

Manuscript Number: HYDROL35559R1

Title: The performance of the IMERG satellite-based product in  
identifying sub-daily rainfall events and their properties

Article Type: Research paper

Keywords: GPM; evaluation; Inter-event time; Depth; Intensity; Duration.

Corresponding Author: Dr. Victor Hugo Rabelo Coelho, Ph.D.

Corresponding Author's Institution: Federal University of Paraíba

First Author: Emerson S Freitas, MSc

Order of Authors: Emerson S Freitas, MSc; Victor Hugo Rabelo Coelho, Ph.D.; Yunqing Xuan, Ph.D.; Davi Melo, Ph.D.; André N Gadelha, MSc; Elias A Santos Júnior, BEng; Carlos O Galvão, Ph.D.; Geraldo Ramos, MSc; Luis Romero Barbosa, Ph.D.; George J Huffman, Ph.D.; Walt A Petersen, Ph.D.; Cristiano N Almeida, Ph.D.

Abstract: Sub-daily rainfall information is essential for many hydrological applications, but ground-based data availability is still an issue in poorly gauged regions worldwide. Satellite remote sensing missions, such as the Global Precipitation Measurement (GPM) mission, have been playing a key role in estimating sub-daily rainfall data globally. However, the quality of such information needs to be carefully evaluated. Previous studies evaluating sub-daily data from the Integrated multi-satellite Retrievals for GPM (IMERG) product considered only the rainfall depth over pre-defined periods (e.g., hourly or half-hourly), with no analysis of the ability and quality of the product in defining the actual rainfall events and the associated properties. Thus, the objective of this study is to evaluate the performance of the IMERG Final Run Version 06B (V06B) product in capturing sub-daily rainfall events and their properties (depth, duration and intensity) over Brazil. The analysis consisted of comparing the satellite estimates against the ground-based data from 1,757 sub-daily rainfall gauges for a period of three years (2015-2017). This study used the minimum inter-event time (MIT) criterion to define independent rainfall events determined by dry periods: 1, 6 and 24 hours. Results show that IMERG can properly estimate the sub-daily rainfall depth for the three MITs considered, with the best results found in the southern part of the country. This means that the IMERG product represents a good source of sub-daily rainfall depth data for hydrological and hydroclimatic applications in Brazil. On the other hand, the evaluation shows large overestimations and underestimations of the IMERG product for rainfall duration and intensity properties, respectively. The results obtained from this study provide a reference for IMERG users who require sub-daily rainfall data based on events and further knowledge about its properties.

Suggested Reviewers: Guoqiang Tang  
tgq14@mails.tsinghua.edu.cn

1 **The performance of the IMERG satellite-based product in identifying**  
2 **sub-daily rainfall events and their properties**

3 Emerson da S. Freitas<sup>a</sup>, Victor Hugo R. Coelho<sup>b,\*</sup>, Yunqing Xuan<sup>c</sup>, Davi de C. D. Melo<sup>d</sup>, André N. Gadelha<sup>a</sup>,  
4 Elias A. Santos Júnior<sup>a</sup>, Carlos de O. Galvão<sup>c</sup>, Geraldo M. Ramos Filho<sup>a</sup>, Luis Romero Barbosa<sup>a</sup>, George J.  
5 Huffman<sup>f</sup>, Walt A. Petersen<sup>g</sup>, Cristiano das N. Almeida<sup>a</sup>

6  
7 <sup>a</sup> Department of Civil and Environmental Engineering, Federal University of Paraíba, João Pessoa, 58051-  
8 900, Brazil

9 <sup>b</sup> Department of Geosciences, Federal University of Paraíba, João Pessoa, 58051-900, Brazil

10 <sup>c</sup> College of Engineering, Swansea University, Bay Campus, Swansea, SA1 8EN, UK

11 <sup>d</sup> Department of Soils and Rural Engineering, Federal University of Paraíba, Areia, 58397-000, Brazil

12 <sup>e</sup> Technology and Natural Resources Centre, Federal University of Campina Grande, Campina Grande, 58429-  
13 900, Brazil

14 <sup>f</sup> NASA Goddard Space Flight Center, Greenbelt, MD 20771, USA

15 <sup>g</sup> NASA Marshall Space Flight Center, Huntsville, AL 35805, USA

16  
17 \* Corresponding author. Tel.: +55-83-3216-7684.

18 E-mail address: victor.coelho@academico.ufpb.br (V.H.R. Coelho)

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20 **ABSTRACT:** Sub-daily rainfall information is essential for many hydrological applications, but ground-  
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22 such as the Global Precipitation Measurement (GPM) mission, have been playing a key role in estimating  
23 sub-daily rainfall data globally. However, the quality of such information needs to be carefully evaluated.  
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25 product considered only the rainfall depth over pre-defined periods (e.g., hourly or half-hourly), with no  
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28 06B (V06B) product in capturing sub-daily rainfall events and their properties (depth, duration and intensity)  
29 over Brazil. The analysis consisted of comparing the satellite estimates against the ground-based data from  
30 1,757 sub-daily rainfall gauges for a period of three years (2015–2017). This study used the minimum inter-  
31 event time (MIT) criterion to define independent rainfall events determined by dry periods: 1, 6 and 24 hours.  
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36 rainfall duration and intensity properties, respectively. The results obtained from this study provide a  
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39 **Keywords:** GPM, evaluation, Inter-event time, Depth, Intensity, Duration.

## 40 **1. Introduction**

41 Rainfall is one of the main components of the hydrological cycle and its accurate quantification is  
42 fundamental to providing primary information for understanding and predicting some regional physical  
43 processes such as floods, landslides, soil erosion and severe storms (Kidd et al., 2017; Skofronick-Jackson et  
44 al., 2017). Sub-daily rainfall data are necessary for quantifying the characteristics of extreme events that  
45 trigger the physical processes mentioned above (Blenkinsop et al., 2018; Guerreiro et al., 2018; Lewis et al.,  
46 2019, 2018). Therefore, for hydrological application, dividing the rainfall into events is essential for a better  
47 understanding of such processes. For instance, Dunkerley (2012) showed that the rain event profile influences  
48 the partitioning of rainfall into ponding, infiltration and runoff.

49 Sub-daily rain event properties are also important for quantifying the soil erosion. For instance, this  
50 information is indispensable to the Universal Soil Loss Equation (USLE) and Revised Universal Soil-Loss  
51 Equation (RUSLE) developed by Wischmeier and Smith (1978) and Renard et al. (1997), respectively. Both  
52 the USLE and RUSLE equations are based on the so-called rainfall erosivity index, which is calculated with  
53 the maximum rainfall intensity during the 30-min period. The delineation of individual rain events is also the  
54 first step to generate the hyetographs for analysing the spatiotemporal variability of rainfall (Barbosa et al.,

55 2018; Coutinho et al., 2014; Dolšak et al., 2016). Moreover, the development of robust Intensity-Duration-  
56 Frequency (IDF) curves for extreme rainfall studies, which are the key to many engineering designs, is  
57 sometimes interfered with by sparse, infrequent or short-record sub-daily observations in many locations  
58 (Courty et al., 2019; Lumbroso et al., 2011). Therefore, rain event properties are particularly relevant for  
59 studies related to hydrological and ecological processes (Haile et al., 2012; Molina-Sanchis et al., 2016).

60 As revealed by Dunkerley (2008a), most reported studies of rainfall event data regarded a fixed  
61 rainless period (a minimum inter-event time, MIT) as the common criterion to define events. The use of the  
62 MIT criterion is important for analysing the relationship between the yield of catchments (e.g., water,  
63 sedimentation and nutrients) and the rainfall events with regards to their properties (e.g., depth, duration,  
64 intensity, dry time and intermittency). Moreover, adopting a fixed time interval (hourly or 30 minutes) to  
65 define rainfall events is not appropriate because such an interval may encompass different events or part of  
66 one rainfall event; hence the MIT criteria provides a better way to recognise and understand single rainfall  
67 events. According to Dunkerley (2008a), the common values of MIT used for defining rainfall events varies  
68 between 3-min and 24-h. Following this, Dunkerley (2015, 2010, 2008a) carried out a series of studies in  
69 Australia to understand the influence of the MIT criterion on the rainfall event and its properties. These  
70 studies showed that longer MITs yield rainfall events with lower intensity, and conversely, longer MITs yield  
71 larger depth and duration. Similar studies highlighting the influence of the MIT criterion on the rainfall  
72 properties have been reported in other countries, e.g. see Haile et al. (2011); Medina-Cobo et al. (2016);  
73 Meier et al. (2016) and Molina-Sanchis et al. (2016).

74 However, characterising the sub-daily rainfall variability over large areas by in-situ data is still  
75 difficult because such records sparsely cover the entire global landmass, never mind the key tropical regions  
76 (Hegerl et al., 2015). The lack of sub-daily in-situ rainfall data is probably due to the higher implementation  
77 costs of rain gauges able to measure sub-daily events, compared with those that measure on a daily time-scale.  
78 Blenkinsop et al. (2018) identified more than 23,000 sub-daily gauges worldwide providing freely available  
79 rainfall data, with 60% of them concentrated in five countries: the United States (7,197), Australia (1,882),  
80 United Kingdom (1,869), Japan (1,723) and Germany (1,011). Countries from Africa and Latin America have  
81 the lowest availability of sub-daily data. For instance, at the time, they have identified only 45 rain gauges  
82 with sub-daily freely available rainfall data in Brazil. Consequently, rain rates, event durations and other

83 rainfall properties at sub-daily time-scales have not been properly studied and are still poorly understood in  
84 such low-density gauge areas (Blenkinsop et al., 2018; Dunkerley, 2008b; Westra et al., 2014).

85         During the last few decades, the use of cutting-edge satellite-borne remote sensing technology has  
86 played a crucial role in providing valuable distributed observations of water resources, including precipitation  
87 data at sub-daily temporal resolution (Famiglietti et al., 2015; Levizzani et al., 2018; O and Kirstetter, 2018).  
88 The remotely sensed precipitation products mainly rely on algorithms that combine the data observed from  
89 microwave and infrared sensors together with other ancillary ground-based data (Hou et al., 2001; Kidd and  
90 Levizzani, 2011). Launched in 1997, the Tropical Rainfall Measuring Mission (TRMM) was one of the first  
91 dedicated and arguably most important satellites for obtaining information about precipitation in the latitude  
92 band 50° North and 50° South (Huffman et al., 2007). The TRMM Multi-satellite Precipitation Analysis  
93 (TMPA) dataset provides rainfall data at 0.25° spatial resolution and 3-hour temporal resolution. Several  
94 studies evaluated the performance of the TMPA products in many countries (e.g., Baik and Choi, 2015;  
95 Dembélé and Zwart, 2016; Dinku et al., 2008; Fang et al., 2013; Naumann et al., 2012; Pombo and de  
96 Oliveira, 2015), including Brazil (e.g., Buarque et al., 2011; Collischonn et al., 2008; Franchito et al., 2009;  
97 Melo et al., 2015), but most of them are mainly focused on daily or coarser time-scale evaluation. Even fewer  
98 studies checked the ability of the TMPA products for sub-daily (3-hour) applications such as flood forecasting  
99 (e.g., Nikolopoulos et al., 2013; Yuan et al., 2019). Specifically in Brazil, the studies evaluating the sub-daily  
100 performance of the TMPA products only used a few rain gauges at small and medium river basin scale (e.g.,  
101 Laverde-Barajas et al., 2018).

