

Introduction

While the accuracy of Tropical Cyclone (TC) track prediction has been greatly improved during the last decades, predicting TC intensities still has a long way to go. One of the key issues is the insufficiency of real-time Ocean Surface Vector Wind (OSVW) observations with high spatial resolution.

Spaceborne scatterometers (e.g., the ASCAT data used in this paper) have relatively low spatial resolutions but with great advantages of large coverage and short revisit time. Today, it has been the primary source of satellite wind observations and a favorable asset at meteorological institutes. However, the blurring effects in scatterometers remain a huge issue, which impedes the research of (thermo-) dynamical behavior for TC inner-core regions and the contributions to TC forecasts.

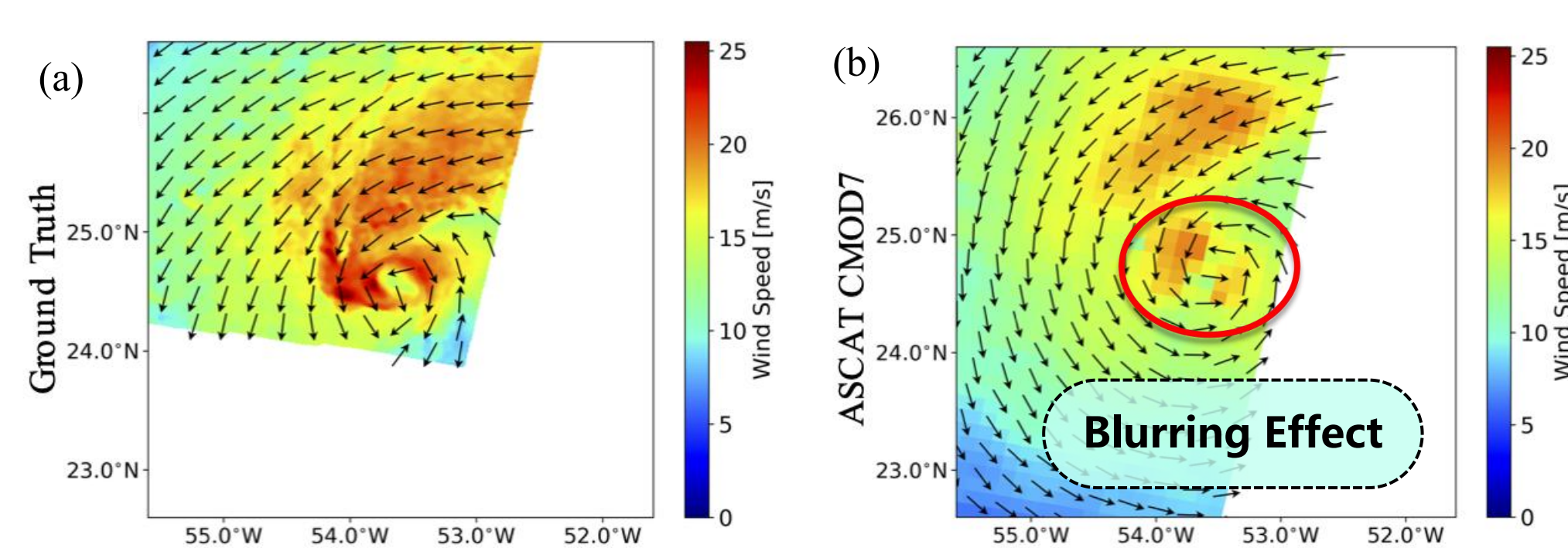


Fig 1: (a) TC Florence (September 8, 2018) imaged by SAR observations; (b) TC Florence retrieved from ASCAT data. See the severe blurring effect in the TC eyewall region.

To address this issue, a novel method for generating SR winds from low-resolution wind scatterometers is proposed by “learning” the specific TC spatial details from Synthetic Aperture Radar (SAR) winds at high spatial resolution for different classes of TCs. We produce the high-quality output fields by running a variational two-dimensional scheme, called 2DVAR. The empirical structure functions account for observed physical TC characteristics and contribute to generating physically realistic, small-scale wind details.

