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Research Article

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Posted Date: October 15th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11106993/v1>

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Additional Declarations: No competing interests reported.

Changing temperature and precipitation regimes in the Everest region

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Acknowledgments: N/A

Abstract

High-elevation meteorological records are essential for resolving climate variability in the Himalayan region, where sparse observations limit assessment of changes in temperature and precipitation. Temperature analyses used the 1994-2023 Pyramid International Laboratory–Observatory automated weather system (AWS) record, with Namche Bazaar providing a lower-elevation comparison of diurnal temperature range (DTR). Regional precipitation variability was evaluated using CHIRPS v3.0 gridded data extracted at Namche Bazaar, Phortse, Pheriche, and Everest Base Camp for 1981–2022. Mann-Kendall tests, Sen slopes, generalized additive models, principal component analysis, residual time-series models, and change-point detection were used to distinguish monotonic trends from changes in variability and regime. Mean-temperature change at Pyramid AWS was strongly seasonal, whereas DTR declined in all months, with statistically significant decreases in 10 of 12 months under the Mann-Kendall test. Namche Bazaar showed a less uniform but directionally similar pattern, with significant DTR decreases in five calendar months and significant seasonal decreases during the pre- and post-monsoon seasons. Precipitation was strongly coherent across stations, with the first principal component explaining approximately 95% of annual and monsoon (June-September) variability, but no extraction location exhibited a significant monotonic annual or monsoon trend. Instead, a persistent regional shift occurred around 1991, followed by low variability during 1996-2005 and renewed variability after 2006. Following a period of low variability during 1996–2005, dry monsoon anomalies became more frequent and persistent and cumulative deficits increased during 2006–2022, whereas extremely wet months became larger without becoming comparably more frequent. Recent hydroclimatic change is therefore better characterized by contracting DTR and reduced monsoon reliability than by uniform warming or a simple decline in precipitation totals.

Keywords: diurnal temperature range; high-elevation climate; Himalaya; monsoon reliability; precipitation variability; temperature asymmetry

1 Introduction

Mountain environments are particularly sensitive to climatic change because relatively small shifts in temperature and precipitation can alter snow accumulation, glacier mass balance, seasonal runoff, ecosystem processes, and downstream water availability (Hock et al. 2019; Pepin et al. 2022). Observations from mountain regions worldwide indicate that warming is spatially heterogeneous and may vary with elevation, season, and temperature metrics (Mountain Research Initiative EDW Working Group 2015; Pepin et al. 2022). Proposed drivers of this elevation dependence include snow-albedo feedbacks, atmospheric moisture, cloud cover, radiation, aerosols, and changes in surface energy exchange. Maximum and minimum temperatures may also change at different rates, producing shifts in the diurnal temperature range (DTR) that are not evident from trends in mean temperature alone (Easterling et al. 1997; You et al. 2016). Because minimum temperature influences freezing conditions, snow persistence, and melt processes, changes in DTR may be particularly consequential in high-elevation environments.

The Hindu Kush-Himalayan region has experienced widespread warming during recent decades, although the magnitude and seasonality of the observed changes vary considerably across the region (Shrestha et al. 1999; Krishnan et al. 2019). Warming has generally been stronger during winter and at higher elevations in some parts of the Himalayan region, but the available evidence does not support a uniform response across all locations or elevation zones (Krishnan et al. 2019; Pepin et al. 2022). Local topography, land-surface conditions, snow and glacier cover, and valley-scale atmospheric circulation can modify regional climatic signals. Near glacierized terrain, for example, enhanced sensible heat exchange may strengthen katabatic airflow and suppress daytime warming, potentially producing stable or declining maximum temperatures even while the broader atmosphere warms (Salerno et al. 2023). Separating maximum and minimum temperature trends is therefore necessary for identifying changes that may be obscured in analyses of mean temperature.

Reliable assessments of high-elevation temperature change remain limited by the scarcity and incompleteness of long-term observations (Thornton et al. 2022). Conventional meteorological networks are strongly biased toward lower elevations, while sustained records above 5000 m are exceptionally rare. Regional climate products and gridded datasets consequently may not

adequately represent local topographic effects, glacier-atmosphere interactions, or the steep climatic gradients of the upper Himalaya (Pepin et al. 2022). Individual high-elevation records are scientifically valuable, but comparisons with stations at lower elevations are needed to determine whether observed changes represent localized conditions or a more spatially coherent regional response.

Precipitation change in the Himalayan region is even more complex. Regional assessments have found substantial spatial, seasonal, and interannual variability, with little evidence of a uniform historical trend across the Hindu Kush-Himalayan region (Palazzi et al. 2013; Krishnan et al. 2019). Along the southern Himalayan slopes, precipitation is strongly influenced by elevation, valley orientation, and topographic exposure, as well as by interactions between the South Asian summer monsoon and mid-latitude westerly circulation. In the Everest region, precipitation generally increases with elevation to an intermediate zone before declining toward the highest elevations (Salerno et al. 2015). Measurement uncertainty also increases at high elevations because of wind-induced gauge undercatch and difficulties in recording mixed and solid precipitation (Goodison et al. 1998; Pepin et al. 2022).

The absence of a significant trend in annual precipitation does not necessarily indicate that the precipitation regime is stable. Changes in seasonality, temporal concentration, persistence, and interannual variability can occur without a corresponding change in annual totals. This distinction is especially important in monsoon-dominated environments, where most annual precipitation falls within a relatively short period (Salerno et al. 2015; Wood et al. 2020). A shorter or less reliable wet season can produce longer intervening dry periods even if seasonal totals remain similar. Likewise, increasingly variable monsoon conditions can generate both severe rainfall deficits and occasional large wet-month anomalies. Such changes can affect runoff generation, soil moisture, erosion, slope stability, groundwater recharge, and the seasonal reliability of springs and other water sources (Hock et al. 2019; Pepin et al. 2022).

Observations from the Everest (known locally as Sagarmatha) region provide an unusual opportunity to investigate these processes across a large elevation gradient. The Pyramid Meteorological Network extends from Lukla at approximately 2660 m to the South Col at nearly 8000 m and has collected observations since 1994 (Salerno et al. 2025). Its principal long-term high-elevation station is located near the Pyramid International Laboratory-Observatory (Pyramid

AWS) at approximately 5035 m above sea level and provides the principal high-elevation observational record, while Namche Bazaar provides a lower-elevation temperature comparison. Regional precipitation was evaluated using CHIRPS v3.0 gridded data extracted at Namche Bazaar, Phortse, Pheriche, and Everest Base Camp, providing complementary records from inhabited valleys and intermediate elevation zones. Together, these stations permit evaluation of whether changes observed in the upper Khumbu are restricted to the immediate high-elevation environment or form part of a broader regional hydroclimatic pattern.

Previous studies using observations from the region have characterized the elevation dependence of precipitation, examined temperature and precipitation variability, and investigated interactions between glaciers and the surrounding atmosphere (Salerno et al. 2015, 2023, 2025). Nevertheless, several questions remain unresolved. In particular, the spatial consistency of DTR change across elevations has received limited attention, and regional precipitation assessments have generally emphasized trends in annual or monsoon totals rather than changes in the persistence and sequencing of dry and wet conditions. A multi-station analysis that distinguishes maximum from minimum temperature and evaluates precipitation totals, variability, anomalies, and regime shifts can therefore provide a more complete representation of recent climatic change.

Climate records also contain seasonality, persistence, and serial dependence that are not fully represented by conventional linear trend analysis. Non-parametric trend tests, time-series models, principal component analysis, and change-point detection offer complementary means of evaluating monotonic change, temporal dependence, regional coherence, and structural shifts (Mann 1945; Sen 1968; Box et al. 2015; Killick et al. 2012; Jolliffe and Cadima 2016). Trend and change-point analyses describe observed changes, whereas ARIMA and SARIMA models characterize temporal structure and conditional short-term behaviour rather than providing deterministic projections of future climate.

