Chinese Journal of Oceanology and Limnology
Vol. 33 No. 5, P. 1201-1209, 2015
http://dx.doi.org/10.1007/s00343-015-4145-3

An improved wind retrieval algorithm for the HY-2A scatterometer*

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Received Jun. 11, 2014; accepted in principle Jul. 25, 2014; accepted for publication Aug. 18, 2014

Abstract Since January 2012, the National Satellite Ocean Application Service has released operational wind products from the HY-2A scatterometer (HY2-SCAT), using the maximum-likelihood estimation (MLE) method with a median filter. However, the quality of the winds retrieved from HY2-SCAT depends on the sub-satellite cross-track location, and poor azimuth separation in the nadir region causes particularly low-quality wind products in this region. However, an improved scheme, i.e., a multiple solution scheme (MSS) with a two-dimensional variational analysis method (2DVAR), has been proposed by the Royal Netherlands Meteorological Institute to overcome such problems. The present study used the MSS in combination with a 2DVAR technique to retrieve wind data from HY2-SCAT observations. The parameter of the empirical probability function, used to indicate the probability of each ambiguous solution being the “true” wind, was estimated based on HY2-SCAT data, and the 2DVAR method used to remove ambiguity in the wind direction. A comparison between MSS and ECMWF winds showed larger deviations at both low wind speeds (below 4 m/s) and high wind speeds (above 17 m/s), whereas the wind direction exhibited lower bias and good stability, even at high wind speeds greater than 24 m/s. The two HY2-SCAT wind data sets, retrieved by the standard MLE and the MSS procedures were compared with buoy observations. The RMS error of wind speed and direction were 1.3 m/s and 17.4°, and 1.3 m/s and 24.0° for the MSS and MLE wind data, respectively, indicating that MSS wind data had better agreement with the buoy data. Furthermore, the distributions of wind fields for a case study of typhoon Soulik were compared, which showed that MSS winds were spatially more consistent and meteorologically better balanced than MLE winds.

Keyword: HY-2A scatterometer; wind retrieval; maximum-likelihood estimation (MLE); multiple solution scheme (MSS); two-dimensional variational analysis method (2DVAR); typhoon Soulik

1 INTRODUCTION

Scatterometer-derived winds are significantly important data sets for many meteorological and oceanographic applications. A radar scatterometer is designed to determine the normalized radar cross section (sigma0) from the surface, following which the subsequent processing stages from sigma0 to wind vectors, including calibration, inversion, and ambiguity removal, collectively affect the quality of the scatterometer-derived winds. For the calibrated sigma0 with metadata, greater effort has been devoted to improving the algorithms for both inversion and ambiguity removal in order to obtain high-quality winds. Various algorithms have been developed and implemented in operational systems. Typical of this inversion approach is the maximum-likelihood estimation (MLE) method and its variants based on the Bayesian approach (Pierson, 1989; Stoffelen and Portabella, 2006) and the normalized standard deviation algorithm based on the criterion of a

* Supported by the National High Technology Research and Development Program of China (863 Program) (No. 2013AA09A505), the Shandong Joint Fund for Marine Science Research Centers (No. U1406404), the National Natural Science Foundation of China (No. 41106152), and the National Key Technology R&D Program of China (No. 2013BAD13B01)
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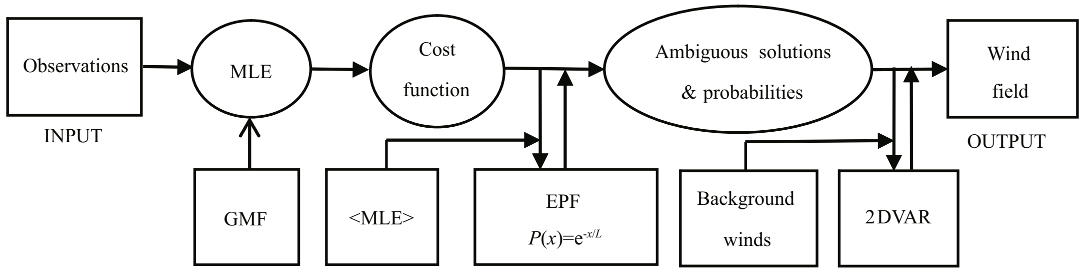

Fig.1 Schematic of scatterometer wind retrieval process using MSS and 2DVAR

minimum normalized standard deviation of wind speed derived from backscatter measurements using a geophysical model function (GMF) (Gohil et al., 2008). The circular median filtering approach is widely used for ambiguity removal (Schultz, 1990).

