

ABSTRACT

This poster investigates the problem of estimating sea surface rainrate using only Ku-band satellite scatterometer data by employing artificial neural network methods. All data is coming from the ADEOS-II satellite mission which generates collocated scatterometer and radiometer data needed to train and test the neural network algorithms. The main goal of this work is to produce useful algorithms to estimate rainrate from future satellite missions using scatterometer data alone.

Recent studies [2, 3] used neural network methods to derive wind speeds from scatterometer data. Their goal was to produce more accurate estimates of wind speed in the presence of rain and/or in extreme wind conditions. They used hierarchical NNs trained with satellite generated backscatter measurements in each wind cell, wind speed and direction, and cross-track distance. In the low-wind speed range the NN gives two to three times better estimates than existing methods in both rain and no-rain conditions, while in high-wind speed range the NN performs slightly worse in no-rain situations. The new method in [3] aims at improving the wind estimates in high-wind conditions such as those encountered in tropical cyclones.

Neural networks have been used before to estimate surface rainrates. For example, Ghosh et al. [1] trained NN models with OSCAT-2 data (NRCS and brightness temperature) with external sources of rain data for calibration coming from TRMM and AMSR-E satellites. Their purpose was to estimate rain effects (rain flag or rain rate) or to account for rain effects in wind estimates. Their method was applied to global rainfall estimates on regional and seasonal scales.

In this presentation we show results obtained with NNs trained with data from the ADEOS-II NRCS (SeaWinds) and rainrate (AMSR) data. The inputs in the NN are the mean and variance of the four NRCS measurements in each wind cell (H- and V-pol, and their azimuth parameters), their relative position in the 1800 km satellite swath, SRAD, and wind speed. The input measurements are readily extracted from the L2A and L2B standard products, for approximately 6 months. The AMSR rainrate product here is collocated and coincident with NRCS and wind data and is ideal for training the NN.

OBJECTIVE

The main goal of this work is to investigate whether rain estimates from satellite data can be improved. Current rain estimates, such as SRAD result in approximately 76% of data points with relative errors bigger than 20% from the independently measured AMSR rate and with 10% of the data with errors greater than 100%. ADEOS-II data provides a unique collocation of scatterometer data with AMSR measure rain rate. We propose to use NN to estimate rain rate with AMSR values used for training purposes. Once the NN is trained, its parameters can be used for independent rain estimation from just satellite data.

METHODS

In our current approach we divide the estimation problem into a 2-step classification and estimation problems using a hierarchy of two feed-forward NNs. Figure 1 shows the diagram of the model:

