Analysis of spatial patterns of daily precipitation and wet spell extremes in Southeast Asia

Mandapaka, Pradeep Venkata; Qin, Xiaosheng; Lo, Edmond Yat Man

2017

Mandapaka, P. V., Qin, X., & Lo, E. Y. M. (2017). Analysis of spatial patterns of daily precipitation and wet spell extremes in Southeast Asia. *International Journal of Climatology*, 37(S1), 1161-1179.

<https://hdl.handle.net/10356/85462>

<https://doi.org/10.1002/joc.5073>

© 2017 Royal Meteorological Society. This is the author created version of a work that has been peer reviewed and accepted for publication by *International Journal of Climatology*, Royal Meteorological Society. It incorporates referee's comments but changes resulting from the publishing process, such as copyediting, structural formatting, may not be reflected in this document. The published version is available at:
[<http://dx.doi.org/10.1002/joc.5073>].

Downloaded on 26 Apr 2023 21:02:22 SGT

1 Analysis of spatial patterns of daily precipitation and wet spell
2 extremes in Southeast Asia

3 Pradeep V. Mandapaka, Xiaosheng Qin*, and Edmond Y.M. Lo

School of Civil and Environmental Engineering
Nanyang Technological University, Singapore

4 January 2, 2017

*Corresponding author email: xsqin@ntu.edu.sg

Abstract

5

6 The study investigates the spatial distribution of extreme daily rainfall and wet spells in
7 Southeast Asia (SEA) at annual, seasonal, and intraseasonal scales using 16 years of data from
8 the Tropical Rainfall Measurement Mission. A detailed analysis is conducted using various
9 indices that characterize exceedance probabilities and relative contribution of extremes to the
10 total rainfall. The selected indices include the Gini index, which is a measure of overall inequality,
11 and is employed for the first time to examine SEA rainfall characteristics. The favored regions
12 (hotspots) of rainfall extremes during each season are identified, and their linkages with terrain
13 and seasonal winds discussed. The intraseasonal variability in rainfall extremes is investigated
14 by focusing on different phases of the Madden-Julian Oscillation (MJO). At the annual scale,
15 four main hotspots are observed, which are located off the coast of Myanmar, over eastern Indian
16 ocean, northwestern Borneo, and over Philippines. A majority of indices shows considerable land-
17 sea contrast, with lower values over land. Lower Gini index as obtained for land regions indicate
18 that the rainfall distribution, and the relative contribution of each class to the total rainfall are
19 more uniform over land compared to sea. The land-sea contrast in indices is stronger during
20 boreal summer and winter, and weaker during boreal fall. During boreal spring, the Myanmar
21 coast has high probability of extremes, which further increases during boreal summer. The most
22 evident hotspot regions during boreal fall and winter are along the coast of Vietnam, and the
23 eastern coast of Malay Peninsula, respectively. The wind-terrain interactions play a crucial role
24 in determining the location of most hotspots. In general, the impact of active (suppressed) MJO
25 phases is to increase (decrease) the probability of extremes in the study domain. However, local
26 scale departures from this general pattern are observed, which are discussed in this work.

1 Introduction

The Southeast Asian region (SEA, Figure 1) is characterized by complex land-sea structure with more than 20,000 islands along with large topographic variability, and intense convective activity (e.g., Ramage, 1968; Neale and Slingo, 2003; Qian, 2008). It is well recognized that latent heat released during precipitation in this region is a major driver of global atmospheric circulation (e.g., Neale and Slingo, 2003). The SEA weather systems are strongly influenced by the land-sea structure and wind-terrain interactions (e.g., Hendon, 2003; Chang et al., 2005b; Juneng and Tangang, 2005). In particular, the rainfall patterns over the region were shown to be highly variable in both space and time (e.g., Hamada et al., 2002; Hendon, 2003; Yokoi et al., 2007; Xavier et al., 2014). Moreover, the region is home to 600 million people, with many densely populated cities, making it highly vulnerable to extreme events (e.g., UNPD, 2015). The 2006 and 2014 December floods in Peninsular Malaysia (e.g., Tangang et al., 2008; Shamsuddin et al., 2016), October 2011 flooding of the Chao Phraya River in Thailand (e.g., Komori et al., 2012; Liew et al., 2016; Promchote et al., 2016), and January 2013 floods in Jakarta, Indonesia (e.g., Wu et al., 2013) are recent examples of destructive events. Therefore, quantifying the spatial distribution of SEA rainfall extremes is crucial for delineation of potential high-risk flood areas, and efficient disaster management.

Previous studies on SEA rainfall variability can be broadly classified into: i) Investigations on the interannual variability and relationship with ENSO (e.g., Haylock and McBride, 2001; Hendon, 2003; Chang et al., 2004; Juneng and Tangang, 2005), ii) Analyses of the annual cycle and monsoon-related variability (e.g., Hamada et al., 2002; Chang et al., 2005b), iii) Studies on diurnal variability (e.g., Wu et al., 2009; Teo et al., 2011; Oh et al., 2012; Rauniyar and Walsh, 2011, 2013), and iv) Analyses of relative impacts of synoptic disturbances such as cold surges and the Borneo vortex on rainfall variability (e.g., Chang et al., 2005a; Hattori et al., 2011; Koseki et al., 2014). These studies analyzed the spatial variability of rainfall averaged over a specific time period (e.g., a specific season) or the temporal variability of a particular area-averaged rainfall index such as IndoP (for Indonesia, Hendon (2003)) or MalayP (for Malaysia, Tangang and Juneng (2004)). The few studies which focused on SEA extreme rainfall analyzed specific cases such as 2007 and 2013 January torrential rains over Java Island (Wu et al., 2007, 2013),

and December 2006 extreme rainfall over Malay Peninsula Tangang et al. (2008). Xavier et al. (2014) studied SEA rainfall extremes, but with an emphasis on the impact of Madden-Julian Oscillation (MJO). Moreover, the variability of SEA wet spell characteristics has not received much attention (e.g., Mandapaka et al., 2016), though such information is important from both the flooding and agricultural perspectives.

This study addresses the aforementioned research gaps by characterizing the spatial and temporal structure of daily rainfall and wet spell extremes at time scales ranging from intraseasonal to annual. We employed threshold-based indices as well as the concept of the Lorenz curve to characterize rainfall and wet spell extremes. The Lorenz curve is widely used in the field of economics to study inequality in variables such as income distribution (e.g., Lorenz, 1905; Gastwirth, 1972). In the last decade, Lorenz curve and the associated Gini index were employed in many hydrologic studies to characterize distribution of variables such as rainfall, catchment discharge, and solute transport (e.g., Martin-Vide, 2004; Zhang et al., 2009; Jawitz and Mitchell, 2011; Shi et al., 2013; Rajah et al., 2014; Jiang et al., 2016). The Lorenz curve and Gini index are advantageous in characterizing the overall “concentration” of the variable of interest, and therefore complement results obtained using predefined thresholds as used here. We used 16 years (1998 to 2013) of Tropical Rainfall Measurement Mission Multisatellite Precipitation Analysis (TMPA 3B42-V7) data here. The 0.25° spatial resolution of TMPA data allows us to analyze spatial patterns of extremes in detail. Section 2 provides a short description of the general climatology of SEA. The indices employed and their estimation procedure are described in section 3. The spatial, seasonal, and intraseasonal variability of rainfall and wet spell extremes are discussed in section 4, followed by concluding remarks in section 5.

2 Study area - General climatology

The SEA region is characterized by the tropical climate comprising rainforest, monsoon, and savanna subclasses (Köppen-Geiger classification; Peel et al., 2007). The low latitude regions including Malay Peninsula, Sumatra, Borneo, and Sulawesi are characterized by the tropical rainforest climate. The southwest coasts of Myanmar and Thailand, and northeast Vietnam are characterized by the tropical monsoon climate, whereas the interior regions in continental SEA

(Myanmar, Thailand, Cambodia, Vietnam, and Laos) belong to the tropical savanna climate. The number of rainy days per year (threshold of 0.2 mm d^{-1} was used to determine rainy days) and the mean daily rainfall during the study period exhibit complex spatial variability, as evident in Figures 2(a) and 2(b), respectively. For example, the region off the southwest coast of Sumatra, the Malacca Strait and Central Borneo receive rainfall $\sim 75\%$ of the year, whereas the frequency drops to less than 30% in Central Thailand and Cambodia. The spatial gradient in average daily rainfall is very steep along the southwest-northeast transect near the Myanmar coast, with the southwest side receiving almost four times more rainfall compared to the inland areas in Thailand (Figure 2(b)). The average daily rainfall is also high near southwest Sumatra, and northwest Borneo with values above 12 mm d^{-1} .