Methodology

2DVAR Scheme

The idea of analysis estimation behind 2DVAR follows the approach by Daley and is similar to methods applied in 3DVAR and 4DVAR systems, i.e., aiming to obtain wind analyses (x) from observations (x_o , e.g., the nominal ASCAT-12.5 wind products) and prior background wind fields (x_b , e.g., the ECMWF IFS forecasts) using a variational technique.

$$J(x_o, x, x_b) = J_o(x_o, x) + J_b(x, x_b)$$

where

$$J_o = \sum_{m=1}^{N_{obs}} \left\{ \sum_{k=1}^K \left[\frac{(\delta t_m - \delta t_{m,k}^{(o)})^2}{\sigma_t^2} + \frac{(\delta l_m - \delta l_{m,k}^{(o)})^2}{\sigma_l^2} - 2 \ln P_k \right] \right\}^{-\frac{1}{\lambda}}$$

$$J_b = (\delta \xi)^T B_{\hat{\psi}, \hat{\chi}}^{-1/2} B_{\hat{\psi}, \hat{\chi}}^{-1/2} \delta \xi$$

The new background error co-variance matrix $B_{\hat{\psi}, \hat{\psi}}$ can be approximated as:

$$B_{\hat{\psi}, \hat{\psi}}^{-1/2}(p, q) = \sqrt{\frac{\pi}{2}} (1 - v^2) \varepsilon_l R_{\hat{\psi}}^2 e^{-\frac{1}{2} \pi^2 R_{\hat{\psi}}^2 (p^2 + q^2)}$$

$$B_{\hat{\chi}, \hat{\chi}}^{-1/2}(p, q) = \sqrt{\frac{\pi}{2}} v \varepsilon_t R_{\hat{\chi}}^2 e^{-\frac{1}{2} \pi^2 R_{\hat{\chi}}^2 (p^2 + q^2)}$$

7 parameters remain
for adjustment

$R_{\hat{\psi}}, R_{\hat{\chi}}, v^2,$
 $\varepsilon_l, \varepsilon_t, \sigma_l, \sigma_t$