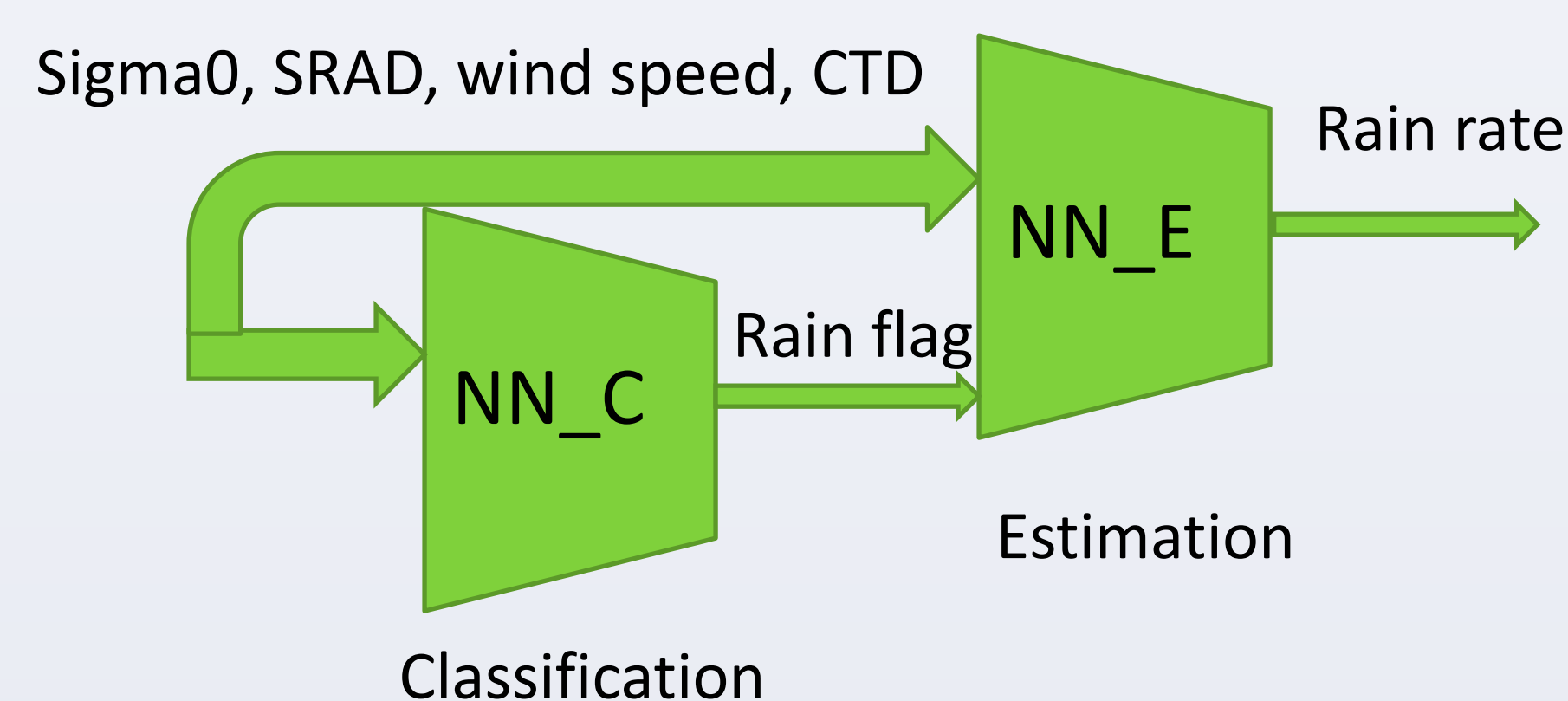


Figure 1: Rain rate estimation model

The first NN (NN_C) receives combined satellite generated input such as sigma0, SRAD, wind speed and CTD. The NN_C output produces a rain flag, which is 1 if the input corresponds to rain or 0 if no rain. The second NN (NN_E) takes the input from NN_C only in case it is deemed rain by the NN_C. The output of the NN_E is an estimate of the rain rate in mm/hour.

A simpler model would use only one NN estimating the rain rate for both rain and no rain points. The main reason for choosing a two network architecture is that satellite data is dominated by no rain (over 80%). We also hypothesized that the estimation of rain rate for rain points only might increase the precision of the estimates.

ADEOS II DATA

The ADEOS II NRCS and rain rate (AMSR) values were extracted between February 2003 and October 2003. The data comes from the following data collections: SeaWinds L2A (sigma0), SeaWinds L2B (wind speed), and AMSR L2B. We only kept the measurements from a region around the equator. All variables were averaged in 25 km square cells. The remaining data consists of approximately 13 million points of: collocated average sigma0 both H- and V- pol and their azimuth parameters, average wind speed, CTD, SRAD and AMSR rain rate values. Figure 2 contains plots of sigma0: inner and outer aft, wind speed, and SRAD as a function of AMSR rain rate:

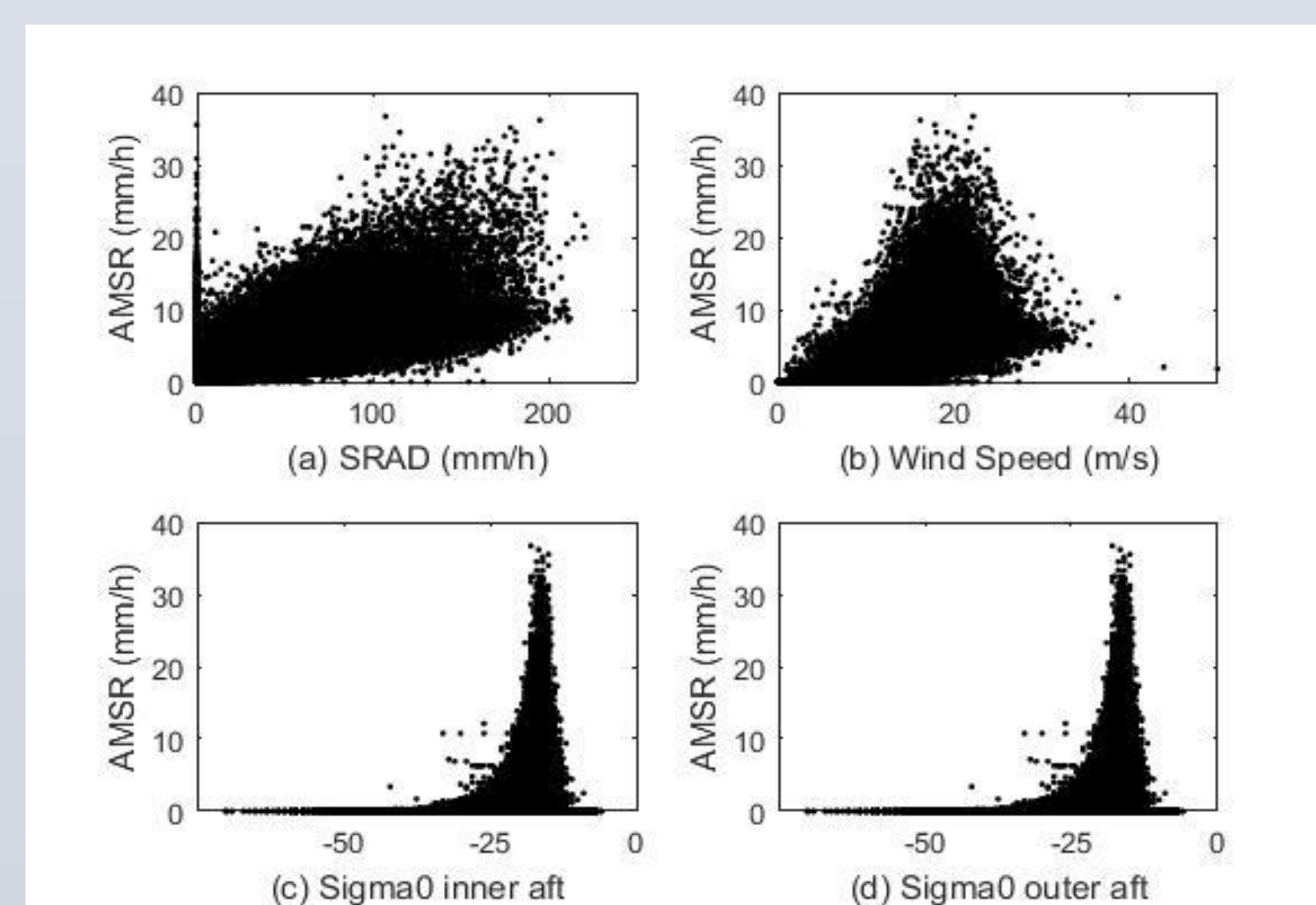


Figure 2: AMSR rain rate as a function of: (a) SRAD, (b) Wind speed, (c) sigma0 inner aft and (d) sigma 0 outer aft

The data was preprocessed as follows: SRAD was divided by 10 to approximate better the AMSR values, sigma0 was brought to the positive range by adding a constant, and the absolute value of CTD was taken. All data was then normalized in the [0, 1] interval before being used in the NN training.

