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Changes of daily rainfall intensity in Thailand from 1955 to 2019

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Abstract

Analysis of daily rainfall intensity in Thailand from 1955 to 2019 revealed remarkable changes in lower and upper distribution tails, highlighting a significant decrease in light rainfall events but a significant increase in heavy rainfall events. Leading patterns of trends in all ten rainfall categories for wet-season, dry-season and annual periods demonstrated that most areas of Thailand experienced increasing contribution of heavy rainfall events. Results also indicated a significant correlation between contribution trends of light and heavy rainfall events in Thailand and changes in global mean temperature (GMT), supporting the notion that increased heavy rainfall intensities at both local and national levels followed anthropogenic-induced increase in atmospheric moisture. Regression-based extrapolated values for future levels of global warming at 1.5 °C and 2 °C indicated that an additional half-degree of warming will result in almost a 50% increase in heavy rainfall events in Thailand. This study presents scientific information to support effective management of water in the agriculture sector and adapt to the impacts of climate-related extremes and disasters. Studies based on high-resolution simulated climate data and space and ground-based observations are important to better understand the associations between anthropogenic-induced effects, large-scale atmospheric circulation and local changes in Thailand's rainfall intensity distribution, especially for daily and sub-daily time scales.

Keywords: Rainfall, Intensity, Trend, Thailand, Global mean temperature

1. Introduction

Rainfall changes at different intensities have received great attention because their formation mechanisms and social-ecological impacts are substantially distinctive. Heavy rainfall events usually forming in fast-growing convective clouds fueled by rising moisture often cause flash floods as devastating global natural hazards [1-3]. By contrast, low-intensity rainfall is intimately associated with cloud convective physical processes and soaks into soil to alleviate drought [1-3]. Increases in atmospheric moisture induced by global warming result in greater intensity of extreme rainfall [4-8]. Under global warming, thermodynamic and dynamic contributions are the two main factors which influence rainfall intensity through changes in atmospheric water vapor and vertical motion [9-11]. Atmospheric moisture-holding capacity increase following the basic physical principle governed by the Clausius-Clapeyron equation [8,10,12-13]. However, rainfall intensity can vary, even with uniform surface warming, because regional variations in thermodynamic and dynamical factors are linked to changes in moisture advection, local boundary conditions and atmospheric circulation [2-3,10,14].

Several observation and climate model-based studies revealed an anthropogenic-induced increase in extreme rainfall intensity and frequency [3,6-8,14-17]. Increases in extreme daily rainfall intensities were observed in most continents from 1951 to 2010 [15]. Global averages of annual maximum daily rainfall intensity have increased during this period by 5.9 to 7.7%, with a near-surface atmospheric temperature rise of 1 °C [16]. Changes in rainfall intensities also showed a significant spectral shift from less light to more heavy rainfall [2-3, 6,14,18].

Changes in extreme rainfall events impact both humans and environmental systems. Updated information at sub-national and national levels is required to support effective adaptation actions. This study extended the conclusions presented by Limsakul and Singhruck [19] on rainfall extremes by further analyzing how daily rainfall intensity distribution has changed in Thailand from 1955 to 2019. The relationship between extreme rainfall events and global mean temperature (GMT) as a sign of anthropogenic influence was also examined.

2. Materials and methods

2.1 Data used and their quality testing

Long-running records of daily rainfall data measured regularly at major weather stations across Thailand were obtained from the archives of the Thai Meteorological Department (TMD). Records were selected on the basis of completeness, length and availability from 1955 to 2019. Selection of daily rainfall data followed the criteria used by Limsakul and Singhruck [19]. Each of the selected data records was at least 99% complete. The quality of all selected data including extremely high or low value checking, data gap filling and discontinuities was evaluated using commonly used objective statistics [20,21]. Extremely high or low values in data records were checked with the adjacent and same-day values at neighboring stations. Linear regression, following the method of Eischeid et al. [20] was applied to fill data gaps using the nearest nearby data.

Statistical techniques following Wang et al. [21] and Wang [22] were used to check discontinuities in the data records. These methods detected and identified any sudden changes or jumps presented in time series, based on the penalized t-test and the penalized maximal F-test [21,22]. A relative test described by Limsakul and Singhruck [19] was employed to examine discontinuities in the monthly rainfall series. Three stations with significant discontinuities were identified and the data were excluded from further analysis [23]. Finally, 41 quality-controlled daily records were prepared (Figure 1) for rainfall intensity analysis covering the period 1955 to 2019.

Monthly global surface temperature data periodically updated by the Goddard Institute for Space Studies (GISS) (https://climate.nasa.gov/vital-signs/global-temperature) developed by combining temperature measurements both on land and at sea were also used. Data were presented as global land-ocean temperature deviations from the base period 1951 to 1980 at a spatial resolution of $2° \times 2°$, with spatial coverage of 89.0ºN-80.0ºS, 1.0ºE-359.5ºE [24]. The GISS analyses of global surface temperature change used various independent input data including the Global Historical Climatology Network (GHCN), the Scientific Committee on Antarctic Research (SCAR), the Hadley Centre Global Sea Ice and Sea Surface Temperature (HadISST) and the Optimum Interpolation Sea Surface Temperature (OISST) as a combination of bias-adjusted observations from different platforms (satellite, ships, buoys) [24]. The basic GISS temperature analysis scheme was employed to estimate global temperature change and compared with one-dimensional global climate model [24]. The GISS analysis method used linear inverse distance weighting to infill grid boxes, with records from stations up to 1200 km distant. The scheme also included quantitative estimates of the error in annual and 5-year mean temperature change, the effect of incomplete station coverage, and adjustment of urban-warming bias [24]. This dataset is popularly used to monitor global and regional temperature variability and trends.

