nonreflective land and characterize the degree to which each atmospheric layer contributes to the radiances viewed from space at the indicated frequencies. These weighting functions approach zero at high altitudes where the atmosphere becomes transparent, or at low altitudes where the overlying atmosphere is so thick as to be fully opaque.

Because the radio-frequency shielding of AMSU-B was insufficient to fully reject the excessive sidelobe radiation from certain transmitting antennas on the NOAA-15 spacecraft, the

TABLE I
AMSU CHANNEL FREQUENCIES

AMSU-A Channels		
Channel	Center Freq.(s) (MHz)	Bandwidth (MHz)
1	$23,800 \pm 72.5$	2×125
2	$31,400 \pm 50$	2×80
3	$50,300 \pm 50$	2×80
4	$52,800 \pm 105$	2×190
5	$53,596 \pm 115$	2×168
6	$54,400 \pm 105$	2×190
7	$54,940 \pm 105$	2×190
8	$55,500 \pm 87.5$	2×155
9	$57,290.344 = f_{LO} \pm 87.5$	2×155
10	$f_{LO} \pm 217$	2×77
11	$f_{LO} \pm 322.2 \pm 48$	4×35
12	$f_{LO} \pm 322.2 \pm 22$	4×15
13	$f_{LO} \pm 322.2 \pm 10$	4×8
14	$f_{LO} \pm 322.2 \pm 4.5$	4×3
15	89000 ± 900	2×1000

AMSU-B Channels		
Channel	Center Freq.(GHz)	Bandwidth (GHz)
1	89 ± 1	2×1
2	150 ± 0.9	2×1
3	183.31 ± 1	2×0.5
4	183.31 ± 3	2×1
5	183.31 ± 7	2×2

AMSU-B channels suffer variable radio frequency interference which slowly increased over the first 17 months of the mission. Fortunately the 183 ± 1 and 183 ± 7 GHz channels experienced minimal interference prior to October 13, 1998, so that these data can be used for precipitation estimation with 15-km resolution without modification. Although incorporation of the other three AMSU-B channels would improve precipitation estimates in the absence of interference, careful removal of their greater levels of interference would be required. This problem is being remedied in other AMSU instruments and recently improved in NOAA-15 when most of the offending transmitters ceased operations in October 1999.

AMSU-B scans laterally through nadir every 2.67 s, with small portions of this cycle time being allocated for space calibration, ambient load calibration, and movement between these stations. The AMSU-A antennas employed a similar scanning protocol, but they paused briefly to view each of the 30 spots and they used a period of 8 s.

III. PHYSICAL BASIS FOR 183-GHz PRECIPITATION RETRIEVALS

Convective precipitation is generally characterized by ascending saturated air masses and wet adiabatic temperature

Fig. 1. Temperature weighting functions for AMSU-A channels.

Fig. 2. Water vapor weighting functions for AMSU-B channels.

profiles. In the absence of hydrometeors, each 183-GHz frequency would penetrate a frequency-dependent water vapor burden and sound the average temperature in the corresponding atmospheric layer, as characterized by the water vapor weighting functions presented in Fig. 2. For idealized wet adiabatic atmospheres saturated at all altitudes, this relation between the water vapor burden and temperature at any altitude is fixed, and since each 183-GHz channel penetrates

Fig. 3. Calibrated AMSU-B brightness temperatures for Typhoon Rex over the Pacific Ocean on August 26, 1998, at 22:37 UTC at (a) 89 GHz, (b) 183 ± 7 GHz, and (c) 183 ± 1 GHz.

a fixed water vapor burden, the idealized observed brightness temperature for each channel is also fixed for such saturated atmospheres. For saturated atmospheres with wet-adiabatic lapse rates in the hypothetical absence of microwave-visible hydrometeors, the brightness temperature near 183-GHz would therefore be largely independent of surface temperature and latitude, although small second order effects arise from the pressure-dependence of water vapor absorption. Hydrometeors contribute both microwave scattering and absorption, lowering brightness temperatures below their frequency-dependent nominal values for a saturated atmosphere. This cold precipitation signature is unique because brightness temperatures below those corresponding to saturation generally cannot be generated otherwise. Variable lapse rates or relative humidities introduce small ambiguities; for example, low altitude precipitation might occur under a dry air mass. Additional ambiguities appear because the relative contributions of hydrometeor scattering and absorption depend on the particle temperature and the distributions of drop size and shape. Because hydrometeor size and temperature are correlated with precipitation rate, their

uncertainties generally do not detract unduly from precipitation retrieval accuracy, as demonstrated later.

