

Bayesian rain estimation and correction for Ku-band scatterometers

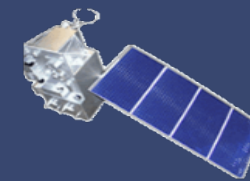
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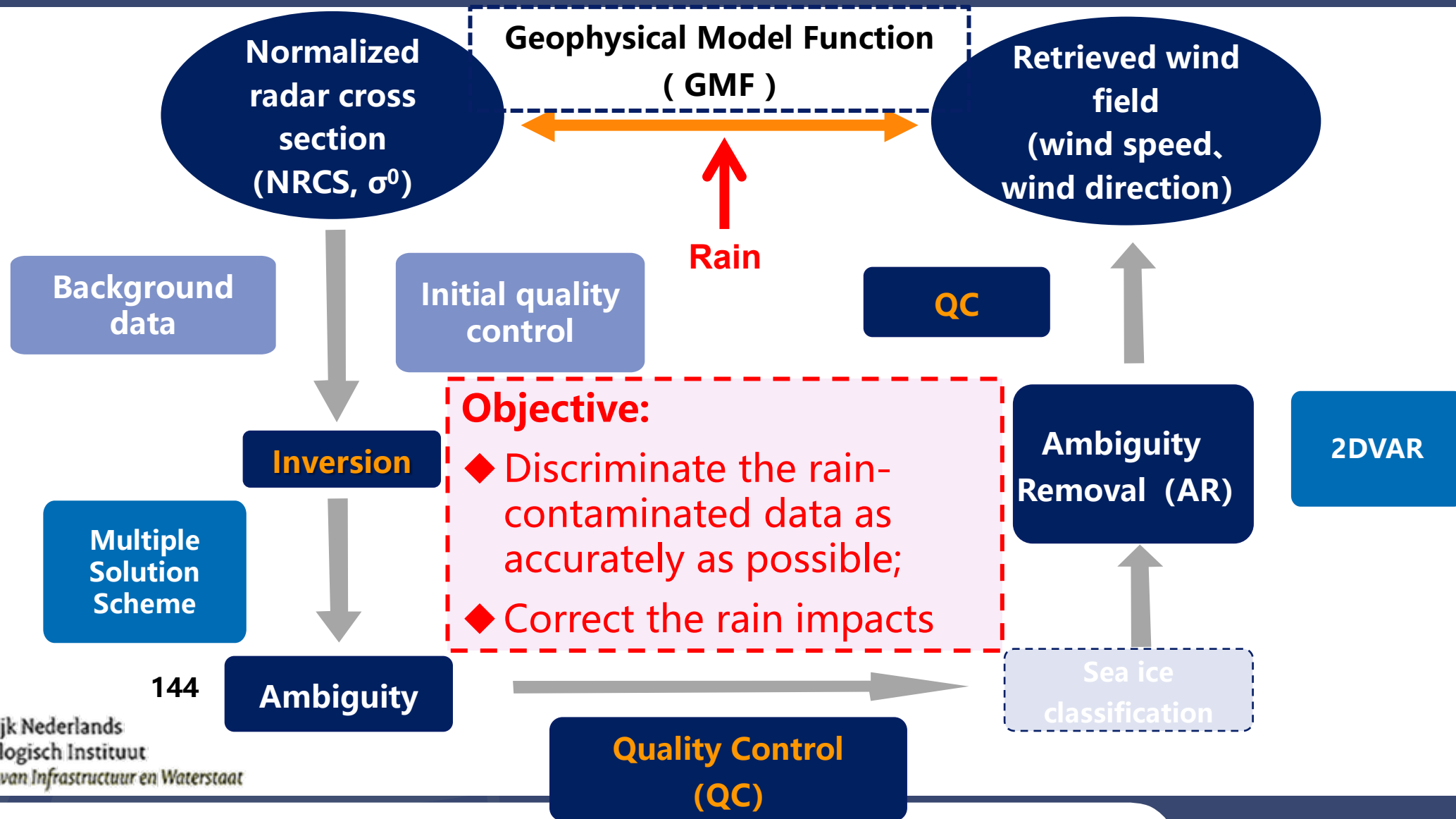
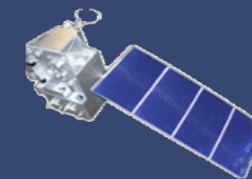
Contents

- Rain effects on HY-2C measurements
- Bayesian algorithm for rain detection
- A Conceptual rain effect model
- Summary and outlook



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- November 2020 - September 2021
- within $\pm 20^\circ$ latitude

After QC, the accepted ASCAT winds are generally not affected by rain and can be seen as the true sea surface wind field reference

Preliminary QC

Preliminary QC

Eliminate the PDF biases

Calculate the average rain rate for each WVC

$$RR_{WVC} = \frac{\sum_i RR_{i,GPM} \times A_{i,GPM}}{\sum_i A_{i,GPM}}$$

Bayesian method

SR: 2,860,974
NR: 1,694,335

ASCAT-HSCAT collocation data

HSCAT-GPM collocation data

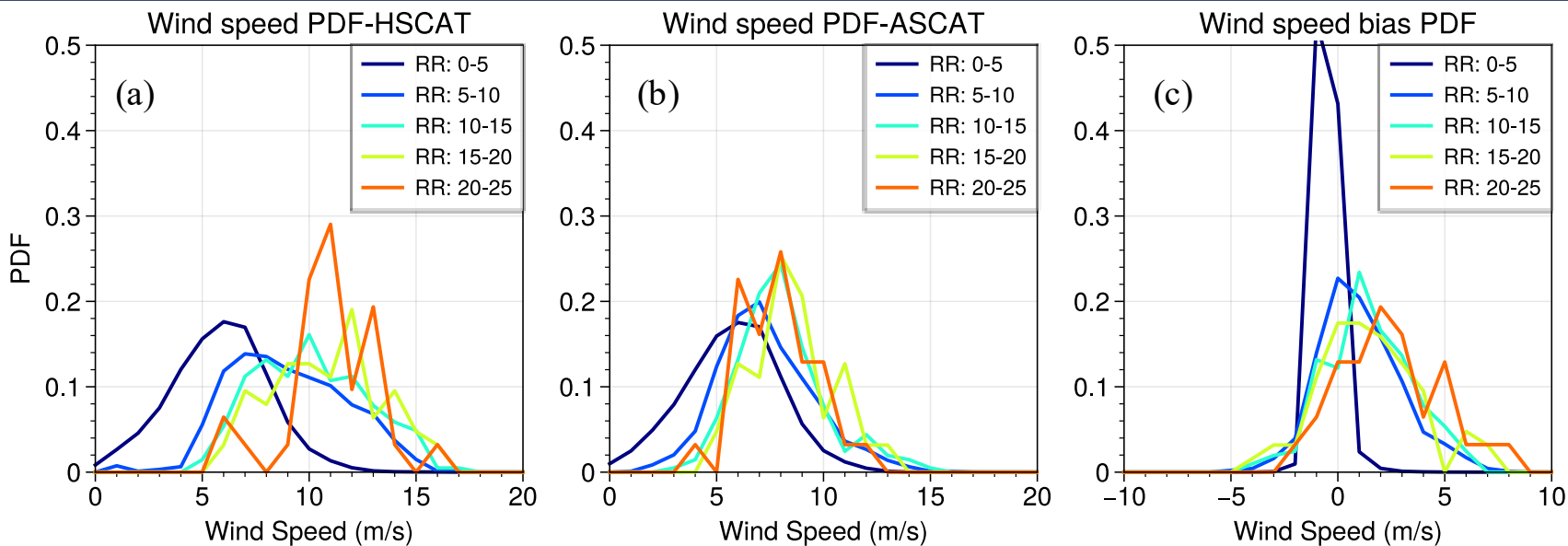
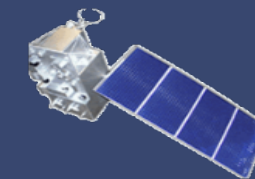
Bayesian method

SR: 3,555,645
NR: 2,038,307

ASCAT-HSCAT-GPM collocation data

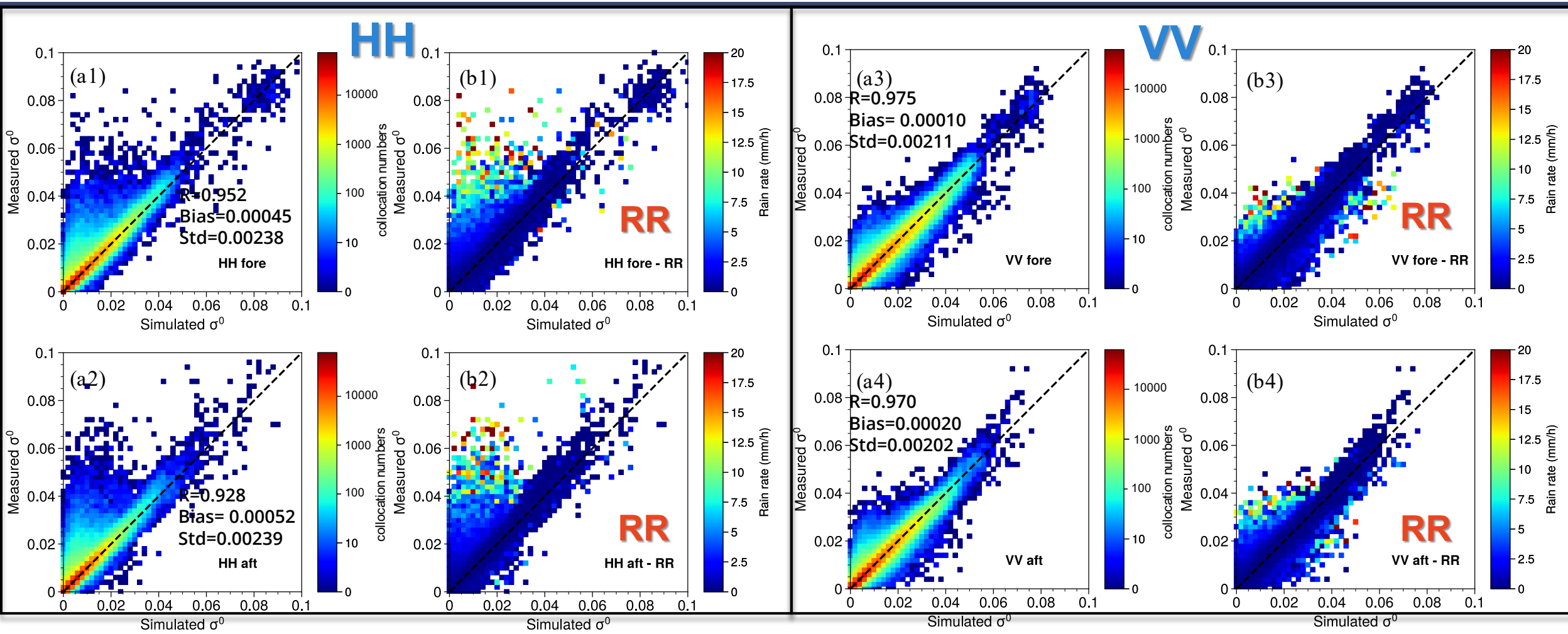
Rain model

SR: 425,363



Wind speed PDFs of HSCAT (panel (a)), ASCAT (panel (b)) and the wind speed bias (HSCAT-ASCAT) PDFs (panel (c)) under different rain rate bins.

