Spatiotemporal patterns of satellite precipitation extremes in the Xijiang River Basin: From statistical characterization to stochastic behavior modeling

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ABSTRACT

Given the threats from rainstorm events that have been intensified due to climate change, the investigation of heavy/extreme precipitation is attracting increasing attention. The investigation of extreme precipitation, with its restricted tools and data, is quite different from that of non-extreme precipitation. Satellite precipitation estimates (SPEs) are promising precipitation measurements due to fine spatial resolution. However, the spatiotemporal patterns of SPE extremes remain unclear. Therefore, this study attempted to systematically analyze the spatiotemporal patterns of extreme SPEs

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provided by the Tropical Rainfall Measurement Mission (TRMM) research product from statistical characterization to stochastic behavior modeling. The statistical characterization was depicted using comprehensive extreme precipitation indices (EPIs), while the stochastic behavior was modeled using the generalized Pareto distribution (GPD) to fit the “peak over threshold” samples and employing the max-stable process to fit the “block maximum” samples (Max: annual 1-day maximum, RX1day: monthly 1-day maximum, and RX5day: monthly 5-day maximum) of the TRMM data. The TRMM extremes were analyzed across the Xijiang River Basin, China. The results of the statistical characterization revealed that compared with gauge precipitation, most TRMM EPIs were discovered to have higher temporal dynamic levels. Moreover, the spatial median of the return level for each return period derived from temporal TRMM extreme modeling with the GPD was lower than that from gauge extremes. The spatial dependence of Max in TRMM was weaker than that of either RX1day or RX5day, primarily due to different precipitation-generating processes existing between two extreme events at annual scale compared with monthly scale. Each of the Max, RX1day, and RX5day in TRMM exhibited stronger spatial dependence than that in gauge extreme precipitation, maybe related to the area-average-based representation of the SPEs. These findings can enhance our insight into the spatiotemporal patterns of extreme satellite precipitation, which is beneficial for

operational flood risk management.

KEYWORDS: heavy/extreme precipitation, satellite precipitation, TRMM, generalized Pareto distribution, max-stable process

1. INTRODUCTION

The IPCC Fifth Assessment Report (AR5) revealed that heavy/extreme precipitation events are predicted to increase in many regions around the world, as increasing global atmospheric temperatures lead to the atmosphere having a greater capacity to hold moisture (Allan and Soden, 2008; Field, 2014). Therefore, investigating extreme precipitation, which typically includes the description and prediction of its temporal evolution and spatial distribution, is becoming increasingly important when making flood forecasts and taking precautions against landslide (Alexander et al., 2006; Wu et al., 2017; Subba et al., 2019).

Satellite precipitation estimates (SPEs), due to their quasi-global extent and unprecedented resolution in space and time, are promising alternatives to gauge rainfall measurements. There are now more than a dozen commonly used satellite precipitation products, including the Tropical Rainfall Measuring Mission (TRMM) (Huffman et al., 2007; Liu, 2015), Integrated Multi-satellite Retrievals Global Precipitation Measurement (IMERG) (Huffman et al., 2015; Foelsche et al., 2017), Global Satellite Mapping of Precipitation (GSMaP) product (Kubota et al., 2007; Ushio et al., 2009),

and Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) (Hsu et al., 1997; Sorooshian et al., 2000; Nguyen et al., 2018).

Evaluation of measurement precision using gauge rainfall as a benchmark or comparison with other precipitation products contributes significantly to the current study of SPEs. The spatiotemporal patterns of SPEs over river basins and geographical regions have frequently been investigated. The study of extreme precipitation, with its restricted tools and data, is quite different from that of non-extreme precipitation. Traditionally, however, attention has primarily been paid to total precipitation, whereas the extreme rainfall in SPEs has been less scrutinized, possibly due to the lack of suitable tools and/or long-term SPE datasets (Evin et al., 2018). Due to the threat of stronger and more intense rainstorm events as a result of climate change in recent years, the investigation of extreme SPEs has been attracting significant attention.

The statistical investigation of the extreme value process in heavy precipitation events is primarily based on two sampling techniques: “peak over threshold” (POT) (Davison and Smith, 1990; Coles et al., 2001) and “block maxima” (BM) (Katz et al., 2002; Langousis et al., 2016). Specifically, a POT sample is constructed by selecting all the records exceeding a given threshold (e.g., 95% or 99% quantiles). According to this rule, the days exceeding, for example, precipitation of 10 mm per day can be used to describe precipitation frequency, and the amount exceeding 10 mm per day can be used

to quantify the precipitation intensity (Davison and Smith, 1990). In contrast, a BM sample is generated by extracting the maximum record over a specified time period (e.g., one month or one year). Exploiting the BM rule, the set of precipitation amounts and days of the maxima in given temporal intervals can be used to describe the characteristics of precipitation in terms of intensity and frequency, respectively (Langousis et al., 2016).

Using the extreme precipitation extraction measures of POT and BM, the statistical characterization of extreme precipitation based on surface gauge (Deng et al., 2014) and GCM/RCM outputs (Janssen et al., 2016; Innocenti et al., 2019) has been comprehensively assessed in order to identify the temporal evolution and/or spatial patterns of extreme precipitation events. Recently, spatiotemporal analysis of SPE extreme events has drawn increasing attention. Jiang et al. (2017) introduced extreme precipitation indices (EPIs), including precipitation of the 95% threshold, the highest 1-day, and the highest 7-day to analyze the extreme features in the TRMM 3B42RTv7 and 3B42v7 products across the Ganjiang River Basin. Innocenti et al. (2019) compared the annual and diurnal cycles of annual maximum daily and sub-daily precipitation relevant to the satellite precipitation product generated with “Climate Prediction Center MORPHing technique” (CMORPH) v1.0 CRT and the Multi-Source Weighted-Ensemble Precipitation (MSWEP) v2.0 product among multiple sources of

precipitation datasets. In addition, a set of EPIs recommended by the Expert Team on Climate Change Detection and Indices (ETCCDI) is more comprehensive for depicting the climatic extremes from precipitation frequency and intensity data (Data, 2009; AlSarmi and Washington, 2014; Wu et al., 2016). The ETCCDI, which is still the only source for publicly available evaluation systems concerning precipitation extremes in many parts of the world, is a potentially powerful tool for quantifying the spatiotemporal patterns of SPE extremes.

With regard to the POT and BM extreme sampling approaches, another focus of current extreme precipitation research is the temporal and spatial stochastic behavior modeling of extreme precipitation occurrence. Extreme value theory provides a powerful tool with a solid theoretical basis to deal with the stochastic modeling of extreme precipitation (Castillo, 2012). For the case of temporal modeling, many studies based on surface gauge rainfall observations have been conducted to obtain return level or return period (Demirdjian et al., 2018; Wu et al., 2018), exceedance probability (Nathan et al., 2016), and tail behavior (Mascaro, 2018), which are of paramount importance for storm-dependent risk control and prediction. For SPE precipitation, however, investigations associated with the extreme value distribution of temporal extreme series have been undertaken less frequently, perhaps due to the relatively short-term records which contribute to unconfident sample sets. Nevertheless, POT samples, the

asymptotic distribution of which over a high enough threshold belongs to the domain of the generalized Pareto distribution (GPD) complying with the Pickands theorem (Pickands III, 1975), as illustrated above, can improve the fitting accuracy of temporal extreme precipitation series by increasing the sample capacity and can provide potential applicability for extreme precipitation modeling with relatively short records (Demirdjian et al., 2018).

