Retrieval of Total Perceptible Water (TPW) From NOAA -16 Satellite Data over Land

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Abstract

Radiance measurements from satellites offer the opportunity to retrieve atmospheric variables at much higher spatial resolution than is presently afforded by *in situ* measurements (e.g., radiosondes). However, the accuracy of these retrievals is crucial to their usefulness, and the ill-posed nature of the problem precludes a straight forward solution. In this paper, an inversion neural network method has been investigated to retrieve Total Perceptible water (TPW), over Iran, from Advanced Microwave Sounding Unit-B (AMSU-B) measurements on NOAA-16 satellite. Because this satellite passes over Iran at approximately the radiosonde launch times, 0000 GMT, collocated radiosonde data were available for training and comparison with the satellite brightness temperature. The collocated radiosonde observations, at 00.00 GMT, and AMSU-B data during 2003 – 2007 are employed to build the neural network training and testing data sets. Overall 1250 days of collocated AMSU-B and radiosonde data were matched in this period. The Root Mean Square Error (RMSE) of TPW retrieved with neural network algorithm is about 3.45 mm and mean bias of 0.86 for entire sounding over Iran land. The RMS errors of the TPW retrieved with the trained neural network are compared with the errors from the multi-linear regression method. It is show that the neural network - based algorithm can provide much better results in the experimental region in all weather conditions.

Key words: AMSU-B, TPW Retrieval Over Land, Remote Sensing.

1. Introduction

The Advanced Microwave Sounding Unit (AMSU) on board the latest generation of the National Oceanic and atmospheric Administration (NOAA) polar orbiting satellite measure outgoing radiances from the atmosphere and earth surface. The second of this new series of satellites, NOAA-16, was launched on 21 September 2000. The NOAA-16 is in a circular sun-synchronous–polar orbit at an altitude of 833 km. the orbit period is 101.35 min, and the equator crossing time is at 0330 local solar time (LST) for ascending node and at 1530 LST for descending node. The AMSU composed of two separate units: AMSU-A and AMSU-B. The AMSU-A consists of 12 channels in the oxygen absorption band (50-60 GHz), one channel at 89 GHz and two lower-frequency channels at 23.8 and 31.4 GHz (Kramer 1996 and Goodrum 2002).The AMSU-A is designed to retrieve the atmospheric temperature from about 3hPa (~45 km) down to the Earth's surface. AMSU-

B module makes measurements in the vicinity of strong water vapor absorption line at 183 GHz and is used for atmospheric water vapor sounding. Thus the use of AMSU (A and B) measurements in operational Numerical Weather Prediction (NWP) models can potentially provide accurate monitoring of both air temperature and moisture profiles with good temporal and spatial resolution.

There are several studies [e. g. Mallet (2002); Singh (2005) and Gairaola (2006)] that have made use of neural networks to calculate Total Precipitable Water (TPW) from satellite Microwave data. Recent efforts to assimilate AMSU radiances over ocean/land are performed at many NWP centers [*TOVS study conference*, 2003]. Over ocean, the AMSU measurements are now routinely assimilated in NWP systems and they provide unique atmospheric profiling capabilities. Over land however, the AMSU measurements are not fully exploited.

Contrarily to the ocean emissivity, the land surface emissivity is high, often close to unity, leading to difficulties in discriminating between surface and atmosphere contributions. In addition, the land emissivity exhibits complex temporal and spatial variations, depending on surface types, roughness, and moisture content, among other parameters. As a consequence an accurate estimate of the microwave land emissivity is a prerequisite for a full exploitation of satellite sounding measurements over land. Recent works focused on the development and analysis of emissivity estimates at AMSU frequencies and observation conditions (*Karbou et al.*, 2004). It is thus now possible to develop retrieval techniques to fully benefit from microwave sounder measurements over land, as it has already been done for microwave imagers [*Prigent and Rossow*, 1999; *Aires et al.,* 2001].

Several retrieval techniques have been developed for moisture (in any form) sounding with the AMSU-B and other microwave radiometer measurements. Rosenkranz (2001) used surface and atmospheric modeling to retrieve temperature-moisture profiles from AMSU data. Kuligowski and Barros (2001) combined the AMSU-A and HIRS channels and used layer-by-layer (LBL) method to retrieve temperature and dew point temperature, at 9 atmospheric levels. A neural network technique has been utilized by Karbou et al (2005) to investigate AMSU atmospheric temperature and relative humidity retrievals capabilities over land and on a global scale. There also are several studies [e. g. Gairaola (2006); Mallet (2002) and Singh (2005)] that have made use of neural networks to calculate Total Precipitable Water (TPW) over ocean from satellite Microwave data. This study presents an approach using artificial neural network (ANN) as the data processing technique for developing relationships between collected AMSU-B brightness temperatures and in situ measurements of Total Precipitable Water.