This study evaluates temperature and precipitation change across the Everest region using station observations and gridded precipitation estimates spanning the middle and upper Khumbu. The objectives are to: (1) quantify annual, seasonal, and monthly changes in maximum and minimum temperature and DTR at Namche Bazaar and the high-elevation Pyramid AWS; (2) determine whether DTR changes are consistent between the two elevation zones; (3) evaluate annual, monsoon, and dry-season precipitation behaviour in CHIRPS grid-cell series extracted at Namche

Bazaar, Phortse, Pheriche, and Everest Base Camp; (4) assess regional coherence, temporal concentration, anomaly persistence, and possible shifts in the monsoon precipitation regime; and (5) characterize the temporal dependence and seasonal structure of the temperature and precipitation records using ARIMA and SARIMA models. By integrating temperature and precipitation evidence across elevations, the study distinguishes changes in precipitation amount from changes in precipitation reliability and evaluates whether climatic signals observed at the highest station extend into downstream portions of the Everest region.

2 Materials and methods

2.1 Study record and variables

Monthly mean, maximum, and minimum air temperature and precipitation were examined at Pyramid AWS for 1994-2023 using the quality-controlled Pyramid Meteorological Network record described by Salerno et al. (2025). The temperature dataset comprised 360 monthly observations. Analyses were conducted for annual series and for each calendar month to distinguish annual-scale change from seasonally contrasting responses. DTR was calculated as the difference between maximum and minimum temperature. Monsoon precipitation was represented by the June-September total (JJAS), and the monsoon contribution was calculated as JJAS precipitation divided by annual precipitation and expressed as a percentage. Seasons were defined as winter (December–February), pre-monsoon (March–May), summer monsoon (June–September), and post-monsoon (October–November).

The daily precipitation record contained 9,882 observations within the 10,957-day study period, corresponding to 90.19% coverage. Monthly observational coverage was calculated as the number of days with precipitation observations divided by the number of calendar days in each month. Reconstruction was performed in two stages. First, for months containing at least 75% of observation days, the observed monthly sum was adjusted in proportion to coverage:

$$P_m = \sum P_{\text{obs}} \left(\frac{N_m}{N_{\text{obs}}} \right),$$

where P_m is the reconstructed monthly precipitation total, N_m is the number of calendar days in the month, and N_{obs} is the number of days with observations. Months containing fewer than 75% observed days were classified as sparse and excluded from this initial calculation. In the second

stage, the 19 sparse or completely missing monthly totals were reconstructed separately for each calendar month using time-based linear interpolation between values for the same month in surrounding years; where necessary at the beginning or end of the record, interpolation was extended using the nearest available value. The completed series contained no missing monthly totals. Annual and June–September precipitation totals were calculated from the reconstructed series, while coverage-screened analyses based on observed data were retained as sensitivity tests. The anomalously low 2009 monsoon total was entirely observed: none of the four JJAS monthly totals required reconstruction, and each was below its corresponding long-term monthly mean.

A complementary regional analysis used CHIRPS v3.0 monthly gridded precipitation for 1981–2022. Precipitation series were extracted from the 0.05° CHIRPS grid at the coordinates of Namche Bazaar, Phortse, Pheriche, and Everest Base Camp. These series represent gridded precipitation estimates rather than observations from local rain gauges. At the 0.05° CHIRPS resolution, the Pyramid AWS and Everest Base Camp coordinates fall within the same grid cell. The Everest Base Camp CHIRPS series therefore also represents the grid cell containing Pyramid AWS, but it is distinct from the observed Pyramid AWS precipitation record obtained from the Pyramid Meteorological Network. Annual and JJAS totals were evaluated at each extraction location using Mann–Kendall tests and Sen slopes. Regional coherence was assessed using pairwise Pearson correlations and principal component analysis of the standardized location-based series (Jolliffe and Cadima 2016). The first principal component (PC1) was retained as the regional precipitation index. Mean, piecewise-linear, and variance-focused pruned exact linear time PELT analyses (Killick et al. 2012) were applied to the individual grid-cell and regional series to distinguish monotonic trends from changes in level, slope, and variability. Predefined periods identified from the recurring breakpoints were then used to compare precipitation means, anomaly persistence, cumulative deficits, and wet- and dry-side variability.

Monthly precipitation anomalies were calculated relative to the 1981–2022 climatology for each calendar month and standardized as z-scores. The regional anomaly was calculated from the standardized records of the four CHIRPS extraction locations. Regional monsoon months were classified as extremely dry when $z \leq -1.0$ and extremely wet when $z \geq 1.0$. Months with $z < 0$,

but not necessarily $z \leq -1.0$, were classified as below-normal or dry-anomaly months when evaluating persistence and cumulative deficits.

2.2 Trend and nonlinear analyses

Linear changes were estimated using ordinary least-squares (OLS) regression and are reported per decade with 95% confidence intervals. The non-parametric Mann-Kendall test (Mann 1945; Kendall 1975) and Sen slope estimator (Sen 1968) were used to evaluate the robustness of monotonic trends to distributional assumptions and influential observations. Reported p-values are nominal and were not adjusted for the full set of monthly comparisons; consequently, isolated results close to $p = 0.05$ were interpreted cautiously.

Preliminary 5-, 10-, and 15-year linear regressions produced unstable and sometimes contradictory DTR trends, particularly at Namche Bazaar because of its sparse record and sensitivity to the selected time window. These short-window regressions were therefore excluded from interpretation in favour of Mann-Kendall trend tests and Sen slopes calculated from the fuller available record. These non-parametric methods do not require an assumed linear rate of change and are less sensitive to individual extreme years.

Generalized additive models (GAMs) were fitted to describe nonlinear temporal variation following Wood (2017). Basis dimensions and smoothing penalties were evaluated using model fit and residual diagnostics. The JJAS precipitation GAM was fitted after a Box-Cox transformation (Box and Cox 1964; $\lambda = 2.574$), and predictive errors were calculated after inverse transformation to millimetres. GAM effective degrees of freedom (EDF) describe model flexibility, whereas R^2 , mean absolute error (MAE), and root mean-square error (RMSE) summarize historical fit or predictive error as specified.

2.3 Residual dependence and change-point analysis

Residual normality and serial dependence were assessed using the Jarque-Bera (Jarque and Bera 1987) and Ljung-Box (Ljung and Box 1978) tests, respectively. An autoregressive error of order one was retained for annual DTR. No additional ARIMA structure was required for annual precipitation after removal of the GAM component. Candidate structural changes were identified using the PELT algorithm (Killick et al. 2012) across multiple cost functions and penalty values and were subsequently evaluated using segmented regression (Muggeo 2003). Because the

breakpoint was selected from the data, the corresponding regression p-values and confidence intervals are conditional on the selected breakpoint and are interpreted as supporting rather than independent confirmatory evidence. Equality of variance between selected periods was evaluated with the median-centred Brown-Forsythe test (Brown and Forsythe 1974).

2.4 Forecast evaluation

Five-year rolling validation was used to compare candidate forecasting approaches. DTR forecasts from naive persistence, linear trend extrapolation, and GAM with AR(1) residuals were compared using RMSE. Monthly precipitation forecasts were evaluated against a seasonal baseline, and monthly mean temperature was modelled using an STL-ARIMA framework combining seasonal-trend decomposition (Cleveland et al. 1990) with autoregressive integrated moving-average modelling (Box et al. 2015; Hyndman and Khandakar 2008). Forecasts for 2024-2028 are treated as conditional extensions of the fitted series rather than projections of externally forced climate change.

3 Results

3.1 Seasonal changes in mean temperature

Mean-temperature trends differed markedly among months (Fig. 2a). The annual OLS trend was $+0.081\text{ }^{\circ}\text{C decade}^{-1}$, and the annual GAM explained only 2.5% of the variance, indicating little coherent change in the annual mean relative to interannual variability.

