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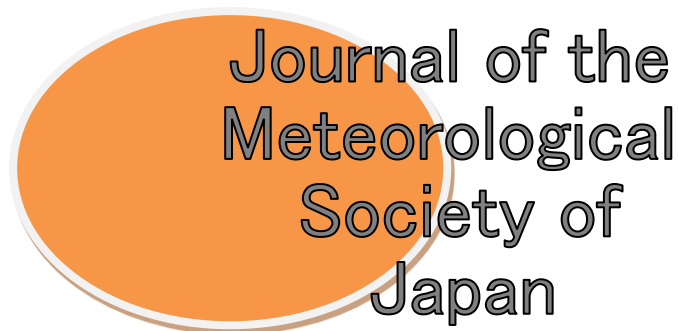
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Thermodynamic scaling of extreme daily precipitation over the tropical ocean from satellite observations

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22 **Abstract**

23 Extreme precipitation theory has been matured over the last decade and stipulates
24 that the intensity of the extreme precipitation scales with the surface humidity.
25 Surface humidity changes can further be approximated by the surface temperature
26 changes. The analytically derived scaling coefficient based on the Clausius-
27 Clapeyron derivative is $\sim 6\%K^{-1}$ in the tropics. While frequently confronted with
28 observations over land, the theory has so far only been marginally evaluated against
29 precipitation data over the ocean. Using an ensemble of satellite-based precipitation
30 products and a suite of satellite-based SST analysis all at the 1° -1day resolution, the
31 extreme scaling is investigated for the tropical ocean ($30^\circ S$ - $30^\circ N$). The focus is set
32 on the robust features common to all precipitation and SST products. It is shown that
33 microwave constellation-based precipitation products are characterized by a very
34 robust positive scaling over the 300 to 302.5K range of 2-day lagged SST. This SST
35 range corresponds to roughly 60% of the tropical precipitation amount. The ensemble
36 mean scaling varies between $5.67\%K^{-1} \pm 0.89\%K^{-1}$ to $6.33\%K^{-1} \pm 0.81\%K^{-1}$
37 depending on the considered period and is found very close to the theoretical
38 expectation. The robustness of the results confirms the fitness of the current
39 generation of constellation-based precipitation products for extreme precipitation
40 analysis. Our result further confirms the extreme theory for the whole tropical ocean.
41 Yet, significant differences in the magnitude of the extreme intensity across the
42 products prompts the urging necessity of dedicated validation efforts.

43

44 1 INTRODUCTION

45 The energy and water exchanges within the Earth system are related to the major
46 feedback processes responsible for the fate of the Earth climate under increasing
47 greenhouse gases concentrations (Stephens et al. 2020). The second principle of
48 thermodynamic and the Clausius Clapeyron law indeed dictate that water vapor in
49 the atmosphere increases at a rate of 6-7% with each degree warming which is at the
50 heart of the strongly positive water vapor feedback. The increased loading of water
51 vapor in the atmosphere has a strong impact on both the mean precipitation
52 (Stephens and Ellis 2008) and the distribution of its extreme (Trenberth 1999).

53 Theory for extreme precipitation dependence on surface temperature has indeed
54 matured significantly over the last decade and a physically based framework is now
55 well established (Gorman and Schneider 2009; O’Gorman 2015; Fischer and Knutti
56 2016). Yet cloud resolving model idealized simulations over tropical oceans exhibit
57 diverging sensitivities and a number of open questions remains in the tropics (Muller
58 and Takayabu 2020). Land based studies using conventional precipitation
59 observations over tropical land also suggests contrasting results (Westra et al. 2014).
60 Recent investigations using satellite observations nevertheless have identified robust
61 extreme precipitation regimes in agreement with the theoretical expectations from
62 thermodynamics (Roca 2019). Over the ocean, on the other hand, the scarcity of
63 conventional in-situ precipitation observations (Serra 2018) precluded much
64 investigations of the scaling of extreme precipitation with surface temperature with
65 notable exceptions.

66 Using early instantaneous satellite observations from Special Sensor
67 Microwave/Imager (SSM/I) and monthly SST from Hadley Centre Sea Ice and Sea

68 Surface Temperature data set (HadISST) (Rayner et al. 2003), Allan and Soden
69 (2008) calculated the rate of change of $2.5^{\circ}\times 2.5^{\circ}$ daily precipitation to tropical mean
70 monthly SST anomalies. Extreme precipitation shows a scaling ranging from slightly
71 above, to much larger than their value derived from the Clausius-Clapeyron response
72 depending on the base line for the anomaly computations. The analysis further
73 pointed out systematic underestimation of the response of the climate models
74 prompting for a more in-depth analysis of the behavior of the extremes over the
75 oceans. The use of tropical mean SST anomaly nevertheless prevents from further
76 addressing the processes at play.

77 More recently, using the OceanRAIN dataset of ship based disdrometer precipitation
78 measurements (Klepp et al. 2018), the scaling of instantaneous (at 1 minute scale)
79 extreme precipitation to the *local simultaneous* SST has been revisited for the global
80 ocean (Burdanowitz et al. 2019). The disdrometer data exhibits a single increasing
81 regime of the 99th percentile with local SST. The scaling is computed by pooling
82 available data over a large range of SST (0°C - 30°C) and is shown to vary between
83 $6\%K^{-1}$ and $\sim 9\%K^{-1}$ depending on the regression technique used. Yet, the small
84 sample of the ship-based measurements prevents a definitive conclusion and the
85 relative role of the convective dynamics and of thermodynamics remains to be
86 clarified at these scales.

87 In summary, many observation-based assessments of the scaling theory have taken
88 place under continental conditions while model-based assessments are performed
89 under oceanic conditions. In comparison, the tropical ocean so far benefited from
90 very few observationally based investigations. In this paper, we propose to improve
91 this situation by pooling recent satellite observations at the $1^{\circ}\times 1^{\circ}$ daily scale of both
92 precipitation and surface temperature all over the tropical oceans.

93

94 Over the ocean, the evaluation of these satellite-based products is generally
95 performed using the few available data from buoys networks (Wu and Wang 2019),
96 atolls rain gauges observations (Greene et al. 2008) or island based radar
97 measurements (Henderson et al. 2017). More recently, the release of a new ship-
98 based disdrometer measurements database (Klepp et al. 2018) provides a
99 complementary reference dataset over some commercial ship routes and research
100 vessel campaigns. For large space and time scales, consistency analysis can be
101 performed through water and energy budget conservation analysis (L'Ecuyer et al.
102 2015). As a consequence of these limited verification references, compared to land,
103 the capability of these satellite-based products to describe the precipitation field is
104 generally not very well documented (Sun et al. 2018), not mentioning under the
105 extreme rainfall conditions. Instead of elaborating on the difficulty to quantify the
106 accuracy of the products, the rationale of this study is to focus on the robustness of
107 the analysis across many satellite products to investigate the thermodynamic scaling
108 of extreme precipitation with sea surface temperature.

109

110 Section 2 introduces a number of satellite-based products of both precipitation and
111 SST and details the methodology followed in this study. Section 3 is dedicated to the
112 presentation of the results and a sensitivity of the results to various assumptions.
113 Finally, a summary and discussion section ends the paper.

114 2 DATA AND METHOD

115 2.1 PRECIPITATION

116 The list of the various products under consideration is provided in Table 1. All the
117 datasets are used at the same 1°x1° daily resolution over the 30°s-30°n region and
118 originate mostly from the Frequent Rainfall Observations on GridS (FROGS)
119 database (Roca et al. 2019) under the DOI <https://doi.org/10.14768/06337394-73A9-407C-9997-0E380DAC5598>. While the products share some of the raw satellite
120 observations, they differ in many aspects that can influence their capability of
121 describing precipitation. They are built from different instantaneous rain rates
122 algorithms. The daily accumulation from the various products further benefits from
123 different sampling from single or multiple platforms, from infrared and/or microwave
124 imagers and/or sounders. Finally, some products also incorporate in-situ corrections.

