MODEL-BASED WIND FIELD ESTIMATES FROM WIND SCATTEROMETER MEASUREMENTS

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ABSTRACT

In a recent paper (Long and Mendel, 1988) we introduced a fundamentally new model-based approach to estimating wind fields over the ocean's surface using wind scatterometer measurements. In this approach, a model for mesoscale near-surface wind fields was formulated. The model is based on the geostrophic approximation and simplistic assumptions about the wind field vorticity and divergence, but includes ageostrophic winds. The model parameters are estimated from the scatterometer measurements using maximum-likelihood (ML) principles. An objective function for the model parameters, based on the log-likelihood function, is formulated from the scatterometer measurements. The model parameter vector which minimizes the objective function is the ML estimate of the model parameters. The wind field estimate is then computed from the estimated model parameters.

In this paper we use simulated radar backscatter measurements of realistic mesoscale wind fields to compare the accuracy of model-based wind field estimates and estimates obtained using the traditional two-step approach to wind estimation consisting of point-wise wind estimation followed by "dealiasing", or ambiguity removal. The traditional approach wind field estimates were made using the algorithms currently planned for processing of NASA scatterometer (NSCAT) data (Shaffer, *et al.*, 1989). The backscatter measurements are generated using a realistic simulation of the NSCAT scatterometer. Our results show that the model-based approach to wind field estimation produces more accurate estimates of the wind field than the traditional wind estimation procedure. A quantitative example is given. Techniques for reducing the amount of computation required to compute the model-based wind field estimate are discussed.

1. INTRODUCTION

From measurements of the normalized radar backscatter (σ^o) made by a spaceborne scatterometer, the near-surface wind over the ocean can be inferred using a geophysical model function (which will be denoted by $\mathcal{M}$) which relates σ^o to the vector wind. In our research we have used the SASS[1] (Bracalente, *et al.*, 1980) model function. Traditionally, a point-wise approach, in which only the σ^o measurements corresponding to a particular sample point are used to estimated the wind at that sample point, is used. Since this point-wise wind retrieval produces non-unique esimates of the wind vector, a second step known as "dealiasing" or ambiguity removal is used to select a unique wind vector estimate (see Shaffer, *et al.*, 1989).

We recently developed a new, model-based approach to wind estimation which estimates the wind field over the entire swath simultaneously (Long and Mendel, 1988). This fundamentally new approach is based on physical principles for modeling the underlying true wind field. The parameters of the wind field model are directly estimated from the measurements of σ^o; then the wind field estimate is computed from the estimated model parameters. This approach results in more accurate estimates of the wind field and provides the ability to quantify the accuracy of the wind field estimates, a difficult task with the present approach. A description of our model-based estimation approach is provided in (Long and Mendel, 1988) with more detail provided in (Long, 1989).

In this paper we describe an application of the approach to NSCAT and provide a comparison of the wind estimation performance. The merits of the approach are discussed as well as methods of reducing the computational requirements. Finally, we summarize our conclusions.

2. MODEL-BASED WIND FIELD ESTIMATION

In our model-based wind field estimation technique we use a mathematical model for describing a "snapshot" of the near-surface mesoscale wind field. The model provides a description of the wind field over the scatterometer measurement swath at a fixed instant of time and a resolution of 25-50 km (corresponding to the scatterometer sampling) over limited-area regions with a maximum spatial extent of approximately 600 km corresponding to the swath width of NSCAT. The model is based on the geostrophic equation and simplistic approximations for the vorticity and divergence of the wind field. However, the model also includes the capability of describing ageostrophic winds. A detailed derivation of our wind field model is provided in (Long, 1989) (see also, Long and Mendel, 1988).

