Climatology and Interannual Variability of Floods during the TRMM Era (1998–2013)

YAN YAN,^{a,b} HUAN WU,^{a,b,c} GUOJUN GU,^c ZHIJUN HUANG,^a LORENZO ALFIERI,^d XIAOMENG LI,^a
NERGUI NANDING,^a XINSHUN PAN,^a AND QIUHONG TANG^c

^a *Guangdong Province Key Laboratory for Climate Change and Natural Disaster Studies, and School of Atmospheric Sciences, Sun Yat-sen University, Guangdong, China*

^b *Southern Marine Science and Engineering Laboratory (Zhuhai), Guangdong, China*

^c *Earth System Science Interdisciplinary Center, University of Maryland, College Park, College Park, Maryland*

^d *European Commission, Joint Research Centre, Ispra, Italy*

^e *Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, China*

(Manuscript received 7 June 2019, in final form 18 October 2019)

ABSTRACT

Spatial and temporal variations of global floods during the TRMM period (1998–2013) are explored by means of the outputs of the Dominant River Routing Integrated with VIC Environment model (DRIVE) driven by the precipitation rates from the TRMM Multisatellite Precipitation Analysis (TMPA). Climatological and seasonal mean features of floods including frequency (FF), duration (FD), and mean and total intensity (FI and FTI) are examined and further compared to those for a variety of precipitation indices derived from the daily TMPA rain rates. In general, floods and precipitation manifest similar spatial distributions, confirming that more precipitation (both amount and frequency) often indicates higher probability of floods. However, different flood indices can be associated with different precipitation characteristics with a highly region-dependent distribution. FF and FD tend to be more related to daily precipitation frequency globally, especially the mid- to high-end precipitation frequencies (F10, F25, F50). However, FI and FTI tend to be more associated with the mean volume/magnitude of those (extreme) daily precipitation events (Pr10 and Pr25). Nonetheless, daily precipitation intensity except the very high end one (R50) generally has a relatively weak effect on floods. The precipitation–flood relations at the 10 large regions are further examined, providing an improved understanding of precipitation-related flood-generating mechanisms in different locations. On the interannual time scale, El Niño–Southern Oscillation (ENSO) can significantly affect floods in many flood-prone zones. However, it is noted that even though the ENSO effect on floods is mostly through modulating various aspects of precipitation events, significant ENSO signals in precipitation cannot always translate to an effective, simultaneous impact on floods.

1. Introduction

Among various natural disasters, floods have been the most common one, causing human fatalities, property losses, and infrastructure damages likely worth billions of dollars every year across the world (Munich Re 2012; IFRC 2015; UNDRR 2019). In particular, inundated areas and human population affected by floods have been increasing steadfastly and flood-related losses/damages have been rising steeply during the recent decades (UNISDR 2011; Paprotny et al. 2018; CRED 2015, 2019). Therefore, it is an urgent task to

improve our capability of promptly monitoring and accurately forecasting flood events for both scientific significance and societal implication. To accomplish this task, we should first have an improved understanding of flood formation mechanisms, spatial distribution, and temporal variability/change on various time scales. However, despite that a few previous studies have focused on variations and changes of river discharges (e.g., Bonsal and Shabbar 2008; Stephens et al. 2015; Berghuijs et al. 2016; De Perez et al. 2017), a detailed global account of floods is still lacking primarily due to limited (spatial and continuously consistent temporal) coverage of in situ streamflow observations.

Hydrologic models have been demonstrated to be an effective and efficient tool for simulating, monitoring, and forecasting floods (Dutta et al. 2000; Reed et al. 2007; Yilmaz et al. 2010). Developing a global flood

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Corresponding author: Dr. Huan Wu, wuhuan3@mail.sysu.edu.cn

forecasting system based on hydrologic models has the potential for providing useful information for flood estimation, especially for underdeveloped and remote regions (Wu et al. 2012a). Although flood forecasting/warning systems have been established at regional scales (e.g., Reed et al. 2007; Voisin et al. 2011), few are directly targeted on the global scale (e.g., Reed et al. 2007; Voisin et al. 2011). This led to the development of the Dominant river Routing Integrated with VIC Environment model (DRIVE) through coupling the DRTR model with the VIC land surface model (Wu et al. 2014). The DRIVE model has been running routinely for global flood forecasting and monitoring for many years (Wu et al. 2014), by ingesting the high-quality, high spatiotemporal resolution satellite-based precipitation estimates from the National Aeronautics and Space Administration (NASA) Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis (TMPA) (Huffman et al. 2007). Composed of multiple satellite rainfall estimates calibrated, or adjusted, to the information from the TRMM satellite, which carried a unique spaceborne radar and passive microwave sensors (Huffman et al. 2007), the TMPA product has been successfully applied in many hydrologic modeling studies (Harris et al. 2007; Su et al. 2011). The success of the DRIVE model in global flood simulation has been demonstrated by comparing its outputs against in situ streamflow observations at 1121 global river locations, a remote sensing-based global flood inventory of 2086 events, and many real-time event evaluations over the years (Wu et al. 2014). Further relevant validations and uncertainty analyses for the DRIVE-based flood simulations are still necessary (Wu et al. 2017). For example, we recently compared the DRIVE flood simulation results with NASA Soil Moisture Active Passive (SMAP)-based global inundation mapping. These two independent approaches show good concurrence (at the same time) and consistency (over time) regarding land surface water dynamics in most of the global areas (Wu et al. 2019). Hence, given the lack of an observed global account of floods as stated above, utilizing the outputs from the DRIVE model to quantify and improve our understanding of global floods is a natural and feasible strategy. Thus, the first objective of this study is to furnish a climatological quantification of global floods (frequency, duration, and intensity) during the TRMM period (1998–2013) including their spatial distributions and seasonal variations, providing a context for further exploring their variability on the longer-than-seasonal time scales.

