BAYESIAN BASED RAIN RETRIEVAL OVER OCEAN

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KEY WORDS: Precipitation, Bayes Theorem, TRMM

ABSTRACT: Precipitation plays a key role in hydrological cycle and its accurate and timely measurement is very important to understand global water fluxes and energy balance of the Earth's systems. Despite its importance, it is one of the most difficult parameter to measure because it is highly dynamic on spatial and temporal scale. Although measurements of precipitation using weather radar and rain gauges are accurate, their spatial coverage is poor and limited to land. Satellite observations overcome this limitation. Satellite sensors operating at microwave frequencies (10 to 185 GHz) allow global measurement of precipitation on high temporal and spatial scale. Precipitation retrieval algorithm from space born passive microwave sensor is either based on empirical or physical methods. Empirical methods primarily applied over land are based on relation between observed radiance and precipitation. Whereas, physically based methods are applicable for ocean surface which uses Radiative Transfer Model (RTM) to calculate brightness temperature at the top of atmosphere for different atmospheric conditions. Beside these conventional methods, state-of-the art probabilistic approach for rain retrieval is presented here. To develop the algorithm, we used Liu's Radiative Transfer Model (RTM). Using RTM, brightness temperature (BT) simulations have been performed on the same set of frequencies used by Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI). Global forecast system (GFS) atmospheric profiles and TMI-2A12 hydrometeors profiles (Cloud liquid water, Cloud ice, Rain, Snow and Graupel) are used as inputs for the simulations. A case study is performed, to classify in different clusters to get the posterior probability of rain. Statistical analysis is carried out for 16, 32 and 40 clusters for the posterior calculation using Bayesian approach. Among all these clusters (16,32 and 40), rain derived at cluster-40 is showing good correlation to observed rain for different rain range.

1. **INTRODUCTION**

The measurement of precipitation is very difficult because of its large variability with time and space. Satellite sensors which use visible and infrared frequencies are used in the estimation of precipitation. Since visual and infrared radiation cannot penetrate the clouds, the presence of clouds affects precipitation measurements. At any given time, approximately 40% of the earth is covered with clouds. Microwave remote sensing is a valuable way of measuring geophysical parameters because it can partially penetrate the clouds, and microwave radiometers are able to measure blackbody emissions day or night and are nearly independent of weather conditions. Satellite born passive microwave sensors ability to detect precipitation has been shown by many investigators.

It is the fact that for different frequencies, effect of the vertical distribution of various hydrometeors on the upwelling brightness temperatures from the atmosphere is different and the Earth's surface characteristics is effecting on the upwelling brightness temperature. Precipitation retrieval by using space born microwave radiometers is based on this fact [1].The problem of finding the upwelling brightness temperatures have good solutions if all the parameters are known. This forward problem can be solved with the radiative transfer theory. But it is difficult to solve the inverse problem where inverse problem is to find the physical parameters from the knowledge of upwelling brightness temperatures at different frequencies and it is difficult because required parameters are influenced by other atmospheric parameters. Microwave remote sensing problems are of the general class of inverse problems.
Several algorithms have been developed and applied to retrieve the vertical hydrometeor profile. Among them some algorithms have used Bayes theorem to retrieve vertical hydrometeor profiles and a single instantaneous rain rate

[2]-[4]. A detailed review of literature shows that the Bayesian theorem has proven potential and flexibility [5]-[6].In the present study we have used very basic method to retrieve rain. We applied basic formula of Bayes theorem. In the following sections, this paper describes the data and methodology for carrying out the study. The results are then discussed in the subsequent sections.

2. DATA USED

In the present study TRMM (Tropical rainfall measuring mission) data and GFS (Global Forecast System) analysis data have been used. TRMM was launched on 27 November 1997 into a near circular orbit [7]. It was a joint space mission between National Aeronautics and Space Administration (NASA) and the Japan Aerospace Exploration Agency (JAXA). Along with other four sensors it had carried a nine-channel passive microwave radiometer, the TRMM Microwave Imager (TMI). TMI were operating on10.65, 19.35, 21.3, 37.0, and 85.5 GHz. Every frequency had observed on both horizontal and vertical polarizations except 21.3 GHz which had vertical polarization only. Vertical hydrometeor profiles (Cloud liquid water, Cloud ice, Rain, Snow and Graupel) data from 2A12 (TMI) is used in this study. Vertical hydrometeor profiles are given in 28 layers along with latent heat and surface rain in TMI-2A12 data. BT data from the standard product 1B11 (TMI) is used.