SeaWinds is a rotating pencil-beam scatterometer deployed onboard QuikSCAT, which has proven a highly successful mission, and this has been followed by two similar instruments onboard Oceansat-2 (OSCAT) and HY-2A (HY2-SCAT), launched in September 2009 and August 2011, respectively. Studies have demonstrated that the nadir region of the QuikSCAT swath has poor azimuthal diversity, which could result in low-quality wind retrievals (Portabella and Stoffelen, 2002). Several advanced algorithms have been proposed to improve wind retrievals, especially over the nadir and extreme swath regions. For example, the Directional Interval Retrieval with Threshold Nudging algorithm, developed to improve the accuracy of QuikSCAT winds (Stiles et al., 2002), and the Directional Stability and Conservation of Scattering algorithm, designed to obtain operational wind products from OSCAT (Gohil et al., 2010). An improved scheme, i.e., a multiple solution scheme (MSS) in conjunction with a two-dimensional variational ambiguity removal (2DVAR) method, has been proposed by the Royal Netherlands Meteorological Institute. For most cases, there is no relatively correct solution among the limited number of selectable ambiguities output from the standard MLE procedure; the difference is the MSS method retains more ambiguous wind solutions. Studies have shown that MSS combined with 2DVAR is an effective method for wind retrieval from SeaWinds, and it has been used in wind retrieval from OSCAT (Stoffelen et al., 2010; Vogelzang et al., 2011).

The HY2-SCAT instrument is carried onboard the HY-2A polar satellite, and its products have been operationally released by the National Satellite Ocean Application Service since January 2012. The current operational system provides retrieved winds using the MLE method followed by a median filtering ambiguity removal process. However, the quality of winds retrieved from HY2-SCAT depends on the sub-satellite cross-track location, and poor azimuthal separation or diversity between views in the nadir region result in low-quality wind retrievals (Portabella, 2002).

In this study, the MSS inversion is used for HY2-SCAT wind retrieval, in conjunction with a 2DVAR algorithm, to both overcome the problems in the nadir region and improve the spatial consistency of the retrieved winds. The MSS and 2DVAR algorithm are introduced in Section 2. Section 3 focuses on the practice of HY2-SCAT wind retrieval based on MSS and 2DVAR. Evaluation of the improved winds is then performed, including a comparison of wind fields for a case study of typhoon Soulik. Finally, the conclusions are drawn in Section 4.

2 MSS AND 2DVAR ALGORITHM

The wind retrieval procedure using MSS and 2DVAR for scatterometer data is illustrated schematically in Fig.1. A set of radar backscatter measurements (observations) with metadata including sigma0, incidence angle, and relative azimuth, are grouped together in each wind vector cell (WVC) for the wind retrieval. The MLEs of the assumed wind speeds and directions are calculated using the backscatter observations and the data calculated from the GMF. Then, the minimum MLE as a function of wind direction, called the MLE cost function, is extracted by searching for the minimum MLE within the entire wind domain. Compared with the standard MLE skill, MSS retrieval skill is improved in the additional procedure of the MLE cost function. For the standard procedure, ambiguous wind solutions are determined by searching the minima of the MLE cost function; however, the MSS skill retains all those solutions that consist of the MLE cost function. The probability of every solution being the "true" wind is given through the empirical probability function (EPF), which depends on the scatterometer instrument

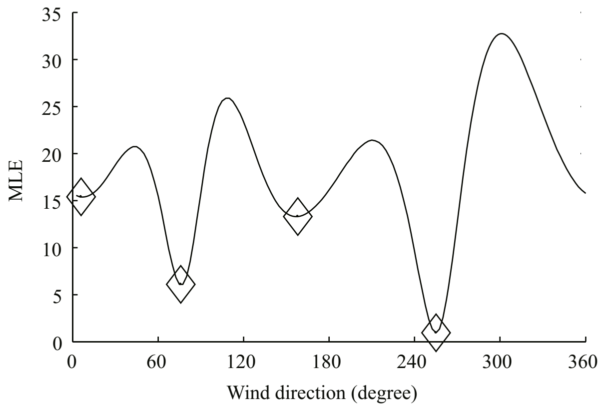

Fig.2 Example of MLE cost function for HY2-SCAT

The diamond symbols indicate the locations of the minima.

and measurement noise. Finally, the 2DVAR technique is applied together with some additional information (e.g., background winds, spatial consistency constraints) to select one of the ambiguous wind solutions as the observed wind for every WVC. This step, known as ambiguity removal (AR), involves the spatial filtering of many neighboring WVCs at once (Portabella, 2002). Another important aspect of wind retrieval is the quality control. However, this study focuses on the wind retrieval algorithm and therefore, quality control will not be included.

2.1 Multiple solution scheme

The Bayesian approach is widely applied to inverting variables from a given set of observations. The MLE, which is one of the optimization techniques based on the Bayesian approach, is commonly used in scatterometry because the inversion process is highly nonlinear (Pierson, 1989; Stoffelen, 1998). An MLE function, used to select a set of wind vector solutions that optimally matches the observed sigma0, is generally defined as:

$$\mathrm{MLE}=\frac{1}{N}\sum_{i=1}^{N}\frac{(\sigma^0_{\mathrm{obs}}(i)-\sigma^0_{\mathrm{GMF}}(i))^2}{Kp}, \tag{1}$$

where N is the number of available measurements σ_{obs} σ_{GMF} is the backscatter simulated by the GMF for given trial values of wind speed and direction, and Kp is the variance of the measurement error. In this study, the NSCAT-3 GMF is used and Kp is set as a constant.

