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Modulation of Rainfall Variability and Potential Predictability in Ecuador: ENSO's Evolving Influence (1981–2018)

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सार – इक्वाडोर अल नीनो-दक्षिणी दोलन (ENSO) के प्रति अत्यधिक संवेदनशील है, और इसकी परिवर्तनशीलता से अंतरवार्षिक वर्षा पैटर्न काफी प्रभावित होते हैं। हालांकि, देश की जटिल स्थलाकृति के कारण, ये प्रभाव अत्यधिक विषम हैं, जिसके लिए यह समझने के लिए स्थानीय विश्लेषण की आवश्यकता है कि विकसित हो रही ENSO गतिशीलता क्षेत्र को कैसे प्रभावित करती है। यह विश्लेषण समरूप और अंतराल-भरे दैनिक वर्षा प्रेक्षणों को कई उपग्रह-आधारित डेटासेट (MSWEP, CHIRPS और IMERG) के साथ एकीकृत करता है, जिससे मौसमी वर्षा विशेषताओं, शुष्क और आर्द्र अवधि सूचकांकों और चरम वर्षा मापदंडों का तुलनात्मक मूल्यांकन संभव हो पाता है। नीनो 1+2, नीनो 3, नीनो 3.4 और नीनो 4 क्षेत्रों में समुद्र सतह तापमान (SST) विसंगतियों से प्राप्त जलवायु सूचकांकों का उपयोग ENSO-संबंधी प्रभावों का मूल्यांकन करने के लिए किया जाता है।

बहुदशकीय परिवर्तनों का आकलन करने के लिए, दो उप-अवधियों (1981-1999 और 2000-2018) की तुलना की गई है। अनुभवजन्य ऑर्थोगोनल फ़ंक्शन (ईओएफ) विश्लेषण और सहसंबंध तकनीकों से वर्षा परिवर्तनशीलता के प्रमुख तरीकों और ENSO सूचकांकों के साथ उनके संबंधों में महत्वपूर्ण बदलाव सामने आए हैं। परिणाम ENSO-संबंधित मॉड्यूलेशन के पुनर्गठन का संकेत देते हैं, जिसमें 2000 के बाद पूर्वी प्रशांत महासागर के SST विसंगतियों का प्रभाव कम हो गया है और मध्य प्रशांत महासागर की परिवर्तनशीलता की भूमिका बढ़ गई है, जो विशेष रूप से शुष्क और आर्द्र अवधि की निरंतरता और चरम वर्षा सूचकांकों को प्रभावित करती है। इस पुनर्गठन में तीन समवर्ती परिवर्तन शामिल हैं: स्रोत क्षेत्र पूर्वी प्रशांत से मध्य प्रशांत की ओर स्थानांतरित होता है, युग्मन का संकेत उलट जाता है, और सबसे अधिक प्रभाव वाला त्रिविध मौसम आर्द्र ऋतु (AMJ) से उत्तरी गोलार्ध की ग्रीष्म ऋतु (JAS) की ओर स्थानांतरित हो जाता है। ये निष्कर्ष इक्वाडोर में गैर-स्थिर ENSO-वर्षा संबंध को उजागर करते हैं, जिसका मौसमी पूर्वानुमान, जलवायु जोखिम मूल्यांकन, जल विज्ञान, जलविद्युत और कृषि प्रबंधन और योजना पर प्रभाव पड़ता है, जो कि एक ऐसे क्षेत्र में है जो मजबूत स्थलाकृतिक और जलवायु विषमता से चिह्नित है।

ABSTRACT. Ecuador is highly vulnerable to the El Niño–Southern Oscillation (ENSO), with interannual rainfall patterns significantly influenced by its variability. However, owing to the country's complex orography, these impacts are highly heterogeneous, requiring localized analyses to understand how evolving ENSO dynamics affect the region. The analysis integrates homogenized and gap-filled daily precipitation observations with multiple satellite-based datasets (MSWEP, CHIRPS, and IMERG), enabling a comparative assessment of seasonal precipitation characteristics, dry and wet spell indices, and extreme rainfall metrics. Climatic indices derived from sea surface temperature (SST) anomalies in the Niño 1+2, Niño 3, Niño 3.4, and Niño 4 regions are used to evaluate ENSO-related influences.

To assess multidecadal changes, two sub-periods (1981–1999 and 2000–2018) are contrasted. Empirical Orthogonal Function (EOF) analysis and correlation techniques reveal significant shifts in the dominant modes of precipitation variability and in their associations with ENSO indices. Results indicate a reorganization of ENSO-related modulation, with a reduced influence of eastern Pacific SST anomalies and an increased role of central Pacific variability after 2000, particularly affecting dry and wet spell persistence and extreme precipitation indices. The reorganization

involves three concurrent changes: the source region shifts from the eastern to the central Pacific, the sign of the coupling reverses, and the trimester of strongest influence migrates from the wet season (AMJ) to boreal summer (JAS). These findings highlight a non-stationary ENSO–precipitation relationship in Ecuador, with implications for seasonal predictability, climate risk assessment, hydrology, hydropower and agriculture management and planning in a region characterized by strong topographic and climatic heterogeneity.

