International Ocean Vector Winds Science Team Meeting · 2-4 June 2014, Brest, France

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Estimation of Sea Surface Rainrate from SeaWinds Data Using Neural Network Methods

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Abstract

This study seeks to demonstrate that estimates of sea surface rainrate can be computed by using Ku-band satellite scatterometer radar cross section data alone, without auxiliary information or data. This presentation will focus on one specific satellite mission, ADEOS-II, which fortuitously contained the optimum combination of sensors needed to train and test the algorithms that are being developed for this purpose. This mission had a lifetime of less than one year, but it is supported by fully processed scatterometer and radiometer data products that are readily available.

These are the ingredients in our development of a neural network that can accomplish the intended capability. We expect that this effort would also lead to a new and useful rainflag for future scatterometers.

In the way of background, a recent study [Stiles and Dunbar, 2010] used neural networks show a promising new approach that derives wind speeds alone, but their approach may also be applied in the pursuit of rain estimates. The goal of their study was to produce estimates of wind speed in the presence of rain that was superior to other, previous methods. They used a hierarchical structure of NNs trained with satellite only data (averaged sigma0's, wind speed and direction, cross-track distance). They trained the model in both rain and no rain conditions. 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 open literature shows that direct estimates of surface rainrate (alone) can be made using this new approach. This capability, based on feed-forward neural networks, has been demonstrated by Ghosh, et al, [2014] using OSCAT-2 data (NRCS and brightness temperature) with different sources of rain data for calibration. Their methodology includes external rain sensors on satellites: TRMM and AMSR-E. The approach is aimed either at estimating rain effects (rain flag or rainrate) or including rain effects in wind estimates. They also find application to global rainfall estimates on regional and seasonal scales.

I. Objective

Based on extensive previous data analysis of Quikscat sigma0 data in the presence of rain, supported by in-situ surface rain measurements, we believe that a neural network (NN) model function using the NRCS for both polarizations (and their fore and aft look directions) as an input, can be developed to estimate sea surface rainrate. Auxiliary inputs necessary to the NN are surface wind speed and cross track distance from the satellite ground track. This developmental approach is possible due to the multiple sensors and data products onboard the ADEOS-II satellite, which provide surface winds and rainrate for training purposes. This will lead to a neural network method to provide autonomous estimates of surface rainrate directly from single scatterometers in space such as QuikSCAT and its successors, OCEANSAT-II and the future RapidSCAT. These approaches will also need supporting data wind from ECMWF and/or NCEP resources.

II. Background

When rain is within the scatterometer beam and is roughening the surface, the total radar cross section estimate depends not only on surface wind, but also on a variety of inherent rain parameters; the drop size distribution and the 3-D spatial distribution including the height of the rain column and beam filling effects. Previous studies have lead to knowledge about the volume density of the NRCS and the two way attenuation for both polarizations for the QuikSCAT geometry. We have learned that the two polarization are affected to different degrees. Our plan to develop an artificial neural network (ANN) employs the four NRCS measures (two polarizations and two azimuth angles) to surface rainrate. The azimuth look directions will not affect the NRCS associated with rain volume backscatter, but it may respond to the wind driven part of the sea surface radar cross section, that is part of the NN input structure.

III. Previous QuikSCAT Work Using Passive and Active Sensing to Estimate Rain

The development of the rain measuring capability of QuikSCAT using the passive radiometric capabilities became of interest shortly after its launch in1999 [Jones, et at, 2000a, Jones, et al 2000b]. The QScat design is optimized for operation as a radar rather than as a radiometer. As a radiometer, it is sub-optimum even though good quality radiometric measurements can be made. In making measurements of sigma-0 (NRCS), QScat also measures the system noise power in between the returning radar pulses. These noise measurements, whose physical origin is mainly from the earth's surface, can be converted into measurements of the apparent brightness temperature of the earth (oceans or land). Over the ocean, rain results in higher observed brightness temperatures than would be measured over the ocean at the same wind speed, when rain is not present. Considerable, sustained effort has been dedicated, by the group in the Central Florida Remote Sensing Laboratory (UCF) to refine this capability to produce a data product for ocean surface rain estimation This instrument function has become known as the QuikSCAT Radiometer (QRad). After extensive testing and validation with TRMM, they have produced a publicly available product for oceanic precipitation climatology that can be used to improve to improve the diurnal estimation of global rainfall, which is the goal for the future Global Precipitation Mission (GPM). [Ahmad, K., et al; 2005]. Other active approaches using the QuikSCAT NRCS data have found some success in using QScat NRCS data alone to measure rain [Draper and Long, 2004; Allen and Long, 2005].

