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► **To cite this version:**

Davide Faranda, Gabriele Messori, Pascal Yiou, Soulivanh Thao, Flavio Pons, et al.. Detecting intense hurricanes from low resolution datasets via dynamical indicators. 2021. hal-03219409v1

**HAL Id: hal-03219409**

**<https://hal.science/hal-03219409v1>**

Preprint submitted on 6 May 2021 (v1), last revised 7 Dec 2022 (v4)

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1 **Detecting intense hurricanes from low resolution datasets via dynamical**  
2 **indicators**

3 Davide Faranda\*

4 *Laboratoire des Sciences du Climat et de l'Environnement, CEA Saclay l'Orme des Merisiers,*  
5 *UMR 8212 CEA-CNRS-UVSQ, Université Paris-Saclay & IPSL, 91191, Gif-sur-Yvette, France;*  
6 *London Mathematical Laboratory, 8 Margravine Gardens, London, W6 8RH, UK; LMD/IPSL,*  
7 *Ecole Normale Supérieure, PSL research University, 75005, Paris, France*

8 Gabriele Messori

9 *Department of Earth Sciences, Uppsala University, and Centre of Natural Hazards and Disaster*  
10 *Science (CNDS), Uppsala, Sweden; Department of Meteorology, Stockholm University, and Bolin*  
11 *Centre for Climate Research, Stockholm, Sweden.*

12 Pascal Yiou, Soulivanh Thao, Flavio Pons

13 *Laboratoire des Sciences du Climat et de l'Environnement, CEA Saclay l'Orme des Merisiers,*  
14 *UMR 8212 CEA-CNRS-UVSQ, Université Paris-Saclay & IPSL, 91191, Gif-sur-Yvette, France*

15 Berengere Dubrulle

16 *SPEC, CEA, CNRS, Université Paris-Saclay, F-91191 CEA Saclay, Gif-sur-Yvette, France*

<sup>17</sup> \**Corresponding author address*: Davide Faranda, Laboratoire des Sciences du Climat et de  
<sup>18</sup> l'Environnement, CEA Saclay l'Orme des Merisiers, UMR 8212 CEA-CNRS-UVSQ, Université  
<sup>19</sup> Paris-Saclay & IPSL, 91191, Gif-sur-Yvette, France  
<sup>20</sup> E-mail: [davide.faranda@lsce.ipsl.fr](mailto:davide.faranda@lsce.ipsl.fr)

## ABSTRACT

21 Although the life-cycle of hurricanes is well understood, many of the un-  
22 derlying physical processes occur at scales below those resolved by global  
23 climate models (GCMs), so that projecting future changes in hurricane char-  
24 acteristics remains challenging. We assess the capability of dynamical system  
25 metrics to identify intense cyclones even in coarse resolution datasets, where  
26 wind speed may be not accurately represented. We compute dynamical indi-  
27 cators, namely the persistence and number of active degrees of freedom, from  
28 the horizontal wind field of 146 tropical cyclones occurred between 2010  
29 and 2018 using ERA5 reanalysis data at  $0.25^\circ$  horizontal resolution, and  
30 link these to the maximum sustained winds as detected from observational  
31 datasets. Our analysis provides a representation of cyclones in phase space  
32 and allows to: i) identify different stages of the cyclones' life cycle as distinct  
33 regions of the phase space; and ii) locate regions of the phase space associated  
34 with intense cyclones (as detected from observations). Specifically, we find  
35 that the most intense cyclones are associated with a strong decrease of the  
36 instantaneous dimension and an increase in persistence of tropical cyclones.  
37 This relation could be used for detection of intense cyclones in comparatively  
38 coarse resolution datasets, such as those issued from GCM simulations or  
39 century-long reanalyses.

## 40 **1. Introduction**

41 Tropical cyclones are high-impact extreme weather events. In the United States of America,  
42 they are the costliest natural disaster category (Smith and Katz 2013; Grinsted et al. 2019), with  
43 the damage related to hurricane Katrina (2005) alone amounting to about 1% of the country's gross  
44 domestic product (Grinsted et al. 2019). Trends in the frequency of occurrence or intensity of trop-  
45 ical cyclones are difficult to discern in observations, because of the comparative rarity of the events  
46 and of the brevity of highly spatially and temporally resolved datasets, which rely on in-situ and  
47 satellite observations (Chang and Guo 2007). Projections of future climate indicate an increase in  
48 the intensity of hurricanes in the North Atlantic sector, albeit only with medium confidence (Kossin  
49 et al. 2017) because of the difficulties in reproducing the dynamics of the most severe hurricanes  
50 even in the most advanced global or regional climate models (Roberts et al. 2020b). Indeed, while  
51 mid-latitudes synoptic dynamics mostly originates from the chaotic structure of the motions asso-  
52 ciated with baroclinic instability (Lorenz 1990; Schubert and Lucarini 2015), tropical cyclones are  
53 characterized by a rapid organization of convectively unstable flows whose dynamics is turbulent  
54 and highly sensitive to boundary conditions (Muller and Roms 2018).

55 Destructive tropical cyclones often experience rapid intensification, which occurs when a trop-  
56 ical cyclone gains dramatically in strength over a short period of time (Sanders 1986). The rapid  
57 intensification phenomenon, well explained from a theoretical viewpoint (Klein 2010; Soloviev  
58 et al. 2017), results in an enhancement of the destructive potential of the cyclone and in a degraded  
59 predictability of its trajectory (Lee et al. 2016). It is often detected via an increment (generally 40  
60 Kts) of sustained winds over a period of 24h. It is challenging to detect this phenomenon in global  
61 climate models (GCMs), due to the coarse resolution of wind field data. Emanuel (2017) discusses

62 several wide-reaching implications of the poor representation of hurricanes in GCMs for present  
63 and future climates.