Key words – El Niño–Southern Oscillation (ENSO), Precipitation variability, Rainfall extremes, Climate indices, Ecuador, Satellite rainfall estimates.

1. Introduction

Ecuador's mainland climate exhibits strong spatial and seasonal variability associated with its complex geography, including coastal plains influenced by the Humboldt Current, the Andean cordillera, and the humid Amazon basin (Sheppard, 1930; Morán-Tejeda *et al.*, 2016; Peters *et al.*, 2013). Seasonal precipitation patterns (Fig. 1) are strongly modulated by large-scale tropical climate variability, particularly the El Niño–Southern Oscillation (ENSO), which represents the dominant mode of interannual variability affecting the tropical Pacific and adjacent regions (McPhaden *et al.*, 2006).

ENSO arises from coupled ocean–atmosphere interactions that generate sea surface temperature (SST) anomalies in the equatorial Pacific and is commonly classified into El Niño (warm) and La Niña (cold) phases (Capotondi *et al.*, 2015). Beyond this binary classification, two main ENSO flavours have been identified, broadly distinguishing Eastern Pacific (EP, also termed canonical) and Central Pacific (CP) events, each associated with distinct SST footprints and atmospheric teleconnections (Ashok *et al.*, 2007; Kao and Yu, 2009; Kug *et al.*, 2009; Capotondi *et al.*, 2015). Canonical EP El Niño events typically exhibit maximum positive SST anomalies along the South American coast (Niño 1+2 and 3 region), an eastward displacement of the Walker circulation, and a strong enhancement of rainfall along the Ecuadorian and northern Peruvian coast, often accompanied by drier conditions over the Amazon basin and parts of the Andes (Tedeschi *et al.*, 2013; Sanabria *et al.*, 2018; Cai *et al.*, 2020; Thielen *et al.*, 2023). In contrast, CP events are characterized by maximum SST anomalies in the central equatorial Pacific (Niño 3.4 and 4 region) and a more zonal anomalous Walker cell with two convective branches, producing precipitation impacts over Ecuador that are spatially heterogeneous, seasonally complex and considerably less well documented in the regional literature (Tedeschi *et al.*, 2013; Hu *et al.*, 2017). In Ecuador, ENSO impacts therefore vary regionally and depend on the ENSO flavour: enhanced rainfall and flooding along the coast during canonical El Niño events, reduced precipitation in parts of the Andes, and drought conditions in the Amazon basin (Vuille, 1999; Morán-Tejeda *et al.*, 2016; Jiménez-Muñoz *et al.*, 2016). During cold phases, the impacts broadly mirror the warm-phase pattern: canonical (EP) La Niña events are associated with

rainfall deficits along the coast, whereas CP La Niña conditions favour enhanced rainfall over the Andean highlands and the Amazon basin, with marked seasonal dependence (Tedeschi *et al.*, 2013; Sulca *et al.*, 2018; Campozano *et al.*, 2020).

Several studies have reported interdecadal changes in ENSO behaviour, with a clear shift around the year 2000, including a reduction in amplitude, an increased frequency of central Pacific events, and a strengthening of the Walker circulation (Yeh *et al.*, 2009; McPhaden *et al.*, 2011; Capotondi *et al.*, 2015; Hu *et al.*, 2017; Cai *et al.*, 2018). These shifts modify the interaction between ENSO and regional circulation processes, thereby altering precipitation variability across tropical South America (Tedeschi *et al.*, 2013; Cai *et al.*, 2020). Such changes are particularly relevant in the context of monsoon-related variability and predictability under a changing climate, as emphasized in the Eighth WMO International Workshop on Monsoons (IWM-8; WMO, 2025).

Although ENSO-related rainfall variability in Ecuador has been widely documented (Bendix *et al.*, 2011; Campozano *et al.*, 2020), less attention has been paid to the multidecadal evolution of ENSO–precipitation relationships and their implications for rainfall predictability, particularly when assessed using multiple observational and satellite-based precipitation datasets and indices of wet, dry, and extreme events. Addressing this gap is essential for improving climate monitoring and seasonal prediction in a region highly vulnerable to floods, droughts, and extreme precipitation events (Zebiak *et al.*, 2015; Horstmeyer, 2011).

