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Retrieval of TPW over ocean from locally received AMSU measurements

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सार – वायुमंडलीय स्तंभ में कुल वर्षणीय जल (टी. पी. डब्ल्यू.) की मात्रा कुछेक मौसम विज्ञान संबंधी अनुप्रयोगों के लिए उपयोगी महत्वपूर्ण प्राचलों में से एक है। इस षोध पत्र में कुल वर्षणीय जल (टी. पी. डब्ल्यू.) की मात्रा ज्ञात करने के लिए एन. ओ. ए. ए.–16 ए. एम. एस. यू. मापों का उपयोग करते हुए एल्गोरिथ्म विधि के आधार पर तंत्रिका संजाल विकसित किया गया है। भारत मौसम विज्ञान विभाग के उच्च विभेदन बिंब चित्र संप्रेषण केंद्र (एच. आर. पी. टी.) से स्थानीय रूप से प्राप्त किए गए एन. ओ. ए. ए.–16 ए. एम. एस. यू. मापों का उपयोग करते हुए केवल महासागर के ऊपर से लिए गए बिंब चित्रों से प्रायोगिक तौर पर कुल वर्षणीय जल (टी. पी. डब्ल्यू.) की मात्रा ज्ञात की गई है। टी. पी. डब्ल्यू. की मात्रा की पुष्टि रेडियो सौंदे (आर. ए. ओ. बी.) आंकड़ों से प्राप्त किए गए टी. पी. डब्ल्यू. की मात्रा से की गयी है। आर. ए. ओ. बी. से प्राप्त किए गए टी. पी. डब्ल्यू. की मात्रा में प्रभावी और आर. एम. एस. त्रुटियाँ क्रमषः 0.11 मि. मी. और 2.98 मि. मी. पाई गई हैं। एन. ओ. ए. ए. ए. एम. एस. यू. के आंकड़ों का उपयोग करते हुए टी. पी. डब्ल्यू. की परस्पर तुलना एन. ओ. ए. ए./एन. ई. एस. डी. आई. एस. से प्राप्त किए गए टी. पी. डब्ल्यू. की मात्राओं के साथ भी की गई है। इसके अतिरिक्त एन. ओ. ए. ए. ए. एम. एस. यू. आंकड़ों से ज्ञात की गई टी. पी. डब्ल्यू. की मात्रा के उपयोग के मामले का अध्ययन किया गया है। इस मामले के अध्ययन से पता चला है कि क्विकस्कैट स्कैट्रोमीटर से ज्ञात किए गए समुद्री सतह के ऊपर के पवन गति आंकड़ों के संयोजन से प्राप्त अधिकतम वर्षणीय जल की सघनता पष्चिमी भारत के तटीय क्षेत्र में भारी से बहुत भारी वर्षा का पूर्वानुमान करने में काफी उपयोगी पाई गई है। अतः सही समय पर सक्रियात्मक मौसम पूर्वानुमान देने के लिए ए. एम. एस. यू. से ज्ञात टी. पी. डब्ल्यू. को एक महत्वपूर्ण प्राचल के रूप में इस्तेमाल किया जा सकेगा।

ABSTRACT. Total Precipitable Water (TPW) in a column of atmosphere is one of the important parameters useful for a number of meteorological applications. In the present study, a neural network based algorithm has been developed for the retrieval of TPW using NOAA-16 AMSU measurements. The TPW has been derived experimentally using NOAA-16 AMSU measurements locally received from High Resolution Picture Transmission (HRPT) station at India Meteorological Department (IMD) separately over ocean only. The validation of TPW has been carried out against the TPW derived from Radiosonde (RAOB) data. The bias and rms errors against the RAOB derived TPW have been found to about 0.11 mm and 2.98 mm respectively. The inter comparisons of TPW derived using NOAA AMSU data have also been made with that of NOAA/NESDIS derived TPW. Further, case study for the potential use of TPW derived from NOAA AMSU data has been carried out. This case study has revealed that the concentration of maximum precipitable water values in conjunction with high Sea surface wind speed data from Quickscat Scatterometer were found very useful for forecasting the heavy to very heavy rainfall event along the west coast of India. Therefore, AMSU derived TPW could be used as an important parameter for the operational weather forecasting on a real time basis.