Figure 3 shows the seasonally averaged daily rainfall and the ERA-Interim 850 hPa winds for March-April-May (MAM) to December-January-February (DJF) months. During boreal spring (MAM), the winds are light and variable, with only the near-equatorial belt receiving high amount of rainfall (Figure 3(a)). The region of maximum convection during MAM stays mainly along the equatorial belt (Chang et al., 2005b, 2006). During the June-July-August (JJA) months, the position of the maximum solar heating is well north of the equator, which leads to a region of low pressure over the Asian land mass. The pressure gradient between the Australian and Asian land masses leads to southeasterly winds, which change to southwesterlies as they cross the equator. It is observed in Figure 3(b) that JJA monsoon months form the main rainy season in continental Southeast Asia (CSEA). During the September-October-November (SON) months, regions of large rainfall can be observed to extend beyond the equatorial belt, along the northeastern coast of Vietnam, and in South China Sea (SCS; Figure 3(c)). By the DJF season, the pressure gradient of the JJA season is reversed, and the prevailing northeasterly winds interact with the terrain of Malay Peninsula and Sumatra causing the rainy season south of 5°N (Figure 3(d)). The study domain north of 10°N , with an exception of northeast Philippines, is characterized by very low rainfall during this season. In general, it is found that the heavy rainfall is anchored windward side of the terrain, as also reported by Chang et al. (2005b).

3 Methodology

We used 11 indices in this study, nine being threshold-based, and two based on Lorenz curve. While the former were defined to quantify rainfall extremes, the latter were employed to characterize overall distribution of rainfall. The spatial distribution of each index was examined at annual, seasonal and intraseasonal scales.

3.1 Indices for daily rainfall analysis

A fixed threshold of 20 mm d⁻¹ and a variable threshold of 95th percentile were chosen for daily rainfall analysis. Specifically, the latter is location (i.e. pixel) specific. Using these thresholds, we defined five indices to study rainfall extremes (Table 1). The difference between R20 and R20n is that the computation of former (latter) involves normalization with total (rainy) days. In addition to these threshold based indices, we employed the Lorenz curve to gain further insights about the overall distribution of rainfall. Olascoaga (1950) was one of the earliest studies to apply this concept to analyze rainfall distribution. The Lorenz curve is obtained by plotting the ranked cumulative proportion of observations on the abscissa against the corresponding cumulative proportion of total rainfall on the ordinate. Specifically, the method consists of counting the number of observations in predefined rainfall classes, and obtaining cumulative proportions of observations (X_i) and total rainfall (Y_i) via (e.g., Martin-Vide, 2004).

$$X_i = \frac{\sum_{k=1}^i n_k}{\sum_{k=1}^N n_k} \times 100 \quad (1)$$

$$Y_i = \frac{\sum_{k=1}^i r_k}{\sum_{k=1}^N r_k} \times 100 \quad (2)$$

where, N is the total number of classes, n_k is the number of rainy days that belong to class k , and r_k is the corresponding class aggregate rainfall. Throughout this study, the class interval was chosen as 1.0 mm, except for the first class for which lower threshold was 0.2 mm.

Figure 4 shows the Lorenz curves obtained for two randomly selected pixels in SEA. For Pixel 1, first 80% rainy days contribute 48% of total rainfall, i.e. top 20% of rainy days contribute 52% of total rainfall. Similarly, for Pixel 2, top 20% of rainy days contribute about 65% of total rainfall. Therefore, a Lorenz curve closer to the diagonal indicates a more uniform rainfall distribution and a more uniform contribution of each rainfall class to the total rainfall amount. The rainfall Gini index (GI_R) is a metric that quantifies this rainfall “concentration”, and is proportional to the area enclosed between the points (i.e. cumulative percentages) and the diagonal (e.g., Martin-Vide, 2004). There are various ways to estimate the area between the cumulative percentages and the diagonal in Figure 4. One approach is to fit a curve to the cumulative percentages and estimate the area using the parametric form. We fitted the following exponential parametric form as it was employed in various studies (e.g., Olascoaga, 1950; Zhang et al., 2009; Li et al., 2011; Suhaila and Jemain, 2012).

$$Y = aXe^{bX} \quad (3)$$

We estimated parameters a and b using the linear regression equations from Martin-Vide (2004), and evaluated the goodness of fit using R^2 . The area A under the Lorenz curve, and the GI_R were then estimated as

$$A = \left[\frac{a}{b} e^{bx} \left(x - \frac{1}{b} \right) \right]_0^{100} \quad (4)$$

$$GI_R = (5000 - A)/5000$$

The normalization with 5000 ensures that GI_R is bounded between 0 and 1. A higher GI_R indicates that rainfall is concentrated into a fewer rainy days. In other words, extreme rainfall on a few days makes a large contribution to the total rainfall.

3.2 Indices for wet spell analysis

A wet spell is defined here as the number of consecutive days with rainfall ≥ 0.2 mm d⁻¹. The frequency distribution of wet spells were obtained as follows (e.g., Mandapaka et al., 2016).

$$P_{WS}(l) = \frac{n_{WS}(l)}{\sum_{l=1}^{WS_{max}} n_{WS}(l)} \times 100 \quad (5)$$

where $n_{WS}(l)$ and WS_{max} denote the number of wet spells of length l and the maximum wet spell length, respectively. Besides wet spell lengths, we also focused on their fractional contribution to the total rainfall. The frequency distributions of the wet spell fractional contribution were obtained as

$$P_{R_{WS}}(l) = \frac{R_{WS}(l)}{\sum_{l=1}^{WS_{max}} R_{WS}(l)} \times 100 \quad (6)$$

where $R_{WS}(l)$ is the rainfall accumulation from wet spells of length l (e.g., Mandapaka et al., 2016).

Figures 5(a,b) illustrate histograms of wet spells and their fractional contributions to the total rainfall for the same two pixels as in Figure 4. We selected a fixed threshold of 10 days, a variable threshold of 95th percentile of wet spell lengths, and defined four indices for wet spell analysis (Table 1). We also adapted the concept of Lorenz curve for wet spell analysis, and computed corresponding wet spell Gini index (GI_{WS}). The procedure to estimate GI_{WS} is similar to that of GI_R , except that X and Y in Equations 1 to 3 now denote the cumulative proportions of total wet spells and their relative contribution to the total rainfall, respectively. Figures 5(c,d) show the $X_i - Y_i$ plots and the fitted exponential Lorenz curves. The fitted parameters of the exponential curve were then used to estimate GI_{WS} .

4 Results and discussion

The characteristics of extreme daily rainfall at annual, seasonal and intraseasonal scales are described first, followed by the discussion on extreme wet spells. Furthermore, the regional variability within the study domain is quantified using mean and standard deviation of indices

for following five masks/regions: i) the sea mask, ii) the land mask, iii) the CSEA region, iv) Sumatra and Malay Peninsula (SMP), and v) the Borneo island (BOR).

4.1 Daily rainfall extremes

4.1.1 Annual scale

The index R20, which quantifies the annual occurrence of heavy rainfall (Table 1) varies from 2% to 23%. There are four main hotspot regions near coastal Myanmar, southwest coast of Sumatra, northwest Borneo, and around Philippines (Figure 6(a)), where R20 can be as high as 23%. Conversely, R20 is lower on the leeward side of Myanmar highlands, in Central Thailand, and near the southeast corner of the study domain. As for R20n, the hotspot off the coast of Myanmar is more prominent compared to other regions (Figure 6(b)). This is because R20n was obtained by normalizing the number of heavy rainfall days with the number of rainy days, and the latter is higher in Sumatra and Borneo compared to the Myanmar coast (see Figure 2(a)). Thus, the relative number of heavy rainfall days is much larger off the coast of Myanmar. The index R20Tot varies from 30% to 88%, with high values ($>75\%$) near Myanmar coast (Figure 6(c)). In other words, top 30% of rainy days contribute 75 - 85% of annual rainfall in this region (Figures 6(b,c)). Although the SCS has relatively lower probability of heavy rainfall days, their percentage contribution to the annual rainfall is very high. For example, the SCS region east of Vietnam has top 15 - 20% rainy days contributing 65 - 75% of annual rainfall. The lowest values of R20Tot were observed in CSEA, northcentral Borneo, and in parts of Sulawesi Island, which are consistent with the pattern observed in R20 and R20n.

Unlike R20 and R20n, R95P shows a new, narrow band of high values along the northeast coast of Vietnam (Figure 6d). Although, R20 days are less frequent in this corridor, the daily rainfall during these days can be extremely high. In contrast, the equatorial regions such as Sumatra and Borneo have large number of R20 days (Figure 6(a)), but the R95P is mostly under 50 mm/d, indicating a more confined rainfall distribution compared to other regions such as coastal Myanmar. The variation of R95PTot (i.e. contribution from the top 5% rainy days to annual rainfall) is shown in Figure 6(e). Higher values of R95PTot is seen east of Vietnam, near the eastern coast of Philippines, and along the eastern coast of Malay Peninsula. A salient

feature of Figure 6(e) is that the land areas have significantly lower R95PTot compared to sea. The relative contribution from top 5% rainy days to the annual rainfall is $< 24\%$ over CSEA, Sumatra and Borneo, whereas the value is $> 30\%$ for most of the SCS.