To address this gap, the present study explicitly aims to: (i) characterize the seasonal precipitation patterns and the long-term changes of seasonal precipitation totals and of dry-spell, wet-spell and extreme-precipitation indices (PRCPTOT, CDD, CWD, R95p, R99p, Rx1day, Rx5days) across mainland Ecuador using four precipitation datasets (RR-based ground weather stations, MSWEP, CHIRPS and, for 2000–2018, IMERG) over the period 1981–2018; (ii) quantify the dominant modes of interannual variability of seasonal precipitation and of these indices via Empirical Orthogonal Function (EOF) analysis and their correlation with the four standardized HadISST Niño indices (Niño 1+2, Niño 3, Niño 3.4, Niño 4); and (iii) evaluate the multidecadal stability of these ENSO–

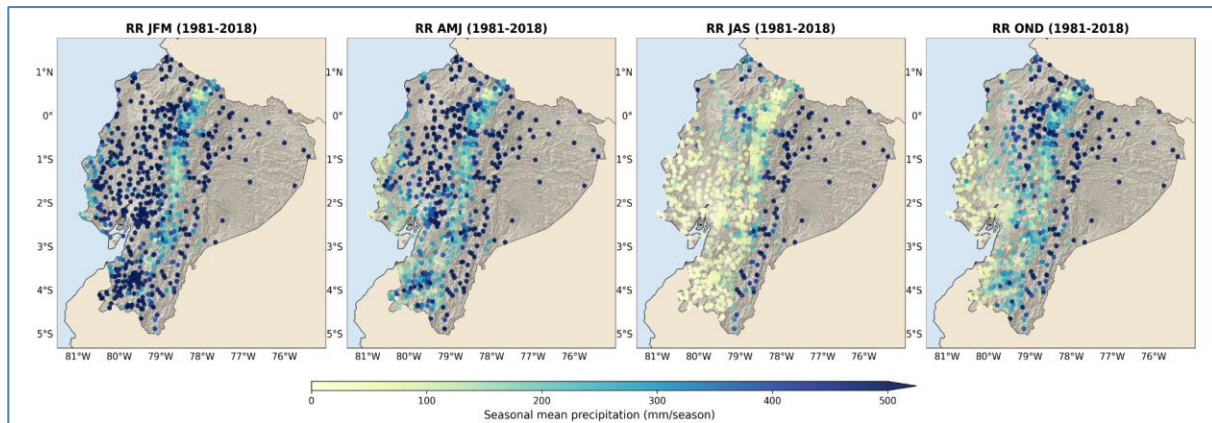


Fig. 1. Climatological seasonal mean precipitation (mm season^{-1}) over mainland Ecuador for the trimesters of a year, computed from the homogenized and gap-filled in situ rain-gauge network (RR; Guijarro, 2016) over the period 1981–2018. Each filled circle represents one of the 1,061 RR stations; circle colour indicates the trimestral climatological mean. Provincial boundaries are shown in dashed gray; neighbouring countries are masked in beige to focus on the Ecuadorian territory

precipitation relationships by contrasting two sub-periods (1981–1999 and 2000–2018). This framework allows us to test the hypothesis that the ENSO regime change reported around the year 2000 has translated into a measurable reorganization of the ENSO–precipitation modulation in Ecuador, with direct implications for seasonal predictability, climate risk assessment, hydrology and water-resources management.

2. Data and methodology

Daily precipitation data from four independent sources were used in this study: in situ observations from the Ecuadorian National Institute of Meteorology and Hydrology (INAMHI; hereafter RR) and three state-of-the-art satellite-based products, MSWEP (1979–2018, 0.1° spatial resolution; Beck *et al.*, 2017), CHIRPS (1981–2018, 0.05° spatial resolution; Geleta and Deressa, 2020) and IMERG (June 2000–2018, 0.1° spatial resolution, Final Run; Huffman *et al.*, 2020), the latter used only for the 2000–2018 sub-period. These products differ in their primary sensing principle: CHIRPS relies on thermal-infrared cold-cloud-duration estimates, which respond mainly to deep convective clouds, whereas MSWEP and IMERG merge passive-microwave retrievals with gauge and reanalysis information, making them comparatively more sensitive to warm-cloud and stratiform rainfall (Funk *et al.*, 2015; Beck *et al.*, 2017; Huffman *et al.*, 2020). These differences should be borne in mind when interpreting dataset discrepancies over the coastal plain and the inter-Andean valleys. The original INAMHI archive contained more than 1,500 stations covering the period 1964–2018; after applying quality control and homogenization, a final network of 1,061 stations with sufficiently long and reliable records was retained for the analysis (Fig. 1). Spatial coverage is denser along the Coastal plains and

the Andean cordillera, where the orographic and Pacific influences are most pronounced, and sparser over the Amazon basin, where station density remains a known limitation for regional climate studies (Espinoza Villar *et al.*, 2009; Contreras *et al.*, 2018). The station data were quality-controlled and homogenized using the Climatol R package (Guijarro, 2016), which detects inhomogeneities by pairwise comparison of each candidate series against synthetic reference series built from its closest neighbours, applies the Standard Normal Homogeneity Test (SNHT) to identify break points, and fills missing values via a normal-ratio interpolation; this widely adopted procedure is appropriate for daily precipitation in regions of complex topography such as Ecuador. For consistency across datasets, all analyses were conducted over the common period 1981–2018. All satellite products were extracted at the locations of the 1,061 stations (nearest grid point), so that every analysis is performed on identical, co-located networks; after homogenization and gap-filling, the residual fraction of missing daily values in RR is below 0.1%, and all 1,061 stations satisfy the completeness requirements of the EOF analyses in both sub-periods.