Key words – AMSU-Advanced Microwave Sounding Unit, TPW-Total Precipitable Water, Sea surface wind speed, CLW-Cloud Liquid Water, HRPT- High Resolution Picture Transmission.

1. Introduction

The Advanced Tirosn Operational Vertical Sounder (ATOVS) is composed of the Advanced Microwave Sounding Unit (AMSU) and the High-resolution Infrared Radiation Sounder (HIRS/3) and flies on board the National Oceanic and Atmospheric Administration (NOAA) polar-orbiting satellites. NOAA-15 and NOAA-16 were launched on May 1998 and September 2000 respectively. The AMSU contains 20-channels and is a replacement of the 4-channel Microwave Sounding Unit

(MSU) and the Stratospheric Sounding Unit (SSU), which were first launched on TIROS-N in 1978. The AMSU-A is a cross-track, line-scanned instrument (15 discrete frequency channels) aimed at retrieving temperature profiles. It has an instantaneous field-of-view of 3.3 degrees at the half-power points providing a nominal spatial resolution at nadir of 50 km (30 contiguous scene resolution cells). The AMSU-B is a cross-track, continuous line scanning, total power radiometer with an instantaneous field-of-view of 1.1 degrees (at the half-power points). Spatial resolution at nadir is nominally

16 km (90 Earth fields-of-view per scan line). Its purpose is to obtain global data on humidity profiles. It works in conjunction with the AMSU-A instrument. The 12-channels within the 50-60 GHz portion of the oxygen band of AMSU-A are used for Temperature profiles. The AMSU also contains window channels at 23, 31 and 89 GHz to derive a number of hydrological parameters. These parameters include, Total Precipitable Water (TPW), Cloud Liquid Water (CLW), Rain Rate (RR), Snow Cover (SC) and sea ice concentration (SI). These parameters also have been derived using the Special Sensor Microwave/Imager.

India Meteorological Department (IMD) had installed High Resolution Picture Transmission (HRPT) Direct Readout ground receiving station at Delhi and Chennai to receive HRPT data for its operational use and research studies. Recently, the upgraded version of HRPT was installed at IMD, New Delhi to receive the NOAA satellite (K, L and M) ATOVS data in real time. The present paper describes the TPW derived from the Advanced Microwave Sounding Unit (AMSU). The attempt has also been made to compare the TPW derived from AMSU to that of derived from SSM/I, TMI and MODIS. The TPW will also be validated against radiosonde data over Oceanic region.

2. Algorithm formulation

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an expert in the category of information it has been given to analyse. Other advantages include: Adaptive learning: An ability to learn how to do tasks based on the data given for training or initial experience. Self-Organisation: An ANN can create its own organisation or representation of the information it receives during learning time. Real Time Operation: ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability. Fault Tolerance *via* Redundant Information Coding: Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage.