102         After nearly two decades of many successful applications of TRMM, its successor, the Global  
103 Precipitation Measurement (GPM) mission launched its Core Observatory in 2014 and began to provide  
104 rainfall and snowfall information globally with better temporal (half-hour) and spatial (0.1° x 0.1°)  
105 resolutions, via the Integrated Multi-satellitE Retrievals for GPM (IMERG) products (Skofronick-Jackson et  
106 al., 2018, 2017). Due to the improvement in its resolution and enhancements for detecting light rain compared  
107 with the TMPA, IMERG opens up new opportunities for sub-daily applications of rainfall data for many  
108 purposes (Asong et al., 2017). Three IMERG products are currently available; depending on the time that the  
109 data becomes available to the end-users and the amount of information incorporated to improve the satellite  
110 estimations, they are referred to as the Early Run, Late Run and Final Run (Huffman et al., 2017). The Early

111 and Late Run products are available at 4 and 12 h after observation, respectively, while the Final Run product  
112 is available 3.5 months after observation.

113         During the last five years, several studies have been carried out to evaluate the IMERG products in  
114 regions with different geographical characteristics worldwide, most of which present good agreement with the  
115 gauge and ground-based radar data (e.g., Asong et al., 2017; Li et al., 2018; O et al., 2017; O and Kirstetter,  
116 2018; Prakash et al., 2018; Satgé et al., 2019, 2017; Tan et al., 2017; Tan and Duan, 2017; Tang et al., 2016b,  
117 2016a, 2018; Wang et al., 2018). Some studies were conducted in Brazil assessing the quality of the IMERG  
118 products from different approaches at local-to-national scales (e.g., Gadelha et al., 2019; Lelis et al., 2018;  
119 Oliveira et al., 2018, 2016; Rozante et al., 2018; Salles et al., 2019). However, all studies performed in Brazil  
120 compared the IMERG estimates against ground-based data at relatively coarse temporal scales (daily or  
121 longer) when compared with the capability of the satellite-based product in detecting rainfall at a higher  
122 temporal resolution (half-hour). Moreover, worldwide, most studies that have assessed the IMERG data  
123 considered only the rainfall depth over pre-defined periods (Li et al., 2018; Tang et al., 2016a), with no  
124 analysis of the ability and quality of the product in defining the actual rainfall events (e.g., based on the MIT  
125 criterion) and the associated properties (rainfall depth, duration and intensity). Such analysis, which is  
126 essential for further applications of sub-daily data to predict the physical processes previously mentioned, is  
127 now possible thanks to the higher temporal resolution of the IMERG products. Furthermore, a more  
128 comprehensive and robust validation of the IMERG products in estimating the number of rain events and its  
129 properties can be done.

130         Considering the importance of high-quality sub-daily distributed rainfall data, the aims of this study  
131 are: (i) evaluating the performance of the IMERG product at sub-daily time-scale, (ii) analysing the potential  
132 of IMERG for delineating rainfall events and defining their properties (rainfall depth, duration and intensity),  
133 and (iii) identifying how the quality of the IMERG product is affected by the choice of MIT criterion (e.g.,  
134 over 1, 6, and 24 h). Based on these aims, this study addresses the following scientific questions: (a) How  
135 does IMERG perform at sub-daily time-scale? (b) Is the IMERG product able to delineate rainfall events and  
136 define their properties for sub-daily applications? (c) Is the quality of IMERG affected by the choice of MIT  
137 criteria and rainfall regimes? This study intends to be a reference for sub-daily analysis of the IMERG  
138 product, covering a large-scale area that encompasses a variety of climate zones, rainfall patterns and terrains.

139 **2. Materials and methods**

140 **2.1. Study area**

141 This study was carried out in Brazil, a continental-wide country covering approximately 8.5 M km<sup>2</sup>  
142 encompassed by 5°16'N-33°45'S and 34°47'W-73°59'W (Fig. 1). Officially, the Brazilian territory is divided  
143 into five geographical regions, namely: South (S), Southeast (SE), Central-West (CW), North-East (NE), and  
144 North (N). Brazil is the largest country in the Southern Hemisphere in area, encompassing different climate  
145 zones and rainfall patterns due to its vast territory. According to the detailed analysis performed by Alvares et  
146 al. (2013), the Brazilian territory has twelve Köppen's climate types divided into three main zones (Tropical,  
147 Semiarid and Humid Subtropical), with a mean annual air temperature ranging approximately from 10 °C to  
148 26 °C. It has five different rainfall regimes that do not fit very well with the geographical regions (Reboita et  
149 al., 2010; Rozante et al., 2018). The annual rainfall in Brazil is characterised by high spatial variability, with  
150 values ranging from 380 (semiarid in the NE) to 4,000 mm (tropical rainforest in the N) (Alvares et al., 2013;  
151 Gadelha et al., 2019; Melo et al., 2015). The rainfall regimes defined by Reboita et al. (2010) are described in  
152 Table 1.

153

154

**INSERT FIG. 1 HERE**

155 **Fig. 1.** (a) Selected rain gauges used as ground truth observations in this study and Köppen's classification  
156 map for Brazil according to Alvares et al. (2013). (b) Selected cells grouped according to homogenous rainfall  
157 characteristics (Section 2.6). The climatic symbol labels A, B and C stand for Tropical, Dry, and Humid  
158 Subtropical, respectively.

159

160

**INSERT TABLE 1 HERE**

161 **Table 1.** Summary of relevant characteristics of each homogeneous rainfall group, including the rainfall  
162 regimes defined by Reboita et al. (2010).

163 **2.2. Observed rainfall data**

164           This study began by considering rainfall data from 3,432 automated rain gauges distributed  
165 throughout the five official geographical regions in Brazil. The ground-based data for the period 1 January  
166 2015 to 31 December 2017 were acquired from tipping bucket gauges with a 10-min temporal resolution  
167 when it rains and 60 min over no-rain periods. These rain gauges are operated by the Brazilian Centre for  
168 Monitoring and Early Warnings of Natural Disasters (CEMADEN) as part of a national-wide network that  
169 was established by the Brazilian Government in 2011 to support its natural disasters risk management (Horita  
170 et al., 2017). Unfortunately, the distribution of the rain gauges is rather uneven, with the largest portion  
171 concentrated along the Brazilian coastal region where the population density is also high. Thus, most rain  
172 gauges obtained from the CEMADEN network are located within the cities. The SE region, where the São  
173 Paulo and Rio de Janeiro metropolitan regions are located, for example, is covered by 1,594 rain gauges, i.e.  
174 46% of the total. In contrast, the number of rain gauges in the N region, where the Amazon rainforest is  
175 located, corresponds to 2% (only 66 gauges) of the entire network. Although uneven, this in-situ rainfall  
176 monitoring network operated by CEMADEN represents an advance for understanding sub-daily rainfall  
177 extremes in tropical regions, since this type of data is currently much less available in other countries from  
178 Africa and Latin America.

179           Sub-daily rainfall data are mostly maintained by national meteorological agencies, but a single  
180 agreed upon global approach for quality assessment and control of the gauge-based measurements is still  
181 unavailable, especially when considering large areas (Westra et al., 2014). Meanwhile, a range of standard  
182 and sophisticated procedures for rainfall quality assessment and control has been proposed and recommended.  
183 The commonly used standard methods involve some of the following procedures (Westra et al., 2014): (i)  
184 checks of the range of values, (ii) changes in values over subsequent measurements, (iii) difference analysis  
185 between neighbouring stations, (iv) comparisons to other data types, (v) checking the range of time  
186 aggregations, and (vi) identification of breakpoints in rainfall time-series.

187           The observed rainfall data used in this study were quality-controlled based on two steps for detecting  
188 possible rain gauge inconsistencies and selecting high-quality data. Firstly, a computational routine selected  
189 only rain gauges with less than 30-days of missing data along each civil analysed year considered in this  
190 study. Thereafter, all the rain gauges meeting this first restriction were visually inspected using some of the  
191 above-mentioned standard methods. The first standard method compared monthly and sub-daily rainfall data



192 of the five nearest stations to verify large discrepancies between them. For this first analysis, the distances and  
193 the differences of altitude between the analysed rain gauge and the nearest stations were considered for  
194 identifying only rainfall patterns corresponding to their specific region. The range of values and changes over  
195 subsequent measurements were then analysed for each rain gauge to identify constant or null rainfall records  
196 that probably indicate gauge clogging. After the data quality check, a total of 1,757 rain gauges were used in  
197 this study for the comparison (Fig. 1a), i.e. almost half of the automated stations were discarded.

### 198 **2.3. IMERG data**

199 The IMERG Final Run (IMERG-F) is a Level 3 GPM product that combines microwave and infrared  
200 estimates from the GPM constellation (Huffman et al., 2017). It also incorporates monthly gauge observations  
201 from the Global Precipitation Climatology (GPCC) and other ancillary data to improve the satellite  
202 estimations. This study compared ground- and satellite-based data independently, since the rain gauges  
203 operated by CEMADEM are not used by GPCC. The IMERG-F product is available 3.5 months after  
204 observations, which is not suitable for time-sensitive applications. Instead, the IMERG-F product is more  
205 suitable for hydrological and climate modelling purposes given its better performance compared to near-real-  
206 time products (Tang et al., 2016a). The IMERG-F dataset provide rainfall and snowfall information at 0.1° x  
207 0.1° (spatial) and half-hour (temporal) resolutions. More information about the IMERG-F product are  
208 described in detail by Huffman et al. (2017) and Skofronick- Jackson et al. (2018). Specifically, this study  
209 used the latest IMERG-F Version-06B, which presents several major changes when compared to the previous  
210 versions, such as: i) the inclusion of additional sensors (particularly in the TRMM era), ii) improvements to  
211 parent GPM products, iii) modifications to the satellite intercalibrations, and iv) refinements to the morphing  
212 component (Tan et al., 2019). The comparison between the IMERG-F product and the rain gauge dataset was  
213 performed in this study at the native 30-minute scale. The IMERG-F dataset used in this study covers the  
214 same period of the ground-based data, i.e. between 1 January 2015 and 31 December 2017.

### 215 **2.4. Rainfall events definition and properties**

216 Many approaches are available for delineating individual rainfall events (Molina-Sanchis et al., 2016).  
217 However, the use of fixed time intervals (e.g. hourly or half-hourly) to define rainfall events can sometimes

218 be inappropriate, since such intervals may contain part of only one or sometimes more than one event; hence  
219 the MIT criteria provide a better way to recognise and understand single rainfall events. This study used the  
220 MIT to discriminate successive independent events by a defined dry period (Dunkerley, 2008a), as previously  
221 mentioned. Some studies define optimum values of MIT depending on the studied region (e.g., Medina-Cobo  
222 et al., 2016; Molina-Sanchis et al., 2016), while others reveal that the definition of MIT is associated with the  
223 application of the study (e.g., Aryal et al., 2007; Bracken et al., 2008; Cattani et al., 2006). According to Chin  
224 et al. (2016), short values of MIT are better used in local studies more sensitive to rainfall variation, whereas  
225 longer values of MIT are preferred for studies considering a whole weather system. Following this, a range of  
226 MITs, e.g. 1, 6 and 24 h, were chosen in this study to define rainfall events.

227 This study also analysed three important properties of the IMERG-F rainfall product: the depth,  
228 duration and intensity. A rainfall depth threshold of 2.5 mm for defining rain/no-rain was established for all  
229 analyses to exclude events deemed insignificant. Any IMERG-F and rain gauge rainfall events below this  
230 threshold were treated as zero. The temporal resolutions of rain gauges and IMERG-F used to define rainfall  
231 events are 10-min and 30-min, respectively. Therefore, these are the possible shortest rainfall event durations.

