

Elevation-Dependent Warming and Monsoon Precipitation Intensification in the Northwestern Highlands of Vietnam: A 16-Year Observational Analysis (2009 - 2024)

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Research Article

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Abstract

The Northwestern highlands of Vietnam represent one of Southeast Asia's most climate-sensitive mountain systems, yet long-term observational studies at sub-regional scale remain scarce. This study analyses monthly temperature and precipitation records from eight meteorological stations across the region (2009–2024; $n = 2,880$ station-months) using linear trend analysis, Pearson and Spearman correlation, anomaly decomposition, and inter-station spatial coherence assessment. Statistically significant warming was detected at Phieng Lanh ($+ 0.955^{\circ}\text{C decade}^{-1}$; $R^2 = 0.655$; $p < 0.001$) and Than Uyen ($+ 0.831^{\circ}\text{C decade}^{-1}$; $R^2 = 0.647$; $p < 0.001$), rates exceeding national averages by 3–4 times and consistent with elevation-dependent warming dynamics. An anomalous cooling at Pha Din ($- 0.804^{\circ}\text{C decade}^{-1}$; $p < 0.01$) is attributed to station-level orographic shielding and warrants metadata verification. Total annual precipitation increased significantly at Tuan Giao ($+ 5,656 \text{ mm decade}^{-1}$; $R^2 = 0.927$; $p < 0.001$) and Ta Bu ($+ 2,634 \text{ mm decade}^{-1}$; $R^2 = 0.986$; $p < 0.001$), indicative of intensifying summer monsoon convection. A robust positive temperature–precipitation coupling (Pearson $r = 0.37\text{--}0.62$; all $p < 0.001$) confirmed monsoon dominance of intra-annual variability. These findings provide baseline evidence for climate-adaptive planning, flash-flood risk management, and highland ecosystem conservation.

1. INTRODUCTION

The present study addresses this knowledge gap by providing the first multi-station, 16-year (2009–2024) quantitative analysis of monthly temperature and precipitation records from eight meteorological stations in the Northwestern Vietnamese highlands. Our specific objectives are to: (1) characterise the spatiotemporal distribution of temperature and precipitation across the study region; (2) detect and quantify long-term linear trends at each station and assess their statistical significance; (3) analyse seasonal cycles and inter-annual variability; (4) quantify the temperature–precipitation coupling at the monthly scale; and (5) contextualise findings within current global EDW and monsoon-change literature to inform regional climate adaptation policy.

Despite the well-documented climate sensitivity of mountain systems, sub-regional observational analyses specifically targeting the Vietnamese Northwest highlands are virtually absent from the international literature. Tran and Nguyen (2020) and Do et al. (2020) examined extreme climate trends across Vietnam using national-scale station networks, but their spatial resolution is insufficient to capture the strong orographic gradients of the Northwest. Regional climate projections from CMIP6 (Cook et al., 2020; Almazroui et al., 2021) indicate that mainland Southeast Asia will experience 10–30% increases in wet-season precipitation and continued surface warming by mid-century, yet downscaled, station-based evidence to verify or contextualise these projections at the sub-provincial scale remains limited. Establishing observational baselines is therefore a prerequisite for credible regional impact assessments and adaptation planning (IPCC, 2021a).

Climatic changes in the Northwest highlands translate directly into heightened hydrometeorological hazard. Flash floods and rainfall-triggered landslides are the primary natural disasters affecting the region (Ngo et al., 2023), and multiple catastrophic events in recent years — including the August 2020 Muong Lat landslides (Thanh Hoa Province) and the September 2022 flooding in Lao Cai — have resulted in significant casualties and infrastructure losses. Vu et al. (2022) demonstrated that extreme precipitation indices in Northern Vietnam have intensified over 1981–2018, a pattern amplified by progressive deforestation and agricultural encroachment on steep slopes (Do et al., 2020; Nguyen et al., 2021). The compound vulnerability of climate-sensitive livelihoods and increasing extreme events underscores the urgency of quantifying current climate trends at fine spatial scales.

Vietnam ranks among the world's most climate-vulnerable nations, experiencing significant warming of approximately $0.39^{\circ}\text{C decade}^{-1}$ since 1960 (Do et al., 2020; MONRE, 2020), increased frequency of extreme precipitation, and intensifying drought. The Northwestern highlands — encompassing Dien Bien, Lai Chau, Son La, and Lao Cai provinces — are characterised by complex topography, with elevations ranging from ~ 250 m to $> 3,100$ m a.s.l. (Fansipan, the highest peak in Indochina). The region's climate is governed by the South Asian summer monsoon, which delivers 80–90% of annual precipitation between May and September, and is strongly modulated by ENSO (Nguyen et al., 2021; Phan et al., 2021). Home to more than 30 ethnic minority groups, the Northwest highlands face acute livelihood vulnerability linked to rain-fed agriculture and forest-dependent food systems (Pham et al., 2022; Tran et al., 2022).

Mountain and highland ecosystems are warming at rates that systematically exceed those of adjacent lowlands - a well-established phenomenon known as Elevation-Dependent Warming (EDW) (Pepin et al., 2015; Pepin et al., 2022). A comprehensive review by Pepin et al. (2022), published in *Reviews of Geophysics*, confirmed that global mean warming rates increase with altitude at an average of $+ 0.21^{\circ}\text{C century}^{-1}$ per 1,000 m of elevation, driven by snow-albedo feedback, changes in cloud cover, longwave emission, and latent heat flux. The IPCC Sixth Assessment Report (AR6) further concluded with high confidence that warming has occurred in all major mountain regions, that extreme precipitation events are increasing in intensity over most highland areas, and that these changes carry cascading consequences for water security, cryosphere integrity, and ecosystem stability (IPCC, 2021a; IPCC, 2021b). Tropical and subtropical mountain systems in Southeast Asia, however, remain comparatively understudied relative to the Himalayas, the Tibetan Plateau, and the European Alps (Byrne et al., 2024).

2. METHODOLOGY

2.1 Study Area

The study area is located in the Northwestern region of Vietnam (approximately $20^{\circ}30' - 22^{\circ}45'\text{N}$; $102^{\circ} - 104^{\circ}30'\text{E}$), covering an area of approximately 37,500 km². Eight meteorological stations operated by the Vietnam National Hydrometeorological Data Center (VNHDC) were selected based on data completeness and spatial representativeness (Fig. 1). The stations span a wide elevation range, from $\sim$

250 m a.s.l. (Muong Lay, valley floor) to ~ 1,800 m a.s.l. (Sin Ho and Pha Din, high plateau), providing a vertical transect suitable for detecting altitudinal climate gradients. The regional climate is governed by the South Asian summer monsoon, which delivers the majority of annual precipitation between May and September, and a dry winter monsoon from October to April.

