

Improved Wind and Rain Estimation Over the Ocean Using QuikSCAT

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Abstract—The QuikSCAT scatterometer has proved to be a valuable tool in measuring the near-surface wind vector over the ocean. In raining conditions the instrument effectiveness is diminished by rain contamination of the radar return. To compensate for rain effects, two alternative estimation techniques have been proposed, simultaneous wind-rain retrieval and rain-only retrieval, which are appropriate under certain conditions. This paper proposes and outlines a Bayes estimator selection technique whereby a best estimate is selected from the simultaneous wind-rain, the rain-only and the conventional wind-only estimates.

In this paper the Bayes estimator selection technique is introduced with a quick overview of the application to QuikSCAT wind and rain estimation. Results are demonstrated at both conventional and high resolutions for a case study which indicate that wind and rain estimates after Bayes estimator selection are more consistent with measured rain and have reduced noise levels over those produced by any of the individual estimators.

I. INTRODUCTION

The QuikSCAT scatterometer was flown by NASA between July of 1999 and November of 2009 and provided a valuable global data set of ocean surface backscatter. The surface backscatter observations are used to infer the near-surface ocean wind-vector, however, the wind vector estimates may be contaminated by rainy conditions which are also radar observable. This paper introduces a method for reducing rain contamination effects by forming several wind and rain estimators. A Bayes estimator selection technique is introduced to choose from among the several estimates a single estimate which has the best performance. This paper can be viewed as an introduction to and a demonstration of the Bayes estimator selection technique as applied to QuikSCAT wind and rain estimation. Although some of the details of the application are omitted, the technique is outlined in great detail in several papers which are forthcoming.

In this paper we motivate the estimator selection problem in Sec. II and introduce the QuikSCAT scatterometer in Sec. III. Bayes estimator selection is outlined in a general sense in Sec. IV and Sec. V gives an overview of the steps required to adapt Bayes estimator selection to the QuikSCAT wind and rain estimation problem. Section VI evaluates a case study at both conventional and ultra-high resolution after which Sec. VII concludes.

II. PROBLEM FORMULATION

The QuikSCAT scatterometer was designed with the express purpose of wind estimation over the ocean. The process by

which wind is estimated in the intended way is what we term wind-only (WO) estimation in the following discussion [1]. QuikSCAT wind-only estimates have good performance in most wind conditions over the ocean; however, the estimates can be degraded by rain, proximity to land and extreme wind cases not included in the wind model. Here we discuss only rain contamination as the other contamination effects are discussed elsewhere. Rain contamination has been traditionally dealt with using one of several rain flagging techniques to identify rain contaminated winds [2]. Rain-flagged wind estimates are typically discarded.

Simultaneous wind and rain (SWR) estimation was first proposed as an alternative solution to rain-flagging of rain-contaminated winds in wind-only retrieval [3]. SWR estimation improves WO estimation by adjusting the wind-only model to account for both wind and rain effects on the radar backscatter [4], [5]. Replacing the wind model with the joint wind-rain model and estimating both the wind and the rain is what we term simultaneous wind and rain estimation [3], [5]. However, it is interesting to note that for non-raining cases SWR estimation often has degraded performance over wind-only estimation. This is in large part due to the fact that noise inherent in the backscatter measurements can sometimes cause non-raining observations to resemble a raining case. The phenomena where SWR estimation has a non-zero rain estimate yet no rain is occurring can be quite common under certain conditions.

SWR estimation in this paper is constrained to ignore solutions with zero rain rates and zero wind-speeds. This makes SWR estimation distinct from WO estimation and rain-only estimation since they cannot retrieve the same solutions. This is an appropriate constraint as the SWR model does not model zero rain or zero wind, conditions which are more appropriately addressed by the wind-only and rain-only estimators.

For rain events with high rain rates and rain-dominated backscatter [6] the wind and rain estimates for SWR estimation may also be degraded. Essentially, for certain wind speed and rain rate combinations the combined wind-rain model breaks down making the SWR estimation process inaccurate. For these rare high rain cases, rain-only estimation can provide improved results.

Rain-only (RO) estimation [7] is a departure from the intended purpose of the QuikSCAT scatterometer. In rain-only estimation, the wind model is discarded entirely and instead only the rain model is used, hence only a rain estimate is

produced. By discarding the wind model entirely, rain-only estimation makes the assumption that wind has essentially no effect on the radar backscatter. In certain cases, the estimation process is much improved by this assumption.

In summary, there are three different estimation techniques which are appropriate under different conditions. If the estimator is used outside of the intended conditions the estimator performance is degraded. Since each estimator is appropriate for specific conditions there is no single estimator which is suitable for all conditions. Instead of choosing one estimator and using it under all conditions we propose a Bayesian estimator selection method whereby the three estimators are compared and a single estimate is chosen from the various estimates for each set of measurements.

III. BACKGROUND

Before discussing estimator selection, an overview of the QuikSCAT scatterometer and wind and rain estimation is prudent. QuikSCAT measures the normalized radar backscatter, σ^o , of the Earth's surface at Ku-band. Measurements are made using a rotating dual-polarization antenna which forms a swath 1800 km wide on the surface.

