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TECHNICAL NOTE

A NEW TRANSFER FUNCTION FOR SSM/I BASED ON AN EXPANDED NEURAL NETWORK ARCHITECTURE

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No. 1. Burroughs, L. D., 1987: Development of Forecast Guidance for Santa Ana Conditions. National Weather Digest, Vol. 12 No. 1, 7pp.

No. 2. Richardson, W. S., D. J. Schwab, Y. Y. Chao, and D. M. Wright, 1986: Lake Erie Wave Height Forecasts Generated by Empirical and Dynamical Methods -- Comparison and Verification. Technical Note, 23pp.

No. 3. Auer, S. J., 1986: Determination of Errors in LFM Forecasts Surface Lows Over the Northwest Atlantic Ocean. Technical Note/NMC Office Note No. 313, 17pp.

No. 4. Rao, D. B., S. D. Steenrod, and B. V. Sanchez, 1987: A Method of Calculating the Total Flow from A Given Sea Surface Topography. NASA Technical Memorandum 87799., 19pp.

No. 5. Feit, D. M., 1986: Compendium of Marine Meteorological and Oceanographic Products of the Ocean Products Center. NOAA Technical Memorandum NWS NMC 68, 93pp.

No. 6. Auer, S. J., 1986: A Comparison of the LFM, Spectral, and ECMWF Numerical Model Forecasts of Deepening Oceanic Cyclones During One Cool Season. Technical Note/NMC Office Note No. 312, 20pp.

No. 7. Burroughs, L. D., 1987: Development of Open Fog Forecasting Regions. Technical Note/NMC Office Note. No. 323., 36pp.

No. 8. Yu, T. W., 1987: A Technique of Deducing Wind Direction from Satellite Measurements of Wind Speed. Monthly Weather Review, 115, 1929-1939.

No. 9. Auer, S. J., 1987: Five-Year Climatological Survey of the Gulf Stream System and Its Associated Rings. Journal of Geophysical Research, 92, 11,709-11,726.

No. 10. Chao, Y. Y., 1987: Forecasting Wave Conditions Affected by Currents and Bottom Topography. Technical Note, 11pp.

No. 11. Esteva, D. C., 1987: The Editing and Averaging of Altimeter Wave and Wind Data. Technical Note, 4pp.

No. 12. Feit, D. M., 1987: Forecasting Superstructure Icing for Alaskan Waters. National Weather Digest, 12, 5-10.

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LIST OF ABBREVIATIONS

BT:	brightness temperature
C:	degrees Celsius
CC:	correlation coefficient
cal/val:	calibration/validation
FXX:	SSM/I instrument number XX
GHz:	10^9 cycles/second
GSW:	Goodberlet, Swift and Wilkerson (1989) - see References
H:	horizontal polarization
K:	degrees Kelvin
KBG:	Krasnopolsky, Breaker and Gemmilll (1995) - see References
***L*:**	columnar liquid water
LIMA:	European oceanic weather ship
MIKE:	European oceanic weather ship
NDBC:	National Data Buoy Center
NN:	neural network
NRL:	Naval Research Laboratory
OMBNNX:	Ocean Modeling Branch Neural Network number X
OWS:	oceanic weather ship
SBB:	Stogryn, Butler and Bartolac (1994) - see References
SD:	standard deviation
SSM/I:	Special Sensor Microwave / Imager
SST:	sea surface temperature
TAO:	tropical atmosphere ocean
TOGA:	tropical ocean global atmosphere
V:	vertical polarization
***V*:**	columnar water vapor

ABSTRACT

A new neural network (NN) SSM/I transfer function (OMBNN3) 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)) is introduced and compared with the current operational (GSW) algorithm and NN algorithms developed earlier (OMBNN1 and OMBNN2). 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. It generates wind speeds up to ~23 m/s for the available test data, and has a theoretical upper limit of about 32 m/s. The retrieval accuracy for OMBNN3 does not depend significantly on the satellite and/or instrument.

1. INTRODUCTION

This report contains a description of a new neural network (NN) SSM/I transfer function (OMBNN3) 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 contained is a detailed comparison of the new algorithm with the current operational (GSW) algorithm (Goodberlet, et al., 1989) and NN algorithms developed earlier (Krasnopolsky et al., 1995a, 1995b). It is shown that our new NN algorithm outperforms all other algorithms in terms of wind speed retrievals. It also retrieves *V* and *L* with an accuracy close to that of cal/val (Alishouse, 1990) and WG (Weng and Grody, 1994) algorithms, and produces low resolution SSTs with moderate accuracy.

SSM/I wind retrieval algorithms encounter two problems: (1) atmospheric moisture and (2) high wind speeds. It was shown (Stogryn et al., 1994; Krasnopolsky et al., 1994, 1995a), that an adaptive nonlinear approach such as NNs can successfully handle 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 control on the level of moisture and on the accuracy of wind speed retrievals.

Several issues contribute to the problems 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 speeds, and (3) very few buoy observations for 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., 1994), demonstrated retrieval accuracies which were significantly better than that for GSW, however, they were not able to generate high 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 to higher wind speeds (up to 25 -26). However, this bias correction is instrument and/or satellite dependent. Here we introduce a new NN algorithm which generates wind speeds up to 23-24 m/s on 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 purpose of this report is to document the development and validation of the new OMBNN3 algorithm. This new development was possible due to (1) new matchup data, and (2) a new approach for empirical retrievals using NNs. Problems mentioned above together with some mathematical and physical ideas which led us to this new algorithm will be described in Krasnopolsky et al. (1996b). In Section 2 of this report, the architecture of the new OMBNN3 algorithm is described. Section 3 describes the data we use and preprocessing procedures. Section 4 describes the NN training process. In Section 5 we perform a detailed validation of the OMBNN3 algorithm, using different criteria and matchups for all SSM/I instruments. Section 6 summarizes our results, and the FORTRAN program which implements OMBNN3 algorithm, is presented in the Appendix[1].

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

2. NEW ALGORITHM ARCHITECTURE

The first-generation wind speed retrieval algorithms, including the GSW algorithm (Goodberlet, et al., 1989), SBB algorithm (Stogryn et al., 1994), OMBNN1 (Krasnopolsky et al., 1994, 1995a) and OMBNN2 (Krasnopolsky et al., 1995b) 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. The architecture of OMBNN3 together with those for OMBNN1 and OMBNN2 are shown in Fig. 1. Including additional outputs in the NN

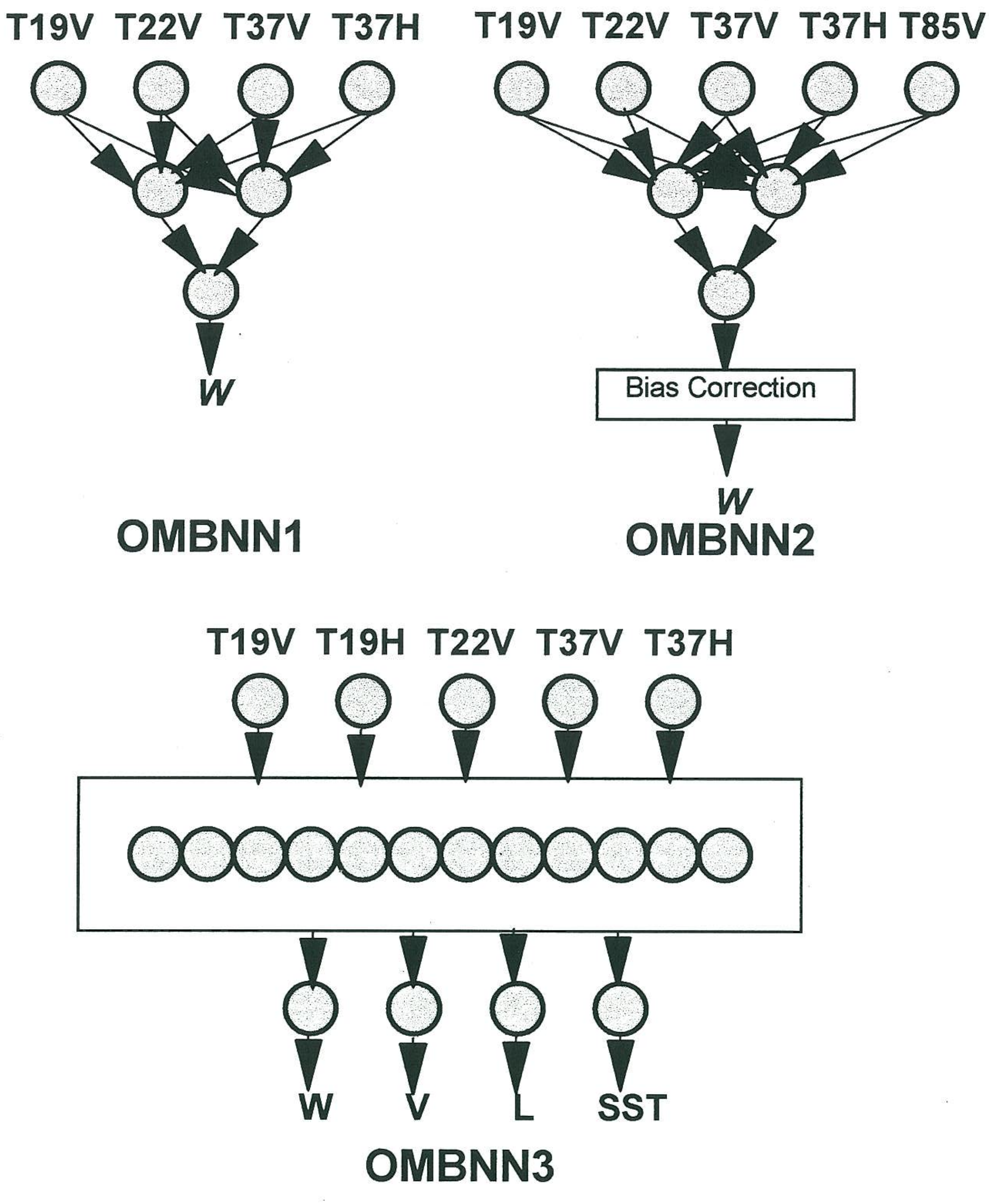

Fig.1 Evolution of the NN architecture from OMBNN1 to OMBNN3.

