MINIMUM INTER-EVENT TIMES FOR RAINFALL IN THE EASTERN MONSOON REGION OF CHINA

W. Wang, S. Yin, Y. Xie, M. A. Nearing

ABSTRACT. *Minimum inter-event time (MIT) is an index used to delineate independent storms from sub-daily rainfall records. An individual storm is defined as a period of rainfall with preceding and succeeding dry periods less than MIT. The exponential method was used to determine an appropriate MIT_{exp} for the eastern monsoon region of China based on observed 1-min resolution rainfall data from 18 stations. Results showed that dry periods between storms greater than MIT_{exp} followed an exponential distribution. MIT_{exp} values varied from 7.6 h to 16.6 h using 1-min precipitation data, which were statistically not different from values using hourly data at $p = 0.05$. At least ten years of records were necessary to obtain a stable MIT. Values of storm properties are sensitive to the change in MIT values, especially when MIT values are small. Average precipitation depths across all stations were 45% greater, durations were 84% longer, maximum 30-min intensities were 27% greater, and average rainfall intensities were 20% less when using an MIT of 10 h, the average value of MIT_{exp} over 18 stations, compared to 2 h. This indicates that more attention should be paid to the use of the MIT index as it relates to storm properties.*

Keywords. *China, Exponential method, Minimum inter-event time, Storm, Storm property.*

Precipitation varies greatly in its duration, intensity, and spatial coverage (Dunkerley, 2008a). It is an important driving force for many hydrological and erosional processes, and precipitation data are common inputs for hydrological and erosion models (Flanagan et al., 2001; Nicks et al., 1995; Gassman et al., 2007). Because observed precipitation records include both wet periods and dry periods, it is important to delineate separate storm events in rainfall records. However, identifying storms from continuous records is not as easy as it may seem at first glance because of the non-uniqueness of the definition of an independent storm (Islam et al., 1990). A simple approach is to delineate rainfall by daily amount, which is defined as the amount of rain accumulated for 24 h from a specific time (such as 8:00 a.m.) on a given day until the same time on the following day. The daily rainfall amount is the most commonly used form of rainfall data in preparing inputs for hydrological and erosional models (Kou et al., 2007; Xie et al., 2016; Yin et al., 2015) and studies of extreme precipitation (Goswami et al., 2006). However, daily data have limitations in depicting rainfall characteristics in detail, such as the duration, depth of the storm, and structure of the inter-storm. Moreover, continuous rainfall that crosses the daily boundary will be divided into precipitation amounts occurring on successive rainy days; as such, the precipitation amount for each rainy day will less than the accumulated storm amount, which in turn may underestimate the hydrologic impact if daily rainfall data are used.

Event-scale rainfall data are required inputs for some hydrological and erosional models, such as the Universal Soil Loss Equation (USLE) and its successors, RUSLE and RUSLE2 (Renard et al., 1997; USDA-ARS, 2013; Wischmeier, 1959). When observed data are not sufficient in spatial and temporal coverage, simulations of the data may be required. A definition of a storm is a specific difficulty in some storm-based and Poison cluster stochastic rainfall simulation models (Bonta, 2004; Koutsoyiannis and Mamassis, 2001; Kim et al., 2013, 2016).

Various criteria have been reported in the literature regarding the identification of individual storms, including specification of a minimum inter-event time (Bonta and Rao, 1988; Bonta, 2001; Huff, 1967; Wenzel and Voorhees, 1981), a minimum rain depth (Ziegler et al., 2006), a minimum duration of record (Cutrim et al., 2000), etc. A brief review is provided by Dunkerley (2008b). The minimum inter-event time (MIT) refers to the threshold duration of the dry period between wet periods that is used to delineate storm events. If a dry period between two rainy (wet) periods is shorter than the MIT, the successive rainy periods will be considered one storm. If the dry period is longer than the MIT, the successive rainy periods will be considered two separate storms (Bonta and Rao, 1988; Svoboda et al., 2017).

The methods used to determine the MIT can be categorized into three types: (1) constant time method, (2) empiri-

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The authors are **Wenting Wang,** Graduate Student, **Shuiqing Yin,** Associate Professor, and **Yun Xie,** Professor, State Key Laboratory of Earth Surface Processes and Resource Ecology, Faculty of Geographical Science, Beijing Normal University, Beijing, China; **Mark A. Nearing,** Research Agricultural Engineer, USDA-ARS Southwest Watershed Research Center, Tucson, Arizona. **Corresponding author:** Shuiqing Yin, No. 19 Xin-Jie-Kou-Wai St., Haidian District, Beijing 100875, China; phone: +86-186-0012-3691; e-mail: yinshuiqing@bnu.edu.cn.

cal method, and (3) statistical method. The constant time method is also called arbitrary separation (Bonta and Rao, 1988). It appoints a fixed time length as a criterion to separate storms. For example, Huff (1967) used 6 h to separate preceding and succeeding storms, and Yu et al. (2007) classified storms using an MIT of 2 h when analyzing hourly rain-gauge data.

The empirical method defines MIT based on observations for a specific application. Wischmeier (1959) used a 6 h criterion to define MIT when developing the rainfall erosion index for USLE by considering the best correlations between soil loss and rainfall erosivity index values. Renard et al. (1997) and the USDA-ARS (2013) followed the same criterion for RUSLE and RUSLE2.

The statistical method involves using a statistical model to analyze the precipitation properties and then determining an MIT value. The exponential method, developed by Restrepo-Posada and Eagleson (1982), is the most commonly used statistical method for identifying individual storms (Bonta, 2001, 2004; Driscoll et al., 1989; Iadanza et al., 2016; Requena et al., 2016; Sordo-Ward et al., 2016; Yoo et al., 2015). It is based on the assumption that storm events are mutually independent and the arrival of each follows a Poisson process (Restrepo-Posada and Eagleson, 1982), which is important for stochastic rainfall simulation (Bonta, 2004). Bonta and Rao (1988) suggested that the exponential method is superior to the rank correlation method, which is another statistical method (Wenzel and Voorhees, 1981).

