

SNOWFALL RATE RETRIEVAL USING AMSU/MHS PASSIVE MICROWAVE DATA

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Abstract

An algorithm has been developed to retrieve snowfall rate (R) over the Continental United States (CONUS) using measurements from NOAA's Advanced Microwave Sounding Unit (AMSU) or EUMATSAT's Microwave Humidity Sounder (MHS). The algorithm derives snowfall rate through a linkage between R and Ice Water Path (I) which is retrieved using a two-stream Radiative Transfer Model (RTM). Two databases are used in the development of the algorithm. One is built to derive an empirical equation that connects I with NEXRAD reflectivity, Z . Then a set of I - R equations is established with the help of existing Z - R relations. A second database is developed to determine the I - R equation to adopt by comparing the retrieved snowfall rate and the hourly snowfall observations from some U.S. weather stations.

INTRODUCTION

Snowfall is a major component in the hydrological cycle of the earth especially in mid- and high-latitude areas. The estimation of snowfall rate and indirectly snow accumulation is important to water resource management, environmental studies, agriculture, transportation, and so on. While the liquid form precipitation, rainfall, has received much attention in the research communities, knowledge about frozen hydrometeors such as snowfall rate remains inadequate. This is possibly due to the complexity of the problem stemming from the microphysics involved. Adding to the difficult situation is the lack of in-situ data except those obtained from limited field campaigns (e.g., The Wakasa Bay and C3VP field campaigns).

With the global coverage and the sensitivity to atmospheric states even under cloud cover, satellite microwave remote sensing provides an excellent tool for studying snowfall. NOAA's Advanced Microwave Sounding Unit-A and Unit-B (AMSU-A and AMSU-B) sensors measure the brightness temperatures at frequencies ranging from 23.8 GHz to 183.31 ± 7 GHz. These measurements, especially the ones at the higher frequencies (≥ 89 GHz), are sensitive to snowfall properties due to the scattering effect of ice particles in the atmosphere. Therefore, AMSU data are suitable for the retrieval of snowfall rate. EUMATSAT's Microwave Humidity Sounder (MHS) has very similar channels as AMSU-B and is also used in this study. It is noted that the Special Sensor Microwave Imager/Sounder (SSMIS) sensor onboard of the Defense Meteorological Satellite Program (DMSP) F16 and F17 offers another possibility for retrieving snowfall rate with its conical scanning mode and similar channels as AMSU-B. Five polar-orbiting satellites (NOAA-15, -16, -17, -18, and MetOp-A) are currently in operation that carry AMSU and/or MHS instruments and can provide up to 10 measurements per day at any given earth location. This extensive temporal coverage represents a significant advantage over in-situ measurements.

METHODOLOGY

Ice Water Path (I) represents the ice water content in a column and is closely related to the snowfall properties in the atmosphere. This fact provides the physical foundation for developing this algorithm which retrieves snowfall rate (R) by establishing a connection between R and I .

Retrieval of Ice Water Path

The first step of the algorithm is to derive I using a scattering-based forward Radiative Transfer Model (RTM) (Yan *et al.*, 2007). The principle scheme of the model is given in eq. (1):

$$\begin{bmatrix} \Delta I \\ \Delta V \\ \Delta D_e \\ \Delta T_s \\ \Delta \varepsilon_{23} \\ \Delta \varepsilon_{31} \\ \Delta \varepsilon_{89} \\ \Delta \varepsilon_{150} \\ \Delta \varepsilon_{183 \pm 7} \end{bmatrix} = (A^T A + E)^{-1} A^T \begin{bmatrix} \Delta T_{B23} \\ \Delta T_{B31} \\ \Delta T_{B89} \\ \Delta T_{B150} \\ \Delta T_{B183 \pm 7} \end{bmatrix} \quad (1)$$

where I is ice water path; V is total precipitable water; D_e is cloud particle effective diameter; T_s is surface temperature; ε_i is emissivity at 23.8, 31.4, 89, 150, and 183.31±7 GHz; A is derivatives of T_{Bi} over I , V , D_e , & T_s ; E is error matrix; and T_{Bi} is brightness temperatures at 23.8, 31.4, 89, 150, and 183.31±7 GHz. The emissivities of the five microwave frequencies are computed using a physical algorithm developed specifically for land surface with snow cover (Yan *et al.*, 2007). The retrieved quantities (I , V , D_e , T_s , and five emissivities) are initialized either by fixed values or by the Global Data Assimilation System (GDAS) data from NOAA's National Centers for Environmental Prediction (NCEP). The RTM follows an iteration scheme and outputs retrieved quantities when the differences between the simulated and the measured brightness temperatures fall under predefined thresholds. A notable feature of the RTM is that it employs more realistic snow crystal shapes and their scattering properties rather than the traditional sphere shape.

