Prior Selection for QuikSCAT Ultra-High Resolution Wind and Rain Retrieval

Michael P. Owen and David G. Long, *Fellow, IEEE*

***Abstract*—QuikSCAT was designed for ocean wind retrieval. However, its wind estimation performance is limited in rainy conditions. Several estimation techniques have been proposed: wind-only (WO), simultaneous wind and rain (SWR), and rain-only, which are appropriate for different levels of rain contamination. To exploit the strengths of each estimation method at mitigating rain contamination, a Bayes estimator selection (BES) technique has been developed for 25-km wind products to select from among the several estimation techniques for each wind vector cell. This paper adapts the BES concept [1] to QuikSCAT ultra-high resolution (UHR) 2.5-km, products and extends BES to include prior selection and noise reduction. Prior selection and noise reduction exploit general spatial characteristics of wind and rain fields to improve the accuracy of estimator selections. Together these techniques enable improved estimator selection performance so that the probability of selecting the estimate with minimum squared error approaches optimal levels. Optimal estimator selection reduces variability of wind estimates during rainy conditions and provides rain estimates when possible without using additional sources of information. Overall, UHR wind estimation performance with the new technique has improved bias and root mean-squared error, −0.16 m/s and 2.15 m/s, respectively, which are lower than either of the UHR WO and UHR SWR estimates.**

***Index Terms*—Remote sensing, resolution enhancement, scatterometry, wind, wind retrieval.**

I. Introduction

The QuikSCAT scatterometer has proven to be a valuable tool for measuring near-surface ocean wind vectors. QuikSCAT was originally designed to produce wind-only (WO) estimates at a conventional resolution of 25 km. WO estimates can be produced at higher resolutions, up to 2.5-km ultra-high resolution (UHR), using irregular reconstruction and resolution enhancement techniques [2], [3]. Although UHR wind products have higher noise levels than conventional resolution products, UHR wind products can be powerful aids for understanding a wide variety of ocean wind phenomena, including storms such as hurricanes, near-coastal winds, and mesoscale wind features [3], [4].

Many interesting ocean wind phenomena are accompanied by rain; however, in rainy conditions, QuikSCAT observations are contaminated by rain-induced backscatter which may cause WO estimates to be unreliable [5]. To improve wind and rain estimation in rainy conditions, a simultaneous wind and rain (SWR) retrieval algorithm was proposed for conventional resolution wind products [6] which has been recently adapted for UHR wind products [7]. Conventional-resolution wind and rain products have low noise levels. Unfortunately, the 25-km resolution is coarser than many rain cells, thereby reducing the utility of the rain estimates. UHR wind and rain products can be valuable for rain studies since their 2.5-km resolution approaches that of rain cells. SWR estimation at UHR improves wind estimates for many raining conditions but has degraded performance in both extreme rain and rain-free conditions. For extreme rain conditions, a rain-only (RO) estimation technique is useful for cases in which rain contamination dominates the wind signal [8]. In rain-free conditions, WO estimation provides more accurate wind estimates than SWR estimation.

Although each estimation technique (WO, SWR, and RO) is optimal for certain conditions, no single estimator is appropriate for all conditions. Bayes estimator selection (BES) selects the estimate (WO, SWR, or RO) for each resolution cell that is most appropriate for the underlying conditions [1].

At UHR, BES is complicated by significantly higher noise levels compared to the conventional 25-km wind resolution and higher variability of the wind and rain fields resulting from small-scale wind features only apparent at the increased resolution. The increased noise and variability in UHR wind and rain estimates have two main consequences: additional variability in UHR estimates and higher estimator selection error. Both of these effects make UHR products more sensitive to the wind and rain prior distribution used to perform BES.

The sensitivity to the prior distribution for UHR BES can be reduced by choosing prior distributions appropriate for each wind situation. Uncommon wind events such as tropical storms and frontal features are particularly sensitive to the prior distribution since each type of event is rare and is thus not well-modeled by the global prior used previously [1]. In this paper, a new technique is proposed whereby a single prior distribution is selected from among several candidate priors for each wind field. This is referred to here as prior selection. This new technique reduces estimator selection errors substantially.

To further decrease the probability of selecting an inappropriate estimator, an estimator selection noise reduction step is applied. Estimator selection noise reduction corrects certain types of estimator selection errors by exploiting the spatial characteristics of wind and rain fields.

This paper adapts the BES developed in [1] for conventional resolution products to the UHR 2.5-km wind product and

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M. P. Owen was with Microwave Remote Sensing Laboratory, Brigham Young University, Provo, UT 84602 USA. He is now with MIT Lincoln Laboratory, Lexington, MA 02420 USA (e-mail: owen@mers.byu.edu).

D. G. Long is with Microwave Remote Sensing Laboratory, Brigham Young University, Provo, UT 84602 USA (e-mail: long@ee.byu.edu).

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further extends the technique to include prior selection and noise reduction, thereby reducing some limitations of BES that are unique to UHR.

Section II gives some background information on QuikSCAT and UHR products, after which Section III reviews BES and introduces some new notation. Prior selection is introduced in Section IV and is applied to QuikSCAT UHR products in Section V. Section VI describes estimator selection noise reduction and Section VII evaluates estimator selection performance using BES, prior selection, and noise reduction, after which Section VIII concludes with a summary.

II. Background

The QuikSCAT scatterometer measures the normalized radar cross section, or backscatter, of the earth's surface at 13.4 GHz [9], [10]. Over the ocean, scattering from wind-induced surface waves can be used to infer wind speed and direction. The wind estimates are widely used to aid weather monitoring and forecasting, while the historical record is a valuable tool to evaluate changes in the global environment.

In addition to scattering from wind-induced waves, QuikSCAT is sensitive to a number of other phenomena, particularly rain. Atmospheric hydrometeors cause volume scattering as well as attenuation of the surface backscatter signal. At the ocean's surface, falling raindrops cause additional surface roughness in the form of rings, crowns, and stalks [11]–[13]. QuikSCAT is sensitive to these rain-induced features, which can attenuate and obscure the wind-induced backscatter [11]. In addition, rain events may by accompanied by downdrafts that can alter the local wind field [14].

The backscatter effects of rain have been described for QuikSCAT at both 25- and 2.5-km resolutions [6], [7]. Given the rain backscatter model and the geophysical model function, which models the expected backscatter for a wind vector [12], estimates of the wind and rain can be produced for each wind vector cell (WVC), or resolution cell, using maximum likelihood estimation [1], [6]. Wind estimates calculated without incorporating the rain model are termed WO estimates; wind and rain estimates produced using the geophysical model function for wind together with the rain model are termed SWR estimates [6], [7]; and rain estimates produced without using the wind geophysical model function are termed RO estimates [8].

The phenomenological effects of wind and rain backscattering can be used to intuitively understand the motivation for each type of estimator. When there is no rain or when the effects of rain are insignificant, the WO estimate reliably estimates the wind vector. When the rain is sufficient to significantly modify the wind-induced backscatter, the SWR estimator can be used to recognize the wind and rain effects and reliably estimate both wind and rain. For high rain rates, the rain backscatter can be strong enough to obscure the surface signal, or the atmospheric rain attenuation can be sufficient to reduce the wind signal to inconsequential levels. When the wind signal is thus masked, the RO estimator should be used to estimate the rain rate since the wind cannot be estimated acurately. Choosing the appropriate estimator optimizes wind and rain measurement performance.

To validate QuikSCAT wind and rain estimates, this paper uses numerically modeled wind estimates produced by the National Center for Environmental Prediction (NCEP) and rain measurements made by the Tropical Rain Measuring Mission Precipitation Radar (TRMM PR). The NCEP winds used in this study are treated as a truth data set but are in reality only an approximation to the true wind field. Although the NCEP winds do not model small-scale variations in the wind field, they do well on a global scale [15], [16]. TRMM PR rain measurements are very reliable and are well-suited as a comparison data set for rain validation. There are some differences in the TRMM PR and QuikSCAT observation geometry and sampling pattern that must be accounted for in order to compare TRMM PR and QuikSCAT rains as in [1], [7].