May exhibited the strongest cooling trend ($-0.490\text{ }^{\circ}\text{C decade}^{-1}$, 95% CI -0.82 to $-0.16\text{ }^{\circ}\text{C decade}^{-1}$; $p = 0.005$). The Sen slope was similar ($-0.456\text{ }^{\circ}\text{C decade}^{-1}$; Mann-Kendall $p = 0.008$), and the May GAM was approximately linear (EDF = 2.00; $R^2 = 0.254$). Trends in January-April were not significant. November showed the largest warming trend ($+0.864\text{ }^{\circ}\text{C decade}^{-1}$, 95% CI $+0.26$ to $+1.47\text{ }^{\circ}\text{C decade}^{-1}$; $p = 0.007$), supported by a Sen slope of $+0.733\text{ }^{\circ}\text{C decade}^{-1}$ ($p = 0.032$). September also warmed under OLS ($+0.206\text{ }^{\circ}\text{C decade}^{-1}$; $p = 0.037$), although its Mann-Kendall result was not significant (Sen slope $+0.140\text{ }^{\circ}\text{C decade}^{-1}$; $p = 0.093$). December had a positive Sen slope ($+0.888\text{ }^{\circ}\text{C decade}^{-1}$; $p = 0.040$), while its OLS trend was weaker ($+0.610\text{ }^{\circ}\text{C decade}^{-1}$; $p = 0.088$).

Full-period trends for June and July were negative but not significant, whereas August showed a weak positive trend ($+0.140\text{ }^{\circ}\text{C decade}^{-1}$; $p = 0.078$). The August GAM indicated nonlinear

behaviour ($EDF = 4.1$; $R^2 = 0.49$), including a pronounced rise near the end of the record. Over 2014-2023, July and August warmed by $+1.03$ and $+1.35$ $^{\circ}\text{C decade}^{-1}$, respectively ($p = 0.005$ for both). These short-window estimates describe the recent segment and should not be interpreted as long-term rates.

3.2 Decline in diurnal temperature range

Mann-Kendall tests and Sen slopes indicated a broad long-term contraction of DTR at both Namche Bazaar and the Pyramid AWS, although the strength and seasonal consistency of the decline differed substantially between stations. At Namche Bazaar, five of 12 months showed statistically significant decreases (January, March, May, August, and October), and several additional months approached significance. Sen slopes were negative in nearly every month, with the strongest decline in May (-3.13 $^{\circ}\text{C decade}^{-1}$), indicating an overall tendency toward DTR narrowing despite the noisier and less complete observational record. The Pyramid AWS exhibited a more uniform signal: Sen slopes were negative in all 12 months and statistically significant in 10 months, with slopes generally between approximately -0.3 and -0.8 $^{\circ}\text{C decade}^{-1}$. The largest seasonal reductions occurred during winter and the pre-monsoon period (Fig. 2b, c).

Seasonal analysis reinforced this common pattern (Table 1). At Namche Bazaar, DTR declined significantly during the pre-monsoon (-1.906 $^{\circ}\text{C decade}^{-1}$, $p = 0.017$) and post-monsoon (-0.955 $^{\circ}\text{C decade}^{-1}$, $p = 0.028$) seasons. The winter decline was suggestive (-1.058 $^{\circ}\text{C decade}^{-1}$, $p = 0.077$), whereas there was little evidence of a monsoon-season trend (-0.360 $^{\circ}\text{C decade}^{-1}$, $p = 0.544$). At the Pyramid AWS, significant DTR decreases occurred in all four seasons, ranging from -0.608 $^{\circ}\text{C decade}^{-1}$ during the monsoon to -1.040 $^{\circ}\text{C decade}^{-1}$ during the pre-monsoon, with particularly strong monotonic declines during the pre-monsoon and winter periods.

Table 1 Seasonal Mann-Kendall and Sen slope results for diurnal temperature range at Namche Bazaar and the Pyramid AWS.

Station	Season	Sen slope ($^{\circ}\text{C decade}^{-1}$)	p- value	Tau	Interpretation
Namche	Winter	-1.058	0.077	-0.324	Suggestive decline

Namche	Pre-monsoon	-1.906	0.017	-0.450	Significant; strongest seasonal decline
Namche	Monsoon	-0.360	0.544	-0.111	Little evidence of change
Namche	Post-monsoon	-0.955	0.028	-0.386	Significant decline
Pyramid	Winter	-0.938	<0.001	-0.557	Strong decline
Pyramid	Pre-monsoon	-1.040	<0.001	-0.628	Strongest monotonic decline
Pyramid	Monsoon	-0.608	0.001	-0.524	Significant decline
Pyramid	Post-monsoon	-0.839	<0.001	-0.569	Strong decline

271

272 Annual DTR increased during the early part of the record and subsequently underwent a
273 pronounced decline to lower values (Fig. 3). A GAM with five basis functions (λ GAM =
274 0.001; EDF = 4.60) explained 85.6% of annual variation. Addition of an AR(1) residual model
275 increased the historical R^2 to 0.904 (MAE = 0.153 °C; RMSE = 0.186 °C). Ljung-Box p-values at
276 lags 1-5 increased from < 0.004 before correction to 0.359-0.766 afterward, indicating adequate
277 treatment of residual dependence.

278 PELT consistently identified a transition at the 2008/2009 boundary. Mean DTR decreased from
279 7.402 °C in 1994-2008 to 6.322 °C in 2009-2023, a reduction of 1.080 °C (14.6%). The breakpoint
280 persisted across the evaluated ℓ^2 and linear-cost penalties. Segmented slopes changed from +0.438
281 °C decade⁻¹ before the breakpoint to -0.372 °C decade⁻¹ afterward, yielding a slope difference of -
282 0.810 °C decade⁻¹ (95% CI -1.11 to -0.51 °C decade⁻¹; conditional p < 0.001) and an estimated
283 immediate level change of -1.17 °C. Variance did not differ significantly between periods (Brown-
284 Forsythe p = 0.532). Thus, the detected transition primarily represented a change in the level and
285 trajectory of DTR rather than a change in its interannual variance.

286 The contraction of DTR reflected changes in both daytime maxima and nighttime minima.
287 Maximum temperature decreased in May, June, and July by -0.796, -0.403, and -0.376 °C decade⁻¹,
288 respectively. Minimum temperature increased from August through December, including trends

of $+0.38\text{ }^{\circ}\text{C decade}^{-1}$ in September and $+1.17\text{ }^{\circ}\text{C decade}^{-1}$ in November. Maximum temperature also exhibited a candidate slope change near 2009 ($-0.966\text{ }^{\circ}\text{C decade}^{-1}$; $p = 0.032$), although the DTR breakpoint was more robust across specifications.

3.3 Annual and monsoon precipitation

Mean annual precipitation was 432.6 mm (SD = 58.2 mm; range 306.8-550.7 mm), and mean JJAS precipitation was 380.7 mm (SD = 48.0 mm; range 222.1-484.5 mm). Annual precipitation showed a wet early period, a decline through the 2000s, and recovery later in the record (Fig. 4a). Its OLS trend was $-19.0\text{ mm decade}^{-1}$ (95% CI -43.5 to $+5.6\text{ mm decade}^{-1}$; $p = 0.124$; $R^2 = 0.082$). The GAM described the multiyear trajectory more effectively ($\text{lambdaGAM} = 0.001$; EDF = 4.60; $R^2 = 0.520$; RMSE = 39.69 mm). Residual autocorrelation was not detected after GAM fitting, and ARIMA(0,0,0) was selected for the residual component.

JJAS precipitation followed a comparable nonlinear trajectory (Fig. 4b). Its linear trend was $-16.7\text{ mm decade}^{-1}$ (95% CI -36.8 to $+3.4\text{ mm decade}^{-1}$; $p = 0.099$; $R^2 = 0.094$). The Box-Cox GAM had an EDF of 4.60 and explained 37.1% of variation on the transformed scale. After inverse transformation, R^2 was 0.347, MAE was 27.88 mm, and RMSE was 38.12 mm. Residual diagnostics did not indicate non-normality or remaining serial dependence. The exceptionally low 2009 JJAS total of 222.1 mm remained well below the fitted smooth.

JJAS precipitation accounted for a mean of 88.2% of the annual total (SD = 6.1 percentage points; range 72.4-99.8%). The trend in JJAS share was negligible ($+0.015\text{ percentage points decade}^{-1}$) and not significant. GAMs explained only 6.1-15.7% of variation in JJAS share, and the coverage-screened Mann-Kendall test was also not significant ($p = 0.602$). Monsoon dominance therefore remained stable despite substantial interannual and multiyear variation in precipitation amount.

