Global Data Assimilation and Forecast Experiments Using SSM/I Wind Speed Data Derived from a Neural Network Algorithm

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ABSTRACT

A neural network algorithm used in this study to derive Special Sensor Microwave/Imager (SSM/I) wind speeds from the Defense Meteorological Satellite Program satellite-observed brightness temperatures is briefly reviewed. The SSM/I winds derived from the neural network algorithm are not only of better quality, but also cover a larger area when compared to those generated from the currently operational Goodberlet algorithm. The areas of increased coverage occur mainly over the regions of active weather developments where the operational Goodberlet algorithm fails to produce good quality wind data due to high moisture contents of the atmosphere. These two main characteristics associated with the SSM/I winds derived from the neural network algorithm are discussed.

SSM/I wind speed data derived from both the neural network algorithm and the operational Goodberlet algorithm are tested in parallel global data assimilation and forecast experiments for a period of about three weeks. The results show that the use of neural-network-derived SSM/I wind speed data leads to a greater improvement in the first-guess wind fields than use of wind data generated by the operational algorithm. Similarly, comparison of the forecast results shows that use of the neural-network-derived SSM/I wind speed data in the data assimilation and forecast experiment gives better forecasts when compared to those from the operational run that uses the SSM/I winds from the Goodberlet algorithm. These results of comparison between the two parallel analyses and forecasts from the global data assimilation experiments are discussed.

1. Introduction

The Special Sensor Microwave/Imager (SSM/I) wind speed data from the Defense Meteorological Satellite Program (DMSP) have been used in the operational global data assimilation system since March 1993 at the National Centers for Environmental Prediction (NCEP). The operational SSM/I wind speed data are derived using the wind speed algorithm originally developed by Goodberlet et al. (1989) and delivered to NCEP through the shared processing agreement between the National Oceanic and Atmospheric Administration, the U.S. Navy, and the U.S. Air Force. Basically it is an empirically derived linear regression algorithm that relates brightness temperatures observed from various microwave spectral channels to ocean surface wind speeds. Before the SSM/I wind speed data were implemented operationally in the NCEP global data assimilation system, a number of impact studies were conducted, and the results showed that the assimilation of wind speed data was slightly beneficial to the NCEP numerical weather analyses and short-range forecasts (Yu and Deaven 1991; Yu et al. 1992). These SSM/I wind speed data are also being used operationally at Fleet Numerical Meteorology and Oceanography Center (Phoebus and Goerss 1991; Goerss and Phoebus 1992).

The current operational algorithm of Goodberlet et al. (1989) assumes a linear dependence of the wind speed on brightness temperatures. This assumption is acceptable when the level of moisture, both water vapor and liquid water, in the atmosphere is very low. As soon as the level of moisture increases, the dependence of the wind speed on brightness temperatures becomes significantly nonlinear (Petty and Katsaros 1993; Petty and Katsaros 1994), and errors in wind speeds retrieved by the current linear operational algorithm become very large. For this reason, only SSM/I wind speed data over the clear-sky area are used in the current operation global data assimilation system at NCEP, and a large number of data points over active weather regions have to be rejected. This is rather unfortunate since it is these developing weather systems that are of most interest and import in weather forecasting. To perform accurate retrievals in these areas with higher levels of moisture (the amount of liquid water should nevertheless not exceed some critical level because the atmosphere becomes opaque to the microwave radiation when the critical level is reached), a nonlinear algorithm that is capable of modeling the nonlinear dependence of the wind speed on brightness temperatures is required.

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Neural networks are known to be good models for a broad class of nonlinear relationship geophysical applications (Bose and Liang 1996). The first neural network SSM/I wind speed retrieval algorithm developed by Stogryn et al. (1994), and later refined by Krasnopolsky et al. (1995a), demonstrated that the retrieval accuracies in wind speeds were significantly better than those using the current operational algorithm both in terms of bias and rms errors. More significantly, their results showed that the neural network wind algorithms were able to expand the areal coverage for retrievals under cloudy conditions where the operational Goodberlet wind algorithm failed. This expanded areal coverage over the cloudy regions could be of particular importance. This is because that it is in the cloudy regions of high moisture contents where active weather is most often to occur, and that the additional wind data generated from the neural network algorithm over these regions can be most useful in improving the numerical weather analyses and forecasts.