Over an $N \times N$ equally-spaced grid our model can be expressed as,

$$\begin{bmatrix} \overline{U} \\ \overline{V} \end{bmatrix} = F\overline{X}. \tag{1}$$

where the N^2 element vectors $\overline{U}$ and $\overline{V}$ are the lexicographic-ordered u and v components of the wind vectors at the scatterometer sample points and where $\overline{X}$ is a N_D element vector containing the model parameters. N_D is the model order which may be selected to tradeoff computational requirements and model accuracy. For purposes of model-based wind estimation from scatterometer measurements, we have found that $N_D = 20$ provides adequate accuracy (Long, 1989). The rectangular matrix F consists of known constants. This wind field model easily lends itself to the parameter estimation formulation: the model parameter vector $\overline{X}$ is estimated from the noisy σ^o measurements provided by the scatterometer then the wind field is computed from the parameters using Eq. (1).

To estimate the model parameter vector from the noisy σ^o measurements made by the scatterometer, we formulate an objective function for $\overline{X}$ from the measurements based on maximum-likelihood (ML) principles. The objective function is the negative log-likelihood function. The vector which minimizes the objective function is the ML estimate of $\overline{X}$.

Disregarding constants, the log-likelihood function for $\overline{X}$ is

$$\begin{aligned} l(\overline{X}) \;=\; & -\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{L_{i,j}}\Big\{\ln[\alpha_{i,j}^2(k)\sigma_{i,j}^{o2}(k) + \beta_{i,j}^2(k)\sigma_{i,j}^o(k) + \gamma_{i,j}^2(k)] \\ & +[z_{i,j}(k) - \sigma_{i,j}^o(k)]^2/[\alpha_{i,j}^2(k)\sigma_{i,j}^{o2}(k) + \\ & \beta_{i,j}^{2}(k)\sigma_{i,j}^o(k) + \gamma_{i,j}^2(k)]\Big\} \end{aligned} \tag{2}$$

where $\sigma_{i,j}^o(k)$ is the value of σ^o obtained by evaluating the wind field model at $\overline{X}$ and using the u and v components of the wind vector at the grid point (i,j) in the $\mathcal{M}$ function, i.e.,

$$\sigma_{i,j}^o(k) = \mathcal{M}\{(F\overline{X})_{i,j}, F\overline{X})_{i,j}, k\} \tag{3}$$

where the index k subsumes the dependence of $\mathcal{M}$ on the azimuth angle, the incidence angle, and the polarization of the σ^o measurement (Long, 1989).

Due to the complicated nature of the objective function we must resort to numerical techniques to optimize the objective function. Numerical minimization of the objective function can be difficult due to the nature of the objective function which inherits its properties from the nature of $\mathcal{M}$. The harmonic form of $\mathcal{M}$ gives rise to (a) numerous local minima, and (b) the potential for multiple global minima in the objective function.

A gradient-based optimzation algorithm can be used for the minimization of the objective function if appropriate initial values can be used. We have found that an appropriate initial value can be computed from a traditionally-derived dealiased wind field. The dealiased wind fields we have used for this purpose are computed using the median filter-based dealiasing algorithm described in (Shaffer, *et al.*, 1989). Given a dealiased wind field ($\overline{U}_D$ and $\overline{V}_D$), an initial value, $\widehat{\overline{X}}$, is computed using a least-squares fit of the wind field model to the dealiased wind field, i.e.,

$$\widehat{\overline{X}} = (F^T F)^{-1} F^T \begin{bmatrix} \overline{U}_D \\ \overline{V}_D \end{bmatrix}. \tag{4}$$

Starting with this initial value, we used standard numerical optimization algorithms to find the value of $\overline{X}$ which minimized the objective function. This value of $\overline{X}$ is the ML estimate of the model parameter vector. The estimated wind field is computed from the ML estimate of $\overline{X}$ using Eq. (1).

3. PERFORMANCE FOR NSCAT

To evaluate our model-based wind estimation technique for NSCAT, we used the same simulated NSCAT σ^o measurements as (Shaffer, *et al.*, 1989). We segmented the NSCAT observation swath into adjacent 600×600 km regions as indicated in Fig. 1. We then used our model-based wind estimation technique to estimate the wind field separately for each region.