## 232 **2.5. Comparison and evaluation procedures**

233 Comparison between the IMERG-F and rain gauge data was based on a pairwise approach (Fig. 2a).  
234 Point-to-cell analysis was performed when there was only one rain gauge available inside the IMERG-F  
235 native cell. On the other hand, an average points-to-cell analysis was considered for IMERG-F grid cells  
236 containing more than one rain gauge. Satellite gridded data without any rain gauges at all within the cell were  
237 excluded from the analyses. As a result, in total, there are 1,065 grid cells of the IMERG-F product  
238 considered in this study for analyses.

239 **INSERT FIG. 2 HERE**

240 **Fig. 2.** Methodological chart showing (a) the cells of the IMERG product considered in the study and (b) the  
241 approaches adopted based on pairwise level for properties' mean values comparison, detection analysis and  
242 error magnitude analysis.

243 Three evaluation procedures (EP) were performed to assess the quality of the IMERG-F product in  
244 detecting the rainfall events and their properties for different MIT values (Fig. 2b). Firstly, the differences

245 between the mean values of the properties of all rainfall events estimated by the IMERG-F product and  
 246 observed by the rain gauges were checked. This is the first evaluation procedure (EP1), which makes use of  
 247 the correlation coefficient (CC) and the mean relative absolute error (MRAE), considering both national- and  
 248 group-scale means.

$$CC = \frac{\sum_{i=1}^n (O_i - \bar{O}) (E_i - \bar{E})}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2} \cdot \sqrt{\sum_{i=1}^n (E_i - \bar{E})^2}} \quad (1)$$

249

$$MRAE = \frac{100}{n} \sum_{i=1}^n \left| \frac{O_i - E_i}{O_i} \right| \quad (2)$$

250 where O is the value observed by the rain gauges,  $\bar{O}$  is the mean observed values, E is the value estimated by  
 251 the IMERG-F product,  $\bar{E}$  is the mean estimated values, and n is the total number of compared pairs.

252 A second evaluation procedure (EP2) was applied to verify whether the actual rainfall events  
 253 correspond to those detected by the satellites. EP2 uses the metrics related to rainfall events detection: (i)  
 254 probability of detection (POD), which shows the fraction of rainfall events that are correctly detected by the  
 255 IMERG-F product; (ii) false alarm ratio (FAR), which exhibits the fraction of events estimated by the  
 256 IMERG-F product but not detected by the rain gauge, and (iii) critical success index (CSI), which measures  
 257 the fraction of IMERG-F events correctly detected for the total number of observed and estimated rainfall  
 258 events:

$$POD = \frac{a}{a + c} \quad (3)$$

$$FAR = \frac{b}{a + b} \quad (4)$$

$$CSI = \frac{a}{a + b + c} \quad (5)$$

259 where a is the number of rainfall events simultaneously identified by both rain gauge and IMERG-F, b is the  
 260 number of rainfall events observed by the satellite product but not so by the ground-based data, and c is the  
 261 number of rainfall events detected by the rain gauges but not observed by the IMERG-F product. The values  
 262 of POD, FAR and CSI range from 0 up to 1. The perfect score for POD and CSI is close to 1, while the  
 263 desirable values for FAR are close to 0. The three metrics applied to compare the detection of rainfall events  
 264 are traditionally used for a defined time-space (e.g., Gadelha et al., 2018; Prakash et al., 2018; Rozante et al.,  
 265 2018; Tan and Duan, 2017; Tang et al., 2016a), which is not the case of this study. Therefore, a sequential

266 approach containing three specific criteria was established to evaluate whether the estimated event is really  
 267 the same as the observed: (i) if the rainfall events are 100% overlapped, (ii) if the rainfall events are  
 268 overlapped by more than 50% or (iii) if the time lag between the centroids are lower than 2.5 times the MIT.

269 Only the events detected according to EP2 were subjected to a third evaluation procedure (EP3),  
 270 which computes the average magnitude of deviations between satellite and ground-based properties of events.  
 271 EP3 only includes the MRAE of each property.

272 In summary, the EPs adopted in this study make it possible to identify whether the rainfall events  
 273 observed by the rain gauges are adequately estimated by the IMERG-F product, as follows: (i) good  
 274 agreement of average rainfall properties, (ii) ability to detect the events, and (iii) conformity of detected  
 275 events properties (Fig. 2b).

## 276 **2.6. Analysis of the rain gauge network density**

277 Differences between point-scale gauge measurements and areal satellite-based rainfall can affect the  
 278 validation conclusions of the IMERG-F product. Interpolation approaches are the only options for transferring  
 279 point-scale rainfall observations into areal estimates before they are compared with the grid-cells of the  
 280 satellite-based data (Tian et al., 2018). Alternatively, pairwise comparisons conducted only in grid-cells  
 281 containing at least one rain gauge can also be used (Asong et al., 2017; Tan and Duan, 2017; Yang et al.,  
 282 2016). However, the reliability of both methods used to compare satellite-based products and rain gauge data  
 283 is intrinsically linked to the density of the ground reference (Tang et al., 2018; Tian et al., 2018). In order to  
 284 ensure the reliability of the results, the dependence of the IMERG-F performance on the density of the rain  
 285 gauge network used in this study was also investigated. There were then four metrics applied to verify the  
 286 deviations of rainfall magnitudes for the IMERG-F product according to different gauge densities available in  
 287 this study. Such metrics include the bias (BIAS), the mean relative error (MRE), the MRAE presented in Eq.  
 288 (2) and the root mean square error (RMSE):

$$\text{BIAS} = \sum_{i=1}^n (E_i - O_i) \quad (6)$$

$$\text{MRE} = \frac{\sum_{i=1}^n (E_i - O_i)}{O_i} \quad (7)$$

$$\text{RMSE} = \frac{\sqrt{\sum_{i=1}^n (E_i - O_i)^2}}{n} \quad (8)$$

## 289 **2.7. Definition of regions based on homogeneous rainfall characteristics**

290 As previously mentioned, the Brazilian territory encompasses a variety of climate zones and rainfall  
291 regimes. Therefore, it is necessary to cluster the rain gauges and their corresponding grids of the IMERG-F  
292 product in regions with similar characteristics, prior to the proposed analyses. The k-means clustering  
293 algorithm was applied to define these regions with similar rainfall patterns (Carvalho et al., 2016). There were  
294 five groups defined in this study based on the number of rainfall regions established for the Brazilian territory  
295 by Reboita et al. (2010) and Rozante et al. (2018).

296 All rain gauges selected after the quality control process were used to define these homogeneous  
297 regions, as shown in Figure 1b. There were six different variables obtained from these rain gauges used to  
298 define the regions: (i) elevation, (ii) annual rainfall, (iii) number of rainfall events, (iv) mean rainfall depth,  
299 (v) mean duration, and (vi) mean intensity. For the last four variables, all three different MITs used for the  
300 analyses were also considered when defining the regions. However, before the clustering analysis, the number  
301 of variables was reduced using Principal Component Analysis (PCA) (Dyer, 1975; Ogallo, 1989; Singh,  
302 2006).

## 303 **3. Results and discussion**

### 304 **3.1. Representativeness of the point(s)-to-cell analysis**

305 The point(s)-to-cell analysis applied in this study was performed using 1,750 rain gauges distributed  
306 throughout 1,065 grid cells of IMERG, which corresponds to an overall density network of 1.64 gauges per  
307 100 km<sup>2</sup>. This represents more than eight times the threshold of one gauge per 575 km<sup>2</sup> recommended by the  
308 World Meteorological Organisation (WMO) for the interior plane and undulating areas (WMO, 1994). The  
309 number of rain gauges per grid cell of IMERG available for this study ranged from 1 to 12, as shown in Table  
310 2. Grid cells with densities lower than four rain gauges per 100 km<sup>2</sup> stand for more than 90% of the analysed  
311 pixels. Conversely, grid cells containing more than seven rain gauges represent less than 1% of the total pixels  
312 evaluated in this study. According to the review carried out by Tian et al. (2018), the rain gauge network used  
313 in this study is denser than in most other previous studies evaluating satellite-based rainfall products.

314

**INSERT TABLE 2 HERE**

315 **Table 2.** Rain gauge densities per grid cells used in this study.

316 Figure 3 shows the evaluation results of the metrics for all available rain gauge density networks.  
317 This evaluation also considers the three rainfall properties and MITs used in this study. Overall, it is not  
318 possible to identify an improvement of the evaluation performance with the increase of the gauge density. For  
319 instance, the BIAS of the rainfall depth and duration remained practically unchanged for the two shorter MITs  
320 considered in this study. In contrast, the results show that denser gauge networks tend to slight increase the  
321 values of RMSE for all MITs and rainfall properties. This result differs from the studies carried out by Tang  
322 et al. (2018) and Tian et al. (2018) that detected a strong dependence of the evaluating metrics for the IMERG  
323 product on the rain gauge densities. Tang et al. (2018) found 2.5 gauges per grid cell at 0.1° spatial scale as  
324 the more reliable density to accurately evaluate satellite precipitation products in a river basin in South China.  
325 However, they recommended that future studies should explore the sensitivity of the results to variations in  
326 topography, climate conditions and precipitation phase (solid or liquid) because this number can be influenced  
327 by the region and season. On the other hand, the study performed by Tian et al. (2018) found that the  
328 evaluation of the IMERG satellite product exhibited better accuracy for most metrics when considering one  
329 gauge or more per grid cell.

330 **INSERT FIGURE 3 HERE**

331 **Fig. 3.** Evaluation metrics for all rain gauge densities and Minimum Intra-event Times (MIT) used in this  
332 study. The symbols ME, MAE, BIAS and RMSE stand for mean error, mean absolute error, bias and root  
333 mean square error.

### 334 **3.2. Homogenous rainfall groups**

335 Fig. 1b shows the spatial distribution cells, separated by groups with homogenous rainfall  
336 characteristics, after the application of PCA and k-means clustering algorithm. Group 1 is mainly located in  
337 the N and NE regions of Brazil, containing 163 cells (Table 1). The main atmospheric systems that have  
338 influence on this group of cells with the same rainfall patterns are those in the Intertropical Convergence Zone  
339 (ITCZ) and the Mesoscale Convective Complex (MCC) (Cohen et al., 1995; Espinoza Villar et al., 2009).  
340 According to Köppen's classification proposed by Alvares et al. (2013), the climates of the region where  
341 Group 1 is placed are tropical monsoon (Am) and tropical with dry winter (Aw), with an average annual  
342 temperature of 26 °C. The annual mean rainfall in the Group 1 ranges from 1,400 to 2,000 mm, most of which

343 is concentrated between January and May (Fig. 4a). Group 2 mostly encompass the cells located along the  
344 Atlantic coastal zone of Northeast Brazil, which is mainly characterised by the Instability Lines (IL) and  
345 Southeast Trade Winds (SETW) atmospheric systems (Kousky, 1988; Reboita et al., 2010). Group 2 presents  
346 a fewer number of evaluated cells in this study – 108 in total. The climate of this group is mainly tropical with  
347 dry summer (As), with historical mean rainfall ranging from 1,200 to 1,800 mm year<sup>-1</sup> and mean monthly air  
348 temperature above 23 °C throughout the year (Fig. 4b). Most of the 209 cells of Group 3 are located in the  
349 region of the Southeast, mainly characterised by a tropical with dry summer (As) climate, with mean annual  
350 rainfall ranging from 1,000 to 1,300 mm and concentrating during the austral summer (Melo et al., 2015)  
351 (Fig. 4c). The main climate systems influencing Group 3 are the South Atlantic Subtropical Anticyclone  
352 (SASA) and the South Atlantic Convergence Zone (SACZ) (Reboita et al., 2010; Rozante et al., 2018), with  
353 the mean monthly air temperature varying between 18°C and 24 °C throughout the year. Groups 4 and 5 own  
354 the largest number of analysed cells in this study (317 and 268, respectively). Both groups are mainly located  
355 in the S and SE regions, with a humid subtropical climate (C). The South Atlantic Subtropical Anticyclone  
356 (SASA) and South Atlantic Convergence Zone (SACZ) are the main climate systems influencing the Group 4,  
357 while Group 5 is influenced more by the Prefrontal Squall Line (PSL) and Cold Fronts (CF) climate systems  
358 (Reboita et al., 2010; Velasco and Fritsch, 1987). The annual rainfall in the cells of Group 4 ranges between  
359 1,300 and 1,900 mm, most of which is concentrated during the austral summer (Fig. 4d). In contrast, the  
360 rainfall is spatially more uniform throughout the year in Group 5, ranging from 1,600 to 2,200 mm (Fig. 4e).  
361 The monthly average air temperature in Group 5 ranges from 12 °C in July to 23 °C in January.

