



Federal University of Paraíba - UFPB

Technology Center

POSTGRADUATE PROGRAM IN CIVIL AND ENVIRONMENTAL

ENGINEERING

– PhD THESIS –

**PERFORMANCE OF RAINFALL THRESHOLD FOR FLOOD
IDENTIFICATION FROM GROUND- AND SATELLITE-BASED
(SUB)DAILY DATA**

By

Geraldo Moura Ramos Filho

*PhD thesis defended at Federal University of Paraíba for attaining the degree
in Doctor of Civil and Environmental Engineering with emphasis on Water
Resources*

João Pessoa – Paraíba

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**PERFORMANCE OF RAINFALL THRESHOLD FOR HYDROLOGICAL
DISASTERS IDENTIFICATION FROM
GROUND- AND SATELLITE-BASED (SUB)DAILY DATA**

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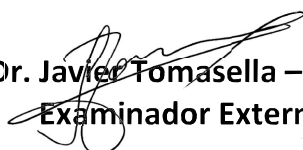
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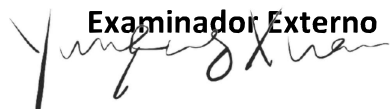


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To my dear mother, Elizabete, and my dear father, Geraldo, who always supported me and believed in my potential. And to those who are part of my life.

I dedicate!

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ABSTRACT

Great effort has been made over the last few decades to develop and improve methods for monitoring hydrological disasters. Among them, rainfall thresholds, defined as the minimum rainfall conditions that are likely to trigger hydrological disasters, are the most popular tool used to study the relationship between rainfall and hydrological disaster occurrences, highlighted due to their straightforward approach for application in different regions. Some factors make it difficult to determine rainfall thresholds, such as the quality of rainfall and disasters data, and the large distances between the rain gauges and the disaster. To overcome these limitations, the use of satellite-based precipitation products is a way out to characterize rainfall events that trigger disasters. Accordingly, this thesis aims to present an improved method of using a threshold of peak rainfall intensity for robust floods evaluation and warnings by applying probabilistic-based methods and taking into consideration the antecedent conditions. Moreover, this study assesses the quality of satellite-based precipitation products to create rainfall thresholds for floods monitoring. São Paulo State was selected as the study area because is a typical hot spot frequented by landslides and floods. In addition, São Paulo is the richest state in Brazil, with the largest number of floods, flash floods, and sub-daily rainfall data made available by public agencies. Results show that the use of tolerance levels and the delineating of an intermediate threshold by incorporating an exponential curve that relates rainfall intensity and Antecedent Precipitation Index (API) helped reduce significantly many uncertainties in the hydrological disasters monitoring. Moreover, the use of satellite-based products showed to be less accurate compared to rain gauges to characterize extreme rainfall events and delineating the thresholds, tending to underestimate the ground-based precipitation mainly for sub-daily scales. Although underestimating the ground-based data, the satellite-based products can be applied as an alternative source to develop warning systems, especially in areas with a lower density of rain gauges. Overall, the results found in this study showed to be helpful for decision-making by the implementation of flood monitoring and early warning systems, and, consequently to contribute to the development of more robust and/or complex flood models able to minimize the hydrological impacts, whether using ground-based or satellite-based data.

KEYWORDS: Natural disasters, Extreme precipitation, Rainfall threshold, Floods, Flash floods.

RESUMO

Grande esforço está sendo realizado durante as últimas décadas para desenvolvimento de métodos de monitoramento de desastres hidrológicos. Dentre eles, os limiares de precipitação, definidos como a condição mínima de precipitação que são susceptíveis a deflagração de desastres hidrológicos, são a ferramenta mais popular usada para estudar a relação entre precipitação e desastres hidrológicos, destacando-se devido à sua abordagem simples. Alguns fatores dificultam a determinação dos limiares de chuva, como a qualidade dos dados de chuva e desastres, e as grandes distâncias entre as estações pluviométricas e os desastres. Para superar essas limitações, o uso de produtos de precipitação por satélite é uma saída para caracterizar os eventos de chuva que desencadeiam desastres. Consequentemente, esta tese tem como objetivo apresentar um método melhorado para a delimitação de limiares de picos de intensidade de chuva para avaliação e alerta dos desastres, através da aplicação de métodos baseados em probabilística e levando em consideração as condições antecedentes ao desastre. Além disso, avaliar a qualidade dos produtos de precipitação baseados em satélite para criar limites de precipitação para o monitoramento de desastres hidrológicos. O Estado de São Paulo foi escolhido por ser uma região típica para ocorrências de deslizamentos e inundações. Além disso, São Paulo é o estado mais rico do Brasil, com o maior número de registros de inundações e enxurradas, bem como dados pluviométricos subsidiários disponibilizados por órgãos públicos. Os resultados mostram que o uso de níveis de tolerância e o delineamento de um limiar intermediário pela incorporação de uma curva exponencial que relaciona a intensidade da chuva e o Índice de Precipitação Antecedente (API) ajudou a reduzir significativamente muitas incertezas no monitoramento de desastres hidrológicos. Além disso, a avaliação dos produtos baseados em satélite mostrou que eles apresentam menor acurácia em relação aos pluviômetros, tendendo a subestimar as medidas observadas in-situ, principalmente, para escalas subsidiárias. No entanto, eles podem ser aplicados como fonte alternativa para o desenvolvimento de sistemas de alerta, principalmente, em áreas com menor densidade de pluviômetros. De forma geral, conclui-se que os resultados encontrados devem ser úteis na tomada de decisão, na implementação de sistemas de monitoramento e alerta precoce de inundações, e na contribuição para o desenvolvimento de modelos mais robustos e/ou complexos para minimizar os impactos, seja utilizando dados in-situ ou baseados em satélite.

PALAVRAS-CHAVES: Desastres naturais, Precipitações extremas, Limiares de precipitação, inundação, enxurrada.

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LIST OF ABBREVIATIONS AND SYMBOLS

a, b, c	– Constants values
API	– Antecedent Precipitation Index
BIAS	– Ratio of estimated and observed means
CC	– Pearson's correlation coefficient
CEMADEN	– Brazilian National Centre for Monitoring Early Warning of Natural Disasters
CENAD	– National Center for Risk and Disaster Management
CEPED	– Center for Studies and Research on Disasters
CHIRP V2.0	– Climate Hazards group InfraRed Precipitation V2.0
CHIRPS V2.0	– Climate Hazards group InfraRed Precipitation with Stations V2.0
CMORPH-CRT V1.0	– CPC MORPHing technique bias corrected V1.0
COBRADE	– Brazilian Coding of Disasters
CODAR	– Coding of Disasters, Threats, and Risks
CPC-Global	– Climate Prediction Center - Global
CRED	– Center for Research on the Epidemiology of Disasters
CRU TS v4	– Climatic Research Unit gridded Time Series version 4
DesInventar	– Disaster effects Inventory system
EM-DAT	– Emergency events Database
FAR	– False Alarm Ratio
FN	– False Negative
FP	– False Positive
G1	– Group of events that represents intensities that likely lead to flood occurrences
G2	– Group of events that represents intensities that may lead to flood occurrences
G3	– Group of events that represents intensities that may not lead to flood occurrences
G4	– Group of events that represents intensities that not likely lead to flood occurrences
GHCN-M v2	– Global Historical Climatology Network Monthly version 2
GPCC-daily	– Global Precipitation Climatology Center - daily
GPM+SM2RAIN	– Integration of IMERG-E with SM2RAIN-based rainfall estimates derived from satellite Soil Moisture products
HK	– Hanssen-Kuiper skill score
i	– number of antecedent days
I	– Intensity (mm.h ⁻¹)
IBGE	– Brazilian Institute of Geography and Statistics
IMERG-E V06	– Integrated Multi-satellitE Retrievals for GPM early run V06
IMERG-F V06	– Integrated Multi-satellitE Retrievals for GPM final run V06
IMERG-L V06	– Integrated Multi-satellitE Retrievals for GPM late run V06
INTENSE project	– INTElligent use of climate models for adaptation to Non-Stationary hydrological Extremes.
IPMET	– Meteorological Research Institute
K	– Decay rate
KGE	– Kling-Gupta Efficiency
MASA	– Metropolitan Area of Santo André

MASP	– Metropolitan Area of São Paulo
MAU	– Metropolitan Area of Ubatuba
MERRA-2	– Modern-Era Retrospective Analysis for Research and Applications 2
MSWEP V2.2	– Multi-Source Weighted-Ensemble Precipitation V2.2
NRCS	– Natural Resources Conservation Service
PDIR-Now	– Precipitation Dynamic Infrared Rain Rate near real-time (PDIR-Now)
PERSIANN	– Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks
PERSIANN-CCS	– Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks Cloud Classification System
PERSIANN-CDR	– Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks Climate Data
V1R1	
PNGR	– National Planning for Risk Management
POD	– Probability of Detection
PPV	– Positive Predictive Value
Pt	– Rainfall for the day t (mm)
S2ID –	– Integrated Disaster Information System
SIDEC	– Integrated Civil Defense System
SIMPAT	– The Integrated Storm Monitoring, Forecasting and Alerting System for the Brazilian South-Southeast Regions
SM2RAIN-ASCAT V1.2	– Precipitation Estimation from the application of the SM2Rain algorithm to the ASCAT soil moisture data
TN	– True Negative
TP	– True Positive
TRMM	– Tropical Rainfall Measuring Mission
UDEL	– University of Delaware
UNDRR	– United Nations Office for Disaster Risk Reduction
USAID/OFDA	– United States Agency for International Development’s Office of Foreign Disaster Assistance
VAR	– Ratio of the estimated and observed coefficients of variation
WHO	– World Health Organization
WMO	– World Meteorological Organization

1 INTRODUCTION

Many natural disasters events occur every year in almost all countries, causing thousands of deaths, considerable structural damages, and significative economic losses worldwide (Hallegatte et al. 2013; Sampson et al. 2015; Dinis et al. 2021). According to the United Nations Office for Disaster Risk Reduction (UNDRR), the number of natural disasters grew 1.75 times between 2000 and 2019 compared to the previous twenty years (i.e., from 1980 to 1999). Among the natural disasters, floods are the most common type of disaster, accounting for 44% of all occurrences considered in the UNDRR report, showing a growth of 2.3 times and accounting for more than 1.65 billion people affected, 104,614 deaths, and 651 billion dollars of economic loss. This growing number of flood events over the years is mainly due to extreme weather conditions, high urbanization rate, and inadequate response to disasters (Špitalar et al. 2014; Tsakiris 2014; Du et al. 2015).

Brazil has continental dimensions with distinct regional characteristics. Therefore, the pattern of natural disasters varies from region to region, whether in terms of the type of disaster and time of year in which they occur. However, drought and floods are the most common phenomena that occur in all regions, causing the larger number of impacts (UNIFESP and UNA-SUS 2016). Specifically, the São Paulo State is a typical hot spot for disasters occurrences due to the region's natural characteristics associated with a high level of urbanization (Tominaga et al. 2015). Thus, it is essential to understand the causes, mechanisms involved, and dynamics of the processes that are happening with new shapes and sizes during each passing year, to seek safer and more economically viable alternatives for planning strategies and scenarios for disaster risk management (Ramos 2017).

During the last few decades, great efforts have been made for monitoring hydrological disasters (Getirana et al. 2020; Young et al. 2021). Complex computer models such as hydrodynamic models have been a new challenge for many researchers and authorities to build warning systems (Azari et al. 2008; González-Cao et al. 2019; Li et al. 2019). Such methods aim to reduce the damages and deaths caused by floods (Froidevaux et al. 2015; Jang 2015; Rijswick 2015). While such practice remains as the mainstream approach, there are situations where empirical methods still prevail. This is because, in many places, it is impossible to carry out detailed modelling of the related physical process (e.g. landslides, floods, flash floods) either due to data availability or being too challenging to model (Behrangi et al. 2011; Blenkinsop et al. 2018; Peres et al. 2018). Among the empirical methods, the rainfall-threshold method is one of the most widely used for monitoring

hydrological disasters (Huang et al. 2015), where the thresholds are determined by the properties derived from rainfall events such as intensity, duration, and antecedent precipitation (Glade et al. 2000; Aleotti 2004; Berti et al. 2012; Papagiannaki et al. 2015; Scheevel et al. 2017; Brunetti et al. 2018; Mirus et al. 2018). However, when compared with the applications in predicting landslides, the number of studies using rainfall thresholds for flood and flash floods warning systems remains low and the area has been poorly explored (Diakakis 2012; Papagiannaki et al. 2015; Santos and Fragoso 2016).

As mentioned before, the data availability is still a big challenge to overcome all over the globe. In Brazil, regarding flood records, official information is still scarce or not unified in a single database. To get around this problem, it is necessary to survey occurrences from various sources of information. However, some problems can be observed, such as the existence of duplicate records, the difficulty in identifying the type of natural disaster that actually occurred, the lack of accuracy of the day and location of occurrence, or the coverage of the affected area (Carvalho 2018). Similarly to the occurrences, the use of accurate and spatially well-distributed sub-daily rainfall data is recognized by the scientific community as an essential source of information to create robust prediction and warning hydrological disaster systems (Dunkerley 2019; Shrestha et al. 2019; Chikoore et al. 2021). However, obtaining the sub-daily rainfall variability over large areas by in-situ data is still a hard task because such records sparsely cover the global landmass (Hegerl et al. 2015; Lewis et al. 2019). The number of in-situ sub-daily rainfall records is even lower for the key tropical regions, probably due to the higher implementation costs of rain gauges able to measure sub-daily events, compared with those that measure on a daily timescale (Kidd et al. 2017; Freitas et al. 2020).

The use of cutting-edge satellite-borne remote sensing technology has played a key role over the recent decades in providing sub-daily rainfall data (Tan et al. 2014; Levizzani et al. 2018; Sungmin and Kirstetter 2018). Currently, a plethora of promising recently released and revised gridded satellite-based products providing valuable distributed information of sub-daily rainfall data are available to be used for many applications (Yuan et al. 2019; Llauca et al. 2021). The characteristics of these rainfall products differ in terms of spatial and temporal resolutions (from 0.04° to 2.5° and from 30 minutes to monthly, respectively), spatial coverage (from continental to fully global), latency (from 15 minutes to several years), among others (Beck et al. 2017b). Despite that, only a few studies have assessed the performance of these products in landslide monitoring (Brunetti et al. 2021), even less for flood monitoring.

This thesis was based on the development of two studies: 1) to address some problems found in existing rainfall threshold methodologies and 2) to evaluate alternatives for the development of tools useful for warning systems applying different satellite-based precipitation products. Firstly, this thesis seeks to propose the improvement of a methodology proposed by Diakakis (2012) for delimitation of rainfall thresholds for flood and flash flood through the reduction of uncertainties and, consequently, minimization of observed false alarms. For this first step of the study, two precipitation thresholds were determined, called upper and lower threshold, in which tolerance limits were applied for each one of them to allow a better adjustment in the warning level settings. In addition, a methodology for delineating an intermediate threshold through the evaluation of different interactions between intensity peaks and API (Antecedent Precipitation Index) was presented, taking into consideration different evaluation metrics. Based on this first study, a considerable amount of flood occurrences in São Paulo State could not be used because of the poor data quality of some rain gauges and/or the lack of rain gauge coverage. Therefore, the second study of this thesis was to evaluate different satellite-based precipitation in characterizing extreme events and delineating rainfall thresholds for flood hazards. Then, 14 satellite-based precipitation products were assessed for different time steps to characterize the rainfall events that trigger floods by applying different metrics for evaluating their performances.

1.1 Hypotheses

The following two hypotheses were addressed in this study:

1. The reduction of uncertainties using rainfall threshold methodologies for floods and flash floods can be achieved by determining tolerance limits, delimiting an intermediate threshold, and performing different interactions between intensity peaks rainfall and the Antecedent Precipitation Index (API);
2. Satellite-based precipitation products can be used to spatially define rainfall thresholds for different time steps based on an existing methodology to develop warning system for floods.

1.2 Main aims

This thesis aims to develop methodologies for analyzing the relationship between the extreme precipitation events and (flash)floods occurrence applying ground- and satellite-based (sub)daily data, to establish a correlation between these variables, define rainfall thresholds with the potential to trigger floods, and assess their performance.

1.3 Specific aims

The specific aims of this thesis are:

- To propose a rainfall threshold estimation approach to improve floods and flash floods hazards monitoring by applying tolerance limits, setting an intermediate threshold, and evaluating performance considering different evaluation metrics to reduce uncertainties and minimize observed false alarms;
- To assess the quality of the current available satellite-based precipitation products to identify extreme rainfall events and delineate rainfall thresholds for floods.
- To perform quality analysis of rainfall data for CEMADEN rainfall gauges and the satellite-based products;
- To survey hydrological disasters from different sources of information, as well as to characterize the rainfall events that triggered them, developing therefore a database for the state of São Paulo between 2015 and 2019;

1.4 Thesis Structure

The thesis was divided into six major items in the following order: 1) Introduction, presenting a contextualization and justification that motivated the development of this thesis; 2) Literature review, covering conceptual and basic topics essential to better understand the study; 3) Study area, presenting the characteristics of the studied area and justifying its selection; 4) Improved rainfall-threshold approach, showing the proposed methodology for delimitation of rainfall thresholds; 5) Characterization of extreme rainfall events by satellite-based products, assessing different satellite-based products to define rainfall thresholds; and 6) Conclusions and recommendations, highlighting the main results found and proposing further studies.

2 LITERATURE REVIEW

The literature review was subdivided into three major items, addressing all subjects of the methodology in the following order: 1) natural disasters, covering basic concepts; 2) extreme rainfall events, definition, precipitation measurement methods; and 3) rainfall threshold methodologies.

2.1 Natural Disasters

2.1.1 Definition

According to the World Health Organization (WHO 1971), a natural disaster is an act of nature of such magnitude as to create a catastrophic situation in which day-to-day patterns of life are suddenly disrupted, and, as a result, they need basic assistance and protection against unfavorable environmental factors and conditions. The Center for Research on the Epidemiology of Disasters (CRED) adds that it is a situation or event overwhelming the local capacity to deal with the situation using its own resources; an unforeseen and often sudden event that causes great damage, destruction and human suffering (Wallemacq and House 2018).

In Brazil, the Normative Instruction nº 1 was published in August 2012 by the Nation Integration Ministry, which establishes procedures and criteria for the decree and recognition of an Emergency Situation or State of Public Calamity by the Municipalities, States, and the Federal District. This document in its first article presents the definition of disaster as the result of adverse events, natural or man-made in a vulnerable scenario, causing serious disturbance to the functioning of a community or society involving extensive human, material, economic or environmental loss and damage, which exceeds the local capacity to deal with the problem using its own resources (Brasil 2012).

Overall, disasters cause intense changes in society and combine different factors such as threats and vulnerabilities, which expose certain populations to the risk of these phenomena occur. Disaster occurs when risks are poorly managed and the population is not prepared to face extreme or unexpected phenomena (Furtado et al. 2014).

2.1.2 Increasing recurrence and databases development

The number of natural disasters has been increasing in recent decades. Several authors justify this increase as a consequence of the intense urbanization process associated with a disorderly growth of regions unsuitable for occupation, due to its unfavorable geological and geomorphological characteristics (Barbería et al. 2014; Papagiannaki et al. 2015). Moreover, anthropic action, such as deforestation, changes in drainage, garbage disposal, and others, mostly without the implementation of adequate infrastructure, increase the dangers and instabilities (Srinivas and Nakagawa 2008; Dhyani and Dhyani 2016). Therefore, when there is an agglomeration of buildings in improper areas, landslides and floods, for example, assume catastrophic proportions causing great economic and social losses (Tominaga et al. 2015).

The development of a natural disasters database is essential to analyze its characteristics, as it aims to assist in the decision-making for disaster preparedness and provide an objective basis for vulnerability assessment and set priorities (Battistini et al. 2017; Segoni et al. 2021). In 1988, CRED launched a worldwide disaster database called Emergency events Database (EM-DAT) with assistance from the United States Agency for International Development's Office of Foreign Disaster Assistance (USAID/OFDA). The data is compiled from a variety of sources, including non-governmental organizations, insurance companies, research institutes, and news agencies. For a disaster to be added to the database, at least one of the following criteria must be met: 10 or more people killed; 100 or more people affected; declaration of a state of emergency; or requesting international assistance (Guha-sapir et al. 2016).

In Brazil, in 2012, the system called Integrated Disaster Information System (S2ID) was developed by the National Planning for Risk Management (PNGR) project in technical cooperation between the Center for Studies and Research on Disasters from Federal University of Santa Catarina (CEPED/ UFSC) and the Ministry of National Integration, through the National Secretariat of Civil Defense. The purpose of the S2ID system is to streamline the procedures to recognize requesting of Emergency Situation or State of Public Calamity and the transfer of federal resources to States or Municipalities affected by disasters (Gimenez 2017). However, some problems can be pointed that significantly compromise the stages of characterization and diagnosis of areas susceptible to natural disasters. Normally, these problems are related to the existence of several discrepancies and incompleteness in the data and recorded information (Carvalho 2018).

The Meteorological Research Institute (IPMET) makes available natural disaster records from São Paulo and Parana State through the Integrated System for Monitoring, Forecasting and Warning of Storms for the South-Southeast Regions of Brazil (SIMPAT), which compiles the information obtained from different sources, for example, Civil Defense and news. However, this information does not undergo any prior analysis, therefore it is necessary to properly verify the occurrences. The Civil Defense information can be consulted through the Integrated Civil Defense System – SIDEC, which is a geo-referenced management platform that facilitates decision-making.

In the near future, the National Center for Monitoring and Alerting of Natural Disasters (CEMADEN) will make available a standardized database, which will provide historical records of the occurrence of disaster related to geo-hydrological risks in at least 958 municipalities. The system is under development and soon this database will be released on the CEMADEN Interactive Map. The objective of CEMADEN is also to integrate this database with the international platform in South America called “DesInventar” (Disaster Effects Inventory System). The “DesInventar” platform is a database of natural disasters conceived in the 1990s by researchers at La Red (Network for Social Studies in Disaster Prevention in Latin America) to bring together several databases within one single platform, serving as data acquisition and query system for disasters of any magnitude. Almost all Latin American countries take part in DesInventar database, except for Brazil.

2.1.3 Disaster Classification

The Brazilian Coding of Disasters (COBRADE) was established through the Normative Instruction No. 1 to replace the Coding of Disasters, Threats, and Risks (CODAR). The new coding was created from the international classification used by Emergency events Database (EM-DAT). According to the National Center for Risk and Disaster Management (CENAD 2014), an important reason to standardize the classification of disasters is the need to record these phenomena in the historical context of the country. Coding allows the formation of a database, which can be used for a contextualized analysis of the occurrence of disasters worldwide or in the national territory, enabling the planning of preventive and preparatory measures to deal with these adverse events. Moreover, the adoption of the EM-DAT classification is important due to the need to adapt the Brazilian classification to the standards established worldwide, and to effectively include Brazil in the expansion of this important international database. Another advantage verified to use EM-

DAT classification for the construction of COBRADE was the need to simplify the classification of disasters contained in CODAR.

The international and national classifications of disasters are divided into two categories: natural or technological. About natural disasters, the international classification recognizes six groups, in contrast to the national classification that recognizes only five, which differs as to the extraterrestrial group. In addition, some adaptations were made to the national classification to better adapt to the Brazilian reality. Among the remaining five groups, EM-DAT defined them as follows:

- **Geophysical:** A hazard originating from solid earth. This term is used interchangeably with the term geological hazard (Figure 1a).
- **Meteorological:** A hazard caused by short-lived, micro- to meso-scale extreme weather and atmospheric conditions that last from minutes to days.
- **Hydrological:** A hazard caused by the occurrence, movement, and distribution of surface and subsurface freshwater and saltwater (Figure 1b e Figure 1c).
- **Climatological:** A hazard caused by long-lived, meso- to macro-scale atmospheric processes ranging from intra-seasonal to multi-decadal climate variability. (Figure 1d, Figure 1e e Figure 1f).
- **Biological:** A hazard caused by the exposure to living organisms and their toxic substances (e.g. venom, mold) or vector-borne diseases that they may carry.



a) Geophysical: Marine Erosion in Natal, RN, in October 2012 (Photo Mauren Carvalho)



b) Hydrological: Flood in the center of Palmares, PE, in June 2010 (photo courtesy of Pernambuco Civil Defense)



c) Hydrological: Flood hitting stilts houses, Manaus, AM, in May 2012 (Photo Aderita Sena)



d) Climatological: Dry shallow pond in Mansidão, BA (Photo courtesy of Bahia Civil Defense, 2012)



e) Climatological: Living with the drought in Andaraí, BA (photo courtesy of Bahia Civil Defense, 2012)



f) Climatological: Fire in Chapada Diamantina, BA, in October 2008 (Photo courtesy of Bahia Civil Defense)

Figure 1 – Examples of recurrent natural disasters in Brazil (Courtesy: UNIFESP and UNA-SUS 2016)

Hydrological disasters, Table 1, have among their causes the action of natural processes that imply excess water in the affected system, usually associated with extremes of floods and/or urban drainage problems (Tingsanchali 2012; Atta-ur-Rahman et al. 2016). The last two decades (1998–2017) represent the largest number of records caused by hydrological disasters in history, mainly, induced by floods (accounting for 43.4% of all-natural disasters) (Wallemacq and House 2018).

