ASSIMILATION OF SCATTEROMETER DATA

Ross N. Hoffman
Atmospheric and Environmental Research, Inc.
Cambridge, Massachusetts, U. S. A.

1. INTRODUCTION

Satellite scatterometers are space borne active radars which measure backscatter from the earth's surface. Over the ocean, surface winds may be deduced from multiple backscatter measurements made from several directions. Ocean surface winds have a wealth of scientific and operational applications—nowcasting of hurricane and typhoon surface winds, enhanced numerical weather prediction (NWP), wave forecasting and optimal ship routing, boundary forcing for ocean circulation models and for studies involving the exchanges of momentum, heat and moisture at the ocean surface. A satellite scatterometer is currently operating on the ESA ERS 1 satellite and current plans of ESA and NASA will maintain a steady stream of scatterometer data for the rest of this decade. If current research on utilization of scatterometer data is successful, similar instruments will be included in many future operational remote sensing satellites. In this report we will be concerned with the various factors affecting the utilization of scatterometer data for NWP and the impact of scatterometer data on NWP.

1.1. Background

The first satellite scatterometer was the Seasat-A Satellite Scatterometer or SASS (*Grantham et al.*, 1977). Only 96 days of data beginning 7 July 1978 were collected because the Seasat mission aborted prematurely. Still SASS demonstrated the potential for satellite scatterometry. A large number of scientific studies have been made with the available data demonstrating the usefulness of satellite scatterometry (*Stewart*, 1988; *Katsaros and Brown*, 1991). However certain problems are seen in these studies. Further for most oceanographic applications much longer data sets are required. The short mission lifetime also worked against demonstrations of operational applications.

During the 1980s plans for new and more capable scatterometers were made by NASA and ESA. The NASA instrument, called NSCAT, was to fly on a U.S. Navy satellite. The Navy satellite program went through several reincarnations before being cancelled. During this time the NSCAT project slowly made progress. The instrument and data systems are now complete. NSCAT will fly on the Japanese ADEOS spacecraft, with an expected launch during 1996 (*Naderi et al.*, 1991). SASS and NSCAT are Ku band instruments. The ESA instrument launched in August 1991 onboard the ERS 1 satellite utilizes the longer wavelength C band (*Francis et al.*, 1991). The three scatterometers have similar orbit characteristics—sun synchonous, near polar orbits, at roughly 800 km altitude, with a period of approximately 100 minutes. Both NASA instruments have antennas on both side of the space craft, affording two simultaneous swaths (500 km wide for SASS and 600 km wide for NSCAT) separated by a nadir gap (450 km wide for SASS and 350 km wide for NSCAT). The ERS 1 scatterometer has antennas only on the right side of the spacecraft. The single 500 km ERS 1 swath covers most of the global ocean in a 24 h period. Due to the geometry of the observations, the backscatter values at a single location are observed within a time span of approximately 70 to 200 seconds, increasing with incidence angle.

Future planned scatterometers include the ESA ERS 2, the ADEOS NSCAT already mentioned, the ESA POEM and the U.S. EOS STIKSCAT. ERS 2 scheduled for launch in 1994 is a copy of ERS 1. The POEM mission is planned to carry an advanced C band scatterometer in 1997. The STIKSCAT instrument will be similar to NSCAT and may fly on ADEOS II or another early EOS mission.

1.2. Measurement methodology

Scatterometers are active radars measuring the backscatter (normalized radar cross section or NRCS or σ^0) from the earth's surface. At moderate incidence angle (20° to 70°) the major mechanism for this scattering is Bragg scattering from centimeter scale waves, which are, in most conditions, in equilibrium with the local wind. Theory is presently inadequate to describe this scattering quantitatively. Consequently empirical relationships, called model functions, which relate the backscatter to the geophysical parameters, are derived from colocated observations (*Jones et al.*, 1977). In current model functions, the backscatter depends very nonlinearly on wind speed and direction. Although the scatterometer winds are usually provided as neutral winds at some reference height, the measurement is physically most closely connected with surface stress (*Brown*, 1986). Several scatterometer measurements are made of the same earth location and winds are obtained by optimally fitting these data.

Because of the nonlinearity of the model function, several wind vectors consistent with the backscatter observations are usually found (*Price*, 1976). These multiple wind vectors are called aliases in the early literature and are now generally referred to as ambiguities. With two measurements SASS typically retrieved 4 ambiguities. With three measurements, NSCAT and ERS 1 will usually retrieve just 2 ambiguities approximately 180° out of phase. The ambiguities are the minima of a cost function, which is a function of wind speed and direction. The cost function measures the difference between the observed σ^0 and those