As for spatial stochastic behavior modeling, SPEs provide finely gridded precipitation fields for modeling the spatial patterns of SPE extremes. An important spatial feature of extreme precipitation is spatial dependence, that is, the distance up to which different extreme precipitation series are dependent (Gaume et al., 2013). It is known that (semi-) variograms have frequently been explored to analyze the spatial dependence of non-extreme precipitation. Extremal dependence, however, cannot be quantified using (semi-) variograms, since it may be unavailable. Instead, the max-stable process is a powerful tool for modeling the spatial dependence of extreme values using extreme value theory (Brown and Resnick, 1977; Kabluchko et al., 2009). The max-stable process has recently been applied to the extreme precipitation field. Zhang et al. (2014) utilized it to analyze the topography-based spatial patterns of precipitation extremes. Le et al. (2018) investigated the influence of a point extreme precipitation event on a surrounding area via the max-stable process. Furthermore, the one-dimensional

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marginal distribution of the max-stable process belongs to the family of generalized extreme value (GEV) distributions, which is the theoretically asymptotic distribution of infinite (or sufficient) BM sampling data complying with the Fisher-Tippett theorem (Fisher and Tippett, 1928).

Under the above-mentioned premises, this study attempted to analyze the spatiotemporal patterns of heavy/extreme precipitation from SPEs in terms of statistical characterization and stochastic behavior modeling, specifically consisting of (1) analyzing the spatiotemporal statistical characterization of EPIs, (2) evaluating return levels of the temporal extreme modeling using the GPD, and (3) quantifying the extremal dependence of the spatial extreme modeling using the max-stable process. We described the statistical characterization primarily via deterministic frequency analysis technique, while modeling the stochastic behavior primarily using random probability distribution and sampling techniques. According to previous comparisons of the PERSIANN and TRMM products in other similar studies, the TRMM 3B42v7 product exhibited superior performance relative to the PERSIANN-CDR product over China (Li et al., 2018). In addition, since TRMM mission initially attempted to measure tropical precipitation, it is more likely to capture heavy precipitation events. Consequently, weighing temporal coverage and precipitation precision, the TRMM non-real-time product 3B42v7 was utilized to provide the SPEs in this study.

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Additionally, the Xijiang River Basin and its surrounding area, located in the southern part of China and featuring complex topography associated with highly heterogeneous precipitation both spatially and temporally, were selected as the study area for analyzing the extremal spatiotemporal patterns of the TRMM precipitation compared with the corresponding gauge precipitation.

Following this introduction, the overview of the study area and precipitation datasets including satellite precipitation and gauge rainfall was provided. Then, the methods of extreme precipitation indices, and GPD and max-stable process modeling based on extreme value theory were described in Section 3. Section 4 aimed to display the results of applying TRMM extremes and gauge rainfall extremes to the methods of Section 3, including temporal evolution and spatial pattern of EPIs, return level derived from GPD modeling, the spatial dependence of the spatial extreme modeling, and discussion on them. Finally, conclusions were given in Section 5.

2. STUDY AREA AND PRECIPITATION DATASETS

2.1 Study area

The Xijiang River Basin and its surrounding region (for the purpose of operational simplicity, SPE is displayed over the Xijiang River Basin covered by a rectangle, see Figure 1), located in the southern part of China, was selected as the study area. Being the largest tributary of the Pearl River, the Xijiang River has a total drainage area of

353,000 km², contributing about 77.83% to the whole Pearl River Basin area (PRWRC, 2005). As shown in the digital elevation model (-1–4058 m) of Figure 1, the terrain decreases broadly from the northwest to the southeast direction in the study area. The basin belongs to transitional zone from sub-tropical to tropical monsoon climate with mean annual precipitation of 1200–2000 mm and mean annual air temperature ranging from 14–22°C for a long-term record. Despite abundant precipitation over the study area, the spatiotemporal variations are significant. For example, 70%–85% of the annual precipitation occurs in the wet season of April to September; higher annual precipitation commonly occurs in the northern region (exceeding 2000 mm), while much lower precipitation appears in the southwest region of the study area (below 800 mm).

<Figure 1>

2.2 Precipitation datasets

The analysis of the spatial and temporal patterns of satellite extreme precipitation was performed on the TRMM Version-7 product. The TRMM precipitation product covers the quasi-global region of 50°S–50°N latitude and 180°W–180°E longitude with a 0.25° × 0.25° spatial resolution, and provides datasets from 1998 to the present. The website of Precipitation Measurement Mission of NASA (<https://pmm.nasa.gov/TRMM>) is accessible to download TRMM products. Details on the TRMM sensors and data

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algorithms were given by Huffman and Bolvin (2007; 2010) and Huffman et al. (2007; 2010). The research product of the post-processed non-real-time 3B42 Version-7 (hereafter abbreviated as 3B42v7) during the period 1 January 2000–31 December 2018 was used in this study, since it features higher accuracy and a superior ability to detect the rainstorm events compared with the near-real-time 3B42 Version-7 product.

For comparison with the TRMM satellite precipitation, the surface precipitation dataset provided by 42 rainfall gauges over the Xijiang River Basin from the Pearl River Water Resources Commission of China (Figure 1) was also utilized to analyze the spatiotemporal patterns of heavy/extreme precipitation. Both TRMM and gauge precipitation were processed at the daily scale using the same time period. In order to guarantee the reliability of the gauge data, the sequential rainfall datasets were first graphically cross-compared with nearby gauges. Second, outlier values were numerically checked and removed. Finally, the missing data in the gauge rainfall series during the study period, which occurred at a very low rate ($< 1.2\%$), were filled in by interpolating the corresponding records measured by the nearest station.

3. METHODS

The identification of extreme precipitation, comprehensive index set used to describe extreme precipitation, and distribution modeling in extreme value theory are provided in this section in order to analyze the spatiotemporal patterns of the TRMM extreme

precipitation. The flowchart in Figure 2 provides a brief overview of this study. Initially, two approaches for extracting extreme precipitation (POT and BM) are described. Subsequently, a set of comprehensive indices composed according to the two extreme precipitation extraction approaches and used to quantify the statistical characterization of extreme precipitation is introduced. Finally, the GPD, which is used to model temporal extreme precipitation series extracted by POT sampling, and max-stable process, which is used to model spatial extremes extracted by BM sampling, are described.

<Figure 2>

3.1 Identification of extreme precipitation

For a given precipitation series, there are multiple approaches for identifying which records are extremes, and the method used to extract the extreme precipitation will affect the subsequent analysis. Two techniques for extracting extremes, the POT and BM, are commonly used. In the POT approach, all the records exceeding a given threshold compose extreme precipitation, while in the BM method, the maximum records within specified time windows or within blocks of equal data length are taken as extreme precipitation. Based on the POT and BM approaches, the extreme precipitation indices to be discussed in Section 3.2 can be classified into two groups. For example, the number of heavy precipitation days (R10mm) and the annual total

precipitation on very wet days (R95p) are generated by the POT data, while the annual maximum 1-day precipitation (Max) and the monthly maximum 1-day precipitation (RX1day) are part of the BM data.

