OCEAN SURFACE RETRIEVALS FROM THE SSM/I USING NEURAL NETWORKS[1]

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ABSTRACT

A new neural network SSM/I transfer function (OMBNN3) which retrieves wind speed, columnar water vapor (*V*), columnar liquid water (*L*), and *SST*, using only satellite data (five SSM/I brightness temperatures) is introduced and compared with the current operational algorithm for retrieving surface wind speed and NN algorithms developed earlier. The new NN algorithm systematically outperforms all algorithms considered for all SSM/I instruments (F8, F10, F11 and F13), under all weather conditions where retrievals are possible, and for all wind speeds. It also retrieves *V* and *L* with an accuracy close to that of cal/val (for *V*) and Weng and Grody (for *L*) algorithms, and produces low resolution SSTs with moderate accuracy. OMBNN3 demonstrates significantly better performance at higher wind speeds (and higher latitudes) than previous NN-based algorithms, generating wind speeds up to ~23 m/s for the available test data, and has a theoretical upper limit of about 32 m/s.

1.0 INTRODUCTION

A new neural network (NN) SSM/I transfer function (OMBNN3) is presented which retrieves wind speed (*W*), columnar water vapor (*V*), columnar liquid water (*L*), and *SST*, using only satellite data (five SSM/I brightness temperatures (BTs)). Also presented is a detailed comparison of the new algorithm with the current operational (GSW) algorithm (Goodberlet, et al., 1989) and several NN algorithms developed earlier (Krasnopolsky et al., 1995a, 1995b).

SSM/I wind retrieval algorithms encounter two basic problems: (1) atmospheric moisture and (2) high wind speeds. It was shown (Stogryn et al., 1994; Krasnopolsky et al., 1995a), that an adaptive nonlinear approach such as NNs can accommodate the nonlinearity of the SSM/I transfer function caused by atmospheric moisture, extending the retrieval capability under cloudy atmospheric conditions. However, it is not yet clear to what extent retrievals can be extended under cloudy conditions. Although an upper limit for retrievals (~0.5 mm in terms of columnar liquid water) has been suggested, it is clear that in particular situations this limit may be significantly lower (e.g., in rain). Because high moisture events are relatively rare, they are poorly represented in development data sets which makes this problem even more difficult. The new OMBNN3 algorithm which estimates two moisture criteria, *V* and *L* together with the wind speed, provides an additional information about the level of moisture and control on the accuracy of wind speed retrievals.

Several problems arise at high wind speed (see Krasnopolsky et al., 1996a): (1) saturation of BT at high wind speeds due to saturation of the area of the ocean surface covered by the persistent fraction of whitecap foam, (2) increasing noise in BT from the transient part of whitecap foam fraction at high wind

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speeds, and (3) very few buoy observations exist at higher wind speeds ($W > 15$ m/s). The linear GSW retrieval algorithm can, in principle, generate high wind speeds; however, validation of this algorithm using buoy observations shows that it has high scatter at high wind speeds and generates high wind speeds in some cases even when observed wind speeds are low. The first NN algorithms, SBB NN (Stogryn et al., 1994) and OMBNN1 (originally called SER NN in Krasnopolsky et al., 1995a), demonstrated retrieval accuracy which was significantly better than that for GSW, however, they were not able to generate wind speeds higher than 16-18 m/s. An improved high wind speed NN algorithm was developed, OMBNN2 (Krasnopolsky et al., 1995b), which is capable of generating higher wind speeds (up to 20-21 m/s without a bias correction). It uses a bias correction to extend retrievals up to wind speeds of to 25 -26 m/s. However, this bias correction is instrument and/or satellite dependent. Here we introduce a new NN algorithm[3] which generates wind speeds up to 23-24 m/s based on the available data sets without any bias correction (theoretical high wind speed limit for OMBNN3 is about 32 m/s) and whose accuracy does not depend significantly on the instrument and/or satellite.

The development of the new OMBNN3 algorithm was possible due to (1) new matchup data, and (2) a new approach for empirical retrievals using NNs. In Section 2, the architecture of the new OMBNN3 algorithm, the data used and the NN training process are described. In Section 3 we perform a detailed validation of the OMBNN3 algorithm, using different criteria and matchups for all SSM/I instruments.