To further understand the relative contribution of each rainfall class to the total rainfall, we produced Lorenz curves and calculated the corresponding GI_R . The GI_R has a lowest value of 0.50 over Central Borneo, whereas the highest value of 0.74 was observed near eastern Philippines (Figure 6(f)). The hatched region in Figure 6(f) indicates pixels, for which the exponential equation (Equation 3) does not provide an acceptable fit (i.e. $R^2 < 0.95$), and these GI_R values should be interpreted with caution. Overall, a clear land-sea contrast in GI_R is observed, with land pixels having consistently lower values compared to sea pixels, implying that land areas in SEA having a more uniform contribution from each rainfall class. For instance, Sumatra and Borneo have a large number of rainy days and a high annual rainfall (see Figure 2), but lower GI_R . The annual rainfall in these regions is maintained by a relatively uniform contribution from a large number of rainy days. In contrast, SCS east of Vietnam has lower annual rainfall and rainy day percentage, but higher GI_R , indicating that much of the annual rainfall amount is concentrated within extreme rainfall days. Within the land region, the eastern coast of Malay Peninsula has high GI_R , with values above 0.61. Figure S1 (supplementary material) shows the values of coefficients a and b of Equation 3 for each pixel. By substituting into Equation 3, we can obtain the relative contribution of first $X\%$ (or top $100 - X\%$) rainy days to the total rainfall amount. For example, the relative contribution of top 5% rainy days, which was quantified using R95PTot (Figure 6(e)), can also be obtained by using coefficients a and b (Figure S1) in Equation 3. In summary, both R95PTot and GI_R represent how much heavy rainfall days contribute to the total rainfall, but the latter is more comprehensive as it considers all rainfall classes.

The regional variability in extremes is quantified by computing mean and standard deviation of indices for five predefined masks/regions. The third column in Table 2 shows the statistics that are relevant to this subsection. Among the three land regions, CSEA has the lowest R20 of 8.12% and Borneo has the highest value of 14.43%. The pattern of R20n is uniform among all five regions, with mean values about 21%. Therefore, it is inferred that $\sim 21\%$ of rainy days in SEA record rainfall ≥ 20 mm. The index R20Tot displays considerable land-sea contrast, with a mean value of 65.8% (58.5%) over sea (land). The mean R20Tot varies only slightly among

the three land regions, but the standard deviation indicates larger variability for CSEA. The R95P index was also found to be larger over sea compared to land. The pattern of R95PTot is similar to that of R20Tot and R95P, i.e. high (low) average values over sea (land), and negligible variation among three land regions. The average GI_R for sea is 0.62, which decreases to 0.56 for land. Unlike other indices, the standard deviation for GI_R is very low, implying a more uniform spatial distribution within all five regions.

4.1.2 Seasonal scale

During boreal spring, the value of R20 ranges from 2 - 28%, with higher values for all major islands such as Sumatra, Borneo, and Java (Figure 7(a1)). R20n as normalized with the number of rainy days, ranges from 5 - 37% (Figure 7(b1)). The spatial distribution of R20n is similar to that of R20, except for a new hotspot near the Myanmar coast. Hence for this region there is a greater probability of daily rainfall exceeding 20 mm when it rains, as compared to other regions. More than 70% of seasonal rainfall near the coast of Myanmar, and near the western coast of Philippines, is from R20 days (Figure 7(c1)). The spatial pattern of R95P is similar to that of R20Tot, with hotspots near the coasts of Myanmar and Philippines (Figure 7(d1)). The R95PTot and GI_R distributions indicate that the contribution from different rainfall classes to the total seasonal rainfall is more uniform over land areas compared to sea (Figure 7(e1,f1)). The MAM statistics listed in Table 2 provides further evidence regarding the land-sea contrast. For example, R20Tot has an average of 61.2% (53.3%) over sea (land).

During boreal summer, the prevailing southwesterlies interact with Myanmar highlands, resulting in persistent rainfall on the windward side (Figure 7(a2)). In this region, the R20n index can be as high as 60%, and heavy rainfall days account for 80 - 90% of seasonal rainfall. Rainfall hotspots were also observed near the western coast of Sumatra, Laos, and near the western Luzon Island (Figures 7(a2,b2)). The CSEA region has high R20n, but also large spatial variability as evident from the standard deviation (Table 2). In particular, about 45% of rainy days on the windward side of Annamite Range receive rainfall ≥ 20 mm/d, and contribute about 80% of seasonal rainfall (Figure 7(b2,c2)). On average, 66% (55.7%) of seasonal rainfall over sea (land) is from R20 days (Table 2). Figure 7(d2) shows that rainfall near coastal Myanmar and western coast of Luzon Island can be very intense, with R95P exceeding 120 mm/d. However, the relative

contribution from top 5% rainy days to the total seasonal rainfall is less than 30% for most of the study domain, except the eastern coast of Vietnam and Luzon Island, where the R95PTot exceeds 40% (Figure 7(e2)). From Figure 7(f2), it is concluded that the coast of Myanmar receives persistent rainfall during boreal summer, with a relatively uniform contribution to seasonal total, leading to a lower GI_R . Conversely, the eastern coast of Vietnam has a much lower rainy day frequency, seasonal rainfall, and R20, but a higher GI_R indicating a larger contribution from the upper tail of rainfall distribution.

During SON months, the southwesterlies of JJA season are replaced by light and variable winds over most of the study area, except near northern SCS, where the average winds are northeasterly (Figure 3c). In general, spatial patterns of indices were found to be smoother during boreal fall than other seasons. A narrow corridor of large R20, R20n, and R20Tot values is evident along the coast of Vietnam (Figure 7(a3) - (d3)). About 40% of rainy days have rainfall ≥ 20 mm, and contribute more than 80% of seasonal rainfall along this narrow coastal region (Figures 7(b3,c3)). Furthermore, the R95P value exceeds 160 mm/d in this region (Figure 7(d3)). Another land region with heavy rainfall during SON is Luzon Island, Philippines. The boreal summer rainfall hotspot off the coast of Myanmar is not quite intense during the SON season due to weakened seasonal winds. However, the hotspot over sea near western Sumatra is still strong, despite weaker prevailing winds. Wu et al. (2009) showed that the presence of mountains along western Sumatra and the resultant thermally induced local circulation play a larger role in the formation and propagation of convection over sea near western Sumatra. Among land areas, SMP has larger values of R20n, R20Tot and R95P. Similar to MAM and JJA months, the GI_R was found to be lower over land regions compared to sea (Figure 7(f3)). However, the land-sea contrast in other indices is weaker during SON compared to other seasons (Table 2).

By December, the prevailing northeasterlies gain strength and extend into the SCS. Although the eastern slopes of Annamite mountains still face strong northeasterlies, these winds are cold and dry, and hence do not lead to heavy rainfall along Vietnam coast. Indeed, the probability of heavy rainfall over CSEA, Andaman Sea, and parts of SCS decreases rapidly from SON to DJF months (Figures 7(a4,b4)). The SON heavy rainfall hotspot over the coast of Vietnam now shifts to the eastern coast of Malay Peninsula, on the windward side of Titiwangsa mountains (Figures 7(b4)). Similarly, the region of heavy rainfall over sea near western Sumatra follows the prevailing

winds, and shifts southeastward during DJF months. Most parts of the Java Island and Java Sea also lie in the region of heavy rainfall. It is during this season that many areas in Java face frequent flooding. The SON hotspot over Philippines is relatively undisturbed during the DJF season, because of strong northeasterlies and availability of moisture from warmer western Pacific Ocean. The R20Tot and R95P values are very high along the eastern coast of Malay Peninsula and eastern region of Philippines (Figure 7(c4)). The land-sea contrast in the mean values of R20Tot, R95P, R95PTot and GI_R is stronger compared to boreal fall (Table 2). Moreover, the DJF season presents the largest variability in indices among the three land regions, with CSEA (SMP) having the lowest (highest) value.

4.1.3 Wind-terrain interactions

The relation between winds, terrain, and the location of rainfall extremes is further evaluated by studying longitudinal variation of R20n within three latitude regions: a) 15N-18N, b) 2N-5N, and c) 5S-8S. These were selected such that they broadly cover major mountains and rainfall hotspots observed in Figures 6 and 7. For 15N-18N section, a peak in MAM R20n occurs just before Myanmar highlands, around 97E longitude (Figure 8(a)). Although MAM months are generally characterized by light and variable winds, the average winds within 15N-18N are westerly, and of moderate strength (see Figure 3). The peak at 97E is due to these westerlies, and lifting by the nearby high terrain. The R20n also peaks just before the Annamite Range in Laos, and over the mountains in Luzon Island. The JJA R20n curve is much similar to that of MAM months, with more prominent peaks, and higher R20n. The sheltering effect of mountains is clearly evident during JJA months, when R20n drops rapidly from 54% (windward side) to 14% (leeward side) within 2°. During the transition season of SON, the winds are northeasterly near the Annamite Range. These moisture bearing winds interact with the orography and lead to a R20n hotspot over the mountains. Comparing JJA and SON curves, it is inferred that the effect of Annamite Range on R20n is stronger during SON, because of steeper eastern slopes of the mountains. The DJF R20n variation is markedly different from the other three seasons. Furthermore, the DJF R20n is lower compared to other seasons for most of the section, except east of Philippines Islands, where the northeasterlies from the Western Pacific interact with the high terrain.

