Determination of the geophysical model function of the ers-1 scatterometer by the use of neural networks

C. Mejia, S. Thiria[1], N. Tran and M. Crépon

Laboratoire d'Océanographie Dynamique et de Climatologie (LODYC), Université de PARIS 6, PARIS, FRANCE

F. Badran

CEDRIC, Conservatoire National des Arts et Métiers, PARIS, FRANCE

Abstract. We present a geophysical model function (GMF) for the ERS-1 scatterometer computed by the use of neural networks. The neural networks GMF (NN GMF) is calibrated with ERS-1 scatterometer sigma 0 collocated with European Center for Medium-Range Weather Forecasts (ECMWF) analyzed wind vectors. Four different NN GMFs have been computed: one for each antenna and an average NN GMF. These NN GMFs do not present any significant differences which means that the three antenna are quasi-identical., The NN GMFs exhibit a biharmonic dependence on the wind azimuth with a small upwind-downwind modulation as found on previous GMFs. In order to check the validity of the NN GMF systematic comparisons with the European Space Agency (ESA) C band model (CMOD4) GMF (version 2 of March 25, 1993) and the Institut Français de Recherche pour l'Exploitation de la Mer (IFREMER) CMOD2 I3 GMF are done. It is found that the NN GMFs are highly accurate and relevant functions to model the ERS-1 scatterometer sigma 0.

1. Introduction

The wind is the major forcing of the oceanic circulation. At basin scale the circulation is strongly dependent on the wind curl, which implies a good knowledge of the space variability of the wind. Unfortunately, it is very difficult to obtain wind measurements at sea with an accurate space and time coverage. Until now, wind data have been provided by measurements done by ships of opportunity with an erratic coverage. The satellite scatterometers sample the wind vector at global scale with an improved coverage. Thanks to these measurements, oceanographers will be able to force oceanic circulation models with adequate wind fields.

Unfortunately, the transfer function allowing to retrieve the wind from the scatterometer signals (sigma 0) is very difficult to determine. It is a nonlinear function which may have ambiguities on the azimuth. Several algorithms have been proposed to compute the wind retrieval transfer function. Most of them are based on the inversion of the geophysical model function (GMF), which gives the sigma 0 with respect to the wind vector. The study of the GMF is then of a fundamental interest. Furthermore, the GMF gives useful information on the physical behavior of the scatterometer. In the present study we propose to determine a GMF for the ERS-1 scatterometer by using neural networks (NN GMF hereinafter). The neural networks are calibrated onto the analyzed wind vectors of the meteorological model of the European Center of Medium-Range Weather Forecasts (ECMWF) collocated with ERS-1 scatterometer sigma 0.

Neural networks (NN) are relevant statistical methods to extract information from data when physical phenomena are very complicated and cannot be described in terms of theoretical analysis. NN provide empirical statistical models estimated from observations in the form of continuous functions. Furthermore, these functions can be analyzed in order to get information about the physical phenomena we study.

The paper is articulated as follows. In section 2 we address the geophysical problem and present two classical algorithms used by the scientific community. In sections 3 and 4 we present the neural networks methodology. The data set used for calibration is presented in section 5. The results are analyzed in section 6. Comparisons with the other algorithms are shown in section 7. A discussion and conclusion make up section 8.

2. Geophysical Problem

Scatterometers are active microwave radar which accurately measure the power of transmitted versus backscatter signal radiation in order to calculate the normalized radar cross section (sigma 0) of the ocean surface. At first order the sigma 0 depends on the sea roughness, which is related to the wind speed, the incidence angle θ (which is the angle between the radar beam and the vertical at the illuminated cell, Figure 1), and the azimuth angle χ (which is the horizontal angle between the wind and the antenna of the radar). Other parameters, including the wave height, the wave direction [*Donelan,* 1990; *Donelan et al.,* 1993; *Janssen and Woiceshyn,* 1992; *Nghiem et al.,* 1993], and the sea surface temperature [*Kahma and Donelan,* 1993], are also supposed to play some role. These parameters, which act at second order, will not be taken into account in the present paper.

The present scatterometers ERS-1 scatterometer (launched in 1992) and the NASA scatterometer (NSCAT) (launched in 1996), scan the ocean surface with three antennas pointing in three different directions (Figure 2). Therefore each scatterometer observation consists in three independent sigma 0, allowing us to compute the wind speed and the wind azimuth.

There are two different approaches for developing a GMF: the analytic and the empirical one. The analytical approach deals with hydrodynamic description of the air-sea interface, which specifies the relation between wind and sea surface geometry and expresses the electromagnetic backscattering from the rough air-sea interface [*Plant*, 1986; *Donelan and Pierson*, 1987; *Chen et al.,* 1992; *Weissman et al.,* 1994]. This leads to very difficult physical and mathematical descriptions as the physics of the above interactions is insufficient to allow the construction of dynamically based geophysical model functions. The empirical approach has thus been widely used. The aim is to reproduce the statistical distribution of sigma 0 measured by the scatterometers from the distribution of wind vectors. The methodology is based on collocations between ERS-1 sigma 0 and wind measurements. The accuracy of the GMF is then related to the number of such collocations and the quality of the collocated data set. Since the GMF is dependent on many parameters including the incidence angle, the wind speed, and the wind azimuth, an accurate GMF estimation requires a large number of data. Unfortunately, the number of collocations of sigma 0 with wind vector measurements done at sea with anemometers fixed on buoys is rather poor. An alternative is to use winds obtained from numerical weather prediction (NWP) models. The advantage is to get a large number of synoptic winds; the problem is to take into account the discrepancies existing between NWP winds and observed winds. As shown by *Liu and Pierson* [1994], the use of NWP can introduce systematic biases in the determination of the GMF.