Rain rate (mm/h)	Mean bias (m/s)	Mean standard deviation(m/s)	Mean bias (deg)	Mean standard deviation(deg)	VRMS	Collocation numbers
0-5	0.05	0.46	-0.32	25.36	1.50	424100
5-10	1.67	1.89	4.68	53.47	7.09	938
10-15	2.12	2.04	3.53	58.12	8.66	205
15-20	2.22	2.29	-1.38	49.92	8.35	63
20-25	3.15	2.41	11.67	50.15	8.87	31
25-30	3.51	3.45	11.41	41.00	8.91	10
30-35	3.06	2.36	15.51	49.34	9.77	7
35-40	2.26	1.31	6.92	40.54	7.48	5



Sample-density scatterplot of measured and simulated σ^0 (left) and the corresponding rain rates (right) for each beam. Panel (a1) and (b1) are of $\sigma_{fore_HH}^0$; panel (a2) and (b2) are of $\sigma_{aft_HH}^0$; panel (a3) and (b3) are of $\sigma_{fore_VV}^0$; panel (a4) and (b4) are of $\sigma_{aft_VV}^0$.

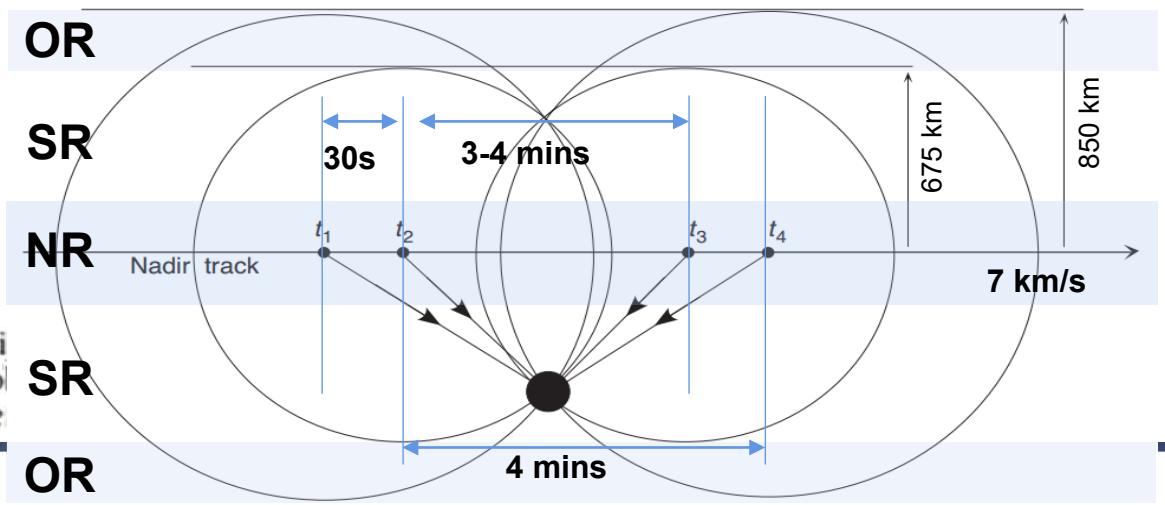
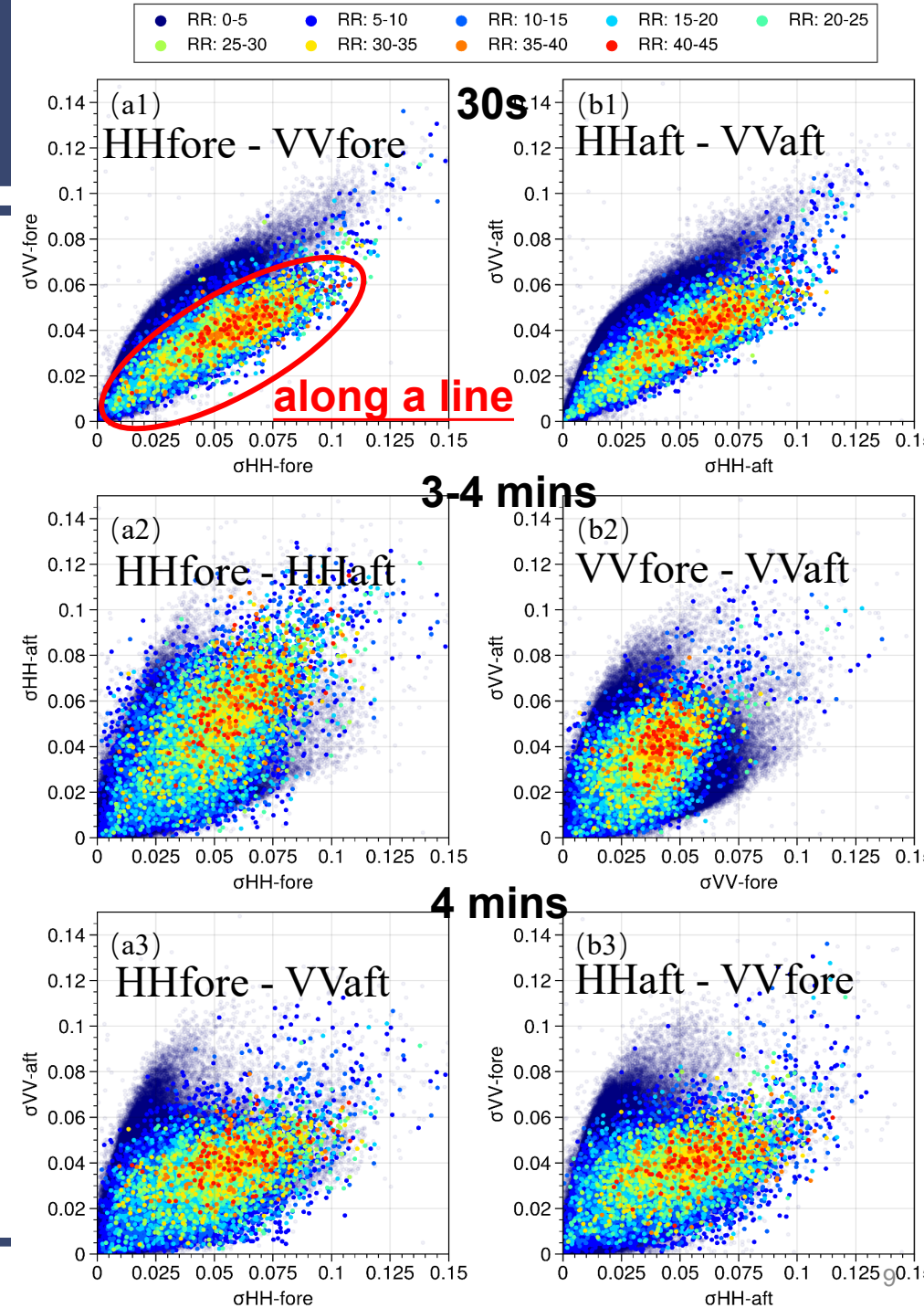


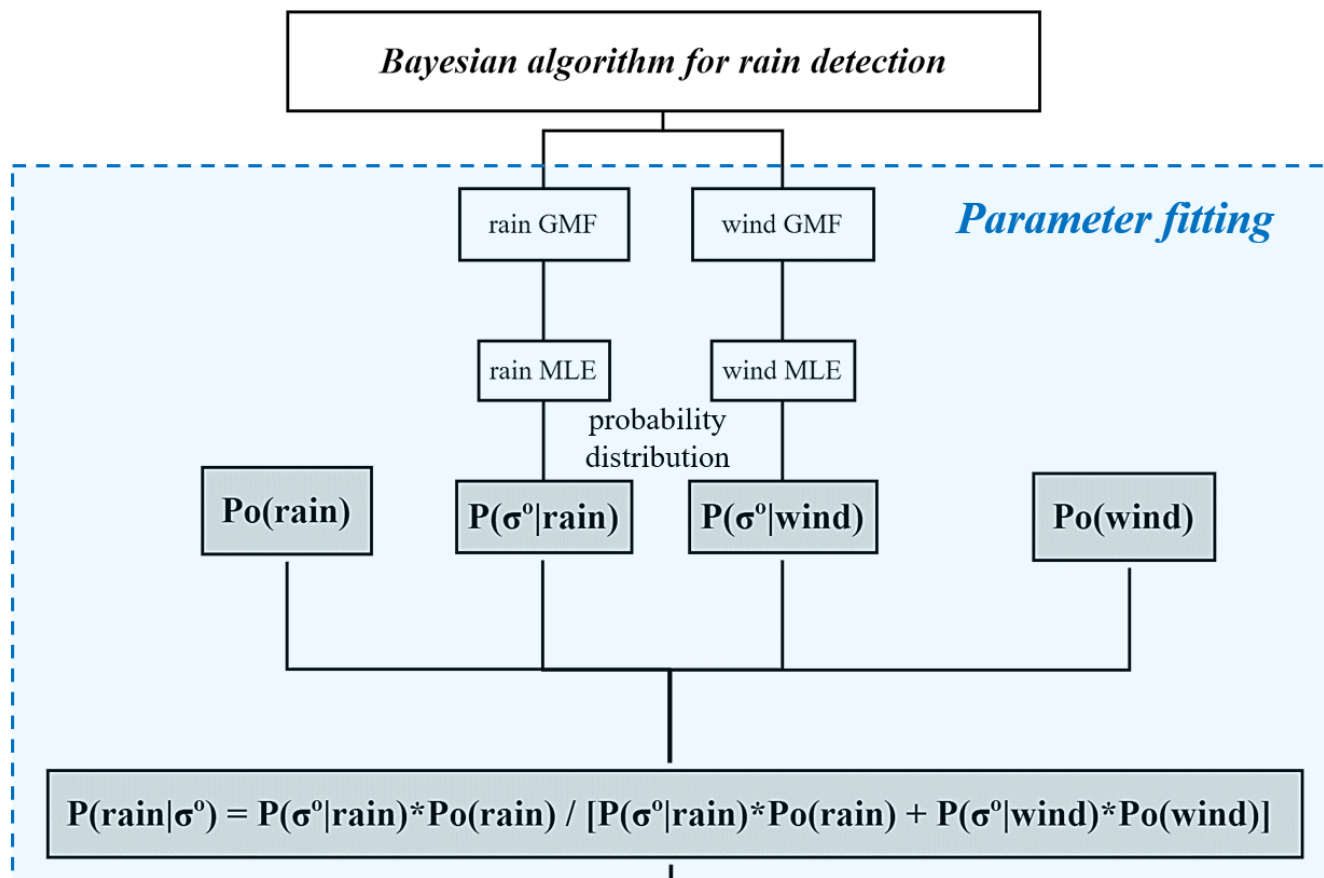
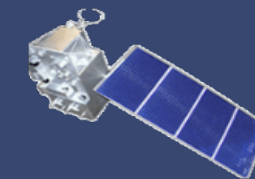
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- Rain clouds in the atmosphere and rain drops hitting the sea surface affect scatterometer received backscatter signal, which will contribute differently to different polarizations.
- Adopting the Bayesian methodology to calculate posterior rain probabilities in each WVC.
- Pure rain backscatter distributes around the linear rain GMF with Gaussian distribution in four-dimensional measurement space.

