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1 **Reexamining the Estimation of Tropical Cyclones Radius of Maximum**
2 **Wind from Outer Size with an Extensive Synthetic Aperture Radar Dataset**

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12 ABSTRACT: The radius of maximum wind (R_{max}), an important parameter in tropical cyclones
13 (TCs) ocean surface wind structure, is currently resolved by only a few sensors, so that, in most
14 cases, it is estimated subjectively or via crude statistical models. Recently, a semi-empirical
15 model relying on an outer wind radius, intensity and latitude was fit to best-track data. In this
16 study we revise this semi-empirical model and discuss its physical basis. While intensity and
17 latitude are taken from best-track data, R_{max} observations from high-resolution (3 km) spaceborne
18 synthetic aperture radar (SAR) and wind radii from an inter-calibrated dataset of medium-resolution
19 radiometers and scatterometers are considered to revise the model coefficients. The new version
20 of the model is then applied to the period 2010-2020 and yields R_{max} reanalyses and trends more
21 accurate than best-track data. SAR measurements corroborate that fundamental conservation
22 principles constrain the radial wind structure on average, endorsing the physical basis of the model.
23 Observations highlight that departures from the average conservation situation are mainly explained
24 by wind profile shape variations, confirming the model's physical basis, which further shows that
25 radial inflow, boundary layer depth and drag coefficient also play roles. Physical understanding will
26 benefit from improved observations of the near-core region from accumulated SAR observations
27 and future missions. In the meantime, the revised model offers an efficient tool to provide guidance
28 on R_{max} when a radiometer or scatterometer observation is available, for either operations or
29 reanalysis purposes.

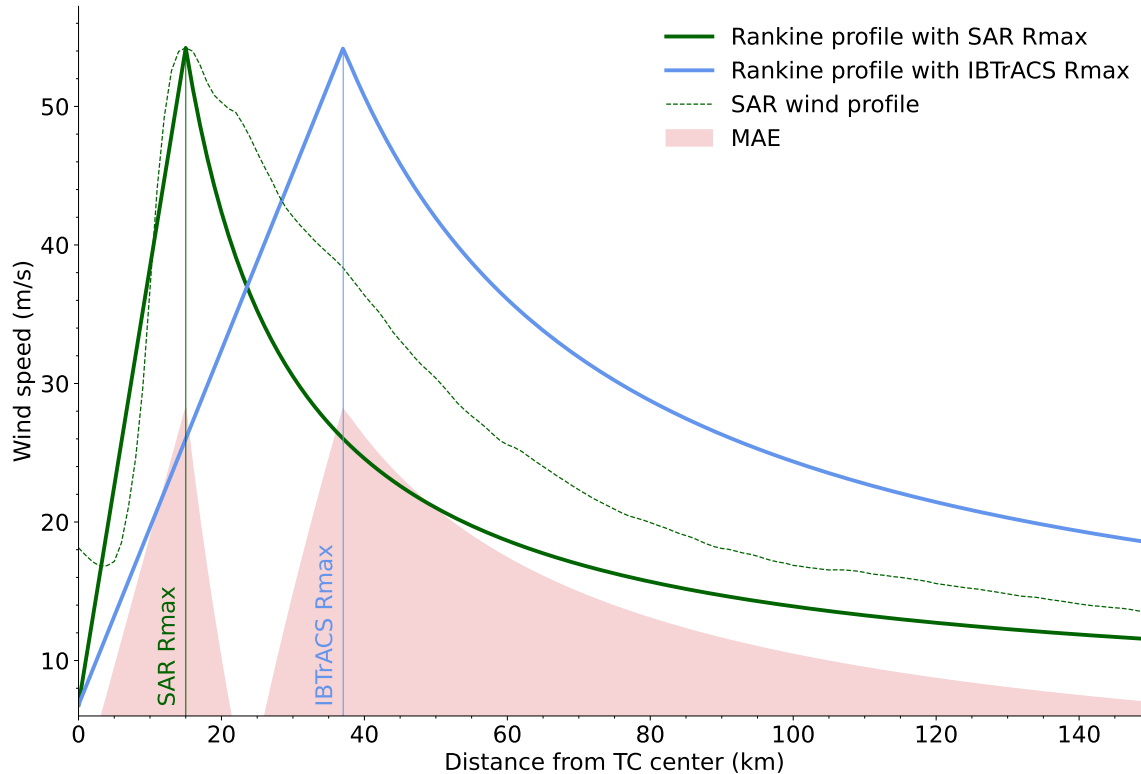
30 1. Introduction

31 Estimating tropical cyclone (TC) ocean surface wind structure is challenging but crucial for
32 several applications. In particular, TC surface wind spatio-temporal distributions are used as input
33 of surface wave studies (Wright et al. 2001; Young 2017; Kudryavtsev et al. 2021), storm surge
34 studies (Irish et al. 2008; Takagi and Wu 2016), or the upper ocean responses to TC passages
35 (Price 1981; Ginis 2002; Kudryavtsev et al. 2019; Combot et al. 2020b). In such studies, the
36 radius of maximum winds (hereafter R_{max}) is a critical parameter that significantly affects the wave
37 developments, surges estimates, sea surface height, temperature and salinity variations within the
38 TC wakes. Most parametric surface wind fields, often used for those applications, assume that
39 R_{max} is known (Holland 1980; Willoughby et al. 2006). Thus, R_{max} errors cascade into errors for
40 the entire spatial distribution of wind speeds. Figure 1 shows a comparison between two Rankine
41 profiles for two different R_{max} values

$$V_{Rankine}(r) = \begin{cases} V_{min} + (V_{max} - V_{min})\left(\frac{r}{R_{max}}\right) & \text{if } r \leq R_{max} \\ V_{min} + (V_{max} - V_{min})\left(\frac{R_{max}}{r}\right) & \text{if } r > R_{max} \end{cases} \quad (1)$$

42 TC Lane, a North Eastern Pacific hurricane that reached category 5 on the Saffir-Simpson scale
43 in 2018, provides an example of such a situation. TC Lane's wind speeds were estimated by a
44 swath of satellite-based SAR observation on 23 August at 0437 UTC. From the SAR wind speeds,
45 the azimuthally-averaged wind profile can be derived (dashed green curve in Fig. 1). The inferred
46 R_{max} is 15 km, about 2 to 3 times smaller than the 37 km value interpolated to the SAR acquisition
47 time in the best-track data (Knapp et al. (2010); hereafter IBTrACS). Such a mismatch between
48 best-track and SAR R_{max} estimates is representative of what has been reported in the literature
49 (Combot et al. 2020a). In the present case (Fig. 1), this discrepancy results into a Mean Absolute
50 Error (MAE) as high as 28 m s^{-1} near the eyewall region when using subsequent Rankine profile
51 estimates.

56 To date, airborne Stepped Frequency Microwave Radiometer (SFMR) surface winds (Uhlhorn
57 et al. 2007) provide means to estimate R_{max} . Yet, airborne measurements have limited azimuthal
58 coverage, and are operated over only few ocean regions and events. From a satellite perspective,
59 high spatial resolution estimates of TC ocean surface wind field are now more systematically carried
60 out, especially from SAR dedicated acquisitions (Mouche et al. 2017; Combot et al. 2020a). More



52 FIG. 1. Comparison between two Rankine profiles inspired by the SAR acquisition over TC Lane on 23 August 2018 at 0437
 53 UTC. Rankine profiles are defined with SAR R_{max} (15 km, solid green) or IBTrACS R_{max} (37 km, solid blue) and the same
 54 V_{max} (54 m s^{-1}) and V_{min} (7 m s^{-1}), consistently with the SAR azimuthally-averaged profile (dashed green). MAE between the
 55 two Rankine profiles is shaded in red.

61 reliable R_{max} estimates are then obtained for all ocean basins, though with limited spatio-temporal
 62 sampling. Presently, the most often available spaceborne observing systems, capable of probing
 63 the ocean surface during TC conditions, are the combined capabilities from active scatterometers
 64 and passive radiometers (Quilfen et al. 2007). Compared to radiometers, scatterometers generally
 65 have an improved medium spatial resolution. Yet, the strong gradients of the surface wind existing
 66 at scales of a few kilometers may still be smoothed to precisely locate the wind maxima, and the
 67 position of the center (Quilfen et al. 1998). In addition, scatterometers, especially those operating at
 68 Ku-band and higher microwave frequencies, can suffer from rain contamination. Signal sensitivity
 69 at high winds, above hurricane force wind (33 m s^{-1}), has also been questioned (Donnelly et al.
 70 1999; Mouche et al. 2019). Radiometer measurements may be less impacted by rain, especially
 71 those operating at L-band (Reul et al. 2012, 2017), and demonstrated to be still highly sensitive

72 above hurricane force winds. However, actual spaceborne radiometers operating at L- or C-band
73 have a lower spatial resolution. High wind speed gradients near the R_{max} region for most intense
74 TCs are then generally indistinct. Direct estimates of R_{max} using scatterometers or radiometers are
75 thus difficult to perform, possibly limited to particular large storm cases.

76 More indirect means to infer R_{max} were also considered. Both Mueller et al. (2006) and Kossin
77 et al. (2007) used geostationary infrared satellite data. For the cases where a clear eye is well-
78 defined on the infrared image, using linear regression to estimate R_{max} results in a MAE of only ~ 5
79 km when compared to aircraft-based estimates. Under less favourable conditions, R_{max} can still
80 be estimated via multiple linear regression in combination with a principal components analysis,
81 but leads to a degraded MAE of $\sim 20 km$. Notably, for the clear-eye case, Tsukada and Horinouchi
82 (2023) trained the linear regression with available SAR R_{max} estimates and improved the method,
83 decreasing the MAE to $\sim 2 km$.

84 In the absence of infrared data, a rough R_{max} estimate can also be obtained, considering the
85 storm intensity and latitude known, as evidenced by Willoughby et al. (2006) and Vickery and
86 Wadhera (2008). Indeed, following the angular momentum conservation, R_{max} must decrease
87 when the intensity increases. On average, such a physical constrain agrees well with observations
88 (see for instance Fig. 9 in Combet et al. (2020a)). In addition, it is also known that R_{max} increases
89 with latitude (e.g. Willoughby and Rahn (2004)), another consequence of angular momentum
90 conservation along with the decrease of intensity with latitude. Solely using intensity and latitude
91 to predict R_{max} yields a root-mean square error of the order $\sim 20 km$. Results from Vickery and
92 Wadhera (2008) show that in several cases, the observed R_{max} is inconsistent with the general
93 principle of angular momentum conservation. This suggests that R_{max} natural variability can
94 hardly be captured by such simple statistical models.

95 More recently, Chavas and Knaff (2022) - hereafter CK22 - suggested to use information on the
96 TC outer-size in combination with latitude and intensity. In CK22 framework, R_{max} is estimated
97 from the TC intensity V_{max} , the radius of gale R_{34} (*i.e* the maximum radial extent of the 34-knots
98 winds) and the Coriolis parameter, defined as $f = 2\Omega \sin(\phi)$, where $\Omega = 7.292 \times 10^{-5} s^{-1}$ is the Earth
99 angular velocity and ϕ is the latitude of the TC center. Such an approach is practical, especially
100 because R_{34} is well estimated by satellite scatterometers and radiometers (Brennan et al. 2009;

101 Chou et al. 2013; Reul et al. 2017). In fact, R_{34} estimates are routinely produced for every TC and
 102 included in IBTrACS.

103 The CK22 framework is based on physical understanding of the radial wind structure (Emanuel
 104 2004; Emanuel and Rotunno 2011) and phrased in terms of absolute angular momentum $M(r) =$
 105 $rV + \frac{1}{2}fr^2$, where f , r and V are the Coriolis parameter, the radius and the tangential wind speed
 106 of an air parcel, respectively. If the ratio $\frac{M_{max}}{M_{34}} := \frac{M(r=R_{max})}{M(r=R_{34})}$ is prescribed, one can then estimate
 107 R_{max} provided estimates for the 3 above-mentioned parameters using:

$$R_{max} = \frac{V_{max}}{f} \left(\sqrt{1 + \frac{2fM_{max}}{V_{max}^2}} - 1 \right) \quad (2)$$

108 CK22 fitted a log-linear regression model to estimate the ratio $\frac{M_{max}}{M_{34}}$ with the two predictors
 109 $X_{34}^{(1)} := (V_{max} - 17.5ms^{-1})$ and $X_{34}^{(2)} := (V_{max} - 17.5ms^{-1})(\frac{1}{2}fR_{34})$.

110 It is tempting to use this framework in combination with best-track data. CK22 used best-
 111 track estimates (in a region west of 50°W) of R_{max} , V_{max} , R_{34} and latitude to fit the log-linear
 112 regression model. As a result, their model inherited best-track biases. In particular, the reported
 113 R_{max} overestimation in best-tracks compared to SAR (Combot et al. 2020a) translated into an
 114 overestimation of the ratio $\frac{M_{max}}{M_{34}}$ during the regression training, further leading to overestimated
 115 R_{max} values.

116 The quality of R_{34} best-track estimates has also already been questioned (Sampson et al. 2017).
 117 This parameter is reanalyzed and compiled in IBTrACS since 2004 for North Atlantic and North
 118 Eastern Pacific and since 2016 for North Western Pacific (Knaff et al. 2021). Yet, surveying
 119 specialists who produce best-tracks in the Atlantic ocean (Landsea and Franklin 2013) are on
 120 average much less confident in their wind radii estimates (~25-50% of relative uncertainty) than
 121 in their intensity estimates (~10-20%).