The NSCAT instrument is designed to provide σ^o measurements at 25 km resolution but the wind will be estimated at 50 km resolution. While our method can be applied to 25 km resolution data, in this example we have resampled the 25 km resolution σ^o measurements on to a 50 km resolution grid. This permits direct comparison with the results presented in (Shaffer, *et al.*, 1989). An illustration of the results is given in Figs 2-4.

The true wind mesoscale wind field [a portion of one of the test wind fields used (Shaffer, *et al.*, 1989)] is shown in Fig. 2. The traditionally-derived dealiased wind field, obtained using the techniques described in (Shaffer, *et al.*, 1989) is shown in Fig. 3. In this example there are few dealiasing errors. Typically, there are several large regions of dealiasing errors (Shaffer, *et al.*, 1989). The results of our model-based estimation procedure are shown in Fig. 4. Table 1 summarizes the total root-mean-square (RMS) errors for each wind field. The vector error in Table 1 is the RMS of the vector-magnitude of the difference between the true wind vector and the estimated wind vector. Also listed in Table 1 is the RMS error for the "closest ambiguity" wind field which would be obtained if the dealiasing were perfect. The closest ambiguity wind field is the best estimate possible using point-wise wind estimation.

Comparison of the model-based and point-wise wind field estimates reveals that the model-based wind field estimates: (1) are less "noisy" and (2) exhibit smaller RMS vector and direction error than *both* the dealiased wind field *and* the closest ambiguity field. The RMS wind speed error is slightly higher than the point-wise results since model-based estimation is, in effect, minimizing the *vector* error. Wind estimate accuracy can be improved by using the wind speed from point-wise estimation and wind direction from the model-based estimation.

4. DISCUSSION

While we have used the dealiased point-wise wind estimates to compute an initial value for the optimization, other methods of computing an initial value can be used (see Long, 1989). The dealiasing is not required in our approach but used only for convenience in computing an initial value. Furthermore, the initial value computation from the dealiased wind field is fairly tolerant of dealiasing errors.

An advantage of model-based wind field estimation over the traditional approach involving dealiasing, is that the model-based results are ML estimates of the wind field for which an error analysis can be made. An error analysis of the traditional point-wise retrieval/dealiasing approach, which is often based on *ad hoc* considerations, is very difficult to develop.

In addition, because our model-based estimation approach takes advantage of the inherent correlation in the wind field over the measurement swath, it is more tolerant of noise in the σ^o measurements than is the point-wise wind estimate technique; the accuracy of the wind fields estimated using a model-based approach degrade gracefully as the SNR of the measurements is reduced. This may permit reductions in the size and weight of future scatterometer instruments by reducing the requirements on the SNR of the σ^o measurements, permitting smaller transmitters, antennas, etc.

The traditional point-wise approach to wind retrieval requires that there be measurements of σ^o from at least two different azimuth angles in order to retrieve the wind. Where there are missing σ^o measurements the wind can not be retrieved. If there is only a single azimuth angle represented at a sample point, the σ^o measurements must be discarded, resulting in "holes" in the estimated wind fields. In the model-based estimation approach, a wind vector is retrieved at every point of the swath–even where there are missing σ^o measurements; hence, there are fewer data gaps in the retrieved wind fields. Furthermore, all of the available σ^o measurements are used at all sample points *even if there is only one σ^o measurement at a given sample point* (Long and Mendel, 1988). These additional measurements help reduce the overall estimate error by taking advantage of the inherent correlation in the winds at different sample points in the swath.

Our wind field model can also be used to check the accuracy of dealiased wind fields (Long, 1989). The difference (known as the model-fit error) between the dealiased wind field and the initial value wind field, which is computed via a least-squares fit of the wind field model to the dealiased wind field, provides a measure of the accuracy of the dealiasing. When the dealiasing algorithm chooses the correct point-wise ambiguity at each sample point, the RMS model-fit direction-error is generally small. However, when there are clustered dealiasing errors, this error is much larger. This leads to a simple threshold-based dealiasing algorithm accuracy check based on the wind field model. When the RMS initial value model-fit direction-error is above a threshold (such as 15-20 deg, depending on wind speed) the dealiased wind field generally contains dealiasing errors (Long, 1989).