The performance of neural network algorithms in the retrieval of SSM/I wind speed data discussed in Krasnopolsky (1995a,b), has been tested mainly by using well-prepared matchup datasets. That is, their wind data were tested only in an experimental retrieval procedure, but not yet in any operational forecast systems. Oftentimes, new data that may be tested and found satisfactory in the experimental procedure are not confirmed when applied to the real forecast operations. For this reason, it is therefore necessary to further investigate the performance of these newly improved wind data in the NCEP operational data assimilation and forecast systems. The main purpose of this paper is to demonstrate that use of the SSM/I wind speed data derived from the neural network algorithm indeed improves initial atmospheric analyses and leads to better short-range weather forecasts. Section 2 briefly describes the architectures and their attendant attributes related to the neural network wind algorithm used in this study. The NCEP operational global data assimilation and forecast system is discussed in section 3. To investigate the impact of the new wind data, a parallel global data assimilation experiment (parallel run) was run using the neural-network-derived SSM/I wind speed data instead of the winds from the operational Goodberlet algorithm in the NCEP analyses during the global data assimilation cycles for about three weeks, beginning 0000 UTC 16 May 1996 and ending 0000 UTC 4 June 1996. Since assimilation of the SSM/I wind speed data derived from the Goodberlet wind algorithm has been implemented in the operational model (control run) since March 1993, the replacement of operational SSM/I wind data by the neural-network-derived SSM/I wind data constitutes the sole difference between the parallel run and the control run. In both the control and parallel runs, the SSM/I wind speed data have been averaged over a 1° lat × 1° long box to reduce the quantity of the data and make the data to be more representative of the T62 resolution of the analysis grid. Comparison of the assimilation and forecast results will give us an indication of the effect of the new algorithm on NCEP numerical operations. It should be pointed out that the operational global data assimilation system underwent a number of improvements since the implementation of SSM/I wind speed data in 1993, notably the direct use of TIROS Operational Vertical Sounder radiance data, for example (see Caplan et al. 1997). Thus, the test results discussed in section 4 represent an investigation on the use of the SSM/I wind speed data with the most current NCEP operational global data assimilation systems.

2. The neural network wind algorithm

A detailed description on the architectures and their attendant attributes related to the neural network wind algorithm used in this study can be found in Krasnopolsky et al. (1995a,b), and therefore only a brief discussion is presented here. Basically, ocean surface wind speeds are determined from the SSM/I observed brightness temperatures by using some neural network transfer functions. Symbolically, this may be expressed as, $\mathbf{G} = f(\mathbf{P})$, where f is a transfer function to be approximated by a neural network, which relates $\mathbf{P}$, the input vector taken from the measured brightness temperatures (TB), that is, $\mathbf{P} = \{$TB19V, TB22V, TB37V, TB37H$\}$, to the output vector $\mathbf{G}$, in this case the ocean surface wind speed. The dimensions of the input and output vectors define a specific neural network architecture with m nodes in the input layer (in this case, four channels of brightness temperatures, and thus $m = 4$) and n nodes in the output layer (wind speed is a scalar in this case, and thus $n = 1$). The neural network has also an internal (hidden) layer that connects input layer and output layer. The hidden layer has two nodes in this case. In general, a neural network consists of processing these nodes where each node is composed of two parts, one linear and the other nonlinear. The linear portion of the node produces a weighted sum of its inputs with the weights and biases determining the behavior of each node. The nonlinear portion employs a hyperbolic tangent squashing function to reproduce the desired output as a function of the linear nodal inputs from the linear portion.