2. Data

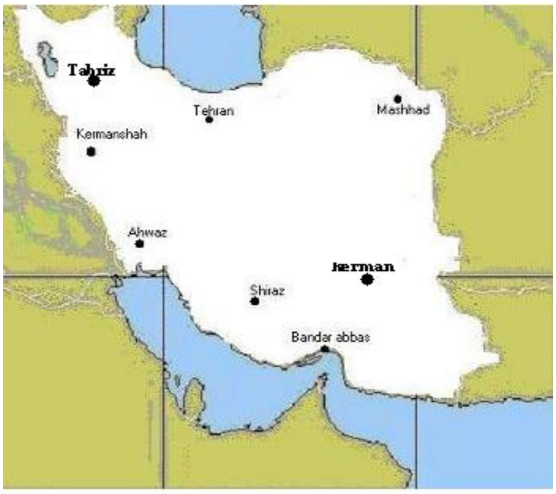
The first stage in developing a Neural Network (NN) retrieval scheme is to obtain a dataset of samples describing the relationships between the inputs (in our case, the satellite observations) and the outputs (i. e., variables to be retrieved, here TPW). For this purpose, AMSU-B measurements and collocated radiosonde observations are selected. Radiosonde measurements were taken from 8 radiosonde stations over Iran (Table 1). Distribution and characteristics of the selected stations are given in Fig. 1 and Table 1, respectively. As can be seen our data are distributed over different parts of county. To include a wide range of TPW conditions, all available coincide AMSU-B and radiosonde measurements (between 2300 to 2400 GMT) from January 2004 to July 2008 have been selected.

The microwave level 1b data from AMSU-B on NOAA-16 satellite have been obtained from the NOAA,s Comprehensive Large Array-data Stewardship System (NOAA CLASS) [NOAA Web Site] and processed using software developed in our department. Because this satellite passes over Iran at approximately the radiosonde launch times at

0000 GMT, collocated radiosonde data were available for training and comparison with the satellite brightness temperature. For selection the AMSU-B data, the procedure is to collect the radiosonde reports for specific station and finding the AMSU-B passes, which cover these reports. Then those AMSU-B passes that fit within the radiosonde measurements are selected. The time difference, allowed, between radiosonde measurements and AMSU-B passes, in this study, is one hour at maximum. To reduce the effects of instrument noise, special averages over a nine pixels area (3×3 pixels) for each AMSU-B channel, whose center was closest to the selected stations (Table-1), were used rather than the individual pixel value. In the experimental period (January 2004 to July 2008), we could get 1250 pairs of corresponding radiosonde observations of TPW and AMSU-B passes, respectively (Table-1).

Table 1 : Station characteristics and no. of data points in each station

Stations	Lat.	Lon.	No. data points
Ahwaz	31.28N	48.72E	179
Bandar Abbas	27.25N	56.25E	26
Kerman	30.15N	56.58E	159
Kermanshah	34.3N	47.06E	75
Mashhad	36.27N	59.57E	240
Shiraz	29.63N	52.57E	195
Tabriz	38.5N	46.17E	178
Tehran	35.67N	51.43E	198
Total			1250



3. Neural Network

An artificial neural network (ANN) may view as a mathematical model composed of many non-linear computational elements, named neurons. Neurons are connected in parallel by links characterized by different weights. An ANN may consist of multiple layers of interconnected neurons. Each layer is referred to as an input layer, a hidden layer or an output layer. An ANN is mainly specified by its topology, namely, the number of input, output and hidden neurons and their interconnection, neuron characteristics and training or learning rules (Lippman, 1987). For this study a three-layer feed-forward back-propagation neural network is used (Fig. 2). It consists of three layers of fully connected neurons. Each hidden or output neuron in the network receives a "signal" from each neuron in a previous layer; these signals are summed and are fed in an activation function to produce a single output signal for that node (Fig.2). The sigmoid function was chosen as the activation function for all the neurons in the hidden layer, given by

$$f(x) = \frac{1}{1+e^{-x}}$$

And the linear function is used for the input and output layers. The sigmoid activation function squashes the input which may have any values between plus and minus infinity, to yields these values in the range [0,1]. The ANN is designed to approximate an unknown input output relation by determining the weight and strength of each connection via learning rules. These rules indicate how to pursue minimization of the error function measuring the quality of the network's approximation on the restricted domain covered by a training set. In present case the error minimization is done using the back propagation algorithm (Rumelhart et al. 1986), which uses a gradient search technique and iteratively adjusts the weight coefficients in the network to minimize an error function equal to mean square difference between the desired and the actual net output.