Table 1: Total Wind Field Estimate Error

Wind Field	Fig. #	RMS Error Vector	Direction	Speed
		(m/s)	(deg)	(m/s)
Closest Ambiguity	—	1.435	9.409	0.481
Point-wise Dealiased	3	1.460	9.794	0.483
Model-Based Estimate	4	1.036	5.737	0.702

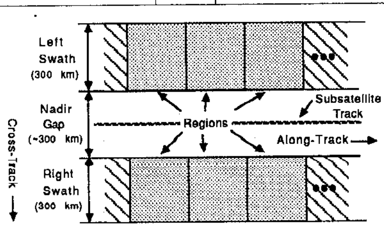

Figure 1: Diagram of the NSCAT swath segmentation scheme.

5. COMPUTATIONAL CONSIDERATIONS

Our model-based estimation approach requires significantly more computation than does the traditional point-wise estimation approach. Most of this time is consumed in optimizing the objective function. We observed that if the initial value has acceptable accuracy, a significant amount of computation can be saved by not optimizing the objective function, i.e., by using the initial value as the estimated $\overline{X}$. We have observed that in general, this accuracy is achieved if: (1) the RMS of the estimated wind speed is larger than 4 m/s and (2) the RMS direction difference between the initial value field and the dealiased field is less than a threshold value (about 15 deg for 50 km resolution wind estimation). These conditions can be checked before starting the optimization. If they are met, we can elect not to optimize, and thereby trade off accuracy of the estimate and computation time.

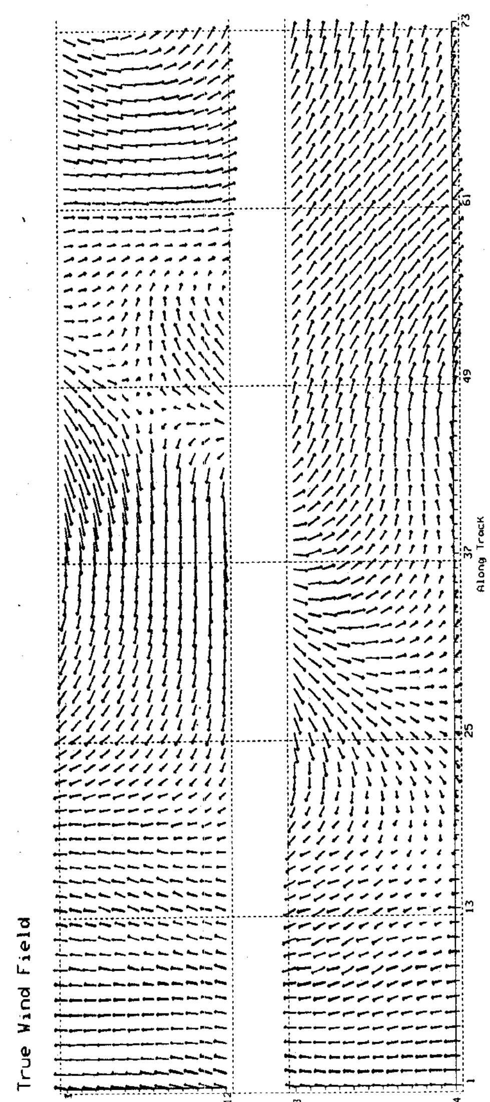

Figure 2: True wind field. Resolution is 50 km. Vector length corresponding to separation between vectors corresponds to 15 m/s wind speed.

6. CONCLUSION

Our model-based wind estimation technique produces more accurate estimates of the wind vector field (as measured using RMS vector magnitude and RMS wind direction error) than does the traditional approach, even when the dealiasing is done perfectly. The improved performance can be attributed to the fact that the model-based approach takes advantage of the inherent correlation between the wind at different sample points to reduce the noise in the final wind estimates.