As we also know, rainfall estimation is the critical meteorological input of a hydrologic model and hence relatively accurate precipitation information should

generally be able to facilitate good flood simulation and forecasting, though other factors could be important for floodiness as well such as soil moisture and antecedent surface conditions. This is consistent with the general notion that floods by default should be closely related to precipitation especially precipitation extremes. Monthly precipitation has even been used as a proxy for flood hazard (e.g., Stephens et al. 2015). Nevertheless, it is still an open question how the occurrence, lasting period, and intensity of floods could be directly ascribed to precipitation (e.g., Berghuijs et al. 2016; Sharma et al. 2018; Emerton et al. 2018). Specifically, we need answers to the following two questions: (i) What aspects of precipitation characteristics, for instance, precipitation frequency, event duration and total amount, etc. could be more relevant to the occurrence, duration, and severity of floods? (ii) Can precipitation (and extreme precipitation) variations translate to variations in floods, and if so how? Several studies have explored this relation on the regional scale from the prospective of using precipitation to forecast floods (e.g., Stephens et al. 2015; De Perez et al. 2017). Stephens et al. (2015) showed that the correlation between monthly floodiness and precipitation is generally weak. De Perez et al. (2017) suggested that the relations between floods and precipitation characteristics could be highly regionally dependent. Berghuijs et al. (2016) also suggested a complicated relationship between floods and precipitation across the United States. Therefore, it is of interest to further explore the relationships between floods and precipitation especially with regards to their possible connections on the seasonal and interannual time scales given the availability of high-quality satellite-based precipitation measurements and the DRIVE model outputs. A specific question that we intend to ask here is which aspects of precipitation events such as precipitation total amount/volume during a time period, daily precipitation frequency and intensity, temporal variation, and spatial pattern, etc. would be more relevant to the occurrence, duration, and/or intensity of floods, respectively. This is directly related to exploring what could be the primary flood-generating mechanisms associated with precipitation, besides other mechanisms such as antecedent soil moisture, snowmelt, etc., though we anticipate that these mechanisms, if they can be identified, could be highly regionally dependent. This hence forms our second major objective for this study. To pursue this, a series of precipitation indices representing precipitation characteristics including daily precipitation frequency, intensity (and extremes), and amount will be defined using daily precipitation rates from the TRMM satellite-based precipitation product.

Understanding temporal variations of global floods especially on the longer-than-seasonal time scales and their connections with a variety of climate physical modes is critical for exploring the potential of accurate flood forecasting not only on the monthly/seasonal time scale, but also on the interannual time scale for distinct regions and river basins. Previous studies indicated that El Niño–Southern Oscillation (ENSO), a dominant physical mode on the interannual time scale, can have an effective impact on floods and precipitation at local/basin to global scales (e.g., Ward et al. 2014, 2016; Emerton et al. 2017; Dai and Wigley 2000; Whan and Zwiers 2017; Lee et al. 2018a,b). For instance, Andrews et al. (2004) quantified the influence of ENSO on flood frequency along the Californian coast; Bonsal and Shabbar (2008) suggested that the variations of streamflow in western Canada could be associated with El Niño events. On the global scale, Dettinger and Diaz (2000) examined the relationship between ENSO and river flows by means of monthly streamflow series from 1345 gauge sites around the world. It was found that the ENSO events are correlated with streamflows in many parts of the Americas, Europe, and Australia. By using the simulated daily gridded discharges from the WaterGAP model, Ward et al. (2014) assessed the influence of ENSO on annual river floods defined as the peak daily discharge in a given year. They found that the ENSO events can exert significant influence on annual floods in river basins covering over a third of the world's land surface, and moreover the impact on annual floods can be much greater than on average streamflows. Ward et al. (2016) further explored the ENSO effect on flood duration/frequency. It was noted that there are strong relationships between ENSO and flood frequency/duration across a larger number of basins, and ENSO in general has a greater impact on flood durations than on flood frequency across large parts of the world.

Among these previous studies, many are focused on the basin or local scale. Ward et al. (2014, 2016) have focused on the global scale; however, streamflows and then floods were simulated at a relatively coarse spatial resolution of $0.5^\circ \times 0.5^\circ$ and more critically only the climate forcing data rather than time-varying observations including precipitation measurements were applied to drive the hydrological model. During the recent decades, satellite-based precipitation products including TMPA have opened a new avenue for global flood estimation. Therefore, further relevant studies are certainly needed specifically with regards to the characteristics of global floods and their temporal variations and possible connections with ENSO. Thus, the third objective of this study is to examine the likely ENSO impact on floods globally and in various regions and

river basins during the TRMM period (1998–2013). Furthermore, we intend to investigate whether and how the ENSO impact on floods, if any, should be translated from the ENSO effect on precipitation given that the ENSO can effectively modulate both precipitation and temperature in many flood-prone regions. To our knowledge, this has not been fully explored in past studies.