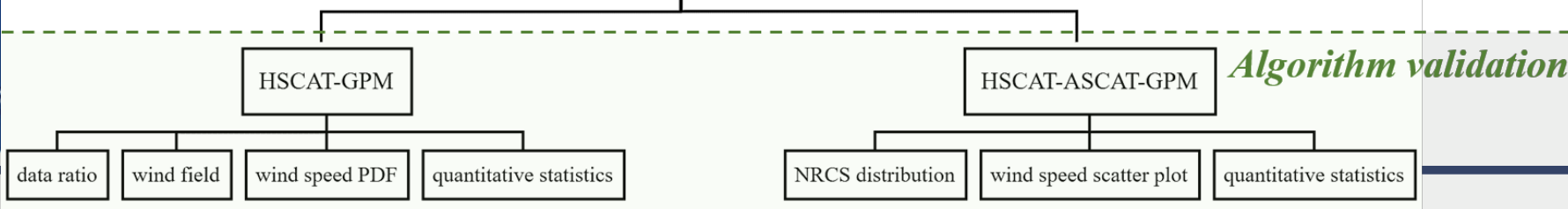




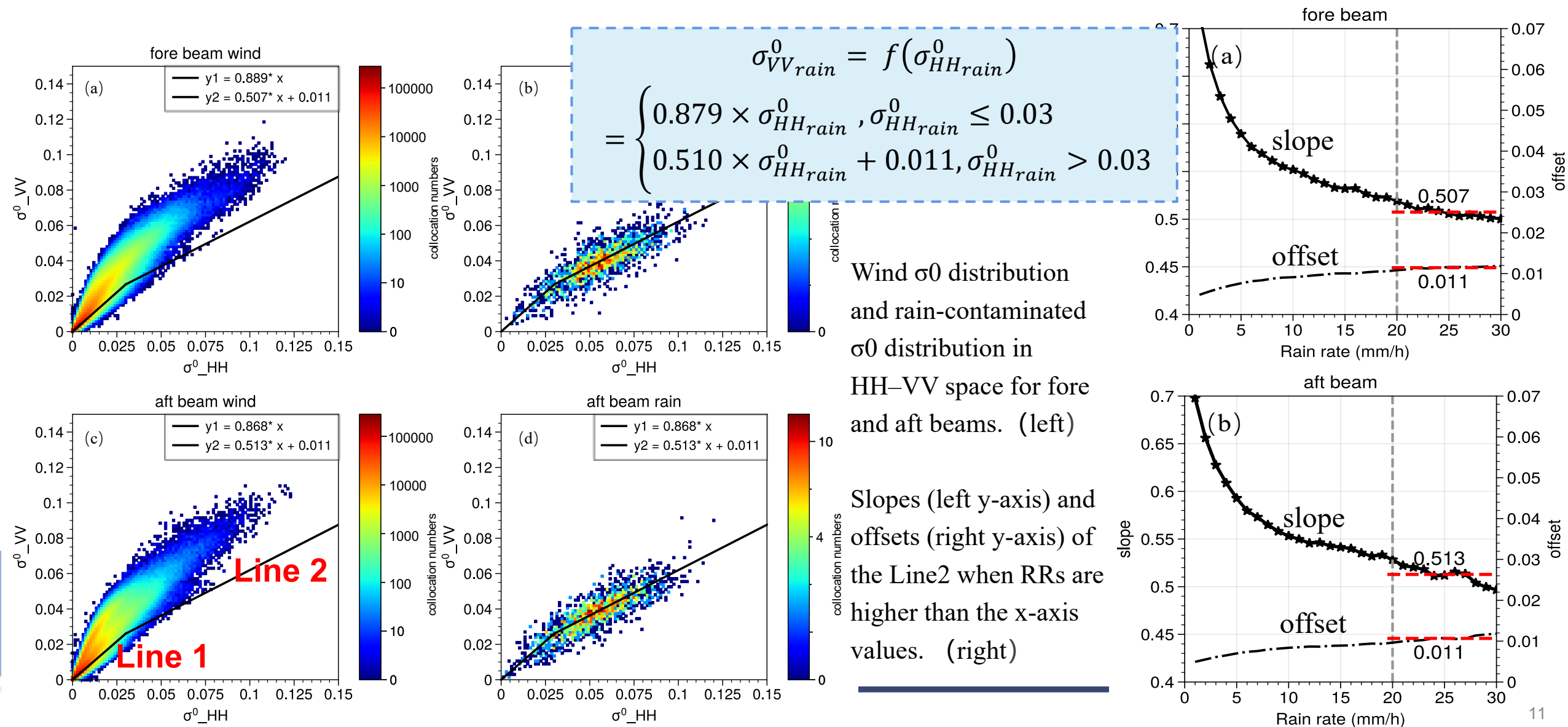
$$P(\text{rain}|\sigma^0)$$

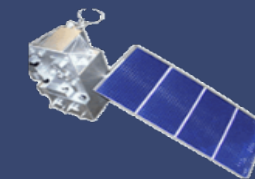
$$= \frac{P(\sigma^0|\text{rain})P_0(\text{rain})}{P(\sigma^0|\text{rain})P_0(\text{rain}) + P(\sigma^0|\text{wind})P_0(\text{wind})}$$

- $P(\text{rain}|\sigma^0)$ is the posterior probability of rain given the σ^0 measurements.
- $P(\sigma^0|\text{rain})$ is the conditional probability of σ^0 given rain, which is the rain contaminated backscatter distribution about a **rain GMF**.
- $P(\sigma^0|\text{wind})$ is the distribution of ocean backscatter measurements about the ocean wind GMF.
- $P_0(\text{rain})$ is the prior rain probability.
- In the tropical region, we assume two possible states in each WVC: rain or no rain. $P_0(\text{wind}) = 1 - P_0(\text{rain})$.



Rain GMF





the **Euclidean distance** of backscatter measurements to the modeled values by the geophysical model function



Wind MLE

$$MLE_{wind} = \frac{1}{\langle MLE \rangle} \sum_{i=1}^n \frac{(\sigma_{obs,i}^0 - \sigma_{wind,i}^0)^2}{var[\sigma_{wind,i}^0]}$$

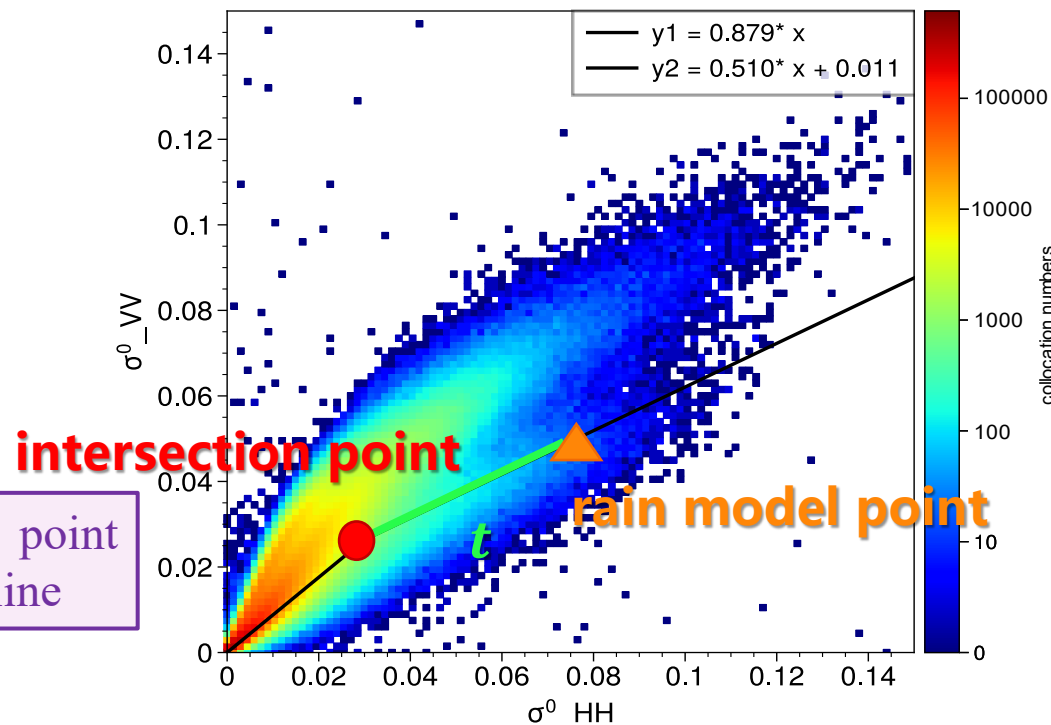


Rain MLE

$$MLE_{rain} = \sum_{i=1}^n \frac{[(\sigma_{obs,i}^0 - \sigma_{rain,i}^0)]^2}{var[\sigma_{rain,i}^0]} + \frac{[(t - average_t)]^2}{cmix \times var[t]}$$

The distribution of pure rain backscatter distances to the rain model point

The rain model point distribution along the line



- n is the number of views per cell ($n = 4$ in sweet swath).
- $\sigma_{obs,i}^0$ is the i -th observation in each WVC.
- $\sigma_{wind,i}^0$ and $\sigma_{rain,i}^0$ are the corresponding respective wind and rain GMF simulated values.
- $\langle MLE \rangle$ is the expected MLE for a WVC.

- $var[\sigma_{wind,i}^0]$ and $var[\sigma_{rain,i}^0]$ is the measurement Gaussian error variance.
- t is the distance of the corresponding rain GMF point from the line intersection point.

