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**Temporal and spatial scales of extremes of daily tropical rainfall : the example of
Thailand (1979-2024)**

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Abstract

We Investigate temporal and spatial properties of extreme daily rainfall (ExtD) from 75 rain gauges across Thailand and three gridded estimates (0.05° CHIRPS v2, 0.25° ERA5 and 0.1° MSWEP v2.8). ExtD is defined locally from all available days as a day reaching the 90th (p90), 95th (p95), 99th (p99) and 99.9th (p99.9) percentiles, corresponding to spatially-averaged daily amounts between 14 (p90) and 121 (p99.9) mm in the observed network. Overall, the most accurate gridded product to reproduce daily rainfall and ExtD occurrence is MSWEP. The spatial scale is estimated through the horizontal distance at which the spatial autocorrelation of ExtD occurrence falls below $1/e \sim 0.37$. p90 has an e-folding distance of 77 km in Thailand Meteorological Department (TMD) gauges and respectively 158, 208 and 274 km for the co-located MSWEP, CHIRPS and ERA5 grid-points. The three gridded products tend to underestimate the percentiles and overestimate the spatial and temporal scales of ExtD. 55% (p90) to 90% (p99.9) TMD ExtD are time-isolated from similar ExtD. Accumulated rainfall amounts on non-overlapped 3-day to 11-day spells tend to enlarge the spatial scales, but this effect is modest for p95, and almost absent for p99 and p99.9 over a 3-day summation. Lastly, the observed yearly frequency of ExtD from p95 increases faster than the mean amount of rainfall at the country scale from 1979 to 2024, suggesting a long-term intensification of rainfall, which is reasonably well reproduced by ERA5, but not by MSWEP suggesting it is not reliable for trend studies over this area.

Keywords: e-folding distance, wet sequence, intensification, MSWEP, CHIRPS, ERA5, monsoon, rainfall extremes

1. Introduction

Rainfall is often considered as a challenging variable to predict due to the myriad of underlying multiscale phenomena, from the basic unit of a single cloud to larger structures, including more or less organized and continuous wet sectors such as cyclones. Even if it is recognized that any rain-bearing phenomenon includes both convective and stratiform clouds (Houze, 1997; Tokay et al., 1999), the tropical rainfall are mostly convective in origin (Houze, 1981), which reinforce the intermittent and anisotropic characteristics of instantaneous rainfall. The basic unit is the cumulonimbus (convective scale, horizontal length ~ 10 km and duration $\sim$ one hour), while the largest instantaneous scale is the planetary intertropical convergence zone, even though it does not correspond to a continuous circumterrestrial belt. An important intermediate scale is the mesoscale (Houze, 1981; Nesbitt et al., 2006; Peters et al., 2009; Rossow et al., 2013), which initially covers a very broad spatial range from meso- γ (2-20 km) to meso- α (200-2000 km) with a typical time scale between a few hours and a day (Orlanski, 1975). For tropical rainfall the domination of convective to meso scales of tropical rainfall is also illustrated by the fact that the majority of continuous wet events recorded at a fixed location, last far less than 24 hours in the tropics (Ricciardulli and Sardeshmukh, 2001; Smith et al., 2005), especially over landmasses and islands (Moron et al., 2025c). The exact definition of the bandwidths associated with each scale is not trivial, especially for the intermediate mesoscale. For example, Maddox (1980) defined meso-scale convective complexes as large continuous cloudy patterns ($> 80\,000$ km² so an horizontal length of ~ 300 km if we assume a near-rounded shape) and lasting at least 6-hours from infrared images on central US. Tropical studies focusing on specific sectors usually reduced the meso-scale to the initial meso- β scale of Orlanski (horizontal length of 20-200 km, so an approximate rounded surface of circa 400-40000 km²), as for example Mathon et al. (2002) across Sahel. Houze (1981) defined clusters rather than meso-scale up to 50000 km² and distinguished squall (minority) and non-squall (majority) clusters. He also defined “monsoonal rainfall” with a similar structure as clusters.

Any temporal aggregation will tend to enlarge the wet patterns associated with instantaneous convective to meso-scale, as soon as the corresponding rain-bearing phenomena move or are synchronized during the time period of aggregation. The first example includes squall-lines, with a curved linear leading convective edge followed by a larger thick stratiform deck (Mathon et al., 2002). Such a pattern tends to propagate fast (≥ 10 -15 m/s) over a few hours, so it tends to have a rounded or elliptic shape at the daily time scale (Houze, 1981). The second example would be the occurrence of several isolated small thunderstorms, each lasting only a few hours and covering tenths of kilometer and randomly occurring over a region,

thus when averaged over a day creating a larger wet pattern than each individual fingerprint. The sources of synchronization are multiple. They include the diurnal cycle systematically triggering the convection over landmasses during the afternoons of the wet season, various land and mountain breezes, still locked to the diurnal cycle, the annual cycle and more generally any quasi-periodic waves/modes of variation at synoptic to intraseasonal such as coupled-convective equatorial waves (CCEWs), and ultimately interannual scales including for example El Nino Southern Oscillation or Indian Oceanic Dipole. In this context the current anthropogenic greenhouse warming (AGW) could be also considered as an efficient source of spatial and temporal synchronization of any instantaneous event. In particular, AGW will increase the moisture content of the atmosphere (+7% by degree) which may intensify the rainfall (O’Gorman, 2012, 2015, Bao et al., 2024 amongst many others).

Extreme rainfall corresponds to the upper (or right) tail of the distribution, depending on a complex combination of the space-time continuum of atmospheric dynamics. The definition of extremes could be *ex-ante* through statistical analyses or *ex-post* through their impact on society and/or environment. The second type of definition may use a myriad of indicators including human loss or costs. The *ex-ante* definition usually relies on a larger sample than the *ex-post* one, so considers a lower absolute threshold, so that a sufficiently large sample could be extracted, enabling a robust statistical analysis. The threshold could be absolute as 2 inches (50.8 mm) or 4 inches (101.6 mm) of daily rainfall in the US (Easterling et al., 2000). Groisman et al. (2012) defined three classes for daily rainfall across the US middle West; between 0.5 and 1 inch (12.7-25.4 mm), 1-3 inches (25.4-76.2 mm) and > 3 inches, respectively referred to as “moderately heavy”, “heavy” and “very heavy” daily rainfall. Such thresholds based on inches could be also used in other English-speaking countries as Australia (Hennessy et al., 1999). Srivastava et al. (2016) analyzed the frequency of extreme daily rainfall above 100 mm and 200 mm across India, while Goswami et al. (2006) defined “heavy” daily rain from 100 to 150 mm and “very heavy” daily rain above the latter threshold. Note that the World Climate Research Program Expert Team on Climate Change Detection and Indices ETCCDI defines “heavy” and “very heavy” rainfall with far lower absolute thresholds (respectively 10 and 20 mm/day). Such absolute thresholds have the advantage of simplicity, do not need to get a long available time series and do usually lead to some impacts on societies and/or environment at least from the “heavy” category, except perhaps for the ETCCDI definition.

Another *ex-ante* option is related to relative percentiles (peak-over-threshold, POT) or time of return. Such a relative definition has the main disadvantage of needing a long complete record, even if some empirical approximations are possible using fitted distributions of the exponential

family (Weibull, Pareto, Generalized Extreme Value -GEV-, etc., Papalexiou et al., 2013). Moreover, the relative percentiles have the advantage to filter out, by definition, the action of several fixed forcings which impact the mean rainfall and thus the absolute level of percentiles. For example, consider two rain gauges on each side of a mountain, broadly perpendicular to the low-level moisture flux. The windward station will be wetter than the leeward one and the ratio between both slopes could be huge as for any tropical islands, as Oahu in Hawaii (Benoit et al. 2020), or New Caledonia (Moron et al., 2016) where the eastern facing slopes and the summits receive more than 2-4 meters per year, while the western lowlands and coasts receive sometimes less than 500-800 mm despite the modesty of the mountains (max = 1220 m asl for Oahu and 1678 m asl for New Caledonia). In that case, considering an absolute amount, as 50 mm per day will limit the co-occurrence at both rain gauges just because this amount is less frequent on the western slopes rather than on the eastern ones. Thus considering a relative percentile will, by definition, increase the potential co-occurrence and thus the spatial scale of the extremes.

An *ex-post* definition of extreme relies on their impacts depending firstly on the amount of rainfall and duration of the extreme event, but also on myriad socio-environmental factors not directly related to rainfall itself, such as slopes, impermeability of soils, intensity of deforestation, degree of urbanization, resilience of infrastructures, efficiency of alert system if any, etc. (Al-Rawas et al., 2024). Extreme rainfall has probably a non-linear impact on society/environment since the socio-environmental resilience is often possible up to a threshold. Clearly, the extreme rainfall events will have a major impact on society, through flash flooding, loss of crops, and other effects. Zhou et al. (2023) indicated that the impact of extreme rainfall crosses time and space scales, from the hourly maximum of 201.6 mm recorded at Zhengzhou (China) on July 20, 2021, to multi-day flooding in Germany -and parts of central Europa in general- in mid-July 2021 (Thieken et al., 2023; Schuttrumpf et al., 2025) and lastly to the exceptional monsoonal season (3-4 months) recorded over Pakistan and NW India in 2022 (Waseem and Rana, 2023, Knippenberg et al., 2024). Speekers et al. (2017) also discussed the impacts of an infra-daily event in Munster (Germany) on July 28, 2014, with 292 mm of rain in 7 consecutive hours (including 220 mm in less than 2 hours). Husile (2025) analyzed the impact of seasonal rainfall extremes on social cohesion in Indonesia. It is also well documented that some of the major economic disasters in monsoon countries are associated with rainfall accumulations over a rather large area over 5 to 8 days. Examples include Cowan et al. (2019) for an Australian monsoon event, Kulkarni et al. (2010) for an Indian event, and Tebakari et al (2018) for documentation of the precipitation causing the December 2016 through January 2017 flooding in Southern Thailand. All these case studies consider a huge amount of rainfall, corresponding to a percentile > 99% or 99.9% of wet days

only, a return time of once in 50 or 100 years or even the maximum of all time for a given temporal sampling. In fact such a definition, restrictive, of impactful extremes is possible, but this is not the sole option. Thailand has experienced several high-impact rainfall events in recent decades, including southern peninsula floods, urban flash floods in Bangkok, and extreme rainfall episodes affecting Hat Yai and surrounding regions. In many cases, operational forecast systems correctly identify favorable monsoon conditions but underestimate embedded convective intensity and persistence.

In this study, we examine the spatial and temporal scales of daily extreme rainfall across Thailand. This country is included in the SE Asia domain with a classical monsoonal climate (Sternstein, 1962; Zhang, et.al , 2002, Moron et al, 2025a,b). The wet season usually lasts from May to October, but the eastern coast of the southern Peninsula is leeward of the W-SW low level boreal monsoon flow and records its wet peak later, in November-December (Moron et al, 2025a). The country is overall wet (usually at least 1 m/year), but exhibits an interesting spread of amounts between the rain-shadowed areas of the central and northern plains, including Bangkok Metropolitan area and the higher rainfall windward coasts on the western side of the southern Peninsula and the extreme Southeastern region close to Cambodia.

We consider a POT approach using four different levels of percentiles (90th, 95th, 99th and 99.9th) computed from all available days to ensure the robustness of the result. We evaluate the temporal scales of extreme daily rainfall through their length of consecutive days and through composite of daily rainfall before and after their occurrence. We evaluate spatial scales of the extremes through two metrics: the conditional probability of local extremes in both TMD (Thailand Meteorological Department) rain gauges and in MSWEP grids, and the area of extreme patterns defined through contiguous local extremes (in MSWEP grids only). The impact of time aggregation into 3- and 5-day rainfall is systematically evaluated. A last subsection investigates the interannual and long-term variations or trends of 24-hour rainfall extremes. The final section summarises the results. That section also discusses and evaluates the relative strengths and weaknesses of the use of gridded rainfall data against gauge or station data to study space and time scales of rainfall extremes.