Information about the DRIVE model and TRMM satellite precipitation data are provided in section 2. Section 3 describes spatial distributions of simulated global floods and satellite-based precipitation during the TRMM period. Seasonal variations of global floods and precipitation are presented in section 3 as well. Section 4 examines the relationships between floods and various precipitation indices on the interannual time scales. Interannual variability of floods and precipitation specifically on their connections with ENSO is further examined in section 5. The conclusions and discussion are given in section 6.

2. The DRIVE model outputs and TRMM satellite precipitation

a. The DRIVE model

The Dominant River Routing Integrated with VIC Environment (DRIVE) model is constructed by coupling a physically based routing model (the DRTR model) with the Variable Infiltration Capacity (VIC) land surface model (Wu et al. 2014). The VIC land surface model (Liang et al. 1994, 1996) directly simulates snow and soil frost related dynamic processes (Storck et al. 2002), which can also be readily validated against streamflow observations in many snowmelt-dominated basins, particularly in mountainous areas (Christensen et al. 2004; Christensen and Lettenmaier 2007; Hamlet et al. 2005; Elsner et al. 2010; Wu et al. 2012a). To balance data availability, heavy computing loads, and model accuracy, it has detailed subgrid parameterizations representing complex physical processes at a spatial resolution commensurate with land surface models (LSMs), resulting in a good performance in runoff generation calculations. Furthermore, these parameterizations include not only a scheme for the subgrid heterogeneity of infiltration capacity through statistical variable infiltration curves (Zhao and Liu 1995) and also the consideration of the processes related to fractional subgrid areas for different land cover types and elevation bands. These schemes have been demonstrated to work very well for large-scale applications (Sivapalan and Woods 1995). The VIC model has been successfully applied in many hydrologic modeling and water resource

TABLE 1. Monthly flood indices: flood frequency (FF), flood duration (FD), flood mean intensity (FI), and flood total intensity (FTI) in a month.

FF (times day ⁻¹)	Total number of flood events/total days in a month
FD (hours per flood event)	Total flood duration/total number of flood events in a month
FI (mm per flood event)	Total flood intensity/total number of flood events in a month
FTI (mm month ⁻¹)	Total flood intensity in a month

management studies (Hamlet and Lettenmaier 2007; Hamlet et al. 2010; Elsner et al. 2010; Voisin et al. 2011; Wu et al. 2014). To be applied for spatially distributed and real-time runoff prediction, the VIC model has further been modified (in particular, from its original point-based model structure to a grid-based model structure) so that the modified VIC as a runoff generation component of the DRIVE model is capable of simulating spatially distributed runoff at each time step (i.e., computing all the grid boxes at each time step) (Wu et al. 2014).

The physically based routing model [the DRT-based runoff routing (DRTR) model] was developed in Wu et al. (2014) and is primarily based on the hierarchical DRT method (Wu et al. 2011, 2012a,c). It includes a package of hydrographic upscaling (from fine spatial resolution to coarse resolution) algorithms and resulting global datasets (flow direction, river network, drainage area, flow distance, slope, etc.) especially designed for large-scale hydrologic modeling. The DRTR model is grid based and very convenient for simulating spatially distributed streamflow by coupling with the modified VIC model. More details about the DRIVE model can be found in Wu et al. (2014).

b. Flood indices

The DRIVE retrospective simulation was carried out for the TRMM period (1998–2013), using the TRMM/TMPA precipitation as input. The outputs include routed runoff and discharges with spatial resolution of $0.125^\circ \times 0.125^\circ$ and time resolution of 3 h. The simulation covers the global land between 50°N and 50°S . Flood characteristics representing flood occurrence, flood event duration, and flood event intensity are defined and estimated at each grid cell as follows. Differences (Δ) between discharge and a predefined threshold (Wu et al. 2012a, 2014) are calculated at grids. If $\Delta > 0$ for four consecutive time steps, one single flood event is determined; if $\Delta \leq 0$ for 24 consecutive time steps, the following event is considered as a different one. The sum of the total hours for $\Delta > 0$ for all flood events in a month is then computed as the duration, and flood intensity is further estimated by summing up the whole values of Δ when $\Delta > 0$ for all flood events in a month at each grid. Finally, the four monthly flood indices are estimated at grid cells (Table 1), including

flood frequency (FF), duration (FD), mean intensity (FI), and total intensity (FTI).

c. TRMM/TMPA precipitation and precipitation indices

The high-quality, high spatiotemporal resolution satellite-based precipitation product, the 3-h TRMM/TMPA, is applied to drive the DRIVE model during the TRMM period (1998–2013). The daily TMPA (3B42) precipitation has also been applied to examine spatial distribution and temporal variations of monthly mean precipitation and its possible associations with the occurrence of floods. As floods (including their occurrence, duration, and intensity) might be related to various aspects of precipitation characteristics, the daily TMPA has further been applied to define a variety of precipitation indices representing not only precipitation frequency and mean precipitation but also precipitation intensity and extreme precipitation. Corresponding to the monthly flood indices (Table 1), in addition to monthly mean precipitation (Pr), the 13 monthly precipitation indices derived from daily rain rates are estimated at grids (Table 2).