The most commonly used approach for optimizing the neural network weights is called error back propagating (EPB) (Chang and Titterington, 1994). This is a gradient descent approach in which each weight is adjusted adaptively in a way that incrementally reduces the total error in the neural network output. Multilayer
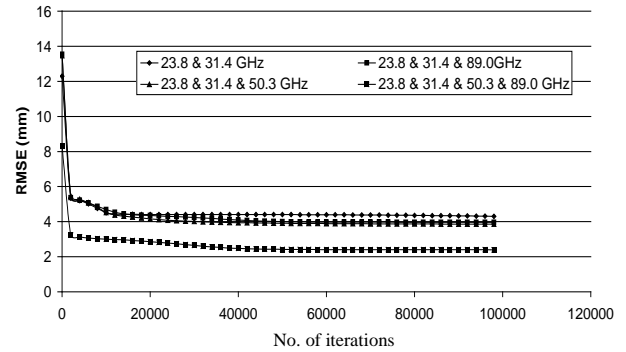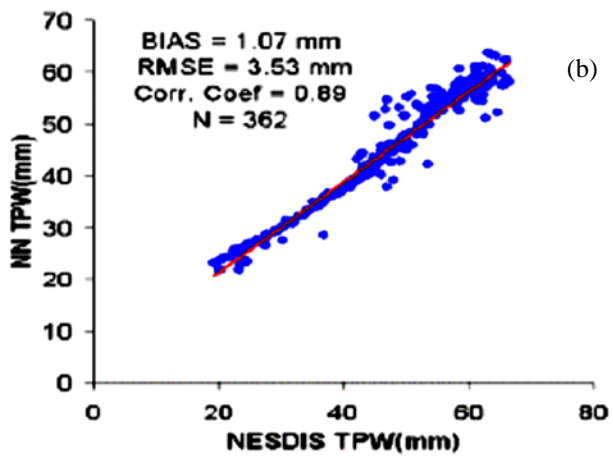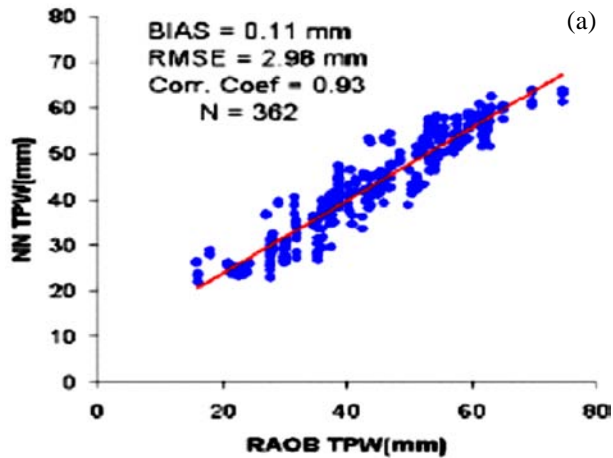

Fig. 1. Root mean square error analysis of limb adjustment of brightness temperatures for AMSU channels.

networks are a variety of learning techniques, the most popular being back-propagation (Miller and Emery, 1997). It minimizes the target output (TPW) and the inputs (function of Tb's) on the data set called training data set using some predefined error functions. The Neural Network algorithm is applied to derive transfer functions relating the AMSU observed brightness temperatures (inputs) to the total precipitable water (output). The training aide involved forward funding of Tb's values in the training set from input layer to the output layer to calculate the total precipitable water on mapping errors. MLP is accomplished by iterative adjustments of the weights associated with each connection in the network. The updating algorithms designed for the MLP is based on the back propagation rate developed by Rumelhart *et al.* (1986), which updates the weights in the network. The Fig. 1 shows the performance of limb adjusted brightness temperatures (Mitchel *et al.*, 2000) as an input during the training period. It has been found that rms error is of the order of 1.89 mm using 23.8, 31.4, 50.8 and 89.0 GHz channels together. Therefore, the combination of all these four channels has been used for the training.
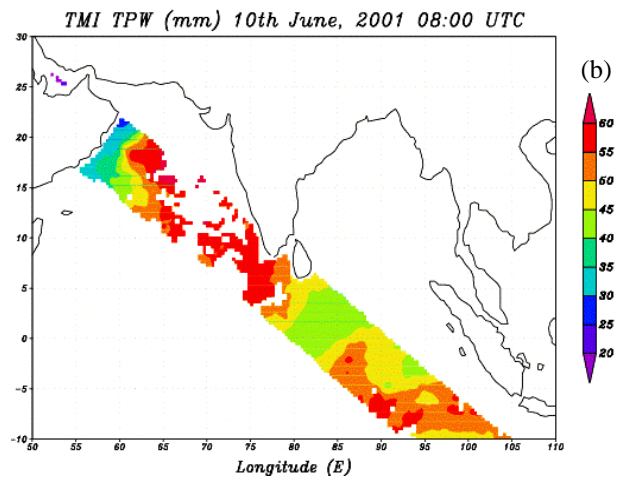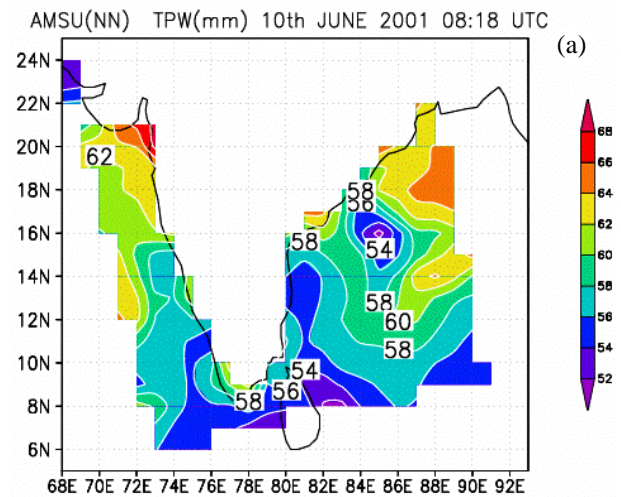
3. Validation of AMSU TPW with RAOB TPW