2. Data and methods

2.1. Daily rainfall

Daily rainfall is extracted from two primary sources: (1) 75 rain gauges from TMD available on 1951-2024. Daily rainfall observations from TMD follow WMO standards and

represent accumulated rainfall during the 24-hour period ending at 00 UTC (07 Local Time Thailand) ; (2) MSWEP grid-points (Beck et al., 2017) (UTC, 0.1° resolution, version 2.8) available on 1979-2024. The two data sources are time-synchronized. All analyses use the 1979-2024 period on which 1.2% of days are missing in the mean per TMD rain gauge (5 stations have more than 5% of missing entries). In addition we replicate the statistical analyses with two alternative gridded datasets of daily rainfall: (i) the CHIRPS dataset version 2 (Funk et al., 2015) at an horizontal resolution of 0.05° and available since 1981 only; (ii) the ERA5 dataset (Hersbach et al., 2020) at an horizontal resolution of 0.25°. We compute the local 90th, 95th, 99th and 99.9th percentiles from all available days, respectively referred to as p90, p95, p99 and p99.9 in the following analyses. The corresponding days reaching these percentiles are referred to as extreme days (ExtD) in the following. Binary matrices are constructed where each cell (rain gauge or grid-point) is equal to 1 when the daily rainfall exceeds or equals the pN threshold and is equal to zero when it falls below the pN threshold. In the mean, there are 1666 p90, 833 p95, 166 p99 and 17 p99.9 observed ExtD for each rain gauge. MSWEP, CHIRPS and ERA5 grid-points contiguous to each rain gauge are referred, by analogy, to as MSWEP, CHIRPS and ERA5 “rain gauges”. Percentiles are defined independently on each database, reducing the mean bias (see section 3.2).

2.2. Empirical estimates of spatial scales of extreme days

The spatial scales of ExtD are evaluated through the conditional probabilities of ExtD amongst couples of stations or grid-points vs their horizontal distances. The conditional probability of a given event (as reaching a specific threshold) equals 1 if all events at the target are also observed at a distant station/grid-point and 0 if none of the events at the target are observed further. This score is not strictly commutative, contrary to a correlation, but it is almost commutative when the marginal probability are identical as here since we consider percentiles thus giving equal samples for each station/grid-point and the climatic regime is similar across the networks. As for spatial autocorrelation, the conditional probability decays almost exponentially. In this case, the e-folding distance (Ricciardulli and Sardeshmukh, 2003), that is the horizontal distance at which the conditional probability reaches $1/\exp(1) \sim 0.3679$, is usually considered as a “length” (L) scale. Length is a reasonable estimate of the spatial scale (equivalent to $(L/2)^2 \times \pi$), if we assume that the area of exceedance of ExtD is nearly circular at daily time scale. It is probably true since, even if some elongated wet patterns are observed, as a squall line, they usually move fast (Houze, 1981; Mathon et al., 2002) and their fingerprint at daily time scale is probably more symmetrical than at hourly or subhourly time scale. It is possible that elongated wet patterns exist at daily time scale, for example when

a stationary moist flow is orographically uplifted by a relief. In this case, the length is a biased estimator of the spatial scales. We assume that this possibility is minor.

3. Results

3.1. Temporal and spatial distribution of daily rainfall

Figure 1 shows three examples of cumulative distribution functions (CDF) of wet days (defined as a daily amount ≥ 1 mm) in time (panels a-c, i.e. a rain gauge across the available days) and in space (panels d-f, i.e. a network of rain gauge in a single day). Fig. 1a-c show the CDFs for a selection of three rain gauges, namely Bangkok-Metro, KhlongYai and Hua Hin (all located on Fig. 2b), the latter two gauges are respectively the wettest (= 4873 mm/year) and the driest (= 926 mm/year) stations in the mean from the TMD network. The observed CDFs are fitted using exponential (= a single parameter which is the empirical mean), Weibull (= two parameters) and GEV (= three parameters) CDFs. Overall, the best fit, i.e. the one minimizing the log-likelihood according to Akaike Information (AIC) and Bayesian information (BIC) criteria, is obtained using GEV parameters. This is observed for 56-57 stations out of 75, while the remaining stations are best fitted using the Weibull CDF. It is also clear that the percentiles 90%, 95%, 99% and 99.9% are better fitted using the Weibull CDF, while GEV systematically overestimates the percentiles, especially the higher ones (Fig. 2a-c). When the mean bias of the 4 percentiles are averaged across the 75 stations, Weibull CDF provides the lowest absolute value (mean bias = +1%, -5%, -12% and -20% respectively for p90, p95, p99, and p99.9) while GEV gives the worst one (mean bias = +17%, +63%, +334%, +2329% respectively for p90, p95, p99, and p99.9).

Figure 1d-f shows the same information for three days selected as those recording at least 72 wet stations receiving at least 1 mm. The best overall fit as well as the estimation of the 90% and 95% percentiles is now either the exponential or the Weibull CDFs. Considering the 5288 days with at least 30 wet stations out of 75 shows that exponential CDFs provide the best fit for 57% of these days according to AIC and 75% according to BIC. Remember that BIC penalizes more complexity (= number of parameters) of the fitted model than AIC, thus relatively favoring the most parsimonious model, that is the exponential fit. The mean bias across the 5288 days is similar between exponential (+4% for p90 and +3% for p95) and Weibull (+5% for both p90 and p95) fits while GEV shows a larger positive bias (+34% for p90 and +141% for p95).

Using a threshold of 0.1 mm instead of 1 mm to define a wet day leads to nearly identical results (not shown). So overall, Fig. 1 illustrates the near-exponential distribution of daily rainfall, both in time and in space, and shows that the best overall fit, provided by GEV, does not guarantee the best estimation of the percentiles studied here (Papalexiou et al., 2013). In the following analyses, we defined the percentiles from all wet and dry days to maximize the sample sizes and get a similar number of cases for any rain gauge / grid-point independently of their frequency of wet days.

3.2. Comparison of daily rainfall and extremes in TMD rain gauges and gridded products

Fig. 2 shows the mean rainfall computed from all available days in the TMD network and MSWEP grid. Most of central Thailand and the northern lowlands appear relatively dry (vs the country mean) due to rain-shadow effects, while rainfall peaks on the western side of the Peninsula and on the extreme SE near Cambodia, which are both windward to the boreal low level monsoon flux. Rainfall tends also to increase on the Thai margins close to the main orographic locations. MSWEP slightly underestimates daily rainfall, but the pattern correlation between mean rainfall evaluated at the 75 TMD rain gauges is 0.95. MSWEP is also accurate to reproduce the temporal variations of daily rainfall at the TMD rain gauges since the average Pearson correlation on the square-rooted daily rainfall is 0.71. The differences among the rain gauges are low (sd of the correlations = 0.05) and there are no obvious factors (such as topography or location) able to explain the spatial spread of temporal correlations (Fig. 2b). The high correlations between rain gauges and co-located grid-points is partly explained by the annual cycle. Mean correlation using square-rooted daily rainfall for TMD wet days > 0 mm (respectively > 1 mm) equals 0.59 (respectively 0.56), so is still largely significant. Note that the correlations between square-rooted daily rainfall and the co-located grid-points in CHIRPS and ERA5 drop respectively to 0.54 and 0.59 (Table 1).

We explore further the accuracy of the gridded products vs TMD network considering now the extremes of daily rainfall (Fig. 3). The comparisons use the same temporal mask considering only available observed days but percentiles are independently computed on both sources. The spatial variations of 90th, 95th and 99th percentiles match almost perfectly what is observed for the mean rainfall (Fig. 3a) with pattern correlations for the TMD network equal respectively to 0.99, 0.99 and 0.96. There are subtle differences for the highest percentiles with a maximum along the leeward side (vs the boreal summer monsoon) of the Peninsula (Fig. 3c,d). It is also obvious that any gridded product underestimates the extremes (except CHIRPS for p90, Table 2) and the bias tends to increase with its absolute values at least up to 99th percentiles. This inflated underestimation for the higher percentiles is also observed

for CHIRPS and ERA5 (Table 1). This underestimation is at least partly explained by the horizontal resolution since any spatial average, even on a small scale as here, will by definition smooth out the highest value. This is intrinsic to daily (or infradaily) rainfall having an exponential (or steeper) distribution (Fig. 1). Again the spatial pattern of the TMD network is well matched by the gridded product, with pattern correlation slightly decreasing from ~0.95 (90th percentile) to 0.81-0.83 (99.9th percentile). Again, this could be explained in theory by the fact that a higher percentile is more concentrated in space (see below), so more challenging to reproduce with any gridded product.

The Heidke skill score (HSS) between TMD and the gridded products is computed for each percentile. Two binary matrices are firstly computed with 0s for daily rainfall < one of the 4 percentiles and 1s for those at least reaching it. Only available days in TMD rain gauges are used. Remember that percentiles are independently computed on both sources, thus neglecting the underestimation of the absolute value of the percentiles by the gridded product. A hit occurs when both products simultaneously exceed their respective local percentile threshold on the same day. HSS is always well above 0, meaning that the detection of ExtD is better than expected by chance, even if HSS decreases with the level of the percentiles (Fig. 3). Again, as for the correlations (Fig. 2b), there is no obvious factor able to systematically explain the spatial variations of HSS (Fig. 3e-h). MSWEP appears to be the most accurate gridded product in the reproduction of daily variations and of the occurrence of ExtD independently on the order of the percentile (Table 1).

	r0	Mean bias	P90 bias	P95 bias	P99 bias	P99.9 bias	P90 HSS	P95 HSS	P99 HSS	P99.9 HSS
MSWEP	0.71	-0.22	-1.1	-6.4	-20	-39.9	0.51	0.46	0.39	0.29
CHIRPS	0.54	0.06	1.4	-3.6	-18.6	-48.4	0.37	0.31	0.21	0.13
ERA5	0.59	-0.07	-1.2	-8.3	-27	-50	0.33	0.27	0.18	0.11

Table 1: Accuracy of the co-located grid-points from MSWEP v2.8, CHIRPS v2 and ERA5 vs the 75 TMD stations. 'r0' is the correlation between the square-rooted daily rainfall from both sources (all available days). 'Mean bias' is the absolute mean bias in mm/day between the climatological means (grid - obs). The bias of percentiles are also shown in mm/day. HSS is the Heidke skill score. All values are the spatial average across the 75 TMD rain gauges.

All the following analyses use ExtD defined independently on the TMD network and the gridded products that are not necessarily on the same days. The occurrence of percentiles computed all year around is obviously modulated by the annual cycle (Fig. 4). The annual cycle of the p90 (Fig. 4a) and p95 (Fig. 4b) follows almost exactly the one of mean rainfall amount, i.e. the probability of exceedance is above the expected one from late April to late October with two separate peaks around a relative minimum centred in June-July, the first peak in May being shorter and below the second one around September. The annual cycles of p99 (Fig. 4c) and p99.9 (Fig. 4d) are noisier than the previous ones, due to smaller samples, and the probability of exceedance tends to be more concentrated during the late wet season, especially for p99.9 (Fig. 4d). The climatological clustering of the occurrence of extreme daily rainfall due to the annual cycle has an impact on some of the forthcoming analyses (as the conditional probability in section 3.4), but is it enough to lead to sequences of extreme days, i.e. successive days all reaching a given percentile ? Such occurrences may increase the detrimental impact of daily extreme but we will see in Figs 5-6 it does rarely happen in the mean.