Sea surface temperature indices for the Niño 1+2, Niño 3, Niño 3.4 and Niño 4 regions were derived from the Hadley Centre Sea Ice and Sea Surface Temperature dataset (HadISST; Rayner *et al.*, 2003), accessed as monthly mean SST fields on a $1^\circ \times 1^\circ$ grid and averaged over the standard geographical boxes defined by NOAA/CPC. The resulting monthly time series were detrended (linear) and standardized over 1981–2018 to obtain the four Niño indices used in this study. Daily precipitation data were aggregated to monthly and seasonal (trimester) scales, and anomalies were computed relative to the corresponding 1981–2018 climatological means.

TABLE 1

Climate indices used in this study

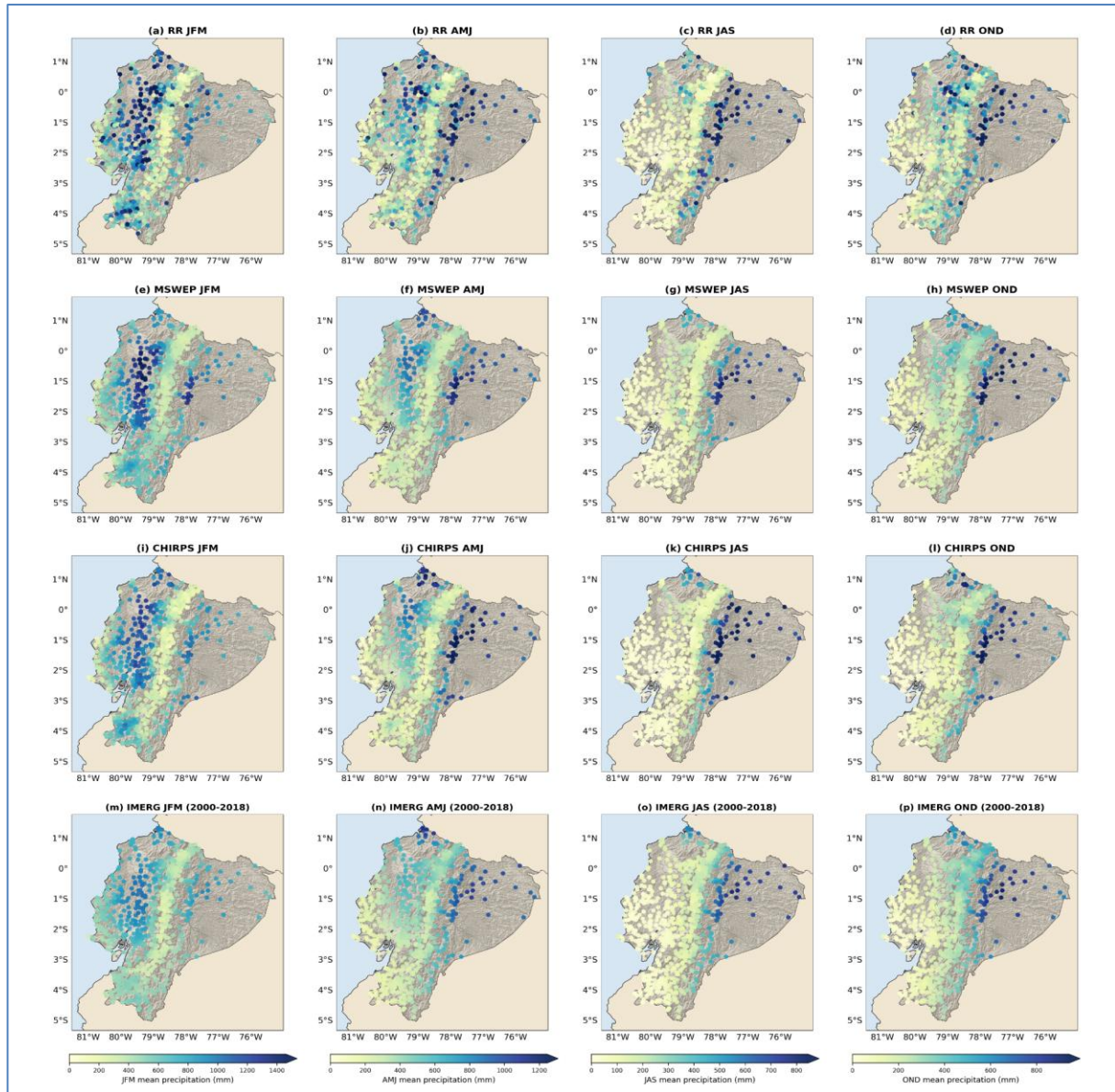
Climate Index	Definition	Units	Source
PRCPTOT	Trimestral total precipitation: sum of daily precipitation over all wet days (daily precipitation ≥ 1 mm) within the trimester.	mm	Klein Tank <i>et al.</i> (2009); Zhang <i>et al.</i> (2011); ETCCDI definitions.
CDD	Consecutive Dry Days: maximum number of consecutive days with daily precipitation < 1 mm within the trimester.	days	Klein Tank <i>et al.</i> (2009); Zhang <i>et al.</i> (2011); ETCCDI definitions.
CWD	Consecutive Wet Days: maximum number of consecutive days with daily precipitation ≥ 1 mm within the trimester.	days	Klein Tank <i>et al.</i> (2009); Zhang <i>et al.</i> (2011); ETCCDI definitions.
R95p	Very Wet Days: trimestral total precipitation accumulated on days when daily precipitation exceeds the 95th percentile of the wet-day distribution (computed over the 1981–2018 reference period).	mm	Klein Tank <i>et al.</i> (2009); Zhang <i>et al.</i> (2011); ETCCDI definitions.
R99p	Extremely Wet Days: trimestral total precipitation accumulated on days when daily precipitation exceeds the 99th percentile of the wet-day distribution (1981–2018 reference period).	mm	Klein Tank <i>et al.</i> (2009); Zhang <i>et al.</i> (2011); ETCCDI definitions.
Rx1day	Maximum 1-day precipitation: largest daily precipitation amount recorded within the trimester.	mm	Klein Tank <i>et al.</i> (2009); Zhang <i>et al.</i> (2011); ETCCDI definitions.
Rx5days	Maximum 5-day cumulative precipitation: largest amount accumulated over 5 consecutive days within the trimester.	mm	Klein Tank <i>et al.</i> (2009); Zhang <i>et al.</i> (2011); ETCCDI definitions.

