Precipitation Retrievals in Typhoon Domains Combining FY3C MWHTS Observations and WRF Prediction Models (Postprint)

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Date: 2017-03-10T00:00:00+00:00

Abstract

A passive sub-millimeter precipitation retrieval algorithm is developed based on observations from the Microwave Humidity and Temperature Sounder (MWHTS) onboard the Chinese FengYun-3C (FY-3C) satellite. Utilizing the validated global reference physical model NCEP/WRF/VDISORT, NCEP data at 6-hour intervals were downloaded to run the Weather Research and Forecasting (WRF) model and derive representative precipitation data on a global scale. The precipitation retrieval algorithm is applicable globally over both land and ocean surfaces. To simplify the computational procedure and reduce training time, principal component analysis (PCA) was employed to filter out redundancies caused by scanning angle variations, surface effects, and system noise. Based on comparison and validation against other precipitation datasets, it is demonstrated that the retrievals are reliable for surface precipitation rates exceeding 0.1 mm/h at 15 km resolution.

Full Text

Preamble

Precipitation Retrievals in Typhoon Domain Combining FY3C MWHTS Observations and WRF Predicted Models

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Abstract

A passive sub-millimeter precipitation retrieval algorithm is presented based on Microwave Humidity and Temperature Sounder (MWHTS) observations from the Chinese Feng Yun-3C (FY-3C) satellite. Using the validated global reference physical model NCEP/WRF/VDISORT, NCEP data at 6-hour intervals are downloaded to run the Weather Research and Forecasting (WRF) model and derive typical precipitation data globally. The precipitation retrieval algorithm operates over both land and seawater worldwide. To simplify the calculation procedure and reduce training time, principal component analysis (PCA) is employed to filter out redundancy caused by scanning angle and surface effects, as well as system noise. Comparison and validation against other precipitation sources demonstrate that the retrievals are reliable for surface precipitation rates higher than 0.1 mm/h at 15 km resolution.

Keywords: FY3C, MWHTS, 118.75GHz, WRF, VDISORT, precipitation

1. Introduction

Global precipitation monitoring is critically important due to its significant impacts on human society. However, the diversity of hydrometeor types and their small-scale and large-scale spatial inhomogeneities make accurate measurements challenging. Rain gauge measurements, for instance, are significantly impaired by wind, poor global coverage, and rainfall non-uniformity. Both ground-based radars and passive microwave satellite sensors observe precipitation aloft and are generally unable to determine how much of that precipitation evaporates before reaching the surface. Both systems are also sensitive to unknown local hydrometeor size, form, and vertical velocity distributions, as are simple single-frequency radars on satellites. This lack of adequate ground truth seriously complicates the development and validation of global precipitation sensing methods.

This paper addresses the consistency between histograms of millimeter-wave atmospheric radiances observed by the FY-3C MWHTS satellite instrument and those predicted by the WRF model (http://www2.mmm.ucar.edu/wrf/users/) in combination with a four-stream radiative transfer model (VDISORT). WRF was initialized by National Center for Environmental Prediction (NCEP) analyses on a 1° grid approximately 6 hours prior to each FY-3C MWHTS transit and employed the Goddard explicit cloud physics model. The scattering behavior of icy hydrometeors, including snow and graupel, was considered. Current precipitation retrievals achieve a correlation coefficient of 0.61, and with increasing observational and validation data from radar and other techniques, this work is continuing and will yield improved results.

2. Instrument Description

MWHTS onboard the FY-3C satellite is a fifteen-channel total power microwave radiometer operating in the 89 GHz to 191 GHz range, launched in September

2013. It combines 13 horizontally polarized channels near 118.75 GHz (the first such channels operated on a current operational polar-orbiting satellite) and 183 GHz, along with window channels at 89 GHz and 150 GHz, to predict precipitation content and path.

Data assimilation of MWHS has been demonstrated to improve numerical weather prediction (NWP) analysis and plays an important role in the ECMWF forecast model. Based on sounding channels operating between 89 and 191 GHz (horizontal and vertical polarization), MWHTS operates in cross-track scanning mode and is used for deriving atmospheric vertical distributions of temperature and humidity, rainfall, etc. The selected observation channels are at 89 GHz (vertical polarization), 118.75 GHz (horizontal polarization, eight channels), 150 GHz (vertical polarization), and 183.31 GHz (horizontal polarization, five channels).

3.1. Data Collection

NCEP datasets (at 6-hour intervals) from January 1, 2014 to October 31, 2014 were selected to run the Weather Research and Forecasting (WRF) model and derive typical precipitation data globally, particularly for extreme weather events such as typhoons, cyclones, and heavy rainfall. Incomplete cases and latitude values smaller than 0° and larger than 30° were removed. The complete global datasets observed by FY-3C MWHTS from January 1, 2014 to October 31, 2014 were used to evaluate and analyze the validation of the retrieval algorithm.

Radiance data in Level-1B format from FY-3C MWHTS were employed for this study. FY-3C has an afternoon-configured orbit. MWHTS is a self-calibrating total-power radiometer with a cross-track step-scan design that completes one full revolution every 8/3 seconds. The MWHTS antenna systems have a nominal field of view (FOV) of 1.1° at half-power points (covering a 16-km diameter footprint at nadir) and execute a cross-track scan with 98 Earth FOVs (within ±53.35° from nadir), one cold space FOV, and one warm blackbody FOV per 8/3-second scan period. FOVs 1 and 98 (at ±53.35° from nadir) are the outermost scan positions, while FOVs 49 and 50 (at ±1.1° from nadir) straddle the nadir. The space view center is at 107.1°. The space views and internal warm target views are used to complete on-orbit two-point calibration for MWHTS.