III. BES

As previously noted, for QuikSCAT wind and rain estimation, there are three types of estimators: WO, SWR, and RO. If the estimators are used under conditions for which they are not appropriate, the estimates are degraded, sometimes severely. This effect is described in detail in terms of the overall Cramér-Rao lower bound (CRB) in [1] where it is demonstrated that the minimum bound can only be achieved using the estimators under conditions for which they are appropriate. For UHR wind products, the observation noise is higher than for 25-km wind products. The higher noise level increases the estimate variability and generally increases the CRB for the different estimators at UHR.

To approach optimal overall wind and rain estimation performance, BES is used to select the most appropriate wind-rain estimate. BES for QuikSCAT conventional resolution is introduced and demonstrated in [1] where it is shown that the estimates selected using BES have overall improved performance, lower bias, and lower mean-squared error than the estimates from any single estimator.

In BES the Bayes risk $r(\phi_j, F_\theta)$ for a decision rule ϕ_k and a prior F_θ is the expected value of the risk function $R(\vartheta, \phi_j)$ and can be written as [1]

$$\begin{aligned} r(\phi_j, F_\theta) &= \int_\theta R(\vartheta, \phi_j) F_\theta(\vartheta) d\vartheta \\ &= \tau E_{\theta|\sim X}\left(C(\vartheta, \hat{\vartheta}_j)\right) + \kappa E_{\theta|X}\left(C(\vartheta, \hat{\vartheta}_j)\right) \quad (1) \end{aligned}$$

where ϑ is the true wind and rain, τ and κ are weighting coefficients, $C(\vartheta, \hat{\vartheta}_j)$ is the squared error cost function between the estimate $\hat{\vartheta}_j$ and the true conditions ϑ, $E_{\theta|\sim X}(C(\vartheta, \hat{\vartheta}_j))$ represents the expected squared error of not selecting $\hat{\vartheta}_j$ when ϑ is true, and $E_{\theta|X}(C(\vartheta, \hat{\vartheta}_j))$ represents the expected squared error of selecting $\hat{\vartheta}_j$ when ϑ is true. In BES, a decision rule is selected by choosing the rule that minimizes (1). The optimal selection, denoted ϕ_{opt}, is to choose the estimate that minimizes $C(\vartheta, \hat{\vartheta}_j)$. Optimal values for τ and κ are selected to maximize the probability of making the optimal selection, $p(\phi_{opt})$, using Monte-Carlo simulation.

As BES is dependent on the wind and rain prior distribution F_θ, it is helpful to explicitly include this dependency. The selected decision rule is written with this dependence as $\hat{\phi}(F_\theta)$, which is a shorthand notation for

$$\hat{\phi}(F_\theta) = \arg\min_j \{r(\phi_j, F_\theta)\}. \tag{2}$$

Similarly, the dependence on the prior can be included in the Bayes risk, or error, for the selected decision rule

$$e\left(\hat{\phi}(F_\theta)\right) = \min_j \{r(\phi_j, F_\theta)\} \tag{3}$$

$$= r\left(\hat{\phi}(F_\theta), F_\theta\right) \tag{4}$$

where $e(\hat{\phi}(F_\theta))$ is the Bayes risk associated with the decision rule selected using F_θ.

BES estimator selection performance is indicated by $p(\phi_{opt})$, the probability of choosing the optimal estimator. It is shown in [1] that at conventional resolution $p(\phi_{opt})$ is high for cases in which the observed wind and rain field is well-represented by the wind and rain prior distribution F_θ. For most wind fields (roughly 80% of winds), the global wind and rain prior used in [1] is appropriate. However, for wind and rain fields that are misrepresented by the prior, BES has diminished performance, i.e., $p(\phi_{opt})$ is low. This reduced performance is not a breakdown of the BES technique but is instead a consequence of using a prior that is inconsistent with underlying conditions.

At UHR, sensitivity to the wind and rain prior distribution is greater due to greater spatial variability in the UHR wind and rain fields. Wind events such as hurricanes are particularly sensitive to the wind and rain prior since they are uncommon on a global scale and are thus not well-represented by a global prior. However, since these rare cases are often of particular interest, it is important that BES can address them reliably. To increase the reliability of BES for wind and rain conditions that are not well-represented by a global prior, we introduce the concept of prior selection.

IV. Prior Selection

Sensitivity to the prior distribution is common to all Bayes techniques, from Bayes decisions to maximum *a posteriori* estimation. When the prior does not reflect the distribution of observations, accuracy and reliability are diminished. To ameliorate this limitation, we want to use a prior which is appropriate for the observed wind and rain field. In this application, we consider multiple priors which are chosen to model a range of wind and rain dynamics. Though not done here, the multiple priors can model regional characteristics such as trade winds or topography. In this paper, a set of reasonable candidate priors is created, from which a suitable prior is selected for each WVC. As a mechanism to select a best prior distribution from among multiple candidate priors, we introduce a prior selection technique based upon a Bayes decision formulation.

Adapting a Bayes decision mechanism for prior selection implies that the true prior distribution is a random variable with some distribution. Because small-scale wind and rain features have unique distributions and are of particular interest at UHR, we consider a set of simple candidate wind and rain distributions representing a variety of wind and rain phenomena at the spatial scales of interest, and select the prior from the set of candidate distributions that best matches the local conditions. This set of wind and rain distributions has an associated prior distribution that can represent the frequency with which each type of phenomena occurs. To decide which of these wind and rain distributions is most appropriate for observed conditions requires a prior selection technique which we now introduce.

Let F_{θ_i} denote a candidate prior and let F_{Θ_t} denote the true prior. To form the Bayes risk for prior selection requires the definition of a loss function $L(\Phi_i(\phi), F_{\Theta_t})$ where $\Phi_i(\phi)$ is the prior selection decision rule based on observing ϕ. The Bayes risk also requires a prior distribution for the candidate priors. We denote the probability of prior F_{Θ_i} being best as $f_\Theta(i)$. The Bayes risk also requires a conditional distribution which represents the probability of prior F_{θ_i} being best given that the "true" prior is F_{Θ_j}. This probability mass function is written as $f(i|j)$. With this notation the risk function can be written

$$\begin{aligned} R(\Phi_i, \Theta_t) &= E_{\theta_j|\Theta_t}\left[L\left(\Phi_i\left(\hat{\phi}\left(F_{\theta_j}\right)\right), F_{\Theta_t}\right)\right] \\ &= \sum_j L\left(\Phi_i\left(\hat{\phi}(F_{\theta_j})\right), F_{\Theta_t}\right) f(i|j). \end{aligned} \tag{5}$$

Forming the Bayes risk requires one final distribution, f_Θ, which represents the distribution of prior distributions. The Bayes risk for prior selection is the posterior expected loss and can be written

$$r(\Phi_i, f_\Theta) = \sum_t \sum_j L\left(\Phi_i\left(\hat{\phi}\left(F_{\theta_j}\right)\right), F_{\Theta_t}\right) f(j|t) f_\Theta(t). \tag{6}$$

A shorthand notation for the rule that selects the prior that minimizes the Bayes risk is

$$\hat{\Phi} = \arg\min_i r(\Phi_i, F_\Theta) \tag{7}$$

where $\hat{\Phi}$ represents the selected prior.

A. Prior Selection Loss Function

The definition of the loss function is fundamental to the success of the prior selection technique. The loss function definition must account for several unique aspects of the estimator selection problem.

For a single WVC, there can be three different estimates: WO, SWR, and RO. The three data points have sufficient information to make an informed estimator selection using BES; however, there may be insufficient information for selecting a prior. Prior selection must therefore include information from more than a single WVC. Additional information is available, particularly at UHR, by changing from a point-wise formulation, where each WVC is considered independently, to a field-wise formulation, where each WVC is related to the surrounding WVCs. Field-wise techniques have been previously implemented for wind retrieval [4], [17], [18]. Prior selection is unique in that it makes field-wise decisions about point-wise estimates.

A field-wise formulation for prior selection exploits spatial consistency in wind and rain fields by incorporating information from the surrounding WVCs. This spatial correlation can be utilized in prior selection by defining a loss function for the prior selection decision rules that incorporates the spatial characteristics of the wind field.