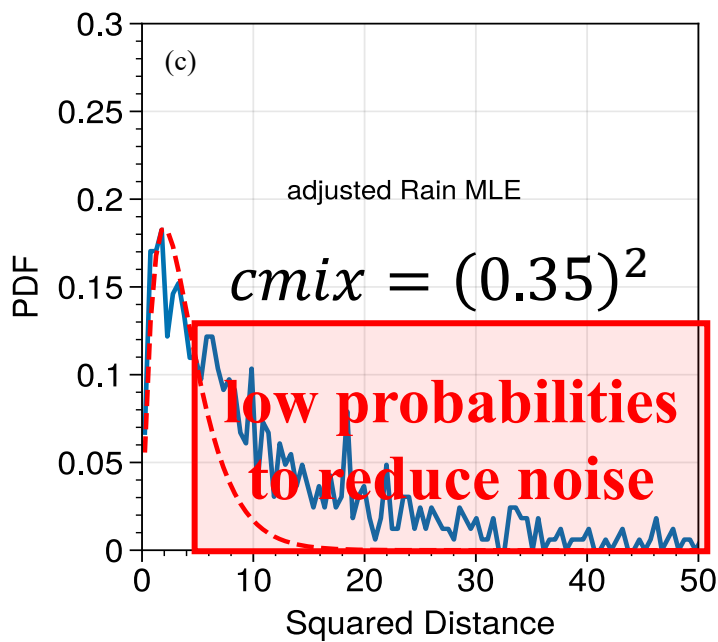
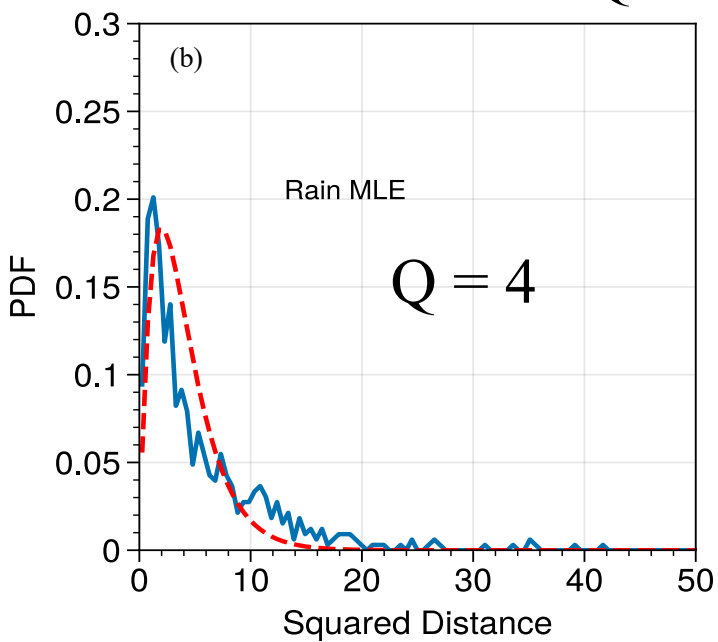
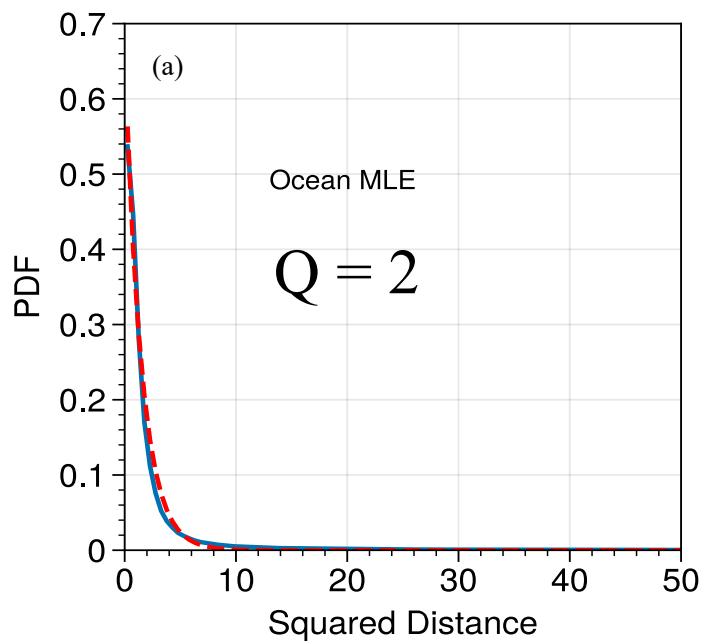
both wind/rain measurements obey a Gaussian distribution around each GMF

MLEs represent sums of squared standard Gaussian variables

obey Chi-square distribution with different degree of freedom (Q)

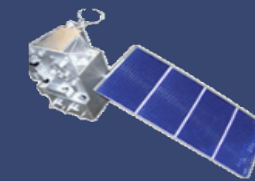
Q = 2
$$P(\sigma^0 | wind) = \frac{1}{L} e^{-MLE_{wind}/L}$$

Q = 4
$$P(\sigma^0 | rain) = \frac{MLE_{rain}}{4} \times e^{-MLE_{rain}/2}$$



Observed (blue solid lines) and expected (red dashed lines) MLE distributions to (a) ocean wind and (b) rain GMF for all collocation data when $cmix = 1$. Blue line in (c) represents the adjusted rain MLE distribution normalized to the expected MLE peak value when $cmix = (0.35)^2$.





$$p(\text{rain} | \sigma^0) = \frac{p(\sigma^0 | \text{rain})P_0(\text{rain})}{p(\sigma^0 | \text{rain})P_0(\text{rain}) + p(\sigma^0 | \text{wind})P_0(\text{wind})}$$

$$\sigma_{VV\text{rain}}^0 = f(\sigma_{HH\text{rain}}^0) = \begin{cases} 0.885 \times \sigma_{HH\text{rain}}^0, & \sigma_{HH\text{rain}}^0 \leq 0.03 \\ 0.505 \times \sigma_{HH\text{rain}}^0 + 0.011, & \sigma_{HH\text{rain}}^0 > 0.03 \end{cases}$$

$$MLE_{\text{wind}} = \frac{1}{\langle MLE \rangle} \sum_{i=1}^n \frac{(\sigma_{\text{obs},i}^0 - \sigma_{\text{wind},i}^0)^2}{\text{var}[\sigma_{\text{wind},i}^0]}$$

$$p(\sigma^0 | \text{wind}) = \frac{1}{L} e^{-MLE_{\text{wind}}/L}, \quad L = 1.5$$

$$P_0(\text{wind}) = 1 - P_0(\text{rain})$$

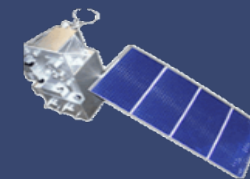
$$MLE_{\text{rain}} = \sum_{i=1}^n \frac{[(\sigma_{\text{obs},i}^0 - \sigma_{\text{rain},i}^0)]^2}{\text{var}[\sigma_{\text{rain},i}^0]} + \frac{[(t - \text{average}_t)]^2}{\text{cmix} \times \text{var}[t]}$$

$$P(\sigma^0 | \text{rain}) = \frac{MLE_{\text{rain}}}{4} \times e^{-MLE_{\text{rain}}/2}$$

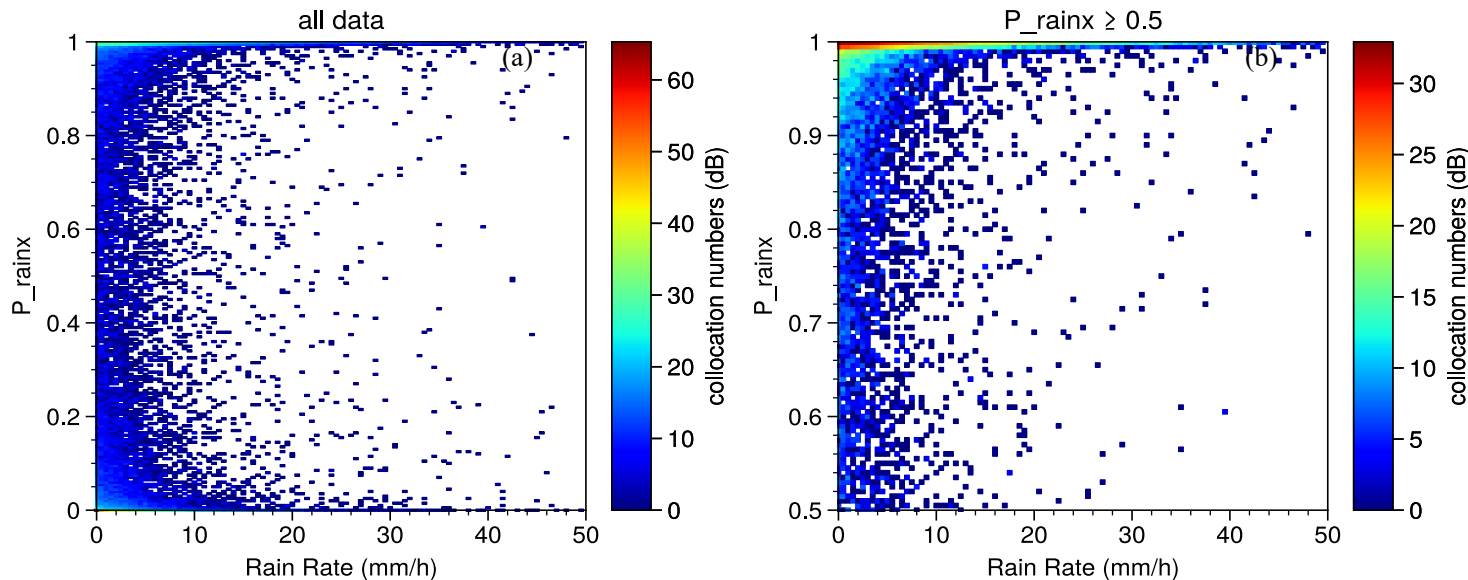
$$P_0(\text{rain}) = 0.0002$$

Rain events can be assumed to occur randomly without favoring specific locations or times.