Results

Classification: To train the classification network (NN_C), the data was separated into two sets, the rain points with an AMSR rain rate greater than 1 mm/h and the no rain points that have lower rain rates. The training data consisted of all rain points and an equal number of randomly chosen no rain points. The target of the NN_C is a two value vector with one value indicating rain and the other no rain. From all data points, 15% were randomly chosen for testing purposes only. Multiple NNs were trained with one or two hidden layers and the misclassification rate on the testing data was measured. We trained several NNs using all 7 inputs (four sigma0, SRAD, wind speed, CTD), or just the four sigma0 and the SRAD.

The best error rate was obtained using all inputs with a NN with two hidden layers with 10 and 7 neurons in each respectively. The overall misclassification error was 6.70% composed of 4.22% error from rain points classified as no rain and 2.48% error from no rain points classified as no rain points. The mean AMSR rate for the misclassified rain points was 1.61 mm/h and the mean AMSR rate for the misclassified no rain points was 1.52 mm/h. The mean wind speed for both rain and no rain misclassified points was around 9.5 m/s. The mean wind speed for all data points in the set is 6.57 m/s. It can be observed that the network is able to classify rain and no rain points fairly well with errors in the low rain rate and high wind speed. Figure 3 shows the AMSR rate versus wind speed for all testing points. The red points are the misclassified points in between the correctly classified rain and no rain points.