Such a loss function can be written

$$L\left(\Phi_i\left(\hat{\phi}\left(F_{\theta_j}\right)\right), F_{\Theta_t}\right)_{(x,y)} = e\left(\hat{\phi}\left(F_{\theta_j}\right)\right)_{(x,y)} * W(x,y)\delta_{ij} \tag{8}$$

where the subscript (x, y) indicates location, $*$ denotes spatial convolution, $W(x, y)$ is a weighting function, and δ_{ij} is a Dirac delta function. The loss function accounts for spatial consistency using the weighting function $W(x, y)$ which reflects the expected spatial consistency of the wind and rain field. This definition for the prior selection loss function ensures that the loss associated with candidate prior F_{θ_j} at pixel (x, y) depends on the BES Bayes risk associated with the estimator selections in the surrounding area. The Dirac delta function δ_{ij} ensures that the loss for candidate prior F_{θ_j} is zero when it is not selected using decision rule Φ_i.

Note that this loss function does not depend on the true prior F_{Θ_t}. This is by design for several reasons. First, identifying the true prior is not the objective; rather, the objective is to choose the candidate prior that results in the lowest estimation error over a region. Second, there is no way to determine the true distribution of wind and rain vectors in a WVC from a single wind and rain estimate without additional information.

V. BES With Prior Selection

This section discusses the application of both BES and prior selection to the QuikSCAT UHR product. Previously [1], BES was applied only to 25-km wind products using a single universal wind and rain prior.

A. Estimator Likelihood Function

The estimator likelihood function $f(i|\vartheta)$ for UHR BES is independent of the wind and rain prior and depends only on the performance of the estimators. For performance evaluation, we use a Monte-Carlo approach. The Monte-Carlo approach we pursue here is advantageous in that it is simple to implement and the results can be easily interpreted. This approach is identical to that pursued for the conventional-resolution estimator likelihood function except that the Monte-Carlo simulation parameters are those for UHR wind products [2], [7]. At UHR, the general structure of the estimator likelihood function is similar to that of conventional resolution; however, the higher noise level in the UHR estimates causes greater variability in the optimal estimator selections since UHR wind and rain retrieval is not as sensitive to low rain events as 25-km wind and rain estimates are.

B. Candidate Priors

The choice of candidate priors is critical to overall algorithm performance. One approach to choosing a wind and rain prior is to estimate the parameters of the wind and rain prior distribution from the data. This approach is complicated for wind and rain estimation because it is unclear which estimates (WO, SWR, or RO) should be used to estimate the prior parameters. Instead, the proposed prior selection is a two-step approach in which BES is performed with each candidate prior, then the selected estimates from each candidate prior are used to select the best prior distribution. While there are a potentially infinite number of viable candidate wind and rain distributions, with some additional information about wind and rain fields in general, a finite set of useful candidate priors may be formed.

Wind fields are relatively smooth on small-spatial scales since wind spectra are dominated by low wavelengths, although storms and weather fronts can cause higher spatial variability. Rain fields, on the other hand, are characterized by high spatial variation, particularly for convective storm systems where rain cells can be as small as 2.5 km [19]. Although rain events modify the wind field via downdrafts, the distribution of wind speeds over the surrounding region remains largely unchanged since it is dominated by the local mean wind flow. Thus, for moderate spatial scales, between 25 and 100 km, there is potentially high variability for rain, but low variability for wind. For larger spatial scales, wind fields have high variability as well. The spatial autocorrelation of wind and rain is estimated using NCEP model winds and TRMM PR-measured rains.

BES with prior selection (BES-PS) reduces the estimator selection errors associated with BES by choosing the appropriate wind and rain prior distribution. BES has the greatest limitations when the mean wind speed over a region is significantly different from the global wind prior. Useful candidate priors can have similar rain distributions with different mean wind speeds.

The candidate priors in this work are selected so that each has a different mean wind speed. To ensure that these prior distributions reasonably match observed wind and rain conditions, they are formed by shifting the mean of the global wind and rain prior density that is formed the same way as the conventional-resolution wind and rain prior in [1] but at UHR. Each candidate prior has a uniform direction distribution, identical marginal distributions for rain, and Weibull wind speed distributions with different means.

BES-PS is not particularly sensitive to the number of candidate priors considered in this paper. To balance simplicity with effectiveness, in this paper we use 12 candidate prior distributions with wind speed means and standard deviations given in Table I. Fewer priors may leave artifacts in the estimator selection fields since BES characteristics are prior dependent. Using more priors can reduce artifacts but significantly increases the required computation for prior selection. The prior distributions used here are selected to represent wind conditions from low to high wind speeds. As low wind speeds occur far more frequently, the candidate priors have mean wind speeds that are spaced more densely at low speeds. For high wind speeds, the candidate priors have slightly greater spacing to reduce the computation involved in prior selection while

TABLE I
CANDIDATE PRIOR MEAN WIND SPEEDS (μ) AND STANDARD DEVIATIONS (σ) IN m/s

μ	σ
5	2.8
7	2.9
9	3.0
11	3.1
13	3.2
15	3.3
17.5	3.3
20	3.4
22.5	3.4
25	3.5
27.5	3.5
30	3.6

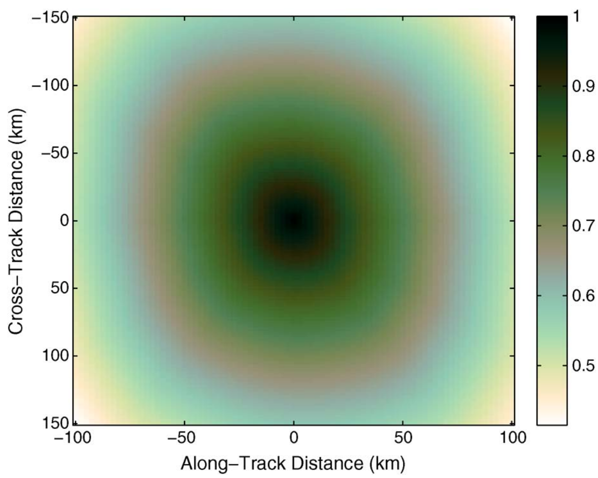

Fig. 1. Normalized wind speed 2-D autocorrelation function used as the prior selection weighting function.

maintaining coverage for higher wind speed conditions. As the candidate priors only differ in the distributions of wind speed, each candidate prior can be uniquely identified by the mean non-raining wind speed (μ in Table I) as is done in the following sections.

C. Prior Selection Weighting Function

The prior selection weighting function $W(x, y)$, shown in Fig. 1, is the 2-D autocorrelation function of the wind field computed from the UHR wind estimates. When the spatially weighted BES error is minimized by a candidate prior, it implies that the surrounding area is well-represented by the candidate prior.

Prior selection is partly motivated by the fact that rain-free high winds can be easily mistaken for lower speed rain-contaminated winds. Since rain events typically have small spatial extent, they can be differentiated from high wind events using prior selection. To differentiate such events, the size of the weighting function $W(x, y)$ must be larger than most rain events. For this paper, the weighting function size is 225 $\times$ 225 km. Prior selection is not particularly sensitive to the size of the weighting function as long as the size is suitably large. If the region of support for $W(x, y)$ is too small, prior selection has diminished performance since the weight function is not large enough to reliably detect changes in the wind speed distribution.

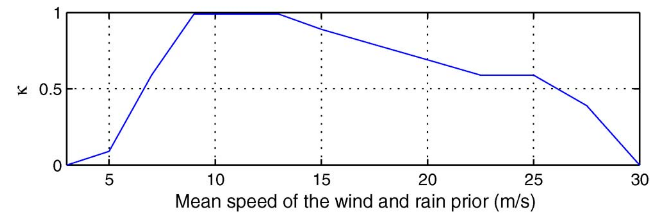

Fig. 2. Optimal values of κ for each of the candidate prior distributions for a single cross-track location determined by Monte-Carlo simulation.