2.0 THE NEW ALGORITHM

The first-generation wind speed retrieval algorithms, including the GSW algorithm , SBB algorithm, OMBNN1, and OMBNN2 followed a standard empirical approach. They retrieved only one value (e.g., wind speed), regressing it on the satellite measurements (e.g., BTs), as

$$W = f\,(BT) \qquad (1)$$

where BT is the brightness temperature vector and f is a regression function (NN in our particular case). Representation (1) assumes (usually by default) that the data set which is used is complete (representative) enough to eliminate dependencies of W on other physical parameters (liquid water, water vapor, SST, etc.) through averaging. This assumption and, hence, representation (1), is obviously not correct at $W > 10$ - 15 m/s where the buoy/SSMI matchup data are sparse, and dependencies of the wind speed on V, L, and SST are not removed through averaging. These dependencies create additional noise with respect to wind speed at higher wind speeds. In this case, (1) gives a biased estimate for the wind speed with a large scatter (large bias and standard deviation).

NNs allow us to solve this problem without including V, L and SST as additional arguments in (1), which is the standard solution, that is not suitable for an operational algorithm. The new NN algorithm (OMBNN3) can be symbolically written as,

$$Y = g\,(BT) \qquad (2)$$

where the output vector is $Y = \{W, V, L, SST\}$, the input vector is $BT = \{T19V, T19H, T22V, T37V, T37H\}$ and g is a NN. The NN, g, which implements (2) has 5 inputs and 4 outputs, it also has one hidden layer with 12 nodes. Including additional outputs in the NN architecture improves the training process, decreases the number of local minima in the error function, and stabilizes and accelerates convergence in the training process. The NN was trained, using the weighting scheme for high wind speed data described in

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[3]The corresponding FORTRAN code which implements OMBNN3 is available upon request from Vladimir Krasnopolsky, e-mail address: wd21kv@sgi78.wwb.noaa.gov, tel. 301-763-8133.

Krasnopolsky et al., (1995b), where the weighting function was inversely proportional to the square root of the wind speed distribution.

For algorithm development and validation several databases were used: (1) A new raw SSMI/buoy matchup database created by NRL. Extensive quality control of the matchups extracted from the NRL database was required. More than 30 different criteria have been applied to both the buoy and the SSM/I data for quality control, including removal of missing and noisy data. Daily locations for TOGA-TAO buoys have been corrected using information from the TAO Web Home page. (2) The F11 matchups collected by high latitude ocean weather ships (OWS) LIMA and MIKE were provided to us by D. Kilham of Bristol University. (3) For F13, we have created a new low resolution matchup database, these matchups have higher noise than the matchups for F8, F10, and F11 which were extracted from the NRL database. The F13 matchup data also only cover the time interval from 11/95 to 4/96. Thus, we only use F13 for a relative comparison of the different algorithms. For more details see Krasnopolsky et al. (1996b).

For all data, wind speeds have been adjusted to a height of 20 m. Clear and cloudy conditions are defined below and correspond to the retrieval flags given by Stogryn et al. (1994).

As shown by Stogryn et al. (1994) and Krasnopolsky et al. (1994, 1995a), NN algorithms can successfully retrieve wind speeds under clear + cloudy conditions. Therefore, for training we used all available matchups which correspond to clear + cloudy conditions, according to Stogryn's retrieval flag. Statistics for clear conditions were then calculated by applying the trained NN to the clear portion of the matchup data. Because higher wind speed events were given extra weight, noise in this portion of the data could reduce the effectiveness of the training process. To minimize this possibility, we additionally removed a number of outliers at higher wind speeds, but no outliers were removed for the test data, or for any other data which were used for further validation.

Five SSM/I BTs *{T19V, T19H, T22V, T37V, T37H}* are used as the NN inputs. The output vector is composed of wind speed and SST taken from the buoy portion of the matchup, columnar water vapor (V) produced by the cal/val algorithm from Alishouse et al. (1990), and columnar liquid water (L) produced by the WG algorithm from the SSM/I BTs taken from the SSM/I portion of the matchup. Standard backpropagation was used to train the NN. After training, the algorithm was applied to the F11 test data (for statistics and more details, see Krasnopolsky et al, 1996b).