126

127 The Global Precipitation Climatology Project (GPCP) is a pioneer effort to provide
128 satellite based precipitation estimates globally (Huffman et al. 1997). We here use
129 the one degree daily climate data record v1.3 detailed in Huffman et al. (2001). The
130 GPCP 1 degree-daily (1DD) product relies on a single microwave platform, infrared
131 measurements and the GPCC analysis over land. The daily estimates are adjusted
132 as to mimic the GPCP monthly product when aggregated over a month. Note that the
133 GPCP monthly product is used in various other products as an adjustment reference.
134 The Precipitation Estimation from Remotely Sensed Information using Artificial
135 Neural Networks (PERSIANN) family of products has various incarnations. We here
136 use the climate oriented product the Climate Data Record (CDR) version, also known

137 as PERSIANN-CDR v1 (Ashouri et al. 2015). PERSIANN is based on infrared
138 imagery and it is adjusted to the GPCP monthly mean. It can be seen as an
139 alternative downscaling of the GPCP monthly data to that of GPCP 1DD. The
140 National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center
141 (CPC) morphing technique (CMORPH) satellite precipitation estimates (Xie et al.
142 2017) rely on the constellation of both microwave imagers and sounders and infrared
143 derived cloud motion winds. The blending of the various data is performed thanks to
144 a Kalman filter (Joyce and Xie 2011). Over the ocean, the product is adjusted onto
145 the GPCP accumulations. Compared to buoys, CMORPH under (over) estimate
146 rainfall over the Atlantic (Pacific) ocean (Wu and Wang 2019). The Tropical Rainfall
147 Measuring Mission Multisatellite Precipitation Analysis (TMPA) product is a widely
148 used dataset that combines radar, infrared, microwave imagers and sounders
149 satellite observations (Huffman et al. 2007). Version 7 is used here. Over tropical
150 Atlantic (Pacific), the TMPA product shows overall under(over)-estimation (Wu and
151 Wang 2019). Over the northern Indian ocean, the TMPA product generally
152 overestimated precipitation compared to the buoys but underestimates heavy
153 precipitation events over 100mm/d (Prakash and Gairola 2014). Note that earlier
154 investigation noted that TMPA monthly means are similar to the GPCP product over
155 tropical ocean (Huffman et al. 2007). The Hamburg Ocean-Atmosphere Parameters
156 and Fluxes from Satellite Data (HOAPS) product provide a satellite based suite of
157 fresh-water budget parameters including precipitation over sea-ice-free ocean
158 surface (Andersson et al. 2010). This microwave only product relies on multi-
159 platforms inter-calibrated measurements from SSM/I and Special Sensor Microwave
160 Imager Sounder (SSMIS) (Fennig et al. 2020). Version 3.2 of the precipitation
161 product is used (Andersson et al. 2014). When compared to the oceanRAIN in situ

162 data, HOAPS instantaneous rain rate underestimates intensity in the intertropical
163 convergence zone especially for high rain rate but at the same time, the HOAPS
164 retrieval overestimates the occurrence of precipitating cases (Bumke et al. 2019).
165 The Tropical Amount of Rainfall with Estimation of ERors (TAPEER) algorithm makes
166 use of geostationary infrared imagery together with microwave imager instantaneous
167 rain rates estimates plus the SAPHIR sounder to estimate daily-precipitation
168 accumulation (Roca et al. 2020). The addition of the Megha-Tropiques platform in the
169 constellation is shown to improve the product compared to imagers only
170 implementation (Roca et al. 2018).The recently released TAPEER product has been
171 extensively evaluated over West Africa (Gosset et al. 2018) but is not well
172 characterized over the tropical ocean yet. The Global Satellite Mapping of
173 Precipitation (GSMaP) product provides high-resolution precipitation estimations
174 using satellite observations from multiple platforms (Kubota et al. 2020) . This product
175 is mainly based on the microwave estimation of rainfall from a suite of microwave
176 imagers and sounders. The microwave instantaneous rain rate estimates (Aonashi et
177 al. 2009; Shige et al. 2009) are propagated based on cloud motion wind vectors
178 originally derived from IR geostationary imagery (Ushio et al. 2009). Here the near
179 real time version 6 product is used. The Integrated Multi-satellite Retrievals for Global
180 Precipitation Measurement mission (GPM) (IMERG) is developed at NASA based on
181 infrared observations and on both microwave imagers and sounders data (Huffman
182 et al. 2020). It takes advantage of the TMPA product, the CMORPH-Kalman Filter
183 approach (Joyce and Xie 2011) and the PERSIANN-Cloud Classification System
184 algorithm (Hong et al. 2004). The most recent v6 release of the final run product is
185 used. Previous evaluation efforts showed that the older version (V4) overestimates
186 rain-rates compared to buoys observations at hourly $0.1^{\circ} \times 0.1^{\circ}$ scale over the north

187 Indian Ocean (Prakash et al. 2017). Version 5 daily 1°x1° estimates are shown to
188 underestimate the OceanRAIN measurements on average that is likely due to the
189 inclusion of very light rain rates in the statistics (Khan and Maggioni 2019). While
190 IMERGv5 has similar biases with respect to in-situ data than CMORPH and TMPA, it
191 overall better performs in the estimation of the mean value with the exception of the
192 Atlantic ocean regime over 4mm/d where the product is shown to significantly
193 underestimate precipitation (Wu and Wang 2019) . Version 6 of the product benefits
194 from a refined intercalibration procedure and better interpolation between the
195 platforms that show improvements on some metrics (Tan et al. 2019) and should
196 also reflect on these prior evaluations. The Multi-Source Weighted-Ensemble
197 Precipitation (MWSEP) is a product that corresponds to a pragmatic approach that
198 average existing products to provide a best estimate. Over land an optimization
199 method based on hydrological modelling and observed stream-gauges data is used
200 (Beck et al. 2017). Over ocean, a merging procedure is also followed. The various
201 source of precipitation used encompass satellite-based products, rain gauge
202 measurements and reanalysis results. We use here Version 2.2 (Beck et al. 2019).
203 From the 2000 on-wards, MSWE estimates over the tropical ocean are weighted
204 much more towards satellite products than reanalysis. CMORPH, GSMaP-MKV v5
205 and TMPA v7 RT are blended in MSWE. Note that over ocean TMPA v7 RT and
206 TMPA v7 are similar and only differ over land. The geographical distribution of the
207 99th percentile of 3-hourly precipitation of MSWEP2.2 is very close to that of
208 CMORPH over the tropical ocean (Beck et al. 2019).

209

210 The resulting variety of precipitation distribution from these nine products is illustrated
211 in Figure 1. The two products that do not rely on the microwave constellation (GPCP

212 and PERSIANN) exhibit strongly decreasing occurrence with the daily precipitation
213 amount; GPCP not having values above 170 mm/d. The TAPEER product exhibits
214 systematic significant underestimation of the probability of the largest rain
215 accumulation compared to other microwave-based products. This is likely due to the
216 relative lack of light rain situations (Roca and Fiolleau, 2020). Note that the TAPEER
217 product is also only available for a limited time period. Owing to their outlier
218 distribution and documented biases, those three products are not considered in the
219 following. The figure further reveals two clusters of products showing both the
220 occurrence declining smoothly exponentially towards the very high daily precipitation
221 accumulation. The first cluster is composed of CMORPH, TMPA and MSWEP. The
222 members of this cluster are very close with MSWEP being built from CMORPH and
223 TMPA. Both CMORPH and TMPA further share the same adjustment to the common
224 reference of GPCP pentads over the ocean. The second one includes GSMaP,
225 HOAPS and IMERG that do not share much in terms of algorithms, methods and
226 input data. While the two clusters show a similar distribution up to 100 mm/d, above
227 that threshold, the first cluster systematically underestimates the occurrence
228 compared to the second cluster. This is consistent with previous analysis that
229 indicate that the climatological mean behavior of the products is a poor predictor of
230 the products extreme precipitation (Masunaga et al. 2019). The first cluster products
231 have further been shown to underestimate the intense rain rates compared to buoys
232 (Prakash and Gairola 2014; Wu and Wang 2019) that could be related to their
233 difference with the second cluster.

234 2.2 SEA SURFACE TEMPERATURE

235 Satellite based SST products readily provide estimations of the foundation SST,
236 defined as the ocean temperature at a depth of ~1 meter, below the diurnal layer, at

237 high space and time resolution over a long temporal record. Most of the products rely
238 on optimal interpolation techniques to merge various satellites observations with in-
239 situ measurements. While such products have a well characterized accuracy under
240 clear sky conditions of $\sim 0.5\text{K}$ (Donlon et al. 2012), their representativity under
241 (extreme) rainfall conditions is not well documented. Indeed, the cloudiness
242 associated with the rainfall prevents the use of infra-red measurements and the
243 microwave signal, while of help in cloudy but non-precipitating cases, is altered by
244 rain drop emission during the heavy precipitation situations, also preventing SST
245 estimation in this case (Wentz et al. 2000). As a consequence, the SST estimates
246 under precipitating conditions mainly rely on the result of the optimal interpolation
247 method and are smoothed over several days and a large distance. In the following,
248 we interpret these fields as “synoptic” SST and assess whether such synoptic SST
249 are a good and robust proxy for the thermodynamics of the extreme precipitation
250 events over the ocean. A suite of 3 products is used to evaluate the sensitivity of the
251 scaling to the input data and to the optimal technique implementation and are
252 summarized in Table 2. All SST products have been regridded at a daily $1^\circ \times 1^\circ$
253 resolution over the 30°S - 30°N region to match the precipitation data using a simple
254 conservative averaging procedure.