For a wind vector $\mathbf{w} = [s, d]$ with wind speed s and direction d , rain rate r and a wind-rain vector $\vartheta = [\mathbf{w}, r]$ the backscatter σ^o can be modeled phenomenologically as [3], [4], [8]

$$\sigma^o = \alpha_r \sigma_w + \sigma_e \quad (1)$$

where σ_w is the backscatter from the ocean surface due to wind, $\alpha_r(r)$ is the attenuation factor of the ocean wind backscatter due to atmospheric rain and $\sigma_e(r)$ is the effective rain backscatter from both the rain volume scattering and attenuated surface scattering due to additional splashes and waves. For wind and rain retrieval the phenomenological model is calculated for each measurement using

$$\mathcal{M}_r(\vartheta, \phi, \psi, p) = \mathcal{M}(\mathbf{w}, \phi, \psi, p) \alpha_r(r, p) + \sigma_e(r, p) \quad (2)$$

where $\mathcal{M}_r(\vartheta, \phi, \psi, p)$ is the combined wind and rain effect model. Here $\mathcal{M}(\mathbf{w}, \phi, \psi, p)$ is the geophysical model function (GMF) which gives the expected wind backscatter for a wind vector \mathbf{w} given the antenna azimuth angle ϕ , incidence angle ψ and polarization p . The rain model terms $\alpha(r, p)$ and $\sigma_e(r, p)$ correspond to the phenomenological model of Eq. 1 with subscripts to indicate they are functions of rain rate r and polarization p . The rain attenuation and backscatter models are assumed to be independent of wind velocity and observation angle. Because the terms ϕ , ψ , and p are all fixed by the measurement geometry, we simplify notation in the following by dropping them and leaving only the wind and rain dependence.

Wind and rain estimation is performed using the backscatter model and the QuikSCAT measurement model. The QuikSCAT measurement model assumes a Gaussian noise distribution with mean $\mathcal{M}_r(\vartheta)$ and can be written

$$f(\sigma_i^o | \vartheta) = \frac{1}{\sqrt{2\pi\zeta}} \exp\left(-\frac{1}{2\zeta^2}(\sigma_i^o - \mathcal{M}_r(\vartheta))^2\right) \quad (3)$$

where σ_i^o is the backscatter observation for the i th measurement, ϑ is the true wind-rain vector, $\mathcal{M}_r(\vartheta)$ is the model backscatter as a function of the true wind-rain vector and ζ^2 is the model variance.

Maximum likelihood estimates for wind and rain can be formed using the log-likelihood function of the measurement model [9]. The maximum likelihood estimate is the wind-rain vector which maximizes the likelihood function and can be written

$$\hat{\vartheta} = \arg \max_{\vartheta} \sum_i \left(-\log(\sqrt{2\pi\zeta}) - \frac{1}{2\zeta^2}(\sigma_i^o - \mathcal{M}_r(\vartheta))^2 \right) \quad (4)$$

where the summation is over the vector of backscatter observations. The wind-only, rain-only and simultaneous wind-rain estimators are each calculated in the same way and differ only by the models used for the mean and variance. For wind-only estimation $\mathcal{M}_r(\vartheta) = \mathcal{M}(\mathbf{w})$, for rain only $\mathcal{M}_r(\vartheta) = \sigma_e(r)$ and for simultaneous wind and rain $\mathcal{M}_r(\vartheta)$ is used as defined in Eq. 2. The variance model for each estimator also changes accordingly.

The motivation for each estimation technique used with QuikSCAT can be readily understood from the simple phenomenological model in Eq. 1. When rain is not present, i.e. $\alpha_r = 1$ and $\sigma_e = 0$, σ^o is only a function of σ_w and wind-only estimation produces the best estimate. Similarly when σ_w is dominated by σ_e and α_r , i.e. $\alpha_r \ll 1$, rain-only estimation is superior. When the wind and rain signals are of similar magnitude it makes sense to estimate them jointly using simultaneous wind-rain estimation. In essence, depending on the true conditions, one of the estimators produces a better estimate.

A subtle difference in the several estimator models is that wind-only retrieval assumes that backscatter is unaffected by rain. This is a stronger statement than assuming simply that the rain is zero. Rather it is the assumption that the backscatter is not affected by rain. Similarly rain-only retrieval operates on the assumption that wind does not affect the backscatter. The wind-only and rain-only retrieval models are thus approximations to the true wind and rain model which are only appropriate under certain conditions.

IV. M-ARY BAYES ESTIMATOR SELECTION

M-ary Bayes estimator selection is a modification of Bayes decision theory which operates on the estimates produced by M different estimators. To introduce the method we follow the discussion and notation for Bayes decision theory outlined in [10].

The object of the Bayes decision technique is to choose a decision rule which minimizes the Bayes risk function given a realization \mathbf{x} of the observation random variable \mathbf{X} . For estimator selection, the observations are the variety of estimates and the parameter θ corresponds to true conditions. Formally, we represent the true conditions as a random variable θ with realizations ϑ . Although in the previous section ϑ referred specifically to a wind vector, here it is a random variable realization. The observations, or estimates, are realizations \mathbf{x}_i of the random variable \mathbf{X} . The decision rule $\phi_j(\mathbf{x}_1)$ is the rule

where the estimate \mathbf{x}_j is chosen as the best estimate based on the observation of the estimate being tested, \mathbf{x}_i .