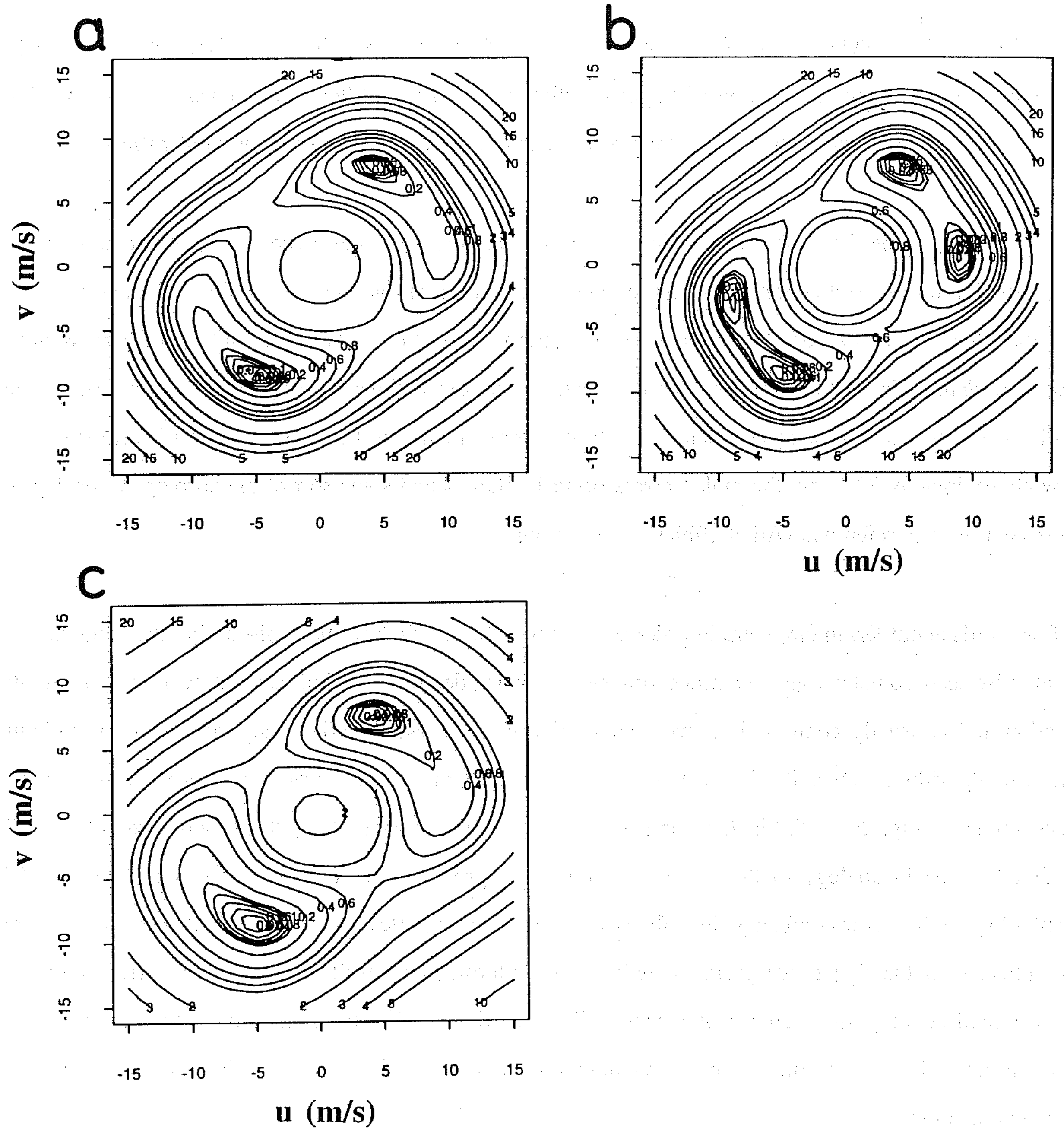

Fig. 1 The cost function, as a function of wind components for triplets of noiseless σ^0 measurements evaluated using either (a,b) CMOD4 or (c) CMOD2. The true wind speed is 10 m/s from 30°. The forebeam incidence angle is 42°. In panel (b) the midbeam σ^0 measurement is assumed to be missing. Note that the contour interval is smaller near the minima.

calculated for the given wind speed and direction (e.g. Fig. 1). Relative minima not sufficiently small are ignored. Thus if the σ^0 data are very inconsistent there may be no ambiguities. Also, no ambiguities are produced at low wind speed since the returned radar signal is too weak to determine wind direction accurately.

Each ambiguity is assigned a probability of being the closest (i.e., the closest ambiguity to the true wind vector). Ambiguities with small relative minima are more likely. The highest probability ambiguity is termed the rank 1 solution. For ERS 1, usually only the first two probabilities are large and the associated ambiguous wind vectors point in nearly opposite directions. Various filtering approaches (called dealiasing or ambiguity removal algorithms) may then be used to extract a horizontally consistent pattern.

In autonomous mode (i.e. with no other data), ambiguity removal schemes achieve 98 or 99 percent accuracy in simulation under ideal conditions—that the rank 1 solution is in fact the closest 60% or more of the time and that there is no horizontal coherence to the pattern of locations where the rank 1 solution is not the closest (*Schultz*, 1990). For the ERS 1 scatterometer initial evaluations of instrument skill (percent of most likely which are closest) were less than 50%. With improvements to the model function instrument skill is now approximately 70%, but the rank 1 errors occur in clumps and some sort of meteorological background must be used for reference (Ad Stoffelen, pers. comm.).

A few words about terminology are in order at this point. So far we have been discussing the ''classical'' or point–wise scatterometer wind data processing system which determines winds separately at each observation location and is usually composed of two distinct algorithms: a wind retrieval algorithm and an ambiguity removal algorithm. Overall, the scatterometer wind data processing system produces winds from σ^0 measurements (Fig. 2a). Within the context of a data assimilation system, these winds might be called retrieved winds in analogy to the retrieved temperature profiles from a satellite sounding system. This terminology is however confusing since the scatterometer ambiguities might also be called retrieved winds. As indicated in the figure, we prefer to refer to the intermediate result as the scatterometer ambiguities and the final result as the scatterometer winds. To be used for NWP, the scatterometer winds produced in this way must then be assimilated in a conventional data analysis, giving due consideration to their special error characteristics.

An alternative processing system for scatterometer data is the variational approach, based on maximum likelihood estimation. The variational method combines the functions of the retrieval, ambiguity removal and analysis algorithms into a single algorithm. In this approach one models the wind field in terms of a set of parameters (the control variable) and seeks a solution in terms of these parameters which minimizes a lack of fit to the observations (the σ^0 measurements). The general scheme for these approaches is illustrated in Fig. 2b. The control variable is evaluated/interpolated to the observation locations, transformed to the observed variables (the pseudo-observations or trajectory values) and compared to the observations in order to compute the loss function. This set of steps is repeated as necessary within a minimization algorithm, as the control variable is varied.

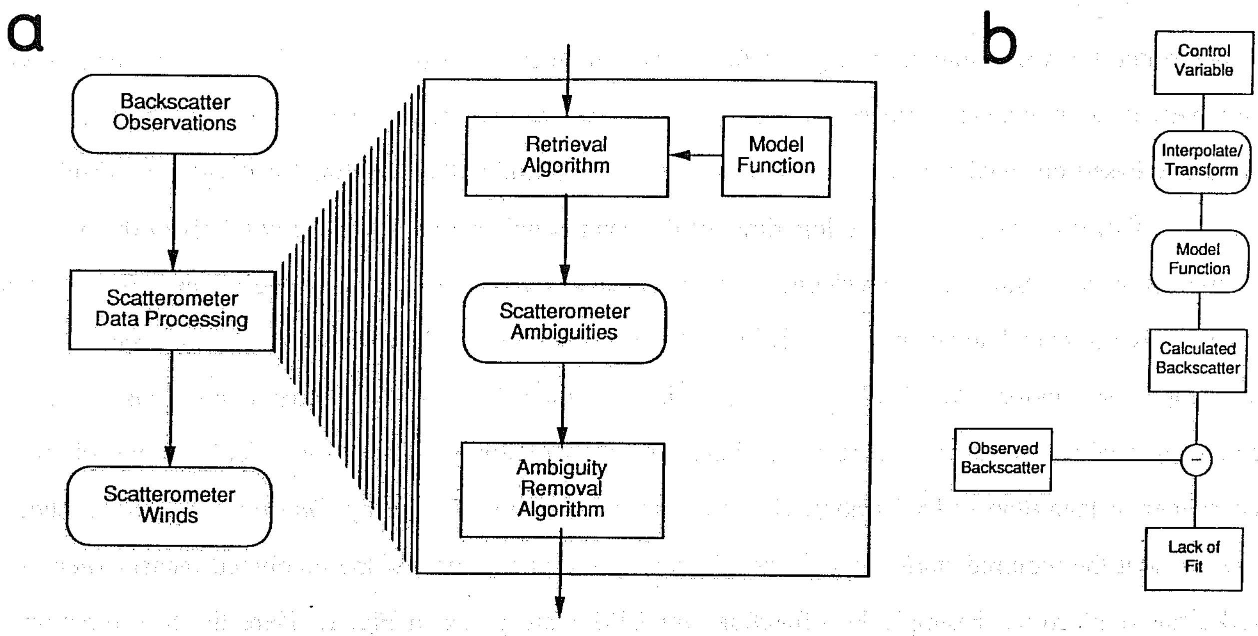

Fig. 2 Flow charts describing scatterometer data processing in (a) the "classical" or point–wise approach and (b) the variational approach.

In order to assimilate scatterometer data one must bear in mind that the geophysical quantity that is measured is backscatter. In the classical or point–wise data processing, the data assimilation system may be presented with winds, or the wind retrieval and ambiguity removal algorithms may be incorporated in the assimilation system. In either case, the details of how the winds are produced may have important consequences for their best use in the data analysis. In Section 2 we review some of the classical data processing systems. One is in fact not so classical, making use of neural nets. Then in Section 3 we review scatterometer impact studies. In Section 4 we will present some results which use σ^0 data directly in variational analyses, both 3d and 4d. In both Sections 2 and 4, the methods require a model function. In our discussion we will take the model function as given. (However as a starting point the interested reader might refer to *Schroeder et al.* (1982) and *Wooding* (1992).)