The neural network used in this study and described in Krasnopolsky et al. (1995a) was trained by applying the brightness temperatures (TBs) to the input and then calculating the wind speed at the output of the network. Then the output was compared with the observed buoy wind speeds contained in the matchup database to determine the difference (i.e., errors) between the neural network output and the observed data. A back propagation procedure was employed to adjust the weights at each node until the errors were minimized. Once the training is completed and the weights have been determined, the desired wind speed, W, is calculated as $W = \mathrm{Net}(\mathbf{P})$, where $\mathbf{P}$, as before, corresponds to the input vector of TBs. It should be mentioned that generaliza-

TABLE 1. Comparison of SSM/I wind speeds generated by the neural network algorithm and the operational algorithm with collocated buoy observations using DMSP *F8* satellite brightness temperature data. There are a total of 1200 collocation data points used in the computation of the bias and rms wind speed errors.

Atmospheric conditions	Wind retrieval algorithms	Bias (m s^{-1})	Rms (m s^{-1})
Clear skies only	Operational	-1.03	2.06
	neural network	0.25	1.46
Clear and cloudy skies	Operational	-1.37	2.63
	neural network	0.47	1.70

tion ability of the neural network was successfully tested when the algorithm was applied to an independent set from the matchup database; furthermore, the neural network operator, Net, was trained to retrieve wind speeds for the entire dataset, with the exception of a small cloudy portion that corresponds to the cloud liquid water amounts of greater than 0.4–0.5 mm (see Krasnopolsky et al. 1995a). The algorithm can be applied to all weather conditions, that is, either clear- or cloudy-sky conditions.

The neural network described in Krasnoplosky et al. (1995a) showed the retrieved winds under cloudy conditions to have acceptable error statistics only for wind speeds that were not greater than 16–18 m s^{-1}. This deficiency in generating high wind speeds was due to the absence of high wind speed matchups in the collocated buoy and SSM/I wind speed database used as the training dataset. Recently, an improved neural network wind algorithm was developed by Krasnopolsky et al. (1995b) using advanced methods in neural network training and an additional 85-GHz microwave channel to partially compensate for the database problem. This new algorithm is designated as OMBNN and it is capable of generating higher wind speeds up to 20–21 m s^{-1} before a bias correction. After the bias correction, the algorithm can extend retrievals of wind speeds to 25–26 m s^{-1}. Table 1 shows the bias and rms errors compared to buoy observations with SSM/I wind speeds derived from the OMBNN algorithm and the Goodberlet algorithm. It is clearly evident from Table 1 that wind products derived from the OMBNN neural network algorithm are of higher quality. The OMBNN wind algorithm is far from being a perfect solution of the SSM/I wind speed retrieval problem, however. This is because the bias correction built into the OMBNN algorithm is dependent on types of microwave instruments and satellites. Now using a new matchup database created by the navy, a further refinement of the OMBNN neural network algorithm is under active development at NCEP (Krasnopolsky et al. 1996), and preliminary results show that this refined algorithm is capable of generating wind speeds of up to 23–24 m s^{-1} without any bias correction, and its accuracy will not depend significantly on the instruments and/or satellites.

In addition to the improved quality of wind products as discussed above, it is equally important that the OMBNN wind algorithm increases areas of coverage over the oceans when compared to the operational algorithm that cannot produce SSM/I wind speed data over regions of high level of moisture contents. As a result, the data coverages are about 10%–15% more over the midlatitude oceans, and about 30% more over the tropical oceans, than those generated by the operational Goodberlet algorithm. This is illustrated in Fig. 1 for the *DMSP F10* satellite (top panel) and *DMSP F13* satellite (bottom panel). Note that the data-void areas produced by the operational algorithm (GSW) represent areas of high moisture contents (cloudy-sky conditions), where the neural network wind algorithm (OMBNN) was able to produce useful wind speed data. These areas of additional data coverage could potentially be very important for improving atmospheric analyses and forecasts of NCEP numerical weather prediction operations.