255

256 The Operational Sea Surface Temperature and Ice Analysis (OSTIA) (Donlon et al.
257 2012) product provides a global foundation SST field derived from satellite
258 observations in the microwave (2 platforms) and in the infrared (6 platforms) and in-
259 situ measurement at $1/20^\circ$ and daily resolution since 2007. The analysis is a multi-
260 scale optimal interpolation using a three days assimilation window centered on the
261 day of the analysis and the background field is the analysis of the previous day. The

262 error correlation length scale used in OSTIA in the tropics is around 100 km. The
263 product Optimum Interpolation Sea Surface Temperature (OISST) (Banzon et al.
264 2016) uses IR measurements from the Advanced Very High-Resolution Radiometer
265 (AVHRR) instruments on board the NOAA satellites since 1981. The interpolation
266 method is similar to that of OSTIA. The error correlation length scales in the tropics
267 are about 150-200km and 3 days. The nominal resolution is daily at 0.25°. Version 2
268 of OISST is used here. Finally, the microwave (MW) optimally-interpolated (OI) SST
269 product from Remote Sensing Systems (Gentemann et al. 2010) is used. As some
270 rain-contaminated SST estimate may persist in the microwave derived dataset, a
271 stringent quality control is performed to prevent potentially biased SSTs retrievals.
272 The error correlation scales used are of 100 km and 3 days, the background field is
273 the analysis of the previous day and the SST represents a foundation SST remapped
274 at a daily 1°x1° resolution. This product is referred to as OIRSS in the following.

275 2.3 METHOD

276 1) Background on the theory

277 The background on the scaling of extreme precipitation with surface temperature has
278 been detailed and reviewed in various publications (O’Gorman 2015; Allan and Liu
279 2018; Roca 2019; Muller and Takayabu 2020) and is only briefly summarized below.
280 Based on the dry static energy budget of the atmosphere (Muller et al. 2011), the rate
281 of extreme precipitation in the tropics can be expressed as follow:

$$282 \quad P_e = \epsilon \int \rho \omega \left(-\frac{\partial q_{sat}}{\partial z} \right) dz, (1)$$

283 where ϵ depicts a precipitation efficiency, ρ the mean density profile, ω the vertical
284 velocity, q_{sat} the saturation mixing ratio and with the integral taken from the surface

285 to the tropopause. Furthermore, the fractional change of extreme precipitation $\frac{\delta P_e}{P_e}$
 286 with warming highlights three contributions, that is the change in microphysics related
 287 to the efficiency term, the change in dynamics through $\rho\omega$ and the change in
 288 thermodynamics through $\frac{\partial q_{sat}}{\partial z}$. At the daily $1^\circ \times 1^\circ$ scale, with the assumption that the
 289 related change of the dynamic and efficiency contributions remain low with warming
 290 and by neglecting the vertical variations in ω , the scaling of extreme precipitation
 291 becomes (Muller et al. 2011)

$$292 \quad \frac{\delta P_e}{P_e} \approx \frac{\delta q_s^{surface}(T)}{q_s^{surface}(T)}. \quad (2)$$

293 It points out that the change in precipitation extremes is expected to be more related
 294 to the surface conditions rather than to the column integrated, and at a rate following
 295 the rate of increase of $q_s^{surface}$ with temperature, that is the Clausius-Clapeyron rate.
 296 In typical tropical sea surface conditions, the expected value ranges between 5.5 and
 297 6.5%K⁻¹.

298

299 2) Methodological aspects

300 Extreme daily precipitation is characterized using high percentiles of the wet-days
 301 ($P > 1\text{mm/d}$) distribution. This index is chosen over others (Zhang et al. 2011) due to
 302 its relevance for scaling investigations (Schär et al. 2016). The scaling of the
 303 precipitation extremes with the sea surface temperature is calculated using the
 304 binning method which is well suited to our investigation given the large number of
 305 available observations (Roca 2019). Indeed, for each 0.5K degree SST interval,
 306 precipitation data from the whole tropical ocean are pooled together and the 99.9th
 307 percentile of the precipitation distribution is estimated. Then after identifying a

308 relevant regime, linear regression (in the logarithm space) is used to compute the
309 scaling factor defined as the rate of change of the 99.9th percentile with sea surface
310 temperature.

311

312 3) Sensitivity studies for robustness determination

313 In order to identify the robust aspects of the thermodynamic scaling estimation using
314 satellite observations, we perform a sensitivity study in complement to the use of
315 various precipitation and SST products. We explore how the timing between the SST
316 and the precipitation influences the scaling and how the overall statistical analysis is
317 sensitive to the selected period.

318

319 As already well explored for continental cases (e.g., Bao et al. 2017) intense
320 precipitation events can strongly alter the surface heat budget and the surface
321 temperature. The strong gust and downdrafts associated with deep convection result
322 in a lower surface temperature compared to the no rain case (Lafore et al. 2016). As
323 a result, the surface conditions may not represent the large-scale environment of the
324 event but are impacted by the event itself. As discussed above, the synoptic SST
325 products assimilation scheme prevents these impacted surface conditions to be used
326 in the estimation, yet the risk to misattribute a rain event to a given temperature
327 range because of this coupling is unclear. As a mean to assess the impact on our
328 findings, the timing of the association between SST and the precipitation event is
329 varied from simultaneous and lagged up to two days before.

330

331 The constellation-based precipitation products are characterized by a changing
332 configuration of the constellation over the last two decades depending on the
333 availability of microwave imagers and sounders that could influence their capability to
334 monitor steadily the precipitation in the tropics (Roca et al. 2020).The SST products
335 are also sensitive to the availability of the microwave imagers and the infrared
336 radiometers. The availability of these platforms since 2001 is summarized in Figure 2.
337 The baseline period for our investigation spans 2007-2017 which is the longest
338 period share by all SST products. It corresponds to the homogeneous cycle of
339 production of OSTIA (Donlon et al. 2012) and to the start of the systematic use of
340 two AVHRR instruments for the OISST product (Banzon et al. 2016). Two other
341 different periods are considered. The first one is longer, extending back in time until
342 2001 for which OIRSS and OISST are available and correspond to the availability of
343 the GSMaP precipitation product. During the 2001 to 2007 era, the microwave
344 imagers fluctuate from 4 to 6 platforms and the sounders from 2 to 4 while the IR
345 radiometers increases from 1 to 3. These constellation configurations are all less
346 populated than the forthcoming period post 2007 and the products are associated
347 with less sampling than during the 2007-2017 that could impact our analysis. The
348 second period is a shorter one and corresponds to a precipitation data rich era that
349 includes the Megha-Tropiques operations (Roca et al. 2018) and partly includes the
350 TRMM and GPM platforms along with the SSM/I and SSMIS platforms. This era is
351 characterized with up to 14 microwave sensors operating simultaneously. The use of
352 three periods of 18, 11 and 5 years, respectively also permits to assess the sensitivity
353 of the estimation of the extreme percentile of the precipitation distribution.

354

355 **3 RESULTS**

356 **3.1 SIMULTANEOUS ANALYSIS**

357 Figure 3 shows the scaling of the 99.9th percentile as a function of the simultaneous
358 SST from the OSTIA product for the 6 constellation-based products. The two clusters
359 of precipitation products previously identified are shown as well. The low cluster
360 99.9th percentile ranges from 120 to 150 mm/d while the high one spans 170 to 240
361 mm/d. There is roughly a factor of two among the least value of CMORPH at 297K
362 and the highest one of IMERG at 302.5K. The dependence of the high percentile to
363 the SST is characterized by three regimes. Up to 300.25K, the products do not
364 exhibit any robust behavior. GSMaP is mainly increasing over this SST range, while
365 HOAPS extremes decrease; the other products rather show no sensitivity to the SST.
366 This regime accounts for only 19% of the total tropical precipitation accumulation.
367 The second regime spans SST from 300K up to 302.5K and is characterized by an
368 increase of all the products. Almost 56% of the total rainfall belongs to this regime.
369 For the last regime, above 302.25K and corresponding to 25% of the total rainfall
370 amount, the precipitation products show a robust decrease of the value of the high
371 percentile. For the second regime, the ensemble mean of the scaling is $\sim 5\%K^{-1}$ with
372 a small coefficient of variation of around 10% and range from 4.21 to 5.75 $\%K^{-1}$
373 (Table 3a). A robust scaling, close to the Clausius Clapeyron, is found in this case.
374 The replacement of OSTIA by OISST does not change the regime decomposition
375 much (not shown) but the ensemble scaling over the regime 2 is much smaller
376 ($3.4\%K^{-1}$) and spreads almost twice much more (Table 3b). The use of the OIRSS
377 data, on the other hand, drastically alters the picture with no well-defined regimes at
378 all. Over the previous SST range of regime 2, the ensemble scaling is even slightly

379 negative ($-0.45\%K^{-1}$). The scaling obtained from simultaneous measurements of
380 precipitation and surface temperature are hence not robust to the selection of the
381 SST products.

