SeaWinds Wind Retrieval Quality Assessment

David G. Long, Andrew S. Fletcher, and David W. Draper
Brigham Young University
Microwave Earth Remote Sensing Laboratory
459 CB, Provo, UT 84602
801-378-4884, FAX: 801-378-6586
long@ee.byu.edu, fletchas@ee.byu.edu, draperd@ee.byu.edu

ABSTRACT

The SeaWinds on QuikScat scatterometer is the first in a series of new scanning pencil-beam Ku-band scatterometers. The viewing geometry is significantly different than previous fan beam instruments, resulting in different characteristics in the retrieved winds. In this paper we provide an assessment of the reliability of the SeaWinds ambiguity selection using a SeaWinds data-only algorithm. An ambiguity selection quality assurance algorithm developed for NASA Scatterometer (NSCAT) data is modified for use with SeaWinds data. The algorithm uses the selected ambiguity field to estimate the parameters of a simple wind field model and examines significant differences between the fields, enabling detection of possible ambiguity errors. Tests against subjectively analyzed selection errors suggest that the algorithm correctly detects more than 94% of all ambiguity errors. Applying the algorithm, we find that the ambiguity selection accuracy exceeds 93%.

INTRODUCTION

The instrument SeaWinds on QuikScat is a Ku-band pencil-beam scatterometer designed to measure ocean winds [3]. The ocean wind vectors are estimated using the normalized radar cross section (σ^o) measurements of the ocean's surface. A geophysical model function relates the σ^o measurements to the wind speed and direction. The σ^o measurements do not yield a unique wind vector estimate; rather, they result in a set of two to four possible solutions known as ambiguities. Generally, the speeds of these estimates are similar, but the directions vary. To determine a consistent estimate across a swath, an ambiguity selection algorithm must be used.

SeaWinds uses a traditional point-wise wind retrieval method in which ambiguous solutions are determined for each wind vector cell (wvc). Ambiguity removal is then performed across the entire swath, selecting one vector per wvc. We note that ambiguity selection errors give rise to inconsistent wind field estimates. Since errors may be introduced by either estimation or ambiguity selection, a quality assessment is necessary to determine the validity of the data.

In this paper, we develop a SeaWinds-only ambiguity selection quality assurance algorithm. We discuss how the algorithm is optimized for detecting SeaWinds ambiguity selection errors and quantify the ambiguity selection performance of SeaWinds as a function of swath position and wind speed. We note that since the algorithm uses strictly SeaWinds data, only the consistency of the estimated winds can be evaluated.

SEAWINDS VERSUS NSCAT

The basis for the SeaWinds quality assurance evaluation is an algorithm developed for the NASA Scatterometer (NSCAT) by [1]. The two instruments have significant differences necessitating modifications in the quality assessment algorithm.

NSCAT employed fixed antenna beams on either side of the spacecraft and had a 50 km wvc resolution. Due to its fixed antenna beams, the azimuth geometry for each NSCAT wvc was identical. NSCAT measured winds over two 600 km (12 wvc) swaths on either side of the spacecraft, leaving a 350 km gap in the nadir region.

SeaWinds employs a scanning pencil beam, which expands the coverage to 1800 km with 25 km wvc resolution. The scanning beam also eliminates the nadir gap. Unlike NSCAT, the azimuth measurement geometry varies from cell to cell. The differing cell geometries affect estimation efficiency across the swath. On either side of the spacecraft, the wide azimuth distribution creates an area of optimum performance known as the "sweet spot." The nadir region and swath edges have a narrow azimuth distribution, increasing the variance of the wind vector estimate.

QUALITY ASSESSMENT

Following [1], the quality assurance evaluation is accomplished by modeling general wind flow and comparing this estimate to the retrieved wind. To do this, the swath is divided into smaller overlapping regions. A model fit of the retrieved wind fields is created using a truncated Karhunen-Loeve (KL) model. This data-driven model minimizes the basis restriction error [2]. Large aberrations from the fit indicate potential wind retrieval problems in the region. These problems may result from noisy wind vector estimates, ambiguity selection errors, or wind field modeling errors [1].

The width of the NSCAT swaths dictated the 12 by 12 wvc divisions employed by [1]. The increased width of SeaWinds' swath implies no such restriction. A smaller

8 by 8 region size was chosen to better pinpoint retrieval problems and reduce the computational load. In addition, the KL truncation point was chosen at 6 model parameters rather than at 22. Due to the the smaller model size and SeaWinds' finer wvc resolution, this choice of truncation point yields approximately the same effective spatial resolution as the model employed by [1].