Triple Collocation for Background and Observation Error Standard Deviation

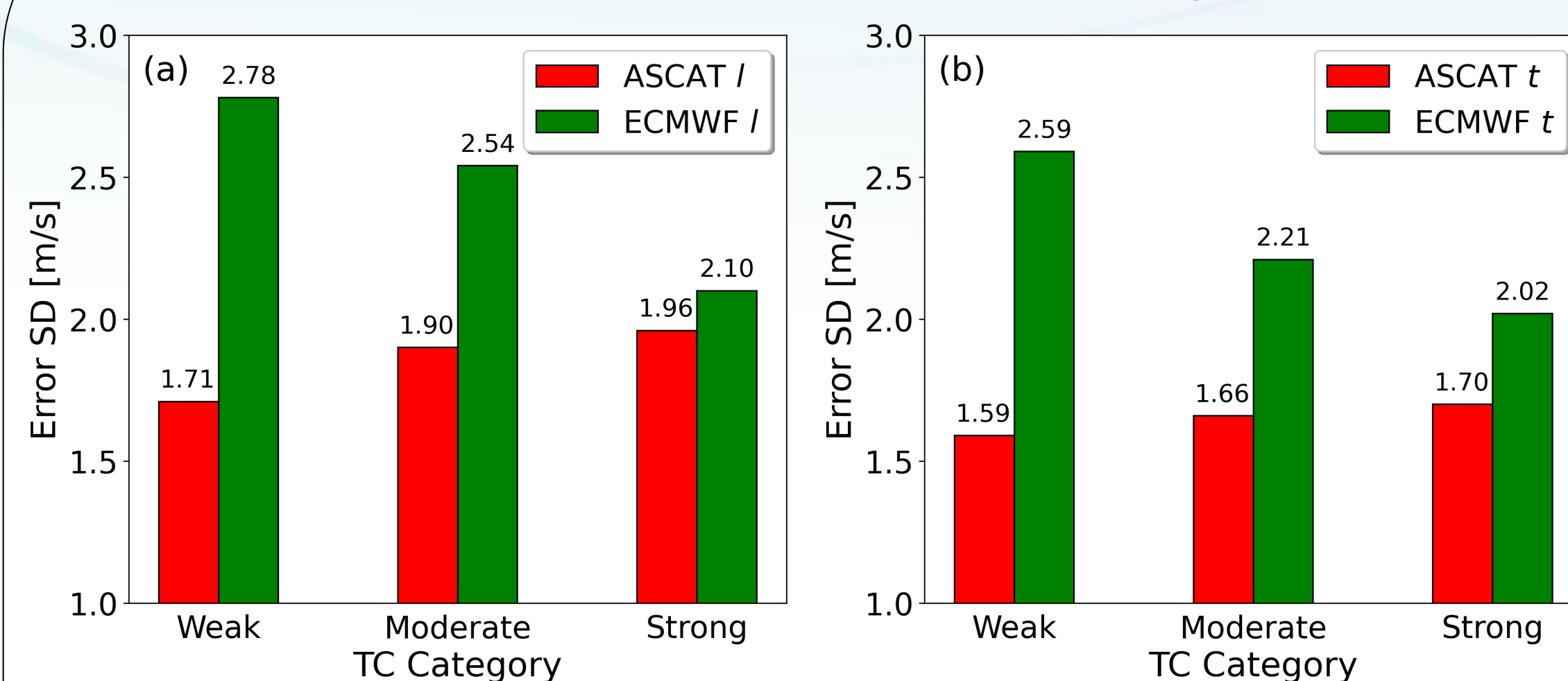


Fig 2: Variability in error SDs of along-track (a) and cross-track (b) wind components for ASCAT and ECMWF winds across different TC categories.

Relation between TC Metrics and (R_{ψ}, R_{χ}) values

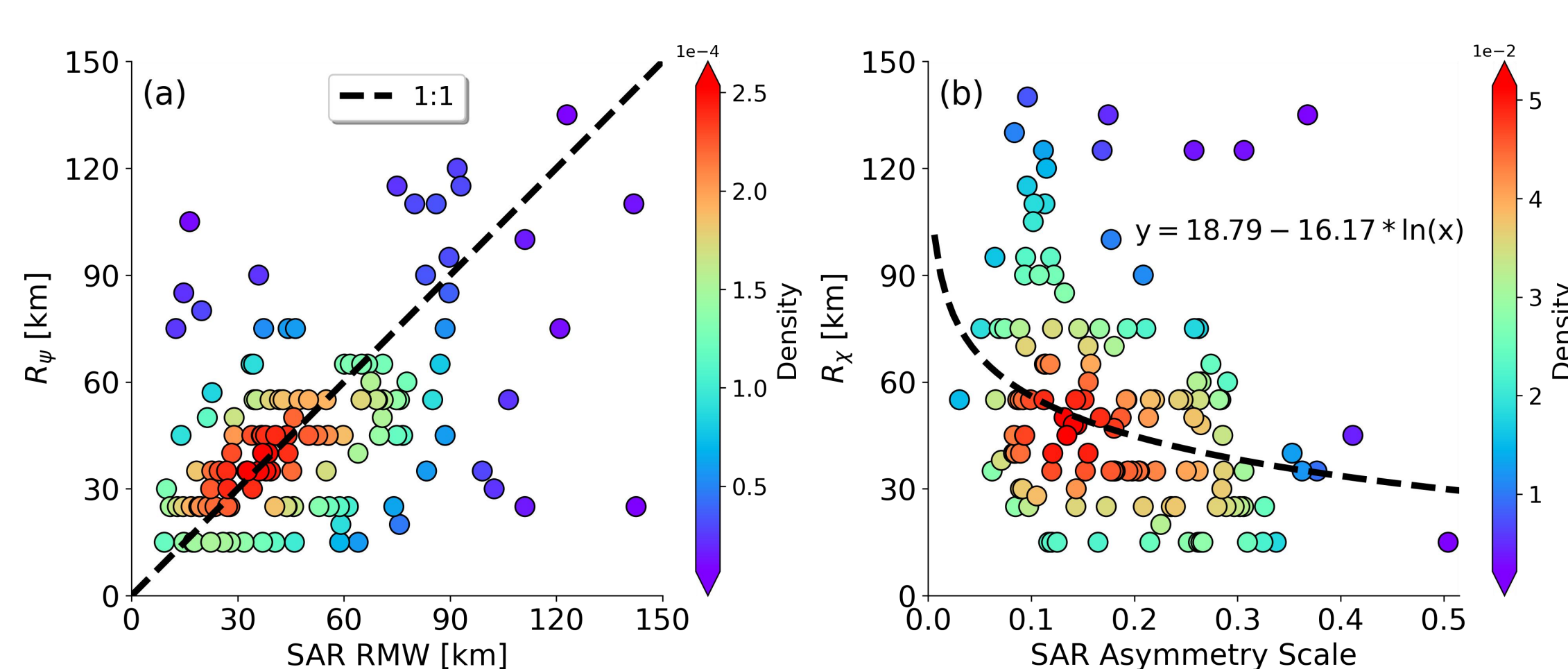


Fig 3: The relationships between the optimal (R_{ψ}, R_{χ}) values and TC characteristics. $v^2 = 0.25$.

Apart from the relatively smaller errors of ASCAT winds than those of ECMWF forecasts, it is worth noting that ASCAT errors increase monotonically with TC category rising. The increasing trend in ASCAT errors is supposed to stem from the contracting of TC eyes as TCs become more intense and the decreased sensitivity of ASCAT at high wind speeds.

