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Compound dry-to-wet transitions and intensifying wet-day rainfall in monsoon-exposed Southern Nghe An, Vietnam

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Abstract

Monsoon rainfall hazards depend on event intensity and sequence, not annual totals alone. We analyzed 8,766 daily observations from four gauges in southern Nghe An during 1998–2021, together with daily 0.05° Climate Hazards Center InfraRed Precipitation with Stations (CHIRPS) rainfall at Nam Dan. Thirteen indices represented amount, wet-day frequency, intensity, extremes, and persistence. A pre-specified core set was evaluated with Sen slopes, modified Mann–Kendall tests, confidence intervals, and within-index false-discovery-rate control. A transition required at least 10 consecutive days below 1 mm followed within seven days by rainfall at or above the station-specific wet-day 95th percentile. Station-level detections ($n = 58$) formed 41 same-day clusters; 18 detections occurred in 1998–2009 and 40 in 2010–2021. The later-to-earlier rate ratio was 2.22 (bootstrap 95% interval 1.10–4.90), the year-label permutation p-value was 0.056, and a Poisson model with station effects gave a rate ratio of 2.02 per decade (95% confidence interval 1.29–3.16). These estimates indicate recent clustering within this short record, not a detected monotonic station trend. CHIRPS underestimated Nam Dan total rainfall by 13.2% and the simple daily intensity index by 17.2%; annual total wet-day precipitation correlation was 0.81, but only one of 14 gauge transitions matched a CHIRPS event within three days. Thus, CHIRPS supported annual-scale variability more strongly than daily event timing. After within-index adjustment, wet-day intensity increased at Do Luong and Dua, while wet-spell duration increased at Dua, Nam Dan, and Yen Thuong. The proposed transition metric is a meteorological screening tool requiring local impact calibration.

Keywords: Compound event; Consecutive dry days; Extreme precipitation; Rainfall concentration; False discovery rate; Vietnam

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1. Introduction

Climate warming is altering not only how much rain falls, but also how rainfall is distributed among wet days, intense events, and intervening dry spells. Annual totals can therefore conceal a shift toward fewer water-delivery episodes with greater intensity or persistence. This distinction is central to current climate-risk assessment because regional heavy precipitation reflects the combined effects of atmospheric moisture, circulation, and land-surface controls.[1-3] Recent global evidence further shows that extreme-event duration and wet-day frequency need not change together.[4] Daily observations are consequently needed to separate amount, occurrence, intensity, upper-

tail contribution, and persistence rather than interpreting a single annual total as a complete description of rainfall change.

The order of events adds another risk dimension. Compound events occur when hazards coincide or follow one another closely enough to produce consequences that cannot be inferred from either component alone.[5] For dry-to-wet transitions, the analytical result depends on how drought or dryness, the following wet extreme, and the permissible transition interval are defined.[6,7] Global studies report increasing precipitation whiplash, but also substantial regional and scale dependence.[8,9] Recent reviews therefore recommend transparent event rules and explicit sensitivity tests rather than choosing one threshold after viewing the results.[10,11] This requirement is especially important for short station records, in which a few years can strongly affect an apparent change in rare-event frequency. Studies incorporating evapotranspiration, soil moisture, and hydrodynamics illustrate information that a precipitation-only screen cannot provide.[12,13]

Operational monitoring often treats water deficit and heavy rainfall separately. Monthly drought indices describe accumulated anomalies, whereas flood preparedness emphasizes short-range rainfall and runoff. A prolonged interval with daily rainfall below 1 mm followed within days by heavy rainfall lies between these systems. Where soil moisture, discharge, or impact variables are unavailable, a precipitation-only detector can serve as a reproducible screening tool but cannot establish observed drought or flood damage. Satellite and merged products extend spatial coverage,[14] although evaluations over Southeast Asia and Vietnamese basins show that daily occurrence and extremes remain product dependent.[15,16] Regional studies also document spatially varying extremes, circulation effects, and monsoon rainfall characteristics across Southeast Asia.[17-20]

El Niño–Southern Oscillation (ENSO) teleconnections to Southeast Asian rainfall vary with event type and interbasin conditions.[21,22] Published studies in Vietnam describe coastal drought, rainy-season timing, and rainfall-based flood hazards.[23-25] These contrasts support analyzing the four southern Nghe An gauges separately rather than averaging them into a province-wide series.

A previous study using the same stations characterized monthly-to-annual rainfall variability and 12-month standardized precipitation index (SPI) behavior.[26] That baseline cannot determine whether annual change comes from wet-day frequency or rainfall per wet day, whether maximum dry and wet runs are changing, or whether a station-specific heavy-rain day follows soon after a prolonged interval below 1 mm. Repeating SPI at another accumulation scale would add limited novelty. A distinct daily analysis is needed because extreme distributions can change through higher moments, dry and wet regimes can respond asymmetrically, and a short record may not yet show a stable time of emergence.[27-29]

This study addresses five questions: (i) was rainfall change during 1998–2021 expressed through wet-day frequency, wet-day intensity, or both; (ii) did short-duration extremes and annual dry- or wet-spell persistence change; (iii) how often did at least 10 consecutive dry days (CDDs) transition within seven days to rainfall at or above the station-specific wet-day 95th percentile, and how sensitive were counts to alternative thresholds; (iv) were wet-season metrics and transition counts associated with antecedent Niño-3.4 anomalies; and (v) how closely did Climate Hazards Center InfraRed Precipitation with Stations (CHIRPS) reproduce gauge-based annual indices and transition timing at Nam Dan? The aim is diagnostic rather than causal.

2. Materials and methods

2.1. Study area and data source

The study used daily rainfall from Dua, Do Luong, Yen Thuong, and Nam Dan, four gauges distributed across southern Nghe An from the higher western terrain toward the lower eastern districts. Figure 1 shows their locations and regional elevation context. The stations sample a west-to-east gradient but do not constitute a spatially exhaustive provincial network; all inferences therefore refer to the four stations or their network summary.

The common quality-controlled period extends from January 1, 1998, to December 31, 2021, and contains 8,766 calendar days per station. Although the earlier monthly/SPI study extended through 2022,[26] a complete 2022 daily record was not present in the files supplied for this analysis; 2022 was therefore not selectively excluded after viewing results. The provider confirmed that a hyphen denotes no recorded rain. Blank cells were provisionally coded as zero. This coding reconciled numeric-plus-hyphen daily sums with stated monthly totals except in three Nam Dan months, which were retained in the baseline and tested under proportional-reconciliation and missing-month scenarios. The interpretation of blank cells was not separately documented in station metadata. No missing date was interpolated, and no extreme daily value was removed solely because of magnitude.

The 24-year period is adequate for descriptive comparison and exploratory monotonic-trend analysis, but it is short for climate attribution and stable return-period estimation. The station network also does not

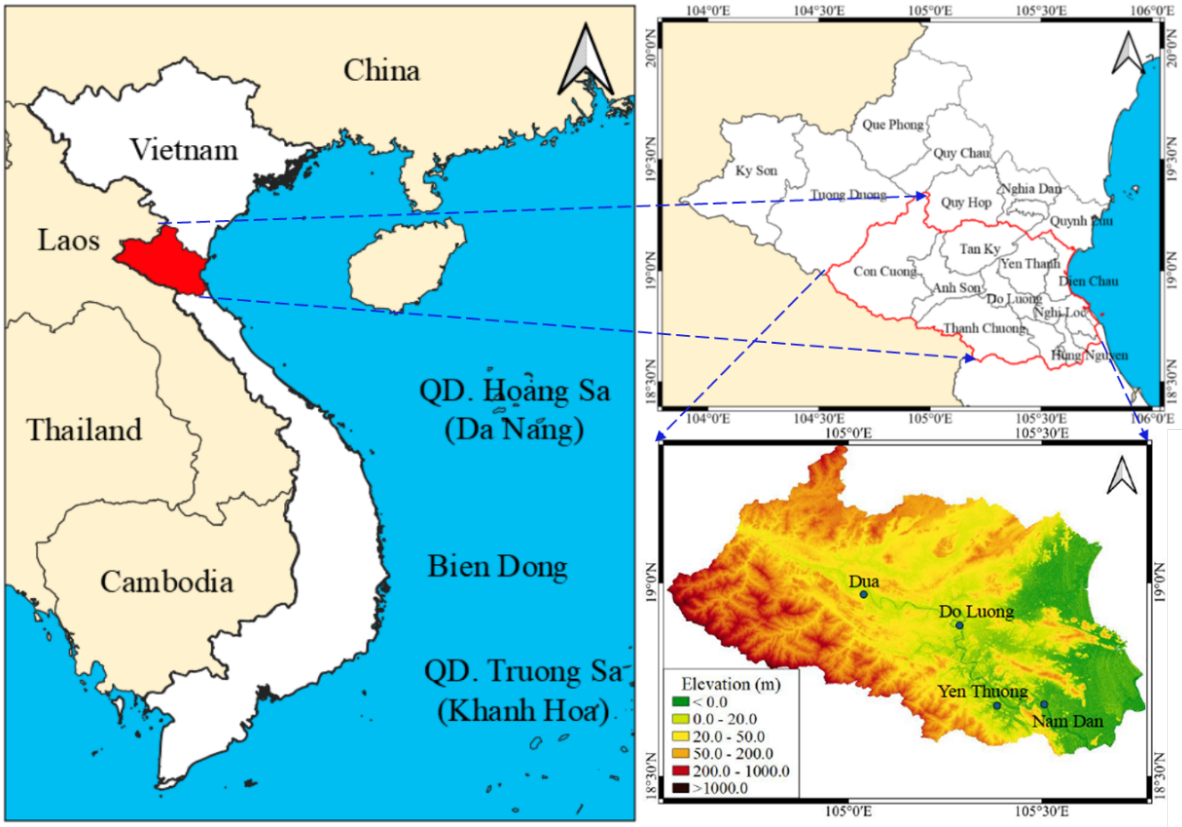


Figure 1. Location of Nghe An Province within Vietnam, regional elevation pattern, and locations of the four rainfall stations

support continuous spatial interpolation across Nghe An. All analyses were therefore conducted separately by station; pooled results are reported only as network summaries and not as estimates for the entire province.