362 **INSERT FIG. 4 HERE**

363 **Fig. 4.** Long-term (1950–1990) mean monthly rainfall and mean air temperature of each group with  
364 homogenous rainfall characteristics, obtained from 891 meteorological stations used by Alvares et al. (2013).

### 365 **3.3. Nation-wide mean values comparison of the properties of rainfall events**

366 In this first analysis, the IMERG data were evaluated by comparing the mean property values of all  
367 rainfall events identified by MIT from both IMERG and rain gauge. Fig. 5 shows the scatter plots based on  
368 the mean values, considering all cells analysed for the entire country. The outliers were visually excluded  
369 from this figure for better visualisation of the point cloud. Overall, the comparison between the two data

370 sources indicates that the IMERG product presented a good agreement with the rainfall depths observed by  
371 the rain gauges, with a solid blotch of points concentrated close to the line of equality for all considered MITs  
372 (Fig. 5a to c). The concentration of most of the points above the line can demonstrate a slight overestimation  
373 of the rainfall depth by the IMERG product for all individual events. Similar behaviour of slight  
374 overestimation was also observed by Rozante et al. (2018) and Gadelha et al. (2019) when evaluating the  
375 rainfall depth of IMERG over Brazil at coarser temporal scales (daily onward). Similar performance  
376 behaviour of the sub-daily mean areal precipitation from IMERG was also noticed in other large-scale studies  
377 carried out in different regions of the World (e.g., Li et al., 2018; Mayor et al., 2017; Tang et al., 2016a). The  
378 CC for the rainfall depth considering the cells of all groups ranged from 0.36 (MIT = 24h) to 0.66 (MIT = 6  
379 h), with values of MRAE ( $< 32\%$ ) indicating low variability of data between the rain gauges and the IMERG  
380 product for all MIT. It is also noticeable that the mean rainfall depth progressively increased for both sources  
381 of data as MIT become greater, as observed in-depth by Dunkerley (2015), Medina-Cobo et al. (2016) and  
382 Molina-Sanchis et al. (2016) using only tipping-bucket rain gauge data.

383 **INSERT FIG. 5 HERE**

384 **Fig. 5.** Scatter plots of the mean gauge values vs IMERG-F categorised into columns (from the left to right:  
385 depth, duration and intensity) and rows (from the top to bottom, the following MIT: 1, 6 and 24 h). The  
386 shaded contours and the line plots along the top and right axes are joint and marginal distributions of the  
387 gauge and IMERG-F. CC and MRAE stand for correlation coefficient and mean relative error, respectively.

388

389 The mean duration and intensity, considering all analysed cells, show a poor agreement between the  
390 IMERG product with the observed rainfall data for all MITs (Fig. 5d to i). For the mean duration, a large  
391 overestimation of the satellite-based product was observed, with negative linear correlations with respect to  
392 the two longer MITs, i.e. 6 h (CC = -0.19) and 24 h (CC = -0.03). These negative and low values of linear  
393 correlations represent an absence of correlation when comparing the two different rainfall datasets. For the  
394 mean intensity, however, the IMERG products presented a large underestimation when compared with the  
395 observed data, showing almost all points concentrated below the line of equality and the CC values ranging  
396 from -0.29 to -0.49. This behaviour was expected because the mean intensity inversely correlates to the mean  
397 duration, as a well-known feature from the relationship between intensity, depth and duration (Dunkerley,



398 2008a). Overall, it is also noticeable that the mean durations of IMERG present far larger amplitudes of data,  
399 with values up to three times higher than that observed in the rain gauges. Accordingly, the mean observed  
400 intensity is inversely proportional to the MIT, with amplitudes of values reducing significantly when rain  
401 events are longer, as also noticed and analysed by Dunkerley (2015) in Australia. In contrast, the mean  
402 intensity estimated by the IMERG product exhibits low dispersion for all MITs, with minimum and maximum  
403 values of 0.2 (MIT = 24 h) and 2.5 mm h<sup>-1</sup> (MIT = 1 h), respectively. The MRAE values vary widely from  
404 141 to 213% for mean duration and from 55 to 69% for mean intensity. The disagreement detected for the  
405 rainfall intensity occurs because the IMERG-F product is adjusted so that the monthly rainfall depth matches  
406 up with the rain gauges represented in the GPCP analysis (Becker et al., 2013; Schneider et al., 2014). This  
407 calibration does not affect the duration of the satellite event, so the intensity will be adjusted to whatever it  
408 takes over the duration of the event to fit the total monthly rainfall.

409 This analysis considering national-wide mean values comparison can lead to a false conclusion when  
410 data from the various regions are evaluated in a single pool. Therefore, the following sections present the  
411 results based on the comparison of homogenous rainfall groups.

#### 412 **3.4. Homogenous group-wide mean values comparison of the properties of event**

413 Fig. 6 shows the box plots of the mean values for all analysed rainfall properties, separated by groups  
414 with homogenous characteristics, with extreme values also visually excluded for better visualisation of the  
415 data. Overall, the rainfall depth estimated by the IMERG-F product shows similar distribution with the data  
416 obtained from the rain gauges for all groups, with groups 3, 4 and 5 having the closest patterns. There is a  
417 slight overestimation in the satellite-based product compared with the observed data for all MITs. In contrast,  
418 Groups 1 and 2 exhibited the worst performance considering longer (24 h) and shorter (1 and 6 h) enclosing  
419 rain events, respectively. Rozante et al. (2018) and Gadelha et al. (2019) also noted low performance of  
420 IMERG-F in capturing daily rainfall depth in regions where the Groups 1 and 2 are predominantly located.  
421 The best CCs for rainfall depth were observed for Group 1, with values equal to or higher than 0.52 for all  
422 MITs (Table 3). Although presenting the best CC values, the variability of data between IMERG and rain  
423 gauges was substantially high for MITs equal to 24 h in Group 1, with MRAE reaching values higher than  
424 90%. The reduction of the number of events registered by IMERG-F for longer MIT probably influenced the

425 increase of the mean rainfall depth and, consequently, the values of MRAE in Group 1. This effect may be  
426 caused by the influence of convective clouds that prevail in this group, since this type of cloud can be falsely  
427 detected by the infrared sensors of the satellite, as also noticed by Rozante et al. (2018) and Gadelha et al.  
428 (2019). Overall, Groups 4 and 5 presented the lowest variabilities of the mean rainfall depth between the two  
429 sources of data ( $MRAE < 30\%$ ), independently of the MIT considered.

430

**INSERT FIG. 6 HERE**

431 **Fig. 6.** Box plots of the mean gauge values and IMERG-F for the five homogenous rainfall groups,  
432 categorised into columns (from the left to right: depth, duration and intensity) and rows (from top to the  
433 bottom, the following MIT: 1, 6 and 24 h).

434

**INSERT TABLE 3 HERE**

435 **Table 3.** Summary of evaluation metrics for the IMERG-F product, considering the mean values of rainfall  
436 properties for each homogeneous group.

437 The mean duration of the events from the IMERG-F product is significantly overestimated compared  
438 with that of the ground-based data for all five homogenous groups (Fig. 6d to f), following the same  
439 characteristics observed for the national-scale mean comparison. Similarly, for the rainfall depth, Group 1 has  
440 the worst performance in terms of using the IMERG-F in detecting the mean duration, with values of MRAE  
441 higher than 300% for all MITs considered in this study (Table 3). The best performance of the IMERG-F in  
442 identifying the duration of the gauge data was observed in Group 5 ( $54\% < MRAE < 150\%$ ), although the  
443 values of CC showed negative correlations for the two shorter MITs. Such performance is most likely caused  
444 by the prevalence of rainfall from Cold Front weather systems with low intensity and long durations, as noted  
445 by Rozante et al. (2018). In general, the shorter MIT of the IMERG-F dataset represented the mean duration  
446 of the rain gauges worse regardless of the homogenous rainfall group ( $150\% < MRAE < 322\%$ ). These  
447 behaviours show that the IMERG-F product can adequately capture the rainfall depth but with longer duration  
448 when compared to the ground-based dataset. The durations of the satellite-based product result in a large  
449 underestimation of the rainfall intensity of IMERG-F. Once again, Group 1 exhibited the largest deviations

450 and errors in the evaluation of the satellite rainfall product, with MRAE obtained for rainfall intensity  
451 exceeding 80% for all MIT. Conversely, lower errors for the rainfall intensity were found in Groups 2 and 5,  
452 although coming with high values of MRAE (from 37 to 58%) and low positive CC ( $< 0.43$ ). This fact limits  
453 the use of the IMERG-F for those purposes that require accurate information about rainfall duration and  
454 intensity, such as soil loss (Medeiros and Araújo, 2014) and production of surface runoff (Figueiredo et al.,  
455 2016).

### 456 **3.5. Mean values comparison of trends by fixed thresholds**

457 This section evaluates the agreement of the mean values of all rainfall properties of the IMERG-F  
458 product according to the level of underestimation or overestimation, which is split into seven categories as  
459 shown in Fig. 7. Overall, the mean rainfall depth of IMERG-F exhibited low relative errors across all groups,  
460 especially for the two shorter MITs, where more than 50% of the cells showed a good agreement for almost  
461 all groups. An exception was noticed in Group 2, where a mix of moderate and slight overestimations  
462 prevailed in more than 50% of the cells. A reduction in the number of cells presenting good agreement was  
463 observed in almost all homogenous groups for longer MIT values, except in Group 2. This effect was caused  
464 by the aggregation of individual rain events that increased the rainfall depth in longer MITs, as deeply  
465 discussed by Dunkerley (2008a). In this study, the increase of rainfall depth within longer rain events was  
466 more accentuated for the IMERG-F product when compared to the observed dataset, which is evidenced by  
467 the considerable number of cells presenting slight and moderate overestimations in all groups. Group 1  
468 concentrates the largest relative errors for the longer MIT, with moderate and large overestimations  
469 representing more than 75% of the cells in this group.

470 **INSERT FIG. 7 HERE**

471 **Fig. 7.** Stacked bars of the relative errors for the five homogenous rainfall groups. The charts are organised  
472 into columns referring to the rainfall property (from left to right: depth, duration, and intensity) and rows  
473 referring to the MIT (from the top to bottom: 1, 6 and 24 h).

474 Generally, the IMERG-F product is unable to successfully represent the mean rainfall duration or  
475 intensity of the events observed by the rain gauges, with most cells displaying large overestimations and  
476 underestimations mainly for shorter MITs, respectively (Fig. 7d to i). The performance of the group 1 does  
477 not practically change across different MITs when comparing duration and intensity. Group 1 demonstrates  
478 very large deviations in duration (overestimation) and intensity (underestimation). On the other hand, Group 2  
479 exhibited a better performance of rainfall duration and intensity, with approximately 30% of the analysed  
480 cells deemed to be in 'good agreement' for the two longer MITs. This analysis confirms the results found in  
481 the previous sections that indicate a limitation of the IMERG-F product to represent the intensity and duration  
482 of the same sub-daily rainfall events observed by the gauges but with complementary information regarding  
483 the percentage of cells in each homogenous group according to the agreement thresholds.