2. POINT–WISE SCATTEROMETER DATA PROCESSING

As described in the introduction, point–wise scatterometer data processing is composed of two steps—wind retrieval and ambiguity removal. The winds thus obtained are then suitable for use in standard analysis systems. However these winds have peculiar wind direction error statistics and suitable quality control is a necessity.

2.1. Wind retrieval

To determine the wind ambiguities, given the σ^0 measurements and the model function, one can choose wind vectors to minimize a measure of the misfit to the measurements. This misfit or loss function is ultimately based on maximum likelihood arguments. To maximize the likelihood it is often convenient to instead minimize the negative of the logarithm of the conditional probability of the wind given the observed backscatter values. Since our knowledge of the necessary statistics is lacking, some assumptions must be made. It is however known that the measurement errors tend to scale with the true σ^0 (*Fischer*, 1972). Convenient assumptions then lead to a loss function specified as the sum of squared residuals or sum of squared normalized residuals, where the residuals are the difference between the calculated and observed backscatter or logarithm of backscatter. Several of these were investigated by *Chi and Li* (1988). It should be noted that the required statistics are those describing the distribution of the combined measurement and model function errors. Example loss functions for ERS 1 are given in Fig. 1. Here the loss function is calculated as simply the sum of squared normalized residuals. Generally global search procedures have been instituted to determine rough estimates of the minima of the cost function followed by a refinement step to obtain more precise estimates (e.g. *Jones et al.*, 1982). The values of wind speed and direction corresponding to the minima are the ambiguities.

A more analytical algorithm has been proposed by *Wentz* (1991), but this requires assuming a special form for the azimuthal dependence of the model function. In general this approach might be used in place of a global search to provide starting values for further refinement.

2.2. Ambiguity removal

A number of ambiguity removal schemes have been devised. On one extreme, *Wurtele et al.* (1982) used teams of meteorologists, while on the other extreme one might simply choose the most likely ambiguity or the ambiguity closest to some reference field. Typically the reference field is a six hour forecast but *Endlich et al.* (1981) used low level cloud motion as the reference field.

Two widely used data sets containing dealiased SASS winds are discussed by *Chelton et al.* (1989). The first is a subjectively dealiased data set prepared by meteorologists at AES (Canada), JPL and UCLA under the direction of Peter Woiceshyn (JPL), following the procedures detailed in *Wurtele et al.* (1982). This data set covers the 14 day period beginning 6 September 1978. The second data set is the objectively dealiased data, which is a by product of the study of the surface wind and flux fields by *Atlas et al.* (1987). This data set covers the entire SEASAT mission and uses techniques detailed by *Baker et al.* (1984) . A number of the studies of section 3 make use of one of these two data sets.

To aid design studies of NSCAT and ERS 1, simulation studies of the new scatterometer instruments were conducted. With three antenna configurations these simulation studies showed that the fraction of most likely ambiguities which are in fact closest to the truth is near 0.60 (*Schroeder et al.*, 1985). This fraction is termed instrument skill. An instrument skill of 1 is perfect. Several new objective and autonomous ambiguity removal schemes have been devised taking advantage of the high expected instrument skill. In simulation these schemes work well. However, as shown by *Schultz* (1990) as the instrument skill decreases from 0.60 to 0.50, the ambiguity removal skill decays from nearly perfect to nearly useless. Schultz also showed that ambiguity removal skill decays rapidly as the horizontal clumpiness of the instrument skill increases. That is when there is a area of incorrect rank 1 ambiguities, spatial filtering cannot help. In practice purely autonomous schemes have not worked well. Fortunately, these techniques do work well if initialized with a good first guess based on a recent forecast (Scott Dunbar, pers. comm.; David Offiler, pers. comm.).

The autonomous ambiguity removal schemes vary widely but all are based on the idea that the true field is horizontally consistent in some sense. The JPL algorithm (*Shaffer et al.*, 1991), like that of *Schultz* (1990) is based on the median filter. This filter is ideal for removing randomly occuring noise. According to the classical definition, the median of a set of values is chosen so that there are the same number of values which are larger and smaller than the median. For image processing a window is chosen and the filtered value at the center of the window is taken to be the median of the data values in the window. This can be applied to wind components. Schultz extended this definition for circular data so that wind directions can be median filtered. A simpler alternative which works well for ordinary, circular or vector values is based on an alternative definition of the median (*Shaffer et al.*, 1991): The median of a set of values is the one which minimizes the sum of the distances (absolute values) between the given value and all other values in the set. The JPL algorithm uses the vector winds in this definition. For ambiguity removal the median filter is used iteratively to determine a reference field, which in turn is used to select the ambiguities to be presented to the filter in the next iteration. The initial selection may be the most likely ambiguities or the ambiguities closest to a recent forecast.

The operational ESA ambiguity removal scheme is named CREO (*Cavanié and Lecomte*, 1987*a,b*; *Graham et al.*, 1989). CREO first produces two horizontally coherent fields in each area by filtering the ambiguous winds. CREO then chooses the field which has the greatest number of mostly likely ambiguities. If this choice is not clear cut CREO instead chooses the field which agrees best with the reference wind field, normally a recent forecast. In this case, if neither CREO field agrees with the reference field, no scatterometer winds are produced. In regions of relatively smooth flow, the two CREO fields will be 180° out of phase and will be the only reasonable fields. In regions of more complicated flow several reasonable alternatives may be possible. Data may then be very wrong or rejected because neither of the two fields generated is the ''right'' one. Further the method of determining the two fields is rather simplistic: Starting with the rank 1 ambiguity in one corner of the area, neighboring ambiguities closest in direction are chosen. This process continues outward from the starting location. The second field is generated in the same way, but starting from the rank 2 ambiguity.

A very different approach to ambiguity removal is described by *Badran et al.* (1991) who train neural nets to resolve the ambiguities. One neural net is trained to answer the question ''Should the central wind vector in the 5 × 5 window be rotated 180°?''. A second neural net is trained to detect 90° rotations. An iterative combination of the two nets produces nearly perfect results in tests with a simulated instrument skill of 0.75. (This group has also recently applied neural nets to the wind retrieval problem (*Thiria et al.*, 1993).)

3. SCATTEROMETER IMPACT STUDIES

In an impact experiment two parallel suites of data assimilation and forecasts are run, differing only in whether or not a particular data type is included in the analysis. In anticipation of the launch of SEASAT, *Cane et al.* (1981) performed a simulation impact study. Substantial positive impacts were obtained. However several simplifying assumptions made in the study may have affected these results. For example, the simulated winds were at the lowest model level, not at the surface. Also no errors or errors with a very simple random statistical structure (and no ambiguity removal errors) were used. The optimistic results of this simulation study have not been reproduced with real data.

3.1. SASS data studies

Because of the long hiatus between the SEASAT and ERS 1 missions, a number of SASS data impact studies have been preformed.