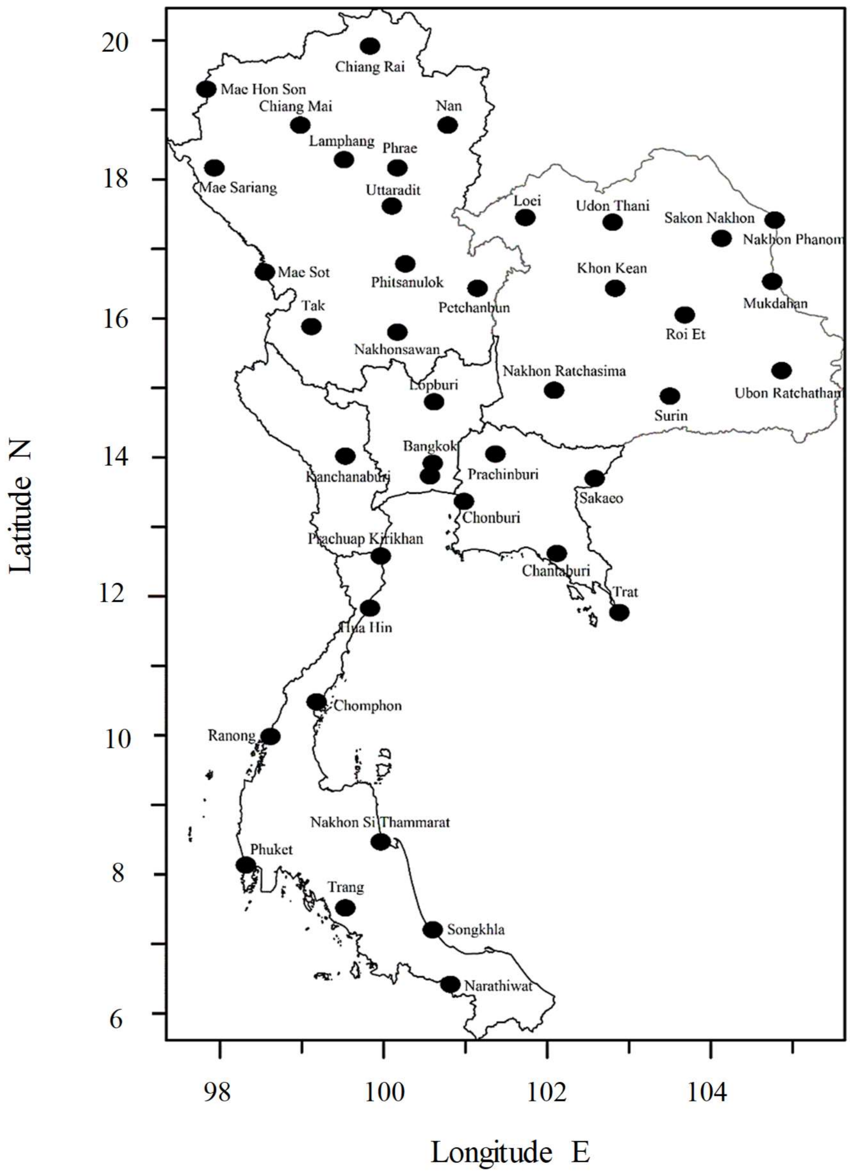

Figure 1 Geographical distribution of quality-controlled and homogenized daily rainfall data in Thailand form 1955 to 2019. Major cities show the locations of the weather stations.

2.2 Analysis methods

The nonparametric method of Osborn et al. [18] and Maraun et al. [14] was applied to define ten categories of different rainfall intensities according to their amount. Firstly, all wet-day daily rainfall total for each station from 1955 to 2019 were sorted into ascending order, and classified into ten different categories from the lightest (C1) to the heaviest (C10). Category ranges were defined as ten equal amount quantities. Events in each category equally contributes 10% of seasonal (annual) rainfall total over a long reference period from 1955 to 2019. Analysis was conducted separately for the wet-season period (May to September of the same year), dry-season period (November of the previous year to March of the next year) and annual period (all months). This seasonal definition captured two contrasting monsoon-induced rainfall regimes in mainland Southeast Asia. The wet-day daily rainfall total varied with location and time of the year. In most cases, the lowest category consisted of the lightest 50% of events, whereas, C10 comprised of fewer heavy events, making up10% of seasonal (annual) rainfall amounts. Unlike the equal frequency quantity approach, this method has the advantages that all amount quantities equally display large contribution trends [14]. For each station, the contribution from wet-day daily rainfall events in each category to seasonal and annual rainfall totals was computed for wet-season, dry-season and annual periods. A time series then represented the percentage of rainfall from a certain category relative to respective seasonal and annual rainfall totals. Regional time series to illustrate Thailand as a whole were created, based on the anomalies of each station relative to the 1955-2019 average. To reduce any bias arising from uneven distribution of stations, the weighted averaging procedure as a function of inverse distance and de-correlation length [14] was applied.

The Mann-Kendall test, widely used to detect trends in hydro-meteorological data, was employed to analyze trend slopes of contribution time series for each category, station and period [15,25] . This technique is nonparametric test used to identify the correlation of observed values ranked in chronological order [25,26]. The Mann-Kendall statistic S is based on the rank not the values of observations, and can be applied to non-normally distributed variables that are less affected by outliers [25,26]. In this study, a modified version proposed by Hamed and Rao [26] was used that accounted for time series autocorrelation by modifying the variance of the Mann-Kendal statistic S. Trends with p-value lower than 0.05 were considered to be statistically significant.

Dominant spatial patterns of contribution trends of all rainfall intensity categories was identified by principal component analysis (PCA). This descriptive multivariate tools is widely used to reduce the dimensionality of a large dataset such that most of the statistical information in the data is retained [27]. PCA is based on a linear transformation into orthogonal functions with maximum variance of a data matrix X (n x p) whose j^{th} column is the vector x_j of observations on the j^{th} variables. Such linear transformation is given by

$$X_a = \sum_{j=1}^{p} a_j x_j \tag{1}$$

where a denotes a vector of constants a_1, a_2, . . . , a_p. The principal components of the dataset (p new linear combination, which successively maximize variance, subject to uncorrelatedness with previous linear combinations) are represented by Xa_k and can be defined as

$$X_{a_k} = \sum_{j=1}^{p} a_{jk} x_j. \tag{2}$$

whereas, the elements of a_{jk} and Xa_k are the PC loadings and the PC scores, respectively [27].