2.2. Quality control and rainfall notation

Quality control followed calendar validation, range screening, internal aggregation, and station-wise inspection.[30-32] No negative values or values above 1,000 mm were found. The longest run of identical positive values was three days at Do Luong, Dua, and Nam Dan and two days at Yen Thuong; these short runs were retained because neighboring-station and CHIRPS totals did not identify a definite error. Daily sums reconciled with the monthly total from each source at Do Luong, Dua, and Yen Thuong. Nam Dan differed by −4.1 mm in November 2000, −2.0 mm in June 2003, and −8.0 mm in September 2003. Corresponding CHIRPS totals were 73.9, 76.6, and 479.3 mm, while the other three gauges averaged 51.5, 69.4, and 462.5 mm. These comparisons confirmed plausible wetness but could not identify which Nam Dan daily entry, if any, was incorrect. The provider has not stated whether daily values or monthly totals are authoritative; the daily series was retained, and both proportional-reconciliation and missing-month scenarios were analyzed. Table 1 summarizes the station records, thresholds, and consistency checks.

Let $P(s,y,t)$ denote daily rainfall in millimeters at station s, year y, and calendar day t. A wet day satisfies $P(s,y,t) \geq 1$ mm, and a dry day satisfies $P(s,y,t) < 1$ mm. The indicator function I(A) equals one when condition A is true and zero otherwise. The number of days in year y is $n(y)$. Station-specific wet-day percentiles q95(s) and q99(s) were calculated from all wet days during 1998–2021. This common-period percentile approach preserves comparability among years while allowing local rainfall regimes to have different heavy-rainfall thresholds.

Descriptive statistics included the mean, standard deviation, median, interquartile range, and observed maximum as appropriate to each index. Calendar-month climatologies were calculated from the 24 monthly totals for each station. September-December rainfall was also summarized because it captures the principal late-year wet season at Nam Dan and Yen Thuong; the monthly analysis showed that one uniform wet-season window would not represent every station equally well.

Table 1. Station records, climatological thresholds, and internal consistency checks

Station	Daily records	Wet days	Annual rain (mm)	P95 (mm)	P99 (mm)	Mismatched months
Do Luong	8,766	2,490	1804.2	69.2	141.9	0
Dua	8,766	2,602	1716.6	61.2	132.0	0
Nam Dan	8,766	2,309	1805.4	74.1	187.7	3
Yen Thuong	8,766	2,505	1829.5	69.8	173.1	0

Notes: P95 and P99 are station-specific wet-day percentiles; Nam Dan mismatches occurred in November 2000, June 2003, and September 2003.

2.3. Daily rainfall amount frequency and intensity indices

The daily indices follow the Expert Team on Climate Change Detection and Indices framework[30,31] with additional local thresholds. Annual total wet-day precipitation (PRCPTOT) is the annual amount received on wet days, and WetDays is the annual wet-day count. These two metrics distinguish total water input from occurrence frequency.

Rx1day and Rx5day describe short-duration magnitude. Rx5day was calculated with a moving five-day window within each calendar year. R10mm, R20mm, and R50mm count days meeting fixed thresholds; 50 mm per day approximates the lower bound of the Vietnamese 24-hour heavy-rain category (>50 mm).[33] Fixed thresholds complement, but do not replace, station-specific percentiles.

The simple daily intensity index separates annual wet-day rainfall from wet-day frequency. The accounting identity PRCPTOT = WetDays × simple daily intensity index (SDII) was used to interpret whether a high-rainfall year was associated mainly with more wet days or with more rainfall per wet day. It was not treated as a causal model.

Upper-tail rainfall was quantified with both R95p and R99p, and R95pTOT expressed R95p as a percentage of annual wet-day rainfall. CDDs and consecutive wet days (CWDs) were the maximum annual run lengths below and at or above 1 mm, respectively. Table 2 defines the daily indices used in this analysis (**Equations 1–9**).

$$PRCPTOT_y = \sum_{t=1}^{n_y} P_{y,t} I\left(P_{y,t} \geq 1\right) \quad (1)$$

where PRCPTOTy is annual wet-day rainfall, P(y,t) is daily rainfall, n_y is the number of days in year y, and $I\left(P_{y,t} \geq 1\right)$ is the indicator function.

$$WetDays_y = \sum_{t=1}^{n_y} I\left(P_{y,t} \geq 1\right) \quad (2)$$

where $WetDays_y$ is the annual number of days satisfying the 1 mm wet-day threshold.

$$Rx1day_y = \max_{1 \leq t \leq n_y} P_{y,t} \quad (3)$$

where $Rx1day_y$ is the largest daily rainfall amount observed in year y.

$$Rx5day_y = \max_{1 \leq t \leq n_y - 4} \sum_{k=0}^{4} P_{y,t+k} \quad (4)$$

where $Rx5day_y$ is the maximum moving sum over five consecutive days, and k indexes the days within each window.

$$SDII_y = \frac{PRCPTOT_y}{WetDays_y} \quad (5)$$

where $SDII_y$ is rainfall per wet day; years with zero wet days would be undefined, although none occurred in this record.

$$R_{\tau,y} = \sum_{t=1}^{n_y} I\left(P_{y,t} \geq \tau\right), \tau \in \{10, 20, 50\} \quad (6)$$

where $R_{\tau,y}$ is the annual count above the fixed threshold tau, evaluated at 10, 20, and 50 mm.

$$R95p_y = \sum_{t=1}^{n_y} P_{y,t} I\left(P_{y,t} > q_{95,s}\right) \quad (7)$$

where $R95p_y$ is the annual rainfall above $q_{95,s}$, the 95th percentile of wet-day rainfall at station s.

$$R99p_y = \sum_{t=1}^{n_y} P_{y,t} I\left(P_{y,t} > q_{99,s}\right) \quad (8)$$

where $R99p_y$ is defined analogously using the station-specific 99th-percentile threshold $q_{99,s}$.

$$R95pTOT_y = 100 \frac{R95p_y}{PRCPTOT_y} \quad (9)$$

where R95pTOTy is the percentage contribution of very wet days to annual wet-day rainfall.

2.4. Dry-to-wet transition algorithm

A precipitation-based transition was defined strictly as a meteorological screening event. A dry spell was a maximal run of consecutive days with rainfall below 1 mm, not necessarily a rain-free interval. Under the primary definition, the run lasted at least 10 days, and a transition

Table 2. Definitions of daily rainfall indices

Index	Unit	Definition	Dimension
PRCPTOT	mm	Annual sum on days with rainfall ≥ 1 mm	Annual amount
WetDays	days	Annual count of days with rainfall ≥ 1 mm	Frequency
Rx1day	mm	Annual maximum one-day rainfall	Extreme magnitude
Rx5day	mm	Annual maximum consecutive five-day rainfall	Extreme magnitude
R10mm	days	Annual count of days with rainfall ≥ 10 mm	Heavy-rain frequency
R20mm	days	Annual count of days with rainfall ≥ 20 mm	Very-heavy-rain frequency
R50mm	days	Annual count of days with rainfall ≥ 50 mm	Local high threshold
SDII	mm/day	PRCPTOT divided by WetDays	Wet-day intensity
CDD	days	Annual maximum run with rainfall < 1 mm	Dry persistence
CWD	days	Annual maximum run with rainfall ≥ 1 mm	Wet persistence
R95p	mm	Annual rainfall above the wet-day 95th percentile	Upper-tail amount
R99p	mm	Annual rainfall above the wet-day 99th percentile	Extreme upper-tail amount
R95pTOT	%	R95p as a percentage of PRCPTOT	Rainfall concentration

Note: Percentile thresholds were estimated separately by station from all wet days during 1998–2021.
Abbreviations: CDD: Consecutive dry days; CWD: Consecutive wet days; PRCPTOT: Annual total wet-day precipitation; SDII: Simple daily intensity index.

occurred when the first subsequent day at or above q95(s) fell within seven days after the run ended. Intervening wet days below q95(s) were allowed; the metric is therefore a dry-to-heavy-rain transition within a window, not necessarily an immediate transition.