We choose a loss function $L[\vartheta, \phi_j(\mathbf{x}_i)]$ which is the loss resulting from choosing the estimate \mathbf{x}_j when ϑ is the true condition. For our application we choose the loss function written as

$$L[\vartheta, \phi_j(\mathbf{x}_i)] = C(\vartheta, \mathbf{x}_j)(\kappa\delta_{ij} + \tau(1 - \delta_{ij})) \quad (5)$$

where $C(\vartheta, \mathbf{x}_j)$ is a cost function, meaning the cost of selecting \mathbf{x}_j when the decision rule is ϕ_j when ϑ is the true condition. Because the decision rule ϕ_j selects estimate \mathbf{x}_j regardless of the estimate being tested, the cost of a decision rule ϕ_j only depends on the estimate \mathbf{x}_j . The term $(\kappa\delta_{ij} + \tau(1 - \delta_{ij}))$, where κ and τ are scalar weighting factors with $\kappa + \tau = 1$ and δ_{ij} is a Kronecker delta function, allows the loss function to vary depending on which estimate is being tested. For example when $\kappa = 1$ and $\tau = 0$ the loss function for the decision rule is zero when testing other estimators. When $\kappa = 0$ and $\tau = 1$ the loss is zero when testing the selected estimator but non-zero when other estimators are tested. The κ and τ terms thus allow for the tuning of the algorithm to meet desired specifications. Additionally, the constraint that $\kappa + \tau = 1$ adds to the interpretation of the loss function by constraining the loss function to be a convex combination of the in-regime and out-of-regime error.

Using the established notation, the risk function for a decision rule and true condition, $R(\vartheta, \phi_j)$, is defined to be the expected loss of using that decision rule under those conditions and can be written

$$\begin{aligned} R(\vartheta, \phi_j) &= E_{\mathbf{X}}(L[\vartheta, \phi_j(\mathbf{x}_i)]) \\ &= \sum_{i=0}^M L[\vartheta, \phi_j(\mathbf{x}_i)] f_{\mathbf{X}|\theta}(\mathbf{x}_i|\vartheta) \\ &= \sum_{i=0}^M C(\vartheta, \mathbf{x}_j)(\kappa\delta_{ij} + \tau(1 - \delta_{ij})) f_{\mathbf{X}|\theta}(\mathbf{x}_i|\vartheta) \\ &= C(\vartheta, \mathbf{x}_j)(\tau + (\kappa - \tau)f_{\mathbf{X}|\theta}(\mathbf{x}_j|\vartheta)) \end{aligned} \quad (6)$$

where $E_{\mathbf{X}}$ denotes the expectation operator over \mathbf{X} .

The Bayes risk, $r(F_{\theta}, \phi_j)$, is the posterior expected risk function and can be written

$$\begin{aligned} r(F_{\theta}, \phi_j) &= E_{\theta}(R(\vartheta, \phi_j)) \\ &= \int_{\theta} R(\vartheta, \phi_j) f_{\theta}(\vartheta) d\vartheta \\ &= \int_{\theta} C(\vartheta, \mathbf{x}_j)(\tau + (\kappa - \tau)f_{\mathbf{X}|\theta}(\mathbf{x}_j|\vartheta)) f_{\theta}(\vartheta) d\vartheta \end{aligned} \quad (7)$$

The Bayes decision rule for estimator selection is the rule which minimizes the Bayes risk. Such a rule can be written

$$\begin{aligned} k &= \arg \min_j r(F_{\theta}, \phi_j) \\ &= \arg \min_j \int_{\theta} C(\vartheta, \mathbf{x}_j)(\tau + (\kappa - \tau)f_{\mathbf{X}|\theta}(\mathbf{x}_j|\vartheta)) f_{\theta}(\vartheta) d\vartheta \\ &= \arg \min_j \int_{\theta} C(\vartheta, \mathbf{x}_j)(1 + (\frac{\kappa}{\tau} - 1)f_{\mathbf{X}|\theta}(\mathbf{x}_j|\vartheta)) f_{\theta}(\vartheta) d\vartheta \end{aligned} \quad (8)$$

where k indicates that the estimator \mathbf{x}_k is best. Factoring τ out of the inner portion of Eq. 8 shows that the decision rule

depends only on the ratio of κ and τ . Although notationally this is not a significant departure from traditional Bayes decisions, the concept is far removed.

In Bayes decision theory decisions are based on realizations of a random variable. Bayes estimator selection makes a distinction from Bayes decisions because the random variable realizations themselves are estimates made from other random variable realizations. Essentially, the estimates themselves are treated as realizations of a random variable where the estimation process is the random variable.