IV. Other Approaches using Neural Networks

This capability, based on feed-forward neural networks, has been demonstrated by Ghosh, et al, [2014] using OSCAT-2 data with different sources of rain data for calibration. Their methodology includes external rain sensors on satellites: TRMM and AMSR-E. The approach aimed either at estimating rain effects (rain flag or rainrate) or including rain effects in wind estimates. All methods have problems modeling a wide range of wind speeds and rainrates, especially in high-rain and/or high-speed conditions. Ghosh et al. used NCEP model wind speed and direction data, rain, humidity, total precipitable water, sigma0 and brightness temperature (Tb) to train a two-stage NN to first flag a rain event, then estimate rainrate for rain events. They trained one NN for each of the five geographical regions covered by the training data. Results show a larger error for the NN model in high-rainrate conditions and a consistent underestimation of the actual rainrate across all regions. The method does not seem to scale across the globe, as a separate NN is needed for each geographical region with distinct annual rain characteristics.

V. Our Current Approach

This presentation is based on the development of a feed-forward multilayer neural network (NN) using the ADEOS-II NRCS (SeaWinds) and rainrate (AMSR) data for training purposes. The functioning of the NN involves inputting the multivariable NRCS data (H- and V-pol, and their azimuth parameters), their relative position in the 1800 km satellite swath, and wind speed information. These are available here with the L2A and L2B standard products, for about 10 months of this mission. Since the AMSR rainrate product is collocated and coincident with NRCS and wind data it is ideal for training purposes. Initial programming efforts have created a combined dataset from these three products that is being used in the NN training and testing. The current data set, from the entire ADEOS-II mission runs February 2003 to October 2003.

The specific products are:

1. SeaWinds NRCS – Level 2A
2. SeaWinds Derived Wind Speeds – Level 2B
3. AMSR – Rainrate (mm/hr) – Level 2A

VI. Data Preprocessing

°The inputs to the NN are: cross-track distance (CTD), 25 km average sigma0 values (HH and VV averaged within fore and aft groups) and wind speeds. The training data comes from multiple satellite data orbits. We limited the area of data collection to the inter-tropical convergence zone between latitudes of -15° to +15°. The present results include approximately 80,000 data points from 2003, Day 100. It is a small sample compared to one month of data, but we used it to get a good understanding of the type and numerical values of the data. We further processed the input data before feeding it to the NN as follows: The CTD values are uniformly distributed, therefore they were divided by the maximum value (712). The sigma0 values were first converted to the linear space (10^(sigma0 db/10)), then normalized by subtracting the mean and dividing by standard deviation. When the whole data will be available we will compute the overall mean and std for sigma0 values. The wind speeds were also normalized similarly. In Figure 1 we show the rainrate (mm/hour) versus non-normalized wind speeds (m/s). We observed that there is not enough rainrate variability in the less than 7 m/sec wind speed range, while there are not enough sample rain points in the large wind speed range (greater than 11 m/sec). For this reason, we selected only the data points in the 7 to 11 m/sec wind speed range (approx. 23,000 points). The rainrate versus wind speed for the filtered data is shown in Figure 2 without the 15,500 zero rain points. While in the original data set the distribution of wind speed values was normal with a peak around 5 m/sec, in the filtered data, it was exponentially distributed. The number of rain points defined as greater than 0.2 mm/hour rainrate is 19% of the filtered data. To help the NN better learn the rain conditions, the training set contained only 10% of the no rain points and double the number of rain data points. We believe this redundancy will help the NN achieve greater accuracy in rain conditions. Figure 3 shows the histogram of wind speeds (top plot) and that of rainrates (bottom plot) of the data set used to train/validate/test the NN.

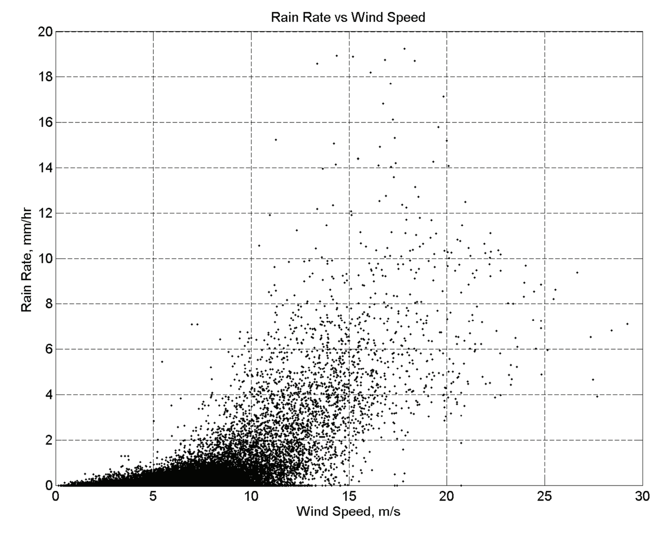

Figure 1: *This shows the rainrate (mm/hour) versus non-normalized wind speeds (m/s).*