Only the first qualifying heavy-rain day was assigned to a dry spell. Later qualifying days in the same multi-day sequence did not create additional detections. The event date was that first qualifying day and determined the event year and month.

Sensitivity analysis crossed three minimum dry durations, 7, 10, and 15 days, with two transition windows, 7 and 14 days. All six definitions used the station-specific wet-day 95th percentile as the following-rain threshold. The primary definition was specified before comparing event counts and was not selected because it produced a particular trend. The full threshold matrix is reported with the results (**Equation 10**).

$$E_{s,j} = I\left(L_{s,j} \geq D, 1 \leq \Delta_{s,j} \leq W, H_{s,j} \geq q_{95,s}\right) \quad (10)$$

where Esj identifies a transition after dry spell *j* at station *s*; L_{sj} is the dry-spell duration; D is the minimum duration; $\Delta_{s,j}$ is the lag to the first qualifying rain day; W is the transition window; H_{sj} is rainfall on that day; and $q_{95,s}$ is the station-specific threshold.

Rare-event uncertainty was evaluated using 20,000 stratified year bootstraps of the early-late count difference and rate ratio, and by 20,000 permutations of year labels. Poisson regressions used station fixed effects with standard errors clustered by year to account partially for storms observed at multiple stations. Dispersion and rate ratios with 95% confidence intervals are reported. Detections were also grouped using 0-, 1-, and 3-day tolerances to quantify network overlap.

2.5. Trend magnitude inference and multiplicity

Trend magnitude was estimated with Sen's median pairwise slope[34] and reported per decade. Two-sided 95% confidence intervals were obtained from the ordered pairwise slopes. The main text reports the seven core indices.

Mann–Kendall inference used the standard Hamed–Rao variance correction based on significant autocorrelations of the detrended rank series.[35] The raw correction factor was calculated exactly as in **Equations 11–15**. We then applied a separately identified, pre-specified variance-inflation-only safeguard, $c_{applied} = \max(1, c_{raw})$, because sub-unit or negative estimates in a 24-year series would deflate the null variance. This safeguard is not part of the original Hamed–Rao method. Raw and applied factors are reported with the trend results. Prewhitening was not used because it can alter hydroclimatic trend magnitude and significance.[36]

For each index, four station-wise *p*-values were adjusted with the Benjamini-Hochberg procedure.[37] After sorting $p(1) \leq ... \leq p(m)$, adjusted values were $q(i) = \min[1, \min(j \geq i)\{m\ p(j)/j\}]$ and then restored to the original station order. $q < 0.10$ was interpreted as network field evidence. Adjustment was not performed across the 13 indices or across the seven ENSO lags; those cross-index and lag-screening comparisons are explicitly exploratory and their *p*-values nominal.

$$\hat{\beta} = median_{(i<j)}\left(\frac{X_j - X_i}{j - i}\right) \tag{11}$$

where beta-hat is Sen's slope, X_i and X_j are annual index values, and the median is taken over all pairs with $i < j$.

$$S = \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} sgn\left(X_j - X_i\right) \tag{12}$$

where S is the Mann–Kendall score and $sgn\left(X_j - X_i\right)$ equals −1, 0, or 1 according to the sign of its argument.

$$Var\left(S\right) = \frac{n\left(n-1\right)\left(2n+5\right) - \sum_p t_p\left(t_p - 1\right)\left(2t_p + 5\right)}{18} \tag{13}$$

where Var(S) is the null variance, n is the record length, and t_p is the size of tie group p, with the summation over all distinct tie groups.

$$Var^*\left(S\right) = Var\left(S\right) \times \left[1 + \frac{2\sum\left(k = 1\ to\ n-1\right)\left(n-k\right)\left(n-k-1\right)\left(n-k-2\right)\rho_k}{n\left(n-1\right)\left(n-2\right)}\right] \tag{14}$$

where rho_k is a significant lag-k autocorrelation of the detrended rank series. The bracketed term is the raw Hamed–Rao correction factor c_{raw}; the separately applied safeguard used $c_{applied} = \max(1, c_{raw})$.

$$q_{(i)} = min\left[1, min_{j \geq i}\left\{\frac{m\ p_{(j)}}{j}\right\}\right], i = m, \ldots, 1 \tag{15}$$

where $p(i)$ is the i-th ordered *p*-value, $m = 4$ station tests within an index, and the reverse cumulative minimum ensures monotonic adjusted q values.

2.6. Niño-3.4 analysis

Monthly Niño-3.4 sea-surface-temperature anomalies were obtained from the US National Oceanic and Atmospheric Administration Climate Prediction Center.[38] September–December was used for every station to preserve inter-station comparability and to represent the shared late-year rainfall season, even though local monthly maxima differed. PRCPTOT, Rx1day, Rx5day, SDII, and annual transition counts were screened at leads of zero to six months.

Spearman correlation was computed as the Pearson correlation of average (mid-) ranks using SciPy, so tied transition counts were handled explicitly (**Equation 16**). For every station-metric pair, the lag with the largest absolute correlation and the full lag surface are reported with the results. All associated *p*-values are nominal because the lag was selected from seven candidates.

$$\rho_s = \frac{\sum\left(Rxi - Rx\right)\left(Ryi - Ry\right)}{\sqrt{\left[\sum\left(Rxi^2 - Rx\right)\ \sum\left(Ryi - Ry\right)\ \right]}} \tag{16}$$

where R_x and R_y are average ranks, including midranks for tied values.

2.7. Climate Hazards Center InfraRed Precipitation with Stations gridded-product comparison

Daily CHIRPS v2.0 rainfall at the 0.05-degree grid cell intersecting Nam Dan (18.483333 N, 105.483333 E) was analyzed for the identical 1998–2021 dates.[39] Daily bias, percent bias, mean absolute error, root mean square error (RMSE), Pearson and Spearman correlations, and wet-day contingency scores were calculated. Annual PRCPTOT, WetDays, SDII, CDD, CWD, Rx1day, and Rx5day were compared before and after a single multiplicative mean-bias factor derived over the full common period. The primary transition algorithm was then applied with each series' own wet-day P95, and event dates were matched within 0, 1, and 3 days. Because CHIRPS blends satellite estimates with gauge information, this is an external gridded comparison rather than fully independent validation.

2.8. Reproducibility and analytical limits

Processing and analysis were performed in Python (3, Python Software Foundation, Netherlands) using pandas, NumPy, SciPy, openpyxl, and Matplotlib. The exact script, annual indices, station-level transition catalog, trend outputs, uncertainty analyses, Nam Dan sensitivity tests, and matched CHIRPS series accompany the revision. The primary station files remain subject to provider redistribution permission.

The analysis did not estimate return periods because 24 annual maxima provide limited tail information,[27] and it did not fit a predictive ENSO model or conduct causal climate attribution. The four-station network cannot support province-wide interpolation.

3. Results

3.1. Data integrity and seasonal rainfall structure

All four series contained 8,766 calendar-day observations. Wet-day counts ranged from 2,309 at Nam Dan to 2,602 at Dua, while mean annual wet-day rainfall ranged from 1,716.6 to 1,829.5 mm (Table 3). Nam Dan had the highest wet-day P95 and P99 thresholds, 74.1 and 187.7 mm.

Under proportional redistribution of the three source-total discrepancies, the largest annual changes were 10.0 mm in PRCPTOT, 0.13 mm wet per day in SDII, 2.0 mm in Rx1day, and 5.0 mm in Rx5day; WetDays, CDD, CWD, and the 14 transition detections were unchanged. Treating all three months as missing left 22 complete years and also retained 14 transitions.

Seasonality also differed systematically across the network (Figure 2). September had the highest mean rainfall at Do Luong and Dua, whereas Nam Dan and Yen Thuong peaked in October. The September–December share rose from 42.7% at Dua and 47.3% at Do Luong to 55.5% at Nam Dan and 55.3% at Yen Thuong, revealing an eastward concentration toward the late-year wet season. Interannual variability was greatest in the same high-rainfall months. Consequently, a single fixed wet-season window would combine dissimilar local regimes and could obscure the timing of extremes.

Annual wet-day rainfall fluctuated strongly, with positive central estimates at all stations (Figure 3). Dua and Yen Thuong had Sen slopes of 268.6 and 221.0 mm per decade, with within-index $q = 0.070$; Do Luong and Nam Dan did not retain $q < 0.10$ (Table 4). These results describe two station-specific signals, not a province-wide trend.

3.2. Intensification without an increase in wet-day frequency

WetDays showed no detectable trend at any station. SDII increased by 3.03 mm per wet day per decade at Do Luong and 2.24 at Dua (both $q = 0.01$), indicating more rainfall per wet day rather than more wet days. CWD increased at Dua (1.67 days per decade, $q = 0.03$), Nam Dan (1.54, $q = 0.04$), and Yen Thuong (2.00, $q = 0.01$). All confidence intervals, raw p-values, q-values, and variance factors are reported in Table 4.

