Estimating Wind Stress at the Ocean Surface From Scatterometer Observations

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***Abstract*—Wind stress is the most important ocean forcing for driving tropical surface currents. Stress can be estimated from scatterometer-reported wind measurements at 10 m that have been extrapolated to the surface, assuming a neutrally stable atmosphere and no surface current. Scatterometer calibration is designed to account for the assumption of neutral stability; however, the assumption of a particular sea state and negligible current often introduces an error in wind stress estimations. Since the fundamental scatterometer measurement is of the surface radar backscatter (sigma-0) which is related to surface roughness and, thus, stress, we develop a method to estimate wind stress directly from the scatterometer measurements of sigma-0 and their associated azimuth angle and incidence angle using a neural network approach. We compare the results with *in situ* estimations and observe that the wind stress estimations from this approach are more accurate compared with those obtained from the conventional estimations using 10-m-height wind measurements.**

***Index Terms*—Atmospheric stability, neutral stability, scatterometer, wind stress.**

I. Introduction

SCATTEROMETERS, active microwave sensors, measure the backscattered signal power which is used to determine the wind direction and equivalent neutral wind speed (ENWS) using an empirical geophysical model function relating the normalized radar cross section (sigma-0) and the vector wind [1], [2]. Scatterometers are calibrated to ENWS. The conversion of the scatterometer-reported ENWS to wind speed is complicated due to conflicting assumptions. Greenaert and Katsaros [3] define ENWS as the mean wind speed in a neutrally stratified atmosphere. In contrast, Tang and Liu [1] and Verschell *et al.* [4] define ENWS as the wind speed based on the stress and roughness length consistent with the observed atmospheric stratification. Since the surface roughness measured by the scatterometer is more closely related to ocean surface stress than wind speed [4], [5], the latter definition of ENWS is more consistent with scatterometry.

Wind stress is the most important forcing in the tropics [6] because ocean surface currents are driven by wind stress. Stress can be described in terms of surface roughness (which is related to scatterometer observations) or in terms of near surface vertical wind shear modified by atmospheric stability, which is how stress is estimated from conventional observations. Wind measurements available from conventional platforms such as buoys and ships are typically collected at a measurement height of about 3 m for buoys and at 10 m for ships. Winds closer to the sea surface usually cannot be measured *in situ* due to the problem with waves that hinder the wind measuring instrument. Hence, stress is estimated from the 3- or 10-m wind measurements, typically assuming that surface motion and sea state have negligible influence on the wind shear, with the aid of a surface layer parameterization scheme. The air density required to calculate stress can be determined from *in situ* measurements of pressure, air temperature, and humidity.

For satellite scatterometry, no information about the local stability is typically available. Errors in the atmospheric stability calculation and errors related to waves and currents introduce errors into the estimation of stress. Scatterometers are also not calibrated to consider variability related to air density [7]. Furthermore, the equations for converting from wind or ENWS to stress are highly nonlinear: Missing information on stability can result in biases in the stress. Crude estimates of error propagation suggest that these biases are important for the relatively small stresses typical of tropical and subtropical conditions. For a given roughness of the sea, wind at 10 m can differ by 1 m/s with atmospheric stability conditions [2]. To avoid these errors, we seek to develop a model function, which relates scatterometer-measured sigma-0 (with its associated azimuth angle and incidence angle) to *in situ* wind stress. The results show that the new algorithm has less errors compared to conventional methods based on root-mean-square error (rmse), scatter index (SI), and standard deviation ratio (SDR).

II. Data and Methods

We use the equatorial Pacific Ocean (EPO) data buoy observations of wind vectors, air temperature and humidity at the buoy height of 3 m, and the sea surface temperature (SST) to calculate stress during 1999–2003. The SeaWinds on QuikSCAT scatterometer operated at Ku-band during this period, collecting 5 × 25 km (slice) and 25 × 35 km (egg) resolution dual-polarization backscatter measurements [8]. We collocate the *in situ* estimates of stress with scatterometer sigma-0 measurements and associated azimuth and incidence