3. Climatology and seasonal variations of global floods and precipitation

Prior to quantifying the climatological characteristics of global floods during the TRMM era using the DRIVE model outputs, we first take a look at spatial distributions of climatological mean precipitation. Monthly mean precipitation (Pr) over global lands between 50°N and 50°S is depicted in Fig. 1a. Major precipitation zones are generally located between 10°N and 10°S as expected, especially over the Maritime Continent, northern South America, and equatorial Africa. Regional maxima of precipitation can also be seen in South Asia and along the southeastern coast of Asia and the southeast United States. Dry zones with limited precipitation amount appear in the subtropics including the Sahara and the Takla Makan deserts, and interior Australia. It is also of interest to note that the mean precipitation in China gradually decreases from the southeast coast to the northwest plateau; over North America, more precipitation tends to appear in its eastern portion.

TABLE 2. Monthly mean precipitation (Pr) and precipitation indices determined from daily rain rates (R) including precipitation frequency (Fxx), intensity (Rxx), and mean precipitation (Prxx) corresponding to various daily rain-rate thresholds.

Pr (mm day ⁻¹)	Monthly precipitation rate
F01 (days day ⁻¹)	Total rainy days ($R \geq 1$ mm day ⁻¹)/total days in a month
F10 (days day ⁻¹)	Total rainy days ($R \geq 10$ mm day ⁻¹)/total days in a month
F25 (days day ⁻¹)	Total rainy days ($R \geq 25$ mm day ⁻¹)/total days in a month
F50 (days day ⁻¹)	Total rainy days ($R \geq 50$ mm day ⁻¹)/total days in a month
R01 (mm day ⁻¹)	Total $R \geq 1$ mm day ⁻¹ precipitation/days with $R \geq 1$ mm day ⁻¹ in a month
R05 (mm day ⁻¹)	Total $R \geq 5$ mm day ⁻¹ precipitation/days with $R \geq 5$ mm day ⁻¹ in a month
R10 (mm day ⁻¹)	Total $R \geq 10$ mm day ⁻¹ precipitation/days with $R \geq 10$ mm day ⁻¹ in a month
R25 (mm day ⁻¹)	Total $R \geq 25$ mm day ⁻¹ precipitation/days with $R \geq 25$ mm day ⁻¹ in a month
R50 (mm day ⁻¹)	Total $R \geq 50$ mm day ⁻¹ precipitation/days with $R \geq 50$ mm day ⁻¹ in a month
Pr01 (mm day ⁻¹)	Total $R \geq 1$ mm day ⁻¹ precipitation/total days in a month
Pr10 (mm day ⁻¹)	Total $R \geq 10$ mm day ⁻¹ precipitation/total days in a month
Pr25 (mm day ⁻¹)	Total $R \geq 25$ mm day ⁻¹ precipitation/total days in a month
Pr50 (mm day ⁻¹)	Total $R \geq 50$ mm day ⁻¹ precipitation/total days in a month

Spatial distributions of three other precipitation indices (F25, R25, and Pr25) derived from daily rain rates during the TRMM period are illustrated in Figs. 1b–d as well. These indices are applied to represent extreme precipitation just as in past studies (e.g., Ricko et al. 2016), though spatial features of other precipitation indices in Table 2 have also been examined (not shown). Pr25 and F25 manifest roughly similar spatial distributions as Pr specifically within the deep tropics, implying that intense (deep-convective) precipitating events with daily rain rates ($R \geq 25$ mm day⁻¹) can significantly contribute to the mean precipitation in these areas. However, in several regions especially over northern Australia, South and Southeast Asia, etc., different spatial structures exist between these two extreme precipitation indices and mean precipitation. Furthermore, the related precipitation intensity index (R25) has in general different spatial distributions from those for Pr and also for F25 and Pr25, suggesting that precipitation frequency (F25) and intensity (R25) represent different aspects of precipitation (events), and total precipitation (Pr25) tends to be dominated by precipitation frequency (F25) other than precipitation intensity (R25) in most regions.

Spatial distributions of the four flood indices during the TRMM period are shown in Figs. 1e–h. Flood frequency (FF) has roughly similar spatial distribution as for Pr, F25, and Pr25. High FF values appear approximately in the same locations as regional precipitation maxima, such as in the Maritime Continent, the southeastern coast of Asia, the southeastern United States, tropical Africa, etc. High correspondences between FF and both F25 and Pr25 can also be readily seen in the major rainy zones across the world. And in some regions, FF tends to be more relevant to F25 and Pr25 than to Pr, for instance, along the northern coast of Australia. However, the correspondence between FF and R25 tends to be weak, suggesting that flood frequency

might be closely related to monthly mean precipitation and extreme precipitation frequency in many regions; however, it is only loosely associated with precipitation intensity. The other three flood indices (FD, FI, and FTI) in general have similar spatial distributions as FF. Nevertheless, their spatial features have many detailed discrepancies from that for FF. In particular, these three indices show much more fragmented spatial features generally lacking focused regional maxima. It is also noted that these three flood indices may be not only associated with Pr, F25, Pr25, and FF, but also related to (extreme) precipitation intensity (R25). For instance, in southeastern South America, there is no regional peak in FF, Pr, F25, and Pr25; however, high values in FD, FI, and FTI appear there seemingly manifesting the regional peak in R25.