In China, both the constant time method and the empirical method have been adopted to identify independent storms. A constant MIT of 2 h (Li et al., 2013; Yu et al., 2007) has been commonly employed in recent studies of rainfall characteristics in China and in the corresponding analysis of temporal change. A constant MIT of 6 h (Huff, 1967) was applied when Yin (2016) used Huff curves to study intra-storm temporal patterns of rainfall. The empirically determined MIT of 6 h developed by Wischmeier (1959) has been used in research related to soil erosion at the storm time scale (Wang et al., 2016; Yin et al., 2015). However, research using a statistical method, particularly the exponential method, to identify storm events has not been undertaken. Application of the exponential method will benefit stochastic rainfall simulation because it is fundamentally based on the assumption that storms are statistically independent (Bonta et al., 2012).

In this study, the exponential method to determine MIT values was applied to the eastern monsoon region of China using long-term 1-min pluviograph rainfall data collected from 18 weather stations for the warm rainy season (from May to Sept.). The objectives of this study were to: (1) verify if dry periods between wet periods follow an exponential distribution, (2) determine the MIT using the exponential method, (3) determine the necessary data length required for application of the exponential method, and (4) evaluate the sensitivity of rainfall properties to the MIT index by comparing the rainfall characteristics using fixed MIT values (from 1 h to 24 h) with those obtained from the exponential method.

Data and Methods

Data Collection

The data used in this study were collected from 18 weather stations distributed over the eastern monsoon region of China (fig. 1) (Zhao, 1983; Wang and Zuo, 2009) with 1-min resolution of precipitation. Basic information on the 18 stations is shown in table 1. These stations covered latitude 25.02° to 49.17° N, longitude 98.5° to 128.73° E, and elevations from 20.6 to 1896.8 m. Annual rainfall varied from 449.7 to 1728.1 mm. Rainfall from May to September accounted for 55% to 86% of the annual total. Distances between pairs of stations ranged from 70.9 to

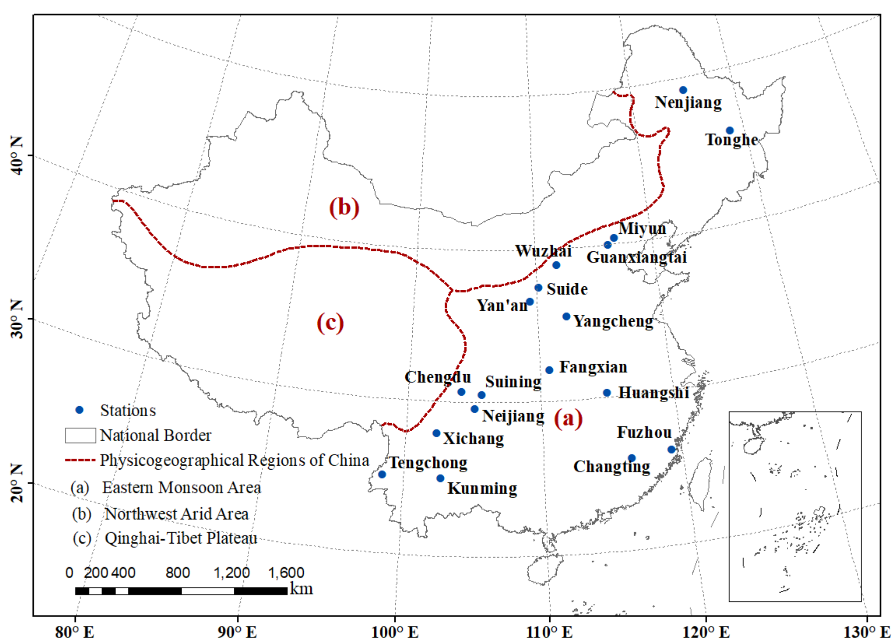

Figure 1. Locations of 18 weather stations used in this study.

Table 1. Information on the 18 weather stations.

Station No.	Station Name	Latitude (°N)	Longitude (°E)	Elevation (m)	Annual Rainfall[a] (mm)	May to Sept. Rainfall (% of annual)	Data Record (years)
Northern stations							
50557	Nenjiang	49.17	125.23	243	485.8	86	30
50963	Tonghe	45.97	128.73	110	596.2	81	38
53663	Wuzhai	38.92	111.82	1402	464.0	78	30
53754	Suide	37.5	110.22	928.5	449.7	79	29
53845	Yan'an	36.6	109.5	958.8	534.6	76	39
53975	Yangcheng	35.48	112.4	658.8	605.9	72	30
54416	Miyun	40.38	116.87	73.1	648.1	85	37
54511	Guangxiangtai	39.93	116.28	54.7	575.0	86	40
Southern stations							
56294	Chengdu	30.67	104.02	506.1	891.8	81	39
56571	Xichang	27.9	102.27	1590.9	1007.5	83	40
56739	Tengchong	25.02	98.5	1648.7	1495.7	73	36
56778	Kunming	25.02	102.68	1896.8	1018.8	74	33
57259	Fangxian	32.03	110.77	427.1	829.5	67	31
57405	Suining	30.5	105.58	279.5	932.7	73	33
57504	Neijiang	29.58	105.05	352.4	1034.1	76	39
58407	Huangshi	30.25	115.05	20.6	1438.5	57	32
58847	Fuzhou	26.08	119.28	84	1365.4	59	39
58911	Changting	25.85	116.37	311.2	1728.1	55	31

[a] Annual rainfall was calculated based on a daily rainfall dataset collected during 1961 to 2000 (Yin et al., 2015).

3559.8 km, with an average of 626.2 km. Miyun and Guanxiangtai were closest together at 70.9 km (Yin et al., 2016).

The climate of China is strongly influenced by the East Asian monsoon system (Zhao, 1983; Wang and Li, 2007). The summer monsoon brings significant moisture from the ocean to the continent, and its impact is mainly limited in the eastern half of China (fig. 1). The annual precipitation decreases from the southeast coast to the northwest due to the distance from the sea and variations in landforms. Frontal rain, orographic rain, and convective rain are common rain types in the eastern monsoon region of China (Li et al., 2009; Wang and Zuo, 2009).

