WEATHER PATTERNS OVER THE OCEAN RETRIEVED BY NEURAL NETWORK MULTI-PARAMETER ALGORITHM FROM SSM/I[1]

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ABSTRACT

New opportunities are now available for "operational" weather analysis and forecasting due to the new SSM/I neural network algorithms providing accurate and detailed fields of meteorological variables over the ocean, as well as due to the extensive global coverage by the increased number of available satellites. Neural networks at NCEP have gone through an evolutionary phase to improve ocean surface wind speed retrievals. The current version of neural networks has been expanded into a system that retrieves simultaneously four geophysical parameters: ocean surface wind speed, columnar water vapor, columnar liquid water, and sea surface temperature. Although, these variables have already been retrieved by other techniques, it is the simultaneous retrieval that is unique about the new algorithm, allowing the information from one variable to contribute to the improvement of the other variables (e.g., improved accuracy of wind speed retrievals at high wind speed). In fact, those wind speed data were recently incorporated as a part of the Global Data Assimilation System. These variables, when viewed together, can provide internally consistent information about synoptic weather patterns over the oceans. Several examples are presented which demonstrate that significant meteorological features like fronts, convective areas, areas with high probability of precipitation can be identified and observed in SSM/I fields retrieved by the new algorithm.

1.0 INTRODUCTION.

Beginning in 1987, a series of Special Sensor Microwave/Imager (SSM/I) instruments have been launched through the Defense Meteorological Satellite Program (DMSP). SSM/I sensors do not measure meteorological variables directly, but measure brightness temperatures from the ocean surface passively, which can be converted into geophysical parameters using transfer functions (retrieval algorithms). With the three satellites in orbit F11, F13 & F14 (each provides coverage over a particular ocean area twice a day) and the fairly wide swath coverage for each of the satellites (about 1400 km), extensive high-resolution coverage is now available over many ocean areas where there was almost no data before. These satellites have substantially increased the amount of "real-time" meteorological data over the oceans, which are used subjectively, by marine meteorologists to improve ocean surface weather map analyses, and objectively, by numerical analyses systems to provide initial conditions for numerical weather prediction models.

Empirical retrieval algorithms have been developed separately for various geophysical parameters such as surface wind speed (Goodberlet, et al, 1989; Petty, 1993), columnar water vapor (Alishouse et al, 1990) and columnar liquid water (Weng and Grody, 1994). The empirical transfer function is usually derived from a high-quality data set that collocates in time and space the satellite brightness temperatures with buoy and/or radiosonde measured geophysical variables. A satellite vs buoy collocated matchup data set requires a large sample in order to be representative of the wide range of possible global meteorological events. For example, high wind speed events have been fairly rare in most matchup data set because of the collocation requirements. Winds speeds of gale force (> 17 m/s) or greater at a given time cover no more than 5 %. of the global ocean surface. Some of the

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initially developed retrieval algorithms are based on a simple statistical technique such as linear regression and, as a result, have limited retrieval capabilities. In reality, careful evaluations of the retrievals over a period of time are required to determine the weaknesses in the transfer functions. That requires validating the data under a wide range of meteorological conditions. Such validations invariably show that the initial algorithms have serious limitations in providing good quality data over regions where weather conditions are actively developing. Hence the necessity to examine the possibility of making improvements to the transfer functions arises (Gemmill et al., 1996).

The purpose of this paper is to discuss the new data sets that are now made available for "operational" weather analysis and forecasting using the latest SSM/I neural network algorithm. This algorithm provides detailed and accurate fields of meteorological variables over the oceans and the coverage is extensive because of the number of satellites that are current in operation. As mentioned before, the new neural network algorithm derives surface wind speed, columnar water vapor, columnar liquid water and sea surface temperature simultaneously from SSM/I brightness temperatures. Although these parameters have already been retrieved separately by other techniques, it is the simultaneous retrieval by the NN's that is unique, allowing the information from one parameter to contribute to a better estimate of the other parameters. These parameters, when viewed together, can provide internally consistent information about synoptic weather patterns over the oceans than when only a single parameter is used.