3.0 VALIDATION

Previous wind speed algorithms have been developed and validated, using the F8 matchup databases. Here we use a newly-created database described in Section 2 for validation for all SSM/I instruments (F8, F10, F11, and F13) and for comparison of the various wind speed algorithms. For comparison with the new OMBNN3 algorithm we have used the current operational algorithm (GSW), our original NN algorithm OMBNN1, and OMBNN2 which was improved for high wind speeds. Because the bias correction for OMBNN2 is instrument and/or satellite dependent (Krasnopolsky et al., 1996a), we do not include it here but use only the NN portion of the OMBNN2 algorithm.

In this section we present statistics for the primary output of the OMBNN3 algorithm - wind speed. By including additional outputs in OMBNN3, the performance of OMBNN3 with respect to wind speed is significantly improved, especially at higher wind speeds. Statistics for the other outputs are presented in Krasnopolsky et al. (1996b).

Table 1 shows total statistics for clear + cloudy conditions (for separate statistics for clear ans cloudy conditions see Krasnopolsky et al., 1996b) for four satellites and four selected algorithms. The table also contains buoy wind speed statistics for each data set: maximum wind speed, mean wind speed, and the SD, σ_w.

We now summarize the information contained in Tables 1 and in Krasnopolsky et al. (1996b): For all weather conditions considered, and for all SSM/I instruments, the NN-based algorithms outperform the GSW algorithm based on the standard deviation (SD) as a criterion. Based on the biases, the new OMBNN3 also outperforms the GSW algorithm for most cases; otherwise it produces similar biases. Wind speeds generated by OMBNN3 have mean values and SDs which are close to those of the observed buoy wind speeds; therefore, the OMBNN3-generated wind speed distributions are properly centered and have proper width. Under cloudy conditions, the biases and SDs are unacceptably high for GSW, whereas OMBNN3 yields a bias and SD which are acceptable for operational use. Wind speeds are higher on .

Table 1. Total statistics for GSW, OMBNN1, OMBNN2 and OMBNN3 algorithms for CLEAR plus CLOUDY conditions and for four different SSM/I instruments. Columns 3 - 5 show statistics for the wind speeds per se (σ_w denotes standard deviation), and columns 6 - 8 for the difference between buoy and algorithm-generated wind speeds. SD denotes standard deviation, and CC denotes correlation coefficient, N is the number of matchups.

Satellite		Max W	Mean W	σ_w	Bias	SD	CC
F08 N = 1637	Buoy	21.5	7.31	3.17	N/A	N/A	N/A
	GSW	25.9	7.65	3.54	-0.34	2.13	0.80
	OMBNN1	17.1	6.32	2.45	0.99	1.62	0.86
	OMBNN2	18.4	6.80	2.92	0.51	1.60	0.87
	OMBNN3	20.6	7.41	3.09	-0.10	1.59	0.87
F10 N = 6879	Buoy	21.6	7.26	3.18	N/A	N/A	N/A
	GSW	26.0	7.81	3.59	-0.55	2.15	0.80
	OMBNN1	16.4	6.42	2.53	0.85	1.74	0.84
	OMBNN2	19.5	6.32	2.77	0.95	1.72	0.84
	OMBNN3	22.5	7.57	3.18	-0.31	1.81	0.84
F11 N = 6129	Buoy+OWS	26.4	7.47	3.51	N/A	N/A	N/A
	GSW	30.3	7.99	3.77	-0.53	2.09	0.84
	OMBNN1	19.4	6.70	2.65	0.76	1.70	0.88
	OMBNN2	20.7	6.56	2.90	0.91	1.70	0.88
	OMBNN3	22.8	7.57	3.27	-0.11	1.61	0.89
F13 N = 1036	Buoy	27.5	10.21	4.58	N/A	N/A	N/A
	GSW	29.0	11.43	4.36	-1.22	2.59	0.83
	OMBNN1	18.5	9.65	3.61	0.55	2.41	0.85
	OMBNN2	20.5	9.55	3.49	0.66	2.40	0.86
	OMBNN3	23.1	10.84	4.04	-0.63	2.26	0.87

average under cloudy conditions and with an rms error of less than 3 m/s, yielding a relative error of 15 - 25% of the wind speed, again acceptable, considering the higher level of noise under cloudy conditions.