122 In addition, best-tracks may also suffer from temporal and spatial heterogeneities (Schreck III
 123 et al. 2014; Wang and Toumi 2021). Indeed, the reanalysis methodology depends on the available
 124 data at each reanalysis time: best-track estimates of TC events covered by aircraft data are for
 125 instance more trustworthy (Landsea and Franklin 2013). Reanalysis is also subjective, each agency
 126 or Regional Specialized Meteorological Center (RSMC) specialist conducting his own weighting of

127 the available observations. Lastly, best-tracks are finalized annually and not updated with evolving
128 reanalysis methodology, creating a temporal discontinuity in the final IBTrACS database.

129 Finally, a possible limitation of the CK22 approach is the arbitrary choice of the outer wind
130 radius R_{34} . Indeed, their model could well be trained using R_{50} or R_{64} . In CK22, the choice of
131 R_{34} was motivated by the fact that best-track estimates of R_{50} and R_{64} are generally more uncertain
132 than R_{34} estimates. With more reliable R_{50} and R_{64} estimates, possibly obtained from radiometer
133 or scatterometer observations, one could assess whether using these wind radii would improve the
134 CK22 model.

135 The physical basis for wind structure relationships such as CK22 is a long-running issue. The
136 assumption that an outer wind radius partly constrains the wind structure dates back to Riehl (1963).
137 Riehl (1963) used a two-layer conceptual model constrained by an angular momentum conservation
138 in the outflow and a potential vorticity (PV) conservation in the inflow layer. Riehl (1963) could then
139 derive a relationship between R_{max} , V_{max} , f , and an outer radius R_{out} , corresponding to a distance
140 where the outflow velocity vanishes. Later, Kalashnik (1994) considered the Holland parametric
141 profile (Holland 1980) within a theoretical framework, to analyze the dependence of the near-core
142 wind structure on the wind profile. Emanuel and Rotunno (2011) also derived an analytical solution
143 for the near-core wind profile based on an assumption on the outflow temperature.

144 While these studies offer theoretical guidance, these theoretical inferences of R_{max} are difficult
145 to apply in practice. Indeed, most actual sensors fail to capture the wind profile shape used in
146 Kalashnik (1994), while the model of Emanuel and Rotunno (2011) relies on parameters that are
147 difficult to evaluate. Following Riehl (1963), the theoretical outer radius R_{out} is unknown and
148 cannot be specified to correspond to a given surface wind speed.

149 Building on the above considerations, the aim of this study is twofold. First, the CK22 model is
150 revised using SAR R_{max} estimates, different wind radii (referring hereafter to R_{34} , R_{50} , and R_{64})
151 estimated on inter-calibrated radiometers and scatterometers, and intensity and latitude best-track
152 estimates. Second, the physical basis of the CK22 model is further assessed through an examination
153 of conservation equations and a thorough analysis of the SAR database.

154 The data used in the present work are introduced in section 2 and further analysed in section 3.
155 Then, the CK22 model is revised and its performance assessed in section 4. Finally, the physical

156 basis of the model is discussed with respect to SAR observations in section 5. Concluding remarks
157 and possible routes for future investigations are provided in the last section.

158 **2. Data**

159 In the present work, different radiometer and scatterometer data (table 1) over the period 2010-
160 2020 were used to estimate wind radii (R_{34} , R_{50} , and R_{64}), while SAR data (table 2) were used
161 to estimate the R_{max} values required to fit the CK22 log-linear model. Furthermore, IBTrACS
162 provided intensity and latitude estimates (V_{max} and f).

163 We used different radiometer and scatterometer missions to constitute the most extensive dataset
164 of R_{max} reanalyses. These sensors rely on different physical principles (passive or active sensors),
165 and have different frequencies (L-band, C-band or Ku-band) and spatial resolutions. In order
166 to ensure homogeneity of the wind radii estimates, we used radiometer and scatterometer winds
167 inter-calibrated by Portabella et al. (2022).

168 A thorough analysis of this database revealed that the wind profiles issued from Ku-band scat-
169 terometer data barely exceed 64 knots, even for most intense TCs, as shown in appendix A. Thus,
170 we chose to remove Ku-band scatterometers from the present analysis.

171 *a. Radiometer missions*

172 Because both the foam coverage and bubble surface layer thickness increase with surface wind
173 speed (Reul and Chapron 2003), passive microwave measurements have long been known to display
174 very high sensitivity under extreme wind conditions. With large ~ 1000 km swaths, satellite-borne
175 radiometers are well suited to monitor TCs. However, they have nominally low spatial resolutions
176 (~ 40 km) that generally prevent accurate retrieval of the extreme surface wind speeds associated
177 with the inner-core of most intense TCs. The radiometer wind products used in this work are at 50
178 km spatial resolution with a 25 km grid spacing (Portabella et al. 2022).

179 In the present study, four different sources of radiometer data were used. Among them, the
180 L-band (1.4 GHz, 21 cm wavelength) radiometers from the European Space Agency (ESA) Soil
181 Moisture and Ocean Salinity (hereafter SMOS) mission and the National Aeronautics and Space
182 Administration (NASA) Soil Moisture Active Passive (hereafter SMAP). The ability of L-band
183 radiometers to retrieve ocean surface wind speeds under TCs has been discussed both in the case

184 of SMOS (Reul et al. 2012, 2016) and SMAP (Yueh et al. 2016; Meissner et al. 2017). Reul et al.
185 (2017) demonstrated that SMOS, SMAP, as well as AMSR-2 can be used to estimate wind radii.

186 The Japan Aerospace Exploration Agency launched the Advanced Microwave Scanning Ra-
187 diometer 2 (hereafter AMSR-2) onboard the Global Change Observation Mission Water 1 satellite
188 in 2012. This instrument is still operating today and uses 7 different frequencies (6.93, 7.3, 10.65,
189 18.7, 23.8, 36.5 and 89.0 GHz. For TCs, the first 3 channels (6.93, 7.3, and 10.65 GHz) are
190 used. With two C-band channels, initially intended for radio-frequency interference identifica-
191 tion, surface wind estimates are improved. Signals at these two C-band frequencies have similar
192 sensitivity to the sea wind speed but differ in sensitivity to rain by about 12%. Accuracy of the
193 AMSR-2-retrieved wind speed in storms is comparable to results obtained from SMOS and SMAP
194 L-band sensors (Zabolotskikh et al. 2015; Reul et al. 2017).

195 Windsat is a polarimetric radiometer onboard Coriolis, a mission designed by the Naval Research
196 Laboratory and the Air Force Research Laboratory, and launched in 2003. The sensor provided
197 data until May 2021. This instrument operates at 5 different channels (6.8, 10.7, 18.7, 23.8 and
198 37.0 GHz). To minimize heavy precipitation impacts, the C-band 6.8 and the X-band 10.7 GHz
199 channels are used for TC wind retrieval algorithms. Again, changes in the respective contribution
200 of wind and rain to the signal measured by each channel can be used to better infer and discriminate
201 both quantities (Klotz and Uhlhorn 2014). Heavy precipitation is still found to complicate surface
202 wind speed retrieval with this sensor (Quilfen et al. 2007), and more recent studies addressed this
203 issue (Meissner et al. 2021; Manaster et al. 2021).

204 *b. Scatterometer missions*

205 Scatterometers are active sensors that emit a pulse and measure the signal backscattered by the
206 rough ocean surface with different viewing angles. Because backscatter signals are dependent
207 upon both wind speed and wind direction, ocean surface wind vectors can be retrieved. The
208 achieved nominal spatial resolution (up to ~ 25 km) is higher than satellite-borne radiometers.
209 Actual scatterometers operate at different frequencies (C-band or Ku-band).

210 The Meteorological Operational satellite programme is a series of 3 satellites (Metop-A, -B
211 and -C) launched by ESA (in 2006, 2012 and 2018, respectively) which include scatterometers
212 (ASCAT, for "Advanced Scatterometer") operating at 5.3 GHz (C-band). With 3 antennas oriented

at 45°, 90° and 135° with respect to the satellite track, the wind direction can be retrieved. ASCAT instruments have 2 sub-swaths, each having a width of ~550 km. At C-band, the signal may be influenced by very heavy rain. Backscatter signals also tend to saturate at high winds (Donnelly et al. 1999), and ASCAT measurements progressively lose sensitivity under high wind speeds (Soisuvarn et al. 2012; Polverari et al. 2021). The ASCAT wind product used in the present study is at 25 km spatial resolution with a 12.5 km grid spacing (Stoffelen et al. 2017; Portabella et al. 2022).

Scatterometers operating at Ku-band (~ 13.5 GHz) usually have larger swaths (~1000 km) than C-band scatterometers, but suffer more contamination in heavy rainfall conditions (see Quilfen et al. (2007) for more details). The Ku-band scatterometer wind products used in Portabella et al. (2022) were finally removed (see appendix A). They include the China National Space Administration (CNSA) Haiyang missions (hereafter HSCAT), the Indian Space Research Organisation (ISRO) OceanSat-2 and SCATSat-1 satellites (hereafter OSCAT), and the NASA RapidScat (hereafter RSCAT) onboard the International Space Station (Table 1).

RADIOMETER	SMOS	SMAP	AMSR-2	Windsat
Period	2010-2020	2015-2020	2012-2020	2010-2019
Spatial resolution	50 km	50 km	50 km	50 km
Pixel spacing	25 km	25 km	25 km	25 km
Frequency	L-band	L-band	C-band, X-band	C-band, X-band
SCATTEROMETER	ASCAT	HSCAT	OSCAT	RSCAT
Period	2010-2020 (Metop-A) 2012-2020 (Metop-B) 2019-2020 (Metop-C)	2012-2015 (HY-2A) 2019-2020 (HY-2B)	2010-2014 (Oceansat-2) 2017-2020 (Scatsat-1)	2014-2016
Spatial resolution	25 km	50 km	50 km	50 km
Pixel spacing	12.5 km	25 km	25 km	25 km
Frequency	C-band	Ku-band	Ku-band	Ku-band

TABLE 1. The radiometer and scatterometer data used in Portabella et al. (2022). The period, spatial resolution, and pixel spacing rows refer to the wind product. The same data were used for the present work, except the Ku-band scatterometers, which were removed from the analysis.

230 *c. SAR missions*

231 The SAR data used here come from three different missions: ESA Sentinel-1A and Sentinel-
 232 1B (hereafter S1A and S1B, respectively), and the Canadian Space Agency (CSA) Radarsat-2
 233 (hereafter RS2). The SAR instrument onboard these three missions is an active sensor operating
 234 at 5.4 GHz (C-band). By analysing the received signal in both co- and cross-polarization, wind
 235 speeds can be inferred under TC conditions including at very high wind speeds (Mouche et al.
 236 2017, 2019). Convincing comparisons with passive radiometers have been performed (Zhao et al.
 237 2018). The ability of SAR-derived wind speeds to accurately capture the TC ocean surface wind
 238 structure, including R_{max} , has further been demonstrated and discussed by Combot et al. (2020a).

239 Today, SAR wide-swath acquisitions cannot be continuously performed over oceans. Based on
 240 track forecasts, it is still possible to best anticipate when the sensor will overpass a TC, and to
 241 trigger a SAR acquisition. ESA started the Satellite Hurricane Observation Campaign (SHOC) in
 242 2016, resulting in more than ~ 500 acquisitions over TCs. The derived wind products (Mouche
 243 et al. 2017) are further interpolated on a regular polar grid based on the TC center (see appendix
 244 in Vinour et al. (2021)). The product has a 3 km spatial resolution, with a 1 km grid spacing. This
 245 spatial resolution approximates a 1-minute wind speed as a 50 m s^{-1} wind moves 3 km in a minute.
 246 In this study, a certain number of SAR cases have been discarded on a qualitative basis, e.g. when
 247 the detected TC center was judged to be wrong, or when the SAR file contained corrupted pixel
 248 values.

SAR	S1A	S1B	RS2
Period	2016-2021	2016-2021	2012-2021
Spatial resolution	3 km	3 km	3 km
Pixel spacing	1 km	1 km	1 km
Frequency	C-band	C-band	C-band

249 TABLE 2. The SAR data used in the present study. The period, spatial resolution, and pixel spacing rows refer to the wind
 250 product.

251 *d. Best-tracks*

252 Here, IBTrACS were used for several purposes: the storm centers (latitude and longitude) allowed
 253 to azimuthally average the radiometer and scatterometer wind fields, while the wind radii (R_{34} ,

254 R_{50} , and R_{64}) were compared to satellite-based wind radii. Both IBTrACS latitude (to compute f)
255 and maximum sustained wind speed (V_{max}) were used in the CK22 framework, and the distance to
256 closest land (from the TC center) enabled filtering of the dataset. These parameters were extracted
257 for the period 2010-2020.

258 In IBTrACS, some storm tracks are given on a six-hourly basis, while others are interpolated and
259 thus given on a three-hourly basis. To account for this varying sampling time, all tracks and their
260 associated parameters were interpolated to an hourly basis with a monotonic cubic interpolation.
261 Lastly, because of varying definitions of the maximum sustained wind speed across the different
262 agencies, we selected only USA agencies (*i.e.* National Hurricane Center, Joint Typhoon Warning
263 Center, and Central Pacific Hurricane Center) which all provide the 1-minute maximum sustained
264 wind speed.

265 *e. Data filtering*

266 To further restrain the analysis to well-formed systems, *i.e.* for which R_{max} can be well deter-
267 mined from the axisymmetric mean profile, and to best ensure consistency with CK22 for further
268 comparison, the following filters have been applied to our dataset:

- 269 1. $V_{max} > 20 \text{ m s}^{-1}$;
- 270 2. $R_{max} < 150 \text{ km}$;
- 271 3. Any wind radius must be $> 5 \text{ km}$;
- 272 4. Absolute latitude $< 30^\circ$;
- 273 5. Distance to closest land $> R_{34}$.