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

3. THE MATCHUP DATA

For algorithm development and validation several databases were used:

a. A raw SSMI/buoy matchup database, created by NRL was provided to us by G. Poe (NRL). This database contains 3,144 F8/buoy matchups for the period 9/91 to 6/93, 12,013 F10/buoy matchups for the same period, and 10,195 F11/buoy matchups for the period 12/91 to 6/93. NDBC buoys and TOGA-TAO buoys have been used in creating these matchups. We carefully quality controlled the matchups extracted from the NRL database. More than 30 different criteria have been applied to both the buoy and the SSM/I data for quality control and to remove missing and noisy data. Daily locations for TOGA-TAO buoys have been corrected using information from the TAO Web Home page. As a result 2,994 F8/buoy matchups, 11,705 F10/buoy matchups, and 9,948 F11/buoy matchups were extracted. As a second step, we selected matchups where the satellite data are collocated with the buoy data in space for $R_s \leq 15$ km and in time for $R_t \leq 15$ min. Eventually, 1765 matchups for F8, 7495 matchups for F10, and 6129 matchups for F11, were selected.

b. The F11 matchups collected by high latitude ocean weather ships (OWS) LIMA (430 matchups) and MIKE (639 matchups) were provided to us by D. Kilham of Bristol University. After quality control and applying a 15 km x 15 min collocation filter, 547 (243 MIKE + 304 LIMA) matchups were selected.

c. For F13, we have created a new matchup database containing 1036 F13/buoy wind speed matchups with a spatial collocation uncertainty $R_s \leq 25$ km, and a temporal collocation uncertainty $R_t \leq 0.5$ hour. Because the buoy data in this case have been preprocessed with a roundoff error of ~0.5 m/sec, an additional random error of approximately 0.3

m/sec rms has been introduced. Because we did not have access to telemetry in this case, only limited filtering was applied to those BTs. As a result, 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 cover a limited time interval from 11/95 to 4/96. Thus, we only use F13 for a relative comparison of the different algorithms.

For all data, wind speeds have been adjusted to a height of 20 m. Some characteristics of the data are shown in Table 1. Clear and cloudy conditions are defined below and correspond to the retrieval flags given by Stogryn et al. (1994):

$$T37V - T37H > 50\ K \qquad \text{for clear case}$$

and

$$\begin{aligned} &T37V - T37H \le 50\ K \\ &T19V < T37V \\ &T19H \le 185\ K \\ &T37H \le 210\ K \qquad \text{for cloudy case} \end{aligned} \tag{3}$$

Table 1. Statistics for data used for algorithm development and validation.

	Number of matchups			Mean W m/s	σ_w m/s	Max W m/s	Max W (Clear+ Cloudy) m/s	Max W (Clear) m/s
	Total	Clear cond.	Cloudy cond.					
F08/Buoy	1765	1437	200	7.4	3.3	26.0	21.5	18.6
F10/Buoy	7495	5953	926	7.3	3.2	25.0	21.6	20.5
F11/Buoy	6633	5274	855	7.5	3.5	26.4	25.0	20.1
F13/Buoy	1071	864	172	10.3	4.7	27.5	27.5	24.7
F11/LIMA	304	253	51	10.4	4.9	26.4	26.4	23.9
F11/MIKE	243	215	27	9.8	4.9	24.2	24.2	21.1

As mentioned above, since F13 data are not extensive, contain additional noise, and cover only several months, we have not used them for algorithm development but only for comparisons with the different algorithms. As seen in Table 1, most of the high wind speed coincide with higher levels of moisture and cloudiness. Matchup data for F8 and F10 do not have buoy wind speeds higher than 21.6 m/s even under clear + cloudy conditions. Several high wind speed events in these data contain levels of liquid water which are so high that no retrievals are possible. Only the F11 data contain high wind speed events under clear + cloudy conditions (up to 25 m/s). Thus, the F11 data provide the only choice for algorithm development. To further improve the coverage for high wind speeds, F11/buoy data have been supplemented with F11/LIMA and F11/MIKE data. These data have wind speeds up to 26.4 m/s and correspond to high latitudes (LIMA was located at ~ 57°N and MIKE at ~ 65°N). The resulting blended F11 matchup database has subsequently been separated into two statistically equivalent sets: one for training and one for testing.

4. TRAINING

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 (3). 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 derived by Alishouse et al. (1990), and columnar liquid water (*L*) produced by the WG algorithm from SSM/I BTs. Standard backpropagation was used to train the NN. After training, the algorithm was applied to the F11 test data.

Table 2 shows wind speed statistics for clear conditions and Table 3 for clear + cloudy conditions for both training and test sets. Under both clear and clear + cloudy conditions, OMBNN3 algorithm gives a small bias, an acceptable standard deviation (SD), and high correlation (CC). It also accurately reproduces not only the mean buoy wind speed but also its SD, σ_w. As for the maximum wind speed, OMBNN3 underestimates high wind speeds by about

Table 2. Training and test statistics for OMBNN3 algorithm under clear conditions. 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.

Data set		Max W	Mean W	σ_w	Bias	SD	CC
Training	Buoy	22.8	7.13	3.27	N/A	N/A	N/A
	OMBNN3	19.5	7.14	2.97	-0.01	1.36	0.91
Test	Buoy	23.9	7.14	3.31	N/A	N/A	N/A
	OMBNN3	20.2	7.21	3.08	-0.08	1.49	0.89

Table 3. Training and test statistics for OMBNN3 algorithm under clear+cloudy conditions. 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.

Data set		Max W	Mean W	σ_w	Bias	SD	CC
Training	Buoy	26.4	7.48	3.49	N/A	N/A	N/A
	OMBNN3	22.8	7.49	3.20	-0.004	1.41	0.91
Test	Buoy	26.4	7.44	3.31	N/A	N/A	N/A
	OMBNN3	22.8	7.66	3.34	-0.21	1.77	0.87

10 - 15%, which we consider acceptable for wind speeds > 22 m/s, where the noise level is highest (see discussions in the introduction here and in Krasnopolsky et al. (1996a)). The differences between the statistics for the training and the test data are mainly due to outliers which have not been removed from the test set. The difference between clear and clear + cloudy case is small but significant. The cloudy case and statistics for other NN outputs (*V*, *L*, and *SST*) are discussed in following sections.

5. VALIDATION AND COMPARISONS

Previous empirical wind speed algorithms have, in most cases, been developed and validated, using the F8 matchup database created by GSW. Here we use a newly-created database described in Section 3 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 (or SER NN), and our OMBNN2 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 part of OMBNN2 algorithm.

5.1 Wind Speed

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 is significantly improved, especially at higher wind speeds. Statistics for the other outputs are presented in following sections.

5.1.1 Total (for all wind speeds) statistics.

Table 4 shows total statistics for clear case, Table 5 for clear + cloudy conditions and Table 6 for cloudy conditions. Tables 4 and 5 contain statistics for four satellites and four selected algorithms. For cloudy case, F8 and F13 cloudy subsets are small and for these satellites strongly overlap with the high wind speed subsets (Table 7), thus only statistics for F10 and F11 are shown for cloudy conditions in Table 6. These tables also contain 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 4 - 6:

- 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 (also see Fig. 2).