SDs for OMBNN3 are comparable with SDs for OMBNN1 and OMBNN2 (sometimes even smaller), which indicates that our NN approach, including the previous weighting of higher wind speeds, is robust enough to prevent decreasing accuracy at lower wind speeds because of high levels of noise at higher wind speeds. Additionally, there is a consistent improvement (from OMBNN1 to OMBNN3) in the ability of these NN algorithms to generate higher wind speeds in each case (for more detailed high wind speed statistics see Krasnopolsky et al., 1996b). In comparing F8, F10, and F11, the variations in SD and bias are relatively small for all algorithms (we do not include F13 here). The largest differences for all algorithms occur for F10 which may be due to the orbit ellipticity for this satellite (G. Poe, personal communication).

Fig. 1 shows binned bias, SD, and rms error for the difference between buoy wind speeds and algorithm-generated wind speeds vs. observed wind speed for GSW, OMBNN2 and OMBNN3 algorithms, where the bin size is 1 m/s. Fig. 1 shows that OMBNN3 is uniformly better than the other two algorithms in terms of SD and rms error (except occasionally at high wind speeds for rms error) for all instruments and all wind speeds. Fig. 2 shows binned bias and rms error for the difference between buoy wind speed and algorithm-generated wind speeds for GSW, OMBNN2 and OMBNN3 algorithms vs. amount of columnar liquid water L, where the bin size is 0.05 mm. For all algorithms, biases and rms errors increase with L; however, OMBNN3 demonstrates better performance for all values of L. These dependencies provide additional information regarding the accuracy of wind speed retrievals under cloudy conditions and can be used to improve the retrieval flags. Fig. 3 shows binned bias and rms error for the difference between buoy wind speeds and algorithm generated wind speeds for GSW, OMBNN2 and OMBNN3 algorithms vs. amount of columnar water vapor V, where the bin size is 5 mm. Bias and rms error increase sharply at $V > 40$ mm for GSW. This agrees with our previous experience which shows that GSW performs poorly in tropical areas. For OMBNN3, the bias is small and almost independent of V; however, rms error increases slowly at $V > 50$ mm. Fig. 4 shows binned bias and rms error for the difference between buoy wind speeds and algorithm-generated wind speeds for GSW, OMBNN2 and OMBNN3 algorithms vs. latitude, where the bin size is 5°. OMBNN1 and OMBNN2 have been developed, using F8 matchup data where high latitudes were poorly represented. As a result, these algorithms may be expected to demonstrate large (up to 1 - 2 m/s) biases at high latitudes. For OMBNN3, the bias and rms error are much smaller at high latitudes which is due to the new matchup data which include matchups at high latitudes where the moisture/wind speed relationships are expected to be different. For GSW, the latitude dependence is not smooth and there are regions where bias and/or rms error are unacceptably high.

4.0 CONCLUSIONS

We have presented a new NN-based OMBNN3 transfer function (i.e., retrieval algorithm) for SSM/I retrievals (including wind speed, columnar water vapor, columnar liquid water, and *SST*) which demonstrates high retrieval accuracy overall, together with the ability to generate high wind speeds with acceptable accuracy. The results demonstrate that OMBNN3 systematically outperforms all algorithms considered for all SSM/I instruments, for all weather conditions where retrievals are possible, and for all wind speeds.

Previous NN-based algorithms have not performed well at high wind speeds. In developing the OMBNN3 SSM/I transfer function, a new NN training strategy which includes preferential weighting at high wind speeds was introduced to compensate for the nonuniformity in the distribution of observed wind speeds. Also, the OMBNN3 algorithm was developed and tested, using a new matchup database. We created this database from F11 SSMI/buoy matchups and high latitude SSMI/OWS matchups which contained a significant number of high wind speed events. As a result, OMBNN3 demonstrates significantly better performance at higher wind speeds and at higher latitudes than previous NN-based algorithms. It generates

