USPROB – A PASSIVE MICROWAVE STATISTICAL ALGORITHM FOR RAINFALL RETRIEVAL OVER THE AMAZON BASIN

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ABSTRACT

We present a new algorithm to estimate rainfall over the Amazon Basin region using the TRMM Microwave Imager (TMI). The algorithm was validated using the TRMM Precipitation Radar (PR) surface rainfall data, and comparisons with others well known methods are also presented. It is shown that the formulation proposed is more efficient and more compatible with the physics and dynamics of the observed systems over the area of interest than the other methods tested.

RESUMO

Neste trabalho apresentamos um novo algoritmo para estimativa de precipitação sobre a Bacia Amazônica usando o *TRMM Microwave Imager (TMI).* O algoritmo foi validado usando os dados de taxa de precipitação à superfície do TRMM Precipitation Radar (PR) e comparações com outros métodos conhecidos também são apresentadas. Mostramos que a formulação proposta é mais eficiente e compatível com a física e a dinâmica dos sistemas observados sobre a região de interesse do que os outros métodos.

INTRODUCTION

The algorithm described in this work, hereafter called USProb – University of São Paulo Probability Algorithm, relies on a probabilistic statistical method that correlates Polarized Correct Brightness Temperature (PCT, Spencer et. al. 1988) and rainfall rate (RR) for different precipitating

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systems. Since the precipitating systems (e.g.: isolate convection, multi-cellular convection, squall lines, etc.) have different cloud and rain process development, it is expected that they have different hydrometeor distributions.

DATA AND METHODS

Datasets

For development purposes, we used the surface rainfall and rain classification from PR (TRMM product 2A25) and the 10_V, 19_V, 22_V and $85_{V,H}$ GHz TMI brightness temperatures (TRMM product 1B11), where the subscript denote the polarization used (V: vertical; H: horizontal). 545 TRMM orbits during the period of January 1st to April 30th of 1999 were used, over the region defined by the latitude of 5N and 16S and longitudes of 76-48W. The data were also interpolated to a grid size of 0.1x0.1 degrees in order to account for the different sensor resolutions.

For validation purposes, 109 TRMM orbits during the whole month of October 2005 were used, with the PR surface rainfall as ground truth. USProb is also compared against the Goddard Profiling Algorithm – GPROF (TRMM product 2A12, version 6, Kummerow et. al. 2001), the Goddard Scattering Algorithm – GSCAT (Adler et. al. 1994), and 2 formulations of the NESDIS SSM/I rain rate algorithm - NESDIS (Ferraro and Marks, 1995). First formulation ($NESDIS_1$) uses the original coefficients described by Ferraro and Marks, and the second one ($NESDIS_2$) uses adjusted coefficients obtained during the calibration process. The GPROF datasets were available through the NASA/DISC[3], and the GSCAT and $NESDIS_1$ rainfall rates were computed using up-to-date references.

Methodology

A raining system is defined as a cluster of pixels with PCT values lower than 277 K. Once delineating the cluster, a screening routine is applied to exclude the non-raining pixels. This screening procedure uses 4 tests to verify if a pixel can be assigned as a raining pixel: a) a PCT threshold; b) the difference between $T19_V$ and $T85_V$; c) the Scattering Index (SI, Grody 1991), and d) the standard deviation of $T85_V$ on a 5x5 pixels window.

After the screening, the clusters are classified according to 5 types based on the size and PCT

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3   http://disc.sci.gsfc.nasa.gov/

distribution (Table 1). The temperature criterion is based on the coldest 10% pixels PCT distribution, where a mean PCT value is computed, which we define as Mean Lower Temperature – MLT, and the 220 K threshold is used.

Table 1: Systems classification criteria.

Class	Threshold 1 (K m²)	Threshold 2 (K)	System Type: Example
1	Area > 15500 K m²	MLT < 220 K	MCS, squall lines
2	Area > 15500 K m²	MLT < 220 K	
3	3000 K m² < Area < 15500 K m²	MLT > 220 K	Supercells, multi-cellular
4	3000 K m² < Area < 15500 K m²	MLT > 220 K	systems
5	Area < 3000 K m²	N.A.	Cumulunimbus

Finally, we applied the *Probability Matching Method* (PMM), developed by Calheiros and Zawadzki (1987), to derive the PCT-RR relationships. To build such relationships, we computed the PCT and RR cumulative density functions (CDFs) for each one of the 5 classes. By relating each pair of CDFs, we were able to develop 5 different PCT-RR look-up tables (LUTs), which are graphically represented on Figure 1. The LUT approach gives better results than a curve-fit method, but demands more processing time.
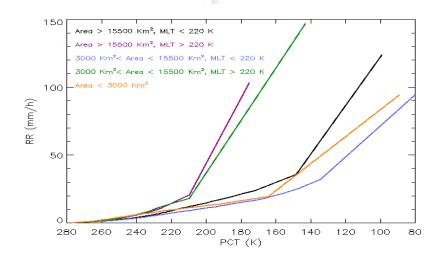

Figure 1: PCT-RR curves for each system class derived with the PMM.

The relationships presented on Figure 1 show that colder systems (classes 1 and 3) will produce less rain for the same PCT value when compared with classes 2 and 4 (warm systems). This can be explained by the differences between the system hydrometeor contents. Colder systems, which present strong convective cores, can produce higher large-sized hail quantities. At 85 GHz, hail has a very high scattering efficiency, which drops the PCT observed, and this PCT drop can be wrongly associated with higher values of rainfall. When comparing PCT and PR surface rainfall from stratiform and convective systems, the non-precipitating hail scattering produced by convective clouds must be taken into account. Therefore, for the same amount of rainfall, convective systems will present lower PCT values.