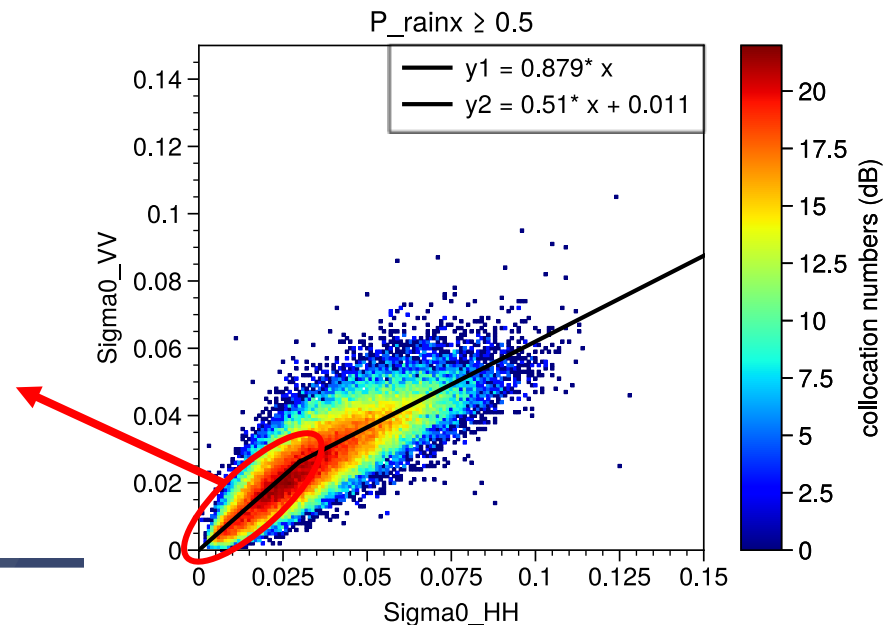


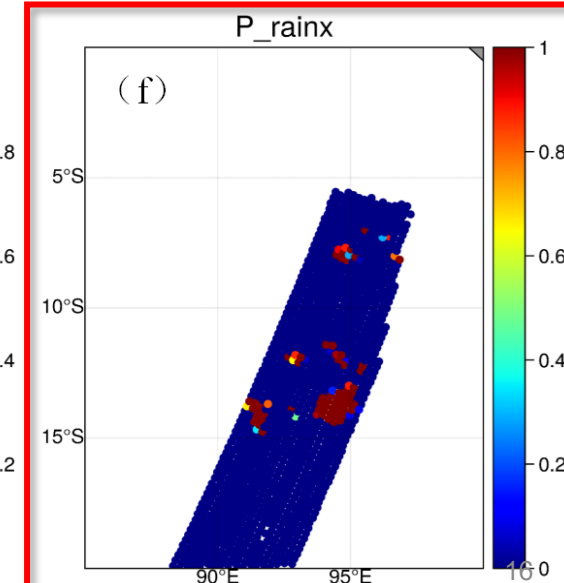
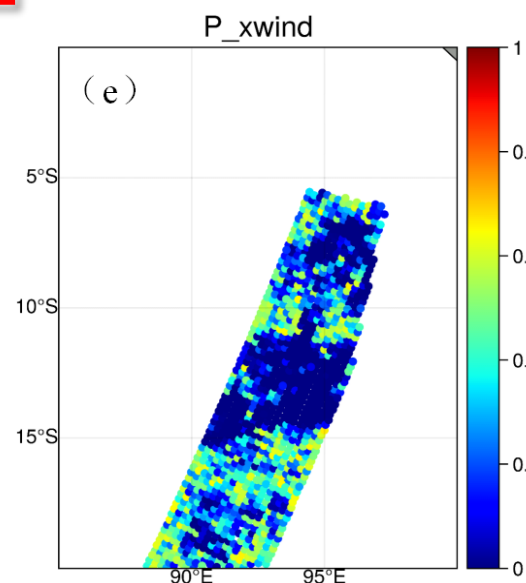
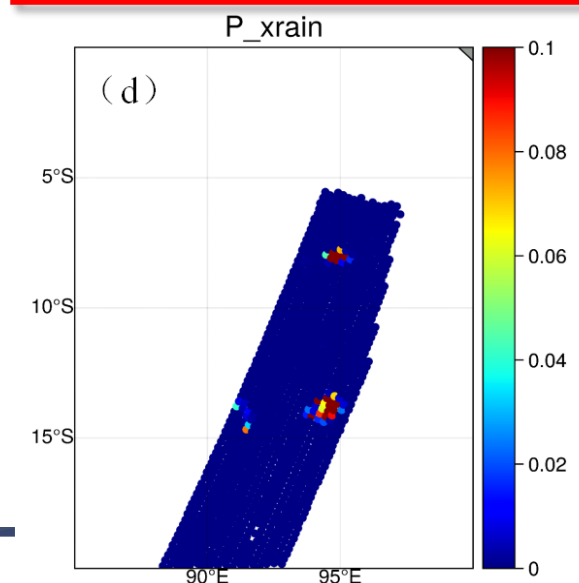
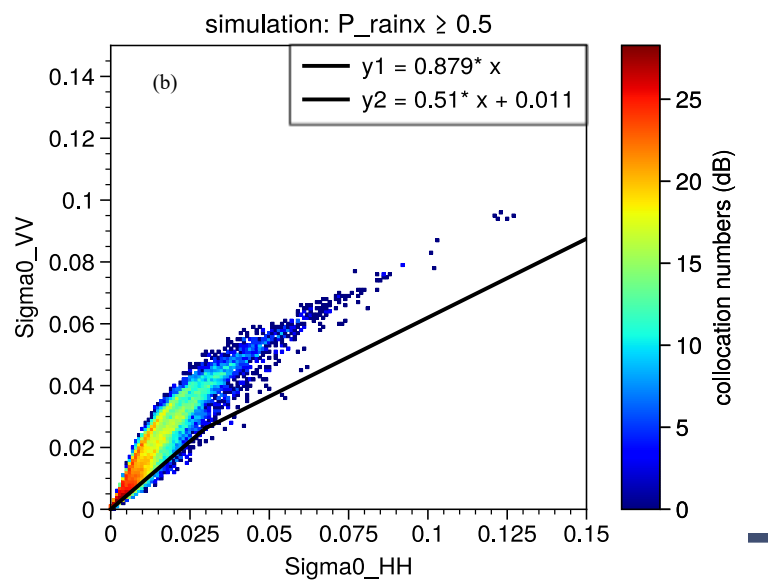
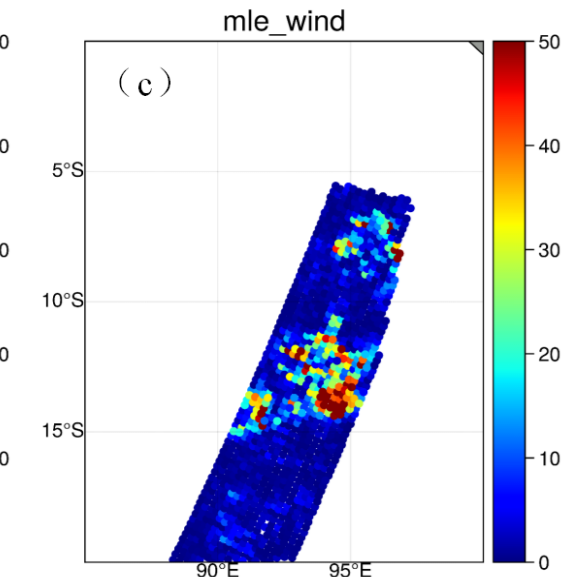
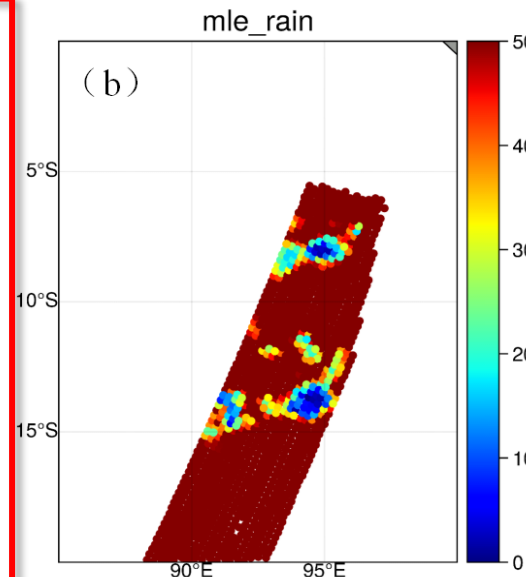
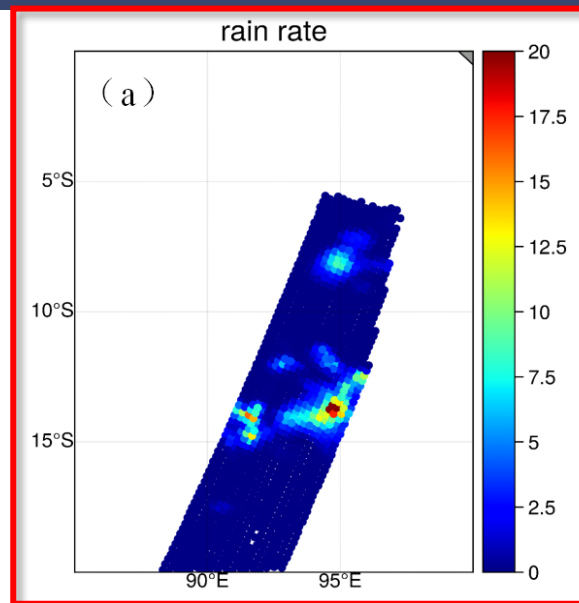
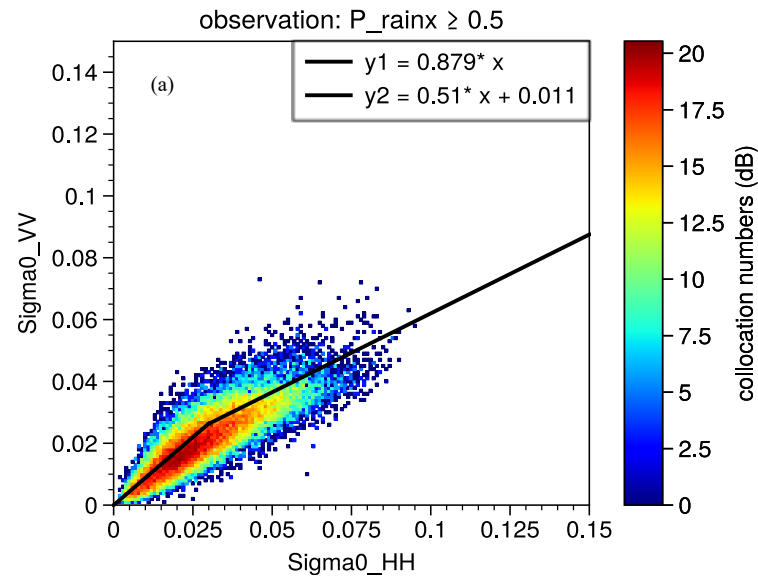


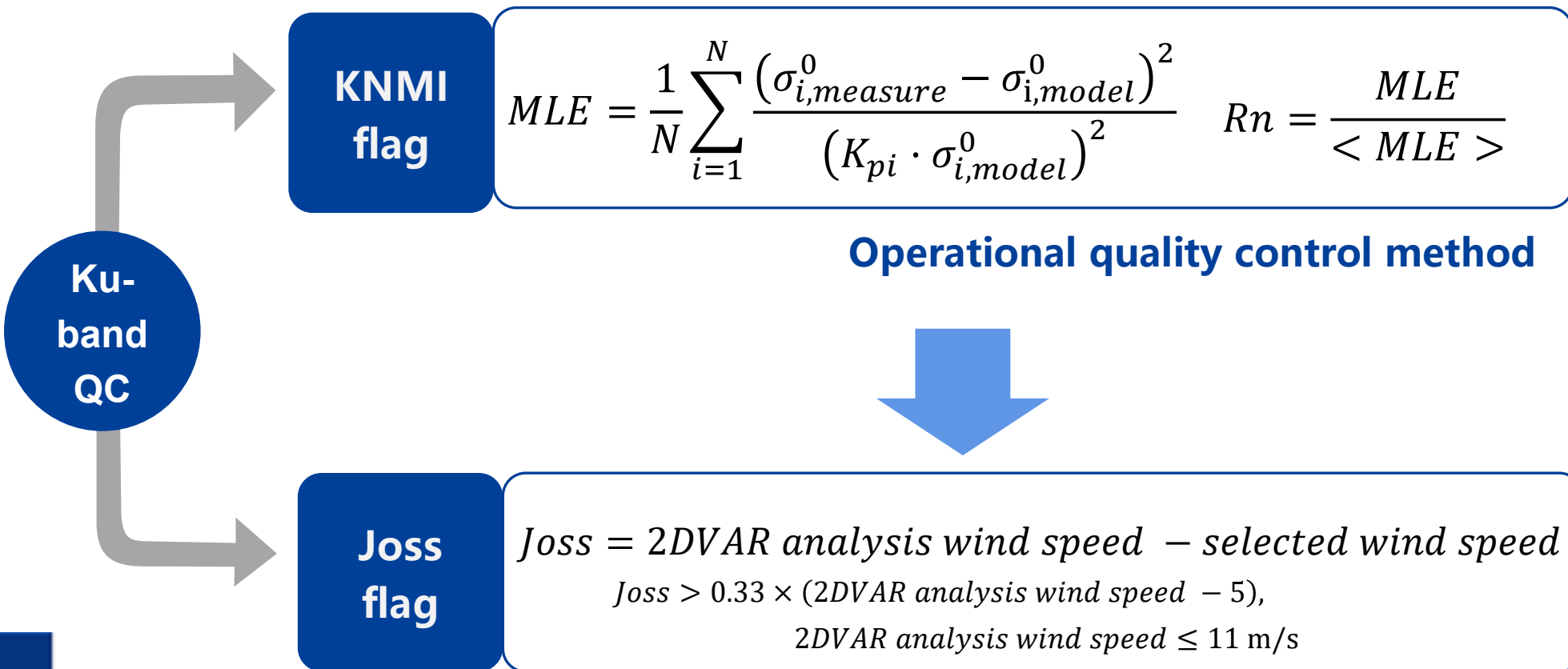
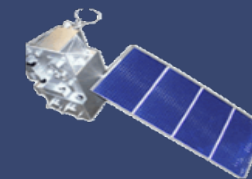
- The average rain rate of the rejected dataset flagged by the current QC method (Rn) is about 2 mm/h and the corresponding average posterior probability is about 0.46.
- When the posterior probability is higher than or equals to 0.5, the data are flagged as poor-quality winds



- Still many points are located **close to the wind backscatter distribution**. That also reflects the aliasing issue and some good quality data are **mis-flagged** by the P flag.