Seasonal accumulated precipitation (PRCPTOT) and indices characterizing wet and dry conditions as well as precipitation extremes (CDD, CWD, R95p, R99p, Rx1day, Rx5days) were computed following the ETCCDI definitions (Klein Tank *et al.*, 2009; Zhang *et al.*, 2011; see Table 1), allowing a consistent assessment of changes in the frequency, intensity and duration of precipitation variability and extremes. Differences between sub-periods (2000–2018 minus 1981–1999) were computed station-by-station for each index, and their statistical significance was evaluated by a non-parametric Monte Carlo permutation test in which the 38 yearly index values were randomly shuffled 10,000 times to build an empirical null distribution of the difference of means; differences exceeding the 2.5th – 97.5th percentiles of this distribution were considered significant at the 95% confidence level ($p < 0.05$; Wilks, 2019). To quantify the relationship between precipitation variability and ENSO, Pearson correlation and ordinary least squares linear regression analyses were applied between the leading principal component (PC1) of each index and the four standardized HadISST Niño indices; analytical Student's *t* thresholds ($|r| \approx 0.456$ for $n = 19$) were used to mark statistically significant stations on the EOF1 loading maps at the 95% confidence level.

Changes in mean seasonal precipitation between sub-periods were additionally assessed using the monthly accumulations within each trimester as samples ($n \approx 57$ per sub-period), applying Welch's *t*-test for the difference of means. Changes in interannual variability were quantified through the ratio of monthly precipitation variances (2000–2018 over 1981–1999) computed from monthly anomalies relative to each sub-period's calendar-

month climatology, thereby removing the intra-seasonal cycle; significance was assessed with a two-sided *F*-test whose degrees of freedom account for the estimated monthly climatologies. The correlations summarized in the PC1–ENSO correlation matrix were tested with a Monte Carlo permutation test (1,000 permutations, $\alpha = 0.01$). Finally, the DJF ENSO events shown in Fig. 13 were defined when the standardized, detrended anomaly of either the Niño 1+2 or the Niño 4 index reached $|z| \geq 0.5$, each event being assigned to the index with the larger absolute anomaly.

The leading modes of interannual variability of each index were identified through an S-mode EOF analysis (Björnsson and Venegas, 1997; von Storch and Zwiers, 1999; Hannachi *et al.*, 2007), applied separately to each dataset, index, trimester and sub-period: the yearly index values were arranged in a $19 \times ns$ (years $\times$ stations) matrix, standardized and linearly detrended station by station, and decomposed by singular value decomposition (Wilks, 2019). The leading PC was then correlated with the four standardized HadISST Niño indices (Niño 1+2, 3, 3.4, 4; Rayner *et al.*, 2003) averaged over the same trimester used in the precipitation analysis. Pearson correlation and ordinary least squares linear regression were computed for each combination, with the statistical significance of the PC1–Niño correlations assessed by the Monte Carlo permutation test described above ($\alpha = 0.01$; Fig. 9). The full mathematical formulation of the S-mode EOF decomposition, including the covariance-matrix interpretation, the homogeneous correlation map, and sampling-error considerations (North *et al.*, 1982), is provided in the Supplementary Material (Section S1).