3.3. Time scales of ExtD occurrence

Fig. 5 shows the temporal clustering of percentile days at local scale. It is obvious that, despite the relative aggregation due to the annual cycle (Fig. 4), most of the ExtD are intermittent, i.e. isolated days, and the fraction of isolated occurrence on all percentile days

increases from 90th ($\sim 55\%$ of ExtD) to 99.9th ($\sim 90\%$ of ExtD). Almost all ExtD occur in sequences lasting at maximum 5 days (p90 and p95), 3 days (p99) and 2 days (p99.9). It is also clear that MSWEP slightly overestimates the temporal clustering with fewer isolated days and more spells lasting at least two consecutive days than for TMD rain gauges (Fig. 5). When the length of extreme spells at the individual stations are analyzed (not shown), there is a moderate negative correlation between the frequency of isolated extremes and the absolute value of the percentiles (i.e. respectively = -0.44 (p90), -0.55 (p95), -0.51 (p99) but only -0.19 (p99.9)). This suggests that a higher percentile corresponds to slightly longer spells in mean or a lower relative frequency of isolated extremes.

A complementary view of the wet sequences associated with ExtD is given by Fig. 6. We computed the length of wet spells with consecutive days all reaching at least 1, 5 or 10 mm associated with ExtD. We show the wet sequences including one extreme but also the whole set of wet sequences (= gray curves on Fig. 6). The overall observed distribution corresponds roughly to the usual behavior over humid tropical landmasses (Ratan and Venugopal, 2013), i.e. a predominance of wet spells lasting a few consecutive days. The differences amongst the four percentiles is less than one day with p99.9 occurring during slightly longer sequences than p90 (Fig. 6). The wet sequences including an ExtD are also very similar to any usual wet sequence (Fig. 6). 90% of all ExtD recorded at the rain gauges occurs in wet sequences lasting at maximum 10-11 days (1 mm, Fig. 6a), 6-7 days (5 mm, Fig. 6c) and 4-5 days (10 mm, Fig. 6e). Again, MSWEP tends to produce too long wet sequences. This bias is clear using a 1-mm threshold to define the wet sequences (Fig. 6b) since 90% of all ExtD are now reached for sequences lasting 25 days. The over-estimation of the lengths of wet spells in MSWEP relative to the TMD network is clearly reduced using 5-mm (Fig. 6d) and 10-mm (Fig. 6f) thresholds to define the wet sequences. Lastly, we compute the probability of ExtD given the length of wet sequences. There is a general positive relationship between the local length of wet spells and the probability of ExtD. For example, the probability of a p99 ExtD equals respectively 4%, 5.3%, 6.3%, 6.8%, 7.9% and 7.9% for all wet days ≥ 5 mm included in a wet spell lasting 1, 2, 3, 4, 5, and at least 6 consecutive days. These p99 ExtD probabilities vary between 6.3 (a single day) to 11.3% (at least 6 consecutive days) for all wet days ≥ 10 mm. So a longer wet sequence slightly increases the probability of ExtD. Note that the statistical analyses of Figs 5-6 have been done also using CHIRPS and ERA5 ExtD (not shown) and leads to very similar results to MSWEP; both gridded products tend to slightly overestimate the temporal clustering of ExtD and also the length of wet spells, this bias tending to be stronger when wet days ≥ 1 mm are used.

3.4. Spatial scale of extreme daily rainfall

Fig. 7 shows the spatial conditional probabilities to reach a given percentile on the same day when four rain gauges (located on Fig. 2b) record an ExtD. In all cases, the conditional probability is over 0.5-0.6 for a tiny circular area a few tens of kilometers around the target station, then decreases quickly. The inner small corona $> 0.5-0.6$ does not change a lot between p90 and p99 and decreases for p99.9. The area with a conditional probability $> 0.5-0.6$ is especially small for Bangkok-Metro compared to the southern stations on each side of the Peninsula. In the latter cases, the quasi-circular shape seen for the former stations tends to slightly evolve toward a more elongated one more or less stretched along the coast. This deformation is especially clear for Hatyai-Airport on the eastern side of the Peninsula (Fig. 7).

Fig. 8 generalizes the display to all conditional probabilities among three samples: the 75 TMD rain gauges, the 75 MSWEP grid-points corresponding to the TMD network and lastly these grid-points with the 19360 ones included in the spatial window used on Fig. 8. The conditional probabilities are not sensitive to the horizontal sampling in MSWEP since the mean values over running ranges of 50-km distances computed on 75×75 grid-points are very close to those using 75×19360 ones (Fig. 8). MSWEP overestimates the conditional probabilities especially for short distances vs TMD network. This overestimation decreases quickly above a horizontal distance of 100 km and is usually then lower than 25% vs the conditional probability estimated with the TMD network. Again, this overestimation is partly explained by the fact that MSWEP grid-point should be considered as a spatial average which by definition cancels the spatial variance smaller than the resolution. It is hard to systematically check this point with TMD rain gauges: if we consider the closest stations of the TMD network (Bangkok Metro and Bang Na : horizontal distance = 8.6 km with almost equivalent percentiles around 14-15 mm for p90, 28-29 mm for p95, 61-62 mm for p99, 120-128 mm for p99.9), the mean conditional probability among both stations equals 0.64, 0.54, 0.39 and 0.31 for respectively 90th, 95th, 99th and 99.9th percentiles. In other words, only around a half ($\frac{1}{2}$) of the daily extremes reaching the 95th (99th or 99.9th) percentile at Bangkok Metro or Bang Na are also observed over the other station, less than 10 km apart. This very steep decrease of conditional probability inside a 0.1° square is obviously cancelled in MSWEP data.

A question raised is the apparent saturation of the conditional probability toward non-zero values at the longest distances (Fig. 7). We may expect, in theory, that the minimum conditional probability would be close to zero, at least for the highest percentiles (Fig. 1c). For example, if we distribute randomly 1% of ones in a 2D matrix (rows = time ; columns = space) filled with 0s, respecting the same marginal probability across the columns, it is possible that all local occurrences of 1s are timely disconnected, that is the local exceedance of p99 may

occur on different days for 75 records. In this case, the conditional probability will always equal 0. At least three different reasons increase the conditional probabilities vs this random occurrence : (i) first, the “instantaneous” (at daily time scale) spatial aggregation of ExtD due to meteorological phenomena (as meso-scale convective complexes or tropical depressions) including together few (or a lot of) rain gauges as soon as their distances are included the spatial scales of the rain-bearing atmospheric system ; (ii) the annual cycle, which tends to concentrate the occurrence of extreme in a specific season (Fig. 4) ; (iii) any intraseasonal and interannual drivers (as waves or air-sea modes of variation) able to synchronize the anomalous occurrence of ExtD over contiguous areas. For example (though to our knowledge not yet demonstrated for Thailand) it is known that “active” and “break” cycles of monsoon rainfall occur over very large scale, thus possibly synchronizing the co-occurrence of ExtD, up to thousands of kilometres (Murakami, 1976; Sikka and Gadgil, 1980; McBride, 1983; Webster et al, 1998; Krishnamurthy and Shukla, 2000).

The effect of the annual cycle is estimated through the random reshuffling of binary yearly sequences of ExtD (i.e. each yearly sequence of 0s (daily rain < percentile) and 1s (daily rain >= percentile) of each rain gauge is independently reshuffled to the other ones), so that the annual cycle is kept but the co-occurrences due to the first and the intraseasonal fraction of the third effects quoted above are set to be random. The conditional probabilities vs distance are computed 500 times from randomized yearly sequences for each percentile for the TMD network and the 95th percentile of the mean vs the same range of distance as in TMD and MSWEP is shown as a dashed line on the right panels of Fig. 8. The expected conditional probability due to the annual cycle is not exactly flat just because the annual cycles of two nearby stations are slightly more similar than two farther ones. This is also explained by the different annual cycle observed on the leeward peninsula whose stations are, in mean, farther from the other ones, concentrated in mainland Thailand. The contribution of the annual cycle to the spatial scales of ExtD is very low.

451

	TMD station	MSWEP station	MSWEP field	ERA5 station	ERA5 field	CHIRPS station	CHIRPS field
p90	77	158	182	274	274	208	214
p95	28	90	114	155	156	114	119
p99	undef.	65	81	91	97	66	64
p99.9	undef.	54	65	67	63	42	53

452

453 **Table 2:** Spatial scales (in km) of ExtD. The spatial scales are estimated from all available
454 couples as the e-folding distance or length (i.e. the horizontal distance where the conditional
455 probability equals 0.3679 with a tolerance of 0.01). This is done on 7 sets ; the 75 TMD rain
456 gauges (second column), the 75 co-located MSWEP, ERA5 and CHIRPS “stations” with the
457 TMD rain gauges (third, fifth and seventh columns) and between these 75 grid-points and all
458 MSWEP, ERA5, CHIRPS field in the window (6.45°N-19.95°N and 97.95°E-104.85°E, i.e. 2°
459 out of the extreme longitude and latitude of the 75 TMD rain gauges) (fourth, sixth and eighth
460 column). The spatial scale is undefined (“undef.”) when the smallest distances have a
461 conditional probability < 0.3579.

462

463 Table 2 gives an estimate of the spatial scales using all available couples of TMD stations or
464 co-located MSWEP, ERA5 and CHIRPS grid-points. A “field” estimate is also computed using
465 the gridded datasets through the conditional probabilities between the 75 “stations” and all
466 grid-points in the window 6.45°N-19.95°N and 97.95°E-104.85°E. The spatial scale is
467 estimated as the e-folding distance or length, that is the one where the conditional probability
468 reaches a value of 0.3679 (+/- 0.01). The conditional probabilities are firstly averaged over
469 running 30-km ranges as in Fig. 8. Then the e-folding distance is estimated through a linear
470 interpolation of the averaged values. The large number of available couples guarantees that
471 the averaged conditional probabilities are already smooth as shown on Fig. 8, thus allowing a
472 robust estimate of the spatial scale. MSWEP, as ERA5 and CHIRPS, overestimates the spatial
473 scale vs TMD but as already suggested above, it is partly due to the horizontal scale of the
474 gridded dataset which already smooths out the initial steep decrease of the conditional
475 probability in the first 10 kilometers. Computing conditional probability between the 75 co-
476 located grid-points and the full MSWEP field increases slightly the spatial scales while this
477 increase is highly reduced for ERA5 and CHIRPS (Table 2). It should be related to a simple
478 geometrical effect which could be large for the rain-gauges located on the edges of the
479 network. We may assume that considering an isotropic space around each grid-point when

the whole field is used allows a better estimate of the spatial scale rather than an heterogeneous network especially along the elongated southern Peninsula.

Fig. 9 shows the spatial scales of ExtD now estimated at each TMD station and each MSWEP grid-point. The estimate of the spatial scale should be relaxed from the previous one, due to the reduction of the sample size (i.e. only 74 conditional probabilities across ~ a maximum distance of 1500 km instead of 74 x 74 ones for the TMD network). So, we estimate the spatial scale as the mean horizontal distance when the conditional probability simply reaches a value around $1/\exp(1)$. We raised the tolerance to 0.05 so that enough couples of TMD stations are included in this estimation. The spatial scale is undefined when the highest conditional probability is below 0.3179 irrespective of the horizontal distance and is considered as unreliable when less than 3 couples of TMD stations are available for the conditional probabilities between 0.3179 and 0.4179. With these criteria, the spatial scales could not be defined for 45 TMD stations for p95 and all stations for p99 and p99.9. The modulation of spatial scale is rather invariant with lower value over the landmass than over the surrounding seas. The spatial scales are especially small over the southern Peninsula and over south-central Thailand around the Bangkok metropolitan area (Figs 7-9). Even if the TMD spatial scales are systematically lower than their MSWEP colocated grid-points, the pattern correlation between TMD and MSWEP spatial scales equals 0.69 for 74 couples (p90) and 0.78 for 30 couples (p95), so reasonably similar. The pattern correlations are slightly lower for ERA5 (0.51 for p90 and 0.65 for p95) and CHIRPS (0.32 for p90 and 0.72 for p95). Note also that the spatial scales for p99.9 are noisier than for lower percentiles.

3.5. Role of temporal summation

We look now at the impact of defining the extremes based on summing rainfall over periods greater than 24 hours. Some analyses are re-done with percentiles computed from non-overlapped 3-, 5-, 7-, 9- and 11-day.. We saw earlier that a 5-day spell includes almost all possible spells when 24-hour percentiles ≥ 90 th are considered (Fig. 4). Table 3 summarizes several metrics using MSWEP.