Connect Ice Water Path and Radar Reflectivity

The retrieved I is connected to NEXRAD (*i.e.* NOAA's WSR-88D) radar reflectivity (Z) through match-up of the two data sets. Figure 1 displays a sample match-up of a single AMSU-B Field-Of-View (FOV) with more than a thousand radar pixels. It is assumed that AMSU-B antenna pattern follows a two-dimensional Gaussian distribution so the radar reflectivity that matches the I of the AMSU-B FOV is a weighted average of all the radar pixels within the FOV. Quality control of the Z is performed using Quality Control Neural Network (QCNN) algorithm developed at University of Oklahoma. The radar data used are from the lowest elevation angle (about 0.4°) and between 20 km to 100 km range. Match-up data from ten snow cases recorded in the central part of the U.S. are used to derive an empirical equation that connects I to Z (Figure 2):

$$I = 5.6 \times 10^{-6} Z^3 - 2.89 \times 10^{-4} Z^2 + 8.94 \times 10^{-3} Z \quad (2)$$

Determine I - R Equation

There have been several studies in the literature on the relationship between snowfall rate R and radar reflectivity Z . Eight such equations were collected and combined with eq. (2) to establish empirical I - R equations. Figure 3 shows the wide-ranging snowfall rates given by the eight equations due to the differences in the radars and snowfall microphysics used in each study.

Hourly snow accumulation data were collected from twelve weather stations in the central U.S. area. Analysis shows that the retrieved snowfall rate has the highest average correlation coefficient with the observed snow data with 1 hour lag. This is because the retrieved R represents snowfall in the atmosphere. The time lag represents the average time it takes the snow mass to fall to the ground. Table 1 shows the average correlation coefficient with various time lags in the observed data:

Time Lag	0-hr late	0.5-hr late	1-hr late	2-hr late	3-hr late	4-hr late
Avg. Corre. Coe.	0.1281	0.2370	0.3239	0.2898	0.2122	0.1921

Table 1. Average correlation coefficient between retrieved and observed snowfall rates

When comparing the retrieved with the observed snowfall rate, it is found that the Z-R equation (eq. 3) developed by Sekhon and Srivastava (1970) has the smallest RMS with the observations with 1-hr lag as shown in Table 2.

Z-R Equation	C&M	VAS	OHT	IMA	PUH	B&W	S&S	FUJ
RMS	0.5140	0.4084	0.3722	0.3735	0.3532	0.3522	0.3514	0.3872

Table 2. RMS of retrieved snowfall rate using I-R relations based on different Z-R equations

The Z-R equation by Sekhon and Srivastava (1970) is

$$Z = 398R^{2.21} \quad (3)$$

This Z-R equation is adopted to establish an I-R relation. An I-R look-up table is created from eqs. (2) and (3) due to the triple order regression relation between I and Z.

To apply this snowfall rate algorithm, an existing snowfall algorithm (Kongoli, *et al.*, 2003) is first used to detect the presence of snowfall. When snowfall is detected for a particular FOV, ice water path is retrieved using the forward RTM, and snowfall rate is derived from the look-up table.

CASE STUDIES

Figure 4 – 6 present 3 case studies. In the first case, the snowfall rate from a snow storm in Lancaster, OH is calculated using the above algorithm for a three-day period from February 15 to 17, 2003. The second case is for the same storm but a different location, Newark, OH. The two cities are about 30 miles away from each other. The third case study is for a large snow/rain system that covers a good part of the Great Plains of the U.S. These cases show that the snowfall rate algorithm developed in this study catches basic snowfall patterns, but might miss snowfall (inherited from the snowfall detection algorithm) or underestimate high snowfall rate that is greater than 0.4 mm/hr.