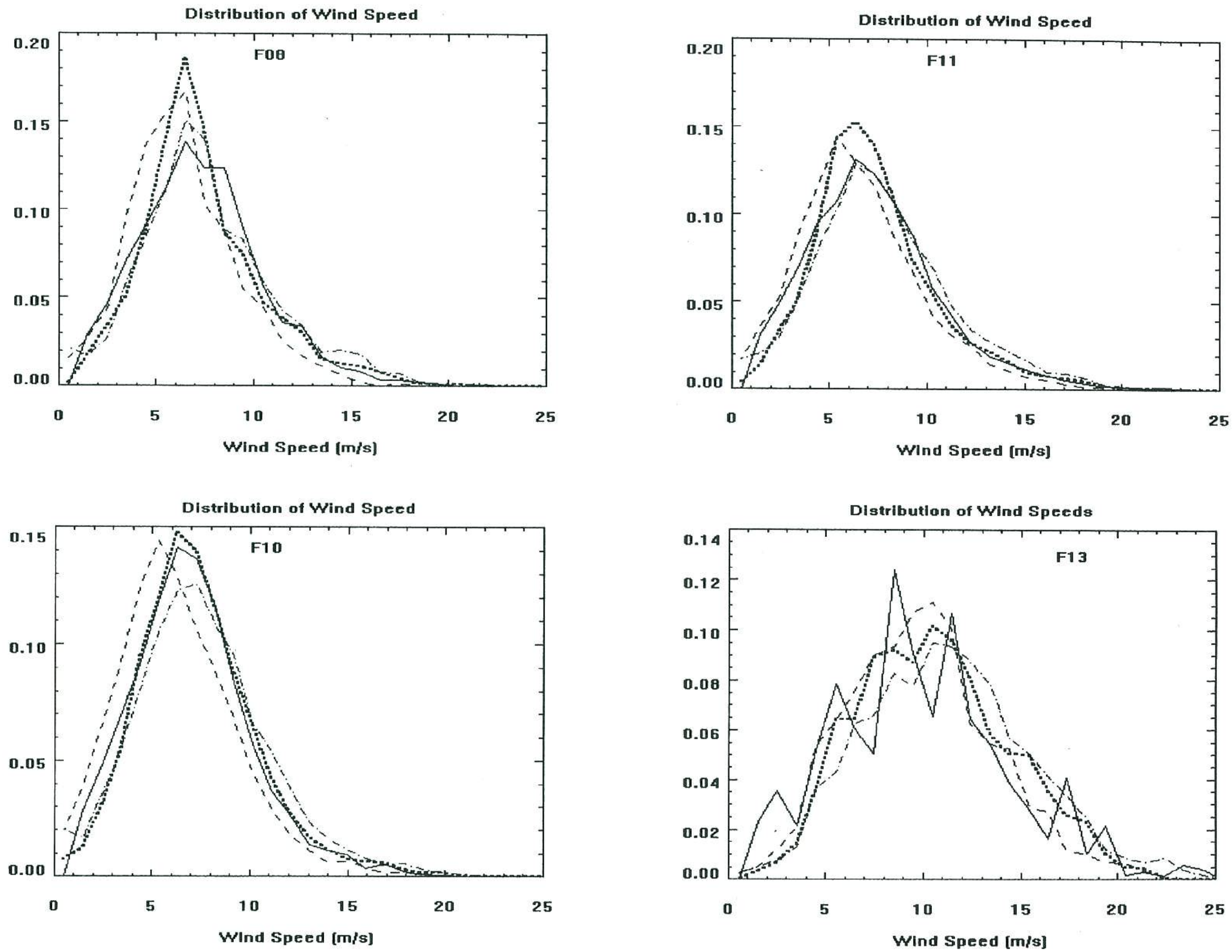

Fig. 2. Wind Speed Distributions: observed buoy (solid line), GSW (dot-dashed line), OMBNN2 (dashed line), and OMBNN3 (dotted line) for F08, F10, F11 and F13 SSM/I instruments.

Table 4 Total statistics for GSW, OMBNN1, OMBNN2 and OMBNN3 algorithms for CLEAR 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.

Satellite		Max W	Mean W	σ_w	Bias	SD	CC
F08 1437 m-ups	Buoy	19.2	7.06	3.01	N/A	N/A	N/A
	GSW	21.4	7.08	3.18	-0.02	1.77	0.84
	OMBNN1	15.1	6.13	2.38	0.93	1.49	0.87
	OMBNN2	16.8	6.56	2.68	0.50	1.48	0.88
	OMBNN3	20.1	7.07	3.01	-0.01	1.43	0.88
F10 5953 m-ups	Buoy	20.5	6.98	2.95	N/A	N/A	N/A
	GSW	20.8	7.20	3.22	-0.22	1.86	0.82
	OMBNN1	14.7	6.23	2.46	0.75	1.63	0.84
	OMBNN2	17.1	6.13	2.61	0.84	1.60	0.84
	OMBNN3	20.2	7.21	2.97	-0.23	1.68	0.84
F11 5274 m-ups	Buoy+OWS	23.9	7.13	3.29	N/A	N/A	N/A
	GSW	20.9	7.34	3.36	-0.21	1.72	0.87
	OMBNN1	16.9	6.47	2.55	0.66	1.55	0.89
	OMBNN2	17.9	6.32	2.72	0.81	1.56	0.88
	OMBNN3	20.2	7.17	3.03	-0.04	1.43	0.90
F13 864 m-ups	Buoy	24.0	9.46	4.16	N/A	N/A	N/A
	GSW	23.6	10.49	3.84	-1.02	2.13	0.86
	OMBNN1	18.5	9.01	3.39	0.45	2.02	0.88
	OMBNN2	21.1	9.35	3.51	0.11	1.96	0.88
	OMBNN3	22.0	10.1	3.70	-0.61	1.87	0.89

Table 5 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.

Satellite		Max W	Mean W	σ_w	Bias	SD	CC
F08 1637 m-ups	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 6879 m-ups	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 6129 m-ups	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 1036 m-ups	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

Table 6 Total statistics for GSW, OMBNN1, OMBNN2 and OMBNN3 algorithms for CLOUDY conditions and for two 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.

Satellite	Algorithm	Max W	Mean W	σ_w	Bias	SD	CC
F10 1068 m-ups	Buoy	21.6	8.90	3.77	N/A	N/A	N/A
	GSW	26.0	11.91	3.48	-3.01	3.19	0.61
	OMBNN1	16.4	7.61	2.58	1.28	2.47	0.76
	OMBNN2	19.5	7.49	3.38	1.41	2.50	0.76
	OMBNN3	22.5	9.97	3.52	-1.08	2.76	0.72
F11 895 m-ups	Buoy+OWS	25.0	8.79	3.63	N/A	N/A	N/A
	GSW	30.3	11.97	3.42	-3.18	3.07	0.62
	OMBNN1	15.8	7.79	2.49	0.99	2.39	0.76
	OMBNN2	20.7	7.65	3.26	1.13	2.40	0.76
	OMBNN3	22.8	9.78	3.39	-0.99	2.59	0.73

- Under cloudy conditions, the biases and SDs are unacceptably high for GSW algorithm, whereas OMBNN3 algorithm yields a bias and SD which are acceptable for operational use. Wind speeds are higher on average under cloudy conditions (see Table 6) and with an rms error of less than 3 m/s yielding a relative error of 15 - 25 % of the wind speed, considered acceptable, taking into account the higher level of noise under cloudy conditions. Thus, the OMBNN3 algorithm extends the retrieval domain from clear, to clear plus cloudy, conditions yielding an increase in areal 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. Since the BT retrieval flags which we use are essentially statistical, they are not highly sensitive to local conditions. In some cases this may lead to corrupted retrievals; therefore, any additional information about local conditions (e.g., such as rain/norain) may help to further improve the accuracy of retrievals 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 the accuracy of 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.
- 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. 3 shows scatter plots of retrieved vs. observed wind speeds for all four instruments and for GSW, OMBNN2 and OMBNN3 algorithms. OMBNN3 yields the lowest scatter both at low and high wind speeds.

5.1.2 High wind speeds statistics.

Table 7 shows statistics calculated separately for wind speeds > 15 m/s, only. Although the sample sizes are small in each case, some conclusions can be drawn from the table. At high wind speeds, the NN-based algorithms perform significantly better than GSW based on the SD. OMBNN1 and OMBNN2 have large positive biases because they significantly underestimate the speed at high wind speeds; however, OMBNN3 demonstrates a smaller bias at high wind speeds.

5.1.3 Binned wind speed statistics

Fig. 4 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. 4 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. 5 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.

Table 7 High winds (W > 15 m/s) statistics for algorithms presented in Table 4, for CLEAR+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 - 7 for the difference between buoy and algorithm-generated wind speeds. SD denotes standard deviation.

Satellite		Max W	Mean W	σ_w	Bias	SD
F08 33 m-ups	Buoy	21.5	16.8	1.55	N/A	N/A
	GSW	21.4	16.9	2.97	-0.10	1.52
	OMBNN1	15.1	12.6	1.21	4.15	1.39
	OMBNN2	17.4	13.6	1.40	3.21	1.47
	OMBNN3	20.6	16.4	1.76	0.42	1.40
F10 155 m-ups	Buoy	21.6	16.8	1.51	N/A	N/A
	GSW	26.0	17.1	2.95	-0.3	2.61
	OMBNN1	15.7	12.5	1.63	4.30	1.64
	OMBNN2	19.5	13.9	1.78	2.90	1.93
	OMBNN3	22.5	16.4	2.62	0.40	2.16
F11 212 m-ups	Buoy+OWS	26.4	17.5	2.34	N/A	N/A
	GSW	30.3	17.0	2.98	0.46	2.68
	OMBNN1	19.4	13.7	1.93	4.33	1.90
	OMBNN2	20.7	14.0	2.23	3.53	2.25
	OMBNN3	22.8	16.3	2.50	1.17	2.25
F13 154 m-ups	Buoy	27.5	18.1	2.51	N/A	N/A
	GSW	29.0	17.5	2.68	0.57	2.48
	OMBNN1	18.5	14.6	1.68	3.45	2.28
	OMBNN2	20.5	14.6	1.91	3.52	2.18
	OMBNN3	23.1	16.8	2.26	1.23	2.17

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. 6 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. 7 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. *SST*, where the bin size is 5°C. Bias and rms error for GSW increases sharply for *SST* > 20°C, which is related to GSW's poor performance in tropical areas. For OMBNN3, the bias does not show a significant dependence on SST.

Fig. 8 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 algorithm, the latitude dependence is not smooth and there are regions where bias and/or rms error are unacceptably high.

