RETRIEVING SNOWFALL RATE USING SATELLITE PASSIVE MICROWAVE DATA

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1. INTRODUCTION

A snowfall rate (water equivalent) algorithm was developed using measurements from National Oceanic and Atmospheric Administration's (NOAA) Advanced Microwave Sounding Unit (AMSU-A and AMSU-B) and European Organization for the Exploitation of METeorological SATellites' (EUMATSAT) Microwave Humidity Sounder (MHS). The algorithm includes four components: snowfall identifier, Ice Water Path (IWP) retrieval, 'cloud top' height retrieval, and snowflake terminal velocity.

2. METHOD

The snowfall identifier is developed using the rule-based RIPPERk machine learning algorithm [1] implemented in the WEKA toolkit [2]. RIPPERk is a data mining technique that is highly effective at deriving classification rules for large noisy datasets with low error rates. The data used to train and test the model combines AMSU-B/MHS measurements with co-located in-situ weather observations. The AMSU-B/MHS data include brightness temperatures and local zenith angles. The ground observations at weather stations across the CONUS and Alaska are used to identify snow/no-snow conditions. The data set contains equal numbers of snow and no-snow events. Given the snow particle's relatively slow terminal velocity, snow is present in the atmosphere for a significant time before it arrives on the ground. To account for this, the satellite data precede their associated ground observations in time. The snowfall identifiers for AMSU and MHS are developed separately because of the different frequencies used by these sensors. The AMSU-B data set contains about 23,000 instances while the MHS data set contains about 11,000 instances. Training and testing were performed using 10-fold cross-validation. The sets of rules derived by RIPPERk are shown to be robust at identifying various snowfall systems.

IWP is derived using a two-stream Radiative Transfer Model (RTM) [3]. The RTM requires the brightness temperatures of four AMSU/MHS window channels (23.8, 31.4, 89, and 150 or 157 GHz) and one water vapor channel (183.31 +/- 7 or 190.31 GHz), local zenith angle, Total Precipitable Water (TPW), and surface temperature (Ts). Its retrievals include IWP, ice particle effective diameter (De), cloud temperature, and the emissivity at the above mentioned five frequencies. Initial values of the retrieved quantities are also part of the required input. The RTM couples with an iteration scheme and outputs retrievals when the differences between the simulated and the measured brightness temperatures fall under predefined thresholds. The initial values of IWP and De are found to be critical to the accuracy of these retrievals due to the nonlinearity of IWP and De versus brightness temperature. In order to achieve more accurate 'first guess' IWP and De, a set of classifiers are developed using the two-stream RTM for different atmospheric conditions and sensor view angles. The classifiers are regression equations of various combinations of AMSU-B/MHS brightness temperatures at 89, 150 / 157, and 183+/-7 / 190 GHz. They are used to derive more realistic initial IWP and De given the satellite measurements and ancillary data. It is noted that this research uses the TPW and Ts data from the NOAA Global Data Assimilation System (GDAS) dataset.

In this study, cloud top is defined as the 'top' of the cloud that is confined to 6 km or lower. The limit is set due to the fact that the AMSU/MHS channels used are less sensitive to cloud particles in winter atmospheres above this height. The 'cloud top' height is derived using an empirical method based on GDAS water vapor and temperature profiles. Some simplifications are made regarding the distributions and fall velocities of snow particles which allow the computation of snowfall rate from the derived IWP and 'cloud top' height.

3. VALIDATION

Validation of the snowfall rate algorithm is conducted using ground hourly observations from the Continental United States (CONUS) and shows reasonable agreement between the retrievals and the observations. Figure 1 presents a case study for a snowstorm befell in Imperial, NE on Dec 19 to 21, 2006. The retrieved snowfall rate is compared to ground hourly snowfall observations with one hour delay. In this case, the snowfall rate retrieval matches well with the ground observations both in occurrence and magnitude. This is demonstrated by an R^2 of 0.93.

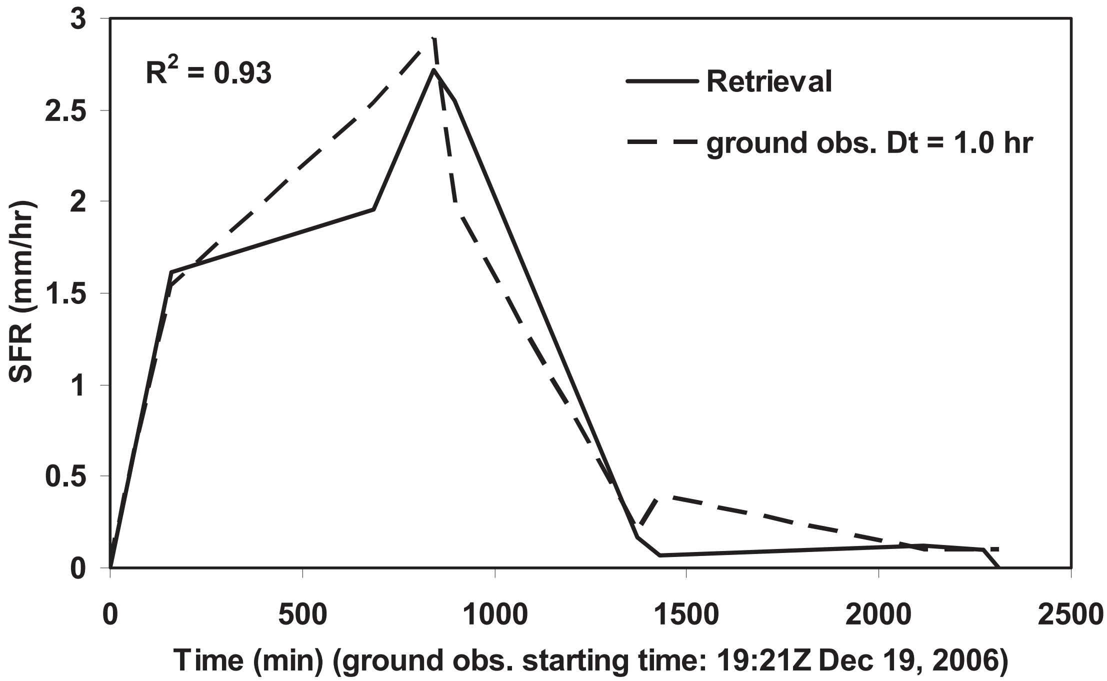

Figure 1. Comparison of retrieved snowfall rate and observed hourly snowfall in Imperial, NE from Dec 19 to 21, 2006. The retrievals precede the observations by 1 hour.

This algorithm is applied to five satellites that carry AMSU/MHS sensors and can provide up to 10 near real-time snowfall rate retrievals per day for any given location on earth. Therefore it is potentially a useful product for users such as weather and river forecasters, as well as global blended precipitation products such as those produced by the Global Precipitation Climatology Project (GPCP).

4. REFERENCES

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