64 Here, we investigate whether it may be possible to obtain a reliable indicator of intense tropical  
65 cyclones from relatively coarse gridded atmospheric data. Specifically, we compute two met-  
66 rics that describe cyclones as states of a chaotic high-dimensional dynamical system, and reflect  
67 the persistence and dimension (i.e. the number of active degrees of freedom) of instantaneous  
68 states of the cyclones. These metrics have recently provided insights on a number of geophysical  
69 phenomena, including transitions between transient metastable states of the mid-latitude atmo-  
70 sphere (Faranda et al. 2017; Hochman et al. 2019), palaeoclimate attractors (Brunetti et al. 2019;  
71 Messori and Faranda 2021) slow earthquake dynamics (Gualandi et al. 2020) and changes in mid-  
72 latitude atmospheric predictability under global warming (Faranda et al. 2019). All these applica-  
73 tions have taken a Eulerian approach, and have thus focused on a fixed spatio-temporal domain,  
74 rather than tracking the evolution of specific physical phenomena. Here, we apply for the first time  
75 the two metrics in a Lagrangian perspective. A Lagrangian dynamical systems framework is par-  
76 ticularly convenient to study the complex behavior of convectively unstable flow systems (Crisanti  
77 et al. 1991; Vulpiani 2010), such as tropical convection. As an additional benefit over previous dy-  
78 namical systems approaches (e.g Wolf et al. 1985; Cao 1997), these metrics can be easily applied  
79 to large datasets, such as climate reanalyses or climate models. Their Lagrangian implementation  
80 enables to characterize the phase-space structure of tropical cyclones in terms of their dimension  
81 and persistence, and observe whether these single out the most intense cyclones. The rationale is  
82 that the signature of intense cyclones propagates through scales due to the presence of inverse cas-  
83 cades as suggested by Levich and Tzvetkov (1985) and, more recently, by Faranda et al. (2018). If  
84 this were indeed the case, we could then use the region of phase space targeted by intense cyclones  
85 in observations to detect the same phenomenon in datasets where we cannot explicitly access the

86 relevant spatial scales. Our study is organized as follows: first, we describe the data, observables  
87 for cyclone dynamics and the theoretical bases supporting the computation of the dynamical indi-  
88 cators. Then, we show the general characteristics of the phase space of tropical cyclones for the  
89 different observables. Finally, we investigate rapid intensification and discuss our results.

## 90 **2. Data and Methods**

### 91 *a. Representation of tropical cyclones in ERA5 data*

92 We follow 146 Atlantic tropical cyclones which occurred between 2010 and 2018 and base  
93 the computation of the two dynamical systems metrics on hourly-mean data from the ERA5  
94 reanalysis (Hersbach et al. 2020) sampled every 6h, and additionally whenever the HURDAT2  
95 database (Landsea and Franklin 2013) displays a cyclone landfall entry. Tracks and classification  
96 of the cyclones are also taken from the HURDAT2 database (Landsea and Franklin 2013). HUR-  
97 DAT2 is the most complete database of tropical cyclone tracks for the Atlantic basin since 1950,  
98 providing 6-hourly sampling of position and speed of the eye, and maximum sustained winds at a  
99 5 kts resolution. No wind speed adjustment has been made, contrary to what is done by Emanuel  
100 et al. (2005).

101 There is a large discrepancy between the maximum sustained winds reported in HURDAT2 and  
102 the closest quantity that we can derive from ERA5, namely the maximum horizontal wind at 1000  
103 hPa over one hour, shown in Figure 1. It is important to remark that, while ERA5 wind speed is  
104 averaged over one hour, tropical cyclone intensity is usually defined using the one-minute average.  
105 This reflects on the large discrepancy between the highest wind values found in ERA5 ( $\approx 80$  kts)  
106 and in HURDAT2 ( $\approx 150$  kts). This affects the capability of ERA5 to both accurately assign  
107 each hurricane to the appropriate Saffir-Simpson category and to detect rapid intensification. In

108 particular, for cyclone intensity estimation, this implies that we are not able to separate hurricanes  
109 between category 2 and 5. Concerning rapid intensification, HURDAT2 points to 47 out of the  
110 146 considered cyclones, while ERA5 detects none. This analysis suggests that ERA5 shares the  
111 difficulties of current state-of-the-art GCMs when it comes to representing the intensity of tropical  
112 cyclones Kim et al. (2018). We also underline that the ERA5 horizontal resolution used here is of  
113 the same order of magnitude as that of the HighResMIP (High Resolution Model Intercomparison  
114 Project, Haarsma et al. (2016)) and PRIMAVERA models, which are amongst the current best  
115 tools to study climate change impacts on tropical cyclones (Roberts et al. 2020a).

### 116 *b. Observables of cyclone dynamics*

117 We adopt a Lagrangian framework, i.e. we consider a domain of size  $\sim 1200 \text{ km} \times 1200 \text{ km}$   
118 ( $41 \times 41$  grid points), centred on the eye of each cyclone. In the vertical dimension, we consider  
119 9 pressure levels from 1000 hPa to 200 hPa. As observables, we chose sea-level pressure (SLP)  
120 maps, horizontal velocity at 1000 hPa (VH), vertical velocity (W) and the 3D kinetic energy field  
121 computed at each grid point as half of the quadratic sum of the velocity components. We relate  
122 these quantities to the maximum sustained winds derived from the HURDAT2 database, a quantity  
123 that can be directly connected to the economic loss caused by tropical cyclones (Zhai and Jiang  
124 2014).