3.4 Regional coherence and precipitation-regime changes

Annual and monsoon precipitation variability was strongly synchronized among Namche Bazaar, Phortse, Pheriche, and Everest Base Camp. Pairwise correlations in annual precipitation ranged from 0.886 to 0.976. PC1 explained 94.8% of standardized annual variability and 94.4% of JJAS variability, with nearly equal location loadings, indicating that the dominant precipitation signal was regional rather than station-specific (Fig. 6). Non-zero-lag autocorrelations of annual monsoon

precipitation remained within approximate 95% confidence limits, providing little evidence of simple linear autoregressive predictability from preceding monsoon seasons.

Mann-Kendall tests detected no significant trend in annual or JJAS precipitation at any extraction location (Fig. 5). Annual Sen slopes were negative at all four locations, ranging from -2.17 mm yr^{-1} at Everest Base Camp to -4.80 mm yr^{-1} at Namche Bazaar. JJAS slopes were also consistently negative, ranging from -2.36 to -4.87 mm yr^{-1} , but none was statistically significant. Monthly analyses similarly identified no significant monotonic trends. These results indicate that interannual variability dominates any persistent monotonic change in precipitation amount.

PELT analyses instead identified regime-like behaviour. A breakpoint around 1991 was the most persistent regional feature in both individual CHIRPS grid-cell series and PC1. Mean JJAS precipitation decreased by approximately 20-27% across the four CHIRPS extraction locations around 1991, recovered around 1996, and declined more modestly after approximately 2006. Piecewise-linear fits indicated positive pre-1991 slopes of approximately $+16$ to $+37 \text{ mm yr}^{-1}$ and near-zero post-1991 slopes, although the individual slope changes were not significant. Segmented models identified significant negative 1991 level shifts at all stations, ranging from approximately -295 to -505 mm . Later changes were less spatially consistent and more sensitive to the selected penalty.

Regional JJAS variability was high during 1981-1995 (Figs. 6, 7), contracted markedly during 1996-2005, and returned to a similarly high level during 2006-2022. The standard deviation of JJAS PC1 declined from 2.29 to 0.82 and subsequently increased to 2.18 across these periods. Extremely dry regional monsoon months were uncommon during 1996–2005, accounting for 2.5% of JJAS months, compared with 13.3% during 1981–1995 and 17.6% during 2006–2022. The proportion of monsoon seasons containing at least two consecutive dry-anomaly months increased from 10.0% to 41.2%, while mean cumulative seasonal deficit increased from approximately 95 to 149 mm. Thus, the recent dry-side change primarily reflected more frequent dry months, greater persistence of below-normal conditions, and larger accumulated seasonal deficits rather than unprecedented severity of individual dry months.

Wet-side variability changed differently (Fig. 7). Mean excess precipitation during very wet regional months increased from approximately 128 mm above monthly climatology during 1981-1995 to approximately 175 mm during 2006-2022; relative excess increased from about 55% to

76%. Extremely wet months did not become comparably more frequent or persistent. July showed particularly strong increases in both dry- and wet-side variability after 2006, indicating reduced reliability in the core monsoon month rather than a unidirectional shift toward wetter or drier conditions.

3.5 Intra-monsoon distribution and rainfall events

No calendar month exhibited a significant long-term trend in total precipitation. June and August had the strongest negative tendencies, whereas July tended to increase. July's fraction of JJAS precipitation increased, but the result was marginal ($p = 0.050049$). Rolling analyses indicated increasing variability in May-July and decreasing variability in March, April, August, November, and December. Because rolling windows overlap, these results are descriptive rather than independent tests.

Event indices did not support a general intensification of rainfall extremes. July showed no significant trends in wet-day frequency, mean wet-day intensity, upper-tail intensity, or the fraction of precipitation contributed by the wettest days. The fraction of June precipitation occurring on the wettest day increased (nominal $p = 0.0484$), while the number of August days above the high-precipitation threshold decreased (nominal $p = 0.0432$). These isolated, unadjusted results indicate possible month-specific redistribution but do not demonstrate a systematic shortening or intensification of the monsoon.

3.6 Forecast performance

For DTR, naive persistence provided the lowest five-year rolling-validation error ($\text{RMSE} = 0.298$ °C), compared with linear trend extrapolation (0.627 °C) and GAM plus AR(1) (0.874 °C). Recent DTR values therefore provided a more reliable near-term baseline than extrapolation of either the long-term decline or the terminal GAM curvature. For monthly precipitation, the seasonal model reduced mean validation RMSE from 22.87 to 16.51 mm relative to the comparison model, although errors remained largest in July and August. Mean-temperature STL-ARIMA validation yielded an RMSE of 1.546 °C, with the largest errors during cold months.

4 Discussion

4.1 Seasonal asymmetry and contraction of DTR

The principal temperature signal at the Pyramid AWS is not a uniform increase in annual mean temperature but a marked redistribution of temperature change across the seasonal and diurnal cycles. May cooling contrasts with warming in September-November, while decreasing warm-season maxima and increasing late-year minima jointly narrow DTR. The broad monthly consistency of the DTR decline, its nonlinear annual trajectory, and the persistent 2008/2009 change point make DTR the most robust feature of the Pyramid AWS record. Namche Bazaar shows a less consistent but directionally similar contraction concentrated outside the monsoon season. Agreement between the stations supports the interpretation that DTR narrowing is not solely a Pyramid AWS-specific phenomenon, whereas differences in magnitude and seasonality demonstrate substantial local spatial heterogeneity within the Everest/Sagarmatha region.

This pattern is consistent with regional evidence that minimum temperature has increased more rapidly than maximum temperature across the Tibetan Plateau. You et al. (2016), using 71 stations over 1961-2013, reported a regional DTR decrease of approximately $0.20\text{ }^{\circ}\text{C decade}^{-1}$, primarily because minimum temperature warmed faster than maximum temperature. Kuang and Jiao (2016) reached the same broad conclusion in their synthesis of Tibetan Plateau climate change. The Pyramid AWS record is distinct because it represents a single extreme-elevation location above 5000 m and a more recent 30-year interval. Direct comparison of trend magnitudes should therefore account for differences in elevation, period, spatial averaging, instrumentation, and local surface conditions (Pepin et al. 2022; Thornton et al. 2022).

Potential physical controls on DTR include changes in cloud cover, humidity, downward longwave radiation, snow cover, and soil or surface moisture (Dai et al. 1999; Mountain Research Initiative EDW Working Group 2015). Greater cloudiness or atmospheric moisture can suppress daytime heating and reduce nighttime radiative cooling, thereby narrowing DTR. Changes in snow cover and precipitation phase may also alter albedo and surface energy exchange (Pepin et al. 2022). In glacierized terrain, enhanced sensible heat exchange and katabatic flow may additionally contribute to local cooling and drying (Salerno et al. 2023). These mechanisms cannot be distinguished using the present temperature and precipitation series alone. The coincidence of the DTR transition with any changes in station exposure, instrumentation, observation practices, or data processing must also be assessed before the 2008/2009 breakpoint is interpreted as a physical regime shift.

4.2 Nonlinear precipitation variability and monsoon organization

Annual and JJAS precipitation show multiyear decline and recovery rather than significant monotonic change. This non-uniform behaviour is consistent with the spatially and temporally heterogeneous precipitation changes reported across the Hindu Kush-Himalayan region (Palazzi et al. 2013; Krishnan et al. 2019). The stable JJAS fraction indicates that the monsoon continued to dominate the annual water input throughout the record, as previously described for the Everest region (Salerno et al. 2015; Wood et al. 2020). Stability in this fraction, however, does not imply stability in precipitation magnitude, timing, wet-day sequencing, or distribution among monsoon months.

The strong correlations and nearly equal PC1 loadings across the four CHIRPS extraction locations show that this non-monotonic variability is not confined to a single site. The early-1990s shift, the unusually stable 1996-2005 interval, and the renewed variability after 2006 recur across the elevation transect. Recent change is therefore better characterized as reduced monsoon reliability than as a simple long-term decrease in precipitation. More frequent and persistent dry anomalies increase cumulative seasonal deficits, whereas larger wet-month departures create a distinct runoff and hazard risk.