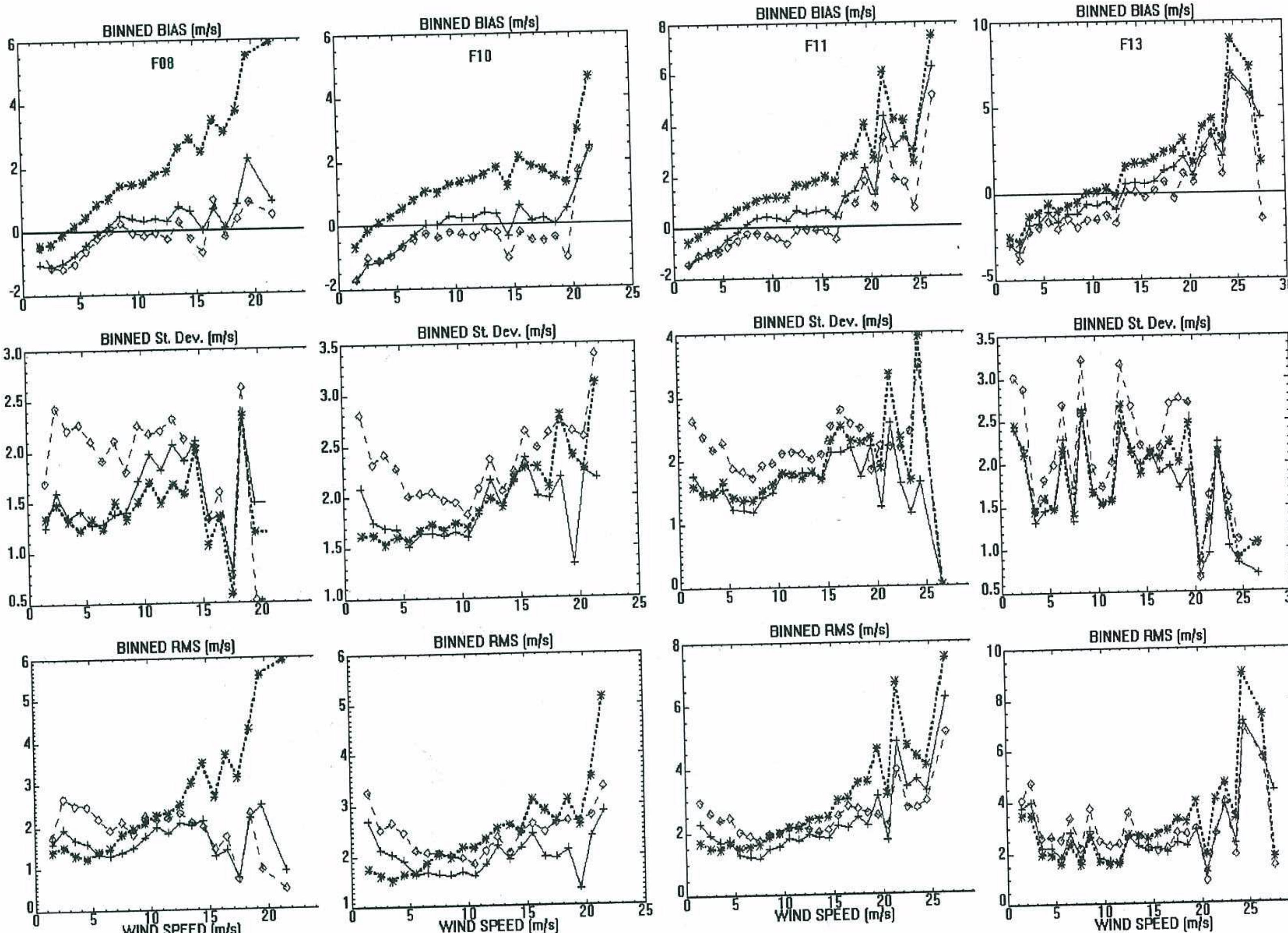

Fig. 1. Binned statistics (bias, SD, and rms errors) for GSW (dashed line with diamonds), OMBNN2 (dotted line with stars) and OMBNN3 (solid with crosses) algorithms for F08, F10, F11 and F13 SSM/I instruments.