382 3.2 LAGGED ANALYSIS

383 The lagged analysis using the SST of the day before the precipitation does not
384 change much the overall picture (not shown). Quantitatively, the ensemble mean of
385 the scaling slightly increases to $5-6\%K^{-1}$ with a coefficient of variation less than 11%
386 for all the OSTIA and OISST products (Table 3a and b). The OIRSS product now
387 exhibits a scaling of $4.4\%K^{-1} \pm 0.6\%K^{-1}$ value. On the other hand, the lagged
388 analysis at two days before confirms the previously identified low and high
389 precipitation products clusters and reveals a very robust pattern across the SST
390 products. Figure 4 confirms the relevance of the range of the scaling regime identified
391 for OSTIA for all the SST products. The sensitivity of the selection of the upper bound
392 $303K$ instead of $302.5K$ (not shown) does not modify the values significantly. With a 2
393 days lag, the ensemble mean scaling is very similar for each SST product: 5.9 , 5.9
394 and $6.0\%K^{-1}$ for OSTIA, OISST and OIRSS, respectively. The ensemble variance is
395 also similar among the products at around 10% (or $0.65\%K^{-1}$). The multi precipitation
396 products and multi-SST products ensemble of 18 combinations statistics reads
397 $5.93\%K^{-1} \pm 0.60\%K^{-1}$. The “cold” regime with $SST < 300K$ remains non-robust at
398 day-2 lag, with the precipitation products not agreeing on the sensitivity of the 99.9th
399 percentile to the SST. The warm regime with $SST \geq 302.5K$ is characterized by a
400 robust behavior of the precipitation products does not appear robust to the SST
401 selection. The marked decrease of the extreme in OSTIA after $302.5K$ is rather
402 associated with a smooth, steady evolution for OISST and OIRSS. Note that the
403 GSMaP product, unlike any other product, indicates a CC-like positive scaling over

404 most of the cold regime. This unique feature deserves further attention and will be
405 investigated in the future.

406 3.3 SENSITIVITY TO THE SELECTION OF THE PERIOD

407 The analysis for the longer period is summarized in Figure 5. The “cold” regime
408 results still hold in this case although its upper limit can be revised to 299.5K. The
409 “warm” regime is now more robust among the SST products but the 302.5K limit is
410 less clearly marked than for the 2007-2017 period. The values of the 99.9th
411 percentile is slightly higher for all precipitation products compared to the previous
412 period. The scaling over the 300K-302.5K regime shows a smoother sensitivity than
413 before with an ensemble mean value of 4.3 and 5.3 %K⁻¹ for the two SST products
414 (Table 3b and c). When the range is slightly adjusted to 299.5K and 302.0K, the
415 regime corresponds to 45% of the total precipitation and the scaling now reads 5.65
416 and 5.69%K⁻¹ for OISST and OIRSS, respectively. In this case, the spread of the
417 ensemble scaling for OISST is diminished to ~17% instead of 24% (Table 3b) and
418 remains the same at ~15% for OIRSS. The ensemble of 12 combinations for all SST
419 and precipitation products in this case is 5.67%K⁻¹ +- 0.89%K⁻¹.

420

421 Figure 6 confirms the three regimes delineation for the shorter period. The magnitude
422 of the extreme precipitation is close to that of the 2001-2017 period. The ensemble
423 mean scaling is slightly larger and now ranges between 6.0 and 6.8 %K⁻¹ while the
424 18 combinations for all SST and precipitation products is 6.33%K⁻¹ +- 0.81%K⁻¹, also
425 in close agreement with the theoretical expectation. Owing to its availability over that
426 period, the TAPEER products is also shown for the sake of completeness but it is not
427 included in the ensemble statistics. It is in line with the other products, although with

428 a much lower magnitude of the p99.9 marker as expected from Figure 1. Yet the
429 scaling mean value is $\sim 5.1\%K^{-1}$ which is slightly less than for the other products.

430 **4 SUMMARY AND DISCUSSION**

431 The objective of this study is to explore the scaling of extreme precipitation with
432 surface temperature over the tropical oceans. The pooling of data originating from an
433 ensemble of 6 constellation-based precipitation products reveals two clusters of
434 products that differ in terms of magnitude of the extreme daily accumulation. The
435 difference between the low cluster (MSWE, TMPA and CMORPH) and the high
436 cluster (HOAPS, GSMaP and IMERG) spans roughly a factor of two at the most. No
437 such clustering is found over land, likely due to the inclusion of rain gauges in most of
438 the products (Roca 2019; Masunaga et al. 2019). While, buoy-based comparison
439 suggests the low cluster products indeed underestimate intense precipitation
440 intensity, no definitive argument yet permits to prefer one cluster from the other.
441 Despite this magnitude difference, the present results highlight a very robust behavior
442 of the satellite products extreme precipitation with respect to the SST. The
443 explanation for the individual product similarities and differences would require a
444 dedicated study and is out of the scope of the present work that focus on the
445 precipitation products ensemble robust features.

446

447 The timing of the SST-precipitation relationship has also been explored and it is
448 shown that the two days lagged investigation exhibits robust regimes across the SST
449 products. This is likely due to the use of the SST analysis that blends data over 3
450 days and $\sim 100\text{km}$ to provide an SST estimate under precipitating conditions. Our

451 study confirms the fitness for purpose of these analyzed SST for precipitation related
452 investigations. Specifically, the two days lagged analysis identifies three distinct
453 regimes:

454

455 A “cold” regime with SST < 300K that corresponds to ~19% of the total tropical
456 precipitation amount. In this case, while the results are not sensitive to the SST
457 product selection, nor to the timing of the precipitation-temperature association nor
458 the length of the record, the various precipitation products exhibit inconsistent
459 behaviors. The lack of robustness of the results might be due to some structural
460 errors in the precipitation retrievals and/or to the weak data sampling preventing a
461 robust estimation of the high percentile of the precipitation distribution. The 99th
462 percentile (not shown), that ranges between 60 and 100mm/d over the cold regime,
463 is less sensitive to the data sampling than the 99.9th percentile and shows a lack of
464 sensitivity that is more reproducible among the products but for HOAPS that still
465 differs from the other five products.

466

467 A “warm” regime with SST > 302.5K corresponding to ~25% of the total precipitation
468 amount, is characterized by a systematic decrease of the values of the 99.9th
469 percentile from 302.5K to the warmest SST under considerations. This warm regime
470 is also observed over land (Roca 2019) and is usually attributed to relative humidity
471 limited conditions at warm surface temperature that decrease the intensity of extreme
472 precipitation over these semi-arid areas. Decrease in the wet-days duration for this
473 regime has also been identified as a key mechanism over mid-latitudes land
474 conditions (Utsumi et al. 2011). Further analysis is needed to assess whether these

475 very high SST are associated with large scale subsidence and simultaneous
476 relatively dry boundary layer that could impact the intensity and/or the duration of the
477 precipitation events and explain the decreasing trend. Burdanowitz et al. (2019) do
478 not report any such decreasing regime when analyzing instantaneous disdrometer
479 derived precipitation rate from ship data. They attribute this departure from the
480 behavior of the continental extreme to the absence of decreasing event duration in
481 this regime. Yet their analysis is restricted to 1K SST bin up to 303K, and hence
482 would miss the warm regime identified here. Furthermore, our study shows that the
483 use of simultaneous SST is detrimental to the scaling computation. It is likely that
484 using a time lagged analysis of the instantaneous precipitation scaling over an
485 extended SST range would permit to better delineate the various regimes relevant for
486 that instantaneous scale.