3.2 Extreme precipitation indices (EPIs)

In order to depict the statistical characterization of extreme precipitation, a comprehensive 11-index set of extreme precipitation was introduced (Table 1). This set of EPIs includes nine climate indices associated with extreme precipitation recommended by an expert team, as well as the Max and annual accumulation precipitation (Sum) due to their essential importance to the precipitation estimation. With the exceptions of Max and Sum, the other nine extreme EPIs were specially designed by the ETCCDI and jointly developed by the World Meteorological Organization (WMO) Commission for Climate Variability and Predictability. As described in Section 3.1, the set of EPIs follows POT and BM extraction approaches for extreme precipitation. From another perspective, these indices can also be partitioned into two groups in which one is based on precipitation frequency and the other on precipitation intensity. The frequency-based indices calculate the number of days on which extreme precipitation events occurred, while the intensity-based indices estimate the amounts of precipitation in extreme precipitation events.

<Table 1>

3.3 Extreme value distribution modeling in extreme precipitation

Extreme value theory is frequently used to guide the analysis of extreme precipitation from distribution fitting to extremal behavior quantification. In extreme value theory, POT and BM are the approaches that are widely used to extract extreme data, of which the limiting distributions are the GPD and GEV, respectively. In this study, POT and BM were applied to analyze the stochastic behavior of extreme precipitation temporally and spatially, respectively, using the fundamental hypothesis of extreme value theory that given the occurrence sequence, variable realizations (daily precipitation intensities in the present context) are assumed conditionally independent and identically distributed (iid). The probability density function (PDF) and cumulative distribution function (CDF) of the GPD and the return level in the GPD fitting were derived for the temporal TRMM extreme precipitation series, while the max-stable process with a univariate marginal distribution of the GEV and the resulting extremal dependence were described for the spatial TRMM extreme precipitation sets as follows.

3.3.1 Temporal extreme precipitation modeling via the GPD

Following the study of Coles (2001), a sample generated from the POT may be regarded as an independent realization of a random variable whose limiting distribution over a high enough threshold can be approximated by a family of GPDs (Thibaud et al., 2013). In addition, for the modeling of daily precipitation time series, POT sampling is

superior to BM sampling, both in theory and oftentimes in practice, since more information on multiple large precipitation events occurring during the same time period can usually be taken into account by POT sampling (Rosbjerg and Madsen, 2004). The CDF of the GPD $F(y)$ for the random variable y that exceeds a high threshold u is defined as follows:

$$F_{gpd}(Y \leq y) = \begin{cases} 1 - [1 + \frac{\xi(y-u)}{\sigma}]^{-\frac{1}{\xi}} & \text{if } \xi > 0, \\ 1 - \exp(-\frac{y-u}{\sigma}) & \text{if } \xi = 0, \end{cases} \quad (1)$$

where ξ , u , and σ ($\sigma > 0$) denote the shape, location, and scale parameters, respectively, and $y - \{1 + \xi(y-u)/\sigma > 0\}$ represents the TRMM satellite precipitation extremes or gauge precipitation extremes. Note that the upper tail of the distribution is controlled by the shape parameter ξ . For $\xi > 0$, the GPD is heavy-tailed or sub-exponential, while for $\xi = 0$, the GPD degrades into an exponential distribution. An appropriate threshold u should strike a balance between bias with poor distribution fitness due to a threshold that is too low and high variance with small samples resulting from a threshold that is too high. Considering both the robustness and the simplicity of the mathematics, the threshold u in this study was set to the 99% quantile of the ordered precipitation series for SPE or gauge precipitation, as has been applied in multiple analogous studies on extreme precipitation (Furrer and Katz, 2008; Wu et al., 2018). The GPD modeling was based on either a time series of gauge precipitation values at a

station or of SPEs on a grid. Thus, given the length of a precipitation time series, the POT sample exceeding the 99% quantile contained 70 values.

The return level (R^T), defined as the value being exceeded on average once within a given time period T under the assumption of stationarity, is of practical interest. T is regarded as the return period, associated with an event of probability $1/T$. Thus, the return level R^T associated with T can also be defined as the quantile that is exceeded with probability $1/T$. The estimate of an extreme quantile R^T of the GPD can be derived by equating the right-hand side of Eq. (1) to $1 - T^{-1}$, and solving for $x = R^T$, where R^T is the T -observation return level with an associated return period T :

$$R^T = F_{gpd}^{-1}\left(1 - \frac{1}{T}\right) \quad (2)$$

For convenience, return levels are usually based on the annual scale. The T -year return level R^T of the GPD can be expressed as the function of estimated shape, location and scale parameters and T :

$$R^T = \begin{cases} \hat{u} + \hat{\sigma} \frac{[(T)^{\hat{\xi}} - 1]}{\hat{\xi}} & \text{if } \hat{\xi} \neq 0, \\ \hat{u} + \hat{\sigma} \log(T) & \text{if } \hat{\xi} = 0. \end{cases} \quad (3)$$

In this study, the parameters in Eq. (3) were estimated using the L-moment method (Hosking and Wallis, 2005). The goodness-of-fit of the GPD modeling was diagnosed using the Kolmogorov–Smirnov test (at the significance level of 0.05) and the graphical

Q-Q plot.

3.3.2 Spatial extreme precipitation modeling via the max-stable process

The max-stable process with a solid formalism in multivariate extreme value theory has been proposed to characterize the spatial dependence of BM-sampled extreme values.

As the extension and development of univariate extreme value modeling, a max-stable process $Z(\cdot)$ is the limiting process of the maxima of iid random fields $Y(x)$, $x \in R^d$.

Namely, if there exist suitable sequences $a_n(x) > 0$ and $b_n(x) \in R$, such that

$$Z(x) = \lim_{n \rightarrow +\infty} \frac{\max_{i=1}^n Y_i(x) - b_n(x)}{a_n(x)}, \quad (4)$$

then $Z(x)$ is a max-stable process. In order to study the two-dimensional spatial precipitation field, let $d = 2$. Here, x denotes the spatial site and $Y(x)$ is the precipitation intensity at x .

All of the finite dimensional marginal distributions of $Z(x)$ are max-stable processes.

Specifically, the univariate marginal $Z(x)$ distribution follows the GEV family:

$$F_{gev}(Z(x) \leq z) = \begin{cases} \exp\left[-\left(1 + \frac{\xi(x)(z - u(x))}{\sigma(x)}\right)^{-\frac{1}{\xi(x)}}\right] & \text{if } 1 + \frac{\xi(x)(z - u(x))}{\sigma(x)} > 0, \\ 1 & \text{otherwise,} \end{cases} \quad (5)$$

where $\xi(\cdot)$, $u(\cdot)$, and $\sigma(\cdot)$ are the shape, location, and scale parameters, respectively, at a fixed site. Since single modeling realization is sensitive to sampling and parameters due to the limited and constrained precipitation data, bootstrap resampling approach was used to generate ensemble realizations to reduce the model sensitivity, and then the

realization with optimal performance was applied. The realization number of bootstrap was determined iteratively by progressively increasing the sample size until a robust estimate of the empirical distribution was achieved (Rulfová et al., 2016).

