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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.

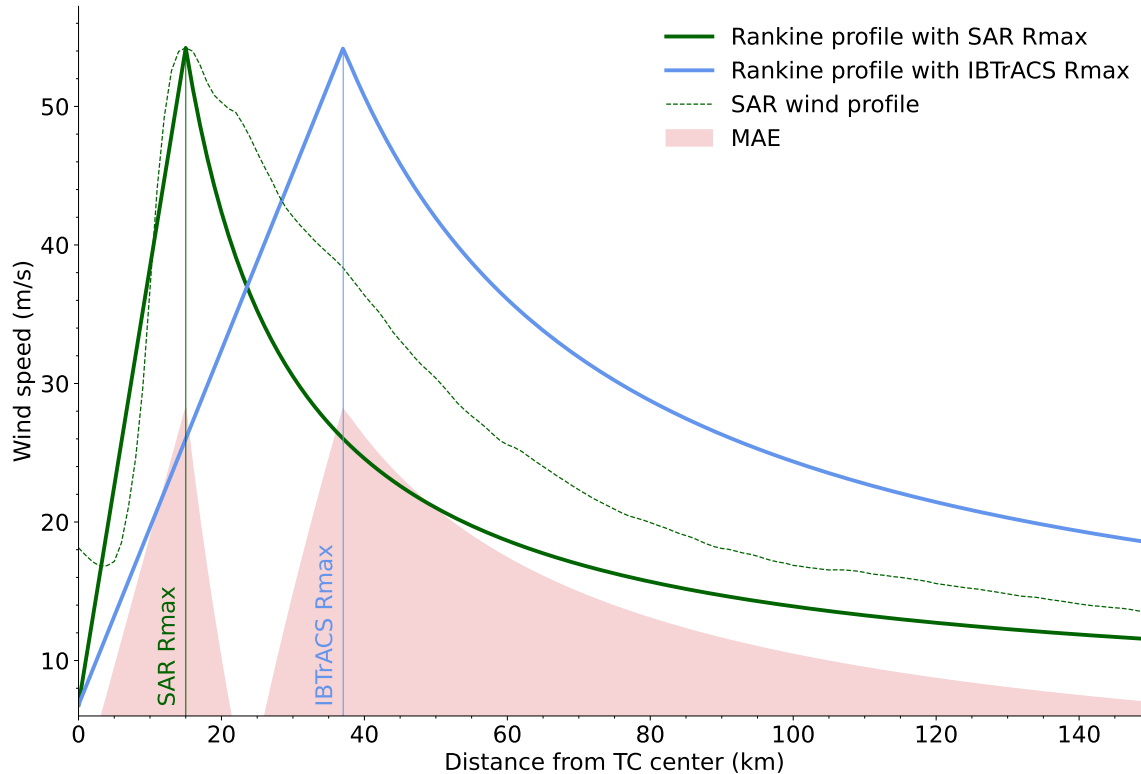
## 30 1. Introduction

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  $28 \text{ m s}^{-1}$  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  $V_{max}$  ( $54 \text{ m s}^{-1}$ ) and  $V_{min}$  ( $7 \text{ m s}^{-1}$ ), 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 ( $33 \text{ m s}^{-1}$ ), 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  $\sim 5$   
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  $\phi$  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  $\sim 1000$  km swaths, satellite-borne  
175 radiometers are well suited to monitor TCs. However, they have nominally low spatial resolutions  
176 ( $\sim 40$  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  $\sim 25$  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).

<b>RADIOMETER</b>	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
<b>SCATTEROMETER</b>	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  $\sim 500$  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  $50 \text{ m s}^{-1}$  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.

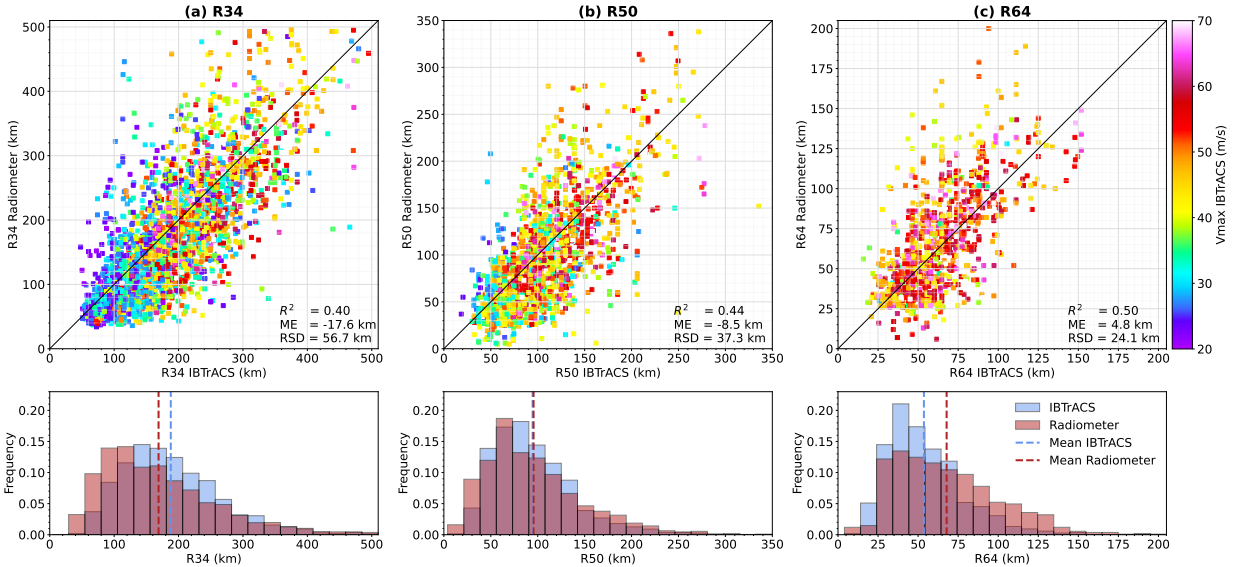
280 Regarding the wind radii, an azimuthally-averaged wind profile was first computed for every  
281 satellite file using the corresponding IBTrACS center linearly-interpolated to the acquisition time.  
282 For each of the three speed values of interest (*i.e.* 34, 50 and 64 knots), we then selected 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.