Table 1 – Hydrological disasters classification (Source: EM-DAT)

<i>Disaster main type</i>	Disaster Sub-type	Description
<i>Flood</i>	Coastal flood	Overflow of water Higher-than normal levels along the coast and in lakes or reservoirs
	Riverine flood	A general term for the overflow of water from a stream channel onto normally dry land in the floodplain
	Flash flood	Rapid inland floods due to intense rainfall. A flash flood describes sudden flooding with short duration. In sloped terrain the water flows rapidly with a high destruction potential.
	Ice jam flood	The accumulation of floating ice restricting or blocking a river's flow and drainage. Ice jams tend to develop near river bends and obstructions (e.g. bridges).
<i>Landslide</i>	Avalanche	A large mass of loosened earth material, snow, or ice that slides, flows or falls rapidly down a mountainside under the force of gravity
<i>Wave Action</i>	Rogue wave	An unusual single crest of an ocean wave far out at sea that is much higher and/or steeper than other waves in the prevailing swell system
	Seiche	A standing wave of water in a large semi- or fully-enclosed body of water (lakes or bays) created by strong winds and/or a large barometric pressure gradient.

2.2 Extreme precipitation events

Rainfall is an intermittent phenomenon with an irregular spatiotemporal distribution that can cause many natural disasters (Dunkerley 2008). It is the natural agent that triggers situations of flood and flash flood, which are the real threats to the socio-economic system (Miguez et al. 2018).

The World Meteorological Organization (WMO) defines extreme precipitation as significant accumulated precipitation that often leads to multiple disasters (e.g., floods, mass movements, flash floods, etc.). However, extreme precipitation varies seasonally and from region to region, so it is not possible to use a single definition of an extreme precipitation event that is suitable for all regions. Thus, it is desirable to quantify multiple time scales of extreme precipitation events for different places. Generally, an extreme precipitation event is recognized when it relates to one of the following contexts: (1) when it exceeds a certain

threshold that has a certain associated impact, i.e., a fixed threshold, or (2) an event of precipitation is considered extreme due to its rarity, that is, a threshold based on the percentile (WMO 2015).

Therefore, the use of accurate and spatially well-distributed sub-daily rainfall data is an essential source of information to create a reliable warning system that provides useful knowledge for decision-making (Dunkerley 2019; Shrestha et al. 2019; Chikoore et al. 2021). The rainfall characteristics analyzed in most studies are the total precipitation, duration, intensity, and temporal and spatial distribution.

2.2.1 Ground-based measurements

Rainfall over the ground can be measured using rain gauges and radars. The first is the most traditional way to provide accurate rainfall data, measuring precipitation directly at the Earth's surface (Kidd 2001). However, obtaining sub-daily rainfall variability over large areas is still a hard task because such records sparsely cover the global landmass (Hegerl et al. 2015; Lewis et al. 2019). The number of in-situ sub-daily rainfall records is even lower for the tropical regions, probably due to the higher implementation costs of rain gauges able to measure sub-daily events, compared with those that measure on a daily timescale (Kidd et al. 2017; Freitas et al. 2020). Consequently, the use of empirical methods that consider properties derived from rainfall events cannot be properly applied in such low-density or inexistent gauge areas.

Thus, new projects emerged aiming to create a reliable precipitation database. The INTENSE project (INTElligent use of climate models for adaptation to non-Stationary hydrological Extremes) is the first major international effort to focus on global extreme sub-daily rainfall, allowing substantial advances in the quantification of observed historical changes. However, the INTENSE project identified after a data collection initiative that countries from Africa and Latin America have the lowest availability of sub-daily rainfall data (Blenkinsop et al. 2018). In Brazil, CEMADEN created a sub-daily monitoring network containing approximately 3,400 automatic rain gauges nationwide. This network was created to support the prediction and development of warning systems of disasters related to precipitation, such as floods and landslides. Thus, most rain gauges are located in cities and the rainfall recording time is 10 minutes under rain and 60 minutes when there is no rain.

Moreover, rain gauges provide only-single point measurements and have a far from ideal spatial distribution around the world, hence they poorly represent the spatial variability

of precipitation, which varies from a few meters to several kilometers, making the sampling requirements for measuring its spatial distribution extremely stringent. In contrast, radars are an alternative to rain gauges and provide real-time measurement with high temporal and spatial resolution, but their coverage is limited only over land and is also affected by the lack of accessibility because of their high cost (Varma 2018).

The radar system emits a beam of energy at the microwave energy that is backscattered from particles in the atmosphere, which can then be converted into a measure of rainfall intensity (Kidd and Huffman 2011). However, the accuracy of radar measurements is in general insufficient, particularly in the case of extreme rainfall magnitudes (Marra and Morin 2015). This is due to the fact that radar rainfall intensity is derived indirectly from measured radar reflectivity instead of being a direct measurement (Ochoa-Rodriguez et al. 2019). As a result, both radar reflectivity measurements and the reflectivity-intensity conversion process are subject to multiple sources of errors (Villarini and Krajewski 2010).

2.2.2 Satellite-based precipitation products

According to Varma (2018), due to the difficulties and limitations of ground measurements, satellite-based precipitation products become the most convenient way to estimate precipitation over large areas. Nowadays, with the advance of the number of satellite sensors and imaging technology, a great number of promising recently released and revised satellite-based products providing valuable distributed information of sub-daily rainfall data are available to be used for many applications (Yuan et al. 2019; Llauca et al. 2021).

The sensors onboard satellites can be classified into three categories: Visible/InfraRed sensors, passive Microwave, and active Microwave sensors (Michaelides et al., 2009; Prigent, 2010). Corresponding methods used to derive precipitation have been developed, including the Visible/InfraRed-based methods, active and passive Microwave techniques, and merged Visible/InfraRed and Microwave approaches (Kidd & Levizzani, 2011). According to Sun et al. (2018) and Varma (2018):

- The Visible/Infrared methods share common characteristics as they provide information only on the top of the cloud, hence rain droplets inside the clouds are not directly sensed. So, the precipitation estimate is indirect through the principle that

cold and bright clouds are related to convection; cold cloud tops suggest greater vertical development in the cloud and therefore more rain. They provide wide coverage over tropical regions with high spatial and temporal resolution (e.g., PERSIANN, PERSIANN CCS).

- Passive microwave techniques are a more direct method of measuring precipitation than the Visible/Infrared techniques because they can penetrate clouds and sense precipitation-sized particles. The most critical disadvantage of passive microwave precipitation estimation is that they have low spatiotemporal coverage (e.g., IMERG-products).
- The use of active microwave observations from satellites for precipitation began with the launch of the first spaceborne precipitation radar in the TRMM mission in 1997, which made it possible to capture the three-dimensional structure of rain. The active microwave techniques offer the most direct of all satellite estimation methods, despite this, it has been limited mainly to TRMM.

As mentioned before, rain gauges provide accurate measurements of precipitation at single points but are sparsely distributed over the globe, as well as can be affected by sampling errors (Habib et al. 2001; Kidd et al. 2017). On the other hand, satellite observations have homogeneous spatial coverage, however random errors and biases can be detected, e.g., deficiencies in the algorithms (Chen et al. 2021; Shen et al. 2021). Therefore, merge different sources of information to overcome these errors and biases combining the individual advantages of the different methods are currently aim at various studies. (Figure 2). For example, combining gauge and satellite data, such as PERSIANN-CDR V1R1, CMORPH-CRT V1.0.

Moreover, reanalysis datasets are also available and are mostly used in the study of weather and climate. Reanalysis generates large variety of atmospheric, sea-state, and land surface parameters across a uniform grid with spatial homogeneity over long time periods through data assimilation, a process that relies on both observations and model-based forecasts to estimate conditions (Dee et al. 2014; Sun et al. 2018). Nowadays, more complex models, multiple observed datasets for multiple variables, and different data assimilation techniques are essential factors that improve their quality (Parker 2016), e.g., ERA-Interim, CHIRPS V2.0, MERRA-2, MSWEP V2.2.

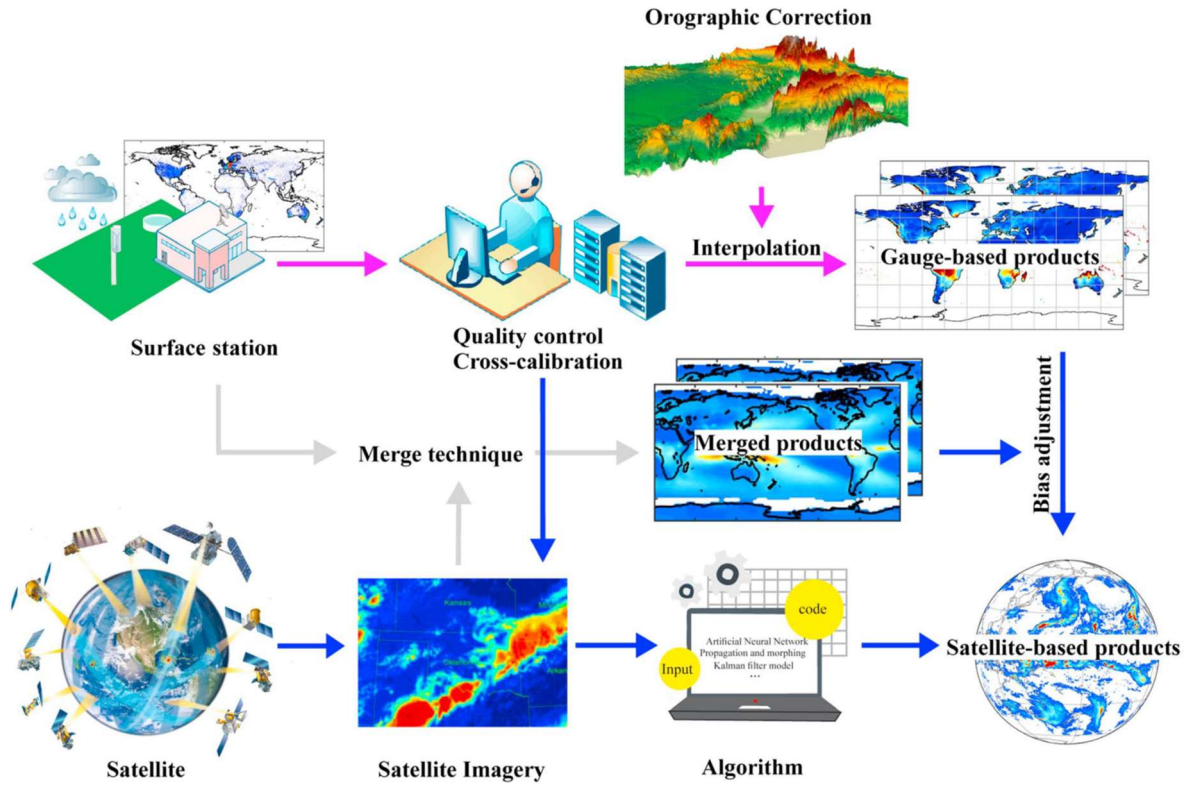


Figure 2 – Flowchart for the precipitation products. (Courtesy: Sun et al. 2018)

2.3 Rainfall threshold methodologies

Great efforts have been made during the last few decades to develop and improve methods for a better flood prediction aiming to reduce the damages and deaths caused by floods (Froidevaux et al. 2015; Jang 2015; Rijswick 2015; Getirana et al. 2020; Young et al. 2021). However, it has been gradually applied more for landslide warning purposes than for flooding (Diakakis 2012; Papagiannaki et al. 2015; Santos and Fragoso 2016).

Among the existing methods for the development of warning systems, they can be grouped into three main categories: (i) methods that combine soil mechanics and hydrology; (ii) exclusively hydrological methods (methods based on the tank model); and (iii) empirical methods (CEMADEN 2018). Among them, the empirical methods still prevail as an alternative approaches to build hydrological disasters warning systems, since other methods require a set of detailed input data or challenging complex models with high computation costs (Yang et al. 2016).

The rainfall threshold approaches are a widely empirical method used for hydrological disasters monitoring (e.g., floods, flash floods, debris flows and landslides) (Glade et al. 2000; Aleotti 2004; Berti et al. 2012; Santos and Fragoso 2016; Scheevel et al.

2017; Mirus et al. 2018). This method aims to delimit a clear line between rainfall events that might or might not lead to disasters (Figure 3a), i.e., the rainfall threshold defines a safe zone and an unsafe zone to the triggering of disasters. However, in many cases, this distinction is not so trivial as other factors can contribute to disaster occurrences. Consequently, an area of uncertainty arises (Figure 3b), in which there is a mixture of records of rainfall events that trigger and did not trigger a disaster. The improvement of the currently available methodologies (i.e., by reducing such uncertainties) is exactly the first main aim of this thesis.

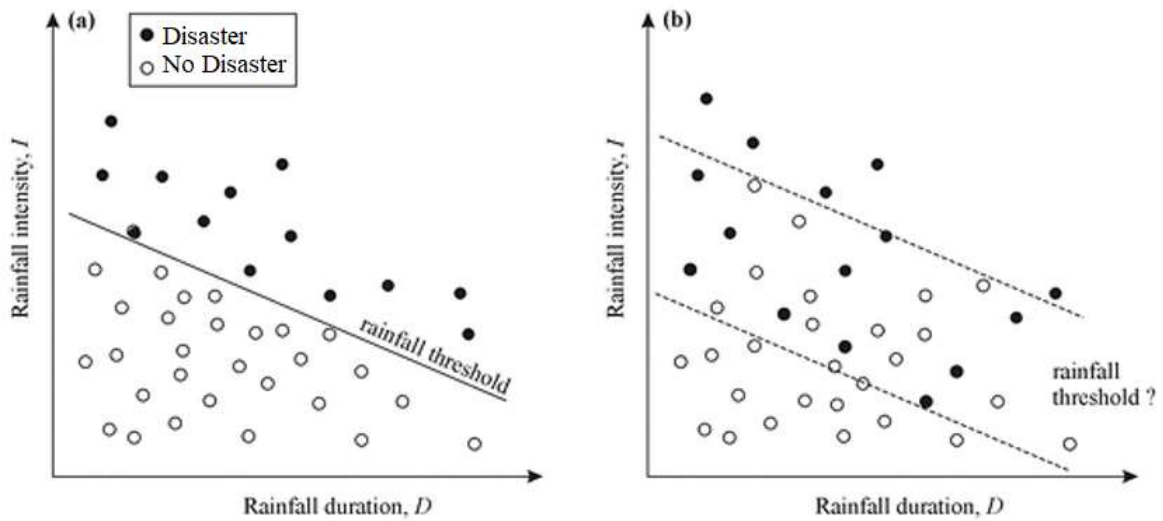


Figure 3 – Concept of rainfall thresholds (a) clearly distinguished (b) not clearly distinguished
(Courtesy: modified from Berti et al. 2012)

In general, it is observed in the literature different approaches to characterize the rainfall events used to determine rainfall thresholds: (i) using precipitation for a specific rainfall event, for example, through the relationship between the intensity/accumulated rainfall and the duration of the event (Cannon et al. 2008; Diakakis 2012; Segoni et al. 2014; Papagiannaki et al. 2015; Rossi et al. 2017; Brunetti et al. 2018; Peres et al. 2018); (ii) considering the antecedent conditions, for example, through the relationship between the intensity/accumulated rainfall and the rainfall that preceded the event (Zêzere et al. 2010; Bai et al. 2014; Huang et al. 2015; Santos and Fragoso 2016; Pan et al. 2018); (iii) among others. Table 2 presents some studies developed for the delimitation of precipitation thresholds to different regions of the world.

Table 2 – Summary of relevant studies on precipitation thresholds

Study	Natural Disaster	Area	Temporal Resolution	Threshold Approach
Diakakis 2012	Flood	Marathons – Greece	Sub-hourly	Intensity vs Duration
Segoni et al. 2014	Landslide	Tuscany – Italy	Hourly	Intensity vs Duration
Huang et al. 2015	Landslide	Huangshan – China	Hourly	Intensity vs Antecedent rainfall
Papagiannaki et al. 2015	Flash Flood	Attica - Greece	Sub-hourly	Intensity vs Duration
Santos and Fragoso 2016	Flood	Corgo basin – Portugal	Daily	Accumulated rainfall vs Antecedent rainfall
Rossi et al. 2017	Landslide	Umbria – Italy	Hourly	Accumulated rainfall vs Duration
Peruccacci et al. 2017	Landslide	Italy	Hourly	Accumulated rainfall vs Duration
Brunetti et al. 2018	Landslide	Italy	Multi Hourly	Accumulated rainfall vs Duration
Muntohar et al. 2021	Landslide	Indonesia	Daily	Accumulated rainfall vs Duration

For flood studies, Diakakis (2012) examined the peak rainfall intensities, total storm accumulation, average intensity, and antecedent moisture conditions of the 52 most important storm records in Greece that triggered flood, and showed that only peak rainfall intensity presented a significant correlation with flood triggering, and defined a rainfall threshold above which flooding becomes highly probable. This methodology was applied later for flash floods in this same area by Papagiannaki et al. (2015). The authors observed that most of the flash floods occurrences area associated with maximum accumulated rainfall of more than 20 mm in 24 h and 3 mm in 10 min, however the number of occurrences increases significantly above the levels of 60 mm in 24 h and 10 mm in 10 min.

For landslides studies, Peruccacci et al. (2017) build a catalogue of 2309 rainfall events with landslides in Italy between 1996 and 2014. It was defined national and 26 regional thresholds for environmental subdivisions based on topography, lithology, land use, land cover, and others. The results showed differences between some of the thresholds, highlighting, that more rainfall is needed to trigger landslides where the mean annual precipitation is high than where it is low.

In one of the first studies evaluating the satellite data to determine rainfall thresholds, Rossi et al. (2017) determined rainfall thresholds in the Umbria region in central Italy. The authors observed that the rainfall thresholds obtained from satellite data are lower than those

obtained from rain gauge measurements, which converges with the literature, where satellite rainfall data underestimate the rainfall registered by rain gauges.

Brunetti et al. (2018) evaluated the capability of different rainfall products to forecast the spatial-temporal occurrence of rainfall-induced landslides using rainfall thresholds. Results showed that satellites products underestimated rainfall with respect to ground observations. However, by adjusting the rainfall thresholds, satellite products are able to identify landslide occurrence, even though with less accuracy than ground-based rainfall observations.

Muntohar et al. (2021) developed a landslide early warning system based on the satellite-based TRMM in Indonesia. The threshold performance was evaluated by seven statistics indices. The results showed a good accuracy rate, even though it still has a fairly error rate that should be further investigated. Thus, it can be implemented in a landslide early warning system by the government authority.

3 STUDY AREA CHARACTERISTICS

This study was carried out in São Paulo State, located in the Brazilian Southeast region with an area of 248,200 km² between 19°55'58"S-25°00'53"S and 50°32'15"W-47°55'36"W (Figure 5). The state is highly urbanised with approximately 45.5 M inhabitants, reaching a level of urbanisation of 95% (IBGE 2018). The study area is divided into two zones with different physical characteristics: 1) the coastal zone which has an altitude lower than 300 m and 2) the plateau zone which comprises most of the area of the state with elevation ranging from 300 to 900 m. This topographical characteristic is an important natural factor in explaining the climate of the state of São Paulo (Setzer 1946). The coastal zone is dominated by the humid tropical climate with a mean annual temperature above 22 °C and average annual rainfall above 2,000 mm. Meanwhile, the plateau zone is mainly characterised by the humid subtropical climate with an annual average temperature of 20 °C and average annual rainfall equal to 1,400 mm year⁻¹ (Alvares et al. 2013). The rainfall in both regions of the state is more concentrated during the austral summer, i.e., between October and March. Generally, April and September are the driest months in São Paulo State (Figure 4). Approximately 70% of the study area is composed of Devonian-Cretaceous deposits of the Paraná and Bauru basins, while the remaining 30% mainly corresponds to a crystalline basement with rocks older than the Neoproterozoic Era (Garcia et al. 2018). Other sedimentary deposits (e.g., intercontinental, and coastal Cenozoic basins) also compose the geology of the São Paulo State but at a small proportion.

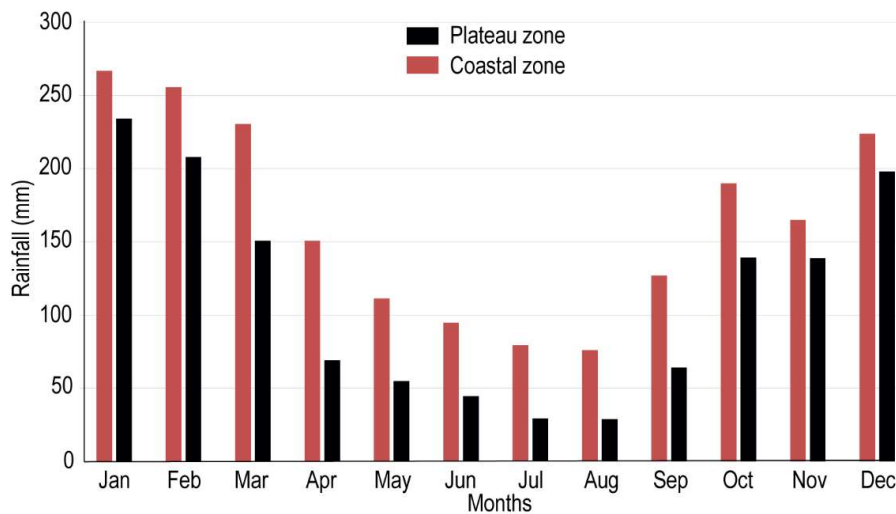


Figure 4 – Long-term (1950–1990) mean monthly rainfall for the coastal and plateau zones obtained from the meteorological stations used by Alvares et al. (2013).

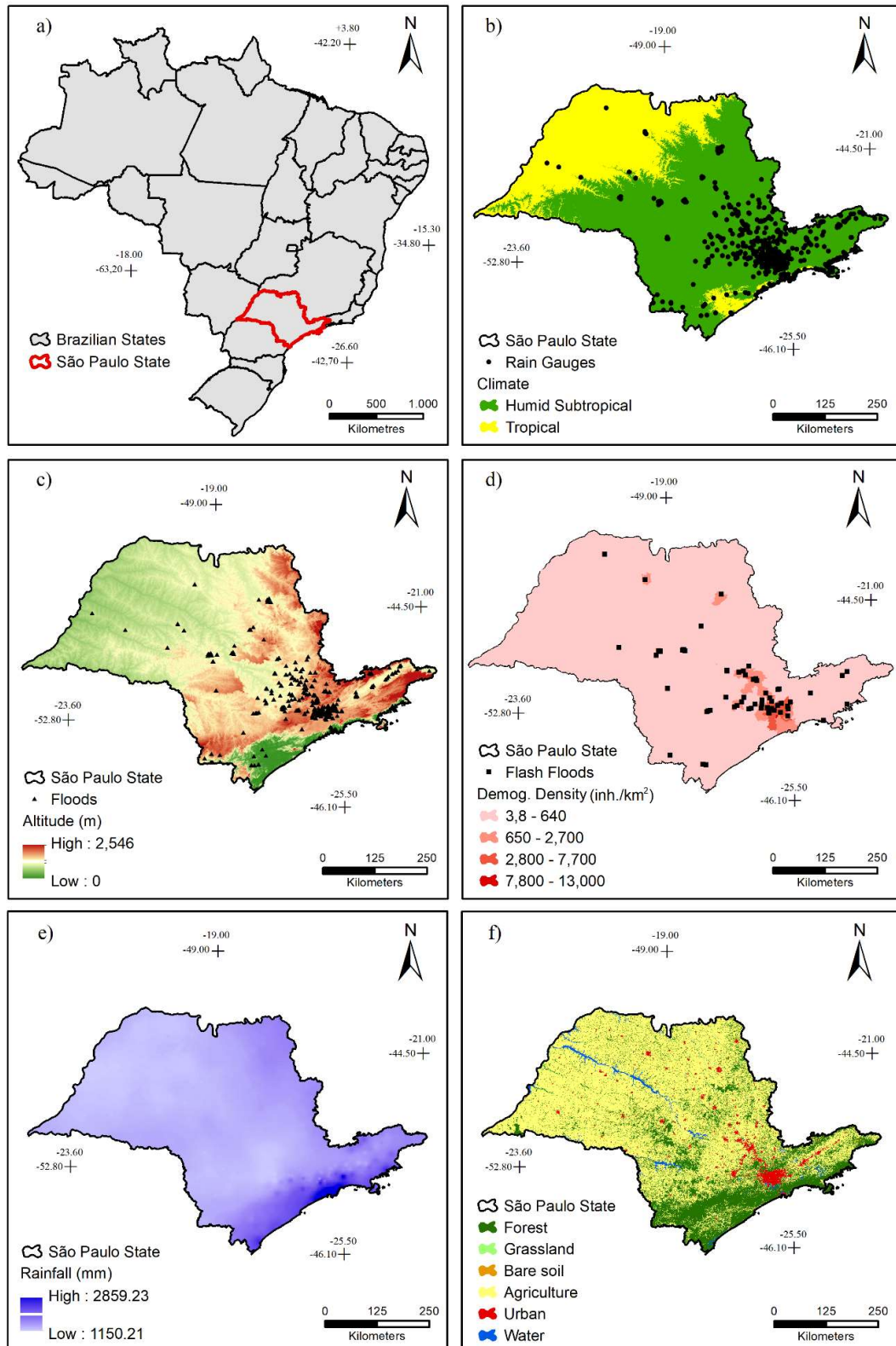


Figure 5 – (a) Map of Brazil showing the São Paulo State. (b) Rain gauges and Köppen's classification map for São Paulo State according to Alvares et al. (2013). (c) Elevation of the São Paulo State and location of the 347 flood occurrences. (d) Demographic density of São Paulo and location of the 71 flash flood occurrences. (e) Long-term (1950-1990) mean annual rainfall obtained from the meteorological stations used by Alvares et al. (2013). (f) Landsat-based land use and land cover map for 2017 provided by the MapBiomas Project (Souza et al. 2020).

