A GLOBAL PRECIPITATION RETRIEVAL ALGORITHM FOR SUOMI NPP ATMS

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ABSTRACT

This paper develops a precipitation retrieval algorithm for the Advanced Technology Microwave Sounder (ATMS) recently launched aboard the U.S. Suomi National Polar-orbiting Partnership (Suomi NPP) satellite. The algorithm is called the ATMS MIT Precipitation retrieval algorithm version 1 (ATMP-1), employs neural network estimators trained and evaluated using the validated global reference physical model NCEP/MM5/TBSCAT/F(λ), and works for snow-free land and seawater with |latitudes|<50°. Signals were carefully chosen and principal component analysis was used to filter out angle and surface effects, and other noises. Retrievals are useful for surface precipitation rates higher than 1 mm/h at 15-km resolution for both land and sea, as evaluated using MM5. Surface precipitation rates retrieved using ATMP-1 for ATMS aboard Suomi NPP satellite are in good agreement with those retrieved using the AMSU MIT Precipitation retrieval algorithm (AMP) for AMSU aboard NOAA-18 satellite.

Index Terms—Advanced Technology Microwave Sounder (ATMS), Suomi NPP satellite, passive millimeter-wave precipitation retrieval algorithm, precipitation, rain, remote sensing, snow.

1. INTRODUCTION

The 22-channel passive millimeter-wave sensor Advanced Technology Microwave Sounder (ATMS) [1] was recently launched aboard the U.S. National Polar-orbiting Operational Environmental Satellite System Preparatory Project (NPP) on October 28, 2011. NPP was renamed the Suomi National Polar-orbiting Partnership (Suomi NPP) on January 24, 2012. [2]-[8] have shown that the ATMS’s predecessor, the Advanced Microwave Sounding Unit (AMSU), aboard National Oceanic and Atmospheric Administration (NOAA) and European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) MetOp satellites provide useful precipitation estimates globally including snow-covered land and sea ice [6]-[8] and the estimates are in good agreement with CloudSat radar observations [6] and global rain gauge measurements [7]-[8]. ATMS has several improvements over AMSU. [1] has predicted the ability of ATMS to estimate surface precipitation rates (millimeters per hour); water path for rain, snow, and graupel (millimeters); and peak vertical wind (meters per second) and has shown that ATMS is more accurate than AMSU for most estimated parameters. ATMS’s Nyquist sampling below 90-GHz channels, which enables discretionary image sharpening, has also been shown to help resolve fine convective cells. With the recent launch of ATMS, this paper is the first to develop an ATMS precipitation retrieval algorithm, which is called the ATMS MIT Precipitation retrieval algorithm version 1 (ATMP-1). This first version focuses on areas with |latitudes|<50°, not including snow-covered land and sea ice.

2. ATMS CHANNEL CHARACTERISTICS

Table I shows ATMS and AMSU channel characteristics, where A1, B1, and H1 stand for channel 1 of AMSU-A, AMSU-B, and Microwave Humidity Sounder (MHS), respectively. Table I also shows altitudes (WF) where each channel’s weighting function peaks, based on nadir views of the 1976 U.S. standard atmosphere over a nonreflecting surface. ATMS channels 1–15 resemble AMSU-A and ATMS channels 16–22 resemble AMSU-B and MHS. ATMS’s improvements over AMSU include 1) the addition of 51.76 GHz channel, which provides more information about surface, stratiform precipitation, and tropospheric temperature profiles, 2) the addition of 183.31±1.8 and 183.31±4.5 GHz channels, which provide more information about precipitation and water vapor, 3) better spatial resolution for 50-GHz channels, i.e., from ~50 to ~33 km at
nadir, 4) Nyquist spatial sampling for channels below 90 GHz, which enables image sharpening [1], [9], and 5) about 400 km wider swaths. On the other hand, ATMS surface channels near 23.8, 31.4, and 88.2 GHz have lower spatial resolution than those of AMSU.

The rms discrepancies were evaluated using evaluating data different from those used for training. The rms discrepancies were low for both land and sea. The neural networks include brightness temperatures for all ATMS channels 1-9 and the secant of the satellite zenith angle.