Compared to the previously used wind retrieval/dealiasing algorithms our model-based wind retrieval technique: (1) can produce more accurate estimates of the wind, (2) has a tractable error analysis, (3) uses all available σ^o measurements including points at which only a single σ^o measurement is available, (4) has fewer "holes" in the estimated wind field, and (5) is less sensitive to the noise level in the σ^o measurements. In addition, our wind field model can be used as a check of the accuracy of the dealiasing process.

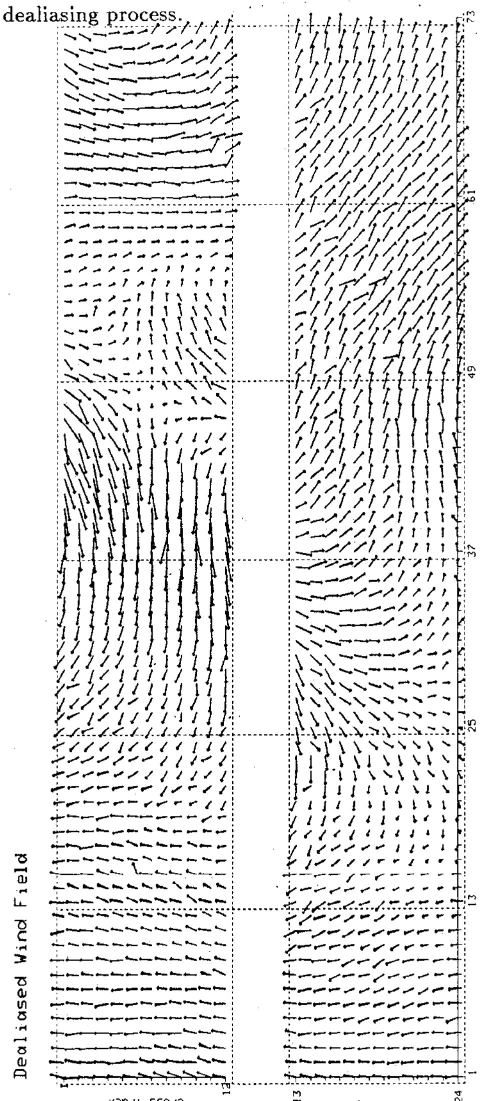

Figure 3: Dealiased wind field obtained using traditional point-wise wind estimation.

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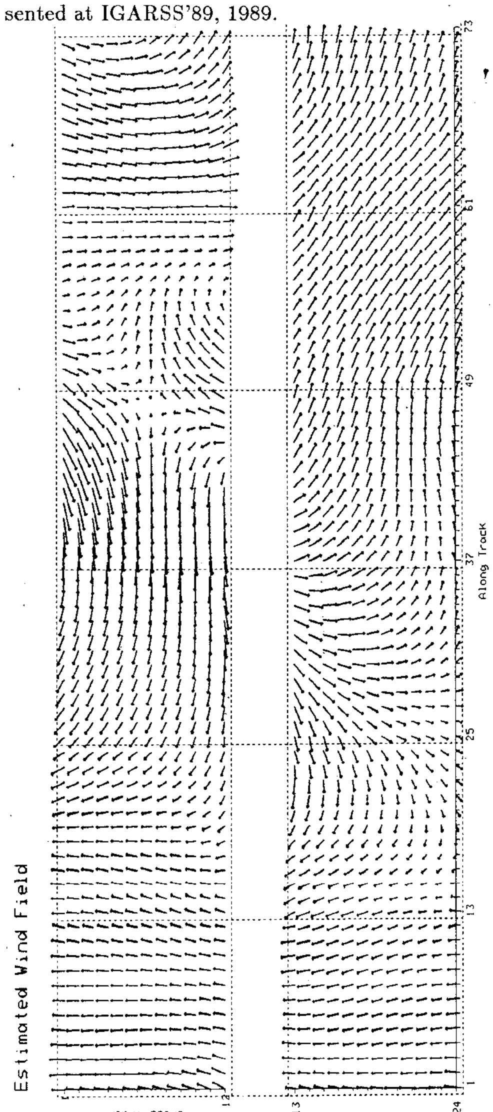

Figure 4: Model-based wind field estimate.