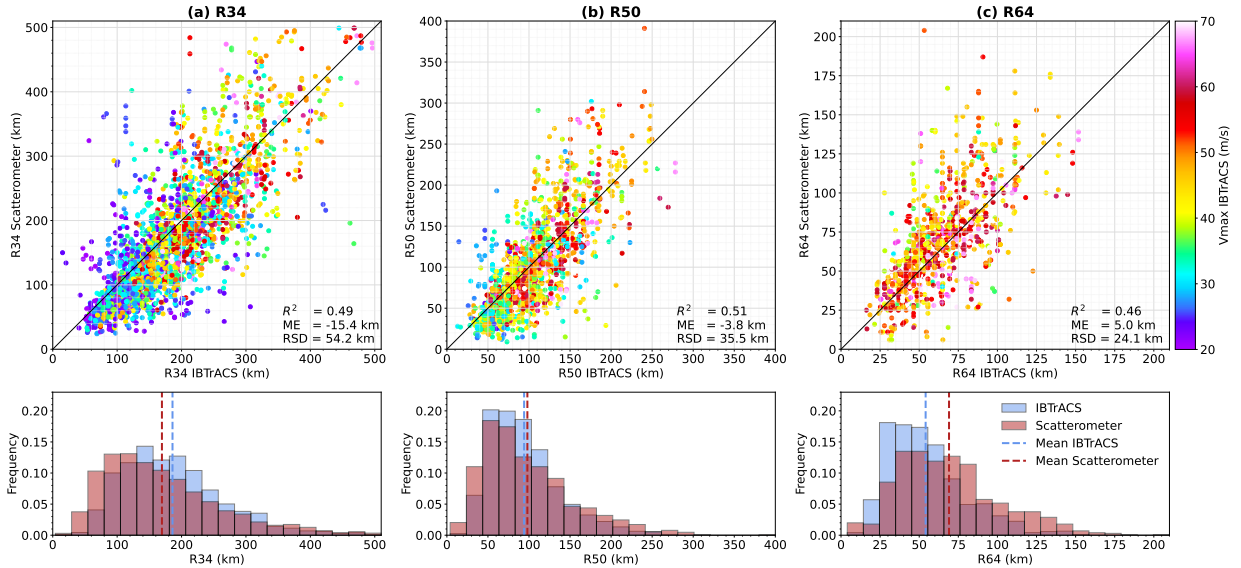


FIG. 3. Same as Fig. 2, but for the C-band scatterometer wind radii.

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



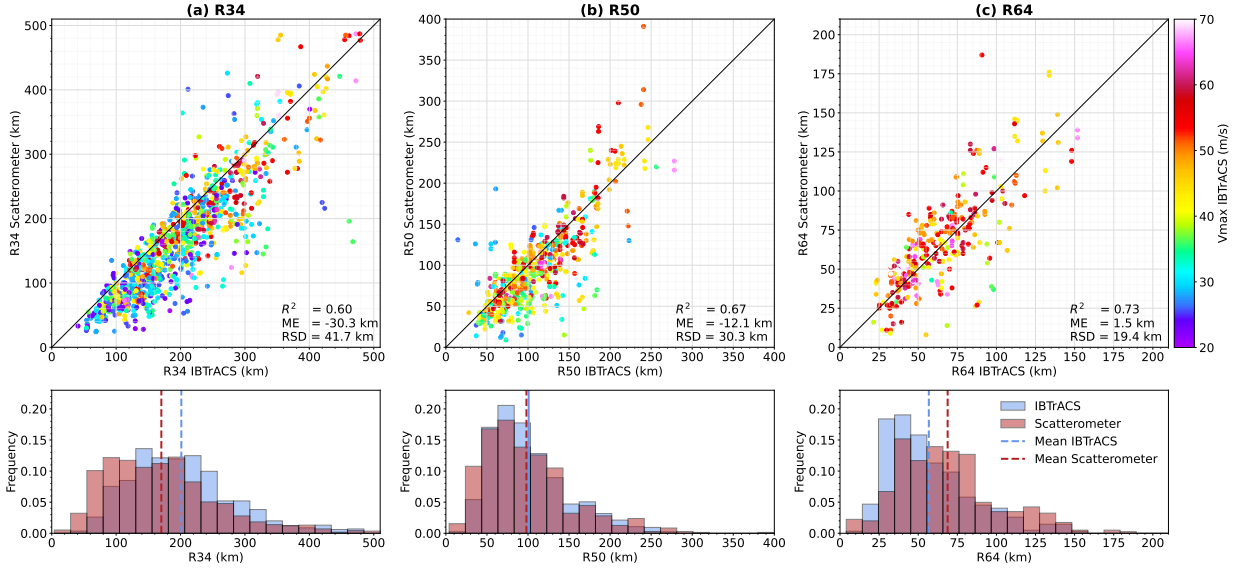


FIG. 4. Same as Fig. 3, but only for the 3-year period 2018-2020.