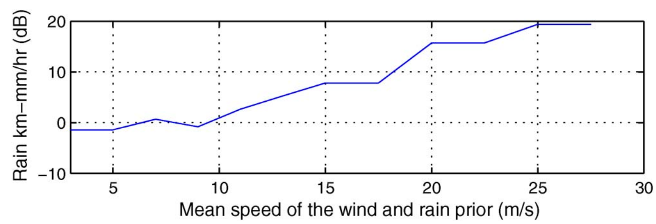

Fig. 3. Minimum acceptable rain rate (dB km-mm/hr) for the candidate prior distributions for a single cross-track location determined by Monte-Carlo simulation.

D. Optimal BES for Candidate Priors

To realize optimum estimator selection using each candidate prior distribution, the optimum value for κ in (1) must be determined for each candidate prior distribution. The optimum values of κ as in [1] are obtained for each candidate prior density using Monte-Carlo simulation for each UHR cross-track location; these values are shown in Fig. 2.

BES can be improved by choosing a minimum acceptable value for rain estimates. Based on the estimator likelihood function, there is a rain rate for each wind speed below which the SWR and RO estimators rarely have lower squared-error than the WO estimate, indicating that for low rain rates the WO estimate should always be selected. By rejecting SWR and RO estimates for rain rates below this threshold, the probability of incorrectly selecting the SWR or RO estimator can be reduced dramatically. The minimum rain threshold for each candidate prior is determined using the estimator likelihood function as the rain rate above which the probability of the SWR estimate being correct is greater than 50%. The minimum rain rate (in dB km-mm/h) for each candidate prior is shown in Fig. 3. The minimum acceptable rain rate increases with the mean speed of the wind and rain prior. For low wind speeds, wind is very susceptible to rain contamination, so only the lowest rain estimates can be neglected. For high wind speeds, the wind is relatively unaffected by rain contamination unless the rain is very high, so low to moderate rain estimates can be discarded.

The optimum values of κ are dependent on both the candidate prior and the observation geometry (cross-track swath location). As the mean wind speed of the prior increases, κ increases sharply. When κ is close to one, in effect, BES attempts to minimize the error associated with the correct estimator selection. This implies that the cost of incorrect selections is similar to that of the correct selection, indicating that the estimates have high noise levels. The decreases in κ above a mean speed of 13 m/s can be partly explained by the minimum acceptable rain threshold.

E. Distribution of Priors

Although the distribution of wind speed can be approximated with a Weibull distribution, it is not as clear how the distribution of priors, f_Θ, should be represented since we have no *a priori* information about the realization of the observed wind field. Without definitive *a priori* information, a maximum entropy argument is a logical approach to forming the distribution. Following this maximum entropy argument for this paper, we adopt a so-called "non-informative" uniform prior for the density of priors, i.e., we make no assumptions about the distribution of priors. Adopting a uniform prior is equivalent to assuming that no single wind and rain prior is favored or expected more than any other. While some high wind speeds occur less frequently, in practice a non-uniform density of priors results in poor prior selection performance and consequently poor estimator selection performance as well. Thus, a uniform prior as a density of priors is appropriate from both a theoretic maximum entropy perspective and from a practical perspective for most regions; for hurricanes, more sophisticated priors should be used [4], [20].

VI. Noise Reduction for Estimator Selections

BES is driven principally by the optimality of the selection parameters and decision rules for point-wise wind and rain estimates. Prior selection is adopted to account for some of the spatial characteristics of wind and rain, but it does not ensure spatial consistency of the selected estimates in all cases. Here, we diverge from strict point-wise estimator selection and investigate spatial consistency of the estimates as a form of noise reduction. Although the point-wise estimator selection uses a statistically optimal criteria, it is a noisy process and some incorrect decisions occur. Incorrect decisions can be apparent due to the spatial structure of the wind and rain field estimates. By exploiting some general features of wind and rain fields, selection errors can be identified and corrected.

The purpose of noise reduction step for wind and rain estimates with prior selection is twofold. First, the BES is subject to some uncertainty due to noise even when the correct prior is used. Noise reduction aims to reduce selection errors due to high noise levels in the estimates. Second, prior selection can introduce artifacts into selected estimate fields since the characteristics of BES change depending on the prior used. Noise reduction also aims to reduce these artifacts, making the selected wind and rain fields spatially consistent. To achieve the objectives of noise reduction, we exploit the spatial consistency of wind and rain fields to both reduce noise and create spatially consistent fields of selected estimates.

A. Estimator Selection Noise Reduction

Wind estimates are inherently noisy, and BES-PS error can increase the noise. Typically estimator selection errors occur for wind and rain events for which no single estimator (WO, SWR, or RO) is clearly superior. These types of rain events can be generally grouped into several populations: low-rain, high-rain, and high-speed.

Low-rain selection errors typically occur as selection errors between the WO and SWR estimates. Selection errors with low rains typically occur because the WO estimator is selected instead of SWR, when the SWR estimate is superior. High-speed errors occur when the wind speed is quite high and the rain is insignificant. For these cases, the WO estimate should be selected. High-rain errors occur when the WO estimate is incorrectly selected because the SWR rain rate is high. To identify areas where these types of estimator selection errors are likely, a filtered field of wind estimates is formed.

Wiener filtering produces estimates that optimally minimize the mean-square error given a field of noisy estimates and the autocorrelation function of the signal [21]. Wiener-filtered signal estimates can reduce noise and help identify areas where it is likely that the estimator selections are incorrect.

The optimal filter coefficients for noisy observations are given by the Wiener–Hopf equations as

$$\left[\mathbf{R}_x + \sigma_v^2 \mathbf{I}\right] \mathbf{w} = \mathbf{r}_x \tag{9}$$

where $\mathbf{R}_x$ is a Hermitian Toeplitz matrix of autocorrelation values for the desired signal, σ_v^2 is the variance of the noise, $\mathbf{w}$ is a vector of the optimal filter weights, and $\mathbf{r}_x$ is a vector of autocorrelation values [21]. Although Wiener filters are typically defined for vectors, they can be extended to 2-D spatial filtering.

Since the autocorrelation can be estimated for both wind and rain, the optimal filter coefficients, given estimates of the wind and rain estimation noise power σ_v^2, can be determined using the Wiener–Hopf equations. The noise power for wind and rain can be approximated as the mean-squared error of the wind and rain estimates over a large data set. For this study, the mean-squared wind and rain error is the error between the ideal estimator selections and NCEP winds and TRMM PR-measured rains. The mean-squared error is calculated from a data set of 17 million co-located TRMM PR and QuikSCAT observations from 1999 and 2000. For this data set the mean-squared wind error is 7.83 $(\mathrm{m/s})^2$ and the mean-squared rain error is 73.3 $(\mathrm{km\text{-}mm/hr})^2$, indicating that the best-case wind estimates have a standard deviation of 2.79 m/s and the best-case rain estimates have a standard deviation of 8.56 km-mm/h.

Equation (9) assumes that the noise is uncorrelated. Strictly speaking, for UHR QuikSCAT data, the observation noise is correlated between WVCs due to the resolution enhancement processing of the σ^o values. Furthermore, the noise is a function of the QuikSCAT swath location. The spatial correlation of the noise is due to the nature of the overlapping slice measurements used in resolution enhancement. Although the resolution enhancement causes correlation of the noise realizations, the extent of the correlation is limited by the spatial extent of the slice spatial response function. The noise is thus only correlated for a maximum extent of 30 km using UHR. Although the QuikSCAT observation noise has some correlation, approximating the noise as uncorrelated is reasonable since the noise level of the estimates is quite high compared to the level of correlation. We thus treat the noise realizations as uncorrelated.

The Wiener filter coefficients give the minimum-squared-error wind and rain given the observations over a region. The Wiener filtered wind and rain fields form smoothed wind and rain fields with reduced noise. The smoothed estimates of the wind and rain fields are useful in identifying and correcting missed rain selections. Missed rain selections occur as two types of errors: WO selections when the SWR estimate should be selected, and WO selections when the RO estimate should be selected. Each type of error is sufficiently different that they must be treated separately.