The 2N-5N section passes through northern Barisan Range of Sumatra, Titiwangsa Mountains in Central Malay Peninsula, and mountains of northeastern Borneo (Figure 8(b)). The seasonal R20n curves are tighter in 2N-5N region compared to 15N-18N. The R20n in the region west of Sumatra is maintained by the interaction between westerlies and the terrain of Sumatra, and the thermally induced local circulations (e.g., Wu et al., 2009). There are considerable variations in seasonal R20n east of Titiwangsa Mountains, where the lowest (highest) values are observed during JJA (DJF) months. This region is on the leeward side during JJA season, whereas strong moisture bearing northeasterlies interact with the terrain leading to high R20n values during DJF months. A broad peak in DJF R20n can be observed between 110E and 115E, to the west of mountains in Borneo. It is well recognized that this region is characterized by the synoptic scale cyclonic circulation, referred to as Borneo vortex, which is further strengthened during the occurrence of cold surges in DJF (e.g., Cheang, 1977; Chang et al., 2005a; Koseki et al., 2014). Therefore, the high R20n observed in Figure 8(b) to the west of Borneo is mainly because of these synoptic scale processes and the associated deep convection. The seasonal variation of R20n in 5S-8S is negligible to the west of Java Island (Figure 8(c)). The JJA R20n then tends to decrease gradually over east-west mountain chain of the Java Island. The probability of extremes over Java is much higher during DJF season compared to the JJA season. However, it is observed from the DJF R20n curve that, despite facing strong westerlies, the Java Island topography has a negligible effect on probability of extremes.

4.1.4 Intraseasonal scale: Role of MJO

The MJO is an envelope of enhanced and suppressed convection, and forms a major component of the intraseasonal variability in the tropical atmosphere. The MJO propagates eastward within the tropics, with an average speed of 5 m s^{-1} , and local periodicity of 30 - 60 days (e.g., Madden and Julian, 1972; Zhang, 2005). The real-time multivariate MJO (RMM) index developed by Wheeler and Hendon (2004) was employed here to assess the impact of MJO on rainfall extremes. Wheeler and Hendon (2004) defined eight phases for the RMM index, with each phase broadly corresponding to the location of deep convection. We obtained RMM index and phase for our study period from the Australian Government Bureau of Meteorology (<http://www.bom.gov.au/climate/mjo/graphics/rmm.74toRealtime.txt>). Figure S3 (sup-

plementary material) shows R20 index derived from composites of each MJO phase, but excluding days when MJO is weak (i.e. $RMM < 1$). The R20 hotspots in the study region are particularly strong during phases 2 to 4 (Figures S3(b) - (d)). During phases 6 to 8, a zone of suppressed convection settles over the maritime continent as the deep convective zone moves towards Pacific Ocean. Therefore, R20 during these phases are much lower than other phases (Figures S3(f) - (h)). The role of MJO in precipitation can be studied for each phase separately. As we have only 16 years of data, some level of aggregation is necessary to minimize sample size effects on the estimated indices. We followed the approach of Xavier et al. (2014), and grouped phases 2 to 4 as “active” MJO period, and phases 6 to 8 as “suppressed” MJO period. Composites of daily rainfall were constructed for active and suppressed MJO periods during each season. Extreme rainfall indices were then calculated for these composites, and anomalies were obtained by subtracting seasonal values.

Figure 9 shows seasonal anomalies of R20, R20n R20Tot, and 850 hPa winds during the active MJO phases. The warmer colors indicate larger values for indices during the active MJO period compared to the seasonal value. During boreal spring, warmer colors were found to lie mainly to the south of 5N (Figure 9(a1) - (c1)). The western Malay Peninsula, southern Sumatra, and northwestern Borneo show large increases in R20 during active MJO phases. The region off the Myanmar coast, northern SCS, western Philippines, and northeast Borneo are areas with considerable reduction in R20. These areas of decreased rainfall extremes are associated with enhanced easterlies (Figure 9(a1)). The warmer colors shift northward into Gulf of Thailand and CSEA with boreal summer (Figure 9(a2) - (c2)). The eastern Indian ocean and a majority of the Borneo Island continue to experience increased heavy rainfall probability. The wind anomalies to the north of 5N are predominantly easterly (Figure 9(a2)), as opposed to the westerly-southwesterly mean seasonal flow (Figure 7(a2)), indicating weaker winds during active MJO phases in this season. During boreal fall, the zone of increased rainfall extremes lies mainly between 5S and 5N (Figure 9(a3) - (c3)). The wind anomaly pattern over the SCS and Borneo suggests weakened winds during active MJO phases compared to the mean seasonal flow (Figures 7(a3) and 9(a3)). During boreal winter, much of the study region, except Myanmar coast and northeastern Borneo, experiences an increase in the probability of extremes (Figures 9(a4) - (c4)). The wind anomaly patterns suggest stronger westerlies over eastern Indian Ocean,

and weaker northeasterlies over SCS during the active MJO phases.

The results in Figure 9 are quantified in Table 3 for sea and land areas, and for three land regions. Note that the statistics in Table 3 are of normalized anomalies of indices (i.e. $100 \times (\text{seasonal anomalies} / \text{seasonal value})$), whereas Figure 9 shows seasonal anomalies. Moreover, pixels with seasonal values < 0.5 are not considered in the computation of mean and standard deviation. On average, the R20 over sea increases by 8.7% during active MJO phases in boreal spring. However, the standard deviation indicates a large spatial variability in values. Over sea (land), the largest relative changes in R20 were observed during boreal winter, with an increase of 23.2% (19.7%) during active phases. In CSEA, the R20 index decreases by 33.8% during boreal spring, whereas it increases during other seasons, with the largest increase of 39.7% during boreal winter. Both SMP and BOR regions show an increase in R20 in all seasons, with the largest change during DJF and JJA months, respectively. For example, the active MJO days during boreal summer increases the R20 index in Borneo by 42%. The pattern is similar for R20n index. The average change in R20Tot was found to be small for all regions, except CSEA, where R20Tot decreases (increases) by 11.1% (7.7%) during MAM (DJF) seasons. The percentage change in R20Tot is considerable also for BOR during JJA season.

During suppressed phases of boreal spring, the areas of increased rainfall extremes lie mostly to the north of 5N (Figure 10(a1) - (c1)). The wind anomalies indicate that the increase in rainfall extremes near Myanmar coast is accompanied by strengthening of southwesterlies. The largest reduction in heavy rainfall probability was observed in the eastern Indian ocean. The Malay Peninsula, Sumatra, Java and much of Borneo Island also lie in the region of reduced extremes. During boreal spring and summer, the probability of heavy rainfall in Borneo decreases by 23.5% and 47%, respectively (Table 4). Moreover, during boreal summer, the warmer colors are mainly confined to Myanmar coast, region around Philippines, and parts of Sumatra and Borneo (Figure 10(a2) - (c2)). During boreal fall, much of the study domain except some areas in CSEA, central Malay Peninsula, northeast Borneo, and western Pacific, is characterized by a decrease in the probability of extremes (Figure 10(a3) - (c3)). The wind anomalies indicate stronger cyclonic circulation over SCS, and weaker easterlies in the southern part of the study domain. The results for boreal winter show that the entire study area except parts of CSEA, Borneo, and Sumatra, experiences a decrease in probability of extremes (Figure 10(a4) - (c4)). The Indian Ocean region

near southwest Sumatra has the largest reduction in the probability of extremes. This region is also accompanied by considerably weaker winds compared to mean seasonal flow as observed in wind anomaly patterns of Figure 10(a4). On average, all three indices are decreasing compared to the seasonal values (Table 4). An exception to this pattern is the CSEA region during the boreal spring, with a 19.35% average increase in the probability of heavy rainfall.

The study also analyzed the effect of different MJO phases on GI_R , but found the percentage change to be very small during all seasons. For example, GI_R decreases by 2.2% over land areas during an active MJO phase in boreal summer. This negligible change for both active and suppressed phases could be because it is an aggregated index, and not based on a specific threshold.

4.2 Wet spell extremes

The wet spell lengths and the corresponding rainfall accumulations were extracted for each pixel, and their spatial distribution was analyzed using indices listed in Table 1.

4.2.1 Annual scale

Figure 11 shows the spatial distribution of number of wet spells (NWS) and five extreme wet spell indices. The southern Malay Peninsula, western Sumatra, coastal Borneo, Sulawesi, and southern Philippines receive the largest number of wet spells. The regions with the largest number of wet spells and the largest frequency of rainy days are not necessarily the same (Figures 2(a) and 11(a)), which indicates a complex clustering pattern of rainy days. For example, the annual wet spell count around Singapore is about 70, with an average spell length < 3 days, whereas Central Borneo receives about 50 wet spells per year, with an average length of ~ 7 days (Figures 11(a) and S4). The index $WS10n$, which quantifies the probability of extreme wet spells, is shown in Figure 11(b). The region around Singapore has a very low probability of extreme wet spells. On the other hand, high percentage of extreme wet spells can be observed near Myanmar coast, southwest Sumatra and central Borneo. The index $WS10Tot$, which quantifies the relative contribution from extreme wet spells to total rainfall, was found to be large for the above three regions, and near west coast of Philippines. For example, top 15% of wet spells contribute about

75% of annual rainfall near Myanmar coast, whereas top 30% of wet spells over central Borneo contribute 50 - 60% of annual rainfall (Figure 11(b,c)).

