

Assessment of Precipitation Characters between Ocean and Coast area during Winter Monsoon in Taiwan

Peter K.H. Wang

Central Weather Bureau

Abstract

SSM/I has been applied in derivation of liquid water and precipitation for many years. Due to the uncertainty in variance of surface emissivity and characters of precipitation, the comparison of rainfall retrieval with ground truth remains a controversial issue. In order to investigate this issue, data set for precipitation from stratus clouds over ocean area were collected for 5 years. Each data set is collocated with satellite observation and ground truth. Neural network is applied to estimate precipitation. Comparison between retrieved rain rate and surface ground truth was made. Based on the analysis, the wind speed does not appear to have close correlation with precipitation. Mean value of precipitation is consists with ground truth, but most of the heavy precipitations are not captured by the estimation. The best result is obtained by using all 7 channel observations and polarized corrected temperatures to estimate precipitation.

Introduction

The SSM/I measurement has been used to retrieve precipitation though many different methods. A comparison of several algorithms was presented by Marzano (2004). In general, validation of the retrievals over ocean has been studied. In this study, we selected rainfall measurement from a small island to provide data for ocean condition. Most of the measurements are rainfall from stratus clouds with uniform precipitation. A non-linear statistical algorithm – neural network is applied in this research. The relationship between rain and wind speed was also investigated in this research.

Data

Weather station 46695 is located on an island in East China Sea, 60km north of Taiwan. Fig. 1 shows the location of this weather station. The period from November to March is the northeast monsoon season in Taiwan, with most days raining during this period (see Fig. 2 for winter monsoon circulation). Raining cloud type is stratus cloud and raining area is more uniform than cumulus cloud rain type, unless cold front is coming. Fig. 3 provides an satellite image of a typical winter monsoon raining event. SSM/I data for Taiwan from

Nov. 2000 to Mar. 2005 were collected. Each co-location of data includes 7 brightness temperatures of SSM/I channels and surface rain rate estimated by Area Time Integration (ATI) method. (Kedem,1990). Polarized Corrected Temperature (Spencer, 1989) of SSM/I is also included for consideration in precipitation retrieval.



Fig1. Position of 46695.



Fig.2 Winter monsoon area in East Asia.

Algorithm

Neural networks have been used in a variety of meteorological applications. An early study by Stogryn et al. (1994) retrieved ocean surface wind speed from SSM/I observation based on a neural network technique. Shi (2001) retrieved atmospheric temperature profiles from NOAA-15 Advanced Microwave Sounding Unit measurements (AMSU) by using neural networks applied to regional direct acquisition and global recorded AMSU-A data. Similar structures of neural networks as used by Shi (2001) are applied in the current study to derive rain rate from SSM/I data.

Data for the neural network training dataset were divided into groups according to the following situations. 1) Rain, no rain, or both; 2) day time, night time, or whole day; 3) SSM/I 7 channels; 4) PCT of SSM/I in 3 frequencies; 5) surface wind speed; 6) surface temperature. Combination of above parameter by different assembly may make a few data sets for Neural Network training.

Back propagation neural networks are used in developing the retrieval scheme. A back propagation neural network is a computer model composed of individual processing elements called neurons. A network consists of multiple layers of neurons interconnected with other neurons in different layers. These layers are referred to as input layer, hidden layer, and output layer. Each layer is generally fully connected to the layers below and above. A three-layer network,

with one input layer, one hidden layer, and one output layer, is constructed for the rain rate retrieval. It is found that using a Gaussian function to propagate to from the input to the hidden layer and a logistic transfer function to propagate to the output layer gives the best network performance for the type of data studied. The definition of the Gaussian transfer function is

$$f(x) = \exp(-x^2), \quad (1)$$

and the definition of the logistic transfer function is

$$f(x) = \frac{1}{1 + \exp(-x)}. \quad (2)$$

The number of neurons in the hidden layer varies between 40 and 60 and the number is adjusted to optimize the performance. The input set includes the seven SSM/I channels, three PCT values, and the surface skin temperature.

Among the collocated patterns, 20% are randomly extracted to construct a testing set, and another 20% are randomly extracted and set aside as a validation set for later statistical studies. A back propagation network is trained by “supervised learning”. The network is presented with a series of pattern pairs, each consisting of an input pattern and an output pattern; in random order until predetermined convergence criteria are met. At this time the network presents the input elements in the testing set and retrieves the output elements. Then the retrieved output elements are compared with the output elements in the testing set, and the averaged root mean square (rms) errors of all the output elements are computed. The network parameters are saved if the averaged rms error is less than that computed previously. This process is repeated until no improvement is found for a specified number of test trials. The network parameters are then saved as the retrieval function.