For WO selections when the SWR estimate is best, the selection errors are recognizable as holes or gaps in larger rain events. These errors can be identified by filtering the selected wind and rain fields. If the Wiener-smoothed rain is greater than 1 km-mm/h and the SWR error is less than the WO error, then the WVC is reclassified as a missed SWR selection. Typically, the missed SWR selections occur for low rain rates, for which the WO and SWR estimates are similar. For these conditions, selecting the SWR estimate instead of the WO estimate has a small impact on the overall estimate error. Although the error is small, without correcting for the selection error, significant rain events may be classified as non-raining conditions.

WO estimator selections that should be RO selections can be corrected in a second step. RO missed selections often occur for moderate to high rain rates when the SWR estimator does not produce a wind and rain estimate. For raining conditions, this condition implies that the RO estimate is likely the better solution than the WO estimate. These errors can be identified as areas where the smoothed rain estimates are high enough to dominate the wind signal that might be expected from the smoothed wind speed. Unlike the missed SWR selections where the effect of using the WO estimate instead of the SWR estimate is generally small, exchanging WO and RO estimates can change the overall estimation error drastically. Thus, the RO estimate should be selected to replace the WO estimate only when the rain rate is high enough that the wind backscatter signal is entirely lost. WVCs for which the rain rate is sufficient to mask the wind signal can be identified using the Wiener-smoothed wind and rain fields. The rain rates that are high enough to mask the wind signal are those for which the estimator likelihood function for the SWR or RO estimator is greater than 0.5. This indicates that smoothed rain in the WVC is large enough to obscure the wind signal entirely and the RO estimate is likely to be a more appropriate estimator than the WO estimate.

B. *Consistency Check*

The second objective for estimator selection noise reduction is to produce spatially consistent wind and rain fields. This is particularly important for areas with high wind speeds where incorrect selections of SWR or RO estimates are common. For these cases, the poor selections can be identified since the estimated rain events do not have a physically consistent structure, as indicated by the known rain spatial correlation. To correct this type of spatial inconsistency, the noise-corrected wind and rain estimates from the previous subsection are smoothed again using the Wiener filters for wind and rain. Then, the estimators that have minimum total squared error, as defined in [1], with the smoothed wind and rain fields are selected as the correct estimates. This step can change the estimator selections adversely if the smoothing is performed on too wide a scale. To minimize over-smoothing while maintaining consistency, the smoothing filters are limited to an extent of 25 km for this step.

C. *Comments*

The estimator selection noise reduction process is not intended to change many of the estimator selections made using BES and prior selection. Rather, the noise reduction steps are designed to reduce small-scale selection errors, remove artifacts in the estimator selections due to prior selection, and increase the spatial consistency of the wind and rain estimate fields. Using noise reduction after prior selection results in small changes in the overall probability of correct estimator selection which can be significant in terms of the overall estimation error.

Although the steps taken during noise reduction are somewhat *ad-hoc* in nature, when used in conjunction with prior selection, they improve the overall estimator selection performance and aid in interpreting the estimator selections as a rain-impact flag. The improvements in estimator selection and rain-flagging performance are quantified in the following section.

VII. Results

To evaluate performance of prior selection and noise reduction on QuikSCAT wind and rain estimates, this section considers both a case study and averages over a large data set.

A. *Case Study*

To demonstrate the advantages of BES with prior selection when applied to UHR, we consider a case study of QuikSCAT rev 10 362 from June 15, 2001. The QuikSCAT wind and rain estimates, TRMM PR-measured rains, estimator selections, and prior selections are shown in Fig. 4. The top of the study area has several rain events that cause rain contamination of moderate winds. The bottom half of the study area depicts a front, while the bottom portion of the study area contains high wind speeds.

The WO wind estimates near the top of the case study are contaminated by the rain events causing spurious high wind speed estimates. Near the bottom of the study area, where there is no rain contamination of the winds, the WO estimates are very accurate.

The SWR wind speed estimates are lower than the WO estimates for nearly the whole study area. In the raining conditions at the top of the study area, SWR wind and rain estimates are accurate. However, in the high wind speeds at the bottom of the area, the SWR speeds underestimate the wind and the SWR rain estimates are too high. Selecting the SWR estimate in the high-speed area of the study area would thus be detrimental to overall performance. Although the presence of RO rain estimates is

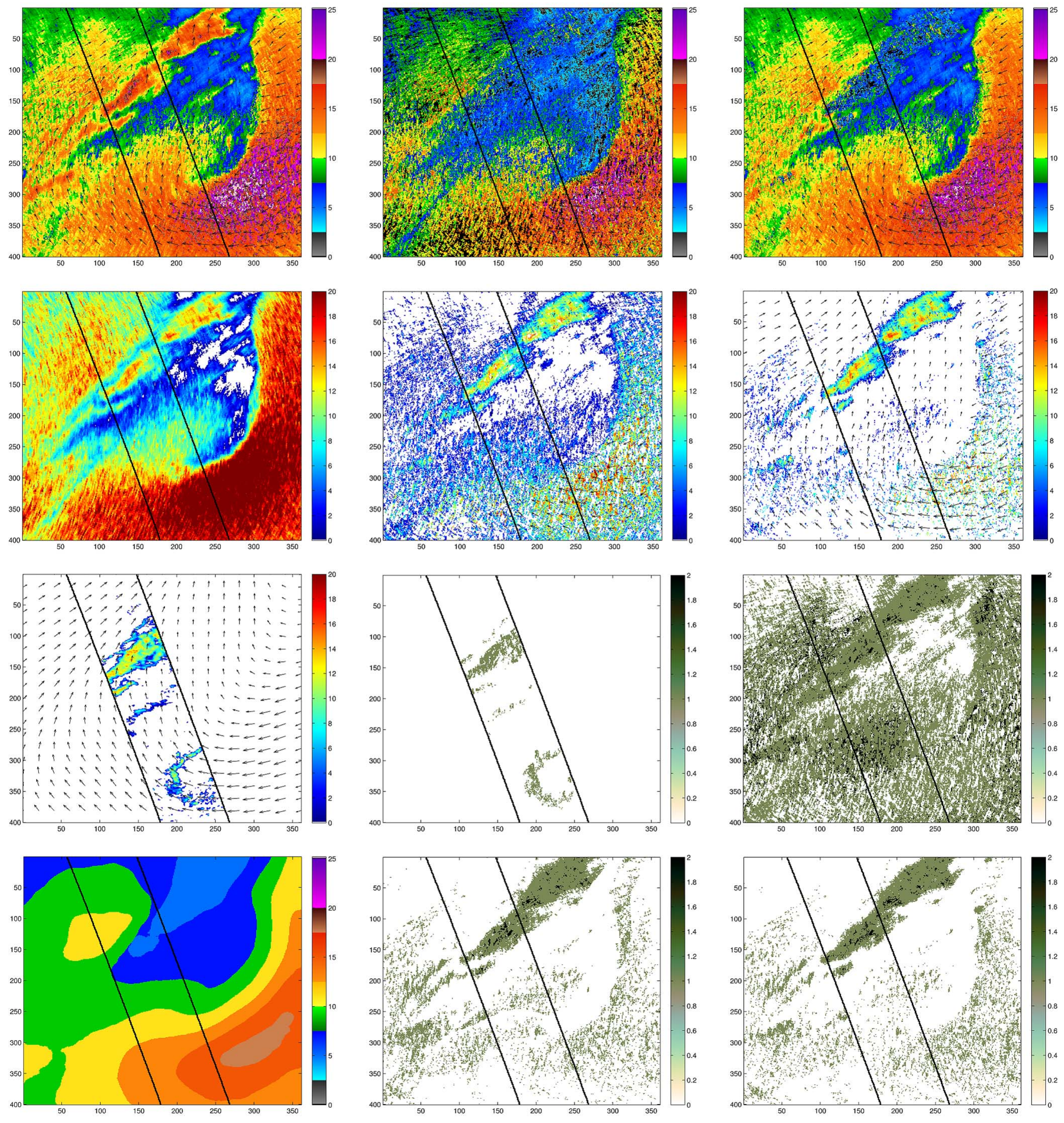

Fig. 4. Estimator results and Bayes estimator selection for QuikSCAT rev 10 362, Jun. 15, 2001. In each image, the x-axis indicates QuikSCAT along-track range in 2.5-km resolution cells and the y-axis represents cross-track range, showing a 900-by-1000-km region in the South Atlantic centered at 35.5° S 4.6° W. The top row shows wind speed estimates (m/s) with overlaid direction vectors. From left to right: WO, SWR, and BES-PS selected wind. The second row shows rain estimates (dB km-mm/h) with relevant direction vectors overlaid. From left to right: RO, SWR, and BES-PS selected rain. For comparison, the third row shows the TRMM PR-measured rain (dB km-mm/h) with the model wind vector field overlaid (left), the ideal estimator selections (center) and the Bayes estimator selections without prior selection (right). The bottom row shows the mean wind speed (m/s) for the selected prior (left), the estimator selections made with prior selection (center), and the estimator selections made with prior selection and noise reduction (right). For estimator selection fields (lower two images in the right two columns), 0 corresponds to a WO selection, 1 to a SWR, and 2 to a RO selection. Note that the Bayes selected estimates (upper two images in the right column) have less noise than the SWR estimates and have smooth wind fields in non-raining cases. Additionally the correspondence between the BES-PS and noise reduction (lower right image) and the ideal selections (middle of third row) is visually consistent, and is identical 87.1% of the time.