This algorithm is currently running at NOAA/NESDIS as an experimental product. It will continue to evolve as we learn more about the relationship between high frequency measurements and the snowfall process.

The views, opinions, and findings contained in this report are those of the author(s) and should not be construed as an official National Oceanic and Atmospheric Administration or U.S. Government position, policy, or decision.

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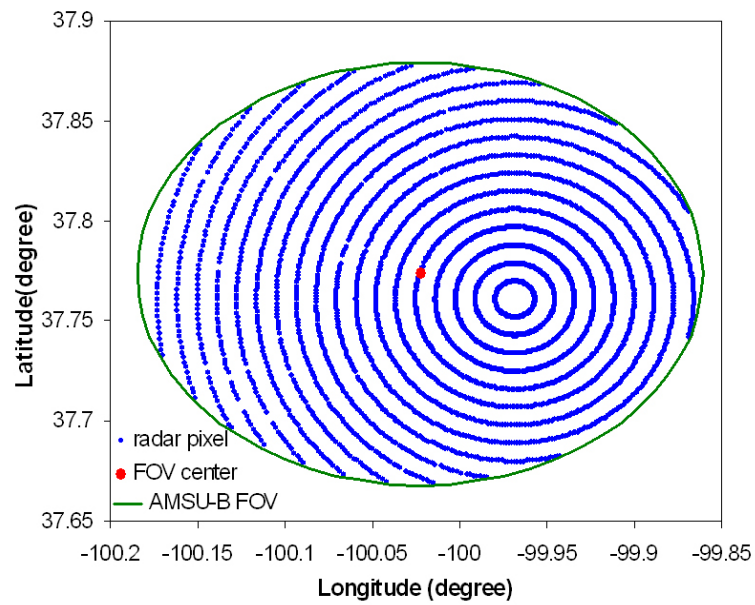