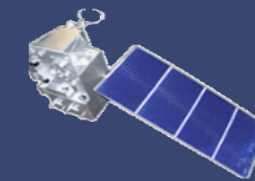






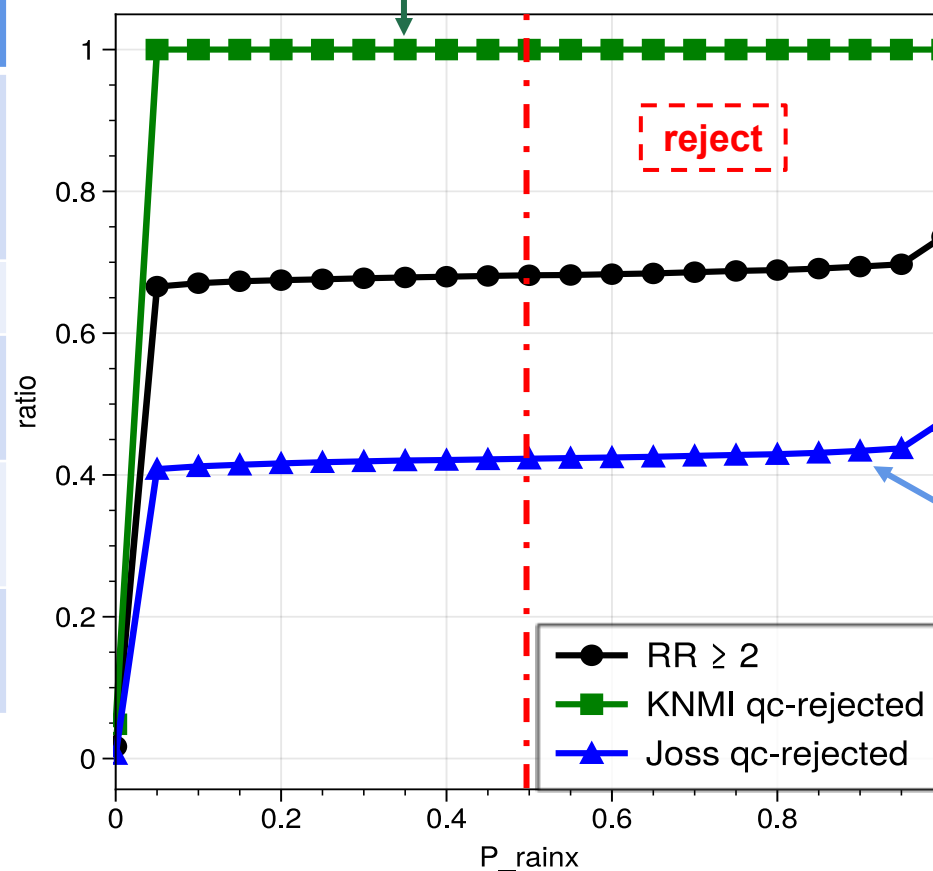
M. Portabella and A. Stoffelen, 2001;
M. Portabella, 2002

X. Xu and A. Stoffelen, 2019.
X. Xu, A. Stoffelen, W. Lin, and X. Dong, 2020.



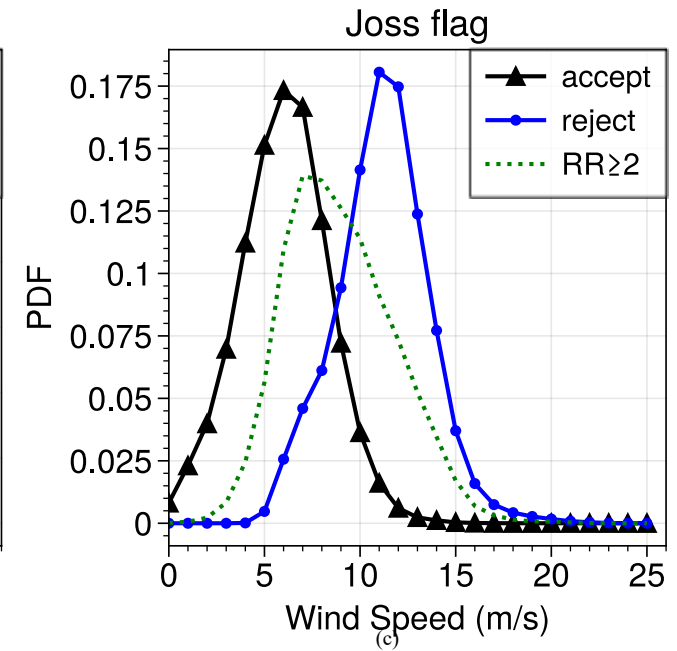
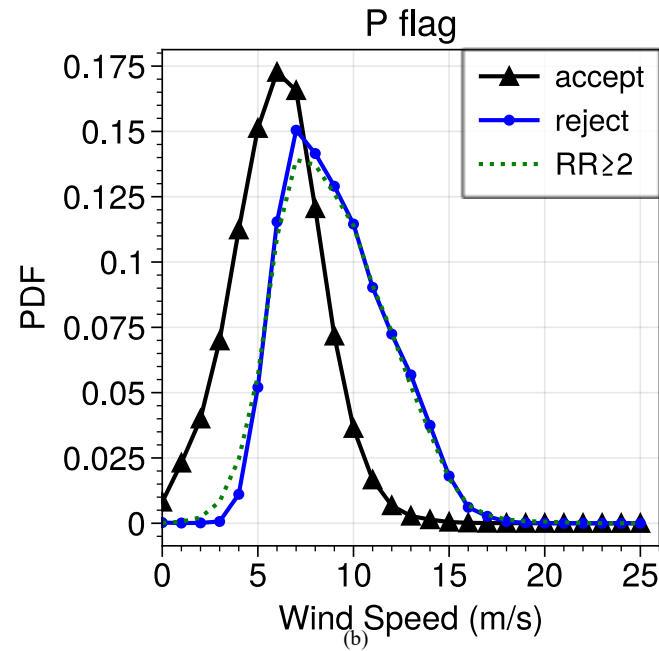
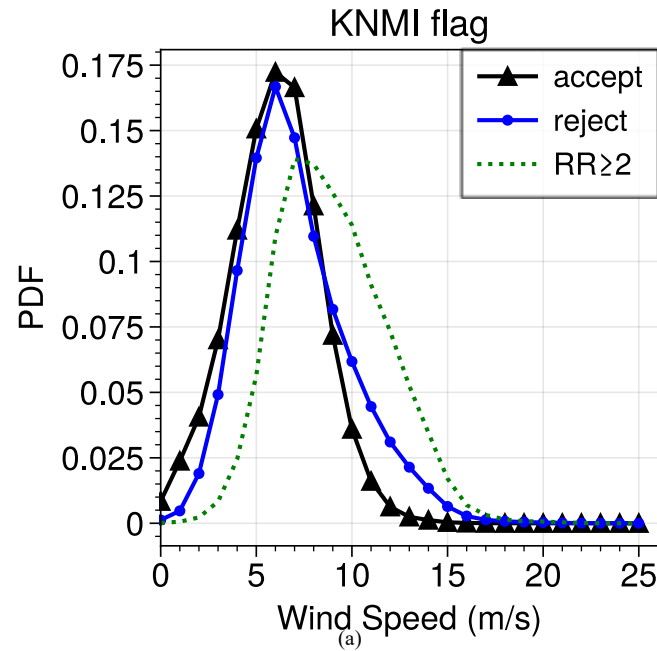
	KNMI flag	P flag	Joss flag
Rejected numbers (rejected ratio)	171,894 (4.83%)	35,363 (0.99%)	29,762 (0.84%)
$RR \geq 2$ mm/h	26.53%	68.16%	69.24%
Mean rain rate (mm/h)	2.05	5.76	6.35
Mean wind speed (m/s)	7.56	9.55	11.65
Mean standard deviation (m/s)	2.82	2.65	2.41

The ratio of KNMI QC-rejected data in each P flag rejected dataset



The ratio of RR>2 data in each P flag rejected dataset

The ratio of Joss rejected data in each P flag rejected dataset



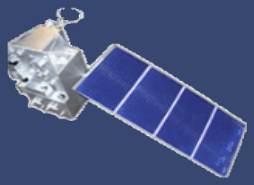
- KNMI flag ensures the best quality of the accepted winds at the cost of a high false alarm rate.
- The rejected winds by Joss are the most likely affected by rain.
- P flag has lower missing rate than Joss and lower false alarm rate than KNMI flag.



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The classic model

VS

The conceptual model

$$NRCS_m = (NRCS_w + NRCS_{sr}) \times \alpha_r + NRCS_{ar}$$

surface effect atmosphere effect

$$NRCS_m = NRCS_w \times \alpha_r + NRCS_{rain}$$

- The physical mechanisms are complex and hard to quantify theoretically
- Didn't eliminate the SST effects
- Using model winds as the $NRCS_w$ may introduce unexpected errors