The AMSU TPW is validated against RAOB data. The TPW has been derived from radiosonde data over Arabian Sea from July 2002 to April 2003. The RAOB data was obtained from monsoon experiment cruise from the Arabian Sea. The match-up data (within ~1 degree of latitude-longitude in space and within +/- 3.0 hour in time) has been accumulated. Since the AMSU TPW is an ocean product, only RAOB data over Ocean have been used for validation in order to avoid land contamination in the AMSU observations. Though this has reduced the number

Figs. 2(a&b). Root mean square error analysis of (a) Neural network and Radiosonde data derived TPW and (b) Neural network and NESDIS data derived TPW

Figs. 3(a&b). AMSU Neural network derived TPW in mm on 10 June 2001 at (a) 0818 UTC and (b) 0800 UTC

of match-up data set and limited the geographical distribution of the match-up sites. However, it provides a more reliable validation data set. To further enhance the quality control, only RAOB profiles with 5 or more levels of good record and without 3 or more levels of lost or bad record under 300 hPa are kept for the validation. Furthermore, only RAOB data under non-precipitating conditions have been used. The match-up data set has been prepared from all AMSU data, which have less than 0.6mm CLW in order to avoid precipitation contamination on the TPW product. The quantitative analysis is shown in Figs. 2 (a&b). The bias and rms error of TPW derived from neural network algorithm to that of radiosonde derived TPW are 0.11 mm and 2.98 mm respectively. Similarly the bias and rms error of TPW derived from neural network algorithm to that of derived by NOAA/NESDIS are 1.07 mm and 3.53 mm respectively.
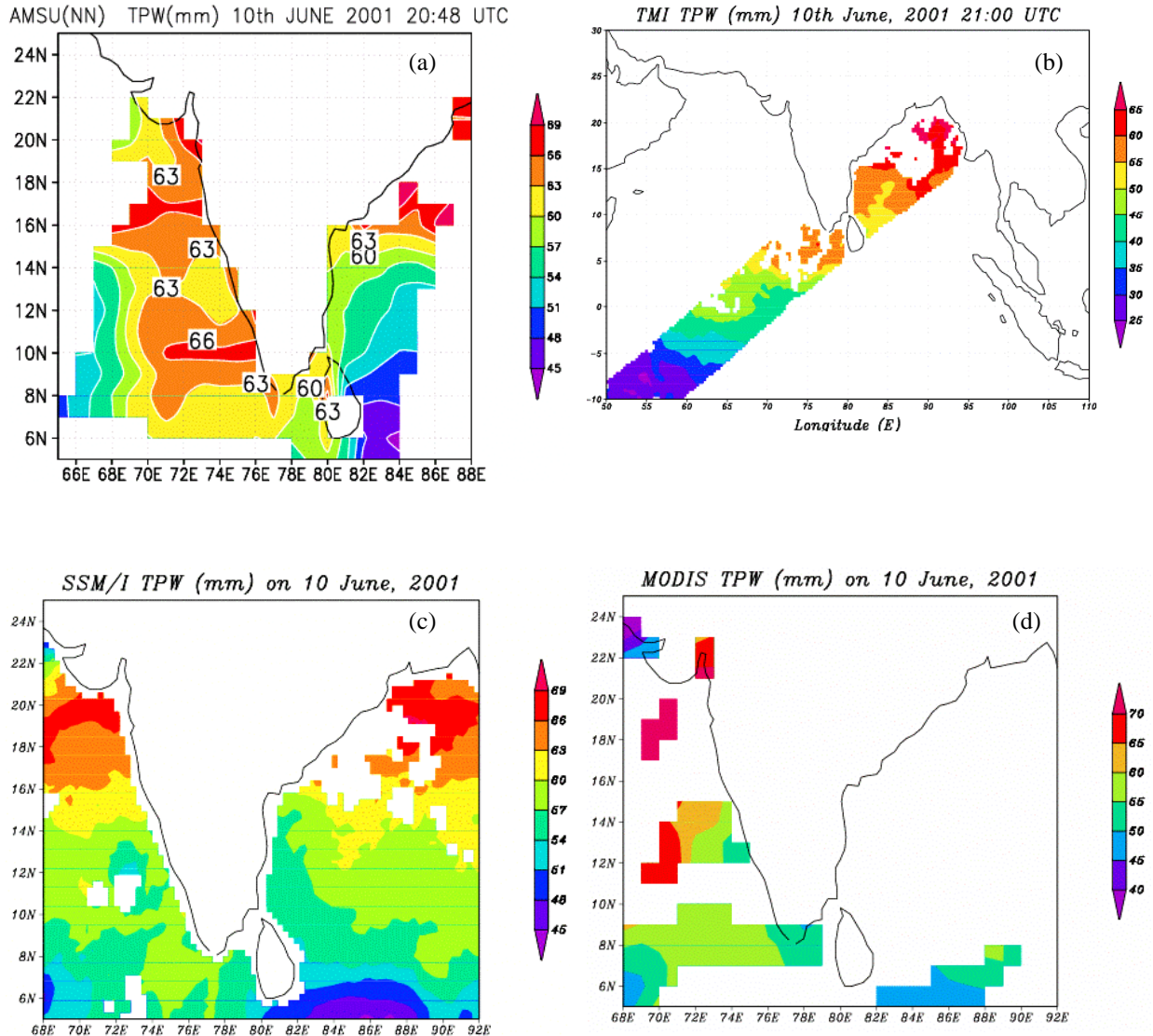
Therefore, it may be stated that neural network derived TPW is in good agreement with that of NOAA/NESDIS derived TPW.