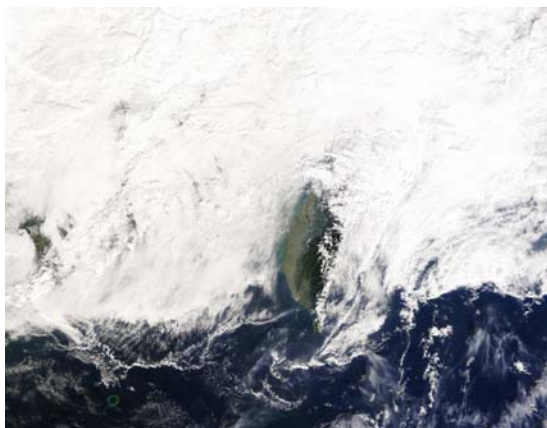


Fig. 3 Most of the winter season, in northeast area of Taiwan is covered by cloud and rainfall all day.

Analysis

In the dataset, the surface wind speed is derived by the algorithm of Hollinger(1989) from the SSM/I measurement. Liquid water content (LWC) estimation was also made from the algorithm of Hollinger (1989). Five-year data were used. The comparison between estimated wind speed, LWC and surface observations are shown in Fig. 4. Small wind speed has more ambiguity distribution. LWC is related to wind speed. High wind speed may caused by higher LWC.

Figs. 5 and 6 show comparisons of estimated precipitation with surface observation. Retrieved rainfall data during day with 3 PCT values show that estimated precipitation values are less than observed values. Estimated rain rate at night has similar characteristics. Retrieval precipitation without PCT shows that rain rate is over estimated.

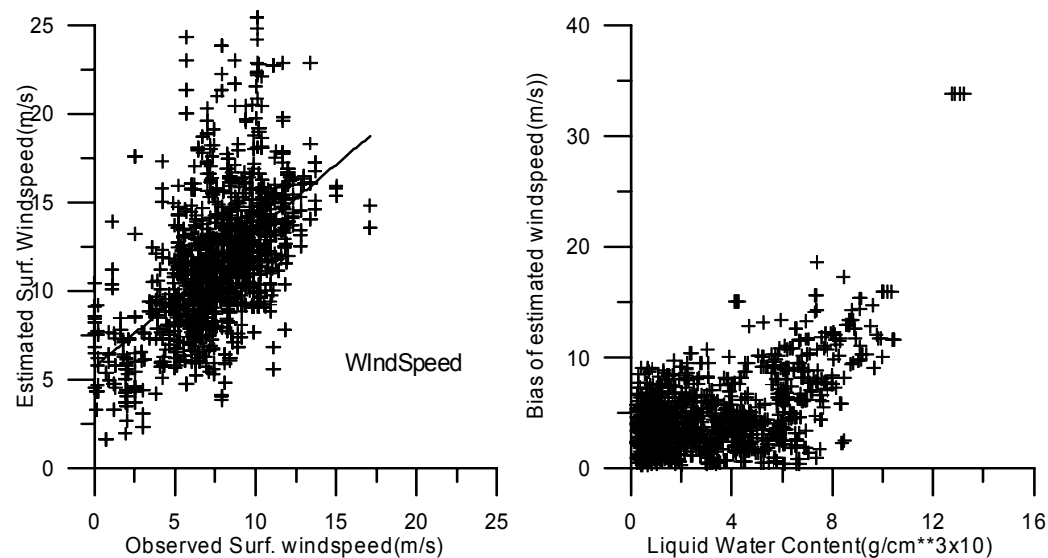


Fig.4 Estimated wind speed (left) and liquid water content (right) compare with surface observation in past 5 years.