In summary, Fig. 1 indicates that mean precipitation (and extreme precipitation) and floods generally have similar spatial distributions, which confirms that more precipitation often corresponds to higher probability of the occurrence of floods. However, differences exist between precipitation and floods regarding their spatial features. For example, regional peaks for Pr, F25, and Pr25 appear in the north parts of South America, but high values for FF, FI, and FTI are generally seen south of them.

Figure 2 further shows a high linear correspondence between climatological mean precipitation (Pr) and flood frequency in the tropics. However, as mentioned above, differences exist between precipitation and floods regarding their detailed spatial features, probably suggesting complex localized flood-generating mechanisms. In particular, different flood indices representing a variety of aspects of floods may be associated with different aspects of precipitation events. It is also worth mentioning that FF would correlate to F25 (high-end precipitation frequency); however, it does not show any correlation with R25.

FIG. 1. Climatology of land precipitation, extreme precipitation, and simulated floods between 50°N–50°S during 1998–2013. (a) Pr; (b) F25; (c) R25; (d) Pr25; (e) FF; (f) FD; (g) FI; and (h) FTI.

Seasonal mean precipitation is further depicted in Figs. 3a–d. Evident seasonal variations appear in mean precipitation, and major precipitation zones move meridionally with season as examined in past studies (e.g., Adler et al. 2017). In MAM, the high values are generally located within the deep tropics including equatorial South America, tropical Africa, and the Maritime Continent and surrounding areas. Regional precipitation maxima can also be seen in southeast China and the southeastern United States. In JJA, major precipitation zones move to the north and intense precipitation covers the large tropical/subtropical domains in the Northern Hemisphere including Central America, the Maritime Continent, and West Africa. Precipitation is also seen covering the eastern portion of North America, and intense precipitation appears over South

and East Asia following the Asian summer monsoons. In SON, precipitation tends to be weaker and primarily located in the deep tropical regions. In DJF, major precipitation zones are located in the Southern Hemisphere, covering the regions including South America, southern Africa, the Maritime Continent, and northern Australian coast.

Seasonal variations are also evident in the four flood indices. Seasonal mean flood frequency (FF) is illustrated in Figs. 3e–h as an example. In general, FF shows similar seasonal migrations as mean precipitation and thus seasonal mean FF manifests similar spatial distributions as seasonal mean precipitation as expected. During JJA, high FF values are mainly located over tropical South America and West Africa, and in South and East Asia, corresponding to regional monsoon

FIG. 2. Flood frequency index (FF) vs (a) monthly mean precipitation (Pr), (b) F25, (c) R25, and (d) Pr25 in the tropics (30°N–30°S). All components are merged to the $2.5^{\circ} \times 2.5^{\circ}$ grids.

rainfall zones. During DJF, high FF values are generally located in the Southern Hemisphere and roughly over seasonal mean precipitation maxima. During MAM, larger FF values are primarily seen in the tropical South America, southeastern China, and the eastern part of North America. It is worth mentioning that regional high FF values north of about 40°N during this season might be more related to snowmelt (e.g., Villarini 2016). During SON, FF tends to be smaller than in the peak season (JJA), though high values can still be found in the deep tropics. It is also noted that in spite of the close relations between seasonal mean precipitation and floods, strong correspondence between these two cannot always be found in many regions. For instance, during SON, high seasonal mean precipitation in the northern South America and the Maritime Continent does not have caused comparable seasonal mean flood events represented by seasonal mean FF compared to other regions such as the central Africa. This tends to be consistent with past studies that the relations between

floods and precipitation might be very complicated and could be even highly regionally dependent (e.g., Stephens et al. 2015; Berghuijs et al. 2016; De Perez et al. 2017).

4. Floods and precipitation

The relationships between floodiness and precipitation are further explored in this section. Given evident variations in both floods and precipitation with location and season shown above, two contrasting seasons, boreal winter (DJF) and summer (JJA) corresponding to the respective peak flood season in the Southern and Northern Hemisphere, are focused on here. Specifically, we are primarily focused on the correlation relations between these four flood indices and a variety of precipitation indices (listed in Table 2) over global lands during the two distinct seasons.

Simultaneous correlations between the four flood indices and the various precipitation indices are first estimated. To emphasize the likely regional dependence of

FIG. 3. Seasonal mean precipitation (Pr) and flood frequency (FF).

their correlation relations, precipitation indices with the highest, statistically significant correlation (above the 90% confidence level) for each flood index are identified at global grids in these two distinct seasons and depicted in Figs. 4 and 5, respectively. Spatial distributions of identified precipitation indices are generally fragmented during the two seasons and for all four flood indices, likely suggesting the nature of certain spatial inhomogeneity, and/or the existence of regional features, of the impacts of

distinct aspects of precipitation events. However, certain collective effects of precipitation indices on floods are still discernible. During both seasons, more blue color grids tend to be seen for FF and FD, while more red color grids seem to appear for FI and FTI. This indicates that FF and FD might be more related to precipitation frequency, while precipitation amount and/or intensity tend to be more relevant to FI and FTI. To provide a more quantitative estimation of the relations between floods and

FIG. 4. Precipitation indices with the largest correlations with flood indices in DJF.

precipitation indices, the total number of grids with the largest correlation coefficient with the various individual precipitation indices for each flood index are counted and then divided by the total number of grids over global lands between 50°N and 50°S. The resulting ratios (percentages) can then be applied to illuminate the

preferences of precipitation factors for each flood index globally (Fig. 6). For FF, F25 is the precipitation index that has the largest number of grids with the highest correlation during both seasons, clearly showing the dominant role of the frequency of extreme precipitation events in the occurrence of floods. The precipitation

FIG. 5. Precipitation indices with the largest correlations with flood indices in JJA.