São Paulo State is a typical hotspot frequented by landslides and floods arising from prolonged or intense rainfall events (Figure 6). The occurrences of these disasters are due to the natural characteristics of the region associated with the high level of urbanisation (Tominaga et al. 2015). From 2000 to 2015, there have been more than 10,800 natural disasters recorded, causing 534 deaths and affecting approximately 971,500 people and 128,500 buildings. Out of all natural disasters recorded in São Paulo, more than 50% were caused by sudden and violent changes in the distribution or movement patterns of water (Brollo and Ferreira 2016). Moreover, São Paulo is the richest state in Brazil, with the largest number of floods and flash floods records as well as sub-daily rainfall data made available by public agencies.



Flash Flood in Rio da Prata – Jaguariúna



Flood in Capivari – SP



Flood in Franco da Rocha – SP



Landslide in Diadema – SP

Figure 6 – Hydrological disaster in São Paulo (Courtesy: CEPED 2013)

4 IMPROVED RAINFALL-THRESHOLD APPROACH

4.1 Contextualization

Among the empirical methods, the rainfall-threshold method is one of the most widely used for predicting and warning some of the hydrological disasters (Huang et al. 2015), where the thresholds are determined by the properties derived from rainfall events such as intensity, duration, and antecedent precipitation (e.g., Glade et al. 2000; Aleotti 2004; Berti et al. 2012; Papagiannaki et al. 2015; Scheevel et al. 2017; Brunetti et al. 2018; Mirus et al. 2018). In the area of flood warning, Diakakis (2012) used rainfall intensity-duration parameters to determine the thresholds after adapting the methodologies proposed by Cannon et al. (2008) and Guzzetti et al. (2008) for landslides. In his study, two thresholds (upper and lower) are defined but large uncertainties still exist, mainly manifested by the considerable number of occurrences and non-occurrences of flooding concentrated in the region between the two thresholds, which often causes many false alarms. Consequently, many warning systems are frequently neglected by the community due to the large uncertainties (Abon et al. 2012). Thus, reducing such uncertainties is crucial to minimise the costs and improve the decision-making processes (Villarini et al. 2010).

The uncertainties of the rainfall thresholds are inevitable as rainfall is not the only factor that triggers flooding and flash flooding events (Papagiannaki et al. 2015). The shortcomings of the intensity-duration thresholds are frequently mentioned in the literature, although this type of method remains as the mostly widespread in the world (Zhao et al. 2019). For instance, choosing rainfall events with short durations to build the threshold would exclude the important antecedent wetness information, whereas selecting rainfall events with long durations can mitigate this but it would also flatten the peak intensity that otherwise can be the real trigger of floods (Bogaard and Greco 2018). Other methods attempt to overcome this by using information of antecedent rainfall (e.g., Chleborad et al. 2008; Lee and Park 2016; Scheevel et al. 2017) or Antecedent Precipitation Index (API) (e.g., Glade et al. 2000; Mirus et al. 2018; Suribabu and Sujatha 2019; Zhao et al. 2019). The use of API, in contrast with the use of the antecedent rainfall, allows for the consideration of the loss of the rainfall over the past days (Suribabu and Sujatha 2019). In addition, some other studies also provided a quantitative assessment of the rainfall threshold approaches for landslides occurrences by applying probability-based methods (Berti et al. 2012). These probability-based methods allow the definition of multiple rainfall thresholds based on different

exceedance probability levels, which makes possible the establishment of various warning levels (Brunetti et al. 2010; Huang et al. 2015).

Still, when compared with the applications in predicting landslides, the number of studies using rainfall thresholds for flood and flash floods warning systems remain low and the area has been poorly explored. It is also clear that reducing the uncertainties in such applications is crucial for the effective issuance of flood warnings. The present chapter of the thesis aims to create a rainfall threshold estimation approach for the robust prediction and warning of floods and flash floods hazards, as previously presented in the section 1.2 of this document. The flood and flash flood warning system proposed in this first study intends to reduce the uncertainties and minimise false alarms observed in the region between the upper and lower thresholds by introducing an intermediate threshold derived by assessing the different interactions between the rainfall peak intensity and API, considering different evaluation metrics. Moreover, the novel inclusion of two tolerance levels in the upper and lower regions of the threshold intends to enable a more fine-tuned flood warning level setting.

4.2 Materials and methods

This study used a series of steps to create a robust rainfall threshold able to reduce the uncertainties of events triggering floods occurrences, as shown in Figure 7. Overall, the implementation of the proposed rainfall threshold approach includes: a) the selection of events, b) the application of rainfall intensity-duration parameters to define thresholds, c) the adoption of tolerance levels to improve the rainfall intensity threshold, and d) the implementation of an intermediate threshold relating rainfall peak intensity and API to better separate the flood and flash flood occurrences from the non-occurrences. These methodological steps are described in detail in the next items of this section.

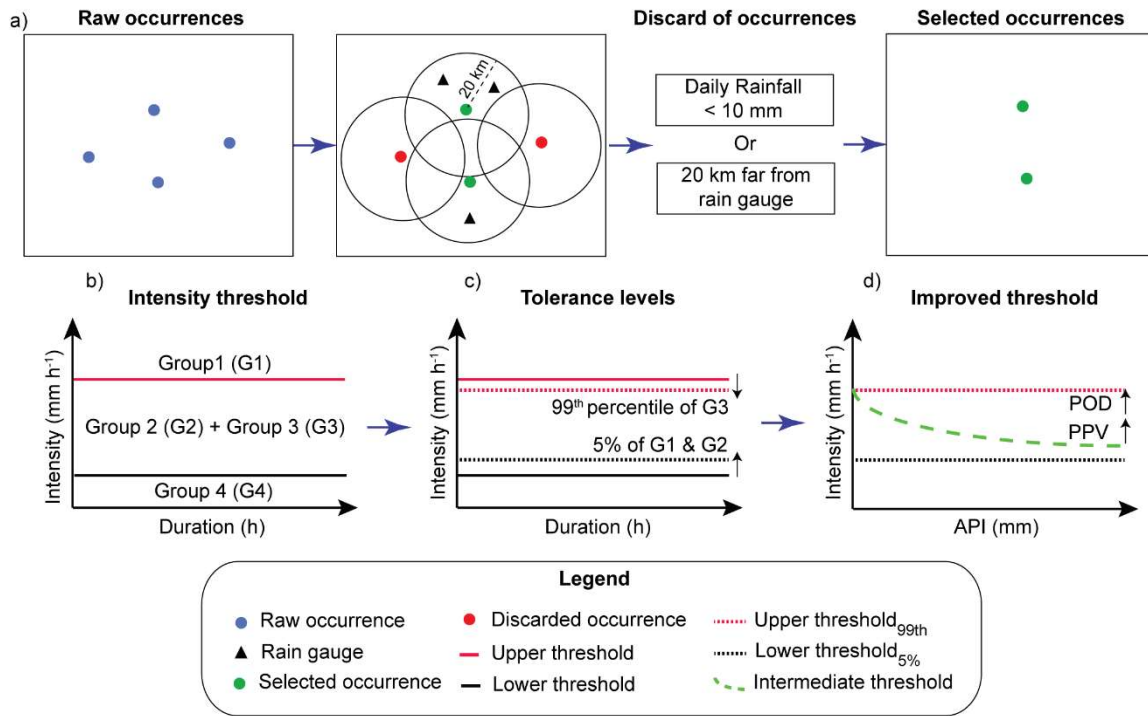


Figure 7 – Methodological chart, showing (a) the raw and selected flood and flash flood occurrences; (b) the rainfall intensity threshold approach; (c) the tolerance levels adopted to improve the rainfall intensity threshold; and (d) the improved threshold relating rainfall peak intensity and antecedent precipitation index (API).

4.2.1 Selection of events

4.2.1.1 Rainfall data

Rainfall data over the period of 1 January 2015 - 31 December 2017 were collected from the 732 rain gauges distributed throughout the São Paulo State. The rain gauges belong to the Brazilian National Centre for Monitoring Early Warning of Natural Disasters (CEMADEN, acronym in Portuguese), a national-wide network established by the Brazilian Government supporting the natural disasters risk management (Bacelar et al. 2020). The ground-based rainfall observation network of CEMADEN is equipped with tipping bucket gauges with a 10-min temporal resolution when it rains and 60-min temporal resolution over no-rain periods. These rainfall data were screened before use in this study. The quality-control procedure is as follows: first, a computational routine was created to select only rain gauges with less than 30-days of missing data along each of the three civil years considered in this study; then, all rain gauges meeting this first requirement were visually inspected using two standard methods, including: 1) a comparison of monthly and sub-daily rainfall data of the five nearest stations was carried out to verify large discrepancies between them;

and 2) an analysis of the range of values and changes over subsequent measurements of each rain gauge to identify constant or null rainfall records that probably indicate gauge clogging. This resulted in the final 590 gauges that were selected for the whole study period (Figure 5b). These data were then used to define the rainfall events and to calculate their respective thresholds. It is worth noting that not all 590 gauges were used for every year because of the quality-check procedures adopted in this study; instead: 1) 216 rain gauges with high-quality data in 2015, 2) 315 rain gauges with high-quality data in 2016, and 3) 355 rain gauges with high-quality data in 2017.

Most rain gauges used to calculate the rainfall thresholds are located within the metropolitan regions of the São Paulo State, including: 1) the Metropolitan Area of São Paulo (MASP), with an estimated density of 7,689 inhabitants/km² and covered by 42 rain gauges, 2) the Metropolitan Area of Ubatuba (MAU), with an estimated density of 121 inhabitants/km² and covered by 18 rain gauges, and 3) the Metropolitan Area of Santo André (MASA), with an estimated density of 3,919 inhabitants/km² and covered by 17 rain gauges.

4.2.1.2 Flood and flash flood data

Detailed information of flood and flash flood occurrences are fundamental for the analysis of their relationship with rainfall events. In this study, flood occurrences were considered as the overflow of water from a stream channel onto normally dry land in the floodplain, whereas flash flood occurrences were regarded as a rapid inland flood due to intense rainfall or a sudden flooding with short duration (Guha-Sapir et al. 2015). The inventory of these occurrences, which comprise the same period of the rainfall data, was obtained from three main sources: 1) The Integrated Storm Monitoring, Forecasting and Alerting System for the Brazilian South-Southeast Regions (SIMPAT, acronym in Portuguese), 2) The Civil Defence of the state of São Paulo, and 3) press news. The data provided by the press news were also used to confirm and differentiate the type of occurrence (floods or flash floods) by analysing some available information such as pictures, rainfall duration, and location. In order to choose the most appropriate rain gauges, only those flood and flash occurrences that could be georeferenced (e.g., via address and coordinates) and dated were selected. This was followed by the application of two more criteria to further filter out the events/occurrences that: 1) come with daily rainfall less than 10 mm near to the flood and flash flood events, or 2) have the nearest rain gauge located more than 20 km from the occurrence. Although choosing only occurrences distant less than 20 km from the rain

gauges as a criterion, almost 72% of the flood and flash flood events were located within 10 km from the stations.

4.2.1.3 Characterisation of rainfall events

In parallel with the selection of the flood and flash flood occurrences, rain gauges were chosen to define the rainfall events that better characterise the disasters. In this study, the relationship between rainfall peak intensities and the antecedent wetness conditions was assessed for the events that might or might not lead to the floods and flash floods. This assessment was performed to avoid two potential issues: 1) the inadvertent exclusion of important antecedent wetness information for rainfall events with short duration, and 2) the flatness of peak intensity for rainfall events with long duration. The procedure is as follows: first, the rainfall peak intensity for all rain gauges was calculated for each day considering ten time-steps (10 min, 30 min, 1 h, 2 h, 3 h, 6 h, 8 h, 10 h, 12 h, and 24 h). Thereafter, the API was tested for different time-steps (1 to 10 days) to estimate the antecedent wetness conditions for the day before the rainfall event (Kohler and Linsley 1951), as in eq. 1:

$$API = \sum_{t=-1}^{-i} P_t k^{-t} \quad (1)$$

where i is the number of antecedent days considered in the study, P_t is the rainfall for the day t (mm), and k is a decay rate that ranges from 0.80 to 0.98 according to Viessman and Lewis (1996). The values of API chosen in this study are within the ranging established by some well-recognised methods such as the Natural Resources Conservation Service (NRCS) method that uses 5 days of antecedent moisture condition (NRCS 1972). Some other studies also suggest values of API ranging from 2 to 6 days to characterise flooding (e.g., Trambly et al. 2012; Froidevaux et al. 2015).

The selection of the rainfall events that better characterise the flood and flash occurrences followed largely the methodology proposed by Rossi et al. (2017), i.e., only those rainfall events with gauges having observed the most critical rainfall for the days of occurrences and situated within 20 km distance from the location where the floods or flash floods occur were selected; whereas the other rainfall events were treated as non-occurrences.

4.2.2 Improvements of the rainfall threshold

4.2.2.1 Definition of the rainfall peak intensity-duration threshold

The most representative peak of rainfall intensity was obtained by plotting peak rainfall intensities of various time intervals against their respective durations. The objective of this first step is to distinguish two clear thresholds (lower and upper) that divide the graph into three parts and four distinct groups: 1) the upper part (Group 1), which corresponds with the peak intensities that always lead to flooding or flash flooding occurrences; 2) the middle part, which contains peak intensities that may (Group 2) or may not (Group 3) lead to flooding or flash flooding events; and 3) the lower part (Group 4), which includes peak intensity values that do not lead to flooding or flash flooding. Accordingly, an analysis of the graph based on the following four criteria was also performed in this study to define the time interval of the peak rainfall intensity that better represents the flood and flash flood occurrences: 1) a higher number of occurrences above the upper threshold, 2) a higher number of non-occurrences below the lower threshold, 3) lower amplitude between the upper and lower thresholds, and 4) values of the metrics presented in section 4.2.3.

4.2.2.2 Application of tolerance levels

Some studies complemented the rainfall threshold method with probabilities of occurrence to reduce the uncertainties of false alarms for hydrological disasters (e.g., Berti et al. 2012; Huang et al. 2015; Wu et al. 2015; Santos and Fragoso 2016; Brigandì et al. 2017). Aiming to reduce the uncertainties in the middle part of the graph but without losing the characteristics of Group 1 and Group 4, two levels of tolerance (sometimes mentioned as exceedance probability) were used in this study to minimise the amplitude between the upper and lower thresholds, e.g.: 1) a new lower threshold defined as the 5% of the occurrences above the lower threshold where the value 5% has also been adopted for landslide studies (Peruccacci et al. 2009, 2012, 2017; Brunetti et al. 2010; Rossi et al. 2017); and 2) a new upper threshold defined as the 99th percentile of non-occurrences above the lower threshold. The first tolerance level leaves 5% of the empirical data points below the lower threshold, while the second tolerance level was adopted to leave a minimum number of the non-occurrences above the upper threshold.

4.2.2.3 Delineating the intermediate threshold

Afterwards, the API was used to analyse the occurrences and non-occurrences of the middle part of the graph after considering the two tolerance levels. The upper and lower parts of the graph were excluded from this further analysis because it is presumed that they are already well-represented by the intensity peaks. Some studies show generally a negative relationship between the antecedent conditions and a critical event rainfall, indicating that with increasingly wet conditions, less rainfall is required to trigger an occurrence (Bai et al. 2014). In this study, the middle part was outlined following the study carried out by Collins et al. (2007) for landslides, which relates rainfall intensity and API by an exponential equation to better identify occurrences and non-occurrences of events at this part of the graph, as follows:

$$I = a e^{b \text{ API}} + c \quad (2)$$

where I is the peak intensity (mm h^{-1}), and a , b , and c are constants to be determined. The constant values were obtained by 50,000 iterations, combining: 1) 50 values of ' a ' ranging from the minimum rainfall intensity to three times the maximum rainfall intensity of the occurrences; 2) 20 values of ' b ' varying between -0.01 and -1; and 3) 50 values of ' c ' ranging from the minimum rainfall intensity to the mean rainfall intensity of the occurrences. The best-fitted constants and the reference day for the API calculation were selected based on the optimal values of the metrics presented in section 4.2.3.

4.2.3 Evaluation procedures

The performance of the upper, intermediate and lower thresholds to identify true or false alarms was evaluated using a binary classifier of the rainfall conditions that do or do not lead to flood and flash flood occurrences (Segoni et al. 2014; Turkington et al. 2014; Zhao et al. 2019). A contingency matrix consisting of four components was used for each threshold, including: 1) true positive (TP), when the threshold is exceeded and the hydrological disaster occurs; 2) false negative (FN), when the threshold is not exceeded and the hydrological disaster occurs; 3) false positive (FP), when the threshold is exceeded and the hydrological disaster does not occur; and 4) true negative (TN), when the threshold is not exceeded and the hydrological disaster does not occur. Three metrics were then applied

using the contingency matrix to assess the skill score of the flood and flash flood thresholds: 1) probability of detection (POD), which measures the fraction of events that are correctly predicted; 2) false alarm ratio (FAR), which exhibits the fraction of events incorrectly predicted; and 3) positive predictive value (PPV), which shows the probability of events correctly predicted:

$$POD = \frac{TP}{TP + FN} \quad (3)$$

$$FAR = \frac{FP}{FP + TN} \quad (4)$$

$$PPV = \frac{TP}{TP + FP} \quad (5)$$

The values of these metrics range from 0% to 100%. The optimal score for POD and PPV is close to 100%, while the perfect value for FAR is close to 0%.

4.2.4 Link to the colour-class warning level systems

In Brazil, national and regional disaster management agencies such as CEMADEN usually use colour-class systems to indicate different levels of risk (e.g., moderate, high, and very high). These systems generally employ classes varying from cold to warm colours to show conditions that could lead to increased risk. Similar risk information, using this colour-class system designed from multiple rainfall thresholds to link threat levels to the emergency, is also used by many disaster management agencies worldwide and scientific studies (e.g., Brunetti et al. 2010; Huang et al. 2015; Jang 2015). Based on this information, the definition of four thresholds using the methodology proposed in this study makes it possible for the implementation of probabilistic schemes for warning level systems predicting flood and flash flood occurrences, defined as follows:

1. Blue alert: rainfall events below the lower threshold that represent a low probability of occurrences when the rainfall conditions are maintained.
2. Yellow alert: rainfall events between the lower and the intermediate thresholds that represent a moderated probability of occurrences when the rainfall conditions are maintained.

3. Orange alert: rainfall events between the intermediate and the upper threshold that represent a high probability of occurrences when the rainfall conditions are maintained.
4. Red alert: rainfall events above the upper threshold that represent an extremely high probability of occurrences when the rainfall conditions are maintained.

4.3 Results and discussion

4.3.1 Characterisation of the flood and flash flood occurrences

Figure 5c & Figure 5d show the spatial distribution of the 347 and 71 occurrences of flood and flash floods, respectively, in the state of São Paulo between 1 January 2015 and 31 December 2017. Represented by separated points in the map, these occurrences were obtained from the three main sources of data described in section 4.2.1.2. The main source of occurrences was acquired from the SIMPAT dataset, with 284 (82% of the total) floods and 58 (82% of the total) flash floods. The spatial distribution of information, collected from the different data sources, shows that a large number of floods (59%) and flash floods (55%) were concentrated in areas with population density higher than 500 inhabitants/km², which includes only 59 of the 645 municipalities of São Paulo State. The largest number of floods were identified in MASP (45), Bauru (12), and Sorocaba (9). On the other hand, the number of observed flash floods was higher in Bauru (8), São Paulo (6), and Campinas (5). The 240 floods and 47 flash floods occurrences considered in this study were mostly triggered during the rainy season (January – March), which represents 69% and 66% of the total, respectively. According to SIMPAT, the number of socio-economic impacts caused by the floods and flash floods in São Paulo State during the studied period amount to more than 4,310 displacements, 26 injuries, and 17 deaths.

4.3.2 Rainfall peak intensity-duration threshold

The results of the rainfall thresholds for floods and flash floods, without the use of tolerance levels, are shown in Figure 8a & Figure 8b. The thresholds of the upper part of the graph for floods range from 171.6 to 4.2 mm h⁻¹ for the rainfall durations of 10 min and 24 h, respectively. The thresholds of the lower part of the graph for floods range from 4.7 to 1.1 mm h⁻¹ for the same durations, respectively. As far as flash floods are concerned (Figure 8b),

the thresholds of the upper part of the graph presented similar values when compared to floods (between 170.4 and 4.3 mm h⁻¹). Conversely, the lower part exhibited values of intensity peaks six times higher (25.2 mm h⁻¹) for shorter time-steps.

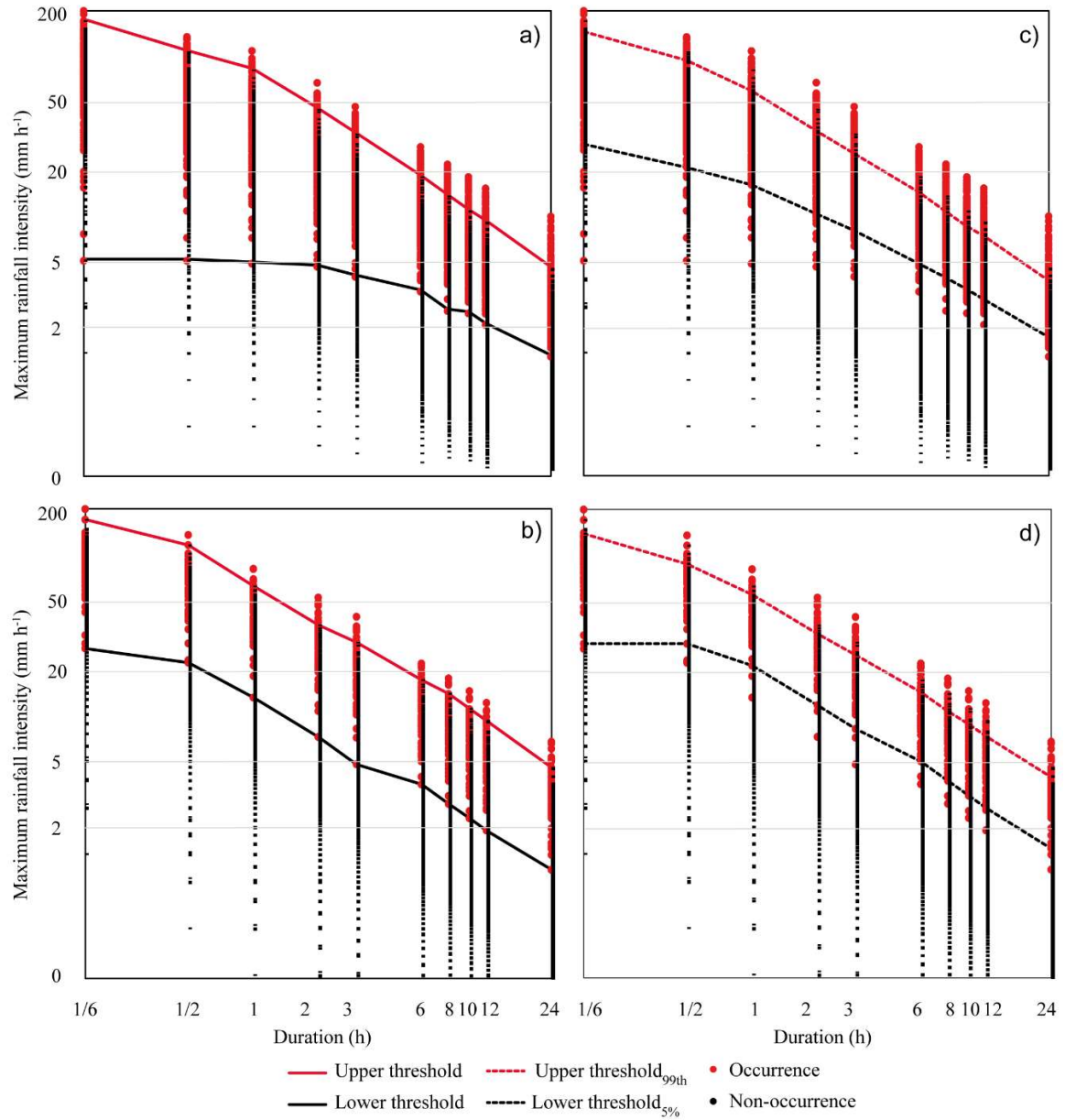


Figure 8 – Rainfall intensities peak versus rainfall duration applying the approach without the tolerance levels for (a) floods and (b) flash floods. Improved application of the methodology using the tolerance levels (99th percentile and 5%) for (c) floods and (d) flash floods. The graphs use logarithmic scale.

It is noticeable that the peak rainfall intensity for longer durations (24 h) presents a better relationship with the eventual flood events, where the upper and lower lines of the threshold tend to be closer. Consequently, the largest number of flood occurrences and non-occurrences was registered above (below) the upper (lower) thresholds, respectively. Thus,

a reduced quantity of events in the middle part of the graph, containing both occurrences and non-occurrences, was also observed. This finding differs from the study carried out by Diakakis (2012) in Greece, which found a better relationship for shorter peak intensity duration due to the upper and lower thresholds being much closer in 10 or 30 min durations than in 24 hours. On the other hand, the amplitude of the middle part of the graph (the distance between the two thresholds) was similar for all time-steps when flash floods were considered. However, the largest number of occurrences/non-occurrences above (below) the upper (lower) thresholds was noticed for the time-steps of 1 and 2 h. Papagiannaki et al. (2015) also observed a better separation between flash floods occurrences and non-occurrences in Greece for shorter peak intensity durations, however only when the analysis is performed on a more local scale.