The MLE can be interpreted as a measure of the distance between a set of σ_{obs} and σ_{GMF}, which is calculated with trial winds using the GMF (Stoffelen and Anderson, 1997a). For a specific direction, the MLE is calculated through a range of wind speeds (below 50 m/s) and the speed with the minimum MLE is taken as a candidate for the wind vector. The same operation is repeated for every direction and the resulting minimum MLE as a function of wind direction, known as the MLE cost function, is established (an example is shown in Fig.2).

According to Bayes' theorem, the MLE value represents the probability that a trial wind vector (solution) is the "true" wind. Generally, as the MLE increases, the probability of any particular solution being the true wind decreases exponentially. As the contribution from observation noise cannot be estimated, suitable parameters for this relationship should be determined based on empirical methodology. The probability of a trial wind being the true wind, based on a set of scatterometer observations, is then defined as (Portabella and Stoffelen, 2001):

$$P(v|\sigma^0)=\frac{1}{k'}e^{-Rn/L}, \tag{2}$$

where v represents the "true" wind, k' is a normalization factor and L is the parameter that must be derived empirically based on the performance of the scatterometer. Equation 2 is the EPF, which is developed to convert the MLE values to equivalent probabilities. In order to account for misestimated measurement noise, a normalized MLE (Rn) with respect to the wind and the cross-track index is defined as:

$$Rn=\mathrm{MLE}/\langle\mathrm{MLE}\rangle, \tag{3}$$

where the MLE value represents any point of the cost function for a particular WVC and <MLE> is the expected MLE for that WVC and wind condition.

The <MLE> is used to respect the misestimation of the measurement noise and theoretically, it can be derived from an instrument error model. However, in practice, an alternative method has to be proposed. If the expected MLE is estimated by the mean MLE, studies have shown that the mean MLE, as a function of cross-track index and wind speed (not statistically dependent on wind direction), can effectively respect measurement noise (Portabella and Stoffelen, 2001, 2002; Portabella, 2002)

Through reviewing the inversion procedure using the MSS method, the multiple solutions, together with the corresponding probabilities calculated by the EPF (Eq.2), retain all the direction solutions corresponding to the MLE cost function. However, for the case of the standard MLE procedure, only solutions at the minima of the MLE cost function—typically up to four minima—are used. This ignores neighboring wind solutions that have comparable probability of being the "true" wind. Apparently, the

MSS method fully retains the information of the cost function and the observations.

2.2 Two-dimensional variational ambiguity removal (2DVAR)

The goal of the AR procedure is to select the best solution based on a set of ambiguous solutions and spatial consistency constraints and it is generally performed using many neighboring WVCs at once. Median filtering (Schultz, 1990) and 2DVAR are the two AR techniques used most commonly in scatterometry (Schultz, 1990; Stoffelen et al., 1997b; Stiles et al., 2002). In this paper, 2DVAR is used because it can explicitly use probability for the multiple solutions. The 2DVAR approach can be divided into two principal steps: firstly, an analysis wind is obtained using variational analysis, which combines background information (winds from NWP model) with the ambiguous solutions; and secondly, among all the ambiguous solutions, the one closest to the analysis wind in the wind direction is selected.

Using probability theory and Bayes' theorem, the joint probability of the true state of the sea surface wind (x) and an ambiguous solution (   ) can be expressed as (Lorenc, 1986):

$$P(x \cap v_{\rm o}^k) \propto P(v_{\rm o}^k|x) \cdot P(x|x_{\rm b}) \, , \tag{4}$$

where k is the ambiguity index and $x_{\rm b}$ is the background field (NWP winds are usually used as the initial guess). The most likely estimate of x, the control variable in the procedure, can be found by maximizing Eq.4, or equivalently, by minimizing the cost function:

$$J(x) = \text{-}2\ln P(v_{\rm o}^k \mid x) - 2\ln P(x \mid x_{\rm b}) \, . \tag{5}$$

To increase computational efficiency, an incremental formulation is used:

$$\delta x = x - x \; ,$$

$$\delta v_{\rm o}^k = v_{\rm o}^k - x_{\rm b} \, . \tag{6}$$

Then, the cost function Eq.5 can be rewritten as:

$$J(\delta x) = J_{\rm o}(\delta v_{\rm o}^k, \delta x) + J_{\rm b}(\delta x) \, , \tag{7}$$

where $J_{\rm o}$ is the observation term and $J_{\rm b}$ is the background term.

The observation term $J_{\rm o}$ represent the misfit between the ambiguous solutions and the control variable on a particular WVC. The contribution of the solutions is weighted by the solution probability. The observation term of the cost function can be expressed as (Stoffelen and Anderson, 1997a; Portabella and Stoffelen, 2004):

$$J_{\rm o} = (\sum\nolimits_{i=1}^{N} K_i^{\lambda})^{-1/\lambda} \, , \tag{8}$$

where N is the number of ambiguous solutions and λ is an empirical parameter that gives the optimal separation between multiple solutions for λ=4 (Stoffelen and Anderson, 1997b). K_i is given by:

$$K_i = (\frac{u - u_i^{\rm o}}{\varepsilon_{\rm u}})^2 + (\frac{v - v_i^{\rm o}}{\varepsilon_{\rm v}})^2 - 2\ln P_i \, , \tag{9}$$

where $u(u_i)$ and $v(v_i)$ are the zonal and meridional components of the control variables (solutions), respectively, $\varepsilon_{\rm u}$ and $\varepsilon_{\rm v}$ are the expected standard deviations of the scatterometer wind components, and P_i is the solution probability that is determined by Eq.2 in the inversion procedure.

