Assimilation and Forecast Experiments Using SSM/I Wind Speed Data Derived From A Neural Network Algorithm

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Abstract

SSM/I wind speed data derived from both the neural network algorithm and the operational Goodberlet wind 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. This suggests that the SSM/I wind data derived by the neural network algorithm are more useful for the analyses than the wind data generated by the 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 which 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). Basically it is an empirically derived linear regression algorithm which relates sea surface 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 1993).

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, 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 can not be used operationally. 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 which is capable of modeling the nonlinear dependence of the wind speed on brightness temperatures is required.

Neural networks are known to be good models for a broad class of nonlinear relationships. 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. Their results showed that the neural network wind algorithm were able to expand the areal coverage for retrievals under the cloudy conditions; however, the algorithm was not able to generate wind speeds of greater than 16-18 m/sec. The deficiency in generating high wind speeds from these two neural network wind algorithms was due to the absence of high wind speed matchups in the collocated buoy and SSM/I wind speed database used as the training data set. It should be pointed out that high wind speed data were available for the operational wind algorithm development by Goodberlet et al (1989).

Recently, an improved neural network wind algorithm was developed by Krasnopolsky et al (1995b) using advanced methods in the neural network training and an additional 85 GHz microwave channel to partially compensate the database problem. This new algorithm is capable of generating higher wind speeds of up to 20-21 m/sec before a bias correction. After the bias correction, the algorithm can extend retrievals of wind speeds to 25-26 m/sec. In addition to the improved quality of wind products as discussed above, it is equally important that the neural network wind algorithm increases areas of coverage over the oceans when compared to the operational algorithm which cannot produce SSM/I wind speed data over regions of high level of moisture contents. As a result, the data coverages are about 10% to 15% more over the midlatitude oceans, and about 30% more over the tropical oceans than those generated by the operational Goodberlet algorithm. These areas of additional data coverage could potentially be very important for improving atmospheric analyses and forecasts of NCEP numerical weather prediction operations.

In view of the above mentioned improvement in the quality of the wind speed data and in the coverage of data points, it is important to find out if the use of the SSM/I wind speed data derived from the neural network algorithm will indeed improve numerical analyses and forecasts of the atmosphere. To accomplish this, 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 May 16, 1996 ending 0000 UTC July 4, 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 run, the SSM/I wind speed data have been averaged over a one-degree by one-degree longitude and latitude 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 recently the operational global data assimilation system has been undergoing a number of new improvements since the implementation of SSM/I wind speed data in 1993, notably the direct use of TOV radiance data, for example (see Pan et al, 1996). Thus, the test results discussed in this paper represent a most recent investigation on the use of the SSM/I wind speed data at the NCEP operational global data assimilation systems.

2. Assimilation and Forecast Experiments

The NCEP T62 global data assimilation system, details of which were given in Kanamitsu (1989), Kanamitsu et al (1992), and Pan, et al, (1996), 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. The forecast model includes identical parameterization of such physical processes as convection, precipitation, radiation, and boundary layer physics as 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 six hour 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 +/ - 3 hour window are then used to update the first guess fields and complete the analyses. This process of a six hour model forecast followed by an analysis update is repeated four times a day, once every six hour interval, until the end of the three weeks of the assimilation period. For each of the parallel and control run experiments, five 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 hours of the 20 forecast cases are used for comparison between the two parallel runs.

3. The Forecast Results

Table 1 shows the mean anomaly correlations for the 1000 mb and 500 mb geopotential heights for the two parallel forecast runs over the Southern Hemisphere. 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 which use the operational SSM/I wind speed data. The evidence of a clear improvement in the forecasts by the use of the neural network derived winds over the operational winds is a very significant result. These improvements are obviously 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.

It should be pointed out however, 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 1. Mean anomaly correlations of geopotential heights at 1000 mb and 500 mb over the Southern Hemisphere for the period from May 16, 1996 to June 4, 1996

Forecast Hours	S.H. 1000 mb		S. H. 500 mb	
	Parallel	Control	Parallel	Control
24	.9508	.9506	.9723	.9704
48	.8786	.8663	.9204	.9085
72	.7820	.7630	.8365	.8162
96	.6991	.6649	.7419	.7015
120	.6332	.5752	.6548	.5850

Table 2a shows the forecast RMS vector wind errors (m/sec) at 10 meters of the two parallel runs over the mid-latitude oceans for the period from May 16, 1996 to June 4, 1996. The buoy observations of winds used for the comparison are adjusted to the same height (10 meter level) as the model forecast winds, and they are located over the mid-latitude oceans (25°N - 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 clearly evident that throughout the entire five day forecast periods, the forecasts made with the use of the neural network SSM/I wind data give a smaller RMS vector wind errors when compared with the mid-latitude 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 run are compared with the buoy pressure reports (Table 2b) over the mid-latitude 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 mid-latitude 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 noticeable differences (Yu and Deaven, 1991, Yu et al, 1993). 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.

Table 2a. Forecast RMS Vector Wind Errors (m/sec) at 10 meters over the Mid-latitude Oceans for the period from May 16, 1996 to June 4, 1996

Forecast Hours	Number of buoys	Parallel Run	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

Table 2b. Forecast RMS Sea Level Pressure Errors (mb) over the Mid-latitude Oceans for the period from May 16, 1996 to June 4, 1996

Forecast Hours	Number of Buoys	Parallel Run	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

Comparison of the 10 meter 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 the neural network wind algorithm are lightly better than those from the operational run. This is consistent with the result over the mid-latitude oceans discussed in Table 2. It should noted that these TOGA buoys are special buoys deployed specifically for the TOGA experiment, and they are only reporting winds.

Table 3. Forecast RMS Vector Wind Errors (m/sec) at 10 meters over the Tropical Oceans (20° S-20° N over the TOGA Region) for the period from May 16, 1996 to June 4, 1996

Forecast Hours	Number of Buoys	Parallel Run	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

4. 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 greater 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 which 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. These improvements are obviously 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.

Acknowledgments:

The author wishes to express his sincere appreciation to D. B. Rao for his reviews of the manuscript and for his continual encouragement throughout the course of this investigation. He also like to thank V. Krasnopolsky for his clarification on the discussions of the neural network algorithm, and for the use of the neural network algorithm in the parallel testing. Thanks also go to W. Gemmill, M. Iredell, and D. Keyser for their programming supports.

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