$$NRCS_{measurement} = A \times NRCS_{rain} + (1 - A) \times NRCS_{wind}$$

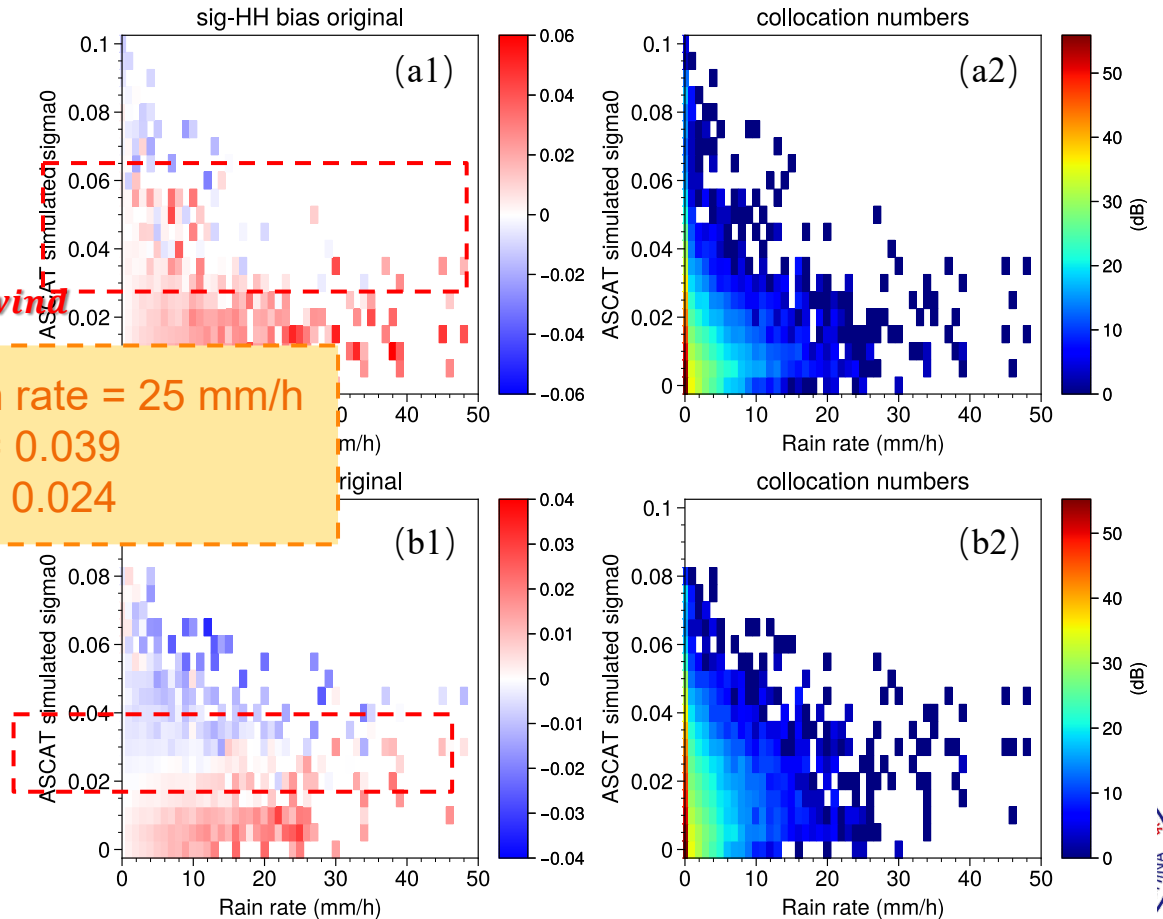
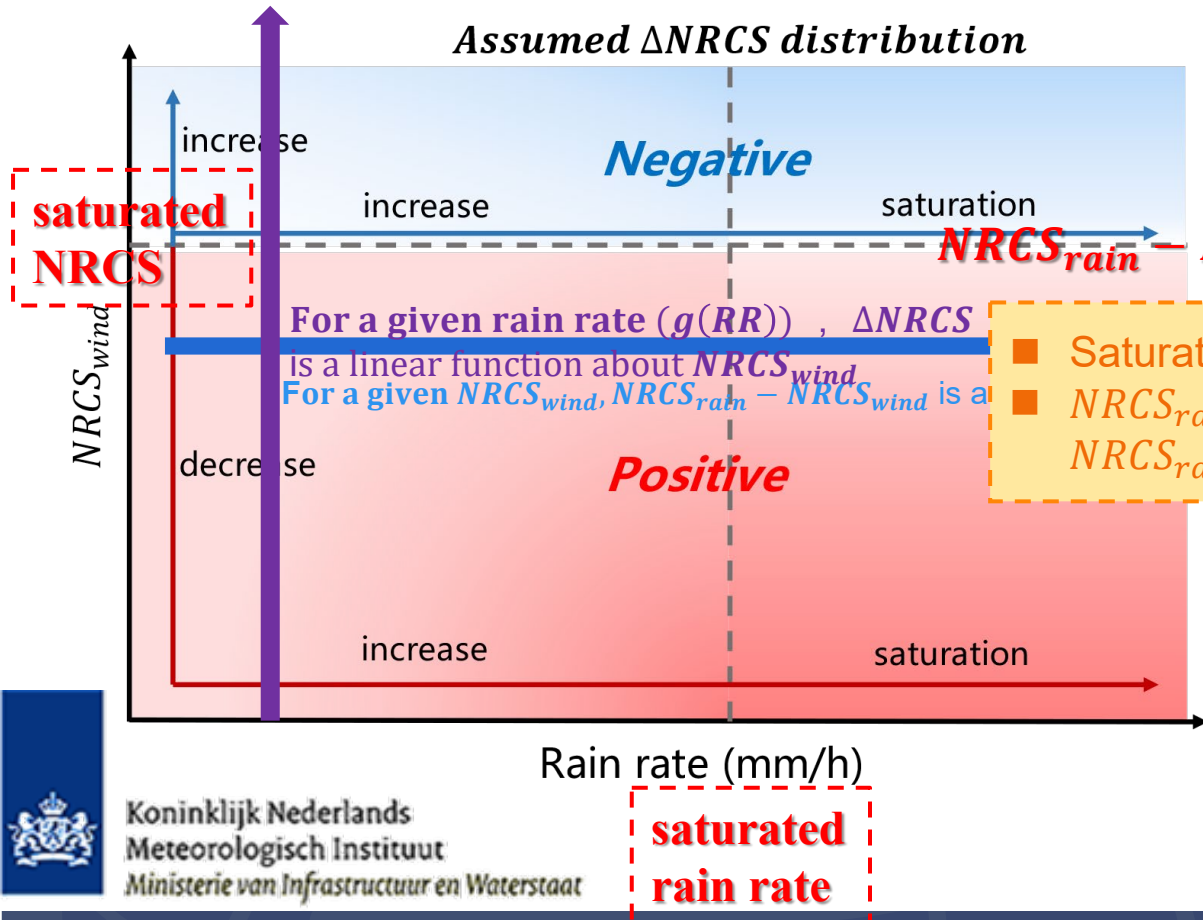
- Assume A is the rain area fraction in one WVC. The WVC accumulated rain rate is relative with A , $A = g(RR)$.

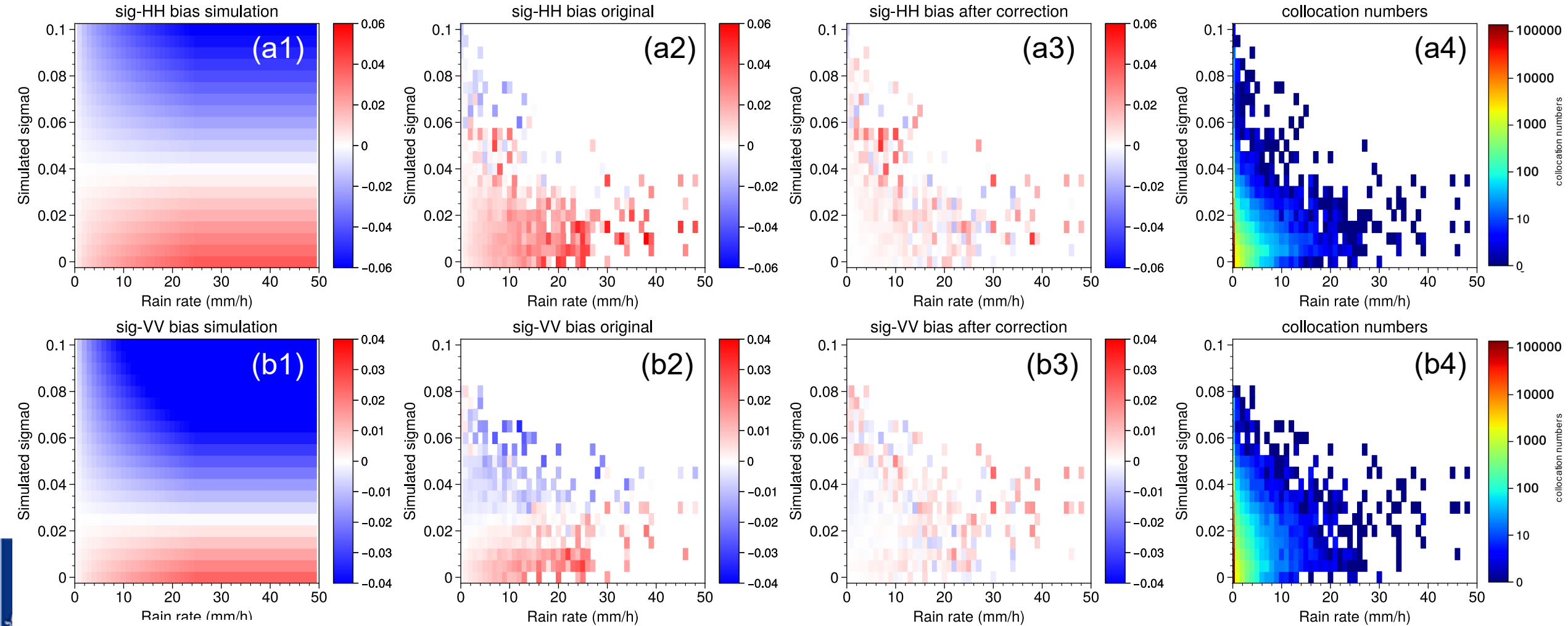
$$\Delta NRCS = NRCS_{measurement} - NRCS_{wind} = g(RR) \times (NRCS_{rain} - NRCS_{wind})$$

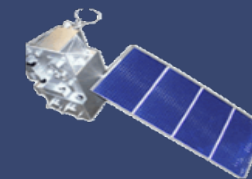
- In the tropics, sub-WVC moist convection dominates the rain effects in WVCs.
- Differences between C- and Ku-band scatterometers are dominated by precipitating cloud effects.

$$\Delta NRCS = NRCS_{measurement} - NRCS_{wind} = g(RR) \times (NRCS_{rain} - NRCS_{wind})$$