The background term quantifies the spatial context of the background field errors and determines the spread of the observational information, which is expressed as (Vogelzang, 2007):

$$J_{\rm b} = (\delta x)^T B^{-1} \delta x \, , \tag{10}$$

where B is the background error covariance matrix and the superscript T indicates the transposition of the matrix. For further details, please refer to Stoffelen et al. (2001), Vogelzang (2007), and Portabella and Stoffelen (2004).

The cost function of Eq.7 can be minimized using a conjugate gradient method, and the wind increments of the control variable vector are added to the background field to obtain the wind analysis. The analyzed wind field is then used for the AR procedure, as discussed earlier.

3 WIND RETRIEVAL AND EVALUATION

3.1 Wind retrieval from HY2-SCAT

The MLE function for HY2-SCAT is defined as Eq.1, which refers to that of SeaWinds, and the NSCAT-3 GMF was used in this study. As wind speeds are overestimated above 15 m/s in NSCAT-2, a linear downscaling of such wind speeds was applied (Verhoef and Stoffelen, 2012).

The MLE cost function is computed as a function of wind direction from 0° to 360° with a step of 2.5°, and an array of solutions is produced (typically 144). Figure 2 shows an example of the MLE cost function for HY2-SCAT.

The probability of every solution being the "true" wind is given through the EPF. In order to provide the probability of each solution in the cost function, the parameters L and the expected MLE—the key parameters of the EPF—must be estimated using an empirical statistical method based on HY2-SCAT data.

To estimate the misestimation of the measurement noise, the mean MLE (<MLE>) was used as an alternative parameter. According to Portabella and Stoffelen (2001), the <MLE> does not depend statistically on wind direction and therefore, the <MLE> can be computed as a function of the cross-track index and wind speed. In this study, the expected MLE was computed based on the winds retrieved by the standard MLE procedure using HY2-SCAT observations from 100 orbits. A rejection process was applied to filter noise, due mainly to geophysical effects such as rain. Finally, the expected MLE was smoothed using a 3×3 median filter to remove the noise (Portabella, 2002). The obtained values of <MLE> used for HY2-SCAT are shown in Fig.3.

In order to derive Eq.2 empirically, the ambiguous solution from the standard MLE procedure closest to the ECMWF wind was considered as the "selected" wind and initially, only those cases that had just two solutions were considered. The relative probability of selecting the 1st and 2nd, as a function of Rn_1 and Rn_2, can be given by:

$$\frac{P(Rn_1)}{P(Rn_2)}=\frac{e^{-Rn_1/L}}{e^{-Rn_2/L}}=e^{-(Rn_1-Rn_2)/L}\,. \tag{11}$$

We processed 100 obits of HY2-SCAT data and obtained the exact two-solutions case. The relative probability can be calculated by using Eq.11 and the statistical results are shown in Fig.4a. The best-fit function was obtained by adjusting the L parameter and it can be represented by the following function:

$$P(x)=e^{-x/1.17}\,, \tag{12}$$

where x represents Rn and $P(x)$ is the EPF for HY2-SCAT, as shown in Fig.4b. For the case of QuikSCAT, parameter L equals to 1.4 (Portabella, 2002).

Equation 12 can be used to determine the probability of the solutions for HY2-SCAT and it can express the probability of any number of solutions of MLE. Finally, the 2DVAR technique was applied, together with the background field, to each WVC in the AR procedure. Generally, the background field is obtained from the ECMWF model by interpolation.

3.2 Evaluation of the retrieved winds

In this section, the wind data retrieved from HY2-SCAT using the standard MLE inversion and median filter AR (called MLE-winds), and those derived using the multiple solution scheme with 2DVAR AR (called MSS-winds) are used to compare the performance of the two different algorithms for wind retrieval.

We processed five months' (Jan. 2012, Feb. 2012, Nov. 2012, Dec. 2012, and July 2013) HY2-SCAT data and collected the operationally released HY2-

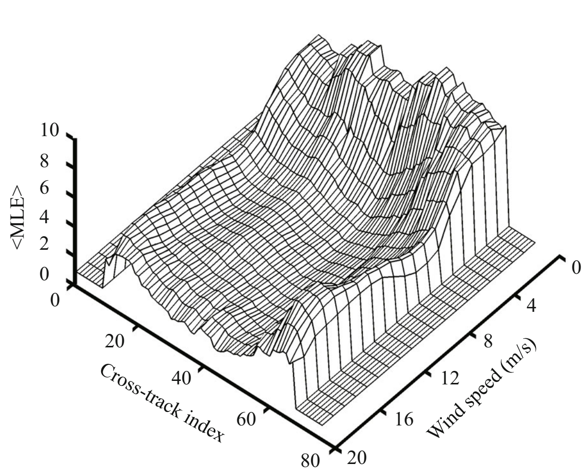

Fig.3 Expected MLE for HY2-SCAT as a function of cross-track index and wind speed

The wind speed binning is 1 m/s and the index binning is 1.