### 484 **3.6. Analysis of rainfall events detection**

485 The results presented in the previous sections show a good agreement between the mean rainfall  
486 depth estimated by the IMERG-F product and observed by the ground-based dataset, which was not noted for  
487 the two other rainfall properties (duration and intensity). This section analyses if the IMERG-F product is able  
488 to accurately match the same rainfall events detected by the rain gauges. Fig. 8 shows considerable  
489 improvement of the IMERG-F product performance in detecting ground-based rainfall events as MIT  
490 increases. An exception was noticed in Group 1, where more events were correctly detected for the MIT of 6  
491 h. Overall, Groups 4 and 5 presented the highest POD values for all MIT, ranging from ~0.3 (MIT = 1 h) to  
492 ~0.8 (MIT = 24h). The results exhibited in Fig. 8a indicate a good skill of IMERG-F in detecting individual  
493 rain events equal to or higher than 6 h in those two groups located in Southern Brazil, as also noted by Lelis et  
494 al. (2018) and Gadelha et al. (2019) in their evaluation of the IMERG-F product from daily to annual time-  
495 scales. This performance of POD is corroborated by the distribution of CSI, which followed the same  
496 characteristics but with lower values due to the high number of detected FAR. Similar behaviour was also  
497 observed by Tang et al. (2016a) who assessed the IMERG-F product in China, where POD presented values  
498 ~20% larger than CSI. On the other hand, Groups 1 and 2 displayed POD values lower than 0.5 for the longer  
499 MIT. Rozante et al. (2018) also observed low detection of IMERG-F along the Atlantic coast of NE Brazil,  
500 where most of Group 2 is located, even considering analyses on a monthly basis. Unlike POD and CSI, the

501 FAR presented an inverse relation with the MIT, with the highest false alarms observed for rain events equal  
502 to 1 h in all groups. The FAR exhibited similar performance for all groups, with the largest proportional  
503 reduction of false alarms identified between the two shorter MITs.

504 **INSERT FIG. 8 HERE**

505 **Fig. 8.** Spider chart representing (a) the probability of detection (POD), (b) the false alarm ratio (FAR) and (c)  
506 the critical success index (CSI) for all homogeneous rainfall groups and Minimum Intra-event Times (MIT).  
507 The symbols G1, G2, G3, G4 and G5 stand for group 1, group 2, group 3, group 4 and group 5, respectively.

### 508 **3.7. Error magnitude analysis**

509 Results relative to EP2 are depicted by the spider charts assessing the magnitude of deviations  
510 between the rainfall properties estimated by the IMERG-F product and observed by the rain gauges (Fig. 9).  
511 The MRAE values presented a general behaviour of remaining unchanged with the aggregation of the rainfall  
512 depth events in almost all groups, with values close to 100%. Only Group 2 exhibited an increase in the  
513 magnitude of the depth error when longer no-rain periods are included within rainfall events. Gadelha et al.  
514 (2019) also found large deviations of rainfall depth in most cells located in the coastal zone of the Brazilian  
515 NE when evaluating the IMERG-F product on coarser time-scales. Such poor performance was attributed by  
516 the authors to the warm-rain process-dominated systems that are not well detected by the passive microwave  
517 sensors over land. The values of MRAE for duration follow the general pattern observed in the rainfall depth  
518 but with higher errors also detected in Group 2, especially for the MIT = 24 h (> 600%). The largest values of  
519 MRAE were noticed for rainfall intensity, wherein the deviations of IMERG-F range from 300 (Group 5) to  
520 2,000% (Group 1) for the longer MIT.

521 **INSERT FIG. 9 HERE**

522 **Fig. 9.** Spider charts representing the mean relative absolute error (MRAE) for (a) rainfall depth, (b) rainfall  
523 duration and (c) rainfall intensity of all homogeneous groups and Minimum Intra-event Time (MIT). The  
524 abbreviations are the same as in Figure 8.

525 **4. Summary and conclusions**

526 This study is the first national-scale assessment of the IMERG-F product at sub-daily temporal  
527 resolution in Brazil. Moreover, the analyses focused on the potential of the satellite-based data in delineating  
528 rainfall events and defining some of its properties, such as depth, duration and intensity. The evaluation was  
529 carried out using 1,065 grid cells of the IMERG-F product, separated into five different groups with  
530 homogenous rainfall characteristics. The main specific findings of this study are summarised as follows:

531 (1) The IMERG-F product exhibited good performance in capturing the rainfall depth for all MITs  
532 considered in this study, with some variations depending on the analysed group. Overall, the rainfall  
533 depth estimated by the satellite product presented better performance in cells located in southern  
534 Brazil, specifically in Groups 4 and 5.

535 (2) IMERG-F presented a slight tendency in overestimation the ground-based rainfall depth data for  
536 all MITs. This overestimation tends to slightly increase when longer rain events are analysed,  
537 although a considerable improvement of the probability of detection was also noticed when more  
538 rain events were incorporated.

539 (3) The evaluations revealed large overestimations and underestimations of the IMERG-F product  
540 for rainfall duration and intensity, respectively. This behaviour was noted for all groups and all MITs  
541 probably because i) the calibration of the IMERG-F product that is made to match the monthly rain  
542 gauges rainfall depth incorporated to improve the satellite estimates, and ii) the capability of the  
543 microwave and infrared sensors for identifying rain/no-rain. In general, these sensors detect longer  
544 rainfall events than those that actually occurred. Such finding limits the use of the IMERG-F product  
545 in Brazil for some applications that require rainfall intensity and duration information with high  
546 temporal resolution.

547 (4) The analyses reveal that the detection of events by the IMERG-F product tends to improve with  
548 the increasing of MIT. However, the rainfall properties remain not well-represented with this  
549 improvement, especially the intensity and duration.

550 (5) Overestimations and underestimations of the IMERG-F product were more evident in regions  
551 with the presence of Mesoscale Convective Systems (Group 1). On the other hand, in regions with

552 the presence of Cold Front weather systems and rainfall characterised by long duration and low  
553 intensity, the IMERG-F product better estimated the sub-daily rainfall data (Group 5).

554 The results obtained from this study provide a reference for IMERG-F V06B use cases that require  
555 sub-daily rainfall data based on events and further knowledge about its properties. Based on our findings, the  
556 sub-daily information on rainfall depth from the IMERG-F product can be a good source of data for  
557 hydroclimatic and hydrological studies in Southern Brazil. On the other hand, sub-daily rainfall depth data  
558 from the IMERG-F product have to be carefully checked when used throughout the NE coastal region  
559 because of the larger overestimations and underestimations associated with the weather systems (IL and  
560 SETW) and the reduced capability of the sensor to detect some precipitation and cloud types. Unfortunately,  
561 the number of rain gauges with sub-daily data from the CEMADEN network is limited over the N region  
562 where the Amazon rainforest is located, which makes a more accurate assessment of the IMERG-F product in  
563 this area difficult. Finally, this study highlights the need for further analyses event-by-event in each cell of the  
564 IMERG-F product to verify the influence of the hydroclimatic variables in the detection of rainfall intensity  
565 and duration events. Moreover, improvements in rainfall intensity and duration estimates of the IMERG-F  
566 product are necessary for better identification of rain/no-rain, since the generation of a rainfall event, however  
567 small it is, leads to a change of the duration and, consequently, the intensity.

568

569 **Acknowledgements:** The Brazilian and British authors would like to acknowledge the financial support from  
570 the Brazilian National Council for Scientific and Technological Development (CNPq) for funding the  
571 Universal MCTI/CNPq No. 28/2018 (Grant REF: 433801/2018-2). This study was also financed in part by the  
572 Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES) – Finance Code 001. The NASA  
573 authors were funded under the Precipitation Measurement Missions and Global Precipitation Measurement  
574 (GPM) mission projects. The British author was also supported by the Fundação de Apoio à Pesquisa do  
575 Estado da Paraíba (FAPESQ-PB), in partnership with the Newton Fund, via CONFAP – The UK Academies  
576 Research Mobility 2017/2018 (Grant REF: 039/2018). Special thanks are given to CEMADEM (Brazilian  
577 Centre for Monitoring and Early Warnings of Natural Disasters) for providing the rainfall database used in  
578 this study. Finally, we acknowledge the three anonymous reviewers and the editors for the constructive  
579 comments that improved a lot the quality of the manuscript.