Annual maxima were large but episodic (Figure 4). Do Luong recorded Rx1day = 508.6 mm and Rx5day = 839.5 mm in 2020; Nam Dan reached Rx5day = 780.2 mm in 2010, and Yen Thuong reached 684.1 mm in 2020. No Rx1day or Rx5day trend was retained at $q < 0.10$. Thus, exposure to exceptional events is evident, but a smooth

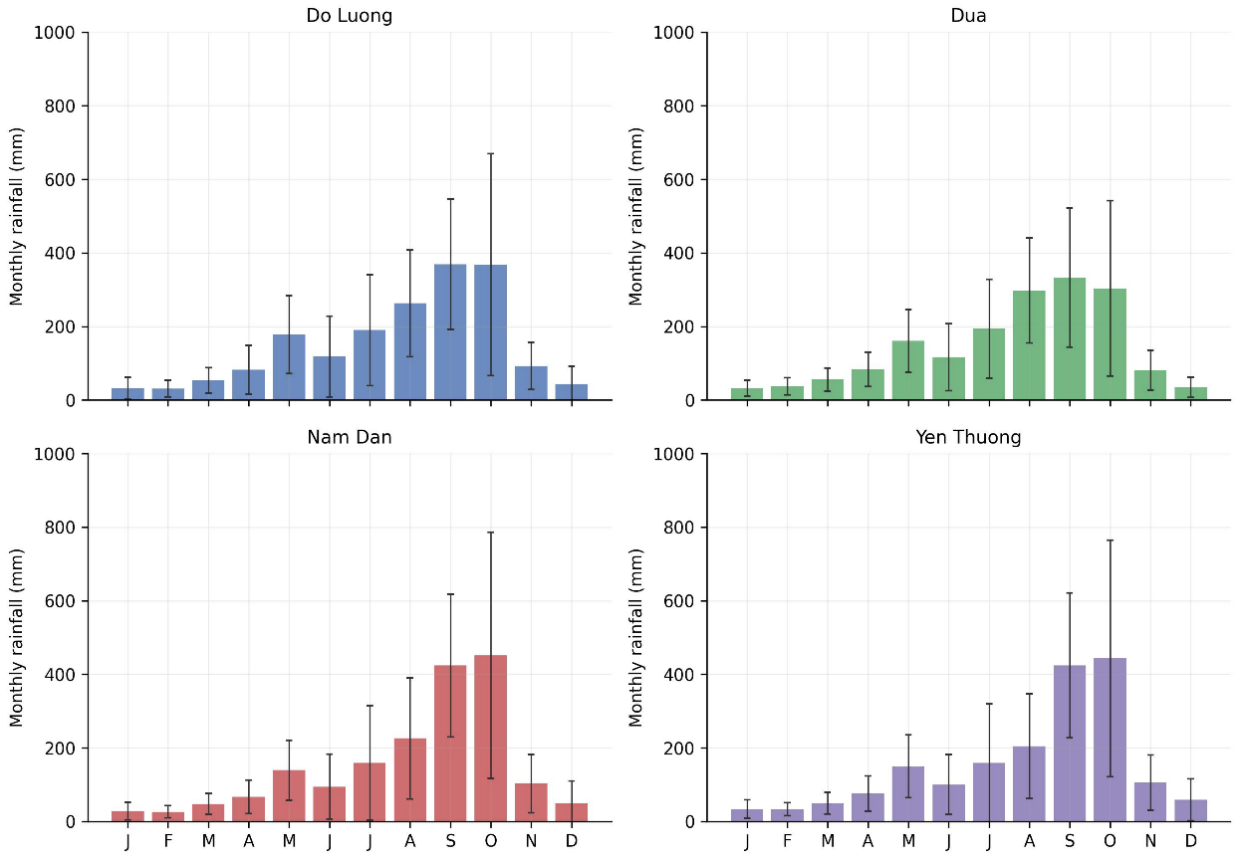


Figure 2. Mean calendar-month rainfall and interannual standard deviation at the four stations during 1998–2021

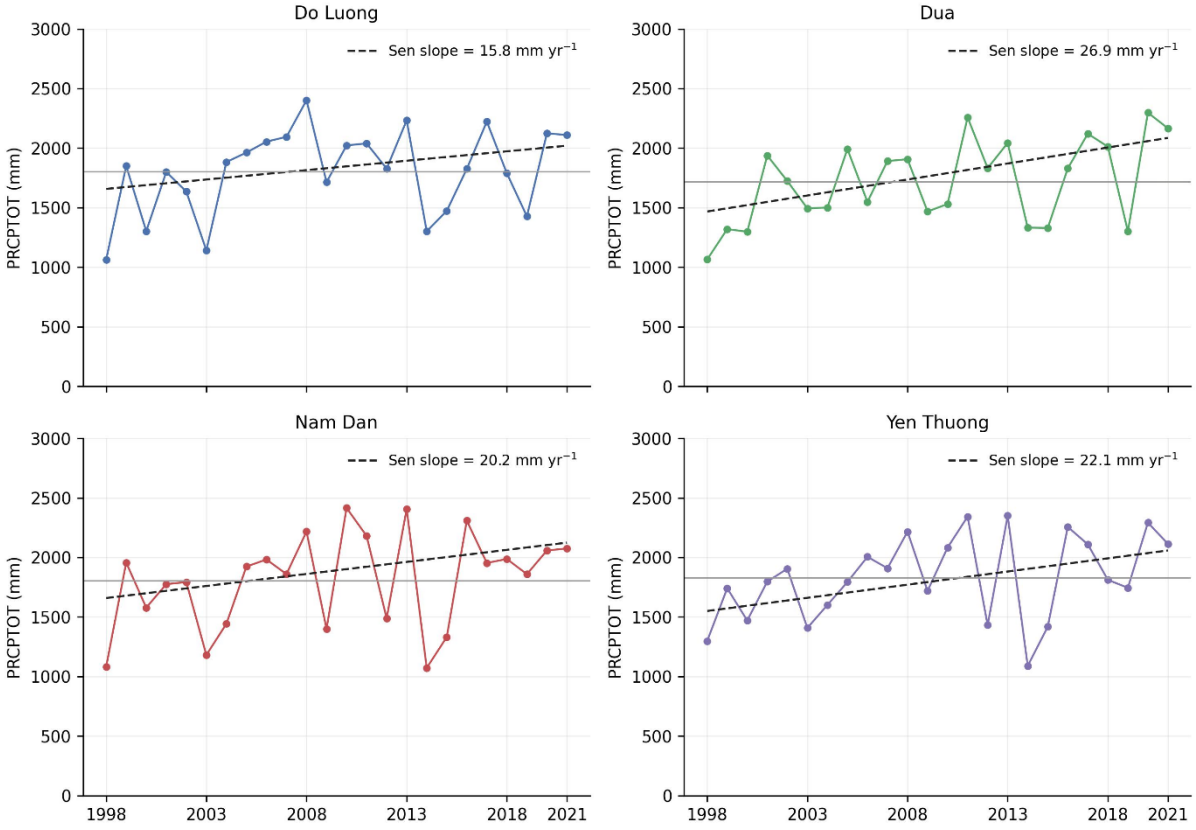


Figure 3. Annual total wet-day rainfall and Sen trend lines. The plotted slopes are descriptive effect estimates; statistical results and false discovery rate-adjusted *q* values are reported in Table 4.
Abbreviation: PRCPTOT: Annual total wet-day precipitation.

Table 3. Annual rainfall-index distributions during 1998–2021

Station	PRCPTOT mean (SD)	Wet days mean (SD)	Rx1day median (IQR)	Rx5day median (IQR)	SDII mean (SD)	CDD median (max)	CWD median (max)
Do Luong	1804.2 (359.7)	103.8 (14.8)	173.1 (131.6–255.3)	335.1 (263.9–401.2)	17.5 (3.2)	20 (41)	8 (14)
Dua	1716.6 (352.3)	108.4 (12.1)	156.2 (144.7–192.2)	299.4 (247.6–352.7)	15.8 (2.8)	21 (35)	8 (12)
Nam Dan	1805.4 (400.5)	96.2 (14.0)	220.2 (153.3–281.7)	384.0 (261.2–464.9)	18.8 (3.9)	24 (35)	8 (15)
Yen Thuong	1829.5 (354.6)	104.4 (12.9)	211.1 (149.2–292.9)	402.2 (273.1–482.9)	17.6 (3.4)	22 (35)	8 (12)

Abbreviations: CDD: Consecutive dry days; CWD: Consecutive wet days; IQR: Interquartile range; PRCPTOT: Annual total wet-day precipitation; SD: Standard deviation; SDII: Simple daily intensity index.

network-wide rise in annual maxima is not. Figure 5 shows annual maximum dry- and wet-spell durations.