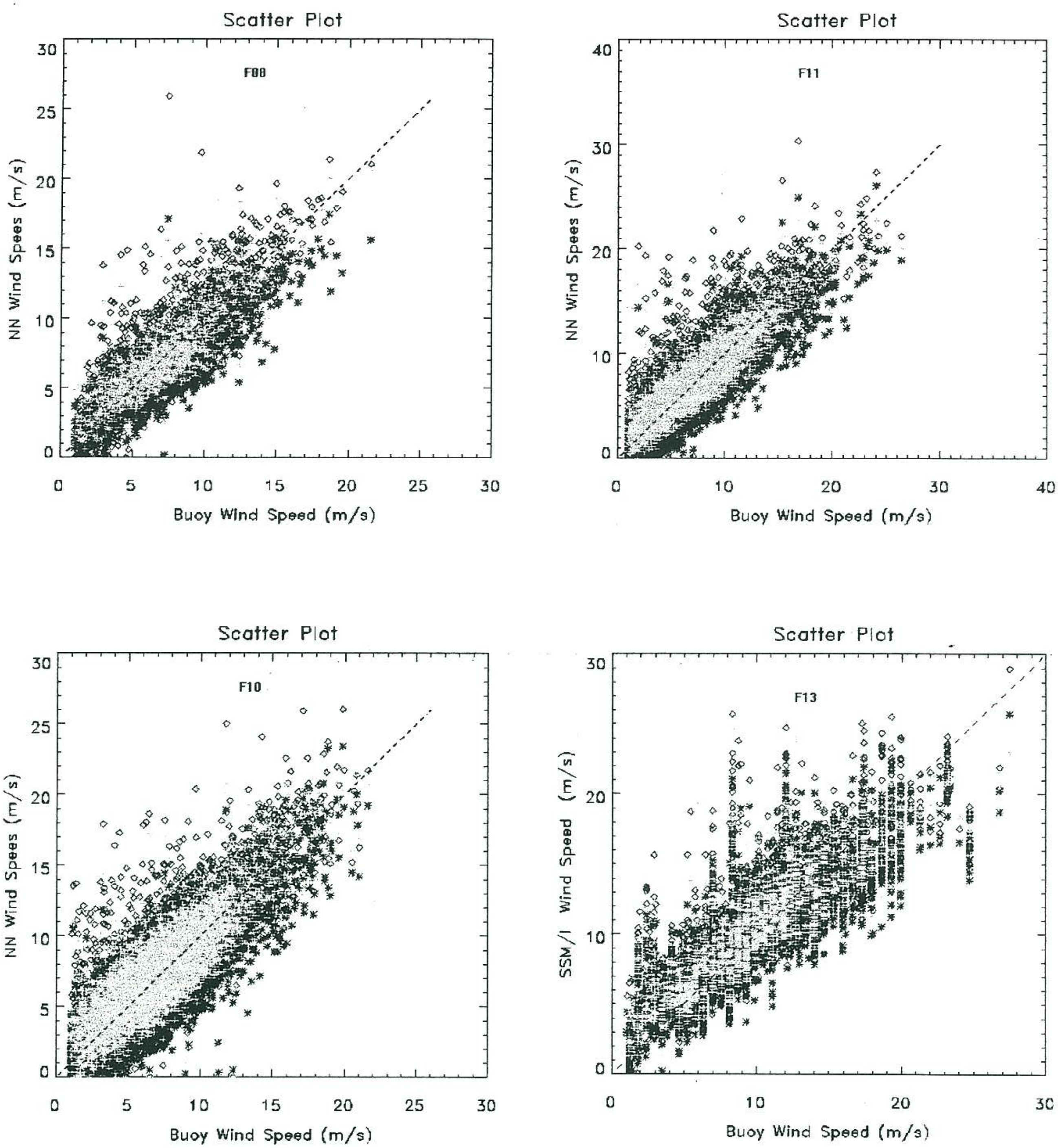

Fig. 3. Scatter Plots for GSW (black diamonds), OMBNN2 (black stars) and OMBNN3 (gray crosses) algorithms for F08, F10, F11 and F13 SSM/I instruments.

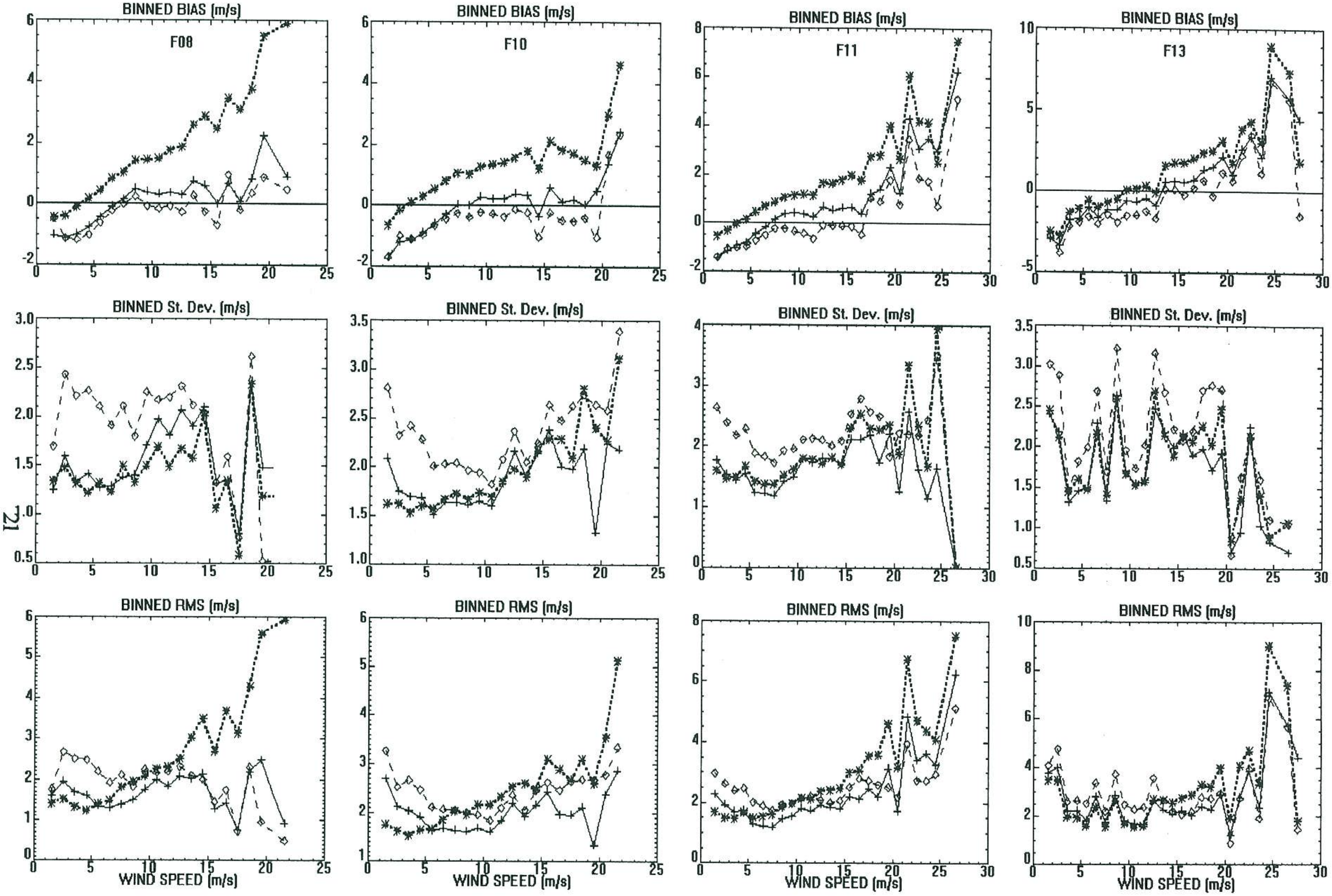

Fig. 4. Binned statistics (bias, SD, and rms errors) for GSW (dashed line with diamonds), OMBNN2 (dotted line with stars) and OMBNN3 (solid with crosses) algorithms for F08, F10, F11 and F13 SSM/I instruments.