In another light, Bayes estimator selection can be viewed as the decision mechanism for functions of random variable realizations whereas in the typical case the estimators are viewed as functions of random variables. With this generalized perspective, the estimates themselves can be produced with any estimation method, such as maximum likelihood or maximum a posteriori or even any function of the realizations. Additionally, Bayes estimator selection places no constraints on the dimensionality of the estimators. It is the lack of constraint on the dimensionality that makes this technique particularly useful to QuikSCAT wind and rain estimation.

A. Cost Function

With the basic framework of Bayes estimator selection established, the structure can be adapted to a specified performance criteria to make decisions between the estimators \mathbf{x}_i . To do so we must first specify the performance criteria or cost function $C(\vartheta, \mathbf{x}_i)$ which reflects the goal of choosing the best estimator given the observations.

Although there are many cost functions which could be appropriate for a particular problem, for this case we consider the squared error of the observed estimator \mathbf{x}_i given ϑ , the true conditions.

$$C(\vartheta, \mathbf{x}_i) = (\vartheta - \hat{\mathbf{x}}_i)^2 \quad (9)$$

where

$$(\vartheta - \hat{\mathbf{x}}_i)^2 \triangleq (\vartheta - \hat{\mathbf{x}}_i)^T N (\vartheta - \hat{\mathbf{x}}_i) \quad (10)$$

is a shorthand notation for the normalized squared error. In this case the matrix N is a diagonal matrix with normalization coefficients to ensure the vector components are comparable.

Inserting this definition of the cost function into Eq. 8 results in

$$r(F_{\theta}, \phi_j) = \int_{\theta} (\vartheta - \hat{\mathbf{x}}_j)^2 (\tau + (\kappa - \tau)f_{\mathbf{X}|\theta}(\mathbf{x}_j|\vartheta)) f_{\theta}(\vartheta) d\vartheta \quad (11)$$

Note that using this cost function with $\kappa = 1$ and $\tau = 0$, the Bayes risk for a given decision rule becomes the posterior expected squared error of the estimator selected by the given decision rule. When $\kappa = 1$ and $\tau = 1$ the Bayes risk becomes the prior expected squared error of the estimator. Thus the weight terms κ and τ can be understood to control the relative weights of the prior and posterior distributions in the Bayes risk.

With this mechanism for estimator selection, what remains is the determination of the conditional distribution $f_{\mathbf{X}|\theta}(\mathbf{x}_j|\vartheta)$, the prior $f_{\theta}(\vartheta)$, the normalization matrix N and the weighting factors κ and τ . Once these have been determined the selection

of a best estimator, in a prior or posterior squared error sense, is straightforward using Eqs. 11 and 8.

B. Limitations and Advantages

There are several advantages of adopting the Bayes estimator selection technique. For instance, there is no requirement on how the estimators be formed. The estimates can be maximum a posteriori estimates, or MLE estimates as long as the estimator performance prior is appropriately adjusted. This advantage allows estimates to be formed with or without priors. Further, the technique can be adapted to include multiple priors based on factors not normally included in the estimation process. For example, in the case of wind and rain estimation such priors could include regional or topographic features, wind models for hurricanes or other phenomena, latitude-dependent rain models or other models which may be appropriate to a local area. Such priors are not addressed here as they are beyond the scope of this paper.

Before applying the Bayes estimator selection technique to QuikSCAT wind and rain estimation, some discussion of the technique's limitations are in order. One limitation is that in a general case the prior densities needed to compute the posterior expected loss may be poorly defined or a good model may not exist. However, an empirical prior may be appropriate in cases where truth data can be obtained, thereby ameliorating some of the difficulty. Another major limitation is that the computation of the posterior expected loss can be computationally intense, especially when it must be computed for every estimator. Fortunately, the posterior expected loss can be tabulated for every possible estimate and the real-time computation can be significantly reduced by approximating the Bayes risk calculation with a look-up table.

V. APPLICATION TO WIND AND RAIN ESTIMATION

To illustrate the utility of the Bayes estimator selection technique, in this section we apply the technique to wind and rain estimation using the QuikSCAT scatterometer. This section discusses each element of Eq. 8 with respect to QuikSCAT wind and rain estimates so that Bayes estimator selection can be utilized to choose between the wind-only, simultaneous wind-rain and rain-only estimates.

A. Prior Distributions

Determining the prior densities used in calculating the Bayes risk is a vital part of reliable estimator selection, however we omit the details of such determination as they are a part of forthcoming publications. Thus it suffices to say that the prior density on wind and rain $f_{\theta}(\vartheta)$ can be estimated empirically based on observed distributions of wind and rain, while the conditional prior density of estimator performance $f_{\mathbf{x}|\theta}(x_j|\vartheta)$ can be calculated empirically, based on actual estimator performance. Although there are certainly other ways in which the prior densities could be generated, the priors we propose are simple to calculate and intuitively represent the desired densities.

TABLE I
NORMALIZATION MATRIX VALUES

Parameter	Maximum Value	Normalization Coefficient
Wind Speed	50 m/s	$1/50^2$
Wind Direction	360 deg	0
Rain Rate	300 km-mm/hr	$1/300^2$

B. Cost Function

The cost function is fundamental to the Bayes estimator selection as it determines what criteria the 'best' estimate corresponds to. For QuikSCAT wind and rain estimation the ideal estimator is the one which yields estimates as close to the true wind and rain as possible. While there are several different cost functions which can satisfy this criteria we choose to use a minimum squared error formulation. When the cost is minimized by the estimator selection procedure the estimate corresponds to a minimum-squared-error (MSE) estimate.