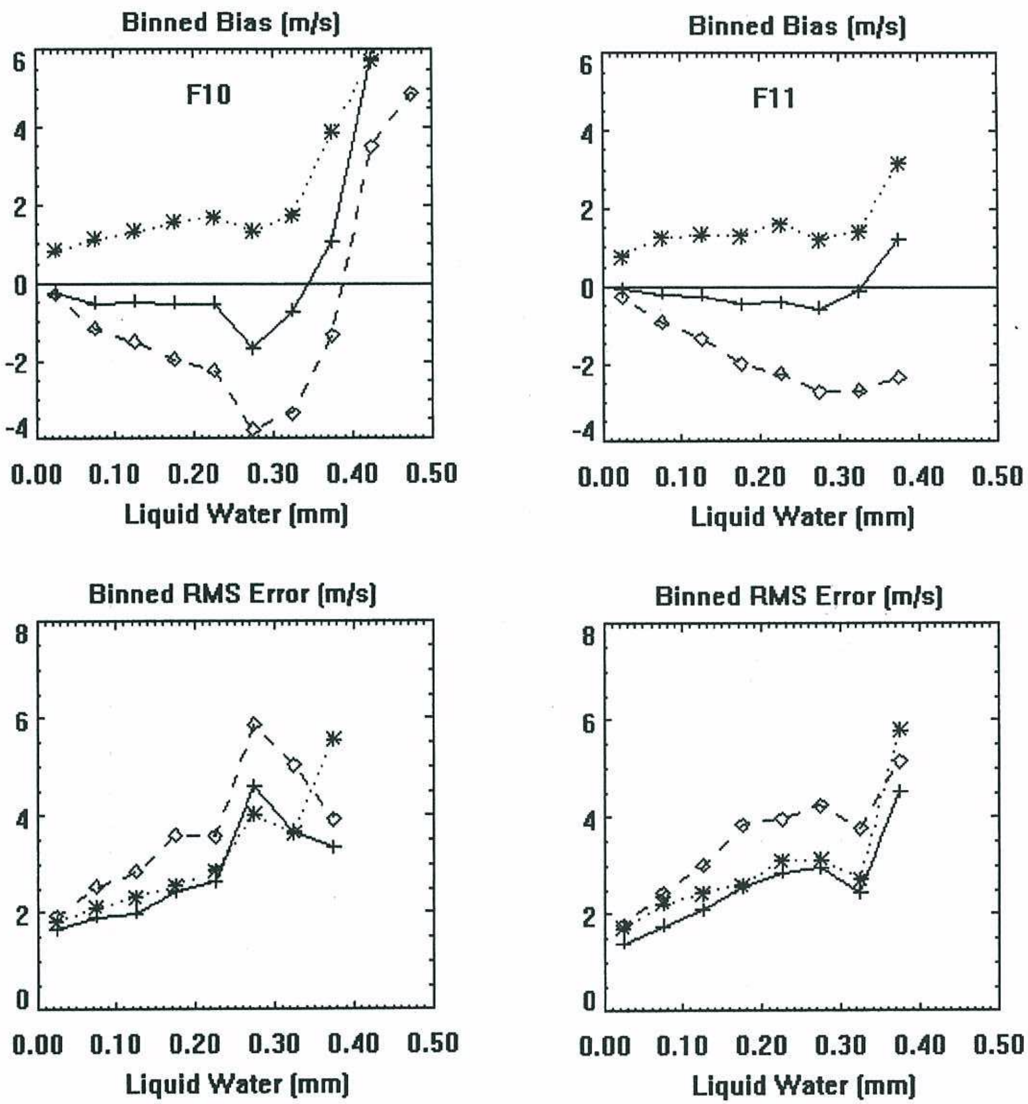

Fig. 2. Bias and RMS error vs. Columnar Liquid Water for GSW (dashed line with diamonds), OMBNN2 (dotted line with stars) and OMBNN3 (solid line with crosses) algorithms for F10 and F11 SSM/I instruments.