4. Case study

One heavy rainfall event occurred on 11th June 2001 along the west coast of India. The TPW derived from NOAA-16 AMSU using neural network algorithm on 10th June 2001 at 0818 UTC is shown in Fig. 3 (a) and on same date and almost same time TPW from TMI is also shown in Fig. 3(b). Similarly TPW from AMSU and TMI on same date and around 2100 UTC are shown in Figs. 4 (a&b). There were no passes available from SSM/I and MODIS data about that time on 10th June 2001. Therefore, the daily mean of TPW was plotted from SSM/I and MODIS derived TPW in Figs. 4(c&d)

Figs. 4(a-d).   AMSU Neural network derived TPW in mm on 10 June 2001 at (a) 2048 UTC, (b) 2100 UTC, (c) SSM/I derived TPW in mm
                and (d) MODIS derived TPW in mm

respectively. It may be stated TPW from all these instruments are in very close agreements and depicted the high value of TPW along the west coast of India. The Fig. 5 (a) shows the wind speed strength derived from Quick Scat data. The heavy rainfall events took place next day along the west coast of India. The rainfall amounts (cm) recorded by a number of rain gauges in west coast of India on 11th June 2001 are also shown in Fig. 5(b). The several stations in west coast reported heavy rainfall on that day, a few with more than 10 cm. The similar results