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).

## 4. Results

### a. Fitting CK22 model

As explained in the introduction, the CK22 model relies on the estimation of the ratio  $\frac{M_{max}}{M_{34}}$  via a log-linear regression model, using  $(X_{34}^{(1)}, X_{34}^{(2)})$  as input. While CK22 used  $R_{34}$  in their study, this method is in fact agnostic from the choice of wind radius. Therefore, the ratio  $\frac{M_{max}}{M_{50}}$  can also be 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  $\frac{M_{max}}{M_{64}}$  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).

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

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

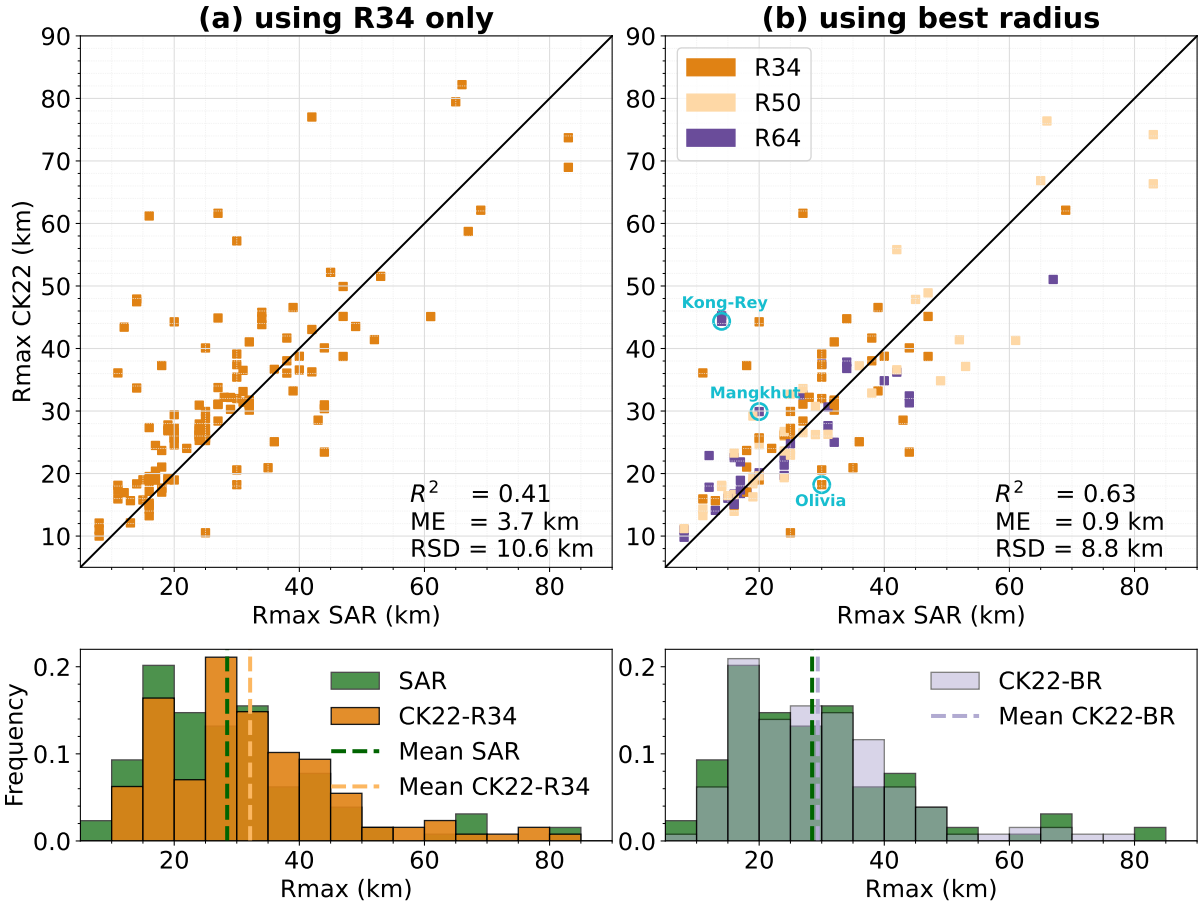
$$\frac{M_{max}}{M_{50}} = 0.626e^{0.00282(V_{max}^{REG}-25.7ms^{-1})-0.00724(V_{max}^{REG}-25.7ms^{-1})(\frac{1}{2}fR_{50})} \quad (4)$$

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

With these formulas,  $R_{max}$  can then be estimated using the steps presented in the introduction (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 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  $33 \text{ m s}^{-1}$ ),

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  $\sim 10$  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  $20 \text{ m s}^{-1}$ . TC Kilo evolved in the Pacific ocean, reaching category  
410 4 on the Saffir-Simpson scale. It intensified from 20 to  $49 \text{ m s}^{-1}$  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.