An important advantage of the max-stable process in spatial extreme modeling is that the spatial covariates with different values in space but not depending on time are often used to infer the spatial dependence of the GEV parameters and construct the resulting max-stable process model. The longitude, latitude, and elevation of the spatial sites were considered as covariates to support the “space-varying” parameters of the marginal distribution GEV in this study (Ribatet, 2009; ZhangXiaoSingh et al., 2014):

$$\begin{cases} \xi(x) = a_1 \\ u(x) = a_2 + b_2 \times loc(x) + c_2 \times lat(x) + d_2 \times elev^{e_2}(x) \\ \sigma(x) = a_3 + b_3 \times loc(x) + c_3 \times [lat(x)]^2 + d_3 \times elev^{e_3}(x) \end{cases}, \quad (6)$$

where e_2 and e_3 , with values of 1 or 0.5 as determined by the Takeuchi Information Criterion (TIC; see below) of the optimal model, are the parameters of the power function; covariate coefficients were optimized using a numerical optimization procedure. The TIC, which is superior to the Akaike Information Criterion (AIC) since it allows for misspecification, is an estimator that weighs the value of the composite likelihood (l_p) and the number of model parameters in order to select the optimal max-stable process model:

$$TIC(\hat{\psi}) = -2l_p(\hat{\psi}, z) + 2 \text{tr}(J(\hat{\psi})H(\hat{\psi})^{-1}), \quad (7)$$

where J and H are the Jacobian and Hessian information matrices given the estimate of parameter set $\hat{\psi}$, respectively. The optimal model is the one that minimizes the TIC. Detailed introduction of the searching process can be referred to Gao and Song (2010). In the max-stable process, the extremal coefficient can measure the degree of spatial dependence for extreme values (maxima in this study) at two locations, x_1 and x_2 . According to Schlather and Tawn (2003), the theoretical extremal coefficient function has the following expression:

$$Pr[Z(x_1) \leq z, Z(x_2) \leq z] = P(Z(x) \leq z)^{\theta(x_1, x_2)} = \exp\left\{-\frac{\theta(x_1, x_2)}{z}\right\}, \quad (8)$$

The extremal coefficient function for the max-stable process models in Eq. (4) can be derived directly from their bivariate distribution by letting $z_1 = z_2 = z$. If $\theta(x_1, x_2) = 1$, the dependence of extreme precipitation between sites x_1 and x_2 is perfect, whereas if $\theta(x_1, x_2) = 2$, the two extreme value series are independent. More precisely, given a specified model of the max-stable process, for example, the Brown-Resnick model used in this study, the extremal coefficient function can be presented explicitly:

$$\theta(h) = 2\Phi\left(\sqrt{\frac{\gamma(h)}{2}}\right), \quad (9)$$

where $\Phi(\cdot)$ is the standard normal CDF and given the Euclidean distance $h = \|x_1 - x_2\|$ denoting the distance between x_1 and x_2 , the variogram is $\gamma(h) = h^\alpha / q$, with $q > 0$ and $\alpha \in (0, 2)$. The Brown-Resnick model of the max-stable process was applied in this

study due to its high flexibility in terms of the various variogram shapes near 0 and its full independence at long distances. On the basis of BM sampling, three extreme precipitation samples—Max, RX1day, and monthly maximum 5-day precipitation (RX5day)—were explored in order to model the max-stable process in the study area encompassing the Xijiang River Basin.

4. RESULTS AND DISCUSSION

4.1 Statistical characterization of TRMM EPIs at spatial and temporal scales

In order to characterize the spatiotemporal patterns of extreme precipitation, the time series of 11 EPIs were calculated for the TRMM precipitation at each grid point (814 grid points in total) across the study area. For comparison, the similar series for gauge precipitation during the same period were derived at each rain station (42 stations in total). The temporal evolution of the TRMM EPIs compared with that of gauge EPIs from 2000–2018 years is illustrated in Figure 3 (for annual-scale-based indices) and in Figure 4 (for monthly-scale-based indices), displaying varying fluctuations between the TRMM EPIs and gauge EPIs. In the figures, the bands of the 95% confidence intervals (CIs) of the TRMM extremes for six EPIs, including consecutive wet days (CWD), R10mm, R20mm, Sum, annual total wet day precipitation (RRCPTOT), and simple daily intensity index (SDII), were wider than those of the gauge precipitation extremes, since the upper boundaries of the 95% CIs for the TRMM EPIs were significantly

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higher than the corresponding upper boundaries of the gauge EPI 95% CIs. Similar to the upper boundaries of the 95% CIs in the above six annual EPIs, the median of the TRMM EPIs over the various grids was also higher than that of the gauge EPIs over the various stations. The levels of the 95% CI bands and the median curves for the monthly-scaled TRMM EPIs of R95p and annual total precipitation on extremely wet days (R99p) were comparable with those for the R95p and R99p of the gauge EPIs, respectively. In contrast with the above EPIs, the upper boundary of the 95% CIs for Max derived from the TRMM data was lower than that from the gauge precipitation, while the median curve of the TRMM Max was almost the same as that of the gauge Max. Furthermore, for the monthly-based EPIs, the lower boundaries of the 95% CI and median of the TRMM monthly maximum 1-day precipitation RX1day (9.99 mm and 34.40 mm for the temporally averaged lower boundary and median, respectively) were both slightly higher than those for the gauge RX1day (6.54 mm and 28.62 mm, respectively), while the upper boundary of the 95% CI for the TRMM RX1day (94.19 mm) was slightly lower than that of the gauge RX1day (97.12 mm). The RX5day displayed similar trends in the 95% CI band and the median of the ensemble series between the TRMM and gauge extreme precipitation.

<Figure 3>

<Figure 4>

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In contrast to the temporal dynamics of the EPIs, the spatial patterns of the EPIs for the TRMM values derived by averaging the time series of each EPI from 2000-2018 were then plotted in Figures 5 and 6 for the frequency-based and intensity-based EPIs, respectively. These figures exhibited clear spatial gradients. In general, high values of CWD appeared in the northern and then the eastern region of the study area, with a maximum of 29.0 days, while the low values of CWD were mainly located in the southern region, with a minimum of 5.6 days. The remaining ten EPIs all displayed similar spatial patterns, roughly decreasing from northeast to southwest.

<Figure 5>

<Figure 6>

For comparison with the gauge precipitation, TRMM extreme precipitation at grid points containing at least one surface rainfall station was selected. The scatterplot and fitted regression line of each EPI derived from selected extreme TRMM precipitation versus the corresponding gauge extreme precipitation index are illustrated in Figure 7. It can be observed that there is less difference in R10mm, Sum, and accumulated annual precipitation on wet days (PRCPTOT) than the other EPIs between these two precipitation sources. The performance of the TRMM EPIs versus gauge EPIs evaluated using the correlation coefficient (CC) was further quantified and is listed in Table 2. Among the correlated EPIs, Sum, and PRCPTOT for the TRMM precipitation

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were most significantly correlated with the corresponding gauge Sum and PRCPTOT EPIs (with a mean CC value of 0.86 and a median CC value of 0.88 for both TRMM and gauge precipitation, and p -values < 0.05). Similarly, the CC values of R10mm, R20mm, R95p, and SDII between the TRMM precipitation and corresponding gauge precipitation were also significant, with mean and median values > 0.46 and > 0.50 , respectively. In terms of extreme value classification, these six EPIs were all focused on the assessment of precipitation (frequency or intensity) exceeding a threshold. In other word, these six EPIs were derived from the extreme for POT which provides larger extreme data than BM extraction approach. Therefore, the POT extreme may lead to higher CC between TRMM and gauge extremes.