To account for the different wind speed and rain rate scales we choose to use the normalized squared error cost function defined in Eq. 10. The normalization matrix N is selected to weight the components according to the selection criteria. For wind and rain estimation we select values for the matrix N to weight each component according to the maximum retrievable value. Thus the normalization factors for wind speed and rain rate in Table I are both the reciprocal of the maximum retrievable value squared.

Additionally, although directional ambiguities exist [11] in both wind-only and simultaneous wind and rain estimates, the estimated wind speeds and rain rates for each estimator are typically quite close in magnitude for all ambiguities. Selecting a single ambiguity of the several possible solutions is a complicated process. To generally avoid the complexity of ambiguity selection when performing estimator selection we choose to ignore the direction error. Thus the normalization factor for wind direction in Table I is 0 implying that direction information is ignored when selecting an estimator.

The cost function is also very dependent on the parameters κ and τ . Finding an ideal combination is somewhat complicated but we can use a simple empirical method to determine a combination which functions well. One function of the estimator selection method is to identify areas where rain is occurring. With this in mind, we can use a probability of error formulation to select κ and τ . Since the objective is to identify raining areas we define a correct detection to be the selection of the RO or SWR estimator when the true rain rate is greater than 2 km-mm/hr. We choose 2 km-mm/hr as the threshold since it is difficult for QuikSCAT to detect rain events with lower rain rates. As in any detection problem there are two types of errors, missed detections and false alarms. As a criteria for choosing κ and τ we choose minimum probability of error.

Determining the κ and τ combination which minimizes the probability of error consists of several steps. For each combination, the Bayes risk is calculated for all wind and rain vectors for each estimator. Estimator selection is then performed on 1 year of co-located QuikSCAT and TRMM PR

observations. The probability of false alarm and probability of missed detection is calculated for the Bayes selected estimates. Finally, we select the κ and τ combination which has the minimum overall probability of error over the 1 year training data. Although the steps taken to determine the best κ and τ require a training data set, the resulting Bayes risk table, as calculated using Eq. 11, reliably identifies rain events and estimates wind in non-raining conditions.

VI. RESULTS

To illustrate the typical performance of the individual estimators as well as the overall Bayes estimator selection we consider a single case study from QuikSCAT rev 2882 on January 7, 2000. As estimator selection can be adopted at both conventional (25 km) and ultra-high resolution (2.5 km) we compare and contrast results for both resolutions.

The WO estimates are shown in the upper left image of Figs. 3 and 4. Comparing the WO estimates to the TRMM PR measured rain rates (lower left image in the same figures) illustrates the effects of rain contamination. Rain events cause an increase in the wind estimates which may range as large as 10-20 m/s. Note that for this case the true underlying wind field varies between 5 and 10 m/s. In locations where TRMM PR did not measure rain, the WO estimates are between 5 and 10 m/s corresponding to the true wind field.

The corresponding RO estimates are shown in the middle left image in Figs. 3 and 4. Again comparing the RO estimates to the TRMM PR measurements shows that the RO estimates are spatially correlated with the TRMM PR measured rain rates. However, the RO estimates where TRMM PR measured no rain are biased high and in fact the RO estimator rarely estimates a zero rain rate.

The SWR estimates overcome many of the problems associated with the WO and RO estimators but have limitations of their own. The SWR wind estimates are shown in the upper middle image of Figs. 3 and 4 and the SWR rain estimates are shown in the center image. The SWR wind estimates are visually noisier than the WO estimates particularly in areas where there is no rain. Interestingly, the opposite is true of the SWR rain estimates. The SWR rain estimates correspond fairly well with the TRMM PR measured rain estimates for moderate rain rates, however for the most extreme rain events there is no SWR rain estimate. In essence, this corresponds to the case where the rain backscatter so completely dominates the wind backscatter that a wind estimate is not possible.

The wind-rain estimates produced using the Bayes estimator selection attempt to use the best features of each estimator. The Bayes selected wind estimates are shown in the upper right image in Figs. 3 and 4, the Bayes selected rain rates are shown in the middle right image and the Bayes estimator selections are shown in the lower right image. Note the visually improved wind and rain performance. Rain estimates match the TRMM PR measured rain rates quite well. The wind field is visually smoother in non-raining conditions and the high wind speeds due to rain contamination are no longer apparent. For reference the ideal estimator selections, the selections which minimize the normalized squared-error between the estimate and the true

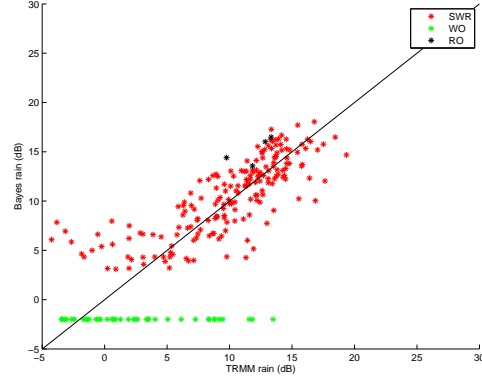


Fig. 1. Conventional resolution Bayes selected rain estimates as a function of TRMM PR measured rain rates. Both axis show rain rate in dB km-mm/hr. The red points correspond to SWR rain estimates, the black to RO estimates and the green to WO estimates of zero-rain. The one-to-one line is shown for comparison. Note that above a TRMM rain rate of 5dB the correlation is quite good.