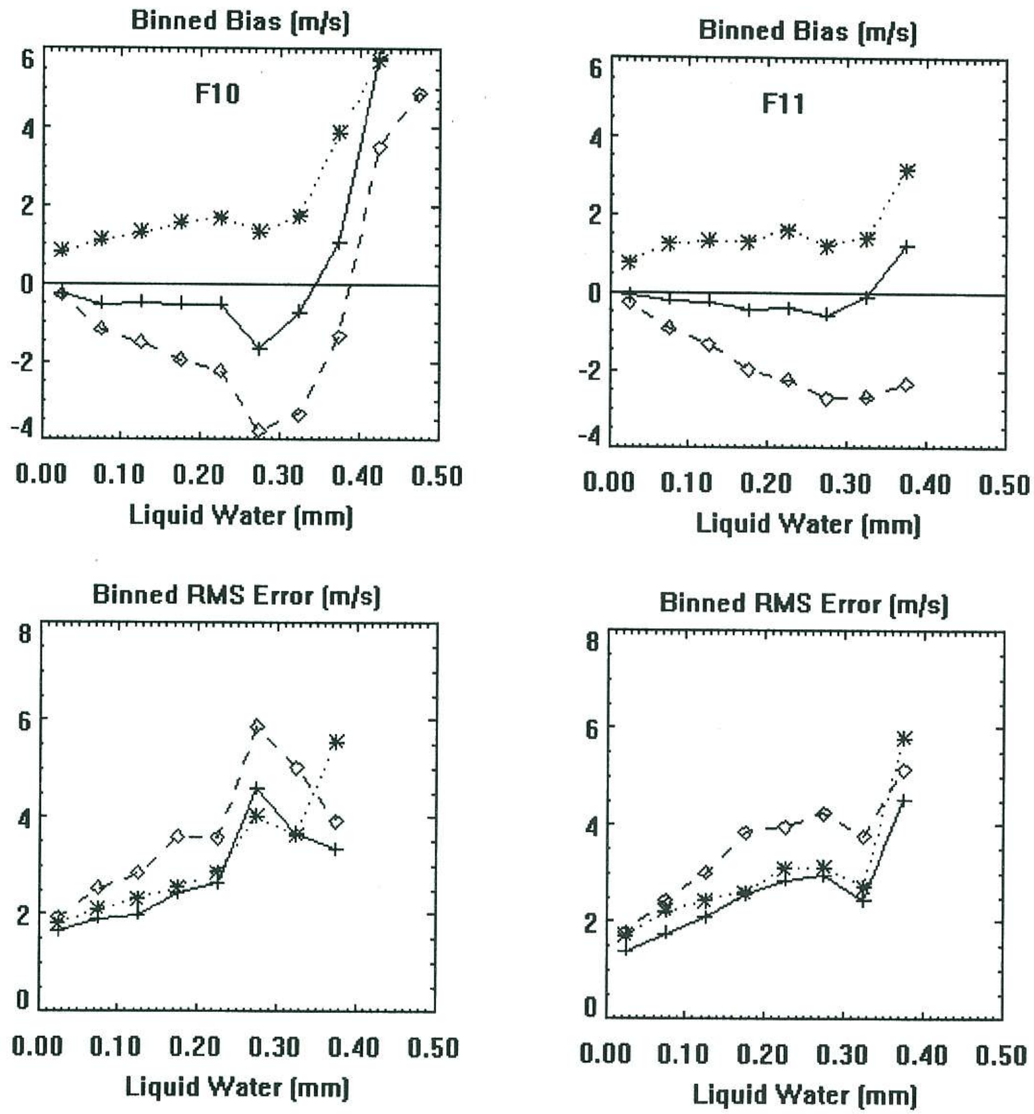

Fig. 5. Bias and RMS error vs. Columnar Liquid Water for GSW (dashed line with diamonds), OMBNN2 (dotted line with stars) and OMBNN3 (solid line with crosses) algorithms for F10 and F11 SSM/I instruments.

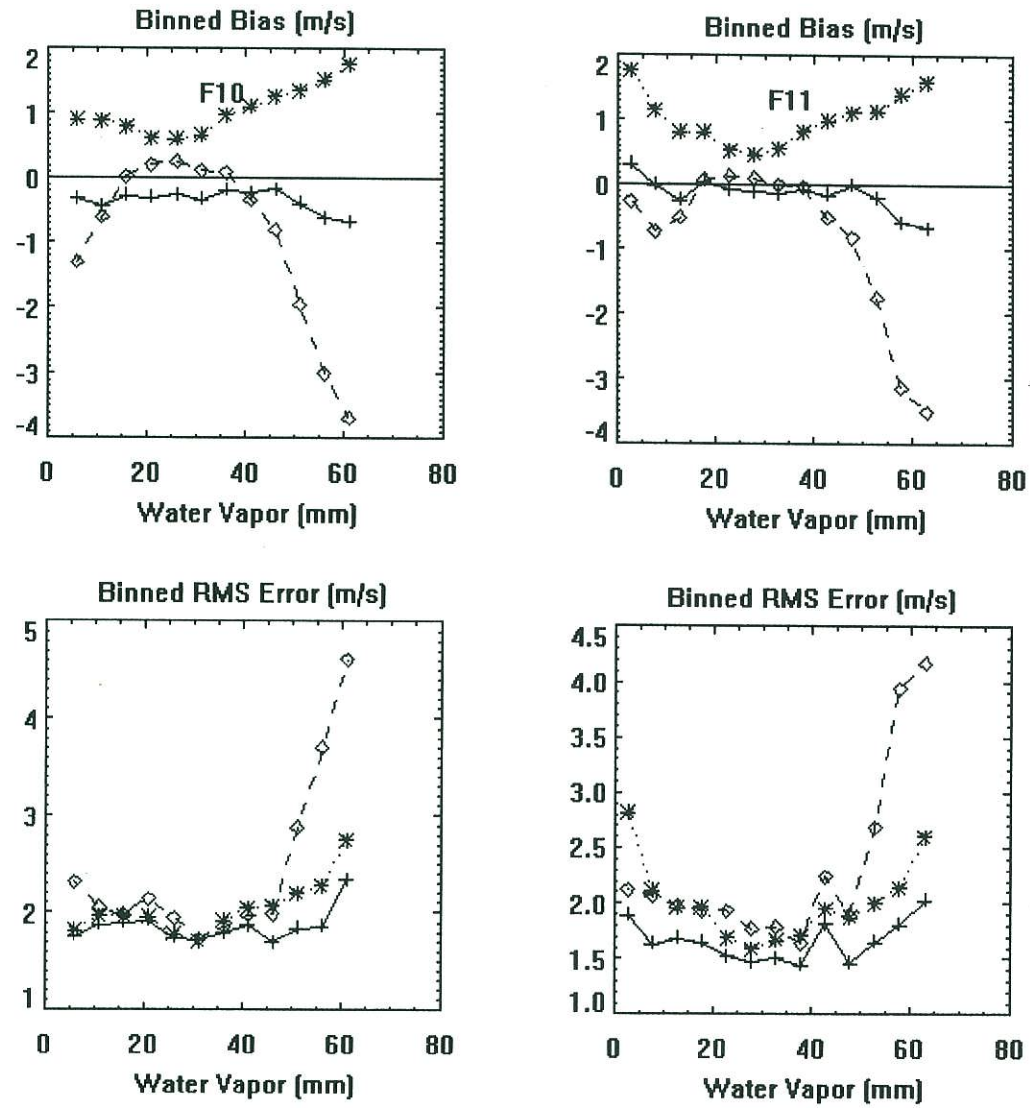

Fig. 6. Bias and RMS error vs. Columnar Water Vapor for GSW (dashed line with diamonds), OMBNN2 (dotted line with stars) and OMBNN3 (solid line with crosses) algorithms for F10 and F11 SSM/I instruments.

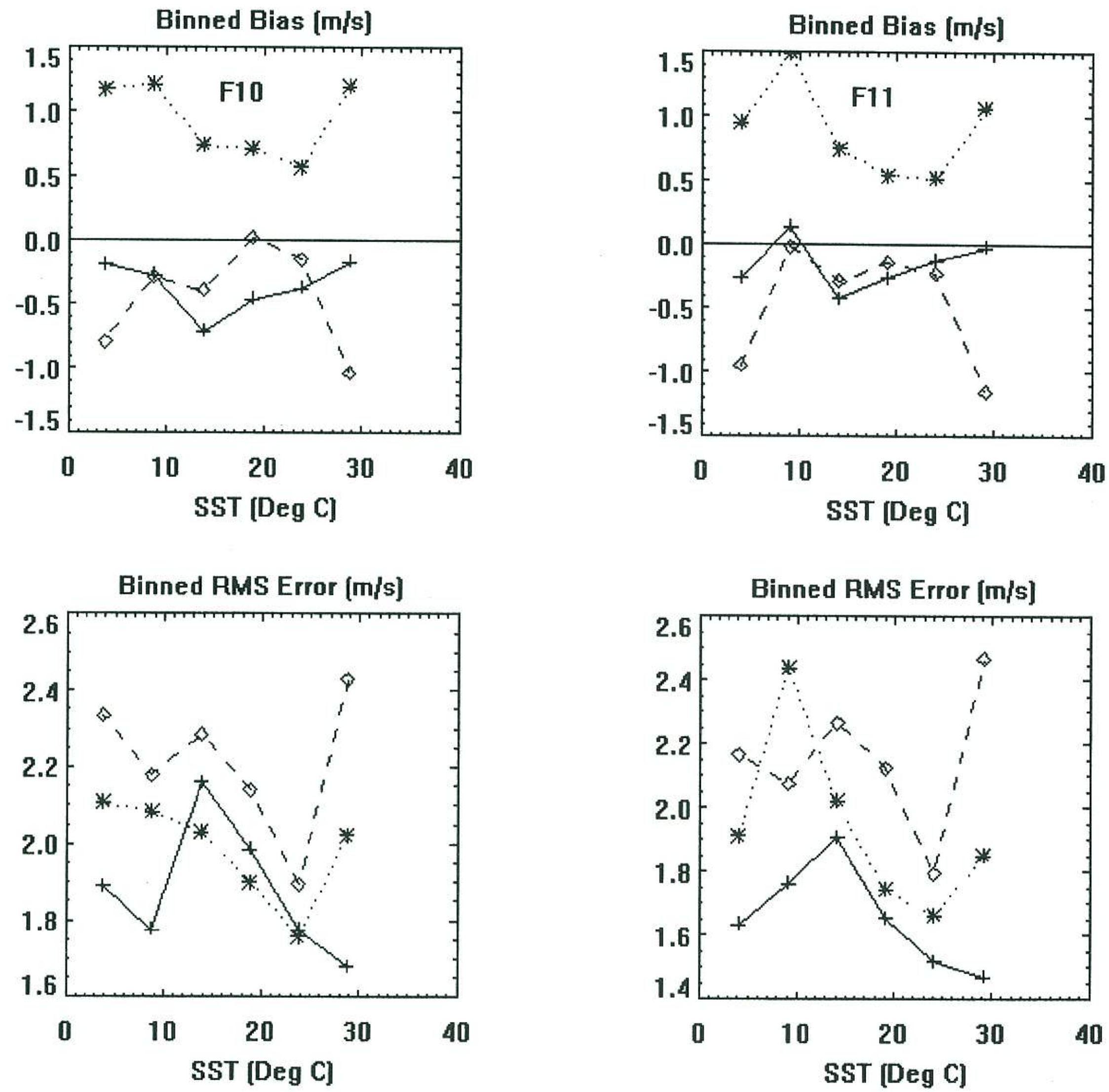

Fig. 7. Bias and RMS error vs. SST for GSW (dashed line with diamonds), OMBNN2 (dotted line with stars) and OMBNN3 (solid line with crosses) algorithms for F10 and F11 SSM/I instruments.

