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# OBSERVING WEATHER OVER THE OCEANS FROM SSM/I USING NEURAL NETWORKS.

by

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## 1). INTRODUCTION

New data sets are now available for operational weather analysis and forecasting using the latest neural network (NN) algorithm developed at the National Centers for Environmental Prediction (NCEP) (Krasnopolsky , et al. 1999) using the Special Sensor Microwave/Imager (SSM/I) instrument flown aboard the satellites of the Defense Meteorological Satellite Program (DMSP). This NN 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 currently in operation. The new NN algorithm derives surface wind speed (W), columnar water vapor (V), columnar liquid water (L) and sea surface temperature (SST) simultaneously from SSM/I brightness temperatures. Although these parameters have already been retrieved separately by other techniques, it is the simultaneous retrieval by the new NN that is unique, allowing the information from one parameter to contribute to a better estimate of the other parameters.

The DMSP satellites are polar orbiting satellites which provide coverage over a particular ocean area twice a day, once during a descending orbit and once during an ascending orbit. The spatial resolution is about 50km. The SSM/I infers brightness temperatures from the ocean surface passively through seven channels receiving microwave radiation emitted by the ocean surface and passed through the atmosphere. The emission is effected by the surface wind speed (which changes the roughness of the ocean surface) and by SST. The propagation of the microwave radiation through the atmosphere is influenced by the integrated amounts of water vapor and liquid water in the atmospheric column. As a result the brightness temperatures carry signals from all these geophysical parameters and can then be converted into geophysical parameters (surface wind speed, columnar water vapor, columnar liquid water, and SST) using retrieval algorithms. These data are used by marine meteorologists to improve ocean surface weather map analyses, and by numerical analysis systems to improve initial conditions in numerical weather prediction models. With three satellites in orbit (F11, F13 and F14) and with a swath width of about 1400 km for each of the satellites, almost complete high-resolution coverage is now available over the global oceans on a daily basis.

Empirical retrieval algorithms have been previously 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 retrieval algorithm is usually derived from a high-quality data set that collocates the satellite brightness temperatures with buoy- and/or radiosonde-measured geophysical variables in time and space. The physically based algorithms use a large amount of such empirical data for parameterizations (Wentz, 1997). 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 conditions. High wind speed events have been fairly rare in most matchup data sets 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.

The purpose of this paper is to discuss the history of developing SSM/I retrievals at NCEP and the new data sets that are now made available for operational weather

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analysis and forecasting using the latest SSM/I NN algorithm.

## 2. IMPROVEMENT OF ACCURACY OF SSM/I RETRIEVALS

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 based on linear regression and is primarily limited to low moisture conditions. Further, there were no wind speed observations in the high 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 retrieving high winds. Because of these limitations, wind speeds cannot be accurately determined with this algorithm in areas with significant levels of atmospheric moisture and cannot be retrieved in the vicinity of storms and fronts. Petty (1993) introduced a nonlinear correction to the GSW algorithm (GSWP algorithm) which improves the accuracy of the wind speed retrievals in areas with higher amounts of the water vapor.

For the past five years, NCEP has concentrated 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. A succession of algorithms has been formulated using NN, each one more complex and accurate than the previous one. NNs were chosen because they have been highly successful in meteorological and oceanographic applications (Hsieh and Tang, 1998) They can deal with nonlinear relations and do not need *apriori* assumptions on the nature of the non-linearity. Hence, they have been able to provide an effective method for dealing with high moisture conditions while deriving wind speeds.

In 1994 (Krasnopolsky et al., 1995), an initial NN algorithm (OMBNN1) was formulated using the same satellite matchup data base of satellite brightness temperatures 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 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 the GSW algorithm. But when the OMBNN1 algorithm was applied to global SSM/I data for operational use, the algorithm was unable to provide high wind speeds ( > 15 m/s) with acceptable accuracy (wind speed RMS errors < 2m/s under all weather conditions) . This problem is usually attributed to the lack of high winds in the matchup data. A bias correction was developed in the next algorithm (OMBNN2) to correct this problem.

More recently, a rather comprehensive SSM/I and buoy matchup data set was provided by the Naval Research Laboratory (NRL) for algorithm development. The NRL data set contains more data and has better coverage of high wind events than the previous data set used by GSW. Further, other high latitude SSM/I ocean weather ship matchup data sets were obtained from Bristol University (D Kilham, personal communication).

This expanded database permitted us to develop a new NN architecture which takes into account the interdependence of physically-related atmospheric and oceanic parameters (wind speed, columnar water vapor, columnar liquid water and sea surface temperature). The new OMBNN3 algorithm (Krasnopolsky, et al., 1999, 1998) utilizes five SSM/I brightness temperature channels. It simultaneously produces all four parameters. This algorithm was trained to preserve proper physical relationships among these parameters. The algorithm has extended the range of wind speeds over which useful retrievals can be obtained. It not only improves the accuracy of the wind speed retrievals, especially at high wind speeds, but makes available three additional fields. Evaluation of the simultaneous multi-parameter retrievals from the OMBNN3 algorithm, using buoy data, shows that it reduced the bias and RMS errors of wind speed more than retrievals from any other algorithms. Validation of water vapor and liquid water is difficult due to lack of data. However, tentatively these retrievals appear to be consistent with other algorithms. Validation of the NN SST retrievals with buoy data showed that they were less accurate than the operational high resolution radiometer (AVHRR) SST retrievals, and will not be discussed further. But it is important to note, that by retrieving SST the accuracy of the wind speed retrievals, especially at high wind speeds, was improved. Because this algorithm is inherently nonlinear, it increases areal coverage in areas with significant levels of atmospheric moisture and under more active and critical weather systems such as storms and fronts.