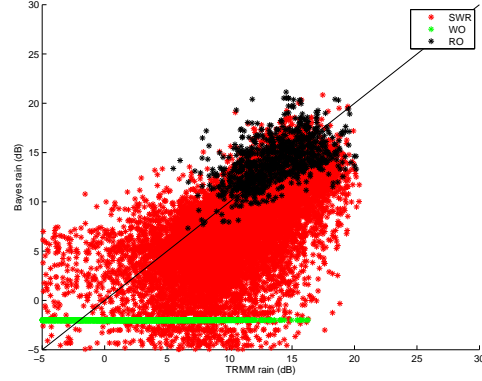


Fig. 2. Ultra-high resolution Bayes selected rain estimates as a function of TRMM PR measured rain rates. Both axis show rain rate in dB km-mm/hr. The red points correspond to SWR rain estimates, the black to RO estimates and the green to WO estimates of zero-rain. The one-to-one line is shown for comparison. Note that above a TRMM rain rate of 5dB the correlation is quite good for both the SWR and RO estimates.

values, are shown in the bottom image. Note that the Bayes estimator selections and the ideal selections are noisy but are often identical.

Although there is significant improvement gained by using the Bayes selected estimates, some drawbacks remain. For the highest rain rates, the RO estimator is selected and consequently there is no wind estimate. Similarly, the wind estimates corresponding to moderately high rain rates where the SWR is selected have wind estimates which underestimate the true wind speed. These wind under-estimates correspond to cases where the rain attenuation of the wind signal is significant enough to lower the wind estimates but not quite large enough to make wind estimation impossible.

The visual correlation between the Bayes selected rain estimates and the TRMM PR measurements is good but gives no information about the point-wise accuracy of the estimates. To evaluate the point-wise performance of the estimator selection the estimates and the TRMM measurements are shown in the scatter plots in Figs. 1 and 2. The correlation for QuikSCAT rain estimates and TRMM PR rain measurements above -5 dB

