ESTIMATION OF RAINFALL FROM TRMM-TMI AND PRECIPITATION RADAR USING NEURAL NETWORK APPROACH

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Abstract

In present study two different radiative transfer models are used for initial sensitivity studies and for conceptually simple consideration of spatial distributions of cloud and rain conditions from ECMWF database. These models are based on Discrete Ordinate Method (DOM) upto N streams by Moreau (1999) and Eddington's approximation applied to DOM by Kummerow et al (1993). Both of the these models allow for a full optical thickness and cloud absorptivities. The main purpose of the simulations is to delineate the frequencies that are most sensitive (as far as brightness temperatures are concerned) to the surface and rainfall characteristics. Following these sensitivity analysis, a combination of passive and active microwave observations from TRMM Microwave Imager (TMI) and Precipitation Radar (PR) of Tropical Rainfall Measuring Mission (TRMM) satellite is used to estimate rainfall using Neural Network (NN) technique. The correlation coefficients of 0.914 and 0.904 between the desired and estimated rainfall for both training and testing data of collocated TMI and PR are achieved. The effectiveness of the rainfall estimation by using NN can be influenced by many factors, such as the representativeness and sufficiency of the training data set, the generalization capability of NN, seasonal and location change etc. and thus NN needs to be dynamically updated.

1. Introduction

Precipitation is associated with various atmospheric phenomena both in small and large scale. 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. Various techniques use microwave brightness temperature data, obtained from remote sensing orbiting platforms, to calculate rain rates. Most commonly used techniques are based on regressions or other statistical methods. Recent research has shown that NN techniques can be used successfully for the rainfall estimation from radiometric measurements from SSM/I type of sensors (Moreau et al. 2000, Tsintikidis et al. 1997). NN is a non-parametric method for representing the complex relationship between satellite measurements (radar or radiometers) and rainfall rates for instance. The NN's are mathematical models that are capable of learning complex relationships, such as in case of multichannel brightness temperatures and rainfall. They consist of highly interconnected, interactive data processing units.

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The study is conducted in two parts. First aspect is the radiative transfer simulations based on two different models to test the sensitivity of various channels to the rainfall and surface variability to help the creation of matched data sets from most sensitive TMI channels and PR collocation position for brightness temperatures and rainfall rates respectively. The second aspect is to examines the performance of neural network solutions. A systematic series of radiative transfer simulations for different sensitivity experiments have been carried out to gain insight for the selection of proper TMI channel combinations for the retrieval of rainfall .

2. Radiative Transfer Models:

The interpretation of rain and cloud remote sensing data requires, accurate accompanying radiative transfer calculations in order to establish the link between the observed radiances and the state of the atmosphere which causes these radiances. Many investigators have reviewed the basic physics of radiative transfer. However here we describe briefly the radiative transfer models to the extent relevant for present study. The simulation of upwelling radiances measurable by TRMM-TMI type of sensors are based on the equations that describe the transfer of microwave radiances through a horizontally infinite and vertically structured plane parallel atmosphere. It forms the basis for calculations of upwelling radiances measurable by radiometric channels. The brief description of radiative transfer is outlined below. The basic equation for the differential radiant intensity can be written as (Chandrasekhar 1960):

$$ -\mu \frac{dI(\tau,\mu)}{d\tau} = -I_v(\tau,\mu) + J(\tau,\mu) \qquad (1) $$

where $I(\tau,\mu)$ is the radiant intensity at optical depth τ and $\mu = \cos(\theta)$ where θ is the zenith angle and $J_v(\tau,\mu)$ is the source function. In essence, the above radiative transfer equation states that the change in radiant intensity results from the attenuation in intensity along the path of propagation due to absorption and outward scattering, and from the enhancement of intensity due to scattering of the incoming radiation and thermal emission by the atmospheric constituents.

2.1 RT Model I:
Description of this model may be found in Weinman and Devis (1978), Kummerow (1993), and Viltard et al. (1998), among many others. Basically the Kummerow's model used here is based on the discrete ordinate method but with the Eddington's approximation, where the radiances and phase function are expanded in series of Legendre and associated Legendre functions and

first few orders are selected to simplify the phase matrices. The solution of resulting equation which is a second order differential equation has a suitable solution with the constants to be determined from the boundary conditions. In order that the above conditions are satisfied in each atmospheric layer, the atmospheres are generally divided into homogeneous layers. The fluxes at the top and bottom of the layer which are downward and upward fluxes respectively from the upper and lower boundary conditions. At the layer interfaces the flux continuity is assumed. The radiant intensity can be expressed in more conventional units as the brightness temperature, which is the thermodynamic temperature of a black body emitting an equivalent intensity.