First, the maps of the 4 percentiles are basically identical among the six time- samplings, since pattern correlations with daily value are always ≥ 0.96 for a given percentile. Then, the absolute value of percentile increases by 2-3 times between 1- and 3-days, then in a slower ratio (+20% to +30% between 9-day and 11-day sums). The accuracy (through correlation and HSS) of MSWEP vs TMD improves, but very slowly from 5-day (Table 3).

517

	daily	3-day	5-day	7-day	9-day	11-day
p90 (in mm) TMD stations	14	42	66	88	110	131
p95 (in mm) TMD stations	26	64	94	121	149	174
p99 (in mm) TMD stations	60	120	166	207	241	277
p99.9 (in mm) TMD stations	121	220	285	338	377	423
MSWEP bias vs TMD for p90	-3%	-13%	-13%	-12%	-11%	-11%
MSWEP bias vs TMD for p95	-23%	-19%	-16%	-15%	-15%	-14%
MSWEP bias vs TMD for p99	-32%	-23%	-21%	-19%	-18%	-17%
MSWEP bias vs TMD for p99.9	-32%	-22%	-18%	-19%	-17%	-18%
r (lag0) between TMD and MSWEP	0.71	0.83	0.86	0.88	0.89	0.90
HSS of MSWEP vs TMD for p90	0.51	0.60	0.63	0.64	0.65	0.65
HSS of MSWEP vs TMD for p95	0.46	0.57	0.59	0.61	0.61	0.62
HSS of MSWEP vs TMD for p99	0.39	0.50	0.52	0.52	0.53	0.52
HSS of MSWEP vs TMD for p99.9	0.29	0.41	0.40	0.36	0.31	0.34

518

519 **Table 3:** rows 2-5: absolute values of the percentiles spatially averaged across the 75 TMD
520 stations for daily rainfall, and running 3- and 5-day up to 11-day sums. row 6-9: relative bias
521 ($= ((\text{MSWEP}-\text{TMD})/\text{TMD}) \times 100$) spatially averaged across the 75 TMD stations. r(lag0) is the
522 spatial average of the correlations between square-rooted daily, 3-day and 5-day up to 11-day
523 amounts in TMD and MSWEP and the last four rows are the spatial averages of the Heidke
524 Skill Score (HSS) for the four percentiles and the six time-samplings.

525

526 Figure 10 shows the spatial scale estimated as before through the e-folding distances from
527 daily to 11-day summations. As before, we consider three samples (TMD network, MSWEP
528 co-located grid-points only and with all other grid-points). Note that the spatial scales could be
529 never estimated for the TMD rain gauges for p99 and p99.9, i.e. the average conditional
530 probability for the shortest range between 1 and 30 km is below 0.3579. The conditional

probability increases with the length of time aggregation, but the increase in spatial scale is larger for p90 (Fig. 10) but tiny or even absent beyond a 3-day sum for p99 and p99.9 ExtD. Such behavior is also observed for ERA5 and CHIRPS (not shown). Thus the impact of time aggregation on spatial scales of extremes is modest. It is not a big surprise since we noted earlier that exceeding the local percentile during multi-day sequences is not frequent, especially for the highest extremes (Fig. 5) and that wet sequences including an ExtD are not especially long (Fig. 6). Moreover, it also suggests that intermittent multi-day ExtD sequences, especially for p99 and p99.9, may be located over close neighbors, so related to quasi-stationary processes. If for example an extreme day located over a group of stations in a radius of 100 km is followed by another group in a close but distinct radius of 100 km, it will double a given conditional probability from 1- to 2-day sum. Clearly, such a space-time extension is not frequent, if it ever happens.

3.6. *Interannual and long-term variability of extremes*

As a last subsection, we document variability of mean annual values of extremes from 1979 to 2024. Annual sum or mean on a calendar year is relevant for most of Thailand since the wet season lasts usually from late April to early November. It is a less relevant choice for the leeward Peninsula since the wet season could last till mid-January. Figure 11 shows the country average of several yearly values. Each local time series from the TMD network is firstly normalized as a fraction of the long-term local mean. We considered the annual amount and marginal probability of occurrence of the 4 percentiles studied so far. The 5 time series are by definition strongly related to each other with positive correlations usually ≥ 0.8 for TMD. The p99.9 time series is slightly less related to the others but its minimal correlation still equals 0.69 with p90 for TMD. It is also clear that the increasing trend is stronger when the level of percentiles increases (Fig. 11). So the mean rainfall increases but occurrence of daily extremes becomes even more frequent, especially for the highest ones, consistent with an overall intensification of daily rainfall. This result is corroborated by the fact that the country average of the annual frequency of wet days ≥ 1 mm does not significantly change between 1979 and 2024 (+2% for the country average, p-value = 0.66), while the country average of the daily mean intensity (= annual amount/frequency) significantly increases (+ 9% for the country average, p-value < 0.001). The lack of a significant trend in the frequency of wet days somewhat contrasts with the results of Rajah et al. (2014) but their significant decreasing trend was established in the 1976-2000 period. The variations observed in the sample of the 75 co-located MSWEP grid-points are consistent with observations for p90 but then after, the accuracy with TMD variations decreases (Fig. 11), especially because MSWEP tends to overestimate the probability of ExtD during the two first decades, especially in 1994. The

MSWEP increasing trend is no more significant for p95 and even turns to be negative for p99 and p99.9. CHIRPS and especially ERA5 are more accurate in the reproduction of the increasing trends (Table 4). But it remains that the discrepancies amongst the gridded products are higher for the higher percentiles.

	percentiles	TMD	MSWEP	CHIRPS	ERA5
Trend (in %) over the whole period (1979-2024 except for CHIRPS on 1981-2024)	p90	8.3	20.8	16.5	8.3
	p95	14.4	11.8	22	18.1
	p99	26.1	-3.7	29.3	40.1
	p99.9	45.1	-33.5	10.5	30.1
P- value of the trend	p90	0.07	<0.01	0.03	0.28
	p95	0.04	0.11	0.02	0.04
	p99	<0.01	0.81	0.05	<0.01
	p99.9	<0.01	0.08	0.65	0.20
Correlation vs TMD	p90	1	0.9	0.85	0.88
	p95	1	0.73	0.81	0.85
	p99	1	0.46	0.70	0.77
	p99.9	1	0.36	0.53	0.67

Table 4 : Summary of the trend analysis of the annual marginal probabilities of ExtD, spatially-averaged over the 75 TMD stations and the col-located grid-points in MSWEP, CHIRPS and ERA5. The bold value shows the significant trend at least at the two-sided 95% level. The last rows show the correlations between the spatial average of annual marginal probabilities of the TMD stations with the gridded products.

4.Discussion

Our study provides a systematic analysis of the spatial and temporal scales of extreme rainfall occurring across Thailand. We believe that at least some of the results could be relevant for other tropical countries, at least those with a similar monsoonal regime and mean amount of rainfall (roughly 1000 to 3000 mm concentrated in 6-8 months). First, as advocated by Palaixiou et al. (2013), the definition of extremes impacts the results of any analysis. We consider here a statistical approach based on relative percentiles defined from all wet and dry days. This approach has the advantage to consider similar samples across the rain gauges or grid-points and also to guarantee enough cases to achieve a robust statistical analysis. Obviously, the results from p99.9 ExtD are the least robust due to the fact that it corresponds to only 16-17 days per rain gauge in 46 years. Of course, a study based on impacts should consider far higher thresholds than here. For example, the spatial average of p90 is “only” 14 mm and has probably no detrimental impacts on Thai society or environment. It is probable that impacts increase non linearly with amounts of rainfall and well-established examples across Thailand are associated with multi-day rather large events as the huge rainfall and associated floods in November 2025 recorded mostly on the eastern side of the southern Peninsula where some stations exceed p95 or even p99 5 or 6 consecutive days. We should quote here that such multi-day occurrence of ExtD is indeed very uncommon (Fig. 5).

Rainfall extremes are well-known to lead to serious damages and also are challenging to predict. These characteristics are partly explained by the fact that daily rainfall follows a near-exponential distribution both in time and in space (Fig. 1). We showed here that, even if 3-parameter GEV usually provides a better fit of the whole temporal distribution of wet days (> 1 mm) at a single rain gauge, a simpler 2-parameter Weibull distribution is better to minimize the mean bias of the 4 percentiles analyzed in this study. In space, the distribution of local rainfall during the days recording at least 30 wet stations (out of a theoretical maximum of 75) tends to be better fitted with an exponential distribution, especially according to the BIC criteria which penalizes more the number of parameters than AIC criteria. The near-exponential distribution in space induces, in theory, a reduction of the rain-gauges exceeding a given value (as a percentile) as this value increases. So, it statistically reduces, by definition, the spatial scale of extreme rainfall, defined here through conditional probability of exceedance.

MSWEP appears to be the best gridded product to reproduce daily rainfall variations (Fig. 2b) and occurrence of ExtD (Fig. 3), slightly ahead of CHIRPS and ERA5 (Table 1), even if, as expected for any gridded product, the absolute levels of extremes are underestimated and this bias tends to be stronger for the highest ones (p99 and p99.9 vs p90 and p95). First, even a high resolution (minimum = 0.05° here ~ 5 km for CHIRPS) cancels by definition any spread internal to a grid-point. The comparison between Bangkok-Metro and Bang Na, which are less

than 10 kilometers apart, shows that conditional probability of the co-occurrence of a daily extreme at both stations has already decreased, especially for the largest percentiles, at this short distance (i.e. the mean conditional probability equals only 0.31 for p99.9). By definition, any gridded product can not resolve this small-scale variability and smooths it. In consequence, any gridded product slightly overestimates the spatial scales relative to the ground truth of the rain gauges. They also tend to overestimate the temporal clustering of ExtD. This space-time overestimation of scales should be always remembered when gridded products are used to evaluate the spatial scales of rainfall variability, especially over tropical land masses where convective rainfall is the norm. The correlations of the square-rooted daily rainfall (Fig. 2b) and Heidke skill scores applied to each percentile exceedance (Fig. 3) are variable across the country, but there is no obvious reason able to systematically explain the spatial variations of these scores.

Another consequence of the smoothing of small-scale variability by any gridded product is to slightly increase the temporal clustering of daily extremes (Fig. 4). Daily extremes mostly occur as isolated days, and this tendency clearly increases with the level of the percentiles (55% of p90 extreme days and 90% of p99 ones are isolated). Again, it could be understood, as a first guess, as a statistical consequence of the near-exponential shape of the rainfall distribution itself (Fig. 1). If we randomly reshuffle 10% of 1s (= a local exceedance) in a 2D matrix of 0s (= no exceedance), we increase the probability of co-occurrence in time and in space vs a random reshuffling of 0.1% of 1s. Of course, considering the right tail of a near-exponential distribution tends to isolate the exceedance of a given percentile, but Fig. 6 shows that even if ExtD are usually included in multi-day wet sequences, these sequences are rather short, even if a modest threshold as 5 mm is used to define the wet days. The differences with the whole sample of wet sequences is reduced to around 1 day for the highest percentile (Fig. 6).

It is possible to estimate the spatial scale of any event from myriad ways. We used the conditional probability of ExtD vs horizontal distances, i.e. the “length” scale of phenomena analogous to correlogram/variogram which are based on different metrics of the co-occurrence of a given event between two distant locations. There are one fundamental limits of this approach ; it assumes an isotropic decrease of the co-occurrence function, i.e. a near rounded shape. Assuming a near-rounded shape at daily time scale makes some sense. If we assume that instantaneous elongated shape, as squall-lines, indeed exists, their spatial shift during a day and the larger associated stratiform deck may, in theory, tend to lead to a near-rounded shape at the daily time scale. It should be noted that, as any wet event lasts usually far less than 24 hours, (Ricciardulli and Sardeshmukh, 2001; Smith et al., 2005; Moron et al., 2025c), the daily time scale already enlarges the spatial scale vs higher time resolution (hourly) or, of

course, vs an instantaneous point of view. It should be also noted that even an elongated instantaneous structure, as a squall line, will be efficiently aggregated toward a round shape at the end of the day because it tends to move fast (typically 10-15 m/s; Houze, 1981). A possible elongated shape at daily time scale may be related to long interaction between a moist flow nearly perpendicular to an orography, at least one able to trigger deep or shallow convection through the release of latent heat through uplifting. In case of moist warm air close to saturation, the needed orography could be very modest. But this should not occur very frequently. Here, we see that the conditional probability for Hat Yai airport, is slightly stretched parallel to the coast (Fig. 7), but this shape is not really observed for conditional probability > 0.4-0.5 which tends then to be rounded as elsewhere.

