GLOBAL MAPPING OF RAINFALL FROM TRMM RADAR LINKING GROUND BASED RADARS AND IN-SITU OBSERVATIONS

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Abstract

Tropical Rainfall measuring Mission Precipitation Radar is known to be the first spaceborne observation platform for mapping precipitation over the tropics. TRMM measured rainfall is important in order to study the precipitation distribution. Ground validation is a critical important component in TRMM system. However, the ground sensing systems have different sampling and observation characteristics from TRMM. In this paper a novel hybrid Neural Network model is presented to train ground radars for rainfall estimation using rain gauge data and subsequently using the trained ground radar rainfall estimation to train TRMM PR based Neural networks, to create Global maps of precipitation.

1. Introduction

Rainfall on the ground is dependent on the distribution of precipitation aloft. Prior research has shown that neural networks can be used to estimate ground rainfall from radar measurements [1][2][3]. The usefulness of the rainfall estimation using neural networks is subject to many factors such as the representativeness and sufficiency of the training dataset, the generalization capability of the network to new data. The key challenge in radar rainfall estimation is the space-time variability in precipitation microphysics, such as rain drop size distribution. In addition, radar rainfall estimation is a practical application problem that involves numerous implementation considerations that are important [4]. TRMM Precipitation Radar (PR) is a unique instrument, capable of providing high-resolution vertical profile of precipitation on a global scale. However, fundamental challenges exist in performing TRMM comparison analysis or integration with ground observations. The horizontal resolution of TRMM PR is about 4.5km, much coarser compared to representative area of rain gauges. Another challenge is that during a single weather event, available data pairs for comparison (TRMM vertical profile of reflectivity versus rain gauge measurement) are scarce because of TRMM's limited coincident overpasses; which makes it impractical to deploy a dense gauge network for TRMM PR validation. However, ground radar observations, though they have some spatial scale difference from gauges can make coincident temporal observations over rain events, more often. Similarly, ground radars measure rainfall over large spatial extent can be used to obtain large amount of coincident samples with TRMM. Our goal is to build an adaptive relation for TRMM PR rainfall estimation using neural networks with rain gauges as ground truth. This will be done using ground validation (GV) radars to bridge the scale gap between TRMM PR and rain gauges.

2. A Hybrid Neural Network Technique for TRMM-PR Rainfall Estimation

2.1 TRMM PR and ground radar

The goal of this hybrid neural network model is to develop a link between the rain gauges, TRMM PR and ground radar. These three systems sample precipitation in completely different geometrical aspects. The TRMM PR has a horizontal resolution of about 4.5km but fine vertical resolution. The ground radars on the contrary have fine radial resolution but varying vertical resolution depending on distance from radar. In order to use the TRMM PR, this means the two data sets have to be aligned first. The alignment process developed by Bolen and Chandrasekar [5] is used to align TRMM-PR reflectivity product with the ground radar reflectivity measurements. Re-sampling the ground-based and spaceborne datasets to a common grid provides a means by which the radar reflectivity factors can be compared between the two radars. Fig. 1 shows the geometry between TRMM-PR and Ground Radar (GR) based measurements.

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An example of the alignment output is shown in Fig. 2. Data were taken from KMLB radar in Melbourne. It can be seen from Fig. 2 that there is good match between these two products.

The second neural network is designed using TRMM reflectivity vertical profiles using observations between 1km and 4 km, with the rainfall estimate from ground radar as target output. The target of this network is the rainfall estimated by the first neural network with GR data that is aligned to TRMM data which will be used to train the second network. Training this neural network was based on the same technique used in the GV neural network. The only difference between them is that the first neural network was trained for every precipitation event while the second neural network was trained for every coincident overpass. Fig. 3 shows the schematic of the process of training TRMM–PR neural network.

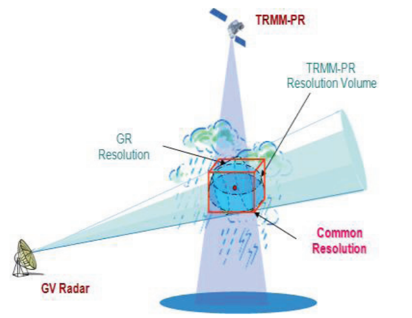
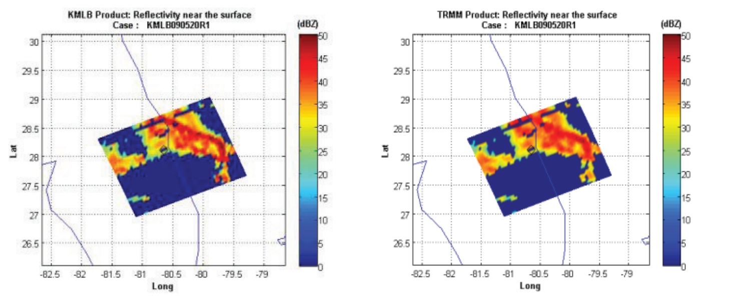