487

488 The third regime which we call the « Clausius-Clapeyron » regime is ranging from
489 300K to 302.5K and includes almost 56% of the total precipitation amount. It is
490 characterized by a steady increase of the extremes with surface temperature. This
491 regime is robust to the precipitation product, to the SST product and to the length of
492 the record. When simultaneous SST data are used, the scaling is diminished but for
493 OIRSS where it simply does not exist. The one day lagged scaling results are robust
494 to the SST product selection and lead to a scaling around $5.17\%K^{-1} \pm 0.85\%K^{-1}$. The
495 two days lagged scaling value ranges from $5.67\%K^{-1} \pm 0.89\%K^{-1}$ for the 2001-2017
496 period to $6.33\%K^{-1} \pm 0.81\%K^{-1}$ for 2012-2016 for all the SST and precipitation
497 products considered here. While the actual, direct validation or evaluation of the
498 representation of intense rain accumulation in these products remains challenging,
499 their common and physically sound behavior indicates that the products are fit for

500 exploring the extreme precipitation over the ocean. The robustness of the scaling
501 analysis across the satellite precipitation products is further very close to the
502 theoretical expectation for the thermodynamic scaling of $\sim 6\%K^{-1}$. This gives us even
503 more confidence in this generation of satellite precipitation products at the 1° 1-day
504 resolution over the ocean. The frequency of occurrence of the precipitation greater
505 than the 99.9th percentile and surface conditions corresponding to the Clausius
506 Clapeyron regime have been mapped in Figure 7. The figure points out that this
507 regime is not associated with the climatological ITCZ location as previously noted
508 (Masunaga et al. 2019). On the other hand, it is associated with the known
509 climatological rainfall maxima, off the Colombian Coast and in the northern Bay of
510 Bengal and also seems to align with the climatological distribution of cyclones
511 occurrence in the East Pacific, West Atlantic, South Indian Ocean and China sea.

512

513 An avenue for further research lies in identifying the contribution of the organized
514 convection to the scaling physics (Pendergrass 2020; Muller and Takayabu 2020;
515 Roca and Fiolleau 2020). Our results further prompt for a dedicated investigation of
516 the contribution of the cyclone precipitation to the scaling physics that is so far not
517 much promoted. Our results also suggest that community efforts, possibly under the
518 umbrella of the International Precipitation Working Group (Levizzani et al. 2018) and
519 the GEWEX/WCRP core-project, are needed to further characterize the absolute
520 accuracy of precipitation products over the ocean and clarify which clusters of
521 products is to be understood as a reference, if any.

522

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529

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728

TABLES

Product shortname	Product name and version	Period used	Use of IR satellite data	Use of MW satellite data	Constellation based products	References
GSMaP	GSMaP-NRT-no gauges v6.0	2001-2017	Yes	Yes	Yes	Kubota et al. (2009)
CMORPH	CMORPH V1.0 CRT	2001-2017	Yes	Yes	Yes	Xie et al. (2017)
MSWE	MSWEP 2.2	2001-10.2017	Yes	Yes	Yes	Beck et al. (2017)
TMPA	3B42 v7.0	2001-2017	Yes	Yes	Yes	Huffman et al. (2009)
HOAPS	HOAPS	2001-2016	Yes	Yes	Yes	Anderson et al. (2014)
IMERG	IMERG V06 final run	2001-2017	Yes	Yes	Yes	Huffman et al. (2018)
PERSIANN	PERSIANN CDR v1	2001-2017	Yes	No	No	Ashouri et al. (2015)
GPCP	GPCP 1DD v1.3 CRD	2001-2017	Yes	Yes	No	Huffman et al. (2001)
TAPEER	TAPEER-BRAIN v1.5	2012-2016	Yes	Yes	Yes	Roca et al. (2020)

Table 1: List of gridded precipitation products and their acronyms. Note that the MWSEP v2.2 data have been acquired directly from H. Beck. The constellation products are using multiple microwave platforms.

Product shortname	Product name and version	Use of satellite data	Period used	References
OSTIA	OSTIA Near Real Time Level 4 SST	IR + MW	2007-2017	Donlon et al. (2012)
OISST	NOAA CDR OISST AVHRR-only v2	IR	2001-2007	Reynolds et al. (2008)
OIRSS	RSS OI SST MW v5	MW	2001-2017	Gentemann et al. (2010)

Table 2: List of sea surface temperature products and their acronyms. IR stands for Infra-red and MW for Microwave.

a.

Products	OSTIA	OSTIA	OSTIA	OSTIA	OSTIA	OSTIA
	2007- 2017 T(t) 58%	2007- 2017 T(t-24h) 56%	2007- 2017 T(t-48h) 55%	2012- 2016 T(t) 57%	2012- 2016 T(t-24h) 56%	2012- 2016 T(t-48h) 54%
GSMaP	4.21	5.37	5.38	5.43	6.09	6
CMORPH	5.26	6.02	6.11	5.74	6.21	6.7
MSWEP	4.69	5.61	5.52	5.89	6.69	6.77
TMPA	5.09	5.51	5.75	4.93	5.29	5.61
HOAPS	5.75	7.14	7.05	5.76	6.82	6.9
IMERG	5.19	5.81	5.5	4.85	5.24	5.24
ENS	5.04	5.95	5.9	5.41	6.05	6.17
Mean ENS	5.03	5.91	5.89	5.43	6.06	6.2
STD ENS	0.52	0.65	0.62	0.45	0.67	0.69
Cvar ENS	10.43	10.93	10.62	8.26	11.1	11.09

Table 3.a: Summary of the sensibility analysis with the value of the slope of the 99.9th percentile as a function of the SST from the OSTIA product over the CC regime ([300K,302,5K]) in $\%.K^{-1}$. Mean ($\%.K^{-1}$), standard deviation ($\%.K^{-1}$) and coefficient of variation (%) for the ensemble of all the products (ENS), as well as the total rainfall accumulation within the regime, are also reported.

b.

Products	OISST	OISST	OISST	OISST	OISST	OISST	OISST	OISST	OISST
	2007- 2017 T(t) 58%	2007- 2017 T(t-24h) 57%	2007- 2017 T(t-48h) 57%	2012- 2016 T(t) 56%	2012- 2016 T(t-24h) 55%	2012- 2016 T(t-48h) 54%	2001- 2017 T(t) 60%	2001- 2017 T(t-24h) 59%	2001- 2017 T(t-48h) 58%
GSMaP	2.64	4.88	6.08	4.27	5.69	6.91	2.78	4.02	4.54
CMORPH	3.15	4.89	5.37	4.34	5.7	6.4	1.07	1.97	2.42
MSWEP	3.35	5.52	6.03	4.87	6.83	7.54	3.08	4.46	4.7
TMPA	3.68	5.1	5.44	4.98	5.73	5.88	3.11	4.2	4.47
HOAPS	4.5	6.1	7.06	5.19	6.67	7.86	4.18	5	5.58
IMERG	3.21	4.84	5.43	3.88	5.7	6.21	2.92	3.93	4.37
ENS	3.43	5.23	5.95	4.56	6.06	6.84	2.96	4.02	4.46
Mean ENS	3.42	5.22	5.9	4.59	6.05	6.8	2.86	3.93	4.35
STD ENS	0.63	0.5	0.65	0.5	0.54	0.78	1.01	1.04	1.04
Cvar ENS	18.27	9.6	10.99	10.89	8.95	11.48	35.26	26.35	23.94

Table 3.b: Summary of the sensibility analysis with the value of the slope of the 99.9th percentile as a function of the SST from the OISST product over the CC regime ([300K,302,5K]) in $\%.K^{-1}$. Mean ($\%.K^{-1}$), standard deviation ($\%.K^{-1}$) and coefficient of variation (%) for the ensemble of all the products (ENS), as well as the total rainfall accumulation within the regime, are also reported.

C.

Products	OIRSS	OIRSS	OIRSS	OIRSS	OIRSS	OIRSS	OIRSS	OIRSS	OIRSS
	2007- 2017 T(t) 60%	2007- 2017 T(t-24h) 58%	2007- 2017 T(t-48h) 57%	2012- 2016 T(t) 58%	2012- 2016 T(t-24h) 56%	2012- 2016 T(t-48h) 55%	2001- 2017 T(t) 61%	2001- 2017 T(t-24h) 59%	2001- 2017 T(t-48h) 59%
GSMaP	-1.54	3.76	5.43	-0.6	3.76	5.07	-2.09	3.01	4.54
CMORPH	-0.19	4.59	6.82	-0.83	4.8	7.01	-2.82	2.2	4.38
MSWEP	-1.56	4.1	6.05	-1.02	4.9	6.64	-2.39	3.22	5.3
TMPA	2.26	5.46	6.27	1.85	5.21	5.91	1.2	5.37	6.5
HOAPS	-0.65	4.23	6.36	-1.3	3.79	6.33	-1.14	3.96	5.78
IMERG	-1.03	4.05	5.1	-1.03	3.77	4.91	-0.88	3.99	5.51
ENS	-0.61	4.28	5.9	-0.62	4.25	5.86	-1.34	3.65	5.34
Mean ENS	-0.45	4.36	6	-0.49	4.37	5.98	-1.35	3.63	5.34
STD ENS	1.43	0.6	0.63	1.17	0.67	0.85	1.45	1.08	0.79
Cvar ENS	-316.64	13.73	10.54	-239.42	15.31	14.19	-107.5	29.81	14.86

Table 3.c: Summary of the sensibility analysis with the value of the slope of the 99.9th percentile as a function of the SST from the OIRSS product over the CC regime ([300K,302,5K]) in $\% \cdot K^{-1}$. Mean ($\% \cdot K^{-1}$), standard deviation ($\% \cdot K^{-1}$) and coefficient of variation (%) for the ensemble of all the products (ENS), as well as the total rainfall accumulation within the regime, are also reported.