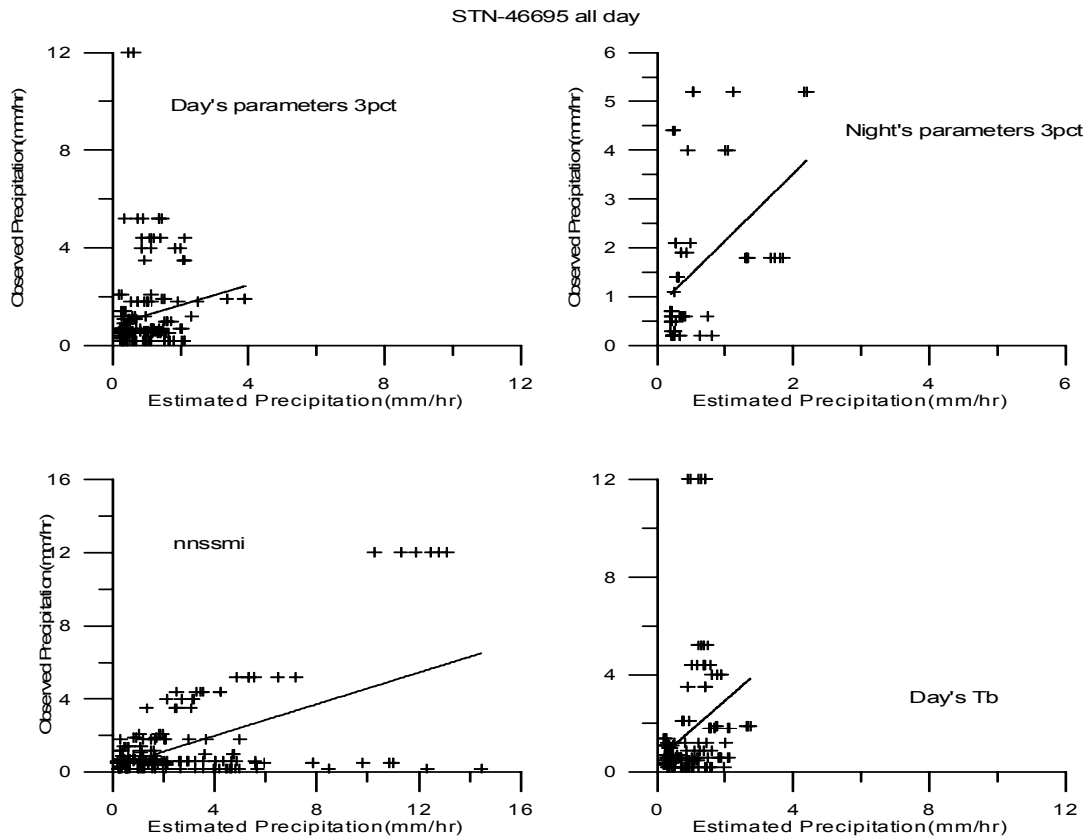


Fig. 5 Comparison between estimated precipitation from neural network and ground truth data by different data set.

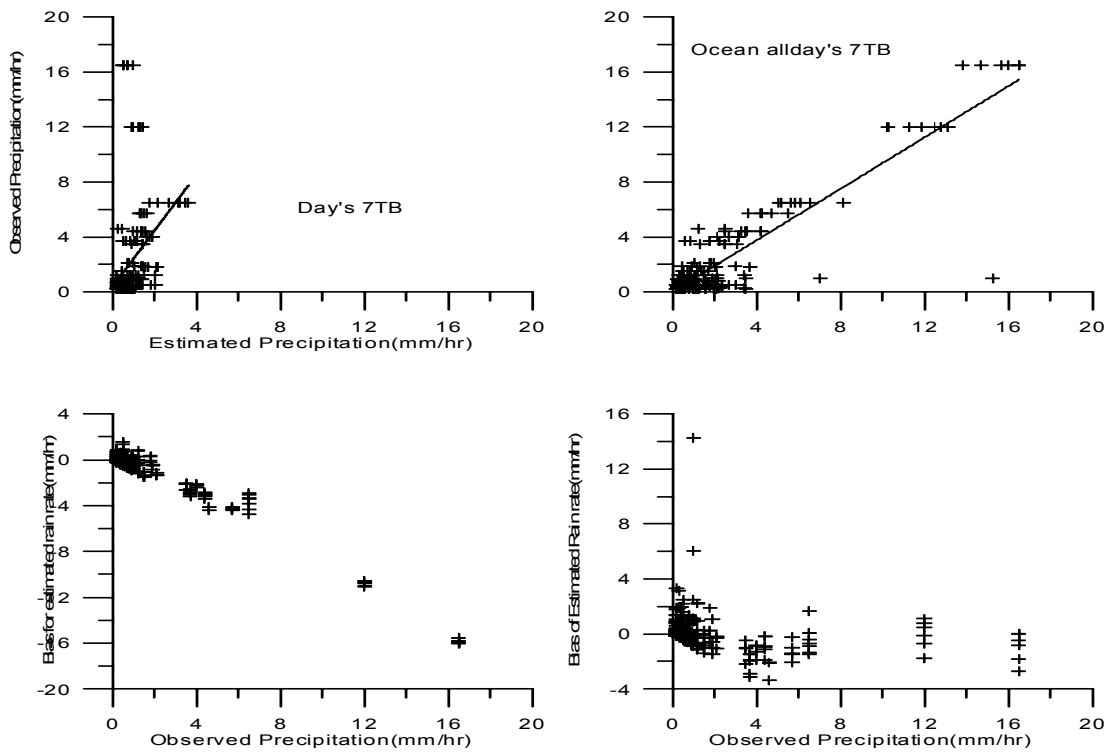


Fig. 6 Comparison between estimated precipitation and observation by different input data set in neural network.

Whole day data set not classified into day or night has better correlation between estimated and observed rain rate. For day and night data sets, the correlation between estimated and observed precipitation are less than the whole day data set (Table 1).