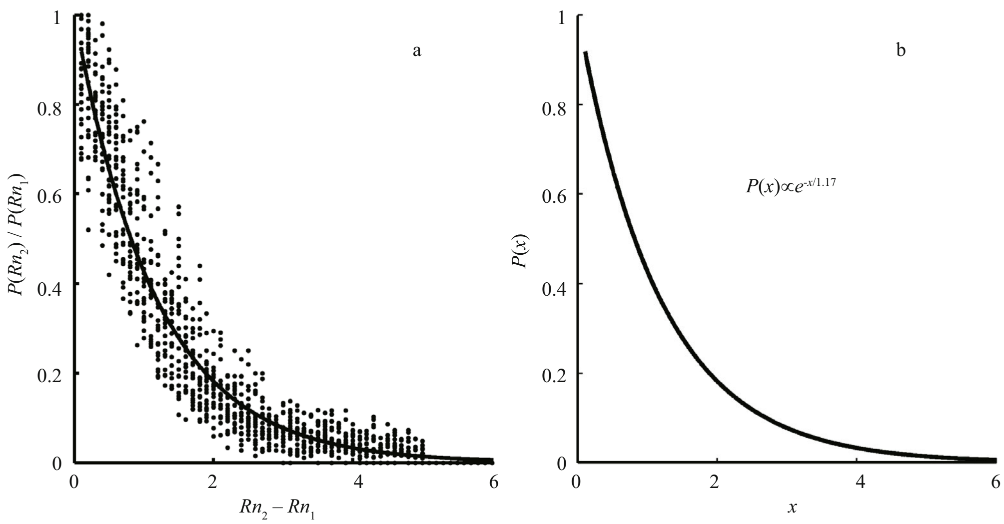

Fig.4 Relative probability of selecting the 1st and 2nd as a function of Rn_1–Rn_2 (a), EPF based on HY2-SCAT data (b)

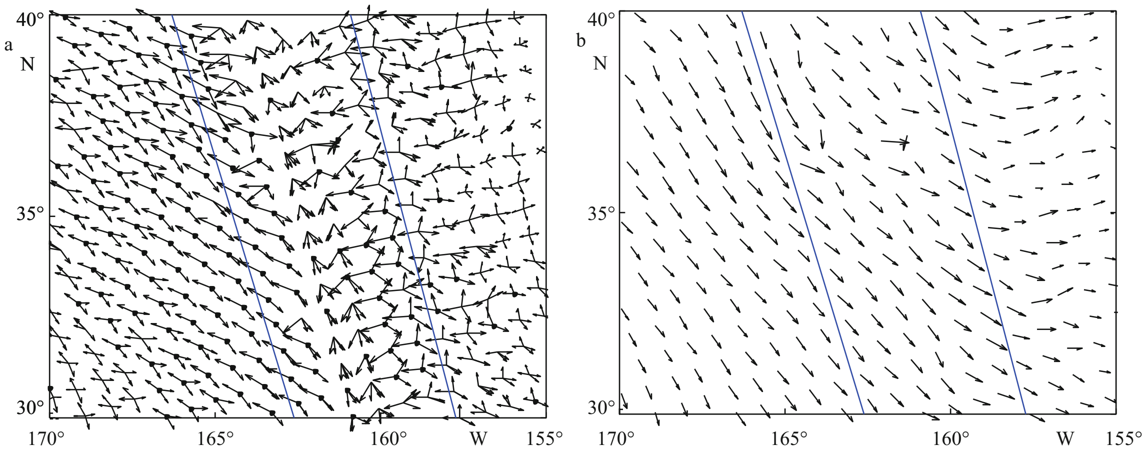

Fig.5 HY2-SCAT wind field using standard MLE inversion output (a) and the 7 × 7 median filter AR (b)

Area between the two solid lines is nadir region of HY2-SCAT swath.

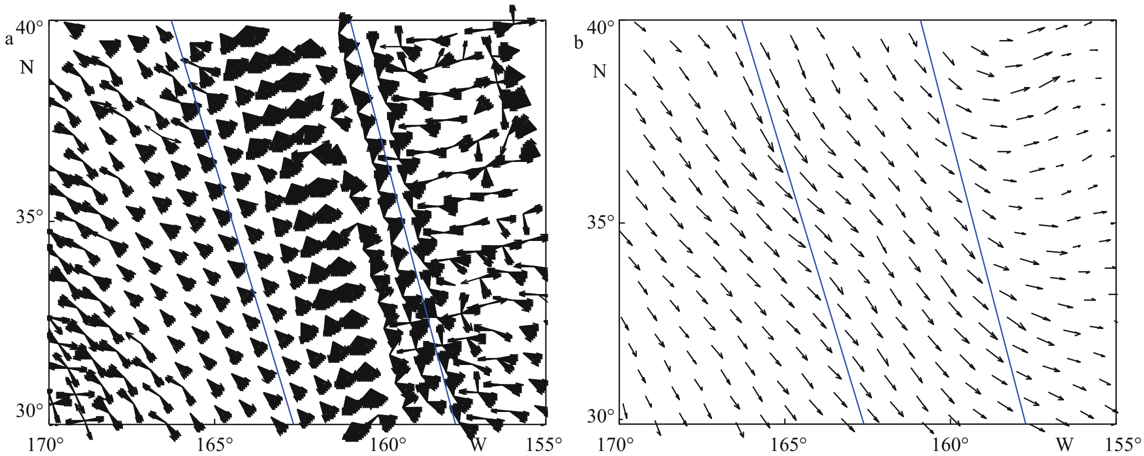

Fig.6 Same as Fig.5, but for the HY2-SCAT ambiguous wind field using the MSS inversion (a) and variational analysis (b)