In fact, the space-time distribution of the daily extreme is not random but at least three factors increase their spatial scales ; (i) the annual cycle; (ii) the size of the rain-bearing processes at daily time scale ; and '(iii) any intraseasonal (as CCEWs) to interannual (as ENSO) drivers able to synchronize in space and in time the occurrence of ExtD. The annual cycle is due to the regular alternance of a dry season and a monsoonal season and tends to relatively concentrate the occurrence of percentiles (computed over all the year) on a specific period of time. It increases the spatial scales almost at country scale, the only exception being the leeward side of the southern Peninsula, which exhibits a latter peak of rainfall when the low level climatological alizean flow replaces the monsoonal westerlies over the still warm Gulf of Thailand in November-December. The random reshuffling of the yearly sequences of the local exceedance of percentiles (Fig. 8) suggests that the effect of the annual cycle on the conditional probabilities of ExtD vs horizontal distances is close to twice the marginal probability (i.e. around 0.2 for p90 or 0.002 for p99.9) and almost independent to the horizontal distance. This statistical independence vs distance is simply due to the fact that most of the 75 rain gauges share the same boreal monsoon season from early May to late September or so.. In a previous analysis based on the same network, Moron et al. (2025a) shows that 13 rain gauges out of 75 record their annual peak in October-December on the eastern side of the southern Peninsula. This dephasing has a minor effect here.

The role of any rain-bearing phenomenon is to include several rain gauges or grid-points, i.e. integrating in space the basic convective scale which is a single cumulonimbus in case of convective rainfall, so increasing the spatial scale at the daily time scale. Any intraseasonal or interannual modes of variation able to synchronize the temporal occurrence of ExtD will also increase the spatial scale, but this effect should relatively grow when multi-day sequences are considered instead of a single day. Overall, we may assume that the contribution of the rain-bearing processes and the intraseasonal modes of variation is major and large at short distances but quickly decreases beyond a few hundreds of kilometers, especially for the

largest percentiles, so broadly corresponds to the meso- β scale (Table 2). The spatial modulation of spatial scales revealed by Figs 7 and 9 deserves more analyses. It is now well established that large urban areas may artificially intensify rainfall due to a combination of factors, including impervious surfaces which increases the diurnal temperatures, increased roughness promoting vertical turbulence, etc. (Li et al., 2021, 2025 ; amongst many others). These effects are usually detected through temporal analyses, i.e. a larger intensification over urban areas due to current AGW, and are particularly pronounced in coastal cities where the moisture supply is abundant (Li et al., 2025). Here, we detect such a possible urban fingerprint mostly through the relatively small spatial scales of ExtD observed over the Bangkok Metropolitan area, which is, by far, the most populated agglomeration of the country (Figs 7,9). More studies are needed to explore this pattern since the small scale geography of the coast of the Bangkok Metropolitan area, with a small bay only open to the south may also play a role in the space-time scales of convection.

The temporal summation on non-overlapped 3- to 11-day wet sequences does increase the spatial scales (Table 3 and Fig. 10). A progressive increase of spatial scales with increasing length of aggregating period as seen here especially for p90 and p95 ExtWP (Fig. 10) is consistent with the action of multiple intraseasonal modes of variation able to synchronize in time separate small clusters of ExtD. The degree of synchronization will depend on the specific time scale of the intraseasonal modes. For example a typical Kelvin wave will smooth out the variations in the bandwidth of 2-4 days (so mostly between 1- and 3-days aggregation analyzed here) while the quasi-biweekly mode of variation will efficiently increase the spatial scale close to the longest aggregation analyzed here, i.e. 11-day). An interannual signal, near-constant during a season, may also have a progressive effect since its relative smoothing impact may increase as the temporal aggregation grows in length, cancelling progressively the short noisy scales. We also showed that the smoothing effect due to temporal aggregation is indeed very modest or even absent on p99 and p99.9. It suggests that a multi-day sequence including some ExtD should be merely related to quasi-stationary phenomenon, unique or combined.

Lastly, it seems that the daily extremes have intensified since 1979. The signal issued by the frequency of percentiles is very clear in the TMD network since the linear trend appears to be stronger as the level of percentile increases (Fig. 11). It is consistent with a right expansion of the upper tail of the distribution. It is fully consistent with the signal related to AGW (Westra et al. 2014; O'Gorman, 2012, 2015, Bao et al., 2024). The comparison between TMD and gridded products clearly raises the issue of the detection of long-term trends using such products. Surprisingly, ERA5 is the most accurate product to match the observed increasing trend while

MSWEP fails to capture it, especially for p99 and p99.9. This accuracy of ERA5 is surprising since observed rainfall is not assimilated in the reanalyses (Hersbach et al., 2020). One output of this study is that a trend analysis of rainfall should at least consider several different gridded products, especially when extremes are analyzed, and ERA5 should be definitively one of these databases.

5. Conclusion

In this paper we analyzed the spatial and temporal scales of daily rainfall extremes through a network of 75 almost complete rain gauges and three gridded products (MSWEP v2.8, CHIRPS v2 and ERA5). Even if a single tropical country (i.e Thailand) is considered, some of the findings may be generalized to other tropical areas, at least most of monsoonal sectors with a 5-8 months wet season. Our principal results could be shortly summarized before a discussion ;

- The daily extremes of rainfall (ExtD) are defined using a POT method, so a statistical approach to get a large sample. Considering also all available days pursues this goal of large and equal-sized samples so that robust results can be obtained. We analyzed four different percentiles (p90, p95, p99 and p99.9). Using relative percentiles also has the advantage to cancel at least partly the impacts of fixed effects, for example due to orography, which may reduce the spatial scales when absolute amounts exhibit large gradients over short distances. But we must also remember that the lower percentile considered here (p90) has probably no socio-environmental impacts.
- Overall, MSWEP is slightly better than CHIRPS and ERA5 to reproduce the local rainfall variations and the occurrence of ExtD (r_0 and HSS in Table 1). From that point of view, ERA5 and CHIRPS show similar accuracy, slightly below MSWEP ones. All products tend to underestimate the values of percentiles (except CHIRPS for p90), especially the larger ones (i.e. p99 and p99.9). It is not a big surprise if we assume an exponential distribution of daily rainfall in space and the spatial smoothing of the extremes due to the gridding even when the resolution equals 0.05° as for CHIRPS.
- The ExtD occur in “usual” wet sequences, in the sense that wet sequences including any daily extreme do not appear especially longer than those without a daily extreme. The wet sequences including p99.9 are less than 1 day longer than those including p90.
- The spatial scales of ExtD are defined using the e-folding distance (or length) of their conditional probabilities. These spatial scales decrease as expected with the values of percentiles and are consistent with the intermediate meso- beta scale (Orlanski, 1975) that is between 20 and 200 km, or an area between ~ 300 and $\sim 3000 \text{ km}^2$ if we assume

a near-rounded shape. MSWEP overestimated the spatial scales, but it can be related at least to the intrinsic smoothing of the scale shorter than the horizontal resolution of any grid which seems to be huge for the higher percentiles. The TMD network used in this paper does not allow an estimate of the spatial scales for p99 and p99.9, as the e-folding distance is smaller than can be resolved by the spacing between stations..

- The summation over running 3- to 11- days slightly enlarges the spatial scales, but this increase is modest or nearly absent for p99 and p99.9 over 3 days. Even with a 11-day summation, the TMD network used in this paper does not allow an estimate of the spatial scales for p99 and p99.9, meaning that the mean conditional probabilities are below $1/\exp(1)$ even for the shortest distances considered here (1-30 km). In gridded products, the spatial scale for p99 (p99.9) is near 100 (40-60 km) for 3- to 11-day sequences.
- The frequency of ExtD has increased over the 47 years 1979-2025, and the increase is steeper for the higher percentiles (p99 and p99.9) suggesting an overall intensification of rainfall while the frequency of wet days is stationary for the country average of the TMD network. The three gridded products are reasonably consistent with the TMD network for p90 and p95 while their accuracy is not so good for p99 and especially p99.9. For these high percentiles, ERA5 is surprisingly the most accurate product to mimic the observed interannual variations as well as the intensity of the increasing trend, while MSWEP is the worst one especially for p99 and p99.9.

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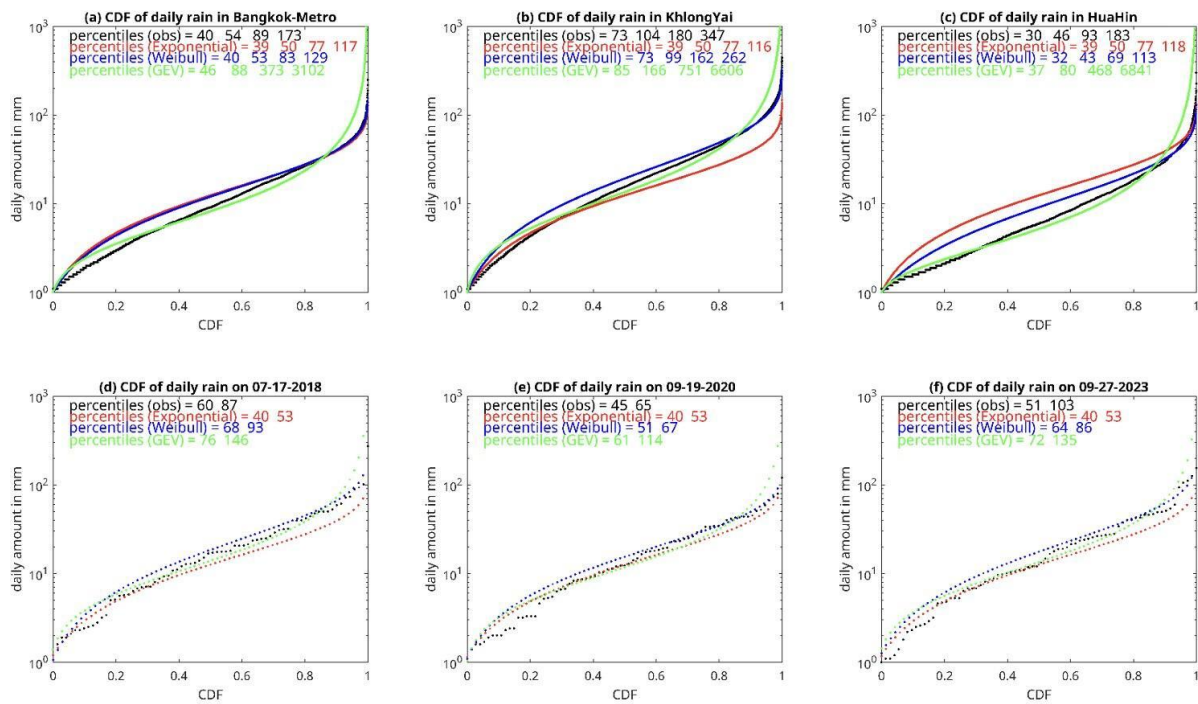


Figure 1: Examples of CDF of observed daily rainfall ≥ 1 mm (black dots) with 3 different fits (exponential CDF in red, Weibull CDF is blue and GEV CDF in green). Panels (a-c) show the CDFs for all wet days ≥ 1 mm for (a) Bangkok-Metro, (b) the wettest rain gauge (i.e. KhlongYai) and (c) the driest one (Hua Hin). Panels (d-f) show the daily rainfall for the three days having at least 72 wet stations. The 90%, 95%, 99% and 99.9% (90% and 95% only for the 3 days since fitted 99% and 99% percentiles are then meaningless) of all wet days or stations are indicated with the same colors as the CDFs.