### 125 *c. A dynamical systems view of tropical cyclones*

126 We follow tropical cyclones in phase space as states of a chaotic high-dimensional dynamical  
127 system. Each instantaneous state of the cyclone, as represented by a given atmospheric variable,  
128 corresponds to a point along the trajectory representing the evolution of the system, which we  
129 sample at discrete intervals determined by the temporal resolution of our data. For example, we

130 may have 6-hourly SLP latitude-longitude maps which, at every time step, are centred on the  
 131 cyclone’s eye. Our aim is to diagnose the dynamical properties of the instantaneous (in time) and  
 132 local (in phase-space) states of the cyclone, as represented by the chosen atmospheric variable  
 133 and chosen geographical domain (physical space in Fig. 2). To do so, we leverage two metrics  
 134 issuing from the combination of extreme value theory with Poincaré recurrences (Freitas et al.  
 135 2010; Lucarini et al. 2012, 2016)

136 We first consider a long trajectory  $x(t)$ , which in our example would be given by  $x$  =SLP maps  
 137 of all time steps for all tropical cyclones in our dataset, always centred on their eye. We thus  
 138 effectively construct a Lagrangian observable. We further consider a state of interest  $\zeta_x$ , which  
 139 would correspond to a single SLP map drawn from this dataset (state  $\zeta$  in Fig. 2). We then define  
 140 logarithmic returns as:

$$g(x(t), \zeta_x) = -\log[\text{dist}(x(t), \zeta_x)] \quad (1)$$

141 Here, *dist* is the Euclidean distance between two SLP maps, but it can be any distance function  
 142 between two vectors which tends to zero as the two vectors increasingly resemble each other. We  
 143 thus obtain a time series of logarithmic returns  $g$ , which takes large values at times when  $x$  closely  
 144 resembles  $\zeta_x$ .

145 We next define exceedances as  $u(\zeta_x) = \{t, g(x(t), \zeta_x) > s(q, \zeta_x)\}$ , where  $s(q, \zeta_x)$  is a high thresh-  
 146 old corresponding to the  $q$ th quantile of  $g(x(t), \zeta_x)$ . These are effectively the previously-mentioned  
 147 Poincaré recurrences, for the chosen state  $\zeta_x$  (phase space in Fig. 2). The Freitas-Freitas-Todd the-  
 148 orem (Freitas et al. 2010; Lucarini et al. 2012) states that the cumulative probability distribution  
 149  $F(u, \zeta)$  converges to the exponential member of the Generalised Pareto Distribution. We thus have  
 150 that:

$$F(u, \zeta_x) \simeq \exp \left[ -\vartheta(\zeta_x) \frac{u(\zeta_x)}{\sigma(\zeta_x)} \right] \quad (2)$$

151 The parameters  $u$  and  $\sigma$  depend on the chosen state  $\zeta_x$ , while  $\vartheta$  is the so-called extremal index,  
 152 namely a measure of clustering of points near  $\zeta_x$  (Moloney et al. 2019). We estimate it here using  
 153 the Suveges Estimator (Suveges 2007).

154 From the above, we can define two dynamical systems metrics: local dimension ( $d$ ) and persis-  
 155 tence ( $\theta^{-1}$ ). The local dimension is given by  $d(\zeta_x) = 1/\sigma(\zeta_x)$ , with  $0 < d < +\infty$ . The persistence  
 156 by  $\theta^{-1}(\zeta_x) = \Delta t / \vartheta(\zeta_x)$ , where  $\Delta t$  is the time step of the data being analysed and  $0 \leq \theta \leq 1$ .

157 While the derivation of  $d$  and  $\theta^{-1}$  may seem very abstract, the two metrics can be related  
 158 intuitively to the physical properties of the tropical cyclones.  $d$  is a proxy for the active number of  
 159 degrees of freedom of the cyclones' instantaneous states, while  $\theta^{-1}$  measures the persistence of  
 160 such states.

### 161 **3. Dynamical properties of tropical cyclones and their connection to sustained winds**

162 We now turn to analysing the properties of tropical cyclones in phase space for the different  
 163 observables described in Sect. 2 against the maximum sustained winds. We begin with SLP and  
 164 KE. SLP is widely used in cyclone tracking (Elsner 2003), and provides a first approximation of  
 165 the horizontal velocity stream function. KE is relevant to the study of cyclones because of both its  
 166 direct connection with the wind speed and its link with the phases of rapid intensification/decay of  
 167 the cyclones (Krishnamurti et al. 2005).

168 Figure 3 shows the values of dimension  $d$  and inverse persistence  $\theta$  for SLP (a) and KE (b)  
 169 against the maximum sustained wind. The values of  $d$  are bounded by  $d < 35$  for both the observ-  
 170 ables, despite the kinetic energy being derived from the 3D wind field, while SLP is 2D. The range  
 171 of local dimensions found is relatively low compared to the number of grid-points used, which is

172 order of 1600 for SLP and 16000 for KE. This means that the majority of the degrees of freedom  
173 are frozen when we follow coherent convective phenomena such as tropical cyclones. Moreover,  
174 although the range of values spanned by the local dimensions is similar for KE and SLP, the lag-0  
175 correlation coefficient between  $d_{SLP}$  and  $d_{KE}$  is relatively low, at 0.2. The persistence range is  
176 different for SLP and KE, with  $0.1 < \theta_{SLP} < 1$  and  $0.1 < \theta_{KE} < 0.6$ . If we convert these values  
177 to hours, we get that the SLP persistence range is between 1 and 10 hours and the KE persistence  
178 ranges between 2 and 10 hours. Despite the different range of values, the lag-0 correlation between  
179  $\theta_{SLP}$  and  $\theta_{KE}$  is 0.4, higher than for  $d$ , suggesting that the two carry more mutual information.