274 Unlike CK22, we didn't apply any filter on longitude. Therefore, the method presented here
275 applies in every basin and does not depend on the availability of aircraft analysis.

276 **3. Methods and data analysis**

277 *a. Estimation of the CK22 predictors*

278 In order to apply the CK22 framework to the inter-calibrated dataset of radiometer and scat-
279 terometer data, estimates of the predictors (V_{max} , R_{34} , f) were needed for every satellite file.

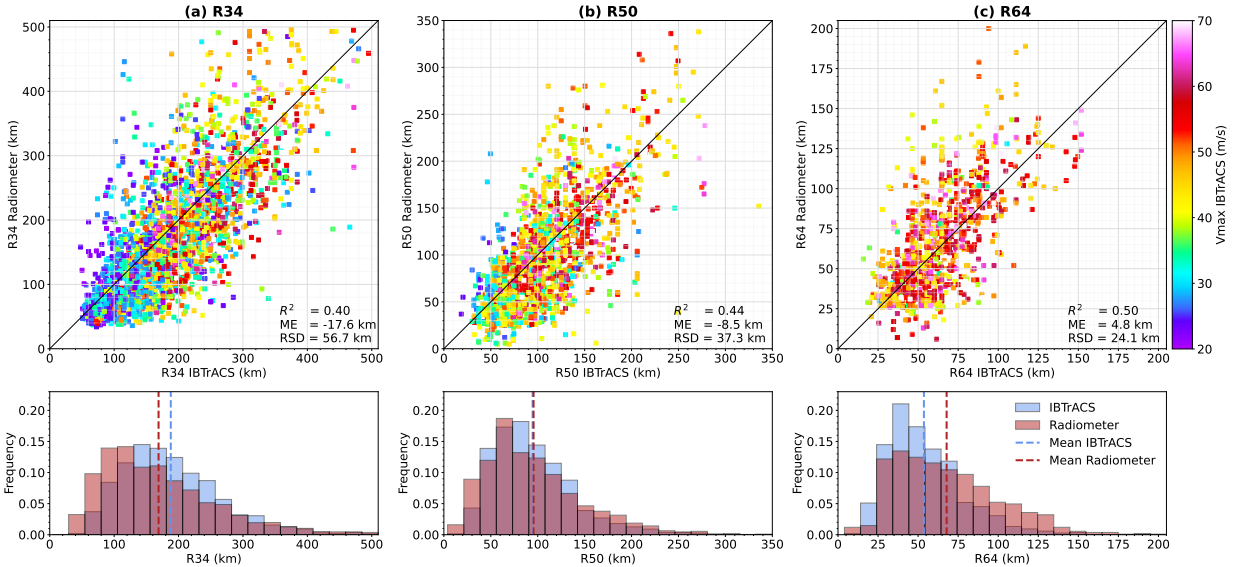
280 Regarding the wind radii, an azimuthally-averaged wind profile was first computed for every
281 satellite file using the corresponding IBTrACS center linearly-interpolated to the acquisition time.
282 For each of the three speed values of interest (*i.e.* 34, 50 and 64 knots), we then selected the radius
283 where the outer-profile matches this value to the closest kilometer. Should there be more than one
284 radius value, the wind radius was defined as the smallest of the radii.

285 Unlike the wind radii, V_{max} and f cannot be accurately estimated from radiometer and scatterom-
286 eter data, especially for intense small TCs, but both parameters are systematically reanalyzed in the
287 best-tracks. However, IBTrACS V_{max} definition does not strictly coincide with the axi-symmetric
288 view adopted here. In particular, the analysis (appendix A) highlighted that V_{max} estimated using
289 SAR azimuthally-averaged profiles were, on average, lower than IBTrACS V_{max} . This can be
290 modeled by applying a linear regression (dashed grey line in Fig. A1) to IBTrACS V_{max} estimates.
291 The resulting intensity estimates are denoted by V_{max}^{REG} and were used (instead of the raw IBTrACS
292 V_{max}) to ensure the consistency with the wind radii defined on azimuthally-averaged wind profiles.
293 The pair of parameters (V_{max}^{REG} , f) was then linearly-interpolated to the satellite acquisition time for
294 every file.

295 *b. Quality assessment of radiometer and scatterometer wind radii estimates*

296 To assess the quality of the satellite-based wind radii, comparisons were performed with IBTrACS
297 wind radii. A strict comparison cannot be achieved because of varying definitions. In IBTrACS,
298 wind radii are relative to the geographical quadrants and correspond to the maximum radial extent
299 of the associated wind speed in each of the four quadrants. To make IBTrACS values as close
300 as possible to the satellite-based wind radii, the nonzero IBTrACS values were averaged over all
301 the quadrants. Furthermore, both the methodologies and the available observational data can vary
302 across the IBTrACS dataset. Here, the adopted strategy was to compare the whole IBTrACS
303 wind radii dataset (including non-USA agencies for this section) to the satellite-based wind radii.
304 Accounting for the differences between the specialists and agencies is beyond the scope of this
305 study. Finally, after removing the Ku-band sensors (see appendix A), we separated radiometer
306 wind radii from the C-band scatterometer wind radii to further investigate possible discrepancies
307 between the remaining sensors.

308 Figure 2 shows a comparison between radiometer wind radii and IBTrACS values (top) and
 309 their corresponding distributions (bottom). While radiometer wind radii look well correlated with
 310 IBTrACS values, with R^2 -scores ranging from 0.4 to 0.5, large discrepancies arise, with a Residual
 311 Standard Deviation (RSD) as high as 56.7 km for R_{34} . The RSD decreases to 37.3 km for R_{50} , and
 312 further to 24.1 km for R_{64} , reflecting the decrease of the mean wind radius, i.e. 181 km for R_{34} to
 313 51 km for R_{64} in IBTrACS. In terms of relative uncertainties, this leads to $\sim 31\%$, $\sim 36\%$, and $\sim 41\%$
 314 for R_{34} , R_{50} , and R_{64} , respectively. Interestingly, the Mean Error (ME) is negative for both R_{34} and
 315 R_{50} , showing that, on average, these wind radii are lower when extracted from azimuthally-averaged
 316 radiometer profiles than from IBTrACS. This is likely the result of the differing definition of the
 317 wind radii in the satellite data and in IBTrACS. Indeed, on average, a wind radius extracted from an
 318 azimuthally-averaged profile is expected to be smaller than the maximum radial extent of the same
 319 wind speed. Biases due to the differing definition are lower for R_{50} and R_{64} than for R_{34} , because
 320 these radii are smaller on average. This definition effect is illustrated on the distribution for R_{34} ,
 321 where the radiometer R_{34} distribution is biased toward lower values compared to IBTrACS.



322 FIG. 2. (Top) Comparison between radiometer (y-axis) and corresponding IBTrACS (x-axis) wind radii. Coefficient of
 323 determination (R^2), Mean Error (ME) and Residual Standard Deviation (RSD) are displayed. (Bottom) Corresponding distributions
 324 and averages.

325 Figure 3 shows comparisons between C-band scatterometer wind radii and IBTrACS values.
 326 Again, an overall consistency emerges between both data sources for all wind radii. RSD values

327 and R^2 scores are comparable to the previous comparisons between radiometer and IBTrACS.
 328 Data and methodology are thus consistent with IBTrACS (which is expected since radiometer and
 329 scatterometer data are often used during the reanalysis process), but it also shows that there is a
 330 good consistency between the various sensors in terms of wind radii.

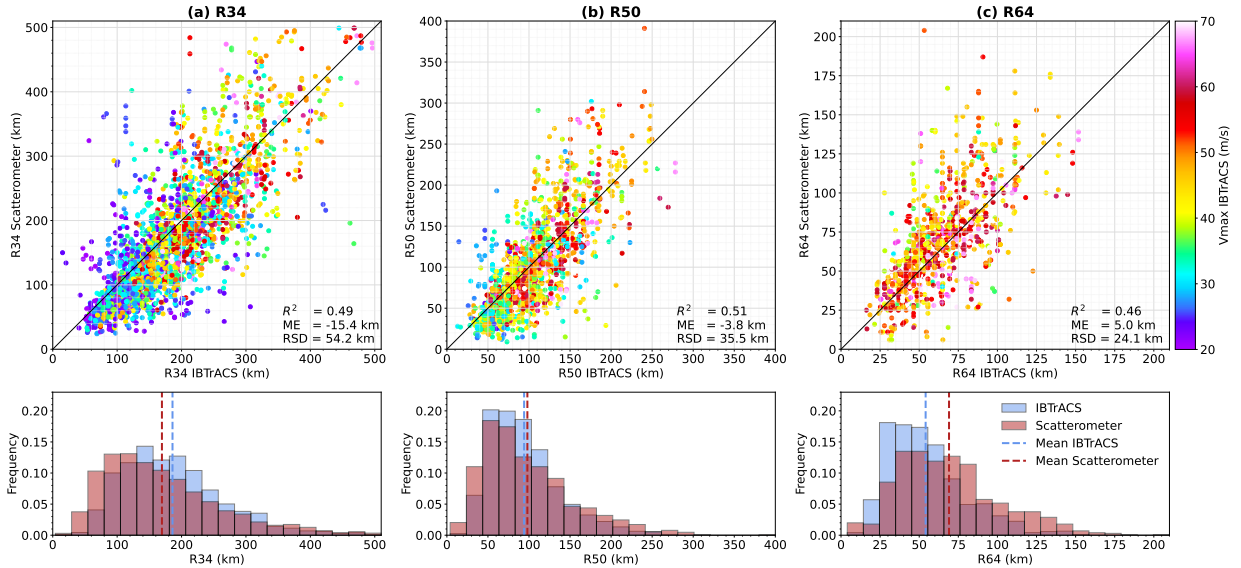


FIG. 3. Same as Fig. 2, but for the C-band scatterometer wind radii.

331 Regarding R_{64} , the ME is slightly positive for both radiometer and scatterometer data (Figs. 2c
 332 and 3c), with a distribution of R_{64} skewed toward higher values for the satellite data compared
 333 to IBTrACS. First, this could be attributed to the satellite data limitations, such as low spatial
 334 resolution, signal saturation or rain contamination. Yet, Fig. 4 offers a different explanation. It
 335 again shows comparisons between scatterometer wind radii and IBTrACS values, but only over
 336 the 3-year period from 2018 to 2020. For such a period, the computed ME for R_{64} is only 1.5
 337 km (Fig. 4c), and the RSD drops to 19.4 km (compared to 24.1 km for the period 2010 to 2020).
 338 Consistency between scatterometer and IBTrACS also improves for both R_{34} and R_{50} over the same
 339 period (Figs. 4a and 4b). The positive ME for R_{64} in Fig. 3 likely corresponds to the improving
 340 quality of IBTrACS over the years. Mentioned in the introduction, wind radii best-track values
 341 were not necessarily reanalyzed depending on the year and the basin. Similar conclusions were
 342 obtained with radiometer data (not shown).

343 To summarize, the comparison between IBTrACS and the inter-calibrated dataset shows that
 344 radiometers and scatterometers provide reliable wind radii estimates. Thus, for every radiometer

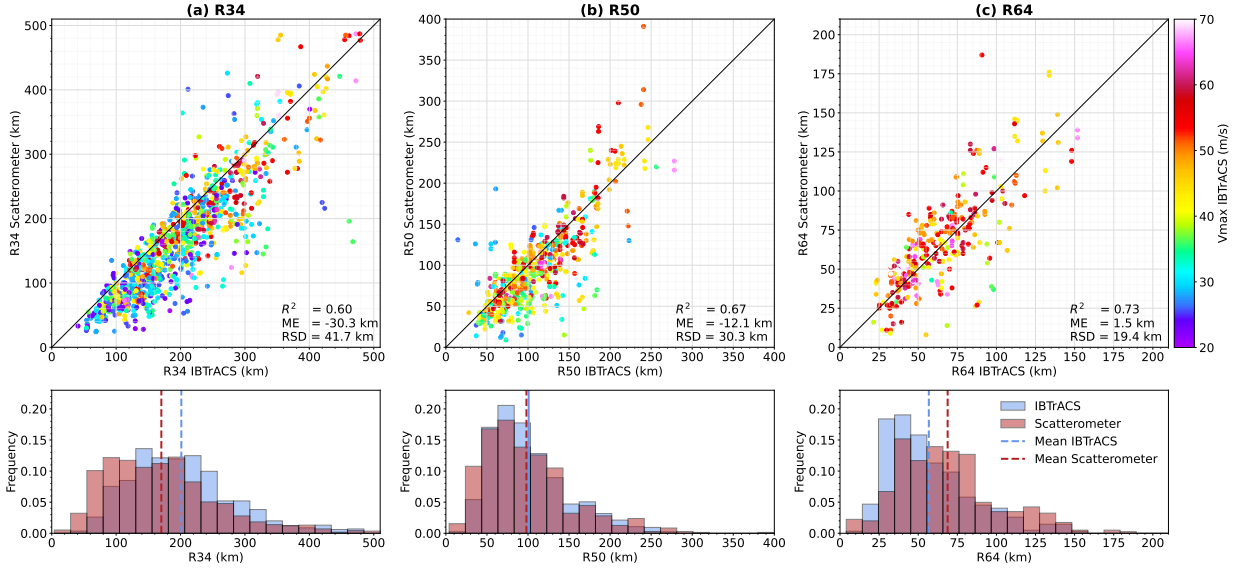


FIG. 4. Same as Fig. 3, but only for the 3-year period 2018-2020.