The precipitation data were measured using siphon self-recording rain gauges at the individual stations. The pluviograph self-recoding papers were collected and digitized by the Meteorological Bureaus of Heilongjiang, Shanxi, Shaanxi, Sichuan, Hubei, Fujian, and Yunnan provinces and the municipality of Beijing using a color scanning digitizing processing system to convert the original data to precipitation amount per minute (Wang et al., 2004). The resolution of the interpreted data was 0.01 mm min^{-1}. Because the rain gauges do not collect data in northern China during the cold season (Oct. to Apr.) to avoid breakdown due to freezing, only rainfall data for the warm rainy season (May to Sept.) are available for the eight northern stations (Nenjiang, Tonghe, Wuzhai, Suide, Yan'an, Yangcheng, Miyun, and Guanxiangtai). The data records spanned from 1961 through 2000 for all stations except Wuzhai (53663) and Yangcheng (53975), which spanned from 1971 through 2000. Following Yin et al. (2015), all data used in this study were quality controlled, and only reliable observation years were used in the analyses (table 1).

Exponential Method

The exponential method assumes that the arrival of independent storms follows a Poisson process, and the distribution of inter-event time (IET, dry periods equal to or longer than the MIT) between successive storms is given by:

$$f(t) = \alpha \exp(-\alpha t),\ t \geq 0 \tag{1}$$

where $f(t)$ is probability density function, t is IET, and α is the reciprocal of the mean time between storms. One property of the standard exponential distribution is that the coefficient of variation (CV) is unity. Details of an approximate and convenient iterative algorithm were presented by Restrepo-Posada and Eagleson (1982) to obtain MIT from historical rainfall data. First, the CV was computed for all dry periods between wet periods using an initial value of MIT. If the CV was greater than unity, the shortest dry period was deleted, and the remaining dry periods were used for computing the CV. This calculation procedure was repeated until the CV was less than unity. The smallest dry period that resulted in CV = 1 was then determined by interpolation between the dry period producing CV < 1 and the previous dry period with CV > 1. The interpolated dry period was considered the MIT for the dataset (Bonta and Nayak, 2008). In this study, MIT determined using the exponential method is denoted as MIT_{exp}.

Data Analyses

To investigate the influence of data resolution on MIT_{exp} values, the 1-min data were also aggregated into hourly data. For comparability among stations, only data from the warm rainy season (May to Sept.) were used in the calculations for both the 1-min and hourly data. Both the 1-min data and hourly data were processed for each station following the iterative procedure to obtain the MIT index with the exponential method. Considering the 1-min data to be more accurate, the relative difference for the MIT from the hourly data was calculated as:

$$RD_i\ (\%) = \frac{MIT_{hourly} - MIT_{1\text{-min}}}{MIT_{1\text{-min}}} \times 100 \tag{2}$$

$$\text{MRD} = \sum_{i}^{18} \left|\text{RD}_i\right| \times 18^{-1} \tag{3}$$

where RD_i (%) is the relative difference for the ith station listed in table 1, $MIT_{1\text{-min}}$ MIT_{hourly} are the calculated MIT_{exp} values using 1-min and hourly data, respectively, and MRD is the mean relative difference between 1-min and hourly data for the 18 stations. Meanwhile, a comparison of means test (two-sample t-test) was used to determine if the data resolution statistically affected the MIT_{exp} values obtained using the exponential method.

The necessary record length required to obtain a stable MIT_{exp} was determined using 1-min data by varying the number of years used to calculate MIT_{exp} from 1 to 30 years (denoted below with subscript m) and by using all available years (denoted k), where 50 subsets (denoted n) of each data length were randomly sampled from all available years for each station. The mean and standard deviation (SD) of MIT_{exp} for subsets of each record length (m = 1, ..., 30, and k) were calculated. The relative differences (RD, %) for mean and SD between m and k were calculated for comparison:

$$\text{RD}_{\text{mean},m}\ (\%) = \left\{ \frac{\left|(\text{Mean}_m - \text{Mean}_k)\right|}{\text{Mean}_k} \right\} \times 100 \tag{4}$$

$$\text{RD}_{\text{SD},m}\ (\%) = \left\{ \frac{\left|(\text{SD}_m - \text{SD}_k)\right|}{\text{SD}_k} \right\} \times 100 \tag{5}$$

The mean relative differences (MRD, %) of the 18 stations for mean and SD were then obtained as:

$$\text{MRD}_{\text{mean}} = \sum_{m=1}^{18} \text{RD}_{\text{mean},m} \times 18^{-1} \tag{6}$$

$$\text{MRD}_{\text{SD}} = \sum_{m=1}^{18} \text{RD}_{\text{SD},m} \times 18^{-1} \tag{7}$$

Storm properties, including total precipitation amount (P, mm), duration (D, h), and mean intensity (I, mm h^{-1}), for the 1-min data were calculated for the sets of independent storms obtained using a fixed MIT ranging from 1 h to 24 h and the MIT values obtained using the exponential method for each station.

The effective duration of rainfall (ED, h) was calculated by removing all 1-min periods with rainfall amounts less than 0.01 mm from D for each storm. The storm duration-normalized time to peak intensity (tp), which represents the relative time to peak intensity over the effective duration, is a dimensionless index with a range of 0 to 1 and was calculated using the 1-min data as well by:

$$tp = \frac{T}{\text{ED}} \tag{8}$$

where ED is the total effective duration (h) of the storm, and T is time from the beginning to the mid-point of the data interval containing the peak intensity. The variable tp is important for the CLIGEN model (Nicks et al., 1995). The maximum continuous 30-min rainfall intensity (I_{30}) in a storm was also calculated, which is an important index in calculating rainfall erosivity for soil loss prediction (Dunkerley, 2010; Wischmeier, 1959; Renard et al., 1997; USDA-ARS, 2013).

The storm properties calculated using 2 h, 6 h, an average value of MIT_{exp} over 18 stations, and MIT_{exp} values for each station were then compared statistically using a comparison of means test (two-sample t-test) to determine if different MIT values resulted in different storm properties. A uniform value of MIT is more useful for many practical applications, so distributions of storm properties obtained using an average value of MIT_{exp} were compared with those obtained using MIT_{exp} values station by station by the non-parametric Kolmogorov-Smirnov (K-S) test to determine if storm properties changed with the average value of MIT_{exp} over 18 stations instead of with MIT_{exp} for each station.