While the overlap of regions for the NSCAT quality assurance algorithm is only possible in the along track direction, SeaWinds' larger swath allows overlap in the cross track direction as well. Thus for SeaWinds, regions overlap by half in both directions.

After the swath is divided and modeled, each point-wise wind vector is individually compared to the model fit. In [1] a 23° angle and 2.7 m/s speed fixed error threshold for individual wind vectors was employed. If a vector exceeded either of these thresholds, it was flagged as "poor." If the region contained more than 20% poor wvc's, the entire region was considered poor. Other sets of thresholds were also used; these are neglected for analysis of SeaWinds data. In quality assessment for SeaWinds, a fixed 23° angle error threshold is used to locate cells that are unrealistic. Through observation we concluded that a flat speed threshold is biased to flagging realistic vectors with a high wind speed where the modeling error is only a small percentage of the wind vector's magnitude. Thus the speed threshold was changed to be 1/2 the root mean square (RMS) wind speed of the region for region RMS wind speeds above 5.4 m/s and 2.7 m/s otherwise.

Like the NSCAT algorithm, the SeaWinds algorithm identifies a region as "poor" if the number of wvc's flagged is above 20%. The region is considered "good" if less than 5% of the cells are flagged as poor, and "fair" for regions in between. This flagging only identifies possible ambiguity selection errors. Noisy vectors are also included in the identification.

Table 1: *Quality Assessment Results for SeaWinds*

Region Type	Percentage
"good"	64
"fair"	19
"poor"	17

Over six months of SeaWinds data, ranging from July 22, 1999 to February 15, 2000 of the QuikScat mission, was evaluated using this algorithm. Table 1 summarizes the results. Of the vectors flagged as "poor," a large portion were located the nadir region and in slow wind regions as illustrated in Figures 1 and 2.

DETECTING AMBIGUITY SELECTION ERRORS

While the quality assurance algorithm accurately flags regions with potential retrieval problems, retrieval errors

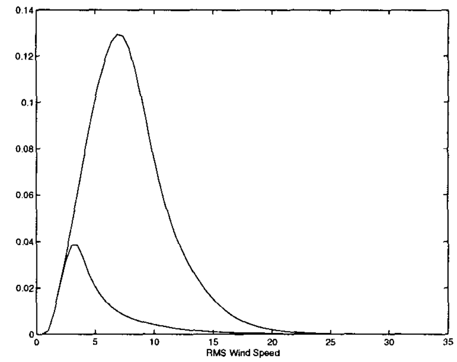

Figure 1: *A histogram of the RMS wind speeds of regions examined (top line) and regions flagged as "poor" (bottom line) for 6 1/2 months of SeaWinds data. Note the high percentage of "poor" regions with low wind speed.*

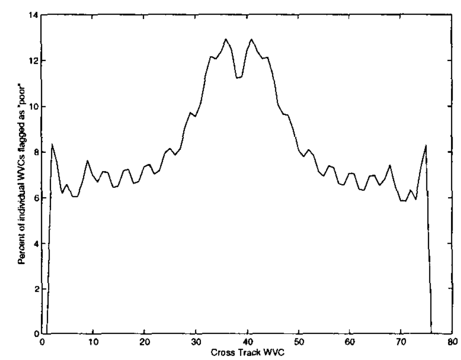

Figure 2: *Distribution of "poor" wind vectors according to cross track position. Nadir is at wvc 36. Note the large percentage of poor vectors in the nadir region. (Bumps in the curve are due to poor modeling on region edges.)*

result either from poor wind vector estimates or ambiguity selection errors. Using a point-wise approach, improving wind vector estimates is not possible; however, regions with ambiguity selection errors can potentially be improved if identified. Thus, it is valuable to differentiate between regions with ambiguity selection errors and those with noisy wind vector estimates.

Noisy wind estimates are mainly found in the nadir region or regions of low RMS wind speed. Lack of azimuth variation for colocated measurements in the nadir region reduces the wind estimate accuracy. Also, the weak return from low wind speed wvc's decreases the signal to noise ratio, creating unreliable estimates. In these regions, a fixed angle threshold for all wind speeds and cross track positions flags many regions as "poor" due only to noisy wind estimates. In order to detect regions of ambiguity selection error while minimizing the effect of noise near nadir and in slow wind regions, a variable angle threshold can be used.