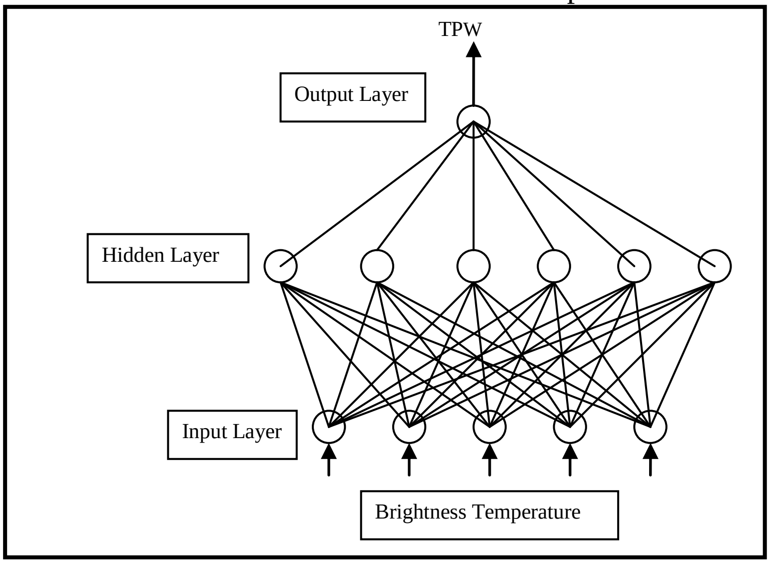


Fig.2 : A neural network architecture conecting inputs (brightness temperatures) and output (**TPW**).

A natural variability of the parameters or uniform one is desirable. But dataset is expected to be representative of natural seasonal variability of the parameters to be retrieved. In such dataset a great number of data have medium values and few data have extreme values. An ANN algorithm developed on such a natural dataset will lead to good performance for medium values but it unable to approximate the inverse transfer function for extreme values. In fact, the lack of samples, these extreme values will not be learned correctly during the training stage. Our aim in this study is to build an algorithm capable of giving the same accuracy over the whole filed of values. We selected 1250 days to create the two necessary dataset (Table 2) in which all range of TPW are presented with similar proportions.

Table 2 : Maximum and minimum of TPW values and number of training and testing data points.

Data points	TPW_{min}	TPW_{max}	No. of data points
Training data	0	34.02	1000
Testing data	0	31.1	250

4. Research Methodology

As mentioned above, ANN must be trained for processing inputs before they can be applied. The first task is to create training datasets. For this task the brightness temperatures from AMSU-B on NOAA-16 satellite and the TPW from the radiosonde measurements, over all available stations in Iran(table.1) have been used. In neural network training, it is usual to split the available data between the training and the validation dataset. In our case, 4 out of every 5 patterns (80%) have been randomly extracted for the training dataset and 1 out of every 5 patterns (20%) has been randomly extracted for the testing as well as validation dataset (Table 3). The training dataset consists of input and output pairs of typical brightness temperature and corresponding TPW. A test dataset, used for evaluating the training performance of ANN during the training phase, was also prepared. Ideally, a validation dataset is used to measure the generalization capability of a trained ANN for actual use; therefore it should be completely independent of the data used for training and testing. For TPW retrieval, because of insufficient coincident TPW and AMSU-B measurements, testing dataset also used for validation.

Table-3: The ANN structures, the number of Training, Validation, as well as total patterns.