3. Results and discussion

3.1 Trends in rainfall totals and rainfall intensity categories

The prominent feature of seasonal and annual rainfall totals in Thailand, similar to the earlier results [19], was large year-to-year variations superimposed on noticeable interdecadal fluctuations (Figure 2). As previously documented [19] and supported by this study, about 30% of total interannual variability in Thailand's annual rainfall total could be explained by fluctuations of El Niño–Southern Oscillation (ENSO) phenomenon that tended to be greater (lower) amounts during La Niña (El Niño) years. Regime shifts characterized as abrupt, dramatic and persistent changes with a fast transition [28,29] were also evident in annual rainfall total series (Figure 2). A persistently dry regime occurred during the mid-1970s to the mid-1990s, with mostly wet periods from the 2000s onwards (Figure 2). Linear trend showed significant increase only in dry-season rainfall total series (8.4 mm per decade; p=0.02), consistent with the study of Limsakul and Singhruck [19], indicating that recent increases in dry-season rainfall total, especially in Southern Thailand coincided with decadal variations of the East Asian winter monsoon (EAWM).

Time series of rainfall intensity categories averages at all stations for wet-season, dry-season and annual periods showed similar patterns, indicating a significant decrease in light rain events but a significant increase in heavy rain events (Figures 3-5). The lightest three quantiles (C1-C3) of rainfall events in wet-season and annual periods exhibited significantly decreasing trends ranging from -0.15 to -0.10% per decade (Figures 3 and 4). A larger significant decline in these rainfall events (-0.60 to -0.27% per decade) was seen in dry season (Figure 5). By contrast, the heaviest two quantiles (C9-C10) of rainfall events for all periods showed significant increases, ranging from 0.18 to 0.46% per decade (Figures 3-5). However, no significant changes in the medium rainfall categories (C5-C7) were found (Figures 3-5). Dry-season rainfall events from C5 to C10 showed positive trends (Figure 5). Evidence presented in Figures 3-5 indicated general shifts in distributions of wet-day daily rainfall amounts from light categories toward heavy categories for both seasonal and annual time scales. These results were supported by the earlier study of Limsakul and Singhruck [19], highlighting that rainfall events in Thailand between 1955 to 2014 became more intense with an increase in heavy rainfall events. The results also concurred with a report from the United Kingdom, demonstrating that winter-season daily rainfall distribution between 1961 and 2006 shifted from light-medium events to heavy events [14]. Furthermore, Wu and Fu [2] highlighted the significant increase of heavy precipitation and a decrease of light precipitation in summer and winter seasons in south of Eastern China, while Goswami et al. [30] found an insignificant trend of monsoon-season rainfall amount over Central India between 1951 and 2000, partially because the contribution from increasing heavy events was offset by decreasing light-medium events. Such an offset was believed to be a plausible cause of insignificant trends of wet-season and annual rainfall totals observed in Thailand but may not be the case for dry-season rainfall totals. Increases in both heavy rainfall events and also medium rainfall events that outweighed a decrease in light rainfall events (Figure 5) most likely contributed a significant rising trend observed in dry-season rainfall total series.