3.3. Dry-to-wet transitions: Timing, change, and sensitivity

The primary rule detected 58 station-level transitions, not 58 independent regional storms (Table 5). Grouping identical event dates produced 41 clusters, including 11 multi-station clusters; tolerances of one and three days produced 39 and 34 clusters. Fifty detections (86.2%) occurred during May–October. Dry duration, lag, and following-rain magnitude remained distinct event attributes (Figure 6).

Station-level detections rose from 18 in 1998–2009

Table 4. Core-index Sen slopes, confidence intervals, modified Mann–Kendall inference, and within-index *q* values

Station	Index	Slope	95% CI	*p*	*q*	c_{raw}	$c_{applied}$	Lags
Do Luong	PRCPTOT	157.6	−47.5 to 389.4	0.11	0.11	1.00	1.00	None
Dua	PRCPTOT	268.6	24.2 to 472.4	0.02	0.07	1.00	1.00	None
Nam Dan	PRCPTOT	202.2	−26.4 to 443.5	0.07	0.10	1.00	1.00	None
Yen Thuong	PRCPTOT	221.0	8.4 to 451.8	0.03	0.07	1.00	1.00	None
Do Luong	WetDays	−7.8	−16.0 to 2.7	0.11	0.47	1.00	1.00	None
Dua	WetDays	−1.2	−8.8 to 9.1	0.76	0.94	1.00	1.00	None
Nam Dan	WetDays	0.0	−6.6 to 11.8	0.94	0.94	1.00	1.00	None
Yen Thuong	WetDays	−1.0	−8.0 to 8.0	0.84	0.94	1.00	1.00	None
Do Luong	SDII	3.0	1.2 to 4.7	0.001	0.01	1.00	1.00	None
Dua	SDII	2.2	0.6 to 3.7	0.001	0.01	1.00	1.00	None
Nam Dan	SDII	1.6	−0.9 to 4.3	0.26	0.26	1.00	1.00	None
Yen Thuong	SDII	1.9	−0.2 to 3.9	0.09	0.12	0.67	1.00	6
Do Luong	CDD	−0.7	−5.0 to 3.1	0.70	0.94	1.00	1.00	None
Dua	CDD	−1.1	−5.0 to 2.0	0.49	0.94	1.00	1.00	None
Nam Dan	CDD	0.0	−3.7 to 5.0	0.94	0.94	1.00	1.00	None
Yen Thuong	CDD	0.5	−4.3 to 5.4	0.84	0.94	1.00	1.00	None
Do Luong	CWD	0.5	0.0 to 2.1	0.27	0.27	−0.05	1.00	2,8
Dua	CWD	1.6	0.0 to 2.8	0.01	0.03	1.00	1.00	None
Nam Dan	CWD	1.5	0.0 to 2.5	0.03	0.04	1.00	1.00	None
Yen Thuong	CWD	2.0	0.7 to 3.3	0.003	0.01	0.41	1.00	3
Do Luong	Rx1day	22.1	−34.6 to 98.0	0.47	0.47	1.00	1.00	None
Dua	Rx1day	14.1	−18.1 to 50.6	0.47	0.47	1.00	1.00	None
Nam Dan	Rx1day	49.1	−13.3 to 98.5	0.18	0.47	0.53	1.00	5
Yen Thuong	Rx1day	26.4	−23.8 to 89.8	0.26	0.47	0.54	1.00	5
Do Luong	Rx5day	41.0	−33.9 to 131.4	0.45	0.45	1.66	1.66	2
Dua	Rx5day	29.1	−34.0 to 95.7	0.20	0.41	1.00	1.00	None
Nam Dan	Rx5day	69.8	−3.6 to 146.0	0.05	0.22	1.00	1.00	None
Yen Thuong	Rx5day	46.0	−64.0 to 124.3	0.33	0.44	1.00	1.00	None

Notes: Slopes and confidence limits are per decade; c_{raw} is the standard Hamed–Rao correction factor; $c_{applied} = \max(1, c_{raw})$ is the separately identified variance-inflation-only safeguard; Benjamini–Hochberg *q*-values are computed across four stations within each index.
Abbreviations: CI: Confidence interval; CDD: Consecutive dry days; CWD: Consecutive wet days; PRCPTOT: Annual total wet-day precipitation; SDII: Simple daily intensity index.

to 40 in 2010–2021 (rate ratio 2.22). A stratified year bootstrap gave a 95% interval of 1.10–4.90 for the ratio and 3–41 detections for the difference; permutation of year labels gave $p = 0.056$. Poisson regression with station fixed effects and year-clustered robust standard errors estimated a rate ratio of 2.02 per decade (95% confidence interval 1.29–3.16, $p = 0.005$), with dispersion 0.79. The corresponding late-period model gave 2.22 (1.07–4.61, $p = 0.043$). Because only 24 years were observed, stations shared storms, and station-wise Sen slopes were zero with no $q < 0.10$, these models quantify recent clustering rather than establish a persistent monotonic trend. Threshold

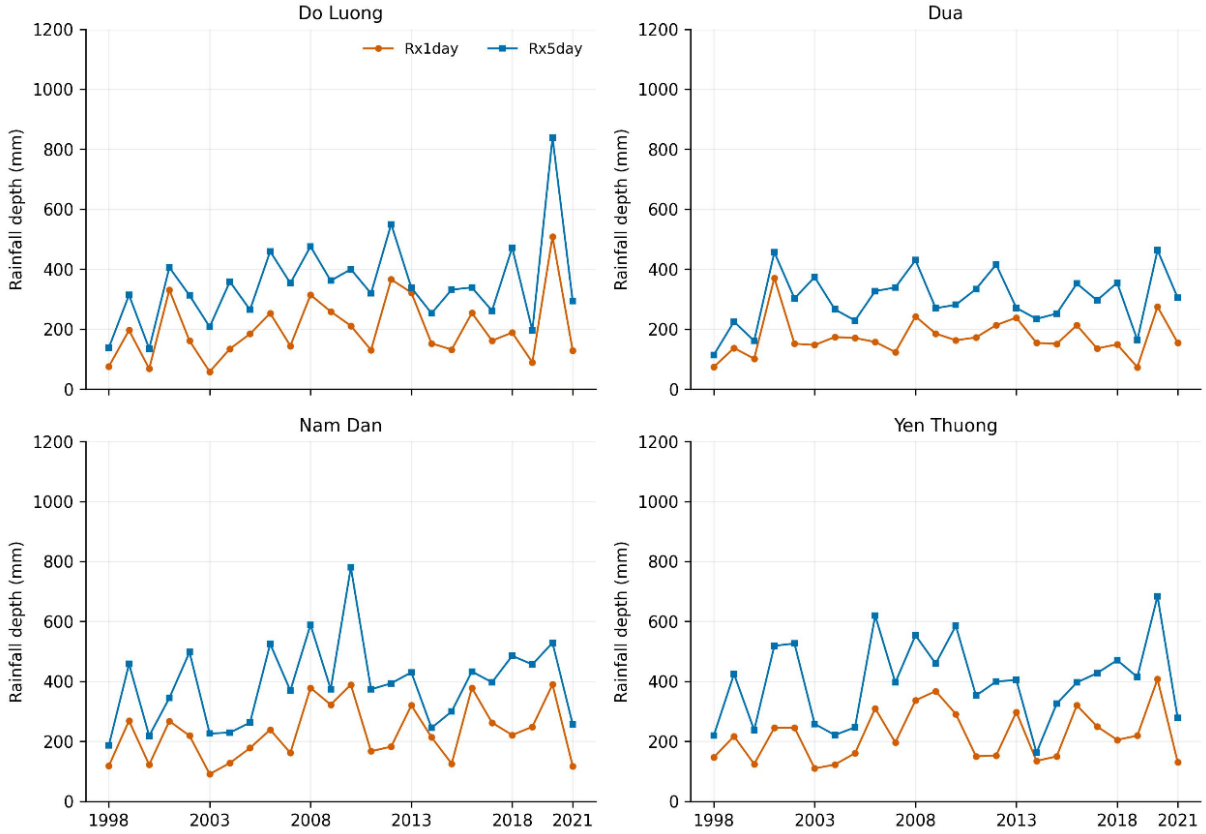


Figure 4. Annual maximum one-day (Rx1day) and consecutive five-day (Rx5day) rainfall at the four stations

Table 5. Dry-to-wet transition characteristics under the primary definition

Station	Events	Rate/year	Dry duration (day)	Following rain (mm)	1998–2009	2010–2021	MK *p*
Do Luong	13	0.54	11	115.4	4	9	0.127
Dua	16	0.67	13	78.7	5	11	0.064
Nam Dan	14	0.58	14	96.5	4	10	0.048
Yen Thuong	15	0.62	13	106.0	5	10	0.165

Notes: Primary rule: at least 10 consecutive days below 1 mm followed within seven days by the first rainfall day at or above the station-specific wet-day P95; rows are station-level detections; shared dates may represent one storm; Man–Kendall (MK) *p*-values are local, and no station retained $q < 0.10$.

sensitivity remained large: totals ranged from 13 to 166. The complete threshold matrix is presented in Table 6.