Table 3 shows the evaluation metrics for predicting floods and flash floods using the two thresholds but without adding of the tolerance levels. It is noticeable that the upper threshold is a precise approach for predicting flood and flash flood occurrences, presenting FAR and PPV values equal to 0% and 100% for all time steps, respectively. However, the upper threshold is only applicable to a very limited number of occurrences, since the POD for this threshold presented low values for floods (from 1 to 17%) and flash floods (from 3 to 15%) for all time steps. The lower threshold exhibits high and low values of FAR (from 15 to 93%) and PPV (from 9 to 19%) for floods, respectively. For flash floods, reduced values of FAR (from 12 to 19%) and PPV (from 4 to 7%) are found for the lower threshold when compared to those observed for floods. These results show that the application of the rainfall peak intensity-duration threshold presents a high number of non-occurrences above the lower threshold, albeit displaying POD values equal to 100% for both type of floods. This behavior suggests that the approach can detect most occurrences only above the lower threshold, but with a considered level of false alarms regardless of the time-step adopted. Similar performance has also been observed in the application of rainfall intensity-duration thresholds for floods and landslides worldwide (e.g., Santos and Fragoso 2016; Brunetti et al. 2018; Zhao et al. 2019). For both upper and lower thresholds, the rainfall peak intensity-duration threshold without the use of tolerance levels presented better results for time steps equal to 1 and 24 h for flash floods and floods, respectively.

Table 3 – Summary of evaluation metrics for the flood and flash flood thresholds, considering the approach without the use of tolerance levels.

		Metrics	Peak Intensities (h)									
			1/6	1/2	1	2	3	6	8	10	12	24
Flood	Upper threshold	POD	1%	7%	4%	7%	8%	12%	12%	13%	14%	17%
		FAR	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
		PPV	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
	Lower threshold	POD	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
		FAR	93%	83%	72%	48%	41%	24%	26%	20%	20%	15%
		PPV	4%	4%	5%	7%	8%	13%	12%	15%	15%	19%
Flash Flood	Upper threshold	POD	3%	3%	14%	15%	11%	10%	7%	7%	8%	13%
		FAR	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
		PPV	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
	Lower threshold	POD	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
		FAR	19%	13%	13%	15%	17%	12%	13%	13%	13%	13%
		PPV	4%	7%	6%	6%	5%	7%	7%	7%	6%	7%

4.3.3 Tolerance levels

Figure 8c & Figure 8d show the rainfall thresholds for floods and flash floods after introducing the tolerance levels of 99th percentile for the non-occurrences below the upper and 5% of the occurrences above the lower thresholds. The two tolerance levels were defined to seek to reduce the uncertainties of the middle part of the graph. The application of the tolerance level of 99th percentile corresponded to a mean inclusion of 11 and 6 non-occurrence events of floods and flash floods above the upper threshold, respectively. However, it also brings in an increase of 14% of the number of floods and flash floods occurrences above the upper threshold. For the tolerance level at 5% percentile, the number of occurrences included below the lower threshold was 17 and 4 for floods and flash floods, respectively. However, it was also observed a considerable reduction in the number of non-occurrences of floods (63%) and flash floods (53%) in the middle part of the graph. Similarly, the study carried out by Brunetti et al. (2018) also presented a significant reduction (68%) in the number of non-occurrences for landslides above the threshold after the use of the same tolerance level. However, it is worth highlighting that, in our study, without these tolerance levels, the inclusion of occurrences/non-occurrences in the lower/upper threshold was zero.

It is observed that there is a noticeable decline of the amplitudes between the lower and upper thresholds when floods are considered using the tolerance levels, mainly for the

time-steps ranging from 10 min to 2 h (Figure 8c). This reduction of the amplitude between the two thresholds predominantly occurred because of the significant rising of the lower threshold. This leads to the fact that approximately half of the non-occurrences above the lower threshold are excluded and in the meantime the number of flood occurrences above upper thresholds are included, respectively. As far as flash floods are concerned, the largest variations of the lower threshold using the tolerance levels mainly occur between the time-steps 1 and 3 h, excluding more than half of the non-occurrences above the originally defined lower threshold (Figure 8b & Figure 8d). Conversely, the upper threshold for flash floods remained practically unchanged. Table 4 shows the assertiveness of the rainfall thresholds for floods and flash floods after the use of the two tolerance levels. The results reveal a considerable improvement of POD for the upper threshold applying the tolerance level of 99th percentile for the non-occurrences, ranging now from 8 to 31% for floods and from 4 to 32% for flash floods. These outcomes obtained for POD correspond to an improvement of 14% for floods and flash flood compared to those acquired by the application of this methodology without the use of the proposed tolerance levels, while the FAR values remained negligible for all time-steps.

Table 4 – Summary of evaluation metrics for the floods and flash floods thresholds considering the tolerance levels (99th percentile and 5%) and the intermediate thresholds.

		Metrics	Peak Intensities (h)									
			1/6	1/2	1	2	3	6	8	10	12	24
Flood	Upper threshold (99 th)	POD	8%	13%	20%	24%	27%	27%	31%	31%	29%	31%
		FAR	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
		PPV	82%	87%	91%	92%	93%	93%	94%	94%	94%	94%
	Lower threshold (5%)	POD	95%	95%	95%	96%	95%	95%	95%	95%	95%	95%
		FAR	31%	18%	14%	12%	9%	8%	7%	6%	5%	6%
		PPV	10%	16%	19%	22%	26%	29%	32%	35%	38%	34%
Flash Flood	Upper threshold (99 th)	POD	4%	15%	27%	32%	30%	23%	25%	24%	25%	28%
		FAR	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
		PPV	38%	69%	79%	82%	81%	76%	78%	77%	78%	80%
	Lower Threshold (5%)	POD	96%	97%	96%	96%	96%	97%	96%	96%	96%	96%
		FAR	15%	8%	5%	4%	4%	6%	6%	6%	6%	7%
		PPV	5%	10%	15%	18%	16%	13%	13%	13%	12%	11%

Overall, the PPV values after the use of the tolerance level of 1% for the upper threshold presented a slight decreasing about 9% for floods and 26% flash floods, presenting

now variations above 80% and 70% for almost all intensity peaks, respectively. This fact represents a slight loss in the predictive capacity of the threshold using the tolerance level, however, a higher number of occurrences can be found. Thus, the upper threshold with the application of the tolerance level of 1% remains a robust approach for predicting the occurrences. Like the methodology without the application of the tolerance levels, the optimal scores of the metrics for floods and flash floods were observed for longer (8 h) and shorter (2 h) time-steps, respectively.

The lower threshold applying the tolerance level of 5% for the flood occurrences resulted in an increase of 16% of the PPV (now ranging from 10 to 38%) and a reduction of 32% of the FAR (now ranging from 5 to 31%), when compared to the approaches without the tolerance level (Table 4). Similar increases can be observed for flash floods, with improvements of 6 and 7% for PPV and FAR rates after adopting this tolerance level, respectively. The better performance of PPV and FAR noticed for floods applying the tolerance level for the lower threshold mainly occurred because: 1) the lower values of rainfall peak intensities observed for its outbreak, and 2) the higher number of flood records included in the lower threshold (17 floods against 4 flash floods). The values of POD equal to ~95% for both floods and flash floods also indicate that almost all occurrences remain represented for all time-steps after the use of the tolerance level for the lower threshold.

4.3.4 Intermediate threshold

This section analyses the use of an exponential equation relating rainfall intensity and API for improving the separation between occurrences and non-occurrences of the intermediate threshold, which represents the main contribution of this study. Figure 9 & Figure 10 show the results of the application of this methodology for floods and flash floods, respectively. It is noticeable that for floods the curves were more influenced by the API for shorter time-steps, especially for those equal to 10 min, 1 h, and 3 h. Accordingly, the curves for floods remained barely influenced by the API for time-steps equal to 2 and 8 h. For flash floods, the curves presented good sensitivity for almost all time-steps, except for 1 h. In general, the intensities for floods and flash floods tended to be constant and not dependent to API for durations higher than 1 h.

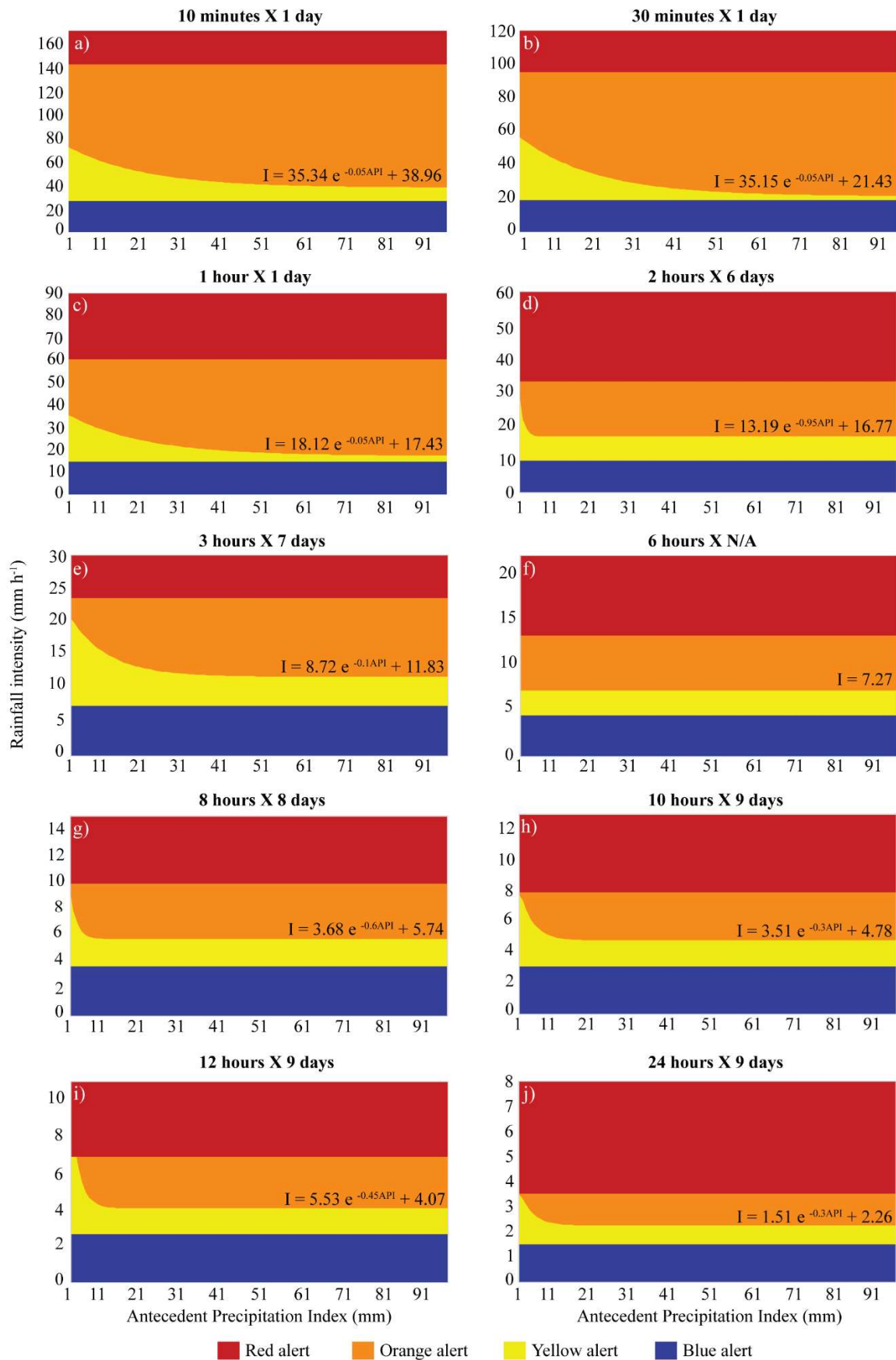


Figure 9 – Peak rainfall intensity versus Antecedent Precipitation Index (API) graphs for each time-step and delimitation of the exponential curves for warning level systems applied for floods.

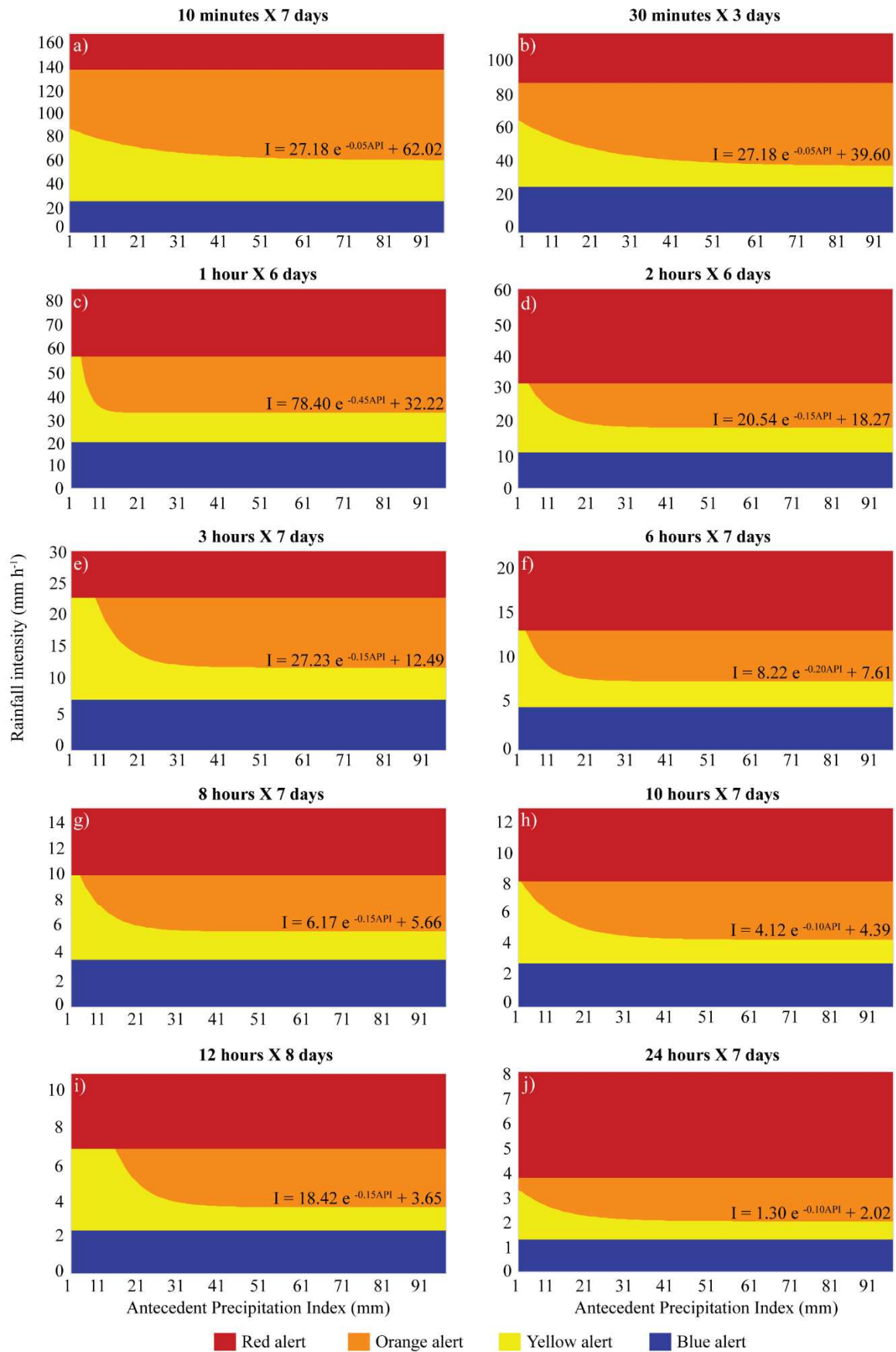


Figure 10 – Peak rainfall intensity versus Antecedent Precipitation Index (API) graphs for each time-step and delimitation of the exponential curves for warning level systems applied for flash floods.

Overall, the curves generated by the exponential equations well-characterise the intermediate threshold, where the occurrences and non-occurrences can be obtained correlating rainfall intensity and API. The proposed methodology better includes the occurrences and excludes the non-occurrences for rainfall events with higher and lower values of API, respectively. Moreover, adoption of the exponential curves can help regions with a moderate probability of occurrences (yellow alert) based on limit values of API, regardless of the rainfall intensity (e.g., peak intensities of 1 to 8 hours for flash floods in Figure 10). Also, the exponential curves can determine a region capable of triggering occurrences with low values of API and intensity (e.g., peak intensity of 2 hours for flood in Figure 9).

The application of this approach for floods and flash floods, using an exponential equation for better separating the occurrences from the non-occurrences, presented considerably improved results for almost all analysed metrics and nearly all time-steps considered (Table 5). The most representative result for floods was observed for longer time-steps, especially for 8 h. Specifically for this time step of 8 h, the POD, FAR and PPV metrics presented values equal to 81%, 1% and 82%, respectively. Meanwhile, the time steps ranging from 1 h to 12 h presented similar results for flash floods, highlighting the time steps equal to 2 (POD = 79%, FAR = 1%, and PPV = 43%) and 6 h (POD = 79%, FAR = 1%, and PPV = 44%) which presented the best metrics. Indeed, the use of methodologies considering the API to delineate thresholds has proven to be an outstanding instrument for flood and flash flood hazard predictions and warning systems.

Table 5 – Summary of evaluation metrics for flood and flash flood occurrences applying the improved thresholds that use rainfall intensities and Antecedent Precipitation Index (API).

Intensities (h) X API (day)	Floods			Intensities (h) X API (day)	Flash Floods		
	Metrics				Metrics		
	POD	FAR	PPV		POD	FAR	PPV
1/6 x 1	77%	6%	30%	1/6 x 7	85%	3%	21%
1/2 x 1	75%	4%	41%	1/2 x 3	82%	1%	33%
1 x 1	78%	3%	48%	1 x 6	79%	1%	40%
2 x 6	83%	3%	51%	2 x 6	79%	1%	43%
3 x 7	82%	2%	57%	3 x 7	80%	1%	39%
6 x N/A	83%	2%	61%	6 x 7	79%	1%	44%
8 x 8	81%	1%	82%	8 x 7	79%	1%	41%
10 x 9	80%	1%	66%	10 x 7	80%	1%	39%
12 x 9	79%	1%	66%	12 x 8	82%	1%	39%
24 x 9	78%	1%	66%	24 x 7	85%	1%	37%

5 CHARACTERIZATION OF EXTREME EVENTS AND DELINEATION OF RAINFALL THRESHOLDS BY SATELLITE-BASED PRECIPITATION PRODUCTS

During the last decades, several studies have assessed the accuracy of one or a set of satellite-based rainfall data at various spatial and temporal scales, most of which using independent gauge or radar observations (Tan and Duan 2017; Gadelha et al. 2018; Wang et al. 2018; Beck et al. 2019a). Some of these studies evaluated the performance of the satellite-based rainfall products regionally or globally for hydrological applications, such as water resources management (Ranghetti et al. 2018; Sheffield et al. 2018), groundwater storage and depletion (Vasco et al. 2019; Singh and Saravanan 2020), hazard monitoring (Pandey and Srivastava 2019; Parker et al. 2021), and stream flow modelling (Su et al. 2019; Kha et al. 2020). However, applications of satellite-based rainfall data for hydrological disasters warning purposes through the use of empirical methods have been scarce, mainly, because: 1) the bias in near real-time rainfall estimates, 2) the latency of products, and 3) insufficient spatial and temporal resolutions (AghaKouchak et al. 2015; Brocca et al. 2017). Based on a literature review, we identified that only a few studies evaluated the capability of the satellite gridded rainfall datasets in detect landslide events with the use of empirical rainfall thresholds (e.g., Nanda Pratama et al. 2017; Brunetti et al. 2018, 2021; Monsieus et al. 2019; Chikalamo et al. 2020; He et al. 2020), with no similar analysis for flood events, especially over large areas. A study carried out by Brunetti et al. (2018), for instance, showed that the four analysed precipitation satellite-based products were able to identify landslides occurrences in Italy by adjusting the rainfall thresholds, but with less accuracy than ground-based rainfall observations. More recently, a study performed by Brunetti et al. (2021) in India, also using empirical rainfall thresholds derived from the analysis of historical landslide events, found that the two analysed satellite-based rainfall products outperformed the ground observations thanks to their better spatial and temporal resolutions.

Clearly, satellite-based data are an important data source for improving the spatial representativeness of rainfall-threshold approaches and, consequently, providing tools to create more robust warning systems for flood occurrences, especially in many parts of the world with low-density sub-daily rain gauge networks. Therefore, we commissioned this study to addresses the following scientific questions: (a) How do the currently available rainfall satellite-based products perform for flood events detection? (b) Which satellite-based product performs better in defining empirical rainfall-threshold methods for floods?

The main aims of this study are: (i) to assess the quality of satellite-based precipitation products for identifying extreme rainfall events able to produce flood events, and (ii) to evaluate the use of satellite-based precipitation products to create rainfall thresholds for flood hazards. To achieve the proposed objectives, we used detailed information on flood occurrences available for the São Paulo State in Brazil for a period of five years (2015-2019). In addition, we used ground-based sub-daily rainfall dataset obtained from a network of around 730 rain gauges and 14 satellite-based precipitation products with different temporal and spatial resolutions. This study is intended then to provide a valuable tool for flood warning systems using satellite-based rainfall products in tropical regions.

5.1 Materials and methods

5.1.1 Satellite-based rainfall products

The performance of the 14 (sub-) daily satellite-based rainfall products were evaluated in this study based on a point-to-cell analysis comparison between these estimated datasets and the rain gauges. Table 6 provides an objective-focused tabular information of all estimated rainfall datasets considered in this evaluation. All analysed products are global or quasi-global, with data available to cover the entire study period, except the GPM+SM2RAIN that provides rainfall data only until 2018. The spatial resolution of the evaluated rainfall products ranges from 0.04° to 0.5°, while the temporal resolution varies between 30-min and daily. Among the 14 rainfall products, eight of them are fully based on satellite data (hereafter referred to as the uncorrected products, which includes CHIRP V2.0, IMERG E, IMERG-L, PDIR-Now, PERSIANN, PERSIANN-CCS, SM2RAIN-ASCAT V1.2, and GPM+SM2RAIN) and six products combine gauge and satellite data (hereafter corrected products, which includes CMORPH-CRT V1.0, IMERG F, PERSIANN-CDR V1R1, CHIRPS V2.0, MERRA-2, and MSWEP V2.2). Some of them also use (re)analysis data to generate the products (e.g., CHIRP V2.0, CHIRPS V2.0, MERRA-2, and MSWEP V2.2). A rainfall depth threshold of 0.1 mm day⁻¹ was established to define rain/no-rain and to exclude daily events deemed insignificant, following Li and Liu (2020).

Table 6. Summary of 14 precipitation estimates products evaluated in this study, similar to as presented by Beck et al. (2019).

Name	Description	Spatial resolution	Spatial Coverage	Temporal Resolution	Temporal Coverage	Reference
CHIRP V2.0	Climate Hazards group InfraRed Precipitation (CHIRP) V2.0	0.05°	50°S	Daily	1981- present	Funk et al. 2015
CHIRPS V2.0	Climate Hazards group InfraRed Precipitation with Stations (CHIRPS) V2.0	0.05°	50° N/S	Daily	1981- present	Funk et al. 2015
CMORPH-CRT V1.0	CPC MORPHing technique (CMORPH) bias corrected (CRT) V1.0	0.07°	60° N/S	30 min	1998-2019	Joyce et al. 2004; Xie et al. 2017
PDIR-Now	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks - Dynamic Infrared Rain Rate near real-time (PDIR-Now)	0.04°	60° N/S	Hourly	2000- present	Nguyen et al. 2020
IMERG-E V06	Integrated Multi-satellitE Retrievals for GPM (IMERG) early run V06	0.1°	60° N/S	30 min	2000- present	Huffman et al. 2019
IMERG-L V06	Integrated Multi-satellitE Retrievals for GPM (IMERG) late run V06	0.1°	60° N/S	30 min	2000- present	Huffman et al. 2019
IMERG-F V06	Integrated Multi-satellitE Retrievals for GPM (IMERG) final run V06	0.1°	60° N/S	30 min	2000- present	Huffman et al. 2019
MERRA-2	Modern-Era Retrospective Analysis for Research and Applications 2	~0.5°	Global	Hourly	1980- present	Gelaro et al. 2017
MSWEP V2.2	Multi-Source Weighted-Ensemble Precipitation (MSWEP) V2.2	0.1°	Global	3-hourly	1979- present	Beck et al. 2017a, 2019b
PERSIANN	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN)	0.25°	60° N/S	Hourly	2000- present	Sorooshian et al. 2000
PERSIANN-CCS	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) Cloud Classification System (CCS)	0.04°	60° N/S	Hourly	2003-Present	Hong et al. 2004
PERSIANN-CDR V1R1	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) Climate Data Record (CDR) V1R1	0.25°	60° N/S	Daily	1983- present	Ashouri et al. 2015
SM2RAIN-ASCAT V1.2	Precipitation Estimation from the application of the SM2Rain algorithm to the ASCAT soil moisture data	12.5km	Global	Daily	2007-2019	Brocca et al. 2019
GPM+SM2RAIN	Integration of IMERG-E with SM2RAIN-based rainfall estimates derived from three different satellite Soil Moisture products	0.25°	60° N/S	Daily	2007-2018	Massari et al. 2020

5.1.2 Flood dataset

Detailed and accurate information of floods that occurred between January 2015 to December 2019 in the São Paulo State was obtained from the following four sources: (1) The Integrated Storm Monitoring, Forecasting and Alerting System for the Brazilian South-Southeast Regions (SIMPAT); (2) the Brazilian National Centre for Monitoring Early Warning of Natural Disasters (CEMADEN); (3) The Civil Defence of São Paulo State; and (4) press news. The survey encloses detailed information of the disaster classification, location (address or coordinate), day of occurrence, besides, when possible, the number of deaths and affected people, and references in the press. Only georeferenced occurrences (e.g., via address and coordinates) confirmed in at least two of the above-mentioned sources of data were selected for this study. Moreover, the occurrences with (1) daily rainfall less than 10 mm registered near to the flood events or (2) the nearest rain gauge located more than 20 km from the flood events were excluded for further analyses. We identified 762 occurrences of floods in the São Paulo State during the studied period. After the restrictions mentioned above, a total of 551 occurrences of floods were used for the further analyses. The mean distance between the occurrences and the nearest rain gauge was ~ 7 km. Most of the 211 flood events were excluded for the analyses because the lack of rain gauges distant less than 20 km from the occurrences. This exclusion is a consequence of the uneven distribution of rain gauges over the region, which are more concentrated in larger cities.