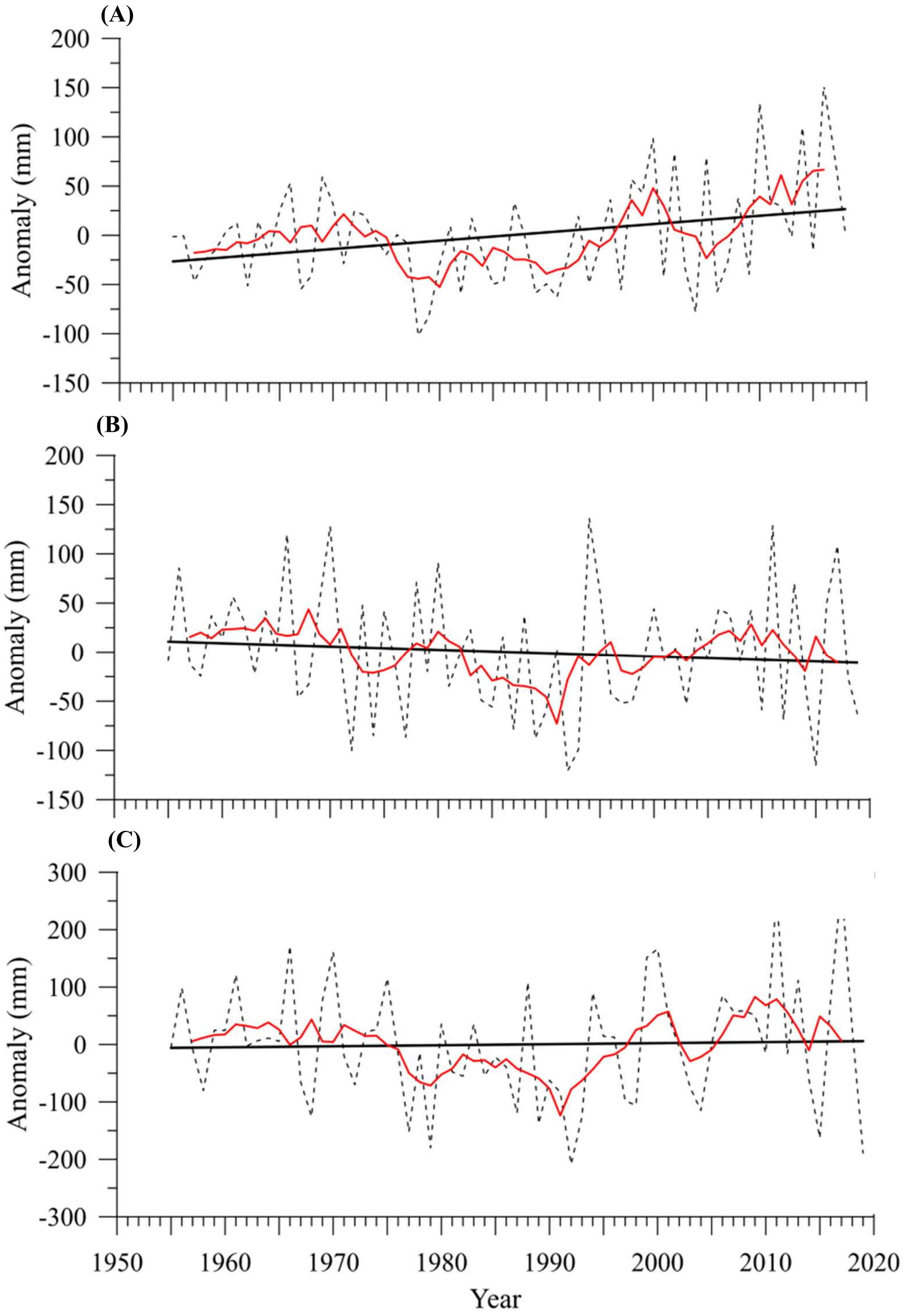

Figure 2 All-station average anomalies of (A) dry-season rainfall total, (B) wet-season rainfall total and annual rainfall total (C). Back and red solid lines represent linear trends and 5-year running averages, respectively.

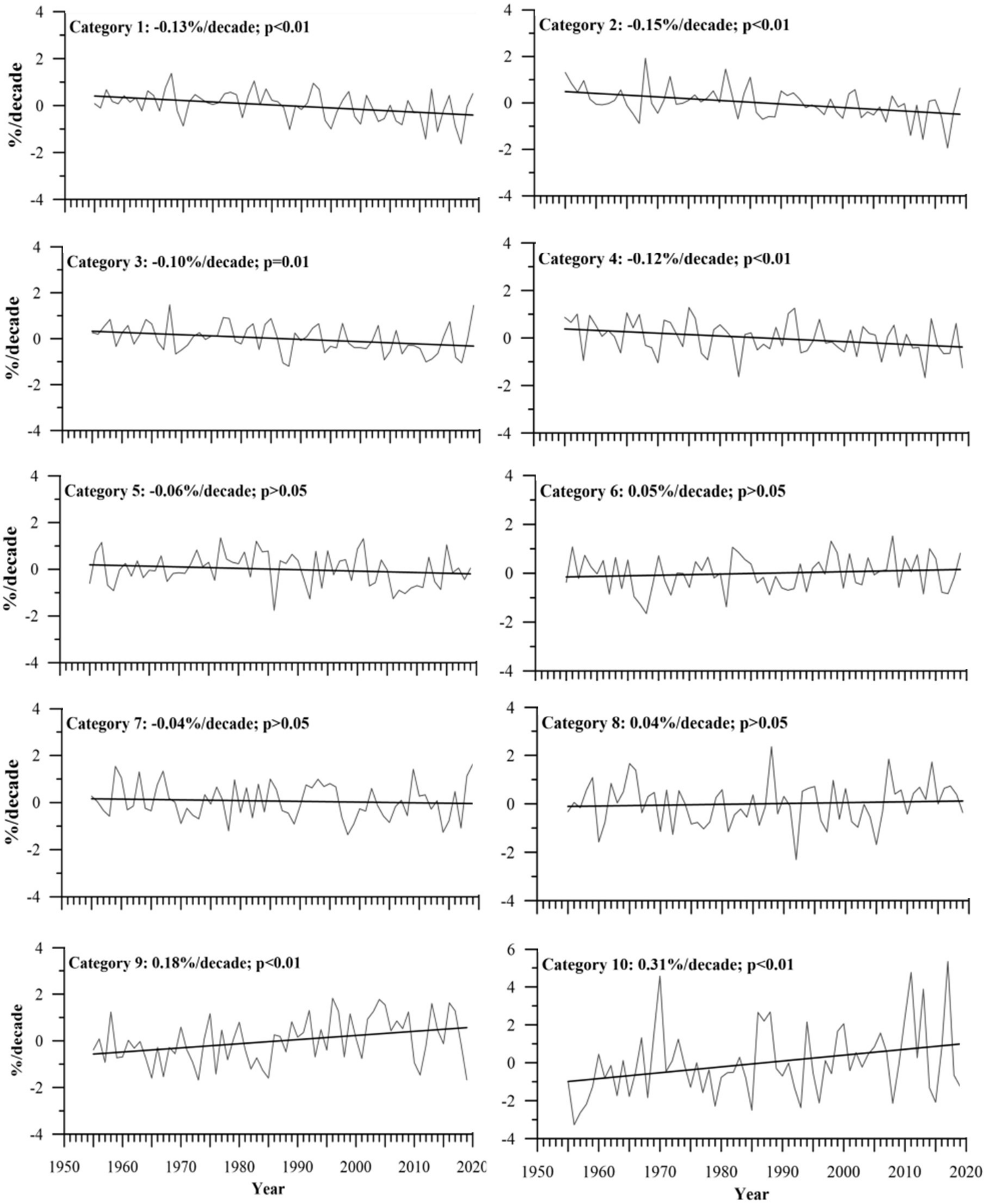

Figure 3 Contribution trends of all-station average anomalies for annual period (all months) relative to annual rainfall total for each of the ten rainfall categories.