- Though relatively noisy, the optimal R_{ψ} values increase linearly along with TC RMW, i.e., $R_{\psi} \approx \text{RMW}$.
- The fitting curve between R_{χ} and TC asymmetry scales resembles a family of rectangular hyperbolas.

It is reasonable to infer that the size of the TC eyewall controls R_{ψ} value while R_{χ} depends on the TC asymmetry scales.

Results

2DVAR SR Products

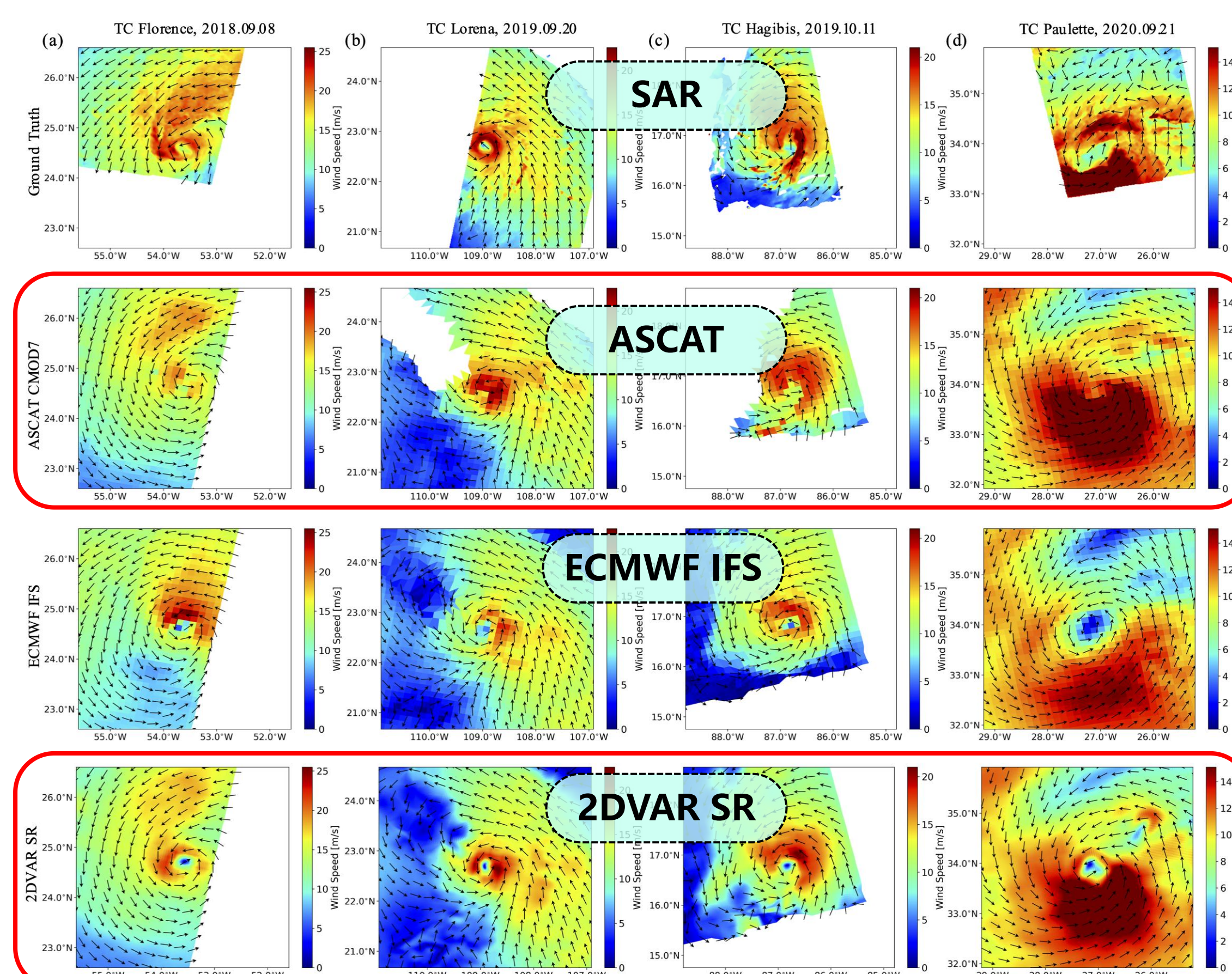


Fig 4: 2DVAR SR results and relevant wind observations for TC Lester (a), Ava (b), Michael (c), and TC Mindulle (d).