were also found out using SSM/I derived TPW (Bhatia *et al.* 2001). NOAA-16 derived total perceptible water (TWP) and Scatterometer surface wind speed have been found to be very useful for forecasting heavy rainfall events along the west coast of India at least 24 hours in advance. These data product can bring out areas of low-level moisture convergence over oceanic region, which are represented by high TPW contents in the atmosphere together with high oceanic surface wind speed. It has been found that TPW of the order of 70 mm accompanied
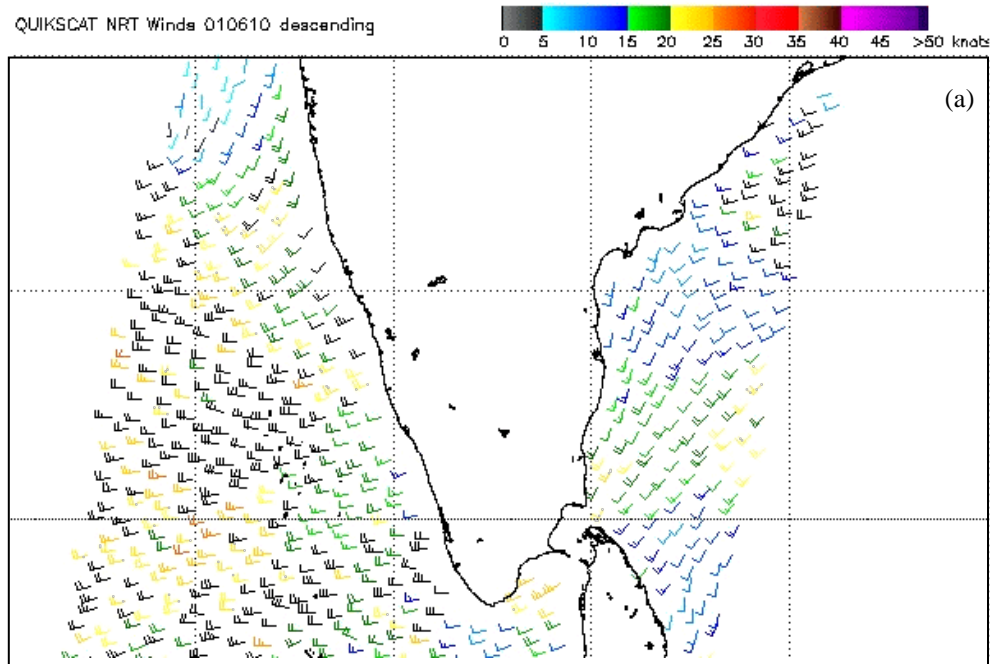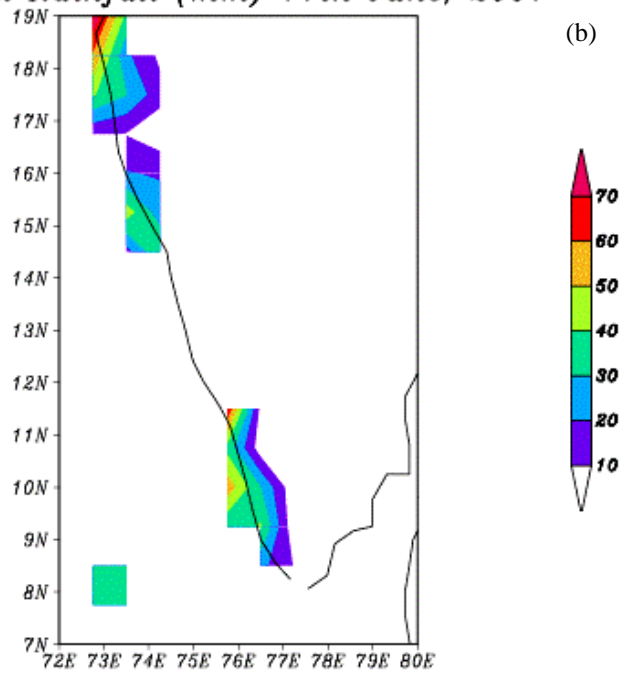
Figs. 5(a&b). (a) QUICKSCAT winds on 10 June 2001 and (b) actual rainfall in mm on 11 June 2001

by favorable wind sped over the eastern Arabian sea is one of the important factor contributing to heavy rainfall during next 24 hrs over the west cost of India and neighborhood. The TPW derived from AMSU measurements have an advantage of being utilized on an operational basis in real time, since AMSU observations from NOAA satellites are received locally from HRPT station at Delhi. However, TPW derived from other instruments is not available in real time and therefore may not be used on a real time operational basis.

5. Conclusions

The neural network algorithm has been developed for the retrieval of TPW using NOAA-16 AMSU measurements. The validation of TPW has been carried out against radiosonde derived TPW. The TPW retrieved from AMSU data over Indian Oceanic region is in good agreements with that of other Instruments and radiosonde data. The major advantage of locally retrieved TPW from AMSU measurements is that it is available in real time compared to the TPW from other sources to be used operationally by the field forecaster and numerical weather prediction centers. TPW along with Sea Surface Winds could be used to forecast heavy rainfall events at least 24 hours in advance.

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