180 Maximum sustained winds are closely connected to the values of  $d$  and  $\theta$  for SLP and KE. For  
181 SLP (Figure 3a) we note a strong dependence of  $\theta$  on the maximum sustained winds. Low-to-  
182 moderate winds are associated with non-persistent states of the cyclones, while stronger winds  
183 typically point to more persistent states. High but not extreme wind speed values (60 to 85 kts)  
184 are concentrated on particularly low values of  $\theta_{SLP}$ . For large values of  $d_{SLP}$ , maximum sustained  
185 winds are typically weak. An even clearer relation emerges between  $d_{KE}$ ,  $\theta_{KE}$  and the maximum  
186 sustained winds (Figure 3b). There, the strongest winds are associated with the lowest values of  $d$   
187 and  $\theta$ .

188 Fig. 3c,d) shows the distributions of  $d$  and  $\theta$  conditional on the HURDAT2 classification of the  
189 cyclones; the least organised states (tropical storms, blue) are characterised by low persistence and  
190 relatively high dimension. On the opposite end, low dimensional and highly persistent states cor-  
191 respond to Hurricanes (red) or extratropical transitions of tropical cyclones (black). As a caveat,  
192 we note that the most intense events somewhat deviate from the modal shifts between the distribu-  
193 tions. For example, the  $d_{KE}$  distribution for Tropical Storms (blue line in the lower panel of Fig.  
194 3d) shows a much higher mode than that for Hurricanes (red line).

195 We test for significant differences in storm dynamics separately for  $d_{SLP}$ ,  $d_{KE}$ ,  $\theta_{SLP}$  and  $\theta_{KE}$   
196 by comparing the three densities for the cases of tropical storms, hurricanes, and extratropical  
197 transitions under the null hypothesis that they have the same distribution (side and bottom panels  
198 of 3c,d)). We choose the significance level  $\alpha = 0.05$ . In particular, we apply a Kruskal-Wallis  
199 test to determine if there are significant differences in location and a  $k$ -sample Anderson-Darling  
200 test for more general shape differences among the three distributions. Then, we perform pairwise  
201 Wilcoxon signed rank tests to determine which distribution is stochastically dominant compared to  
202 the others. Finally, we also repeat the Anderson-Darling test in a pairwise fashion to determine if  
203 there are differences in scale between distributions that do not show significant location shifts. All  
204 the grouped Anderson-Darling and Kruskal-Wallis tests reject  $H_0$  (all p-values  $< 2.2 \times 10^{-16}$ ),  
205 suggesting that at least one distribution is significantly different from the others in all cases, possi-  
206 bly due to a location shift. The pairwise Wilcoxon tests suggest that both  $d_{SLP}$  and  $d_{KE}$  for tropical  
207 storms are larger than for hurricanes and extratropical transitioning storms; moreover,  $d_{KE}$  for  
208 hurricanes is also larger than for extratropical storms. The pairwise Anderson-Darling test points  
209 to a difference in scale between hurricanes and extratropical storms even in  $d_{SLP}$ . All tests are  
210 significant for  $\theta$ , showing the lowest persistence in the tropical storm stage and the highest during  
211 extratropical transitions (see Table 1).

212 Figure 4 shows the same analysis as in Figure 3 but for VH and W. VH is the closest quantity to  
213 the maximum sustained winds and W may be related to convection.  $d_{VH}$  and  $\theta_{VH}$  show a strong  
214 dependence on the maximum sustained winds (Fig. 4a), with the extreme values all located in  
215 correspondence of minima of the dynamical indicators. For W, the distribution of  $\theta$  exhibits two  
216 modes, resulting in the partial separation of two clouds of points in the in  $d$ - $\theta$  scatterplot (Fig. 4b).  
217 The largest sustained winds are found in correspondence with the  $d$  and  $\theta$  minima of the cluster  
218 corresponding to larger  $\theta$ . The analysis conditioned to different phases of the cyclones (Figure 4

219 c,d) shows that VH is possibly the observable that separates most clearly hurricanes from tropical  
220 storms, as the modes are distinct in both  $d_{VH}$  and  $\theta_{VH}$ , whereas for  $W$  the separation is less evident.

221 As for Figure 3 we have tested the statistical significance of the differences among the distribu-  
222 tions of  $d_{VH}$ ,  $d_W$ ,  $\theta_{VH}$  and  $\theta_W$ . The grouped Anderson-Darling and Kruskal-Wallis tests reject  
223  $H_0$  at all levels (all p-values  $< 2.2 \times 10^{-16}$ ), suggesting at least one distribution being signifi-  
224 cantly different from the others. The pairwise Wilcoxon tests (Table 1) suggest that  $d_{VH}$  is shifted  
225 towards significantly larger values for tropical storms than for hurricanes, while  $d_W$  is centered  
226 around lower values for hurricanes. However, while the distributions of  $d_W$  for hurricanes and  
227 extratropical storms do not differ significantly in terms of location shift, the distribution of  $d_W$   
228 for tropical storms is stochastically dominant respect to the case of extratropical storms, despite a  
229 visually small difference in the figure. Similar results hold for the persistence:  $\theta_{VH}$  displays sig-  
230 nificantly larger values for tropical storms, while the distributions of hurricanes and extratropical  
231 storms are not statistically different. In the case of  $\theta_W$ , the distribution for the hurricanes is shifted  
232 towards significantly lower values, while no difference is found between tropical and extratropical  
233 storms.