The following sections will summarize our work on using neural networks to improve the retrieval of marine variables from the SSM/I sensor. In Section 2 we briefly review recent algorithm developments at NCEP. In Section 3 we discuss possible approaches to interpret the data fields derived from SSM/I. Section 4 presents several examples which show that significant meteorological features like fronts, convective areas, areas with high probability of precipitations can be identified and observed in SSM/I fields retrieved by the new algorithm.

2.0 WORK ON IMPROVEMENT OF ACCURACY OF SSM/I RETRIEVALS AT NCEP

Most algorithms designed originally for SSM/I retrievals retrieve one variable at a time. The original global algorithm for retrieving surface wind speed from SSM/I was developed by Goodberlet, et al in 1989 (GSW algorithm). This algorithm is a linear regression type and is limited to low moisture conditions because, above a certain threshold, moisture in the atmosphere makes the retrieval problem nonlinear. Further, there were no wind speed observations above the moderate range (> 18 m/s) available in the matchup data set used in the formulation of the algorithm, so the GSW algorithm could not be expected to perform well at high winds. Because of these limitations, wind speeds cannot be accurately determined with this algorithm in areas with significant levels of atmospheric moisture (e.g., in tropics) and cannot be retrieved at all under the more active and critical weather situations such as storms and fronts. Petty (1993) introduced a nonlinear correction to GSW algorithm (GSWP algorithm) which improves the accuracy of the wind speed retrievals in areas with higher level of the water vapor (in tropics). Recently this algorithm became operational for shared data processing.

Several algorithms have been developed for columnar water vapor (Alishouse 1990; Petty 1993) and columnar liquid water (Weng and Grody, 1994; Weng et al., 1997). However, all these algorithms (including wind speed algorithms) have been developed independently using their own different data sets. They were formulated without taking into account co-dependency of these parameters and without accounting for their physical relationships.

For the past five years, NCEP has been working on improving the accuracy of SSM/I satellite derived ocean wind speeds, columnar water vapor, and columnar liquid water for both marine meteorology applications and numerical weather prediction (NWP). A series of algorithms (see Fig. 1) has been formulated using neural networks (NNs), each one more complex and accurate than the previous one. Neural networks were chosen because they have been highly successful in dealing with nonlinear problems, and hence, seemed to be an appropriate method to pursue to deal with high moisture conditions in deriving wind speeds initially. In 1994 (Krasnopolsky et al, 1994; 1995a), an initial NN algorithm (OMBNN1) was formulated using the same satellite

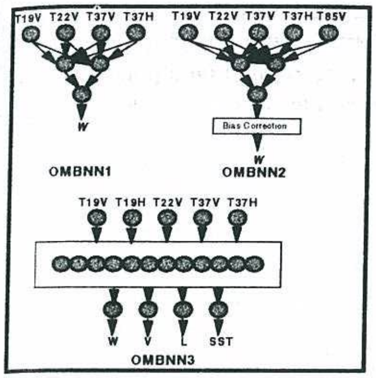

Fig. 1. Evolution of our NN approach.

match up data base of satellite "brightness temperatures" (from the F8 satellite) with buoy wind speeds that was used to develop the GSW algorithm. The OMBNN1 algorithm used brightness temperature from four of the SSM/I channels to produce one output, wind speed. That initial study showed that neural network OMBNN1 was capable of providing ocean surface wind speeds from SSM/I "brightness" temperatures with better accuracy and in areas with higher levels of atmospheric moisture than GSW algorithm. But, when the OMNNN1 algorithm was applied to global SSM/I data for operational use, the algorithm was unable to provide high wind speeds (> 20 m/s) with acceptable accuracy. This was attributed to the lack of high winds in the original data set used for algorithm formulation.

In order to improve the high wind speed range, a new neural network, OMBNN2 (Krasnopolsky et al, 1995b) was developed by emphasizing the high winds that were in the original data set, and including a bias correction. Also, OMBNN2 algorithm used brightness temperature from five of the SSM/I channels to produce one output, wind speed. Wind speed fields produced by OMBNN2 were able to show high-resolution structure of the wind speed patterns over the ocean that is normally not observed. The data from the OMBNN2 algorithm have been evaluated within the NCEP global prediction model (Yu et al, 1997) to determine their impact. The evaluation showed that the wind speeds derived from the OMBNN2 neural network were better than the wind speeds derived from the standard "operational" GSW algorithm. The OMBNN2 algorithm did improve the ocean surface wind speeds compared to OMBNN1, but still could not produce higher wind speeds with the desired accuracy.