RESULTS

EVALUATION OF EXPONENTIAL METHOD

The cumulative frequency distribution of IET between storms for two stations with the least and most annual precipitation (Suide and Changting, respectively) are shown in figure 2 as examples to illustrate the distribution of IET following the exponential distribution. There were 34,945 and 82,073 dry periods in total for Suide and Changting,

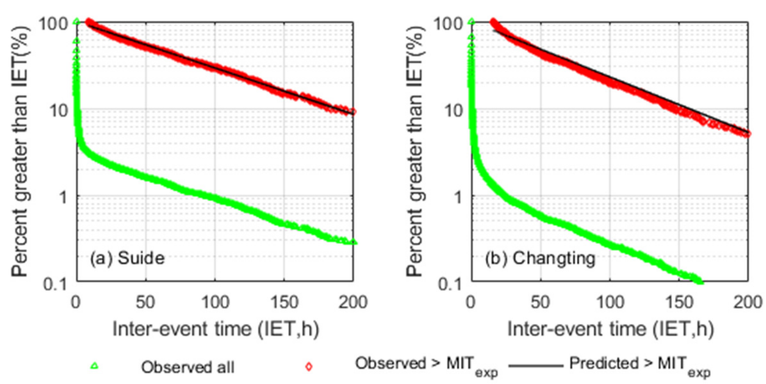

Figure 2. Cumulative frequency distribution of IET between storms for (a) Suide and (b) Changting. Green triangles represent observations of all inter-event times (IET) between storms, red diamonds represent all IET values greater than MIT_{exp} (minimum IET obtained using exponential method), and solid black lines represent the distribution of IET values greater than MIT_{exp} predicted by the exponential method.

and 1080 and 1062 IET values greater than MIT_{exp}, respectively. Good agreement was shown between the IET values greater than MIT_{exp} (red diamonds) and the predictions from the exponential distribution (black line) for both Suide and Changting, indicating that storms delineated by MIT_{exp} may be treated as statistically independent.

Comparison on MIT Values Based on 1-Min and Hourly Data

The MIT values obtained using the exponential method (MIT_{exp}) for the 18 stations for the warm rainy season (May through Sept.) are shown in table 2. Results indicated a regional difference in MIT_{exp}. The mean MIT_{exp} was 9.9 h for the eight northern stations and 11.2 h for the ten southern stations. The coastal stations, Fuzhou (58847) and Changting (58911), had the longest MIT values of all the stations.

The MIT_{exp} values calculated using hourly data for the 18 stations are also shown in table 2. These hourly MIT_{exp} values were found to be systematically lower than those obtained from the 1-min data, except for the Guanxiangtai station, whose 1-min and hourly MIT_{exp} values were equal. The average MIT_{exp} over the 18 stations using both the 1-min and hourly data was approximately 10 h. Two-sample t-tests showed that MIT_{exp} values obtained using the 1-min and hourly data statistically provided the same means at p = 0.05. Therefore, the more readily available hourly data for China (Li et al., 2013; Yu et al., 2007) can be adopted to calculate MIT_{exp} values using the exponential method in further research.

Table 2. Minimum inter-event times calculated using exponential method (MIT_{exp}) from 1-min and hourly data for May through September.

Station No.	Station Name	MIT_{exp} 1-min Data (h)	MIT_{exp} Hourly Data (h)	Relative Difference (%)
Northern stations				
50557	Nenjiang	10.2	9.2	-9.8
50963	Tonghe	12.9	11.9	-7.8
53663	Wuzhai	7.9	6.8	-13.9
53754	Suide	8.9	8.0	-10.1
53845	Yan'an	9.0	7.8	-13.3
53975	Yangcheng	8.6	7.7	-10.5
54416	Miyun	10.1	9.3	-7.9
Southern stations				
54511	Guangxiangtai	11.9	11.9	0.0
56294	Chengdu	7.9	7.1	-10.1
56571	Xichang	9.1	8.4	-7.7
56739	Tengchong	11.1	10.8	-2.7
56778	Kunming	12.7	11.8	-7.1
57259	Fangxian	7.8	6.8	-12.8
57405	Suining	8.2	7.6	-7.3
57504	Neijiang	7.6	6.9	-9.2
58407	Huangshi	14.7	14.0	-4.8
58847	Fuzhou	16.6	15.6	-6.0
58911	Changting	16.5	15.6	-5.5
Mean		10.7	9.8	-8.1
SD		3.0	3.0	3.6

Minimum Data Lengths Required for Exponential Method

Results for the Suide and Changting stations are plotted in figure 3 as examples to illustrate the variation in trends of MIT_{exp} values with increasing data length. Greater variability was found for shorter data lengths, especially for lengths shorter than 5 years. MIT_{exp} tended to converge with an increase in data length. The pattern leveled off at 10 to 15 years, indicating that MIT_{exp} tended to be stable beyond that length of the record. The trend was consistent for the two stations.

The relative differences for mean and standard deviation of MIT_{exp} calculated using the full data length and varied data lengths from 1 to 30 years are listed in table 3 and plotted in figure 4. The RD range stabilized with increasing record length, consistent with the mean and SD. Based on these results, at least 10 to 15 years of data are recommended to obtain reliable MIT_{exp} values for a specific station.

Sensitivity of Rainfall Properties to Variation in MIT Values

The MIT value used to separate continuous rainfall data had an influence on the characteristics of the derived storms. As expected, there were fewer storm events as the MIT became longer for all 18 stations (fig. 5), and precipitation amount and duration increased with longer MIT. This was expected because, as the MIT became longer, some of the successive rainfall events that were recognized as independent for shorter MIT values were merged into single events. Mean storm intensity showed a relatively moderate decreasing tendency (fig. 5).