FIGURES

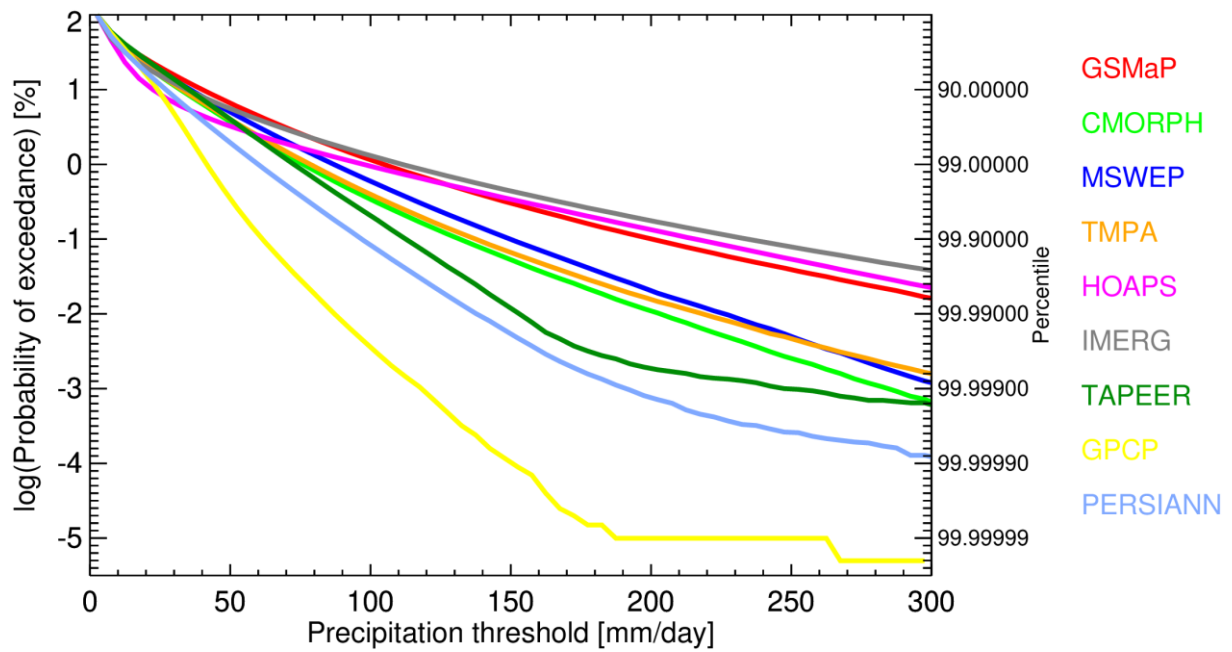


Figure 1: Probability of exceedance of daily $1^{\circ} \times 1^{\circ}$ accumulated precipitation over the tropical ocean (30°S - 30°N) for the period 2017-2017 except for the TAPEER product where it is restricted to the 2012-2016 period. The probability of exceedance is computed with respect to wet-days with precipitation above 1mm/d.

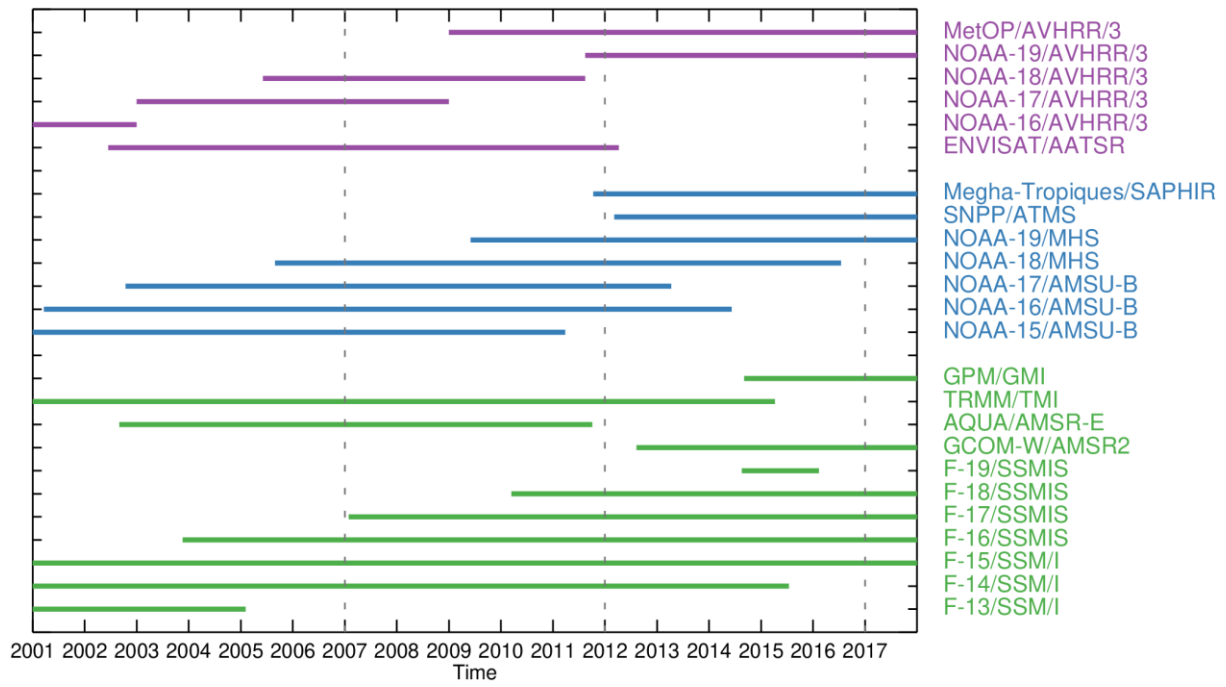


Figure 2: Time series of the availability of microwave imagers and sounders used in the precipitation products of the study. Vertical dashed lines indicate the different time periods explored in the study.