More recently, a rather comprehensive SSM/I and buoy match up database was made available by the Naval Research Laboratory (NRL). The NRL dataset contained not only more data, but it has a better coverage of high wind events than the previous dataset used by GWS. Further, other high latitude SSM/I ocean weather ship match up data sets were obtained from David Kilham (Bristol University). A new NN architecture was then formulated (Fig. 1) which takes into account co-variability of physically related atmospheric and oceanic parameters (wind speed, columnar water vapor, columnar liquid water and sea surface temperature). The new OMBNN3 algorithm utilizes five SSM/I brightness temperature channels. It produces now simultaneously four parameters: wind speed, columnar water vapor, columnar liquid water and sea surface temperature. The importance of the inclusion of water vapor in wind speed retrieval algorithms was indicated by Petty (1993). The OMBNN3 algorithm was trained to preserve proper physical relationships between these parameters. The algorithm has extended the range of wind speeds over which useful geophysical retrievals can still be obtained. It not only improves the accuracy of the wind speed data, especially at high wind speeds but makes available three additional retrieval fields. The validation and comparison statistics for the OMBNN3 algorithm presented in (Krasnopolsky et al, 1998 in these proceedings) demonstrate that it outperforms other existing SSM/I wind speed retrieval algorithms, especially above moderate wind speeds > 15 m/s. Because this algorithm is inherently nonlinear, it was able to increase areal coverage in areas with significant levels of atmospheric moisture and under the more active and critical weather situations such as storms and fronts.

NN retrievals for columnar water vapor and columnar liquid water are in good agreement with existing SSM/I algorithms. No attempt was made to verify the retrieval versus the observed data because of the lack of collocated observational data.

3.0 INTERPRETATION OF NEURAL NETWORK DERIVED DATA FOR WEATHER ANALYSIS

In this section we show that three meteorological fields: 1) ocean surface wind speed, 2) columnar water vapor and 3) columnar liquid water which are produced simultaneously by the new OMBNN3 algorithm can be interpreted together. Moreover, we show how the interpretation of the three variables together can give a more complete description of the marine weather than by using the ocean wind speed data alone.

The ocean surface wind speed data have the most direct use in marine weather analysis and weather forecasting. Even though these data provide wind speed only (not direction), the extensive coverage of these data from three satellites can depict " high-resolution" wind speed patterns across synoptic weather patterns. These data can be used to improve directly ocean surface wind analyses, and indirectly sea level pressure analyses.

The columnar water vapor and columnar liquid water are not so easily used. These variables are the vertically integrated values through the entire atmosphere, so it is difficult to assign these parameters to any specific level of the atmosphere. The columnar water vapor is also known as "total precipitable water", which is the amount of water that would fall on the ocean if all the water vapor were condensed into precipitation. Columnar water vapor is an air mass characteristic closely related to synoptic scale features. Its source is the warmer waters of the tropics and it is advected into northern latitudes by storms and low and mid-level jet streams. As a result, regions of large gradients of the columnar water vapor have been shown to be a good objective indicators of the position of an ocean surface front (Katsaros et al, 1989) .

The liquid water is that water that resides in clouds, and is more directly related to regions of precipitation and related to active weather systems of storms and fronts (McMurdie and Katsaros, 1996). The higher cloud liquid water amounts are generally associated with strong deep convective activity (cumulus clouds), with turbulent surface weather conditions; whereas the lower amounts of cloud liquid water are more associated with near neutral or stable activity (stratiform clouds), with constant or steady surface weather conditions.

OMBNN3 has been carefully tested at NCEP using real-time data from F10, F11, F13 and F14 SSM/I instruments since mid-1997. Simultaneous retrievals of wind speed, columnar water vapor and columnar liquid water fields using OMBNN3 were analyzed to reveal significant information concerning weather patterns over the ocean. Several important features have been observed: 1) The NN algorithm successfully separates wind speed, columnar water vapor, and columnar liquid water signals contained in the SSM/I Brightness Temperatures. Multi-parameter retrievals preserve the correct physical relationships between the retrieved parameters. 2) The new algorithm generates high wind speeds (> 20 m/s) in areas where these events are well supported by other data. These winds and sea level pressure analyses are in close agreement. Regions of large pressure gradients match well with high wind speeds. 3) High gradients of the columnar water vapor are related to the position of ocean surface fronts. On the other hand, the structure of the water vapor field is very different from both wind speed and liquid water, and its high values are related to a moist atmosphere which originates from subtropical sources. 4) Higher amounts of columnar liquid water are related to areas of water vapor convergence which are closely associated with active storms and frontal locations and with clouds.