345 or scatterometer acquisition, we can extract a corresponding set of predictors constituted by a
 346 satellite-based wind radius along with IBTrACS V_{max}^{REG} and f estimates.

347 c. Collocations of radiometers and scatterometers with SAR

348 In order to fit the CK22 model, we also needed an estimate of the predictand (R_{max}) for each set
 349 of predictors. The latter cannot be directly evaluated from radiometer and scatterometer data, but is
 350 well observed on SAR data by taking the location of the wind profile maximum. Thus, we looked
 351 for collocations between SAR and radiometer or scatterometer TC overpasses. Two images were
 352 considered to be collocated if their absolute acquisition time difference is less than 90 minutes.

353 Regarding radiometer data (table 3, first four columns), this procedure resulted in a total of 269
 354 collocations, which further reduced to 145 collocations after applying filters presented in section
 355 3e. Notably, no collocation was found between any of the 3 SAR missions (S1A, S1B, RS2) and
 356 AMSR-2.

357 Regarding scatterometer data, no collocation was found between SAR and ASCAT (Table 3,
 358 penultimate column). In what follows, we thus refers to the dataset obtained by this collocation
 359 procedure as the "SAR-radiometer collocation dataset". It consists in predictors estimated on
 360 radiometer data (wind radii) or corresponding IBTrACS values (V_{max}^{REG} and f), and predictands
 361 estimated on SAR (R_{max}).

	SMOS	SMAP	AMSR-2	Windsat	ASCAT	TOTAL
Before filtering	106	63	0	100	0	269
After filtering	67	33	0	45	0	145

TABLE 3. Number of collocations between SAR and the inter-calibrated dataset (radiometer and ASCAT).

362 4. Results

363 a. Fitting CK22 model

364 As explained in the introduction, the CK22 model relies on the estimation of the ratio $\frac{M_{max}}{M_{34}}$ via a
365 log-linear regression model, using $(X_{34}^{(1)}, X_{34}^{(2)})$ as input. While CK22 used R_{34} in their study, this
366 method is in fact agnostic from the choice of wind radius. Therefore, the ratio $\frac{M_{max}}{M_{50}}$ can also be
367 estimated using $X_{50}^{(1)} := V_{max} - 25.7ms^{-1}$ and $X_{50}^{(2)} := (V_{max} - 25.7ms^{-1})(\frac{1}{2}fR_{50})$ as input (or $\frac{M_{max}}{M_{64}}$
368 using $X_{64}^{(1)} := V_{max} - 32.9ms^{-1}$ and $X_{64}^{(2)} := (V_{max} - 32.9ms^{-1})(\frac{1}{2}fR_{64})$ as input).

369 CK22 estimated the coefficients of the log-linear regression model based solely on IBTrACS
370 rather than direct observational estimates, and only for the ratio $\frac{M_{max}}{M_{34}}$. In the present work,
371 we use observational data not only to obtain improved estimates of the predictors in the CK22
372 model framework, but also to obtain improved estimates of the model coefficients that relate the
373 parameters to one another. We also extend the CK22 model for the ratios $\frac{M_{max}}{M_{50}}$ and $\frac{M_{max}}{M_{64}}$. A log-
374 linear regression model was fitted for each of the three ratios using the SAR-radiometer collocation
375 dataset previously presented. The following relationships were obtained:

$$\frac{M_{max}}{M_{34}} = 0.531e^{-0.00214(V_{max}^{REG} - 17.5ms^{-1}) - 0.00314(V_{max}^{REG} - 17.5ms^{-1})(\frac{1}{2}fR_{34})} \quad (3)$$

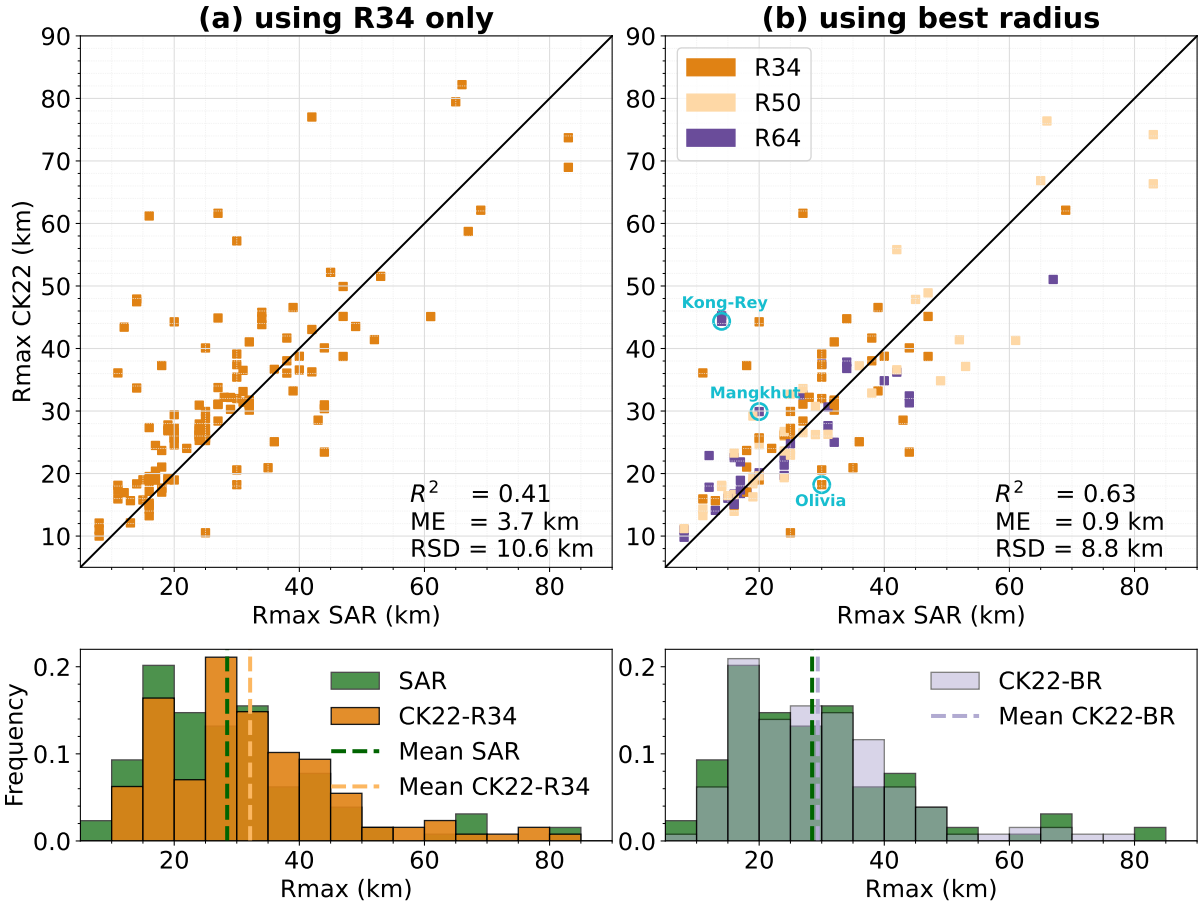
$$\frac{M_{max}}{M_{50}} = 0.626e^{0.00282(V_{max}^{REG} - 25.7ms^{-1}) - 0.00724(V_{max}^{REG} - 25.7ms^{-1})(\frac{1}{2}fR_{50})} \quad (4)$$

$$\frac{M_{max}}{M_{64}} = 0.612e^{0.00946(V_{max}^{REG} - 32.9ms^{-1}) - 0.01183(V_{max}^{REG} - 32.9ms^{-1})(\frac{1}{2}fR_{64})} \quad (5)$$

376 With these formulas, R_{max} can then be estimated using the steps presented in the introduction
377 (eq. 2). Subsequent estimates will be referred to as $R_{max}^{CK22-R_{34}}$, $R_{max}^{CK22-R_{50}}$, or $R_{max}^{CK22-R_{64}}$ depending
378 on which wind radius is used.

379 *b. Assessment of the resulting R_{max} estimates*

380 To check the fitting procedure, we compared $R_{max}^{CK22-R_{34}}$ estimates and SAR R_{max} (Fig. 5a). The
 381 consistency between both is reasonably good, with a R^2 -score of 0.41 and a RSD of 10.6 km. A
 382 low ME of 3.7 km is observed, which can be related to the distribution of $R_{max}^{CK22-R_{34}}$ being slightly
 383 skewed toward higher R_{max} values compared to SAR.



384 FIG. 5. Comparison between R_{max} estimates using the CK22 model and SAR R_{max} (top) and corresponding distributions
 385 (bottom) for $R_{max}^{CK22-R_{34}}$ (a) and $R_{max}^{CK22-BR}$ (b). For analysis purposes, color reveals which radius was used to define $R_{max}^{CK22-BR}$
 386 for each case.

387 Because R_{50} and R_{64} are closer to R_{max} than R_{34} , using one or the other wind radii thresholds
 388 should improve the quality of the ratio estimate compared to R_{34} . Ideally, an estimate of R_{max}
 389 should be performed with R_{64} if available. If R_{64} is not defined (*i.e* if V_{max} is less than 33 m s^{-1}),

390 R_{50} should be used. R_{34} should only be used if both R_{64} and R_{50} were not defined. Following this
391 procedure, we further estimated R_{max} using the "best" available wind radius.

392 Figure 5b shows a comparison between these estimates (hereafter $R_{max}^{CK22-BR}$) and SAR R_{max} .
393 The R^2 -score increased to 0.63 and the ME decreased to 0.9 km compared to the $R_{max}^{CK22-R34}$
394 methodology, while RSD decreased from 10.6 km to 8.8 km. Therefore, using wind radii closer to
395 R_{max} does improve the estimate quality. In addition, such a low RSD demonstrates the efficiency
396 of the fitted CK22 relationships (eqs. 3-5) to provide reliable R_{max} estimates.

397 In their paper, the R_{max} predicted by CK22 had a systematic bias that could be bias-adjusted
398 in post-processing to improve the model. Here we find that our model does not require a bias
399 adjustment, which may be an indication of the benefit of using direct observational data for R_{max}
400 (SAR).

401 While the method is successful on average, it is remarkable that errors can be large (more than
402 ~ 10 km), even for cases where R_{64} predictors are used (see for instance Kong-Rey and Mangkhut
403 in Fig. 5b). Before discussing how to explain these large uncertainties, a single TC life cycle was
404 chosen to illustrate the potential of the present methodology.

405 *c. Application to TC Kilo life cycle*

406 Producing $R_{max}^{CK22-BR}$ estimates every time a radiometer or a scatterometer TC overpass is available
407 can be an efficient tool for characterizing the time evolution of R_{max} for any given TC. Figure 6
408 shows TC Kilo R_{max} and V_{max}^{REG} time series between 27 August and 10 September 2015, a period
409 over which V_{max}^{REG} was larger than 20 m s^{-1} . TC Kilo evolved in the Pacific ocean, reaching category
410 4 on the Saffir-Simpson scale. It intensified from 20 to 49 m s^{-1} between 27 August and 30 August
411 before entering a weakening phase. In the meantime, R_{max} first varied between 55 and 15 km
412 according to IBTrACS, then stagnated at 37 km between the 30 August and the 2 September, before
413 varying again after these date. Stagnation phases of R_{max} from IBTrACS are likely not physical
414 according to the V_{max}^{REG} variations during that time interval (see section 5). $R_{max}^{CK22-BR}$ estimates
415 show much more pronounced variations during those phases, with an increasing trend between 30
416 August and 8 September. This particular phase corresponds to an overall decrease of V_{max}^{REG} and an
417 overall increase of R_{64} in our data (not shown), both of which would be expected to be associated
418 with an increase in R_{max} .

419 For reference, 3 SAR R_{max} estimates were available during TC Kilo’s life cycle (green stars). The
420 first SAR R_{max} (10 km) on 27 August, doesn’t match with our first estimate of R_{max} (35 km). This
421 illustrates the limitations of our proposed methodology and is discussed hereafter. The second and
422 third SAR R_{max} estimates are in better agreement with R_{max} estimates, especially if we account for
423 the overall R_{max} trend given by our estimates.

424 Notably, there is more spread in the CK22 estimates on the last two days of the study period.
425 Despite this increasing uncertainty, the increase of R_{max} is well depicted, suggesting R_{max} to
426 significantly increase much before 8 September in contradiction with the IBTrACS trend.