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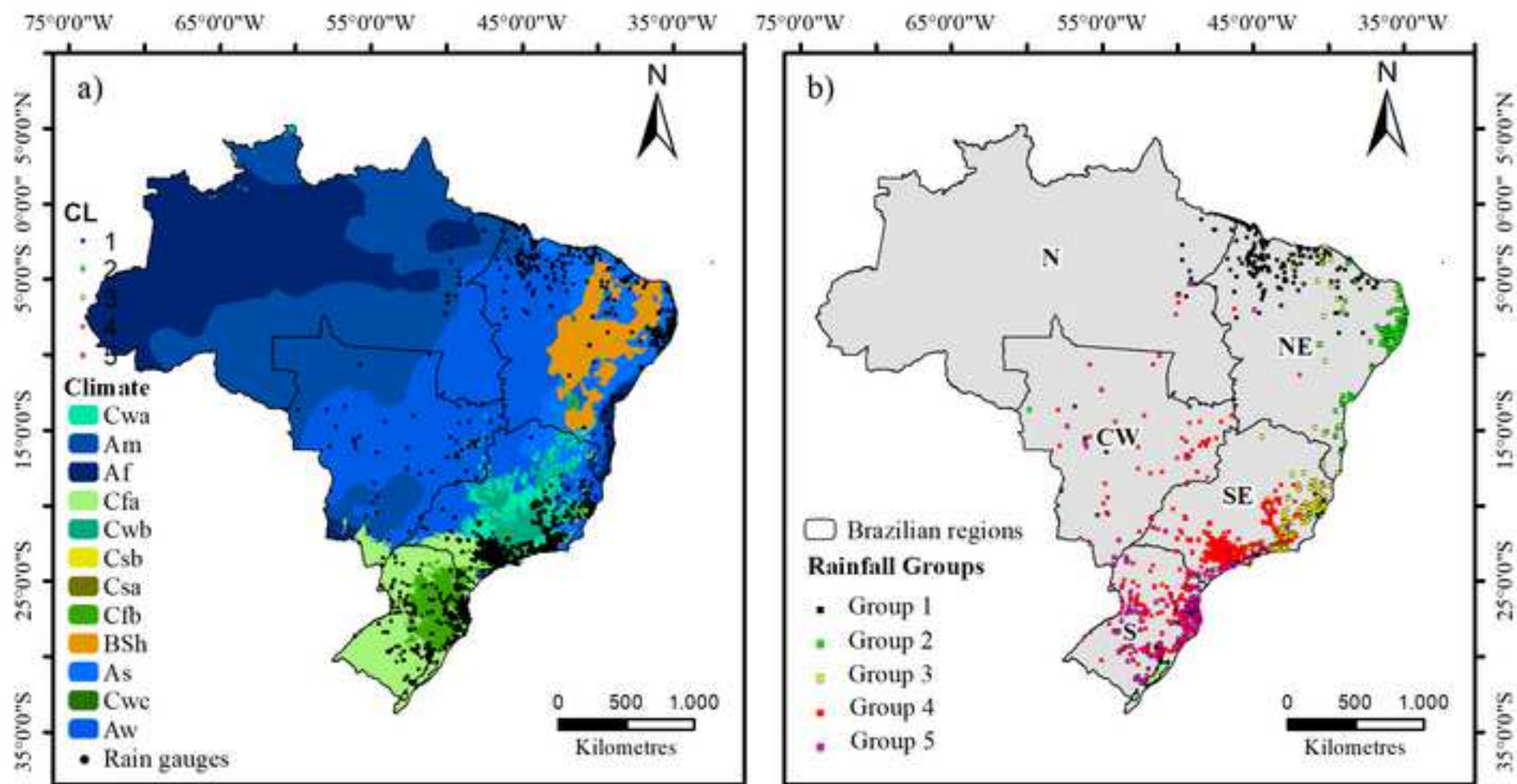
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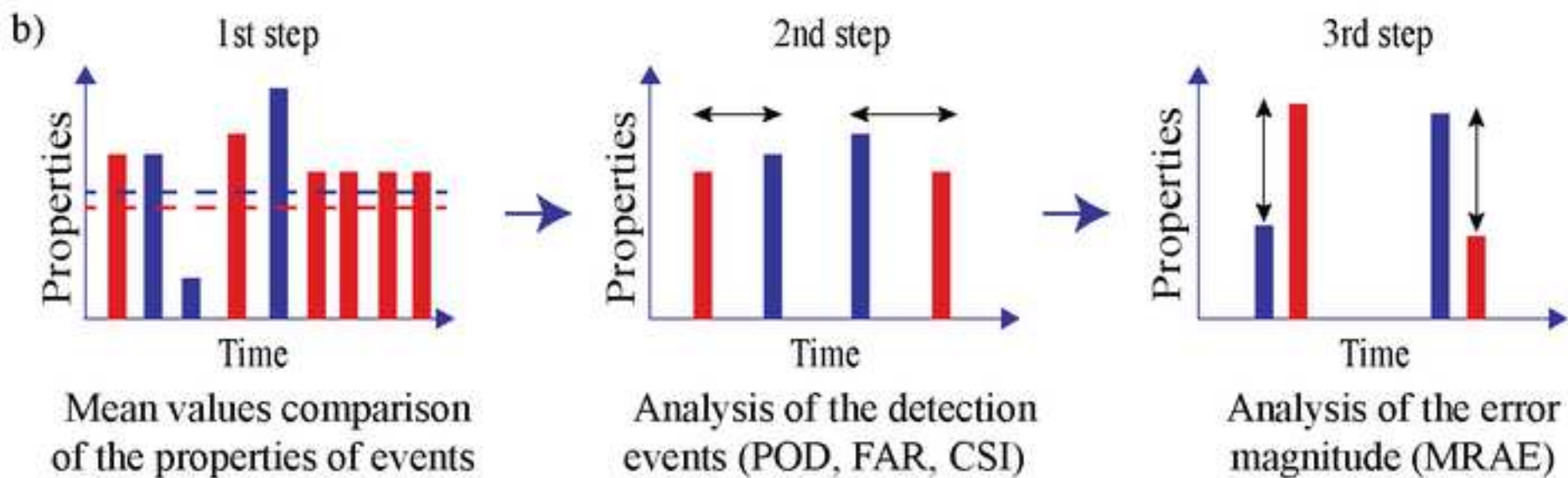
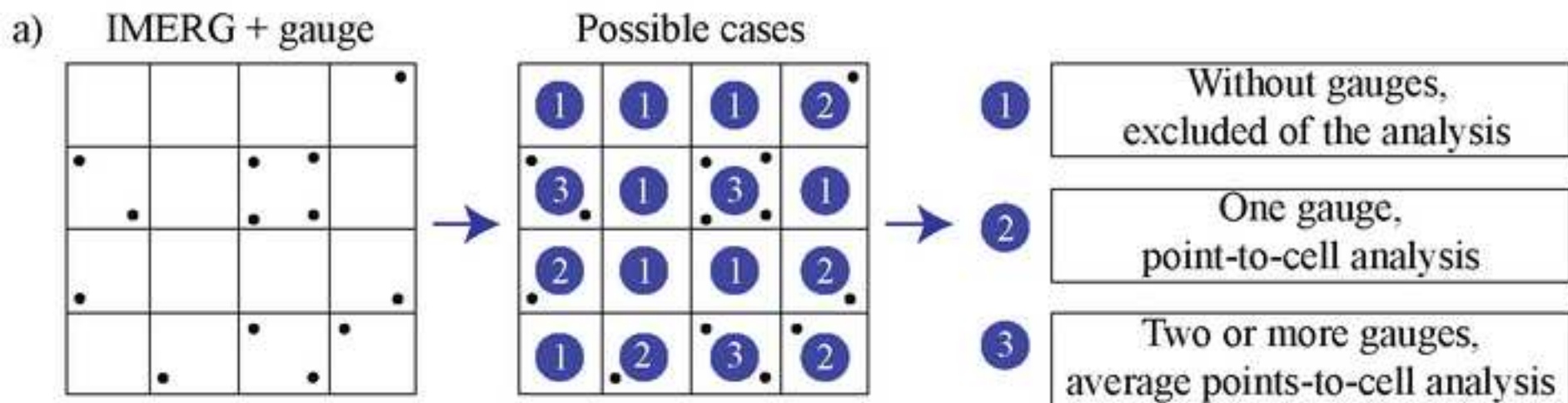
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Figure 1  
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Figure\_2

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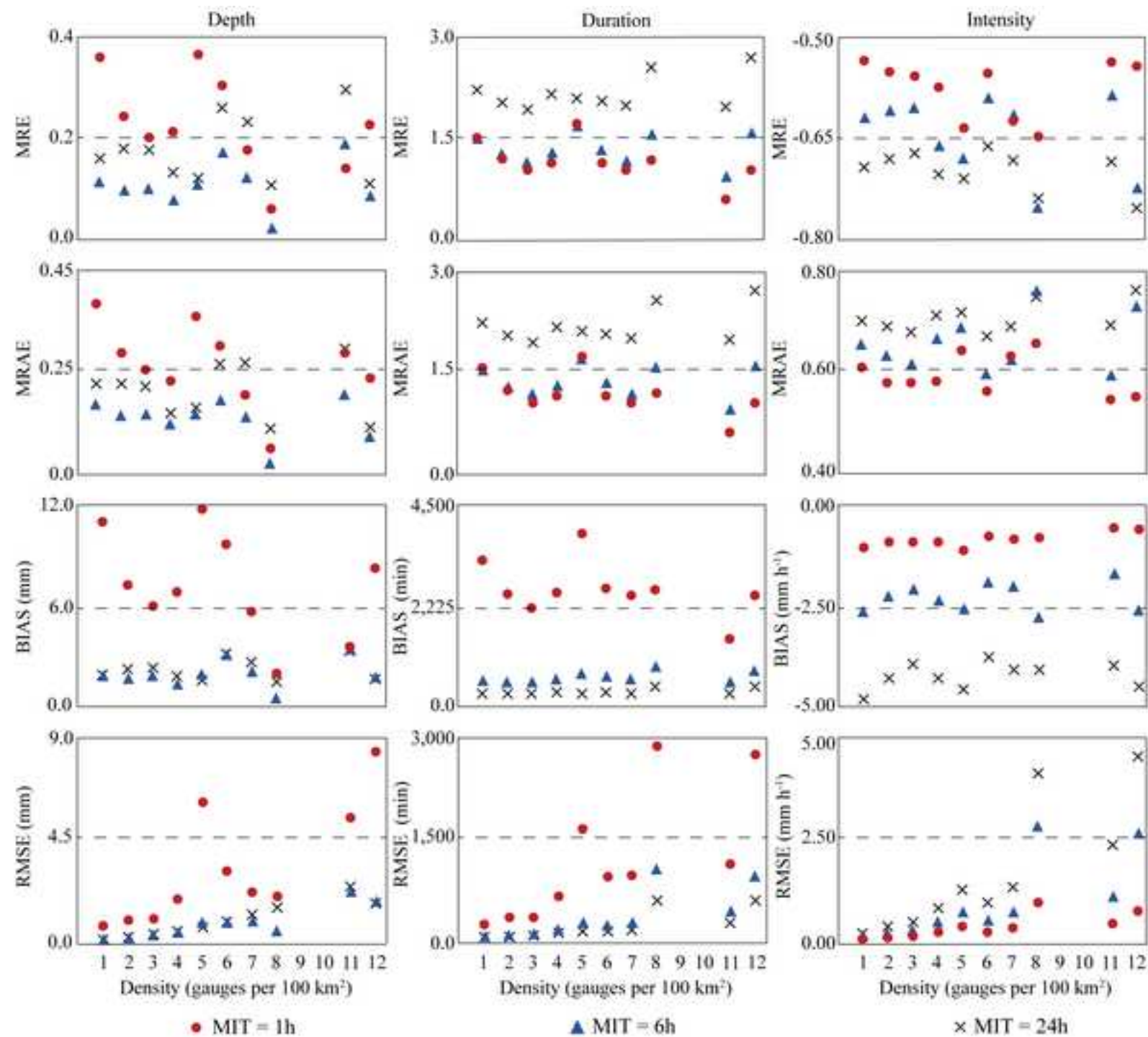


**Legend**

- IMERG events
- Gauge events
- - - IMERG average properties
- - - Gauge average properties
- ↔ Temporal distance
- ↕ Magnitude difference