5.1.3 Observed rainfall dataset

This study began by considering ground-based sub-daily rainfall data from 730 automated rain gauges operated by CEMADEN over the period between January 2015 and December 2019. CEMADEN has a national-wide ground-based rainfall network consisting of tipping bucket gauges with a 10-min temporal resolution when it rains and 60-min over no-rain periods. The observed rainfall data used in this study underwent the same quality control measure as that used by Freitas et al. (2020) to detect possible rain gauge inconsistencies and selecting only high-quality data. Therefore, only those rain gauges with less than 30 days of missing data along each civil year were considered in this study. Moreover, the gauges that met this criterion were visually inspected as follows: 1) comparing the monthly and sub-daily rainfall data with the five nearest stations to verify large discrepancies between them; and 2) analysing the range of values and changes over subsequent measurements of each rain gauge to identify constant or null rainfall records that

probably indicate gauge clogging. After the quality control procedure adopted in this study, a total of 583 gauges were selected to define the rainfall events and calculate its respective rainfall thresholds.

5.1.4 Rainfall events and threshold definition

The delineation of the thresholds was based on an empirical model that evaluates the amounts of precipitation that may or may not lead to flooding events through the analyses of the exceedance or not of a certain threshold. Six aggregation periods (3 h, 6 h, 12 h, 1 d, 3 d, and 10 d) were considered to determine the accumulated precipitation. For the sub-daily aggregations, we considered the maximum moving sum of the accumulated precipitation. The daily precipitation was classified according CEMADEN in light rain (< 10 mm), moderate rain (≥ 10 mm and < 30 mm), heavy rain (≥ 30 mm and < 70 mm), and severe (≥ 70 mm).

The rainfall thresholds were determined for the observed data and each satellite-based rainfall product separately by applying the adapted empirical methodology used by Diakakis (2012) and Papagiannaki et al. (2015). Specifically, in this study we used the accumulated rainfall-duration thresholds for detecting the occurrence of floods, i.e., by plotting the cumulated rainfall of various time intervals against their respective durations. An analysis of the graph based on the following three criteria was performed to define the time interval of the cumulated rainfall that better represents the flood events: (1) the higher number of occurrences above the threshold, (2) the higher amount of non-occurrence below the threshold, and (3) the values of the metrics presented in the next section of this manuscript. Multiple rainfall-duration thresholds were defined from the application of 5%, 10%, 20%, 30%, 40%, and 50% non-exceedance probability aiming to reduce the uncertainties of false alarms.

5.1.5 Comparison and evaluation procedures

The first evaluation step was to apply the Kling-Gupta Efficiency (KGE) scores to assess the performance of the satellite-based rainfall products in characterising the rainfall events that trigger are able to floods. KGE is an objective performance metric combining correlation (CC, represented by the Pearson's correlation coefficient), BIAS (represented by

the ratio of estimated and observed means), and variability (VAR, represented by the ratio of the estimated and observed coefficients of variation):

$$KGE = 1 - \sqrt{(CC - 1)^2 + (BIAS - 1)^2 + (VAR - 1)^2} \quad (6)$$

$$BIAS = \frac{\mu_e}{\mu_o} \quad (7)$$

$$CC = \frac{\sum_{i=1}^n (O_i - \bar{O}) (E_i - \bar{E})}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2} \cdot \sqrt{\sum_{i=1}^n (E_i - \bar{E})^2}} \quad (8)$$

$$VAR = \frac{CV_e}{CV_o} = \frac{\sigma_e/\mu_e}{\sigma_o/\mu_o} \quad (9)$$

where O is the value observed by the rain gauges, $\bar{O}$ is the mean observed values, E is the value estimated by satellite-based products, $\bar{E}$ is the mean estimated values, μ is the distribution mean and σ is the standard deviation. The subscripts e and o correspond the estimated and observed data, respectively. KGE values range from $-\infty$ to 1, with desirable values close to 1.

A second evaluation step was to verify the performance of the rainfall threshold determined by each rainfall products to identify true or false alarms using a binary classifier of the rainfall conditions that do or do not lead to floods occurrences. The same contingency matrix applied in the section 4.2.3, consisting of four components, was used for each threshold, including: 1) true positive (TP), when the threshold is exceeded and the flood occurs; 2) false negative (FN), when the threshold is not exceeded and the flood occurs; 3) false positive (FP), when the threshold is exceeded and the flood does not occur; and 4) true negative (TN), when the threshold is not exceeded and the flood does not occur. The following three metrics were then applied using the above-mentioned contingency matrix to assess the skill score of the floods thresholds: 1) probability of detection (POD), which measures the fraction of events that are correctly predicted by the satellite-based products; 2) false alarm ratio (FAR), which exhibits the fraction of events incorrectly detected by the satellite-based products; and 3) Hanssen-Kuiper (HK) skill score, which measures the applicability/quality to identify the usability and accuracy of the threshold:

$$POD = \frac{TP}{TP + FN} \quad (10)$$

$$FAR = \frac{FP}{FP + TN} \quad (11)$$

$$HK = POD - FAR \quad (12)$$

The values of these three metrics range from 0% to 100%. The perfect values for POD and HK are close to 100%, while the desirable values for FAR are close to 0%.

5.2 Results and discussion

5.2.1 Characterisation of rainfall events that triggers floods

Figure 11 presents the classifications of the daily rainfall considering the values registered by the rain gauges and the analysed products only for the days where floods events were registered. The results show that the ground-based data presented only heavy (45%) and severe (55%) rain records during the analysed period. Conversely, all satellite-based rainfall products presented light rain and moderate rain records ranging from 19% (CHIRPS V2.0) to 53% (SM2RAIN-ASCAT V1.2) and from 36% (MERRA-2) to 62% (GPM+SM2RAIN). This indicates an underestimation of the daily accumulated precipitation by all analysed products. Among the dataset able to detect daily heavy and severe rains when flood occurrences were registered, the following products stand out: 1) PDIR-Now, represented by 31% of heavy rain and 6% of severe rain; 2) CMORPH-CRT V1.0, characterised by 32% of heavy rain and 5% of severe rain; 3) PERSIANN-CCS, which presented 26% of heavy rain and 6% of severe rain; and 4) IMERG-F, showing 25% of heavy rain and 5% of severe rain.

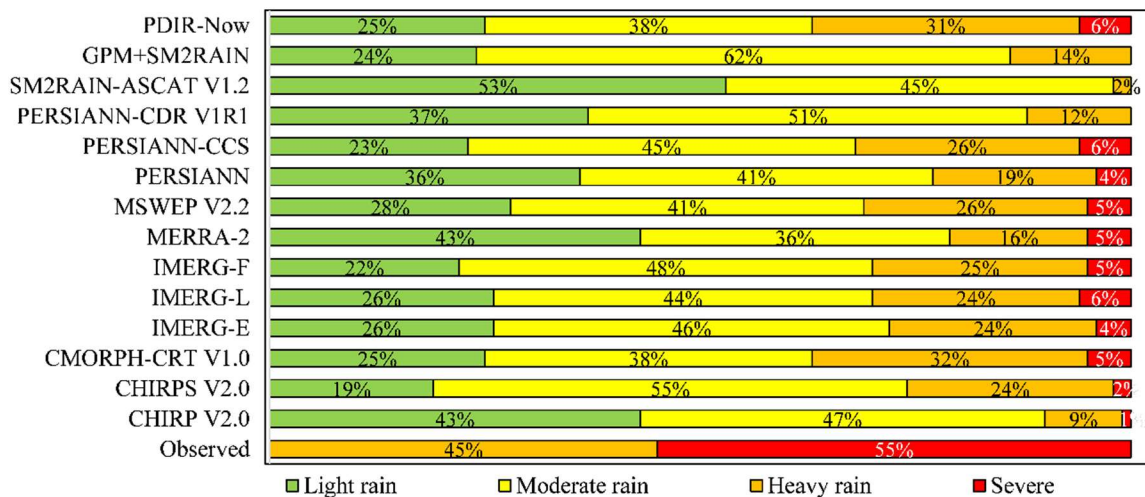


Figure 11. Daily precipitation classification that leads flood occurrences in São Paulo State

Satellite-based underestimations of these extreme precipitation events, when compared with the rain gauge observations, were also reported by others researchers previously for a variety of products (e.g., Mayor et al. 2017; Solakian et al. 2020; Xuan et al. 2020). Thus, it is important to analyse the performance of multiple precipitation products over the region of interest instead of relying on randomly chosen products (Masugana et al., 2019), because the performance of these products in capturing the spatiotemporal variability of extremes rainfall depends on season, regions, time period, and inexistence or scarcity of rain gauges to bias-correct products (Chen et al., 2020).

Figure 12 presents the mean KGE scores of the 14 satellite-based rainfall products considering the six accumulated rainfall periods. The results of the KGE show that all products presented negative mean scores for time steps ranging from 3 h to 1 day (-0.64 to -0.41, on average). The best and worst performances of the mean KGE scores for the sub-daily dataset, considering these first four aggregation periods (from 3 h to 1 day), were identified to be IMERG-F (i.e., -0.38) and MERRA-2 (i.e., -1.28) products, respectively. When only the daily datasets are considered, the best and worst performances of the daily mean KGE scores were observed as the GPM+SM2RAIN (i.e., -0.08) and PERSIANN-CDR V1R1 (i.e., -0.44) products, respectively. Overall, it is noticeable an improvement in the KGE values when longer rainfall accumulation times are considered. Null to positive mean KGE scores were observed for the time steps of 3 and 10 days (-0.02 to 0.18, on average). Variability was the main responsible for the poor performance for time steps varying between 3 hours and 1 day (2.12 to 1.87, on average), but the bias (0.25 – 0.27, on average) and CC (0.08 to 0.19, on average) also presented their worst results for such time steps. For longer time steps (3 days and 10 days), the variability presented results closer to ideal (1.45 – 1.18, on average), while the bias (0.39 – 0.57, on average) and CC (0.34 – 0.35, on average) remained furthest from the desirable values for all products.

Overall, the best values of the analysed metrics were found for all products when the rainfall was accumulated over 10 days. Two gauge-based uncorrected products (PDIR-Now and GPM+SM2RAIN) presented the highest values of KGE (i.e., 0.36) for the time step equal to 10 days. However, PDIR-Now presented the highest bias (i.e., 0.76), indicating that this product better represents the total precipitation compared to GPM+SM2RAIN (bias = 0.54). On the other hand, the data from GPM+SM2RAIN better linearly correlates with the observed data (CC = 0.55) when compared to the PDIR-Now product. The performance of these two above-mentioned uncorrected products was followed by the following corrected

products: CHIRPS V2.0 (KGE = 0.34), MSWEP V2.2 (KGE = 0.28), and IMERG-F (KGE = 0.27).

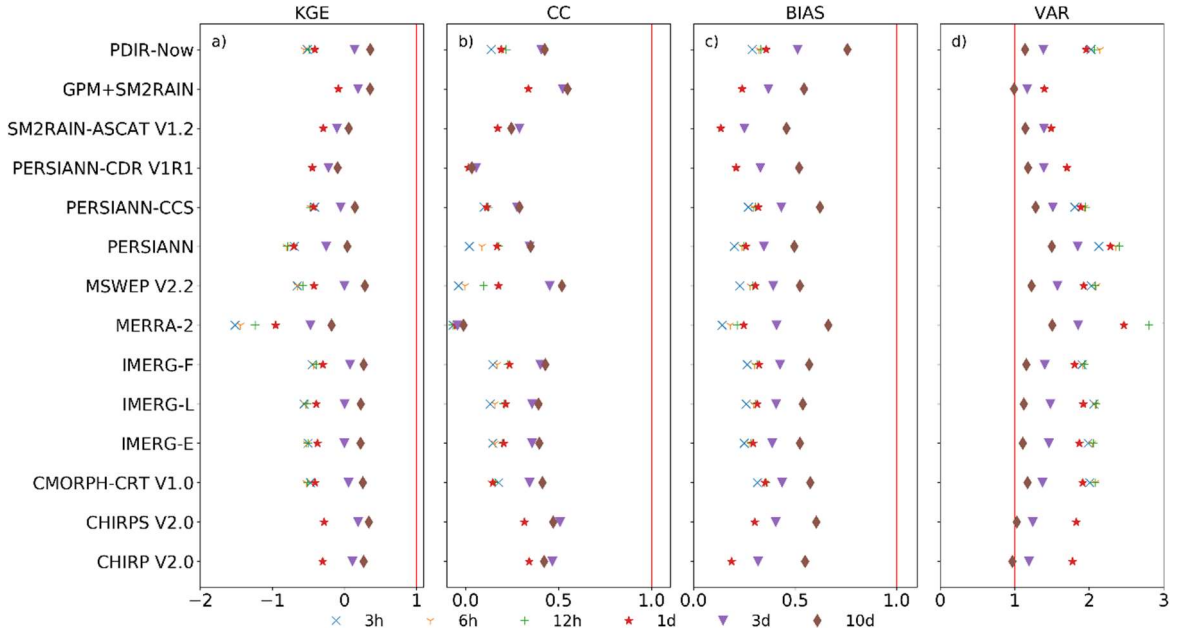


Figure 12. Graph showing the (a) KGE, (b) CC, (c) BIAS, and (d) VAR scores for the 14 satellite-based rainfall, considering only extreme precipitation events for time steps ranging from 3 hours to 10 days. The red lines represent the perfect values.

5.2.2 Overall analysis of the uncorrected dataset

Among the eight uncorrected satellite products (i.e., PERSIANN, PERSIANN-CCS, PDIR-Now, SM2RAIN-ASCAT, GPM+SM2RAIN, IMERG-E, IMERG-L, and CHIRP V2.0), the GPM+SM2RAIN product performed better for extreme precipitations when considering the daily time step onwards, with mean KGE value of 0.15, followed by PDIR-Now and CHIRP V2.0, with KGE values equal to 0.03 for both. PDIR-Now is a product, intended to replace the PERSIANN-CCS datasets, which considers the errors and uncertainties resulting from the use infrared images (Nguyen et al. 2020). Nevertheless, PERSIANN-CCS performed slightly better than PDIR-Now for sub-daily time steps, reversing the position for daily time steps onward. The PERSIANN product presented the lowest values of KGE among the uncorrected analysed products, ranging from -0.60 (3 hours) to 0.04 (10 days). All sub-daily uncorrected products presented extremely low values of KGE for time steps below 1 day, with means ranging from -0.76 (PERSIANN) to -0.45 (PERSIANN-CCS). Overall, the GPM+SM2RAIN product performed noticeably better than SM2RAIN-ASCAT V1.2 (mean KGE = -0.11), i.e., the other product that also uses satellite-based soil moisture data. The two microwave-based datasets (IMERG-E and IMERG-L)

showed similar results for all analysed time steps, with mean KGE values equal to -0.05 when considering daily onward time steps, i.e., slight worse than that observed for CHIRP V2.0 (KGE = 0.03).

5.2.3 Overall analysis of the corrected dataset

The products corrected by ground observations use daily, pentadal (5-day), decadal (10-day), and/or monthly precipitation data in their algorithms. Among the gauged corrected products, CHIRPS V2.0 presented the higher values of KGE for extreme precipitations, varying for daily time step onwards between -0.28 (1-day) and 0.34 (10-days). The performance of this product was followed by MSWEP V2.2 and IMERG-F, with KGE values ranging from -0.65 (3-hours) to 0.28 (10-days) and from -0.45 (3-hours) to 0.27 (10-days), respectively. The CMORPH-CRT V1.0 product presented similar performance than those observed for MSWEP V2.2 and IMERG-F, with KGE values varying between -0.47 (3-hours) and 0.26 (10-days). MERRA-2 and CMORPH-CRT V1.0 exhibited the lowest values of KGE among the products corrected by ground observations, with overall performances even worse than all those observed for the uncorrected products. The performance of these products may be affected by some factors in rain gauges, such as miscellaneous technical errors, different reporting times, different quality control procedures, network density, among others (Derin and Yilmaz 2014; Sun et al. 2018; Beck et al. 2019a; Shen et al. 2021).

5.2.4 Rainfall thresholds

5.2.4.1 Evaluation for different tolerance levels

Figure 13 shows the heatmaps with the main values of POD, FAR, and HK for the six considered tolerance levels. The values of POD are set by the adopted tolerance levels, with values varying between 0.95 and 0.50 for the no-exceedances probabilities of 5 and 50% for all satellite-based and the observed data, respectively (Figure 13a). On the other hand, the FAR values presented reductions as the tolerance levels increased, with the worst performance observed for CHIRPS V2.0, PERSIANN and PERSIANN-CDR V1R1 (FAR $\approx$ 0.75) adopting a tolerance level of 5% tolerance (Figure 13b). The rainfall products CMORPH-CRT V1.0, IMERG-F, and GPM+SM2RAIN exhibited the lower values of FAR (0.11) when a tolerance level of 50% was considered, i.e., like the observed data but with a

tolerance level of 5% only (FAR = 0.13). The product that performed better overall in the number of false alarms (IMERG-F) showed values varying between 0.50 (5%) and 0.11 (50%), i.e., much higher than those observed for the rain gauges, which ranged from 0.13 to 0.02, respectively.

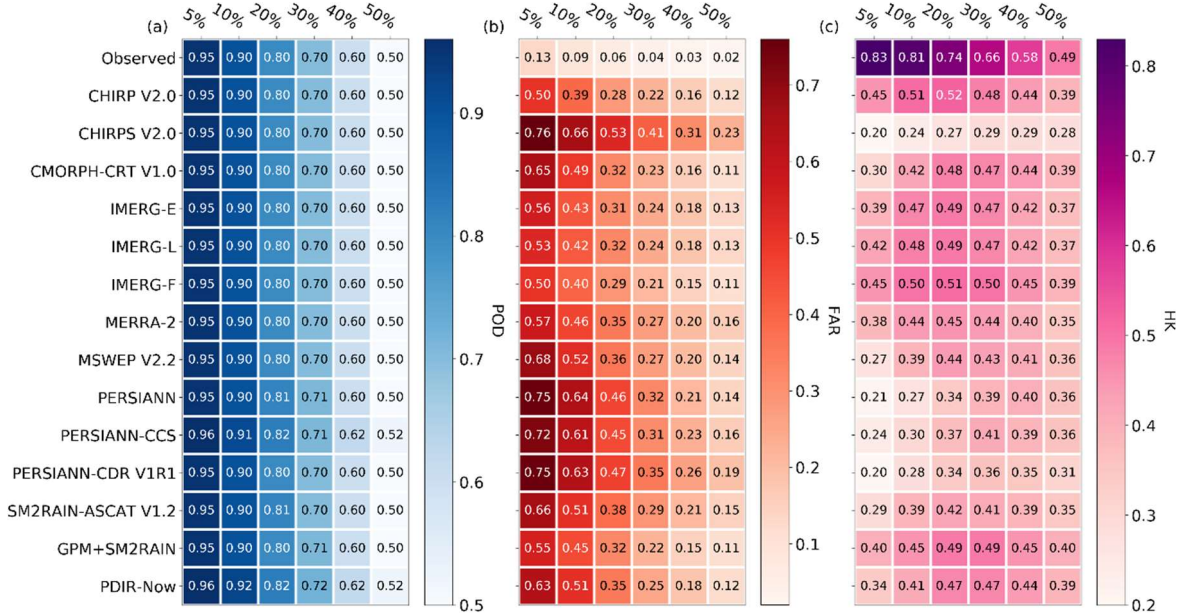


Figure 13. Heatmap of the mean values of (a) POD, (b) FAR, and (c) HK using different no-exceedance probability.

Overall, all analysed products showed similar patterns in of HK, with an increase in the values until a certain peak value, mostly between the application of tolerance levels of 10% and 30%, before a decline in the values of this metric for higher tolerance levels. The difference is that the CHIRPS V2.0, PERSIANN, PERSIAN-CCS, and PERSIAN-CDR V1R1 products exhibited peak values of HK for tolerance levels varying between 30% and 40%. The HK values indicate a better performance for the observed data utilising a tolerance level of 5% (HK = 0.83), followed by the CHIRP V2.0 and IMERG-F products, which presented HK values equal to 0.51 and 0.52, respectively, for tolerance levels of 20%. Although presenting the highest values of HK, these two mentioned products still exhibited a considerable rate of false alarms, around 28%. CHIRPS V2.0 and PERSIANN-CDR V1R1 also had the worst performance for this metric, as expected, with highest HK values equal to 0.29 and 0.36 for a tolerance level of 30%, respectively. The study carried by Brunetti et al. (2018), which analysed 4 satellite products for delimitation of landslide thresholds in Italy, showed that the SM2RAIN-ASCAT V1.2 product presented the highest values of HK equals

to 0.42 for exceedance limits between 20-25%, while the PERSIANN product performed worse, with HK value equals to 0.31 for a tolerance level of 25%. Jia et al (2019) also analysed 4 rainfall products for landslide thresholds on a global scale, including CMORPH, which better performed among the evaluated, presenting a HK value equals to 0.43 for a tolerance level of 22%. The same global scale study identified that PERSIANN presented the lowest values of HK among the analysed products, with the best result (HK = 0.14) found for a tolerance level equals to 9%.

5.2.4.2 Determination of rainfall thresholds

Figure 14 presents the six precipitation thresholds obtained from the tolerance limits of 5, 10, 20, 30, 40, and 50% for the observed data and all analysed precipitation products. It is possible to observe a considerable underestimation of the thresholds delineated by the satellite-based products compared to those elaborated by the observed data, with larger differences noticed for shorter time steps (3h–1d), which were smoothed for longer considered periods (3–10 days). For instance, the CHIRPS V2.0, GPM+SM2RAIN, and PDIR products presented, respectively, values for 10-days accumulated rainfalls equal to 54.6, 53.0, and 67.0 mm considering a tolerance level of 20%, which correspond, respectively, to biases of 0.6, 0.58, and 0.72 (Figure 15) when compared to the thresholds using the observed data (i.e., 91,8 mm). This behaviour was expected as it is difficult for the satellite-based rainfall products to capture the precipitation peaks, resulting in values with more spaced in time compared to those identified for the observed dataset. The worst performances of the satellite-based products for longer time steps (i.e., daily onwards) were verified for 3 days accumulated rainfall considering tolerance levels of 5%, with PERSIANN (2.71 mm) and MSWEP V2.2 (3.73 mm) presenting the largest differences to the observed data (42.6 mm), i.e., biases of 0.06 and 0.09, respectively. For shorter time-steps ranging from 3h to 1d, the worst results were found for tolerance levels of 5%, where almost all products presented bias values equal to or lower than below 0.1. An exception, considering a tolerance level of 5%, was observed for the CHIRPS products, with bias value equals to 0.17 for accumulated rainfall of 1 day (6.41 mm, i.e., still much lower than the 37 mm obtained with the observed data). The best results found for shorter time-steps were verified for 1-day accumulated rainfall considering tolerance levels of 50% tolerance level. For this combination of accumulated rainfall and tolerance level, for instance, the products CMORPH-CRT V1.0, IMERG-F V06, and PDIR presented values equal to 22.75, 20.17,

and 20.0 mm, while the observed data, for the same time-step and no-exceedance probability, exhibited a value of 73.5 mm. Overall, it is noticed in Figure 15 that the time steps presented greater relevance in the improvement of the bias values compared to the tolerance limits.