SASS global data studies have been carried out by a number of institutions, including NMC (Washington) (*Yu and MacPherson*, 1984), ECMWF (*Anderson et al.*, 1991), the UKMO (*Ingleby and Bromley*, 1991), NASA (Goddard) (*Baker et al.*, 1984; *Lenzen et al.*, 1993) and the U.S. Navy (*Duffy et al.*, 1984). In these experiments, generally small insignificant differences are seen in the Northern Hemisphere analyses. Significant differences are seen in the tropics and larger differences are seen in the Southern Hemisphere analyses. Forecast impacts tend to reflect the degree of difference in the analyses. For the most part the forecast impacts are interpreted as neutral in the Northern Hemisphere and tropics and slightly positive in the Southern Hemisphere.

The results reported in these experiments are qualified and preliminary because of small sample sets and the inadequacy of the ground truth in the Southern Hemisphere. Additionally, it has been suggested that the SASS data may have had a greater potential usefulness than current scatterometer data, because of the paucity of other data sources in 1978. In particular the drifting buoys in the tropics and southern oceans and the advances in infrared satellite retrieval techniques may make it even more difficult to obtain positive forecast impacts from present day scatterometers. Furthermore advances in data assimilation systems may have a similar effect.

A number of impact studies examined the *Queen Elizabeth II* storm, a very difficult forecast case of explosive cyclogenesis (*Anthes et al.*, 1983). We mention two papers which examined the impact of the SASS winds on the forecast skill of a limited area model for this case. At NASA (Goddard), *Duffy and Atlas* (1986) using a limited area model with a 100 km grid, showed positive impact. In this study, the positive impact was obtained using a vertical correlation function to spread the influence of the data in the vertical. Duffy and Atlas found that data inserted at a single level had little effect.

The QE II case was also studied with a high resolution limited area model (60 km grid) at KNMI by *Stoffelen and Cats* (1991). In this study the NOSCAT forecast was already quite good. SCAT minus NOSCAT analysis differences were small scale and the forecast impact of the SCAT data was positive. This suggests that the scatterometer data can provide useful information on the small scale which is otherwise unobserved.

3.2. A preliminary ERS 1 impact study

We have recently completed a preliminary assessment of the impact of the ERS 1 scatterometer wind data on the "current" (T106, L19) ECMWF analysis forecast system (*Hoffman*, 1993). In our experiments, at the start of each analysis the current 6 hour forecast (hereafter referred to as the "first guess") is used as the reference field in the CREO ambiguity removal algorithm. Within the statistical interpolation procedures (collectively called OI here), the ERS 1 data are thinned to 100 km resolution and a strict quality control on the scatterometer wind directions is imposed. Only 5-10 percent of the thinned scatterometer winds, produced by the ambiguity removal algorithm, are rejected for any 6 hour period by OI.

The impact of the data is found to be neutral. This conclusion is based on comparing analyses and forecasts from assimilation cycles which are identical in all respects except that the control experiment uses no scatterometer data.

The two sets of analyses are very similar except for the low level wind fields over the ocean. Impacts on the analyzed wind fields are greater over the Southern Ocean, where other data are scarce. In the Northern Hemisphere, analysis differences are very small, except directly at the scatterometer locations. For the most part the mass field increments are too small to balance the wind increments. While the effect of the nonlinear normal mode initialization on the analysis differences is negligible, the differences tend to wash out in the subsequent 6 hour forecast. This tendency affects the longer forecasts as well. The observed forecast impacts appear to be the result of analysis ''noise'', i.e., quasi-random differences in the analyses which arise in the assimilation in regions of poor data coverage.

On the other hand the low level wind analysis differences are clearly directly related to the inclusion of the scatterometer data. Comparison of the time averaged analyzed wind fields and subsequently of the scatterometer observational increments suggest that, in the Southern Hemisphere, the scatterometer corrects the tendency of the model to overestimate the wind speed under conditions of warm air advection.

These experiments are preliminary in several respects. Greater impacts might be expected in the future following refinements to the scatterometer model function, the ambiguity removal algorithm and the analysis procedures.

4. VARIATIONAL METHODS

Recently, in collaboration with the ECMWF, we have added the capability to analyze ERS 1 σ^0 data to the new (under development) 3d and 4d variational analysis procedures (3dVAR and 4dVAR). The advantage of the variational techniques for NWP is that the resulting analysis is perfectly adapted to the forecast model in terms of representativeness and initialization. Furthermore for scatterometer data, all other available data as well as the forecast, balance constraints and, in the case of 4dVAR, the model dynamics, are used naturally to remove the ambiguity of the scatterometer data. Thus, these procedures approach the goal of using all available data to remove the ambiguity of the scatterometer winds.

4.1. 3dVAR

The idea of using the σ^0 measurements directly in a variational analysis was first suggested by *Hoffman*

(1982). *Roquet and Ratier* (1988) presented some preliminary calculations along these lines. *Long and Mendel* (1990*a*, 1990*b*, 1991) present a complete methodology and theory for the case when the wind field is modeled in terms of polynomials in along and across track directions for the divergence and vorticity in the region. *Long* (1993) further extended this work and presents several interesting examples using SASS σ^0 values.

Within the context of 3dVAR the surface wind field is deduced from the control variable in just the same manner as any trajectory variable—the model variables are interpolated to the observation locations and then transformed into the observed quantity (Fig. 2b).

In 3dVAR and 4dVAR the observation function for scatterometer σ^0 data is J_{scat}, which calculates the misfit to the scatterometer data as

$$J_{scat} = e^T O^{-1} e.$$

Here

$$e = (\sigma^0(calculated) - \sigma^0(observed)) \,/\, sd(\sigma^0),$$

are the normalized departures, O is the observational error correlation matrix and σ^0 is the normalized backscatter at the scatterometer frequency (using a linear not logarithmic scale). Some alternatives to this definition are possible but have not been examined. Currently all observational correlations are taken to be zero.

The standard deviation of the observation, $sd(\sigma^0)$, is key in the definition of J_{scat}. For scatterometer data the expected error of the observation is reported as a percent, denoted K_p. In this case the observational standard deviation is

$$sd(\sigma^0) = (K_p/100)\sigma^0(observed).$$

K_p should include three error sources, namely communication, radar equation and model function uncertainties. In addition, for an analysis, the variability on the scales of motion smaller than the analysis grid but larger than the instrumental cell size, should be added to these error sources. Of course that part of K_p corresponding to model function uncertainties depends on instrument viewing geometry, polarization and the true (but unknown) value of the surface stress. In the calculations presented here, we take K_p as a known constant in the variational analysis calculated in terms of $\sigma^0(observed)$. According to maximum likelihood theory however $\sigma^0(calculated)$ should be used here and an additional term added to J_{scat}. The calculation of instrumental K_p can be quite complicated (*Chi et al.*, 1986). However, other sources of variability must be estimated in a much simpler manner and errors in these may well dwarf the instrumental K_p.