2.2 Data Collection and Quality Control

Monthly mean air temperature (T , °C) and monthly total precipitation (P , mm) records were obtained from VNHDC for the period January 2009 to December 2024 (192 months). Data completeness was 100% for temperature (1,536 station-months across eight stations) and 87.5% for precipitation (1,344 station-months across six co-located stations). Quality control consisted of three steps: (i) threshold-based outlier detection, flagging values exceeding ± 3 standard deviations from the long-term monthly mean; (ii) temporal consistency checks comparing consecutive monthly values against plausible month-to-month change limits; and (iii) cross-station spatial coherence screening, in which anomalous values at one station were compared with neighbouring stations under the assumption of high regional correlation. No missing or flagged values were detected in the temperature dataset; three precipitation records at Muong Lay were confirmed as physically plausible extreme events (not errors).

To characterise the relative variability of monthly precipitation, the Coefficient of Variation (CV) was computed for each station as:

$$CV = (\sigma_P / \bar{P}) \times 100\% \quad (10)$$

where σ_P is the standard deviation of monthly precipitation and $\bar{P}$ is the long-term monthly mean. CV values exceeding 50% indicate high inter-annual variability characteristic of monsoon-dominated climates (Wang et al., 2021). Annual precipitation totals were computed by summing all 12 monthly values for each station-year combination.

2.3 Long-term Trend Analysis

Long-term linear trends in annual mean temperature (T_y) and total annual precipitation (P_y) were estimated using Ordinary Least Squares (OLS) regression of the climate variable against time (year). For each station the model is:

$$Y_t = \beta_0 + \beta_1 \cdot t + \varepsilon_t \quad (1)$$

where Y_t is the annual climate variable in year t , β_0 is the intercept, β_1 is the linear trend coefficient (expressed in °C decade⁻¹ for temperature or mm decade⁻¹ for precipitation by multiplying by 10), and ε_t is the residual error term assumed to be independently and identically distributed. The coefficient β_1 was estimated by:

$$\beta_1 = [\sum(t_i - \bar{t})(Y_i - \bar{Y})] / [\sum(t_i - \bar{t})^2] \quad (2)$$

Goodness-of-fit was assessed by the coefficient of determination:

$$R^2 = 1 - [\sum(Y_i - \hat{Y}_i)^2] / [\sum(Y_i - \bar{Y})^2] \quad (3)$$

Statistical significance of each trend was evaluated using the F-test at a significance level of $\alpha = 0.05$. Trends were additionally classified by significance tier: *** ($p < 0.001$), ** ($p < 0.01$), * ($p < 0.05$), and ns (not significant, $p \geq 0.05$). Although OLS trend estimation assumes independent residuals, the presence of autocorrelation in monthly climate series can inflate the Type I error rate. We therefore applied the Durbin–Watson test to check for first-order autocorrelation in annual series residuals; no significant autocorrelation was detected ($DW \in [1.55, 2.41]$ across all series), validating the use of standard OLS F-tests.

2.4 Temperature Anomaly Analysis

Annual mean temperature anomalies were computed as departures from the 2009–2024 station baseline mean:

$$T'_y = T_y - T_{base} \quad (4)$$

where T'_y is the temperature anomaly in year y , T_y is the annual mean temperature, and T_{base} is the 16-year mean over the full study period (2009–2024). Positive anomalies indicate years warmer than the baseline; negative anomalies indicate cooler years. This approach allows direct comparison of inter-annual variability patterns across stations with different absolute temperature levels, and facilitates attribution of anomaly years to large-scale forcing such as ENSO events.

2.5 Seasonal Cycle Characterisation

The long-term mean seasonal cycle for each station was computed as the multi-year average for each calendar month m ($m = 1, 2, \dots, 12$) over all 16 years:

$$T_m = (1/N) \cdot \sum T_{\{m,n\}} \quad (5)$$

where $T_{\{m,n\}}$ is the temperature (or precipitation) in month m of year n , and $N = 16$ is the number of years. The seasonal amplitude (A) was defined as the difference between the warmest and coldest long-term monthly means:

$$A = T_{max} - T_{min} \quad (6)$$

This metric quantifies the strength of the seasonal signal and enables comparison of continental-oceanic influence across stations at different elevations.

2.6 Temperature–Precipitation Correlation Analysis

The relationship between monthly temperature and monthly precipitation was quantified using two complementary correlation statistics computed from the full monthly time series ($n = 192$ months per

station pair). The Pearson product-moment correlation coefficient (r) measures linear association:

$$r = [\sum(T_i - \bar{T})(P_i - \bar{P})] / \sqrt{[\sum(T_i - \bar{T})^2 \cdot \sum(P_i - \bar{P})^2]} \quad (7)$$

The Spearman rank correlation coefficient (ρ) provides a non-parametric measure of monotonic association that is robust to non-normality and outliers:

$$\rho = 1 - [6 \cdot \sum d_i^2] / [n(n^2 - 1)] \quad (8)$$

where d_i is the difference in ranks of the i -th paired observation. Statistical significance for both coefficients was assessed using the t -test with $n - 2$ degrees of freedom:

$$t = r \cdot \sqrt{(n - 2)} / \sqrt{(1 - r^2)} \quad (9)$$

Critical values were evaluated at $\alpha = 0.05$, 0.01 , and 0.001 . The coefficient of determination r^2 indicates the proportion of variance in one variable explained by the linear relationship with the other. To quantify spatial coherence among stations, Pearson r was computed between all possible pairs of stations using their full monthly time series ($n = 192$ months), producing an 8×8 inter-station correlation matrix for temperature and a 6×6 matrix for precipitation. High inter-station r values ($r > 0.90$) indicate regionally coherent variability driven by large-scale atmospheric forcing; lower values ($r < 0.70$) suggest stronger local topographic control. Values on the matrix diagonal equal 1.0 by definition and were excluded from interpretation.