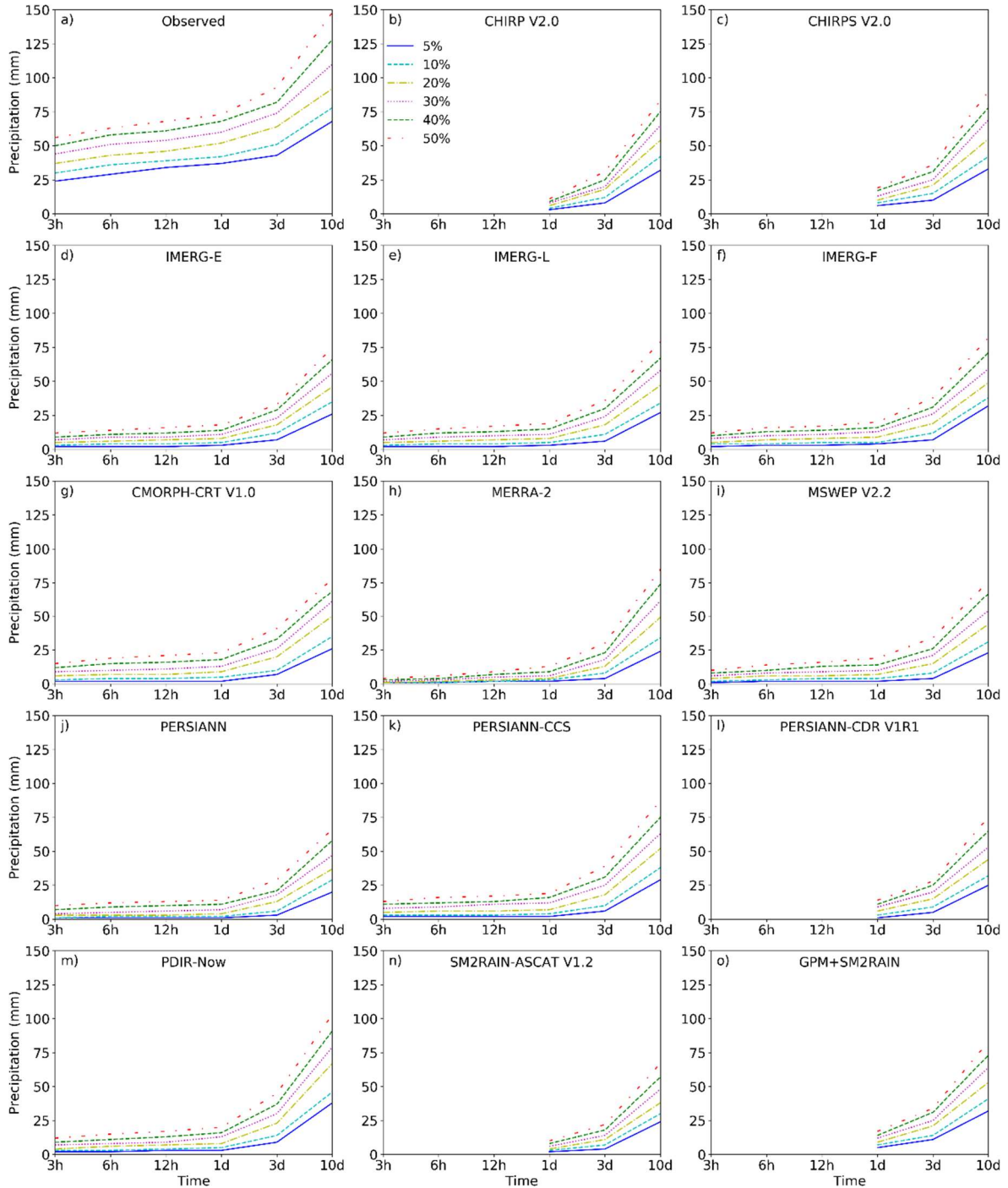


Figure 14. Accumulated precipitation versus duration applying the tolerance levels of 5, 10, 20, 30, 40, and 50% for the (a) rain gauges, (b) CHIRP V2.0, (c) CHIRPS V2.0, (d) IMERG-E V06, (e) IMERG-L V06, (f) IMERG-F V06, (g) CMORPH-CRT V01, (h) MERRA-2, (i) MSWEP V2.2, (j) PERSIANN, (k) PERSIANN-CCS, (l) PERSIANN-CDR V1R1, (m) PDIR-Now, (n) SM2RAIN-ASCAT V1.2, and (o) GPM+SM2RAIN.

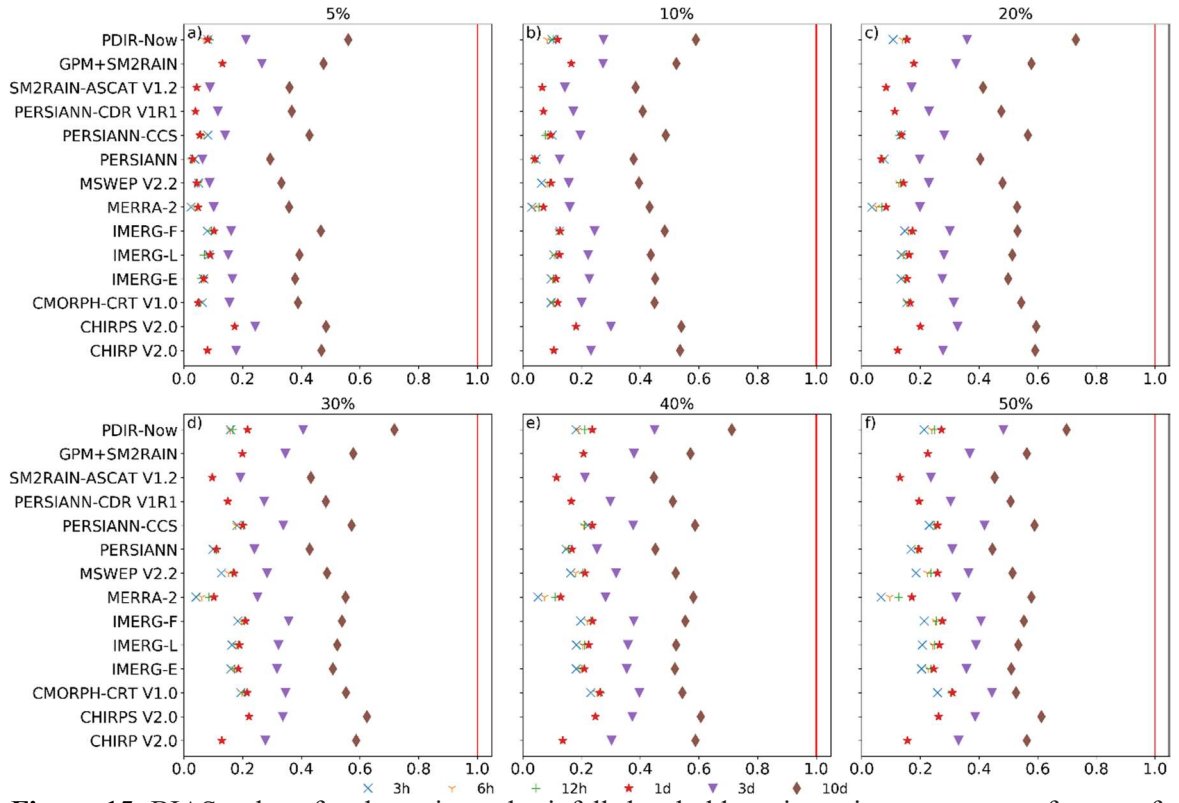


Figure 15. BIAS values for the estimated rainfall thresholds, using rain gauge as a reference, for tolerance levels of (a) 5, (b) 10, (c) 20, (d) 30, (e) 40, and (f) 50%. The red lines represent the perfect values.

6 CONCLUSIONS AND RECOMMENDATIONS

This thesis seeks to improve disaster monitoring and prediction, developing techniques and methods that will increase the effectiveness of warnings systems. The proposed methodology presented an evaluation of extreme precipitation events for the state of São Paulo, becoming a methodological contribution to monitor the occurrence of (flash) floods.

The first part of this thesis improved an existing peak rainfall intensity threshold method capable of better separating the occurrences from the non-occurrences of floods and flash floods. The improvement of this new approach included the use of two tolerance levels and the delineation of an intermediate threshold represented by an exponential curve relating rainfall intensity and API. The application of the tolerance levels proposed in this study presented noticeable improvements for the rainfall peak intensity thresholds, with substantial reduction of false alarms after the application of a tolerance level of 5% for the lower threshold. Meanwhile, the number of occurrences above the upper threshold increased by two times after the use of a tolerance level of the 99th percentile, improving the effectiveness of the issuance of warnings. The delineation of the intermediate threshold also presented improvements for almost all time-steps considered in this study, although the scores of the metrics showed a slightly worse performance for flash floods when compared to floods. This better performance noted for floods probably occurred because the higher amount of data available for this type of event when compared to those observed for flash floods. Additionally, the use of a denser rain gauge network, with stations closer to the flash flood occurrences than those used in this study, could be more effective in capturing this type of event.

It must be mentioned that a considerable amount of flood and flash flood information in São Paulo State could not be used in the first study because of the poor data quality of some rain gauges and/or the lack of rain gauge coverage at all. Thus, (sub)daily rainfall data from 14 different satellite-based products were evaluated to characterise rainfall events that trigger floods. The applicability of a methodology for determining precipitation thresholds using the satellite-based products was then also evaluated. The two main findings of the second study are summarised as follows:

(1) Overall, all analysed products tend to large underestimate the extreme rainfall events (i.e., when and where flood events were registered) observed by the rain gauges, mainly for sub-daily scales. This underestimation primarily occurred due to the difficulty of

the estimated products to capture precipitation peaks, as their values are more distributed over time with longer durations. The point-to-pixel analysis used in this study tended to contribute more to the underestimation of the observed peak intensity due to the representation of a spatial average of precipitation at the pixel scale. The best results evaluating the extreme rainfall events were expected for products corrected by ground-based rainfall stations, but they were found for the PDIR-Now and GPM+SM2RAIN products considering 10-days accumulated precipitation, followed by the corrected CHIRPS V2.0, MSWEP V2.2, and GPM IMERG-F, although the results (i.e., KGE values ranging from 0.36 to 0.27) indicate that all products are far from ideal ($KGE=1$).

(2) Large underestimations were also identified for the rainfall thresholds delineated by the satellite-based products. Despite the large underestimations, the delineation of rainfall thresholds using satellite-based products is possible but with lower precipitation values and a greater probability of false alarm occurrences. The observed rainfall data, considering tolerance limits of 5%, presented mean HK and bias values for daily rainfall data ~60 and 65%, respectively, higher than the two products that better delineated the rainfall thresholds (e.g., CHIRP V2.0 and IMERG-F) but considering tolerance levels of 20%.

Based on our findings, the rainfall satellite-based products dataset, even less accurate than the ground-based observations, can be applied, when multi-daily accumulated data are considered, as an alternative source of data for determining precipitation thresholds in some regions that presents low-density of rain gauges. PDIR-Now showed to be an interesting source of data to characterise flood events since this product provides near-real-time information, followed by the SM2RAIN products, which correct the satellite rainfall data without the use of ground-based information. For regions with a high-density of rain gauges with sub-daily data available, the use of ground-based data will still provide a much better source of information to characterise events that trigger floods.

The results found for this thesis can help in decision-making to consider new rain gauges networks expanding the existing ones, especially in areas susceptible to floods, and also in the development, and implementation of flood monitoring and warning systems. However, some limitations and recommendations for further work can be pointed out:

(1) The information inconsistency brings great limitations for carrying out more precise analyzes, so it is primordial the development of methods for analyzing the quality of information and the creation of an inventory of occurrences of floods properly characterized with the rainfall that triggered them. Concomitantly, it is recommended proper dissemination of this information through the development of systems that allows the community to access

the information in real-time, also including forecast rainfall, locations susceptible to flooding, and access to alerts issued by Civil Defense.

(2) The basic limitation is that rainfall thresholds inevitably just represent a simplification of the relationship between rainfall and flood occurrence, because there is more than one causative factor, such as urbanization rate, topography, land use, among others, that it can be accounted for uncertainties in the proposed method. Therefore, improvements of the rainfall thresholds methodology to reduce even more the uncertainties can be done by 1) analyzing more rainfall properties correlated with other variables (e.g., soil moisture); 2) using different approaches to characterize rainfall events (e.g., Minimum Inter-event Time); and 3) further analyzing the APIs (e.g., longer antecedent periods).

(3) A more local threshold can vary substantially and can have very different rainfall threshold. Therefore, the replication of the methodology subdividing the study area into several zones to be analyzed independently, to set up a specific threshold for each of them. As a consequence, a mosaic of several local rainfall thresholds is set up in place of a single regional threshold.

(4) Rain gauges provide only-single point measurements and have a far from ideal spatial distribution around the world, hence they poorly represent the spatial variability of precipitation, which has great relevance for floods events. As an alternative solution, it should be replicated the methodology with radar data, with the aim of a better representation of the areal rain, giving new insight to the study with more detailed observations of rainfall variations in a region.

(4) The use of new approaches (e.g., merging of products or improving the products algorithms) must be explored for the satellite-based products by using, for instance, machine learning techniques, to enable better identification and characterisation of extreme rainfall events over areas with low availability of in-situ sub-daily data and, consequently, improve the delineation of thresholds for monitoring flood hazards.

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APPENDIXES A

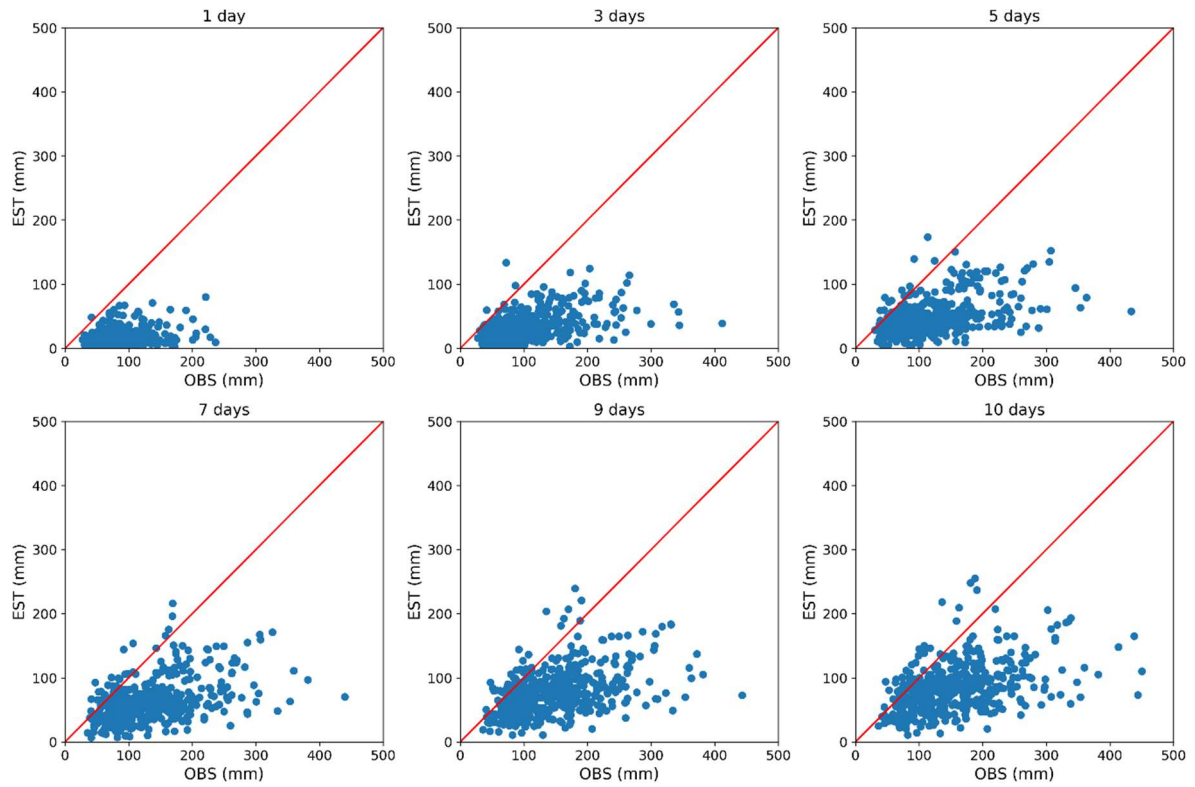


Figure 16 – Scatter plots of rainfall observed values (rain gauges) vs estimated values (CHIRP V2.0) that lead to floods at different timescales.

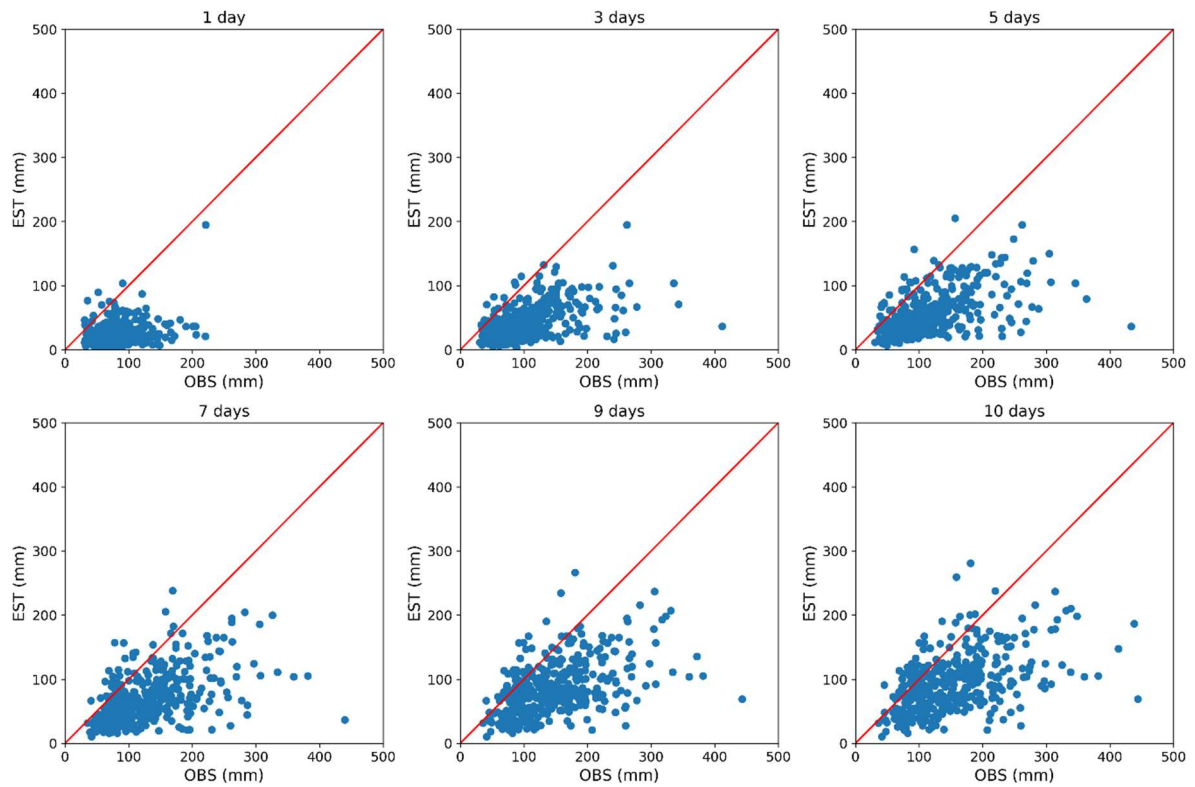


Figure 17 - Scatter plots of rainfall observed values (rain gauges) vs estimated values (CHIRPS V2.0) that lead to floods at different timescales.

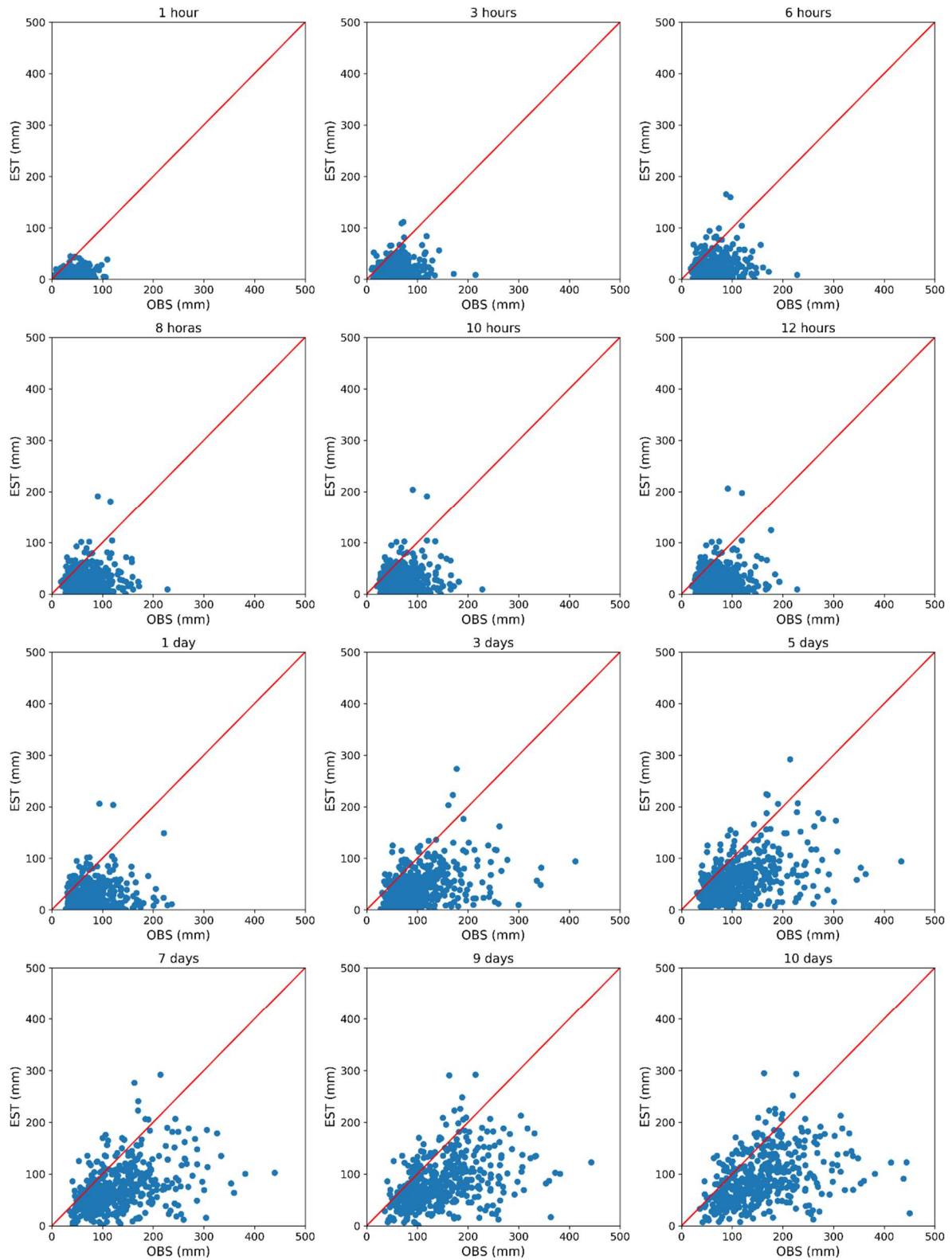


Figure 18 – Scatter plots of rainfall observed values (rain gauges) vs estimated values (CMORPH-CRT V1.0) that lead to floods at different timescales.

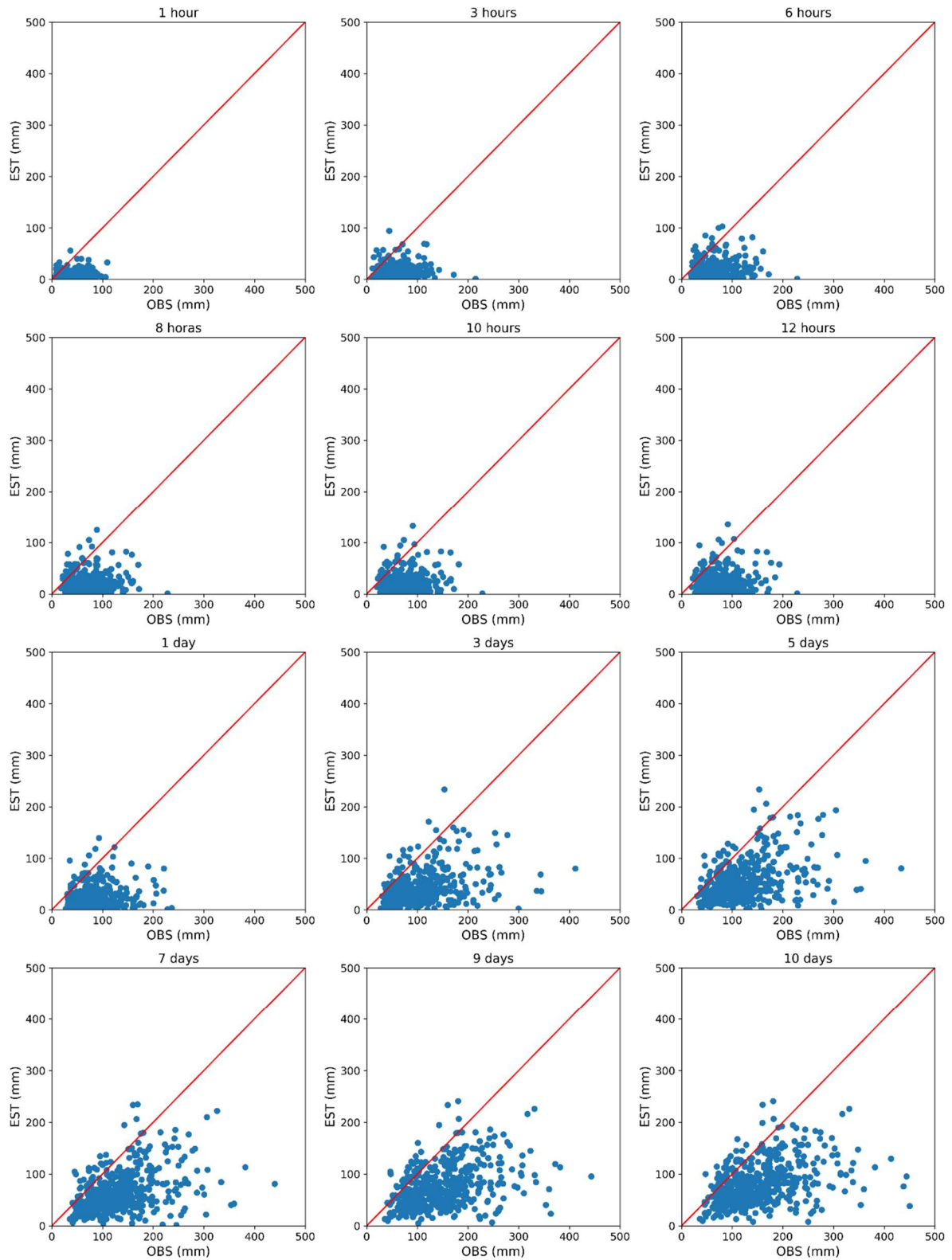


Figure 19 - Scatter plots of rainfall observed values (rain gauges) vs estimated values (IMERGHHE V06) that lead to floods at different timescales.