4.0 SOME EXAMPLES

In this section we present two descriptive cases showing the use of the satellite derived data retrieved from the OMBNN3 neural network and illustrating general conclusions presented in previous section. We have selected two synoptic situations one for the Northeast Pacific Ocean and one for the Northwest Atlantic Ocean. Each situation is further supported by a series of plots: 1) SSM/I ocean surface winds speed, 2) SSM/I columnar water vapor, 3) SSM/I columnar liquid water followed by 4) ocean surface wind data from buoys and ship, 5) ERS2 scatterometer wind vector data (ERS data reprocessed at NCEP (Gemmill et al., 1996)), and 6) the sea level pressure analysis available from the NCEP Global Data Analysis System (figures 3 & 5). The plots of satellite data are within a +/- 3 hour time window about the analysis time. The SSM/I data are a composite of three DMSP satellites: F11, F13 & F14, which is capable of extensive regional coverage. The two cases are for synoptic weather patterns that were fairly well described from other "real-time" data sources, so there are no conflicts between data sets in terms of the meteorology. Their purpose is to show that the variables retrieved from the SSM/I through the NN algorithms were able to give information consistent with the actual weather situation. These examples demonstrate that neural networks have the capability to retrieve useful meteorological information from SSM/I brightness temperatures, and provide a level of confidence for using them routinely in analyses and forecasts.

(a)

(b)