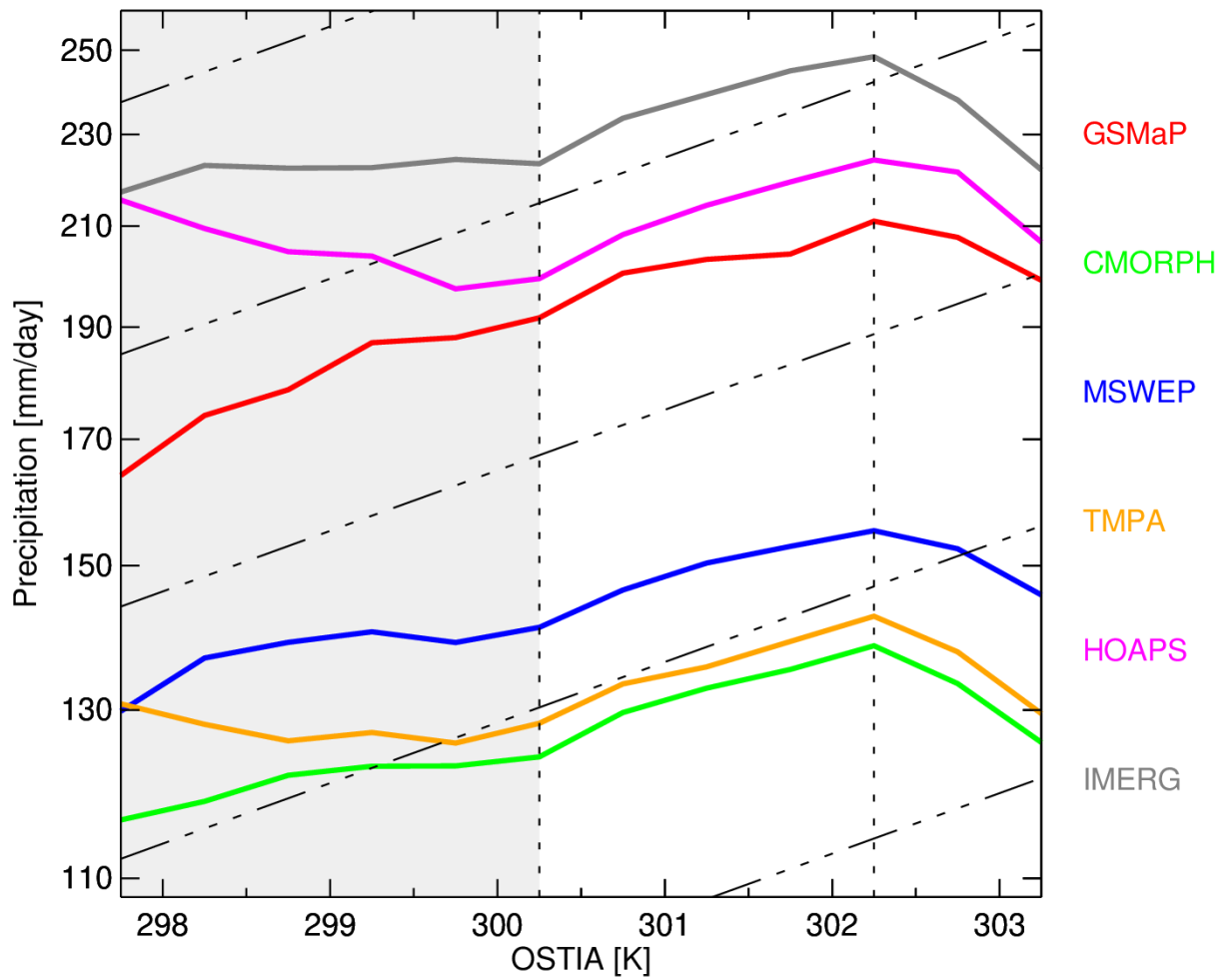


Figure 3: The value of the 99.9th percentile of the 1°x1° daily accumulated precipitation as a function of the contemporaneous SST from the OSTIA product. Each color corresponds to a precipitation product. For the period 2007-2017. Regimes are separated by vertical dashed lines. The grey shaded area indicates the non-robust cold regime between precipitation products. Black dash-dotted lines correspond to the Clausius-Clapeyron 6%K⁻¹ rate. See text for details.

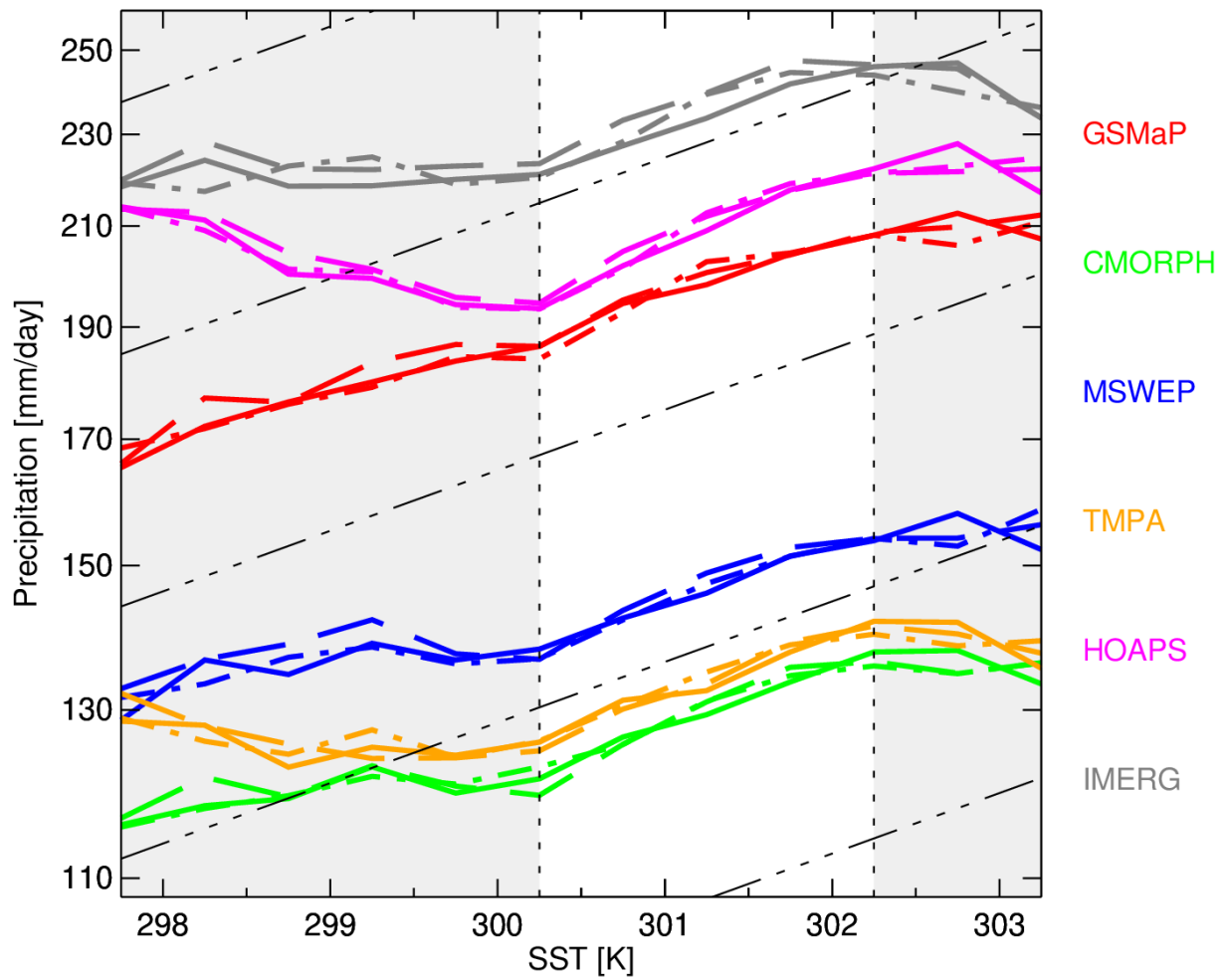


Figure 4: The value of the 99.9th percentile of the $1^\circ \times 1^\circ$ daily accumulated precipitation as a function of the SST lagged by 2 days. Each color corresponds to a precipitation product. Solid line for OSTIA, dashed line for OISST and dash-dotted lines for OIRSS. For the period 2007-2017. Regimes are separated by vertical dashed lines. The grey shaded areas indicate the non-robust cold regime between precipitation products (left) and the non-robust warm regime between SST products (right). Black dash-dotted lines correspond to the Clausius-Clapeyron $6\%K^{-1}$ rate. See text for details.