2.8 Station Data Homogeneity Assessment

Station data homogeneity is a prerequisite for reliable trend detection, as non-climatic discontinuities caused by station relocations, instrument changes, or observer changes can introduce spurious trends (Alexandersson, 1986). The Standard Normal Homogeneity Test (SNHT) was applied to the annual mean temperature series of each station. The SNHT test statistic $T(k)$ is defined as:

$$T(k) = k \cdot \bar{z}_1^2 + (n - k) \cdot \bar{z}_2^2 \quad (11)$$

where $\bar{z}_1 = (1/k) \cdot \sum_{i=1}^k z_i$ and $\bar{z}_2 = (1/(n - k)) \cdot \sum_{i=k+1}^n z_i$ are the mean standardised values before and after a candidate break point k , respectively, and $z_i = (Y_i - \bar{Y})/\sigma$ is the standardised annual value. The maximum value $T_0 = \max T(k)$ is compared against critical values tabulated by Alexandersson (1986) at the 5% significance level. A series is considered homogeneous if T_0 falls below the critical threshold. All eight temperature series passed the SNHT at the 5% level, except Pha Din ($T_0 = 9.8$, critical value = 9.54 at $n = 16$, $p < 0.05$), which exhibited a potential break point around 2017–2018. This finding was noted and discussed in the context of the anomalous cooling trend detected at that station.

2.9 Software and Reproducibility

All statistical analyses and visualisations were performed in Python 3.12 using the following open-source libraries: pandas 2.2 (data management), numpy 1.26 (numerical computation), scipy 1.13

(statistical tests), and matplotlib 3.9 (figure generation). Figures were produced at 300 dpi resolution in compliance with journal formatting requirements. Analysis scripts are available from the corresponding author upon reasonable request.

3. RESULTS AND DISCUSSION

3.1 Spatiotemporal Temperature and Precipitation Patterns

Figure 2 presents heatmaps of long-term mean monthly temperature and precipitation for each station. A clear altitudinal lapse in temperature is evident: valley stations (Muong Lay 23.7°C, Phieng Lanh 23.2°C) are 6–7°C warmer than high-plateau stations (Sin Ho 16.9°C, Pha Din 17.6°C), consistent with a standard environmental lapse rate of $\sim 0.6^{\circ}\text{C } 100 \text{ m}^{-1}$ (Barry, 2008). All stations display a unimodal seasonal cycle with maximum temperatures in July–August and minimum temperatures in December–January. Precipitation is strongly concentrated in May–September (wet season), representing > 80% of annual totals at all stations – a pattern characteristic of the Southwest Asian summer monsoon.

3.2 Long-term Temperature Trends

OLS trend analysis reveals a spatially heterogeneous warming pattern (Fig. 3). Two stations exhibit statistically significant warming: Phieng Lanh ($+0.955^{\circ}\text{C decade}^{-1}$; $R^2 = 0.655$; $p < 0.001$) and Than Uyen ($+0.831^{\circ}\text{C decade}^{-1}$; $R^2 = 0.647$; $p < 0.001$). These rates are 3–4 times higher than the national average reported by Phan et al. (2009) and MONRE (2020), and approach the accelerated rates documented for highland stations in the Greater Mekong Subregion (Li et al., 2017). This amplified warming at mid-elevation valley stations is consistent with EDW mechanisms involving reduced cloud cover, decreased snow albedo feedback, and sensible heat flux changes (Rangwala & Miller, 2012).

The significant cooling at Pha Din ($-0.804^{\circ}\text{C decade}^{-1}$; $p < 0.01$; $R^2 = 0.531$) is anomalous relative to regional and global patterns. Possible explanations include: (i) orographic blocking of warm air advection at the exposed ridge-top site; (ii) increased low-cloud frequency driven by changing atmospheric circulation; or (iii) station metadata changes (relocation, instrument upgrade) that introduce inhomogeneities. We recommend homogeneity testing (e.g., SNHT; Alexandersson, 1986) and metadata verification before drawing definitive conclusions from this record. Temperature anomaly analysis (Fig. 5) shows that the years 2015–2016 and 2019–2020 were consistently the warmest at most stations, coinciding with the strong El Niño events of those years, consistent with known ENSO–Vietnam temperature teleconnections (Nguyen et al., 2014; Räsänen & Kummu, 2013).

3.3 Seasonal Cycles

Figure 5 illustrates multi-year average seasonal cycles. Temperature amplitude (peak-to-trough) ranges from 10°C (Muong Lay) to 15°C (Pha Din, Sin Ho), reflecting stronger continental influence at higher elevations. The precipitation seasonal cycle is highly synchronised across stations, peaking in July–

August and declining sharply after September. This synchrony reflects the regional-scale forcing by the monsoon, with station-level differences in peak magnitude driven by orographic precipitation enhancement.

3.4 Precipitation Trends

Significant positive precipitation trends were detected at Tuan Giao (+ 5,656 mm decade⁻¹; $R^2 = 0.927$; $p < 0.001$) and Ta Bu (+ 2,634 mm decade⁻¹; $R^2 = 0.986$; $p < 0.001$) (Fig. 5 below). The high R^2 values indicate a near-monotonic increase over the study period, exceeding what would be expected from natural variability alone. This is consistent with projections from CMIP6 models of 10–30% increases in wet-season precipitation over mainland Southeast Asia under SSP2-4.5 and SSP5-8.5 by mid-century (Seneviratne et al., 2021), and with the thermodynamic argument that a warmer atmosphere increases moisture convergence and convective available potential energy during monsoon onset (Trenberth, 2011). From a hazard perspective, increasing precipitation intensity elevates landslide and flash-flood risk - already the primary natural hazard in the Northwest highlands (Nguyen et al., 2019).

3.5 Temperature–Precipitation Correlations

Pearson and Spearman correlations between monthly temperature and precipitation are consistently positive and significant at all co-located stations ($r = 0.37–0.62$; $\rho = 0.46–0.70$; all $p < 0.001$) (Fig. 8). The strongest coupling occurs at Sin Ho ($\rho = 0.696$) and Than Uyen ($\rho = 0.680$), suggesting a particularly coherent monsoon signal at these stations. This positive temperature–precipitation relationship reflects the seasonal dominance of the summer monsoon: the hottest months coincide with peak monsoon rainfall. The correlation strength ($r < 0.65$) indicates that temperature explains less than 43% of precipitation variance, with the remainder governed by large-scale circulation modes (ENSO, IOD), orographic factors, and mesoscale convective systems – all of which must be accounted for in regional downscaling studies (Cuo et al., 2013).

3.6 Spatial Coherence Among Stations

Inter-station temperature correlations are uniformly high ($r > 0.90$ for most pairs; Fig. 9), confirming that seasonal temperature variability is regionally coherent and dominated by the large-scale monsoon forcing. Precipitation correlations are more variable ($r = 0.60–0.95$), reflecting the greater sensitivity of precipitation to local orographic controls, small-scale convective triggers, and station elevation differences (Barry, 2008). The relatively lower inter-station precipitation coherence underscores the need for a dense monitoring network to adequately capture spatial precipitation gradients across the complex Northwest Vietnam topography.