<Figure 7>

<Table 2>

4.2 Stochastic behavior analysis of extreme value modeling of the TRMM

4.2.1 Return level detected by temporal extreme value modeling of GPD

The temporal extreme precipitation series extracted using the POT sampling approach (with a threshold of the 99% quantile) were modeled to fit the GPD at each grid point of the TRMM precipitation and at each station of the gauge precipitation sources. All of the optimal GPD modeling of both the TRMM and gauge extreme precipitation passed the Kolmogorov–Smirnov test of equal distribution at the 0.05 level of

significance. In order to graphically observe the modeling efficiency, the PDF and CDF of the GPD and the diagnostic Q-Q for the TRMM and gauge extreme precipitation series at one specified station site (see the insets of Figure 8a and b) were plotted as an example. The PDF curve of the TRMM precipitation (threshold: 36.84 mm) was higher than that of the gauge precipitation (threshold: 34.82 mm), especially in the lower tail, while the CDF curve of the TRMM precipitation was slightly lower than that of the gauge precipitation across the existing extreme precipitation range (Figure 8a). The Q-Q plot of the optimal GPD models exhibited comparatively good fitting qualities between the TRMM and gauge precipitation at the selected site (Figure 8b). Next, the log-likelihood function values of the optimal GPD models for the TRMM extremes at the sites of rainfall stations and the gauge extreme precipitation values at 42 stations are presented in Figure 8c. The averaged log-likelihood function values of the TRMM extremes (282.39) were slightly lower than that of the gauge extreme series (288.88), indicating that the TRMM has better modeling performance for the GPD likelihood function. In addition, the GPD parameters for the optimal models of the TRMM extremes at all grid points and of the gauge extreme precipitation at 42 stations are summarized in Figure 8d–f. The threshold u of the TRMM extremes displayed a higher median, mean, and upper quartile than the gauge extremes, while the median, mean, and quartile box of the shape and scale parameters of the TRMM extremes were lower

than those of the gauge extremes.

<Figure 8>

On the basis of the optimal GPD models, the spatial patterns of the 100-year, 50-year, 20-year, and 10-year return levels for the TRMM and gauge precipitation extremes were derived and compared (Figure 9). Four return levels of the TRMM and gauge extremes were higher in the east, and lower in the west of the study area, which changed broadly in an inverse relationship with the elevation. The quantitative correlation analysis in Table 3 revealed that the return levels of both the TRMM and gauge extremes displayed significant negative correlations with elevation. The median of the return level of the TRMM extremes at each return period was lower than that of the gauge extremes. In addition, the TRMM return levels at the sites of rainfall stations for the four return periods had a significantly positive correlation (> 0.78) with the corresponding gauge return levels.

<Figure 9>

<Table 3>

4.2.2 Extremal dependence of spatial extreme value modeling on max-stable process

The spatial extreme precipitation sets extracted using the BM sampling approach (Max, RX1day, and RX5day) were modeled to fit the max-stable process. Next, the goodness-of-fit was assessed for the optimal models. As discussed in Section 3.3, the spatial

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covariates of latitude, longitude, and elevation were introduced in order to improve the modeling by connecting the extreme precipitation variations with spatial locations and elevation. The changes of the location and scale parameters of the GEV marginal distribution in the optimal max-stable process model with three spatial covariates, that is, latitude, longitude, and elevation, are summarized in Table 4 for three BM extreme value cases of Max, RX1day, and RX5day. For the three cases, in general, the location and scale parameters for both the TRMM and gauge extremes displayed similar monotonically decreasing trends with increasing latitude and increasing elevation, while there was no uniform monotonic trend associated with longitude. This result demonstrated that both the location and scale parameters were negatively correlated with the latitude and elevation covariates. The additional parameters of the range and smooth, and TIC values used to select the optimal models of the max-stable process are also listed in Table 4. Slightly smaller TIC values in the Max and RX5day cases and slightly larger TICs in the RX1day case for the TRMM precipitation relative to the gauge precipitation can be seen in this table, indicating reasonable efficiency of the optimal modeling.

<Table 4>

The extremal coefficients (Ext.coeffs), including the pairwise F-madogram estimates (Ribatet, 2009) and theoretical Ext.coeff functions of Max, RX1day, and RX5day for

the gauge extreme precipitation across the study area, are displayed in Figure 10a–c, respectively. The theoretical Ext.coeff functions of Max, RX1day and RX5day were equal to 1 at the distance $h = 0$, corresponding to “complete dependence”. When the distance $h > 0$, the dependence decreased with increasing distance. As can be seen, the theoretical Ext.coeff curve of the RX1day was very similar to that of the RX5day. Compared with those of the RX1day and RX5day, the theoretical Ext.coeff curve of Max was higher and increased more sharply with increasing distance, and was more closely surrounded by pairwise and binned estimated Ext.coeff scatters. These results suggest that the spatial dependence of annual extreme precipitation was much lower and decreased much faster than that of the monthly extreme precipitation.

<Figure 10>

Similarly, the Ext.coeffs of Max, RX1day, and RX5day for the TRMM precipitation are displayed in Figure 11. For the TRMM precipitation, the Max Ext.coeff increased faster than the RX1day and RX5day Ext.coeffs, also indicating that the spatial dependence of the Max annual extremes decreased faster than those of RX1day and RX5day monthly extremes. For the purpose of comparison, the theoretical Ext.coeff curves of the gauge precipitation were also added to Figure 11. It is obvious that all of the theoretical Ext.coeff curves of the TRMM extremes were lower than those of the gauge extremes. Specifically, the range of the Max Ext.coeff for the TRMM extreme precipitation

(1.626–1.998, corresponding to $0.234 \leq h \leq 8.793$) was comparable to that of the gauge extreme precipitation (1.607–2.000, corresponding to the same h range). Nevertheless, the Max curve of the TRMM extreme precipitation increased more sharply than the gauge extreme precipitation curve. The curves of RX1day and RX5day for the TRMM extremes (ranging from 1.228–1.691 and 1.180–1.612 for RX1day and RX5day, respectively) were significantly lower than those of the gauge extremes (1.406–1.898 and 1.369–1.870, respectively), indicating the higher spatial dependence of TRMM extreme precipitation relative to the gauge extreme precipitation.

<Figure 11>

4.3 DISCUSSION

Precipitation measurements from remotely sensed satellites and surface rain gauges both have their own advantages and disadvantages. The TRMM 3B42v7 product provides more extreme information due to its higher spatial resolution compared with gauge precipitation, while gauge precipitation has higher precision at the point scale. It should be noted that the comparison between the 3B42v7 precipitation and gauge precipitation for extreme analysis was conducted using the 3B42v7 data in grids where there is at least one surface rainfall station. For the extreme precipitation indices, Sum and PRCPTOT were consistent between 3B42v7 and gauge precipitation, while SDII and R99p exhibited large discrepancies between 3B42v7 and gauge precipitation

(Figure 7). Large errors were observed in indices with high extremity, which suggests that the more extreme the precipitation, the more difficult it is for both the surface gauge and the remote sensing satellite to measure.

Extreme precipitation displays a strong spatial dependence pattern, in other words, close-enough locations are likely to experience concomitant extremes. It can be clearly observed that the spatial dependence of annual extreme precipitation was much lower and decreased much faster than that of the monthly extreme precipitation. This is because the annual maximum precipitation events at two different locations likely occurred across different seasons, in close association with different precipitation-generating processes (Zheng et al., 2015). Accordingly, the annual maximum precipitation between two sites from different generating processes exhibited less spatial dependence than the monthly maximum precipitation that tended to be generated by the same process. In addition, the higher spatial dependence of the TRMM extremes relative to the gauge extreme precipitation is presented in Figure 11. The higher spatial dependence of the TRMM extremes may have resulted from the method used by the remote-sensing satellite to measure precipitation. Since satellite precipitation measurement uses a value to represent the areal average precipitation across a surface grid, less spatial heterogeneity is inherent in the TRMM precipitation compared with the gauge precipitation which represents a point value (Zorzetto and Marani, 2019).