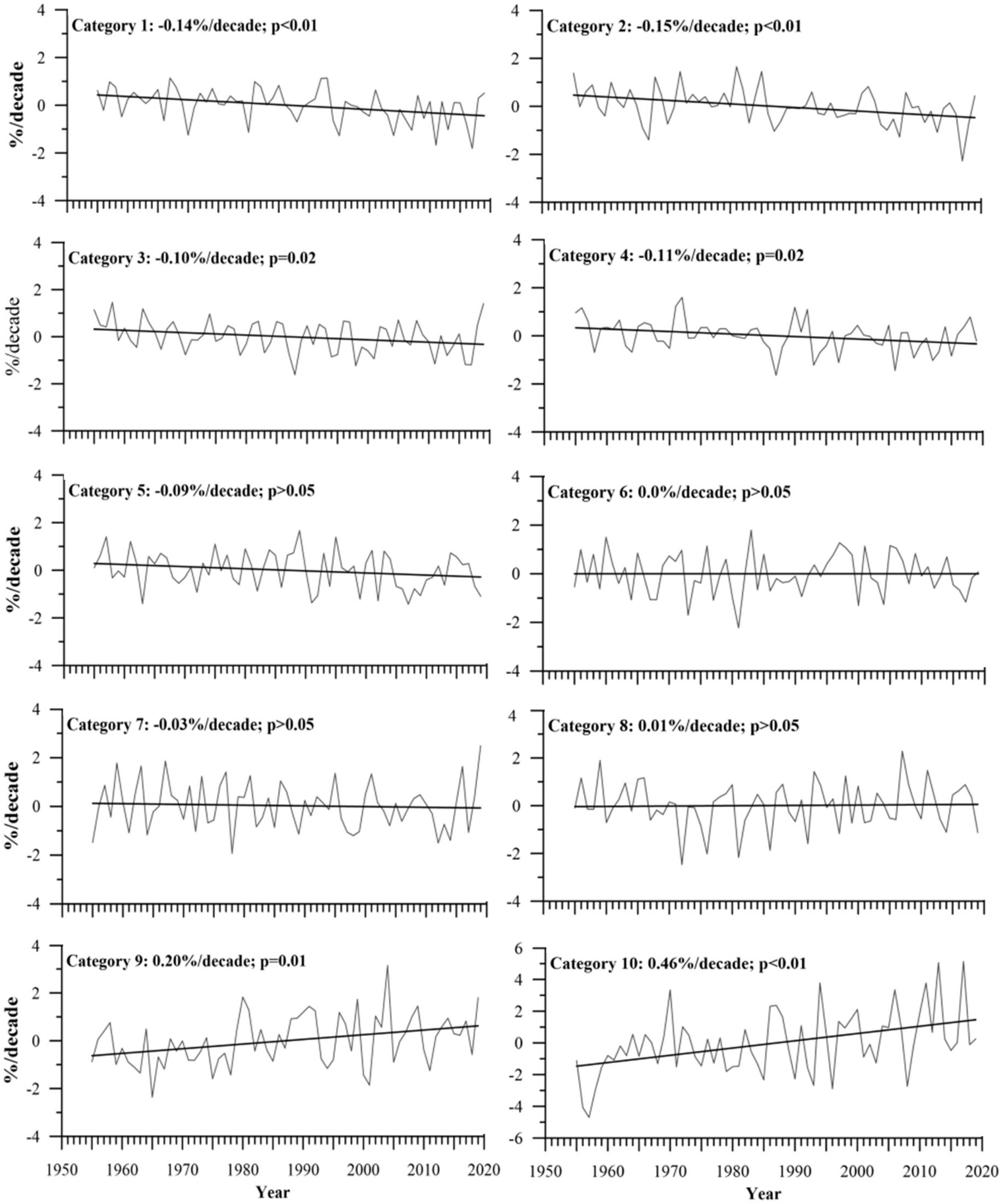

Figure 4 Contribution trends of all-station average anomalies for wet-season May to September (MJJAS) relative to seasonal rainfall total for each of the ten rainfall categories.