3. Assimilation and forecast experiments

The NCEP T62 global data assimilation system, details of which were given in Kanamitsu (1989), Kanamitsu et al. (1991), and Caplan et al. (1997), was used to investigate the impact of the neural network SSM/I wind speed data on analyses and forecasts. Basically, the assimilation system consists of a forecast model and an analysis scheme. The forecast model is a global spectral forecast model of triangular truncation with 62 waves for the horizontal spectral resolution. In the vertical it has 28 sigma layers. It includes parameterization of such physical processes as convection, precipitation, radiation, and boundary layer physics that are identical to those employed in the full-resolution NCEP operational forecast T126 model. The analysis scheme is a spectral statistical analysis scheme (Parrish and Derber 1992). Since the SSM/I wind data contain only wind speeds but no directions, the use of SSM/I wind speed data in the analyses is accomplished by assigning the first-guess wind directions to the SSM/I wind speed data before their use in the spectral statistical analyses.

The assimilation experiment is proceeded by a 6-h forward integration of the forecast model, starting from the beginning of the data assimilation period, to produce first-guess fields of winds (u, v), temperatures (T), and specific humidity (q). The observations within a $\pm$3-h window are then used to update the first-guess fields and complete the analyses. This process of a 6-h model forecast followed by an analysis update is repeated four times a day, once every 6 h, until the end of the three weeks of the assimilation period. For each of the parallel and control run experiments, 5-day forecasts were made at the 0000 UTC cycle of the daily data assimilation, so that there were a total of 20 cases of forecasts. In this study the forecasts valid at 24, 48, 72, 96, and 120 h of the 20 forecast cases are used for comparison between the two parallel runs. Standard statistics of anomaly correlations and rms forecast height errors are calculated for each of the two parallel forecasts. In addition,