### TABLE I

<table>
<thead>
<tr>
<th>Ch.</th>
<th>Center Frequencies (GHz)</th>
<th>Predicted NEΔT(K)</th>
<th>Resolution at Nadir (km)</th>
<th>WF (km)</th>
<th>AMSU Ch.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>23.80</td>
<td>0.28</td>
<td>75</td>
<td>0</td>
<td>A1</td>
</tr>
<tr>
<td>2</td>
<td>31.40</td>
<td>0.35</td>
<td>75</td>
<td>0</td>
<td>A2</td>
</tr>
<tr>
<td>3</td>
<td>50.30</td>
<td>0.42</td>
<td>33</td>
<td>0</td>
<td>A3</td>
</tr>
<tr>
<td>4</td>
<td>51.76</td>
<td>0.31</td>
<td>33</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>5</td>
<td>52.80</td>
<td>0.32</td>
<td>33</td>
<td>0</td>
<td>A4</td>
</tr>
<tr>
<td>6</td>
<td>53.596±0.115</td>
<td>0.35</td>
<td>33</td>
<td>3.6</td>
<td>A5</td>
</tr>
<tr>
<td>7</td>
<td>54.40</td>
<td>0.32</td>
<td>33</td>
<td>6.7</td>
<td>A6</td>
</tr>
<tr>
<td>8</td>
<td>54.94</td>
<td>0.32</td>
<td>33</td>
<td>9.2</td>
<td>A7</td>
</tr>
<tr>
<td>9</td>
<td>55.50</td>
<td>0.35</td>
<td>33</td>
<td>11.9</td>
<td>A8</td>
</tr>
<tr>
<td>10</td>
<td>f0±57.2903±44</td>
<td>0.49</td>
<td>33</td>
<td>15.9</td>
<td>A9</td>
</tr>
<tr>
<td>11</td>
<td>f0±0.217</td>
<td>0.67</td>
<td>33</td>
<td>19.7</td>
<td>A10</td>
</tr>
<tr>
<td>12</td>
<td>f0±0.3222±0.048</td>
<td>0.70</td>
<td>33</td>
<td>24.2</td>
<td>A11</td>
</tr>
<tr>
<td>13</td>
<td>f0±0.3222±0.022</td>
<td>1.06</td>
<td>33</td>
<td>29.2</td>
<td>A12</td>
</tr>
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<td>14</td>
<td>f0±0.3222±0.010</td>
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<td>33</td>
<td>34.4</td>
<td>A13</td>
</tr>
<tr>
<td>15</td>
<td>f0±0.3222±0.0045</td>
<td>2.40</td>
<td>33</td>
<td>39.8</td>
<td>A14</td>
</tr>
<tr>
<td>16</td>
<td>88.2</td>
<td>0.29</td>
<td>33</td>
<td>0</td>
<td>B1 (H1)</td>
</tr>
<tr>
<td>17</td>
<td>165.6</td>
<td>0.44</td>
<td>15</td>
<td>0</td>
<td>B2 (H2)</td>
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<tr>
<td>18</td>
<td>183.31±7.0</td>
<td>0.34</td>
<td>15</td>
<td>1.2</td>
<td>B3 (H3)</td>
</tr>
<tr>
<td>19</td>
<td>183.31±4.5</td>
<td>0.39</td>
<td>15</td>
<td>2.5</td>
<td>-</td>
</tr>
<tr>
<td>20</td>
<td>183.31±3.0</td>
<td>0.48</td>
<td>15</td>
<td>3.5</td>
<td>B4 (H4)</td>
</tr>
<tr>
<td>21</td>
<td>183.31±1.8</td>
<td>0.49</td>
<td>15</td>
<td>4.7</td>
<td>-</td>
</tr>
<tr>
<td>22</td>
<td>183.31±1.0</td>
<td>0.62</td>
<td>15</td>
<td>5.6</td>
<td>B3 (H3)</td>
</tr>
</tbody>
</table>

*Center frequencies for AMSU-B channels 1 and 2 are 89 and 150 GHz, respectively. Center frequencies for MHS channels 1, 2, and 5 are 89, 157, and 190.311 GHz, respectively. AMSU’s resolution at nadir is 50 km below 60 GHz and 15 km otherwise.