The spatial pattern of the 95th percentile of wet spell lengths (WS95P) is similar to that of WS10n, with three main hotspots (Figure 11(d)). The contribution of top 5% of wet spells to the total rainfall is lower over land than over sea (Figure 11(e)), a pattern that is more evident in GI_{WS} (Figure 11(f)). Thus the wet spell distribution and their relative contribution to the total annual rainfall are more uniform over land compared to sea. The spatial distribution of fitted parameters of the wet spell Lorenz curve is shown in Figure S5. These parameters and Equation 3 provide estimates of the relative contribution of any wet spell percentile to the total rainfall. The average and standard deviation of indices for sea, land, CSEA, SMP, and BOR masks are listed in Table 5. The land-sea contrast is most evident in indices characterizing relative contribution (WS10Tot, WS95PTot, and GI_{WS}). Among the three land regions, Borneo (CSEA) has the largest (smallest) values for a majority of indices.

4.2.2 Seasonal scale

From Figures 12(a1) - (a4), it is observed that Singapore and the surrounding regions in Malay Peninsula and eastern Sumatra receive the most number of wet spells (NWS) during all seasons except DJF. The CSEA region receives large NWS during boreal summer, which decreases rapidly as we progress into SON and DJF seasons. On average, CSEA receives four time more wet spells during boreal summer compared to boreal winter (Table 5). In contrast, central Borneo has much less variability, with 10 - 15 wet spells each season. When it comes to extremes (WS10n), central Borneo always has a hotspot, except boreal summer, when the probability is slightly lower (Figure 12(b1) - (b4)). The largest probability of extreme wet spells was observed during boreal summer near the coast of Myanmar and on the windward side of Annamite mountains in Laos (Figure 12b2), but the probability decreases dramatically as we move into SON and DJF seasons (Figures 12(b3,b4)). In fact, the average WS10n for the CSEA region drops from 9.24% in JJA to almost zero in DJF season (Table 4). Moreover, during the DJF season, the region in and around Java Island has a large probability of extreme wet spells.

The seasonal patterns of WS10Tot and WS95P indices are similar to that of WS10n, with

hotspots near Myanmar coast and Annamite mountains, and a sharp decrease in CSEA WS10Tot from JJA to DJF season. For SMP the WS10Tot drops rapidly from SON to DJF season, whereas BOR has a relatively consistent contribution from extremes during all seasons except JJA, when the values are lower (Figures 12(c1) - (c4), (d1) - (d4), and Table 4). The largest WS95P of ~ 60 days was observed during JJA months in the hotspot near Myanmar coast. The index WS95PTot displays a noisy pattern during all seasons (Figure 12(e1) - (e4)). It should be noted that this index, which quantifies the relative contribution of top 5% of wet spells to the total seasonal rainfall, is quite sensitive to the sample size (i.e. prone to sampling errors). For example, the CSEA region receives, on average, only 4 wet spells per each DJF season. Nevertheless, we included this result for completeness. Other regions such as Borneo and Sumatra, which receive larger number of wet spells, are not affected by sampling issues. The pattern of GI_{WS} suggests that in regions such as Sumatra, southern Malay Peninsula and coastal Borneo, the wet spell distribution is more uniform compared to other regions such as central Borneo (Figures 12(f1) - (f4)).

The threshold based extreme wet spell indices do not present much land-sea contrast, with the exception of DJF season (Table 5). Much of the land-sea contrast during DJF season is because of extremely low values of indices in CSEA. In general, as we move from MAM to DJF seasons, the corresponding hotspot regions progress southeastward starting from Myanmar coast in MAM to southern Sumatra and Java Island in DJF. Chang et al. (2005a) also observed this southeastward progression, but in seasonal rainfall totals. The intraseasonal variation of wet spells is not examined in this study because unlike analysis of daily rainfall, analysis of wet spells is about continuity of rainy days, and the extreme spells tend to break when we segregate them based on RMM index. For example, a wet spell of 10 days length may span days with different MJO phases.

5 Concluding Remarks

This study characterized extreme daily rainfall and wet spell characteristics by employing various indices that quantify not only the occurrence of extremes (e.g., for threshold of 20 mm d^{-1} for daily rainfall, and 10 days for wet spell), but also their relative contribution to the total

rainfall. The employed set of indices included the Gini index, a metric of inequality derived from Lorenz curve to characterize “concentration” of rainfall and wet spells. By focusing on relative contribution from extremes to the total rainfall in addition to their occurrence probability, this study provided a more comprehensive characterization of extremes. Moreover, this is the first application of Lorenz curve and Gini index concepts to examine SEA rainfall characteristics. The selected indices were calculated for each TRMM pixel, and favored regions (hotspots) for extremes were identified. In addition, regional variability was assessed separately for sea and land masks, and for three land regions (CSEA, SMP, and BOR).

At the annual scale, about 21% of rainy days in the study region receive rainfall ≥ 20 mm. Although this percentage is the same for both sea and land areas, the relative contribution of these heavy rainfall days to the annual rainfall was found to be considerably higher over sea than over land, with an average contribution of 66% and 58.5%, respectively. Other indices such as R95P, R95PTot, and GI_R have also shown considerable land-sea contrast, with larger values over sea. Lower GI_R for land regions indicate that the rainfall distribution and the relative contribution of each class to the total rainfall are more uniform over land compared to sea. This study also provided the spatial distribution of Lorenz curve parameters, which can be used to obtain the relative contribution of any percentile of rainy days to the total rainfall. The wet spell analysis showed that the southern Malay Peninsula and the surrounding region receive the largest number of wet spells per year, whereas Myanmar coast, southwest Sumatra, and central Borneo have large probability of extreme wet spells. The indices of wet spell extremes also displayed considerable land-sea contrast, with lower values for land areas, indicating a more uniform wet spell distribution over land.

The seasonal analysis showed that the land-sea contrast in indices is stronger during boreal summer and winter seasons. The CSEA region has a stronger annual cycle, with indices peaking in boreal summer and fall, and dropping rapidly during boreal winter. The indices for SMP region peak during boreal fall and winter, and has smaller values during boreal summer. The probability of rainfall extremes was found to be large near the Myanmar coast during boreal spring and summer. Additional hotspot regions during boreal summer were observed in Laos, western side of Luzon Island, and in eastern Indian Ocean. The heavy rainfall days in these regions were found to contribute 70 - 80% of summer rainfall. The most evident hotspot region during boreal

fall is along the coast of Vietnam, with the 95th percentile of daily rainfall exceeding 160 mm/d. The favoured regions for rainfall extremes during boreal winter include western Philippines, eastern Malay Peninsula, northwestern Borneo, Sumatra and Java. The probability of extremes for northern parts of the study domain such as CSEA, and Andaman Sea dropped rapidly from SON to DJF months. In general, as we move from boreal spring to winter, the hotspot regions move south and eastward. This southeastward progression, which was also reported by Chang et al. (2005b) for seasonal rainfall, is more evident in indices of wet spell extremes compared to extreme rainfall indices.

Wind-terrain interactions were found to play a crucial role in determining the location of most hotspots. It was observed that the hotspot near the coast of Myanmar during boreal summer is due to the interaction of southwesterlies with the highlands of Myanmar. The hotspots on the western (eastern) side of Annamite Range during boreal summer (fall) are mainly due to the interactions of prevailing southwesterlies (northeasterlies) with the terrain. Similarly, a narrow corridor along the eastern Malay Peninsula is the preferred region for extremes during boreal winter because of the interaction between moisture bearing northeasterlies and Titiwangsa mountains in central Malay Peninsula.

Composite analysis conditioned on MJO phases showed that during active (suppressed) phases in boreal spring, the favoured regions of rainfall extremes mainly lie to the south (north) of 5N. In this season, the probability of heavy rainfall in CSEA decreases (increases) by 34% (19%) during active (suppressed) phases. In boreal summer, a 42% (47%) increase (decrease) in the probability of heavy rainfall was observed for Borneo during active (suppressed) MJO phases. The eastern Indian ocean, Gulf of Thailand, and CSEA also showed an increase (decrease) in heavy rainfall probability during active (suppressed) MJO phases in this season. In boreal winter, much of the study region experiences an increase in rainfall extremes during active MJO phases. On average, the active (suppressed) MJO phases during boreal winter increases (decreases) the probability of heavy rainfall in CSEA by 40% (19%).

This study quantified the regional variability of extreme daily rainfall and wet spells, and provided a qualitative description of linkages between rainfall hotspots, wind patterns, and topography. There are however other factors such as moisture supply and upward motion, which

play important roles in determining the strength and location of extremes. Further research is needed to identify specific large-scale dynamic and thermodynamic conditions that would lead to rainfall and wet spell extremes within each SEA subregion.

Acknowledgements

This study was supported by Academic Research Fund Tier 2 (M4020182.030) and Tier 1 (Ref188/14; WBS: M4011420.030) projects from Ministry of Education, Singapore. The authors also acknowledge partial support from the Singapore ETH Center Future Resilience Systems project. ERA-Interim data were obtained from the ECMWF data portal (<http://apps.ecmwf.int/datasets/data/interimfull-daily/>).