Figure 3

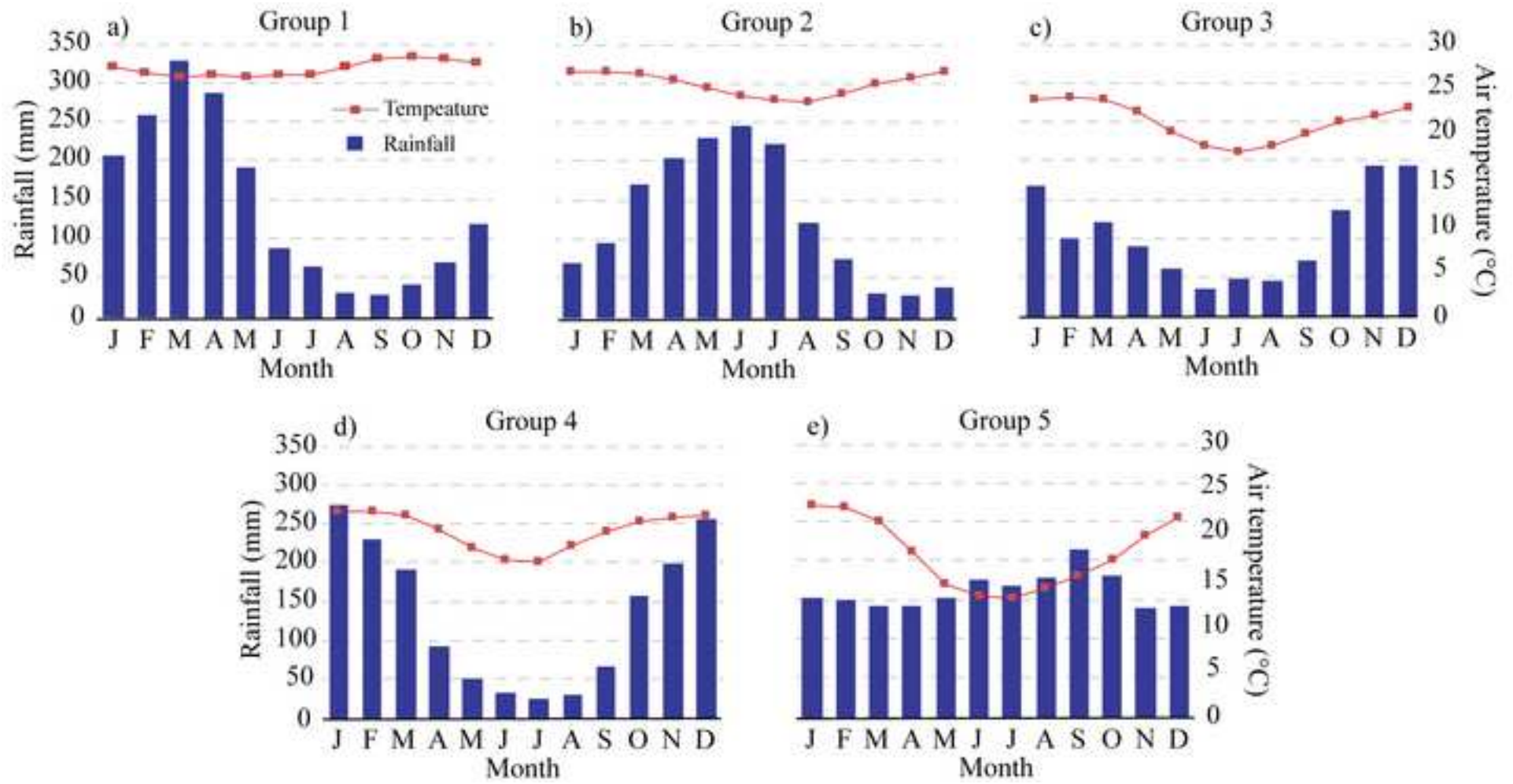
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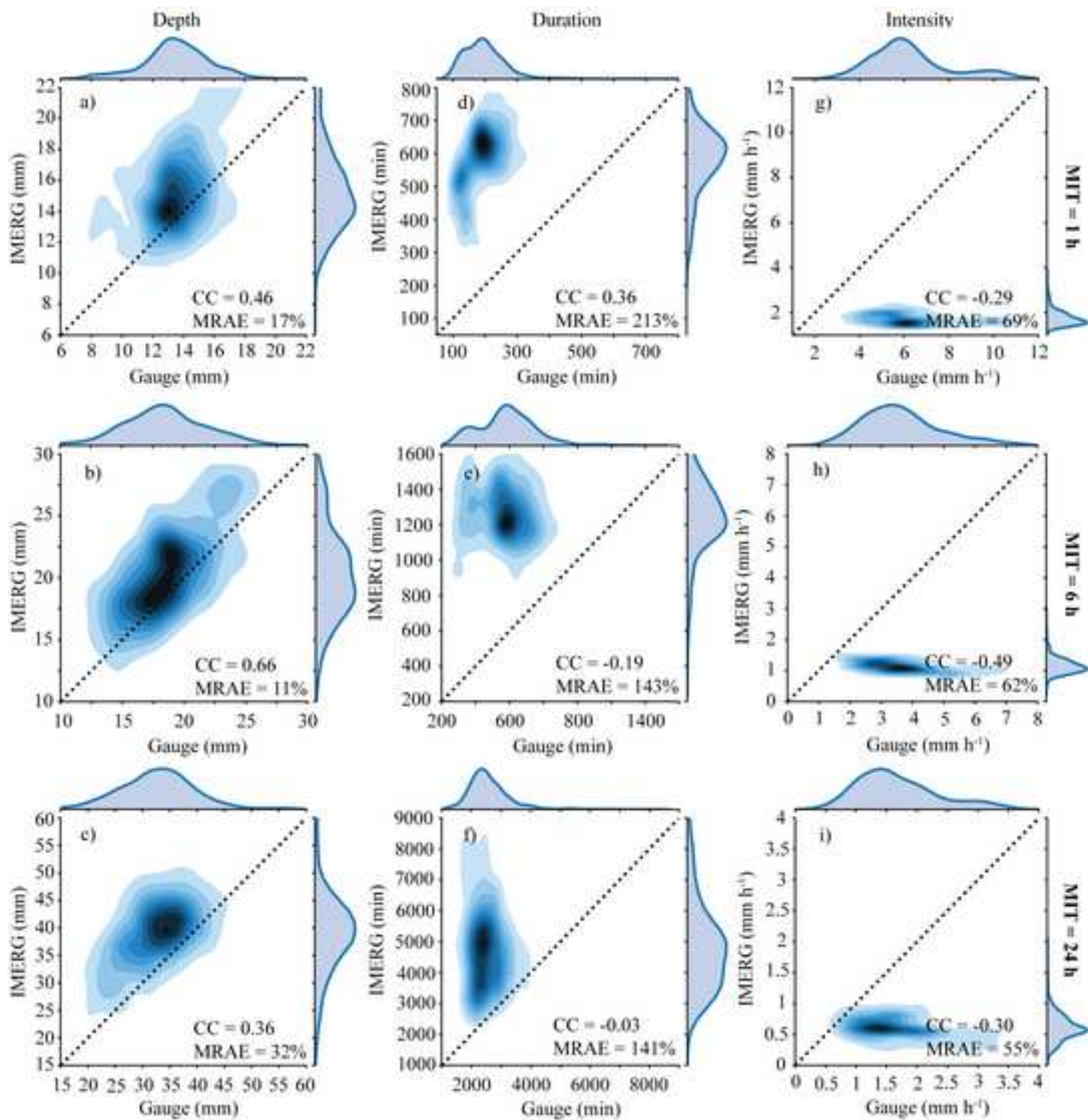


Figure\_4

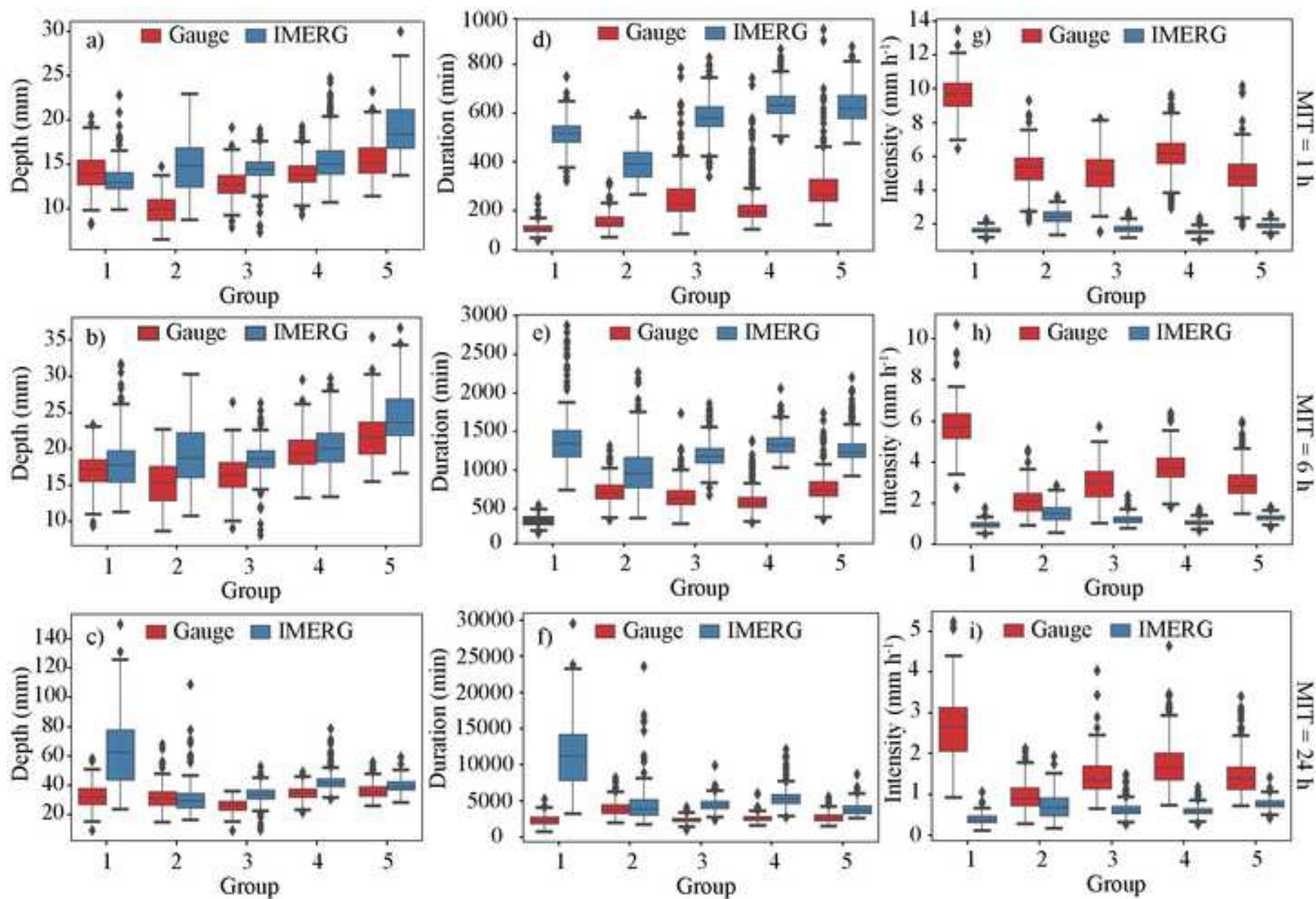
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Figure\_5  
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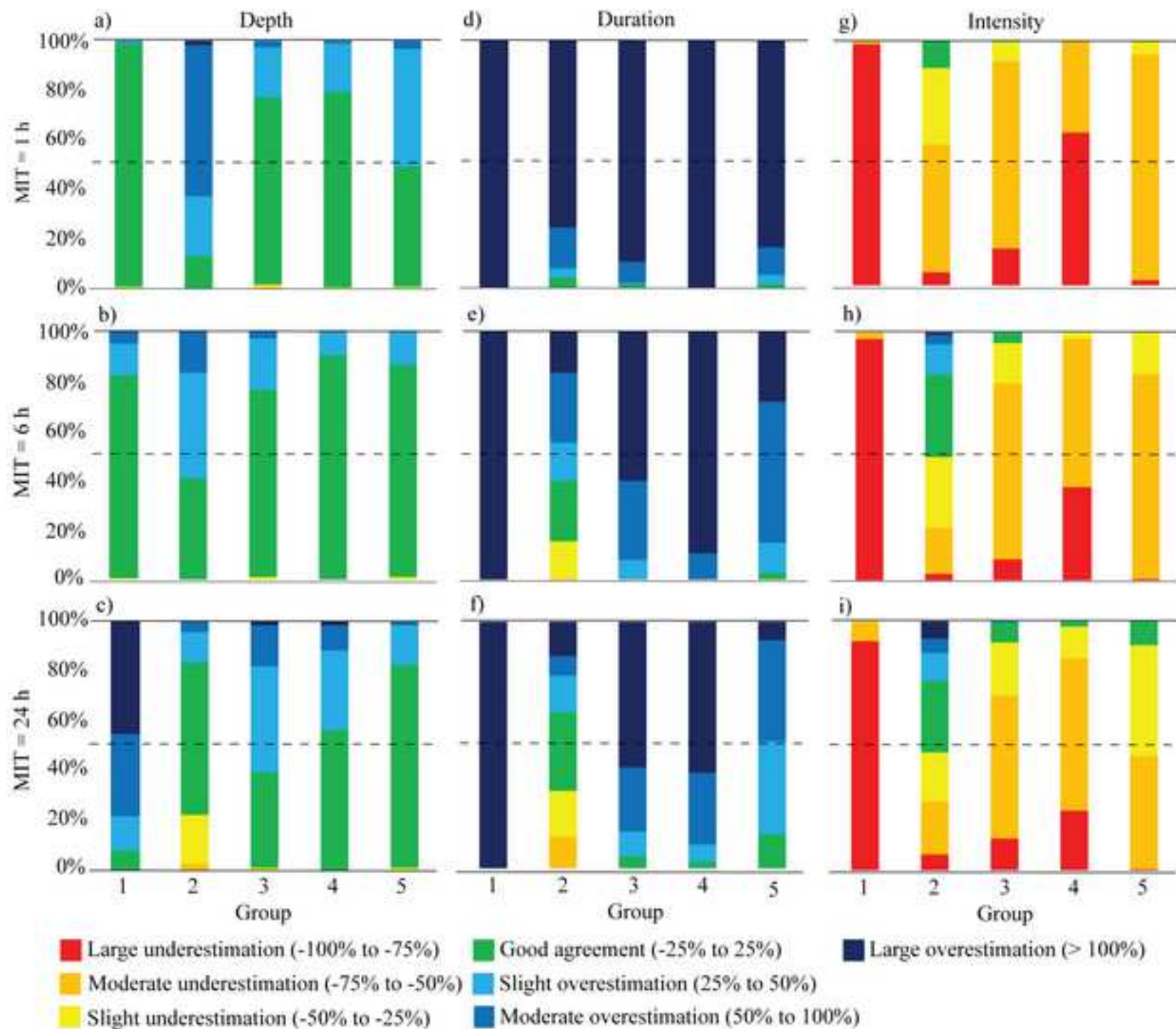
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Figure\_7