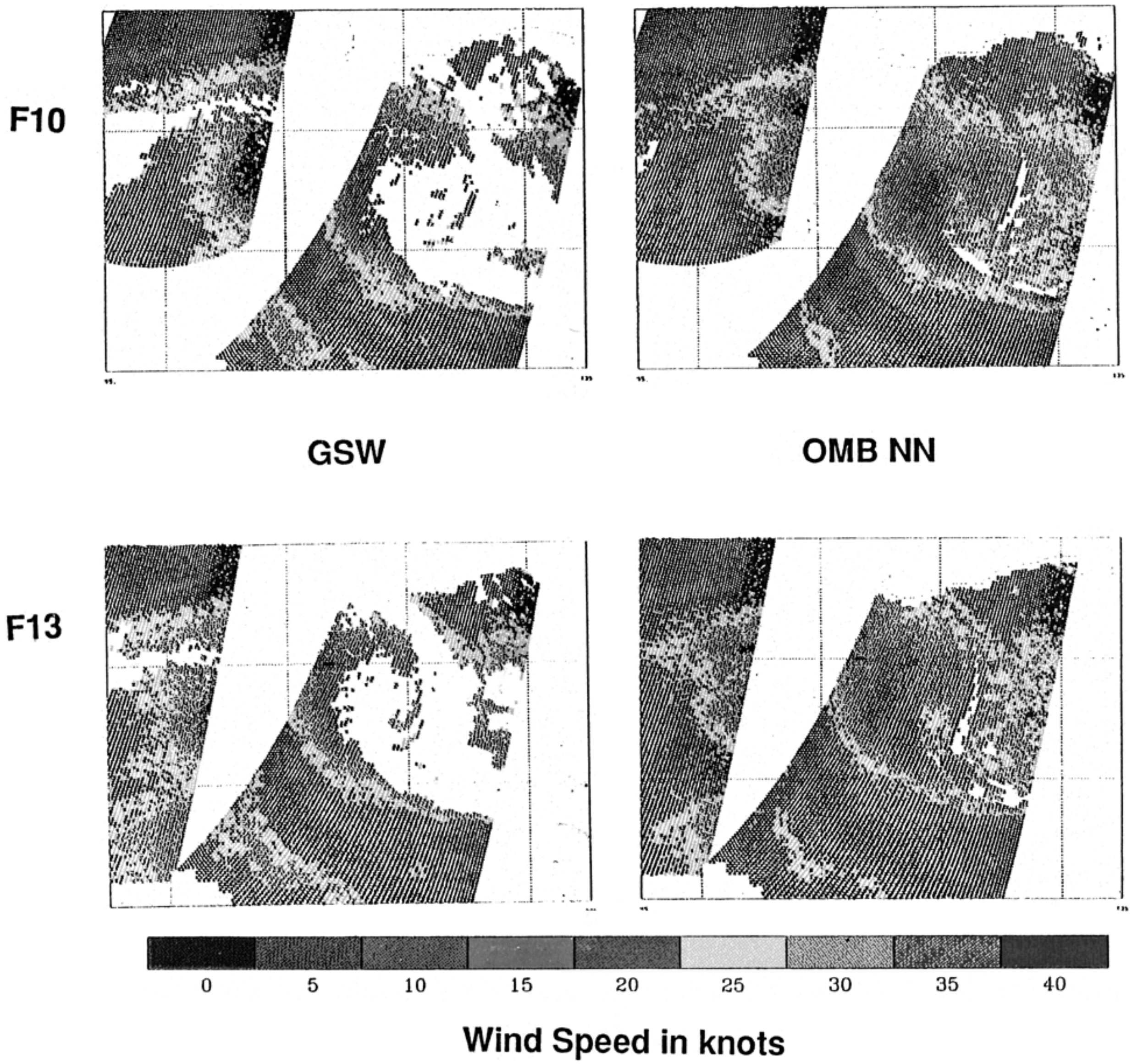

FIG. 1. Marine winds (in kt) retrieved from the SSM/I brightness temperatures using the operational Goodberlet algorithm (GSW, left), and the neural network algorithm (OMBNN, right) from the DMSP *F10* (top) and *F13* (bottom) satellites. The blank area (left) depicts the area of null wind data due to high atmospheric moisture contents.

forecast errors of sea level pressures and 10-m winds with reference to midlatitude deep ocean buoys and tropical Tropical Ocean Global Atmosphere (TOGA) buoys for the two parallel experiments are compared.

4. The parallel run test results

With the use of Goodberlet SSM/I wind data in the control run, and the use of neural network SSM/I wind data in the parallel run, one can compare the extent to which each system's first-guess wind fields are affected by the use of these different wind datasets in the analyses between the two parallel assimilation runs. Figure 2 shows vector wind rms difference between the first-guess 10-m winds (6-h model forecast) and SSM/I winds derived from the operational Goodberlet algorithm, and those derived from the neural network algorithm. It shows clearly that the wind speeds derived from the neural network algorithm are closer to the first guess than those derived from the Goodberlet algorithm.

Similarly, comparison of the fit of first-guess wind fields to the observed *ERS-1* vector winds between the two parallel runs is shown in Fig. 3. It is further evidenced that use of SSM/I wind data derived from the neural network improves the initial analyses. This is reflected by the smaller rms wind difference between the model first-guess winds and *ERS-1* wind observations for the parallel run when compared to those for

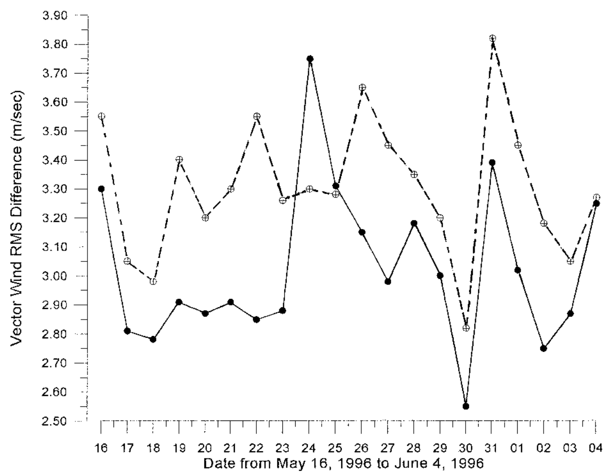

FIG. 2. Fit of the first-guess winds to SSM/I wind data derived by using the operational Goodberlet algorithm (dashed line) and the neural network algorithm (solid line).