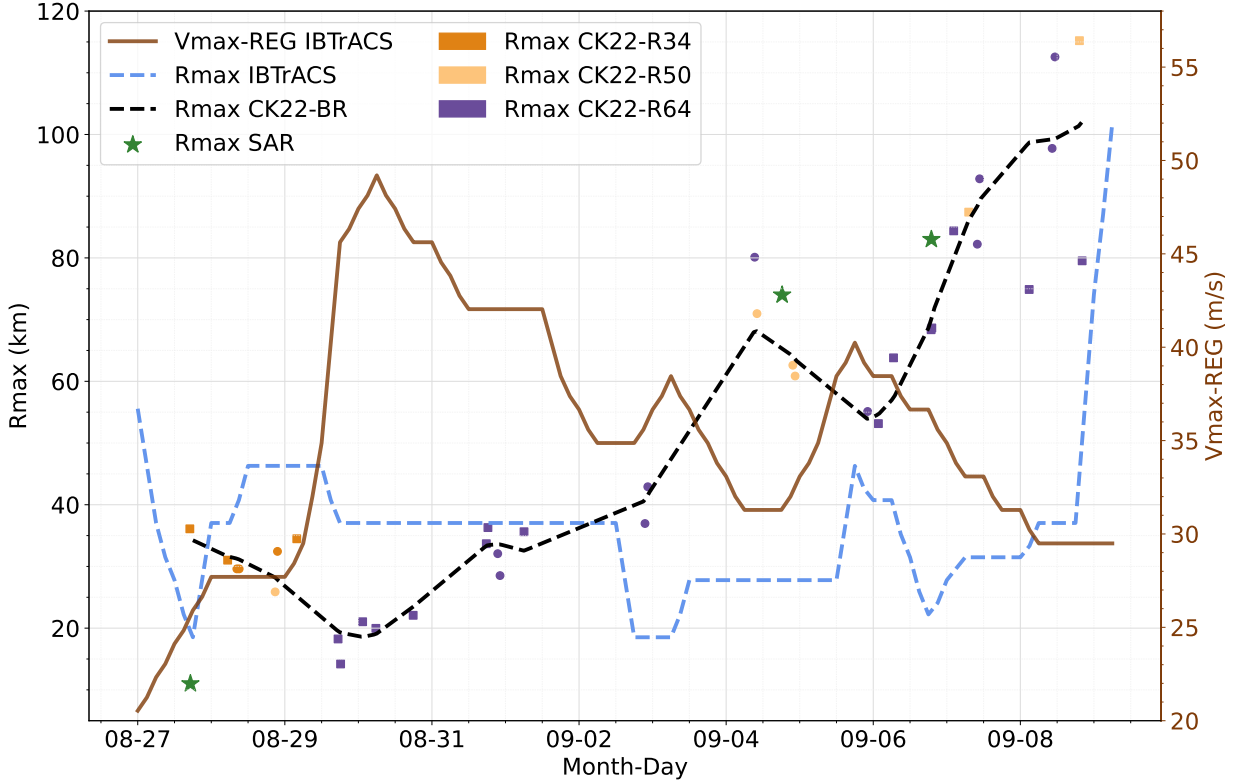
427 In summary, every time a radiometer or scatterometer wind profile is available, a subsequent  
428  $R_{max}^{CK22-BR}$  estimate can be obtained, using the proposed objective method. In such a way, one can  
429 estimate  $R_{max}$  trends that are more realistic than IBTrACS, less impacted from 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  $32 \text{ m s}^{-1}$  (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  $10 \text{ ms}^{-1}$ , 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  $\sim 3$  km error between  $R_{64}$  estimates from the two sensors. Still, the estimate given by  $R_{max}^{CK22-BR}$  ( $\sim 30$  km) largely overestimates the actual SAR  $R_{max}$  ( $\sim 20$  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  $R_{max}$ .