Figs. 2(a-p). Seasonal climatology of trimestral mean precipitation (mm) over mainland Ecuador for (columns) JFM, AMJ, JAS and OND and (rows) the four datasets: (a–d) RR, (e–h) MSWEP, (i–l) CHIRPS, averaged over 1981–2018, and (m–p) IMERG, averaged over 2000–2018. All satellite products are sampled at the locations of the 1,061 RR stations

3. Results and discussion

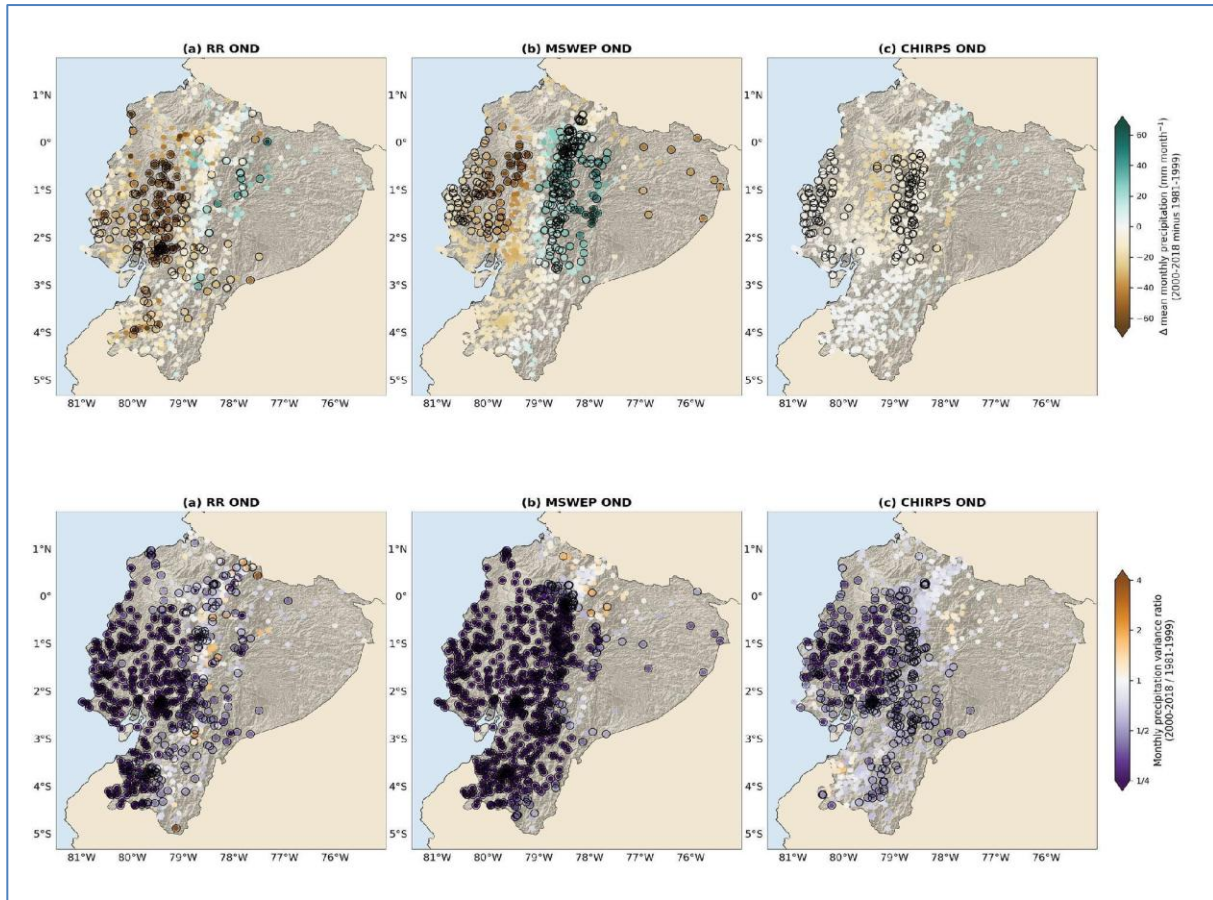
3.1. Seasonal patterns and dataset comparison

The seasonal climatologies of the four datasets (Fig. 2) show a consistent representation of the main rainfall regimes of mainland Ecuador: the JFM–AMJ wet season and the JAS dry season over the Coast and the inter-Andean region, and the year-round rainfall maxima along the eastern Andean foothills. The leading spatial patterns are captured by all products; their differences lie in the regions that each dataset resolves best. RR and CHIRPS reproduce localized features of the inter-Andean valleys

and coastal gradients more sharply, whereas MSWEP and IMERG provide a smoother, spatially coherent large-scale signal that tends to underestimate the orographic maxima of the eastern foothills. These complementary sensitivities - rather than the superiority of any single product - are exploited throughout this study: conclusions are considered robust where the datasets agree (Section 3.7).

3.2. Long-term changes in dry, wet and extreme precipitation indices

Fig. 3 shows the change in mean seasonal precipitation between 2000–2018 and 1981–1999, assessed