For FY-3C MWHTS, channel 9 and channel 15 are sensitive to precipitation. Combined with window channels at 89 GHz and 150 GHz, precipitation rate can be retrieved using neural network estimators.

[Figure 1: see original paper]

3.2. Data Processing

3.2.1. Surface Classification

MWHTS-observed footprints were classified as snow-free land, seawater, or sea ice and snow-covered land using a surface classification algorithm adapted from Chinnawat’ s work [8][9] (Surussavadee, C 2006, 2008), where inputs include MWHTS channels 1 and 10, land/sea flag, and surface temperature, which has been validated. This paper focuses on MWHTS footprints classified as snow-free land or seawater globally.

3.2.2. Matching

The Microwave Humidity and Temperature Sounder (MWHTS) onboard the Chinese FY-3C satellite is a cross-track scanning radiometer with a swath width of 2650 km. MWHTS has a nadir footprint size of 15 km and 98 fields of view per scan line. The absolute revisit period is 5.5 days. The matching domain threshold is 0.05° for both latitude and longitude with a 20-minute temporal window.

Atmospheric and surface conditions are used to produce global simulations of brightness temperatures measured by MWHTS. Vertical profiles of temperature, specific humidity, and pressure, along with surface parameters including skin temperature, 2-m wind speed, and wind direction from NCEP 6-hour reanalysis data, are used as input to WRF. The NCEP/WRF data fields have a horizontal resolution of 0.05°×0.05° and 29 vertical levels, with the highest level near 0.1 hPa.

3.2.3. Correction for Brightness Temperature Biases

Considering calibration accuracy and model error, bias correction of brightness temperature is necessary. Based on bias calculations and error corrections for cold and warm targets, variable targets, nonlinearity error, and system random noise, the primary calibration results can be derived, as shown in Figures 2 and 3, which meet the design and development requirements of MWHTS onboard the FY-3C satellite. To demonstrate that system requirements are appropriate and achievable, this paper provides analysis of brightness temperatures through the calibration process and profile retrievals using MWHTS observational data.

[Figure 2: see original paper]

[Figure 3: see original paper]

3.2.4. Omission of Extreme Values

The following values are omitted: (1) any brightness temperature for a footprint less than 50 K or greater than 400 K, which is invalid; (2) surface altitude above 2 km for $|\text{latitude}| < 60°$, above 1.5 km for 60° $|\text{latitude}| < 70°$, or above 0.5 km elsewhere, which could be snow-covered and sensed more strongly (termed "too-high"); or (3) MWHTS channel 9 less than 190 K, which implies the atmosphere is so cold and potentially dry that precipitation is unlikely and that even the most opaque channel (183±1 GHz) may sense the surface and yield false precipitation detections (termed "too-cold").

3.2.5. Principal Component Analysis (PCA)

Principal component analysis extracts only good signals that provide useful precipitation information while being insensitive to most angle and surface effects and other noises. This method filters out redundancy caused by scanning angle and surface effects, as well as system noise. Additionally, it reduces the dimensions of the data matrix, which helps save time and simplifies retrievals.

4. Retrievals and Analysis

An artificial neural network (ANN) is essentially a nonlinear statistical regression between a set of predictors (in this case the observation vectors X) and a set of predictands (in this case profiles of atmospheric temperature Z). The ANN model consists of three layers: layer 1 (input), layer 2 (hidden), and layer 3 (output), as shown in Figure 4.

The input layer neurons are represented by vector Xi (X , X , X , ···, X), where L is the number of input neurons. The hidden layer neurons are represented by vector Yi (Y , Y , Y , ···, Y), where M is the number of hidden neurons. The output layer neurons are represented by vector Zi (Z , Z , Z), where Z represents rain detection and precipitation rate for different surface types and situations [10-12].

[Figure 4: see original paper]

Estimates over land are usually slightly less accurate than those over sea, particularly at lower rain rates where the surface remains visible. Using the artificial neural network retrieval algorithm for rain detection and precipitation described above, and considering distributions of brightness temperature differences as model inputs along with observing angles, the global rain detection map can be retrieved as shown in Figure 5.

In Table 2, for most cases, the root mean square (rms) errors are within the rain rate range, while for rain rates larger than 30 mm/h, the rms error is less than the lower bound, suggesting good retrieval performance. In typhoon regions, rain rate retrievals are slightly worse and require more training data to improve the retrieval model.

[Figure 5: see original paper]

The correlation coefficients between rain rate detection and retrievals were found to be approximately 0.79 and 0.81 for land and sea, respectively.

5. Conclusion

In this work, the surface is classified as land and sea, and observational data are used to test and validate rain rate accuracy. The current work is insufficient, and the authors are pursuing further improvements, such as considering surfaces covered by snow, ice, and rainforest. Additionally, according to convection and stratiform types, different rain rates from 0.1 to 50 mm/h are being classified in greater detail to improve retrievals. Radar data are also needed to validate rain detection accuracy. All of these aspects will be described in future papers.

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Note: Figure translations are in progress. See original paper for figures.