$$g(RR) \in [0, 1]$$



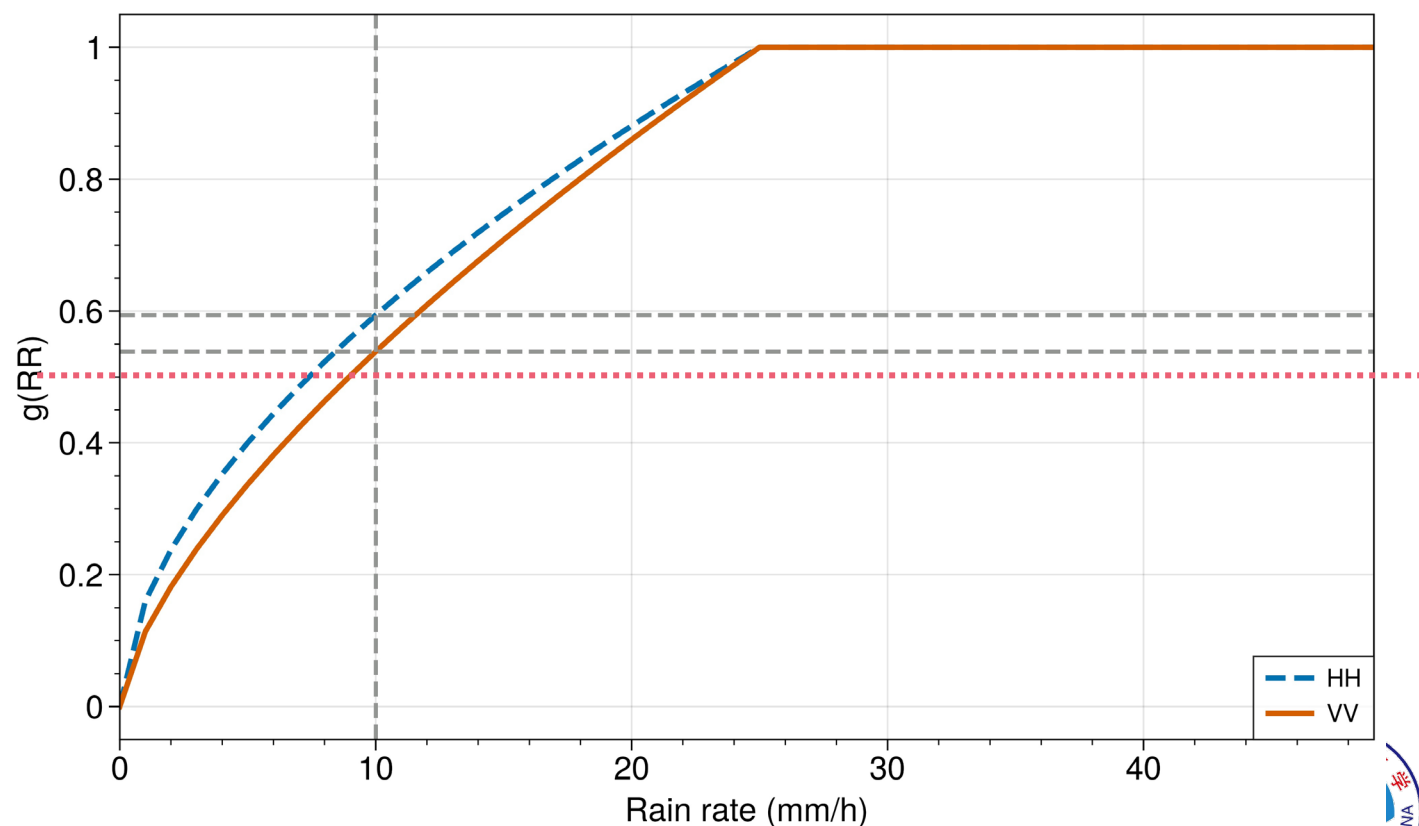




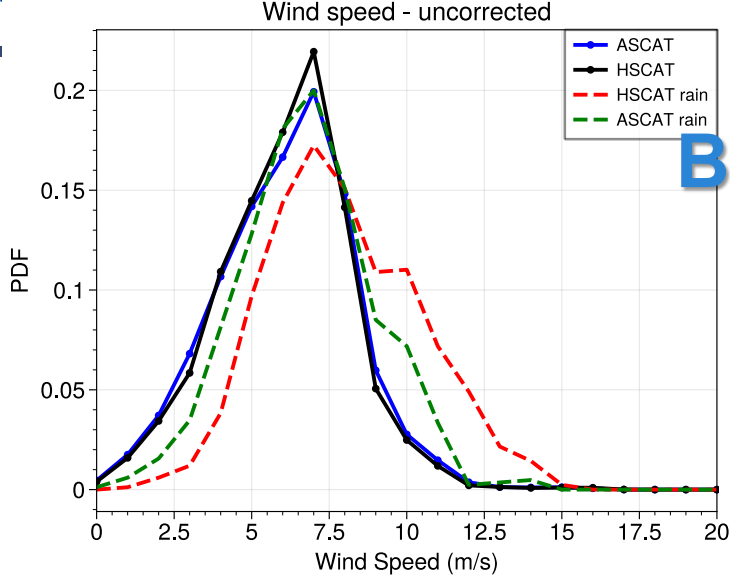
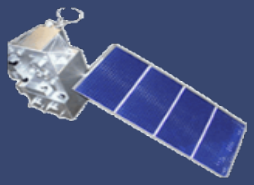
$$f(bias) = NRCS_{measurement} - NRCS_{wind} - \Delta NRCS(RR, NRCS_{wind})$$

$$= NRCS_{measurement} + (1 - g(RR)) \times NRCS_{wind} - g(RR) \times NRCS_{rain}$$

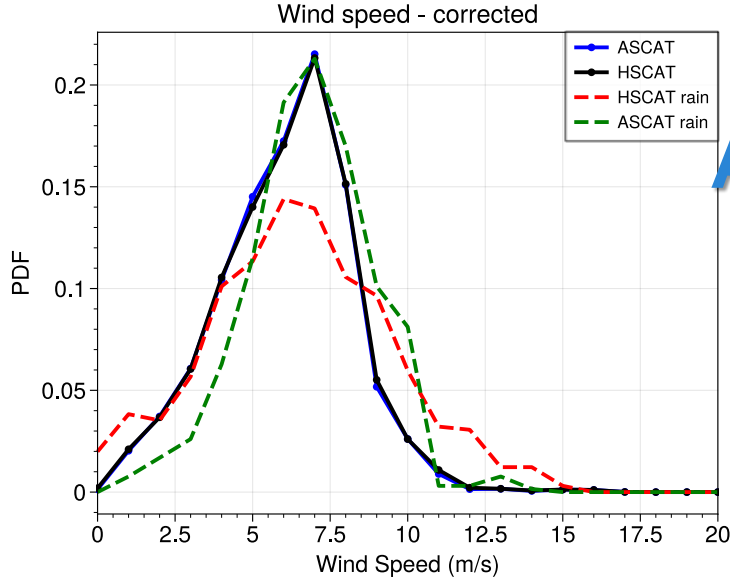
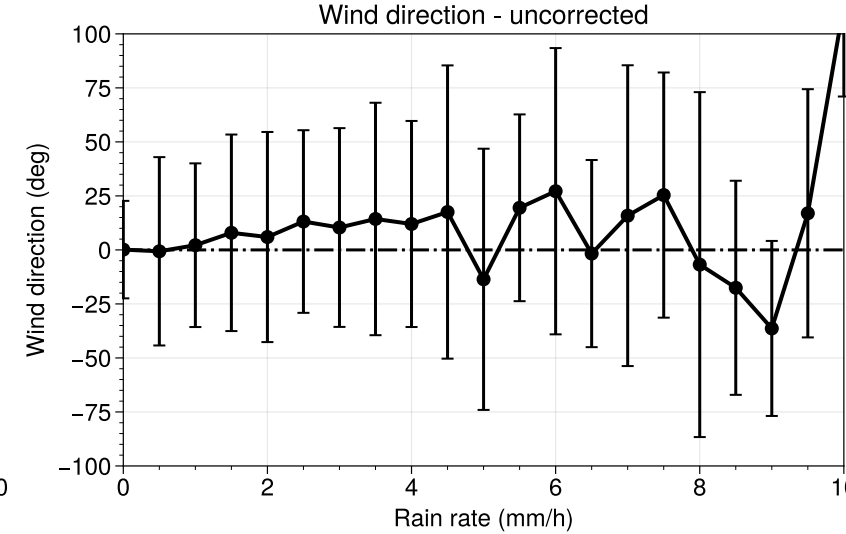
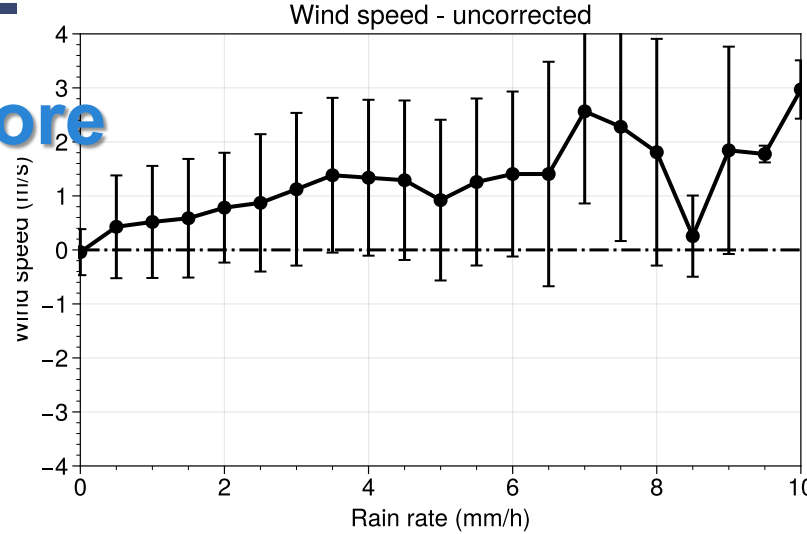
- For a given rain rate, $f(bias)$ is a function of $NRCS_{wind}$.
- Find a possible true sea surface wind NRCS solution by minimizing the absolute value of $f(bias)$.
- The less available wind information is will cause a large computation error.
- When rain rates are less than 10 mm/h, this model can much reduce the rain effects.



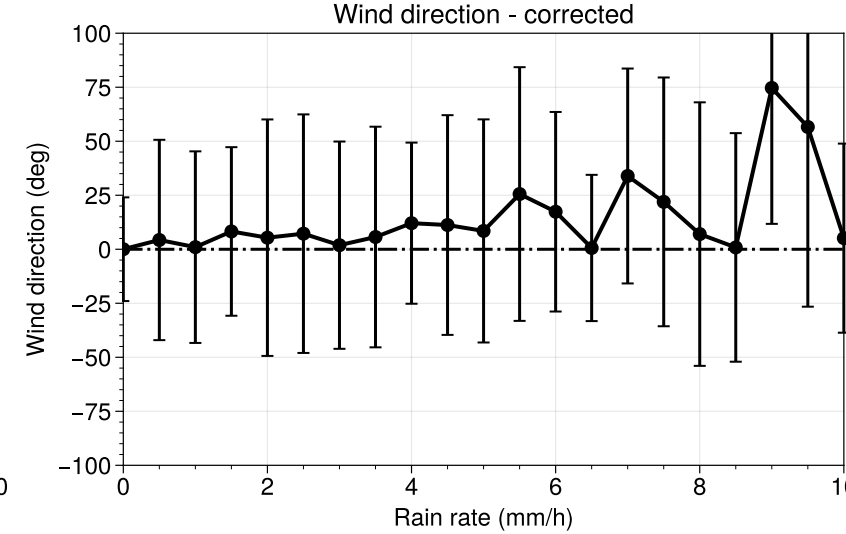
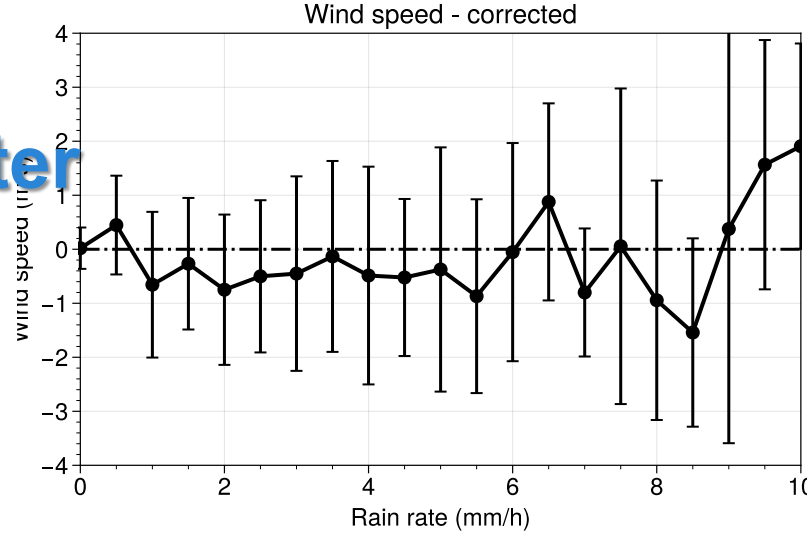
Preliminary correction



Before



After





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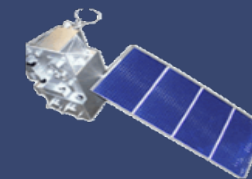


Summary:

- ◆ Ku-band scatterometers are much more affected by rain than C-band scatterometers, due to the shorter wavelength.
- ◆ HH polarization radar views are more sensitive to rain than VV polarization views.
- ◆ A Bayesian method can be applied for the HY-2C scatterometer data to identify rain-contaminated data.
- ◆ Scatterometer received signals are mixed ocean surface wind and precipitating cloud responses. If a WVC is full of precipitating clouds, no effective sea surface wind signal can be received.
- ◆ A loop-search method to minimize the bias between the corrected NRCS and $NRCS_{wind}$ can be applied to the wind retrieval procedure without C-band data collocation.

Outlook:

- The model can be further tested outside the tropical region and the correction method can be refined further.
- Different QC flags have their advantages and disadvantages. The combination of all flags is important for wind retrieval under rainy conditions and in marine and atmospheric applications.
- The dual-frequency wind radar **WindRAD** on FY-3E is a powerful instrument to explore rain effects for its unique **C-band and Ku-band simultaneous observation**.



Thanks for your attention!

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