GFS is a weather forecast model produced by the National Centers for Environmental Prediction (NCEP). GFS data is provided parameter profiles (Temperature, Relative Humidity, U-component, V-component etc.) on 26 pressure levels. GFS analysis data profiles (Temperature and Relative Humidity) of 0.5° grid scale given at 00, 06, 12 and 18 UTC are used.

3. METHODOLOGY

TMI Brightness Temperature (BT) values at frequencies (10.65, 19.35, 21.3, 37.0, and 85.5 GHz) were simulated using Radiative Transfer Model (RTM), which is developed by Liu (1998) [8]. Liu-RTM apply discrete ordinate method (DOM) to solve microwave radiation transfer for the plane parallel atmosphere. Simulations of BTs are carried out for the oceanic region. As an input RTM needs hydrometeor profiles (Cloud liquid water, Cloud ice, Rain, Snow and Graupel) and atmospheric profiles (Temperature, Height, Pressure and Relative Humidity) at different vertical levels and output of RTM would be (Rain Rate, Snowfall Rate, Graupel Rate, Liquid Watwer Path, Ice Water Path, BT(V) and BT(H)). For the simulations hydrometeor profiles (Cloud liquid water, Cloud ice, Rain, Snow and Graupel) and atmospheric profiles (Temperature, Height, Pressure and Relative Humidity) at desired vertical levels are taken from the standard product of TMI-2A12 and GFS analysis data respectively as an input to run RTM. GFS analysis data sets have (0.5° × 0.5°) resolution, which is given at 00, 06, 12 and 18 UTC. Since TMI data and GFS data are at different resolution, to prepare input data set of RTM hydrometeor profiles of TMI- 2A12 and atmospheric profiles of GFS analysis are collocated. This collocated data set is generated for the period of (2014-08-01 to 2014-08-15). These profiles are interpolated for 15 km vertical level with level step of 1 km. Collocated data set of hydrometeor profile and atmospheric profile is made at spatial scale of 0.5° and temporal scale of 5 minutes over ocean. With these conditions we are getting 947838 collocated data set points. To check the performance of simulated BT, these values are compared with TMI-1B11 observed BT values for all frequencies of TMI.

Rain identification is an important part of any rain retrieval procedure. Over the oceans, the variations in the surface temperature, water vapour, cloud liquid water or wind speed may often produce the BT variations of the same order as the due to low rain rates. As well as, the uncertainties observed in the brightness temperature versus rain rate relationship due to horizontal and vertical rain variability within satellite instantaneous field of view (IFOV) makes it extremely difficult to differentiate low rain rates from the background field [9]. Thus identification of rain and no-rain condition is important for the rainfall retrieval. To identify rainy and non-rainy pixels probability density functions (PDF) for all frequencies (V and H polarization) of TMI are calculated. To compute PDFs, only those pixels are considered as rainy pixels which have rain greater than 0.5 mm/hr. It is observed from the PDF plots that for 19GHz and 37 GHz there is clear discrimination in between rain and no-rain and as 19GHz and 37GHz are sensitive to precipitation over ocean, we use information from these frequencies' PDFs to rainfall retrieval. Then Bayesian approach is used for the inverse problem.

Bayes theorem states that given the data P (e.g., microwave observations), the distribution of the parameters R (e.g., rain rate) is proportional to the conditional likelihood times the prior distribution.

$$\pi\,(R \mid P) = \frac{f\,(P \mid R)\cdot\pi\,(R)}{\int f\,(P \mid R)\cdot\pi(R)\cdot dR} \qquad (1)$$

In equation (1) f (P|R) is a conditional probability density function that expresses statistical and physical information about the relationship between P and R. π(R) describes our prior knowledge of rain rate. The interactions of the physical and statistic conditional and the prior probability distribution determines posterior probability, π (R|P). For the present study prior information of rain is taken from standard product of TMI-2A12.Conditional probability is computed for rainy pixels which are identified by the PDFs of 19GHz (V) and 37 GHz (V). For the computation of posterior probability, conditional probability and prior information of rain is calculated on different number of clusters like 16, 32 and 40 cluster. For different cluster and different range of rain posterior probability is calculated. Then computed rain from posterior probability is compared with the observed rain for all clusters.