234 We remark that the dynamical systems indicators obtained using 1000 hPa horizontal veloc-  
235 ity (Figure 3, panel c) provide the best separation between TS and HU/EX storms, with higher  
236 velocity values concentrated at low values of both indicators. We parameterize the relation-  
237 ship between maximum sustained wind  $v_{max}$  and  $d_{VH}, \theta_{VH}$  with a multiple linear regression  
238  $v_{max,i} = \alpha + \beta_d d_{VH,i} + \beta_\theta \theta_{VH,i} + \varepsilon_i$ , where  $i$  denotes the observation and  $\varepsilon_i$  is a Gaussian white  
239 noise sequence. Both dynamical systems indicators have a significant explanatory effect on  $v_{max}$   
240 (p-values  $< 3 \times 10^{-16}$ ), with  $\beta_d = -1.14$ , and  $\beta_\theta = -72.16$ . The persistence coefficient is two  
241 orders of magnitude larger (in absolute value) than the one of the dimension, despite there be-  
242 ing only roughly one order of magnitude difference in the scales of the two variables, pointing

243 to a larger effect of  $\theta_{VH}$ . The goodness of fit is  $R^2 = 0.22$ . This indicates that a large fraction  
244 of  $v_{max}$  variability cannot be explained by the two indicators alone, and/or the presence of strong  
245 nonlinearities that are not caught by linear regression.

246 In the dynamical systems framework, a collapse of degrees of freedom and an increase of per-  
247 sistence are indicative of approaching unstable fixed points, i.e. special states of the dynamics  
248 where temporal and spatial scales are deformed. An example is the behavior encountered in the  
249 Lorenz 1963 attractor (Lorenz 1963) near the unstable fixed points corresponding to the centres  
250 of the wings of the butterfly-shaped attractor, where both  $d$  and  $\theta$  attain low values [Figure A1  
251 in Faranda et al. (2017)]. We discuss the implications of this result for the numerical modelling of  
252 tropical cyclones in Sect. 6.

#### 253 **4. Dynamical Indicators and Rapid intensification**

254 In the previous section, we have established that the dynamical indicators provide a clear sepa-  
255 ration of the different meteorological phases of tropical cyclones. Now we focus on the analysis  
256 on the transitions from tropical storms (TS) to hurricanes (HU). Our goal is to understand whether  
257 we can use the dynamical indicators to discriminate the transitions associated with rapidly intensi-  
258 fying cyclones from the others, and whether the dimension and persistence analysis could be used  
259 to detect rapid intensification in a statistical sense in coarse-resolution climate datasets. Rapid in-  
260 tensification is usually quantified using the increment  $\Delta v$  of maximum sustained winds over 24h.  
261 Several numerical thresholds to define rapid intensification exist (Knaff et al. 2020). Here, we use  
262 thresholds of  $\Delta v > 50$  Kts or  $\Delta v > 40$  Kts, namely the highest thresholds proposed by (Knaff et al.  
263 2020).

264 In phase space, rapid changes of the dynamics correspond to transitions through different basins  
265 of the attractor (Ghil et al. 2008; Dijkstra 2013). The variation of the dynamical systems indicators

266 can track these transitions because of their direct connection with the underlying entropy of the  
267 system: the local dimension  $d$  is an instantaneous measure of the active degrees of freedom,  
268 and the persistence  $\theta$  is related to the dominant time scale of the dynamics, i.e. the Lyapunov  
269 exponent (Faranda and Vaienti 2018). Both these quantities are known to be connected to the  
270 dynamical (Kolmogorov-Sinai) entropy, since the seminal work of Young (1982).

271 Results relating the dynamical system metrics to rapid intensification are presented in Figure 5,  
272 for the four observables used in this study: SLP (a), KE (b), VH (c) and W (d). Median values  
273 are represented by magenta stars (40 KtS) and crosses (50 KtS); ellipses represent one standard  
274 deviation from the median. Blue (red) large circles represent the median  $d$  for all tropical storms  
275 (hurricanes). The green crosses (ellipses) represent the median (standard deviation) of the values  
276 of the dimension and persistence for all the tropical storm to hurricane transitions. The results  
277 show that transitions associated to rapid intensification target a special region of the  $d, \theta$  space  
278 for KE and for VH. They correspond to lower-dimensional and higher-persistence phases of the  
279 dynamics of the cyclones.

280 The decrease in local dimension and inverse persistence implies a decrease of the dynamical  
281 (Kolmogorov-Sinai (Young 1982; Latora and Baranger 1999)) entropy of the cyclones, namely a  
282 reduction of the kinetic degrees of freedom, as discussed in the previous section. Specifically, the  
283 Kolmogorov-Sinai entropy is linked to the Lyapunov exponents (van Beijeren and Dorfman 1995),  
284 whose number of positive values is related to  $d$  and whose leading value is linked to  $\theta$  (Faranda  
285 and Vaienti 2018). It is counterintuitive that large dissipating systems such as rapidly intensifying  
286 cyclones yield low entropy states. However, one can observe that the tendency to the order in  
287 the dynamical entropy is balanced by enhanced thermodynamic entropy leading to convection and  
288 diabatic phenomena.

289 Finally, we remark that the relationship between rapid intensification and decrease in  $d_{KE}, d_{VH}$   
290 and  $\theta_{KE}, \theta_{VH}$  is not systematic: the number of cyclones visiting the magenta balls in Figure 5 is  
291 larger than those experiencing rapid intensification, i.e. one cannot use the values of  $d$  and  $\theta$  to  
292 identify in a deterministic sense cases of rapid intensification.