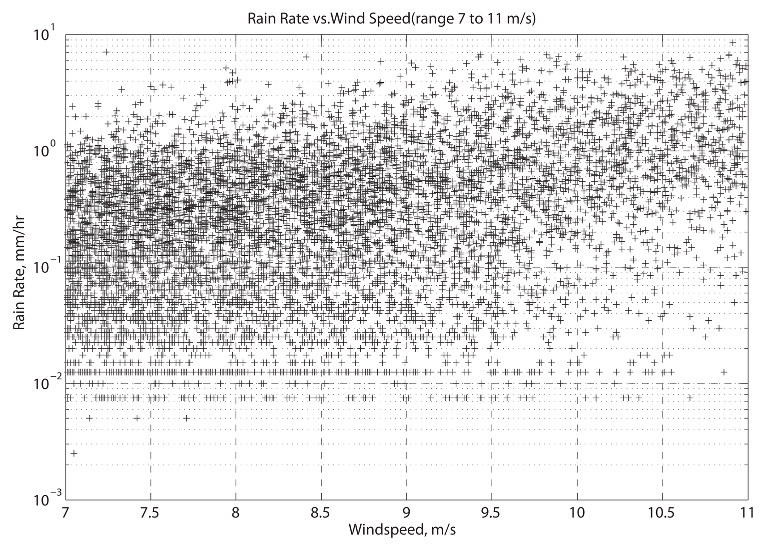

Figure 2: *The rainrate versus wind speed for the filtered data is shown in without the 15,500 zero rain points. The data shown consist of 7,900 data points.*

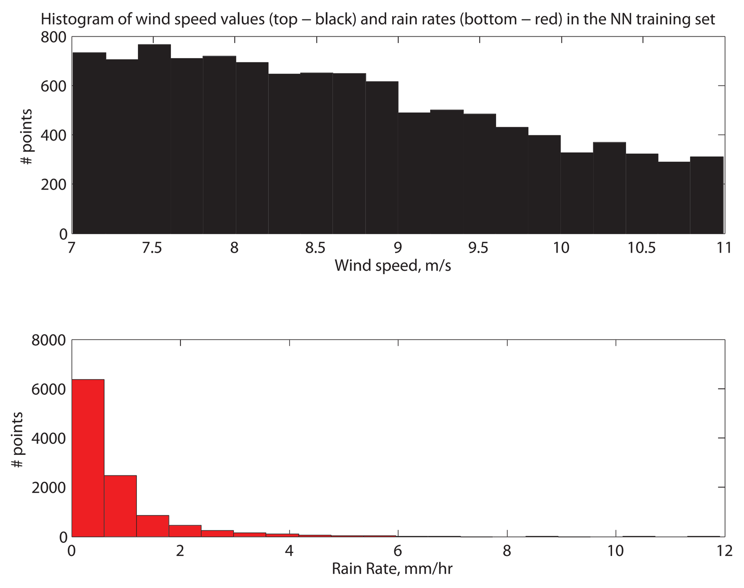

Figure 3: *This shows the histogram of wind speeds (top plot) and that of rainrates (bottom plot) of the data set used to train/validate/test the NN.*

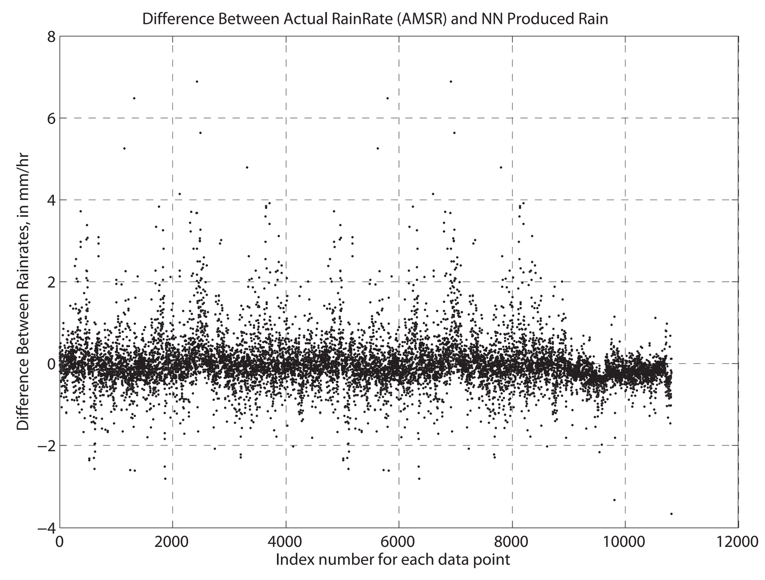

Figure 4: *This shows the difference between actual rainrate and the NN produced rainrate for all 10,813 data points*