4. RESULTS AND DISCUSSIONS

Table 1 and table 2 are showing the statistics of simulated BTs with observed BTs of TMI-1B11 for the vertical polarization and horizontal polarization of TMI's frequencies respectively. RTM which is used for simulations of BT having maximum error about 2 K [8] which is depending on the viewing angle and frequency. In the computation of statistics model error is considered. This computation is performed on 947838 collocated dataset points. Computation is done on both rainy as well as no-rainy pixels together. As model has maximum error about 2 K for 85 GHz [8], one can see this thing from table 1 and table 2 that for all frequencies has better correlation and RMSD (Root Mean Square Difference) than 85 GHz. But when we distinguish rainy and no-rainy pixels and check the sensitivity of model, model is more sensitive to non-rainy pixels then rainy pixels. As 19GHz and 37GHz are more sensitive to precipitation over ocean, but here at 37GHz RMSD is more than the RMSD of 19GHZ. It may be because of hydrometeor profile and as model is more sensitive for non-rainy condition.

As already mentioned in previous section, pixels having more than 0.5 mm/hr rain rate are considered as rainy pixels. With this condition we are getting 904368 as non-rainy pixels while 43470 as rainy pixels among 947838 collocated data points. Figure1 and figure 2 demonstrates PDFs for rainy and non-rainy pixels of all frequencies of TMI. It can be seen from figure 1 and figure 2 there is overlap between rainy and non-rainy pixels at all frequencies. Despite having overlap area between PDFs of rainy and non-rainy cases, the figure 1 and figure 2 show clear and distinct peaks of PDFs for seven cases in all the 9 frequencies of TMI, this suggest sensitivity of the BTs to rain. Sensitivity of these frequencies will use for further calculations of Bayes theorem. In figure 1((a) and (b)) and figure 2 ((g) and (h)) there is clean peak for non-rainy pixels. In figure 2 ((g) and (h)) overlap area between rainy and no-rainy pixels is more than the others while figure 1((a) and (b)) has not that much overlapping area but it is less sensitive to rainy pixels. So as 19 GHz and 37GHz are more sensitive to rainy as well as non-rainy pixels. From the PDFs of 19GHz (v) and 37GHz (v) threshold value of BT for rain retrieval is decided. From figures (c) and (e), we consider only those pixels to retrieve rain whose BT values are greater than 240(K).

Table 3 shows the comparison of retrieved rain with the standard product of TMI-2A12 for 16, 32 and 40 clusters. Retrieval of rain is performed only on those pixels having more BT value than the threshold (240 K) value. Selection of cluster is random. Total numbers of pixels for the rain retrieval are 24212 where pixels have rain greater than 5 mm/hr are 6717 and 2316 for greater than 10 mm/hr. It can be seen that in the estimation that as rain rate is increasing correlation is become coarser for all clusters. But as cluster is increased for these different ranges of rain correlation is become well and among all, at cluster (40) there is good correlation between estimated rain and observed rain.

Table 1: Comparison of Simulated BT values with TMI-1B11 BT values for vertical polarization of frequencies.

Frequncy(GHz)	Correlation(r)	Bias	Standard Deviation	RMSD
10.65(V)	0.922	0.289	2.394	2.411
19.35(V)	0.984	-0.131	2.439	2.443

21.3(V)	0.989	-0.071	2.910	2.911
37.0(V)	0.966	4.470	2.870	5.314
85.5(V)	0.853	3.551	5.979	6.954

Table 2: Comparison of Simulated BT values with TMI-1B11 BT values for horizontal polarization of frequencies.

Frequency(GHz)	Correlation(r)	Bias	Standard Deviation	RMSD
10.65(H)	0.907	1.845	4.078	4.477
19.35(H)	0.967	0.207	5.876	5.872
37.0(H)	0.969	2.956	5.329	6.094
85.5(H)	0.953	3.714	6.835	7.778