FIG. 6. The ratios between the number of grids with the largest correlations between flood indices and precipitation indices and the total grids between 50°N and 50°S during DJF and JJA.

indices with the second and third largest number of grids with the highest correlation are F10 and F50, further confirming the importance of precipitation frequency in the occurrence of floods. As FF, FD also has a similar relation with precipitation frequency. For FI and FTI, the precipitation indices that produce the largest number of grids of the highest correlation are Pr25 during both seasons and Pr25 (Pr10) during DJF (JJA), respectively, suggesting that over most regions, in contrast to FF and FD, flood intensity (FI and FTI) tends to be more associated with total precipitation volume/magnitude especially for those extreme precipitation events. A further examination of Fig. 6 indicates that monthly mean precipitation (Pr) and precipitation frequency in particular F25 could impact flood intensity (FI and FTI) as well. It is further noted that precipitation intensity except the very high end one (R50) has a relatively weak impact on floods globally.

The 10 specific regions are further chosen to explore the regional relationships between floods and precipitation (Table 3). Given the fragmented spatial distributions shown in Figs. 4 and 5, focusing on relatively large domains may help derive a clearer picture of the collective impact of precipitation on floods. During DJF (Fig. 7), FF and FD tend to be significantly correlated with daily precipitation frequency (Fxx) and mean precipitation amount (Prxx) at many locations, while their correlations with daily precipitation intensity (Rxx) are generally weak, roughly consistent with depicted in Fig. 4. In particular, significant correlations between FF and precipitation frequency (Fxx) can be found in South America, the southeastern United States, South Africa, central South Africa, Australia, and South China. Significant correlations between FF and Prxx can also be seen in these regions. It is further noted that the correlation relations of both FF and FD with all precipitation indices are weak in central West Africa,

likely suggesting other flood-generating mechanisms in this region and certainly warranting further exploration. Also, in northern South America, FF and FD tend to be negatively correlated with high-end precipitation intensity (R25 and R50), and the negative correlations between FD and both R25 and R50 are even above the confidence level. This may imply the frequent occurrence of flash floods in this region, certainly warranting a further exploration. In South Asia, FF is only marginally correlated to Fxx and Prxx, while its correlations with R01 and R50 are very strong; on the other hand, FD in this region is strongly correlated to high-end daily precipitation frequency (F25 and F50) and precipitation amount indices (Prxx). Obviously, all these regional characteristics need to be further explored in the future by focusing on possible physical mechanisms.

During DJF, FI and FTI have in general weaker correlation relations with precipitation than FF and FD do. However, significant correlations of both FI and FTI with precipitation indices can still be seen in several regions including Australia, central South America, South Asia, and northern South America. It is also of interest to note that FI in central South America tends to be correlated to most of precipitation indices, while FTI does not. In northern South America, both FI and FTI have strong correlation relations

TABLE 3. The 10 focus regions.

Southeast United States	30°–35°N, 75°–100°W
Northern South America	5°S–10°N, 45°–80°W
Central South America	5°–20°S, 40°–60°W
Southern South America	25°–35°S, 50°–65°W
Central West Africa	5°–15°N, 15°W–10°E
Central South Africa	15°N–20°S, 10°–35°E
South Africa	20°–35°S, 15°–35°E
South China	20°–30°N, 110°–122°E
South Asia	7°–30°N, 75°–110°E
Australia	10°–40°S, 120°–155°E

FIG. 7. Correlations between flood indices and various precipitation indices in 10 regions during DJF. Horizontal dashed lines indicate the 90% confidence level.

with daily precipitation intensity indices, while their correlations with either Fxx or Prxx are weak.

The correlation relations between floods and precipitation indices during JJA are illustrated in Fig. 8. Seasonal differences tend to be more evident than illustrated in Figs. 4 and 5, though FF and FD seem to be more associated with Fxx and Prxx in most regions. However, in several regions such as South Africa, southeastern United States, Australia, and South China, FF and FD are also significantly correlated with daily precipitation intensity indices. In particular, in the southeastern United States and South Africa, FF and FD are correlated to almost all precipitation indices except between FD and F50 in South Africa. Furthermore, negative correlations between FF and daily precipitation

intensity appear in several regions and even become statistically significant in South Asia and central South Africa.

The correlations of both FI and FTI with precipitation indices during JJA, particularly with Fxx and Prxx, are stronger than during DJF, though regional differences are still evident. As mentioned above, these regional features might suggest distinct flood-generating mechanisms and warrant further explorations especially in the context of individual river basin scales in that the possible collective effects for each basin could be quantified.

5. The ENSO impact on floods and precipitation

The ENSO effects are also focused on the two distinct seasons (DJF and JJA) for comparison. Niño-3.4

FIG. 8. Correlations between flood indices and various precipitation indices in 10 regions during JJA. Horizontal dashed lines indicate the 90% confidence level.