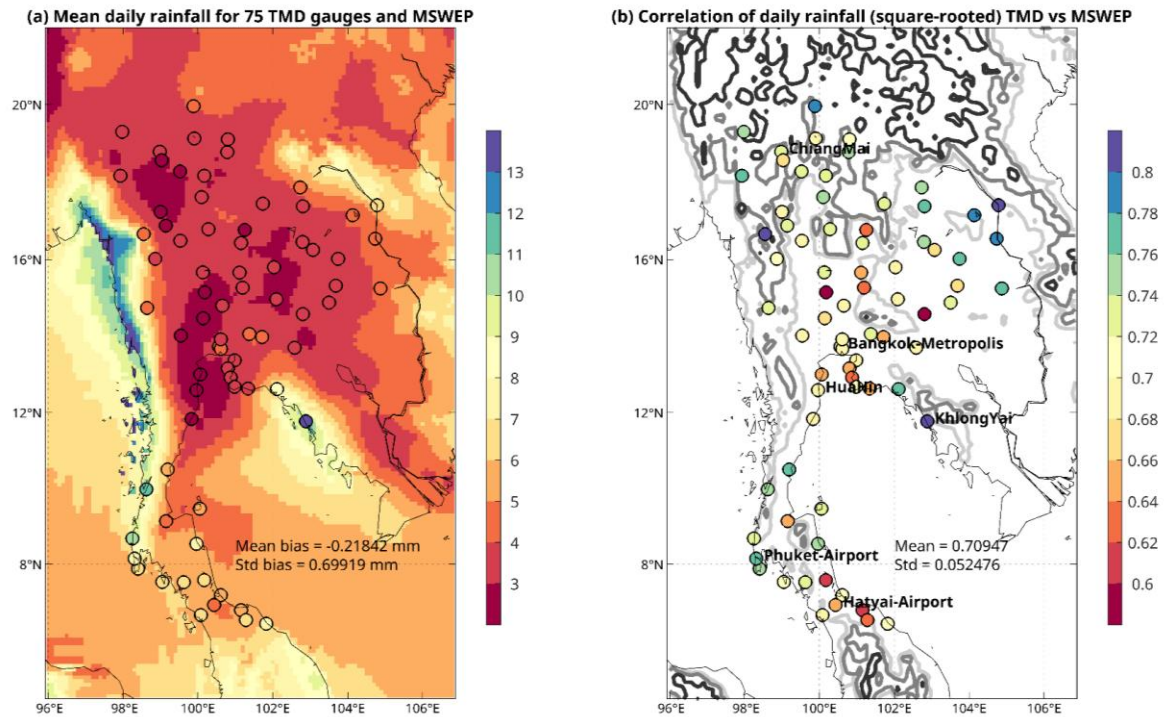


Figure 2: (left) Mean rainfall in mm/day in MSWEP (shadings) and TMD rain gauges (dots). The mean and standard deviation of the bias between the 75 TMD rain gauges and the closest MSWEP grid points (as the difference MSWEP - rain gauge) are indicated. (right) Pearson correlations between the square-rooted daily rainfall at the 75 TMD rain gauges and the closest MSWEP grid-point. The 250, 500 and 1000 m isohypsies have been added as light, medium and dark gray contours. Several stations quoted in text have also been added.

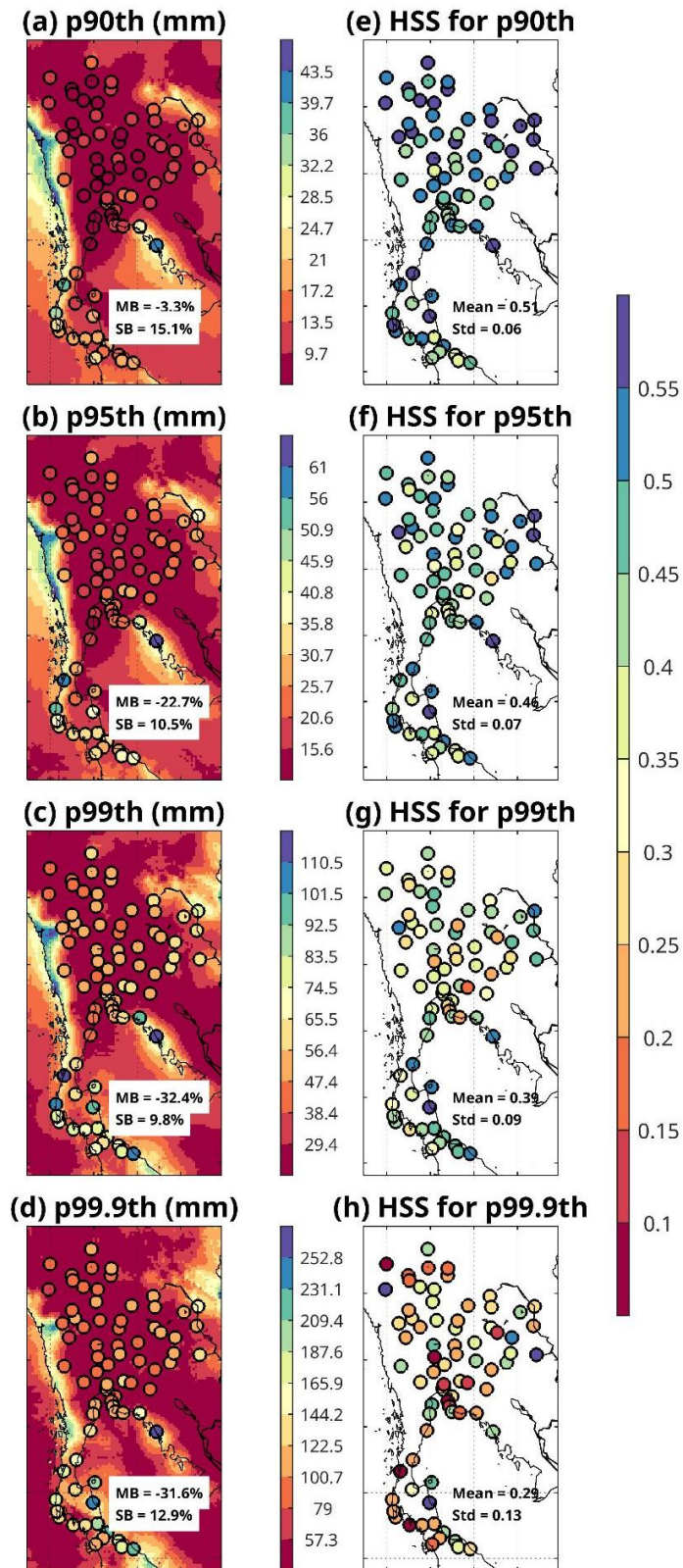
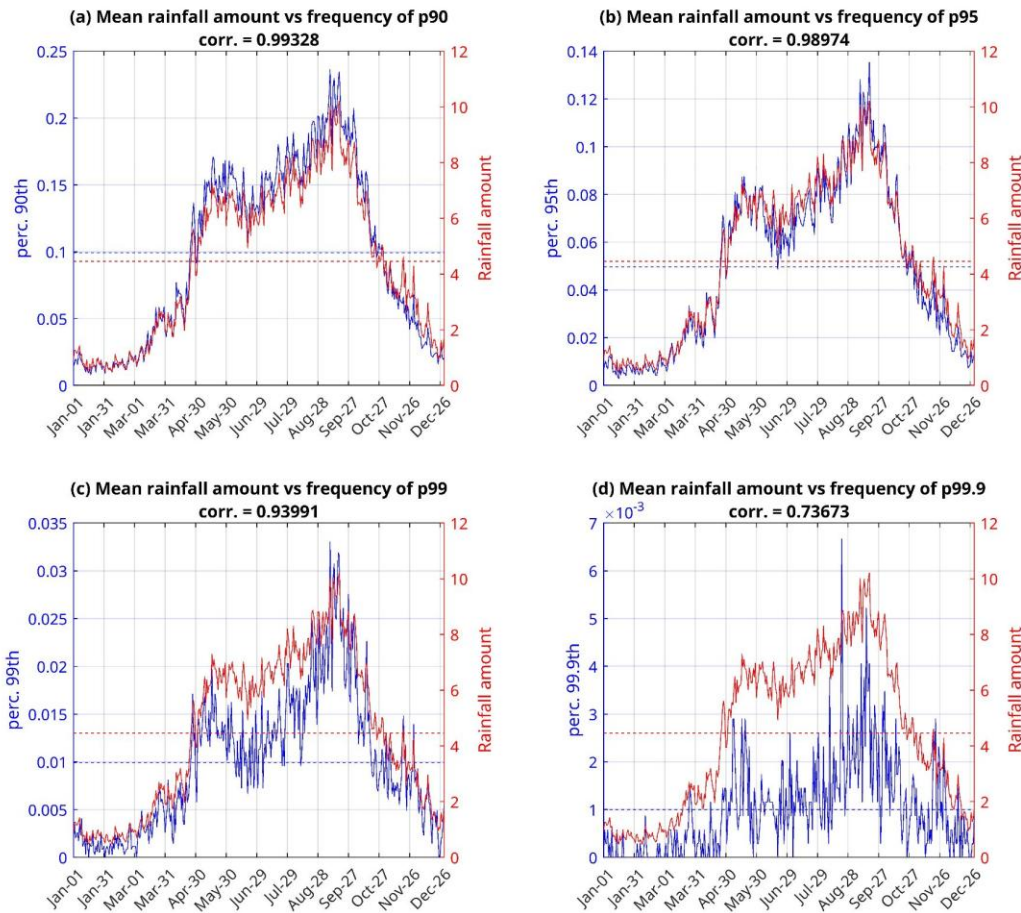


Figure 3 : (a-d): 90th, 95th, 99th, 99.9th percentiles of daily rainfall (in mm) in MSWEP (shadings) and TMD network (dots) defined from all days. The mean (MB) and standard deviation (SB) of the bias between TMD and the co-located MSWEP grid-points are indicated

977 as percentage of the observed values. (e-h): Heidke skill score of the 90th, 95th, 99th, 99.9th
 978 percentiles of daily rainfall at the closest MSWEP grid-point vs TMD rain gauges.



979
 980 **Figure 4:** Mean annual cycle (= unfiltered spatial average of the climatological daily mean
 981 across the 75 stations) of mean rainfall amount (in mm/day, red curve, right ordinate) and
 982 probability of exceedance of (a) p90, (b) p95, © p99, (d) p99.9 percentiles (blue curve, left
 983 ordinate). The annual means of percentile and amount are displayed as a dashed blue and
 984 red horizontal lines.