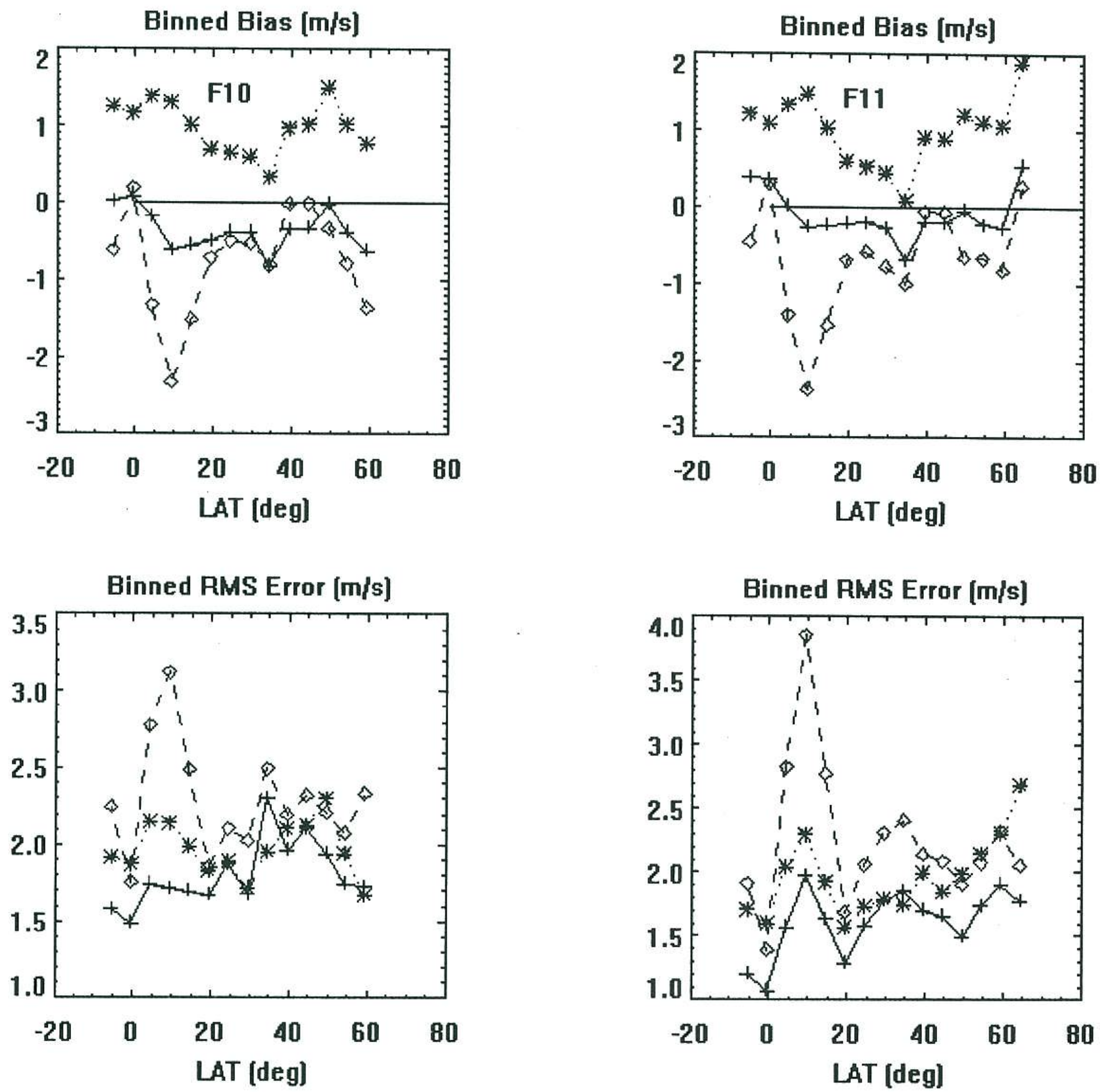

Fig. 8. Bias and RMS error vs. Latitude for GSW (dashed line with diamonds), OMBNN2 (dotted line with stars) and OMBNN3 (solid line with crosses) algorithms for F10 and F11 SSM/I instruments.

5.2 Columnar Water Vapor.

OMBNN3 has been trained to retrieve the amount of columnar water vapor V, using SSM/I BTs. Values of V generated by the cal/val algorithm developed by Alishouse et al. (1990) were used as ground truth during the training. Therefore, OMBNN3 simulates V-retrievals produced by the cal/val algorithm. Table 8 shows retrieval statistics for columnar water vapor (max V, mean V, and standard deviation σ_V) for the cal/val and OMBNN3 algorithms. It also shows bias, SD for the difference between the cal/val and OMBNN3 and the correlation coefficient (CC) between cal/val and OMBNN3 retrievals. OMBNN3 reproduces the cal/val retrievals with an rms difference of about 1 mm and a bias of $\leq$ 0.3 mm.

5.3 Columnar Liquid Water.

OMBNN3 has also been trained to retrieve the amount of columnar liquid water L, using SSM/I BTs. Values of L generated by the WG algorithm developed by Weng and Grody (1994) were used as ground truth during the training. Table 9 shows retrieval statistics for columnar liquid water (max L, mean L, and standard deviation σ_L) for the WG and OMBNN3 algorithms. It also shows bias, SD for the difference between WG and the OMBNN3, and CC between WG and OMBNN3 retrievals. OMBNN3 reproduces WG retrievals with an rms difference of about 0.015 mm and a bias of $\leq$ 0.05 mm.

Table 8. Total statistics for columnar water vapor V (in mm) retrieved by cal/val and OMBNN3 algorithms for CLEAR + CLOUDY conditions and for F10 and F11 SSM/I instruments. Columns 3 - 5 show statistics for the columnar water vapor per se (σ_V denotes standard deviation), and columns 6 - 8 for the difference between cal/val and OMBNN3 algorithm-generated columnar water vapor. SD denotes standard deviation, and CC denotes correlation coefficient.

Satellite	Algorithm	Max V	Mean V	σ_V	Bias	SD	CC
F10 6947 m-ups	Alishouse	60.8	31.0	14.7	N/A	N/A	N/A
	OMBNN3	59.2	30.9	15.4	0.1	1.1	1.0
F11 5673 m-ups	Alishouse	64.4	31.6	15.2	N/A	N/A	N/A
	OMBNN3	60.1	31.4	15.7	0.3	0.9	1.0

Table 9. Total statistics for columnar liquid water L (in mm) retrieved by WG and OMBNN3 algorithms for CLEAR + CLOUDY conditions and for F10 and F11 SSM/I instruments. Columns 3 - 5 show statistics for the columnar liquid water per se (σ_L denotes standard deviation), and columns 6 - 8 for the difference between WG and OMBNN3 algorithm-generated wind speeds. SD denotes standard deviation, and CC denotes correlation coefficient.

Satellite	Algorithm	Max L	Mean L	σ_L	Bias	SD	CC
F10 6847 m-ups	WG	0.44	0.034	0.058	N/A	N/A	N/A
	OMBNN3	0.38	0.039	0.058	0.005	0.016	0.96
F11 5673 m-ups	WG	0.38	0.034	0.058	N/A	N/A	N/A
	OMBNN3	0.36	0.036	0.057	0.00	0.015	0.97

5.4 Sea Surface Temperature.

OMBNN3 has been trained to retrieve *SSTs* from SSM/I BTs, using buoy *SST* measurements. Table 10 shows retrieval statistics for *SST* (max *SST*, mean *SST*, and standard deviation σ_{SST}) based on the OMBNN3 algorithm. It also shows bias, SD and CC for OMBNN3 vs. the buoy observations. OMBNN3 reproduces buoy *SSTs* with an rms error of < 5 °C, and bias < 0.7°C. Although these retrievals have relatively low resolution (of order of SSM/I footprint size), as mentioned above, incorporation of *SST* as an additional output for the NN improves the overall accuracy of the training process.

Table 10 Total statistics for SST (°C) retrieved by OMBNN3 vs. buoy for CLEAR + CLOUDY conditions for F10 and F11 SSM/I instruments. Columns 3 - 5 show statistics for the SST (σ_{SST} denotes standard deviation), and columns 6 - 8 for the difference between buoy and OMBNN3-generated SST. SD denotes standard deviation, and CC denotes correlation coefficient.