Using four different definitions of MIT (fixed 2 h, fixed 6 h, fixed 10 h, and MIT_{exp}), main storm properties were derived and are compared in tables 4 and 5. Among these definitions of MIT, 2 h (Li et al., 2013; Yu et al., 2007) and 6 h (Wang et al., 2016; Yin et al., 2015, 2016) are two commonly used MIT values in China. The 10 h value was

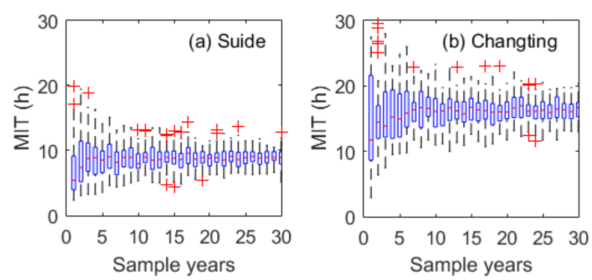

Figure 3. Results of random sample test with number of sampled years ranging from 1 to 30 for (a) Suide and (b) Changting. For each record length, 50 subsets of years were randomly sampled.

Table 3. Mean relative differences (MRD, %) for mean and SD between MIT_{exp} values calculated with all records and different record lengths.

Sample Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
MRD for mean	13.3	7.7	6.1	4.9	3.8	4.7	4.3	3.0	3.4	3.7	3.0	3.2	2.9	2.9	2.5
MRD for SD	595.0	345.1	249.6	216.9	186.6	163.3	133.6	113.8	114.9	104.9	81.8	80.3	67.1	63.4	55.4

Sample Year	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
MRD for mean	2.6	3.1	2.2	2.7	2.3	2.7	1.7	2.5	2.6	2.0	1.9	2.0	2.8	2.4	2.9
MRD for SD	60.0	58.6	44.3	32.3	36.2	36.9	35.0	39.5	26.6	23.6	20.7	16.4	17.8	20.2	13.0

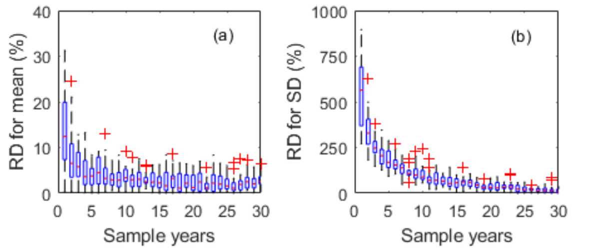

Figure 4. Relative differences (RD) for (a) mean and (b) standard deviation (SD) between MIT$_{exp}$ values calculated with all records and different record lengths for 18 stations. For each record length, 50 subsets of years were randomly sampled.

the approximate average MIT obtained in the current study using the exponential method with both the 1-min and hourly data for the 18 stations, as discussed previously.

Storm properties varied with location and MIT index (tables 4 and 5). For the same station, different MIT values resulted in different storm properties, such that longer MIT corresponded to greater precipitation, longer duration, and lesser intensity. The maximum 30-min intensity (I30) showed that longer MIT values corresponded to greater I_{30} values. No obvious differences were found for time to peak. The relative differences (RD values) for the average of mean storm properties of the 18 stations between MIT of

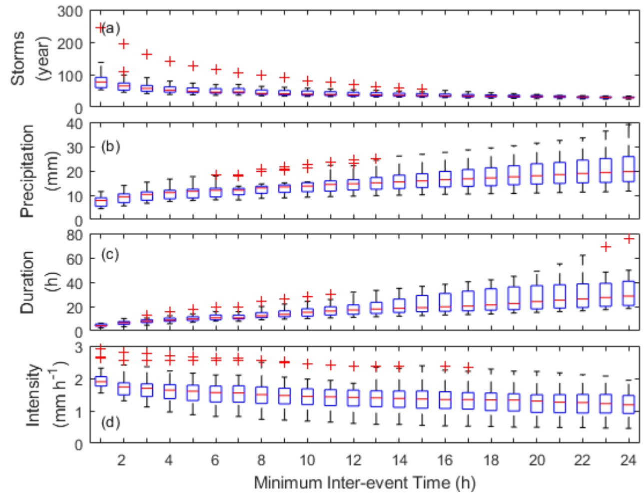

Figure 5. Variation in mean number of storm events, precipitation amount, duration, and intensity as MIT increased from 1 h to 24 h for the 18 stations.

Table 4. Mean storm properties when using 2 h, 6 h, 10 h, and MIT$_{exp}$ to delineate independent storms.

	Precipitation (mm)				Duration (h)				Effective Duration (h)			
Station Name	2 h	6 h	10 h	MIT$_{exp}$	2 h	6 h	10 h	MIT$_{exp}$	2 h	6 h	10 h	MIT$_{exp}$
Nenjiang	6.3	9.1	11.3	11.3	6.6	15.8	24.1	24.5	2.5	3.7	4.5	4.6
Tonghe	6.3	8.8	10.8	12.0	5.5	11.7	18.1	22.5	2.5	3.5	4.3	4.8
Wuzhai	6.3	8.1	9.1	8.6	5.2	8.3	10.8	9.5	2.9	3.8	4.3	4.0
Suide	7.1	9.1	10.1	9.8	5.6	9.2	11.6	10.8	3.2	4.0	4.5	4.4
Yan'an	8.2	10.3	11.4	11.1	6.7	10.2	12.9	12.2	3.9	4.9	5.4	5.3
Yangcheng	9.5	12.0	13.3	13.0	8.4	13.0	15.9	15.2	4.2	5.4	5.9	5.8
Miyun	10.5	12.8	14.3	14.4	5.2	7.9	10.2	10.2	2.9	3.6	4.0	4.0
Guangxiangtai	9.6	12.3	13.6	14.5	4.7	8.3	10.7	12.6	2.6	3.4	3.7	4.0
Chengdu	10.1	12.7	14.7	13.6	7.6	12.3	16.3	14.2	3.7	4.7	5.5	5.1
Xichang	8.4	12.0	14.4	14.3	5.8	10.8	14.9	14.7	3.4	4.9	5.9	5.9
Tengchong	5.6	9.3	13.4	14.8	3.4	8.3	15.5	18.2	1.8	3.0	4.4	4.8
Kunming	6.9	11.5	15.1	17.1	5.3	13.6	21.3	26.2	2.0	3.3	4.4	4.9
Fangxian	9.2	12.0	13.8	13.0	7.9	12.3	15.9	14.3	4.3	5.5	6.4	6.0
Suining	10.2	12.3	13.7	13.1	7.3	9.8	12.1	11.0	4.0	4.9	5.5	5.2
Neijiang	10.6	13.8	15.5	14.8	6.7	10.5	13.2	12.1	3.7	4.9	5.5	5.2
Huangshi	14.0	18.4	21.0	23.2	6.9	10.7	13.5	16.4	4.0	5.2	5.9	6.6
Fuzhou	12.4	18.2	22.8	28.4	10.1	19.9	28.4	39.9	4.2	6.3	7.8	9.7
Changting	12.9	17.9	21.3	26.8	8.5	15.4	21.0	30.0	3.7	5.1	6.1	7.7
Mean	9.1	12.3	14.4	15.2	6.5	11.6	15.9	17.5	3.3	4.4	5.2	5.4