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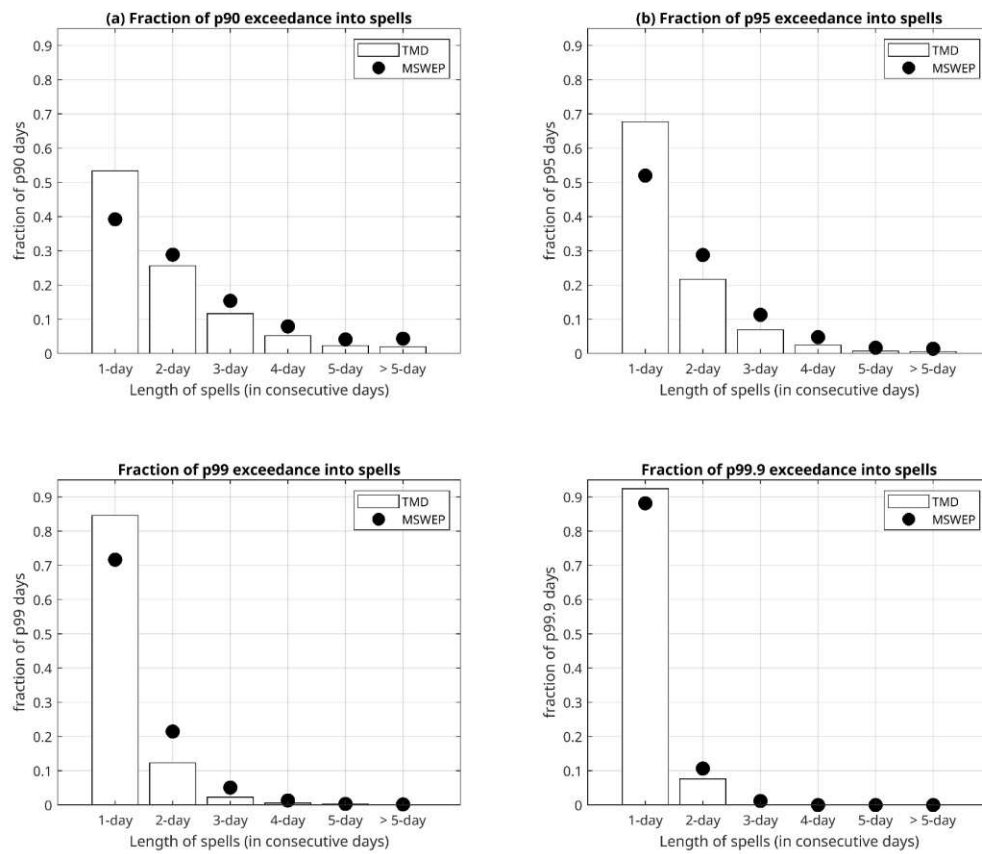


Figure 5 : Fraction of local percentile days intermittent or clustered into sequence of consecutive days (from 1-day to spells lasting more than 5 consecutive days). The bars are for TMD rain gauges and the black dots are for the closest MSWEP grid-points.

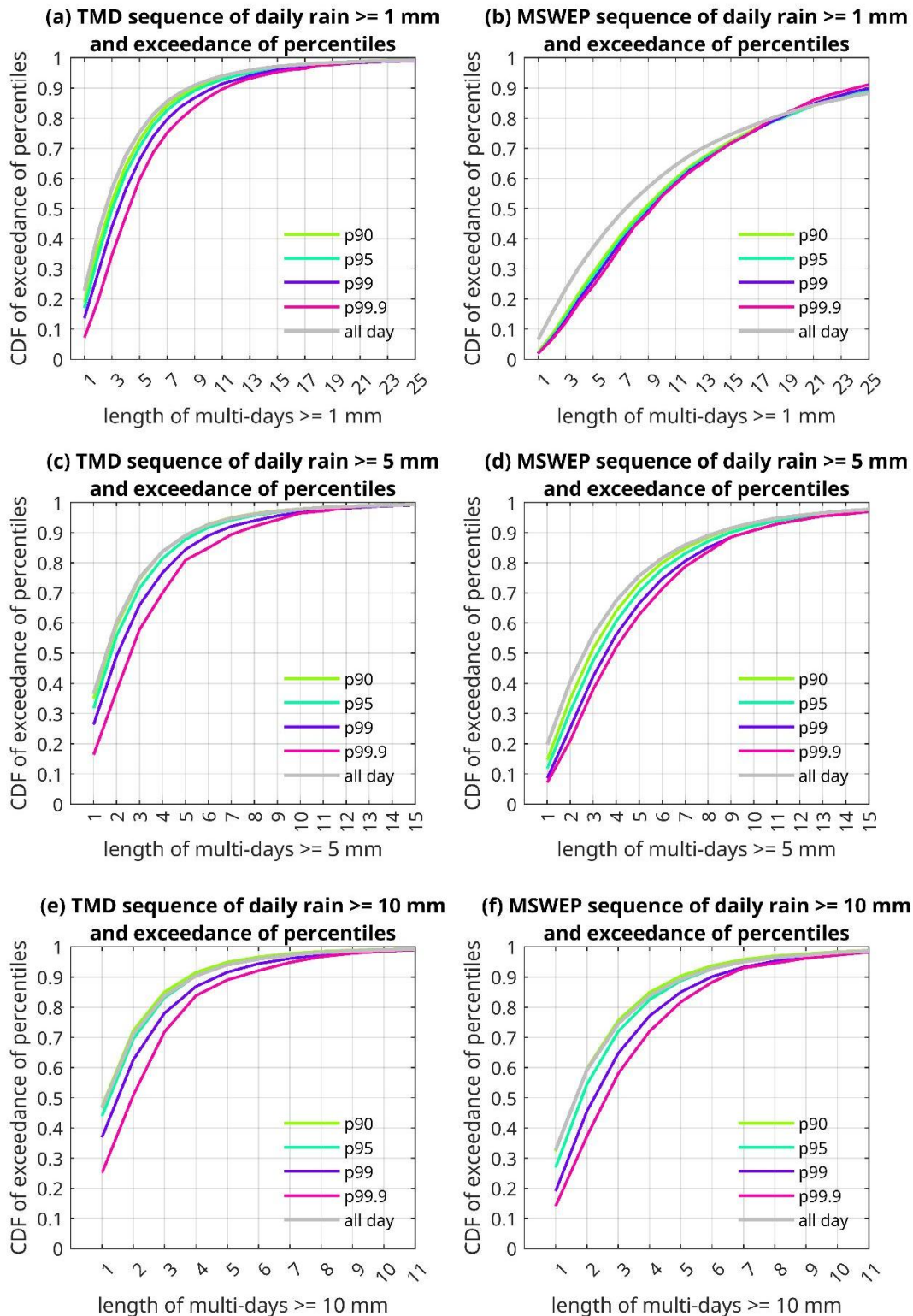


Figure 6 : CDF of multi-day wet sequences including the exceedance of a percentile (colored lines): the sequences are estimated with a threshold of (a,b) 1 mm, (c,d) 5 mm and (e,f) 10 mm based on the exceedance of a given percentiles on (a,c,e) the 75 TMD rain gauges and (b,d,f) the closest MSWEP grid-points. The gray curve is the CDF of all wet sequences, independently on the occurrence of ExtD.

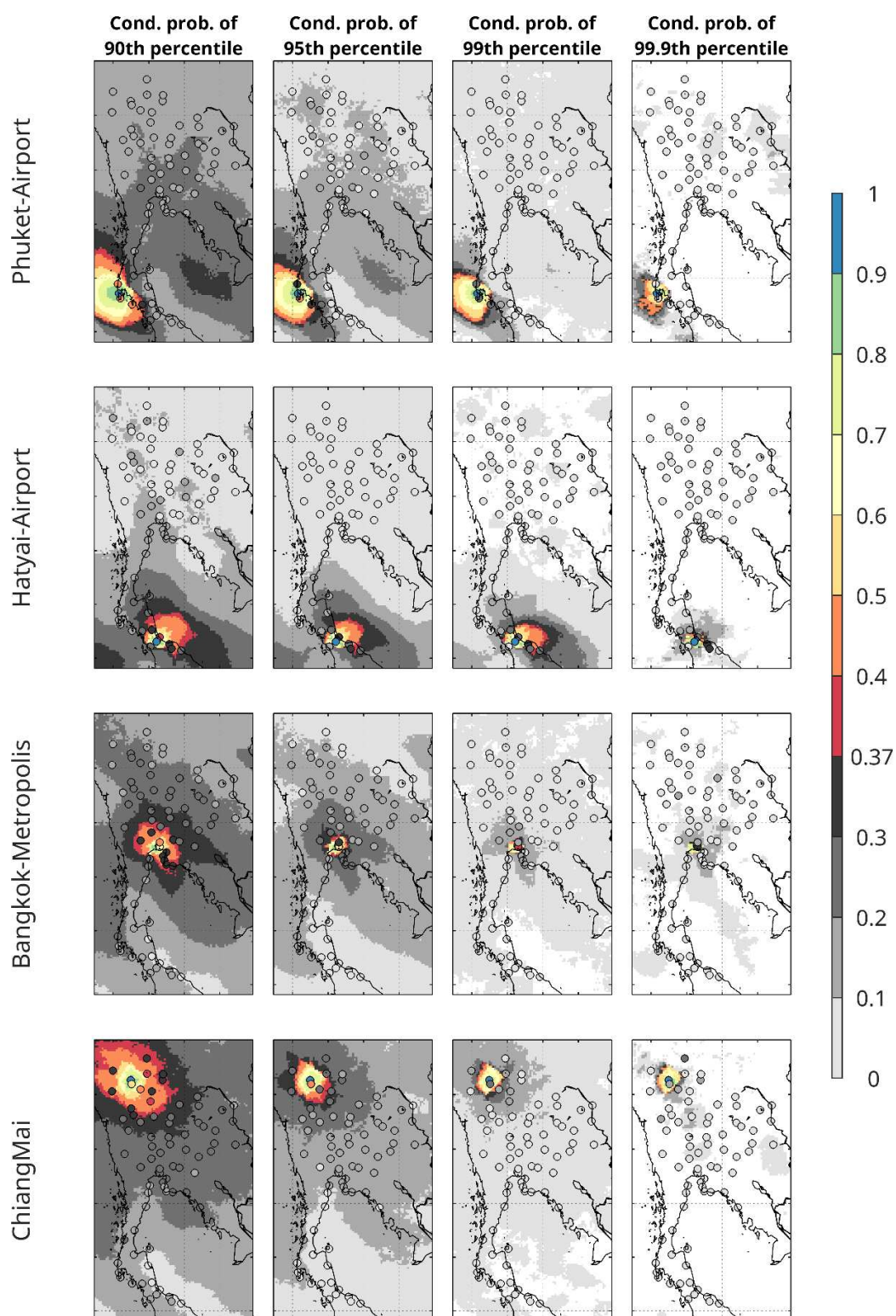


Figure 7: Spatial conditional probabilities of ExtD at 4 rain gauges across Thailand (in rows) for the 4 percentiles (in columns). The dots are for rain gauges and the shadings are for the MSWEP grid-points closest to each rain gauge. A value of 0 is displayed as white.