The nominal brightness temperature sounded near 183 ± 1 GHz in saturated atmospheres is ~ 235 K, corresponding to ice, whereas that for 183 ± 7 GHz is ~ 260 K, corresponding to both water and ice. Therefore, 183 ± 7 GHz responds more strongly to stratiform rain and low precipitation rates than does 183 ± 1 GHz, which responds strongly only when strong convection thrusts large ice particles substantially higher in the atmosphere. This sensitivity to convective strength is suggested in Fig. 3, where Typhoon Rex is imaged by AMSU-B at 89, 183 ± 7 , and 183 ± 1 GHz. Note how only the strongest convective cells are highlighted at 183 ± 1 GHz. These images have been bilinearly interpolated to minimize checkerboard image artifacts. Note the typhoon eye, the rather sharp edges bounding likely precipitation zones, and the strings of well isolated small cold convective cells most evident at 183 ± 7 GHz. The warm bands seen in emission at 89 GHz over the colder ocean also reveal convective activity prior to formation of scattering hydrometeors.

By comparing the radiometric signatures at 183 ± 1 and 183 ± 7 GHz it is possible to estimate precipitation rates with useful accuracy. A simple physical relationship between rain rate and the 183-GHz spectrum arises in part because the equilibrium precipitation rate approximately equals the rate at which convective updrafts transport saturated water vapor into low temperature regions that dehumidify the air, and greater updraft velocities produce greater hydrometeor populations, altitudes, and sizes, where all of these properties coherently impact the 183-GHz emission spectrum. Finally, large convective systems and their associated high precipitation rates often cover areas larger than ~ 15 -km diameter, as evident in the AMSU-B data, and their observed areas can facilitate retrievals, although our evidence for this is not presented here.

The dominant effect of view angle is associated with the increase in atmospheric path length as AMSU scans away from $\theta = 0$ at nadir. The function $\cos \theta$ exhibits the same low angular dependence expected near nadir relative to the greater angular dependence expected at larger values of θ , whether they are due to path length or other geometric effects. This angular dependence is largely compensated by including $\cos \theta$ as an input to the neural network used to estimate precipitation.

These qualitative plausibility arguments for 183-GHz precipitation sensitivity may also be considered in light of the difficulties. First, precipitation is complex. It has varied hydrometeor types, densities, and sizes within a single 15-km footprint, as well as varied vertical velocities and cell-top altitudes. The fallout times of the smaller hydrometeors can be longer than the growth times of strong convection, and hydrometeors can change form as they fall. Variations in available potential energy, natural aerosol content, surface type (e.g. ocean versus land), gravity wave effects, wind shear, and electrification state can also modulate the results. They do not impact strongly, however, the basic observation that higher vertical velocities in saturated atmospheres generally yield higher precipitation rates and stronger precipitation signatures near 183 GHz, as demonstrated by the data presented in Section IV.

IV. 183-GHz PRECIPITATION RETRIEVAL ALGORITHM AND RESULTS

A simple feed-forward neural network was used to represent the nonlinear relation between these microwave radiances and precipitation. Its inputs were the calibrated antenna temperatures at 183 ± 1 and 183 ± 7 GHz, together with the cosine of the scan angle, which ranges from 0° at nadir to $\pm 48.95^\circ$. These three inputs plus a constant term (four inputs total) fed three hidden nodes followed by one linear output node trained to estimate precipitation in units of millimeters per hour. Each of the three hidden nodal outputs H_i ($i = 1, 2, 3$) equaled the hyperbolic tangent H_i of the sum of its respective four weighted inputs. The final output equaled $\sum_{i=1}^3 a_i H_i + b$, where a and b were constants also trained along with the other weights characterizing the network.

Precipitation is highly nonuniform in both space and time. When only a limited number of days are available for analysis, the extensive NOAA NEXRAD radar network probably offers the best statistical comparison for AMSU retrievals. The neural

network was trained using the most nearly coincident edited NEXRAD 5-minute average precipitation estimates prepared at 15-min intervals by Weather Services International Corporation (WSI), Boston, MA, and smoothed to 15-km spatial resolution so as to match the AMSU-B data. About half of the 3903 independent training data vectors which were used corresponded to precipitation over 0.05 mm/h. The training and test data were obtained from four passes of AMSU over the eastern United States on June 11, September 28 and 30, and October 7, 1999, at 13:37, 13:42, 00:39, and 13:43 UTC, respectively.