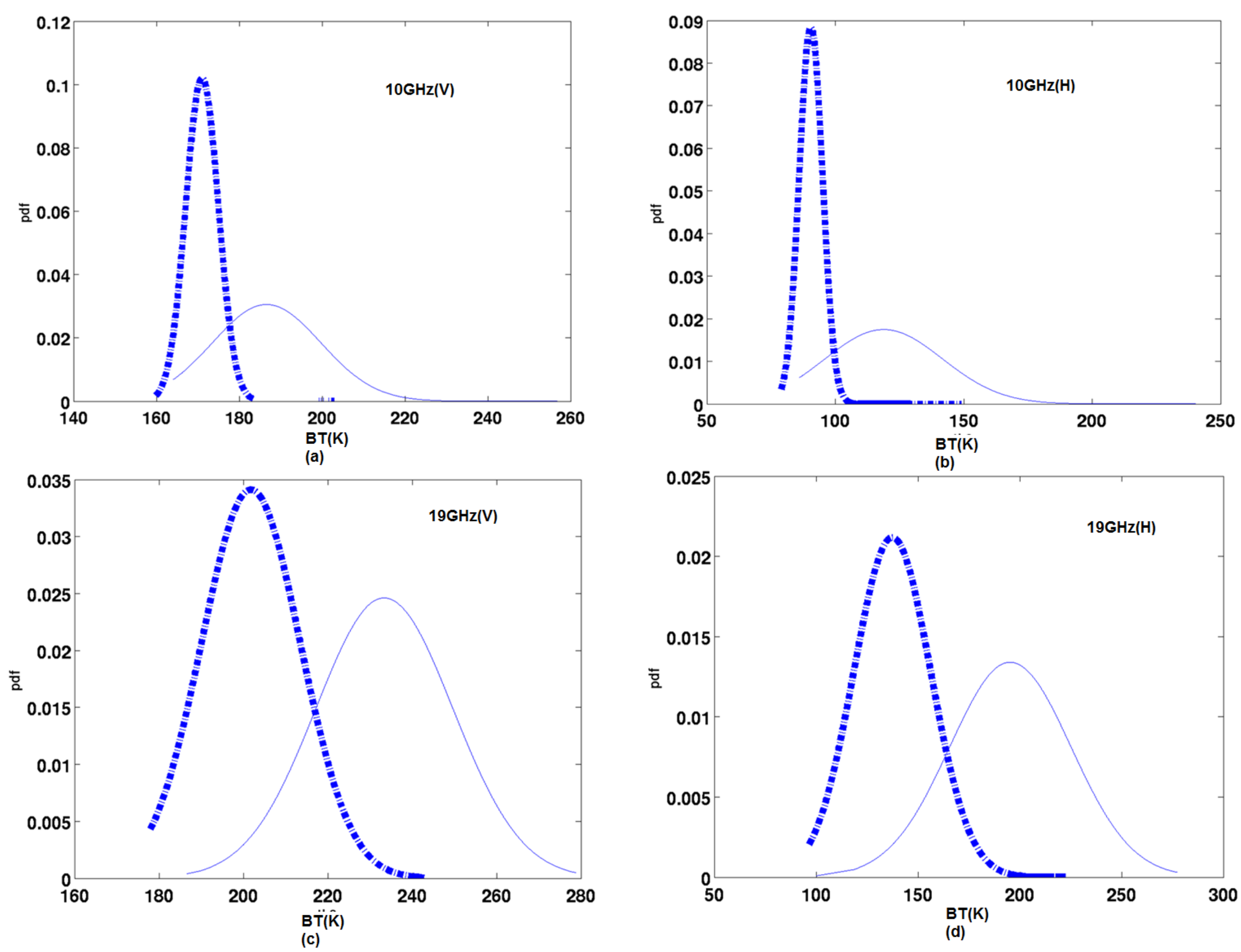

Figure 1: PDF plot of (a) 10GHz (v), (b) 10GHz (H), (c) 19GHz (V) and (d) 19GHz (H)