The resulting GMF can be approximated by quite simple mathematical functions, where the model parameters are fitted to the observations in a least square sense or maximum likelihood estimation [*Chi and Li*, 1988]. The existing functions are based on truncated Fourier series in order to take into account the upwind downwind and crosswind modulations. [*Long*, 1985]. Recently, different GMF have been proposed for the ERS-1 scatterometer. One can mention the Institut Français de Recherche pour l'Exploitation de la Mer (IFREMER) C band model (CMOD2 I3) GMF [*Bentamy et al.,* 1994a, b], which is of the form in linear scale

$$\sigma° = B_0(1 + B_1 \cos\chi + B_2 \cos 2\chi)$$

where χ is the wind direction with respect to the antenna (or wind azimuth), and the European Space Agency (ESA) CMOD4 GMF [*Stoffelen and Anderson*, 1995], which is of the form

$$\sigma° = B_0'(1 + B_1' \cos\chi + B_2' \cos 2\chi)^{1.6}$$

The coefficient B_1 (B'_1) characterizes the upwind-downwind modulation, and B_2 (B'_2) characterizes the biharmonic behavior of the GMF. These coefficients are complex functions of the wind speed v and the incidence angle θ (Figure 1), whose complexity is related to the nonlinear character of the GMF. They imply the use of many thresholds.

The ESA CMOD4 GMF was estimated by using ECMWF-analyzed wind vectors collocated with ERS-1 scatterometer sigma 0 [*Stoffelen and Anderson*, 1995] between September 14, 1991, and February 24, 1992. In order to reduce the bias due to numerical weather prediction models the IFREMER CMOD2 I3 GMF used both buoy and model winds. CMOD2 I3 GMF was estimated on ERS-1 sigma 0 collocated with National Oceanic and Atmospheric Association (NOAA) buoy winds and analyzed winds provided by the Norwegian Meteorological Institute (DNMI) fine grid mesh numerical weather prediction model developed in the Norwegian Sea [*Bentamy et al.,* 1994a, b]. The calibration period was between March 2, 1992, and July 9, 1992.

In this paper we present a new GMF estimated by using neural networks. Neural networks allow us to get empirical models similar to those described above. They are statistical models which require a large number of data regularly sampled in the (θ, χ, v) space to accurately estimate the parameters and give robust GMFs with small model error bars.

The NN GMF is calibrated by using collocations between ERS-1 sigma 0 and NWP wind analysis, which is the procedure that allows us to get the largest data set. We first use the ECMWF wind analysis in order to avoid bias when comparing the performances of the NN GMF with the CMOD4 GMF. In section 7 we provide another NN GMF, calibrated by using NOAA buoy winds only, and compare and discuss the validity of the calibration for both GMF.

We now present the NN GMF we have developed. In the following we use a particular architecture for neural networks, the so-called "Multilayer Perceptron" (MLP), trained by the classical back propagation algorithm [*Badran et al.,* 1991; *Thiria et al.,* 1993]. This work is an extension of a previous study of *Mejia et al.,* [1994].

3. Neural Networks

A neuron is an elementary transfer function which provides an output s when an input A is given.

$$s = f(A)$$

Here f is the transition function.

A neural network (NN) is a set of interconnected neurons. Each neuron receives and sends signals only from the neurons to which it is connected (Figure 3). Thanks to this association of elementary tasks, a neural network is able to solve very complicated problems. This ability is related to the number of neurons and to the topology of their connections.

In the following we assume that the state s_i of neuron i is a nonlinear function f of its total input A_i.

$$s_i = f(A_i) \qquad (1)$$

with

$$A_i = \Sigma_h w_{ih} s_h$$

where f is the sigmoid function. The w_{ih} are the connection weights from h to i (Figure 3). They are real numbers weighting the various influences of the connected neurons.

The Multilayer Perceptron (MLP) is a particular class of neural networks in which neurons are connected in layers. One layer is receiving the system input (input layer). One layer is providing the network response to the input (output layer). One or more layers are internal to the network (hidden layers) (Figure 4). The layers are fully connected (each neuron of a layer is connected to every neurons of the next layer), and the signals propagate from input to output (no backward information).

The weights W={w_{ih}}of the connections are computed by a calibration process (the so-called learning phase) from a learning data set D of the form

$$D = \left(\mathbf{x}_i,\ \sigma_i^0\right) \qquad i = 1, \dots, n$$

where $\mathbf{x}_i$ and σ_i^{-} represent the input and the output set of observed data used to calibrate the neural network. The weights are determined by minimizing a quadratic cost function $C(w)$ of the distance between the desired output σ_i^{υ} and the output s_i computed by the neural network. In the present study, $\mathbf{x}$ is a vector (wind speed, wind azimuth, incidence angle), and σ_i^{υ} is the sigma 0

$$C(w) = \sum_{i=1}^{n} \left\| s_i - \sigma_i^0 \right\|^2 \qquad (2)$$

At the end of the learning phase the neural "machine" is completely determined. Information is encoded into the connections, and the neural network is able to process new sets of data which have not yet been learned. The learning phase may lead to long computations due to the minimization process and the large number of parameters (the connections w_{ij}). But during the operational phase the computation time is very fast because all the minimizations have been done during the learning phase and the only computations are simple algebraic operations.

The performances of the computed NN strongly depend on (1) the quality of the learning data set *D*, i.e., accuracy of the measurements, sufficient number, and statistical representativeness of the observations over the whole range of the function and (2) the number of parameters w_{ij} to be estimated. This number is related to the difficulty of the problem to solve and also to the quality of the data set mentioned above as in statistical estimation [*Vapnik*, 1995]. In order to be statistically significant the computation of the w_{ij} requires a learning data set whose number of elements *n* should be 10 times the number of w_{ij} at least [*Bishop*, 1995].