reasonable in the raining portions of the study area, RO rain estimates should not be used in the rain-free areas. The ideal estimator selection (shown in Fig. 4) is to use the WO estimates for the rain-free cases in the top of the image and for the high-speed cases at the bottom of the image; for the raining areas the SWR or RO estimates should be used.

For this case, BES using the global prior with a mean speed of 7 m/s correctly identifies the raining areas in the moderate wind speeds near the top of the study area. Unfortunately, BES with the global prior falsely identifies rain events and incorrectly selects the SWR and RO estimators in the high wind areas in the lower part of the study area. This is not surprising since the global prior does not model the high-speed region well. BES with the global prior results in correct estimator selections 66.9% of the time for this case.

BES-PS reduces incorrect selections in the high-speed region while maintaining correct selection in the rainy portions. Note that the mean wind speed of the selected priors resemble those of the wind estimates, albeit biased slight lower. The corresponding BES-PS selections identify the raining regions while significantly reducing the incorrect estimator selections associated with the high wind speed area. However, some selection artifacts attributable to the small number of candidate priors remain. BES-PS improves the percentage of correct estimator selections to 85.6%.

Noise reduction of the BES-PS selections further reduces the noise due to incorrect selections while improving the spatial consistency of the selected wind and rain fields. Although there are still some incorrect estimator selections in the region, noise reduction increases the percentage of correct estimator selections to 87.1%. By design, noise reduction only makes small changes that increase overall spatial consistency. These changes are most important and most effective in very high-speed and high-rain cases, which occur rarely.

For this case study, we conclude that prior selection and noise reduction increase the probability of optimal estimator selection substantially compared to conventional BES. This reduces the frequency of both false and missed rain selections while simultaneously improving the selected wind and rain fields substantially. Although this case study was selected to highlight the improvements that are possible when using prior selection and noise reduction, the performance increase can be also observed over much larger data sets that have a wide variety of wind conditions.

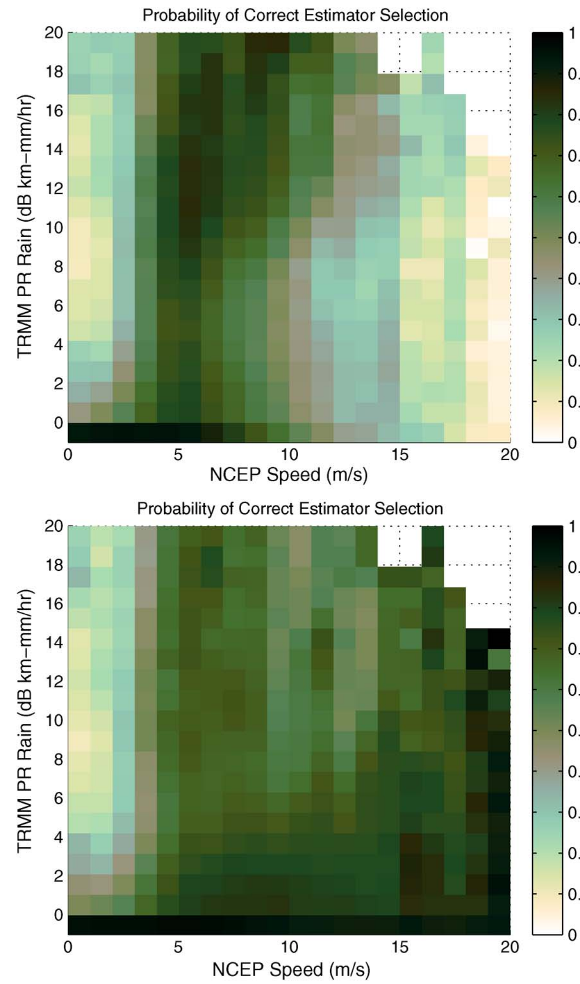

Fig. 5. Probability of optimal estimator selection for UHR wind estimates as a function of NCEP wind speed and TRMM PR-measured rain rate. Top: Bayes estimator selection using a single wind-rain prior. Bottom: Results using prior selection and noise reduction. Although using prior selection slightly reduces the probability of optimal estimator selection for low speeds and moderate to high rain rates, it increases the probability of optimal selection for moderate to high winds for all rain rates and results in lower overall error.

B. Overall Performance

To evaluate the overall performance of the prior selection technique, two separate comparisons are made: 1) How well do prior selection and noise reduction approach the optimal estimator selection? and 2) How do the selections affect the accuracy of the selected wind and rain estimates? The first question can be answered by evaluating the estimator selections and the second by evaluating the selected estimates. These evaluations are performed on a 2-year-long data set of QuikSCAT and TRMM PR co-located observations where TRMM PR-observed rain from September 1999 through August 2001, a data set of 11.2 million 2.5-km WVCs.

1) Estimator Selection Accuracy: The performance of estimator selection varies as a function of the true conditions whether prior selection and noise reduction are incorporated or not. Fig. 5 shows the probability of optimal estimator selection as defined in [1] for BES and BES-PS with noise reduction as a function of NCEP wind speeds and TRMM PR-measured rain rates. Optimal estimator selections are those which have minimum total squared-error [1] where NCEP winds and TRMM PR rains are used as the comparison truth data. When prior selection is not used, the probability of optimal estimator selection is high for wind speeds close to 5 m/s. For moderate and high wind speeds, however, the estimator selection performance is low when prior selection is not used. Although the addition of prior selection and noise reduction reduces the probability of optimal selection for some low to moderate speed cases, the majority of the time, it significantly increases the probability of optimal estimator selection. For moderate and high wind speeds, the increase in the probability of optimal estimator selection due to prior selection and noise reduction can be as much as 90%.

The improvements in the probability of optimal estimator selection incurred by adopting prior selection and noise reduction are summarized in Table II for the data set. Without prior selection, the probability of a wind and rain vector occurring for which the probability of optimal selection is below 75% is 39.4%; with prior selection, it is reduced to 9.2%; and with

TABLE II
PROBABILITY OF WIND AND RAIN VECTORS THAT HAVE ESTIMATOR SELECTION PERFORMANCE IN THE INDICATED RANGES

Probability of optimal selection range	Without prior selection	Prior selection	Prior selection and noise reduction
0 - 25%	0.8%	0.2%	0.2%
25% - 50%	10.4%	0.9%	1.0%
50% - 75%	28.2%	8.1%	7.1%
75% - 100%	60.6%	90.7%	91.7%

TABLE III
OVERALL PROBABILITY OF OPTIMAL ESTIMATOR SELECTION FOR 1 YEAR OF CO-LOCATED DATA

Method	Probability of optimal selection
Without prior selection	77.2%
Prior selection	90.5%
Prior selection and noise reduction	92.5%

noise reduction, it is reduced to 8.3%. Additionally, although Table II indicates that there are wind and rain vectors for which the probability of optimal estimator selection is below 25%, these wind and rain vectors only occur 0.2% of the time when prior selection and noise reduction are used.