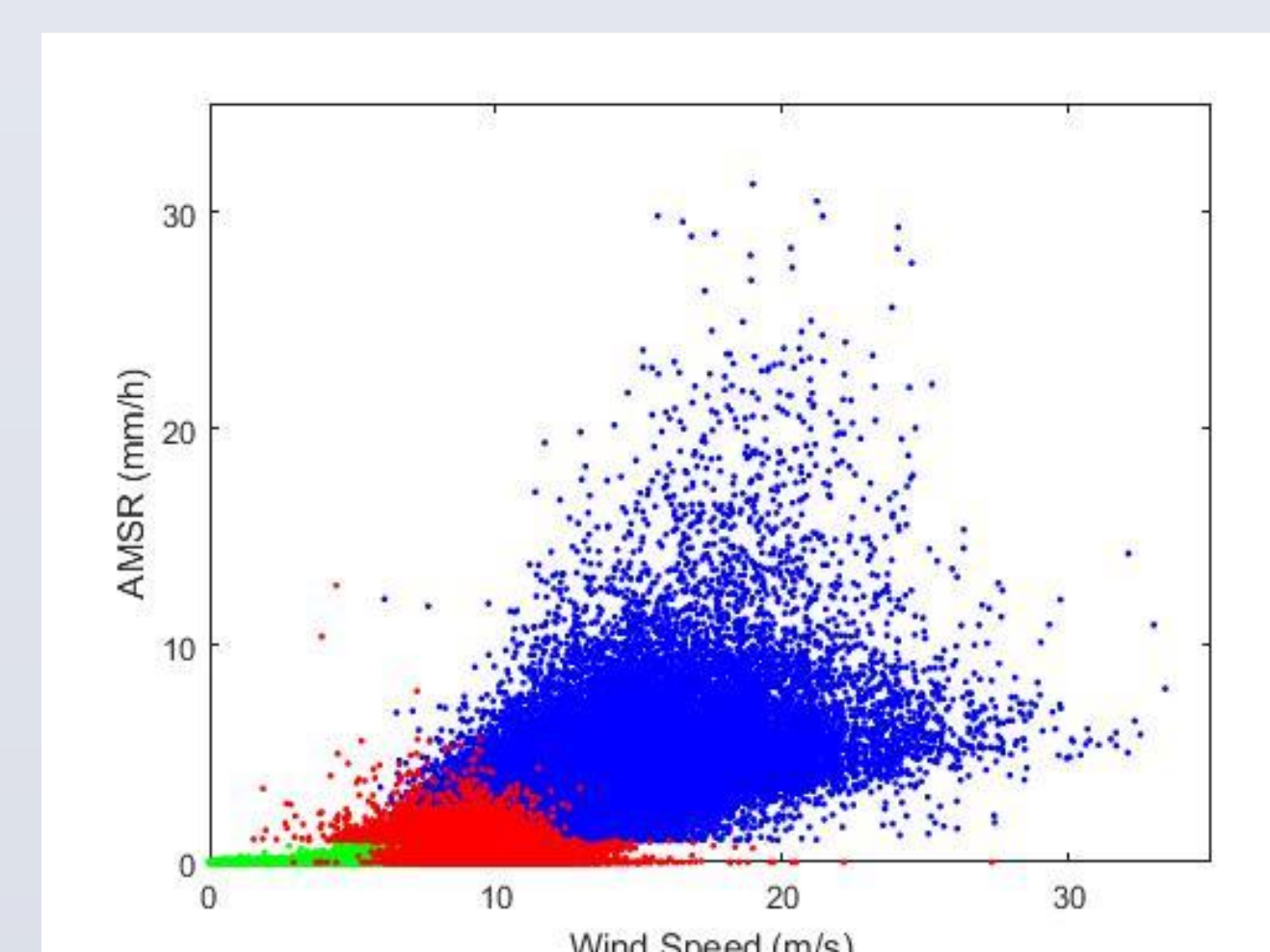


Figure 3: Classification results: red points – misclassified, blue points – rain, green points – no rain

Estimation: The NN_E network was trained with all rain points from the original data set (AMSR > 1 mm/h). We trained several NN with different number of hidden layers and number of hidden neurons. The best result was obtained using all rain points was with a two hidden layer NN with 20 and 10 hidden neurons. The mean square error (MSE) for the testing data was 2.64 with 1.46% of the testing points having an absolute error compared to the target AMSR value larger than 5.

To compare the SRAD with the new estimate produced by our model we looked at the relative absolute error for all testing points:

$$RelError_{NN} = \frac{abs(AMSR - y_{NN,E})}{AMSR}$$

$$RelError_{SRAD} = \frac{abs(AMSR - SRAD)}{AMSR}$$

The mean value of RelError_{NN} is 0.37 or 37% off the AMSR target while that of RelError_{SRAD} is 0.56 or 56% off the same values. There are 62.85% of testing points with RelError_{NN} > 0.2 while there are 77% of testing points with RelError_{SRAD} > 0.2 or 20% off the target values. We can conclude that the NN output estimates slightly better the AMSR rain rates than SRAD.

Figure 4 shows a comparison of the NN_E output ($y_{NN,E}$) and AMSR values versus wind speed on the testing points.