The experimental results suggest that the designed SR method is capable of preserving the general TC vortex features exhibited in ASCAT observations while complementing the blurred small-scale information.

The ECMWF IFS forecasts, despite having smoothed vortex structures, contribute to improving TC inner-core structures under the guidance of appropriate background error covariance structures, learned from the SAR data.

Spatial Variance Estimates

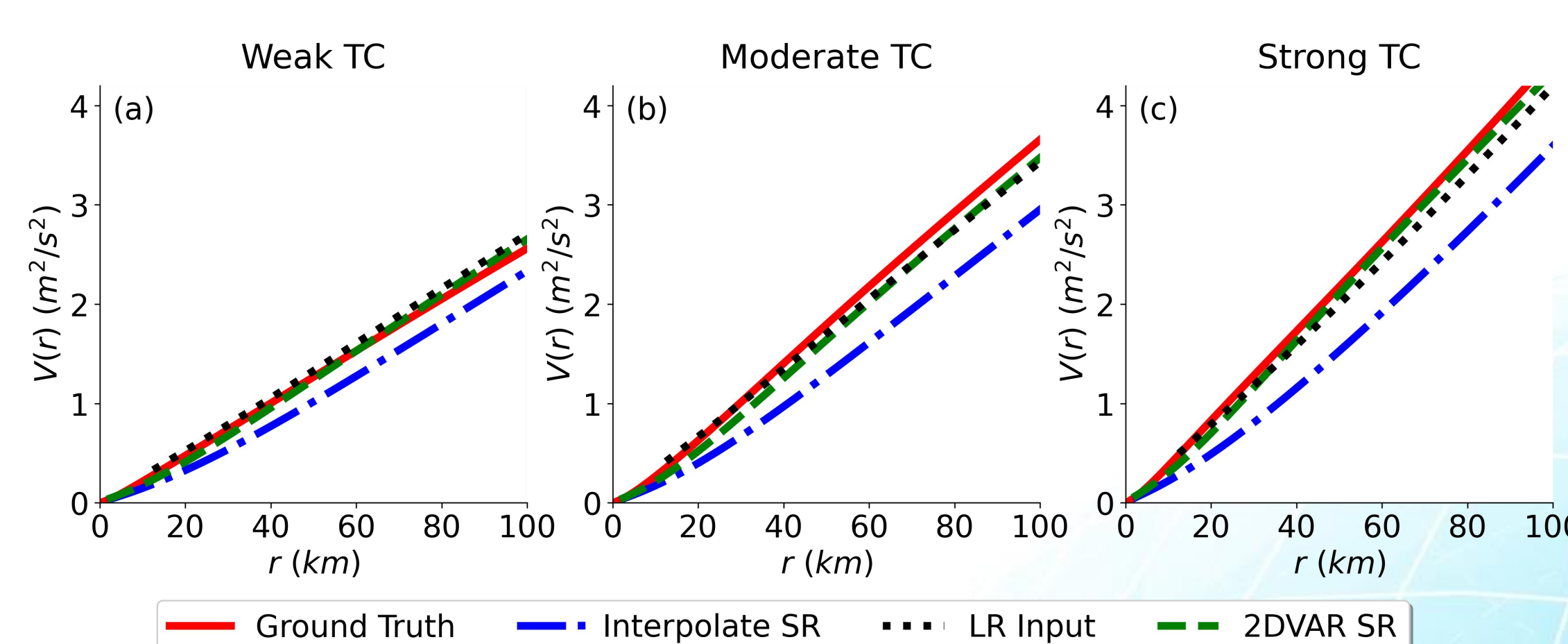


Fig 5: Spatial variance estimates from different wind products under “Weak” (a), “Moderate” (b) and “Strong” TC category.

The spatial variances derived from 2DVAR SR products (green curves) align well with the estimates from SAR observations (“Ground Truth”, red curves), while the bilinear interpolated SR (blue curves) shows significant deviations from the desired variance development, regardless of TC category.

Conclusion

1. The proposed SR method is capable of preserving consistency at large scales with original ASCAT winds while compensating for the ASCAT footprint blurring effect of the small-scale information and enhancing TC vortex structures in a physically meaningful manner, regardless of TC strength category.
2. The obtained SR products possess the correct small-scale properties of TC inner-core structures, such as Radius of Maximum Wind, TC asymmetry and wind variability.
3. The promising results demonstrate the capability of the proposed SR method in spatially enhancing the abundant scatterometer winds, thereby initiating potential future advancements in TC forecasting and advisories.

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