### 3. RETRIEVAL ALGORITHMS

ATMP-1 employs neural networks trained and evaluated separately for land and sea using atmospheric parameters and corresponding brightness temperatures for 106 global storms simulated by the validated global reference physical model, NCEP/MM5/TBSCAT/F(λ), composed of the U.S. National Center for Environmental Prediction (NCEP) analyses, the fifth-generation National Center for Atmospheric Research/Penn State Mesoscale Model (MM5), a radiative transfer model, TBSCAT, and electromagnetic scattering models for icy hydrometeors, F(λ) [2]-[3]. The best of ten neural networks was used for each task.

Data preprocessing is composed of 1) correction for small brightness temperature biases between NCEP/MM5/TBSCAT/F(λ) and ATMS, 2) omission of some ATMS footprints, 3) correction of brightness temperatures to those that would have been observed at nadir, 4) surface classification, and 5) principal component analysis (PCA) to extract only good signals that provide useful information about precipitation but are insensitive to most angle and surface effects, and other noises. Only the good signals were used for precipitation retrieval.

As shown in Table I, since ATMS channels 10-15 sense mostly at altitudes higher than most precipitation, these channels were not used. ATMP-1 starts with the correction for small brightness temperature biases between NCEP/MM5/TBSCAT/F(λ) and ATMS channels 6 – 9 computed by comparing Suomi NPP ATMS and NOAA-18 AMSU observed brightness temperature means for five days of data with |latitude| < 5° and satellite zenith angle less than 2°. NOAA-18 brightness temperatures have been calibrated against 122 MM5 global storms [2]-[3].

ATMP-1 omits ATMS footprints for which: 1) any brightness temperature for that footprint is less than 50 K or greater than 400 K, which is invalid, 2) the surface altitude is above 2 km for |latitude| < 60°, or above 1.5 km for 60° ≤ |latitude| < 70°, or above 0.5 km elsewhere, which could be covered by snow and are sensed more strongly and is called too-high, or 3) ATMS channel 6 is less than 242 K, which implies that the atmosphere is so cold and potentially dry that precipitation is unlikely and that even the most opaque channel, i.e., 183±1 GHz, may sense the surface and yield false detections of precipitation, and is called too-cold.

### 3.1. Correction of Observed Brightness Temperatures to Nadir and Surface Classification

The dependency of observed brightness temperatures on zenith angles can confuse estimators. ATMP-1 employs neural network estimators to correct angle-dependent brightness temperatures to those that would have been observed at nadir. One neural network per channel is used for both land and sea. The neural networks were trained using brightness temperatures simulated for 106 MM5 storms at nadir and at all ATMS zenith angles. Those at nadir were used as target.

As Fig. 1 shows, to estimate brightness temperatures at nadir for any channel of ATMS channels 1-9, the inputs to the neural networks include brightness temperatures for all ATMS channels 1-9 and the secant of the satellite zenith angle. To estimate brightness temperatures at nadir for any channel of ATMS channels 16-22, the inputs to the neural networks include brightness temperatures for all ATMS channels 16-22 and the secant of the satellite zenith angle. The rms discrepancies were evaluated using evaluating data different from those used for training. The rms discrepancies...
for opaque channels 4-9, and 18-22 are 0.37-0.56 K. The
rms discrepancies for surface channels 1-3 are 0.92-
1.13 K. The worst channel is the surface channel 16 near 89
GHz with the rms discrepancy of 2.1 K. These residual
nadir correction errors are small compared to most
precipitation signatures, which exceed ten degrees, and will
be filtered out further using principal component analysis in
the later step.

ATMS-observed footprints were classified as snow-free
land, snow-covered land, seawater, or sea ice using the
surface classification algorithm adapted from [10], where
inputs include ATMS channels 1-3, 5, and 16, land/sea flag,
and climatological surface temperature, as Fig. 1 shows.
ATMP-1 only focuses on ATMS footprints classified as
snow-free land or seawater.

3.2. Precipitation Retrieval Algorithm for Land

Fig. 2(a) shows the block diagram for precipitation retrieval
algorithm for land. Since frequency-dependent variations in
surface emissivity over land often confound precipitation
signatures, only opaque channels 5-9 and 20-22 were used.
Principal components (PCs) were computed for ATMS
channels 5-9 using all ATMS observations over land for 5
days in year 2011. The first PC, designated PC#1, and
PC#3-5 have strong surface effects, residual angle
dependence, or other noises, as Fig. 3 shows. Only PC#2
shows good precipitation signatures, but not other noises.
Hence, inputs to land precipitation neural network include
PC#2, estimated brightness temperatures at nadir of ATMS
channels 20-22, and the secant of the satellite zenith angle.