It can be shown that the above minimization used in the determination of MLPs is related to nonlinear estimation as defined by *Tarantola* [1987] and is close to the determination of the maximum of likelihood with adequate hypothesis on the noise. The major difference with classical methods comes from the family of functions used to approximate the transfer function [*Bishop*, 1995].

MLPs with linear output neurons are nonlinear functions able to uniformly approximate a wide class of functions encountered in physics [*Bishop*, 1995; *Cybenko*, 1989; *Funahashi*, 1989; *Hornik et al.,* 1989], which include continuous and derivable functions with respect to each variable. The minimization used allows a global optimization of the set of parameters. The classical empirical GMF are more restrictive as they use a priori functions and several thresholds estimated from observations which may

lead to suboptimal procedures and noncontinuous functions. Moreover, contrary to most of the classical empirical GMFs, NN GMF does not contain any a priori hypothesis on the functional relationship with respect to the variables. As an example in the following, we make no hypothesis on the biharmonic behavior, and we retrieve this information by analyzing the characteristics of the NN GMF (see section 7). Generally, the study of the NN GMF allows us to obtain new information on the behavior of the GMF and to check the relevance of hypotheses introduced in the estimation of classical GMFs.

4. Determination of the NN GMF

Since we assumed that the scatterometer physics yields a continuous function in θ, χ, and v, which is a weak constraint, the computed NN GMF can be modeled by a Multilayer Perceptron (MLP), whose inputs are the above variables. The obtained performances strongly depend on the input parameters and their coding. In order to limit the strong nonlinearity due to the large dynamical range of the sigma 0 values we decided to code them in decibels. The angles are coded with their associated trigonometric values. The architecture of the MLP has an input layer with five neurons corresponding to the wind speed ν, $\cos\chi$ and $\sin\chi$ (χ is the wind azimuth), and $\cos\theta$ and $\sin\theta$ (θ is the incidence angle), a hidden layer with five neurons and a linear neuron for the output (Figure 4) which is denoted (A5×5×1). The NN GMF thus has 36 parameters (the weights w_{ij} of the connections), which are estimated by using the back propagation algorithm.

We have computed four NN GMF, one for each antenna and a composite NN GMF which combines all the information provided by the three antennas. These four NN GMF have the same architecture which is of the form (A5×5×1). They only differ from the values of the parameters determined during the learning phases.

Let us first study the three NN GMF each associated with a given antenna. They are denoted NN A1 (forward antenna), NN A2 (central antenna), NN A3 (backward (aft) antenna) (see Figure 2). The parameters of each NN A^i (i = 1, 2, 3) are estimated from collocated sigma 0 associated to antenna A_i with the corresponding ECMWF winds. About 10 000 collocations were used for each antenna. Comparisons of the NN A^i may give useful information on the behavior of the scatterometer.

In the present study we consider 10 incidence angles; these values are the same for antennas A1 and A3 and different for the central antenna A2, which deals with smaller incidence angle values. Each incidence angle corresponds to a cell of 50×50 km on which an averaged wind vector is measured.

The composite NN GMF which is denoted NN C hereinafter, uses the combination of all the above collocations. The size of the learning set therefore is 3 times larger than the above individual learning sets. Furthermore, the number of incidence angles is higher, and also the incidence angle range is higher which shall lead to a better estimation for the NN C with respect to the NN A^i.

The quality of the data set used during the calibration phase is of prime importance for determining an accurate NN GMF, since no a priori information is provided. We now describe the data set we dealt with during the learning and the test phase.

5. The Data Set

As already mentioned, the NN GMF were computed onto ECMWF-analyzed wind vectors collocated with ERS-1 scatterometer sigma 0 from March 1992 to March 1993 onto the North Atlantic Ocean. The collocated data set was kindly provided by A. Stoffelen (personnal communication [1992]) who applied the same collocation procedure to build the CMOD4; because of the small space variability of winds provided by a numerical weather prediction (NWP) model the scatterometer sigma 0 is collocated with the nearest wind of the ECMWF model. The North Atlantic Ocean wind is suspected to be of good quality owing to the relatively high number of observations which are assimilated in the forecasting numerical model. From March 1992 the sigma 0 values were computed by ESA using a new algorithm and are of good quality. The overall data set used consists in 30, 000 collocated pairs (sigma 0, analyzed ECMWF wind vectors). In fact, at each collocated point we have three sigma 0 denoted σ_1°, σ_2°, and σ_3°, corresponding to the three antennas, which allows us to compute a NN GMF for each antenna. The calibration (learning phase in NN dialect) of the NN A^i uses about 10, 000 collocated pairs where we tried to equally represent all speeds and azimuths in order to get a statistically representative data set without bias. The number of wind speed data higher than 15 m/s is small, and wind speed values higher than 18 m/s are absent. In order to increase the number of high wind speed values, new data should be considered as the wind over the Antarctic Ocean, but with such a choice, we have to face the problem of using less accurate NWP-analyzed wind speeds. In the following we give the priority to the accuracy of the NN GMF on the range [3 m/s; 15 m/s] and do not use supplementary high wind speeds. Performances and comparisons are done using a test set of 4514 pairs (sigma 0 versus wind vector) taken at random from the data which have not been used for the learning phase. Figures 5a and 5b give the distribution of the wind speed and azimuth angle for the overall data set and the test set showing that the test set is representative of the overall data set. We also used all the data provided by ESA without any specific quality test on the learning set, as on the test set.

The method is sensitive to potential errors in the NWP model surface wind analyses; so the GMF is NWP model dependent. The use of validated wind fields as those used by *Lefevre et al.* [1994] or *Freilich and Dunbar* [1993] should improve the accuracy of NN GMF. For the constitution of an improved data base, *Lefevre et al.* [1994] compared altimeter winds and NWP-analyzed winds, while *Freilich and Dunbar* [1993] compared and used analyzed winds given by different NWP models. Data which are too different according to certain criteria were withdrawn. The data set used for calibration and, consequently, the computed GMF are thus NWP model independent.

