RAINFALL RETRIEVAL ALGORITHM OVER INDIAN LAND AND OCEANIC REGIONS USING TRMM DATA

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Abstract

The Tropical Rainfall Measuring Mission (TRMM) satellite is a joint US-Japanese mission to explore tropical rainfall and its effects on the earth's energy budget, general circulation, and climate. In the present study, a method has been developed here for rainfall retrieval over Indian land and oceanic regions from remotely sensed microwave (MW) brightness temperature (BT) data obtained from the TRMM Microwave Imager (TMI) and the near-surface rainfall rate from the Precipitation Radar (PR). Artificial Neural Network (ANN) and Multiple Regression (MR) technique both have been applied for rainfall retrieval over Indian Ocean and land regions. It has been found that, over ocean, ANN model with TMI and PR data as inputs and output field vectors works more consistently than MR. On the other hand, MR performs well with selected predictor features like scattering index (SI), polarization correction temperatures (PCT) and the BTs difference (T19V-T37V) over land. The rainfall-rate retrieved from both the techniques is also compared with the TMI surface rain rate based on Goddard Profiling (GPROF) Algorithm [1]. Instantaneous precipitation estimates demonstrated correlations of 0.69 to 0.91 with GPROF rain rate for independent datasets over land while 0.54 to 0.61 over oceanic regions. Developed algorithms have also been successfully applied for various case studies during northeast and southwest monsoon over the area of study.

1. Introduction

Rainfall is an important environmental parameter, which influences the global hydrological cycle and the nature of climate variability. It is also a highly discontinuous process both in space and time. Assessment of precipitation contributes to improved weather forecasting, in small and large spatial scales, and a study of global rainfall leads to better understanding of global climate variability. Though the insitu measurements of rainfall rate cover a comparatively large area but still they cover only a small fraction of the whole globe. Therefore the remote sensing technique from the space-based sensors is a feasible method for estimating global rainfall. During the last few years, various satellite missions have been dedicated to the measurements of global precipitation, which mostly employ microwave radiometers [2]. The TMI and PR based on same platform of TRMM provide a good opportunity to study the instantaneous rainrate. Microwave techniques are physically more direct than VIS/IR TMI and PR produce nearly simultaneous observations over ocean and land under different weather conditions. The BTs measured by the TMI represents the upwelling microwave radiations that have undergone interaction with atmospheric constituents. Upwelling radiation at high microwave frequencies (50-100GHz) are scattered by the raining system, leading to the reduction in BTs. whereas at low microwave frequencies (<50 GHz) the absorption/emission property is the primary mechanism, which affects the transfer of microwave radiation in the atmosphere. On the other hand, PR measures the reflectivity factor, Z, representing the backscatter of the microwave radiation [3]. Various algorithms have been developed that estimate rainfall from microwave data as reviewed by [4-6]. Several of them utilize BT values obtained by SSM/I instrument at various frequencies and polarizations, and attempt to solve the inverse problem. ANN techniques are also widely used for rainfall retrieval nowadays. More recently, Gairola et. al. has successfully demonstrated the ANN for real-time rainfall estimation using microwave

sensor data[7]. In this paper, we have developed two models for the rainfall retrieval over Indian land and oceanic regions separately using ANN and MR compared its results with standard GPROF based operational rain product. The algorithms are also demonstrated with various case studies.

2. Database

TRMM represents the first precipitation radar and passive microwave radiometer as dual deployment of sensors on a low inclination earth-viewing satellite. Both radiometers and radars have been widely used independently to retrieve rainfall, as these instruments are designed to measure precipitation based on different physical principles. Three TRMM standard data products, version-6, utilized for the present study are 1B11; TMI Brightness temperatures, 2A12; TMI surface rain rate and 2A25; PR surface rain rate. TMI-2A12 algorithm uses different algorithm over land and ocean. TMI and PR being on the same platform cover a common swath of scanning of about 220 km. Within this common swath, the TMI and PR data sets are collocated. In the present study, BTs and PR data are collocated over Indian Land (covering an area between 60^0E to 100^0E and 5^0N to 30^0N) and Oceanic regions (covering an area between 50^0E to 100^0E and 10^0S to 30^0N). We have taken four months i.e. june-2006 to September-2006 orbital data (i.e. about 260 orbits) for algorithm development and june-2007 to September-2007 for the validation of the algorithm.