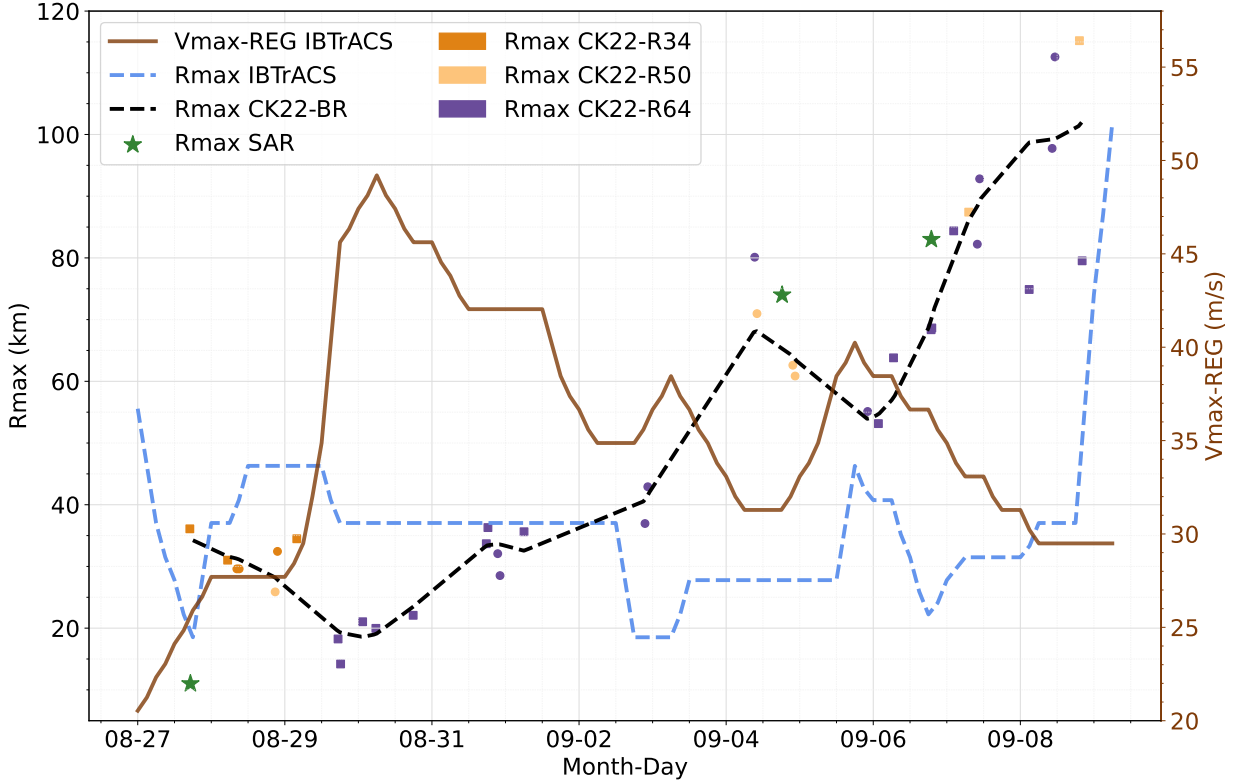
427 In summary, every time a radiometer or scatterometer wind profile is available, a subsequent
428 $R_{max}^{CK22-BR}$ estimate can be obtained, using the proposed objective method. In such a way, one can
429 estimate R_{max} trends that are more realistic than IBTrACS, less impacted from spatial or temporal
430 heterogeneities. Such a framework could also be used operationally.

436 5. Discussion

437 The previous section demonstrated the potential of the CK22 model fitted with SAR, when used
438 in combination with inter-calibrated medium-resolution radiometer and scatterometer data. Still,
439 $R_{max}^{CK22-BR}$ estimates can display rather large uncertainties, despite the expected improved use of
440 R_{64} as predictor. To better understand the sources of such uncertainties, three other case studies
441 (cyan circles on Fig. 5a) were considered before examining theoretical aspects and drawing a
442 picture of the average situation.

443 a. Case studies from the SAR-radiometer dataset

444 The first case (Fig. 7, left column) is TC Olivia in 2018, an Eastern Pacific ocean hurricane
445 that reached category 4 on the Saffir-Simpson scale. It reached a first intensity peak ($\sim 56 \text{ m s}^{-1}$)
446 on 5 September, then weakened before restrengthening ($\sim 59 \text{ m s}^{-1}$) during the night between 6
447 and 7 September. On 8 September, both RS2 at 1510 UTC and Windsat at 1533 UTC overflow
448 Olivia (Figs. 7a and 7d). Its eyewall, depicted by the high-resolution SAR observation, was clearly
449 defined though asymmetric. With its rather low spatial resolution, the radiometer failed to map
450 the inner core areas with high wind speed gradients, and eyewall asymmetries. From the SAR
451 observation, Olivia’s R_{max} was 30 km at that time, with a V_{max} of 32 m s^{-1} (Fig. 7g). Notably,



431 FIG. 6. Kilo (2015) time series of IBTrACS R_{max} (left axis, dashed blue), radiometer- and scatterometer-based $R_{max}^{CK22-BR}$ (left
 432 axis, dashed black), and IBTrACS-based V_{max}^{REG} (right axis, solid brown). Also displayed are radiometers (squares), scatterometers
 433 (circles) $R_{max}^{CK22-BR}$ estimates (color reveals which radius was used to define $R_{max}^{CK22-BR}$ for each observation), and SAR R_{max}
 434 estimates (green stars). The dashed black line was obtained by applying a support vector regression to the radiometer- and
 435 scatterometer-based $R_{max}^{CK22-BR}$ estimates.

452 Windsat failed to estimate V_{max} correctly, with a negative bias of almost 10 ms^{-1} , which is largely
 453 attributable to sensor spatial averaging effects. In fact, the entire azimuthally-averaged wind profile
 454 is negatively biased, leading to an underestimation of R_{34} , further reflected in $R_{max}^{CK22-BR}$. This case
 455 illustrates how wind radii uncertainties translate into $R_{max}^{CK22-BR}$ uncertainties.

456 The second case (Fig. 7, middle column), Mangkhut, was a super typhoon (category 5 on Saffir-
 457 Simpson scale), causing considerable damages in the Western Pacific ocean in 2018. It reached its
 458 peak intensity ($\sim 80 \text{ ms}^{-1}$) on 12 September. On 11 September, both S1B at 2048 UTC and Windsat
 459 at 2126 UTC overflow Mangkhut (Figs. 7b and 7e). According to the SAR observation, Mangkhut
 460 had a clearly-defined symmetric eyewall at that time. Note that the eyebrow shape near the eyewall
 461 (Fig. 7b) is probably due to rain contamination (for discussion about such a feature see Mouche

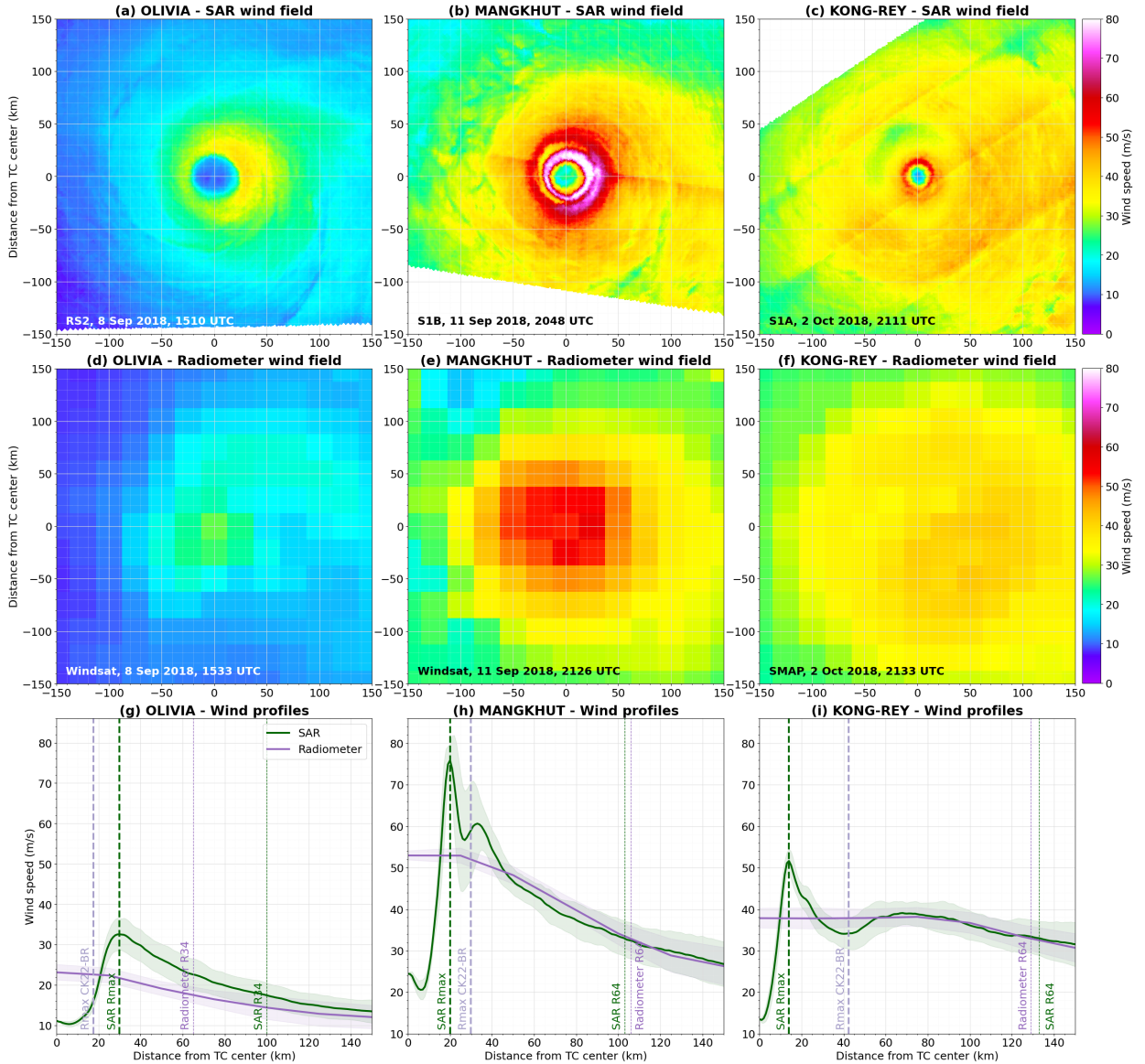
et al. (2019)). The extent of high winds was seemingly well captured by the radiometer sensor, but the eye was not resolved. Nevertheless, a very good agreement between S1B and Windsat wind outer-profiles is obtained for this case (Fig. 7h), with only ~ 3 km error between R_{64} estimates from the two sensors. Still, the estimate given by $R_{max}^{CK22-BR}$ (~ 30 km) largely overestimates the actual SAR R_{max} (~ 20 km). With its large R_{64} and small R_{max} at that time, Mangkhut illustrates the high variability that occurs in nature. Such a case is likely to depart from any statistical relationship (like CK22) that links a wind radius to R_{max} .

The last case study (Fig. 7, right column), Kong-Rey, in 2018, was a super typhoon reaching category 5 on the Saffir-Simpson scale, also evolving over the Western North Pacific ocean. Following a ~ 72 ms^{-1} peak intensity on 2 October Kong-Rey experienced an eyewall replacement cycle (ERC) and entered its weakening phase. Kong-Rey was captured on 2 October by both S1A at 2111 UTC and SMAP at 2133 UTC (Figs. 7c and 7f). The SAR observation depicts a well-defined symmetric eyewall, with a secondary ring of maximum winds further out from the TC center. In fact, Kong-Rey exhibited two eyewalls in 89 GHz imagery at this time (not shown). These two high wind regions were not well captured by the radiometer. The radiometer wind profile saturates in the 80 km inner-part of the TC, while the SAR wind profile exhibits two wind speed local maxima (Fig. 7i). Despite the inability of the radiometer sensor to capture the duel wind maxima observed at this time, the outer-part of the azimuthally-averaged wind profiles match well, both yielding a R_{64} estimate of ~ 128 km. Though, $R_{max}^{CK22-BR}$ is 42 km, far from the 14 km of SAR R_{max} . However, it is noteworthy that $R_{max}^{CK22-BR}$ lies between the two SAR wind maxima. The complex shape of Kong-Rey during its ERC is the main cause to explain such a huge discrepancy. Indeed, the R_{64} estimate is pushed to an outer radius due to the existence of secondary wind maxima.

b. Structural aspects

From these examples, we see that neither the use of high quality data (SAR) to train the algorithm nor the use of a radius that is very close to R_{max} (*i.e.* R_{64}) precludes large uncertainties of R_{max} estimates using the CK22 framework. Underlying CK22, the use of an outer wind radius (*e.g.* R_{34} ¹) to estimate R_{max} is justified by the angular momentum conservation principle: an air parcel, advected from the outer radii to the innermost radii, must lose angular momentum due to surface friction. The ratio $\frac{M_{max}}{M_{34}}$ thus represents the ability for an air parcel to keep its angular momentum

¹In this section we chose R_{34} as outer wind radius for clarity, but the reasoning well applies to any other wind radius (*e.g.* R_{50} and R_{64}).



484 FIG. 7. Comparison of SAR and radiometer wind fields (top and middle rows, TCs are translating toward the top of each panel)
 485 and corresponding wind profiles (bottom row) for Olivia (left column), Mangkhut (middle column) and Kong-Rey (right column).

493 while being advected from R_{34} to R_{max} . In the log-linear framework, this ratio solely depends on
 494 V_{max} , R_{34} , and f .

495 The use of these three parameters to estimate $\frac{M_{max}}{M_{34}}$ was discussed in Chavas et al. (2015) and
 496 Chavas and Lin (2016). In these studies, the ability of a radial parametric wind profile to represent
 497 the variability of observational data was tested. In brief, the radial parametric profile geometrically
 498 merges an inner-part profile with an outer-part profile, previously anticipated from theoretical

499 studies (Emanuel and Rotunno 2011; Emanuel 2004). Chavas and Lin (2016) concluded that the
500 ratio $\frac{M_{max}}{M_0}$ between the angular momentum at R_{max} and at an outer-radius R_0 solely depends on
501 four parameters: V_{max} , fR_0 , $\frac{C_k}{C_d}$, and $\frac{W_{cool}}{C_d}$, where C_k and C_d are the heat and momentum exchange
502 coefficients, while W_{cool} models the radiative-subsidence rate in the free troposphere of the outer-
503 part model. Considering $R_0 = R_{34}$, a log-linear dependence of $\frac{M_{max}}{M_{34}}$ on (V_{max}, R_{34}, f) thus neglects
504 the variations of both $\frac{C_k}{C_d}$ and $\frac{W_{cool}}{C_d}$.