FIG. 9. Correlations between seasonal mean flood indices and Niño-3.4 during DJF. Black slant lines denote those above the 90% confidence level.

(<http://www.cpc.ncep.noaa.gov/data/indices/>) is used to represent the El Niño–Southern Oscillation events, which is estimated by averaging sea surface temperature anomalies over the domain of 5°N–5°S, 120°–170°W. Correlations between seasonal mean flood indices and Niño-3.4 are estimated and depicted in Figs. 9 and 10. Correlations between seasonal mean precipitation and Niño-3.4 are also computed for these two seasons (not shown). As shown in past studies (e.g., Dai and Wigley 2000), during DJF, strong positive correlations between precipitation and Niño-3.4 are located over the southern portion of North America, southeastern South America,

tropical eastern Africa, and many parts of Asia; at the same time, significantly negative correlations can be observed in northern South America, southern Africa, and western Australia.

For flood indices during DJF, the ENSO impact tends to be weaker in the Northern Hemisphere and the major ENSO impact zones are primarily located in the Southern Hemisphere following seasonal shift of mean precipitation and floods, except in the southeastern United States and over a small portion of southeastern China. Two regions with strong positive correlations are located in southeastern South America, the central

FIG. 10. Correlations between seasonal mean flood indices and Niño-3.4 during JJA. Black slant lines denote those above the 90% confidence level.

FIG. 11. Precipitation indices with the largest, second, and third largest correlations with Niño-3.4 during DJF (left) and JJA (right).

portion of Africa, and Madagascar. It is readily recognized that the strong ENSO impact on precipitation in many regions during DJF does not necessarily translate to the occurrence of floods especially in the Northern Hemisphere likely due to relatively weak mean precipitation amount during the season and also cold surface temperature specifically over the extratropical lands. Also, in several regions with intense negative correlations between precipitation and Niño-3.4 such as in northern South America, southern Africa, and western Australia, similar ENSO signals are not seen in floods, probably implying a relatively weak impact of La Niña events or a nonlinear (asymmetrical) relationship between ENSO and precipitation (e.g., [Emerton et al. 2017](#); [Lee et al. 2018a,b](#)) and/or the involvement of other factors in the generation of flood events.

During JJA, positive correlations between precipitation and Niño-3.4 are located in part of the southern United States, South America, South Africa, and northern and eastern Asia. Negative correlations appear in several regions including the western United States, northern South America, the Maritime Continent, and portions of Australia.

Compared to those during DJF in which the ENSO events usually reach their mature phase, ENSO-related precipitation anomalies during JJA are generally weak.

Significant ENSO impacts on floods can be seen in several regions during JJA ([Fig. 10](#)), though they tend to be weaker than during DJF. As in DJF, the correlation relations with Niño-3.4 are similar for these four flood indices. Positive correlations occur in the eastern United States, northern South America, central Africa, and South China. Negative correlations can be seen in several regions including over a small portion of South America, the Maritime Continent, and south India; however, they are generally not as strong as the correlations between precipitation and Niño-3.4, similar to during DJF. Also, over southern Africa, high positive correlation between precipitation and Niño-3.4 does not have similar counterparts between flood indices and Niño-3.4. There is a further surprise that in southeastern China floods tend to have a positive correlation relation with Niño-3.4, while the correlations between precipitation and Niño-3.4 are weak and can even become

FIG. 12. Correlations between flood/precipitation indices and Niño-3.4 in 10 regions during DJF and JJA. Horizontal dashed lines indicate the 90% confidence level.

negative. In Australia, negative correlations between precipitation and Niño-3.4 are followed by weak correlation relations between floods and ENSO.

Figure 11 further shows the impact of ENSO on a variety of precipitation indices during DJF and JJA. Obviously, the ENSO impact manifests a highly fragmented spatial distribution. However, certain collective ENSO effects in particular on Pr and Fxx are discernible in many regions during both seasons. During DJF, Pr and Fxx tend to have the largest correlations with Niño-3.4 in Mexico, northern parts of South America, eastern and southern parts of Africa, South China, the western coast of Australia, and the Maritime Continent. During JJA, Pr and Fxx tend to have largest correlations with Niño-3.4 as well in the regions such as the northern parts of South America, South Asia, and the Maritime Continent. Though relatively weaker, precipitation intensity (Rxx) can also be modulated by ENSO during both seasons as the second and third largest correlations indicate (Figs. 11c–f).

The correlations between flood/precipitation indices and Niño-3.4 are further estimated for the 10 specific regions (Fig. 12) during DJF and JJA, respectively. During DJF, significant positive correlations with Niño-3.4 can be found in FF and FD in southern South America and

southeastern United States; high positive correlations are also seen between FF and Niño-3.4 in South China and the central South America. It is noted that these significant correlations are generally consistent with the ENSO impact on precipitation indices except in central South America. Furthermore, significant negative correlations with Niño-3.4 appear as well in several other regions. In particular, all flood indices in South Africa tend to be correlated with Niño-3.4, and the correlation coefficients become statistically significant for FF, FD, and FTI; and these high correlations can also be seen in all precipitation indices. In northern South America, ENSO can have an impact on several precipitation indices. FI in South Asia is also significantly correlated with Niño-3.4, likely due to the ENSO impact on F25.