VII. NN Training and Result Analysis

We trained the NN using the Levenberg-Marquardt training algorithm provided by the NN Matlab toolbox. The initial data set after the manipulations described above had 10,813 data points. Eighty percent was used for training, 10% for validation and 10% for testing. We trained the network repeatedly for different number of hidden neurons - 10, 15, 20. The best mean square error was 0.3934 and it was obtained with a NN with 15 hidden neurons. The Figure 4 shows the difference between actual rainrate and the NN produced rainrate for all 10,813 data points. It can be seen that a few data points have errors larger than 3 mm/hour. We further looked at those data points and we saw that all the points with errors larger than 3 mm/hour correspond to rainrate values between 3.5 mm/hour and 11.91 mm/hour. There are only 278 data points in this range in the whole training/testing/validation set or 2.5% of the data. This is insufficient for the NN to better understand this range of rainrates in a large variety of wind speed conditions. In our continuing study we will use larger data sets and we hope that the error in the large rainrate range will decrease. In Figure 5 we show the rainrates for each of the 10,813 points: top plot – actual rainrates, bottom plot - NN generated rainrates. The points on the right end side of each plot correspond to the no rain condition. Figure 6 shows the rainrate versus the wind speed for all data points: top plot – actual rainrates, bottom plot – NN produced rainrates. To get a better sense on the accuracy of the trained NN, over 61% of data points have an error less than 5% of the actual rainrate, and only 7.5% of data points have errors over 60% of the actual rainrate.

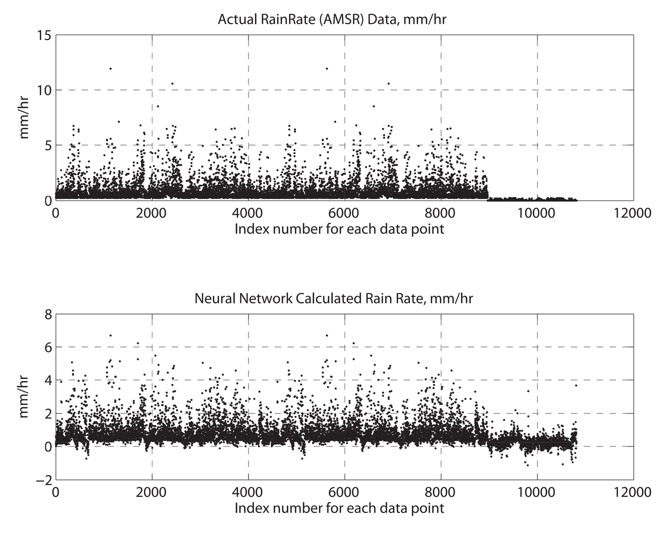

Figure 5: *This shows the rainrates for each of the 10,813 points: top plot – actual rainrates, bottom plot - NN generated rainrates. The points on the right end side of each plot correspond to the no rain condition.*

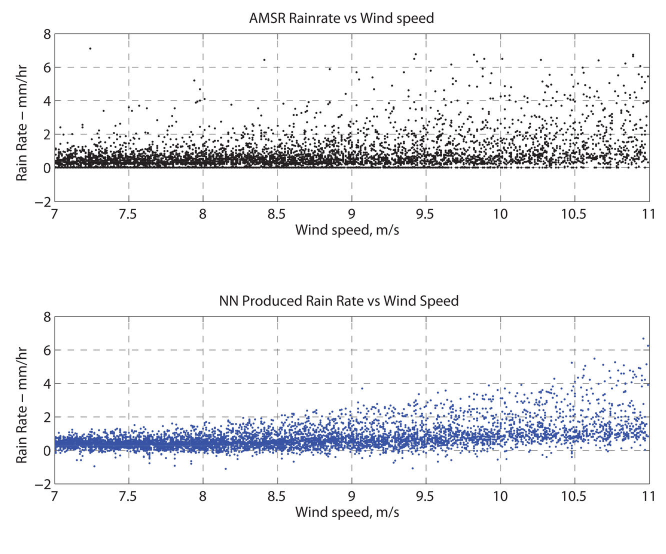

Figure 6: *This shows the rainrate versus the wind speed for all data points: top plot – actual rainrates, bottom plot – NN produced rainrates.*

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