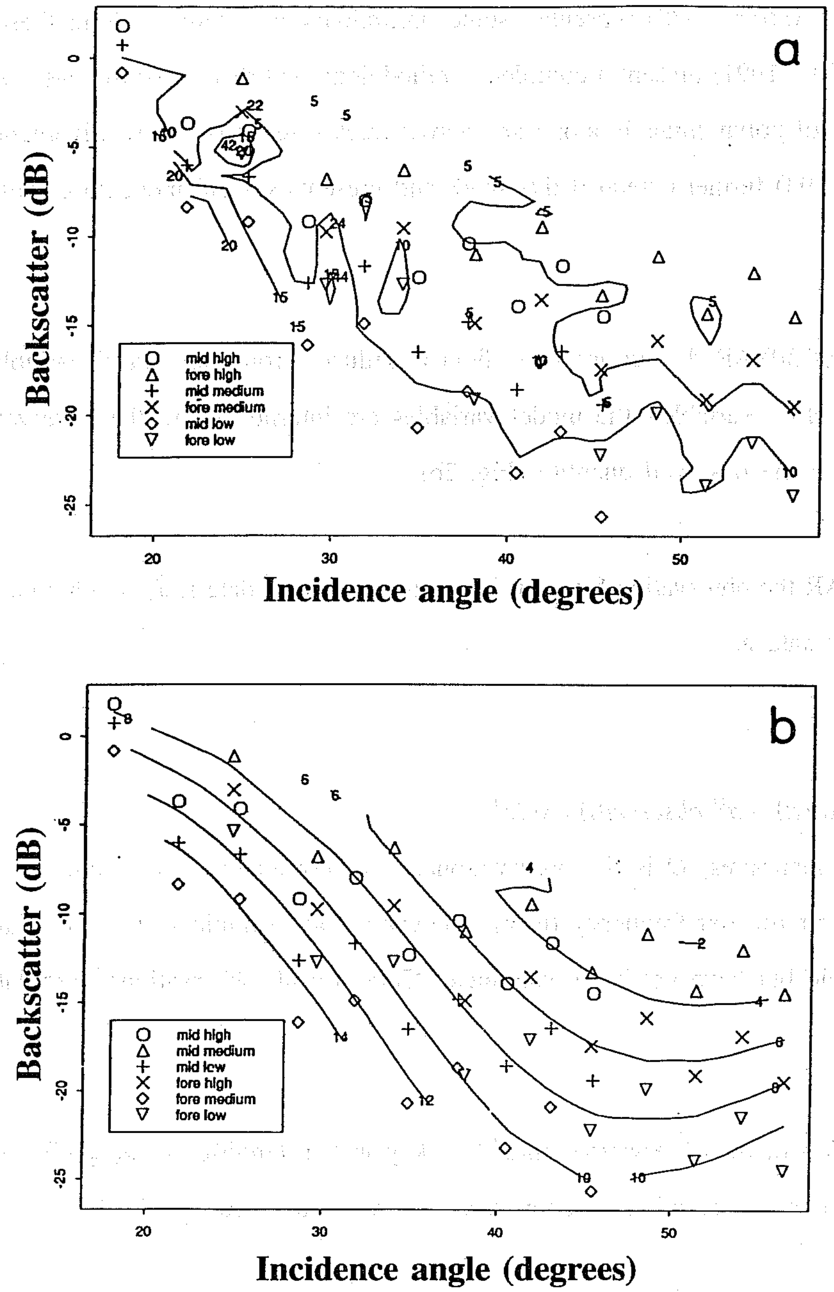

Fig. 3 Estimates of K_p (%) plotted as a function of incidence angle and σ^0 (a) and a smoothed fitted version (b). The locations of the raw estimates for mid and fore beam and for low, medium and high wind speeds are shown.

The formulation of K_p currently used is based on fitting estimates made while tuning the model function (*Stoffelen and Anderson*, 1992). A reasonable fit to these estimates is linear in $\ln(\sigma^0)$ (σ^0 in dB) and quadratic in incidence angle (θ in degrees). The fit is statistically significant but captures only half the variance of the original noise estimates. Fig. 3 shows the raw data contoured and the fitted surface.

For ERS 1 scatterometer data, the trajectory calculation includes evaluating the 10 m winds and then evaluating the model function. (Present model functions depend only on the 10 m wind.) To do this properly one must know the roughness height, z_0, but this in turn is related to the surface stress through the Charnock relationship. This results in an implicit function for z_0 which must be solved iteratively. We choose to use a Newton method to accomplish this. The advantage of this is that the solution quickly converges to machine precision and we may then linearize the implicit relationship directly. By this means the linearized operator may be taken to be independent of the iteration.

Ideally, the 10 m winds should be corrected to neutral stability conditions, because the backscatter observations are more closely related to surface stress. The effect of stability on the calculation of the 10 m winds can also be included in the variational analysis. This effect can be substantial (easily 10%) on the calculated neutral stability winds, but the sensitivity of the mass (temperature and surface pressure) and moisture fields to the scatterometer winds should be small (*Hoffman and Louis*, 1990). However recent preliminary work including the stability correction in 3dVAR suggest that this approach may be troublesome without strong dynamical constraints on the solution. In one particular case of cold air advection over the North Atlantic, the initial 10 m winds were stronger than the scatterometer winds. Consequently, the analysis reduced the wind speeds at the lowest model level. It also increased the lowest model level temperature, thereby increasing stability. This also has the effect of reducing the 10 m wind speed. However, the initial stability was close to neutral and the increase in stability resulted in a final analysis of a stable atmospheric boundary layer, inconsistent with the synoptic state.

As a simple demonstration of 3dVAR we present results using σ^0 data for the North Atlantic on 19 November 1991 at 1200 UTC. There are a fair number of ship reports at the time. For this case the 72 h forecast anomaly correlation coefficient is very good, .98 over Europe and .96 for the Northern Hemisphere. The large scale weather pattern over the Atlantic and Europe changed significantly over this 72 time period. For these reasons we are confident that the analysis is good at the time of data acquisition (1311 UTC). Data within a small latitude longitude window were selected. In this example the reported K_p values (approximately 5%) are used directly and a constant factor is used to correct the wind to 10 m. The analysis resolution is T21.

For this case there are 118 observations containinng 351 σ^0 values and the background is a 6 h forecast. The cost function is J_{scat} plus a simple 2d background cost function. The total cost function is reduced from 13351 to 6268 after 19 iterations and the gradient from 7.42e8 to 2.46e4. Fig. 4 shows the background wind field, an intermediate solution (after 10 iterations) and the minimizing solution (after 19 iterations), evaluated at the scatterometer locations, in the top row of panels. The bottom row of panels, shows differences from the background and the evolution of J_{scat} (solid) and of J_{total} (dots). The importance of the background should be noted: The scatterometer data could be equally well fit by a generally northerly flow.

4.2. 4dVAR

A four-dimensional variational assimilation (4dVAR) seeks an optimal balance between observations scattered in time and space over a finite 4d analysis volume and *a priori* information. The advantage of this approach is that the governing dynamics constrain the solution, essentially providing an additional source of information. In 4dVAR the analysis increments may actually amplify away from the observation locations. In particular, this occurs generally for surface data, because of the damping effect of surface exchange processes.

We conducted 4dVAR experiments with and without ERS 1 backscatter measurements (*Thépaut et al.*, 1993). For scatterometer data, the advantage of the variational approach is that it embeds the ambiguity problem in a large data fitting problem which includes other observations, a background constraint based on balanced error covariances and the model dynamics. The last two factors lead necessarily to a dynamically consistent use of the data. As expected and in contrast to conventional approaches, the impact of scatterometer data in 4dVAR is not confined to the lower troposphere and the analysis increments are balanced.