Fig. 1: Geometry between TRMM-PR and GR-based measurements



(a) (b)

Fig. 2: An example of aligned snapshot of TRMM PR reflectivity and GR reflectivity. The snapshot was taken in May 20, 2009 at 03:37:02 UTC in Melbourne FL (a) KMLB reflectivity (b) TRMM-PR

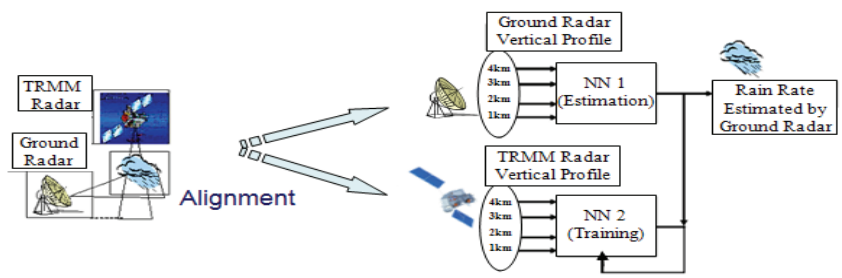


Fig. 3: Training TRMM-PR neural network using GV neural network rain rate estimate.

2.2 Validation

To validate this novel method for global rainfall estimation and mapping, we compare the rain rate estimated by the first network and the second network to the rain gauges. TRMM-PR rain rate product was also compared directly to the rain gauges in order to perform a comparison between TRMM-PR rain rate product and the neural network product.

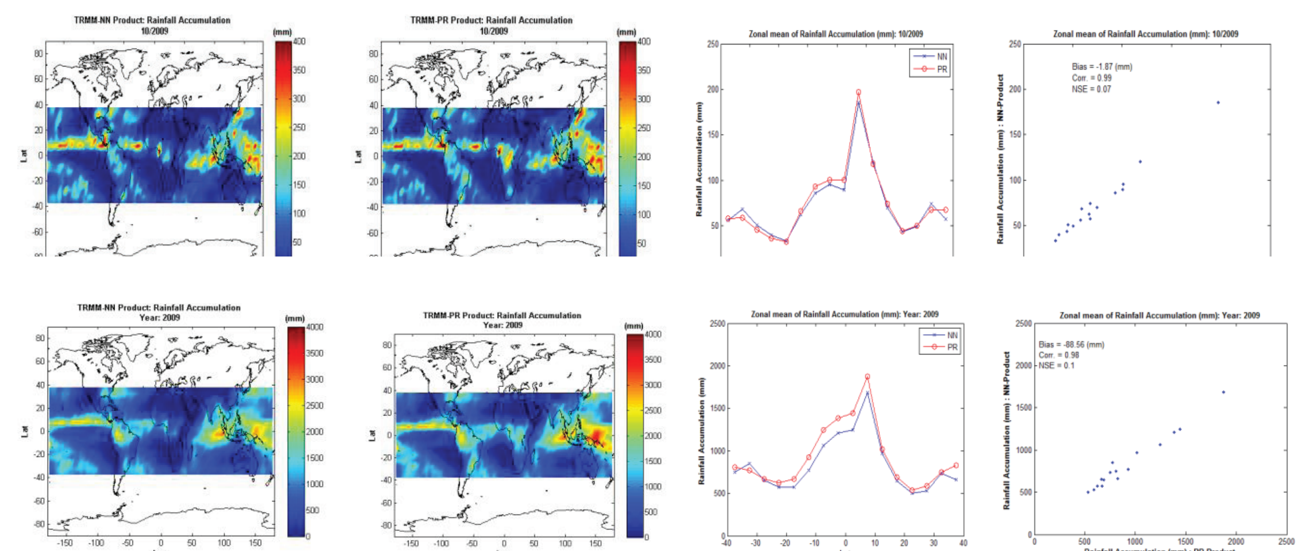
Ground Radar data and rain gauge observations over a year in the Melbourne FL region were used to test this technique during the year 2009. Radar data were collected by Melbourne NEXRAD (KMLB) radar Constant Altitude Plan Position Indicator (CAPPI) scans. The lowest level of the CAPPI scans is 1 km and the highest level is 4 km. The spacing between levels is chosen to be 1 km. The gauge data were maintained by the NASA TRMM program. Around KMLB radar, the gauge networks that were used are the Kennedy Space Center (KSC), South Florida Water Management District (SFL), and St. Johns Water Management District (STJ) data sets. Data within 100km of ground radar were only considered. The radar parameter of interest in this work was radar reflectivity factor at horizontal polarization, Z_h. CAPPI data containing Z_h values at 1km, 2km, 3km, and 4km heights with 1km horizontal resolution were generated from the radar data as shown in Fig. 4. TRMM data were collected from coincident overpasses over Melbourne FL. There were around 542 overpasses during the year 2009. Among those overpasses there were around 70 overpasses where there was some precipitation in both GV and PR observations. Those overpasses were used to evaluate the performance of the second neural network.