	Intensity (mm h^{-1})				I_{30} (mm h^{-1})				Time to Peak			
Station Name	2 h	6 h	10 h	MIT$_{exp}$	2 h	6 h	10 h	MIT$_{exp}$	2 h	6 h	10 h	MIT$_{exp}$
Nenjiang	1.3	0.8	0.7	0.7	5.5	6.7	7.6	7.6	0.3	0.4	0.4	0.4
Tonghe	1.6	1.1	0.8	0.7	5.7	6.7	7.5	7.8	0.3	0.4	0.4	0.4
Wuzhai	1.7	1.5	1.4	1.5	4.9	5.7	6.0	5.8	0.4	0.4	0.4	0.4
Suide	1.9	1.8	1.7	1.7	5.4	6.3	6.7	6.6	0.3	0.3	0.3	0.3
Yan'an	1.9	1.7	1.5	1.6	5.7	6.5	6.9	6.8	0.3	0.3	0.3	0.3
Yangcheng	1.4	1.3	1.2	1.2	6.5	7.6	8.1	8.0	0.3	0.3	0.3	0.3
Miyun	2.8	2.6	2.5	2.4	9.2	10.5	11.2	11.3	0.3	0.3	0.3	0.3
Guangxiangtai	2.4	2.1	2.0	1.8	8.2	9.7	10.4	10.7	0.3	0.3	0.4	0.4
Chengdu	1.6	1.3	1.2	1.2	7.4	8.5	9.3	8.9	0.3	0.3	0.3	0.3
Xichang	1.5	1.4	1.3	1.3	5.7	7.4	8.2	8.2	0.3	0.3	0.3	0.3
Tengchong	1.9	1.6	1.5	1.4	5.1	6.7	7.9	8.3	0.3	0.3	0.4	0.4
Kunming	1.7	1.3	1.1	1.1	6.3	8.4	9.8	10.4	0.3	0.3	0.3	0.3
Fangxian	1.5	1.4	1.4	1.4	6.1	7.3	8.1	7.8	0.3	0.3	0.3	0.3
Suining	1.8	1.7	1.6	1.7	7.2	8.2	8.8	8.5	0.3	0.3	0.3	0.3
Neijiang	1.9	1.8	1.7	1.7	7.5	8.9	9.6	9.3	0.3	0.3	0.3	0.3
Huangshi	2.6	2.6	2.4	2.4	9.8	11.7	12.6	13.4	0.3	0.3	0.3	0.4
Fuzhou	1.4	1.0	1.0	0.9	8.5	10.7	12.4	13.9	0.3	0.3	0.4	0.4
Changting	1.9	1.6	1.5	1.5	10.2	12.0	13.1	14.6	0.3	0.3	0.4	0.4
Mean	1.8	1.6	1.5	1.5	6.9	8.3	9.1	9.3	0.3	0.3	0.3	0.3

Table 5. 95th percentile rain properties when using 2 h, 6 h, 10 h, and MIT_{exp} to delineate independent storms.

	Precipitation (mm)				Duration (h)				Effective Duration (h)			
Station Name	2 h	6 h	10 h	MIT_{exp}	2 h	6 h	10 h	MIT_{exp}	2 h	6 h	10 h	MIT_{exp}
Nenjiang	26.3	36.3	44.5	44.6	21.1	44.0	67.6	69.7	9.3	13.7	16.2	16.2
Tonghe	26.5	34.4	40.9	44.0	16.9	35.1	51.2	62.2	9.3	12.5	15.2	16.4
Wuzhai	24.6	30.0	32.5	31.5	17.6	26.4	34.2	29.8	11.2	13.4	14.6	13.8
Suide	29.1	37.1	40.1	38.9	18.5	29.2	36.4	34.2	12.0	15.0	16.1	16.0
Yan'an	35.4	42.5	46.8	45.9	22.8	35.2	42.4	41.0	15.2	18.4	21.1	20.9
Yangcheng	39.8	47.2	50.2	49.8	28.6	38.6	49.2	45.6	17.2	21.8	22.9	22.4
Miyun	43.9	55.4	61.2	61.4	19.2	28.0	35.0	35.3	10.7	13.5	14.7	14.7
Guangxiangtai	45.2	52.4	56.9	60.6	17.4	28.6	36.3	40.6	10.3	12.9	14.0	14.9
Chengdu	42.4	53.2	61.1	57.1	23.4	36.5	48.4	42.8	12.2	15.7	18.0	16.6
Xichang	36.5	46.4	53.9	53.3	17.0	35.1	49.9	48.7	11.4	16.3	19.3	18.9
Tengchong	24.2	36.5	55.5	60.6	11.8	28.8	61.5	75.0	6.8	10.1	17.6	20.8
Kunming	30.6	49.3	62.4	68.0	17.8	45.8	71.8	91.5	7.5	12.2	16.6	18.6
Fangxian	38.4	48.3	52.2	51.1	25.0	39.5	49.0	45.8	15.1	20.1	21.2	20.9
Suining	44.3	52.3	57.2	55.1	21.3	33.1	42.0	37.4	13.3	16.6	19.4	18.2
Neijiang	48.5	58.8	65.2	63.2	20.6	35.8	44.6	39.8	12.9	18.0	19.5	19.2
Huangshi	58.3	74.7	85.1	90.4	24.6	38.6	45.4	57.2	15.3	20.4	22.1	23.6
Fuzhou	54.5	81.0	93.3	114.8	35.4	64.5	90.7	116.9	17.7	26.6	32.8	38.4
Changting	54.1	74.0	96.2	121.6	27.9	55.2	70.7	106.1	16.1	21.8	25.7	32.8
Mean	39.0	50.5	58.6	61.8	21.5	37.7	51.5	56.6	12.4	16.6	19.3	20.2