The assimilation experiments of *Thépaut et al.* (1993) are for the 24 hour period 12 UTC 30–31 December 1991. A violent storm struck the coast of Norway 24 hours later. As expected, the impact of the σ^0 data is large in the Southern Hemisphere, with differences of up to 10 hPa in the surface pressure field. Substantial differences can also be observed in the Northern Hemisphere, especially in the North Atlantic. Generally the σ^0 data strengthen the activity of the affected systems. The impacts on the analysis and forecast of the New Year's Day storm are small but the scatterometer data do have an apparently positive impact on the 4dVAR analysis in this case.

4.3. Other variational approaches

As an alternative to using the σ^0 values directly, one could use scatterometer winds or ambiguities obtained using a point–wise data processing system in a variational analysis. *Hoffman* (1982, 1984) used SASS ambiguities to derive wind analyses using a variety of additional data and smoothness constraints. *Harlan and O'Brien* (1986) used the subjectively dealiased SASS data to simultaneously analyze surface pressure and vorticity subject to a weak constraint on the kinetic energy of the solution. The fact that this technique

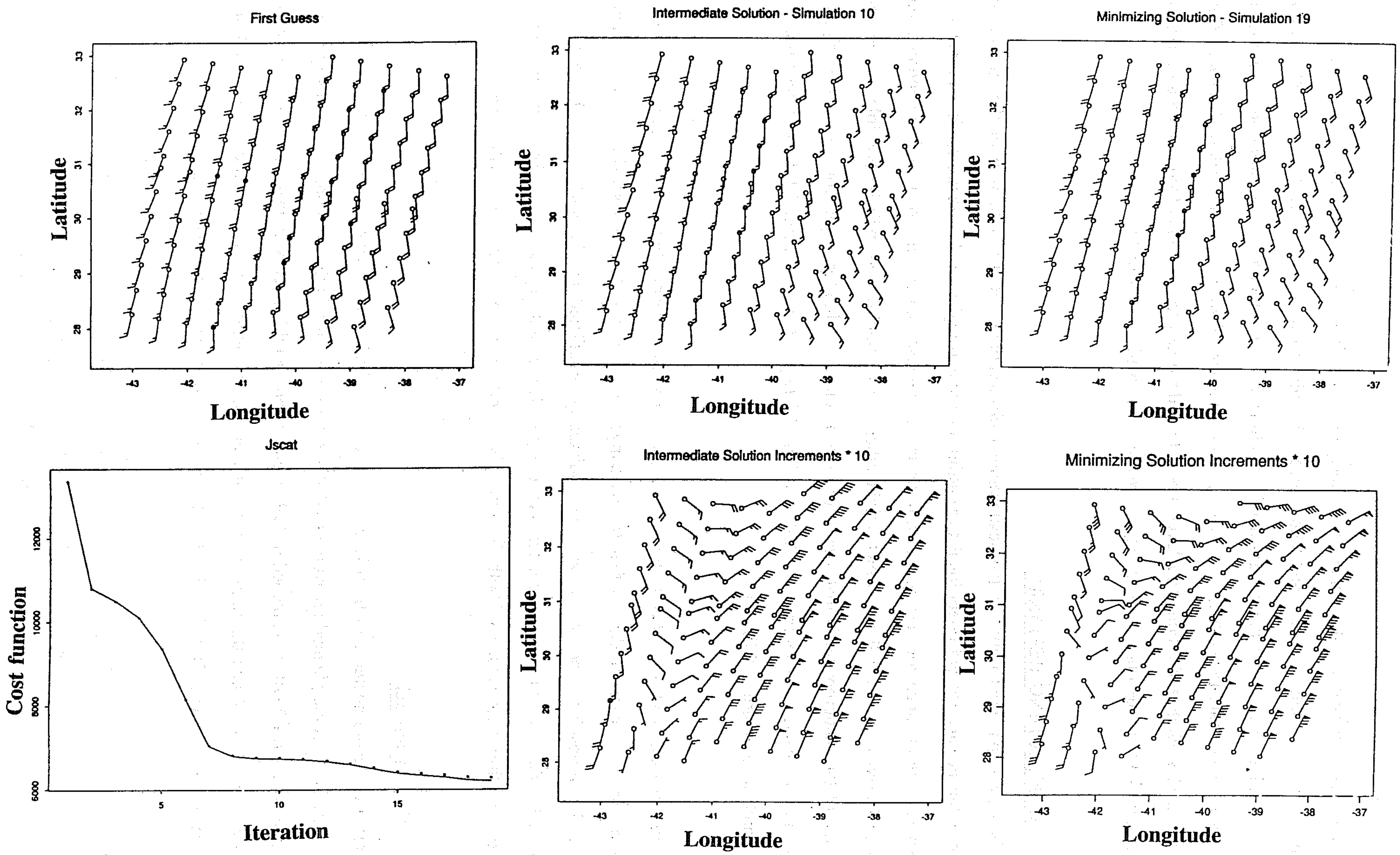

Fig. 4 Winds evaluated at scatterometer locations (top row) and the evolution of the objective function and analysis increments (bottom row) for the case of 19 November 1991 at 1200 UTC.

affects the surface pressure analysis may be advantageous since in studies where winds only are assimilated, changes to the mass field are small and tend to decay in subsequent forecasts (*Duffy et al.*, 1984; *Hoffman*, 1993). We might mention in this regard another technique, which though not a variational method, uses scatterometer wind data to produce a surface pressure analysis: *Brown and Levy* (1986; *Levy and Brown*, 1991) use SASS winds and a boundary layer model to deduce geostropic winds from which an estimate of the pressure field can be obtained if a single pressure observation is available.

5. CONCLUDING REMARKS

There is a great potential utility to the scatterometer observations. Better definition of the surface wind field over the oceans can aid operational forecasting of meteorological and oceanographic parameters. In addition very short range forecasting and nowcasting of intense, small scale or rapidly evolving oceanic storms and associated wave fields, which might otherwise be unobserved, will be possible. A particular advantage of the scatterometer is that it is unaffected by clouds or light precipitation. (Heavy precipitation corrupts the Ku band radar returns of SASS and NSCAT (e.g. *Guymer et al.*, 1981), but does not effect the C band radar returns of ERS 1.)

Scatterometer data is also invaluable for a variety of scientific investigations. The main reason for the importance of scatterometer data is that the exchanges of energy—latent and sensible—and momentum between the atmosphere and the oceans are nonlinearly modulated by the surface wind speed. Thus scatterometer data are vital for understanding the coupled climate system, and for providing accurate boundary conditions for studies of both the atmosphere and ocean on a variety of spatial scales.

5.1. Current research

The stream of scatterometer data from ERS 1 has been relatively constant and uninterrupted since August 1991. (There were some planned interruptions due to orbit shifts early in the mission.) As a consequence and considering that ERS 2 will be launched in 1994 there is considerable interest in using the data at operational and research centers. While the total effort is substantial, the number of persons directly involved at any one organization is small. Here is a brief and incomplete summary of current research.

At the UKMO (David Offiler, pers. comm.) a parallel run was made during the last three weeks of March using the latest model function and their own wind retrieval and ambiguity removal algorithms. Impacts on the 5 day forecasts were neutral in the Northern Hemisphere, marginally positive in the tropics and substantially positive in the Southern Hemisphere. ERS 1 data will begin to be used operationally in September 1993.

At the ECMWF (Ad Stoffelen, pers. comm.) a very considerable effort has gone into model function development and developing the capability of using the scatterometer data in the variational analysis. Further refinement of the ambiguity removal is underway and further additional parallel runs are planned shortly.