References

- Chang, C., Z. Wang, J. Ju and T. Li, 2004: On the relationship between western Maritime Continent monsoon rainfall and ENSO during northern winter. *J Climate*, **17**, 665–672.
- Chang, C., P. Harr and H.-J. Chen, 2005a: Synoptic disturbances over the equatorial South China Sea and western maritime continent during Boreal winter. *Mon Wea Rev*, **133**, 489–503.
- Chang, C., Z. Wang, J. McBride and C. Liu, 2005b: Annual cycle of Southeast Asia-Maritime Continent rainfall and the asymmetric monsoon transition. *J Climate*, **18**, 287–301.
- Chang, C.-P., Z. Wang and H. Hendon, 2006: The asian winter monsoon. In *The Asian Monsoon*, pp. 89–127. Springer.
- Cheang, B. K., 1977: Synoptic features and structures of some equatorial vortices over the South China Sea in the Malaysian region during the winter monsoon, December 1973. *Pure Appl Geophys*, **115**, 1303–1333.
- Gastwirth, J. L., 1972: The estimation of the Lorenz curve and Gini index. *Rev Econ Stat*, pp. 306–316.
- Hamada, A., M. D. Yamanaka, J. Matsumoto, S. Fukao, P. A. Winarso and T. Sribimawati,

2002: Spatial and temporal variations of the rainy season over Indonesia and their link to ENSO. *J Meteorol Soc Jpn*, **80**, 285–310.

Hattori, M., S. Mori and J. Matsumoto, 2011: The cross-equatorial northerly surge over the maritime continent and its relationship to precipitation patterns. *J Meteorol Soc Jpn*, **89**, 27–47.

Haylock, M. and J. McBride, 2001: Spatial coherence and predictability of Indonesian wet season rainfall. *J Climate*, **14**, 3882–3887.

Hendon, H. H., 2003: Indonesian rainfall variability: Impacts of ENSO and local air-sea interaction. *J Climate*, **16**, 1775–1790.

Jawitz, J. W. and J. Mitchell, 2011: Temporal inequality in catchment discharge and solute export. *Water Resour Res*, **47**, W00J14.

Jiang, P., D. Wang and Y. Cao, 2016: Spatiotemporal characteristics of precipitation concentration and their possible links to urban extent in China. *Theor Appl Climatol*, **123**, 757–768.

Juneng, L. and F. T. Tangang, 2005: Evolution of ENSO-related rainfall anomalies in Southeast Asia region and its relationship with atmosphere–ocean variations in Indo-Pacific sector. *Clim Dynam*, **25**, 337–350.

Komori, D., S. Nakamura, M. Kiguchi, A. Nishijima, D. Yamazaki, S. Suzuki, A. Kawasaki, K. Oki and T. Oki, 2012: Characteristics of the 2011 Chao Phraya River flood in central Thailand. *Hydrol Res Lett*, **6**, 41–46.

Koseki, S., T. Y. Koh and C. K. Teo, 2014: Borneo vortex and mesoscale convective rainfall. *Atmos Chem Phys*, **14**, 4539–4562.

Li, X., F. Jiang, L. Li and G. Wang, 2011: Spatial and temporal variability of precipitation concentration index, concentration degree and concentration period in Xinjiang, China. *Int J Climatol*, **31**, 1679–1693.

Liew, S. C., A. Gupta, A. S. Chia and W. C. Ang, 2016: The flood of 2011 in the lower Chao Phraya valley, Thailand: Study of a long-duration flood through satellite images. *Geomorphology*, **262**, 112–122.

597 Lorenz, M. O., 1905: Methods of measuring the concentration of wealth. *Publ Am Stat Assoc*,
598 **9**, 209–219.

599 Madden, R. A. and P. R. Julian, 1972: Description of global-scale circulation cells in the tropics
600 with a 40-50 day period. *J Atmos Sci*, **29**, 1109–1123.

601 Mandapaka, P. V., X. Qin and E. Yat-Man Lo, 2016: Seasonal and interannual variability of wet
602 and dry spells over two urban regions in the western maritime continent. *J Hydrometeorol*,
603 **17**, 1579–1600.

604 Martin-Vide, J., 2004: Spatial distribution of a daily precipitation concentration index in penin-
605 sular Spain. *Int J Climatol*, **24**, 959–971.

606 Neale, R. and J. Slingo, 2003: The maritime continent and its role in the global climate: A GCM
607 study. *J Climate*, **16**, 834–848.

608 Oh, J.-H., K.-Y. Kim and G.-H. Lim, 2012: Impact of MJO on the diurnal cycle of rainfall over
609 the western Maritime Continent in the austral summer. *Clim Dynam*, **38**, 1167–1180.

610 Olascoaga, M., 1950: Some aspects of Argentine rainfall. *Tellus*, **2**, 312–318.

611 Peel, M. C., B. L. Finlayson and T. A. McMahon, 2007: Updated world map of the Köppen-
612 Geiger climate classification. *Hydrol Earth Syst Sci*, **11**, 1633–1644.

613 Promchote, P., S.-Y. Simon Wang and P. G. Johnson, 2016: The 2011 great flood in Thailand:
614 Climate diagnostics and implications from climate change. *J Climate*, **29**, 367–379.

615 Qian, J.-H., 2008: Why precipitation is mostly concentrated over islands in the Maritime Con-
616 tinent. *J Atmos Sci*, **65**, 1428–1441.

617 Rajah, K., T. O’leary, A. Turner, G. Petrakis, M. Leonard and S. Westra, 2014: Changes to the
618 temporal distribution of daily precipitation. *Geophys Res Lett*, **41**, 8887–8894.

619 Ramage, C. S., 1968: Role of a tropical “Maritime Continent” in the atmospheric circulation.
620 *Mon Wea Rev*, **96**, 365–370.

621 Rauniyar, S. P. and K. J. E. Walsh, 2011: Scale interaction of the diurnal cycle of rainfall over
622 the Maritime Continent and Australia: Influence of the MJO. *J Climate*, **24**, 325–348.

- Rauniyar, S. P. and K. J. E. Walsh, 2013: Influence of ENSO on the diurnal cycle of rainfall over the Maritime Continent and Australia. *J Climate*, **26**, 1304–1321.
- Shamshuddin, J., Q. A. Panhwar, R. Othman, R. Ismail, H. Jol and M. A. Yusoff, 2016: Effects of December 2014 great flood on the physico-chemical properties of the soils in the Kelantan Plains, Malaysia. *Journal of Water Resource and Protection*, **8**, 263.
- Shi, W., X. Yu, W. Liao, Y. Wang and B. Jia, 2013: Spatial and temporal variability of daily precipitation concentration in the Lancang River basin, China. *J Hydrol*, **495**, 197–207.
- Suhaila, J. and A. A. Jemain, 2012: Spatial analysis of daily rainfall intensity and concentration index in peninsular malaysia. *Theor Appl Climatol*, **108**, 235–245.
- Tangang, F. and L. Juneng, 2004: Mechanisms of Malaysian rainfall anomalies. *J Climate*, **17**, 3616–3622.
- Tangang, F. T., L. Juneng, E. Salimun, P. N. Vinayachandran, Y. K. Seng, C. J. C. Reason, S. K. Behera and T. Yasunari, 2008: On the roles of the northeast cold surge, the Borneo vortex, the Madden-Julian Oscillation, and the Indian Ocean Dipole during the extreme 2006/2007 flood in southern Peninsular Malaysia. *Geophys Res Lett*, **35**, L14S07.
- Teo, C.-K., T.-Y. Koh, J. C.-F. Lo and B. C. Bhatt, 2011: Principal component analysis of observed and modeled diurnal rainfall in the maritime continent. *J Climate*, **24**, 4662–4675.
- UNPD, 2015: *World Urbanisation Prospects: The 2014 Revision (ST/ESA/SER.A/366)*. United Nations Department of Economic and Social Affairs, Population Division, New York.
- Wheeler, M. C. and H. H. Hendon, 2004: An all-season real-time multivariate MJO index: Development of an index for monitoring and prediction. *Mon Wea Rev*, **132**, 1917–1932.
- Wu, P., M. Hara, H. Fudeyasu, M. D. Yamanaka, J. Matsumoto, F. Syamsudin, R. Sulistyowati and Y. S. Djajadihardja, 2007: The impact of trans-equatorial monsoon flow on the formation of repeated torrential rains over Java Island. *SOLA*, **3**, 93–96.
- Wu, P., M. Hara, J.-I. Hamada, M. D. Yamanaka and F. Kimura, 2009: Why a large amount of rain falls over the sea in the vicinity of western Sumatra Island during nighttime. *J Appl Meteorol Clim*, **48**, 1345–1361.

650 Wu, P., A. A. Arbain, S. Mori, J. Hamada, M. Hattori, F. Syamsudin and M. D. Yamanaka, 2013:
651 The effects of an active phase of the Madden-Julian oscillation on the extreme precipitation
652 event over western Java Island in January 2013. *SOLA*, **9**, 79–83.

653 Xavier, P., R. Rahmat, W. K. Cheong and E. Wallace, 2014: Influence of Madden-Julian Os-
654 cillation on Southeast Asia rainfall extremes: Observations and predictability. *Geophys Res*
655 *Lett*, **41**, 4406–4412.

656 Yokoi, S., T. Satomura and J. Matsumoto, 2007: Climatological characteristics of the intrasea-
657 sonal variation of precipitation over the Indochina Peninsula. *J Climate*, **20**, 5301–5315.

658 Zhang, C., 2005: Madden-Julian oscillation. *Rev Geophys*, **43**.

659 Zhang, Q., C.-Y. Xu, M. Gemmer, Y. D. Chen and C. Liu, 2009: Changing properties of pre-
660 cipitation concentration in the Pearl River basin, China. *Stoch Env Res Risk Assess*, **23**,
661 377–385.