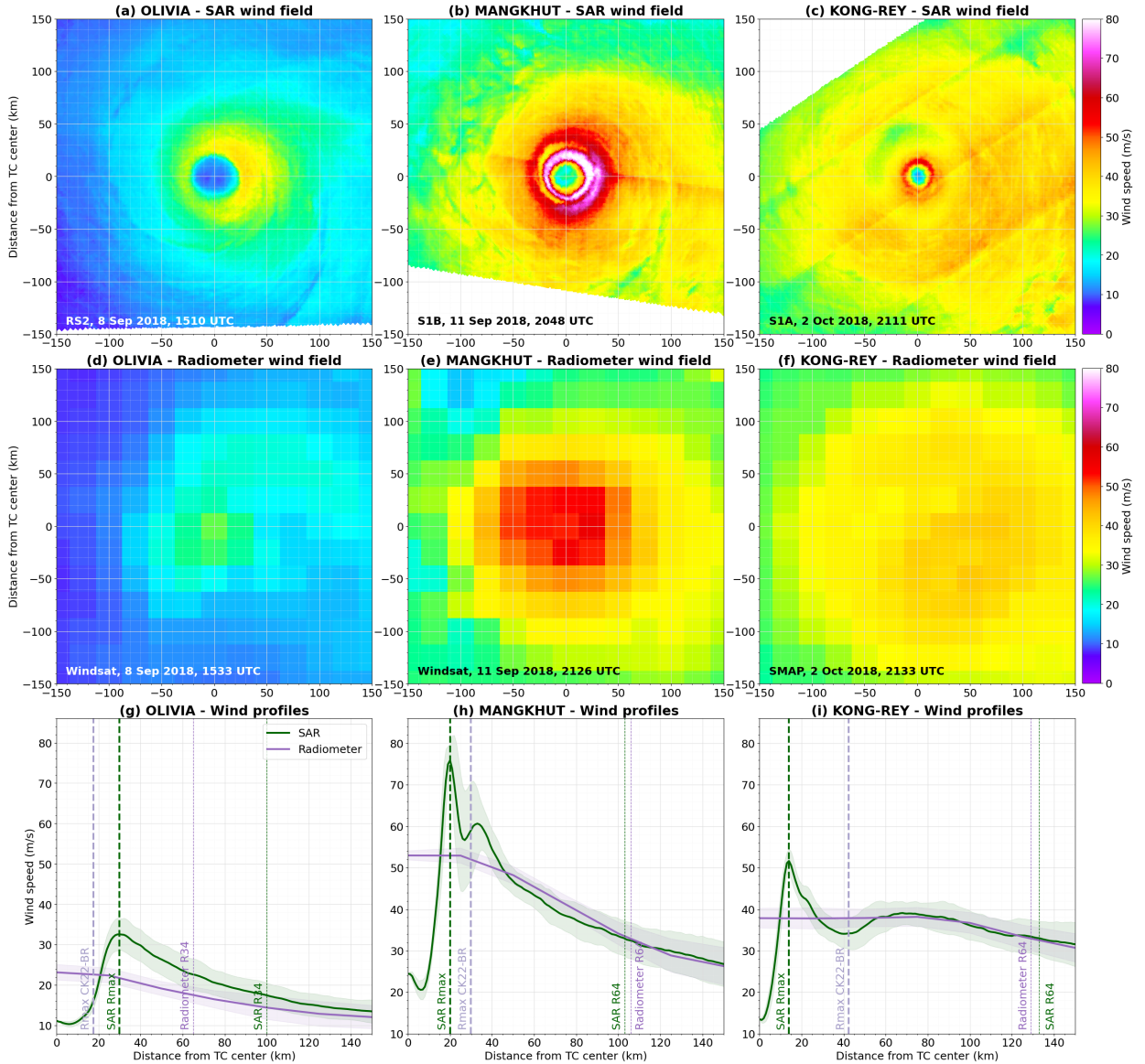
The last case study (Fig. 7, right column), Kong-Rey, in 2018, was a super typhoon reaching category 5 on the Saffir-Simpson scale, also evolving over the Western North Pacific ocean. Following a  $\sim 72$   $ms^{-1}$  peak intensity on 2 October Kong-Rey experienced an eyewall replacement cycle (ERC) 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  $\sim 128$  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.*  $R_{34}$ <sup>1</sup>) 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

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<sup>1</sup>In 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

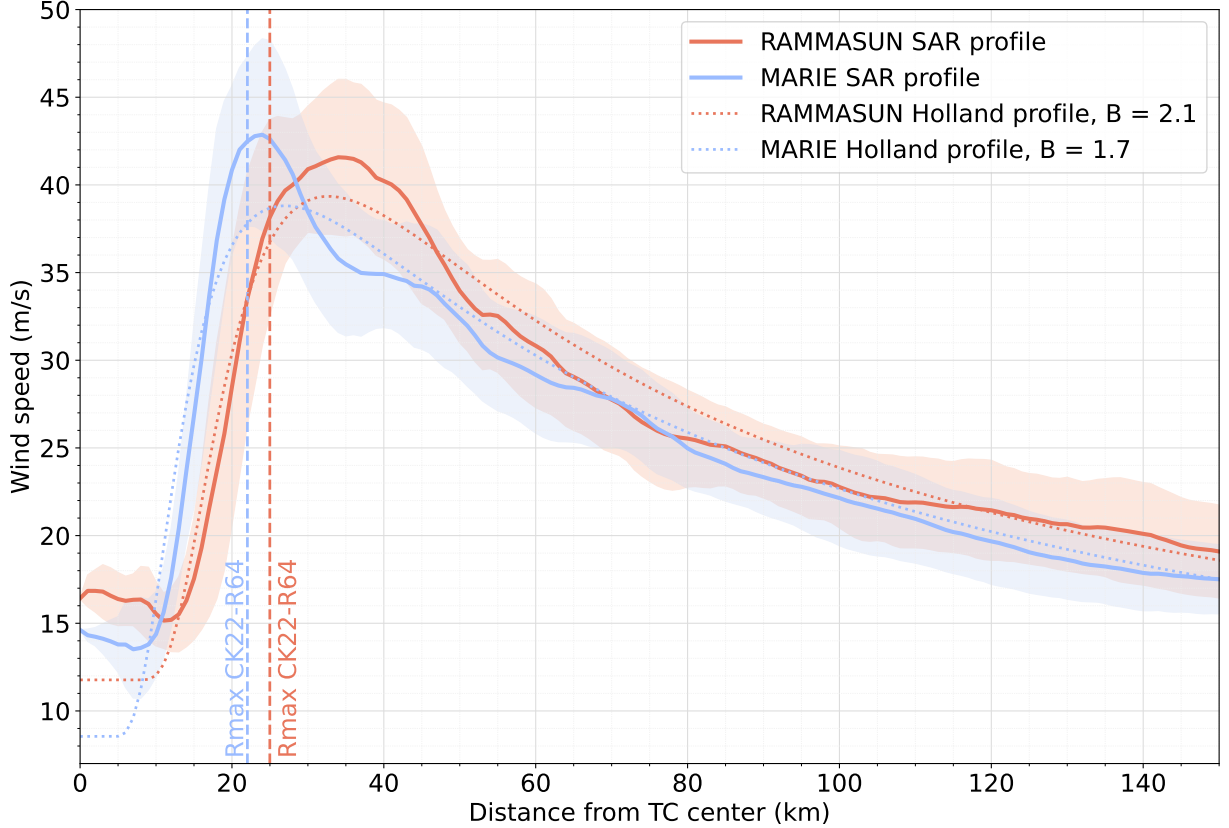
$$\frac{M_{max}}{M_{34}} = \pi\left(\frac{C_k}{C_d}\right) \quad (6)$$