The increase in July's share, greater variability during May-July, the increased contribution of the wettest June day, and fewer threshold exceedances in August collectively suggest possible reorganization within the monsoon. Nevertheless, the statistical evidence is not sufficient to conclude that the monsoon has become shorter or that precipitation has become generally more concentrated. A direct test of monsoon concentration would require predefined metrics such as onset and withdrawal dates, precipitation concentration index, fraction received within the wettest consecutive 5-, 10-, or 20-day window, spell duration, and seasonal entropy. Application of these measures to the daily record would provide a stronger basis for the proposed concentration hypothesis.

4.3 Implications for high-mountain water resources

Seasonal temperature asymmetry may be more hydrologically consequential than the weak annual mean trend. May cooling could affect pre-monsoon snow persistence and the timing of melt, whereas warming during late monsoon and early winter may influence precipitation phase, freezing conditions, and the duration of seasonal snow cover (Hock et al. 2019; Pepin et al. 2022).

A reduction in DTR may additionally affect freeze-thaw frequency where daily temperatures cross 0 °C. These implications remain hypotheses because snow cover, snow-water equivalent, glacier mass balance, runoff, and water use were not response variables in the present analysis.

Precipitation timing is similarly important in a catchment where annual water availability depends on the interaction of monsoon rainfall, snow accumulation, glacier melt, and groundwater storage. Previous work in the Khumbu Valley found that snow and glacier melt supplied an average of approximately 65% of sampled domestic water during the dry pre-monsoon season, underscoring the sensitivity of local supplies to seasonal climate and cryospheric change (Wood et al. 2020). A stable annual or JJAS total can coexist with longer dry intervals or a greater fraction of rainfall delivered during a small number of days, potentially reducing infiltration and increasing runoff or erosion. Linking the location-based CHIRPS series with streamflow, snow, glacier, isotope, and community water-supply observations would permit direct testing of these pathways.

The increase in monsoon seasons containing consecutive dry-anomaly months provides a plausible climatic context for community observations of decreasing water availability and drying springs. Earlier research in Sagarmatha National Park has demonstrated relationships between precipitation and drinking-water conditions and has emphasized the vulnerability of local sources to seasonal climate variability (Nicholson et al. 2018, 2019; Wood et al. 2020). Sequences of moderately dry months may restrict recharge and replenishment more strongly than an isolated dry month because deficits accumulate and opportunities for recovery diminish. Conversely, larger wet-month surpluses may produce rapid runoff, erosion, and slope instability without proportionally improving groundwater recharge. These statistical associations do not establish climate as the sole cause of changes in individual springs; local hydrogeology, earthquake effects, land-use change, infrastructure, abstraction, and tourism demand remain potential interacting controls.

4.4 Forecast interpretation and study limitations

The validation results favour recent-level persistence for DTR and a recurring seasonal structure for precipitation. These forecasts are useful as near-term reference conditions against which new observations can be evaluated, but they do not constitute climate projections. In particular, the end curvature of a historically fitted GAM should not be extrapolated as evidence of an emerging reversal without out-of-sample support.

The principal limitations are the 30-year duration and predominantly single-station scope of the detailed temperature and daily precipitation analyses, incomplete precipitation coverage and consequent reconstruction, and data-selected change points. The extreme elevation that makes Pyramid Station scientifically valuable also limits direct comparison with lower stations and increases the importance of metadata and homogeneity assessment. The Namche Bazaar DTR comparison is constrained by its sparse record and sensitivity to short analysis windows, while monthly precipitation cannot determine whether regional anomalies reflect longer dry spells, fewer events, reduced event intensity, or event clustering. Because CHIRPS is a gridded satellite–gauge product, the regional series may not fully represent fine-scale precipitation differences associated with elevation and complex Himalayan topography. Physical attribution requires independent observations of radiation, cloud, humidity, wind, snow cover, discharge, groundwater, land use, and changes in station operation. Accordingly, the results establish statistical characteristics of the observed records but do not by themselves identify causal mechanisms.

5 Conclusions

The 1994–2023 Pyramid AWS record reveals pronounced seasonal asymmetry in temperature change, a persistent contraction of DTR, and nonlinear precipitation variability. May cooled significantly, whereas November warmed strongly, and annual mean temperature showed little coherent change. DTR declined in all months at the Pyramid AWS, with statistically significant Mann-Kendall trends in 10 of 12 months, and shifted from a mean of 7.40 °C before 2009 to 6.32 °C afterward, a reduction of 14.6%. This decline reflects both cooling of maximum temperature during part of the warm season and warming of minimum temperature later in the year. Predominantly negative monthly and seasonal Sen slopes at Namche Bazaar provide independent, although less uniform, evidence that DTR contraction extends to a lower-elevation station in the region.

Annual and JJAS precipitation did not exhibit significant monotonic trends but underwent marked changes in level and variability. Correlations and PCA among the four CHIRPS grid-cell series identify a coherent regional signal, including a persistent early-1990s shift, suppressed variability during 1996–2005, and renewed variability after 2006. Relative to the low-variability period of 1996–2005, dry monsoon months became more frequent and persistent during 2006–2022, and cumulative deficits increased, while extreme wet months became larger without becoming

comparably more frequent. These results indicate declining monsoon reliability rather than a simple reduction in seasonal precipitation. Daily concentration, dry-spell, and onset-withdrawal metrics should be evaluated explicitly before changes in event intensity or monsoon duration are inferred.

The results identify DTR, pre-monsoon temperature, late-year minimum temperature, and intra-monsoon precipitation distribution as priorities for continued monitoring. Integration with snow, glacier, runoff, and water-use observations will be required to determine whether these climatic changes are affecting seasonal water availability in the Everest region.

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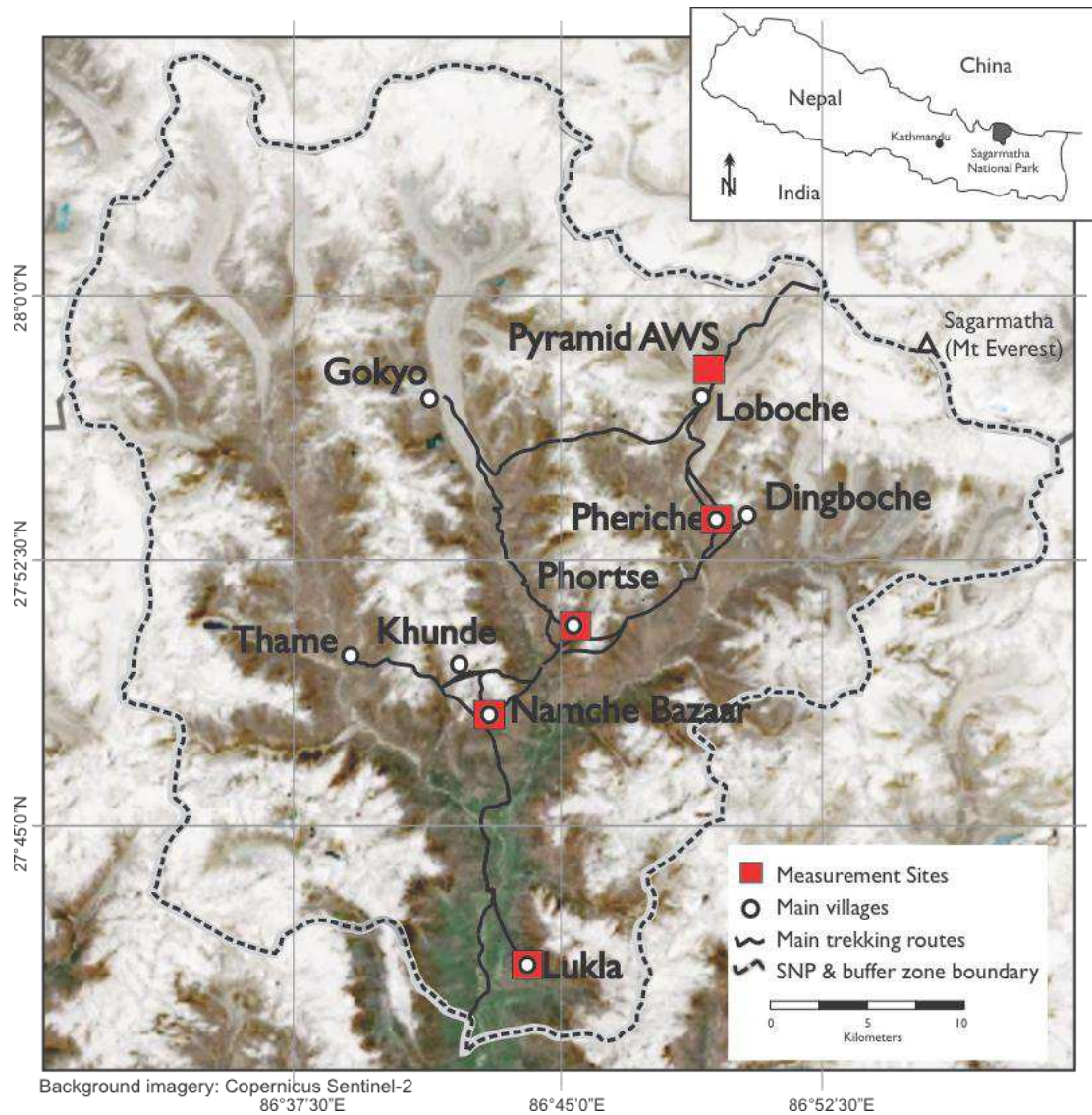