662 List of Tables

663	Table 1:	List of indicators employed to characterize daily rainfall and wet spell extremes	27
664	Table 2:	Mean and standard deviation of extreme rainfall indices calculated separately	
665		for sea, land, continental Southeast Asia (CSEA), Sumatra and Malay Penin-	
666		sula (SMP), and Borneo (BOR) at annual and seasonal scales.	28
667	Table 3:	Mean and standard deviation of R20, R20n and R20Tot calculated separately	
668		for sea, land, continental Southeast Asia (CSEA), Sumatra and Malay Penin-	
669		sula (SMP), and Borneo (BOR) for active (2 - 4) MJO phases.	29
670	Table 4:	Same as Table 3 but for suppressed (6 - 8) MJO phases.	30
671	Table 5:	Mean and standard deviation of extreme wet spell indices calculated separately	
672		for sea, land, continental Southeast Asia (CSEA), Sumatra and Malay Penin-	
673		sula (SMP), and Borneo (BOR) at annual and seasonal scales.	31

Table 1: List of indicators employed to characterize daily rainfall and wet spell extremes

Indicator	Description	Units
Daily Rainfall		
R20	Percentage of days when rainfall ≥ 20 mm d ⁻¹	%
R20n	Percentage of rainy days when rainfall ≥ 20 mm d ⁻¹	%
R20Tot	Percentage of annual rainfall from days when rainfall ≥ 20 mm d ⁻¹	%
R95P	95th percentile of daily rainfall	mm d ⁻¹
R95PTot	Percentage of annual rainfall from days when rainfall $\geq$ R95P mm d ⁻¹	%
GI _R	Daily rainfall Gini index	-
Wet spells		
WS10n	Percentage of wet spells with length ≥ 10 days	%
WS10Tot	Percentage of annual rainfall from spells ≥ 10 days	%
WS95P	95th percentile of wet spell lengths	days
WS95PTot	Percentage of annual rainfall from spells $\geq$ WS95P days	%
GI _{WS}	Wet spell Gini index	-

Table 2: Mean and standard deviation of extreme rainfall indices calculated separately for sea, land, continental Southeast Asia (CSEA), Sumatra and Malay Peninsula (SMP), and Borneo (BOR) at annual and seasonal scales.

Indicator	Mask	Annual	MAM	JJA	SON	DJF
R20 [%]	Sea	10.77 (3.33)	8.42 (3.54)	12.48 (7.22)	12.03 (5.19)	10.13 (6.44)
	Land	10.61 (3.72)	9.71 (4.74)	12.48 (6.80)	12.01 (4.19)	8.19 (8.18)
	CSEA	8.12 (2.75)	5.84 (1.74)	15.65 (8.00)	10.27 (3.49)	0.57 (0.70)
	SMP	12.54 (2.02)	12.57 (2.94)	8.27 (1.97)	14.84 (3.14)	14.54 (4.04)
	BOR	14.43 (2.69)	14.94 (2.69)	10.76 (2.50)	14.83 (3.53)	17.24 (3.84)
R20n [%]	Sea	20.82 (4.69)	17.59 (4.67)	21.78 (7.62)	20.97 (5.81)	18.21 (7.27)
	Land	20.78 (4.82)	17.71 (4.71)	19.88 (7.28)	22.40 (5.53)	16.60 (9.75)
	CSEA	20.54 (5.89)	15.01 (4.17)	22.27 (8.83)	23.89 (5.83)	8.15 (5.43)
	SMP	20.85 (2.57)	19.65 (3.35)	15.91 (2.79)	21.63 (3.29)	26.18 (4.27)
	BOR	20.91 (3.16)	20.25 (2.86)	18.24 (3.75)	20.85 (4.11)	24.09 (4.54)
R20Tot [%]	Sea	65.83 (6.27)	61.19 (7.41)	66.06 (10.75)	64.58 (9.15)	61.39 (11.90)
	Land	58.47 (8.28)	53.30 (8.14)	55.74 (10.48)	59.66 (9.60)	49.91 (19.53)
	CSEA	58.50 (9.48)	50.15 (8.33)	58.46 (11.39)	62.24 (9.62)	35.22 (17.50)
	SMP	58.86 (4.75)	55.74 (6.03)	50.65 (5.93)	58.27 (5.34)	66.80 (7.89)
	BOR	57.21 (5.84)	55.84 (5.69)	53.23 (7.36)	56.50 (6.84)	61.37 (6.66)
R95P [mm d ⁻¹]	Sea	50.32 (9.33)	44.65 (10.46)	52.30 (14.73)	49.81 (12.14)	45.78 (14.61)
	Land	44.60 (10.18)	38.97 (7.60)	42.31 (12.20)	47.38 (16.52)	39.51 (20.12)
	CSEA	44.89 (11.72)	35.85 (7.24)	45.50 (14.09)	51.16 (19.95)	25.95 (11.75)
	SMP	43.85 (5.40)	40.86 (5.68)	36.34 (4.70)	43.22 (5.66)	57.48 (20.04)
	BOR	42.51 (5.49)	41.45 (5.31)	38.70 (6.02)	42.01 (6.18)	47.28 (9.51)
R95PTot [%]	Sea	29.37 (4.32)	30.02 (4.83)	29.22 (5.15)	28.46 (4.46)	30.52 (6.37)
	Land	24.38 (3.00)	24.10 (2.50)	23.68 (2.52)	23.46 (2.80)	25.58 (5.93)
	CSEA	24.78 (3.04)	25.19 (2.22)	23.38 (2.46)	23.68 (2.77)	27.23 (7.43)
	SMP	24.38 (2.70)	23.19 (1.97)	24.01 (1.61)	23.04 (2.24)	24.41 (3.00)
	BOR	22.94 (1.63)	22.74 (1.80)	22.91 (1.68)	22.55 (1.80)	22.66 (1.68)
GI _R	Sea	0.62 (0.04)	0.62 (0.04)	0.62 (0.04)	0.62 (0.04)	0.62 (0.04)
	Land	0.56 (0.03)	0.56 (0.03)	0.55 (0.02)	0.55 (0.03)	0.57 (0.04)
	CSEA	0.56 (0.02)	0.57 (0.02)	0.55 (0.02)	0.55 (0.03)	0.58 (0.05)
	SMP	0.56 (0.02)	0.55 (0.02)	0.56 (0.02)	0.54 (0.02)	0.57 (0.04)
	BOR	0.54 (0.02)	0.54 (0.02)	0.55 (0.02)	0.54 (0.02)	0.54 (0.02)

Table 3: Mean and standard deviation of R20, R20n and R20Tot calculated separately for sea, land, continental Southeast Asia (CSEA), Sumatra and Malay Peninsula (SMP), and Borneo (BOR) for active (2 - 4) MJO phases.

Indicator	Mask	MAM	JJA	SON	DJF
R20 [%]	Sea	8.69 (51.82)	18.28 (33.19)	3.48 (26.31)	23.21 (33.12)
	Land	-5.82 (36.90)	17.33 (27.14)	6.41 (18.80)	19.72 (42.74)
	CSEA	-33.80 (22.87)	9.20 (20.04)	5.52 (17.33)	39.73 (76.99)
	SMP	22.93 (15.91)	17.60 (21.37)	10.58 (14.25)	24.61 (15.44)
	BOR	24.16 (24.78)	42.08 (27.15)	12.01 (18.30)	8.20 (19.05)
R20n [%]	Sea	0.27 (35.69)	5.19 (24.13)	1.24 (20.05)	12.36 (29.10)
	Land	-3.42 (26.72)	4.42 (19.91)	1.80 (15.37)	14.11 (55.69)
	CSEA	-19.91 (23.15)	2.22 (15.66)	-0.62 (14.22)	24.41 (79.52)
	SMP	12.87 (14.79)	1.36 (16.70)	5.22 (12.34)	7.67 (10.97)
	BOR	14.81 (19.45)	17.71 (18.72)	7.11 (14.30)	3.65 (14.68)
R20Tot [%]	Sea	-4.39 (21.30)	-1.10 (13.90)	-0.82 (11.57)	1.25 (19.44)
	Land	-3.14 (16.67)	-0.07 (12.60)	-0.24 (8.95)	4.15 (40.65)
	CSEA	-11.14 (18.21)	-0.73 (8.96)	-1.59 (8.21)	7.68 (59.29)
	SMP	5.63 (8.08)	-1.14 (10.33)	2.03 (7.44)	2.36 (5.20)
	BOR	4.85 (9.81)	6.64 (10.39)	1.63 (7.31)	0.89 (7.50)

Table 4: Same as Table 3 but for suppressed (6 - 8) MJO phases.