3. Methodology

In the present study, we have developed an ANN model for the rainfall estimation over ocean and MR model over land using various predictor features. These models are described in details as follows:

3.1 Over Ocean

ANN's have become extremely popular for prediction and forecasting as it provides a convenient and powerful means of performing nonlinear classification and regression [8]. It consists of several layers of neurons like input layer, hidden layer and output layer. These neurons are interconnected by links or weights [9]. The output nodes through hidden nodes connect the input nodes. The hidden nodes capture the non-linearity in the mapping between input and output information. The inputs are processed using interconnecting weights by weighted summation functions to produce a sum that is passed through a transfer function and the output of this transfer function is the output of the node. ANN learning can be supervised or unsupervised. In the supervised learning scheme, adjusting the input weights on each node in such a manner that the output of the network is consistent with the desired output does the ANN training. In unsupervised learning scheme, the network output for ANN training uses no external criteria. The most popular supervised learning scheme is back-propagation. A description of ANN architectures, learning schemes and other specifics is given in [10].

ANN architecture used in this study consists of an input layer, a hidden layer, and an output layer. The four inputs of ANN are BT's corresponding to 10.7GHz (H), 19.4GHz (H), 21.3GHz (V) and 37.0GHz (H) channels of TMI and the output is PR rainfall. Here we have used two hidden layers, first hidden layer having eight neurons while second has 16 neurons. Before applying to the ANN the collocated database is preprocessed to avoid the unwanted behavior of ANN [11]. There are about 6000 collocated TMI and PR field-vectors. The dynamic range of rainfall (0.0 to 60.0 mm/hr) is quite sufficient for ANN training. After the preprocessing, the original data is randomly divided into two parts training (4000) and testing (2000) [12]. Once the internal weights are fixed, the ANN performance is checked with the independent test data sets, which were not included in the training.

3.2 Over Land

Because of different orography and emissivity of the land surfaces, the algorithm developed for the Indian oceanic region cannot be used over land. So here we use various predictor features like scattering index (SI), polarization correction temperatures (PCT) and the BTs difference (T19V-T37V) to estimate the rainfall over land. The basis of SI, follows the method used by [13], who used global scattering index (SI) at 85 GHz with SSM/I sensor. Further the technique was refined by [14]. However it is found that this scattering index is highly variable with regions and seasons as well as the platform. In the present study a scattering index is developed for the Indian land regions using 10V, 19V, 21V and 85V TMI-channels data and then a relationship is established between

rainfall and scattering index for the land using TMI and PR observed rainfall. The PCT is calculated according to Spencer et. al. The BTs difference is calculated to minimize the error caused by the weaker extinction and a broader footprint compared to the 85 GHz channel [15]. MR is applied with the help of these three proxy predictor variables to estimate the rainfall rate.

4. Results

The algorithm developed over ocean and land regions are tested with some independent datasets over northeast and southwest monsoon of 2007 and algorithm performance is compared with standard GPROF based operational rain product i.e. TMI-2A12 rainfall. Here GPROF algorithm is chosen for the comparison because it is standard operational product from NASA and widely used all along the TRMM launch since November-1997. Various case studies were carried out and only two of them, one over land region and one over ocean, will be discussed in the present paper for brevity.

Over ocean, the best result for the estimation is obtained with ANN training for 5000 iterations; learning rate parameter η ranges from 0.01 to 0.03 and the momentum parameter μ ranges from 0.5 to 0.6. The final result is taken as an average of several trained networks so that the error is minimized. Then the developed algorithm is applied to many case studies in 2007. One of the case studies discussed here is orbit number 54673 over bay of Bengal. The Fig. 1 shows the good correlation between the present technique and GPROF. Here the correlation coefficient is 0.685, observed mean and calculated mean both are approximately same and also the rmse 3.196 is less than the observed mean 3.847 of the data.

On land we have chosen orbit number 55813 passing over most parts of the country on 01st September 2007 and captures significant rain rate. Fig.2 shows the comparison of present algorithm with GPROF-rain rate. From the figure, it is clear that present technique matches quite well with the GPROF algorithm but however the present technique underestimates the high rain rates.

The results of both MR (over land) and ANN (over ocean) are in general agreement with GPROF rain rates. However the high rain rates are underestimated by present algorithm in both the cases. This is the matter of further investigation; either in terms of ANN architecture & channel optimization in MR or the criterion for preparation of TMI-PR databases itself. This is being persuaded critically.