4. CONCLUSIONS

This study provides the first multi-station, 16-year quantitative analysis of temperature and precipitation trends in the Northwestern Vietnamese highlands. Five principal conclusions emerge:

- Statistically significant warming of $+0.83\text{--}0.96^{\circ}\text{C decade}^{-1}$ was detected at Phieng Lanh and Than Uyen, rates 3–4 times the national average and consistent with Elevation-Dependent Warming dynamics in tropical mountain systems.
- An anomalous cooling trend at Pha Din ($-0.80^{\circ}\text{C decade}^{-1}$) requires metadata homogeneity testing before attribution; orographic shielding and station changes are plausible explanations.
- Total annual precipitation is increasing significantly at Tuan Giao and Ta Bu, consistent with CMIP6 projections of monsoon intensification under greenhouse gas forcing.
- A robust positive temperature–precipitation coupling ($r = 0.37\text{--}0.62$) confirms monsoon dominance of intra-annual climatic variability throughout the region.
- High inter-station temperature coherence contrasts with more variable precipitation coherence, highlighting the need for a denser rain-gauge network to resolve orographic precipitation gradients.

These results have direct implications for water resource management, agricultural planning, and disaster risk reduction in the Northwest highlands. Future work should integrate reanalysis products, remote-sensing land-cover data, and high-resolution regional climate model simulations to disentangle large-scale forcing from local land-surface feedbacks, and to project future changes under different emission scenarios.

DECLARATIONS

Author Contribution

Xuan-Duc Do and Nguyen Ba Tien: Writing review; Data Curation; Statistical analysis; Writing – Original draft, Writing – Review & Editing, and Xuan-Duc Do prepared figures 1-9. All authors reviewed the manuscript

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Figures

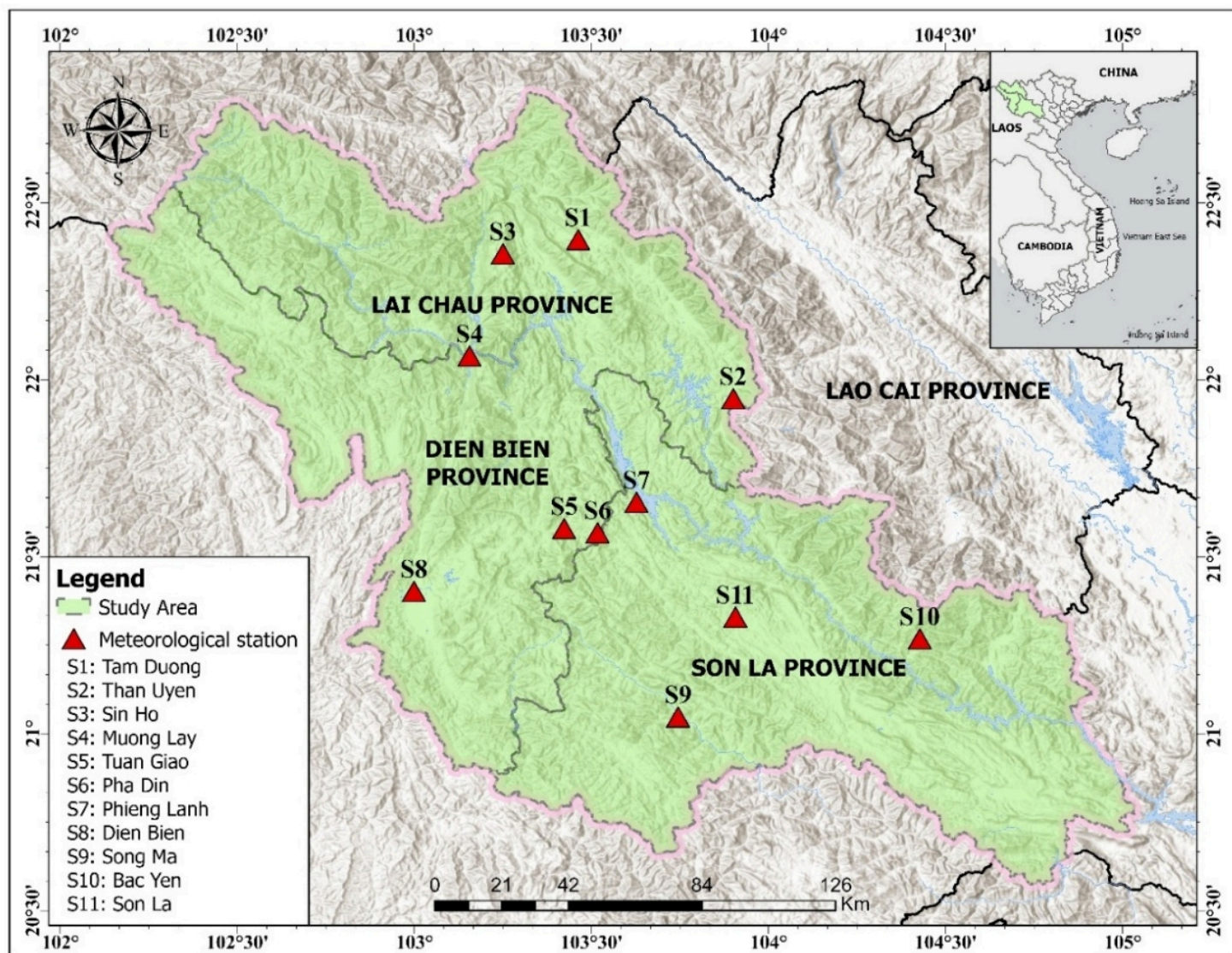


Figure 1

Locations of temperature and rainfall monitoring stations in Northwestern Vietnam