RESULTS

We tested the USProb rainfall retrieval efficiency comparing the estimated the rain volumes computed for each cloud (quantitative estimative), and the total estimated rainfall distributions (qualitative estimative), as well as the errors distribution, using the PR surface rain rates as the ground truth.
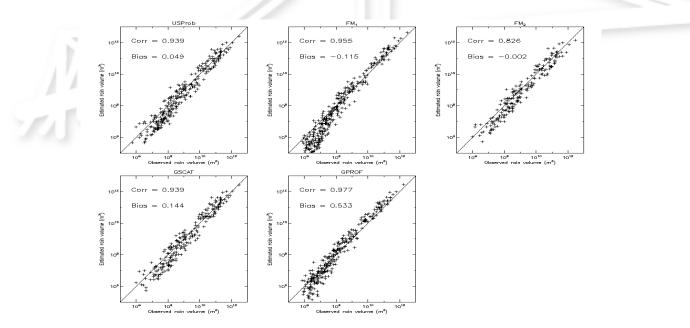

Figure 2: Scatterplots of the estimated rain volumes versus the PR-observed rain volumes, using VIRS to determine cloud areas.

The rain volume was computed using the 10.8 μm channel of the TRMM Visible and Infrared Scanner (VIRS) to determine cloud areas. A cloud is defined as a region with brightness

temperatures lower than 273 K, and within a cloud the number of raining pixels (observed by PR and estimated by each algorithm) is computed.

Figure 2 shows the scatterplots of the estimated and PR-observed rain volumes. The NESDIS2 algorithm was the only algorithm with a correlation coefficient lower than 0.9, but its bias value was the lowest of all algorithms (-0.002). On the other hand, GPROF scored the highest correlation (0.977), but it is high biased (0.533). Both NESDIS1 and GPROF underestimate rain volumes for observed rain volumes lower than 10^9 m^3 and overestimate rain volumes for observed rain volumes higher than 10^9 m^3. USProb presented low bias (0.049) and high correlation coefficient (0.939), which indicates a realistic estimative of rain volumes.
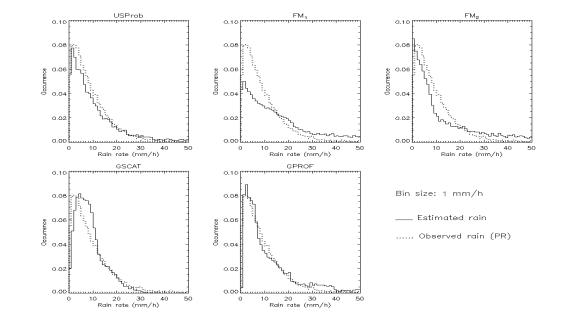

Figure 3: Rainfall distributions for each algorithm (solid) and the PR reference (dotted). From upper left to bottom right: USProb, NESDIS1, NESDIS2, GSCAT, and GPROF.

The rainfall distribution histograms were created using a bin size of 1 mm h^{-1}, and dividing the amount of rain of each bin by the total rain. Results are presented on Figure 3. USProb and GPROF algorithms achieved the best results, but with 2 main differences: GPROF slightly overestimates the rainfall until 5 mm h^{-1}, and shows a second peak from 28 to 39 mm h^{-1}, which leads to a bi-modal distribution. The NESDIS$_1$ distribution shows a quasi-linear behavior, underestimating the rainfall under 15 mm h^{-1}, and overestimating over this value. The NESDIS$_2$ shows better coincidence than the NESDIS$_1$, due its adjusted coefficients, which reinforces the idea of generate a unique coefficients set for each location, instead of using a global coefficients set.

GSCAT overestimates the rainfall from 4 to 12 mm h^{-1}, but shows accurate results over 12 mm h^{-1}.

CONCLUSIONS

USProb presented more accurate results than the others algorithms tested, what shows that PCT-rainfall relationships are clearly system-type dependent, and an algorithm that attempts to use single relationship between brightness temperatures and rainfall rates may lead to unrealistic results that are amplified on instantaneous retrievals. However, for monthly and weekly averages a single-relationship algorithm can achieve good results, as demonstrated by Adler et. al. (1994), and Ferraro and Marks (1995).

REFERENCES

Adler, R. F., G. J. Huffman, and P. R. Keehn, 1994: Global tropical rain rate estimates from microwave-adjusted geosynchronous IR data. *Remote Sens. Rev.*, **11**, 125-152.

Calheiros, R. V., and I. Zawadzki, 1987: Reflectivity-rain rate relationships for radar hydrology in Brazil. *J. Climate Appl. Meteor.*, **26**, 118-132.

Ferraro, R. R., and G. F. Marks, 1995: The development of SSM/I rain-rate retrieval algorithms using ground-based radar measurements. *J. Atmos. Ocean. Technol.*, **12**, 755-770.

Grody, N. C., 1991: Classification of snow cover and precipitation using the special sensor microwave imager. *J. Geophys. Res.*, **96**, 7423-7435.

Kummerow, C., W. Barnes, T. Kozu, J. Shiu, and J. Simpson, 1998: The tropical rainfall measuring mission (TRMM) sensor package. *J. Atmos. Ocean. Technol.*, **15**, 809-817.

Kummerow, C. , Y. Hong, W.S. Olson, S. Yang, R. F. Adler, J. McCollum, R. Ferraro, G. Petty, Dong-Bin Shin, and T. T.Wilheit, 2001: The evolution of the Goddard Profile Algorithm (GPROF) for rainfall estimation from passive microwave sensors. *J. Appl. Meteor.*, **40**, 1801-1820.