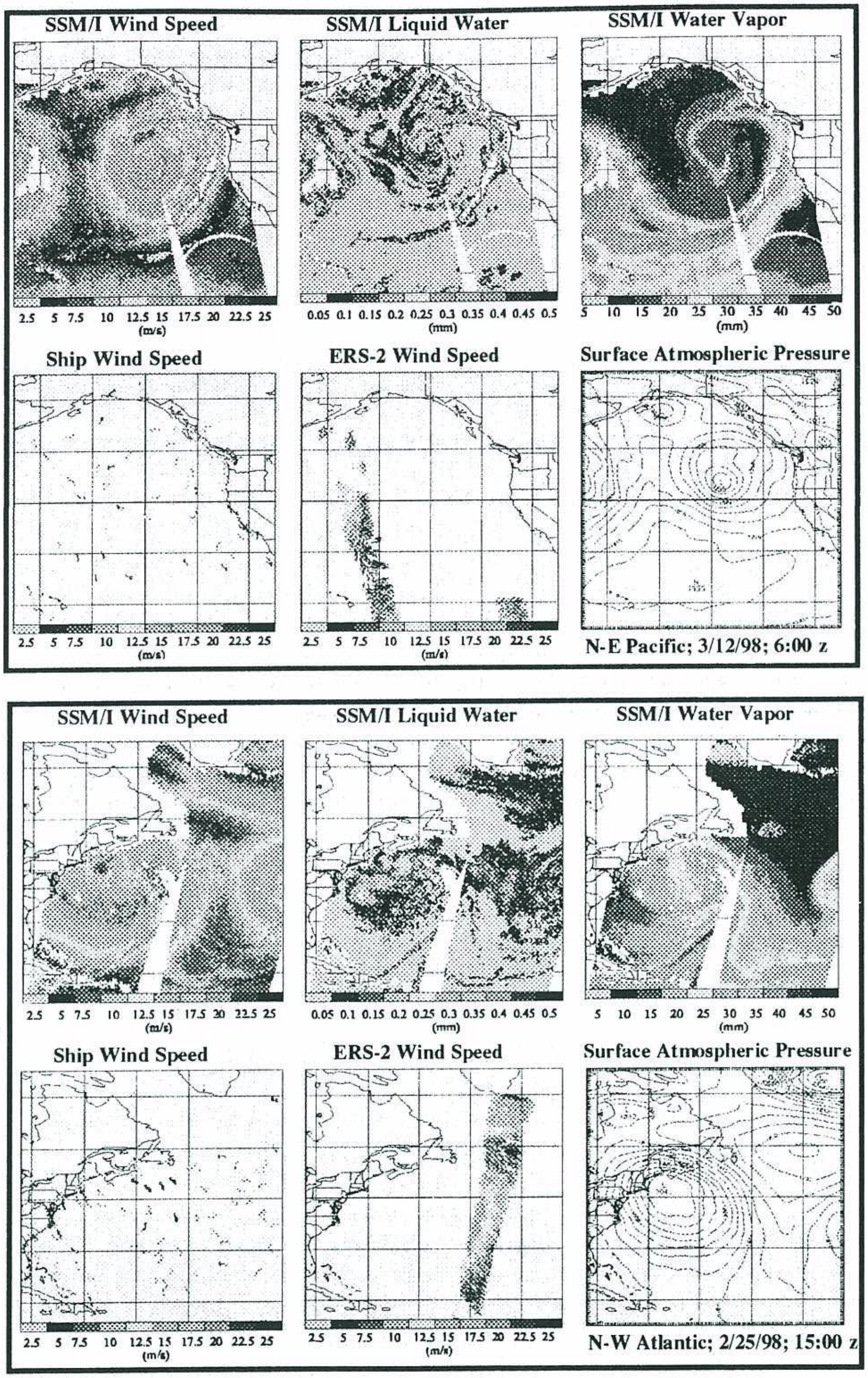

Fig 2. Northwest Pacific (a) and Northeast Atlantic (b) examples.

4.1 EXAMPLE 1. NORTHWEST PACIFIC OCEAN, 12 MARCH 1998, 06UTC.

Marine weather maps are manually analyzed over the North Pacific Ocean and the North Atlantic Ocean every 6 hours the Marine Prediction Center. These analyses are the combination of a variety of data sources, including the 6 hour sea level pressure forecast from the global numerical prediction model as a first guess, AVHRR satellite cloud imagery, and quality controlled surface data from ships, fixed and drifting buoys and coastal stations.

The marine weather analysis for the northeast Pacific on 12 March 1998, 06UTC is presented in figure 2a. The main weather feature in the northeast Pacific is a moderate storm with a central pressure of 982 mb, located near 43 N and 138 W, 600 n mi west of the Oregon coast. The storm itself is labeled a GALE indicating winds above 33 knots. Within its circulation this storm has wrapped around the occlusion from the north to the northwest of the center, with a cold front to the east, located about 300 n. mile from Washington to California coasts near 131 W. The front trails back toward the west, and eventually toward the northwest to the leading edge of the next storm which is in the central Pacific near the date line. There is another small low just off the southern coast of Alaska. A major high pressure ridge lies across the southern part of the region along 26-28 N. From that map, winds are near 30 knots to the southwest of the storm, but closer to the storm center wind speeds are nearer to 40 knots.

The sea level pressure analysis from the global model at 06 UTC shows little difference from the MPC analysis. The MPC analysis has the storm slightly deeper by 4 mb than the global model analysis (figure 2a). The SSM/I wind field shows the storm to be fairly circular and moderate size, the yellow coded area shows the outer limit of the 20 knot winds, and the orange region shows the Gale force region southwest of the center and 40 knot winds near the center. There are areas of no wind speed data, because the moisture content was so high as to make a retrieval impossible, and occasionally due to a bad scan line. The northward moving occluded front is associated with a band of moderately high wind speeds (30 knots). Just ahead of the eastward moving cold front there is a moderate wind band up to 25-30 knots, but, the highest winds are masked due to high moisture contamination (possible rain). The weak low south of Alaska has winds near 30 knots right along the coast. The storm further west is already generating 40-45 knot winds ahead of the occlusion.

The liquid water shows a wrap around pattern along the cold front, along the occlusion into the center. The highest liquid water values precede the occlusion and cold front. Drier air is being pulled in behind the fronts. The higher values of liquid water are quite likely to be associated with rain areas. The water vapor shows the distinct pattern associated with the air masses. The strong water vapor gradient zone clearly depicts the location of the cold front. The strong water vapor gradient zone was recognized as a quantitative parameter for the location of oceanic fronts by Katsoras et al (1989). The water vapor shows a strong flow of moist air moving from north of Hawaii to the U.S. northwest coast.