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  $R_{64}$  ( $\sim 52$   
 529 and  $\sim 49$  km),  $V_{max}$  ( $\sim 42$  and  $\sim 43$  m.s $^{-1}$ ) and  $f$  ( $\sim 4.3$  and  $\sim 4.6$  s $^{-1}$ ). Applying CK22 to these cases  
 530 (vertical dashed lines) thus leads to almost the same  $R_{max}^{CK22-BR}$  value ( $\sim 25$  and  $\sim 22$  km). However,  
 531 SAR derived wind profiles provide different estimates,  $R_{max}$  ( $\sim 34$  and  $\sim 24$  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,  $\sim 2.1$  and  $\sim 1.7$ , 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  $\rho$  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:

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

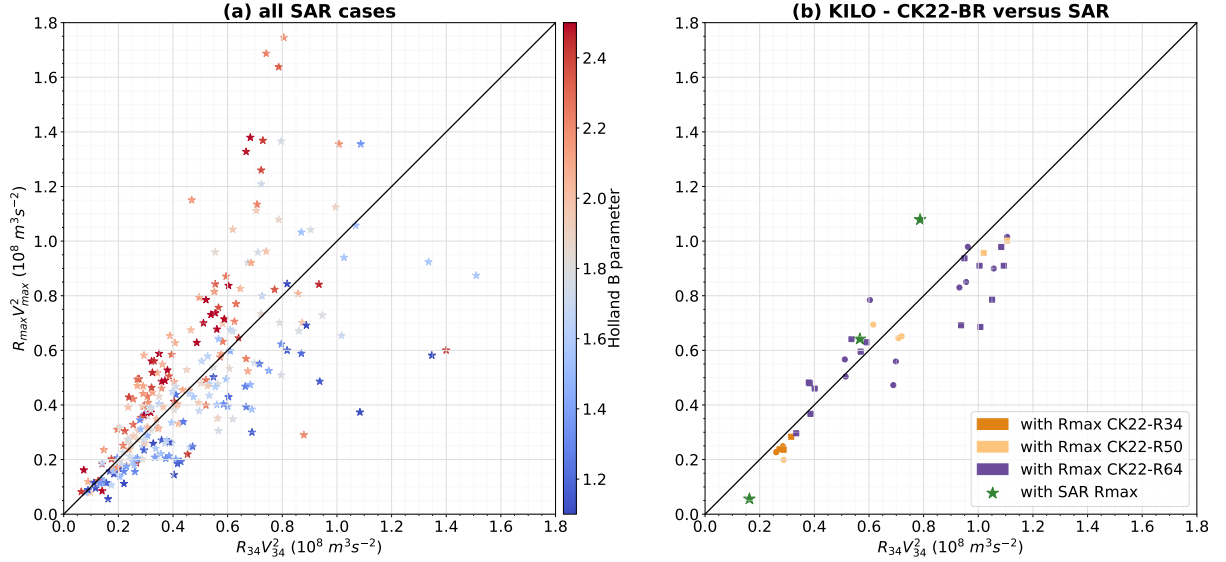
566 where  $\frac{dM}{dr}$  is the radial gradient of absolute angular momentum at the top of the boundary layer.  
 567 Assuming the latter closely related to its value at the surface, eq.13 then explicitly links the shape  
 568 of the wind profile  $\frac{dM}{dr}$  to  $r V^2$ .

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  $B$  values<sup>2</sup>. 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  $(V_{max}, R_{34}, f)$ .

---

<sup>2</sup> $B$ , 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.