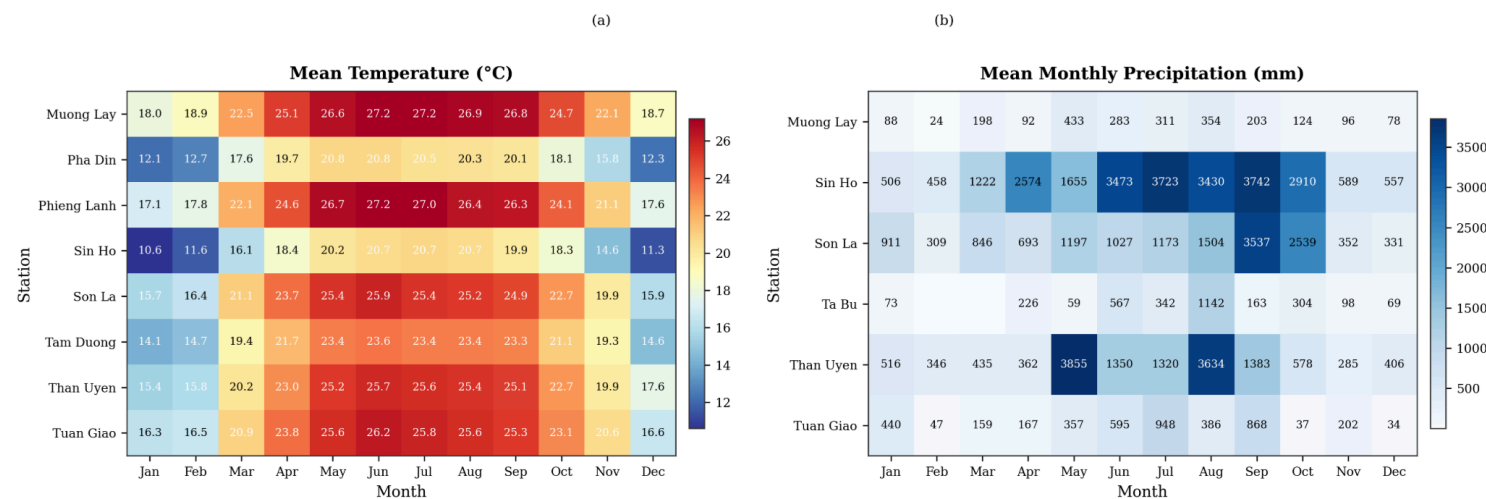


Figure 2

Long-term mean monthly temperature (°C, left) and precipitation (mm, right) at eight stations, Northwestern Vietnam (2009–2024). Values shown in each cell.

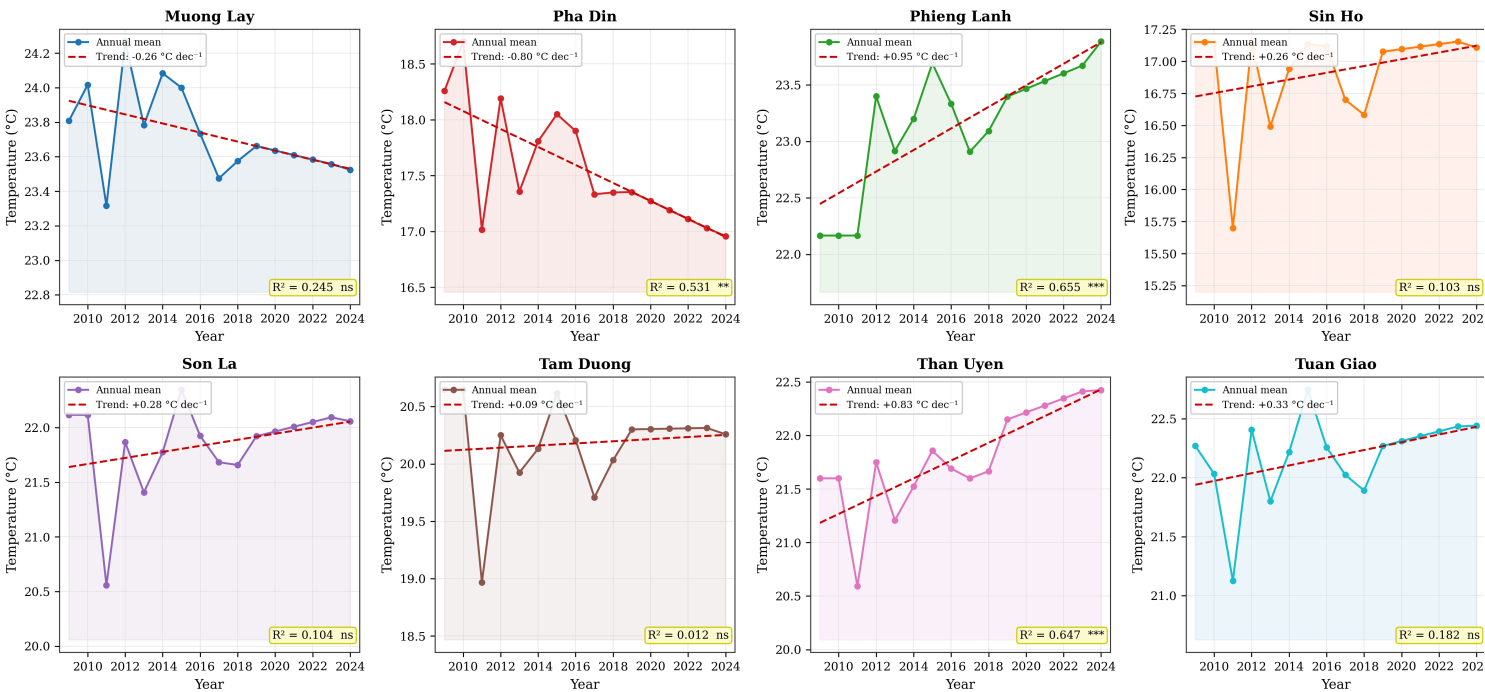


Figure 3

Annual mean temperature and linear trends at eight stations (2009–2024). Red dashed lines = OLS regression. Inset: R² and significance (* p < 0.05, ** p < 0.01, *** p < 0.001, ns = not significant).