Only solutions with normalized probabilities above 0.01 are shown.

SCAT wind products from the National Satellite Ocean Application Service with wind components from the ECMWF.

Figure 5a shows the ambiguous solutions for HY2-SCAT using the standard MLE inversion output, and the 7×7 median filter AR results are shown in Fig.5b. The two solid lines identify the nadir region of the HY2-SCAT swath. Several WVCs within the nadir region exhibit wind directions that are clearly spatially inconsistent (Fig.5b). The reason for this problem is most likely attributable to the ambiguous solution distribution for which no relative accurate solution is available, as shown in Fig.5a. Therefore, there is no mean by which to select a consistent wind field from such a solution pattern. In order to avoid the plotted lines are too dense, WVCs in both Figs.5 and 6 are sampled with one third along longitude and latitude separately.

Figure 6a shows the multiple ambiguous solution distribution for the same case as in Fig.4, and the variational analysis AR results are shown in Fig.6b. In Fig.6a, only solutions with normalized possibilities above 0.01 are shown. In comparison with Fig.5a, the MSS inversion provides much more information to the AR. As discussed earlier, the 2DVAR is able to use the information in a more appropriate manner to provide a spatially consistent wind field (Fig.6b).

To validate the accuracy of the wind speed and direction at different ocean states, the bias and standard deviations of the wind speeds with respect to the ECMWF winds were calculated as a function of the ECMWF wind speeds in bins of 1 m/s, as shown in Fig.7a, and the mean absolute differences of wind direction are shown in Fig.7b.

Figure 7a and 7b shows that the -deviations of MSS-winds -vary with increasing wind speed. In Fig.7a, the bias decreases from 2.0 to 0.2 m/s as the wind speed increases from 0 to 5 m/s, while the RMS error remains about 2 m/s. The wind speed RMS error becomes

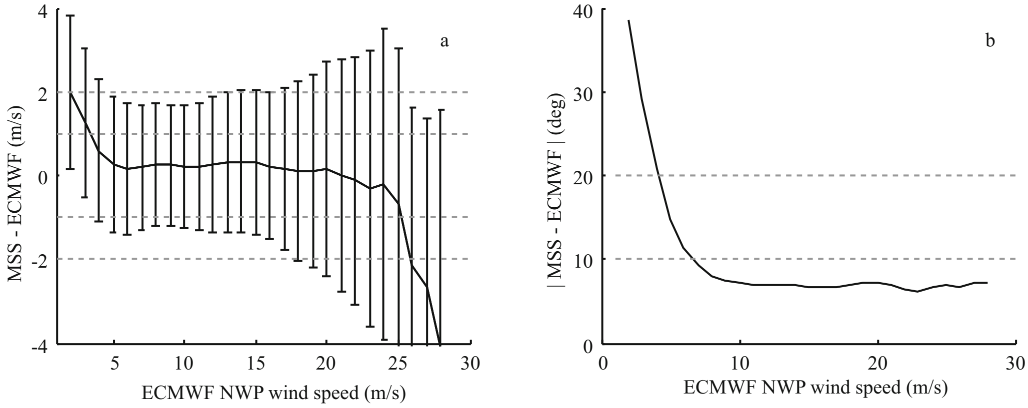

Fig.7 Wind speed (a) and direction (b) bias referred to ECMWF winds as a function of wind speed in bins of ECMWF wind speed of 1 m/s

Table 1 Comparison of MLE-winds (left column) / MSS-winds (right column) with buoy data

Wind data	Num. of data	Wind speed RMS difference	Wind direction RMS difference
All	4 936/4 812	1.3/1.3 m/s	24.0/17.4°
Sweet swath	2 874/2 806	1.2/1.2 m/s	22.5/17.2°
Nadir swath	1 433/1 398	1.5/1.4 m/s	24.7/17.7°

changeable at speeds above 17 m/s, although the absolute bias remains within 1 m/s up to a wind speed of 24 m/s. In Fig.7b, the bias of wind direction also decreases as the wind speed increases from 0 to 9 m/s and then it falls to 20° at a wind speed of 5 m/s. The bias shows little variation for wind speeds above 9 m/s.

A comprehensive analysis of Fig.7a and b reveals that wind speed is noisy at both low wind speeds (below 4 m/s) and high wind speeds (above 17 m/s), whereas the wind direction is reproduced well at wind speeds between 5 m/s and 24 m/s or higher.