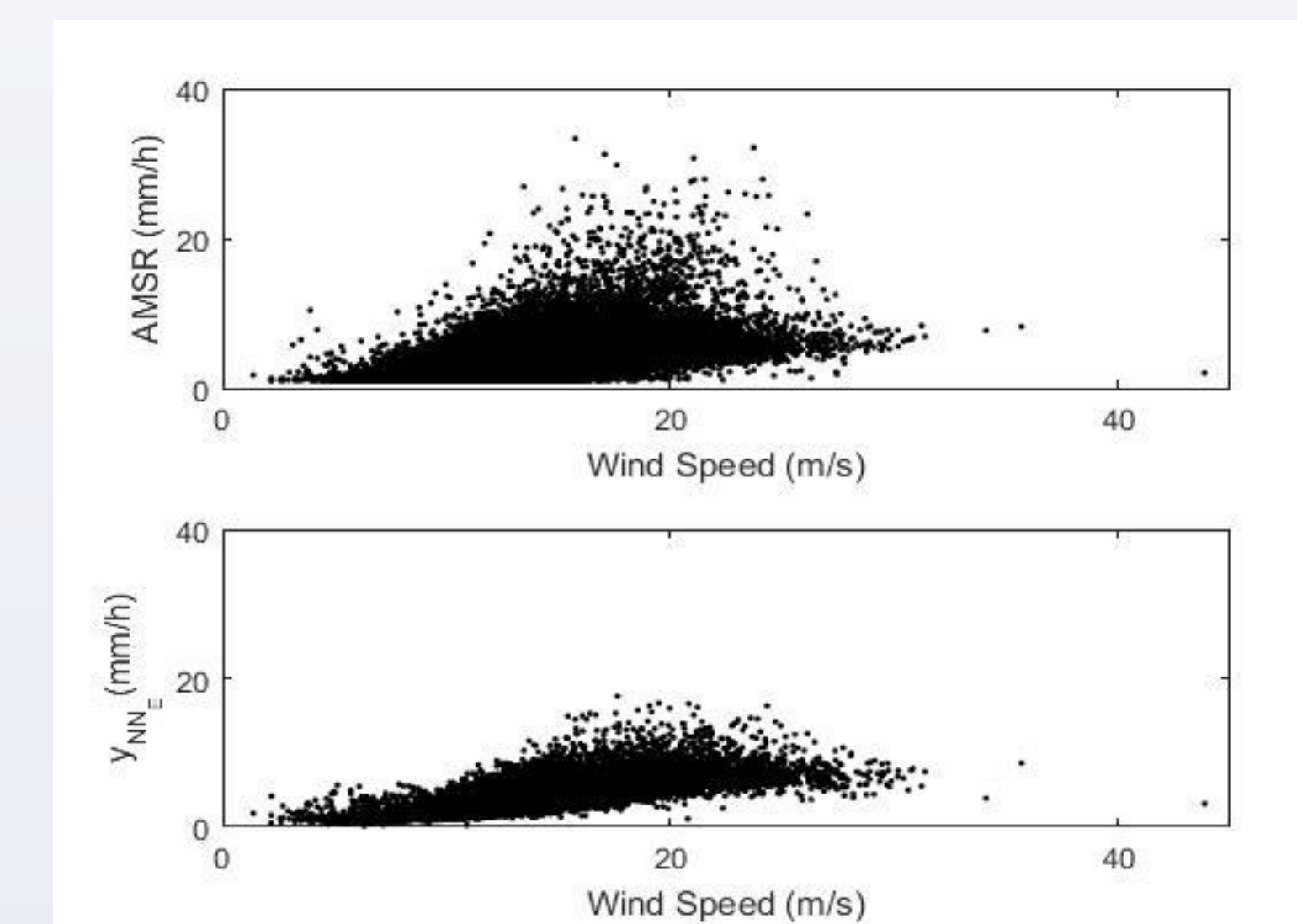


Figure 4: AMSR versus wind speed (top) and $y_{NN,E}$ versus wind speed (bottom)

The mean wind speed for testing points with absolute errors greater than 5 was 16.95. This is higher than the mean wind speed for all rain points (12.63). We attempted to improve the precision of the NN_E by restricting its training to data with limited wind speeds. We trained several NNs with two hidden layers same dimensions 20 and 10. The results are summarized in Table 1:

Wind Max Limit (m/s)	MSE	% Abs(Error)> 5
20	2.40	1.21%
12	0.87	0.2%

Table 1: Results NN_E trained with limited wind speed data

It can be seen that NN_E trained with limited wind speeds reduces the the mean square error on testing data.

CONCLUSIONS

This work aims to improve the rain estimate from scatterometer generated data. The data is coming from the ADEOS II satellite for a period of 6 months. Collocated backscatter, wind speed, cross-track distance, SRAD, and AMSR measured rain rate were used with a 2-step NN method: classification of rain versus no rain and estimation of rain rate. This method was used before in [1]. The results are in line with those reported in [1]. The estimation results are affected strongly by high-winds. Compared to the SRAD estimate of rain rate, the NN methods gives better results.

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