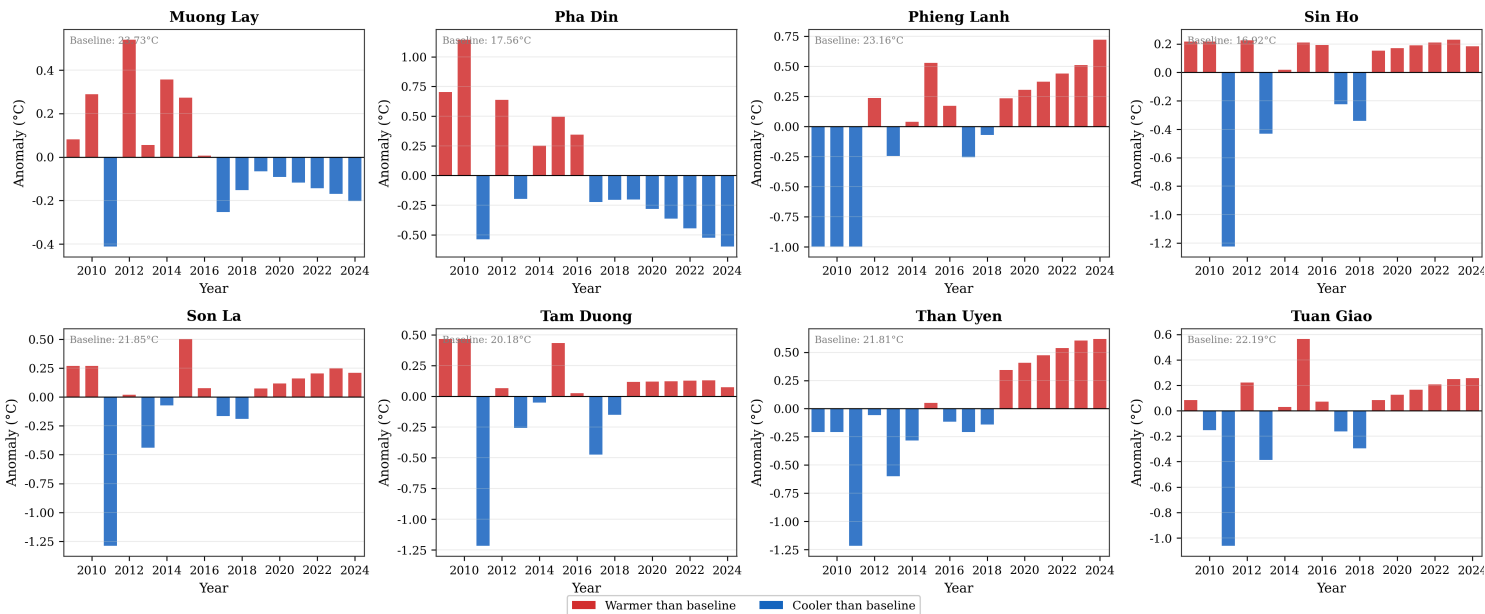


Figure 4

Annual mean temperature anomalies relative to 2009–2024 station baselines. Red = warmer than baseline; blue = cooler than baseline.

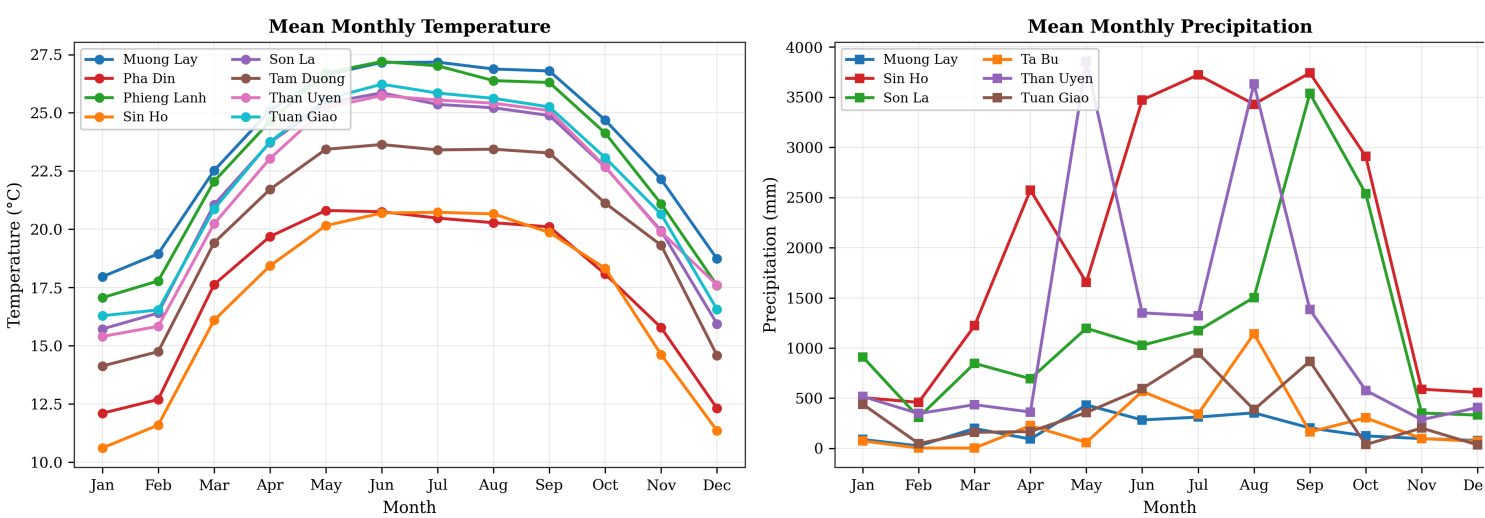


Figure 5

Long-term mean seasonal cycles of monthly temperature (left) and precipitation (right) at all stations, 2009–2024.