To validate the MSS-winds and MLE-winds, we also compared these winds with in situ observations from 29 offshore buoy stations. The buoy data were collected from the National Data Buoy Center for the same five months (as mentioned earlier) as the MSS-winds; and the MLE-winds use the same time period. Only wind speeds are above 2 m/s and below 30 m/s are considered in this validation. The matched winds are limited to less than 10 min and 0.25° for the temporal difference and spatial separation, respectively. Buoy data are converted to 10-m height using the logarithmic profile method (Peixdto and Oort, 1992). The results of the comparison are shown in Table 1.

A total of 4 936 points were matched and the data are presented in Fig.8a for wind speed and Fig.8b for wind direction. In the comparison of the MLE-winds with buoy winds, the RMS errors of wind speed and wind direction are 1.3 m/s and 24.0° for all swath data, respectively. In the comparison of the MSS-winds with buoy winds, 4 812 points were matched and the data are shown in Fig.9a for wind speed and Fig.9b for wind direction. The RMS errors of wind speed and wind direction are 1.3 m/s and 17.4° for all swath data, respectively. Comparisons for sweet swath (nodes 9–28 and 49–68) winds and nadir swath (nodes 29–48) winds are also calculated. The results listed in Table 1 shows that MSS-winds are more improved in wind direction domain. Besides, the MSS-winds narrow the differences of accuracy between sweet swath data and nadir swath data. All matched points within triple standard deviations were considered in this study.

Finally, we compared two wind field data sets of MLL-winds and MSS-winds for the case study of typhoon Soulik. Soulik was a powerful typhoon that caused widespread damage in Taiwan Island and East China in July 2013. The storm originated to the northeast of Guam on July 6, and became a tropical depression early on July 7. The depression underwent a period of rapid intensification starting on July 8 that culminated in Soulik attaining its peak strength early on July 10.

Figure 10 shows a HY2-SCAT-retrieved wind field using the standard MLE inversion and median filter AR. In the region of the red rectangle, it is clear that the wind vectors do not conform to the vortex structure. Figure 11 shows the improved winds using the MSS inversion in combination with 2DVAR for the same case as shown in Fig.10. In order to avoid the plotted lines are too dense, WVCs in both Fig.10 and 11 are sampled with odd number along longitude and latitude separately.

4 CONCLUSION

In this study, the MSS algorithm is used in combination with the 2DVAR technique to improve

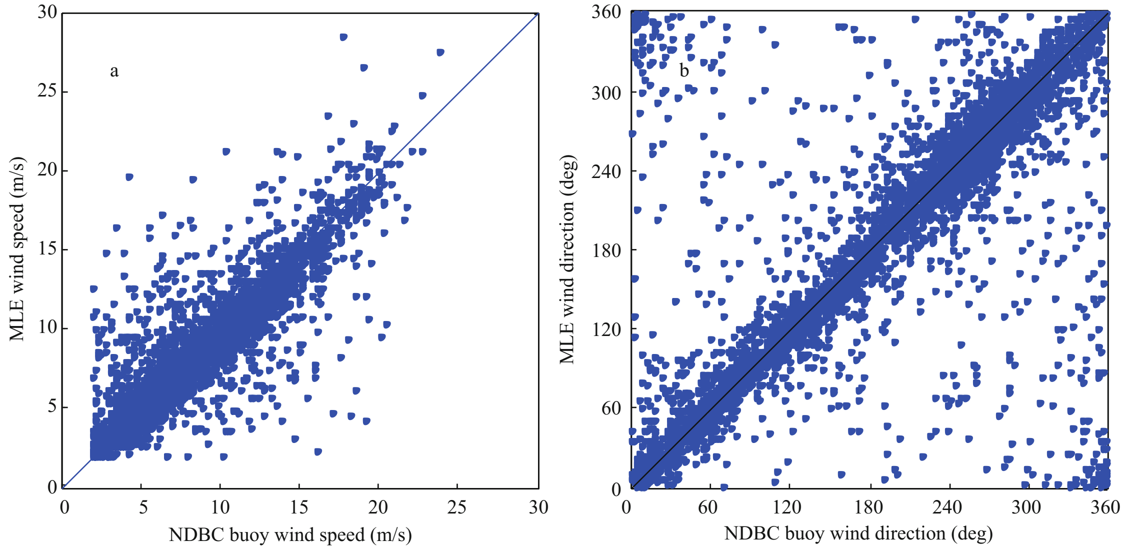

Fig.8 Comparison of MLE-winds with buoy winds from the National Data Buoy Center

a. Wind speed; b. wind direction.