3.4. Niño-3.4 associations

September–December rainfall was negatively correlated with Niño-3.4 at each station's strongest selected lag (rho = −0.287 to −0.349), but all *p*-values were nominal, and the full seven-lag surface lacked a coherent network pattern (Figure 7). The same caveat applies to the selected Do Luong transition-count result (rho = 0.411, $p = 0.046$). No predictive or causal ENSO claim is made. Table 7 reports the strongest selected lag for each station-metric pair.

3.5. Climate Hazards Center InfraRed Precipitation with Stations comparison at Nam Dan

Figure 8 illustrates the first-qualifying-day assignment used to compare event dates. For 8,766 matched days, CHIRPS had percent bias −13.2%, RMSE 17.7 mm per day, Pearson $r = 0.47$, and Spearman rho = 0.329. Annual PRCPTOT correlation was $r = 0.80$, whereas SDII was

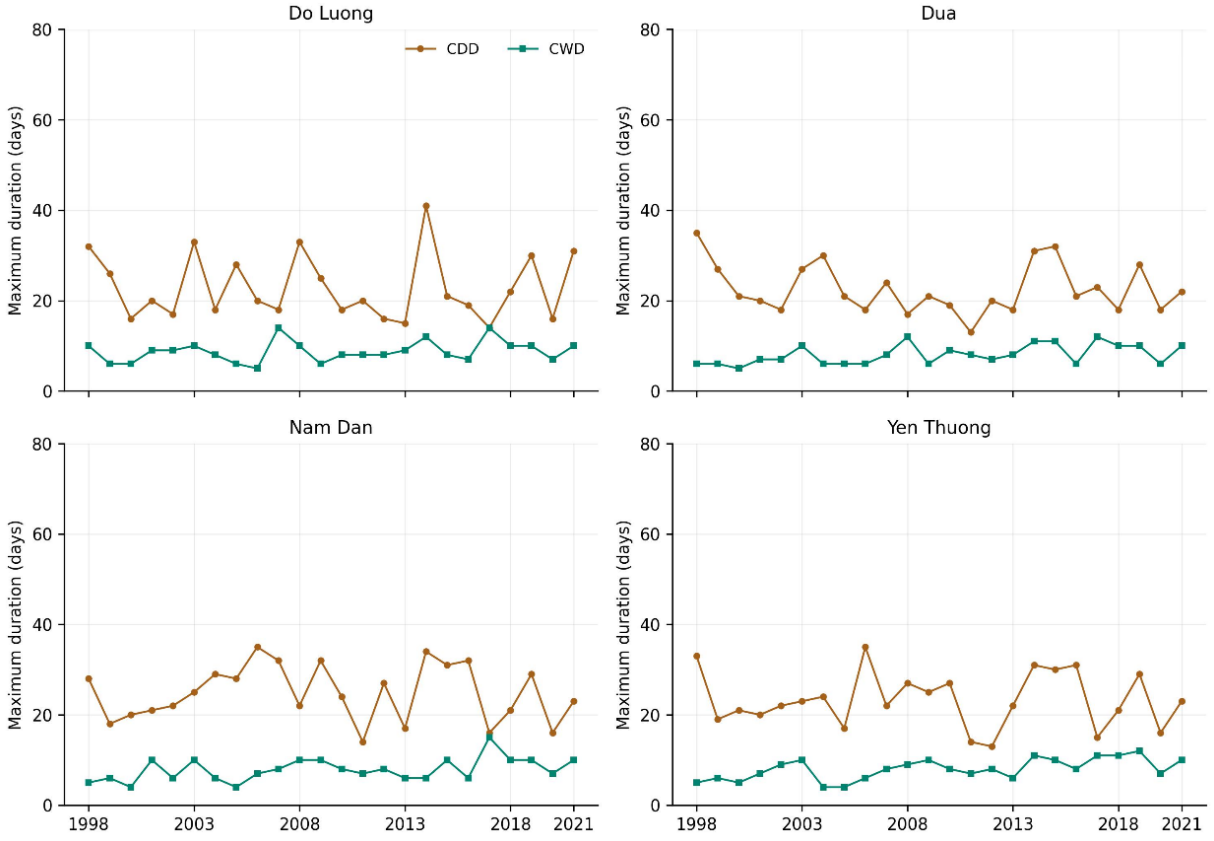


Figure 5. Annual maximum consecutive dry day (CDD) and consecutive wet day (CWD) durations. A wet day is defined as a day with at least 1 mm of rainfall.

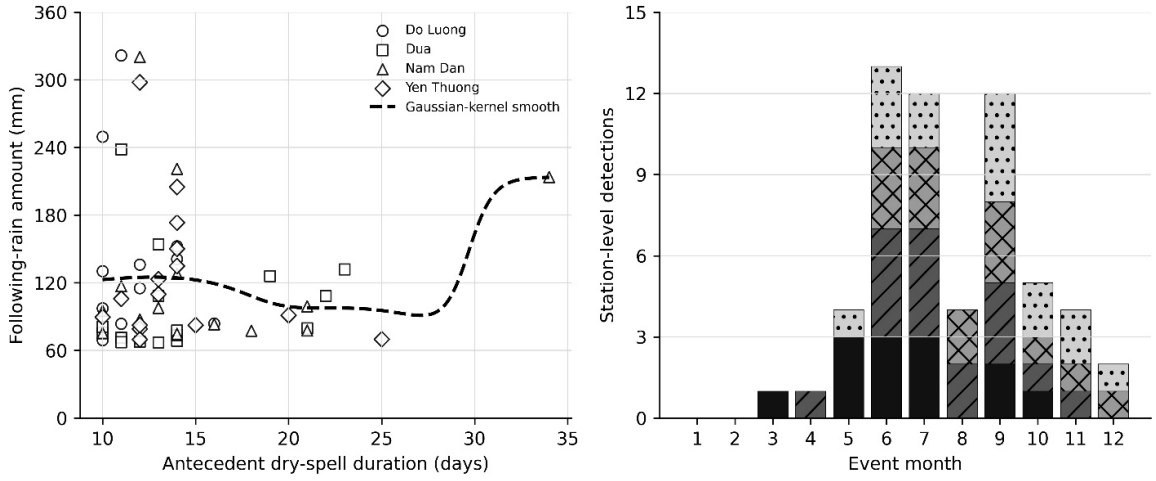


Figure 6. Station-level transition characteristics under the primary definition. Symbols identify stations; the dashed line is a Gaussian-kernel smooth. Stacked bars use greyscale and hatching. Detections sharing dates may represent the same storm.

underestimated by 17.2%, Rx1day by 55.9%, and Rx5day by 46.2% (Table 8; Figure 9). Mean-bias scaling reduced annual PRCPTOT bias to 0.6% and SDII bias to −4.7%, but annual correlations and timing were essentially unchanged. Using series-specific P95 thresholds, the gauge and CHIRPS detected 14 and 13 transitions, respectively;

Table 6. Sensitivity of event counts to dry-spell and transition-window thresholds

Dry days	Window (day)	Do Luong	Dua	Nam Dan	Yen Thuong	Network total
7	7	31	33	25	27	116
7	14	45	47	33	41	166
10	7	13	16	14	15	58
10	14	18	21	18	20	77
15	7	1	4	5	3	13
15	14	2	8	7	4	21

Note: All definitions use the station-specific wet-day 95th percentile as the following-rainfall threshold.

Table 7. Strongest Niño-3.4 lag association for each station and rainfall metric

Station	Metric	Lead (months)	Spearman rho	*p*-value
Do Luong	Transition count	0	0.411	0.046
Dua	Transition count	5	0.313	0.136
Nam Dan	Transition count	1	0.299	0.155
Yen Thuong	Transition count	3	0.111	0.606
Do Luong	Sep–Dec PRCPTOT	6	−0.305	0.148
Dua	Sep–Dec PRCPTOT	0	−0.287	0.174
Nam Dan	Sep–Dec PRCPTOT	2	−0.349	0.095
Yen Thuong	Sep–Dec PRCPTOT	2	−0.306	0.146
Do Luong	Sep–Dec Rx1day	6	−0.143	0.506
Dua	Sep–Dec Rx1day	6	−0.140	0.514
Nam Dan	Sep–Dec Rx1day	2	−0.220	0.302
Yen Thuong	Sep–Dec Rx1day	5	0.096	0.657
Do Luong	Sep–Dec Rx5day	6	−0.170	0.428
Dua	Sep–Dec Rx5day	5	−0.243	0.252
Nam Dan	Sep–Dec Rx5day	1	−0.173	0.419
Yen Thuong	Sep–Dec Rx5day	1	−0.097	0.654
Do Luong	Sep–Dec SDII	6	−0.261	0.219
Dua	Sep–Dec SDII	6	−0.334	0.111
Nam Dan	Sep–Dec SDII	2	−0.244	0.250
Yen Thuong	Sep–Dec SDII	4	−0.229	0.282

Notes: For each station-metric pair, the largest absolute correlation among seven screened leads is shown; *p*-values are nominal and not adjusted for lag selection; the full surface is shown in Figure 7.
Abbreviations: PRCPTOT: Annual total wet-day precipitation; SDII: Simple daily intensity index.

only one event matched within three days. Similar aggregate counts therefore did not demonstrate daily event agreement.