6. Analysis of the Different NN GMF

We now analyze the four NN GMF. In order to quantify their accuracy and evaluate their differences and similarities we computed their bias and their root mean square (rms) with respect to the incidence angle on the test set. The bias is defined as

$$\overline{\mathrm{BIAS}} = \frac{\sum\left(\sigma_{\mathrm{NNGMF}} - \sigma_{\mathrm{ERS-1}}\right)}{N} \qquad (3)$$

and the rms is defined as

$$\mathrm{RMS} = \sqrt{\frac{\sum\left(\sigma_{\mathrm{NNGMF}} - \sigma_{\mathrm{ERS-1}}\right)^{2}}{N}} \qquad (4)$$

where σ_{NNGMF} is the sigma 0 computed by the GMF, $\sigma_{\mathrm{ERS-1}}$ is the sigma 0 observed by ERS-1, and N is the number of collocated pairs.

In Figure 6a we present the bias computed on the test set versus the incidence angle for NN-A1, NN-A2, and NN-A3. The bias is always less than 0.35 dB. In particular, the central antenna bias is almost zero. The fore and aft antennas show a similar behavior, with the aft antenna giving better results.

In Figure 6b we present the rms computed on the test set versus the incidence angle for NN-A1, NN-A2, and NN-A3. The rms increases with the incidence angle; it is minimum at 17.9° with a value of 1.31 dB for A2 and maximum at 56.8° with a value of 2.67 dB for A1. As A1 and A3 have the same incidence angles, they should present the same characteristics; however, we denote a small difference which increases at large incidence angles. The aft antenna, A3, gives better performances than the fore antenna, A1, at large incidence angles. This is probably due to some difference in the hardware quality of the antennas. At small incidence angles, i.e., between 23. and 45., the three curves are superposed. From these tests it is concluded that the three antennas have a quitte similar behavior. This leads us to determine a unique GMF independent of the antennas.

In Figure 7 we have plotted the bias and the rms with respect to the incidence angle for NN C which is a composite NN GMF calibrated by using the data provided by the three antenna. In order to compare NN C with the bias , we tested the sigma 0 computed for each antenna separately by using NN C. These values are close to these obtained with the NN A^{i} and presented in Figure 6. We can conclude than NN C reproduces the behavior of each antenna and can be used as a unique transfer function for the three antennas. NN C is a function of good quality since it is approximated by fitting the function on a larger number of incidence angles than NN A^{i} (i = 1, 2, 3). In the subsequent sections we study the physical behavior of NN C, which is considered as a good estimate of the NN GMF for the ERS-1 scatterometer.

NN C reproduces the major characteristics of the previous GMF. Figure 8 displays the variations of NN C with respect to the azimuth for different wind speeds and at three different incidence angles. NN C exhibits the periodic structure with respect to the wind azimuth as found on other GMF as CMOD2 I3 and CMOD4. A small upwind downwind modulation with an upwind component larger than the downwind one is observed. Furthermore, the two minima are found at angles close but not equal to the two crosswind azimuths. The two minimum values are not equal., Such a phenomenon is quite surprising, but its possibility has been suggested by *Liu et al.* [1993]. The sigma 0 decreases with respect to the incidence angle, and the dynamical range is similar to that of CMOD4 or CMOD I3.

Figure 9 displays the mean values, the upwind minus downwind values, and the upwind minus crosswind values with respect to the wind speed at different incidence angles of the NN C GMF. The upwind minus cross-wind values being quite large, the most probable wind azimuths will be obtained quite easily; whereas the upwind minus downwind being small, the ambiguity removal will be somewhat difficult, especially at low wind speed.

In order to check the consistency of NN C we performed several tests. In Figure 10 we present the scatterplots of NN C-computed sigma 0 versus ERS 1-observed sigma 0 at three different incidence angles (21.7°, 31.8°, 43.6°). It is seen that these different scatterplots are consistent, and clusters are centered on the diagonal., We found a correlation of 0.68, 0.72, and 0.76 between the observed and computed signals at the three incidence angles. These results were similar to those provided by previous GMF proposed to decode ERS-1 (see section 2). The quite small values of the correlation are due to the fact that we used raw data without any quality control or filtering.

Figure 11 displays comparisons between the distributions on the whole test set of the ERS-1-observed sigma 0 with respect to NN C-computed sigma 0. This test set includes the data from the 10 tracks and the three antennas, i.e., 5000×10×3 data. It is found that the two distributions are very similar, which proves the good performances of NN C. The differences observed at the extremities of the function can be explained by the lack of data at small and high wind speeds, where the NN C is not enough accurate.

In order to check the regularity of NN C we estimated the variance between the computed and the observed sigma 0 for different velocity v_k and azimuth angle $\chi_{k'}$ intervals. These estimates have been normalized with respect to the variance of the observed sigma 0 at a given incidence angle in order to get comparable values. Table 1a displays the normalized variance for wind speed intervals of 1 m/s between 2 and 18 m/s and for azimuth intervals of 20°. Table 1b gives the number of collocations used for each interval of 1m/s and 20. to estimate the normalized variance; this number is denoted $N_{kk'}$.

$$\mathrm{VAR}\left(v_k, \chi_{k'}\right) = \frac{1}{N_{kk'}} \sum_{j} \frac{1}{\mathrm{Var}(\sigma_{j}^{0})} \sum_{n} \left(s_{nj} - \sigma_{nj}^{0}\right)^{2} \qquad (5)$$

here σ_{nj}^{0} represents a signal observed at incidence angle j, s_{nj} is the corresponding computed sigma 0, and $\mathrm{Var}(\sigma_{j}^{0})$ is the variance of the signal relative to incidence angle j. We see in Table 1b that the variance is estimated with an adequate number of samples in each interval for winds < 12 m/s.