The satellite precipitation extremes of the TRMM 3B42v7 product were comprehensively quantified under various extremity conditions using multiple extreme precipitation indices and were stochastically modeled in terms of both temporal and spatial aspects using the up-to-date generalized Pareto distribution and max-stable process, respectively. The assessment of the satellite precipitation extremes can be applied to further exploring the extremal spatiotemporal relationship in the resulting flood events. The results analyzed above also demonstrated the usefulness of both the statistical indices and the stochastic modeling tools, which can be used to other satellite precipitation products and other rainstorm-prone areas to study gridded heavy precipitation data.

5. CONCLUSIONS

In order to analyze the spatiotemporal patterns of heavy/extreme precipitation in satellite precipitation estimates, that is, a TRMM product, this study preliminarily quantified the statistical characterization via comprehensive extreme precipitation indices (EPIs), and then used the GPD and max-stable process to fit the stochastic behavior of the temporal extreme series and spatial extreme sets of TRMM precipitation, respectively. The Xijiang River Basin and its surrounding region were selected as the study area, due to its complex topography, which generates extreme precipitation, as well as its generally pluvial climate type. The primary conclusions were as follows:

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- (1) The median curves of the temporal evolution of the EPIs for TRMM precipitation were comparable with or slightly higher than those for gauge precipitation, and most bands of the 95% confidential intervals of the TRMM EPIs were wider than those of the gauge EPIs, indicating generally greater temporal dynamics in TRMM extreme precipitation. Spatially, the high EPI values mainly appeared in the northern and eastern sections of the study area, while the low EPIs mainly occurred in the southwestern section.
  - (2) The return levels at 100-year, 50-year, 20-year, and 10-year return periods derived from TRMM extreme modeling with the GPD were separately and significantly correlated with those from gauge extreme precipitation. The changes in return levels at the four return periods for both the TRMM and gauge extremes exhibited inverse relationships with the elevation.
  - (3) The spatial dependence of the TRMM extremes, including annual 1-day maximum (Max), monthly 1-day maximum (RX1day), and monthly 5-day maximum (RX5day), was higher relative to the corresponding gauge precipitation extremes. The higher spatial dependence of the TRMM extremes may result from the lower spatial heterogeneity of the TRMM areal average precipitation measurements across a grid. For both TRMM and gauge extreme precipitation, the spatial dependence of the annual extreme precipitation was lower and decreased much

faster than that of the monthly extreme precipitation.

In summary, the heavy/extreme precipitation of the TRMM research product was analyzed using two extreme precipitation identification techniques—POT and BM—for both temporal and spatial scales. Further investigation may extend the analysis to other popular satellite precipitation products and other areas threatened by extreme precipitation events, and explore the teleconnection of satellite precipitation extremes with synoptic circulation patterns or ocean anomalies in order to achieve a comprehensive analysis of satellite rainfall products in attempt to develop the effective water resource management and disaster preparedness.

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REFERENCES

Alexander, L.V., Zhang, X., Peterson, T.C., Caesar, J., Gleason, B., Klein Tank, A., Haylock, M., Collins,

D., Trewin, B. and Rahimzadeh, F. (2006) Global observed changes in daily climate extremes of temperature and precipitation. *Journal of Geophysical Research: Atmospheres*, **111**(D5).

Allan, R.P. and Soden, B.J. (2008) Atmospheric warming and the amplification of precipitation extremes. *Science*, **321**(5895): 1481-1484.

AlSarmi, S.H. and Washington, R. (2014) Changes in climate extremes in the Arabian Peninsula: analysis of daily data. *International Journal of Climatology*, **34**(5): 1329-1345.

Brown, B.M. and Resnick, S.I. (1977) Extreme values of independent stochastic processes. *Journal of Applied Probability*, **14**(4): 732-739.

Castillo, E. (2012) *Extreme value theory in engineering*, Academic Press.

Coles, S., Bawa, J., Trenner, L. and Dorazio, P. (2001) *An introduction to statistical modeling of extreme values*, Springer.

PRWRC. (2005) Pearl River flood prevention handbook. *Pearl River Water Resource Commission, Guangzhou*, **150**.

Data, C. (2009) Guidelines on analysis of extremes in a changing climate in support of informed decisions for adaptation. *World Meteorological Organization*.

Davison, A.C. and Smith, R.L. (1990) Models for exceedances over high thresholds. *Journal of the Royal Statistical Society: Series B (Methodological)*, **52**(3): 393-425.

Demirdjian, L., Zhou, Y. and Huffman, G.J. (2018) Statistical modeling of extreme precipitation with TRMM data. *Journal of Applied Meteorology and Climatology*, **57**(1): 15-30.

Deng, H., Chen, Y., Shi, X., Li, W., Wang, H., Zhang, S. and Fang, G. (2014) Dynamics of temperature

and precipitation extremes and their spatial variation in the arid region of northwest China. *Atmospheric Research*, **138**: 346-355.

Evin, G., Favre, A. and Hingray, B. (2018) Stochastic generation of multi-site daily precipitation focusing on extreme events. *Hydrology and Earth System Sciences*, **22**(1): 655-672.

Field, C.B. (2014) *Climate change 2014 – Impacts, adaptation and vulnerability: Regional aspects*, Cambridge University Press.

Fisher, R.A. and Tippett, L.H.C. (1928). *Limiting forms of the frequency distribution of the largest or smallest member of a sample*. Paper presented at the Mathematical Proceedings of the Cambridge Philosophical Society.

Foelsche, U., Kirchengast, G., Fuchsberger, J., Tan, J. and Petersen, W.A. (2017) Evaluation of GPM IMERG Early, Late, and Final rainfall estimates using WegenerNet gauge data in southeastern Austria. *Hydrology and Earth System Sciences*, **21**(12): 6559-6572.

Furrer, E.M. and Katz, R.W. (2008) Improving the simulation of extreme precipitation events by stochastic weather generators. *Water Resources Research*, **44**(12): W12439.

Gao, X. and Song, P.X.K. (2010) Composite likelihood Bayesian information criteria for model selection in high-dimensional data. *Journal of the American Statistical Association*, **105**(492): 1531-1540.

Gaume, J., Eckert, N., Chambon, G., Naaim, M. and Bel, L. (2013) Mapping extreme snowfalls in the French Alps using max - stable processes. *Water Resources Research*, **49**(2): 1079-1098.

Hosking, J.R.M. and Wallis, J.R. (2005) *Regional frequency analysis: an approach based on L-moments*, Cambridge University Press.

Hsu, K., Gao, X., Sorooshian, S. and Gupta, H.V. (1997) Precipitation estimation from remotely sensed information using artificial neural networks. *Journal of Applied Meteorology*, **36**(9): 1176-1190.

Huffman, G.J., Adler, R.F., Bolvin, D.T. and Nelkin, E.J. (2010) The TRMM multi-satellite precipitation analysis (TMPA). In: *Satellite rainfall applications for surface hydrology*, Springer.

Huffman, G.J., Bolvin, D.T., Braithwaite, D., Hsu, K., Joyce, R., Xie, P. and Yoo, S. (2015) NASA global precipitation measurement (GPM) integrated multi-satellite retrievals for GPM (IMERG). *Algorithm Theoretical Basis Document (ATBD) Version*, **4**: 26.

Huffman, G.J., Bolvin, D.T., Nelkin, E.J., Wolff, D.B., Adler, R.F., Gu, G., Hong, Y., Bowman, K.P. and Stocker, E.F. (2007) The TRMM multisatellite precipitation analysis (TMPA): Quasi-global, multiyear, combined-sensor precipitation estimates at fine scales. *Journal of Hydrometeorology*, **8**(1): 38-55.