The overall improvements in the probability of optimal estimator selection are shown in Table III. Adopting prior selection increases the probability of correct estimator selection by 23.3% and using noise reduction increases the probability by an additional 2%. Thus, while BES alone makes the correct selection 77.2% of the time, BES with prior selection and noise reduction makes the correct estimator selection 92.5% of the time.

2) *Accuracy of Selected Estimates:* To evaluate how estimator selection affects the overall estimation accuracy, we first define the concept of rain impact. For estimator selection, we define rain impact to indicate when a rain event causes sufficient contamination to cause the SWR or RO estimate to have lower squared-error than the WO estimate. Thus, for conditions with rain impact, the SWR or RO estimate is the optimal selection; when there is no rain impact, the WO estimate is the optimal selection. BES-PS with noise reduction results are evaluated in the following.

Without BES or BES-PS, there are essentially two alternatives for wind and rain estimation: choose to use the WO estimates and discard winds with rain impact, or reduce the effects of rain impact by choosing the SWR estimates and live with degraded wind performance in non-raining cases. BES-PS attempts to make the optimal selections, i.e., it chooses the SWR estimates when there is rain impact and chooses the WO estimates for cases without rain impact.

The effects of non-optimal estimator selections can be illustrated by analyzing the wind estimates in cases with and without rain impact. Fig. 6 shows the scatter density of the wind estimates as a function of the co-located NCEP model wind speed. The mean estimated wind speed and standard deviation are also plotted for reference in each image. For the cases with rain impact, BES-PS has the same performance as the SWR estimates, which have optimal performance for rain impact. For cases without rain impact, BES-PS ideally has the same performance as the WO estimates. For the optimal estimates, with and without rain impact, the bias between the NCEP and QuikSCAT speeds is quite low and the standard deviations are relatively small.

For rain impact conditions, although the bias and standard deviations are not as low as the optimal SWR estimates, the wind estimates from BES and prior selection have reduced bias and variability when compared with the corresponding WO estimates. Similarly, for conditions without rain impact, the BES-PS wind estimates have nearly identical performance to the WO estimates, which is much improved over the corresponding SWR estimates.

The advantages of BES-PS are also apparent by evaluating the wind speed root mean-squared (RMS) error as a function of NCEP model wind speed and TRMM PR-measured rain rate. As indicated in Fig. 7, the BES-PS wind speed RMS error is related to the minimum of the WO RMS error and the SWR RMS error. For wind-dominated conditions the BES-PS RMS error corresponds to the WO RMS error, and for substantial rain events, the BES-PS wind speed RMS error matches the SWR performance. For rain-dominated conditions in which wind speeds are low and rain rates are high, BES-PS has little effect on the wind speed RMS error as observations are dominated by rain contamination. It is interesting to note that for moderate winds and moderate rains, the wind speed RMS error for BES-PS is lower than either the WO or SWR estimates, indicating that BES-PS is more effective than either estimator individually.

The overall wind speed RMS error and bias is shown in Tables IV and V for the WO, SWR, and BES-PS, for cases with and without rain impact. For cases free of rain impact, the BES-PS have lower RMS error than the WO or SWR estimates but the estimates are slightly more biased than the WO speed estimates. For cases with rain impact, the BES-PS RMS error is substantially lower than the WO estimates and somewhat greater than the SWR estimates. The BES-PS wind speed bias for rain-impact cases is somewhat greater than the SWR estimates but substantially lower than the WO estimates.

An advantage of BES-PS is that it does not need a separate rain impact indicator. In fact, the advantages of BES-PS are clear without differentiating between cases with and without rain impact. The overall RMS error and bias for the entire data set are also shown in Tables IV and V for the WO, SWR, and BES-PS wind speed estimates. The overall RMS error and bias for BES-PS are smaller than both those of WO and SWR, indicating that the BES-PS has performance which surpasses the individual estimators. The fact that the BES-PS RMS error and bias are lower overall than both the WO and SWR estimates indicates that BES-PS yields improved overall wind and rain estimates in both raining and rain-free conditions.

The overall performance for wind direction estimation is also shown in Tables VI and VII. The wind direction performance indicates that BES-PS has lower bias overall compared to the SWR and WO estimators individually. While the BES-PS bias

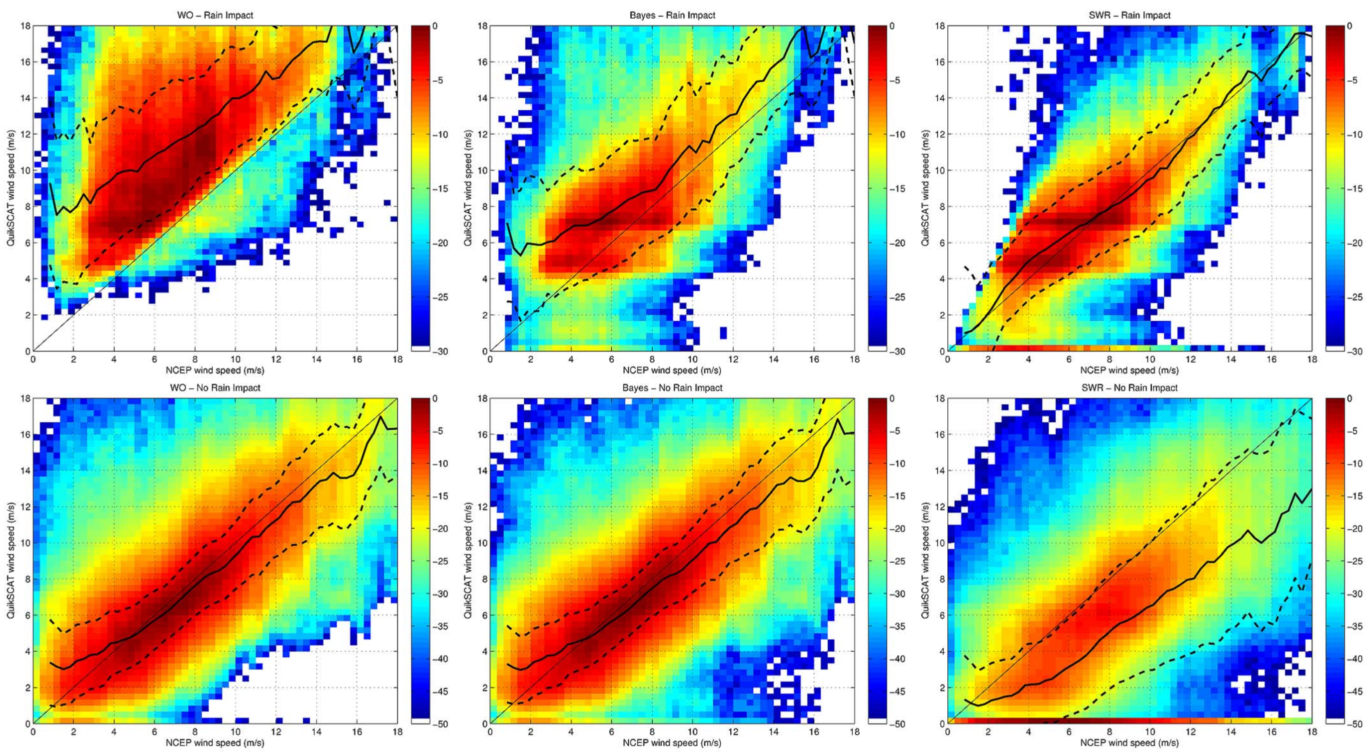

Fig. 6. Scatter densities (in dB) for NCEP and QuikSCAT wind estimates for the 2-year data set separated into during rain (top row), and rain-free (bottom row) conditions. From left to right, the columns show the WO estimates, the Bayes selected estimates, and the SWR estimates. The BES-PS selected estimates (middle column) have significantly reduced the wind bias compared to the WO estimates in rain cases for all but the lowest wind speeds, and have little bias in cases without rain impact. Ideally, the Bayes estimates (center column) have the same performance as the WO estimator in rain-free conditions (bottom-left), and the same performance as SWR in conditions with rain (top-right). Discrepancies between the BES-PS performance and the ideal performance are due to non-optimal estimator selection.