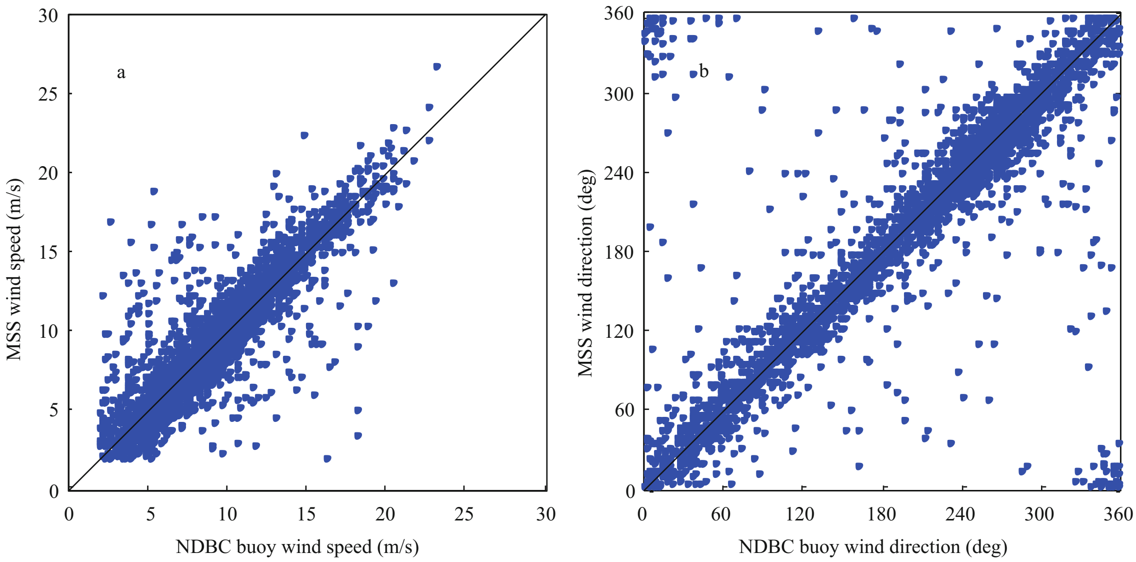

Fig.9 Comparison of MSS-winds with buoy winds from the National Data Buoy Center

a. Wind speed; b. wind direction.

HY2-SCAT wind retrievals. The current operational system using standard MLE wind retrieval procedures, which only considers the local MLE cost-function minima as ambiguous solutions, produces inaccurate winds in the HY2-SCAT nadir region.

The MSS algorithm retains all the direction solutions corresponding with the MLE cost function. The probability of each ambiguous solution being the "true" wind is calculated using the EPF, the parameters of which are derived empirically based on HY2-SCAT data. In the AR procedure, a variational analysis AR (i.e., 2DVAR) is used instead of a median filter AR, because it is capable of explicitly using the probabilities for multiple solutions and ensuring the spatial consistency and meteorological balance of the retrieved winds.

The study shows that the MSS wind direction is substantially better than the MLE wind in the nadir region. The comparison between the MSS winds and ECMWF winds shows that wind speed is noisy at low wind speeds (below 4 m/s) and at high wind speeds (above 17 m/s), while the wind direction shows lower bias and stability, even at high wind speeds above 24 m/s. Furthermore, the wind field of a vortex structure is reproduced well by the MSS winds, showing spatial consistency. However, the quality of derived wind speeds above 20 m/s is still poor and further study is required. This should include a greater number of observations of high wind speeds (e.g., from buoys,

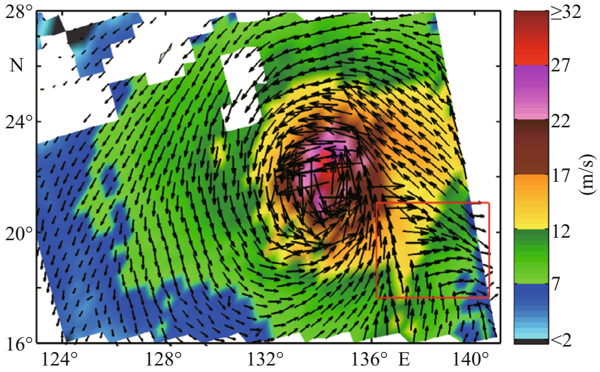

Fig.10 Wind field retrieved using standard MLE inversion and median filter AR for the case of typhoon Soulik MLE on July 10, 2013

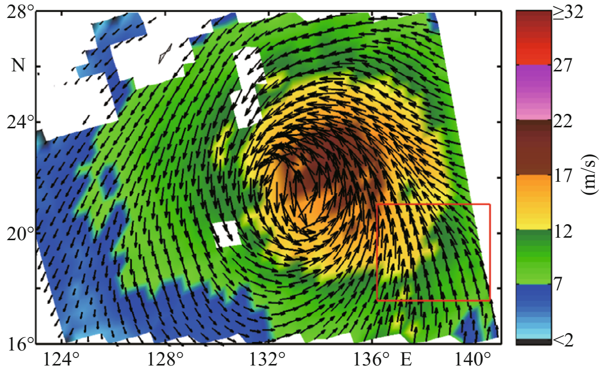

Fig.11 Wind field retrieved using MSS inversion in combination with 2DVAR for the same case as shown in Fig.10

dropsondes, oil rigs, and WindSat) to refine the geophysical model function of the scatterometer.

5 ACKNOWLEDGEMENT

We greatly appreciate the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT), National Data Buoy Center (NDBC), and National Satellite Ocean Application Service (NSOAS) for their freely available data sets. We thank the Royal Netherlands Meteorological Institute (KNMI) scatterometer team for answering our detailed questions.

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