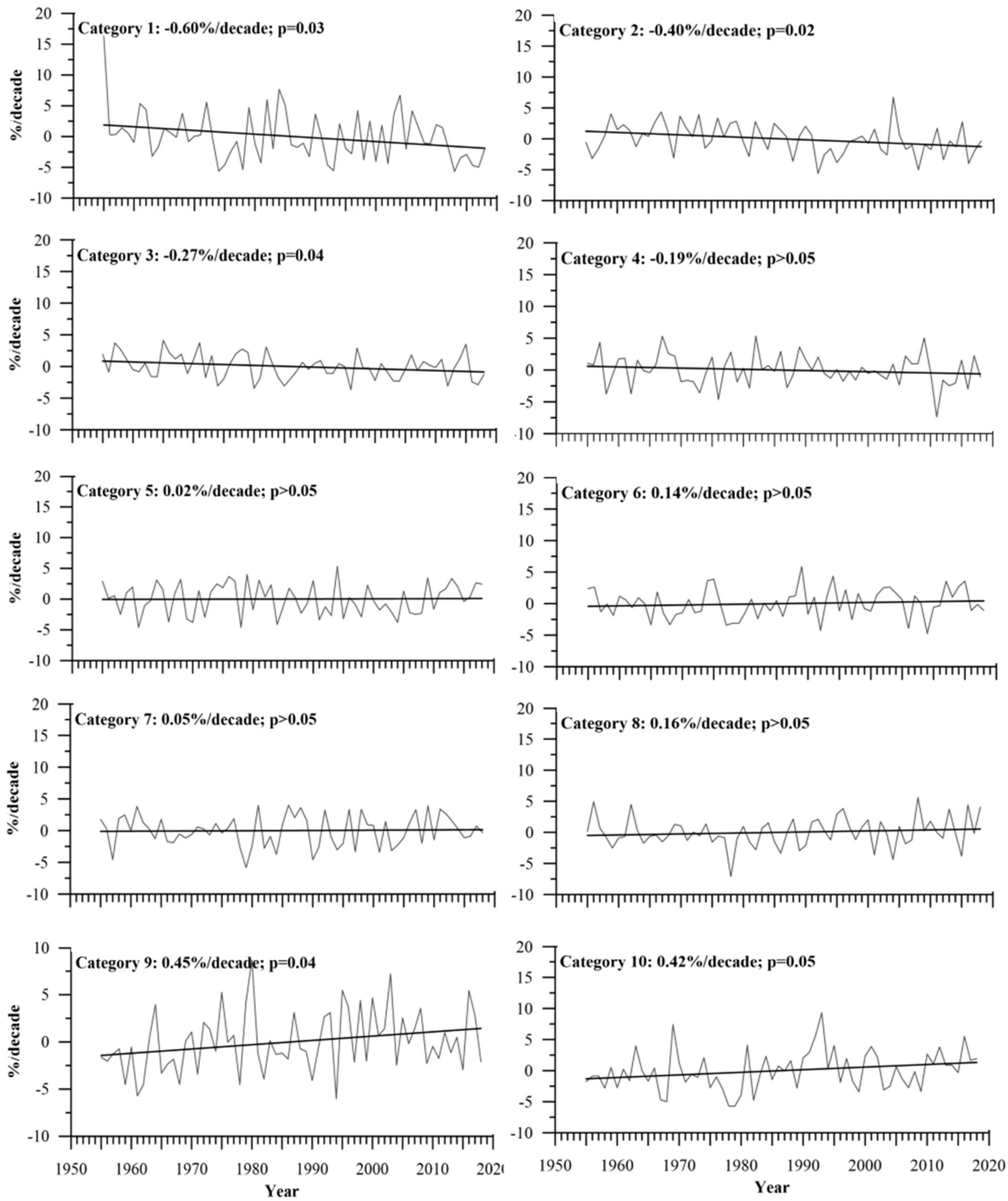

Figure 5 Contribution trends of all-station average anomalies for dry-season November to March (NDJFM) relative to seasonal rainfall total for each of the ten rainfall categories.

3.2 Spatial and dominant patterns of rainfall-intensity trends

Dominant patterns of contribution trends in all ten rainfall categories for each period were extracted by PCA, following the methos of Osborn et al. [18] and Maraun et al. [14]. PCA was performed on the correlation matrix of each element containing the individual trend of the given category station. Results showed that the leading mode accounted for 30%, 29% and 23% for annual period, wet season and dry season, respectively (Figures 6-8). For the wet-season and annual periods, the PC1 loadings and scores showed relatively similar patterns because rainfall amounts during the summer monsoon wet season accounted for 60-90% of the annual totals (Figures 6,7). This trend was widespread across Thailand, with relatively large magnitudes at the stations located in the Northeast, Central and South (Figures 6, 7). However, a few stations exhibited smaller magnitudes (Figures 6,7). This homogeneity of loadings on PC1 indicated that contribution trends in all of the ten categories were equally important in defining PC1. Scores associated with PC1 revealed a shift from the light-medium seven quantiles to the heaviest three quantities, indicating an increase in heavy-event contribution both wet-season and annual periods. In dry season, the leading mode explained less of the variance in the data set, suggesting that daily rainfall events during this period exhibited larger spatial variability. The dominant mode of daily rainfall intensity trends in dry season, as illustrated by PC scores, revealed a shift from the light four quantiles to medium-heavy six quantiles (Figure 8), in contrast to those of wet-season and annual periods. The spatial pattern of PC1 presented by its loadings, indicated strong signals concentrated at the stations located in the North, South and some areas of Northeast (Figure 8). Mixed changes were observed in the Central (Figure 8). The shift from light to medium-heavy rainfall events may be linked to increased frequency of summer thunderstorm observed during the dry season in recent years. Decadal changes in EAWM, especially its re-amplification, with increased frequency of the strong EAWM since the early/mid 2000s [31] may offer another reason for these changes in rainfall intensity characteristics.

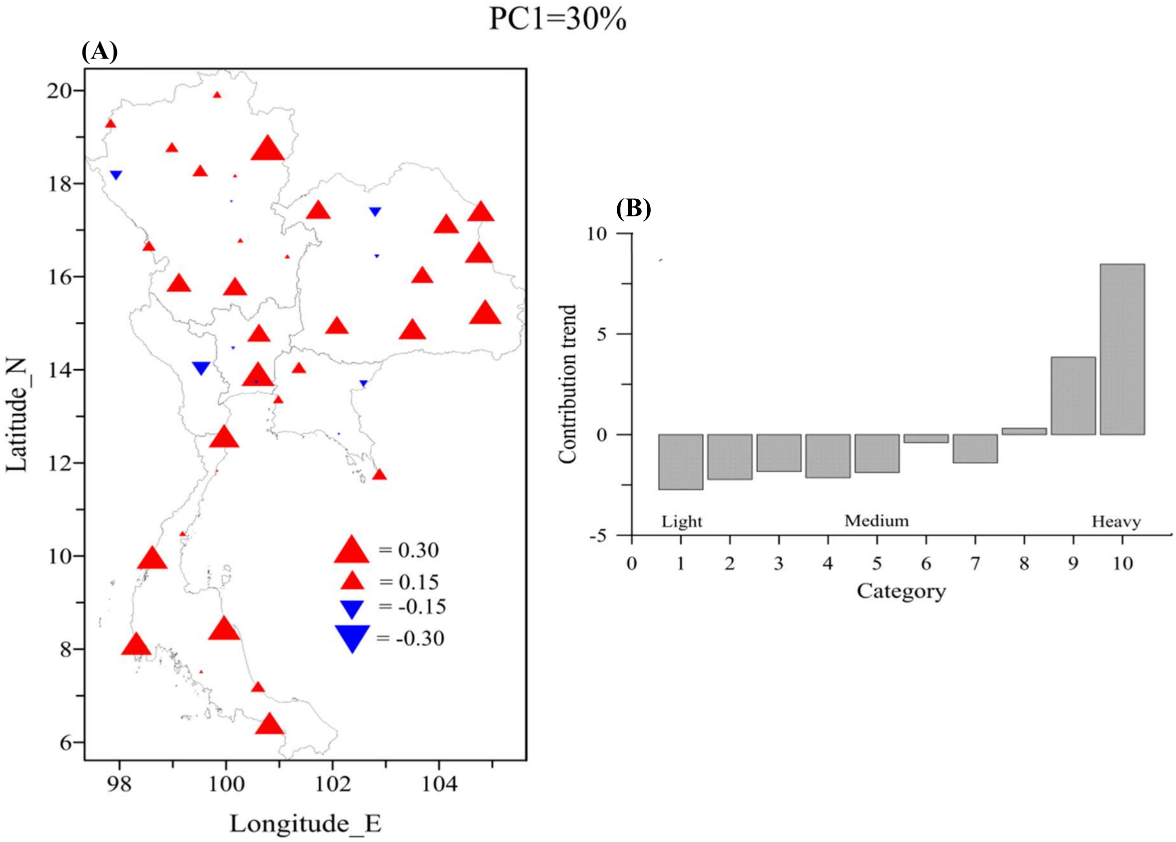

Figure 6 Leading PC and its associated loadings and scores of rainfall trends between 1955 and 2019 as the contribution of ten different categories of wet-day daily rainfall for all months.