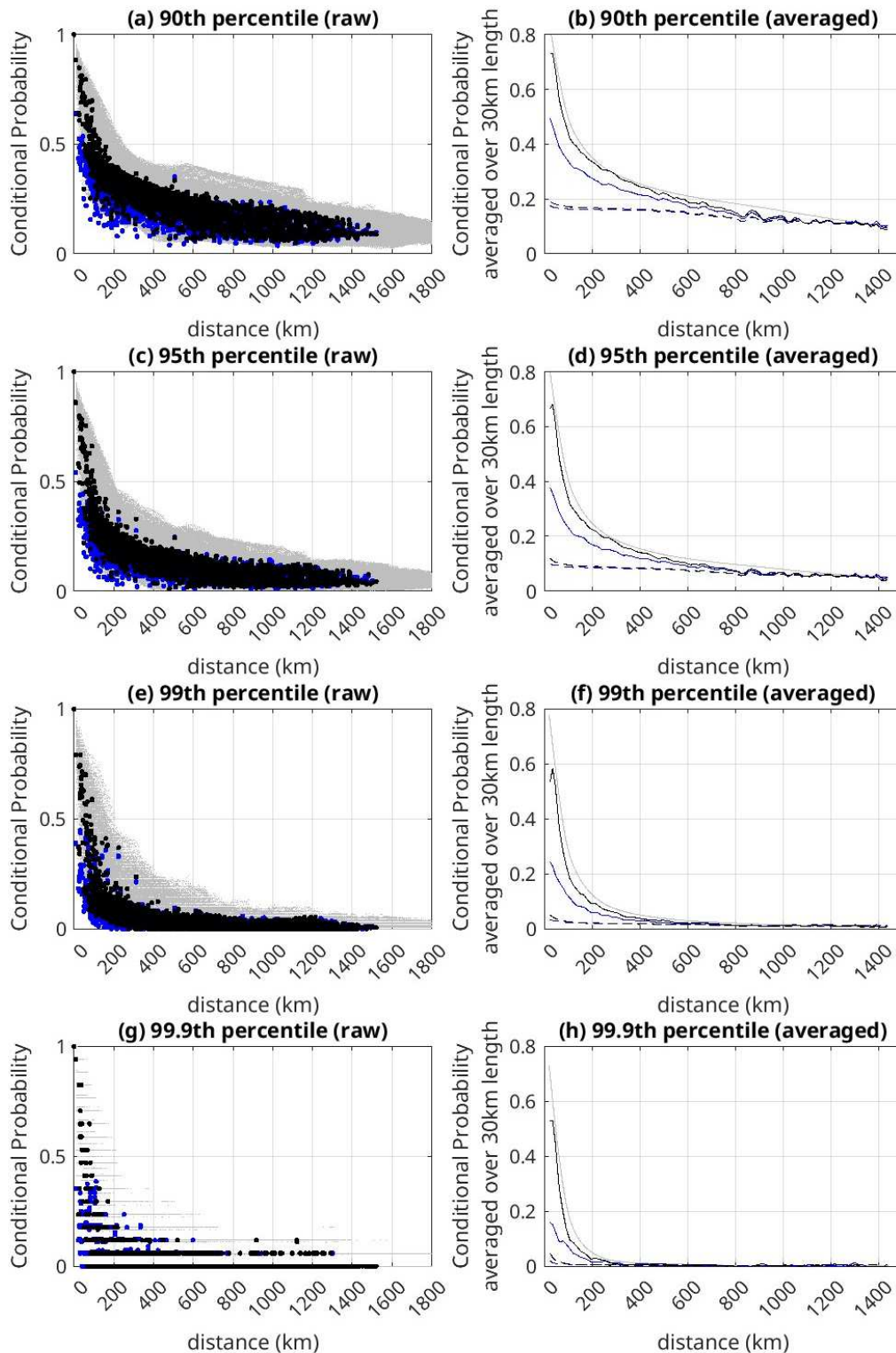


Figure 8: Scatter plots of the spatial conditional probability of (a,b) p90, (c,d) p95, (e,f) p99, (g,h) p99.9 ExtD occurrences vs horizontal distances. On the left panels, the grey dots represent the values for the 75 MSWEP grid-points vs all grid-points in the window (2.45°N-23.95°N and 93.95°E-108.85°E). The black dots are the 75 MSWEP grid-points only and the blue dots are the 75 TMD rain gauges. On the right panels, the mean conditional probabilities

are shown for running 30-km ranges from 1 km (step of 15 km between each successive range, i.e. the first is 1-30 km, the second is 15-45 km etc.) considering the same color code. The dashed blue and black lines are the 95th expected spatial conditional probability due to the climatological annual cycle only and is obtained through a random reshuffling of yearly sequences of local exceedance of the percentiles (see text).

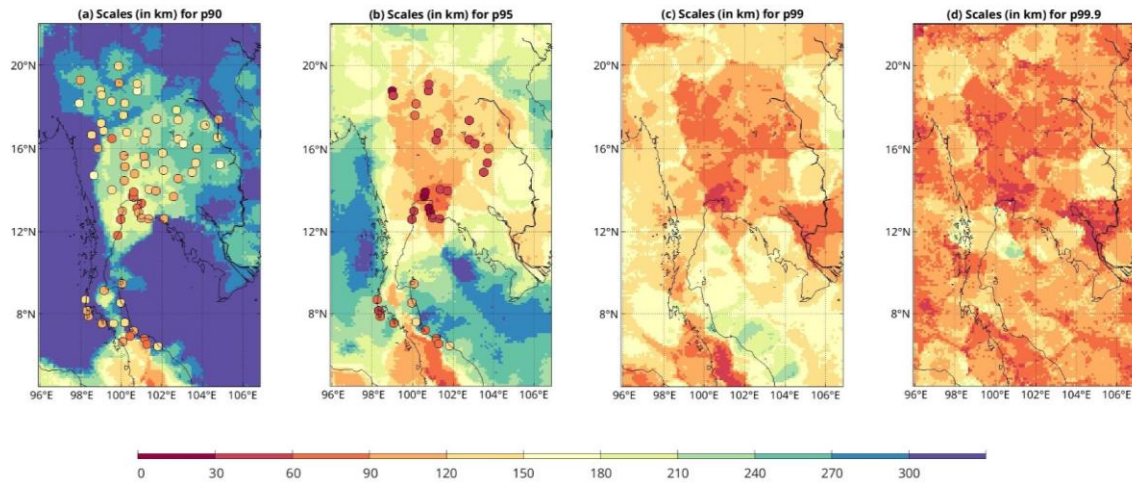


Figure 9: Spatial scale (in km) of (a) p90, (b) p95, (c) p99, (d) p99.9 exceedance in MSWEP (shadings) and TMD rain gauges (dots). The spatial scale is defined as the mean horizontal distance where the conditional probabilities are between 0.3179 and 0.4179. This distance is not defined when all conditional probabilities are below 0.3179 irrespective of the horizontal distances. When less than 3 couples of TMD stations do not reach the requested conditional probability, the distance is considered as unreliable and the spatial scale is not shown (as for p99 and p99.9 where all TMD spatial scales are either undefined or unreliable).

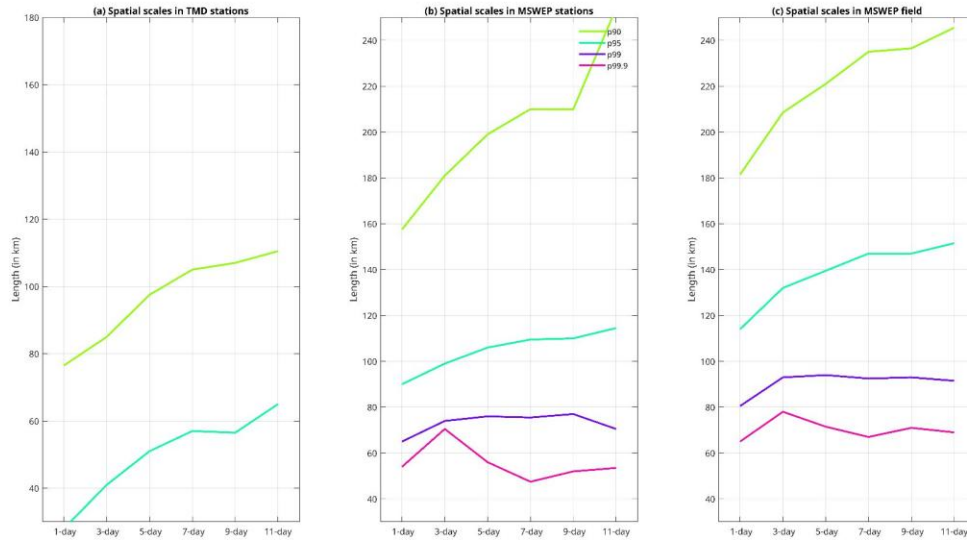


Figure 10: Variations in spatial scales of ExtD in (a) TMD stations, (b) MSWEP co-located grid-points and © MSWEP co-located grid-points vs all grid-points in the window xx-xx according to the temporal aggregation (from daily to non-overlapped 11-day windows as indicated in abscissa). The spatial scales are computed as the e-folding distance, that is the horizontal distance where the conditional probabilities firstly averaged on 30-km ranges equals $1/\exp(1)$ with a tolerance of 0.01.

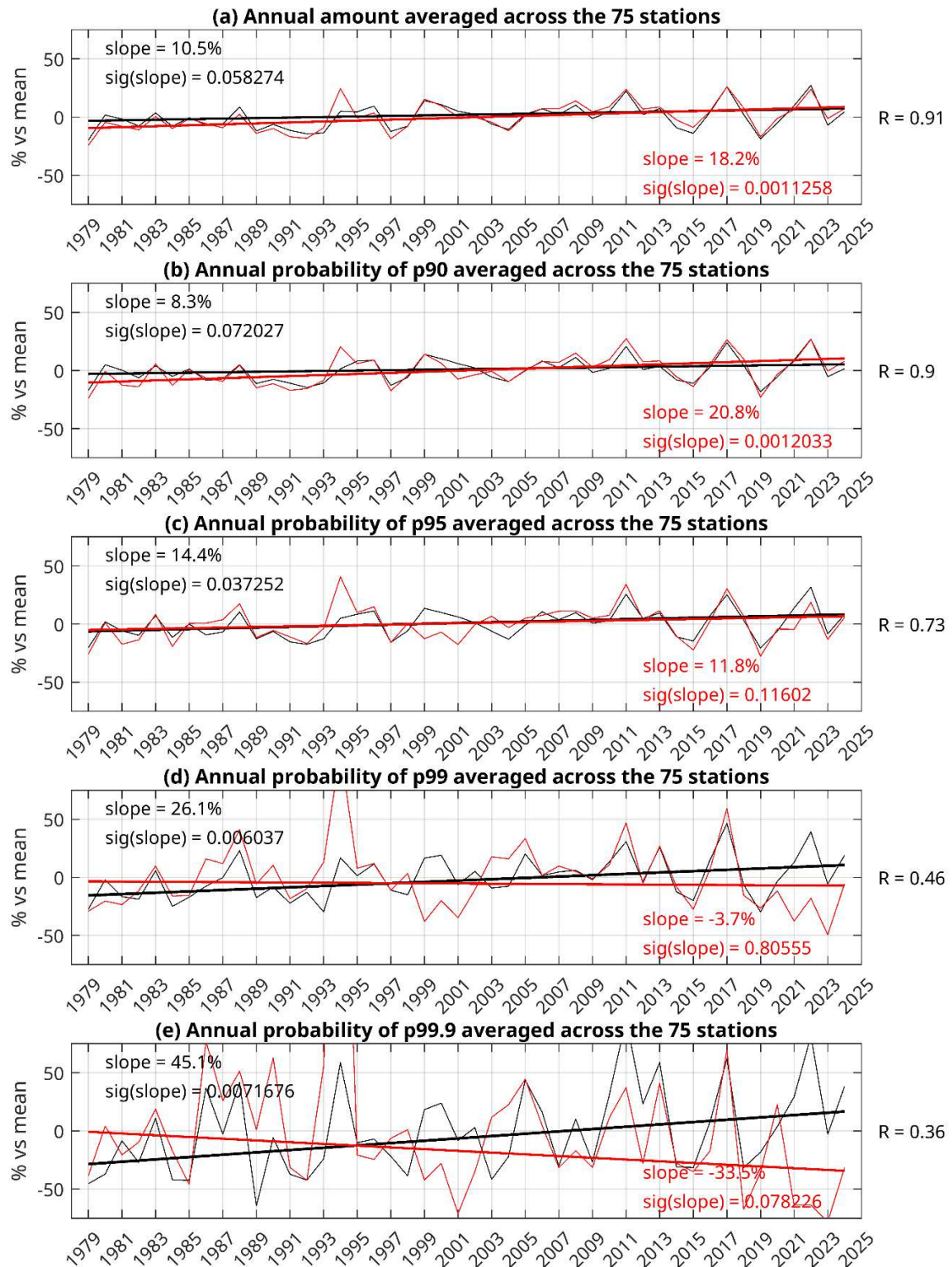


Figure 11: Interannual average of yearly (a) amount of rainfall, (b) probability of occurrence of daily rainfall $\geq$ p90, (c) probability of occurrence of daily rainfall $\geq$ p95, (d) probability of occurrence of daily rainfall $\geq$ p99, (e) probability of occurrence of daily rainfall $\geq$ p99.9 for the TMD network (in black) and the MSWEP grid-points corresponding to the TMD rain gauges (in red). The interannual values at each rain gauge are firstly expressed as a relative deviation vs the local long-term (in %) then spatially averaged. The line is the Sen's estimate of the

1039 slope (from the first to the last year) which is indicated on the upper left corner with its bilateral
1040 significance. The Pearson's correlation (R) between observed and MSWEP time series is
1041 indicated on the right of each panel.

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