ANN	ANN structure	Training DATA	Testing data	Total data point
ANN	5-4-1	1000	250	1250

Once the training datasets have been generated, the Stuttgart Neural Network Simulator (SNNS) version 4.2 is used to train the neural Networks. SNNS program is freely available in http://www.ra.cs.uni-tuebingen.de/SNNS/. Between all neural network types, the Multilayer back propagation has been selected as being the most adequate.
For selecting the inputs, correlation coefficient between TPW and brightness temperature of AMSU-B channels [89, 150, 176.31, 180.31, and 182.31 GHz], as well as brightness temperature differences of AMSU-B channels [$(T_B)_{150}-(T_B)_{89}$, $(T_B)_{176}-(T_B)_{89}$, $(T_B)_{180}-(T_B)_{89}$ and $(T_B)_{182}-(T_B)_{89}$] were analyzed to evaluate the influence of each variable on TPW (Fig. 2). Finally, the 5 variables, with highest correlation [1-$(T_B)_{89}$, 2-$(T_B)_{150}$, 3- $(T_B)_{180}$, 4- [$(T_B)_{89-180}$], 5-[$(T_B)_{89-180}]^2$] have been selected as input variables (Fig. 3). Several neural network structures (1 to 3 hidden layers) were trained to find the most appropriate topology. The best architecture consisted of three-layer network with 5 neurons in the input layer, one hidden layer with four neurons, and one neuron in output layer (5:4:1). The training cycle involved forward feeding brightness temperature values in the training set from the input layer to the output layer to calculate the TPW mapping errors. The training occurs in a supervised manner and involves the development of a training data, for a maximum of 30000 iterations. Sigmoid and linear activation functions were used in the neurons of the hidden layer and output neuron, respectively. The selection of the network was performed considering a minimum value of RMSE for the validation dataset.

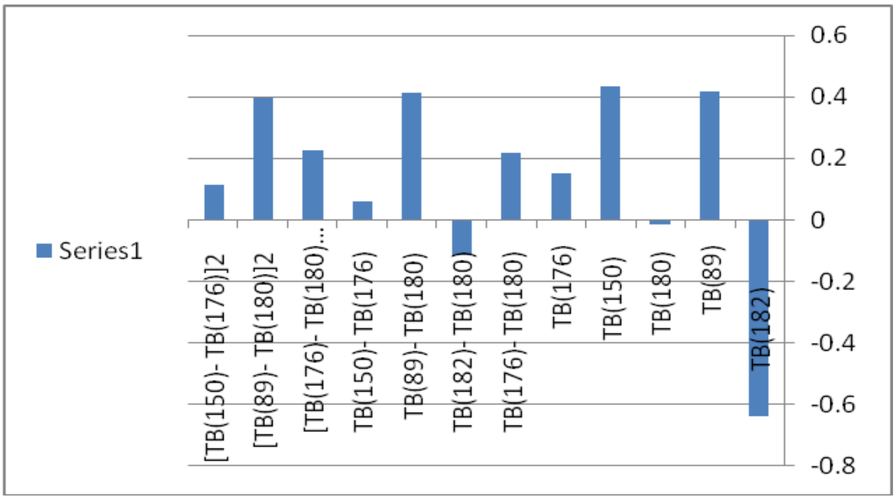


Fig.3 : Correlation coefficients of input variables for selecting proper inputs for TPW estmating.

A graphical representation of the observed and estimated TPW values for the training datasets are given in Fig. 3. It can be seen, from the Figure, that for most of the training days the estimated TPW values are close to the observed values. The TPW are mostly over estimated at the beginning of training days, which may be dew to low training data with these cloudy conditions as reported by Iran meteorology organization.

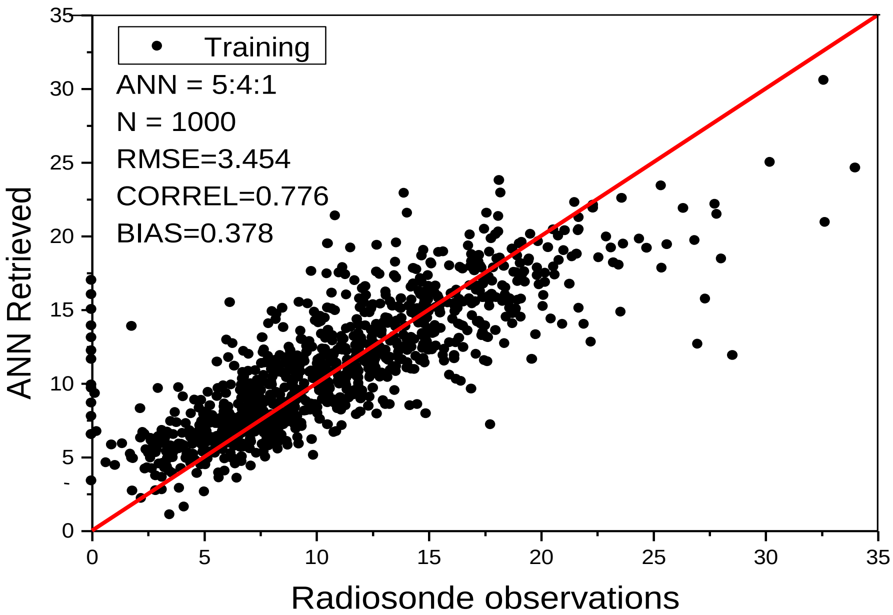


Fig.3: The scatter plots of TPW for the training data.