505 Besides, the axisymmetric and steady-state theory of Emanuel and Rotunno (2011) invokes a
506 direct relationship between $\frac{M_{max}}{M_{34}}$ and $\frac{C_k}{C_d}$, that can be stated as

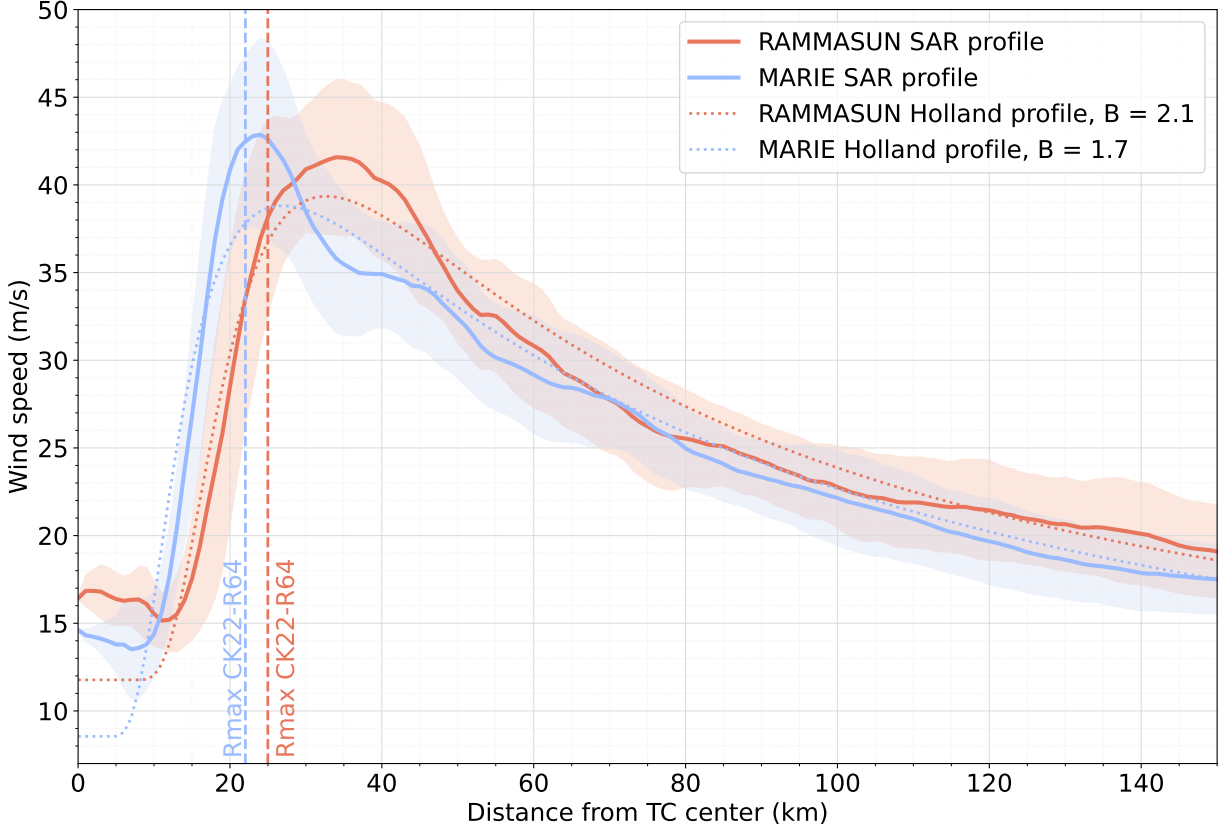
$$\frac{M_{max}}{M_{34}} = \pi\left(\frac{C_k}{C_d}\right) \quad (6)$$

507 with $\pi(x) := \left(\frac{1}{2}x\right)^{\frac{1}{2-x}}$ a monotonically increasing function (see their eq. 38). This relationship
508 assumes the TC is in steady-state and the Richardson number in the outflow is slightly below
509 one. The latter implies the outflow is self-stratified by small-scale turbulence. Using numerical
510 simulations that resolved convection, Emanuel and Rotunno (2011) showed that such an assumption
511 was satisfied in an outflow region near R_{max} . This assumption might then not hold true further out.
512 Chavas et al. (2015) suggested that the optimal merging radius between the inner- and outer-part
513 of the model was $\sim 2 - 3R_{max}$ when fitting the complete parametric profile to observational data.
514 While not strictly corresponding to the region where the theoretical developments of Emanuel and
515 Rotunno (2011) could remain valid, it identifies the region where the inner-part of the model is
516 most likely to apply to the observations.

517 When writing eq. 6, one assumes that the model of Emanuel and Rotunno (2011) is still valid at
518 R_{34} , which largely exceeds $3R_{max}$ in nature. This might be a strong approximation, but it offers an
519 instructive relationship between the rate of conservation of angular momentum (left-hand side) to a
520 function of $\frac{C_k}{C_d}$, characterizing the balance between energy generation and friction loss (right-hand
521 side). Most importantly, $\frac{C_k}{C_d}$ controls the shape of the parametric radial wind profile, with higher
522 values corresponding to more peaked profiles. In practice, unlike $\frac{C_k}{C_d}$ values, this shape of the
523 near-peak radial wind profile is more easily quantifiable using SAR data.

524 To highlight these considerations, we present TC cases that have the same CK22 predictors (V_{max} ,
525 R_{64} , f) but different wind profile shapes near their peak intensities. Figure 8 is representative of
526 such a situation. SAR acquisitions over TC Rammasun (West Pacific, red curve) and TC Marie

527 (East Pacific, blue curve), occurred on 17 July 2014 at 1027 UTC and on 3 October 2020 at 1419
 528 UTC, respectively. Both storms display similar outer-core profiles, with almost the same R_{64} (~ 52
 529 and ~ 49 km), V_{max} (~ 42 and ~ 43 m.s $^{-1}$) and f (~ 4.3 and ~ 4.6 s $^{-1}$). Applying CK22 to these cases
 530 (vertical dashed lines) thus leads to almost the same $R_{max}^{CK22-BR}$ value (~ 25 and ~ 22 km). However,
 531 SAR derived wind profiles provide different estimates, R_{max} (~ 34 and ~ 24 km, respectively).



532 FIG. 8. SAR wind profiles for Rammasun (solid red) and Marie (solid blue) and associated Holland best-fit profiles (dotted
 533 curves) fitted on $0 \leq r \leq 500$ km.

534 Comprehensively, the CK22 model cannot fully adjust to peculiar local wind profiles. To quantify
 535 the wind profile shapes, a Holland parametric profile (Holland 1980) was adjusted to each SAR
 536 azimuthally-averaged wind profile:

$$V_{Holland}(r) = V_{min} + \sqrt{(V_{max} - V_{min})^2 \left(\frac{R_{max}}{r}\right)^B e^{1 - \left(\frac{R_{max}}{r}\right)^B} + \left(\frac{rf}{2}\right)^2} - \frac{rf}{2} \quad (7)$$

537 This parametric formulation is useful to quantify variations in the shape of observed wind
 538 profiles. In particular, the empirical B parameter controls the rate of radial decay of the tangential
 539 winds, with higher (smaller) values corresponding to narrower (broader) vortices. In addition, this
 540 parameter was found to be sensitive to TC intensity and size while independent of R_{max} (Knaff
 541 et al. 2011).

542 Note, Holland's profiles were designed for gradient-level wind and are not necessarily suited
 543 for surface wind profiles with nonzero wind speeds at the TC center, well captured using SAR
 544 observations. A complementary degree of freedom (V_{min}) was thus included in eq. 7 to cope with
 545 the existence of nonzero minimum wind speeds.

546 Using the full extent of the wind profile, a solution for V_{min} , V_{max} , R_{max} and B can be estimated via
 547 least squares. Applied to TC Rammasun and Maria, the fitting procedure results in two different B
 548 values, ~ 2.1 and ~ 1.7 , respectively (Fig. 8). Such a difference quantifies the remaining variability
 549 of the near-core wind profile for comparable outer-core wind profiles.

550 *c. Analysis framework*

551 The shape of the near-core wind profile is generally associated with the radial gradient of absolute
 552 angular momentum and thus the loss of angular momentum when an air parcel is advected from
 553 R_{34} to R_{max} . To guide the analysis, we recall the equation of angular momentum conservation for
 554 an axi-symmetric vortex:

$$\frac{\partial M}{\partial t} + u \frac{\partial M}{\partial r} + w \frac{\partial M}{\partial z} = \frac{r}{\rho} \frac{\partial \tau_{\theta z}}{\partial z} \quad (8)$$

555 with u and w , the radial and vertical velocities, $\tau_{\theta z}$ a tangential stress component, and ρ the
 556 density. The continuity equation links u and w as

$$\frac{1}{r} \frac{\partial (ru)}{\partial r} + \frac{\partial w}{\partial z} = 0 \quad (9)$$

557 Under steady state condition, eq. 8 can be integrated from the surface to a boundary layer height,
 558 h , where the stress vanishes:

$$\int_0^h u \frac{\partial M}{\partial r} dz + \int_0^h w \frac{\partial M}{\partial z} dz = -\frac{r \tau_{\theta s}}{\rho} = -C_d r V^2 \quad (10)$$

559 with $\tau_{\theta_s} \approx C_d \rho V^2$ the surface stress, C_d a drag coefficient and V the tangential surface wind
 560 component. Assuming $w(z=0) = 0$ and the use of the continuity equation (eq. 9), the second
 561 term of the left hand-side in eq. 10 is integrated by parts, following developments presented by
 562 Kalashnik (1994), to obtain

$$\int_0^h u \frac{\partial M}{\partial r} dz + [wM]|_{z=h} + \int_0^h \frac{M}{r} \frac{\partial(ru)}{\partial r} dz = -C_d r V^2 \quad (11)$$

563 Grouping the two integrals yields

$$\frac{1}{r} \frac{d}{dr} \left(r \int_0^h u M dz \right) + [wM]|_{z=h} = -C_d r V^2 \quad (12)$$

564 Defining $\bar{u} := \frac{1}{h} \int_0^h u dz$ we can approximate the integral $\int_0^h u M dz \approx h \bar{u} M|_{z=h}$ and rewrite the
 565 continuity equation $w|_{z=h} = -\frac{h}{r} \frac{d}{dr} (r \bar{u})$. Rearrangement finally yields:

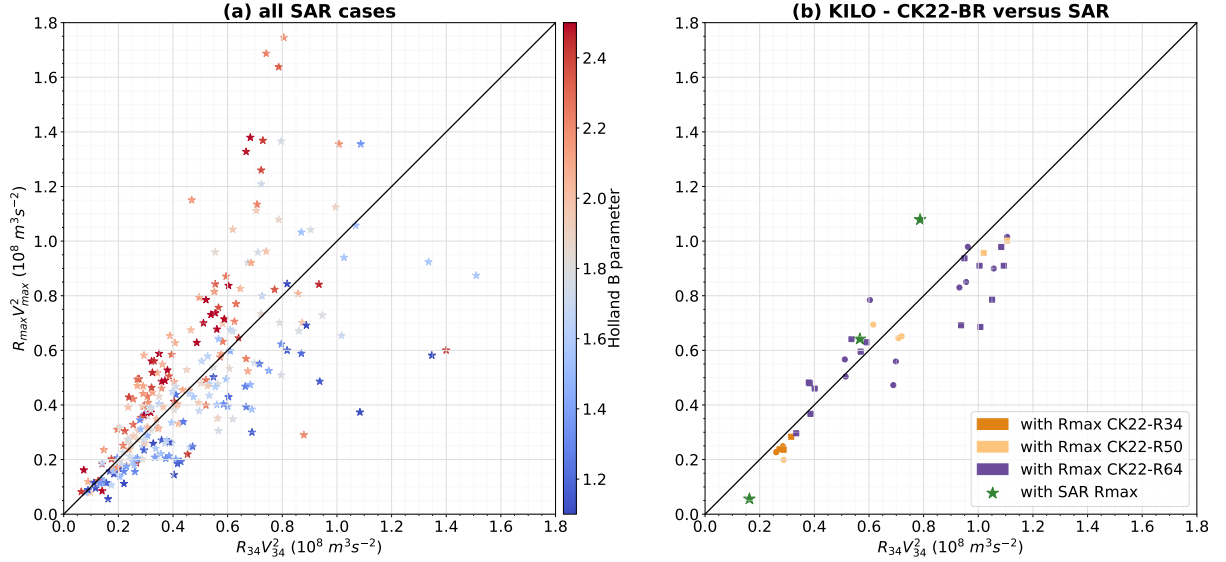
$$r V^2 \approx -\frac{h \bar{u}}{C_d} \frac{dM}{dr} \quad (13)$$

566 where $\frac{dM}{dr}$ is the radial gradient of absolute angular momentum at the top of the boundary layer.
 567 Assuming the latter closely related to its value at the surface, eq.13 then explicitly links the shape
 568 of the wind profile $\frac{dM}{dr}$ to $r V^2$.

569 Using SAR measurements, both quantities can be accurately estimated, and the validity of eq. 13
 570 assessed. Figure 9a represents $R_{max} V_{max}^2$ (y-axis) as a function of $R_{34} V_{34}^2$ (x-axis) and colored by
 571 the fitted B values². On average, *i.e* $B \simeq 1.8$, a relationship emerges when comparing $R_{max} V_{max}^2$ and
 572 $R_{34} V_{34}^2$. Departures from a one-to-one relationship, related to conservation of the $r V^2$ parameter,
 573 are seemingly well explained by B values. Large B , corresponding to very peaked wind profiles
 574 near V_{max} , leads to larger $R_{max} V_{max}^2$ for a given $R_{34} V_{34}^2$. For broader wind profiles, corresponding
 575 to smaller B , smaller $R_{max} V_{max}^2$ are generally found.