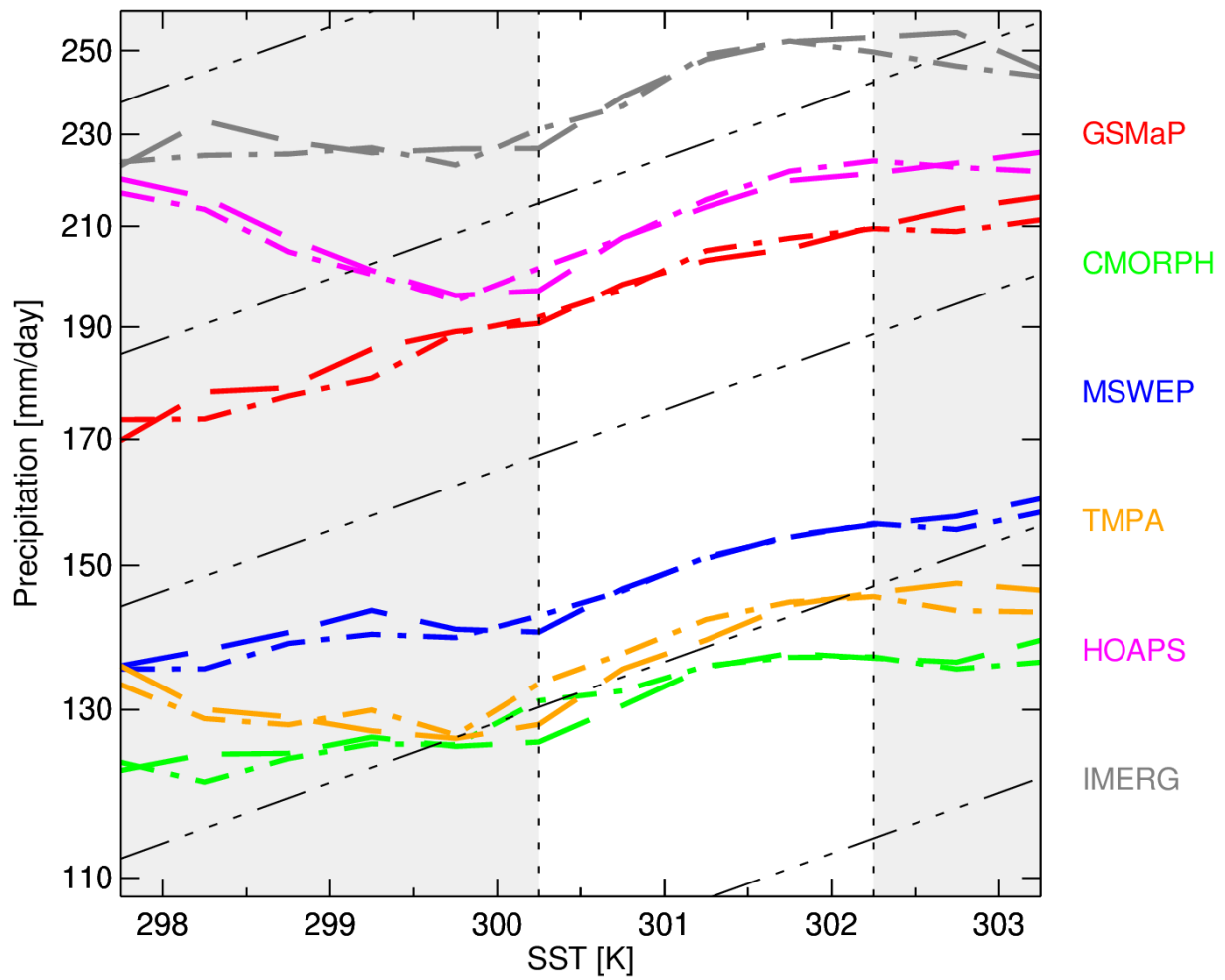


Figure 5: The value of the 99.9th percentile of the $1^{\circ}\times 1^{\circ}$ daily accumulated precipitation as a function of the SST lagged by 2 days. Each color corresponds to a precipitation product. Dashed line for OISST and dash-dotted lines for OIRSS. For the period 2001-2017. Regimes are separated by vertical dashed lines. The grey shaded areas indicate the non-robust cold regime between precipitation products (left) and the non-robust warm regime between SST products (right). Black dash-dotted lines correspond to the Clausius-Clapeyron $6\%K^{-1}$ rate. See text for details.

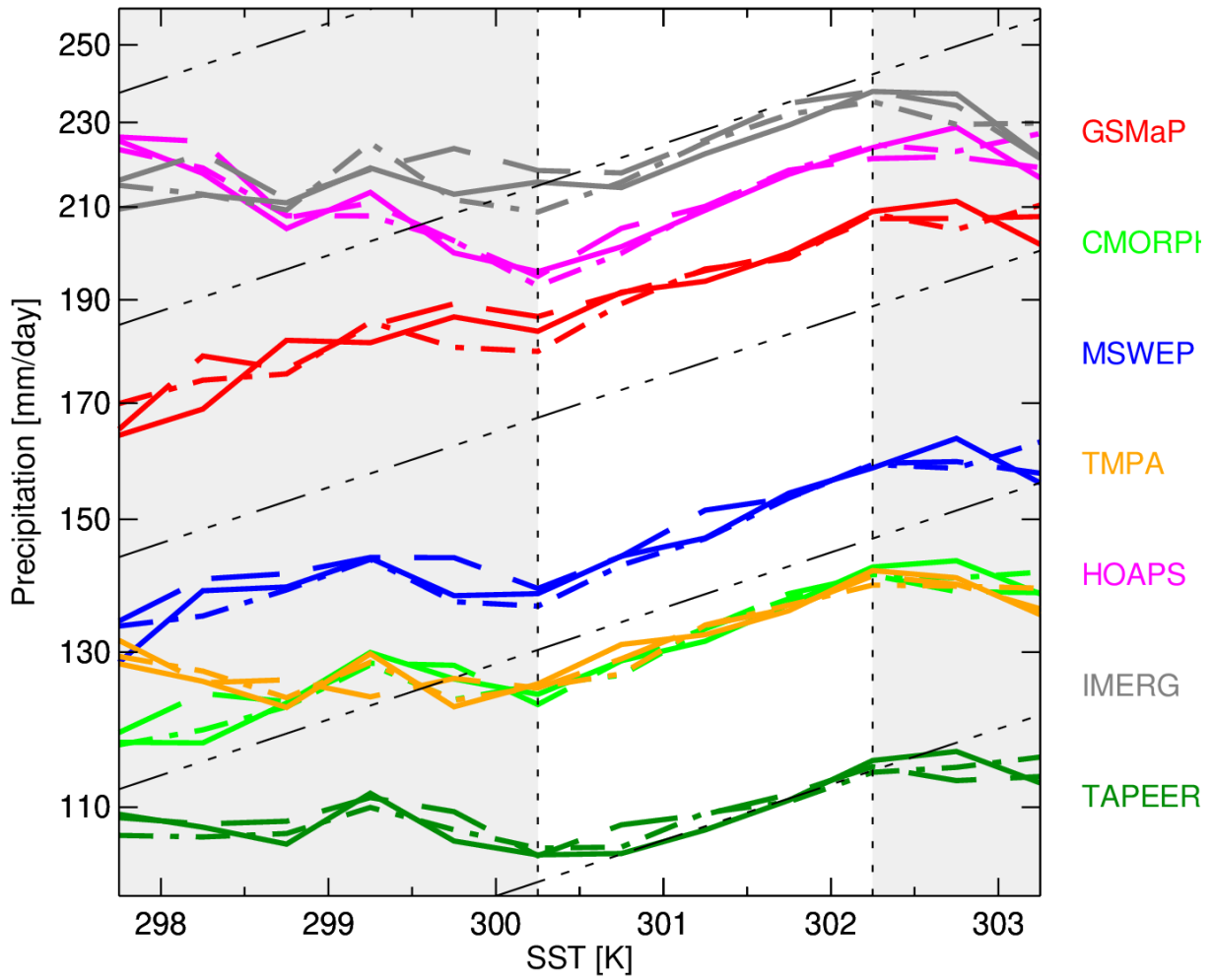


Figure 6 : The value of the 99.9th percentile of the $1^{\circ}\times 1^{\circ}$ daily accumulated precipitation as a function of the SST lagged by 2 days. Each color corresponds to a precipitation product. Solid line for OSTIA, dashed line for OISST and dash-dotted lines for OIRSS. For the period 2012-2016. Regimes are separated by vertical dashed lines. The grey shaded areas indicate the non-robust cold regime between precipitation products (left) and the non-robust warm regime between SST products (right). Black dash-dotted lines correspond to the Clausius-Clapeyron $6\%K^{-1}$ rate. See text for details.

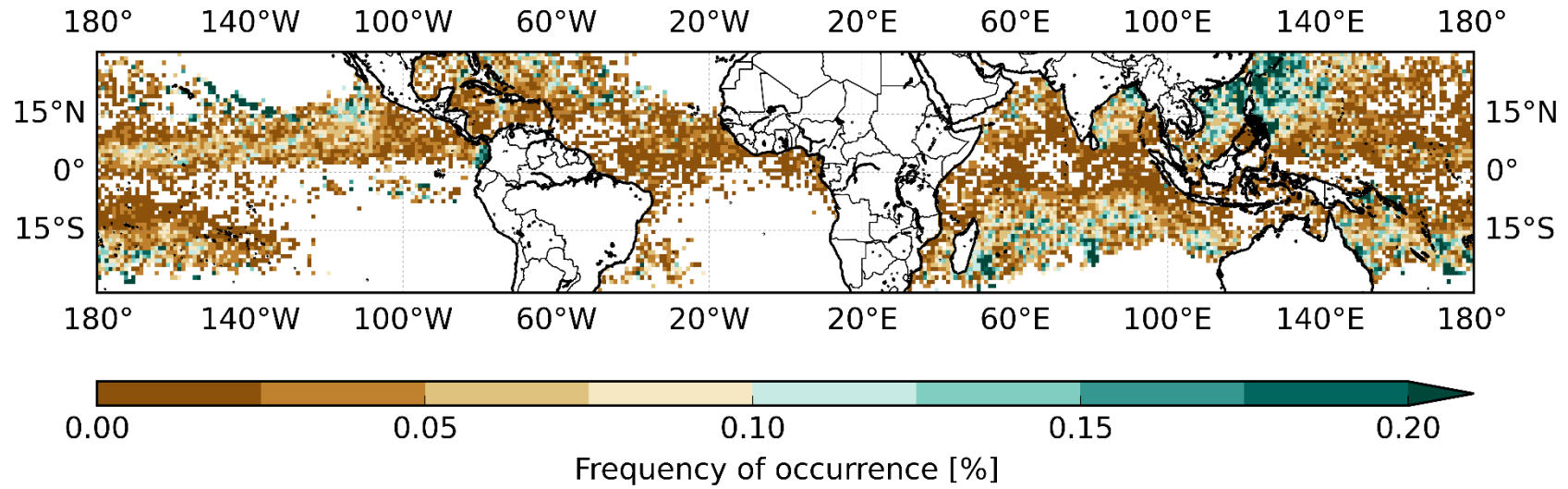


Figure 7: Map of the ensemble mean frequency of occurrence (%) of precipitation greater than the percentile 99.9th for the CC SST regime ([300 K; 302.5 K]). SST from OSTIA over the period 2007-2017, lagged by 2 days, are used to delineate the regime.