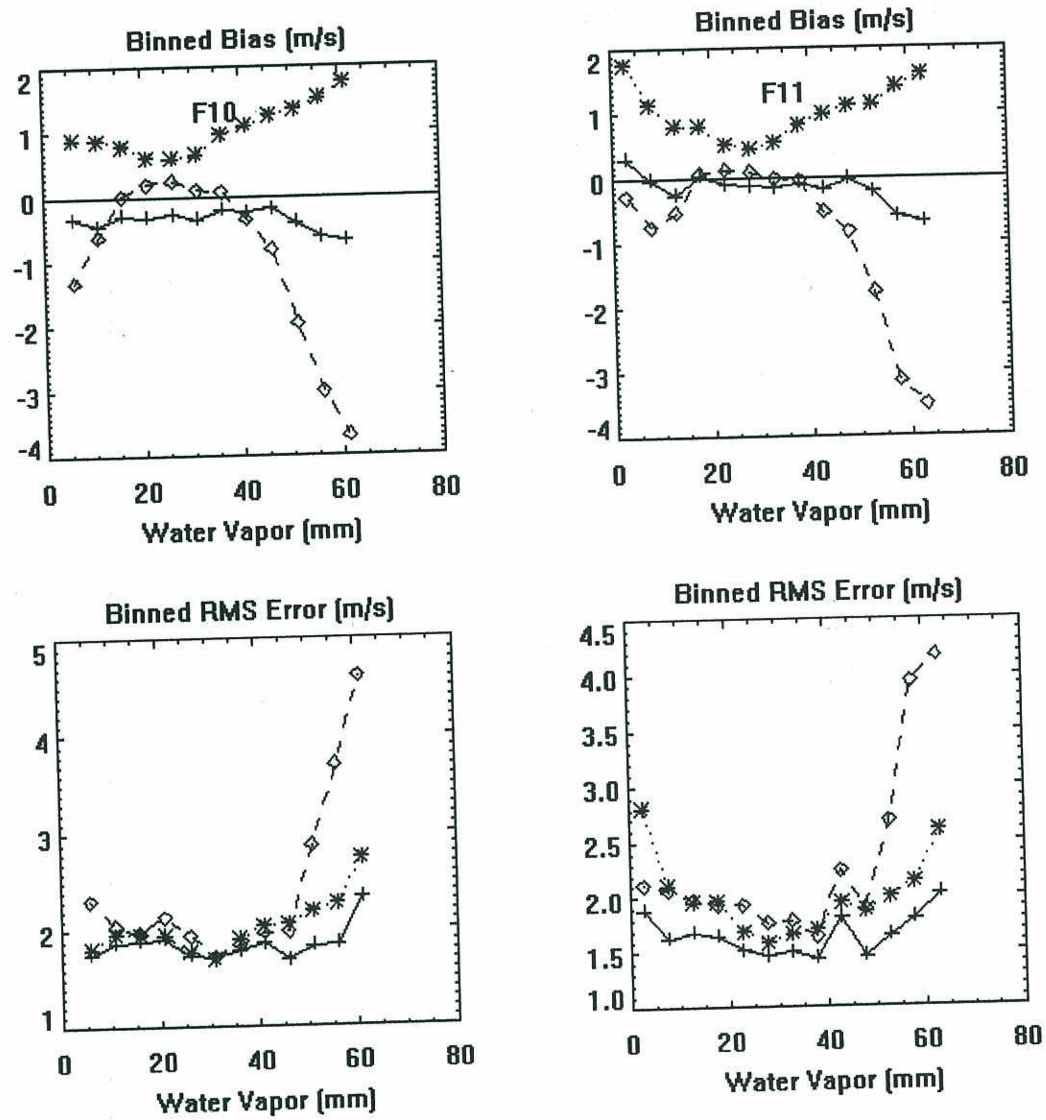

Fig. 3. Bias and RMS error vs. Columnar Water Vapor for GSW (dashed line with diamonds), OMBNN2 (dotted line with stars) and OMBNN3 (solid line with crosses) algorithms for F10 and F11 SSM/I instruments.