At NASA (Goddard) (Robert Atlas, pers. comm.) parallel experiments are underway, comparing the utility of winds from several sources. In addition retrospective work to combine ERS 1 scatterometer data, SSM/I wind speeds and ECMWF operational analyses is planned. The object of this effort is to produce the best possible consistent time series of ocean surface winds.

At NMC (Washington) (Tsann-Wang Yu, pers. comm.) work is proceeding on implementing the use of the scatterometer σ^0 data in the spectral statistical interpolation (SSI) analysis system. This has necessitated some general changes to the SSI to allow for nonlinear observational operators.

At AES (Canada) (Saroja Polavarapu, pers. comm.) work is currently underway on using the ERS 1 scatterometer data for Canadian weather forecast models.

At the Norwegian Meteorological Institute (Lars-Anders Breivik, pers. comm.) work is currently underway on using the ERS 1 scatterometer data in the Institute's data assimilation system.

5.2. Outstanding problems

While the potential of satellite scatterometry is great, a number of outstanding problems remain. First, there is the question of the model function. There are some experimental results showing that backscatter is affected by geophysical parameters other than the vector wind. Atmospheric stability, ocean swell, salinity and others have been suggested (e.g. *Brown*, 1983; *Glazman et al.*, 1988). Should some of these be included in the model function? How will the wind retrieval be effected if this is done? Even without these additional parameters, further work on tuning the model functions is required. One difficulty is the small amount of high quality surface truth data available over the oceans. This is especially true at high wind speeds, precisely the regime we most want to observe.

The ambiguity removal procedures developed for scatterometers have so far been disappointing. While the autonomous procedures work well when tested with simulated data, they have proven inadequate for real data both in the case of SASS and ERS 1. As is the case with satellite temperature retrievals, other information besides the scatterometer data must be included to produce optimal results.

If the use of other data is allowed to retrieve the scatterometer winds, then one should use all available data in the process. From this point of view, the best scatterometer data products are operational analyses produced using the scatterometer data. However, analysis procedures have been optimized for conventional radiosondes and satellite temperature soundings. Research on the best use of scatterometer data for NWP will therefore aid most other uses of the data. In this regard, variational analysis approaches appear most promising.

ACKNOWLEDGMENTS

I have benefited from many discussions with numerous colleagues over the years. My research in scatterometry has been primarily supported by NASA, the United States National Aeronautics and Space Agency. I am currently a member of the science teams for the NASA scatterometer (ADEOS NSCAT) and the EOS scatterometer (STIKSCAT). This work was supported by Jet Propulsion Laboratory contracts 957644 and 959341, subcontracts to NASA contract NAS7-918.

REFERENCES

D. Anderson, A. Hollingsworth, S. Uppala, and P. Woiceshyn. A study of the use of scatterometer data in the European Centre for Medium-range Weather Forecasts operational analysis-forecast model. 2. Data impact. *J. Geophys. Res.*, 96(C2):2635–2647, 1991.

R. A. Anthes, Y.-H. Kwo, and J. R. Gyakum. Numerical simulations of a case of explosive marine cyclogenesis. *Mon. Weather Rev.*, 111:1174–1188, 1983.

R. Atlas, A. J. Busalacchi, E. Kalnay, and S. Bloom. Global surface wind and flux fields from model assimilation of SEASAT data. *J. Geophys. Res.*, 92(C6):6477–6487, 1987.

F. Badran, S. Thiria, and M. Crepon. Wind ambiguity removal by the use of neural network techniques. *J. Geophys. Res.*, 96(C11):20521–20530, 1991.

W. E. Baker, R. Atlas, E. Kalnay, M. Halem, P. M. Woiceshyn, S. Peteherych, and D. Edelmann. Large-scale analysis and forecast experiments with wind data from the Seasat-A scatterometer. *J. Geophys. Res.*, 89(D3):4927–4936, 1984.

R. A. Brown. On a satellite scatterometer as an anemometer. *J. Geophys. Res.*, 88(C3):1663–1673, 1983.

R. A. Brown. On satellite scatterometer capabilities in air-sea interaction. *J. Geophys. Res.*, 91(C2):2221–2232, 1986. Special Section: Frontiers of Remote Sensing of the Oceans and Troposphere from Air and Space Platforms.

R. A. Brown and G. Levy. Ocean surface pressure fields from satellite-sensed winds. *Mon. Weather Rev.*, 114:2197–2206, 1986.

M. A. Cane, V. J. Cardone, M. Halem, and I. Halberstam. On the sensitivity of numerical weather prediction to remotely sensed marine surface wind data: A simulation study. *J. Geophys. Res.*, 86(C9):8093–8106, 1981.

A. Cavanié and P. Lecomte. Vol 1. Study of a method to dealias winds from ERS-1 data. final report, European Space Agency, 1987. Contract 6874/87/CP-I(SC).

A. Cavanié and P. Lecomte. Vol 2. Wind retrieval and dealiasing subroutines. final report, European Space Agency, 1987. Contract 6874/87/CP-I(SC).

D. B. Chelton, M. H. Freilich, and J. R. Johnson. Evaluation of unambiguous vector winds from the Seasat scatterometer. *J. Atmospheric Oceanic Technology*, 6:1024–1039, 1989.

C.-Y. Chi and F. K. Li. A comparative study of several wind estimation algorithms for spaceborne scatterometers. *IEEE Trans. Geosci. Remote Sens.*, 26:115–121, 1988.

C.-Y. Chi, D. G. Long, and F. K. Li. Radar backscatter measurement accuracies using digital Doppler processors in spaceborne scatterometers. *IEEE Trans. Geosci. Remote Sens.*, GE-24:426–437, 1986.

D. Duffy, R. Atlas, T. Rosmond, E. Barker, and R. Rosenberg. The impact of Seasat scatterometer winds on the Navy's operational model. *J. Geophys. Res.*, 89(D5):7238–7244, 1984.

D. G. Duffy and R. Atlas. The impact of Seasat-A scatterometer data on the numerical prediction of the *Queen Elizabeth II* storm. *J. Geophys. Res.*, 91(C2):2241–2248, 1986. Special Section: Frontiers of Remote Sensing of the Oceans and Troposphere from Air and Space Platforms.

R. M. Endlich, D. E. Wolf, C. T. Carlson, and J. W. Maresca. Oceanic wind and balanced pressure-height fields derived from satellite measurements. *Mon. Weather Rev.*, 109:2009–2016, 1981.

R. E. Fischer. Standard deviation of scatterometer measurements from space. *IEEE T. Geosci. Electron.*, GE-10:106–113, 1972.

R. Francis, G. Graf, P. G. Edwards, M. McCaig, C. McCarthy, P. Dubock, A. Lefebvre, B. Pieper, P.-Y. Pouvreau, R. Wall, F. Wechsler, J. Louet, and R. Zobl. The ERS-1 spacecraft and its payload. *ESA Bulletin*, (65):27–48, Feb. 1991. ERS-1 Special Issue.

R. E. Glazman, G. G. Pihos, and J. Ip. Scatterometer wind speed bias induced by the large-scale component of the wave. *J. Geophys. Res.*, 93(C2):1317–1328, 1988.

R. Graham, D. Anderson, A. Hollingsworth, and H. Böttger. Evaluation of ERS-1 wind extraction and ambiguity removal algorithms. Meteorological and statistical evaluation. Technical report, Eur. Cent. for Med. Range Weather Forecasts, Reading, England, Jan. 1989.