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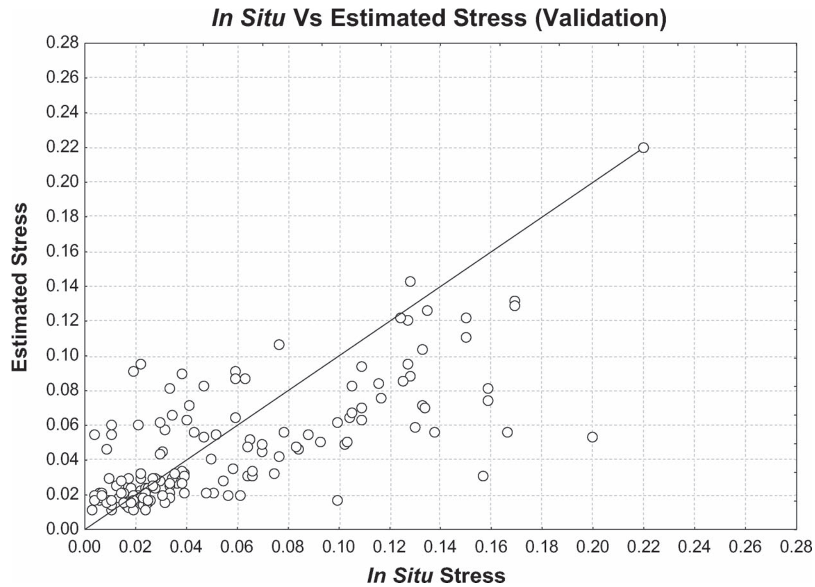

Fig. 1. Scatter between estimated ($S_{\rm ANN}$) and *in situ* ($S_{\rm insitu}$) stresses ($\mathrm{N \cdot m^{-2}}$) for the validation data set.

angles from the SeaWinds sensor during the same period. All the nearest SeaWinds scatterometer sigma-0 measurements (from the Jet Propulsion Laboratory Level 1B data set) of dual polarization, azimuth angles, and incidence angles are collocated with the *in situ* measurements falling within 100 min and 25 km. Only those values passing all quality checks are used in this study. Rain-flagged data are discarded.

A. *Estimation of Wind Stress From Bouy In Situ Measurements*

The wind stress is estimated from the bulk flux algorithm based on the Monin–Obukhov similarity theory (MOST) accounting for changes in stability [9]. This theory relates surface stress, turbulent heat, and moisture fluxes to the variation of wind with height, without considering the effect of surface currents or waves. The algorithm has been validated using Tropical Ocean and Global Atmosphere-Coupled Ocean-Atmosphere Response Experiment [10] direct flux measurements. The required inputs for the estimation of wind stress are wind vectors (speed and direction), air temperature and humidity at 3 m, and SST. These observations are taken from the EPO data buoy observations.

B. *ANN Analysis*

An artificial neural network (ANN) is a massive parallel-distributed computer model consisting of simple processing units called artificial neurons which are the basic functioning units. The neural network formulation is based on the fact that any parameterization of a process can be considered as continuous (with finite discontinuities) mapping (input versus output vector dependence), which is analogous to atmospheric and ocean models with forcing and response. ANN has been widely used in various meteorological [11]–[14] and oceanographic [15]–[18] applications. Richaume *et al.* [19] used ANN technique to retrieve winds from European Remote Sensing Satellite-1 scatterometer data.

The ANN analysis requires three separate data sets used for the following: 1) training; 2) verification; and 3) validation. The data set marked for training is used to train the ANN model through several iterations. The verification data set is used to validate the model during this process so that the model does not overfit during training. At the training stage, the ANN verifies whether the model developed for the training data set holds well outside the training data range in terms of rmse and applies a midterm correction if required. Thus, the training and verification data sets are used to develop the model. The ANN model developed is then stored and used for estimating the output using the input parameters from the data set marked for validation.

With the aforementioned spatial and temporal collocation criteria, we obtained 2000 observations of *in situ* and scatterometer observations during 1999–2003. We used 840 observations during 1999–2000 for training, 1010 observations during 2002 for testing, and 150 observations during 2003 for validating. The 2003 data selection was made to see if the model developed for one period is valid for the other period. In the present analysis, we use multilayer perceptrons, which are feedforward neural networks, with one input layer, three hidden layers, and one output layer, in our ANN.

Empirical studies have demonstrated that, at the incidence angles of the scatterometers, the variation of sigma-0 with radar azimuth angle (χ) is nearly $\cos(2\chi)$ [20]. The reported radar azimuth angles are converted with respect to the true wind direction obtained from the operational European Centre for Medium-Range Weather Forecasting. The dependent variable for the ANN analysis is the wind stress estimated from the *in situ* observations using MOST, while the independent variables are the four sets of SeaWinds-reported sigma-0 along with their associated incident angle and azimuth angle with respect to the true wind and the ancillary values $\cos(\chi)$ and $\cos(2\chi)$.

In addition to using the ANN approach to estimate wind stress, we also compute the wind stress parameter S from the scatterometer-derived ENWS as

$$S = \rho\, CDN\, w^2$$

where CDN is the neutral drag coefficient and w is the ENWS.