2.2 RT Model II:

In this method the continuum of propagation directions is discretized into a finite number of directions so that the integro-differential equations are converted into system of ordinary differential equations with constant coefficients, the solution of which are calculated by eigenanalysis. The discrete ordinate-eigenanalysis method is applicable when the medium has homogeneous absorption and scattering profiles. We follow here the DOM model developed by Moreau (2000) for the simulations similar as in Kummerow's model simulations mentioned above. The difference in two models is evident that later model does not use such an approximation while Kummerow model use Eddington's approximation. This approximation consists in using a simplified phase matrices to offer faster computation of the scattering coefficients. In both radiative transfer models the radiative properties of the atmosphere are computed using the Mie theory and are integrated over the drop size distributions for each input grid cells.

3. Results of Simulations:

The TMI instrument measures brightness temperatures at 5 different frequencies: 10.65, 19.35, 21.3, 37.0 and 85.5 GHz, each being polarized both vertically and horizontally but for the 21.3 GHz which is only polarized vertically. Thus the simulations are carried for these frequencies here out of which many are going to be common in MADRAS (exclusion of 10 GHz and inclusion of 157 GHz). Some of the preliminary results from the radiative transfer simulations based on the Eddington approximation are presented recently by Gairola et al. (2001) for TMI and IRS-P4-MSMR frequencies. Thus for the brevity the results from DOM simulations and comparison with the observations are presented here. In order to keep actual variability of rainfall, we have used ECMWF forecast fields to build a simulated data base. ECMWF profiles

does provide wide variety of dynamical situations, but the microphysical and morphological properties of liquid and ice has to be introduced. However the different assumptions must not introduce a bias, nor should limit the representatively of the simulated data (Moreaue et al. 2001). ECMWF fields provide a wide variety of vertical structures of atmosphere, clouds and rain and thus the situations represent the global applicability for various kinds of hydrometeors like, precipitating liquid water (rain drops), non-precipitating liquid water (cloud droplets), precipitating ice. All the hydrometeors have been assumed to be spherical, thus using Mie formulation. Eventhough the sphericity assumption is not strictly proper, especially for ice particles, the average phase function of a randomly oriented ensemble of non-spherical particles tends, in general, to approach that of polydisperson of equal-volume spheres (Mugnai and Wiscombe, 1980). The gaseous absorption is calculated by Liebe 1993.

Fig. (1)

Fig. (1) shows the scatter plot of the simulated brightness temperatures of 10 to 85 GHz

horizontal and vertical frequencies from DOM solutions. The dynamic ranges of brightness temperatures shows good qualitative agreement with the emission and scattering characteristics of clear and cloudy/rainy atmospheric conditions that would show such a large dynamic range for the TRMM-TMI radiometric channels over the oceans as shown in Fig 2 for a cyclone Bret over the Pacific ocean giving scattering and non scattering signatures clearly. The two branches of the brightness temperatures in 37 and 85 GHz in Fig. 1 shows first the increase in brightness temperature due to the emission and then the decrease due to the scattering and is coherent in both the figures.

Fig. 2

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89.3<T10H<288.5   171.6<T10V<296.0   145.0<T19H<294.3

207.7<T19V<299.2   233.9<T21V<295.8   157.8<T37H<292.6

218.0<T37V<296.3   145.0<T85H<292.6   135.1<T85V<294.9

For brevity, a quantitative comparison between simulation and observed TMI brightness temperature is shown in upper half panel of Fig. (3 a) for the lowest frequency channel, which shows a very good match. In lower half panel we show an interesting result of the simulation from the highest frequency of 89 GHz for MADRAS channel and compare it with the nearest 85 GHz channel measurement from TMI. There is some marked difference in the scatter of the data in the emission domain which is expected due to the difference in frequency, while in the scattering domain the scatter plot from both the channels are quite overlapping. This is also expected as the scattering contribution is very prominent in higher frequencies and not much separable within such a channel difference.

Fig. 3a

Measured and simulated 10 GHz Brightness Temperatures
measured : blue
simulated : red

Fig 3b:

measured 85 GHz Brightness Temperatures in blue
simulated 89 GHz Brightness Temperatues in red

Presently the data from ECMWF used in above simulations was found to have a   limited

dynamic range of the rainfall (upto 15 mm/hr) and thus does not represent the tropical rainfall globally. Thus we have simultaneously arranged to accomplish this part of study using the real data from co-located TMI and PR of TRMM. However, a larger database is being attempted for radiative transfer simulations and retrievals covering all the seasons and tropical regions.

4. TMI and PR Data Base:

In present study, the retrieval method ahead is based on Neural Network approach, described by Moreau (2001). A large data base representing all the possible dynamical ranges of rainfall and brightness temperatures is the prerequisite for applying this method. Here the data base is generated from the collocated sets of observations between TMI and PR which share a common swath of about 200 km on the surface. The PR is the first rain radar in space. The complete description of sensor package of TRMM are given in Kummerow et al. 1998. Within this area of common swath there are very important observations, ie; the vertical profile of reflectivity from PR from rain structures and the brightness temperatures from TMI from almost same cloud and rain systems by nine channels respectively. These sensors makes one of the very suitable pair of coherent observations for estimating rainfall. Two days of TMI and PR data base are used in the present study (1,2 Feb, 1998). The PR data is total rainfall (at 2km height) from PR.