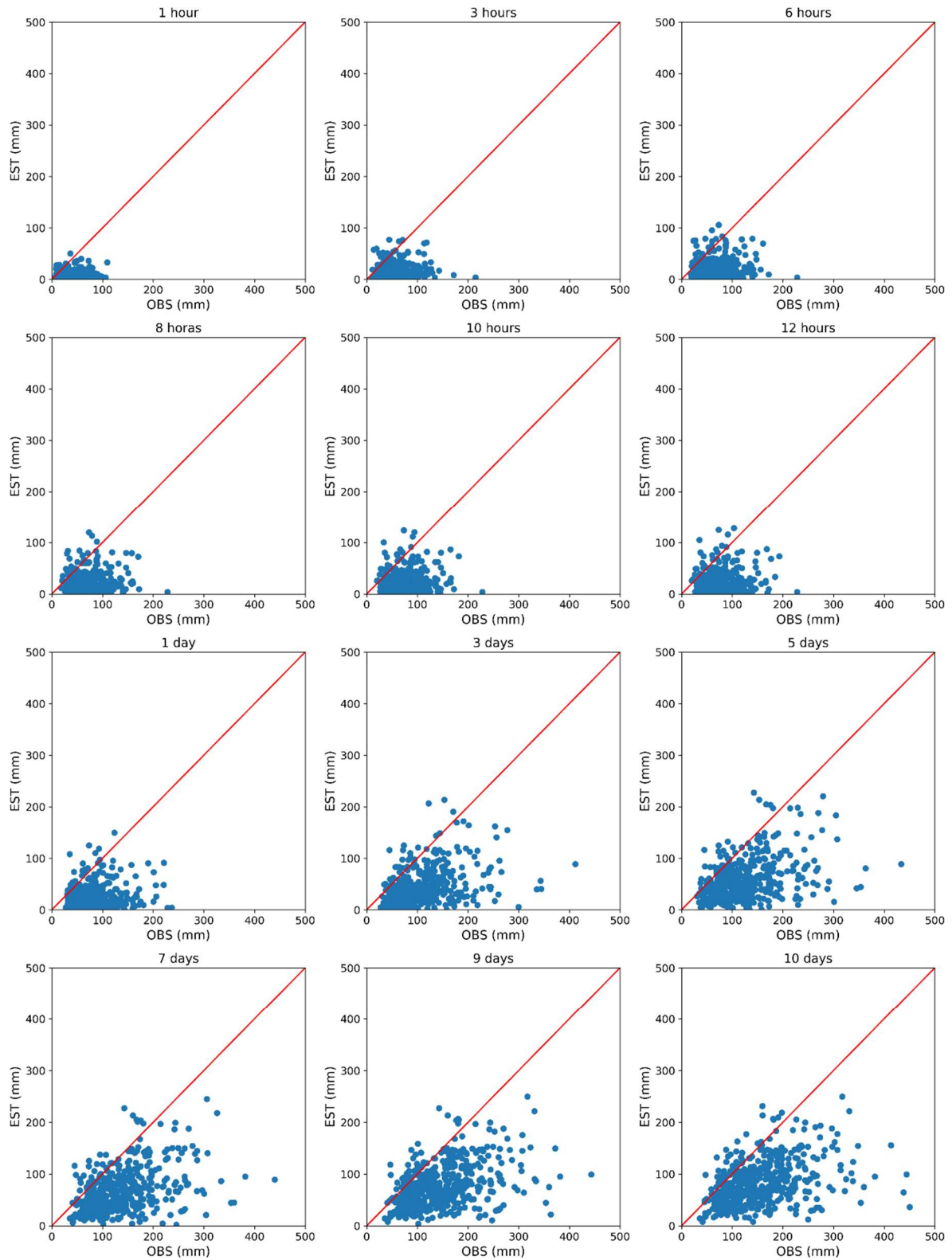


Figure 20 – Scatter plots of rainfall observed values (rain gauges) vs estimated values (IMERGHLL V06) that lead to floods at different timescales.

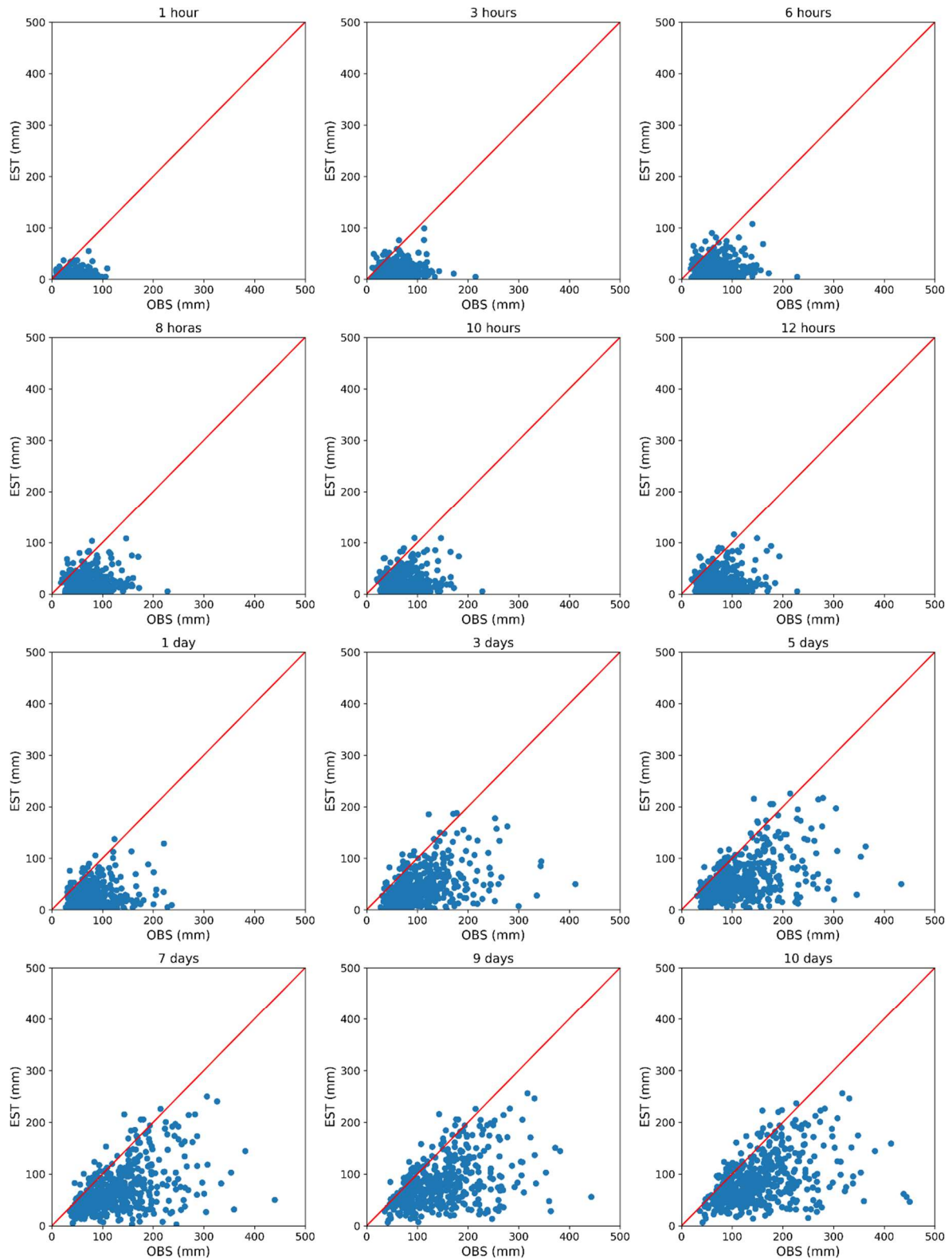


Figure 21 – Scatter plots of rainfall observed values (rain gauges) vs estimated values (IMERGHH V06) that lead to floods at different timescales.

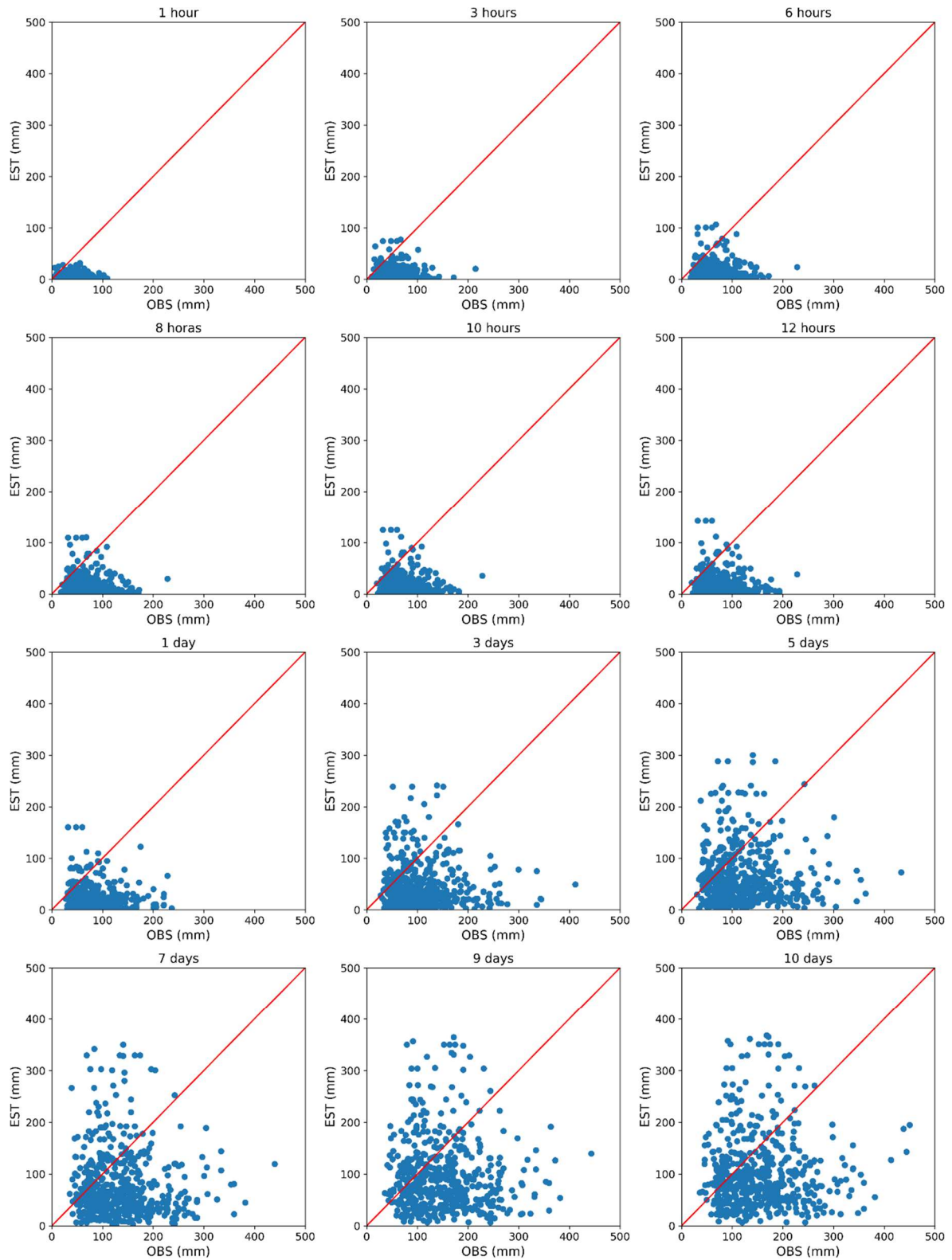


Figure 22 – Scatter plots of rainfall observed values (rain gauges) vs estimated values (MERRA-2) that lead to floods at different timescales.

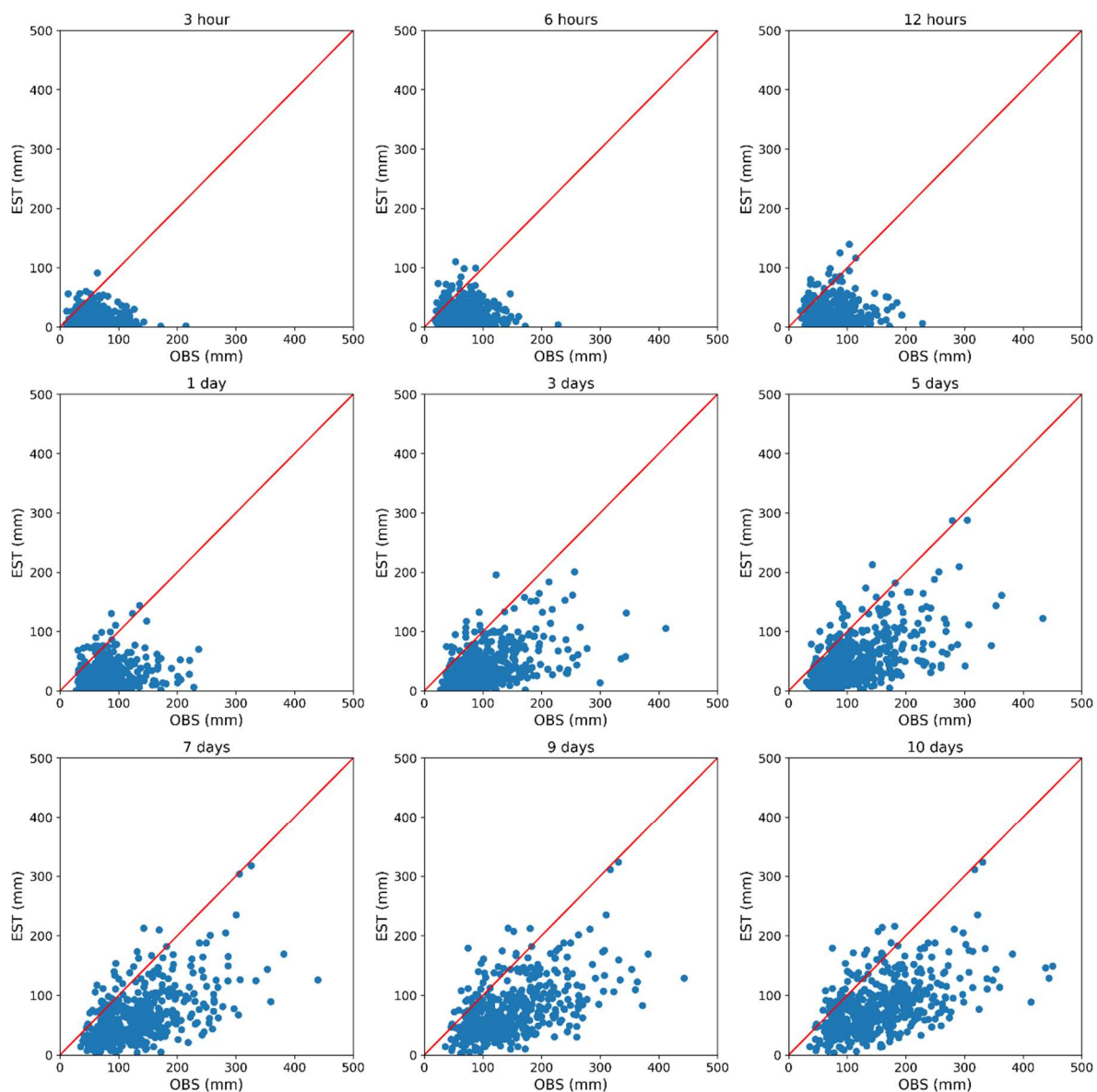


Figure 23 – Scatter plots of rainfall observed values (rain gauges) vs estimated values (MSWEP V2.2) that lead to floods at different timescales.

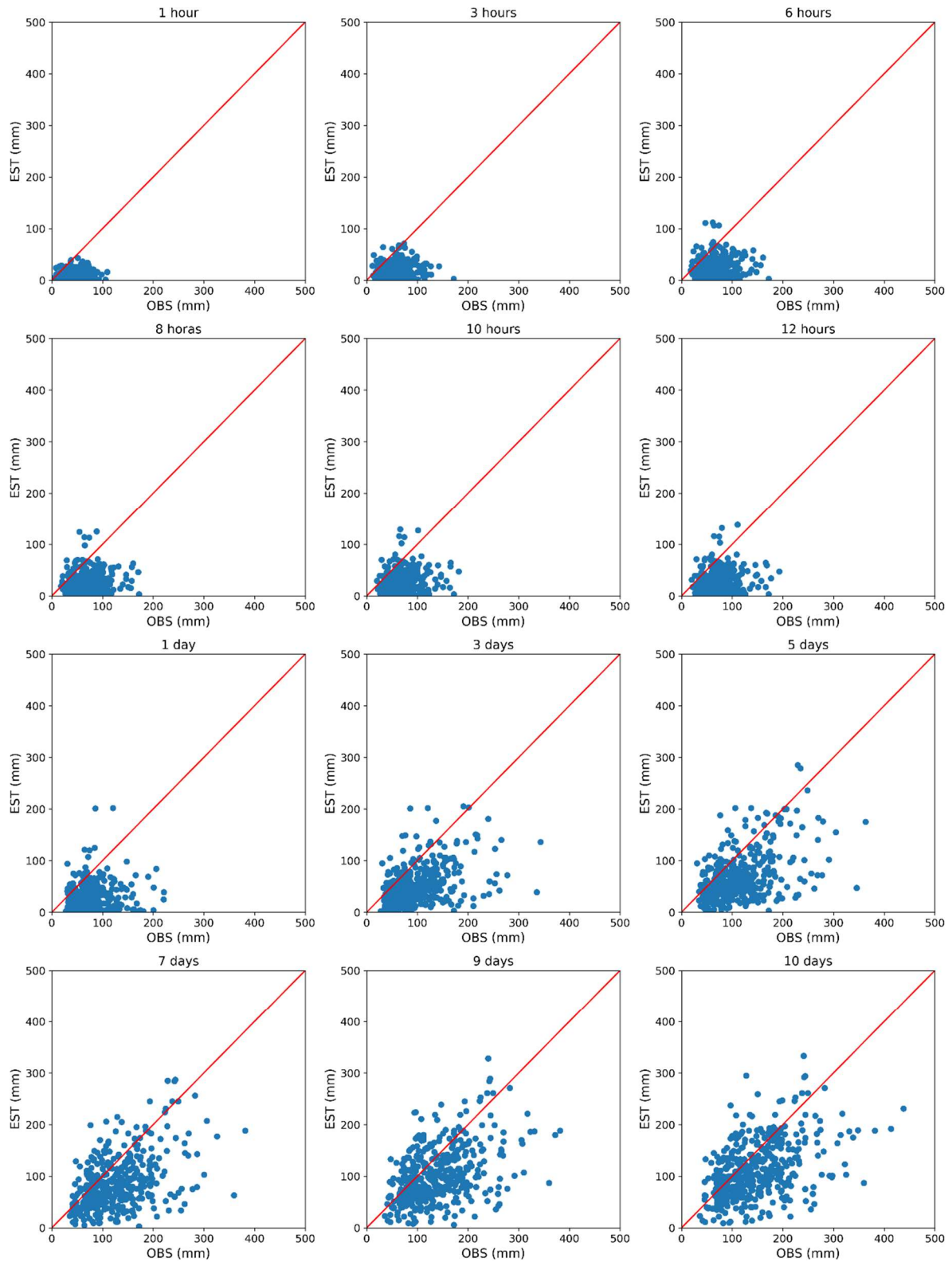


Figure 24 – Scatter plots of rainfall observed values (rain gauges) vs estimated values (PDIR-Now) that lead to floods at different timescales.

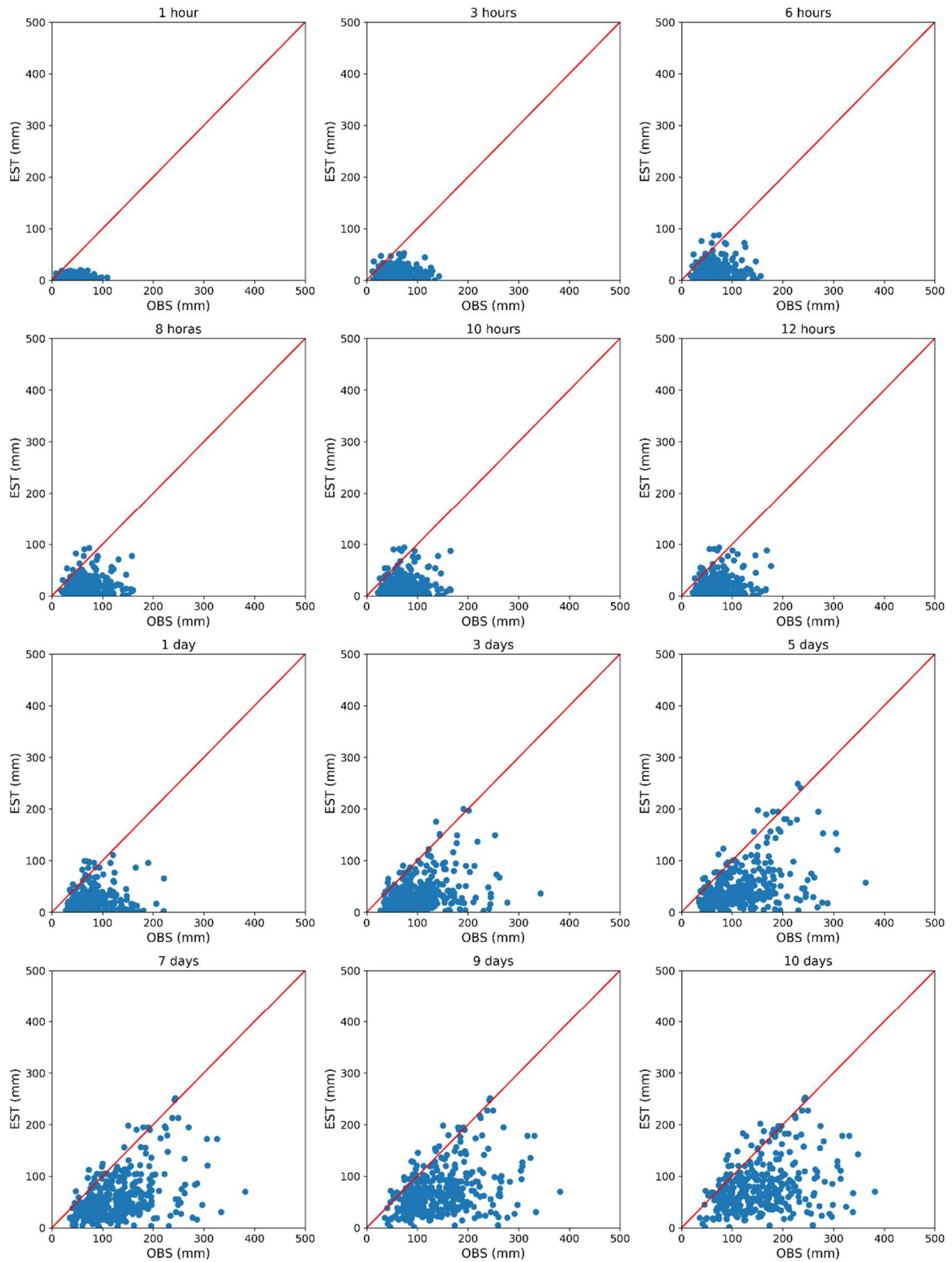


Figure 25 – Scatter plots of rainfall observed values (rain gauges) vs estimated values (PERSIANN) that lead to floods at different timescales.

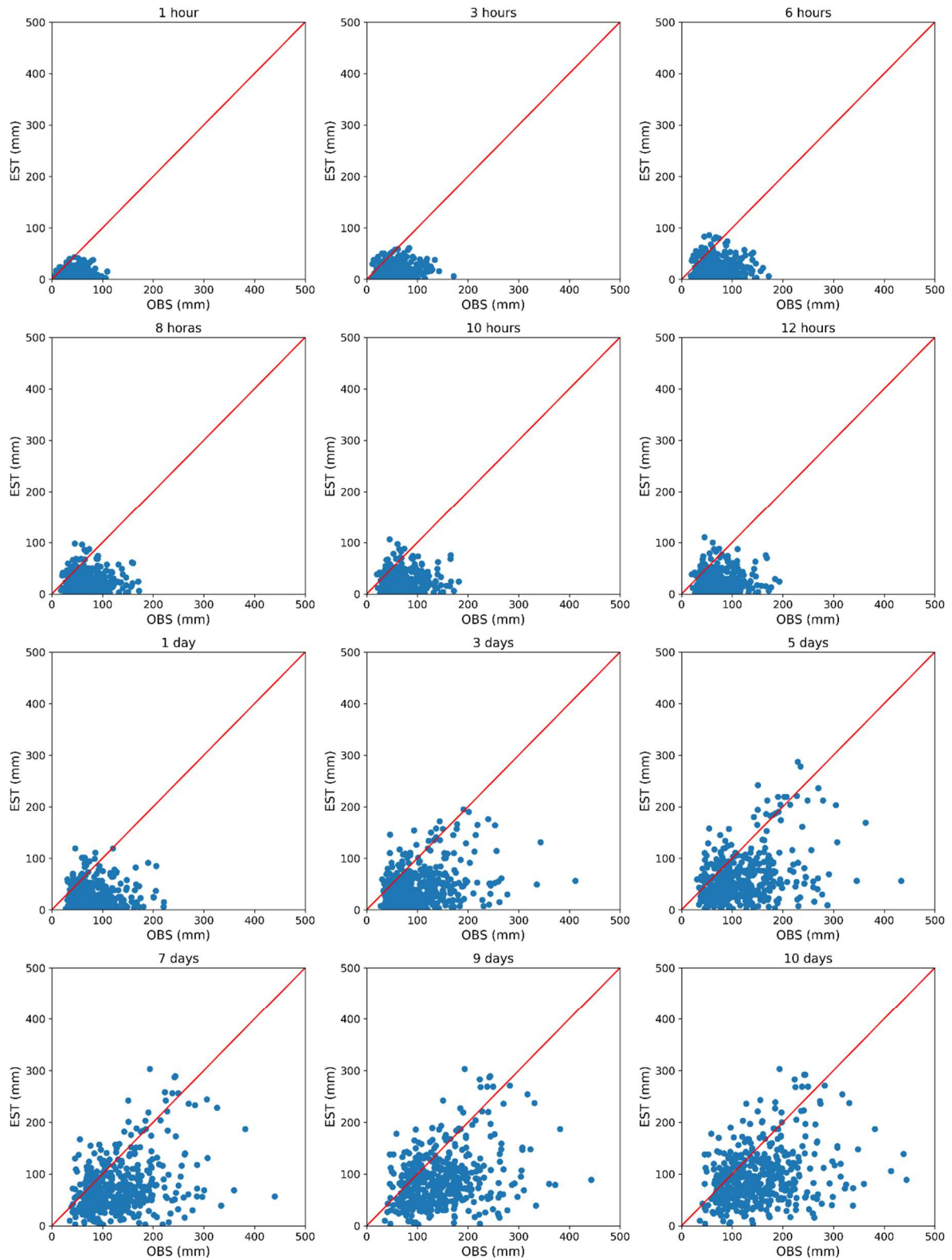


Figure 26 – Scatter plots of rainfall observed values (rain gauges) vs estimated values (PERSIANN-CCS) that lead to floods at different timescales.