Figure 1. Matching of AMSU-B footprint and NEXRAD radar data

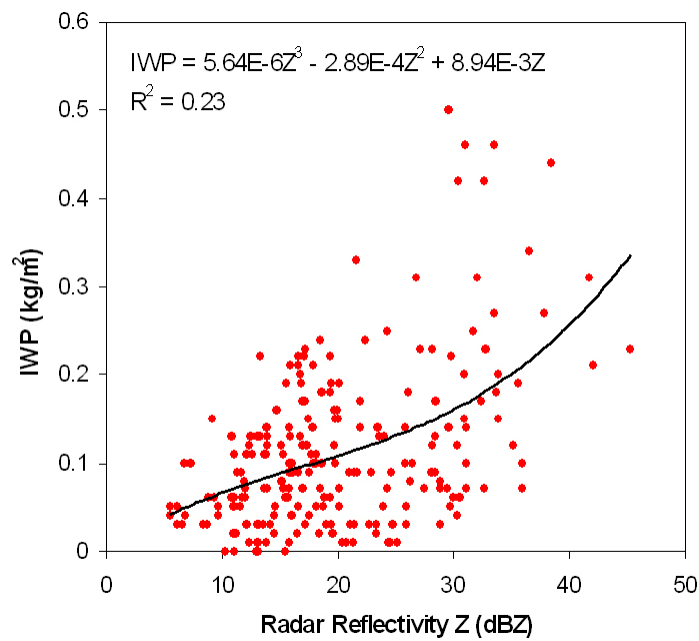


Figure 2. Regression equation between ice water path and radar reflectivity

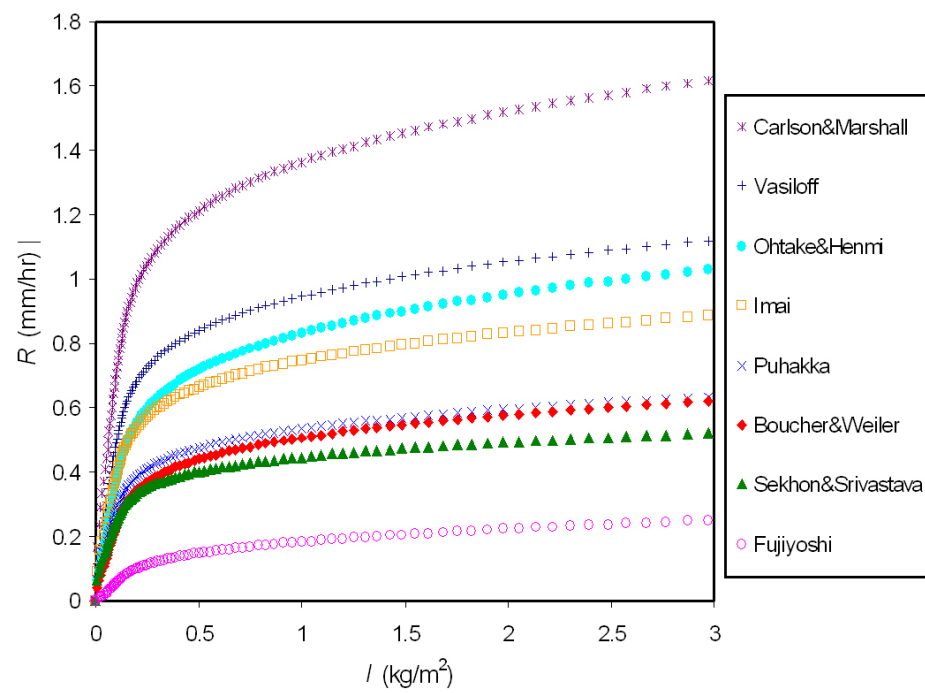


Figure 3. Results showing empirical R-I equations

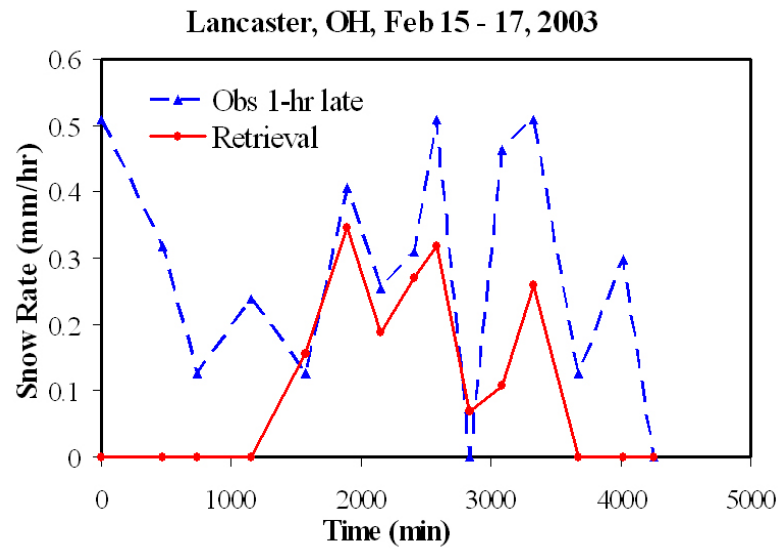


Figure 4. Snowfall rate case study 1: Lancaster, OH, Feb 15 – 17, 2003

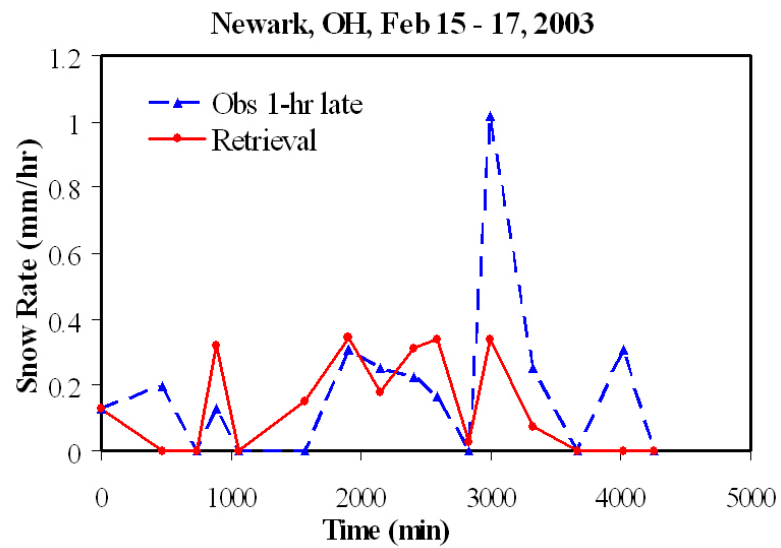


Figure 5. Snowfall rate case study 2: Newark, OH, Feb 15 – 17, 2003.