## 293 **5. Implications of the results for the numerical simulation of tropical cyclones**

294 The computation of the dynamical systems indicators for tropical cyclones has shown that there  
295 is a strong relationship between such indicators computed for coarse atmospheric fields and the  
296 maximum sustained winds taken from observations. In the most intense phase of the cyclones,  
297 large maximum sustained winds are associated to low values of both  $d$  and  $\theta$ , in particular if these  
298 are estimated on the horizontal velocity field. From a dynamical system viewpoint, the explana-  
299 tion is that air parcels behave almost identically, with rotational degrees of freedom oriented along  
300 the global axis of the storm. This behavior is symptomatic of highly persistent, low-dimensional  
301 states found at unstable fixed points of the dynamics. These results imply that intense cyclones are  
302 characterized by different dynamical properties (entropy, stability) from those not accompanied by  
303 large maximum sustained winds and that  $d$  and  $\theta$  give a very good degree of discrimination from  
304 the other, less intense, tropical cyclones. Similarly, transitions from tropical storms to hurricanes  
305 of rapidly intensifying cyclones primarily reside in particular regions of the  $d, \theta$  space. This is par-  
306 ticularly evident for the metrics computed on horizontal velocity (VH), but to a good degree also  
307 on 3D kinetic energy (KE). Vertical velocity (W) provides a less-clear separation, likely because,  
308 while the horizontal wind is driven by the cyclone structure and dynamics, the vertical velocities  
309 are linked to smaller structures such as convective cells not directly resolved in ERA5.

310 These theoretical considerations have a number of concrete implications for current research on  
311 hurricanes. Current GCMs — and even reanalysis products — struggle in reproducing maximum

312 sustained winds comparable to those observed (see Fig. 1). Our study offers a way of mapping  
313 intense cyclones in  $d, \theta$  space and measure, in climate change model experiments or century-long  
314 reanalysis products, shifts towards smaller or larger values of the dynamical indicators. This, in  
315 turn, may provide a strategy for studying changes in hurricane intensity driven by anthropogenic  
316 forcing. Indeed, while  $d$  and  $\theta$  may not be used to provide a deterministic indication of cyclone  
317 intensification, they do provide a robust statistical indication. Furthermore, the fact that the dynam-  
318 ics of intense hurricanes approaches that of fixed points of high-dimensional dynamical systems  
319 may explain why it is so difficult to adequately represent rapidly intensifying tropical cyclones  
320 and hurricanes in numerical models. Parameterizations are devised for typical states of tropical  
321 dynamics (disorganized storms) but not specifically for the organized states of tropical cyclones.  
322 As a caveat, we underline that our Lagrangian approach does not allow to relate the present re-  
323 sults to the predictability of the trajectories of the tropical cyclones, unlike the Eulerian approach  
324 applied to extratropical motions in (Faranda et al. 2017; Messori et al. 2017).

325 *Acknowledgments.* This study is supported by the INSU CNRS LEFE-MANU grant DINCLIC  
326 and the ANR-TERC BOREAS . G. Messori was partly supported by the Swedish Research Council  
327 Vetenskapsrådet (grant no. 2016-03724). B. Dubrulle was partly supported by the ANR, project  
328 EXPLOIT, grant agreement no. ANR-16-CE06-0006-01.

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438 results. The Wilcoxon test detects pairwise location differences, the Anderson-  
439 Darling test general shape differences. . . . . 23

Wilcoxon paired tests, Figure 3															
$d_{SLP}$	TS	HU	EX	$d_{KE}$	TS	HU	EX	$\theta_{SLP}$	TS	HU	EX	$\theta_{KE}$	TS	HU	EX
TS	-	***	***	TS	-	***	***	TS	-	***	***	TS	-	***	***
HU	-	-	n.s.	HU	-	-	***	HU	-	-	***	HU	-	-	n.s.
Wilcoxon paired tests, Figure 4															
$d_{VH}$	TS	HU	EX	$d_W$	TS	HU	EX	$\theta_{VH}$	TS	HU	EX	$\theta_W$	TS	HU	EX
TS	-	***	***	TS	-	***	***	TS	-	***	***	TS	-	***	***
HU	-	-	n.s.	HU	-	-	***	HU	-	-	n.s.	HU	-	-	***
Anderson-Darling paired tests, Figure 3															
$d_{SLP}$	TS	HU	EX	$d_{KE}$	TS	HU	EX	$\theta_{SLP}$	TS	HU	EX	$\theta_{KE}$	TS	HU	EX
TS	-	***	***	TS	-	***	***	TS	-	***	***	TS	-	***	***
HU	-	-	***	HU	-	-	***	HU	-	-	***	HU	-	-	***
Anderson-Darling paired tests, Figure 4															
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TS	-	***	***	TS	-	***	***	TS	-	***	***	TS	-	***	***
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443 **LIST OF FIGURES**