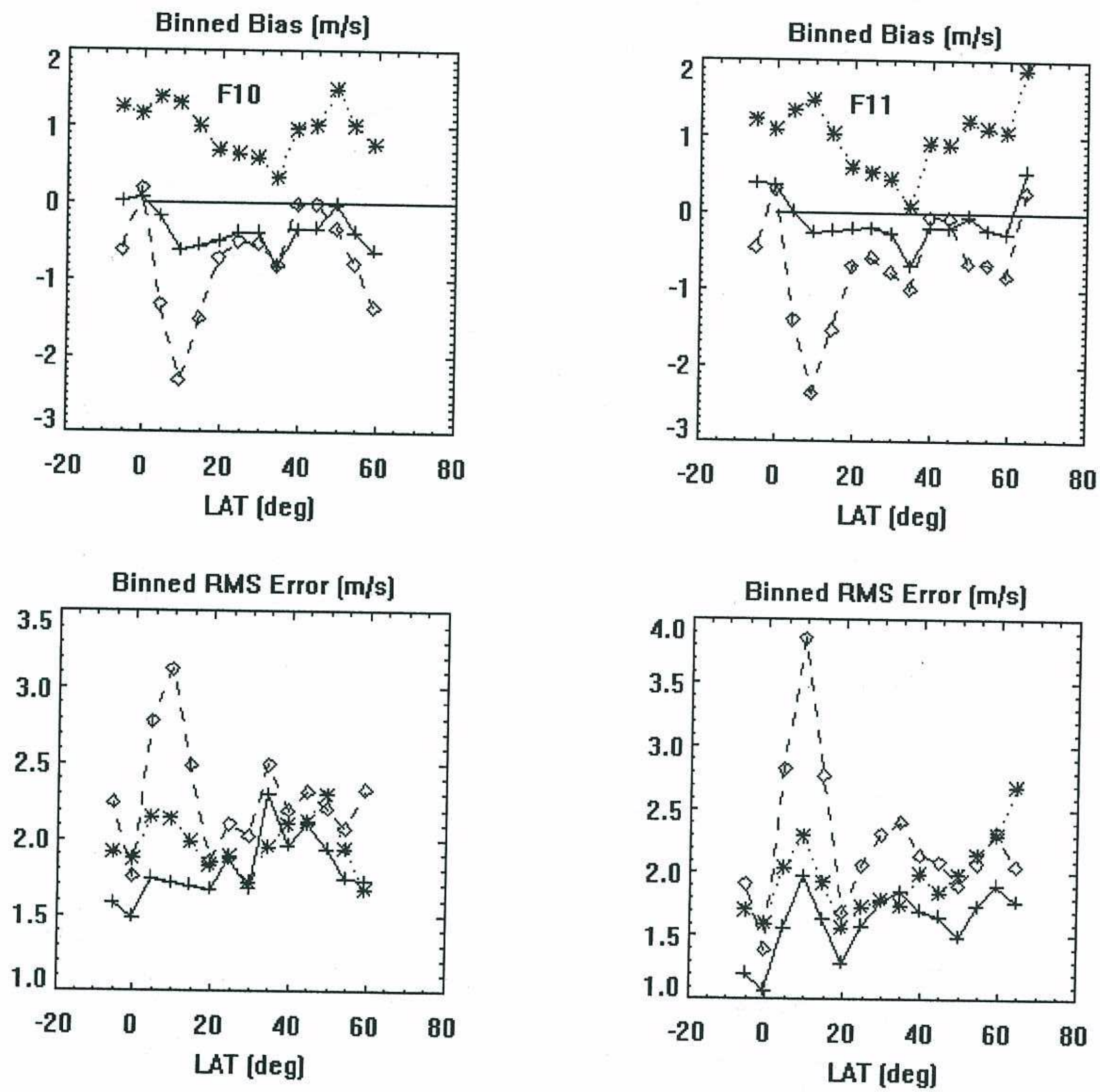

Fig. 4. Bias and RMS error vs. Latitude for GSW (dashed line with diamonds), OMBNN2 (dotted line with stars) and OMBNN3 (solid line with crosses) algorithms for F10 and F11 SSM/I instruments.

wind speeds up to ~23 m/s for the available test data, and has a theoretical upper limit of about 32 m/s (Krasnopolsky et al., 1996a). It was also validated for the F8, F10, and F13 sensors and showed significant improvement in the accuracy of the retrievals for these instruments at higher wind speeds. The retrieval accuracy for OMBNN3 does not depend significantly on the satellite and/or instrument.

The NN-based algorithms demonstrate on average satisfactory retrieval capabilities under cloudy conditions. Under clear plus cloudy conditions, the biases and SDs are unacceptably high for GSW algorithm, whereas the OMBNN3 algorithm yields a bias and SD which are acceptable for operational use. As a result, the NN-based algorithms have also expanded the retrieval domain from clear, to clear plus cloudy, conditions yielding an increase in retrieval coverage of ~15%. This result is particularly significant for obtaining more complete coverage of synoptic-scale weather systems such as extratropical cyclones which are typically characterized by higher levels of moisture and higher wind speeds. In this study we have defined cloudy conditions, according to the BT retrieval flags given by Stogryn et al. (1994). These retrieval flags are based only on BTs and are statistical by definition; therefore, they do not preclude contamination from rain in all cases. If information about local conditions is available, it can be used to improve the accuracy of retrievals under cloudy conditions significantly. Because OMBNN3 generates columnar liquid water, columnar water vapor and SST simultaneously with wind speed, it offers additional opportunities for specifying local conditions and improving retrieval flags. Regarding columnar liquid water L and columnar water vapor V, OMBNN3 was trained to simulate cal/val retrievals for V, and WG retrievals for L. It reproduces the cal/val and WG results with high accuracy. Although, we did not have ground truth data to validate or improve these retrieval estimates, if such data become available (e.g., radiosonde measurements), they could be used in the future during the process of training to further improve the algorithm's retrieval capabilities.

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