Table 1. The correlation between estimated and observation using different input values of neural network.

Input data set	Day All	Day 7TB	Day 2PCT	Day PCT85	Day 7TB	Night All
Correlation	0.16	0.255	0.439	0.268	0.367	0.519

Retrieved precipitation of SSM/I do not appear to be suitable to serve as climate data reference. The 5 year data set is not enough to describe the variance of precipitation inclination. Table 2 shows the total volume of SSM/I data set.

Table 2 Total precipitation (mm) from year 2000-2004

Seasonal	2000	2001	2002	2003	2004
Ground obs.	652.5	432.1	390.5	460.3	670
No of Sat day	20	44	103	106	94
Est. Rainfall	203	234	746	799	661

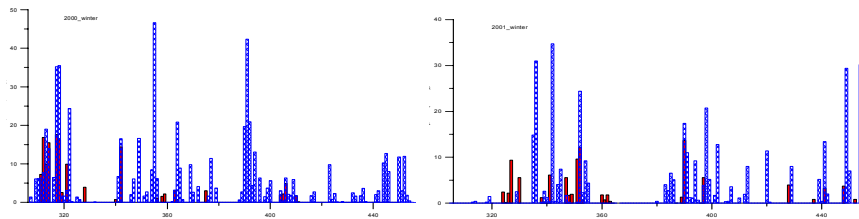


Fig.7a Year 2000-2001

Fig.7b Year 2001-2002

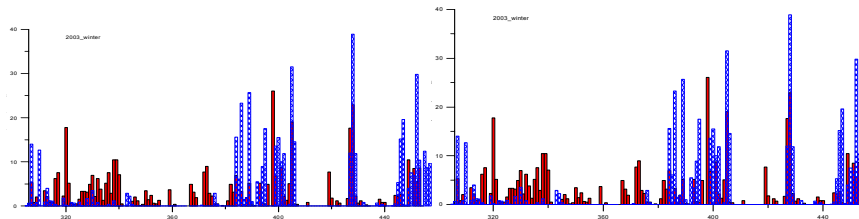


Fig.7c. Year 2002-2003

Fig.7d. Year 2003-2004

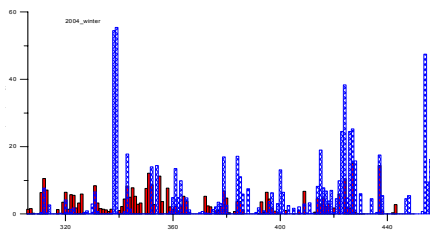


Fig 7e. Year 2004 to 2005.

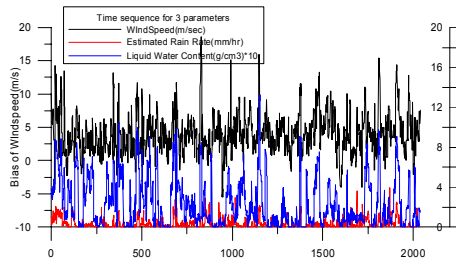


Fig. 8 Upper black line is wind speed, middle blue line is LWC, bottom red line is precipitation. Data are from NOV/2000 to MAR/2005,

In fig. 7, surface precipitation values are plotted as blue column and estimated precipitation values are plotted as red column for each winter season from 2000 to 2004. Most of the heavy rainfall data appear not to be captured. Because of the large time gaps between each satellite observations in a day, the correlation between hourly rain rate from satellite and 24 hours precipitation needs further investigation. The bias of wind speed retrieval is very correlative to LWC and it has little correlation with rain rate.

Conclusion

Over the 5 years analyzed, retrieved precipitation from SSM/I using neural network provides a reasonable estimates for all day whole weather condition, However, the extremely precipitations were not sufficiently identified in the retrieval. Generally speaking retrieval rain rate from satellite is smaller than ground truth. Because of the satellite path passes over one location only twice a day, it may have missed many rainfalls during a day. Taking the mean value of satellite retrieved rain rate to obtain a day's precipitation needs further investigation.

Rainfall retrieval by neural network over all day's ocean area is the best one. If data set is divided as day and night two parts, the bias increases. The bias of estimated rain rate increases with rain rate. The correlation between hourly rain rate from satellite and whole day's precipitation need further investigation. The bias of wind speed retrieval is very correlative to LWC but it is not so much correlation with rain rate. Retrieved surface wind speed is higher estimated than ground truth about 5 m/sec. The difference is larger with higher wind speed and LWC. For this small island station, it is not clear how much the local Land Ocean thermal wind has on precipitation.

Acknowledgements: Lei Shi of NOAA's National Climatic Data Center provided assistance in neural network training.

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Proceedings of the Fourteenth International TOVS Study Conference

Beijing, China
25-31 May 2005