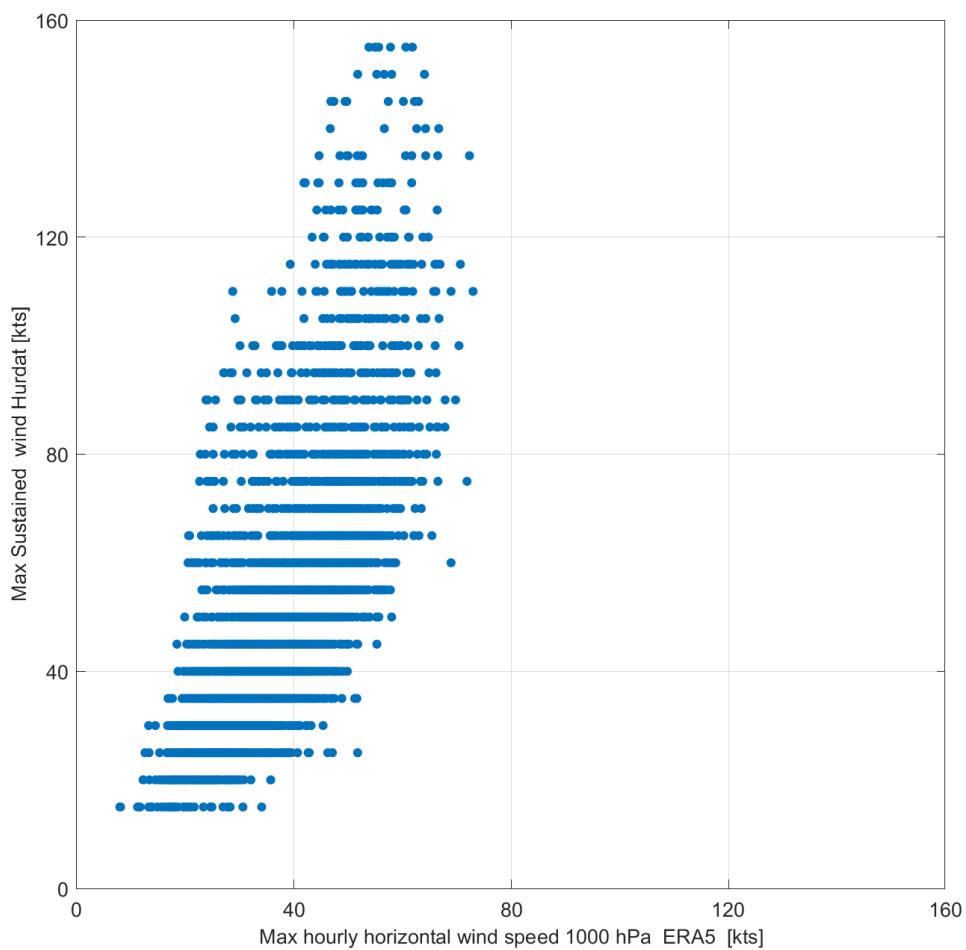
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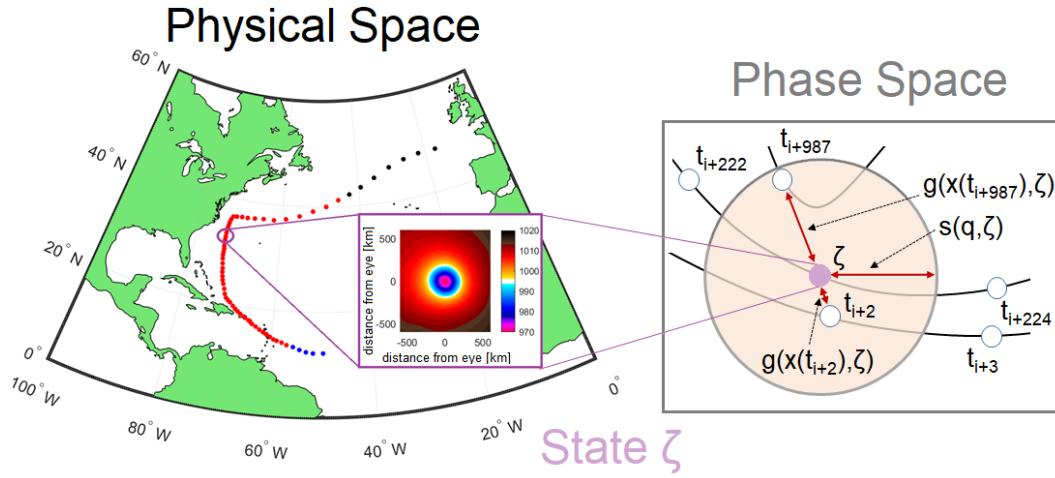
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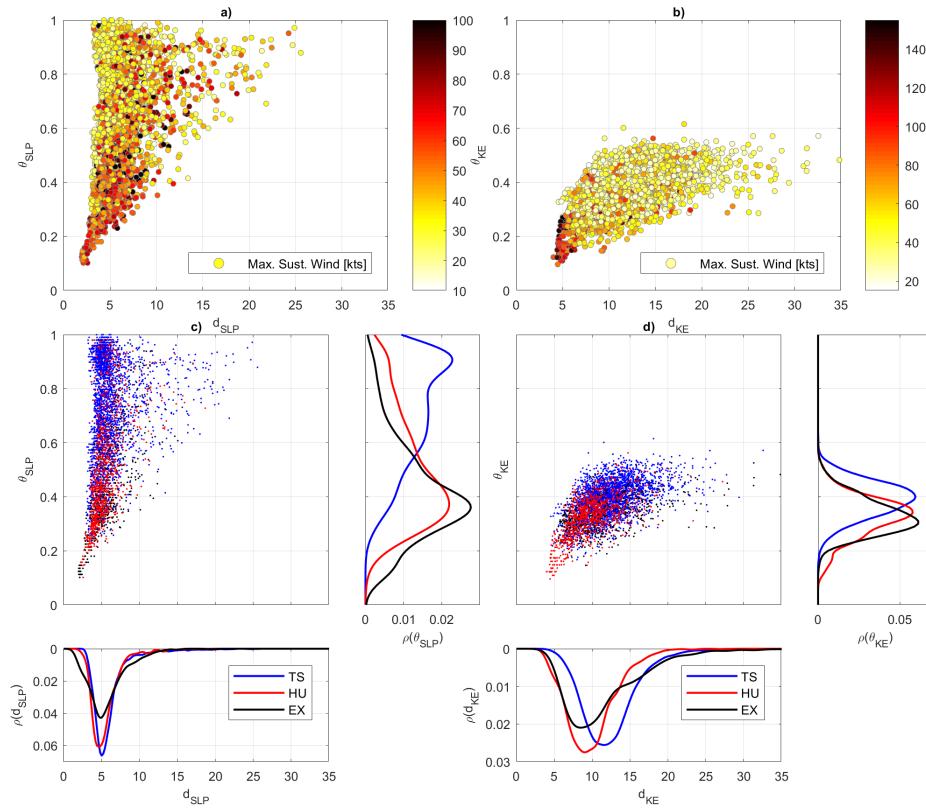