During JJA, the ENSO impact on floods tends to be weak as mentioned above. However, significant correlations with Niño-3.4 can still be found in FF and FD over South Africa, in FI in South Asia, and in FF over South China. As in DJF, the ENSO impact on floods in South Africa and South Asia can be traced to the ENSO effects on various precipitation indices. However, in other regions, even though the ENSO impact on precipitation indices can be found, it seems that this impact may not necessarily be able to translate to an effective

influence on floods or there is a lagged response to ENSO in floods as suggested in [Emerton et al. \(2017\)](#).

6. Summary and conclusions

Spatial distributions and temporal variations of global floods during the TRMM period (1998–2013) are investigated by using the outputs from the Dominant River Routing Integrated with VIC Environment model (DRIVE) driven by the high spatiotemporal resolution TRMM satellite-based rainfall product. Connections between floods and a variety of precipitation characteristics specified by the TRMM daily rain rates are further examined. Climatological and seasonal mean flood activities generally occur over the locations where regional precipitation maxima are usually observed, confirming that more precipitation including both amount and frequency often corresponds to higher probability of flood occurrence. Nevertheless, differences exist regarding detailed spatial distributions and seasonal mean features between floods and precipitation. In particular, flood indices representing distinct flood characteristics ([Table 1](#)) can be related to different aspects of precipitation events denoted by a series of daily precipitation and extreme indices, in addition to monthly mean precipitation, as illustrated in [Table 2](#), and their relations could be highly regionally dependent.

The relationships between floods and precipitation are further examined by focusing on their interannual correlation relations during the two distinct seasons (DJF and JJA). In general, flood frequency (FF) and duration (FD) tend to be more related to daily precipitation frequency globally especially to the mid- to high-end daily frequencies (F10, F25, F50) during both seasons. However, in contrast to FF and FD, flood intensity (both FI and FTI) tend to be more associated with daily precipitation volume/magnitude corresponding to those extreme precipitation events (Pr10 and Pr25) over most regions, though monthly mean precipitation (Pr) and daily precipitation frequency, for instance F25, can have an impact as well. Nevertheless, daily precipitation intensity (Rxx) except the very high end one (R50) seems to have a relatively weak effect on these flood indices.

Regional correlation relations between floods and precipitation indices are further investigated in the 10 large regions ([Table 3](#)) during DJF and JJA, respectively. There are evident regional features. For instance, FF and FD can be strongly correlated with daily precipitation frequency (Fxx) and precipitation amount (Prxx) at some locations, but their correlation relations could become weak in other places during both seasons; similar conclusions can be made also between flood intensity (FI and FTI) and precipitation indices.

Furthermore, seasonal differences exist as well. For example, FI and FTI have in general weaker correlation relations with precipitation indices, but their correlations specifically with Fxx and Prxx could become stronger in several regions during JJA. These regional results can certainly improve our understanding of precipitation-related flood-generating mechanisms in different regions and during distinct seasons.

Interannual variations in floods are further explored by examining possible ENSO modulations. ENSO can effectively affect floods in many flood-prone zones particularly during the peak season (DJF). Furthermore, this ENSO effect often functions through influencing various aspects of precipitation. Nevertheless, intense ENSO signals in precipitation cannot always translate to evident ENSO effect on floods in certain regions. During JJA, in spite of a relatively weak ENSO impact on floods as expected, high correlations between flood indices (FF and FD) and Niño-3.4 can still be found in several regions such as South Africa. As in DJF, the ENSO impact on precipitation cannot always translate to floods in many other regions.

This study is primarily focused on the relations between floods and precipitation at the DRIVE model grids and over the 10 chosen domains. Other mechanisms may also be related to flood generations as mentioned above. Specifically, antecedent soil moisture has been considered an important factor for flooding formation and might become more critical when we intend to assess possible changes in floods due to climate change (e.g., [Woldemeskel and Sharma 2016](#); [Hettiarachchi et al. 2019](#)). Thus, in the next-step work we plan to use the total precipitation amount within the (5 or 7) days prior to the occurrence of individual flood events as a proxy for antecedent soil conditions and then explore its possible impact on floods (e.g., [Bischiniotis et al. 2018](#)). Also, the relationships between floods and precipitation will be further examined at the river basin scale across the world. Streamflow at each individual river basin can effectively integrate spatial information of precipitation within the basin, which might be more convenient for exploring not only concurrent but also lagged relations between floods and precipitation and also their concurrent and lagged connections with ENSO.

Finally, it should be mentioned that even though the outputs from the DRIVE model had been validated in the past (e.g., [Wu et al. 2014](#)), more validations are warranted. In particular, to enhance our confidence in the conclusions made here, it is necessary to further perform certain uncertainty analyses (and actually being one of our ongoing efforts), by means of comparing global flood simulations using other available models

different from the DRIVE model and/or using different precipitation input datasets.

Acknowledgments. This study was supported by the National Natural Science Foundation of China (Grants 41861144014, 41775106, and U1811464) and National Key R&D Program of China (Grant 2017YFA0604300), and also partially by Natural Science Foundation of Guangdong Province (Grant 2017A030313221) and the Program for Guangdong Introducing Innovative and Entrepreneurial Teams (Grant 2017ZT07X355). The authors also want to thank the two anonymous reviewers for their constructive comments/suggestions.

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