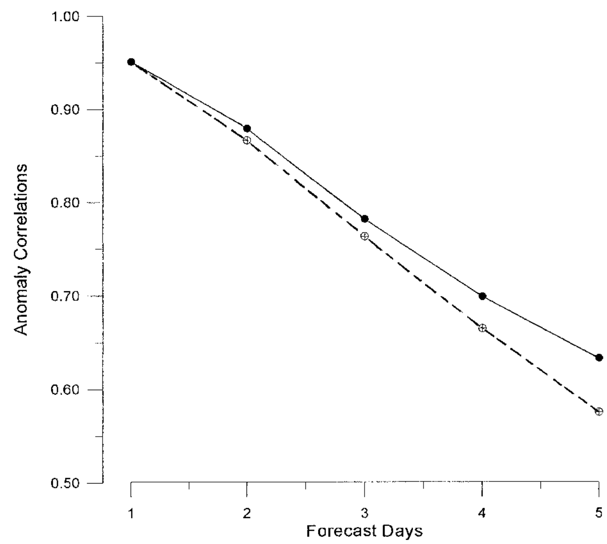

FIG. 4. The 1000-mb mean anomaly correlations calculated from the control run (dashed line) and the parallel run (solid line) over the Southern Hemisphere.

the control run. Thus, we may conclude that the neural-network-algorithm-derived SSM/I wind data are certainly more beneficial to the analyses than the wind data derived from the Goodberlet operational SSM/I wind algorithm.

Having ascertained that use of the neural-network-derived SSM/I wind speed data indeed leads to an improvement on the analyses, one can expect that the use of these new wind data will result in a greater improvement in the forecasts. Figures 4 and 5 show, respectively, the mean anomaly correlations for the 1000- and 500-mb geopotential heights for the two parallel forecast runs over the Southern Hemisphere, verified against each system's own analyses. It clearly shows that use of the neural-network-derived SSM/I wind speed data in the data assimilation and forecasts indeed leads to greater improvement on the forecasts when compared to forecasts that use the operational SSM/I wind speed data. It should be pointed out, however, that comparisons of the anomaly correlations between the parallel run forecasts for the Northern Hemisphere reveal that the impact of the forecasts is not very significantly different, and therefore they are not shown here.

Table 2a shows the forecast rms vector wind errors (m s^{-1}) at 10 m of the two parallel runs over the midlatitude oceans for the period from 16 May 1996 to 4 June 1996. The buoy observations of winds used for the comparison are adjusted to the same height (10-m

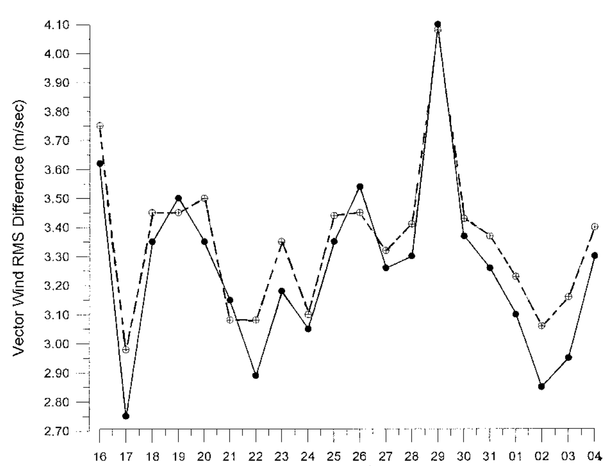

FIG. 3. Fit of the *ERS-1* wind data to the first-guess winds, with the solid line representing the first-guess winds being generated from the parallel run, and the dashed line being generated from the control run.

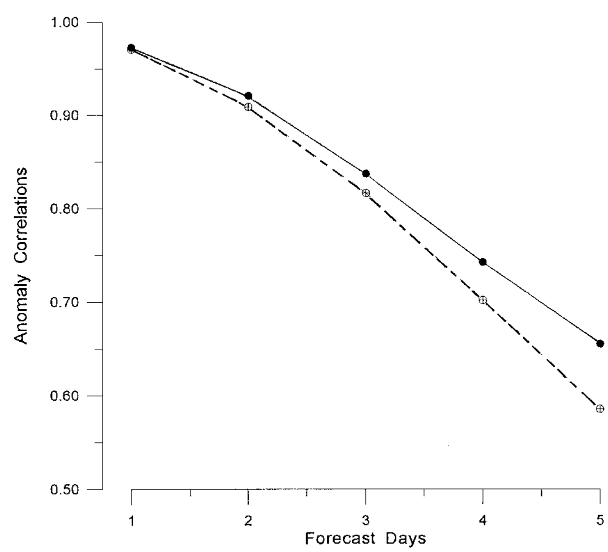

FIG. 5. The 500-mb mean anomaly correlations calculated from the control run (dashed line) and the parallel run (solid line) over the Southern Hemisphere.