4. Discussion

4.1. The importance of frequency-intensity separation

Stable wet-day counts alongside rising SDII at Do Luong and Dua indicate wet-day intensification, while longer CWD at three stations indicates greater persistence once wet conditions were established. These components may influence runoff, erosion, or soil wetness, but no hydrologic or agricultural impact was measured. The separation is consistent with evidence that intensity, duration, and occurrence frequency can evolve semi-independently.[2-4] Studies of temperature-related precipitation asymmetry provide broader context; this four-station analysis does not

Table 8. Annual gauge-CHIRPS comparison at Nam Dan

Metric	Gauge mean	CHIRPS mean	Bias	Bias (%)	RMSE	Pearson *r*
PRCPTOT	1805.42	1575.42	−230.01	−12.7	340.21	0.808
WetDays	96.21	101.38	5.17	5.4	15.09	0.303
SDII	18.85	15.60	−3.24	−17.2	4.74	0.453
CDD	24.83	27.29	2.46	9.9	8.65	0.379
CWD	7.88	9.00	1.12	14.3	4.03	−0.105
Rx1day	229.65	101.36	−128.29	−55.9	156.43	0.296
Rx5day	390.07	209.80	−180.27	−46.2	213.42	0.568

Notes: Raw CHIRPS values are shown; bias is CHIRPS minus gauge.
Abbreviations: CHIRPS: Climate Hazards Center InfraRed Precipitation with Stations; CDD: Consecutive dry days; CWD: Consecutive wet days; PRCPTOT: Annual total wet-day precipitation; RMSE: Root mean square error; SDII: Simple daily intensity index.

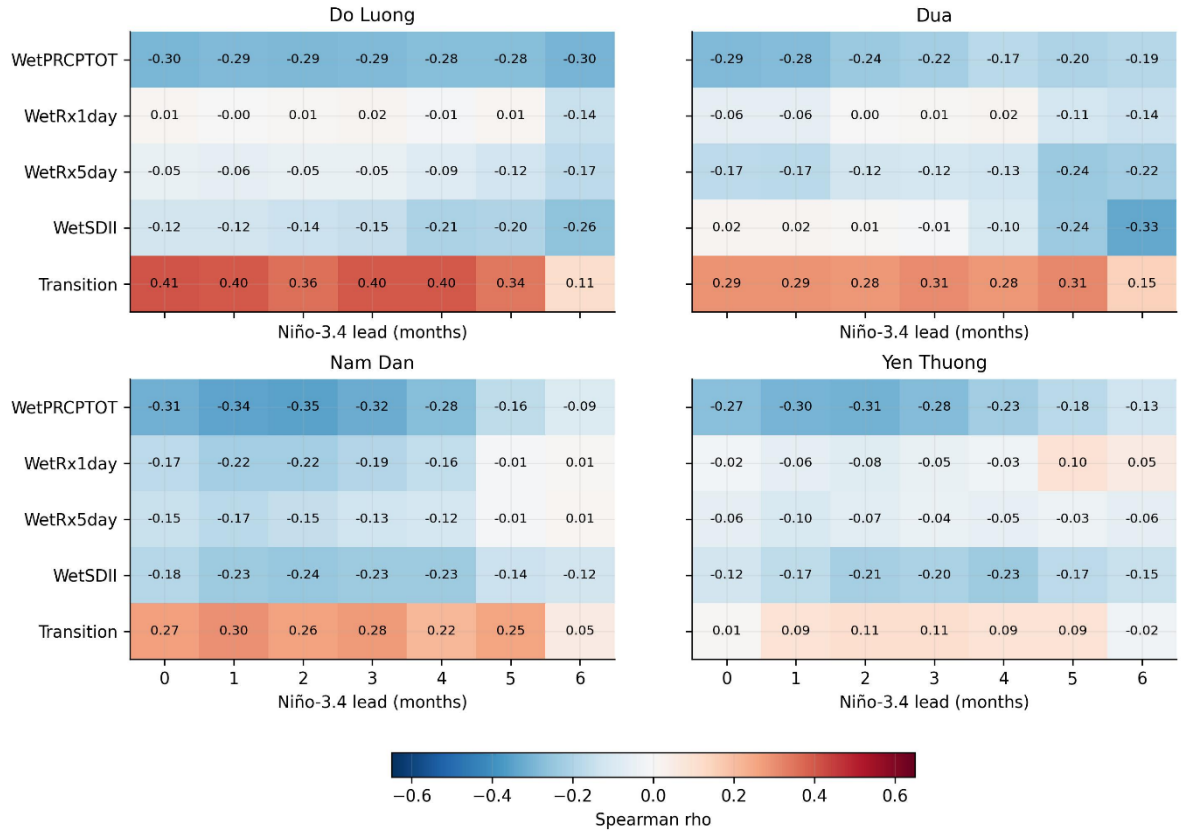


Figure 7. Spearman correlations between rainfall metrics and Niño-3.4 anomalies at leads of zero to six months. Correlations are exploratory and are not interpreted as causal attribution.

test global forcing.[28]

The within-province contrasts sharpen this interpretation. Dua combined increased annual wet-day rainfall with increasing SDII; Do Luong showed SDII intensification without annual rainfall change, which remained significant after field adjustment; and Yen Thuong combined higher annual rainfall with longer wet spells. Nam Dan had the heaviest percentile thresholds but

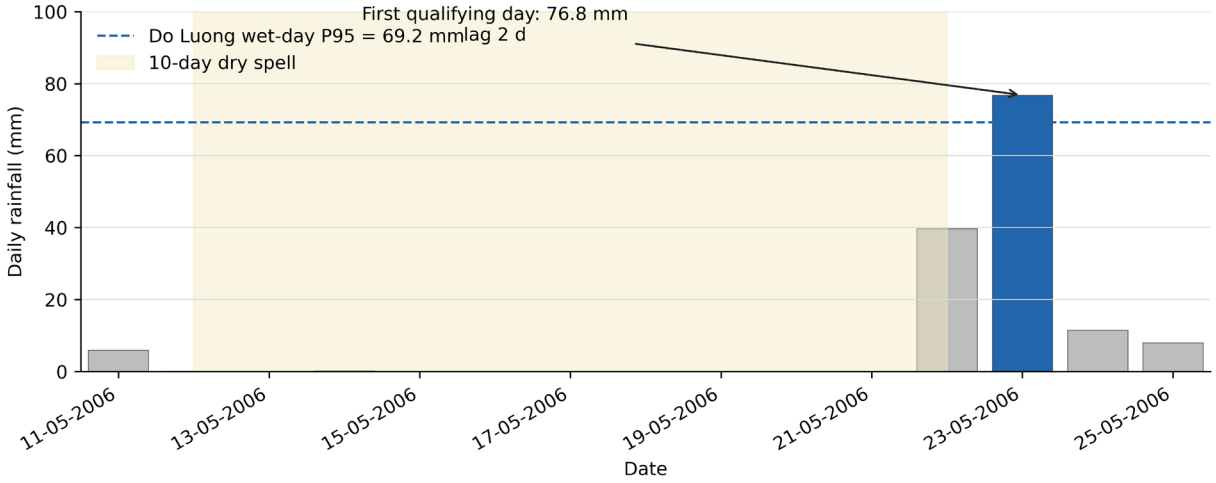


Figure 8. Observed Do Luong transition ending on May 23, 2006. Bars show daily rainfall; shading marks the qualifying dry spell and transition window. The first day reaching the station-specific P95 is assigned as the event date.