Satellite		Max SST	Mean SST	σ_{SST}	Bias	SD	CC
F10 6847 m-ups	Buoy	31.0	20.7	8.57	N/A	N/A	N/A
	OMBNN3	31.0	20.16	8.29	0.58	4.87	0.83
F11 5673 m-ups	Buoy	31.3	20.0	8.86	N/A	N/A	N/A
	OMBNN3	30.7	20.7	7.91	-0.68	4.52	0.86

6. 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. This problem may be due to several factors including increased buoy wind speed errors at high wind speeds, nonuniformity of the wind speed distribution itself, collocation errors in the matchups, and systematic and random errors which occur at high wind speeds due to increasing complexity of the ocean surface as an emitter of microwave radiation (e.g., whitecaps and foam) (Krasnopolsky et al., 1996a). Thus, a practical upper limit for making SSM/I wind speed retrievals may be as low as ~30 m/s in some cases (for some ocean surface states). 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 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 largest bias and rms error occur for F10 (not taking into consideration the noisy data from F13) which may be due to the increased orbit ellipticity for this satellite.

for GSW algorithm, whereas the OMBNN3 algorithm yields a bias and SD which are acceptable for operational use. Therefore, 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*. As shown in Sections 5.2 and 5.3, 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 improve the algorithm's retrieval capabilities.