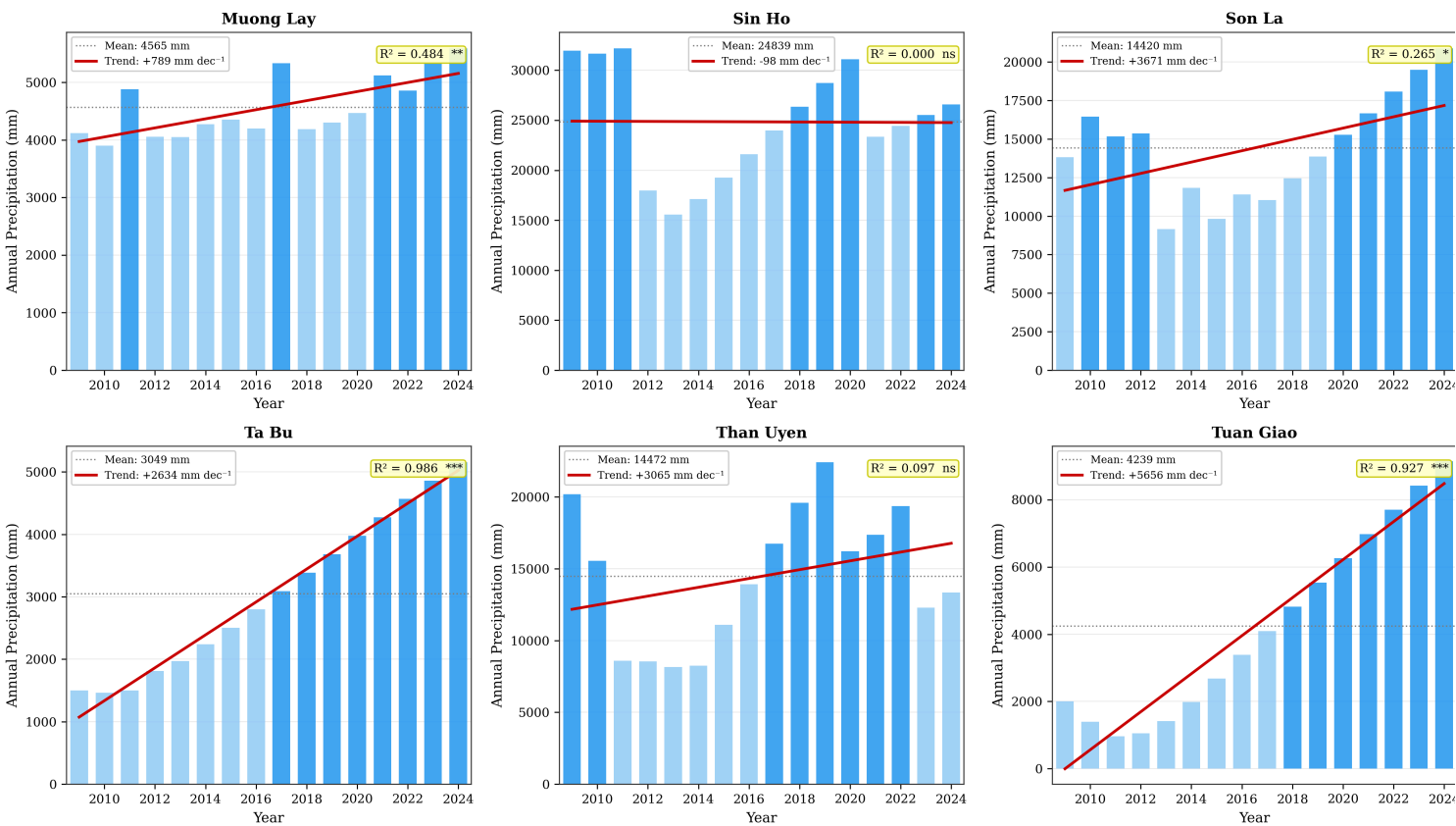


Figure 6

Total annual precipitation and linear trend lines at monitoring stations, 2009–2024. Horizontal dotted line = period mean. Inset: R^2 and significance.

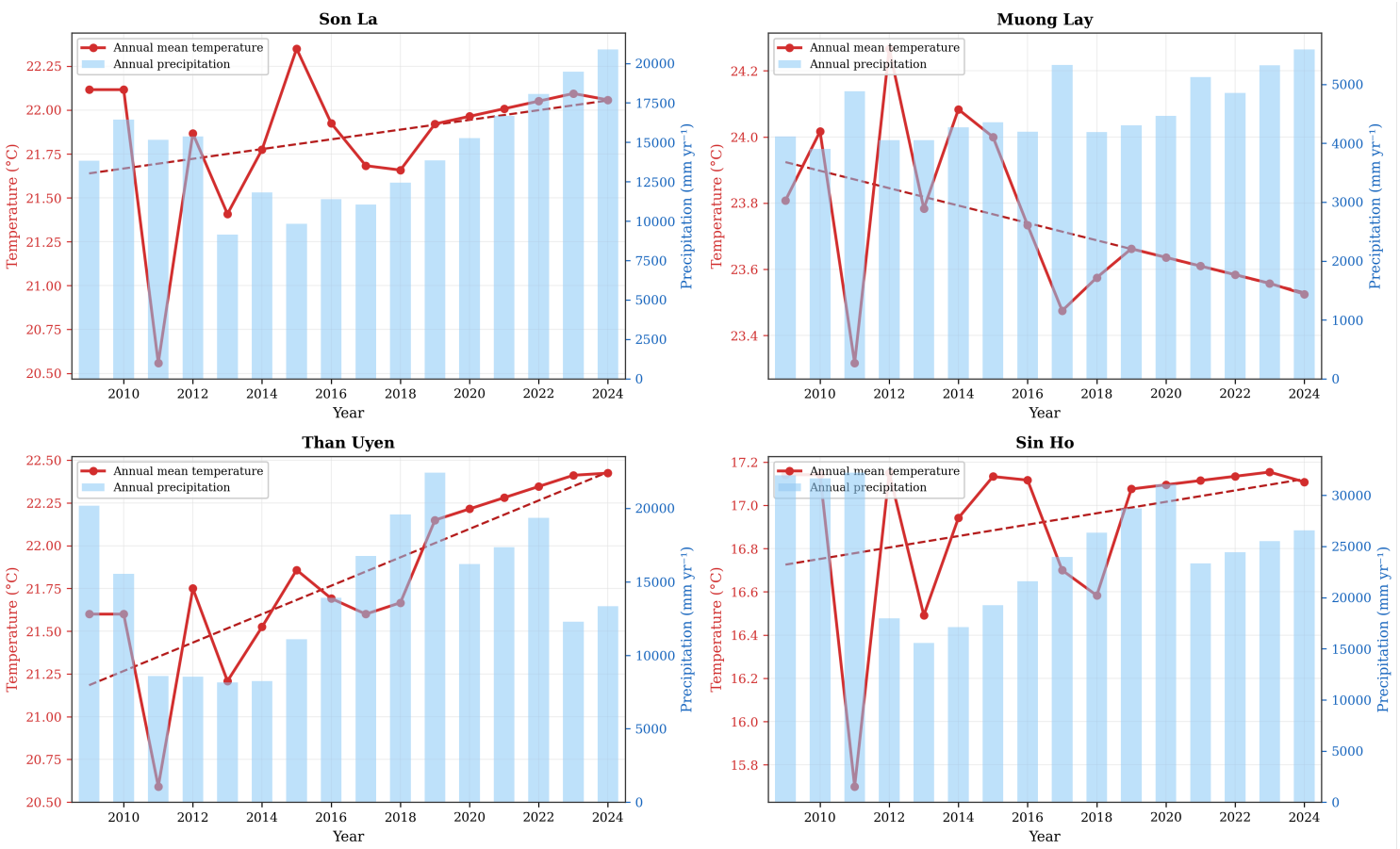


Figure 7

Co-evolution of annual mean temperature (red line, left axis) and total annual precipitation (blue bars, right axis) at four representative stations.