Innocenti, S., Mailhot, A., Frigon, A., Cannon, A.J. and Leduc, M. (2019) Observed and simulated precipitation over northeastern North America: how do daily and sub-daily extremes scale in space and time? *Journal of Climate*, **32**(24): 8563–8582.

Janssen, E., Sriver, R.L., Wuebbles, D.J. and Kunkel, K.E. (2016) Seasonal and regional variations in extreme precipitation event frequency using CMIP5. *Geophysical Research Letters*, **43**(10): 5385-5393.

Jiang, S., Zhang, Z., Huang, Y., Chen, X. and Chen, S. (2017) Evaluating the TRMM multisatellite precipitation analysis for extreme precipitation and streamflow in Ganjiang River Basin, China. *Advances in Meteorology*, **2017**(ID 2902493): 1-12.

Kabluchko, Z., Schlather, M. and De Haan, L. (2009) Stationary max-stable fields associated to negative

definite functions. *The Annals of Probability*, **37**(5): 2042-2065.

Katz, R.W., Parlange, M.B. and Naveau, P. (2002) Statistics of extremes in hydrology. *Advances in Water Resources*, **25**(8-12): 1287-1304.

Kubota, T., Shige, S., Hashizume, H., Aonashi, K., Takahashi, N., Seto, S., Hirose, M., Takayabu, Y.N., Ushio, T. and Nakagawa, K. (2007) Global precipitation map using satellite-borne microwave radiometers by the GSMaP project: Production and validation. *IEEE Transactions on Geoscience and Remote Sensing*, **45**(7): 2259-2275.

Langousis, A., Mamalakis, A., Puliga, M. and Deidda, R. (2016) Threshold detection for the generalized Pareto distribution: Review of representative methods and application to the NOAA NCDC daily rainfall database. *Water Resources Research*, **52**(4): 2659-2681.

Le, P.D., Davison, A.C., Engelke, S., Leonard, M. and Westra, S. (2018) Dependence properties of spatial rainfall extremes and areal reduction factors. *Journal of Hydrology*, **565**: 711-719.

Li, C., Tang, G. and Hong, Y. (2018) Cross-evaluation of ground-based, multi-satellite and reanalysis precipitation products: Applicability of the Triple Collocation method across Mainland China. *Journal of Hydrology*, **562**: 71-83.

Liu, Z. (2015) Comparison of precipitation estimates between Version 7 3-hourly TRMM Multi-Satellite Precipitation Analysis (TMPA) near-real-time and research products. *Atmospheric Research*, **153**: 119-133.

Mascaro, G. (2018) On the distributions of annual and seasonal daily rainfall extremes in central Arizona and their spatial variability. *Journal of Hydrology*, **559**: 266-281.

- Nathan, R., Jordan, P., Scoriah, M., Lang, S., Kuczera, G., Schaefer, M. and Weinmann, E. (2016) Estimating the exceedance probability of extreme rainfalls up to the probable maximum precipitation. *Journal of Hydrology*, **543**: 706-720.
- Nguyen, P., Ombadi, M., Sorooshian, S., Hsu, K., AghaKouchak, A., Braithwaite, D., Ashouri, H. and Thorstensen, A.R. (2018) The PERSIANN family of global satellite precipitation data: a review and evaluation of products. *Hydrology and Earth System Sciences*, **22**(11): 5801-5816.
- Pickands III, J. (1975) Statistical inference using extreme order statistics. *the Annals of Statistics*, **3**(1): 119-131.
- Ribatet, M. (2009) A user's guide to the SpatialExtremes package. *EPFL, Lausanne, Switzerland*.
- Rosbjerg, D. and Madsen, H. (2004). *Advanced approaches in PDS/POT modelling of extreme hydrological events*. Paper presented at the Hydrological Society International Conference.
- Rulfová, Z., Buishand, A., Roth, M. and Kysely, J. (2016) A two-component generalized extreme value distribution for precipitation frequency analysis. *Journal of hydrology*, **534**: 659-668.
- Schlather, M. and Tawn, J.A. (2003) A dependence measure for multivariate and spatial extreme values: Properties and inference. *Biometrika*, **90**(1): 139-156.
- Sorooshian, S., Hsu, K., Gao, X., Gupta, H.V., Imam, B. and Braithwaite, D. (2000) Evaluation of PERSIANN system satellite-based estimates of tropical rainfall. *Bulletin of the American Meteorological Society*, **81**(9): 2035-2046.
- Subba, S., Ma, Y. and Ma, W. (2019) Spatial and temporal analysis of precipitation extremities of Eastern

Nepal in the last two decades (1997-2016). *Journal of Geophysical Research: Atmospheres*, **124**(14): 7523-7539.

Thibaud, E., Mutzner, R. and Davison, A.C. (2013) Threshold modeling of extreme spatial rainfall. *Water Resources Research*, **49**(8): 4633-4644.

Ushio, T., Sasashige, K., Kubota, T., Shige, S., Okamoto, K., Aonashi, K., Inoue, T., Takahashi, N., Iguchi, T. and Kachi, M. (2009) A Kalman filter approach to the Global Satellite Mapping of Precipitation (GSMaP) from combined passive microwave and infrared radiometric data. *Journal of the Meteorological Society of Japan. Ser. II*, **87**: 137-151.

Wu, X., Guo, S., Yin, J., Yang, G., Zhong, Y. and Liu, D. (2018) On the event-based extreme precipitation across China: Time distribution patterns, trends, and return levels. *Journal of Hydrology*, **562**: 305-317.

Wu, X., Wang, Z., Guo, S., Liao, W., Zeng, Z. and Chen, X. (2017) Scenario-based projections of future urban inundation within a coupled hydrodynamic model framework: a case study in Dongguan City, China. *Journal of Hydrology*, **547**: 428-442.

Wu, X., Wang, Z., Zhou, X., Lai, C., Lin, W. and Chen, X. (2016) Observed changes in precipitation extremes across 11 basins in China during 1961–2013. *International Journal of Climatology*, **36**(8): 2866-2885.

Zhang, Q., Xiao, M., Li, J., Singh, V.P. and Wang, Z. (2014) Topography-based spatial patterns of precipitation extremes in the Poyang Lake basin, China: Changing properties and causes. *Journal of Hydrology*, **512**: 229-239.

Zhang, Q., Xiao, M., Singh, V.P. and Chen, Y.D. (2014) Max-stable based evaluation of impacts of climate indices on extreme precipitation processes across the Poyang Lake basin, China. *Global and Planetary Change*, **122**: 271-281.

Zheng, F., Westra, S. and Leonard, M. (2015) Opposing local precipitation extremes. *Nature Climate Change*, **5**(5): 389.

Zorzetto, E. and Marani, M. (2019) Downscaling of rainfall extremes from satellite observations. *Water Resources Research*, **55**(1): 156-174.