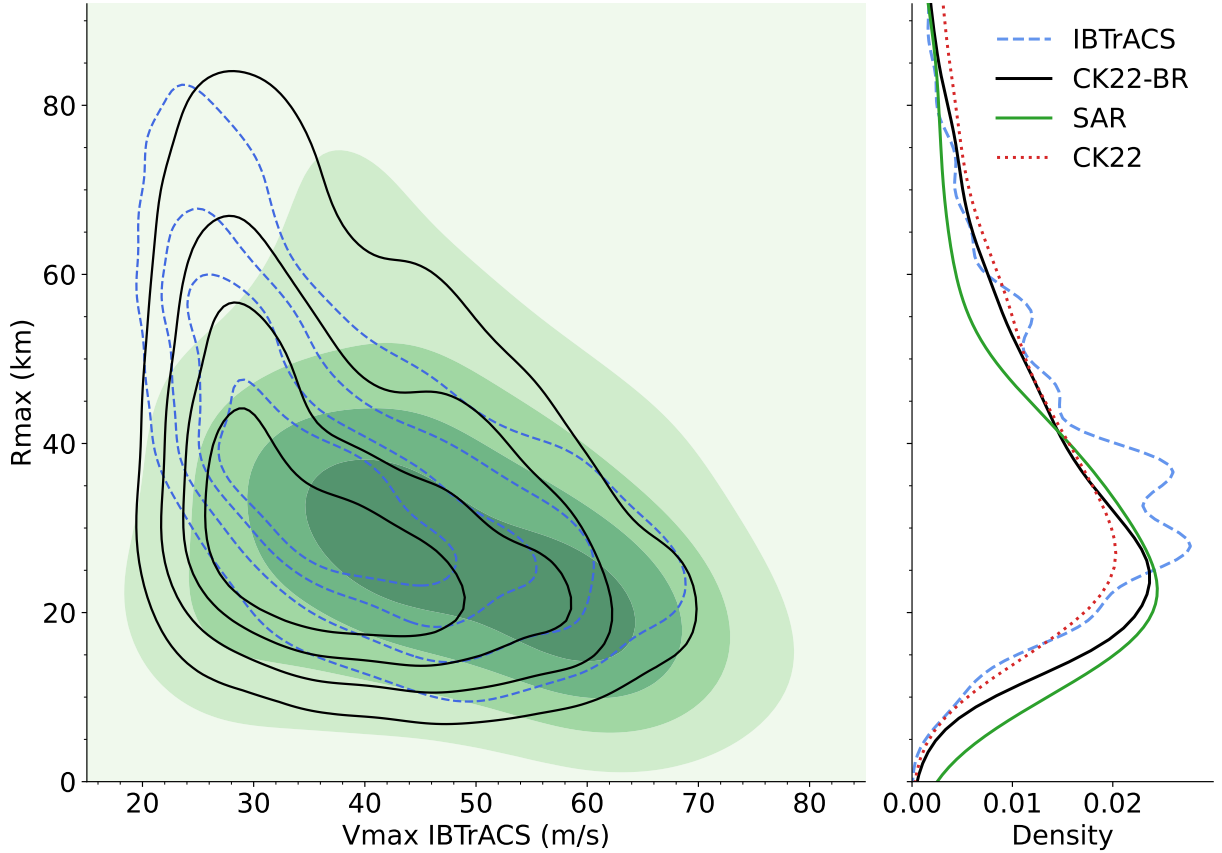
#### 602 *d. Comparison of $R_{max}^{CK22-BR}$ with existing $R_{max}$ estimates*

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  $R_{max}$ .



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  $\sim 9$  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  $V_{max}^{REG}$ :

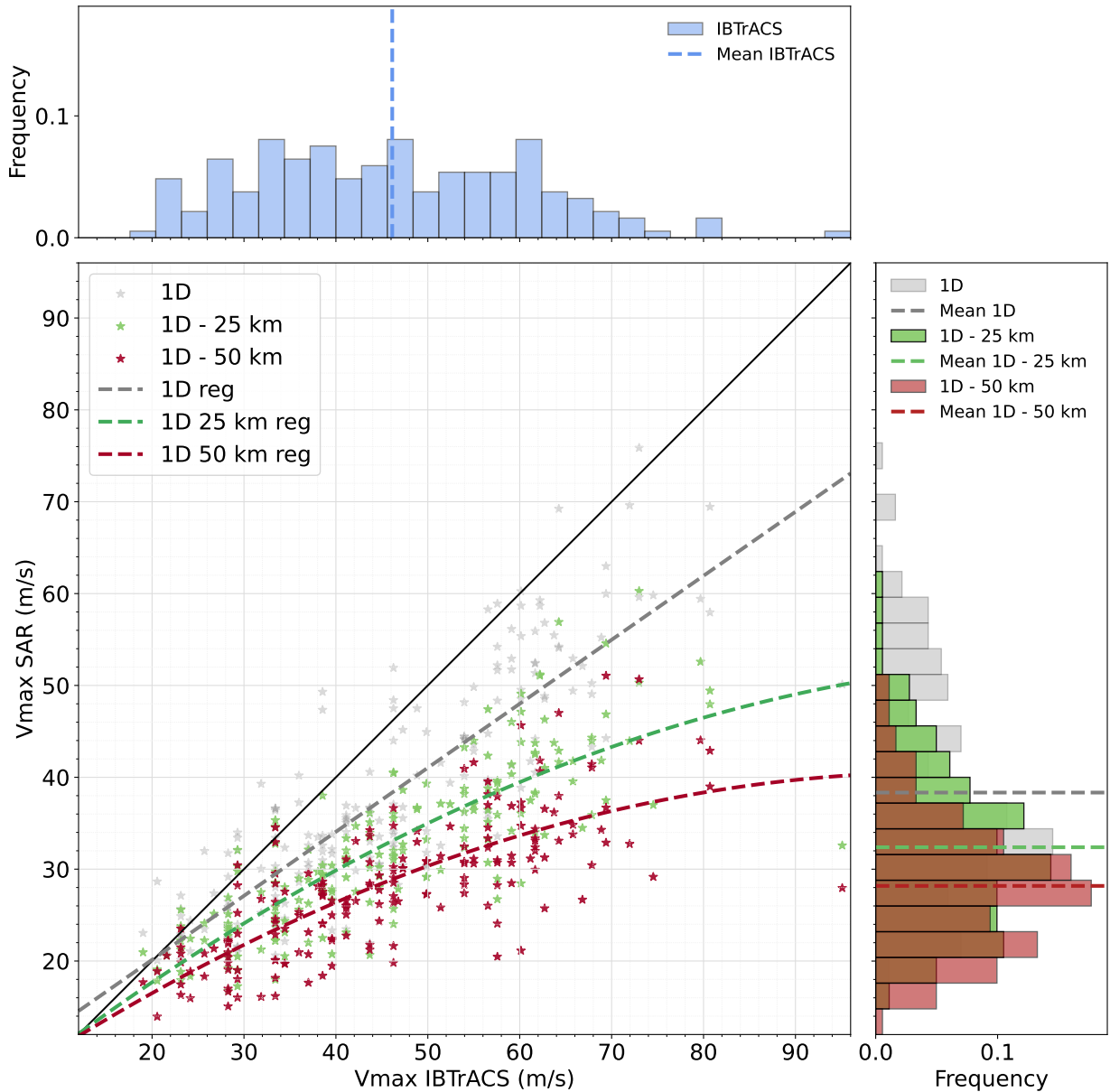
$$V_{max}^{REG} = 0.6967V_{max}^{IBTrACS} + 6.1992 \quad (A1)$$