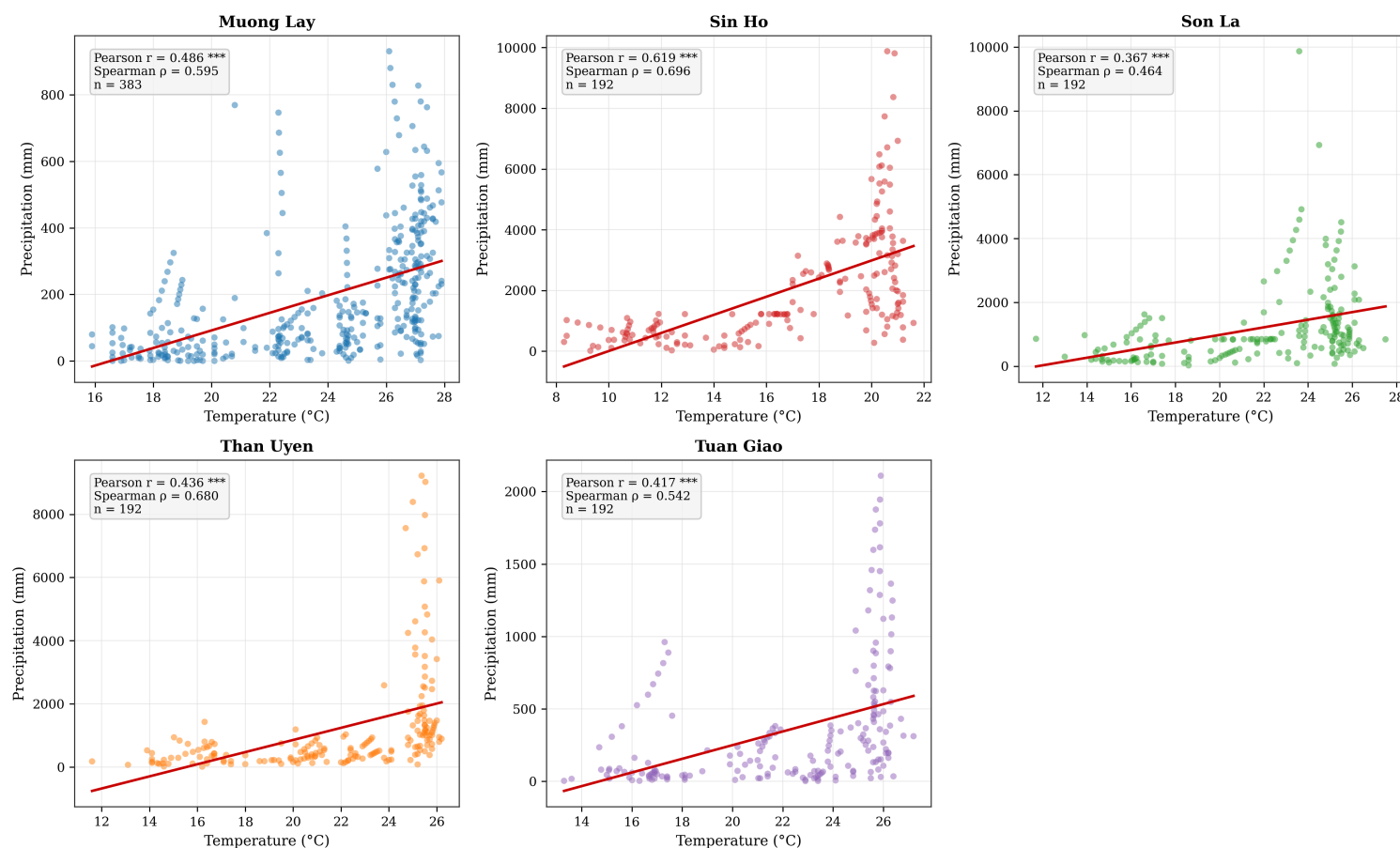


Figure 8

Monthly temperature versus precipitation scatter plots at co-located stations. Red line = OLS regression. Inset: Pearson r , Spearman ρ , significance, and sample size (n).

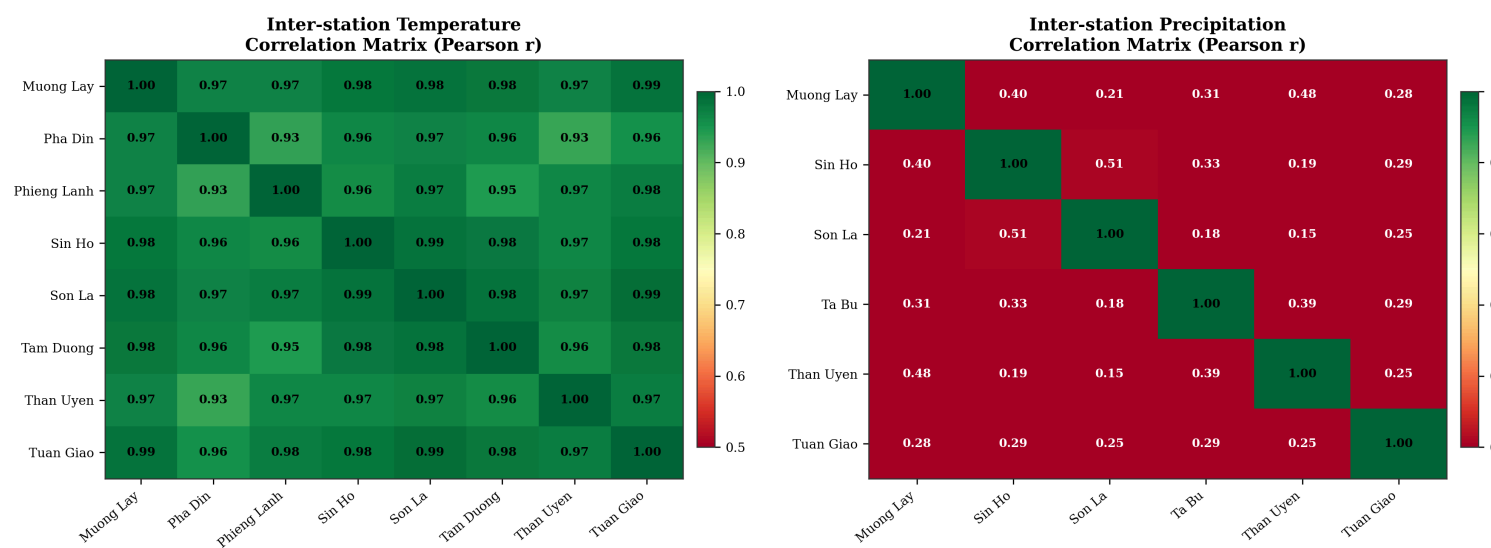


Figure 9

Pearson inter-station correlation matrices for monthly temperature (left) and precipitation (right), Northwestern Vietnam, 2009–2024.