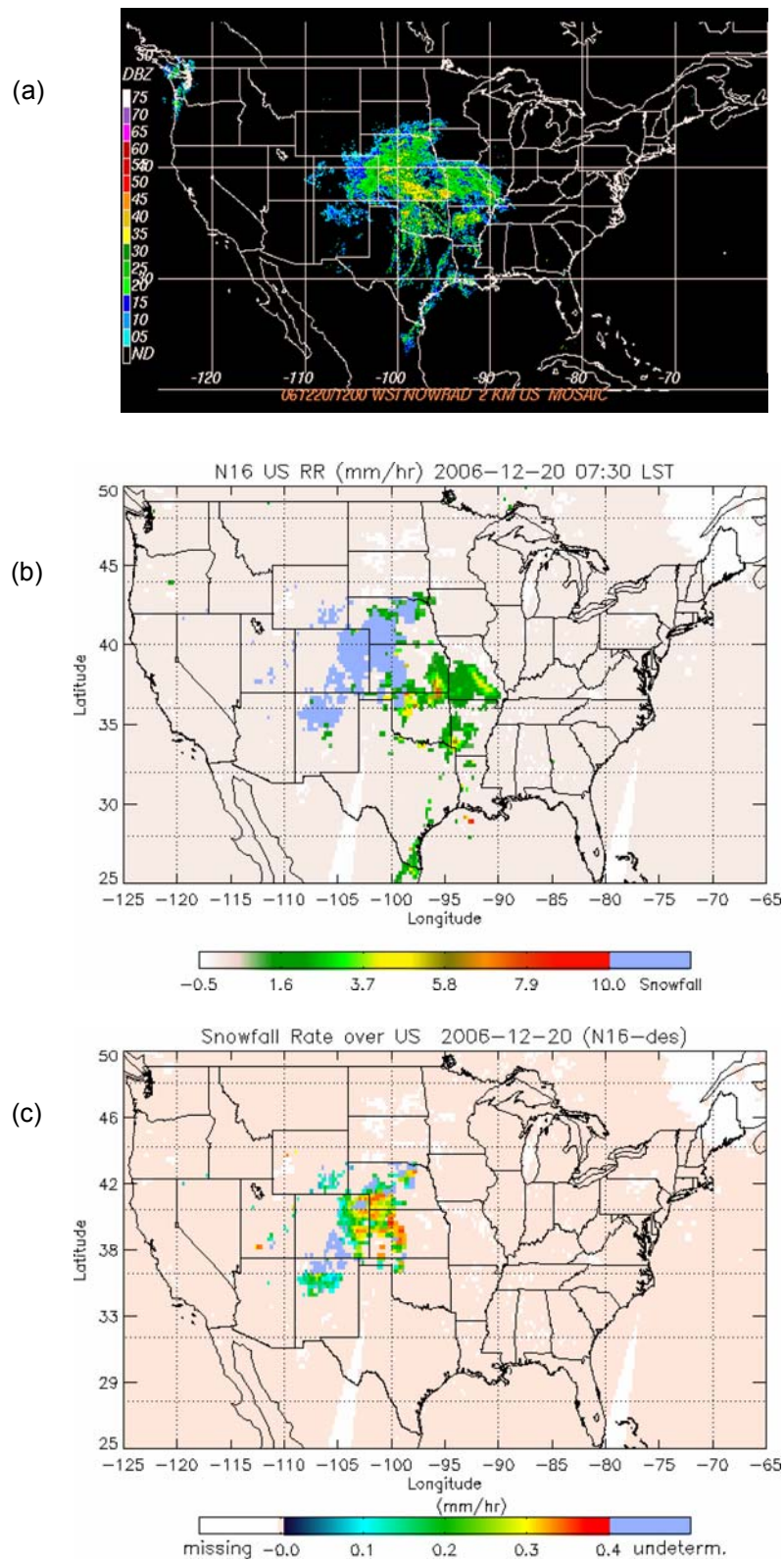


Figure 6. Snowfall rate case study 3: snowfall in the Great Plains of U.S. on December 20, 2006. (a) NEXRAD image, (b) NOAA/NESDIS AMSU rain rate retrieval with embedded snowfall derived from a snowfall detection algorithm, (c) snowfall rate retrieval.