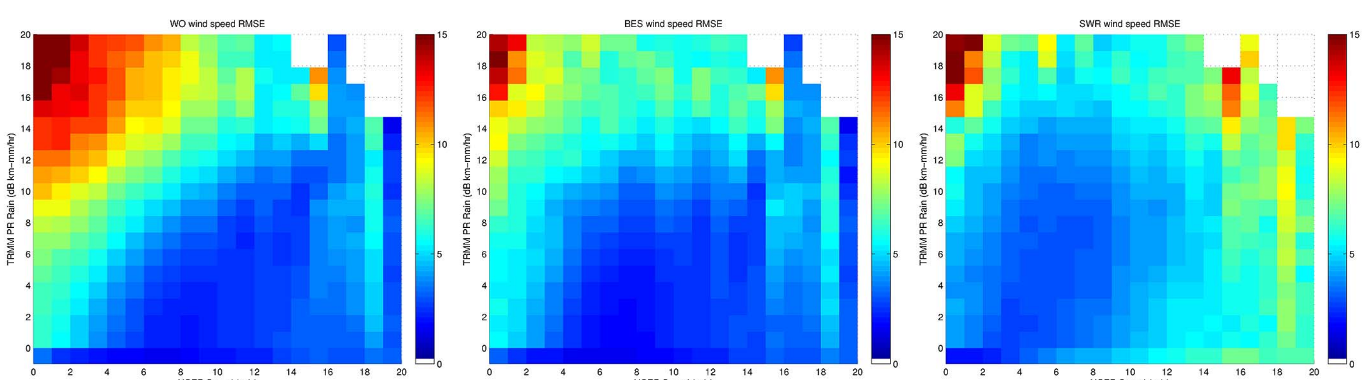

Fig. 7. Wind speed RMS error (m/s) for WO (left), SWR (right), and BES-PS (center) wind estimates as a function of NCEP estimated wind speed (m/s) and TRMM PR-measured rain rate (dB km-mm/hr). Rain-free cases are included as rain rates below 0 dB km-mm/hr. Note that the BES-PS wind estimates often have lower RMS error than either the WO or SWR estimates.

TABLE IV
WIND SPEED RMS ERROR FOR 1-YEAR DATA SET

	WO	BES-PS	SWR
Rain	5.66 m/s	3.71 m/s	2.36 m/s
Rain-free	1.91 m/s	1.88 m/s	4.21 m/s
Overall	2.51 m/s	2.15 m/s	4.14 m/s

TABLE V
WIND SPEED BIAS FOR 1-YEAR DATA SET

	WO	BES-PS	SWR
Rain	4.57 m/s	1.67 m/s	0.24 m/s
Rain-free	-0.21 m/s	-0.34 m/s	-2.80 m/s
Overall	0.19 m/s	-0.16 m/s	-2.55 m/s

has slightly larger bias than the SWR estimator during raining conditions, the BES-PS estimator has lower RMS error than the SWR estimator for all conditions. The wind direction RMS error for BES-PS is higher overall than the WO estimator; however, wind direction was not the primary focus of this paper, and it may be possible to improve wind direction estimation by utilizing techniques aimed at improving directional consistency which were developed for lower resolution wind products.

TABLE VI
WIND DIRECTION BIAS FOR 1-YEAR DATA SET

	WO	BES-PS	SWR
Rain	-1.30 deg.	-0.89 deg.	-0.52 deg.
Rain-free	-0.02 deg.	0.12 deg.	7.54 deg.
Overall	-0.10 deg.	0.06 deg.	7.06 deg.

TABLE VII
WIND DIRECTION RMS ERROR FOR 1-YEAR DATA SET

	WO	BES-PS	SWR
Rain	40.7 deg.	51.8 deg.	63.4 deg.
Rain-free	32.9 deg.	34.9 deg.	85.2 deg.
Overall	33.4 deg.	36.1 deg.	84.0 deg.

TABLE VIII
RAIN ESTIMATE BIAS FOR 1-YEAR DATA SET (km-mm/h)

	RO	BES-PS	SWR
Rain-dominated	-3.80	-16.3	-18.6
Non-zero rain	8.08	-6.71	-4.91
Overall	6.31	-8.15	-6.95

TABLE IX
RAIN ESTIMATE RMS ERROR FOR 1-YEAR DATA SET (km-mm/h)

	RO	BES-PS	SWR
Rain-dominated	33.8	38.4	39.9
Non-zero rain	29.7	18.2	16.8
Overall	30.3	22.3	21.8

Rain estimation performance of BES-PS can be evaluated similarly by comparing the RO, SWR and BES-PS performance as indicated in Tables VIII and IX. In both tables, rain estimation performance is separated into rain-dominated and non-zero-rain regimes. Rain dominated observations refer to cases where the RO estimator is the optimal choice. While the BES-PS selected rain estimates have a slightly greater bias overall, the RMS error is preferable to the RO estimator overall and the SWR during rain-dominated cases without large degradation compared to the SWR estimator overall. In the context of the WO estimator, BES-PS makes rain estimation possible while improving wind performance during all conditions.

In addition to providing wind and rain estimates with increased overall accuracy, the BES-PS estimator selections can be used as a rain-impact flag. By definition, when a SWR or RO estimate is selected, it indicates that the WO estimate has greater error due to rain contamination. Thus, for applications where rain-induced wind error levels are intolerable, the BES-PS selections can be used to identify and discard WVCs that may have degraded wind performance.

As previously noted, while large-scale motion dominates the wind field, rain-induced downdrafts can modify the local wind field, and thus the radar-observed backscatter. Our method does not specifically address this issue since we rely on the standard wind GMF which assumes neutral stability wind and fully developed wave fields. Such conditions introduce variability into the wind and rain estimates and thus the estimator selection. While it appears that at the effective resolution of the scatterometer estimates the selection errors are relatively small, their precise impact is not well understood and is a topic of future work.

VIII. SUMMARY

For UHR, BES increases the overall accuracy of the wind estimates in addition to providing estimates of the rain during significant rain events. The addition of prior selection to BES generalizes the technique to a much wider variety of wind conditions and substantially improves the estimator selection performance. The improved estimator selection performance indicates that BES-PS approaches optimal estimator selection for many wind conditions. The results indicate that QuikSCAT is capable of estimating the wind vector, the wind vector and rain, or the rain without additional sources of information. The resulting global wind and rain data set can be used in a wide variety of applications that range from small-scale studies of tropical cyclones and other storms to global climate studies.

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Michael P. Owen received the B.S. and Ph.D. degrees in electrical engineering from Brigham Young University, Provo, UT, in 2007 and September 2010 after completing his dissertation titled *Scatterometer Contamination Mitigation*.

He worked in the Microwave Earth Remote Sensing Laboratory from 2006 to 2010, working toward rain backscatter modeling, simultaneous wind and rain estimation, and Bayesian decision theory applications to ultra-high resolution scatterometry. Currently, he is with the MIT Lincoln Laboratory, Lexington.

David G. Long (S'80–SM'98–F'08) received the Ph.D. degree in electrical engineering from the University of Southern California, Los Angeles, in 1989.

From 1983 to 1990, he worked for NASA's Jet Propulsion Laboratory (JPL), Pasadena, CA, where he developed advanced radar remote sensing systems. While at JPL, he was the Project Engineer on the NASA Scatterometer (NSCAT) project which flew from 1996 to 1997. He also managed the SCANSCAT project, the precursor to SeaWinds which was launched in 1999 on QuikSCAT and 2002 on ADEOS-II. Currently, he is a Professor in the Electrical and Computer Engineering Department at Brigham Young University (BYU), Provo, UT, where he teaches upper division and graduate courses in communications, microwave remote sensing, radar, and signal processing and is the director of the BYU Center for Remote Sensing. He is the Principle Investigator on several NASA-sponsored research projects in remote sensing and has over 400 publications in various areas including signal processing, radar scatterometry, and synthetic aperature radar. His research interests include microwave remote sensing, radar theory, space-based sensing, estimation theory, signal processing, and mesoscale atmospheric dynamics.

Dr. Long has received the NASA Certificate of Recognition several times. He is an Associate Editor for IEEE GEOSCIENCE AND REMOTE SENSING LETTERS.