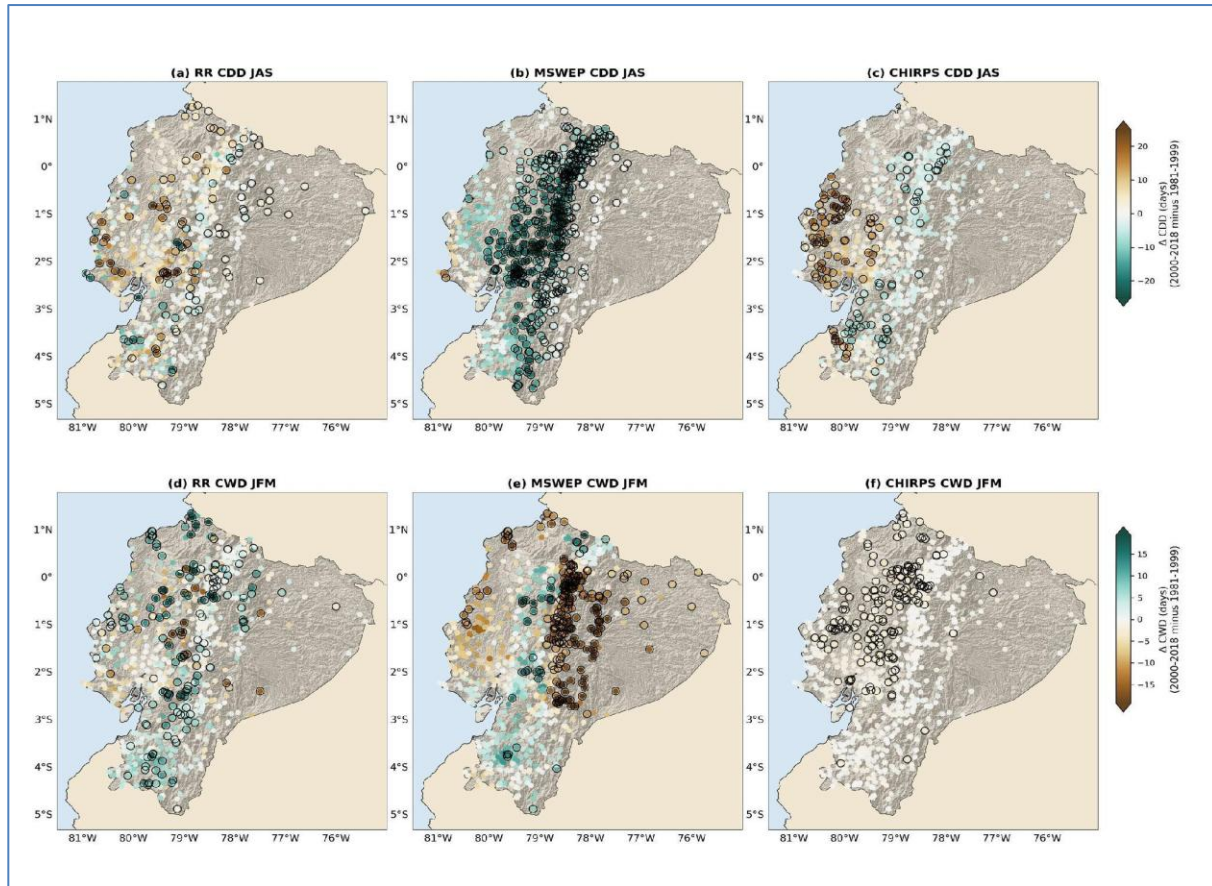
Figs. 3(a-c). Changes between sub-periods (2000–2018 minus 1981–1999) during OND, the trimester in which the reduction of interannual variance is largest in all three datasets (Section 3.2). Top row: difference in mean monthly precipitation (mm month^{-1}) for (a) RR, (b) MSWEP and (c) CHIRPS; outlined circles mark stations with significant differences (Welch's t-test on monthly accumulations, $p < 0.05$). Bottom row: ratio of monthly-anomaly variances (2000–2018 over 1981–1999) computed from deseasonalized monthly anomalies; outlined circles mark significant ratios (two-sided F-test, $p < 0.05$). The remaining trimesters are provided in the Supplementary Material

with Welch's t-test on the monthly accumulations within each trimester (Section 2). In the gauge-based RR dataset, the clearest signal is a significant drying of the Coastal plain and the western Andean slopes during OND - locally above 40–60 mm per month - and JAS, accompanied by significant wetting along the eastern Andean foothills in AMJ and OND and over the southern highlands in JFM. The satellite products reproduce the coastal drying, but disagree over the inter-Andean corridor, where MSWEP indicates significant JFM drying and JAS-OND wetting not corroborated by the rain gauges - a discrepancy consistent with the sensor sensitivities discussed in Section 3.7.

Changes in interannual variability are even more pronounced (Fig. 3). The ratio of monthly-anomaly variances (2000–2018 over 1981–1999) lies below unity at most stations in all four trimesters: in RR the median ratio falls to 0.45 in OND and 0.54 in JAS, with significant

decreases (two-sided F-test, $p < 0.05$) at 60% and 53% of the stations, respectively, concentrated over the Coast and the western slopes, whereas significant increases are rare (below 11% of stations, mostly Andean sites in AMJ). The weakest reduction occurs in JFM (median 0.77), the only season whose leading mode of variability retains its spatial structure after 2000 (Section 3.3). CHIRPS shows the same seasonal hierarchy (medians 0.48–0.88) and MSWEP amplifies the reduction everywhere (0.15–0.44), without affecting the sign of the signal. This collapse of Coastal variance largely reflects the absence of extreme eastern Pacific El Niño events comparable to 1982/83 and 1997/98 during the second sub-period, and anticipates the reorganization of the leading modes described below.