Two neural networks were trained using data from 2009 around Melbourne-Florida ground validation site and the corresponding TRMM overpasses. There were around 542 overpasses over KMLB radar. Around 70 overpasses were found to be precipitation cases and were considered in this study. The data were used to dynamically train both networks. The first network was trained based on ground radar data and its corresponding gauge values at the end of any day. This network was used to do rainfall estimation for the next day. The procedure was done for the second network. The second network was updated every time we have precipitation overpass. The target for this network was the rainfall estimated by the first network at the time of that overpass. Rainfall estimation of any new overpass data was done based on the network built by the previous overpass data. Data were used to evaluate the performance of each network against rain gauge measurements. The following parameters were used to do the evaluation:
where *RFn* and *RFg* represent the estimated rainfall and the actual rain gauge, respectively, Ng is the size of the data, NSE and RMSE are normalized standard error and root mean square error, respectively.

4. Global Rainfall Maps Generation

In this section, monthly global rainfall maps are generated using trained TRMM-NN for year 2009. The monthly rainfall maps are generated and compared to TRMM-PR monthly rainfall maps. TRMM-PR monthly rainfall maps are from TRMM-3A26 product, and they are generated based on TRMM-PR 2A25 product. The map of a certain month is generated pixel by pixel with a resolution of $5^o x 5^o$ (lat, long). For a certain pixel the rainfall accumulation during that month is calculated by multiplying the mean rainfall rate of rain certain profiles within that pixel by the total number of hours in that month. More description of how TRMM-PR rainfall maps are generated can be found at (http://trmm.gsfc.nasa.gov/3a26.html). The resolution of these maps is $5^o x 5^o$ (lat, long).

Fig. 4 shows global rainfall maps. In this figure, the first column is the rainfall accumulation product from the neural network, whereas the second column (b) is the rainfall accumulation from the TRMM product 3A26. The top figures are for one month (October), whereas the bottom figures show the accumulation for the year 2009. Similarly column C shows the zonal ,mean comparison for the rainfall maps for the month of October and whole year respectively and column d shows an inter comparison between the two. The primary purpose of this plot is to demonstrate the application of a trained neural network to generate global rainfall maps. The overall NSE of year 2009 was about 10%, together with the high correlation shown are good indications of how the two outputs are close to each other.



(a) (b) (c) (d)

Fig. 4: (a) Global Rainfall accumulation map generated by the NN (b) Global Rainfall accumulation map generated by TRMM-PR product (c) Zonal mean of the rainfall accumulation. (d) Scatter plot of Zonal mean of the rainfall accumulation. Maps resolution is $5^o x 5^o$ (lat, long), and data from 2009.

To conduct an alternate analysis between the maps generated by the NN and the maps generated by TRMM-PR product; a 10^ox10^o area over KMLB FL area with 0.5^ox0.5^o resolution was considered. The maps generated by the neural network estimator are very similar to the maps generated by TRMM-PR product on average establishing the functionality; however different in numerical values. The detailed results are skipped here for brevity. Quantitative analysis shows that on the average, TRMM-PR product produces slightly lower estimates with respect to the neural network product in this region with high correlation and a small normalized standard error (NSE) which is about 9.1% for the whole year. However, for the individual month, this difference can be higher. This exercise shows the power of using TRMM-PR data to produce accurate regional rainfall maps. The neural network algorithm while maintaining the accuracy of the global mean is also able to produce good spatial and temporal variability extending the potential applications of this technique.

5. Summary and Conclusion

A hybrid neural network technique to estimate rainfall from TRMM measurements is described here. This technique can be used for rainfall estimation from TRMM PR and provides an alternate mechanism for ground validation. Data from one year of observations during 2009 over KMLB validation site was used to evaluate the performance of this new technique against rain gauge measurements and compare it to TRMM PR product. Comparison results show good performance of this technique over TRMM PR product. The new technique has less bias and lower RMSE than TRMM PR product when compared to gauges while at the same time compares well with zonal mean global rainfall product. Rainfall maps generated by this technique show the ability to capture spatial variability. This technique can be a potential product for TRMM rainfall estimation and mapping.

The main approach was based on a hybrid neural network technique where a two-stage neural network was designed. The first network was based on rain gauges and ground radar measurements. This network was used to map the relation between the ground radar reflectivity factor and the rain gauges as first stage to a second stage of the hybrid network where TRMM-PR measurements aligned with the ground radar measurements that were used in the first stage were used to train another network with rainfall estimated based on those ground radar measurements by the first network as a target. In addition, subsequent to the training process, the TRMM PR products were used for generating global rainfall maps. These were compared to TRMM standard generated rainfall maps, and the hybrid neural network show the potential to produce global rainfall maps. As a third application, the annual rainfall accumulation map over a small region such as over Southern Florida was generated using the TRMM NN map. These rainfall maps shown similar spatial structures once again establishing the utility of the rainfall maps at the local scales.

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6. References

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