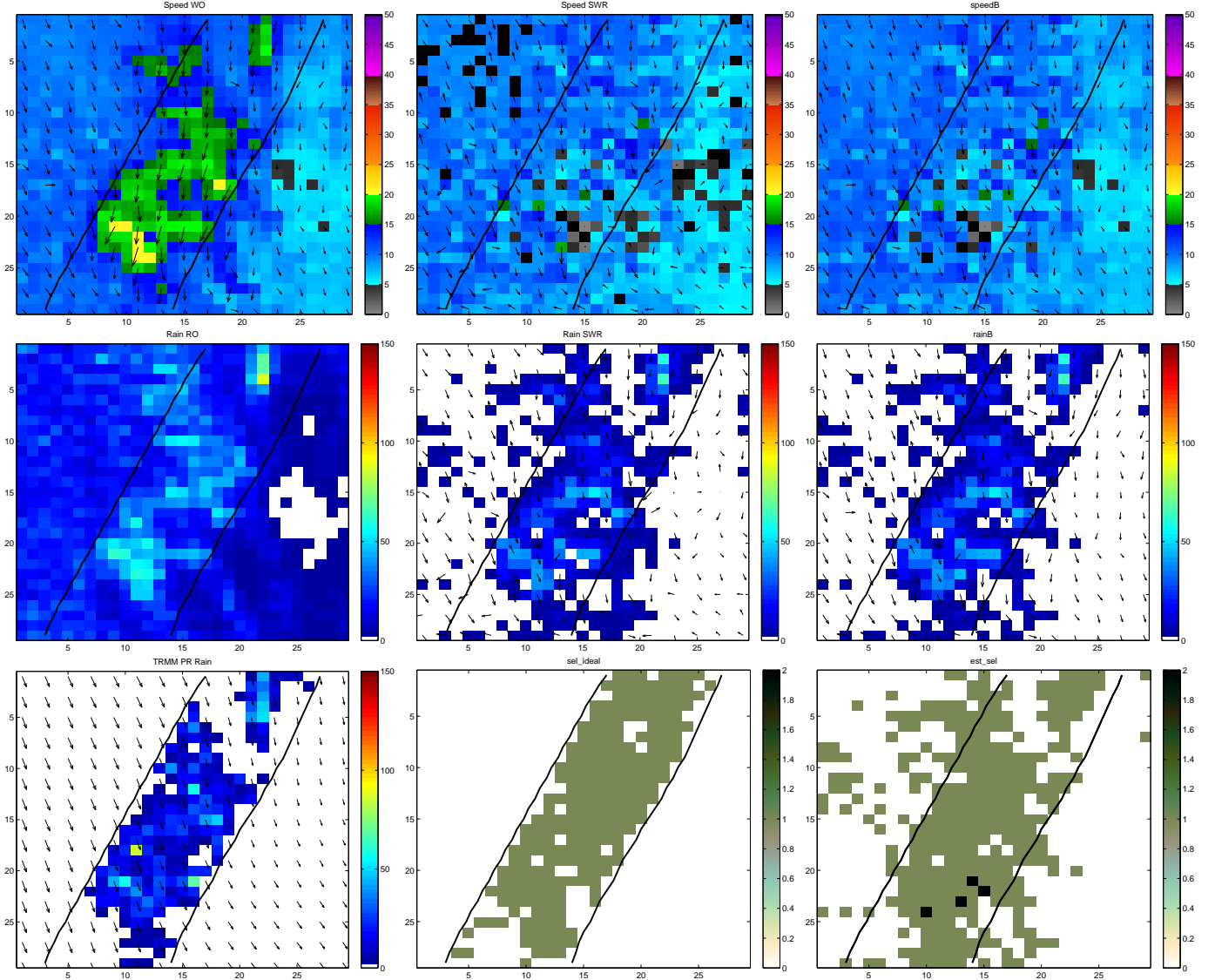


Fig. 3. Conventional resolution estimator results and Bayes estimator selection for a single case (QuikSCAT rev 2882, Jan. 7, 2000). The top row shows wind speed estimates with overlaid direction vectors. From left to right: wind-only, simultaneous wind-rain, Bayes selected wind. The middle row shows rain estimates with relevant direction vectors overlaid. From left to right: rain-only, simultaneous wind-rain, Bayes selected rain. For comparison, the bottom row shows the TRMM PR measured rain with the model wind vector field overlaid (bottom left), the ideal estimator selections (bottom center) and the Bayes estimator selections (bottom right). For estimator selections 0 corresponds to a wind-only selection, 1 to a simultaneous wind-rain, and 2 to a rain-only selection. Note that the Bayes selected estimates have visually less noise than the SWR estimates and have smooth wind fields in non-raining cases.

km-mm/hr is .76 for conventional resolution and .61 for ultra-high resolution. The lower correlation of the UHR estimates is in part due to limitations on the capability of QuikSCAT rain estimation, but is largely due to differences in observation times and the resolution enhancement of QuikSCAT data.

Comparing the conventional and ultra-high resolution results, it is apparent that although there is more noise in the ultra-high resolution estimates, there is also more spatial consistency in the wind and rain fields. This highlights the advantages of wind and rain estimation at ultra-high resolution. Although the conventional wind and rain estimates are good, the small spatial scales of rain events makes the additional spatial information found in the ultra-high resolution products very useful.

VII. CONCLUSIONS

Although we have omitted some of the details, we have demonstrated that Bayes estimator selection is both a practical and useful method for QuikSCAT wind and rain estimation. In addition to reliably identifying rain events, the Bayes selected estimates have lower squared error than those produced by any of the individual estimators. This overall improvement suggests that, if utilized properly, scatterometers like QuikSCAT can be a valuable tool in aiding understanding of wind and rain events on a global scale.

REFERENCES

- [1] D. Long, "High resolution wind retrieval from Seawinds," in *Proceedings of the International Geoscience and Remote Sensing Symposium*. Toronto, ON, Canada: IEEE, 24-28 June 2002, pp. 751-753.