Fig. 1 Location of the study area in the Sagarmatha National Park and Buffer Zone of northeastern Nepal. The main map shows Pyramid AWS and the settlements of Gokyo, Loboche, Dingboche, Pheriche, Phortse, Khunde, Thame, Namche Bazaar, and Lukla, together with measurement sites, main trekking routes, and the Sagarmatha National Park and Buffer Zone boundary. The inset shows the location of Sagarmatha National Park within Nepal.

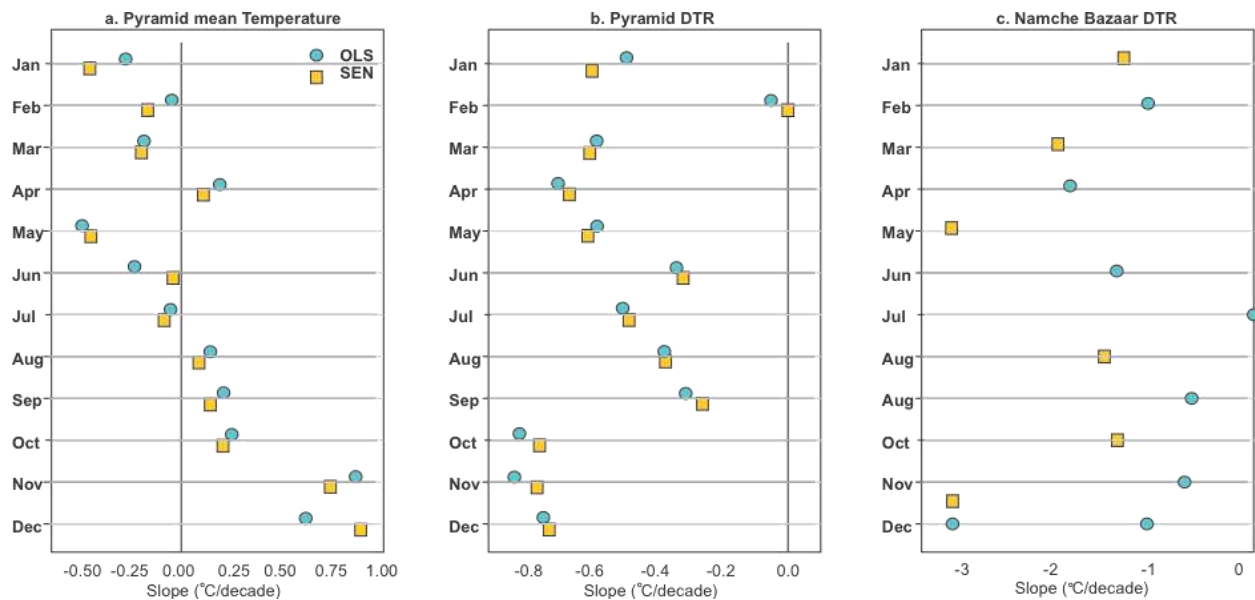


Fig. 2 Monthly temperature trends at Pyramid AWS and Namche Bazaar. (a) Ordinary least-squares and Sen slopes in monthly mean air temperature at Pyramid AWS for 1994-2023. (b) Ordinary least-squares and Sen slopes in monthly diurnal temperature range (DTR) at Pyramid AWS. (c) Sen slopes in monthly DTR at Namche Bazaar. Trends are expressed in $^{\circ}\text{C decade}^{-1}$. In panel c, filled symbols denote statistically significant trends at $p < 0.05$ and open symbols denote nonsignificant trends. The vertical reference line represents no change. The Namche Bazaar record is less complete than the Pyramid AWS record and therefore produces greater uncertainty in the monthly estimates.

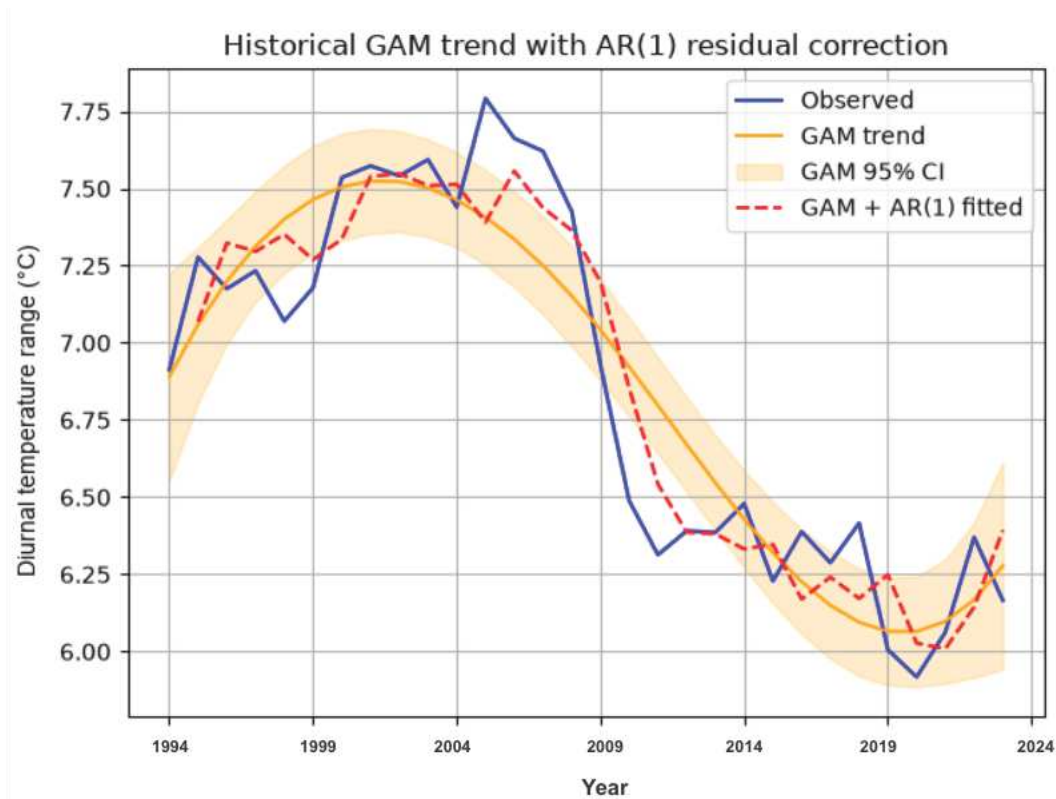


Fig. 3 Annual diurnal temperature range (DTR) at Pyramid AWS during 1994-2023. The solid blue line shows observed annual values, the orange line shows the fitted five-basis generalized additive model (GAM; $\lambda_{\text{GAM}} = 0.001$), and shading denotes the 95% confidence interval. The dashed red line shows the GAM with AR(1) residual correction. Change-point analysis identified a persistent transition at the 2008/2009 boundary; mean DTR decreased from 7.402 °C during 1994-2008 to 6.322 °C during 2009-2023.