	Intensity (mm h^{-1})				I_{30} (mm h^{-1})				Time to Peak			
Station Name	2 h	6 h	10 h	MIT_{exp}	2 h	6 h	10 h	MIT_{exp}	2 h	6 h	10 h	MIT_{exp}
Nenjiang	5.1	2.9	2.3	2.2	21.3	25.9	27.2	27.2	0.8	0.9	0.9	0.9
Tonghe	5.8	3.7	2.9	2.5	22.0	25.9	28.7	29.4	0.8	0.9	0.9	0.9
Wuzhai	6.2	5.6	5.0	5.4	17.3	19.9	20.7	20.5	0.9	0.9	0.9	0.9
Suide	7.2	7.1	6.7	6.7	21.8	24.6	25.0	24.9	0.8	0.9	0.9	0.8
Yan'an	6.8	6.5	5.9	6.0	23.2	25.2	26.2	25.8	0.8	0.9	0.9	0.9
Yangcheng	5.2	4.5	4.5	4.4	28.0	30.0	32.5	31.8	0.8	0.8	0.8	0.8
Miyun	10.9	10.1	9.6	9.6	39.4	42.2	43.2	43.2	0.8	0.8	0.9	0.9
Guangxiangtai	9.0	7.9	7.4	7.0	36.1	40.3	41.8	42.2	0.8	0.8	0.9	0.9
Chengdu	5.9	4.6	4.2	4.3	32.1	35.2	38.1	37.0	0.8	0.8	0.8	0.8
Xichang	4.8	4.6	4.3	4.3	22.7	27.5	29.1	29.0	0.8	0.8	0.8	0.8
Tengchong	6.2	5.1	4.6	4.9	19.3	23.8	27.1	28.0	0.8	0.8	0.9	0.9
Kunming	6.0	4.6	4.3	4.3	24.9	30.3	33.9	35.0	0.8	0.8	0.8	0.9
Fangxian	5.7	5.7	5.7	5.7	25.1	29.8	32.1	31.0	0.8	0.8	0.8	0.8
Suining	6.7	6.2	5.9	6.1	34.3	36.3	38.0	37.1	0.8	0.8	0.8	0.8
Neijiang	7.5	6.9	6.3	6.6	33.9	39.0	42.3	40.4	0.8	0.8	0.8	0.8
Huangshi	10.2	10.3	10.2	10.0	37.6	43.0	46.2	49.0	0.8	0.8	0.8	0.8
Fuzhou	5.1	3.4	3.0	2.7	35.7	42.5	44.9	46.7	0.8	0.8	0.9	0.9
Changting	7.2	5.9	5.9	6.0	39.4	43.2	46.2	49.0	0.8	0.8	0.8	0.9
Mean	6.7	5.9	5.5	5.5	28.6	32.5	34.6	34.8	0.8	0.8	0.8	

2 h and 10 h were 45%, 84%, 45%, -20%, 27%, and 6% for precipitation amount, duration, effective duration, I_{30}, and time to peak, respectively. Corresponding RD values for the average of 95th percentile storm properties were 40%, 82%, 43%, -21%, 19%, and 3%, respectively. These results indicate a significant impact of MIT on storm properties, especially precipitation amount, duration, and intensity.

Two-sample t-tests for mean and 95th percentile of storm properties were conducted between different MIT values (table 6). Results showed that only the properties obtained using 10 h and MIT_{exp} were statistically the same for all mean and 95th percentile storm properties, with most properties statistically the same at p = 0.05 and mean time to peak statistically the same at p = 0.01. For the t-tests between 2 h and 6 h, between 2 h and 10 h, and between 2 h and MIT_{exp}, most of the mean and 95th percentile storm properties were not the same. For the t-tests between 6 h

Table 6. Statistical p-values of two-sample tests conducted for storm properties derived from different MIT values.[a]

	Storm Property	2 h vs. 6 h	2 h vs. 10 h	2 h vs. MIT_{exp}	6 h vs. 10 h	6 h vs. MIT_{exp}	10 h vs. MIT_{exp}
Mean	Precipitation	0.002	<0.001	<0.001	0.072**	0.057**	0.626**
	Duration	<0.001	<0.001	<0.001	0.004	0.007	0.508**
	Effective duration	<0.001	<0.001	<0.001	0.025*	0.019*	0.607**
	Intensity	0.134**	0.033*	0.026*	0.528**	0.467**	0.922**
	I_{30}	0.027*	0.001	0.002	0.235**	0.190**	0.805**
	Time to peak	0.066**	0.006	<0.001	0.271**	0.002	0.048*
95th Percentile	Precipitation	<0.001	<0.001	<0.001	0.002	0.006	0.532**
	Duration	<0.001	<0.001	<0.001	0.020*	0.016*	0.610**
	Effective duration	<0.001	<0.001	<0.001	0.026*	0.009	0.576**
	Intensity	0.107**	0.018*	0.014*	0.454**	0.409**	0.946**
	I_{30}	<0.001	<0.001	<0.001	0.077**	0.069**	0.672**
	Time to peak	0.120**	0.013*	<0.001	0.270**	0.003	0.056**

[a] Asterisks indicate two tested sample sets have equal means and variances at (*) p = 0.01 and (**) p = 0.05 significance levels.

and 10 h and between 6 h and MIT_{exp}, some of the storm properties were statistically not the same.