## 3. INTERPRETATION OF SSM/I NEURAL NETWORK DERIVED DATA FOR WEATHER ANALYSIS.

The three meteorological variables (ocean surface wind speed, columnar water vapor and columnar liquid water) which are produced simultaneously by the new OMBNN3 algorithm can provide a clear descriptive analysis of the weather over the ocean. Moreover, we show how the interpretation of the three variables together can give a more complete description of marine weather than by using the ocean surface wind speed data alone.

The ocean surface wind speed data have the most direct use in marine weather analysis and weather forecasting. Although these data provide wind speed only, the extensive coverage of the three satellites depicts high-resolution wind speed patterns across synoptic weather system. These data can be used directly to improve ocean surface wind analyses, and indirectly to improve sea level pressure analyses.

The columnar water vapor and columnar liquid water are :the vertically integrated values through the entire atmosphere. The columnar water vapor is also known as "total precipitable water", which is the depth of water that would fall on the ocean if all the water vapor were condensed and precipitated. Columnar water vapor is an air mass characteristic closely related to synoptic scale features. Its primary source is the warmer waters of the tropics, and it is advected to higher latitudes by storms and low- and mid-level jet streams. As a result, regions with large gradients of columnar water vapor have been shown to be good objective indicators of the position of an ocean surface front (Katsaros et al. 1989) .

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

## 4. CASE STUDIES

Since the 1997, the use of the satellite derived data retrieved from the OMBNN3 neural network has been investigated in more than 60 case studies at NCEP. These studies supported general conclusions discussed in the previous section. Two regions have been investigated and discussed (Gemmill and Krasnopolsky 1999): one for the eastern North Pacific, and one for the western North Atlantic Oceans. For each case, a marine weather map analysis, which identifies major weather features over the region, was used as an independent source of information for comparison and validation. Marine weather maps for the North Pacific Ocean and the North Atlantic Ocean are produced every six hours by the Marine Prediction Center. These analyses combine a variety of data sources, including the six hour sea level pressure forecast from the global numerical weather prediction model as a first guess, AVHRR satellite cloud imagery, and quality controlled surface data from ships, fixed and drifting buoys and coastal stations.

Each study included a series of fields: SSM/I ocean surface winds speed, SSM/I columnar water vapor, SSM/I columnar liquid water, ocean surface wind data from buoys and ship, ERS2 scatterometer wind vector data, and the sea level pressure analysis available from the NCEP Global Data Analysis System. The fields of satellite data are within a +/- 3 hour time window about the analysis time. The SSM/I data are a composite from three DMSP satellites (F11, F13 and F14), which together provide almost complete and extensive regional coverage. The selected cases dealt with synoptic weather patterns that were in agreement with other real-time data sources. We showed (Gemmill and Krasnopolsky 1999, Krasnopolsky et al. 1999) that the variables retrieved from the SSM/I through the NN algorithms can provide information that augments interpretation and is consistent with the actual weather situation. These studies demonstrate that neural networks have the capability to retrieve useful meteorological information from SSM/I brightness temperatures.

In particular:

- 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 among the retrieved parameters.
- The new algorithm generates high wind speeds (>15 m/s) in areas where such winds 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.
- Large 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 large values are related to a moist atmosphere which originates from subtropical sources.
- Greater amounts of columnar liquid water are related to areas of water vapor convergence which are closely associated with active storms, frontal locations, and extensive clouds.

It is important to stress that the conventional data set of ships and buoys cannot in itself produce accurate detailed ocean surface analysis. These data are much too sparse. Although these winds can depict the circulation associated with a storm, the intensity and location of the storm center can be not determined from the ship and buoy data alone. Improvements to interpretation of the weather situation are aided by the SSM/I derived data, and where there are in-situ surface wind reports, they corroborate the values of the SSM/I derived wind speed data. Likewise, the ERS2 scatterometer wind retrievals also provide further information to augment and substantiate other data and improve the analysis.

## 5. CONCLUSIONS

Examining simultaneous retrievals of wind speed, columnar water vapor and columnar liquid water fields using OMBNN3 can reveal significant information concerning weather patterns over the ocean. These data can be used to improve the interpretation of the weather at the ocean surface. These fields can be viewed every 6 hours at:
**http://polar.wwb.noaa.gov/winds/.**

In general, positive impact has been demonstrated from the assimilation of wind speed retrieved by the NN algorithm into the global operational numerical weather prediction model (Yu et al., 1997) at NCEP. The new algorithm has been tested and implementation for operational use at NCEP since April 1998.


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