579 Moreover, the space spanned in the $(R_{34} V_{34}^2, R_{max} V_{max}^2)$ -plane is still apparently large, even at
 580 constant B . From eq. 13, this increased variability is possibly associated with the factor $\frac{h \bar{u}}{C_d}$.
 581 Overall, these results suggest that the variability encountered in nature does not solely depends on
 582 the three predictors (V_{max}, R_{34}, f) .

² B , as a scalar value, was used instead of a criterion based on $\frac{dM}{dr}$ to describe the shape of the wind profile



576 FIG. 9. Evaluation of the PV conservation assumption in the SAR dataset (a) and for Kilo's life cycle (b) using R_{34} estimated
 577 on radiometer and scatterometer data along with corresponding $R_{max}^{CK22-BR}$ estimates and V_{max}^{REG} . The three SAR cases (green
 578 stars) are also displayed for reference.

583 To further illustrate this diagnosis, Fig. 9b displays the same $(R_{34}V_{34}^2, R_{max}V_{max}^2)$ -plane, but
 584 using the radiometer and scatterometer database, and corresponding V_{max}^{REG} , R_{34} and $R_{max}^{CK22-BR}$
 585 estimates. As expected, the variability captured by using R_{34} or R_{50} to estimate R_{max} via CK22 is
 586 poor. While using R_{64} increases this variability, the overall spread is reduced compared to Fig. 9a,
 587 suggesting that the variability of the wind profile shapes associated with the $R_{max}^{CK22-BR}$ estimates
 588 is low.

589 Note, the average situation $rV^2 \approx \text{constant}$ which is depicted in our study thanks to the SAR
 590 database has already been discussed by Riehl (1963) when he argued that PV is conserved within
 591 the inflow layer. PV conservation implies the vertical component of the curl of the frictional force
 592 to be zero, or

$$\frac{r}{\rho} \frac{\partial \tau_{\theta z}}{\partial z} = \text{constant} \quad (14)$$

593 Integrating this equation over the boundary layer height yields (assuming constant density):

$$\frac{r\tau_{\theta s}}{\rho} = C_d r V^2 = \text{constant} \quad (15)$$

594 Thus, for a constant or slowly varying drag coefficient C_d , PV conservation leads to $rV^2 \approx \text{constant}$
 595 (Riehl 1963). Mentioned above, such a relationship is, on average, consistent with the SAR
 596 estimates. However, for this relationship, the only source of variability comes from C_d . From
 597 arguments raised above (eq. 13), h and \bar{u} should also be further considered.

598 Lastly, one limitation of our observational analysis is that SAR V_{max} is an estimate of the
 599 maximum total wind speed rather than the maximum tangential wind speed. Knowing how the
 600 total wind speed is distributed between its tangential and radial component near the eyewall region
 601 would allow to better estimate the impact of \bar{u} on PV conservation and its variability.

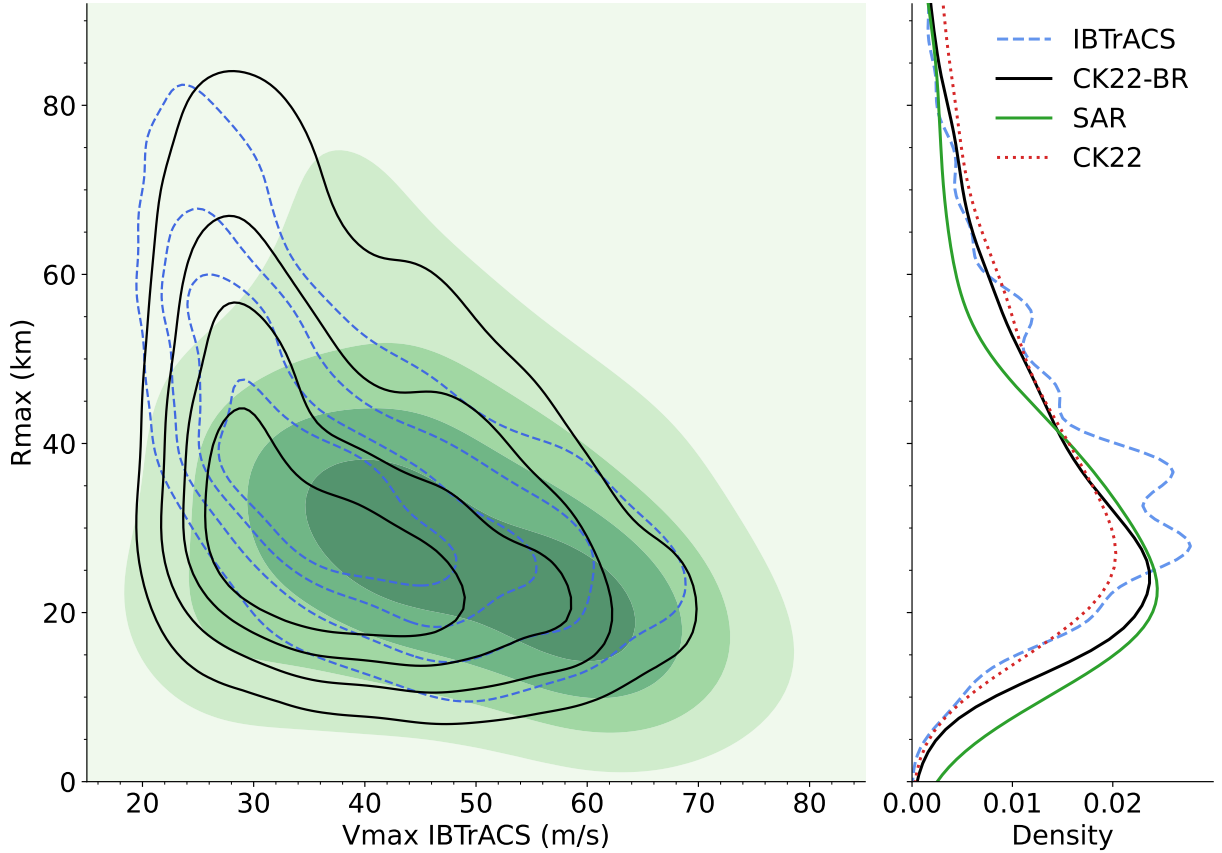
602 *d. Comparison of $R_{max}^{CK22-BR}$ with existing R_{max} estimates*

603 With these results in mind, we assessed how much $R_{max}^{CK22-BR}$ estimates improved existing R_{max}
 604 estimates. Figure 10 displays density contours of (V_{max}, R_{max}) joint distributions using IBTrACS
 605 R_{max} (dashed blue) or $R_{max}^{CK22-BR}$ estimates (solid black). For comparison, the same density contours
 606 are shaded for the SAR dataset (green).

607 We remind readers that SAR wide-swaths acquisitions cannot be continuously performed over
 608 the ocean. As a consequence, not only does the SAR dataset contain much fewer cases, it is also
 609 biased towards higher intensities. Indeed, acquisition orders are most often requested to observe
 610 higher intensity systems. Thus, for the lowest V_{max} (less than $\sim 30 \text{ m s}^{-1}$), possible inconsistencies
 611 in R_{max} densities arise when comparing SAR to radiometer and scatterometer or IBTrACS. The
 612 density contours suggest that both IBTrACS R_{max} and $R_{max}^{CK22-BR}$ estimates are larger than SAR
 613 R_{max} , while, in fact, this is just a consequence of the lack of SAR data at these intensities.

614 Nevertheless, and more importantly for high surface winds, discrepancies in R_{max} densities are
 615 observed. Indeed, on average IBTrACS density contours are centered on a higher R_{max} ($\sim 30 \text{ km}$)
 616 than SAR (progressively decreasing to $\sim 20 \text{ km}$). Confirming the efficacy of the revised model,
 617 radiometer- and scatterometer-based density contours display an average $R_{max}^{CK22-BR}$ ($\sim 20 \text{ km}$) that
 618 is consistent with SAR R_{max} . Depicted by the R_{max} density curves (right panel), for low R_{max} ,
 619 IBTrACS density is lower than both SAR and $R_{max}^{CK22-BR}$ values.

620 For further comparison, we computed R_{max} estimates from R_{34} on the radiometer and scatterom-
 621 eter data using eq. 7 of Chavas and Knaff (2022). The corresponding density curve (dotted red)
 622 shows only a minor improvement compared to IBTrACS at low R_{max} .
 623



614 FIG. 10. Density contours of (V_{max}, R_{max}) joint distribution for the SAR dataset (shaded green, V_{max} based on IBTrACS),
 615 for the dataset based upon radiometers and scatterometers with $R_{max}^{CK22-BR}$ (solid black) and based on corresponding IBTrACS
 616 R_{max} values (dashed blue). The corresponding R_{max} density curves are displayed on the right panel, along with R_{max} estimates
 617 obtained by applying eq. 7 of Chavas and Knaff (2022) to the radiometer- and scatterometer-based dataset (dotted red).

627 Finally, the density contours of the radiometer and scatterometer dataset with $R_{max}^{CK22-BR}$ span a
 628 larger space than IBTrACS in the (V_{max}, R_{max}) -plane. This shows that the former captures more
 629 variability than best-track data. This is likely due to the use of R_{64} in the regression, a result
 630 already suggested by Fig. 9b. Even though the datasets don't have the same V_{max} distributions,
 631 Fig. 10 also suggests that the radiometer and scatterometer density contours span less space than
 632 SAR observations in the (V_{max}, R_{max}) -plane. While this is consistent with the above analysis, more
 633 SAR cases are needed to properly interpret Fig. 10.

634 **6. Conclusions and perspectives**

635 Understanding TC intensity changes certainly remains an observationally challenging problem.
636 As expressed during the Tenth International Workshop on Tropical Cyclones (IWTC-10, rec-
637 ommendation 4), both the operational and research communities recognize the need for more
638 homogeneous and standardized datasets for TC wind structure parameters, such as R_{max} and the
639 wind radii. The fact that R_{34} was not systematically reanalyzed in all basins, and that R_{max} is still
640 not reanalyzed today (best-track R_{max} value typically stems from its operational estimate) hampers
641 the consolidation of such a dataset. Systematic and standardized wind radii are needed when using,
642 and further improving, a semi-empirical model such as CK22. Although satellite sensors have their
643 limitations, especially regarding the inter-calibration of different missions and sensors, resulting
644 multi-modal observations shall serve for such a systematic and global approach, at least for wind
645 radii estimation.

646 More specifically and thanks to high-resolution (SAR) data, it is now possible to more systemati-
647 cally estimate R_{max} . Fitted with SAR estimates and used in conjunction with the closest wind radius
648 to R_{max} , our study proposed a revised CK22 model. It is shown to be an efficient tool to provide
649 improved reliable estimates, with an average uncertainty of ~ 9 km. Because outer-core wind radii
650 can be estimated from radiometer or C-band scatterometer data, the developed framework thus
651 allows to produce a more extensive dataset of reanalyzed R_{max} estimates. The resulting time series
652 are generally more realistic than those obtained from best-track R_{max} estimates. The method can
653 also be used to provide operational guidance on the location of the maximum intensity every time
654 a radiometer or C-band scatterometer overflies the TC, as long as its intensity and location are also
655 estimated, noting that such estimates are routinely available from operational centers. Furthermore,
656 the proposed method could also be used to guide the best-tracking process when no reliable R_{max}
657 observation is available.

658 The efficacy of the semi-empirical CK22 model stems from fundamental conservation principles.
659 Indeed, the high-resolution SAR database highlights that TCs, on average, conserve their PV, with
660 a resulting approximation $rV^2 \approx \text{constant}$. Accordingly, the use of CK22 to retrieve R_{max} , based
661 on an outer-radius wind observation coupled with an intensity estimate is, on average, justified.
662 Single cases can still depart considerably from the PV conservation assumption, especially those

663 at very high intensity (V_{max}) or with large inner- (R_{max}) or outer-size (R_{34}). And, to first order,
664 those deviations are well explained by variations of the observed wind profile shapes.

665 While the use of R_{64} can account for some of the deviations due to the radial gradient of
666 absolute angular momentum, the CK22 model seems to fail to capture the remaining variability
667 observed in the SAR database. Large variability is apparently still occurring near the TC core.
668 To further advance our understanding, there continues to be a need for spaceborne SAR and
669 airborne SFMR sensors as these are the only tools that resolve surface winds in this area. Both
670 sensors however suffer from a lack of spatio-temporal sampling, and airborne measurements suffer
671 from a lack of azimuthal coverage. The future is bright with the recently launched RADARSAT
672 Constellation Mission (RCM) operated by CSA, which should improve the satellite SAR spatio-
673 temporal sampling. RCM has already proved useful by providing significantly more R_{max} estimates
674 than anticipated for the 2022-2023 season. And, increasing the number of available SAR cases will
675 certainly allow to better understand how absolute angular momentum gradients are constrained in
676 the near-core region.