Table 1c compares the variances of the NN C, CMOD4, CMOD2 I3 at different velocities and azimuth angles. It is found that NN C has the lowest variance in 203 cases versus 288 possible cases, which means that NN C presents the best performances.

The results obtained when dealing with NN can be dependent on the initial conditions of the parameters w_{ij} , which are set to random values at the initial time. This leads us to define a procedure to estimate the modeling error of the NN GMF as a function of the model parameters. In order to control the validity of our computation we have determined 10 different NN C having the same architecture, estimated on the same data set, but initialized with different values of the connection weights.

These 10 NN C give quasi identical results as shown by the small values of standard deviation of the 10 rms (Table 2). This shows the robustness of the NN determination. It is concluded that the minimization process associated to the back propagation algorithm for determining the weights of the NN is stable and that MLPs provide robust estimators. This procedure allows us to determine model error bars due to the computation process. We have displayed in Figure 12 a NN C' obtained by averaging the computed sigma 0 of the 10 NN C with bars equal to the corresponding rms. It is found that the errors are maximum at crosswind, which is the most difficult situation to learn. Errors are larger at high and low wind speed than at intermediate wind speed.

7. Comparison of NN C with other GMFs

In order to investigate the pertinence of the NN C we systematically compared it against the ESA CMOD4 GMF (version 2 of March 25, 1993) and the IFREMER CMOD2 I3 GMF. For these comparisons we used the above test set (4514 collocated sigma 0 and ECMWF wind vector pairs taken on the North Atlantic Ocean in 1993).

Table 3a displays the bias of the three GMF for different wind speed intervals and at three different incidence angles (21.7°, 31.8°, 43.6°). Table 3b displays the rms of the three GMF computed by using (4) at the same incidence angles.

Figure 13a displays the bias for the three GMF (NN C, CMOD4, and CMOD2 I3) computed for 1 data at different incidence angles. The bias of NN C is smaller than those of the two other GMF. Figure 13b displays the same comparisons for the rms.

In any case the rms of NN C performs better than the rms of CMOD4 and the CMOD2 I3. The rms is quite regular and is dependent of the wind velocity except at low wind speed, where the scatterplots shown in Figure 10 present some inconsistency.

We have compared NN C to the other two GMF in a large variety of meteorological situations. Most of the comparisons exhibit the same behavior; the rms (in decibels) computed on a given swath is better for NN C than for the other two algorithms. Figure 14 presents a ECMWF-analyzed wind field showing a well-developed cyclone in the upper left corner and a less intense one in the lower right corner; Figure 15 displays the absolute value of the error (difference between the observed sigma 0 and the computed sigma 0) at each grid point of the analyzed wind field when computing the sigma 0 by using CMOD4, CMOD2 I3, and NN C.

We have also computed a NN GMF (NN B in the subsequent) estimated from collocated ERS-1 sigma 0 and winds measured by NOAA buoys taken from October 7, 1993, to February 26, 1994, in the North Atlantic and North Pacific oceans. We used 5262 collocations between the buoy winds and the closest ERS-1 sigma 0. The high wind speeds are poorly represented, and there is no wind measurement over 18 m/s. The NN B GMF is displayed in Figure 16; we have computed the error bars by using the procedure described in section 6. NN B is very similar to NN C showing the consistency of the NWP and buoy data despite the small number of buoy data available and the flexibility of the neural network procedure, which can be easily adapted to a new data set.

A NN GMF has been estimated for ERS-2 scatterometer (NN C2 in the subsequent). NN C2 was estimated on collocations between ERS-2 sigma 0 and the analyzed wind vectors of the Météo France model (Arpege) on the North Atlantic Ocean in May-June 1996. The pattern of NN C2 (Figure 17) is slightly different from NN C. When we compare the ERS-2 sigma 0 to the sigma 0 computed from NWP winds by using NN C and NN C2 it is found that NN C2 gives smaller rms showing that the two GMFs are different. It is concluded that thanks to the flexibility of the neural network procedure, it is better to compute a new GMF for a new sensor than to use a GMF not fitted for this new sensor.

8. Spectral Analysis of the GMF

Fourier analysis with respect to the wind azimuth of the GMF at constant wind speed can provide useful information on the upwind/downwind ratio and on the crosswind behavior. We have thus performed such a Fourier analysis by doing a fast Fourier transform (FFT) with respect to the wind azimuth of the sigma 0 computed by the three GMFs at a constant wind speed. By definition, CMOD2 I3 presents two Fourier components only (in the linear space), which can be computed analytically. We assumed that the three GMFs can be expanded in Fourier series of the form

$$\sigma^0 = a_0 + a_1 \cos\chi + a_2 \cos 2\chi + a_3 \cos 3\chi \\ + a_4 \cos 4\chi + b_1 \sin\chi + b_2 \sin 2\chi \\ + b_3 \sin 3\chi + b_4 \sin 4\chi + \dots$$

where χ is the wind azimuth.

The results are displayed in Table 4, where normalized absolute values of the first four coefficients a_n/a_o and b_n/a_o are displayed at an incidence angle of 31°. The terms of the form $a_n\cos(n\chi)$ correspond to an azimuthal symmetry (sigma $0(\chi)$ = sigma $0(-\chi)$), and the terms $b_n\sin(n\chi)$ correspond to an antisymmetry implying that the two crosswind values are not equal., The b_n are set to zero for CMOD4 and CMOD2 I3 by construction. It is found that the b_n of the NN C can be quite important for some wind speeds and at specific incidence angles explaining the dissymmetry of the two crosswind values and explaining that the minimum are not at 90. and 270. exactly.

The coefficient a_1 is related to the upwind-downwind modulation, and a_2 is related to the biharmonic character of the GMF with respect to χ. The largest term is a_2, then the a_n rapidly decrease with n.