3.3. Precipitation Retrieval Algorithm for Sea

Fig. 2(b) shows the block diagram for precipitation retrieval
algorithm for sea. PCs were computed separately for ATMS
channels 1-9 and channels 16-22 using all ATMS
observations over seawater for the 5 days used for land.
PC#1 is the only good PC for ATMS channels 1-9, and only
PC#1-3 are good for ATMS channels 16-22, as Figs. 4 and 5
show. Other PCs have strong surface effects, residual angle
dependence, or other noises. Hence, these four good PCs
and the secant of the satellite zenith angle are the inputs of
the sea precipitation neural network.

4. RETRIEVAL RESULTS

Tables II presents the rms and mean errors evaluated
separately for land and sea using 15-km resolution MMS
surface precipitation rates for evaluating pixels different
from those used for training. Retrievals appear to be useful
for surface precipitation rates higher than 1 mm/h for both
land and sea. Fig. 6 shows scatterplots between MMS
surface precipitation rates and those estimated using ATMP-
1 with good correlation coefficients of 0.70 and 0.72 for
land and sea, respectively.

Fig. 7 compares surface precipitation rate estimates
(mm/h) for AMSU aboard NOAA-18 satellite retrieved
using the AMSU MIT Precipitation retrieval algorithm
version 4 (AMP-4) [7] and those for ATMS aboard Suomi
NPP satellite retrieved using ATMP-1 for December 12,
2011. The local times of ascending node for NOAA-18 and
Suomi NPP are at 14:31 and 13:30, respectively. Only
footprints with |latitude|<50°, snow-free land or seawater,
and not too-high are plotted. Retrievals for too-cold
footprints were set to zero. The image comparison shows
that ATMP-1 ATMS estimates are in good agreement with
AMP-4 AMSU estimates. The differences could be due to
different observation times. ATMS’s wider swaths cover AMSU’s orbital gaps.

<table>
<thead>
<tr>
<th>MM5 (mm/h)</th>
<th>RMS Error</th>
<th>Mean Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Land</td>
<td>Sea</td>
</tr>
<tr>
<td>0.5-1</td>
<td>1.29</td>
<td>1.26</td>
</tr>
<tr>
<td>1-2</td>
<td>1.97</td>
<td>1.53</td>
</tr>
<tr>
<td>2-4</td>
<td>2.08</td>
<td>2.31</td>
</tr>
<tr>
<td>4-8</td>
<td>4.22</td>
<td>4.09</td>
</tr>
<tr>
<td>8-16</td>
<td>7.73</td>
<td>6.91</td>
</tr>
<tr>
<td>32-64</td>
<td>25.65</td>
<td>27.04</td>
</tr>
<tr>
<td>&gt;64</td>
<td><strong>52.29</strong></td>
<td><strong>55.43</strong></td>
</tr>
</tbody>
</table>

Italics highlight rms errors exceeding the upper bound listed in the 1st column, indicating poor utility. Boldfaces highlight rms errors below the minimum listed in the 1st column, indicating good utility.

5. SUMMARY AND CONCLUSIONS

The NCEP/MM5/TBSCAT/F(λ)-trained ATMS MIT Precipitation retrieval algorithm version 1 (ATMP-1) developed in this paper provides useful retrievals for surface precipitation rates above 1 mm/h for both snow-free land and seawater with |latitude|<50°, as evaluated using MM5. ATMP-1 precipitation retrievals for ATMS aboard Suomi NPP agree well with AMP-4 retrievals for AMSU aboard NOAA-18. ATMS precipitation retrievals exploiting image sharpening for channels below 90 GHz and extension to snow-covered land and sea ice are left for future studies.

6. ACKNOWLEDGMENT

The authors are so grateful to David H. Staelin for all his help, and wish to thank Philip W. Rosenkranz for his forward radiance program, TBSCAT, and the Pennsylvania State University and the University Corporation for Atmospheric Research for their MM5. This work was supported by NOAA under Air Force contract FA8721-05-C-0002. Opinions, interpretations, conclusions, and recommendations are those of the authors and not necessarily endorsed by the United States Government.

7. REFERENCES