677 Furthermore, the integrated equations show that both the boundary layer depth (h), the average
678 radial inflow (\bar{u}), and the drag (C_d) also impact the relationship between PV conservation and
679 the near-core wind profile shape. While the C_d behaviour under very high winds is still actively
680 debated (Powell et al. 2003; Bell et al. 2012), measurements of both h and \bar{u} may be facilitated by
681 the Doppler-based motions derived from the Imaging Wind and Rain Airborne Profiler (IWRAP)
682 instrument (Sapp et al. 2022). For the radial inflow, improved estimates at the surface, in the near-
683 core region, shall be made possible with the future Harmony mission (ESA 2022), the ESA Earth
684 Explorer 10. This mission will augment Sentinel 1D observations with two satellite companions,
685 providing azimuth diversity from these bi-static observations. In addition, the Second Generation
686 Meteorological Operational satellite programme (Metop-SG) will operate in both co- and cross-
687 polarization. Unlike the current spaceborne instruments, ASCAT, which have only co-polarization
688 measurements, the higher sensitivity of cross-polarized signals to ocean breaking waves may thus
689 improve the ocean surface wind vectors measured by scatterometers, approaching the TC core
690 regions. Also, the coming Copernicus Imaging Microwave Radiometer (CIMR) promises to offer
691 large swath with improved resolution, low uncertainty observation capabilities, combining L-, C-
692 and X-band frequencies . The presence of 1.4 GHz L-band channel on board CIMR will open

693 up the possibility to further interpret the high-resolution C- and X-band measurements, to provide
694 improved surface wind vector estimates under extreme conditions (Kilic et al. 2018).

695 Finally, in the absence of high-resolution observations, the shape of the near-core wind profile may
696 also be indirectly estimated. Given the relation $rV^2 \approx \text{constant}$ under a steady-state assumption,
697 a departure from this relation can help understand the temporal variations of absolute angular
698 momentum. Estimates of these temporal variations may then be used to evaluate how much the
699 near-core wind profile shape departs from the average relationship. The wind profile shape is
700 also linked to the drag coefficient (see for instance the steady-state view of Emanuel and Rotunno
701 (2011)), which modulates asymmetries in the boundary layer response (Shapiro 1983; Kepert
702 2001). Asymmetries possibly captured by medium- or low-resolution observations (scatterometers
703 or radiometers), may thus help to infer boundary layer frictional drag terms, and to quantify the
704 resulting shape of the wind profile.

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711 The views, opinions, and findings contained in this report are those of the authors and should not
712 be construed as an official National Oceanic and Atmospheric Administration or U.S. government
713 position, policy, or decision.

714 *Data availability statement.* The data used in this study are freely available on-
715 line for both the dataset of radiometer and scatterometer winds ([https://www.
716 odatis-ocean.fr/donnees-et-services/acces-aux-donnees/catalogue-complet/
717 #/metadata/6c56bcde-050f-42eb-92b8-8e882e1f4db9](https://www.odatis-ocean.fr/donnees-et-services/acces-aux-donnees/catalogue-complet/#/metadata/6c56bcde-050f-42eb-92b8-8e882e1f4db9)) and the SAR database
718 (<https://cyclobs.ifremer.fr/>).

719 APPENDIX A

720 Scatterometer wind speed estimates

721 As explained in section 2, the wind speed estimates from different radiometer and scatterometer
722 sensors have been inter-calibrated prior to our study. During this process, the C-band ASCAT
723 missions were calibrated using a 25 km resolution, while the Ku-band scatterometer sensors were
724 calibrated using a 50 km resolution. Spatial resolution was already demonstrated to impact how
725 well TCs intensities are resolved in numerical models (Davis 2018) and observations (Quilfen et al.
726 1998). Here, we expect discrepancies between the C- and Ku-band observational wind products.

727 To quantify this resolution effect, SAR wind fields were degraded to both 25 and 50 km spatial
728 resolution and then azimuthally-averaged. The V_{max} values estimated from these degraded wind
729 profiles were then compared to IBTrACS V_{max} , as represented by the green (25 km) and red (50
730 km) stars of Fig. A1. Here, SAR V_{max} refers to the maximum found in an azimuthally-averaged
731 wind profile. We thus expect slight discrepancies with IBTrACS V_{max} , whose definition does not
732 strictly coincide with a wind profile maximum. The comparison between SAR azimuthal means

733 and IBTrACS is indicated by the grey stars and modelled by a linear fit (grey dashed line in Fig.
734 A1) which defines V_{max}^{REG} :

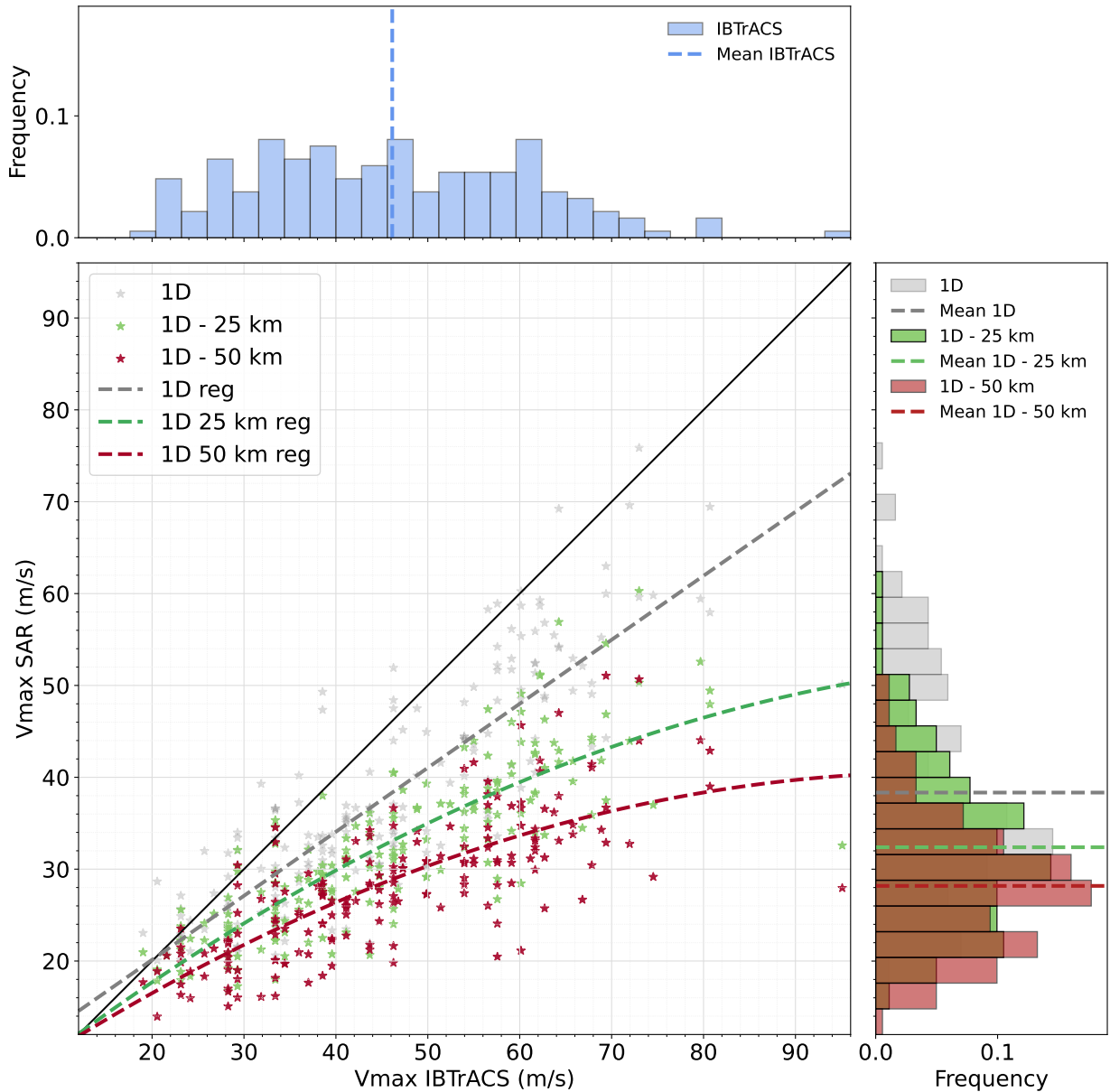
$$V_{max}^{REG} = 0.6967V_{max}^{IBTrACS} + 6.1992 \quad (A1)$$

735 The green and red scatters in Fig. A1 should be compared to this regression line (grey dashed)
736 rather than the 1:1 line. The 25- and 50-km simulated V_{max} values show that as spatial resolution
737 decreases V_{max} also decreases, and the decreasing tendency is more pronounced as intensity
738 increases. On average, a V_{max} of $\sim 38 \text{ ms}^{-1}$ observed at the full-resolution azimuthally-averaged
739 wind profile (*i.e* the raw SAR wind profile) would yield $\sim 32 \text{ ms}^{-1}$ when observed at a 25 km
740 spatial resolution and $\sim 28 \text{ ms}^{-1}$ at a 50 km spatial resolution. Second-order polynomial fits were
741 constructed to model this spatial resolution effect.

742 Using these linear and polynomial fits as reference, we then compared C-band and Ku-band
743 scatterometer V_{max} values with IBTrACS in Fig. A2. It shows that C-band scatterometer V_{max}
744 values are consistent with the 25 km spatial resolution polynomial model (green dashed curve). In
745 contrast, Ku-band scatterometer V_{max} are still underestimated when compared to IBTrACS values
746 following the correction for their 50 km resolution (red dashed curve). In particular, Ku-band
747 scatterometer V_{max} estimates rarely exceed 64 knots (33 ms^{-1}), precluding their use to estimate
748 wind radii in our analysis.

756 References

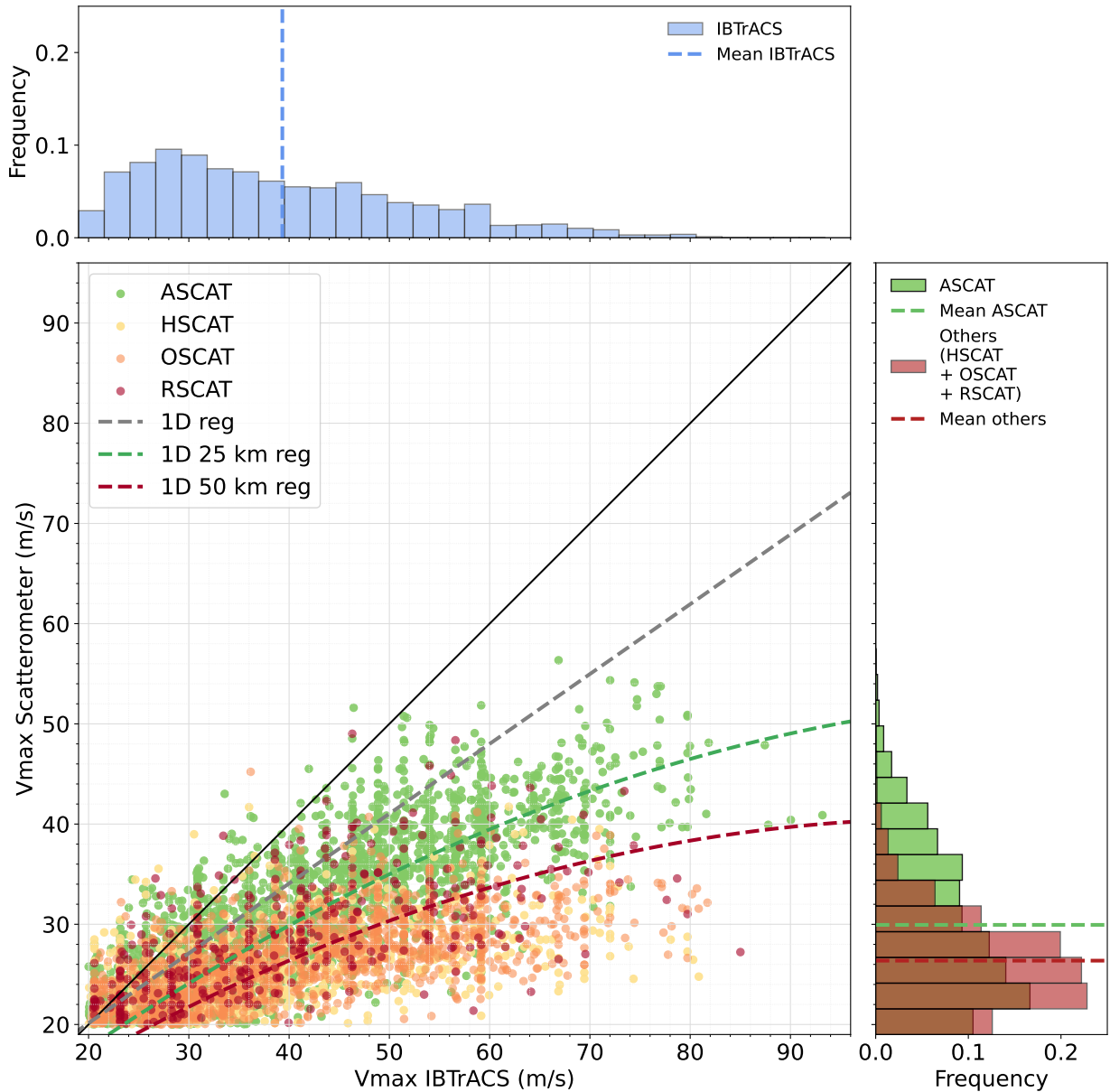
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742 FIG. A1. Comparison between SAR (y-axis) and IBTrACS (x-axis) V_{max} for the raw dataset (grey) and when degraded at
 743 25 km (green) or 50 km (red) resolution. Dashed lines represent best linear fit for the raw dataset (grey) and best second order
 744 polynomial fits for the 25 km (green) and 50 km (red) datasets. A solid black line represents identity. V_{max} distributions and
 745 averages are displayed for the different SAR samples (right) and for corresponding IBTrACS values (top).

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753 FIG. A2. Comparison between scatterometer (y-axis) and IBTrACS (x-axis) V_{max} for ASCAT (green), HSCAT (yellow),
 754 OSCAT (orange), and RSCAT (red). Solid and dashed lines are identical to Fig. A1. V_{max} distributions and averages are displayed
 755 for the different scatterometer datasets (right) and for corresponding IBTrACS values (top).

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