5. Conclusion

Two separate methods have been identified for rainfall retrieval over Indian land and oceanic regions based on the processing of a large collocated database of TMI-PR. Although the algorithms selected for land and ocean as MR and ANN respectively are based on sound basis, their performance in retrieval requires critical examination further. The possible chances have been associated with either the criteria of the TMI & PR database preparation or the ANN architecture design and MR channel optimization.

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7. References

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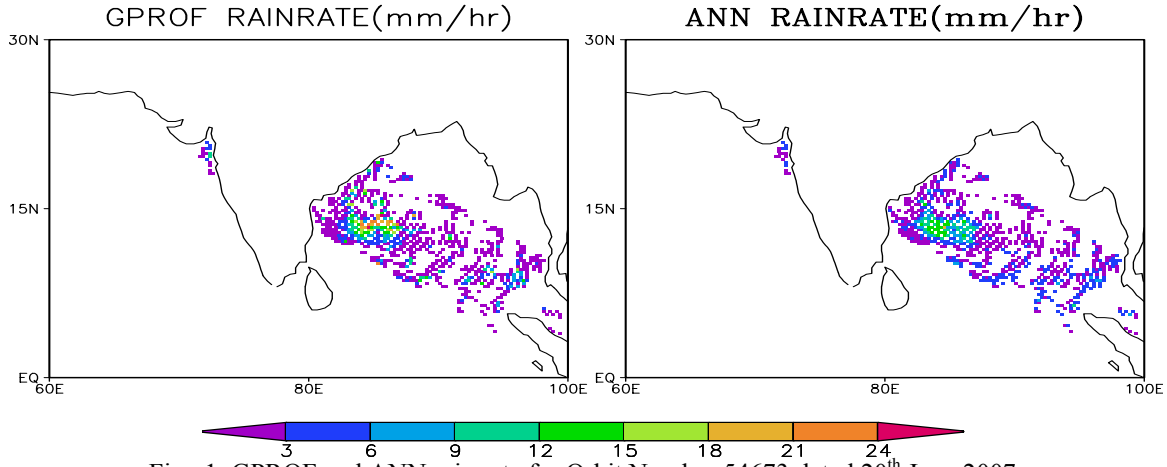

Fig. 1. GPROF and ANN rain rate for Orbit Number 54673 dated 20th June 2007.

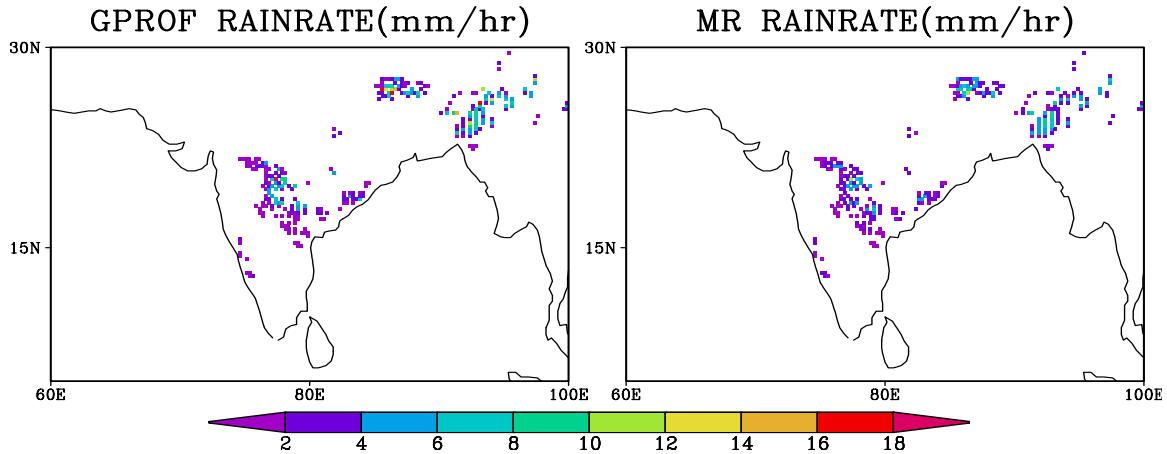

Fig. 2. GPROF and MR rain rate for Orbit Number 55813 dated 1st September 2007.