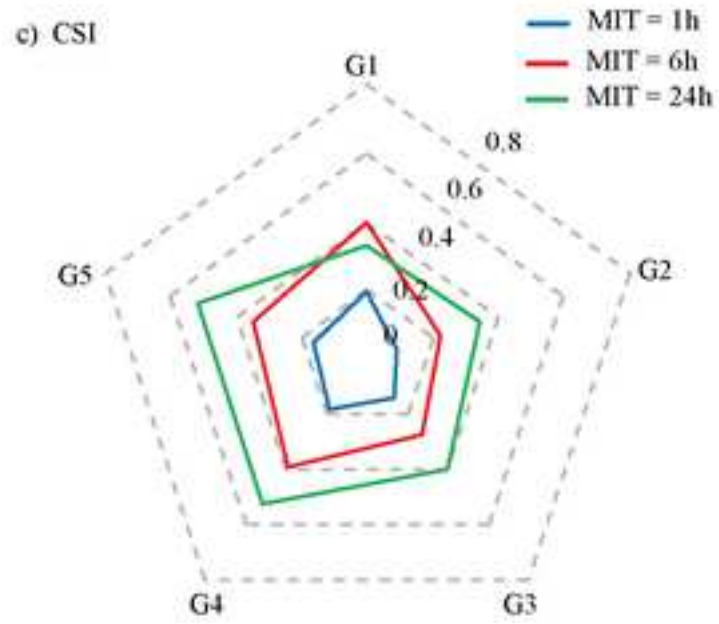
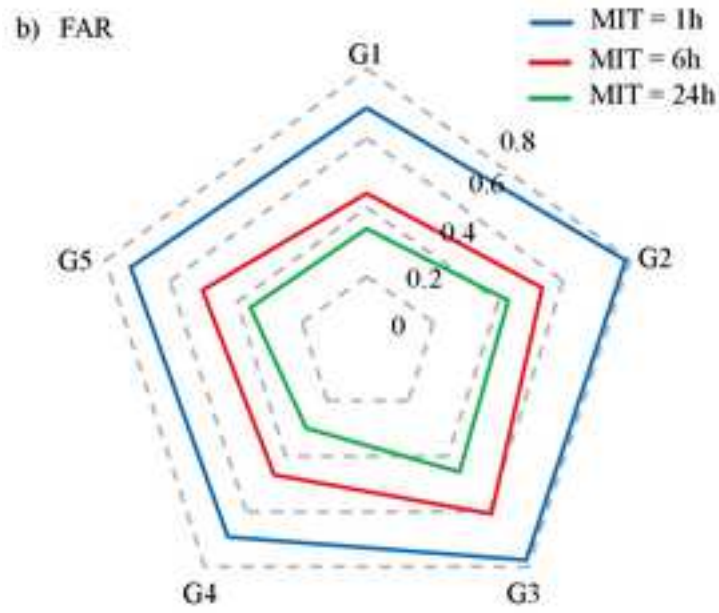
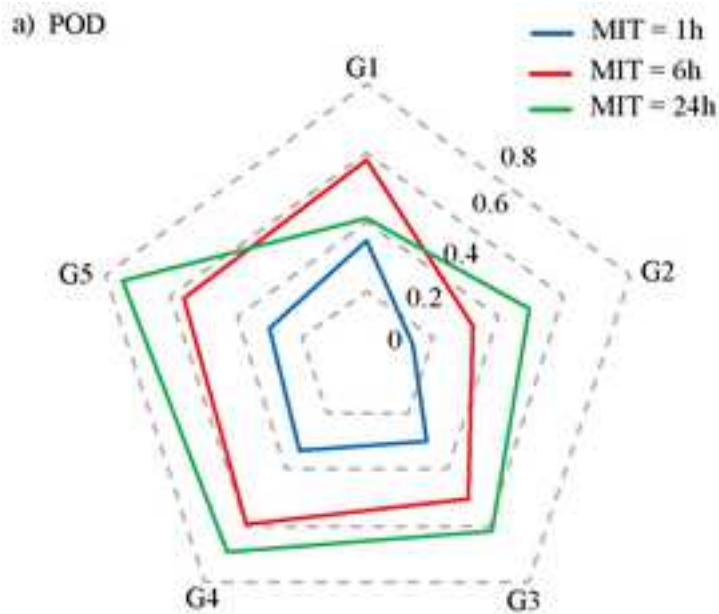
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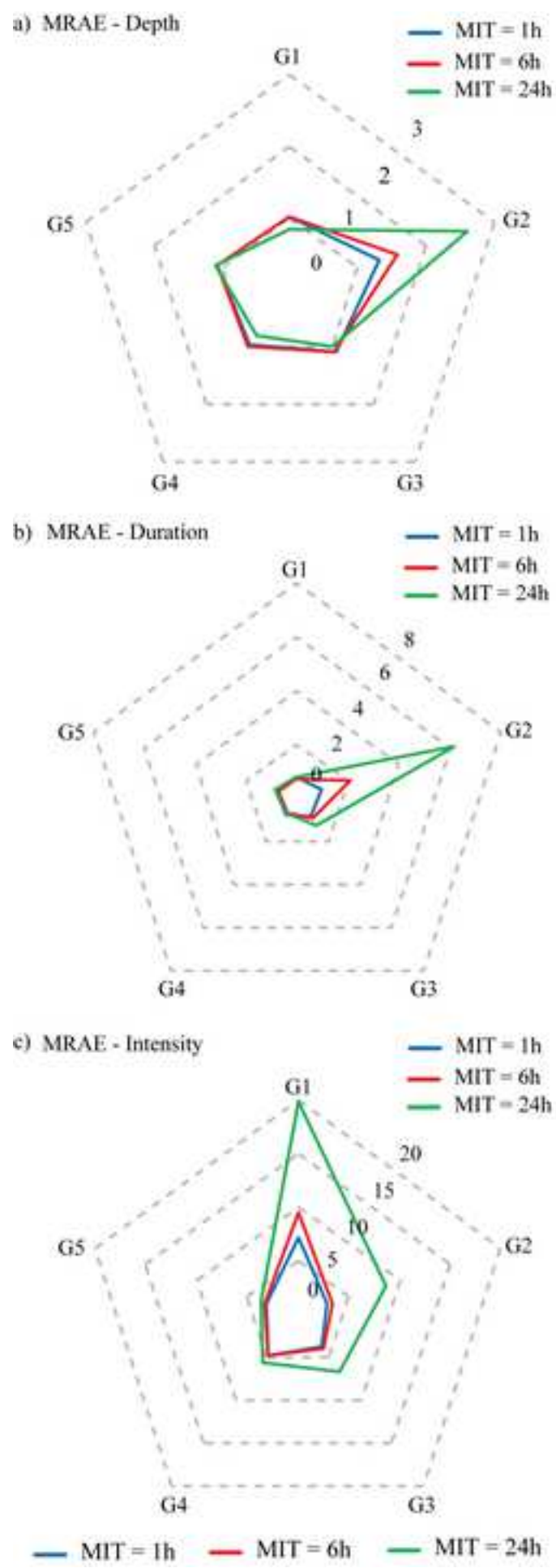
Figure\_8

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Figure\_9

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**Table 1** Summary of relevant characteristics of each homogeneous rainfall group, including the rainfall regimes defined by Reboita et al. (2010).

Group	Number of Pixels	Annual rainfall (mm)	Climate*	Atmospheric Systems
1	163	1,400 – 2,000	Tropical monsoon (Am) and Tropical with dry winter (Aw)	Intertropical Convergence Zone (ITCZ) and Mesoscale Convective Complex (MCC)
2	108	1,200 – 1,800	Tropical with dry summer (As)	Instability Lines (IL) and Southeast Trade Winds (SETW)
3	209	1,000 – 1,300	Tropical with dry summer (As)	South Atlantic Subtropical Anticyclone (SASA) and South Atlantic Convergence Zone (SACZ)
4	317	1,300 – 1,900	Humid subtropical with dry winter (Cw)	South Atlantic Subtropical Anticyclone (SASA) and South Atlantic Convergence Zone (SACZ)
5	268	1,600 – 2,200	Humid subtropical with hot summer (Cfa)	Prefrontal Squall Line (PSL) and Cold Fronts (CF)

\* According to Köppen's classification proposed by Alvares et al. (2013).

**Table 2.** Rain gauge densities per grid cells used in this study.

<b>Gauges per grid cell</b>	<b>Number of grid cells</b>	<b>Percentage of grid cells</b>
1	775	69.0
2	169	15.9
3	82	7.7
4	30	2.8
5	16	1.5
6	18	1.7
7	10	1.5
8	1	0.3
9	0	0
10	0	0
11	3	0.3
12	1	0.1
Total	1065	100.0

**Table 3.** Summary of evaluation metrics for the IMERG-F product, considering the mean values of rainfall properties for each homogeneous group.

Group		Depth (mm)			Duration (min)			Intensity (mm/h)		
		MIT=1h	MIT=6h	MIT=24h	MIT=1h	MIT=6h	MIT=24h	MIT=1h	MIT=6h	MIT=24h
1	CC	0.57	0.52	0.67	0.29	0.64	0.57	-0.12	0.34	0.30
	MRAE (%)	11.0	15.8	98.7	322.2	321.0	415.5	82.7	83.5	84.7
2	CC	0.59	0.69	0.30	-0.36	-0.54	-0.42	-0.37	-0.61	-0.22
	MRAE (%)	55.2	30.7	23.2	158.5	64.4	57.9	48.7	36.9	49.9
3	CC	0.14	0.42	0.55	0.12	0.21	-0.06	-0.11	-0.28	-0.14
	MRAE (%)	17.2	17.3	34.1	177.4	113.7	116.0	66.9	59.7	56.2
4	CC	0.14	0.36	0.22	0.31	0.08	0.01	-0.14	-0.19	-0.16
	MRAE (%)	15.0	11.6	28.5	253.1	153.8	128.0	75.4	72.3	63.8
5	CC	0.38	0.42	0.30	-0.02	0.17	0.47	0.27	0.31	0.43
	MRAE (%)	25.0	14.4	14.9	150.2	81.9	54.3	62.9	57.7	46.2