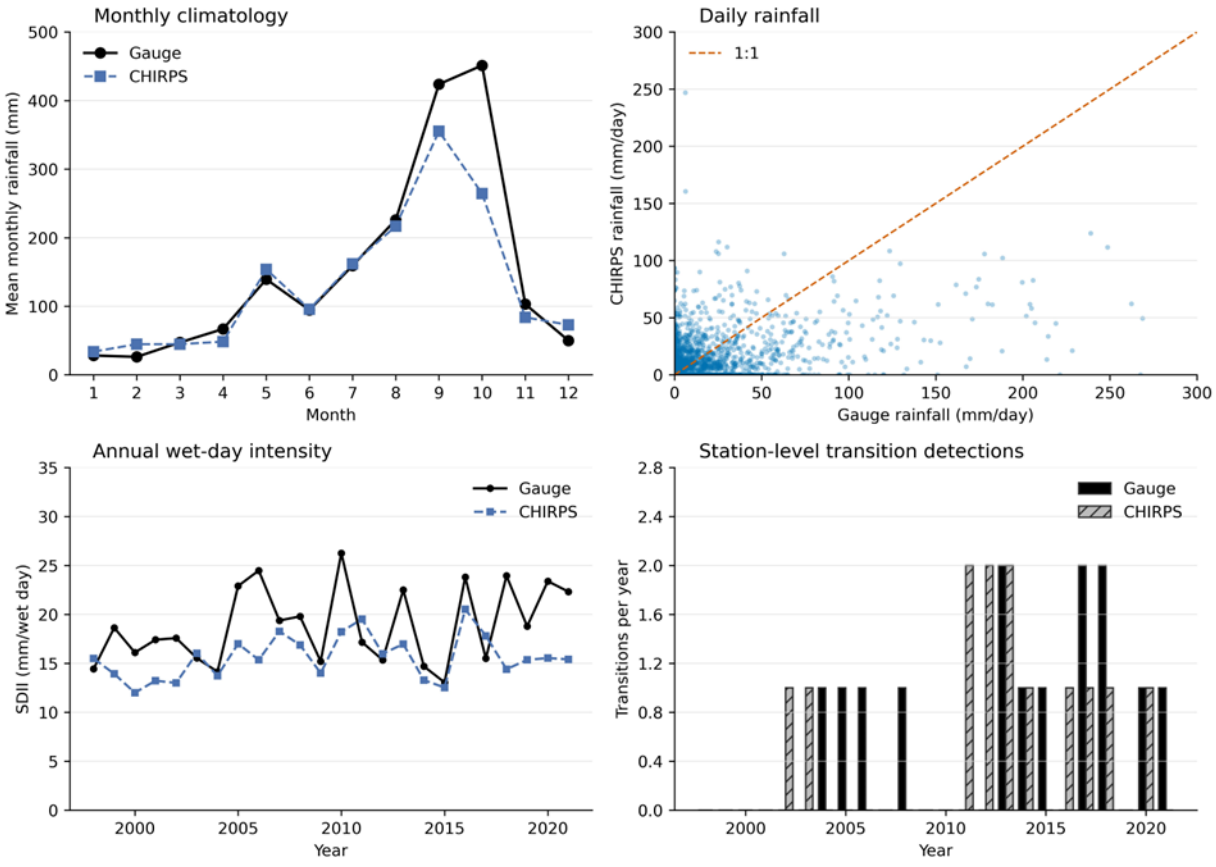


Figure 9. CHIRPS evaluation at Nam Dan, 1998–2021. Panels compare annual PRCPTOT and SDII, daily rainfall density, and gauge/CHIRPS transition dates. CHIRPS reproduces annual totals better than daily extremes or event timing.
Abbreviations: CHIRPS: Climate Hazards Center InfraRed Precipitation with Stations; PRCPTOT: Annual total wet-day precipitation; SDII: Simple daily intensity index.

no corresponding monotonic intensity signal. A network mean would flatten these physically different pathways. The eastward shift from September to October rainfall maxima further suggests that topography, storm approach, and seasonal circulation partition rainfall differently across short distances, consistent with documented Vietnamese variation in coastal drought, rainy-season timing, and rainfall-based flood hazards.[23-25]

Exceptional annual maxima require a separate reading. The absence of a field-adjusted Rx1day or Rx5day trend is not evidence of no hazard; it shows only that ordered monotonic change was not detected in 24 annual values. Distributional skewness and tail estimates are record sensitive.[27]

4.2. Added value and limits of the sequence-aware metric

The transition analysis addresses information that annual totals and SPI necessarily discard: the order and interval between dry and heavy-rain conditions. SPI represents accumulated precipitation anomaly at a chosen time scale; it cannot distinguish heavy rainfall arriving two days after a dry run from the same amount arriving several weeks later. Conversely, the present event detector does not measure cumulative water deficit, soil-water stress, discharge, or inundation. Its value is therefore complementary to the earlier SPI analysis,[26] not a replacement for it. This distinction clarifies the complementary contribution of sequence-based diagnostics relative to accumulated drought indices.

The station-level detections establish recurrence of rapid dry-to-heavy-rain sequencing, but precipitation sequence is only a hazard proxy. Soil-water state, structure, management, rooting conditions, antecedent storage, and routing determine whether a sequence produces stress, beneficial recharge, or damaging flow. Field evidence from semi-arid vineyards shows that tillage-related changes in soil physical and hydraulic conditions can alter infiltration and water movement.[40] These considerations support local calibration against soil moisture, discharge, crop development, loss, and inundation rather than direct impact claims.

The 18-to-40 contrast was consistent in direction across stations, and count models produced positive rate ratios, but the bootstrap interval was wide, and the permutation result was borderline. Same-day grouping reduced 58 station detections to 41 date clusters. Additional years and denser station or impact networks are needed to determine whether recent clustering persists and to separate shared storms from site-specific responses.

Threshold sensitivity is itself a substantive result. Changing dry duration and transition window altered the network total by more than an order of magnitude, confirming concerns that drought-to-flood frequency is definition dependent.[7,10,11] The stable relative prominence of Dua is consequently more credible than any one absolute total. For operational adoption, thresholds should be calibrated against observed crop loss, soil moisture, streamflow, reservoir levels, road disruption, or inundation. That calibration would convert an auditable meteorological screen into an impact-relevant warning rule without constructing an unvalidated composite severity score.

4.3. Regional controls and cautious El Niño–Southern Oscillation interpretation

Weak and lag-sensitive Niño-3.4 correlations are plausible rather than anomalous. Southeast Asian rainfall integrates ENSO type, interbasin interactions, intraseasonal oscillations, monsoon state, and tropical cyclones.[19,21,22] The Do Luong coefficient was nominally significant only after selecting the strongest of seven lags and was neither spatially replicated nor stable across neighboring lags. Treating it as predictive would therefore capitalize on multiple exploration. The heatmap pattern is more informative: it shows no coherent network-wide lag structure and indicates that ENSO alone cannot explain the observed station contrasts.

4.4. Monitoring implications, limitations, and next tests

A compact meteorological screening set comprises PRCPTOT, WetDays, SDII, CDD, CWD, and a transition alert retaining dry duration, lag, and forecast rainfall. Gauge percentiles should anchor local thresholds. At Nam Dan, raw CHIRPS underestimated daily mean rainfall by 13.2% (RMSE 17.7 mm per day) but reproduced annual PRCPTOT variability relatively well (r = 0.80). It underestimated annual SDII by 17.2%, Rx1day by 55.9%, and Rx5day by 46.2%. Multiplicative scaling reduced PRCPTOT bias to 0.6% and SDII bias to −4.7% but did not restore daily event timing (Figure 9; Table 8).

Inference is bounded by four stations, 24 annual observations, incomplete metadata, three source-total discrepancies, CHIRPS gauge blending, and no soil-moisture, discharge, impact, or cyclone-track data. CHIRPS produced 13 versus 14 gauge transitions using series-specific P95 thresholds, yet only one gauge event matched within three days. It is therefore an annual-scale robustness check rather than an independent daily-event validator. The record cannot support province-wide interpolation, causal attribution, or revised engineering return levels.[29]

5. Conclusion

Across four southern Nghe An stations in 1998–2021, rainfall change was expressed more clearly through wet-day intensity and wet-spell persistence than through wet-day frequency. SDII increased at Do Luong and Dua, and CWD increased at Dua, Nam Dan, and Yen Thuong after within-index adjustment; annual maxima remained episodic without field-adjusted monotonic trends. The primary rule yielded 58 station-level detections grouped into 41 same-day clusters. The 18-to-40 later-period contrast, bootstrap, and count-model estimates indicate recent clustering within the observed record, but the short record, shared storms, zero station Sen slopes, and lack of adjusted station significance preclude a persistent-trend claim. CHIRPS captured Nam Dan annual PRCPTOT variability (r = 0.80) but underestimated intensity and extremes and matched only one gauge transition within three days. Consequently, the transition rule should be used only as a locally calibrated meteorological screen, not as evidence of observed agricultural or flood damage. Niño-3.4 relationships were weak, lag-selected, and spatially inconsistent. Longer homogenized records, denser spatial coverage, and linked soil-moisture, discharge, crop, and inundation observations are required for stable impact-relevant inference.

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Conflict of interest

The authors declare no conflicts of interest.

Author contributions

Conceptualization: All authors
Formal analysis: All authors
Investigation: All authors
Writing–original draft: All authors
Writing–review & editing: All authors

Availability of data

The primary station rainfall data were provided by the Nghe An Provincial Hydro-Meteorological Center and remain subject to provider permission. To support reproducibility, this revision supplies the complete analytical script, annual index tables, station-level transition catalog, quality-control and sensitivity outputs, and the matched CHIRPS series. CHIRPS is publicly available; requests for redistribution of the primary station records should be directed to the corresponding author in consultation with the provider.

Further disclosure

OpenAI's ChatGPT assisted with English-language editing and drafting analytical code. Numerical results were generated with the documented Python workflow. The authors reviewed the manuscript and remain responsible for its content and conclusions.

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