Conclusion

As shown in the statistical tests described above, the NN C GMF can be considered as an improved GMF. Its bias is close to zero and its rms is better than those of CMOD4 and CMOD2 I3 for the whole parameter ranges (whatever the incidence angle, wind speeds, wind azimuths are). The dynamical range of the NN C GMF is smaller than the CMOD4-GMF and the CMOD2 I3-GMF. The NN C GMF gives smaller sigma 0 values at high wind speed than CMOD4 and CMOD2 I3 and larger values at low wind speed. This is in agreement of the observations of *Boutin and Etcheto* [1996], who find that ERS-1 underestimates high winds when dealing with CMOD4 GMF for the wind retrieval procedure. The NN C GMF is a good candidate to model the ERS-1 scatterometer transfer function. Since the NN GMF is of good quality and a derivable function of the variables v, χ, and θ, it must lead to an improvement of the wind retrieval algorithms based on the inversion of the GMF as most algorithms do.

The NN C GMF uses 36 parameters (30 connections plus six threshold values), which is of the same amount of CMOD4 (18) and CMOD2 I3 (28). Its analytical expression is given in the appendix (the authors can provide a FORTRAN subroutine). The NN C GMF parameters are estimated in the decibel space, which is supposed to provide better statistical fits owing to the large range of the sigma 0 values in the linear space. In fact, it is still unclear what is the most useful unit to represent the sigma 0 and to deal in the wind retrieval algorithms.

An interesting point is that we were able to empirically determine the error bars of the NN GMF with respect to the parameters. The error bars are small, showing the good estimate of the NN GMF. They present maximum values at the crosswind directions, which are the most difficult situations to estimate.

The determination of the NN GMFs is statistical only. No apriori hypothesis is given on the behavior of the "classical" GMFs as is given by the conventional semiempirical approaches; thus the neural network approach allows additional degrees of freedom in developing functions which must model a complex and highly nonlinear process. The biharmonic dependence with respect to the azimuth and the upwind-downwind modulation angle is always retrieved by all the NN GMF (calibrated with ECMWF or buoy winds, for ERS-1 or ERS-2 scatterometers). Furthermore, in contrast to conventionally derived GMFs, the NN GMFs give minimum sigma 0 values at angles close to but not exactly equal to crosswind directions (wind azimuths perpendicular to antenna direction), and the two minimum values differ by a quite significant amount of the order of the upwind-downwind modulation. This unusual behavior calls for further investigation and may help in developing a better analytical understanding of the scatterometer. This surprising behavior is found on all the networks we used and is thus not dependent on the neural network methodology.

Effects of secondary phenomena, including the long wave heights and directions and the sea surface temperature, have being neglected. The effect of these parameters on a NN GMF does not present any methodological problem. We only have to add supplementary dedicated neurons in the input layer. The major difficulty is to obtain the adequate collocated data set!

AppendixA: Analytical Form of the NN C GMF

Here σ^0_{dB} is given by the formula

$$\sigma^0_{\mathrm{dB}} = \frac{(S+1)(30+39.35)}{2} - 39.35$$

where

$$S = \sum_{j=1}^{5}\left(w_j h_j\right) + k$$

$$h_j = f\left[\sum_{k=1}^{5}\left(C_{jk} i_k\right) + T_j\right]$$

$$i_1 = 0.66\left(\frac{v - 6.91546}{2.78157}\right)$$
$$i_2 = \sin(\chi)$$
$$i_3 = \cos(\chi)$$
$$i_4 = \sin(\theta)$$
$$i_4 = \cos(\theta)$$

v is the wind speed in m/s, χ is the wind azimuth angle, and θ is the signal incidence angle.

Here $f(\bullet)$ is the function

$$f(x) = 1.7159 \tanh(0.6666x)$$

C, T, w, and k coefficients are given by

$C_{11} = 0.17414965$ $C_{21} = 0.25565395$ $C_{31} = 0.15264085$
$C_{12} = -0.00941209$ $C_{22} = -0.20767751$ $C_{32} = -0.03648504$
$C_{13} = -0.94969255$ $C_{23} = 0.30068469$ $C_{33} = -0.10053569$
$C_{14} = 1.42126286$ $C_{24} = 0.11999325$ $C_{34} = 2.93469453$
$C_{15} = -0.18649226$ $C_{25} = -0.31373969$ $C_{35} = 0.02810644$

$C_{41} = -0.29493716$ $C_{51} = 0.21386629$
$C_{42} = -0.30061653$ $C_{52} = -0.00585925$
$C_{43} = -0.13427117$ $C_{53} = 0.70276290$
$C_{44} = 0.11995704$ $C_{54} = 0.99763799$
$C_{45} = 0.28563869$ $C_{55} = 0.25667107$

$w_1 = -0.21210583$
$w_2 = 0.63489199$
$w_3 = -0.53100425$
$w_4 = -0.40575555$
$w_5 = -0.67420989$

$T_1 = -0.64815396$
$T_2 = 0.61963844$
$T_3 = 0.01106284$
$T_4 = -0.78373748$
$T_5 = -0.34257996$
$k = 0.23539357$

Parameters used in σ^0 and i_1 formulae are due to optimal normalization realized at the calibration stage. The mean of v is 6.91546 m/s, and the standard deviation of v is 2.78157 m/s. The minima of σ^0_{dB} are -39.35 dB and the maxima of σ^0_{dB} are 30.0 dB.