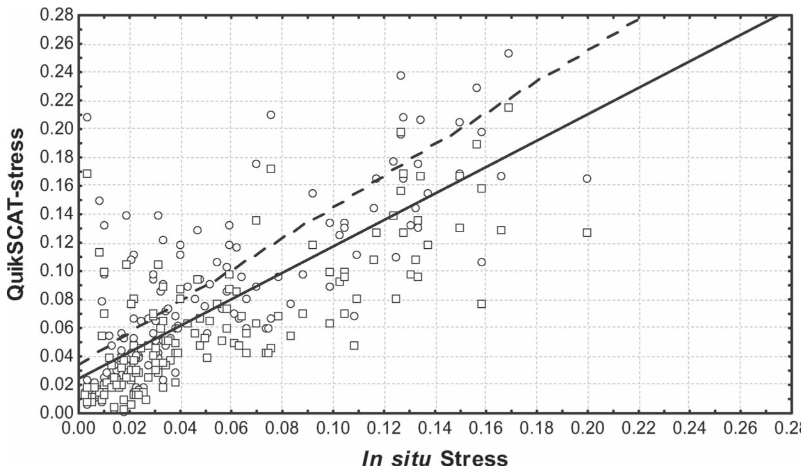

Fig. 2. Scatter between the wind stress estimated from 10 m height wind measurements and that from *in situ* (S_{insitu}) observations. The circles with dashed line (squares with solid line) represent the scatter by using a constant (wind-dependent) CDN.

Two types of drag coefficients are used for this purpose: 1) a constant drag coefficient (CDN_c) of 0.0015 [21] and 2) the wind-speed-dependent drag coefficient (CDN_w) given by [22]

$$CDN_w = (2.7/w + 0.142 + 0.0764w)/1000.$$

III. Validation Results

The scatter (Fig. 1) between the stress estimated using the ANN approach (S_{ANN}) and that estimated from the *in situ* observations (S_{insitu}) using MOST for the validation data set has an rmse of 0.035 $\text{N} \cdot \text{m}^{-2}$ with a Pearson's correlation coefficient r of 0.7. The reference line in the plot is at 45°. In addition to using the ANN approach, we computed wind stress by using the wind magnitudes from SeaWinds wind estimates at 10-m height by using CDN_c and CDN_w as explained earlier. The scatter between the *in situ* stress estimated using MOST (S_{insitu}) and that with CDN_c and CDN_w is shown in Fig. 2.

The statistical analysis of these three approaches is summarized in Table I. rmse between the S_{ANN} and S_{insitu} is less (0.035 $\text{N} \cdot \text{m}^{-2}$) compared to the stress obtained from ENWS (winds at 10-m height) using either a CDN_c (0.083 $\text{N} \cdot \text{m}^{-2}$) or CDN_w (0.078 $\text{N} \cdot \text{m}^{-2}$). Similarly, the r value is also high for the ANN approach compared to the conventional methods. The SI, defined as the ratio of rmse to the data mean, is also less for S_{ANN}. Similarly, the SDR, defined as the ratio between standard deviation errors in estimations to the data standard deviation, is also less for S_{ANN} compared with other two methods. The SI and SDR should be less than 1.0 for an effective model. Higher values of r and lower values (< 1) of SI and SDR for the S_{ANN}-estimated stress compared with conventional estimates from the ENWS indicate that the proposed approach of estimating wind stress is a better and more accurate method.

TABLE I
STATISTICAL COMPARISON OF THE STRESS ESTIMATED USING ANN APPROACH WITH THAT USING THE CONVENTIONAL APPROACHES

Method ►	**ANN-Stress**	**QuikSCAT-Stress**	
		With CDN_c	**With CDN_w**
RMSE (Nm^{-2})	**0.035**	**0.083**	**0.078**
R	**0.70**	**0.54**	**0.48**
SI	**0.64**	**1.79**	**1.43**
SDR	**0.71**	**1.58**	**1.64**

IV. Summary and Conclusion

Ocean surface currents are driven by the winds at the surface through wind stress. Scatterometers indirectly measure the roughness of the sea by measuring sigma-0, which is related to wind stress. Conventionally, scatterometer measurements are related to the neutral-stability speed, from which wind stress is estimated. Here, we have applied a new method to estimate the wind stress directly from the scatterometer backscatter measurements. For this purpose, we estimate the wind stress for EPO data buoy observations using the MOST. We then trained ANN using these *in situ* estimations and the scatterometer-derived sigma-0, azimuth angle, and incidence angle. The trained algorithm is validated with an independent data set. The wind stress estimated using the ANN approach compares well with the *in situ* estimations. This method is better than the conventional approach of estimating wind stress from neutral-stability scatterometer winds at 10-m height.

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