The graphical comparisons of observed and estimated TPW values, for 250 testing days, are also presented in Fig. 5. As it can be seen the network can perform well over testing dataset.

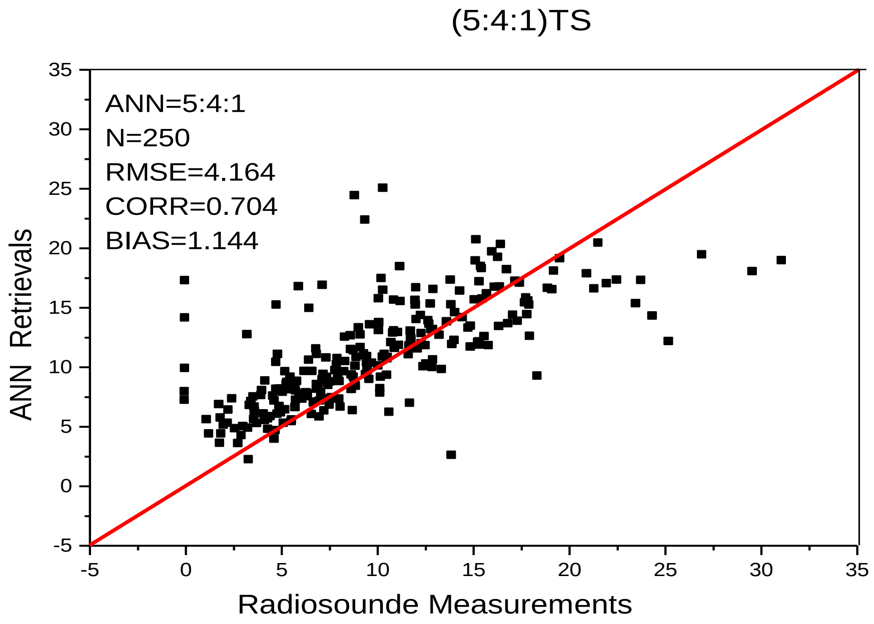


Fig.4: TPW scatter plots for the testing data.

To make the comparison more robust, various statistics, mean and standard deviation (SD) of observed and estimated values of TPW, Correlation coefficient (CORR) between observed and estimated values, the Root Mean Squared Error (RMSE), Mean Bias Error (MBE) Mean Absolute Error (MAE) and Index of Agreement (R), for the training and testing data sets, were calculated and summarized in Table-3. The purpose of calculating this spread of verification parameters is that no single verification parameter is ideal for all purpose. For a good estimation the estimated means and the standard deviations should be close to the observed means and standard deviations, the RMSE should be small, CORR should be close to one. All of these statistics are shows a good TPW estimate using ANN.

Table 3: Various statistics for the training and testing data sets

Statistics Variables	Mean observed	Mean estimated	SD observed	SD estimated	CORR	RMSE	MBE	MAE	R
Training	10.848	11.226	5.44	4.16	0.776	3.454	0.378	2.500	-0.389
Testing	10.21	11.073	5.56	4.35	0.704	4.164	1.144	2.912	0.948

As can be seen from these statistics, the AMSU-B observations have a good ability to measure the TPW with a RMS error of 3.454 mm. Because of data unavailability, the ANN model was trained and validated using limited data. Therefore, the model is currently may not be able to estimate and account for seasonal shift in meteorology regimes. The work is going on using more extensive and varied datasets for training and validation of ANN.

The performance of the neural networks is good in some extend and the low spread suggests that this kind of ANN algorithm could be developed for the AMSU-B instrument.

5. Conclusions

We have developed a neural network method for estimating TPW from AMSU-B brightness temperature data over land in the Iran country. In the region where we tested our model it preformed reasonably well. Therefore it may be useful as an interpolation aid to estimate the TPW field for Iran, where ground observation stations are very limited. The process followed in this paper can be repeated with slight modifications to train neural networks for other parameters, such as liquid water path (LWP),Ice water path(IWP), etc.

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