TABLE 2a. Forecast rms vector wind errors (m s^{-1}) at 10 m over the midlatitude oceans (25°–50°N) for the period from 16 May 1996 to 4 June 1996.

Forecast hours	Number of buoys	Neural network (parallel run)	Operational (control run)
24	486	3.82	3.84
48	486	4.54	4.55
72	486	5.41	5.60
96	486	5.96	6.16
120	467	6.66	6.72

level) as the model forecast winds, and they are located over the midlatitude oceans (25°–50°N) with most of the buoys from the east and west coasts of the United States and a few buoys from the Hawaii region. From Table 2a, it is evident that throughout the entire 5-day forecast periods, the forecasts made with the use of the neural network SSM/I wind data give smaller rms vector wind errors when compared with the midlatitude deep ocean buoys than the forecasts made with the use the SSM/I winds from the operational wind algorithm. Similarly, when the forecast mean sea level pressures of the two parallel runs are compared with the buoy pressure reports (Table 2b) over the midlatitude oceans, the forecasts made with the use of neural network SSM/I winds are consistently better than the results of the control run. These results are very encouraging in view of the fact that the midlatitude buoys used in the verification of the forecasts are mostly over the Northern Hemispheric oceans, where similar assimilation experiments in the past failed to yield consistently noticeable differences (Yu and Deaven 1991; Yu et al. 1992). This would certainly suggest that the use of the neural network SSM/I wind data improves the low-level wind forecast over the Northern Hemisphere.

Comparison of the 10-m wind forecasts from the two parallel assimilation and forecast experiments (Table 3) over the tropical TOGA region (20°S–20°N) also leads to the same conclusion that the forecasts with the use of SSM/I winds derived from the neural network wind algorithm are slightly, but consistently, better than those from the operational run. This is also in agreement with the results over the midlatitude oceans discussed in Table 2. It should be noted that these TOGA buoys are special buoys deployed specifically for the TOGA experiment, and they are reporting winds only.

5. Summary and conclusions

SSM/I wind speed data derived from the neural network algorithm are tested in a parallel global data assimilation and forecast run for a period of about three weeks. The results show that the use of neural network derived SSM/I wind speed data leads to a consistent improvement in the first-guess fields of winds, thereby suggesting the wind data thus derived are more useful for the analyses than the SSM/I wind speed data generated by the use of Goodberlet operational wind algorithm. Similarly, comparison of the forecast results shows that use of the neural-network-derived SSM/I wind speed data in the data assimilation and forecast experiment gives better forecasts when compared to those from the operational run that uses Goodberlet SSM/I wind algorithm. The evidence of a clear improvement in the forecasts by the use of neural-network-derived winds over the operational winds is a very significant result when compared to the results from previous assimilation studies. Invariably, they all showed that the data were only slightly beneficial in forecast skill scores over the Southern Hemisphere but failed to show any noticeable improvements over the Northern Hemisphere. The improvements shown in this study obviously are related to the fact that the neural network algorithm is capable of retrieving high quality winds in regions of active weather development where the operational Goodberlet wind algorithm failed. The neural network algorithm will be implemented in the NCEP global data assimilation system in early 1998.

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TABLE 2b. Forecast rms sea level pressure errors (mb) over the midlatitude oceans (25°–50°N) for the period from 16 May 1996 to 4 June 1996.

Forecast hours	Number of buoys	Neural network (parallel run)	Operational (control run)
24	465	1.57	1.66
48	465	2.50	2.55
72	465	3.50	3.53
96	465	4.03	4.13
120	447	4.35	4.43

TABLE 3. Forecast rms vector wind errors (m s⁻¹) at 10 m over the tropical oceans (20°S–20°N over the TOGA region) for the period from 16 May 1996 to 4 June 1996.