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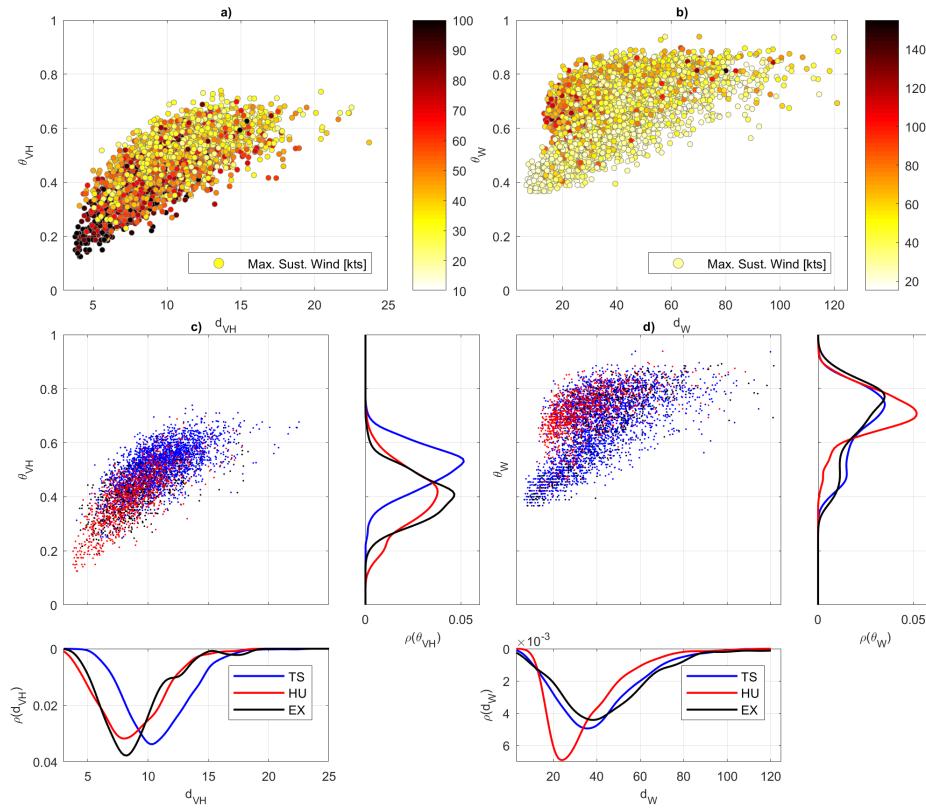
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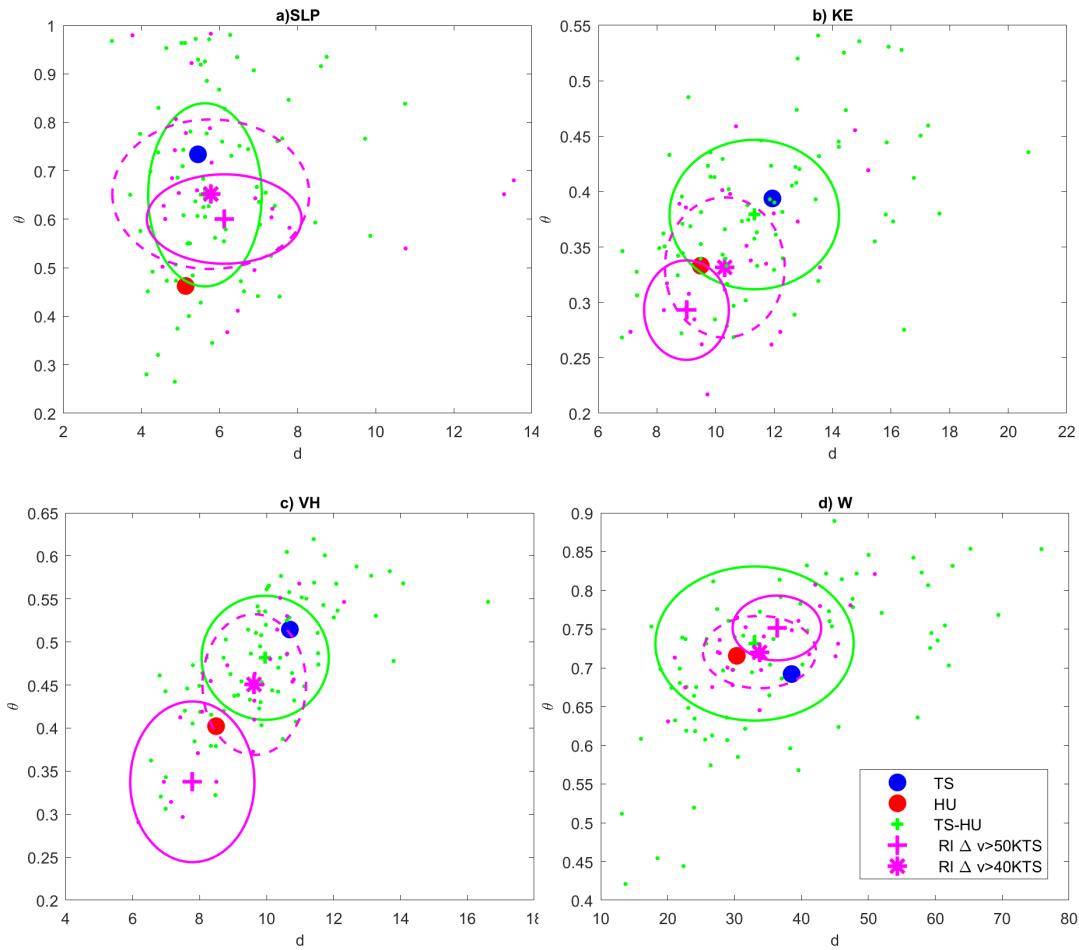
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