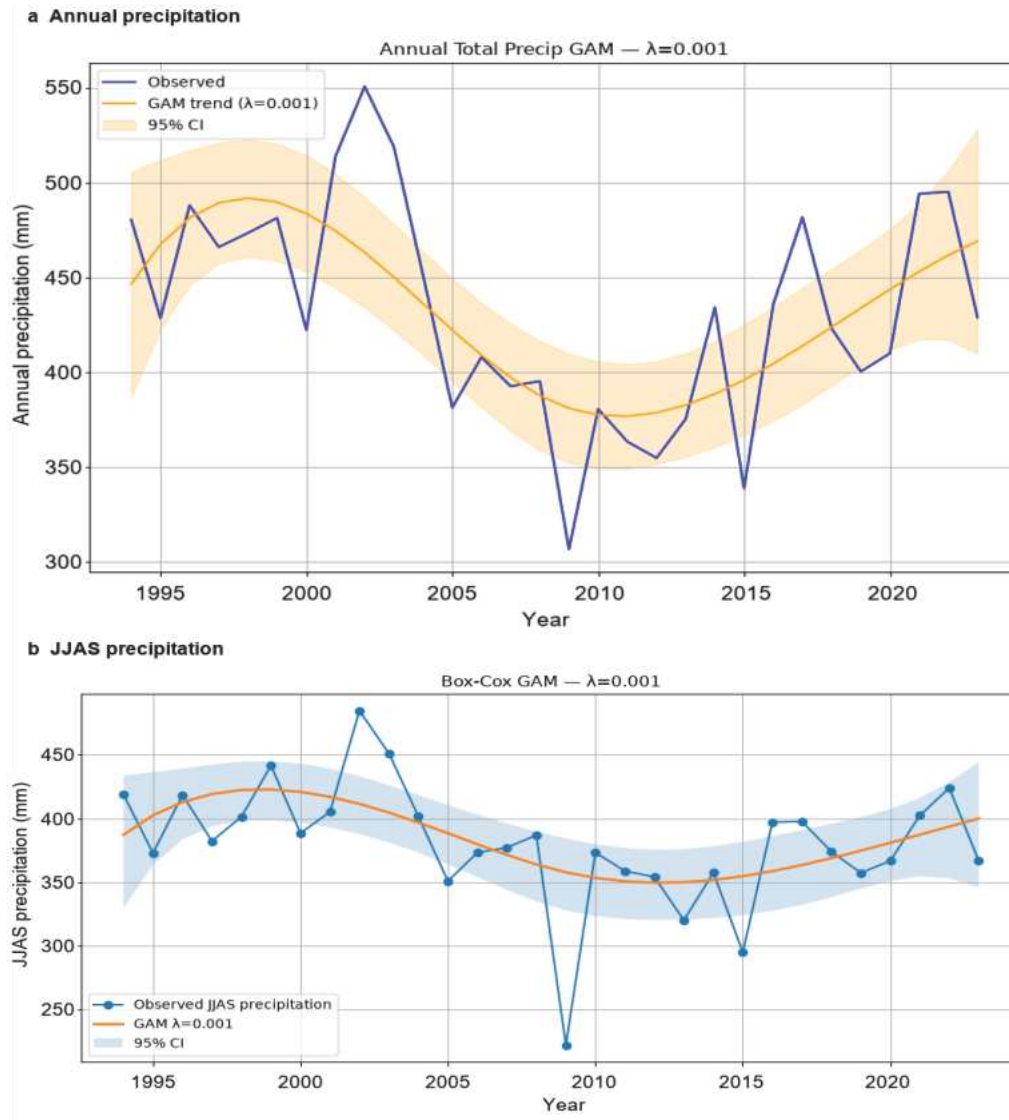
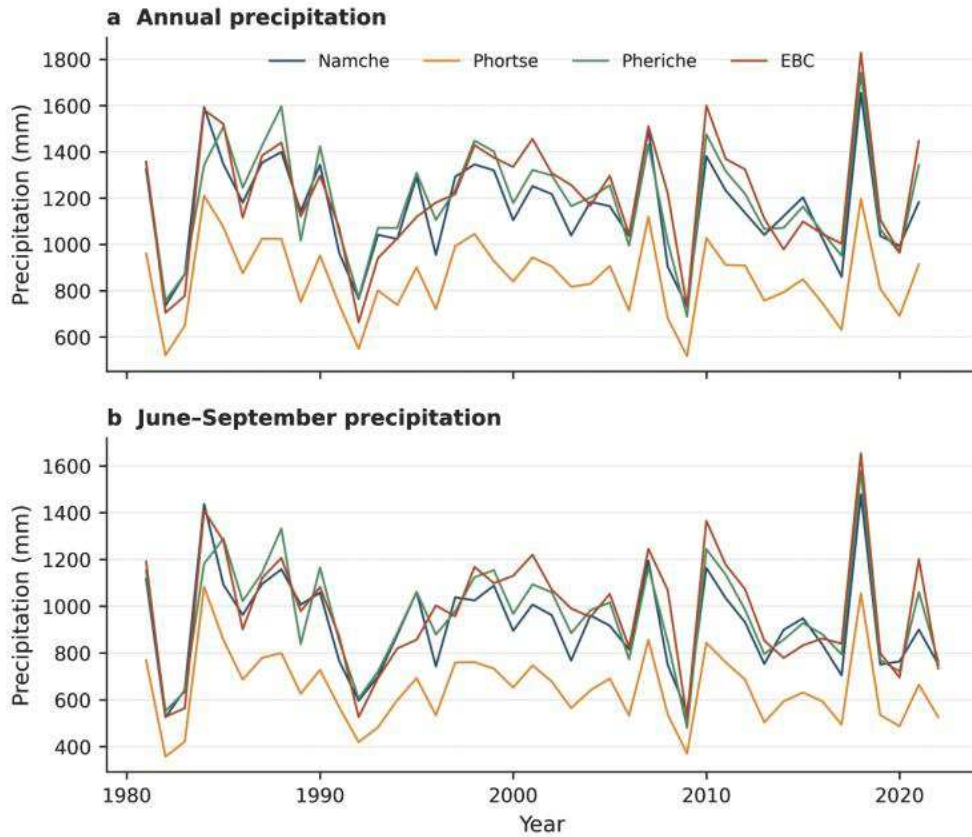


Fig. 4 Precipitation totals and fitted generalized additive model (GAM) trajectories at Pyramid AWS during 1994-2023. (a) Annual precipitation. (b) June-September (JJAS) precipitation. Both models use $\lambda_{\text{GAM}} = 0.001$. The JJAS model was fitted after a Box-Cox transformation and is shown after inverse transformation to millimetres. Shading denotes the 95% confidence intervals.



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631 Fig. 5 Annual and summer-monsoon CHIRPS v3.0 precipitation at four Everest-region
 632 extraction locations during 1981–2022. (a) Annual precipitation estimates at Namche Bazaar,
 633 Phortse, Pheriche, and Everest Base Camp. (b) June–September (JJAS) precipitation estimates at
 634 the corresponding extraction locations. Lines connect annual CHIRPS estimates and do not
 635 represent fitted trends. Mann–Kendall tests detected no statistically significant annual or JJAS
 636 trend at any extraction location.