Fifteen random revs were subjectively inspected for ambiguity selection errors. Each 8x8 region was categorized according to cross track position and region RMS wind speed. The angle threshold was then adjusted for each wind speed/ swath location bin to reduce the probability of false alarm to under 3%. On the tuning set, the resulting probability of detection was greater than 94%, while false alarm rate of ambiguity selection errors was less than 3%. Thus the revised algorithm is very effective in identifying ambiguity selection errors. Figure 3 shows the numerically obtained angle thresholds for cross track position and wind speed. It is informative to note that the thresholds are higher for the nadir region and low RMS wind speeds.

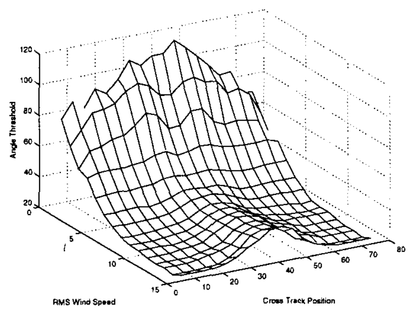

Figure 3: *The angle thresholds versus cross track and RMS wind speed that minimizes the probability of false alarm to beneath 3%.*

Using the variable angle thresholds for locating ambiguity selection errors, the QuikScat mission was reprocessed. It was determined that only 7% of all 8 by 8 regions examined exhibited possible ambiguity selection errors.

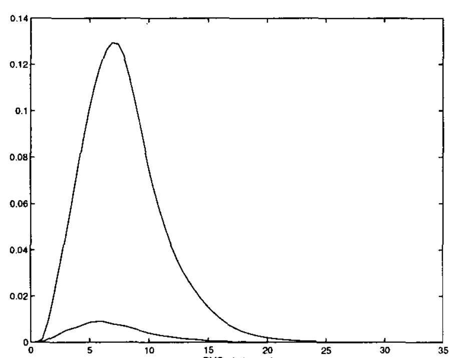

Figure 4: *A histogram of the RMS wind speeds of all wind regions (top line) and regions flagged as "poor" using variable angle thresholds (bottom line). Note that the distribution of ambiguity selection errors closely parallels the overall distribution of wind vectors.*

Figure 4 shows the distribution of wind regions according to RMS wind speed. Using variable angle thresholds, the distribution of regions flagged as "poor" is nearly identical to that of all wind regions. Figure 5 compares the results from fixed angle thresholds and variable angle thresholds for each cross track position. The distribution of regions with potential ambiguity selection errors is much less dependent on swath position. These suggest that the variable angle thresholds are effective in separating noisy wind estimates from ambiguity selection errors.

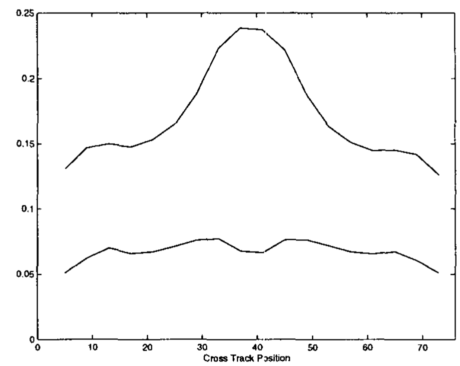

Figure 5: *Fraction of regions flagged as poor with fixed angle thresholds (top line) and variable angle threshold (bottom line) per cross track. Note that the variable threshold suppresses location dependence of flagged regions.*

CONCLUSION

The SeaWinds-only quality assessment algorithm is capable of identifying wind retrieval errors using fixed angle thresholds. Based on the analysis of over 6 months' data we find that approximately 80% of regions are classified as "good" or "fair." In addition, over 93% of regions did not exhibit ambiguity selection errors. We note that due to the false alarm rate, the actual ambiguity selection accuracy is higher than this. Further work is underway to correct regions identified as possible ambiguity selection errors.

REFERENCES

[1] A.E. Gonzales and D.G. Long, "An Assessment of NSCAT Ambiguity Removal," *Journal of Geophysical Research*, Vol. 104, No. C5, pp. 11449-114457, 1999.

[2] J. Gunther and D.G. Long, "Models of the near-surface oceanic vorticity and divergence," *Proc. of the International Geoscience and Remote Sensing Symposium*, Vol. 2, pp. 951-953, 1994.

[3] M.W. Spencer, C. Wu, and D.G. Long, "Improved Resolution Backscatter Measurements with the SeaWinds Scatterometer," *IEEE Transactions on Geoscience and Remote Sensing* , Vol. 38, pp. 89-104, 2000.