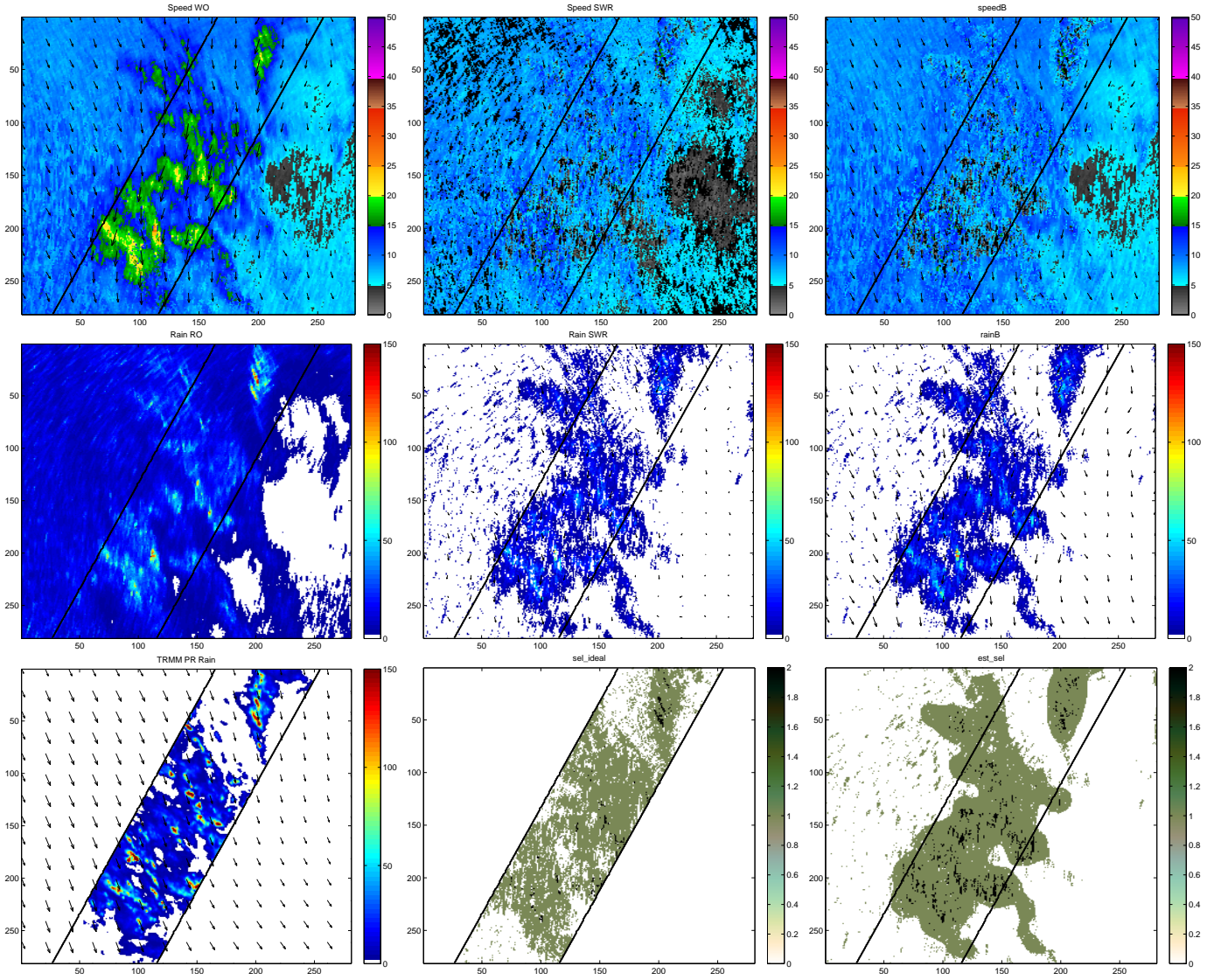


Fig. 4. Ultra-high resolution estimator results and Bayes estimator selection for a single case (QuikSCAT rev 2882, Jan. 7, 2000). The top row shows wind speed estimates with overlaid direction vectors. From left to right: wind-only, simultaneous wind-rain, Bayes selected wind. The middle row shows rain estimates with relevant direction vectors overlaid. From left to right: rain-only, simultaneous wind-rain, Bayes selected rain. For comparison, the bottom row shows the TRMM PR measured rain with the model wind vector field overlaid (bottom left), the ideal estimator selections (bottom center) and the Bayes estimator selections (bottom right). For estimator selections 0 corresponds to a wind-only selection, 1 to a simultaneous wind-rain, and 2 to a rain-only selection. Note that the Bayes selected estimates have visually less noise than the SWR estimates and have smooth wind fields in non-raining cases. Additionally the correspondence between the Bayes estimator selections and the ideal selections is visually consistent.

- [2] J. N. Huddleston and B. W. Stiles, "A multidimensional histogram rain-flagging technique for SeaWinds on QuikSCAT," in *Proc. IGARSS*, vol. 3, July 2000, pp. 1232 – 1234.
- [3] D. Draper and D. Long, "Simultaneous wind and rain retrieval using SeaWinds data," *Geoscience and Remote Sensing, IEEE Transactions on*, vol. 42, no. 7, pp. 1411–1423, 2004.
- [4] —, "Evaluating the effect of rain on SeaWinds scatterometer measurements," *J. of Geophys. Res.*, vol. 109, no. C02005, 2004.
- [5] S. N. Nielsen and D. G. Long, "A wind and rain backscatter model derived from AMSR and SeaWinds data," *Geoscience and Remote Sensing, IEEE Transactions on*, vol. 47, no. 6, pp. 1595–1606, June 2009.
- [6] B. W. Stiles and S. Yueh, "Effect of rain on ku-band scatterometer wind measurements," *Geoscience and Remote Sensing, IEEE Transactions on*, vol. 40, pp. 1973–1983, September 2002.
- [7] J. R. Allen and D. G. Long, "An analysis of SeaWinds-based rain retrieval in severe weather events," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 43, no. 12, pp. 2870–2878, 2005.
- [8] M. P. Owen and D. G. Long, "Progress toward validation of QuikSCAT ultra-high-resolution rain rates using TRMM PR," *IGARSS*, vol. 4, pp. 299–302, July 2008.
- [9] C.-Y. Chi and F. K. Li, "A comparative study of several wind estimation algorithms for spaceborne scatterometers," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 26, no. 2, March 1988.
- [10] T. K. Moon and W. C. Stirling, *Mathematical Methods and Algorithms*. Prentice Hall, 2000.
- [11] D. W. Draper and D. G. Long, "An advanced ambiguity selection algorithm for SeaWinds," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 41, no. 3, March 2003.