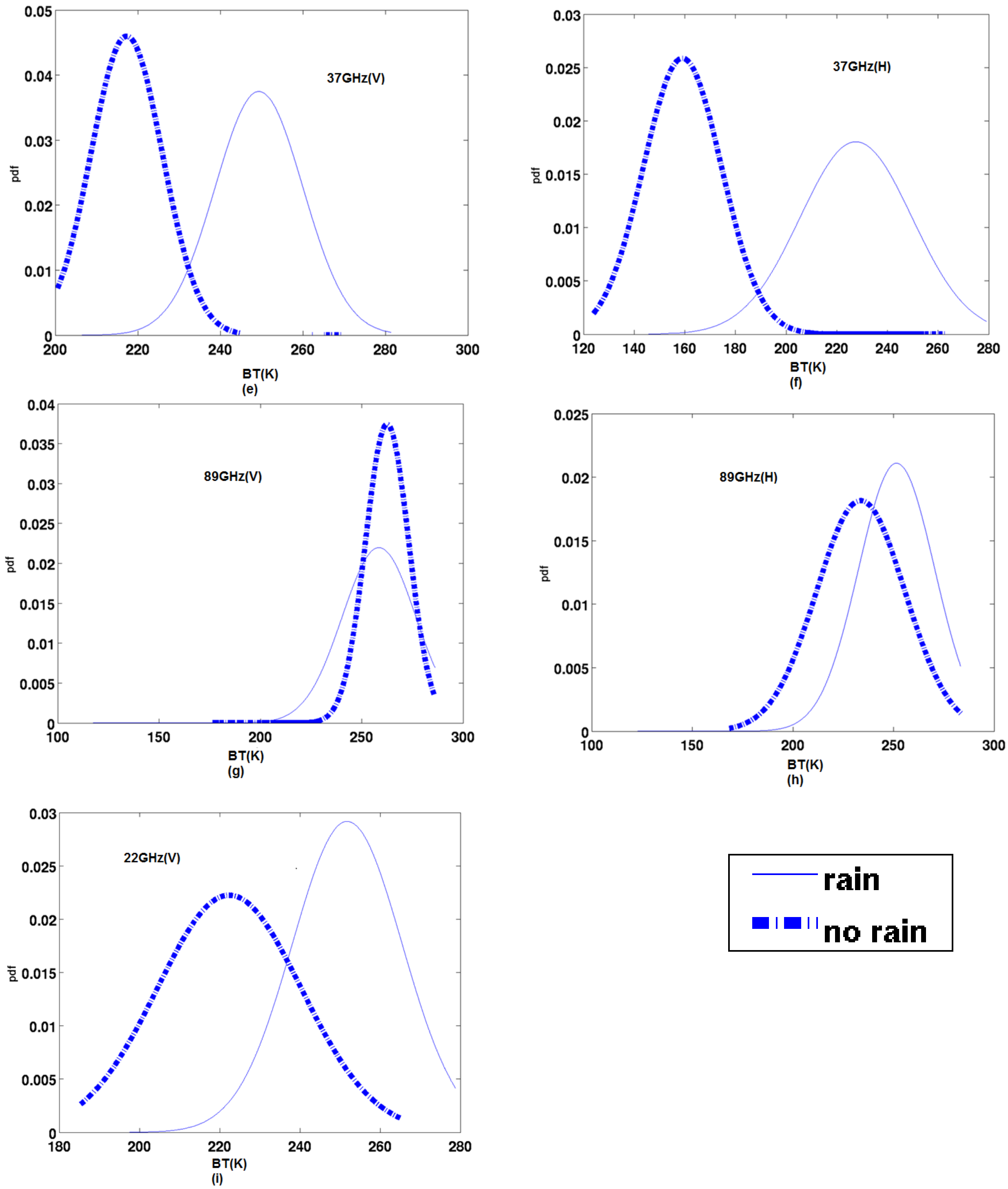

Figure 2: PDF plot of (e) 37GHz (v), (f) 37GHz (H), (g) 89GHz (V), (h) 89GHz (H) and (i) 22GHz (v)

Table 3: Correlation between estimated rain and observed rain for different clusters.

	Cluster-16	Cluster-32	Cluster-40	Rain Rate
Correlation(r) (mm/hr)	0.82	0.82	0.83	>0.5 (mm/hr)
	0.70	0.72	0.73	>5(mm/hr)
	0.57	0.58	0.59	>10(mm/hr)

5. CONCLUSIONS

Through this study**,** we tried to estimate rain using Bayesian approach. For retrieval we tried basic concept of Bayes theorem. Simulation study shows good sensitivity of RTM and simulated BT values to rain rate and well matched with the observed BT values for all frequencies of TMI. With the threshold value of BT (240 K) from PDFs, retrieved rain is related reasonably well with observed rain. Particularly for cluster-40, estimated rain is very well correlated with observed rain for all rain rates. This algorithm is applied on a small data set which can further be modified and extended to larger data set to achieve its applicability and to study the error analysis.

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