5. Neural Network Approach:

Multilayer Perceptron (MLP) Neural networks (Rumelhart et al. 1986) are a computational method of data analysis that are an extension of traditional statistical methods such as regressions, and function approximation. In statistical regressions the modeler has to *a priori* specify the functional form of the relationship likely to exist in the data set (nonlinear vs linear vs multiple regressions). The best functional form for the data is based on an error measure such as the least squares criterion. Neural networks, form an "internal weight" representation of the data as to minimize an error criterion (usually least squares) without too much *a priori* judgements about on the functional form for the data.

Rain Rate

Fig. 4.

Output Layer

Hidden Layer

Input .... Layer

......

Brightness Temperatures

Neural networks in their broadest sense could be defined as a collection of interconnected simple computational units that work together cooperatively to solve linear and nonlinear problems.   The input units are connected to the output units by way of hidden units. The hidden units capture the non-linearity in the mapping between the input and output information.   A simple conceptual architecture (without connecting all input and hidden nodes due to simplicity of the figure) of the NN is shown in Fig. 4. The neural network is first trained on sample data, and the "internal weights" are adjusted to learn patterns and trends in the data. Once trained, the network is used to predict on input data. If there are many more hidden units (free parameters) than there are data available, the network may not be able to generalize (extrapolate), and learning of the network may be hindered by the noise and measurement error in the dataIn the present case the inputs are brightness temperatures from all the polarization states of TMI and the output is the rainfall rate. All inputs and outputs are normalized so that their new values fall in the interval (0 to 1).

6. Results and Discussions:

From the simulations in the previous section it is clear that all channels have considerable effect

of rainfall but all measurements from TMI are resolution dependent (around 50 km for 10 GHz and 5 km for 85 GHz). Yet, as a first experiment, all the channels of TMI are selected for analysis. There are some 9941 collocated TMI and PR points, which have been divided into two halves, first one for training the relationship between the input and output vectors of TMI-TB's and PR rain respectively by 6000 points and finally testing the relationship obtained by neural network training using remaining 3941 set of points. Here the rain rate ranges from 0.01 to 48.5 mm/hr. This dynamic range of rainfall is quite sufficient for NN training. We carried out various experiments and finally opted for 2000 iterations with backpropagation approach that minimizes the cost function. Fig. 5a shows the variation of global error with number of iterations, which is the evolution of the error during the training phase. The error decreases substantially after a few hundred iterations. Continuous line in Fig. shows the absolute error with number of iterations for learning data and dotted for the testing data sets. The desired versus ANN retrieval of rainfall for both training and testing data sets are shown in Fig. 5b,c respectively. The overall bias, standard deviation and rms error are shown in the respective figures (Fig 5d,e) for learning and testing data sets. There are significant correlation's of 0.914 and 0.904 achieved in both sets for the architecture of the NN that was conversed to minimum acceptable error in present case with 2000 iterations and three hidden layers. The figures of error estimates (bias, standard deviation and rms error) for both the training and testing data sets show a bias of 3 m/hr between 15 and

Fig. 5a: NN Errorr Distribution

Fig. 5b: Desired vs. ANN Retrieved Ranfall
for training data sets

Fig. 5c. Desired vs. ANN Retrieved Rainfall
for testing data sets

 25 mm/hr in   Fig (5b and d). The same bias is enhanced in testing data as is seen in respective Fig (5c and e). There could be several reasons for this and one of the obvious reason is the lack of representatively of the data in this range (around 15 to 25 mm/hr) while training the neural network. The remaining data set which is around   60% of the original learning data, is a significant number to believe the stability of the weighting coefficients of the NN for the retrieval of rain rates from TMI observations. However the input data base generation can still be considered a multistage problem which involves many degrees of freedom in case of rain and clouds. This is apparent from Fig (5b,c) while observing the bias and rms errors. Apart from the surface and background atmospheric contributions to the signal the cloud and rain parameters themselves impose the largest uncertainty. Presently the initial success of simulations for both emission and scattering atmospheres and their corroboration with the observations from TMI and PR allows us for more specific and stringent experiments to be carried out using consistent and statistically representative input fields over the Oceanic regions for the treatment of the involved radiative process for the retrieval of rainfall from MADRAS sensor.

Fig. 5d. Data distribution with error statistics (for training data sets)

n :6000
r2 :0.913
bias :0.008
std :1.42
rmse :1.42

Mean empirical Rain Fall (mm/hr)

Fig. 5e: Data distribution with error statistics (for testing data sets)

n :3941
r2 :0.951
bias :0.43
std :0.832
rmse :0.937

Mean(y) empirical Rain Fall (mm/hr)

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