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 ( $33 \text{ ms}^{-1}$ ), precluding their use to estimate  
748 wind radii in our analysis.

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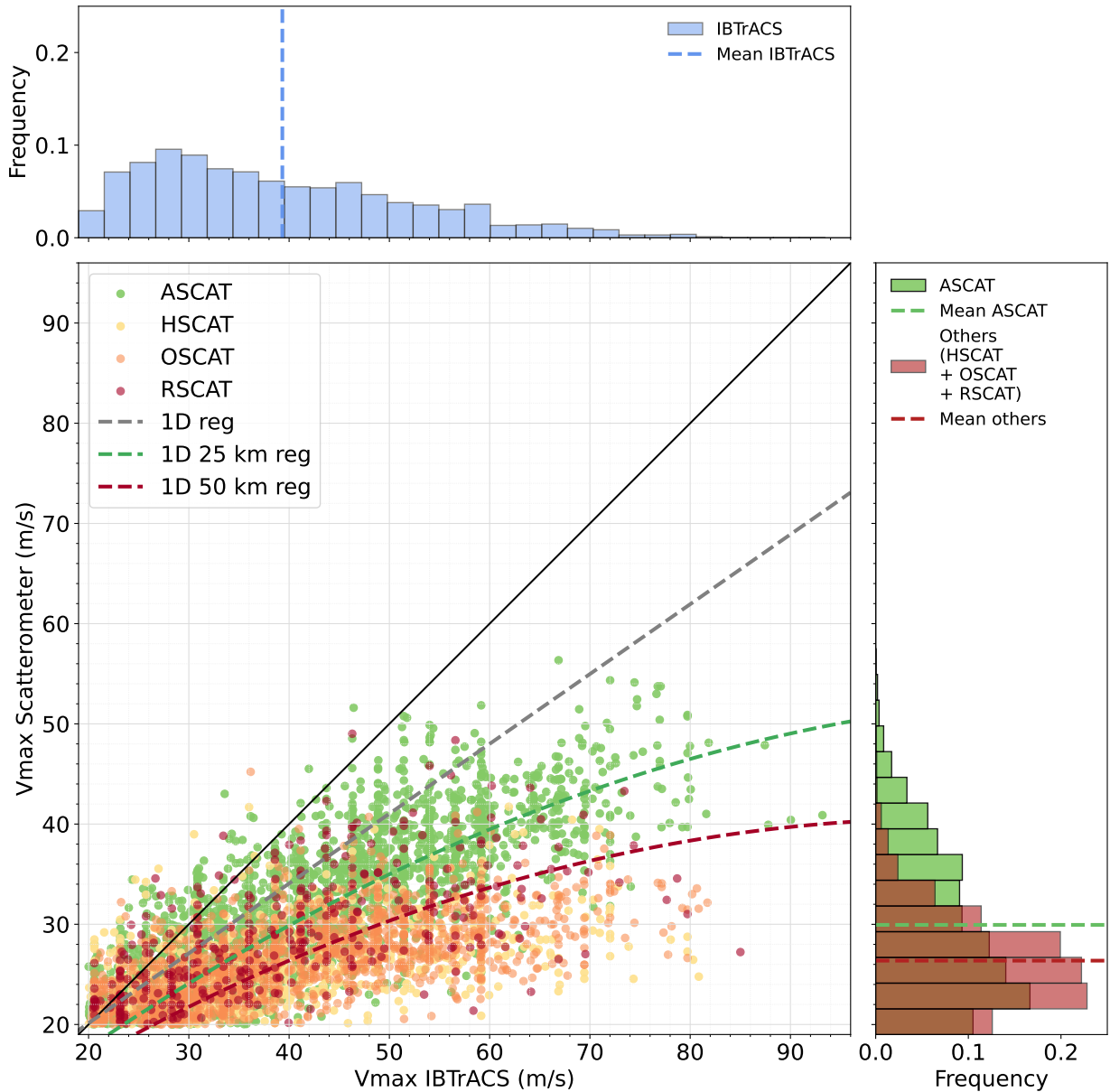
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742 FIG. A1. Comparison between SAR (y-axis) and IBTrACS (x-axis)  $V_{max}$  for the raw dataset (grey) and when degraded at  
 743 25 km (green) or 50 km (red) resolution. Dashed lines represent best linear fit for the raw dataset (grey) and best 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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