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F. Badran: CEIC, Conservatoire National des Arts et Métiers, 292 rue Saint Martin, 75003 Paris, France. (e-mail: badran@cnam.fr) tel: +33 1 40 27 22 69, fax +33 1 42 71 93 29

M. Crepon, C. Mejia, S. Thiria, N. Tran: Laboratoire d'Océanographie Dynamique et de Climatologie, T14, Université de PARIS VI, 4 Place Jussieu, 75005 Paris, France. (e-mail: mc@lodyc.jussieu.fr, carlos@lodyc.jussieu.fr, thiria@lodyc.jussieu.fr, tran@lodyc.jussieu.fr) tel: +33 1 44 27 70 72, fax +33 1 44 27 71 59

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[1]Also at CEDRIC, Conservatoire National des Arts et Métiers, PARIS, FRANCE

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Table 1a. Normalized variance at different wind speed intervals (columns) and different azimuth intervals (rows). A '–' indicates not enough data to compute statistics (n ≤ 3).

VAR	2/3	3/4	4/5	5/6	6/7	7/8	8/9	9/ 10	10/11	11/12	12/13	13/14	14/15	15/16	16/17	17/18
-180/-160	0.92	0.67	0.62	0.75	0.44	0.31	0.23	0.26	0.27	0.23	0.19	0.16	0.21	0.20	-	-
-160/-140	0.79	0.50	0.49	0.40	0.39	0.32	0.30	0.26	0.58	0.29	0.61	0.33	-	-	-	-
-140/-120	2.09	0.76	0.67	0.44	0.27	0.34	0.31	0.22	0.28	0.33	0.19	0.34	0.42	-	-	-
-120/-100	1.28	0.79	0.34	0.29	0.30	0.24	0.16	0.30	0.48	0.45	0.34	-	-	-	-	-
-100/-80	1.59	0.94	0.45	0.38	2.13	0.64	0.34	0.24	0.62	0.47	0.26	0.60	0.73	-	-	-
-80/-60	1.42	0.93	0.49	0.53	0.31	0.27	0.34	0.23	0.19	0.18	0.31	0.27	0.50	0.91	-	-
-60/-40	1.16	0.83	0.50	0.31	0.20	0.26	0.18	0.29	0.27	0.24	0.12	0.17	0.24	0.14	0.44	0.26
-40/-20	0.94	0.93	0.54	0.33	0.40	0.34	0.40	0.22	0.25	0.22	0.13	0.20	0.27	0.01	-	-
-20 /0	0.95	0.97	0.69	0.39	0.35	0.34	0.26	0.51	0.96	0.61	0.22	0.12	0.57	0.06	0.05	0.01
0/20	0.78	0.96	0.89	0.59	0.30	0.21	0.25	0.43	0.57	0.15	0.14	0.54	0.93	0.07	-	-
20/40	1.39	1.11	0.56	0.41	0.37	0.45	0.45	0.57	0.32	0.21	0.25	0.64	0.47	0.24	-	-
40/60	2.42	1.15	0.74	0.49	0.42	0.32	0.23	0.22	0.26	0.16	0.40	0.20	-	-	-	-
60/80	2.75	1.84	0.58	0.39	0.26	0.28	0.23	0.36	0.31	0.12	0.42	-	-	-	-	-
80/100	1.74	0.69	0.36	0.23	1.85	1.11	0.20	0.11	0.12	0.18	0.14	0.11	-	-	-	-
100/120	2.32	0.89	0.31	0.28	0.38	0.17	0.18	0.16	0.16	0.20	0.23	0.27	0.37	0.75	-	-
120/140	0.86	0.65	0.44	0.30	0.27	0.19	0.25	0.19	0.19	0.19	0.11	0.10	0.06	0.04	0.06	0.02
140/160	2.70	3.91	0.45	0.29	0.27	0.22	0.17	0.15	0.20	0.34	0.48	0.47	0.18	0.22	0.14	-
160/180	0.81	1.20	0.48	0.35	0.38	0.30	0.20	0.14	0.35	0.54	0.44	0.20	0.28	0.56	0.39	-

Table 1b. Number of collocations used for each interval to estimate the normalized variance.

N	2/3	3/4	4/5	5/6	6/7	7/8	8/9	9/ 10	10/11	11/12	12/13	13/14	14/15	15/16	16/17	17/18
-180/-160	174	347	378	474	445	423	316	169	104	74	48	29	21	4	3	0
-160/-140	134	260	323	419	399	293	182	188	98	56	27	8	3	0	0	0
-140/-120	112	200	194	207	274	215	110	125	34	32	17	12	6	0	0	0
-120/-100	88	169	212	188	149	173	159	48	42	48	11	0	0	0	0	0
-100/-80	114	176	249	292	211	174	96	87	45	35	22	7	8	2	0	0
-80/-60	114	192	268	252	203	150	130	110	104	62	34	32	14	4	1	2
-60/-40	110	209	351	413	592	501	434	229	228	90	47	48	36	18	8	4
-40/-20	85	159	280	471	460	490	448	373	129	43	37	20	11	7	2	0
-20 /0	100	213	262	408	536	675	552	190	97	70	38	23	11	22	35	6
0/20	112	180	377	480	472	468	301	120	113	70	55	30	23	9	3	0
20/40	102	182	327	412	271	189	192	154	62	25	35	35	18	9	2	0
40/60	98	141	162	142	177	185	158	100	61	37	20	5	0	0	1	0
60/80	83	129	124	152	102	153	106	40	41	18	10	1	1	0	0	1
80/100	96	149	208	262	180	164	140	94	35	27	23	5	1	1	0	0
100/120	127	199	293	295	243	260	260	105	109	103	62	31	21	8	3	3
120/140	140	295	372	545	665	782	675	353	255	155	72	72	53	21	9	4
140/160	76	204	392	678	821	894	790	647	177	70	30	14	13	9	10	0
160/180	141	279	376	513	590	745	587	197	100	66	28	12	11	31	11	3

Table 1c. This table indicates which GMF has the lowest variance for each box: number 1 stands for NN-C , 2 for CMOD4 and 3 for CMOD2-I3.