Fig. 4 presents NEXRAD and AMSU 15-km resolution retrieval comparisons for a cold front on October 7, 1998, and for Hurricane Georges on September 30, 1998. The AMSU and NEXRAD images differ largely because 183 GHz responds much more strongly to small ice particles, while the 3-GHz NEXRAD observations respond best to large rain drops and graupel. Fortunately, the hydrometeors to which 183 GHz is most sensitive are sufficiently large that they typically fall within tens of kilometers of the region where they were thrust aloft. However, the longer fallout time of these small hydrometeors can prolong AMSU precipitation responses relative to those of NEXRAD, and thus can produce a corresponding “blurring” of the AMSU images relative to NEXRAD, particularly if there is strong wind shear aloft. The increased sensitivity of AMSU to smaller hydrometeors also makes it relatively more sensitive to very light precipitation. Additional differences arise because NEXRAD penetrates most precipitating regions in their entirety, suffering blindness only on the far side of very intense precipitation or mountains, or at altitudes and ranges not sampled by its conically scanned radar beams [3]. Anomalous propagation can also lead to interpretation of radar ground clutter as precipitation echos. Finally, at 15-km resolution the ~ 5 min time offsets between NEXRAD and AMSU can also introduce significant discrepancies. Despite all these differences between the two sensing systems, the agreement between the resulting pairs of precipitation images in Fig. 4 is very encouraging.

V. PHYSICAL BASIS FOR PRECIPITATION RETRIEVALS NEAR 54 GHz

Fig. 1 shows that AMSU-A channels above 53.6 GHz are largely surface blind due to oxygen attenuation, and that they sample tropospheric temperatures and hydrometeors in broad layers at altitudes which increase with radio frequency. All solid, liquid, or mixed-phase hydrometeors absorb and scatter electromagnetic radiation, typically introducing cold spots in these AMSU-A surface-blind radiance images. Both ice and liquid hydrometeors above ~ 4 km are generally visible against the warmer opaque atmospheric background below. This contrasts with the tendency of window channels over land to respond to both liquid hydrometeors and random surface variations [12].

Hydrometeors at very high altitudes produce a cold spot across all tropospheric AMSU-A channels, whereas low-altitude hydrometeors impact primarily those AMSU-A channels at the lower, more transparent radio frequencies which see down to those atmospheric depths. Because of this frequency-dependent penetration depth, 54-GHz spectra reveal the altitudes

Fig. 4. Precipitation estimates from NOAA NEXRAD and AMSU-B data, both at 15-km resolution, for a cold front and for Hurricane Georges: (a) NEXRAD data for October 7, 1998 at 13:45 UTC, (b) AMSU-B derived precipitation for case (a); (c) NEXRAD data for September 30, 1998 at 00:39 UTC, and (d) AMSU-B derived precipitation for case (c). Contours are at 1, 2, 4, 8, and 16 mm/h.

of precipitating cell tops even when they are hidden under thin cirrus or other light clouds [15]. In addition, the more transparent 54-GHz channels provide a measure of cloud albedo, which also depends on the hydrometeor particle-size spectrum [16] and type; ice clouds exhibit substantially higher albedos than the water clouds.

The observed cloud-top altitudes of convective cells generally correspond to the top of the graupel cloud thrust aloft, where the average graupel sensed near 183-GHz is typically much smaller than that sensed near 54-GHz, and both populations are much larger and fall out much more rapidly than typical cloud particles sensed at infrared wavelengths. For such convective cells, the rain rate is closely related to the vertical velocity and the absolute humidity of the saturated air. This velocity is also directly related to the cell top altitude, and the humidity can be estimated from nearby nonprecipitating spots. Since higher vertical wind velocities are better able to support larger hydrometeors for long

periods, they permit growth of water droplets and ice particles to sizes sufficient to perturb 54-GHz and lower frequencies.

This predicted relation between cell-top altitude and precipitation rate has been observed by others. For example, G. A. Vicente *et al.* [7] compared 4-km resolution pairs of GOES-8 IR images and instantaneous radar rainfall estimates obtained from operational 5- and 10-cm radars in the central Great Plains and areas adjacent to the Gulf of Mexico. Only rain systems showing clearly delineated convective cores in both the IR and radar images were analyzed. A simple power law relationship between GOES-8 cloudtop temperature T (degrees K) and radar rainfall rate R was obtained for these special cases, $R \cong 1.12 \times 10^{11} e^{-0.0364T^{1.2}}$ mm/hr, yielding an rms discrepancy between GOES-8 and radar rainfall rate estimates of 7.2 mm/h over a dynamic range of 0–150 mm/h.