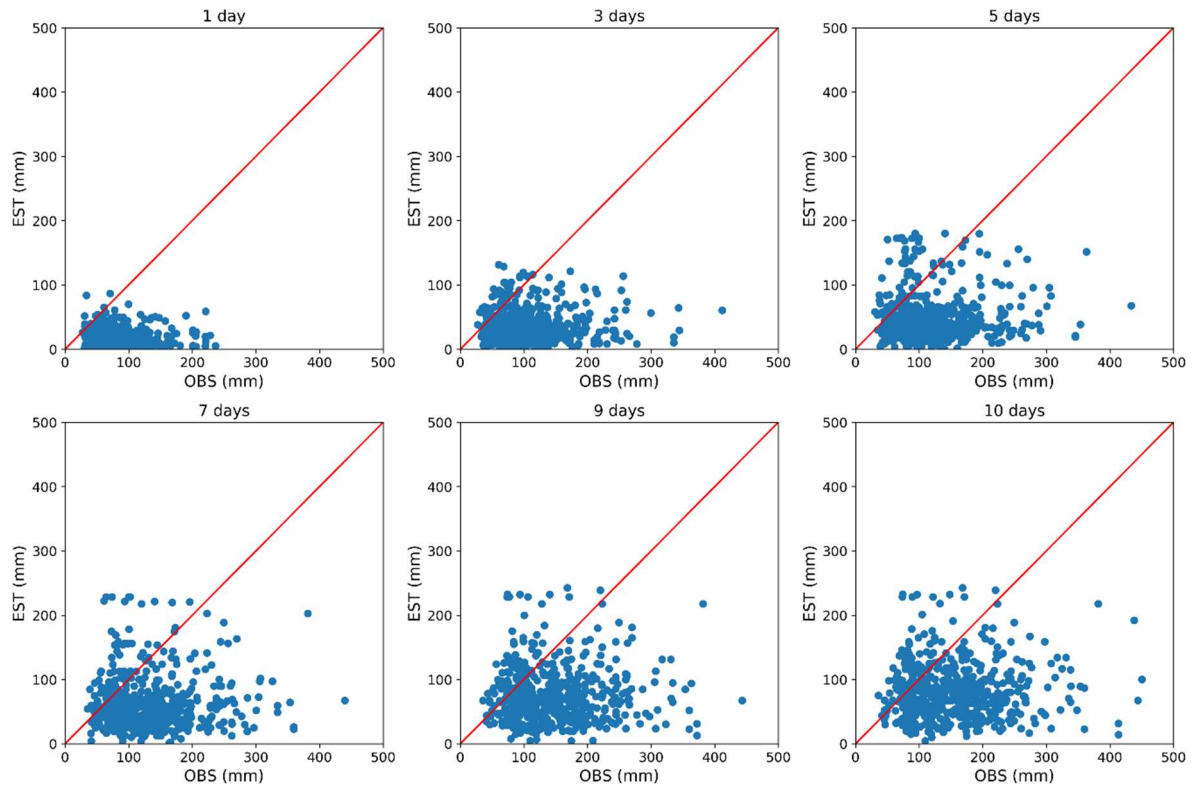


Figure 27 – Scatter plots of rainfall observed values (rain gauges) vs estimated values (PERSIANN-CDR V1R1) that lead to floods at different timescales.

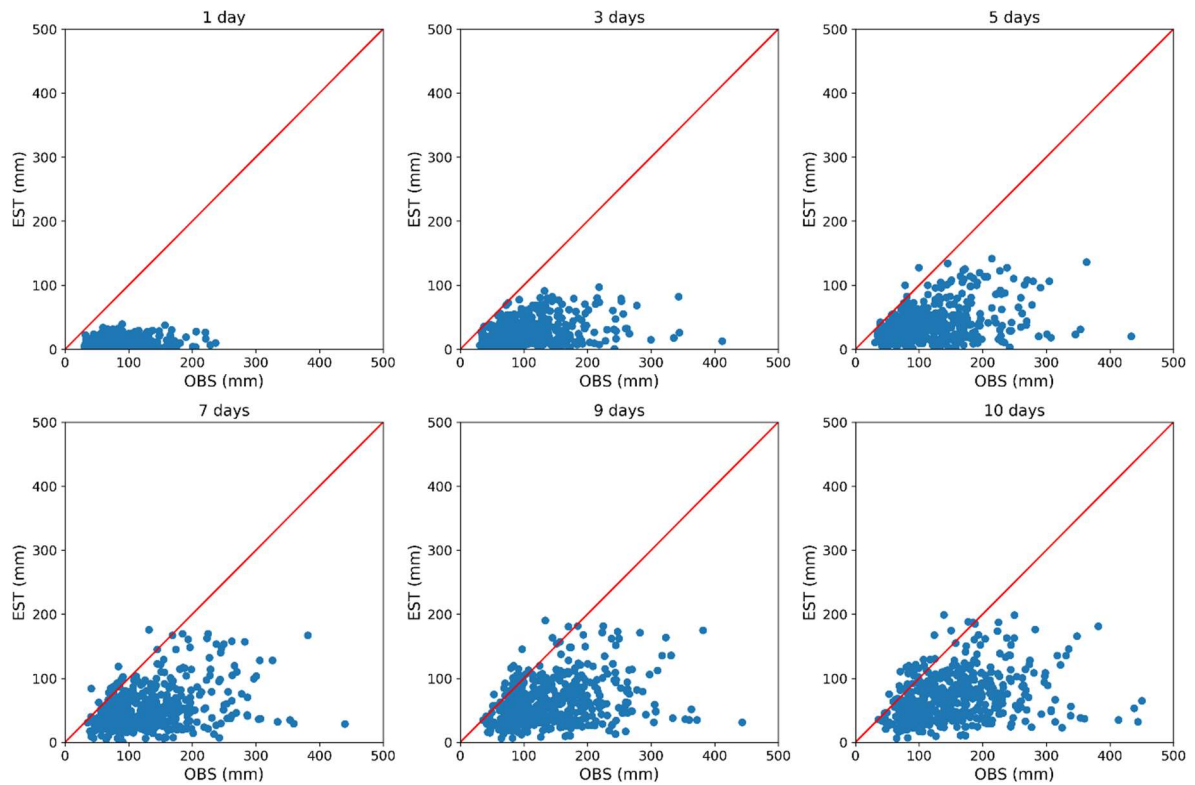


Figure 28 – Scatter plots of rainfall observed values (rain gauges) vs estimated values (SM2RAIN-ASCAT V1.2) that lead to floods at different timescales.

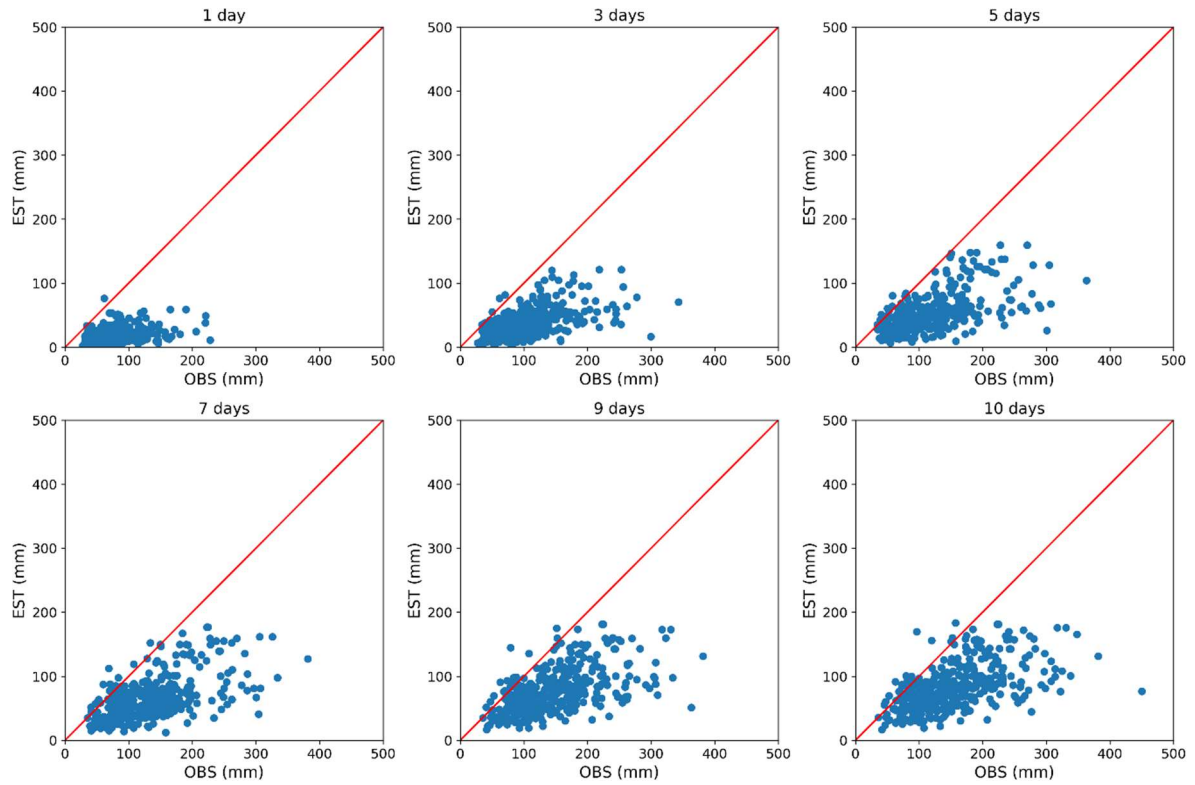


Figure 29 – Scatter plots of rainfall observed values (rain gauges) vs estimated values (GPM+SM2RAIN) that lead to floods at different timescales.

APPENDIXES B

Table 7 – Summary of Mean Relative Absolute Error (MRAE) for estimated precipitation products, considering different timescales

PRODUCTS / TIME	1h	3h	6h	8h	10h	12h	1d	3d	5d	7d	9d	10d
<i>CHIRP V2.0</i>	-	-	-	-	-	-	79.76%	64.98%	54.73%	47.40%	41.36%	38.70%
<i>CHIRPS V2.0</i>	-	-	-	-	-	-	67.16%	56.59%	47.13%	41.62%	36.42%	33.73%
<i>CMORPH-CRT V1.0</i>	72.77%	63.17%	60.18%	59.77%	59.76%	59.88%	60.43%	51.47%	44.05%	40.94%	38.49%	37.66%
<i>PDIR-NOW</i>	72.92%	66.50%	64.18%	64.09%	64.19%	63.67%	60.63%	44.30%	33.12%	25.83%	19.50%	16.78%
<i>IMERGHEE V06</i>	77.30%	70.50%	68.50%	68.25%	68.36%	68.32%	67.52%	57.64%	50.17%	46.20%	43.22%	42.31%
<i>IMERGHHL V06</i>	78.03%	69.05%	66.13%	65.88%	65.79%	65.88%	65.41%	55.52%	48.21%	44.48%	41.73%	40.76%
<i>IMERGHH V06</i>	78.05%	68.82%	65.68%	65.34%	65.23%	65.26%	64.51%	53.94%	46.41%	42.55%	39.45%	38.19%
<i>MERRA-2</i>	88.65%	81.64%	77.76%	76.13%	74.64%	73.48%	69.25%	48.00%	35.58%	27.12%	21.42%	18.85%
<i>MSWEP V2.2</i>	-	71.38%	66.77%	-	-	66.59%	66.17%	58.70%	51.41%	48.11%	45.40%	43.89%
<i>PERSIANN</i>	84.17%	75.96%	73.05%	72.78%	72.79%	72.92%	72.10%	63.37%	55.82%	51.80%	47.90%	46.53%
<i>PERSIANN CCS</i>	73.88%	68.36%	66.21%	65.92%	65.79%	65.54%	63.73%	50.85%	41.40%	36.06%	31.31%	29.68%
<i>PERSIANN-CDR VIR1</i>	-	-	-	-	-	-	74.87%	59.24%	47.64%	41.83%	37.86%	36.77%
<i>SM2RAIN-ASCAT V 1.2</i>	-	-	-	-	-	-	84.84%	72.13%	63.75%	56.30%	50.49%	48.08%
<i>GPM+SM2RAIN</i>	-	-	-	-	-	-	73.99%	60.42%	52.17%	47.08%	42.86%	41.25%

Table 8 – Summary of Root Mean Square Error (RMSE) for estimated precipitation products, considering different timescales.

PRODUCTS / TIME	1h	3h	6h	8h	10h	12h	1d	3d	5d	7d	9d	10d
<i>CHIRP V2.0</i>	-	-	-	-	-	-	74.44	88.10	89.93	90.93	93.53	96.12
<i>CHIRPS V2.0</i>	-	-	-	-	-	-	65.76	78.88	81.52	82.56	85.84	88.34
<i>CMORPH-CRT V1.0</i>	38.58	49.27	55.31	57.72	58.99	60.23	67.00	80.92	84.22	85.87	90.72	94.76
<i>PDIR-NOW</i>	38.55	48.55	53.55	55.65	56.82	58.05	63.62	69.60	70.14	70.71	73.77	76.39
<i>IMERGHEE V06</i>	40.39	52.00	58.01	60.27	61.61	62.94	69.11	84.51	87.96	90.92	95.92	100.03
<i>IMERGHHL V06</i>	40.68	51.77	57.22	59.41	60.56	61.86	68.02	83.11	86.65	89.48	94.69	98.95
<i>IMERGHH V06</i>	40.49	51.23	56.52	58.59	59.70	60.99	67.04	80.49	83.00	85.47	90.67	94.70
<i>MERRA-2</i>	44.54	58.35	64.94	67.24	68.51	69.78	75.51	94.92	102.01	107.28	110.56	113.84
<i>MSWEP V2.2</i>	-	54.10	59.46	-	-	63.77	69.23	82.72	84.96	87.75	94.06	97.07
<i>PERSIANN</i>	43.99	54.70	59.72	61.55	62.56	63.31	69.43	83.77	88.70	91.90	98.47	102.43
<i>PERSIANN CCS</i>	39.16	50.67	56.75	59.06	60.31	61.60	67.63	81.95	84.87	86.43	91.56	95.16
<i>PERSIANN-CDR VIR1</i>	-	-	-	-	-	-	75.31	93.05	99.13	103.34	107.73	111.46
<i>SM2RAIN-ASCAT V 1.2</i>	-	-	-	-	-	-	79.64	97.27	100.57	102.29	108.28	112.07
<i>GPM+SM2RAIN</i>	-	-	-	-	-	-	68.88	79.05	81.37	83.74	87.66	90.39

Table 9 – Summary of Correlation Coefficient (CC) for estimated precipitation products, considering different timescales.

<i>PRODUCTS / TIME</i>	<i>1h</i>	<i>3h</i>	<i>6h</i>	<i>8h</i>	<i>10h</i>	<i>12h</i>	<i>1d</i>	<i>3d</i>	<i>5d</i>	<i>7d</i>	<i>9d</i>	<i>10d</i>
<i>CHIRP V2.0</i>	-	-	-	-	-	-	0.34	0.47	0.47	0.45	0.43	0.42
<i>CHIRPS V2.0</i>	-	-	-	-	-	-	0.32	0.51	0.50	0.49	0.48	0.47
<i>CMORPH-CRT V1.0</i>	0.25	0.18	0.14	0.13	0.14	0.16	0.15	0.34	0.38	0.41	0.42	0.41
<i>PDIR-Now</i>	0.14	0.14	0.20	0.21	0.23	0.22	0.19	0.41	0.45	0.45	0.43	0.43
<i>IMERGHEE V06</i>	0.15	0.15	0.16	0.17	0.19	0.20	0.21	0.36	0.40	0.41	0.40	0.40
<i>IMERGHHL V06</i>	0.14	0.13	0.16	0.17	0.19	0.21	0.22	0.36	0.39	0.41	0.40	0.39
<i>IMERGHH V06</i>	0.14	0.15	0.17	0.19	0.21	0.23	0.24	0.40	0.45	0.47	0.45	0.43
<i>MERRA-2</i>	-0.06	-0.07	-0.06	-0.06	-0.07	-0.07	-0.05	-0.04	-0.03	-0.03	-0.02	-0.01
<i>MSWEP V2.2</i>	-	-0.04	0.00	-	-	0.10	0.18	0.45	0.51	0.54	0.51	0.52
<i>PERSIANN</i>	-0.06	0.02	0.09	0.13	0.15	0.18	0.17	0.34	0.41	0.44	0.37	0.35
<i>PERSIANN CCS</i>	0.13	0.10	0.11	0.11	0.13	0.12	0.11	0.28	0.34	0.35	0.30	0.29
<i>PERSIANN-CDR VIR1</i>	-	-	-	-	-	-	0.02	0.06	0.04	0.03	0.02	0.03
<i>SM2RAIN-ASCAT V 1.2</i>	-	-	-	-	-	-	0.17	0.29	0.37	0.36	0.27	0.25
<i>GPM+SM2RAIN</i>	-	-	-	-	-	-	0.34	0.52	0.58	0.59	0.55	0.55

Table 10 – Summary of BIAS for estimated precipitation products, considering different timescales.

PRODUCTS / TIME	1h	3h	6h	8h	10h	12h	1d	3d	5d	7d	9d	10d
<i>CHIRP V2.0</i>	-	-	-	-	-	-	0.19	0.32	0.41	0.47	0.53	0.55
<i>CHIRPS V2.0</i>	-	-	-	-	-	-	0.30	0.40	0.49	0.54	0.58	0.60
<i>CMORPH-CRT V1.0</i>	0.22	0.31	0.35	0.35	0.36	0.36	0.35	0.44	0.50	0.54	0.57	0.58
<i>PDIR-NOW</i>	0.22	0.29	0.32	0.33	0.33	0.33	0.36	0.51	0.61	0.68	0.74	0.76
<i>IMERGHEE V06</i>	0.18	0.25	0.28	0.28	0.28	0.28	0.29	0.39	0.45	0.49	0.52	0.52
<i>IMERGHHL V06</i>	0.17	0.26	0.30	0.30	0.31	0.31	0.31	0.41	0.47	0.51	0.53	0.54
<i>IMERGHH V06</i>	0.18	0.26	0.30	0.31	0.31	0.31	0.32	0.43	0.50	0.54	0.56	0.57
<i>MERRA-2</i>	0.08	0.14	0.18	0.19	0.21	0.21	0.25	0.41	0.51	0.59	0.64	0.66
<i>MSWEP V2.2</i>	-	0.23	0.28	-	-	0.29	0.30	0.39	0.46	0.49	0.51	0.52
<i>PERSIANN</i>	0.12	0.20	0.24	0.25	0.25	0.25	0.26	0.35	0.42	0.46	0.49	0.50
<i>PERSIANN CCS</i>	0.22	0.27	0.29	0.30	0.30	0.30	0.32	0.43	0.52	0.57	0.61	0.62
<i>PERSIANN-CDR VIR1</i>	-	-	-	-	-	-	0.21	0.33	0.42	0.47	0.51	0.52
<i>SM2RAIN-ASCAT V 1.2</i>	-	-	-	-	-	-	0.13	0.25	0.33	0.39	0.44	0.46
<i>GPM+SM2RAIN</i>	-	-	-	-	-	-	0.24	0.37	0.45	0.49	0.53	0.54

Table 11 – Summary of Variability (VAR) for estimated precipitation products, considering different timescales.

PRODUCTS / TIME	1h	3h	6h	8h	10h	12h	1d	3d	5d	7d	9d	10d
<i>CHIRP V2.0</i>	-	-	-	-	-	-	1.78	1.19	1.12	1.07	0.99	0.97
<i>CHIRPS V2.0</i>	-	-	-	-	-	-	1.83	1.24	1.15	1.15	1.08	1.03
<i>CMORPH-CRT V1.0</i>	1.87	2.01	2.08	2.09	2.09	2.08	1.91	1.37	1.29	1.25	1.21	1.17
<i>PDIR-NOW</i>	1.80	2.02	2.15	2.14	2.11	2.08	1.96	1.39	1.31	1.28	1.20	1.14
<i>IMERGHEE V06</i>	1.96	1.99	2.04	2.07	2.07	2.05	1.87	1.46	1.33	1.25	1.16	1.11
<i>IMERGHHL V06</i>	2.03	2.06	2.08	2.10	2.11	2.09	1.92	1.48	1.34	1.26	1.17	1.12
<i>IMERGHH V06</i>	1.88	1.91	1.92	1.93	1.94	1.94	1.80	1.40	1.33	1.30	1.21	1.16
<i>MERRA-2</i>	3.01	3.11	3.04	2.92	2.86	2.80	2.47	1.85	1.74	1.73	1.58	1.50
<i>MSWEP V2.2</i>	-	2.03	2.10	-	-	2.08	1.93	1.58	1.48	1.41	1.30	1.23
<i>PERSIANN</i>	1.81	2.13	2.35	2.37	2.41	2.40	2.29	1.85	1.73	1.62	1.52	1.50
<i>PERSIANN CCS</i>	1.81	1.81	1.94	1.95	1.97	1.95	1.89	1.51	1.50	1.42	1.33	1.28
<i>PERSIANN-CDR VIR1</i>	-	-	-	-	-	-	1.70	1.39	1.41	1.38	1.25	1.18
<i>SM2RAIN-ASCAT V 1.2</i>	-	-	-	-	-	-	1.49	1.39	1.39	1.33	1.20	1.14
<i>GPM+SM2RAIN</i>	-	-	-	-	-	-	1.40	1.17	1.15	1.11	1.03	0.99

Table 12 – Summary of KGE for estimated precipitation products, considering different timescales.

PRODUCTS / TIME	<i>1h</i>	<i>3h</i>	<i>6h</i>	<i>8h</i>	<i>10h</i>	<i>12h</i>	<i>1d</i>	<i>3d</i>	<i>5d</i>	<i>7d</i>	<i>9d</i>	<i>10d</i>
<i>CHIRP V2.0</i>	-	-	-	-	-	-	-0.30	0.11	0.20	0.23	0.26	0.27
<i>CHIRPS V2.0</i>	-	-	-	-	-	-	-0.28	0.19	0.27	0.30	0.33	0.34
<i>CMORPH-CRT V1.0</i>	-0.39	-0.47	-0.53	-0.53	-0.53	-0.51	-0.41	0.06	0.15	0.22	0.24	0.26
<i>PDIR-NOW</i>	-0.40	-0.51	-0.56	-0.54	-0.51	-0.49	-0.41	0.14	0.26	0.31	0.34	0.36
<i>IMERGHEE V06</i>	-0.52	-0.50	-0.52	-0.53	-0.52	-0.50	-0.37	0.00	0.12	0.18	0.22	0.22
<i>IMERGHHL V06</i>	-0.58	-0.56	-0.54	-0.55	-0.54	-0.52	-0.39	0.00	0.13	0.19	0.22	0.23
<i>IMERGHH V06</i>	-0.48	-0.45	-0.42	-0.41	-0.41	-0.39	-0.30	0.08	0.18	0.23	0.26	0.27
<i>MERRA-2</i>	-1.45	-1.52	-1.44	-1.34	-1.29	-1.24	-0.95	-0.47	-0.36	-0.33	-0.22	-0.18
<i>MSWEP V2.2</i>	-	-0.65	-0.65	-	-	-0.57	-0.42	0.00	0.13	0.20	0.25	0.28
<i>PERSIANN</i>	-0.60	-0.70	-0.80	-0.79	-0.81	-0.79	-0.70	-0.25	-0.11	0.00	0.04	0.04
<i>PERSIANN CCS</i>	-0.42	-0.41	-0.48	-0.48	-0.48	-0.47	-0.43	-0.05	0.04	0.12	0.14	0.15
<i>PERSIANN-CDR V1R1</i>	-	-	-	-	-	-	-0.44	-0.22	-0.19	-0.17	-0.12	-0.09
<i>SM2RAIN-ASCAT V 1.2</i>	-	-	-	-	-	-	-0.29	-0.10	0.00	0.06	0.06	0.06
<i>GPM+SM2RAIN</i>	-	-	-	-	-	-	-0.08	0.19	0.29	0.34	0.35	0.36