Indicator	Mask	MAM	JJA	SON	DJF
R20 [%]	Sea	-7.51 (53.65)	-25.52 (34.74)	-9.34 (27.74)	-29.31 (24.65)
	Land	-1.49 (29.30)	-23.08 (26.84)	-11.35 (20.70)	-14.24 (22.09)
	CSEA	19.35 (22.19)	-9.52 (20.60)	-12.26 (16.90)	-19.24 (37.94)
	SMP	-24.13 (12.75)	-27.09 (16.04)	-10.18 (15.76)	-19.70 (12.85)
	BOR	-23.49 (15.31)	-46.94 (20.11)	-15.24 (20.58)	-6.98 (12.19)
R20n [%]	Sea	-7.81 (36.50)	-12.85 (35.04)	-8.76 (21.68)	-21.84 (27.12)
	Land	-2.25 (19.50)	-8.15 (24.73)	-5.17 (19.79)	-10.14 (53.78)
	CSEA	7.89 (17.93)	-4.31 (18.86)	-2.18 (19.06)	-16.79 (77.75)
	SMP	-13.60 (12.94)	-5.29 (20.33)	-4.56 (14.73)	-6.10 (11.14)
	BOR	-14.25 (13.52)	-20.65 (23.09)	-14.15 (18.14)	-3.54 (10.71)
R20Tot [%]	Sea	-6.27 (17.88)	-6.26 (22.32)	-4.90 (12.89)	-11.77 (22.52)
	Land	-2.22 (11.75)	-4.01 (15.71)	-3.85 (12.00)	-11.83 (45.08)
	CSEA	2.12 (11.54)	-3.57 (12.16)	-2.81 (11.32)	-23.70 (63.81)
	SMP	-7.58 (9.36)	-0.96 (14.31)	-1.64 (9.38)	-2.48 (6.51)
	BOR	-7.52 (9.19)	-7.59 (16.41)	-8.21 (11.09)	-2.19 (5.89)

Table 5: Mean and standard deviation of extreme wet spell indices calculated separately for sea, land, continental Southeast Asia (CSEA), Sumatra and Malay Peninsula (SMP), and Borneo (BOR) at annual and seasonal scales.

Indicator	Mask	Annual	MAM	JJA	SON	DJF
NWS	Sea	53.80 (8.12)	14.24 (2.80)	14.07 (2.42)	13.92 (2.25)	12.73 (3.15)
	Land	51.93 (9.50)	14.39 (2.27)	15.74 (2.60)	13.69 (2.35)	9.36 (5.62)
	CSEA	44.76 (5.19)	13.89 (2.26)	15.65 (2.31)	12.45 (1.74)	3.82 (1.76)
	SMP	62.43 (5.42)	16.18 (1.61)	17.68 (1.78)	15.29 (1.70)	14.63 (1.93)
	BOR	56.77 (7.37)	14.13 (2.22)	15.67 (1.65)	14.57 (2.20)	14.18 (1.78)
WS10n [%]	Sea	6.99 (3.49)	4.71 (3.62)	6.90 (6.77)	7.14 (4.49)	6.53 (6.02)
	Land	7.25 (4.57)	6.53 (6.31)	6.94 (6.27)	7.09 (5.03)	4.55 (6.40)
	CSEA	5.58 (3.38)	2.59 (2.13)	9.24 (7.23)	4.79 (2.81)	0.01 (0.12)
	SMP	6.68 (2.91)	7.33 (4.12)	2.60 (2.26)	9.52 (4.54)	5.89 (5.06)
	BOR	12.01 (5.20)	14.27 (6.83)	7.03 (4.52)	11.88 (5.72)	11.96 (5.79)
WS10Tot [%]	Sea	34.30 (12.88)	23.74 (14.18)	27.50 (16.71)	31.15 (13.84)	27.74 (19.95)
	Land	29.52 (14.41)	24.46 (17.47)	23.73 (16.42)	27.28 (14.68)	15.18 (19.05)
	CSEA	25.69 (13.89)	13.89 (10.17)	28.57 (17.36)	21.42 (11.32)	0.12 (1.32)
	SMP	28.08 (10.27)	28.16 (13.48)	11.55 (8.69)	33.46 (12.08)	21.87 (14.59)
	BOR	40.69 (13.63)	43.61 (15.68)	27.22 (14.23)	39.66 (14.70)	37.77 (13.37)
WS95p [days]	Sea	10.94 (2.92)	9.04 (2.67)	10.37 (4.81)	10.85 (3.37)	9.98 (4.37)
	Land	11.07 (3.34)	10.31 (4.49)	10.31 (3.96)	10.89 (3.63)	7.27 (5.22)
	CSEA	9.92 (2.65)	7.54 (1.80)	11.72 (4.30)	9.33 (2.17)	2.77 (0.75)
	SMP	10.70 (2.12)	11.03 (2.87)	7.50 (1.84)	12.32 (2.87)	9.81 (3.21)
	BOR	14.28 (3.74)	15.59 (4.88)	10.69 (3.00)	14.39 (4.29)	13.42 (3.33)
WS95pTot [%]	Sea	31.03 (4.82)	30.74 (7.03)	28.63 (7.05)	29.23 (6.28)	31.15 (8.29)
	Land	26.24 (3.51)	25.82 (4.32)	23.46 (4.12)	25.57 (4.34)	28.57 (11.60)
	CSEA	27.14 (3.92)	27.27 (4.65)	22.45 (3.24)	26.11 (4.69)	33.14 (14.95)
	SMP	25.66 (2.72)	24.48 (3.55)	23.09 (3.58)	24.22 (3.41)	25.40 (4.82)
	BOR	24.72 (2.09)	24.00 (2.80)	24.61 (3.55)	24.86 (3.17)	23.44 (3.50)
GI _{WS}	Sea	0.61 (0.05)	0.59 (0.06)	0.58 (0.05)	0.59 (0.05)	0.59 (0.06)
	Land	0.53 (0.04)	0.51 (0.05)	0.48 (0.05)	0.52 (0.04)	0.46 (0.11)
	CSEA	0.54 (0.05)	0.50 (0.06)	0.49 (0.04)	0.53 (0.04)	0.39 (0.12)
	SMP	0.51 (0.04)	0.50 (0.05)	0.44 (0.05)	0.50 (0.04)	0.52 (0.06)
	BOR	0.52 (0.03)	0.51 (0.04)	0.50 (0.05)	0.51 (0.04)	0.51 (0.03)

List of Figures

674	Figure 1:	The geography of the study domain (note: the altitude is shown in color shading).	33
675	Figure 2:	Maps of (a) percentage rainy days in a year and (b) mean daily rainfall. . . .	34
676	Figure 3:	Maps showing seasonal mean daily rainfall from TRMM and seasonal mean winds extracted from ERA-Interim reanalysis for the time period of 1998 - 2013	35
677	Figure 4:	Cumulative percentage of number of rainy days plotted against the corresponding cumulative proportion of total rainfall for two pixels in SEA. Figure also shows the exponential parametric form (equation 3) fitted to the cumulative percentages and the line of equality, $y = x$	36
678	Figure 5:	Histograms of wet spell length and their relative contribution to total rainfall for two pixels (a,b), and the corresponding Lorenz curves (c,d). The histograms are truncated at 20 days for clarity.	37
679	Figure 6:	Maps showing the spatial patterns of daily rainfall extremes, as quantified by the indices, at the annual scale. The three land masks (CSEA, SMP, and BOR) are shown in Figure 6a.	38
680	Figure 7:	Spatial distribution of daily rainfall extremes for each season.	39
681	Figure 8:	Topography and R20n index as a function of longitude over three sections: a) 15N - 18N, b) 2N - 5N, and c) 5S - 8S. The dark (light) gray shades indicate the variation of average (maximum) elevation for each cross section.	40
682	Figure 9:	Anomalies of three extreme rainfall indices (R20, R20n, and R20Tot), and 850 hPa winds during MJO phases 2 - 4. The anomalies were calculated by subtracting seasonal values from those of MJO composite.	41
683	Figure 10:	Similar to Figure 9 but for MJO phases 6 - 8.	42
684	Figure 11:	Spatial distribution of the number of wet spells, and indices characterizing extreme wet spells at the annual scale.	43
685	Figure 12:	Seasonal variability of extreme wet spell indices.	44

Figure 1: The geography of the study domain (note: the altitude is shown in color shading).

Figure 2: Maps of (a) percentage rainy days in a year and (b) mean daily rainfall.

Figure 3: Maps showing seasonal mean daily rainfall from TRMM and seasonal mean winds extracted from ERA-Interim reanalysis for the time period of 1998 - 2013

Figure 4: Cumulative percentage of number of rainy days plotted against the corresponding cumulative proportion of total rainfall for two pixels in SEA. Figure also shows the exponential parametric form (equation 3) fitted to the cumulative percentages and the line of equality, $y = x$.

Figure 5: Histograms of wet spell length and their relative contribution to total rainfall for two pixels (a,b), and the corresponding Lorenz curves (c,d). The histograms are truncated at 20 days for clarity.

Figure 6: Maps showing the spatial patterns of daily rainfall extremes, as quantified by the indices, at the annual scale. The three land masks (CSEA, SMP, and BOR) are shown in Figure 6a.

Figure 7: Spatial distribution of daily rainfall extremes for each season.

Figure 8: Topography and R20n index as a function of longitude over three sections: a) 15N - 18N, b) 2N - 5N, and c) 5S - 8S. The dark (light) gray shades indicate the variation of average (maximum) elevation for each cross section.

Figure 9: Anomalies of three extreme rainfall indices (R20, R20n, and R20Tot), and 850 hPa winds during MJO phases 2 - 4. The anomalies were calculated by subtracting seasonal values from those of MJO composite.

Figure 10: Similar to Figure 9 but for MJO phases 6 - 8.

Figure 11: Spatial distribution of the number of wet spells, and indices characterizing extreme wet spells at the annual scale.

Figure 12: Seasonal variability of extreme wet spell indices.