The advantages of AMSU relative to such GOES observations include an improved ability to retrieve temperature

Fig. 5. AMSU-A precipitation-induced cold brightness perturbations observed for channels 5 and 6 on 11 June, 1998. Contours are at 0.5, 1, 2, 4, and 8K.

and humidity profiles near precipitation, and an ability to see through overlying cirrus down to the more substantive graupel. Moreover, the differences in microwave responses near 183 and 54 GHz reveal information about the graupel size distribution. Larger hydrometeors strongly affect both 54- and 183-GHz spectra, whereas smaller ones affect primarily 183-GHz spectra alone. Particle size is a particularly good indicator of vertical updraft velocities because only larger velocities can sustain large particles aloft, and these large velocities are also directly conveying saturated air into low-temperature zones where the humidity must condense and precipitate. Thus a simple relationship linking convective velocity and cell-top altitudes to precipitation rates might be expected. Although GOES can resolve smaller precipitation cells, those with diameters over 15-km produce the most rain.

To summarize, the absolute cell-top altitude, albedo, and area deduced near 54 GHz, and differential 54/183-GHz signatures all add sufficient information to 183-GHz spectral data to support useful precipitation estimates as demonstrated below. However, as noted in the final paragraph of Section III, precipitation is complex and therefore, the relationship is imperfect between

the surface rain rate and hydrometeor size, type, and distribution near the cell top. Because the dynamic complexity of precipitation is difficult to model, validation of proposed retrieval algorithms is best achieved by seeking statistical agreement with independent measurement techniques as discussed in Section VI.

VI. 54- AND 183-GHz PRECIPITATION RETRIEVAL ALGORITHM AND RESULTS

A simple neural network was again used to estimate precipitation in order to capture the nonlinearities that relate AMSU radiances to precipitation rate. This neural net operated on the absolute brightness temperatures near 183 ± 1 and 183 ± 7 GHz, the cosine of the scan angle, and the AMSU-A brightness temperature perturbations introduced near 52.8, 53.6, and 54.4 GHz by the hydrometeors. These perturbations were determined using the spatial filtering technique described below.

In the first step of the algorithm demonstrated here, the 183 ± 7 GHz data were used to delineate those regions where precipitation might be present. In particular, areas with brightness temperatures below 260 K, suggesting precipitation,

TABLE II
NEURAL NETWORK COEFFICIENTS FOR AMSU 50-km PRECIPITATION RETRIEVALS

Weights Between Input Layer and First Layer A

Layer 1	Δch4	Δch5	Δch6	183 ± 1	183 ± 7	$\cos \theta$	Node Bias
Node				GHz	GHz		
A1	-0.071	0.075	0.65	0.13	-0.0039	1.5	-14
A2	0.012	0.056	-0.012	-0.0056	0.0021	0.088	-0.35
A3	0.12	-0.20	0.63	0.040	0.058	5.5	0.86

Weights Between First (A) and Second (B) Layers

Layer 2	A1	A2	A3	Node Bias
Node				
B1	2.1	9.6	2.5	4.7
B2	-1.6	-0.84	0.32	-2.0

Weights Between Second (B) and Output (C) Layers

Output Node	B1	B2	Node Bias
C1	-24	-12	11

were masked and then dilated by one 15-km pixel width around their perimeters. Next, AMSU-A Channels 4–7 were corrected for scan angle using neural networks trained to estimate nadir brightnesses over land from rain-free observations obtained nearly simultaneously at other scan angles. Four orbits from different weeks were used for this training. A pair of neural networks was used to correct Channel 4: one for correcting views over land and another for correcting views over sea. The neural network inputs used for these corrections were AMSU-A Channels 5–12 and $\cos \theta$, where θ is the scan angle. Channel 4 was also input when channel-4 nadir brightnesses were estimated, and the land fraction within the beam was input when estimating Channels 5–7.