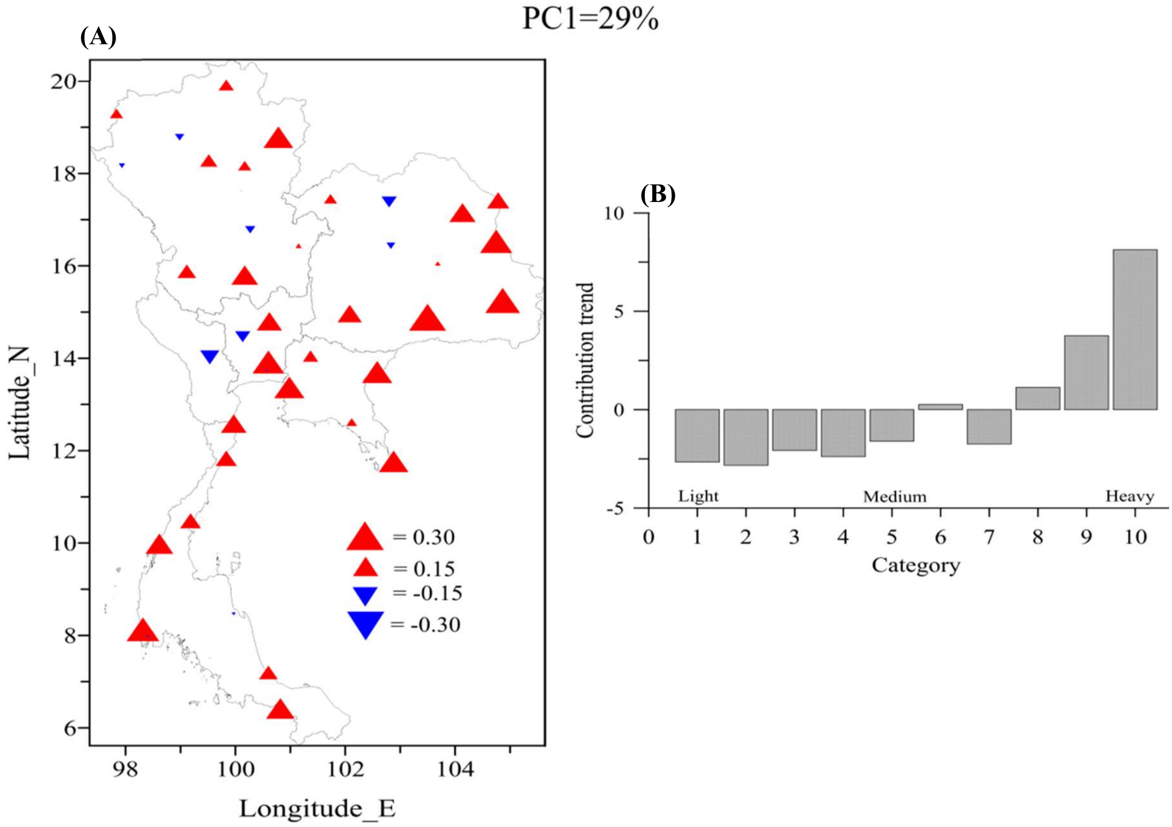

Figure 7 Leading PC and its associated loadings and scores of rainfall trends between 1955 and 2019 as the contribution of ten different categories of wet-day daily rainfall for the wet season.

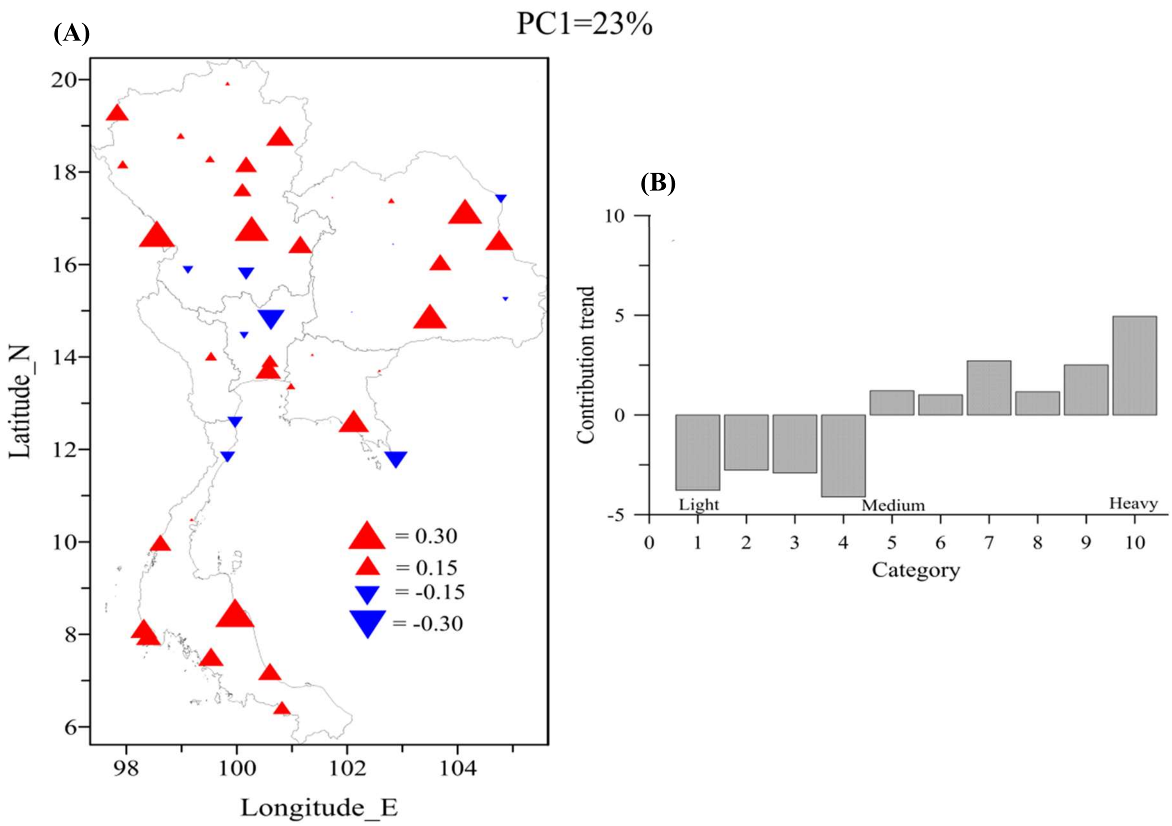

Figure 8 Leading PC and its associated loadings and scores of rainfall trends between 1955 and 2019 as the contribution of ten different categories of wet-day daily rainfall for the dry season.