Comp	2/3	3/4	4/5	5/6	6/7	7/8	8/9	9/ 10	10/11	11/12	12/13	13/14	14/15	15/16	16/17	17/18
-180/-160	1	1	1	1	1	1	1	1	1	1	3	3	1	1	1	0
-160/-140	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
-140/-120	2	2	1	1	1	1	1	2	1	2	1	1	1	0	0	0
-120/-100	3	1	1	1	1	1	1	1	2	2	3	0	0	0	0	0
-100/-80	1	1	1	3	1	2	2	3	2	2	1	3	1	1	0	0
-80/-60	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2
-60/-40	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1
-40/-20	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
-20 /0	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
0/20	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	0
20/40	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	0
40/60	2	2	2	3	3	1	1	1	3	1	1	3	0	0	2	0
60/80	2	2	1	1	1	3	2	2	2	1	1	1	2	0	0	2
80/100	1	1	1	2	3	3	3	1	1	2	2	1	1	2	0	0
100/120	3	3	1	1	3	1	2	1	2	1	1	1	1	1	2	2
120/140	1	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1
140/160	1	1	1	1	1	1	1	1	1	1	1	1	3	1	1	0
160/180	1	2	1	1	1	1	1	1	1	1	2	0	3	1	1	1

Table 2. Values of standard deviation of the RMS of the ten NN-C for different incidence angles.

Incidence Angle	NN-C
17.9	0.0462
21.7	0.0398
25.2	0.0241
28.6	0.0085
31.8	0.0111
34.9	0.0084
37.8	0.0068
40.6	0.0060
43.1	0.0081
45.6	0.0118

Table 3a. Bias for the different GMF at three different incidence angles (21°7, 31°8, 43°6). The number of collocated pairs used is shown in the first column in parenthesis.

Bias for Incidence = 21°7 - inner cell -	NN- C (dB)	CMOD4 (dB)	CMOD2-I3 (dB)
Test set (4514)	-0.04	0.55	0.76
Sub-set test 2-6 m/s (781)	-0.02	0.35	0.75
Sub-set test 6-10 m/s (2219)	-0.04	0.74	0.71
Sub-set test 10-18 m/s (436)	-0.10	0.71	0.90

Bias for Incidence = 31°8 - central cell -	NN- C (dB)	CMOD4 (dB)	CMOD2-I3 (dB)
Test set (4514)	0.31	0.66	0.61
Sub-set test 2-6 m/s (781)	0.29	0.00	0.40
Sub-set test 6-10 m/s (2219)	0.34	1.08	0.73
Sub-set test 10-18 m/s (436)	0.26	1.12	0.82

Bias for Incidence = 43°6 - external cell -	NN- C (dB)	CMOD4 (dB)	CMOD2-I3 (dB)
Test set (4514)	0.17	0.56	0.46
Sub-set test 2-6 m/s (781)	0.31	-0.05	0.21
Sub-set test 6-10 m/s (2219)	0.09	1.15	0.68
Sub-set test 10-18 m/s (436)	0.04	1.25	0.73

Table 3b. RMS of NN-C, CMOD4 and CMOD2-I3 GMFs at three different incidence angles (21°7, 31°8, 43°6). The number of collocated pairs used is shown in the first column in parenthesis

RMS for Incidence = 21°7 - inner cell -	NN- C (dB)	CMOD4 (dB)	CMOD2-I3 (dB)
Test set (4514)	1.45	1.65	1.69
Sub-set test 2-6 m/s (781)	1.87	1.99	2.09
Sub-set test 6-10 m/s (2219)	0.94	1.23	1.19
Sub-set test 10-18 m/s (436)	0.74	1.07	1.19

RMS for Incidence = 31°8 - central cell -	NN- C (dB)	CMOD4 (dB)	CMOD2-I3 (dB)
Test set (4514)	1.65	1.97	1.79
Sub-set test 2-6 m/s (781)	1.89	2.19	2.00
Sub-set test 6-10 m/s (2219)	1.48	1.81	1.63
Sub-set test 10-18 m/s (436)	1.41	1.83	1.65

RMS for Incidence = 43°6 - external cell -	NN- C (dB)	CMOD4 (dB)	CMOD2-I3 (dB)
Test set (4514)	2.02	2.55	2.12
Sub-set test 2-6 m/s (781)	2.37	2.70	2.39
Sub-set test 6-10 m/s (2219)	1.69	2.03	1.82
Sub-set test 10-18 m/s (436)	1.70	2.19	1.94

Table 4. coefficients a_n/a_o for the three GMF functions for different wind speed at an incidence angle of 31°8.

Wind Speed	coeff	CMOD4	CMOD2-I3	NN-C Averaged over 10-Nets	
		(cos)	(cos)	(cos)	(sin)
4 m/s	*mean*	0.0288	0.0307	0.0311	-
	1	0.0469	-0.0195	-0.0168	0.0070
	2	0.2734	0.2621	0.1906	-0.0225
	3	0.0023	0	0.0105	-0.0302
	4	0.0071	0	0.0096	-0.0016
8 m/s	*mean*	0.0675	0.0628	0.0612	-
	1	0.0653	0.0223	-0.0043	-0.0017
	2	0.3819	0.3758	0.3063	-0.0311
	3	0.0044	0	0.0094	-0.0263
	4	0.0139	0	0.0240	-0.0039
12 m/s	*mean*	0.1131	0.1087	0.1029	-
	1	0.0836	0.0642	0.0063	0.0006
	2	0.4447	0.4301	0.3721	-0.0353
	3	0.0064	0	0.0084	-0.0180
	4	0.0190	0	0.0336	-0.0052
16 m/s	*mean*	0.1732	0.1725	0.1458	-
	1	0.1018	0.1060	0.0149	0.0097
	2	0.4711	0.4433	0.3923	-0.0356
	3	0.0083	0	0.0070	-0.0070
	4	0.0214	0	0.0350	-0.0052