These corrected AMSU-A brightness temperatures were then interpolated across all the masked areas from the brightness temperatures bordering them. Laplacian interpolation was used. For those masked areas, intersecting the edge of the swath, the border pixel values along that edge were interpolated from the two pixels bounding the region on that edge. These interpolated surface- and angle-corrected brightness temperatures were then subtracted from the observations to yield the 54-GHz cloud perturbations in AMSU Channels 4–6 (see Table I for channel designations). The AMSU-A brightness perturbations for Channels 5 and 6 are shown in Fig. 5 for June 11, 1998. In this figure, only negative perturbations are shown. Small positive perturbations due to small temperature inhomogeneities within the masked

area occur but are set to zero. The cold perturbations approximate 12 K, 8.5 K, and 2.3 K for the strong convective cell in southern Ohio for Channels 4, 5, and 6, respectively. These three channels were all used because the cell-top altitude affects them differently and is thereby revealed.

To estimate precipitation rate a feed-forward neural network with seven inputs operated on the radiances at 183 ± 1 and 183 ± 7 GHz, the AMSU-A negative perturbations on channels 4–6 near 54 GHz (designated by ΔCh4 , ΔCh5 , and ΔCh6 , respectively), the cosine of the scan angle θ , and a constant (unity). This neural network had three hidden nodes (A1, A2, and A3) followed by a layer with two hidden nodes (B1 and B2), and a final linear output node (C1). The weighting factors for each node and the bias are presented in Table II, which also defines the network architecture. All nodes except the final one computed the hyperbolic tangent of the sum of its seven or three weighted inputs. The cosine of scan angle approximates most path length and other angular dependences, although imperfectly. The algorithm implemented by the neural network is revealed by these weights. For example, node A1 responds most strongly to high altitude precipitation, as seen from the large positive weights for 183 ± 1 GHz and ΔCh5 and ΔCh6 (which respond best to high altitudes), and the significant negative weight for ΔCh4 (which is responsive to low altitudes). These weights operate on brightness temperatures which have comparable variances except for ΔCh6 , which is smaller. Node A2 responds to midaltitudes, and A3 responds to

the lowest altitudes (*viz.*, $\Delta\text{Ch 4}$ and $\Delta\text{Ch 5}$). Node B1 weights all altitudes positively yielding the approximate total precipitation rate, while B2 responds more strongly to the altitude gradient. The final output (C1) is a linear combination of B1 and B2.

The AMSU-B radiances near 183 GHz were first smoothed to 50-km resolution so as to coincide with the corresponding AMSU-A spot. The NEXRAD data was similarly blurred to match the AMSU-A resolution. This neural network was then trained with the 50-km NEXRAD precipitation estimates within the masked areas for four high-precipitation orbits on June 11, September 28 and 30, and October 7, 1998 at 13:37, 13:42, 00:39, and 13:43 UTC, respectively. For these four images there were 857 training vectors available, of which 429 were randomly chosen for training, 214 others were randomly chosen to determine when training should cease, and the remaining 214 were used to provide independent confirmation of retrieval precision and that the estimator is not biased due to small sample sizes. Approximately 40% of these samples were precipitating over 1 mm/h. Only 29% of the samples in this data set exhibited both AMSU and NEXRAD rain rates below 0.3 mm/h.

Fig. 6 shows the resulting correlation between the NEXRAD training data and the neural net retrieval, where the training (+), validation ($\times$), and test (o) data sets are represented differently and are seen to be consistent with each other. The rms precipitation retrieval errors (discrepancies between AMSU and NEXRAD), which would result from using this neural network are ~ 0.4 mm/h for NEXRAD precipitation rates below 0.01 mm/h, ~ 1.1 mm/h for the entire data set (857 vectors; best-fit straight line), and ± 1.4 dB for precipitation rates above 4 mm/h. Future sounders with better spatial resolution are expected to improve significantly on these results.

Figs. 7 and 8 compare corresponding NEXRAD and AMSU precipitation rate retrieval images for all four of the heavily precipitating days chosen for training. Both sensors place the precipitation in approximately the same locations at comparable rates, except for the tendency for AMSU to see precipitation over a slightly wider area, which may be spurious or which may correspond to droplets too tiny to register strongly in the smoothed NEXRAD retrievals. A few NEXRAD cells were not observed by AMSU, perhaps because they were at too low an altitude or were produced by anomalous radar propagation effects. These discrepancies would have limited impact on the hydrological studies, however. For example, only 8.9% of the total AMSU-derived rainfall (and 11.3% of the AMSU precipitation area) was in places where AMSU saw more than 1 mm/h and NEXRAD saw less than 1 mm/h, and only 6.2% of the total NEXRAD-derived rainfall (and 7.8% of the NEXRAD precipitating area) was in places where NEXRAD saw more than 1 mm/h and AMSU saw less than 1 mm/h. Precipitation is presumed when estimates exceed 0.05 mm/h. Furthermore, some of these discrepancies are due to the typical 0–8 min offsets in the AMSU versus NEXRAD observation times, comparable to the evolution times of smaller convective systems, and additional discrepancies are probably due to incomplete radar coverage. For these four rain-filled days, 83% of all 50-km spots had less than 0.1 mm/h precipitation indicated for both AMSU and NEXRAD and 8.4% had AMSU or NEXRAD precipitation estimates above 1 mm/h.