3.3 Relationship between contribution trends of light and heavy rain events and GMT change

A linear regression was employed to illustrate changes in contribution trends of light and heavy rainfall events in Thailand in relation to GMT change. This simple but more robust approach was used to analyze relationship between local and regional variables in response to different levels of GMT change [32]. In the analysis, all-station mean average anomalies of contribution trends for lowest three quantile mean (C1-C3) and highest three quantile mean (C8-C10) between 1955 and 2019 were regressed on the annual GMT. Results showed that contribution trends of light and heavy rainfall events in Thailand significantly correlated with GMT change (Figure 9). Heavy rainfall events at top three quantiles in Thailand increased as GMT roses, while the correlation reversed for light rainfall events at lowest three quantiles (Figure 9). This relationship provided additional evidence supporting the notion that increased heavy-rain intensities at local and national levels correlated with the anthropogenic-induced increase in atmospheric moisture. Warmer air caused by the rise in GMT can hold more water and, consequently, has the potential to provide more moisture to rainfall events [10,12-13]. The linear regression model showed that GMT variations account for 29% and 35% of the changes in light and heavy rain events, respectively. Based on this predictive, contribution trends of lightest and heaviest rainfall events in Thailand will decrease (increase) about -2.1 (2.9) % per decade for a 1 °C increase in GMT. Extrapolated values of contribution trends of the top three heavy rainfall events showed a great difference, with almost a 50% increase between two predicted future levels of global warming (1.5 °C and 2 °C). They were also significantly higher than the 2000-2019 means (>190% increase at 1.5 °C and >270% increase at 2 °C) (Figure 9). This analysis indicates that an additional half-degree of global warming will result in substantial increase in heavy rainfall events in Thailand.

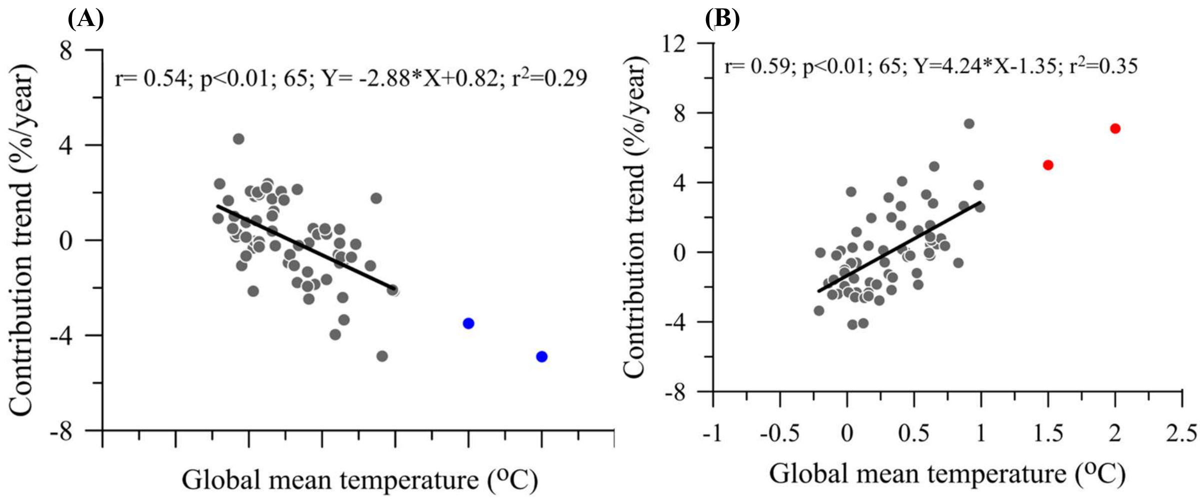

Figure 9 Empirical relationships between global mean temperature (GMT) and all-station average anomalies of contribution trends for (A) lowest three quantile mean (C1-C3) and (B) highest three quantile mean (C8-C10). Blue and red dots are extrapolated values calculated based on a linear regression model for increased GMT at 1.5 °C and 2 °C.

4. Conclusion

Analytical results of daily rainfall intensity in Thailand between 1955 and 2019 showed significant changes in lower and upper distribution tails for both seasonal and annual time scales. The leading mode of ten category contribution trends for wet-season and annual periods illustrated a shift in daily rainfall intensity from light-medium to heavy events. The dry-season period spatial patterns were mainly determined by stations located in the North, South and some areas of Northeast Thailand, and revealed a shift from light to medium-heavy events. Results indicated that most areas of Thailand experienced increasing contributions of heavy rainfall events. A significant relationship was determined between contribution trends of light and heavy rainfall events in Thailand and GMT change, suggesting that an anthropogenic-induced increase in atmospheric moisture resulted in increased heavy-rain intensity at local and national levels. Furthermore, regression model extrapolated values showed a 50% increase between two future scenario levels of global warming (1.5 °C and 2 °C), indicating that an additional half-degree of warming will result in substantial increase in heavy rainfall events in Thailand. However, the relationships between anthropogenic-induced thermodynamic and dynamic effects on large-scale atmospheric circulation, and local changes in rainfall intensity distribution, especially at daily and sub-daily time scales, require further comprehensive study using high-resolution simulated climate data and space and ground-based observations.

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