DISCUSSION

Values of MIT obtained using the exponential method vary greatly for different locations around the world. Restrepo and Eagleson (1982) reported a set of MIT_{exp} values for 17 locations that varied from 1.0 h for Colombia, to 8.1 h and 9.0 h for data from Ohio, and to 101 h, 115 h, and 132 h for data sets from Saudi Arabia. Driscoll et al. (1989) reported a great variation in MIT_{exp} for three stations in the U.S. using the exponential method. The reported MIT_{exp} values were 6 h for an eastern coastal station, 20 h for a station in the central U.S., and 300 h for a western coastal station. However, MIT_{exp} values for nearby locations with similar climates tend to be similar. For two stations in Ohio, Restrepo and Eagleson (1982) reported MIT_{exp} values of 9.0 and 8.1 h, which were similar to the average MIT_{exp} of 9.5 h obtained from seven gauges in Ohio, as reported by Bonta and Rao (1988). In our study, MIT_{exp} varied from 7.6 h to 16.6 h, with an average of 10.7 h. The result of 10 h from South Korea using the exponential method (Yoo et al., 2015) fell within this range. Although one MIT_{exp} value was presented for each station in this study based on data from May to September due to data availability, the MIT_{exp} values for some locations may also have a seasonal variation (Bonta and Rao, 1988) because the rainfall characteristics vary between seasons.

Variations in MIT_{exp} for different regions and seasons may be mainly related to storm types. For example, convective storms, which are most likely to occur in the warm season, usually cover a limited area and last for a few hours. For these storms, MIT values are expected to be shorter. However, precipitation associated with larger-scale systems, such as frontal systems or troughs, may cover several states or provinces and last a longer time. Dry periods within such storms are not uncommon, and MIT values are expected to be longer.

The variations in MIT values for the 18 stations in this study are not large compared those for the entire U.S. (Driscoll et al., 1989), which may be due to the dominant and relatively consistent rainfall types in the eastern monsoon region of China. Two-sample t-tests showed that the storm properties obtained using 10 h and MIT_{exp} were statistically the same for all mean and 95th percentile storm properties (table 6). However, the K-S tests showed significant differences between distributions of two storm properties divided by MIT of 10 h and MIT_{exp} at $p = 0.05$ for some stations, including the distributions of storm precipitation amount for Fuzhou (MIT_{exp} = 16.6 h) and Changting (MIT_{exp} = 16.5 h) and the distributions of storm duration for eight of the 18 stations. However, for storm intensity and I_{30}, the K-S test results were identical for all 18 stations, and the differences were not significant at $p = 0.05$. This indicates that the identical MIT of 10 h for the 18 stations is appropriate for most of the stations, and if the MIT_{exp} for a particular station is not known, then the MIT of 10 h can be applied in the eastern monsoon region of China.

Results of this study indicated that the exponential method was not particularly sensitive to the data resolution. The average MIT_{exp} values were 10.7 h and 9.8 h with the 1-min and hourly data, respectively, with a relative difference of -8.6%. This is consistent with the results of Bonta and Rao (1988), who reported average MIT_{exp} values of 9.73 h and 9.48 h using 3 min and hourly data, respectively, from seven gauges in Ohio. Given this result, analyses of the more readily available hourly data (Yu and Li, 2012; Yu et al., 2010) for China and elsewhere in the world would be expected to provide a reasonably reliable MIT index that can be used to investigate its spatial variation.

Storm characteristics vary with the location using identical an MIT criterion. For example, with an MIT of 2 h, mean storm precipitation amount, duration, and intensity were 1.62 mm, 1.08 h, and 1.99 mm h^{-1}, respectively, for an Australia dryland station (Dunkerley, 2008b). Corresponding values for Malaysia stations were found to be 12.38 mm, 5.1 h, and 2.98 mm h^{-1}, respectively (Shamsudin et al., 2010). For this study, storm characteristics derived from 18 stations in the eastern monsoon region of China ranged from 5.6 to 14.0 mm, from 3.4 to 10.1 h, and from 1.3 to 2.8 mm h^{-1} for precipitation amount, duration, and intensity, respectively.

Storm characteristics also vary with the criteria adopted to define individual storms at a specific location. Dunkerley (2008b) selected eight commonly used MIT values, ranging from 15 min to 24 h, to analyze the influence of MIT on rainfall properties in Australia, and Shamsudin et al. (2010) compared rainfall properties using seven MIT values, ranging from 2 h to 24 h, based on 40 years of hourly records. Both studies reported wide variations in storm properties as MIT increased from short to long. The variation in storm numbers, mean event precipitation amounts, duration, and intensity found in this study were consistent with those previous studies, and this study was based on a greater number of stations and high-resolution 1-min data. Results achieved in this study highlight the sensitivity of rainfall characteristics to MIT criteria, which is an argument for giving more attention to the selection of the MIT index.

The rainfall erosivity (R) factor in USLE and its successors was calculated based on event precipitation data divided by an MIT of 6 h, and the soil erodibility (K) factor was defined as the ratio of the measured soil loss amount to the multiplication of all the other erosion factors, including the R factor (Nearing et al., 2017). This indicates that the R factor may change if the MIT criteria in USLE are changed, and if the change in the R factor is significant, the soil erodibility factor in the equation must be re-parameterized or adjusted correspondingly.

CONCLUSIONS

An exponential method was adopted to determine the minimum inter-event time (MIT) for identifying statistically independent storms using 1-min and hourly data collected from 18 weather stations in the eastern monsoon region of China. Several conclusions can be made:

- The exponential distribution was suitable for representing the distribution of inter-event times for these storms. An exponential frequency distribution fit well with that of the observed inter-event times for each tested station.

- MIT_{exp} for the 18 stations using 1-min data varied from 7.6 h (Wuzhai) to 16.6 h (Fuzhou), with an average of 10.7 h, and the corresponding standard deviation was 3.0 h. The exponential method was only slightly sensitive to the data resolution, with a mean absolute difference of -8.6% between MIT_{exp} obtained from the 1-min and hourly data.
- At least 10 to 15 years of data records were necessary to obtain stable MIT_{exp}.
- Most event storm characteristics were sensitive to MIT values and were characterized by large variations as MIT increased from 1 h to 24 h. Longer MIT values resulted in fewer annual storm numbers, greater precipitation amounts, greater I_{30}, longer durations, longer effective durations, and lesser mean storm intensities. However, no effect was found for the time to peak.
- Based on results achieved in this study using both 1-min and hourly data from 18 stations, MIT of 10 h is recommended for storm event-based studies in the eastern monsoon region of China, with some exceptions discussed above. Further study is expected to determine the seasonal and spatial variation of MIT using hourly data with a high spatial resolution in China.

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