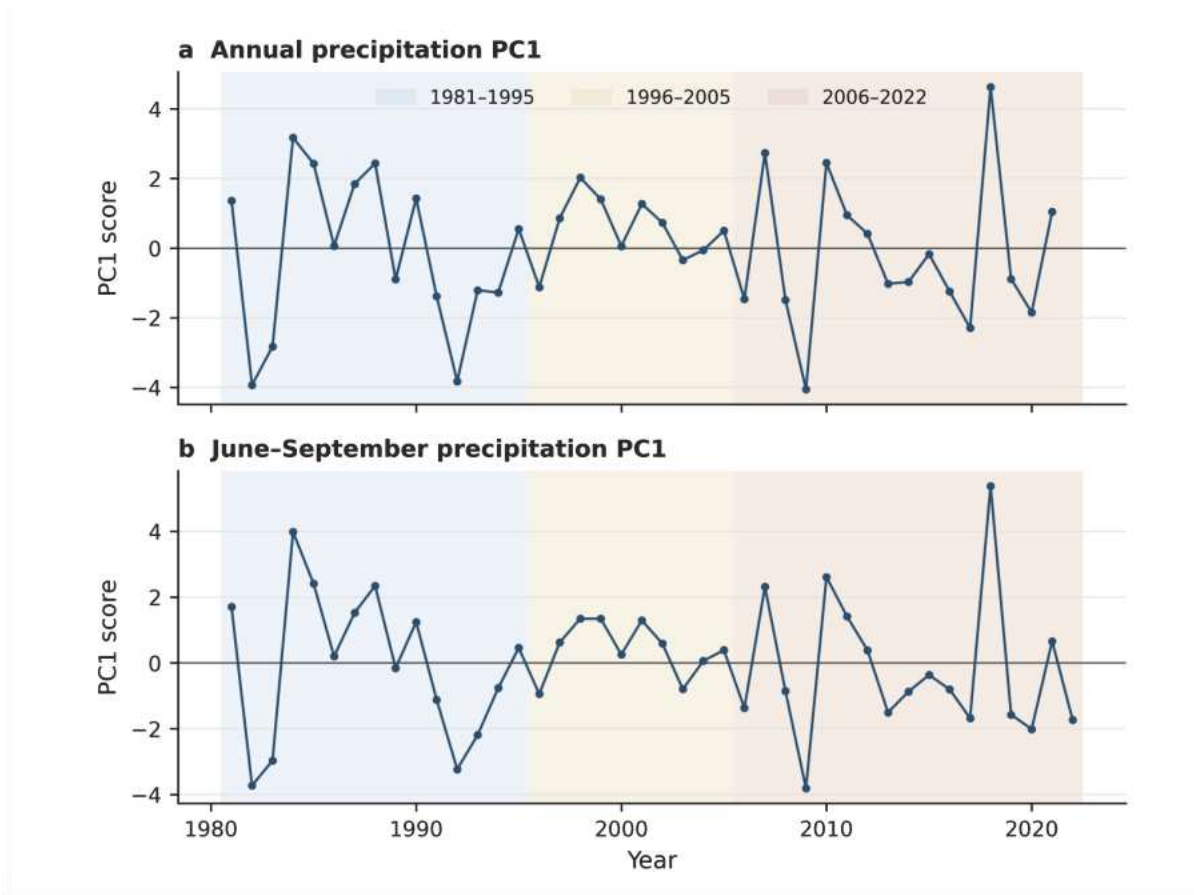


Fig. 6 Regional precipitation variability represented by PC1 of standardized CHIRPS v3.0 series extracted at Namche Bazaar, Phortse, Pheriche, and Everest Base Camp. (a) Annual precipitation PC1, explaining 94.8% of the shared annual variability. (b) June-September (JJAS) precipitation PC1, explaining 94.4% of the shared monsoon variability. Positive and negative scores represent relatively wetter and drier regional conditions, respectively. Background shading distinguishes the 1981-1995, 1996-2005, and 2006-2022 analysis periods.

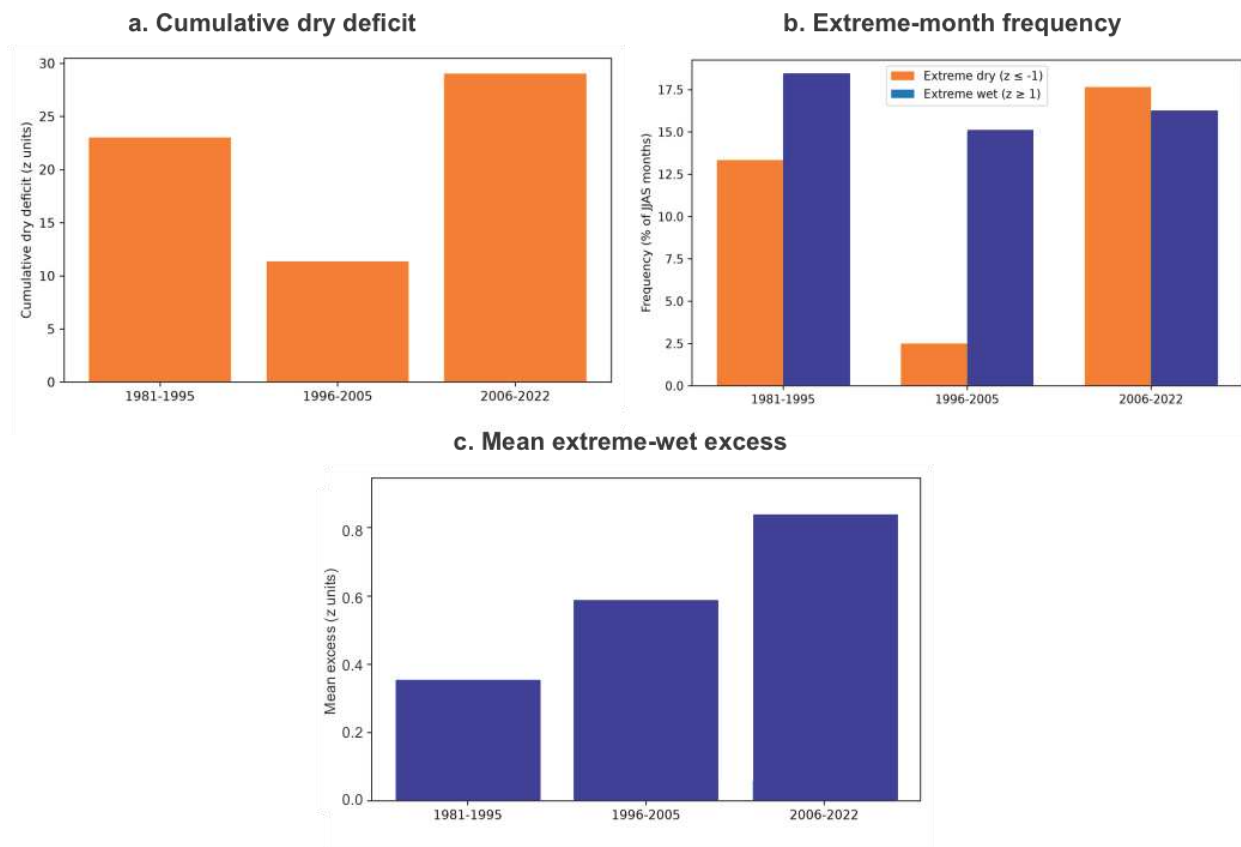


Fig. 7 Changes in monsoon precipitation reliability among the 1981–1995, 1996–2005, and 2006–2022 periods. (a) Cumulative dry deficit. (b) Percentage of June–September months classified as extremely dry ($z \leq -1.0$) or extremely wet ($z \geq 1.0$). (c) Mean precipitation excess during extremely wet months. Standardized regional anomalies were calculated relative to the 1981–2022 calendar-month climatology. Metrics were calculated from the four regional CHIRPS series.

Statements & Declarations

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Author Contributions

All authors contributed to the study conception and design. Data collection and analysis were performed by Kirsten Nicholson and James Dean. All modelling and statistical methods were performed by James Dean. The manuscript was written by Kirsten Nicholson and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Data Availability

The analysis code generated during the current study is available upon reasonable request. The Pyramid Meteorological Network observations are publicly available from Zenodo at <https://doi.org/10.5281/zenodo.15211352>. CHIRPS v3.0 monthly precipitation data are available from the University of California, Santa Barbara Climate Hazards Center at https://data.chc.ucsb.edu/products/CHIRPS/v3.0/monthly/global/netcdf/by_year/.