Forecast hours	Number of buoys	Neural network (parallel run)	Operational (control run)
24	143	3.08	3.09
48	143	3.40	3.57
72	143	3.66	3.69
96	143	3.89	3.90
120	135	3.92	4.13

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REFERENCES

Bose, N. K., and P. Liang, 1996: *Neural Network Fundamentals with Graphs Algorithms and Applications.* McGraw-Hill, 478 pp.

Caplan, P., J. Derber, W. Gemmill, S.-Y. Hong, H.-L. Pan, and D. Parrish, 1997: Changes to the 1995 NCEP operational Medium-Range Forecast model analysis–forecast system. *Wea. Forecasting,* **12,** 581–594.

Goerss, J., and P. Phoebus, 1992: The assimilation of DMSP retrieval products into the Navy's atmospheric prediction system. *Abstracts, NMC/NESDIS/DOD Conf. on DMSP Retrieval Products,* Washington DC, NMC/NESDIS/DOD. [Available from National Centers for Environmental Prediction, Washington, DC 20233.]

Goodberlet, M. A., C. T. Swift, and J. Wikerson, 1989: Remote sensing of ocean surface winds with the Special Sensor Microwave/Imager. *J. Geophys. Res.,* **94,** 547–555.

Kanamitsu, M., 1989: Description of the NMC global data assimilation and forecast system. *Wea. Forecasting,* **4,** 334–342.

——, and Coauthors, 1991: Recent changes implemented into the global forecast system at NMC. *Wea. Forecasting,* **6,** 422–435.

Krasnopolsky, V., L. Breaker, and W. Gemmill, 1995a: A neural network as a nonlinear transfer function model for retrieving surface winds speeds from the special sensor microwave imager. *J. Geophys. Res.,* **100,** 11 033–11 045.

——, W. Gemmill, and L. Breaker, 1995b: Improved SSM/I wind speed retrievals at high wind speeds. NCEP Tech. Note, OMB Contribution 111, 46 pp. [Available from National Centers for Environmental Prediction, Washington, DC 20233.]

——, ——, and ——, 1996:A new transfer function for SSM/I based on an expanded neural network architecture. NCEP Tech. Note 137, 38 pp. [Available from National Centers for Environmental Prediction, Washington, DC 20233.]

Parrish, D., and J. Derber, 1992: The National Meteorological Center's Spectral Statistical-Interpolation Analysis System. *Mon. Wea. Rev.,* **120,** 1747–1763.

Petty, G. W., and K. B. Katsaros, 1993: The response of the SSM/I to the marine environment. Part I: An analytic model for the atmospheric component of observed brightness temperatures. *J. Atmos. Oceanic Technol.,* **10,** 746–761.

——, and ——, 1994: The response of the SSM/I to the marine environment. Part II: A parameterization of the effect of the sea surface slope distribution on emission and reflection. *J. Atmos. Oceanic Technol.,* **11,** 617–628.

Phoebus, P., and J. Goerss, 1991: The operational assimilation of SSM/I wind speed data. Preprints, *Ninth Conf. on Numerical Weather Prediction,* Denver, CO, Amer. Meteor. Soc., 569–572.

Stogryn, A., C. Butler, and T. Bartolac, 1994: Ocean surface wind retrievals from special sensor microwave imager data with neural networks. *J. Geophys. Res.,* **99,** 981–984.

Yu, T.-W., and D. Deaven, 1991: Use of SSM/I wind speed data at NMC's GDAS. Preprints, *Ninth Conf. on Numerical Weather Prediction,* Denver, CO, Amer. Meteor. Soc., 416–417.

——, W. Gemmill, and J. Woollen, 1992: Use of SSM/I wind speed data in the operational numerical weather prediction system at NMC. *Abstracts, NMC/NESDIS/DOD Conf. on DMSP Retrieval Products*, Washington DC, NMC/NESDIS/DOD. [Available from National Centers for Environmental Prediction, Washington, DC 20233.]