W. L. Grantham, E. M. Bracalente, W. L. Jones, and J. W. Johnson. The Seasat-A satellite scatterometer. *IEEE J. Oc. Eng.*, OE-2:200–206, 1977.

T. H. Guymer, J. A. Businger, W. L. Jones, and R. Stewart. Anomalous wind estimates from the SEASAT scatterometer. *Nature*, 294:735–737, 1981.

J. Harlan, Jr. and J. J. O'Brien. Assimilation of scatterometer winds into surface pressure fields using a variational method. *J. Geophys. Res.*, 91(D7):7816–7836, 1986.

R. Hoffman. SASS wind ambiguity removal by direct minimization. *Mon. Weather Rev.*, 110:434–445, 1982.

R. N. Hoffman. SASS wind ambiguity removal by direct minimization. II: Use of smoothness and dynamical constraints. *Mon. Weather Rev.*, 112:1829–1852, 1984.

R. N. Hoffman. A preliminary study of the impact of the ERS1 *C*-band scatterometer wind data on the ECMWF global data assimilation system. *J. Geophys. Res.*, 98(C6):10233–10244, 1993.

R. N. Hoffman and J.-F. Louis. The influence of atmospheric stratification on scatterometer winds. *J. Geophys. Res.*, 95(C6):9723–9730, 1990.

N. B. Ingleby and R. A. Bromley. A diagnostic study of the impact of SEASAT scatterometer winds on numerical weather prediction. *Mon. Weather Rev.*, 119:84–103, 1991.

W. L. Jones, L. C. Schroeder, D. H. Boggs, E. M. Bracalente, R. A. Brown, G. J. Dome, W. J. Pierson, and F. J. Wentz. The SEASAT-A Satellite Scatterometer: The geophysical evaluation of remotely sensed wind vectors over the ocean. *J. Geophys. Res.*, 87(C5):3297–3317, 1982.

W. L. Jones, L. C. Schroeder, and J. L. Mitchell. Aircraft measurements of the microwave scattering signature of the ocean. *IEEE J. Oc. Eng.*, OE-2:52–61, 1977.

K. B. Katsaros and R. A. Brown. Legacy of the Seasat mission for studies of the atmosphere and air-sea-ice interactions. *Bull. Am. Meteorol. Soc.*, 72:967–981, 1991.

A. J. Lenzen, D. R. Johnson, and R. Atlas. Analysis of the impact of Seasat scatterometer data and horizontal resolution on GLA model simulations of the *QE II* storm. *Mon. Weather Rev.*, 121:499–521, 1993.

G. Ley and R. A. Brown. Southern hemisphere synoptic weather from a satellite scatterometer. *Mon. Weather Rev.*, 119:2803–2813, 1991.

D. G. Long. Wind field model-based estimation of Seasat scatterometer winds. *J. Geophys. Res.*, 98(C8):14651–14668, 1993.

D. G. Long and J. M. Mendel. Model-based estimation of wind fields over the ocean from wind scatterometer measurements, part I: Development of the wind field model. *IEEE Trans. Geosci. Remote Sens.*, 28:349–360, 1990.

D. G. Long and J. M. Mendel. Model-based estimation of wind fields over the ocean from wind scatterometer measurements, part II: Model parameter estimation. *IEEE Trans. Geosci. Remote Sens.*, 28:361–373, 1990.

D. G. Long and J. M. Mendel. Identifiability in wind estimation from scatterometer measurements. *IEEE Trans. Geosci. Remote Sens.*, 29:268–276, 1991.

F. Naderi, M. H. Freilich, and D. G. Long. Spaceborne radar measurement of wind velocity over the ocean—an overview of the NSCAT scatterometer system. *Proc. IEEE*, 79:850–866, 1991.

J. C. Price. The nature of multiple solutions for surface wind speed over the oceans from scatterometer measurements. *Remote Sensing Environment*, 5:47–54, 1976.

H. Roquet and A. Ratier. Towards direct variational assimilation of scatterometer backscatter measurements into numerical weather prediction models. In *Proceedings of the 1988 International Geoscience and Remote Sensing Symposium (IGARSS '88)*, pages 257–260, Edinburgh, Scotland, 13-16 Sept. 1988. IEEE, New York.

L. C. Schroeder, D. H. Boggs, G. Dome, I. M. Halberstam, W. L. Jones, W. J. Pierson, and F. J. Wentz. The relationship between wind vector and normalized radar cross section used to derive SEASAT-A satellite scatterometer winds. *J. Geophys. Res.*, 87(C5):3318–3336, 1982.

L. C. Schroeder, W. L. Grantham, E. M. Bracalente, C. L. Britt, K. S. Shanmugam, F. J. Wentz, D. P. Wylie, and B. B. Hinton. Removal of ambiguous wind directions for a Ku-band wind scatterometer using three different azimuth angles. *IEEE Trans. Geosci. Remote Sens.*, GE-23:91–100, 1985.

H. Schultz. A circular median filter approach for resolving directional ambiguities in wind fields retrieved from spaceborne scatterometer data. *J. Geophys. Res.*, 95(C4):5291–5304, 1990. Errata in number C6, page 9783.

S. J. Shaffer, R. S. Dunbar, S. V. Hsiao, and D. G. Long. A median-filter-based ambiguity removal algorithm for NSCAT. *IEEE Trans. Geosci. Remote Sens.*, 29:167–174, 1991.

R. H. Stewart. Seasat: Results of the mission. *Bull. Am. Meteorol. Soc.*, 69:1441–1447, 1988.

A. Stoffelen and D. L. T. Anderson. ERS-1 scatterometer calibration and validation activities at ECMWF: A. The quality and characteristics of the radar backscatter measurements. In *'International Space Year' Conference*, pages 1019–1024, Munich, Germany, 30 Mar.–5 Apr. 1992. European Space Agency, Paris. [ESA SP-341, July, 1992].

A. C. M. Stoffelen and G. J. Cats. The impact of Seasat-A scatterometer data on high-resolution analysis and forecasts: The development of the *QE II* storm. *Mon. Weather Rev.*, 119:2794–2802, 1991.

J.-N. Thépaut, R. N. Hoffman, and P. Courtier. Interactions of dynamics and observations in a four-dimensional variational assimilation. *Mon. Weather Rev.*, 1993. Accepted.

S. Thiria, C. Mejia, F. Badran, and M. Crepon. A neural network approach for modelling nonlinear transfer functions: Application for wind retrieval from spaceborne scatterometer data. *J. Geophys. Res.*, 98, 1993. Accepted for publication.

F. J. Wentz. A simplified wind vector algorithm for satellite scatterometers. *J. Atmospheric Oceanic Technology*, 8:697–704, 1991.

M. Wooding, editor. *ERS-1 Geophysical Validation*, Penhors, Bretagne, France, 27-30 Apr. 1992. European Space Agency, Paris, France.

M. G. Wurtele, P. M. Woiceshyn, S. Peteherych, M. Borowski, and W. S. Appleby. Wind direction alias removal studies of SEASAT scatterometer-derived wind fields. *J. Geophys. Res.*, 87(C5):3365–3377, 1982.

T. W. Yu and R. D. McPherson. Global data assimilation experiments with scatterometer winds from SEASAT-A. *Mon. Weather Rev.*, 112:368–376, 1984.