Acknowledgments

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APPENDIX

```
C*****************************************************************************
C
C Name: OMBNN3
C
C Language: FORTRAN77                Type - FUNCTION
C
C Version: 1.0      Date: 15-07-96      Author: V. Krasnopolsky
C
C ---------------------------------
C
      REAL FUNCTION OMBNN3(XT,V,L,SST)
C
C ---------------------------------
C
C Description:   This retrieval algorithm is a Neural Network
C --------------  implementation of the SSM/I transfer function.
C           It has been developed in EMC of NCEP, NOAA.
C           OMBNN3 means Ocean Modeling Branch (at EMC)
C           Neural Network #3.
C           OMBNN3 retrieves the wind speed (W) at the height 20. m,
C           columnar water vapor (V), columnar liquid water (L) and
C           SST. The NN was trained using back-propagation algorithm.
C
C           OMBNN3 transfer function is described and compared
C           with cal/val and other algorithms in OMB Technical
C           Note No.  "A new neural network transfer function for SSM/I"
C           by V. Krasnopolsky, W. Gemmill and L. Breaker.
C
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C           Tel: 301-763-8133
C           Fax: 301-763-8545
C           address:
C           Environmental Modeling Center,
C           W/NMC21, Room 207,
C           5200 Auth Rd.
C           Camp Spring, MD 20746
C
C Description of training and test data set:
C -----------------------------------------
C   The training set consist of 3460 matchups which were received from
C   two sources:
C   1. 3187 F11/SSMI/buoy matchups were filtered out from a preliminary
C      version of the new NRL database which was kindly provided by
C      G. Poe (NRL). Maximum available wind speed is 24 m/s.
C   2. 273 F11/SSMI/OWS matchups were filtered out from two datasets
C      collected by high latitude OWS LIMA and MIKE. These data sets were
C       kindly provided by D.Kilham (University of Bristol).Maximum
C       available wind speed is 26.4 m/s.
C   Satellite data are collocated with both buoy and OWS data in space
C   within 15 km and in time within 15 min.
C
```

```
C    The test data set has the same structure, the same number of matchups
C    and maximum buoy wind speed.
C
C Description of retrieval flags:
C ------------------------------
C    Retrieval flags by Stogryn et al. are used.  The algorithm produces
C    retrievals under CLEAR + CLOUDY conditions, that is if:
C
C               T37V - T37H > 50.    => CLEAR condition
C               or
C               T19H =< 185.  and |
C               T37H =< 210.  and | => CLOUDY conditions
C               T19H  < T37V      |
C
C=====================================================================
C
C SOME COMPARISON STATISTICS:
C
C=====================================================================
C
C Wind speed statistics on training + test sets (CLEAR + CLOUDY conditions)
C D = Wbuoy - Wnn, SD - standard deviation, CC - correlation coeff.:
C -------------------------------------------------------------------------------------------
C            Max W  Mean W  SD of W   Bias  SD of D   CC (Wbuoy,Wnn)
C             m/s     m/s      m/s     m/s    m/s
C-------------------------------------------------------------------------------------------
C Buoy       26.4     7.47     3.51
C                                     -0.11    1.61         0.89
C OMBNN3     22.8     7.56     3.27
C-------------------------------------------------------------------------------------------
C
C OMBNN3 water vapor statistics vs. cal/val and Wentz algorithms:
C
C
C-------------------------------------------------------
C             Bias    SD    CC
C              mm     mm
C---------------------------------------
C vs. cal/val   0.3    0.9   1.0
C vs. Wentz     0.2    3.8   0.97
C---------------------------------------
C
C OMBNN3 liquid water statistics vs. Weng and Grody (WG) and Wentz algorithms:
C-------------------------------------------------------------
C             Bias    SD     CC
C              mm     mm
C---------------------------------------
C vs. WG        0.0   0.015   0.97
C vs. Wentz    -0.03  0.06    0.94
C---------------------------------------
C
C SST statistics vs. buoys, D = SSTbuoy - SSTnn:
```

```
C------------------------------------------------------------------------------------
C          Max SST  Mean SST  SD of SST  Bias   SD of D  CC(SSTbuoy,SSTnn)
C           deg C    deg C     deg C     deg C   deg C
C----------------------- -----------------------------------------------------------
C Buoy       31.3     20.0      8.86
C                                         -0.7    4.5     0.86
C OMBNN3     30.7     20.7      7.91
C------------------------------------------------------------------------------------
C
C*****************************************************************************
C Arguments:
C ---------
C INPUTS:  OMBNN3 algorithm uses 5 brightness temperatures.
C
C      XT - THE BRIGHTNESS TEMPERATURES IN THE ORDER:
C        XT(1) = T19V
C        XT(2) = T19H
C        XT(3) = T22V
C        XT(4) = T37V
C        XT(5) = T37H
C
C OUTPUTS:
C
C      One value is returned by the function:
C
C        OMBNN3 - wind speed in m/s, at the height 20 m
C
C      Three values are returned as arguments:
C
C        V - columnar water vapor in mm
C        L - columnar liquid water in mm
C      SST - sea surface temperature in deg C
C
C   If brightness temperatures are rejected by the retrieval flag then
C   all outputs are - 99.9 !
C
C*****************************************************************************
C
C CALLING FROM A FORTRAN PROGRAM:
C =============================
C
C   REAL XT(5),V,L,SST,W
C   Input XT
C   W = OMBNN3(XT,V,L,SST)
C
C*****************************************************************************
C
      PARAMETER ( OUT = 4, IN = 5, flag = -99.9 )
C
      logical lq1,lq2,lq3,LQ4
C
      REAL XT(IN),Y(OUT), V, L, SST
```

```
C
      EQUIVALENCE (Y(1),SPN)
C
C -------- Retrieval flag (Stogryn) ------------------------
C
C T19H =< 185
      lq1 = (xT(2).le.185.)
C T37H =< 210
      lq2 = (xT(5).le.210.)
C T19H < T37V
      lq3 = (xT(1).lt.xT(4))
C T37V - T37H =< 50.
      LQ4 = ((XT(4) - XT(5)).LE.50.)
C
      lq1 = (lq1.and.lq2.and.lq3)
C
      if (.not.lq1.AND.LQ4) then
         OMBNN3 = flag
         V = flag
         L = flag
         SST = flag
         RETURN
      endif
C
C --------------- Call NN ---------------------
C
C NN wind speed
C
      CALL N5124b11 ( XT, Y )
      V = Y(2)
      L = Y(3)
      SST = Y(4)
C
C --------- Remove negative values ---------------------------
C
C
      IF (SPN.LT.0.) SPN = 0.
      IF (SST.LT.0.) SST = 0.
      IF (V.LT.0.) V = 0.
      IF (L.LT.0.) L = 0.
C
      OMBNN3 = SPN
C
C
      RETURN
      END
C$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$
C***********************************************************************
C
C Name: NN5124B11
C
C Language: FORTRAN77              Type - SUBROUTINE
```

```
C
C Version: 1.0       Date: 07-15-96      Author: V. Krasnopolsky
C
C ---------------------------------
C
      SUBROUTINE N5124B11(X,Y)
C
C ---------------------------------
C
C Description:  This NN calculates W (in m/s), V (in mm), L (in mm),
C --------------    and SST (in deg C). This NN was trained on blended
C                   F11 data set (SSMI/buoy matchups plus SSMI/OWS
C                   matchups 15km x 15 min) under Clear + Cloudy conditions
C
C***************************************************************************
C
      INTEGER HID,OUT
      PARAMETER (IN = 5, HID = 12, OUT = 4)
C
C Arguments:
C ---------
C INPUT:
C        X(1) = T19V
C        X(2) = T19H
C        X(3) = T22V
C        X(4) = T37V
C        X(5) = T37H
C
      DIMENSION X(IN)
C
C  OUTPUT:
C        Y(1) = Wind Speed in m/s
C        Y(2) = Columnar Water Vapor in mm
C        Y(3) = Columnar Liquid Water in mm
C        Y(4) = SST in deg C
C
      DIMENSION Y(OUT)
C
C
C%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
C
C Internal variables:
C ------------------
C
C     IN - NUMBER OF NN INPUTS
C
C     HID - NUMBER OF HIDDEN NODES
C
C     OUT - NUMBER OF OUTPUTS
C
C     W1 - INPUT WEIGHTS
C
```

```
C     W2 - HIDDEN WEIGHTS
C
C     B1 - HIDDEN BIASES
C
C     B2 - OUTPUT BIAS
C
      DIMENSION W1(IN,HID),W2(HID,OUT),B1(HID),B2(OUT)
C
C     A(OUT), B(OUT) - OUTPUT TRANSFORMATION COEFFICIENTS
C
C##############################################################################
C
      DIMENSION O1(IN),X2(HID),O2(HID),X3(OUT),O3(OUT),A(OUT),B(OUT)
C
      DATA ((W1(I,J),J = 1,HID),I = 1,IN)
     & /-0.0435901,0.0614709,-0.0453639,-0.0161106,-0.0271382,.0229015,
     &-0.0650678,0.0704302,0.0383939,0.0773921,0.0661954,-0.0643473,
     &-0.0108528,-0.0283174,-0.0308437,-0.0199316,-0.0131226, 0.0107767,
     &0.0234265,-0.0291637,0.0140943,0.00567931,-0.00931768,
     &-0.00860661,0.0159747,-0.0749903,-0.0503523,0.0524172,0.0195771,
     &0.0302056,0.0331725,0.0326714,-0.0291429,0.0180438,0.0281923,
     &-0.0269554,0.102836,0.0591511,0.134313,-0.0109854,-0.0786303,
     &0.0117111,0.0231543,-0.0205603,-0.0382944,-0.0342049,
     &0.000524070,0.110301,-0.0404777,0.0428816,0.0878070,0.0168326,
     &0.0196183,0.0293995,0.00954805,-0.00716287,0.0269475,
     &-0.0418217,-0.0165812, 0.0291809/
       DATA ((W2(I,J),J = 1,OUT),I = 1,HID)
     & /-0.827004,-0.169961,-0.230296,-0.311201,-0.243296,0.00454425,
     &-0.0678487,0.428192,0.827626,0.253772,0.112026,0.00563793,
     &-1.28161,-0.169509,0.00190850,-0.137136,-0.334738,0.224899,
     &-0.189678,0.626459,-0.204658,-0.885417,-0.148720,0.122903,
     &0.650024,0.715758,0.735026,-0.123308,-0.387411,-0.140137,
     &0.229058,0.244314,-1.08613,-0.294565,-0.192568,0.608760,
     &-0.753586,0.897605,0.0322991,-0.178470,0.0807701,
     &-0.781417/
      DATA (B1(I), I=1,HID)
     & /-9.92116,-10.3103,-17.2536,-5.26287,17.7729,-20.4812,
     &-4.80869,-11.5222, 0.592880,-4.89773,-17.3294, -7.74136/
       DATA (B2(I), I=1,OUT)
     & /-0.882873,-0.0120802,-3.19400,1.00314/
      DATA (A(I), I=1,OUT)
     & /18.1286,31.8210,0.198863,37.1250/
       DATA (B(I), I=1,OUT)
     & /13.7100,32.0980,0.198863,-5.82500/
C
C
      DO I = 1,IN
       O1(I) = X(I)
      END DO
C
C - START NEURAL NETWORK
C
```

```
C
C - INITIALIZE X2
C
     DO I = 1, HID
      X2(I) = 0.
      DO J = 1,IN
       X2(I) = X2(I) + O1(J) * W1(J,I)
      END DO
      X2(I) = X2(I) + B1(I)
      O2(I) = TANH(X2(I))
     END DO
C
C
C - INITIALIZE X3
C
        DO K = 1,OUT
         X3(K) = 0.
         DO J = 1,HID
          X3(K) = X3(K) + W2(J,K)*O2(J)
         ENDDO
C
         X3(K) = X3(K) + B2(K)
C
C --- CALCULATE O3
C
         O3(K) = TANH(X3(K))
         Y(K) = A(K) * O3(K) + B(K)
        ENDDO
C
     RETURN
C
     END
C
C##########################################################################################
C
C----- Table of results for different input values ------------------------
C
C ***************************************************************************
C  ------ OMBNN3 inputs -----------------   --OMBNN3 outputs ----
C  T19V   T19H   T22V   T37V   T37H      W     V      L    SST
C                                       m/s    mm     mm  deg C
C ---------------------------------------------------------------------------
C 192.19 115.45 215.52 209.78 136.25    .37  19.68  .001  23.23
C 198.44 125.17 226.33 212.71 143.99   1.96  28.41  .001  26.78
C 215.19 154.71 251.70 225.91 167.45   2.57  51.09  .005  29.69
C 181.66 105.93 197.58 206.14 138.10   3.02   8.57  .028   5.70
C 196.86 126.62 223.89 212.94 146.94   3.41  25.77  .003  23.56
C 221.62 167.47 260.36 232.57 182.18   3.73  57.20  .052  29.74
C 182.27 101.32 192.79 201.37 127.06   3.99   8.78  .000  18.30
C 203.23 133.41 231.54 215.77 151.80   4.21  31.83  .002  28.66
C 198.10 130.59 227.79 213.42 149.43   4.43  29.40  .002  22.39
C 204.93 145.16 241.92 223.42 172.41   4.58  38.48  .059  17.62
```

```
C 199.32 132.54 228.22 214.77 151.75  4.75 28.94 .005 23.27
C 218.18 162.99 258.01 228.43 176.90  4.93 56.00 .011 28.87
C 199.57 131.29 228.70 213.81 150.77  5.07 30.08 .002 25.37
C 209.37 146.85 243.83 220.60 162.03  5.18 42.78 .002 28.54
C 213.24 155.29 251.08 224.24 169.45  5.34 50.34 .004 27.85
C 200.10 134.79 230.94 214.91 153.29  5.44 31.66 .003 22.67
C 198.52 136.20 231.10 217.07 160.14  5.54 30.82 .032 12.46
C 189.10 118.23 209.89 210.55 148.15  5.68 14.83 .052 13.15
C 214.12 156.41 250.21 225.56 171.91  5.78 49.13 .017 28.49
C 199.14 140.16 227.20 223.84 174.62  5.90 23.95 .160 11.38
C 212.15 154.86 250.68 224.15 171.21  6.01 49.43 .008 25.97
C 180.47 105.98 190.84 205.38 139.67  6.13  5.92 .039  4.11
C 220.90 166.63 260.82 228.47 177.87  6.26 58.15 .004 30.01
C 215.85 158.74 255.15 224.41 171.30  6.39 54.51 .001 29.18
C 191.51 121.17 214.43 207.94 142.40  6.49 20.28 .001 21.35
C 181.43 108.51 195.97 203.89 137.26  6.58  8.47 .010  6.56
C 226.77 177.02 264.94 235.22 189.37  6.71 59.41 .069 30.41
C 220.79 167.62 260.26 229.29 180.21  6.80 57.62 .012 29.71
C 187.15 118.38 208.22 206.81 141.54  6.89 15.06 .003 10.74
C 213.86 157.83 248.56 230.26 184.39  7.00 45.15 .126 25.62
C 199.33 132.71 227.51 213.59 152.85  7.13 29.09 .004 24.91
C 193.54 126.33 221.72 209.01 146.24  7.24 26.51 .000 19.23
C 207.45 153.14 244.89 225.30 178.54  7.36 41.97 .060 15.88
C 198.60 132.70 226.66 213.09 152.37  7.50 28.65 .004 23.85
C 219.45 167.32 257.96 228.97 180.44  7.63 56.10 .019 29.06
C 180.65 103.87 191.03 200.99 132.24  7.75  7.68 .002 12.28
C 204.99 142.84 236.36 218.38 161.83  7.87 34.80 .012 25.99
C 189.18 118.79 210.99 207.30 144.66  8.00 17.58 .006 17.58
C 200.16 135.66 231.40 213.90 155.70  8.13 32.71 .003 23.45
C 196.67 133.51 226.52 213.34 155.42  8.27 28.54 .010 15.63
C 209.47 150.94 241.13 227.64 181.72  8.42 36.29 .134 23.91
C 210.56 151.34 246.22 220.63 166.96  8.57 45.57 .002 28.14
C 203.59 141.46 234.78 215.93 158.25  8.75 34.93 .002 25.90
C 200.23 136.19 227.98 214.79 156.62  8.92 28.65 .013 24.07
C 203.98 141.14 235.13 215.91 158.97  9.11 35.09 .003 26.76
C 206.30 155.16 235.82 235.40 203.38  9.38 27.34 .321  7.83
C 190.30 124.59 212.88 210.83 153.60  9.62 16.97 .055 11.05
C 185.57 115.67 201.98 206.22 144.51  9.90 11.02 .021 10.65
C 190.79 125.83 216.95 208.68 150.55 10.17 21.98 .008 11.76
C 188.04 124.76 207.30 212.88 160.38 10.49 11.56 .135  5.94
C 200.43 139.99 226.56 222.24 176.21 10.85 22.76 .145 17.37
C 190.71 125.15 214.90 208.40 151.07 11.27 20.16 .013 14.41
C 212.07 159.10 246.02 225.34 179.48 11.77 43.65 .053 24.74
C 214.19 161.07 246.24 226.43 180.56 12.47 43.89 .069 27.09
C 203.49 142.80 233.04 215.09 162.82 13.30 32.84 .008 26.37
C 185.75 118.12 199.78 204.60 145.51 14.48 10.05 .013 11.54
C 197.40 136.88 212.20 221.32 176.01 16.71 10.92 .166 11.92
C 216.55 174.92 237.75 229.32 199.47 22.84 32.77 .121 17.31
C
C##############################################################################
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