Fig. 6. Quantitative comparison of AMSU and NEXRAD 50-km precipitation-rate retrievals for four passes over the eastern United States. Symbols +, $\times$, and o represent neural network training, validation, and test data sets, respectively.

This agreement between the instantaneous 50-km resolution NEXRAD and AMSU retrievals is unexpectedly good, and possibly better than any previously published agreement between any two other dissimilar instantaneous precipitation measurement techniques. Although only four days were examined, they included over 800 independent 50-km comparisons in and adjacent to precipitation, a number far larger than the number of degrees of freedom (32; see Table II) in the neural network used for the precipitation retrieval. Moreover, half of these soundings were not used to adjust the weights, but only to test and validate them. Their error statistics are similar to those of the training data.

However, agreement between two independent measurement techniques, although promising, does not constitute complete validation, because the two techniques may merely exhibit the same systematic errors such as those suggested for WSR-88D and NEXRAD [3], [4]. A desirable second step would be a more precise determination of the systematic errors in NEXRAD so they could be transferred to AMSU precipitation retrievals. Direct comparison of AMSU retrievals to oceanic SSM/I and other window-channel passive microwave sensors would also be helpful, as would comparisons to rain gauges, TRMM and other radar systems, and other *in situ* and remote sensing systems. Comparisons of AMSU and NEXRAD over a wider range of meteorological conditions and AMSU-B channel frequencies is underway.

VII. SUMMARY AND CONCLUSIONS

These examples illustrate that useful precipitation images can be obtained over land using AMSU data and that 50-km resolution instantaneous precipitation rate retrievals agree surprisingly well with NEXRAD results when both 54- and 183-GHz spectral data are employed. The physical arguments presented here in Sections III and V apply almost equally well to 15-km and 50-km resolution data, and so comparable

Fig. 7. Comparison of AMSU and NEXRAD precipitation-rate retrievals for two cold fronts: (a) June 11, 1998 and (b) October 7, 1998. Contours are at 0.5, 1, 2, 4, 8, and 16 mm/h. AMSU central transits were near 1337 UTC and 1343 UTC respectively, while the 5-min NEXRAD data were collected near 1345 UTC on both occasions.

agreement with 15-km resolution NEXRAD data might be obtained with 15-km resolution sensors operating at all AMSU frequencies. Such better AMSU resolutions would have better detected, for example, the small convection cells over Kentucky illustrated in Fig. 8.

These simple examples illustrate that AMSU and similar operational instruments flying on NOAA-15 and other meteorological satellites will provide an important new resource for routine precipitation monitoring on a global scale. Moreover, future AMSU instruments should not be subject to radio frequency in-

terference on the critical 15-km resolution channels. Although NEXRAD-class precipitation data is unfortunately available for training only over the United States and a few other locations, it is hoped that radars and window-channel passive microwave sensors such as those on the NASA TRMM satellite will provide more global validation.

It is clear from comparisons of AMSU 23.8- and 31.4-GHz data with AMSU 50-km precipitation estimates that the tropics contain some low-altitude precipitation which exists primarily below the penetration depth of the 183 ± 7 GHz channel. In this

Fig. 8. Comparison of AMSU and NEXRAD precipitation-rate retrievals for Hurricane Georges on: (a) September 28, 1998 and (b) September 30, 1998. Contours are at 0.5, 1, 2, 4, 8, and 16 mm/h. AMSU central transits were near 1342 UTC and 0039 UTC respectively, while the 5-min NEXRAD data were collected near 1345 UTC and 0045 UTC, respectively

case, the more deeply penetrating AMSU-B 150-GHz channel and other techniques will be required to retrieve such precipitation accurately. Similarly, over polar regions dry atmospheres sometimes permit 183 ± 7 GHz to reach the surface, motivating possible use of 183 ± 3 GHz in the masking and retrieval process. Additional issues such as surface elevation must also be addressed when these techniques are extended to a global scale.

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