TABLE 1 Extreme precipitation indices (EPIs) used to evaluate the spatiotemporal distribution of SPE extreme and gauge precipitation extreme

Index	Short name	Long name	Definition	Unit	Classification
Frequency indices	CWD	Consecutive wet days	Maximum number of consecutive wet days (precipitation of ≥ 1 mm)	day	BM
	R10mm	Number of heavy precipitation days	Annual count of days when precipitation is ≥ 10 mm	day	POT
	R20mm	Number of very heavy precipitation days	Annual count of days when precipitation is ≥ 20 mm	day	POT
Intensity indices	Max	Annual maximum 1-day precipitation	Annual maximum 1-day precipitation	mm	BM
	Sum	Annual sum of 1-day precipitation	Annual accumulated 1-day precipitation	mm	POT
	PRCPTOT	Annual total wet day precipitation	Annual total from days ≥ 1 mm precipitation	mm	POT
	R95p	Annual total precipitation on very wet days	Annual total precipitation of days in > 95 th percentile	mm	POT
	R99p	Annual total precipitation on extremely wet days	Annual precipitation of days in > 99 th percentile	mm	POT
	RX1day	Monthly maximum 1-day precipitation	Monthly maximum 1-day precipitation	mm	BM
	RX5day	Monthly maximum 5-day precipitation	Monthly maximum consecutive 5-day precipitation	mm	BM
	SDII	Simple daily intensity index	Ratio of annual total to the wet days in a year	mm/day	POT

TABLE 2 Correlation coefficient (CC) summary of temporal extreme precipitation indices (EPIs) between gauge precipitation and TRMM precipitation at 42 stations

Index	CC		
	Mean	Median	Range
CWD	0.24	0.20	(-0.26, 0.68)
R10mm	0.75**	0.75**	(0.44, 0.89)
R20mm	0.66**	0.69**	(0.28, 0.91)
Max	0.12	0.11	(-0.35, 0.69)
Sum	0.86**	0.88**	(0.63, 0.97)
PRCPTOT	0.86**	0.88**	(0.62, 0.97)
R95p	0.46**	0.50**	(0.01, 0.84)
R99p	0.16	0.13	(-0.27, 0.64)
RX1day	0.22*	0.01	(-0.19, 0.79)
RX5day	0.27**	0.00	(-0.16, 0.90)
SDII	0.52**	0.50**	(0.21, 0.84)

Note: ** and * represent correlation at significance levels of 0.05 and 0.1, respectively.

TABLE 3 Performance of modeled return levels for TRMM and gauge extreme precipitation at 42 rainfall station sites

	Range for TRMM (mm)	Median for TRMM (mm)	CC with DEM for TRMM	Range for Gauge (mm)	Median for Gauge (mm)	CC with DEM for Gauge	CC between TRMM and Gauge
100-year	(62.58, 339.89)	147.18	-0.56	(89.20, 306.19)	171.10	-0.53	0.78
50-year	(57.97, 293.07)	134.86	-0.58	(81.85, 262.75)	150.99	-0.52	0.82
20-year	(51.56, 245.98)	118.66	-0.59	(71.71, 210.38)	126.11	-0.51	0.86
10-year	(46.41, 211.35)	105.30	-0.60	(63.54, 174.27)	107.51	-0.50	0.87

Note: All correlation coefficient (CC) values have significance of p -value < 0.05 . Gauge represents gauge precipitation.

TABLE 4 Parameters and TIC for optimal max-stable process models

		Max	RX1day	RX5day
Location	T	$u(x) = 200.48 - 4.00 \times lat(x) - 0.02 \times elev(x)$	$u(x) = 92.16 - 2.46 \times lat(x) - 0.37 \times elev^{1/2}(x)$	$u(x) = 164.30 - 4.88 \times lat(x) - 0.01 \times elev(x)$
	G	$u(x) = 312.12 - 8.12 \times lat(x) - 1.16 \times elev(x)$	$u(x) = 87.97 - 2.47 \times lat(x) - 0.32 \times elev^{1/2}(x)$	$u(x) = 140.15 - 3.76 \times lat(x) - 0.55 \times elev^{1/2}(x)$
Scale	T	$\sigma(x) = 89.75 - 0.47 \times lon(x) - 0.02 \times lat^2(x) - 0.005 \times elev(x)$	$\sigma(x) = -101.37 + 1.22 \times lon(x) - 0.01 \times lat^2(x) - 0.07 \times elev^{1/2}(x)$	$\sigma(x) = -202.18 + 2.38 \times lon(x) - 0.03 \times lat^2(x) - 0.002 \times elev(x)$
	G	$\sigma(x) = -96.03 + 1.44 \times lon(x) - 0.04 \times lat^2(x) - 0.15 \times elev(x)$	$\sigma(x) = -55.01 + 0.84 \times lon(x) - 0.03 \times lat^2(x) - 0.09 \times elev^{1/2}(x)$	$\sigma(x) = 42.27 + 0.35 \times lon(x) - 0.07 \times lat^2(x) - 0.34 \times elev^{1/2}(x)$
Range	T	0.12	3.07	5.11
	G	0.18	0.59	0.80
Smooth	T	0.68	0.69	0.73
	G	1.20	0.62	0.63
TIC	T	309053	3629075	4003988
	G	323341	3598977	4011917

Note: T and G represent TRMM and gauge precipitation, respectively.

FIGURE 1 DEM, grid network of TRMM satellite precipitation, and sites of rain gauge stations over the Xijiang River Basin.

FIGURE 2 Flowchart of this study for analyzing the spatial and temporal patterns of satellite heavy/extreme precipitation. The physical meaning of the extreme precipitation indices was listed in Table 1. The GPD is the short name of generalized Pareto distribution. BM and POT represent two approaches of extreme precipitation extraction, i.e., block maximum and peak of threshold, respectively.

FIGURE 3 Temporal evolution of extreme precipitation indices (EPIs) based on the annual scale for TRMM over all grids and gauge precipitation over all stations.

FIGURE 4 Temporal evolution of the extreme precipitation indices (EPIs) based on the monthly scale for the TRMM over all grids and gauge precipitation over all stations.

FIGURE 5 Spatial patterns of the extreme precipitation indices (EPIs) used to detect the heavy/extreme precipitation frequency.

FIGURE 6 Spatial patterns of the extreme precipitation indices (EPIs) used to detect the heavy/extreme precipitation intensity.

FIGURE 7 Scatter plot of each TRMM extreme precipitation index at rainfall stations versus rain gauge extreme precipitation index over all stations and the regression line fitting the scatters.

FIGURE 8 (a) PDF and CDF, (b) diagnostic Q-Q plot at a specific site, (c) log-likelihood function (Loglik) value at sites of rain stations located, and (d)-(f) summary of the parameter in the optimal GPD modeling of the TRMM and gauge extreme precipitation time series. Insets in the subplots displayed which grid points of the TRMM and gauge stations used in that subplot.

FIGURE 9 Return levels at 100-year, 50-year, 20-year, and 10-year return periods of the temporal TRMM and gauge extreme precipitation series modeling via the GPD.

FIGURE 10 Extreme coefficients (Ext. coeffs) of the (a) annual 1-day maximum (Max), (b) monthly 1-day maximum (RX1day), and (c) monthly 5-day maximum (RX5day) of the gauge extreme precipitation modeling via the max-stable process. The distance h is the Euclidean distance of two sites, x_1 and x_2 , where extreme precipitation occurs. Since sites of x_1 and x_2 are in decimal degree of latitude and longitude, the unit of h (similarly hereinafter) is the same with x_1 and x_2 . The plotted theoretical Ext. coeff curve covers the range of $0.234 \leq h \leq 8.793$ (similarly hereinafter).

FIGURE 11 Extreme coefficients (Ext.coeffs) of the (a) annual 1-day maximum (Max), (b) monthly 1-day maximum (RX1day), and (c) monthly 5-day maximum (RX5day) of the TRMM extreme precipitation modeling via the max-stable process.