The in-situ buoy and ship wind data are plotted at standard synoptic time, 06 UTC. The satellite data are taken within three hours of the surface ship and buoy data, figure 2. The winds show the storm and its circulation, but its intensity and location of the center of the storm can be not determined from the ship and buoy data alone, but it was made possible by the SSM/I derived data. However, where there are in-situ surface wind reports, they do collaborate the values of the SSM/I derived wind speed data. The same thing can be stated concerning the ERS2 scatterometer wind data and SSM/I wind data, they too are in close agreement.

4.2 EXAMPLE 2. NORTHEAST ATLANTIC OCEAN, 25 FEBRUARY 1998, 12UTC

The main weather feature in the northeast Atlantic is a moderate storm with a central pressure of 984 mb, located near 42 N and 68 W, 600 n mi just off the coast of New England (figure 2b). That storm is labeled STORM indicating wind speeds above 48 knots. Out of this storm is an occlusion to the north and extending to the southeast, with a cold front far out in the Atlantic trailing back to Jamaica. There is another major storm off Iceland, and a minor storm in the central Atlantic near 30N. A major high pressure ridge lies north south near 42 W, centered at 48 N and 42 W (1037 mb). From that map, the plotted winds show a rather large region of strong winds (35-45 knots), within 600-800 n mi of the center of the storm. The sea level pressure analysis from the numerical global model at 12 UTC shows little difference from the manual MPC analysis (figure 2b).

The SSM/I wind field shows the storm to be fairly circular, the yellow coded area shows the outer limit of the 20 knot winds, and the orange region shows the Gale force region around the center of the system with winds up to 45 knots. The Iceland storm is indicating winds up to 50 knots. Whereas, the weak system in the central Atlantic has a band of 35 knot winds on the western side.

The liquid water values are highest to the southwest of the storm center, East of Cape Hatteras and south of Cape Cod, associated with trough line crossing the area, east of the Gulf Stream.
The water vapor shows the distinct air mass pattern, but does not identify the storm system very well. But, the associated fronts are clearly identified, especially by the strong water vapor gradient across the southwest portion of the figure. The water vapor shows a strong flow of moist air moving from the Caribbean north into the eastern portion of the storm.

The surface wind data reports and the corresponding satellite wind data show close agreement. Note the region near 42 N between 50W - 60 W, where the surface wind speed data is near 50 knots. The satellite wind speed data in that same region is only slightly lower near 45 knots. Also, note the ship with a speed of 60 knots east of Greenland. In that same area the satellite shows a wind speed of 50 knots. The agreement of the ERS2 scatterometer wind data with the SSM/I wind data shows that the speeds and pattern are similar.

5.0 CONCLUSIONS

In this paper we have presented the use of neural networks as a method to retrieve meteorological variables over the oceans from the SSM/I. In its latest form, the neural network (OMBNN3) has been shown to be able to adequately provide weather information on ocean surface wind speed data, columnar water vapor and columnar liquid water over a wide range of values of these parameters.

We have been able to demonstrate that: (1) The neural network (OMBNN3) algorithm is able to correctly separate and retrieve wind speed, columnar water vapor, and columnar liquid water signals contained in the SSM/I BTs. Multi-parameter retrievals preserve the correct physical relationships between the retrieved parameters. (2) The algorithm generates high wind speeds (> 20 m/s) in areas where these events are well supported by other data and are expected from sea level pressure analyses. (3) The algorithm generates columnar water vapor patterns which are able to delineate air masses. Low values are associated with air masses originating in high latitudes that are cold and dry. High values are associated with air originating in tropical areas that are warm and moist. High gradients of the columnar water vapor are related to the position of ocean surface fronts. (4) The algorithm generates columnar liquid water patterns which are related to regions of water vapor convergence, resulting in clouds, which are closely associated with cyclones and active frontal location.

OMBNN3 algorithm was incorporated into the NCEP operational GDAS on April 7, 1998 to retrieve ocean surface wind speed from SSM/I brightness temperatures.

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Current ocean surface wind speed, columnar water vapor, and columnar liquid water fields retrieved by OMBNN3 algorithm can be seen at http://polar.wwb.noaa.gov/winds

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