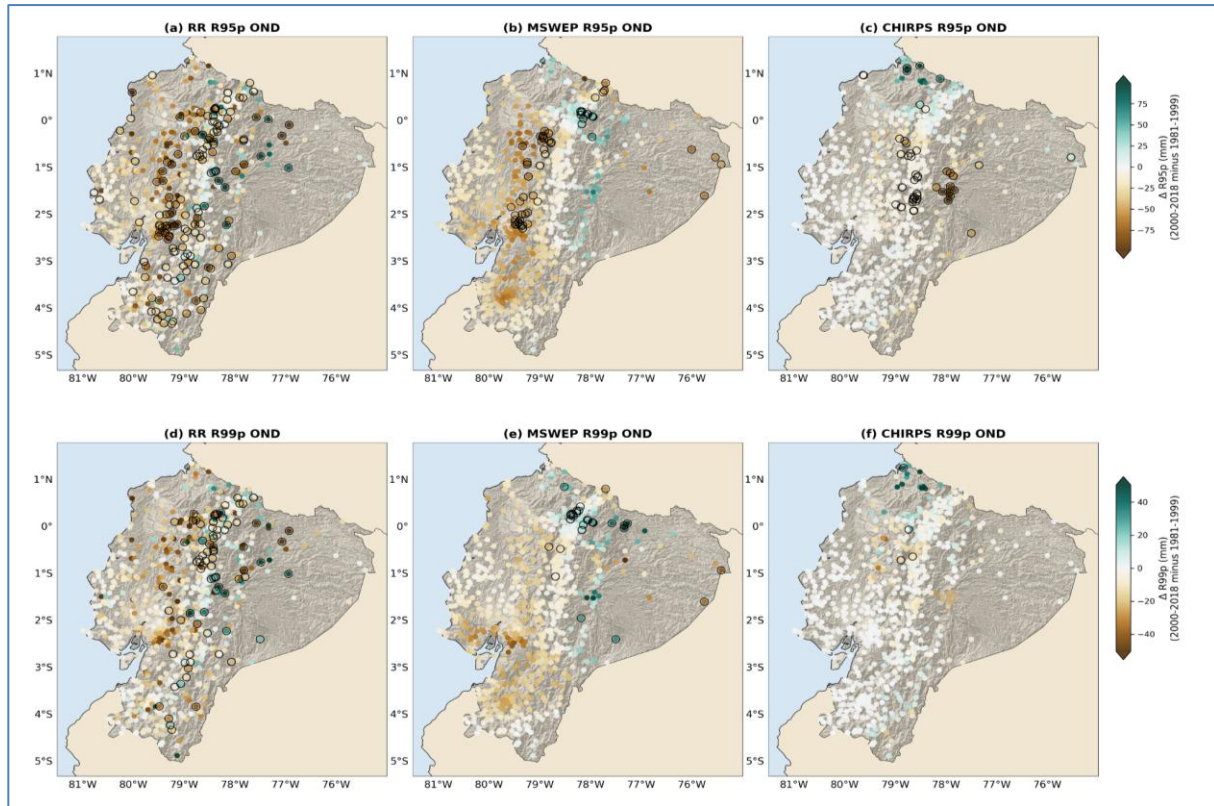
Indices of dry- and wet-spell persistence changed appreciably between the two sub-periods, and the three datasets describe a single spatial pattern whose two regional lobes each product resolves with different



Figs. 4(a-f). Change in dry- and wet-spell persistence between sub-periods (2000–2018 minus 1981–1999). (a–c) Δ CDD during JAS and (d–f) Δ CWD during JFM for RR, MSWEP and CHIRPS. Brown (green) shading denotes a tendency toward drier (wetter) conditions; open black circles mark stations significant at the 5% level (Monte Carlo permutation test, 10,000 iterations). The remaining trimesters are provided in the Supplementary Material (Figures S1–S2)

sensitivity. During the dry seasons (JAS and OND), dry spells (CDD) shorten across the Andean and Amazon basins and lengthen along the Coast (Figs. 4a–c; Supplementary Fig. S1), a dipole spatially consistent with the coastal reduction of mean precipitation documented in Fig. 3. MSWEP resolves the Andean–Amazon lobe most completely, with nearly all of its significant stations sharing the same sign along the inter-Andean corridor (Fig. 4b). The coastal lobe, by contrast, is best defined by the rain-gauge network and by CHIRPS, which agree on a lengthening of dry spells over the lowlands west of the Andes (Figs. 4a, 4c; Supplementary Fig. S1). That the gauge network contains both lobes – an Andean cluster consistent with MSWEP and a coastal cluster consistent with CHIRPS – indicates that the datasets are not in conflict: each resolves most sharply the region in which its observational basis is strongest, an interpretation developed in Section 3.7. At the continental scale, Iacovone *et al.* (2020) report that the mean fields of CDD and CWD over South America tend to be spatially opposite and that CDD is the more strongly ENSO-

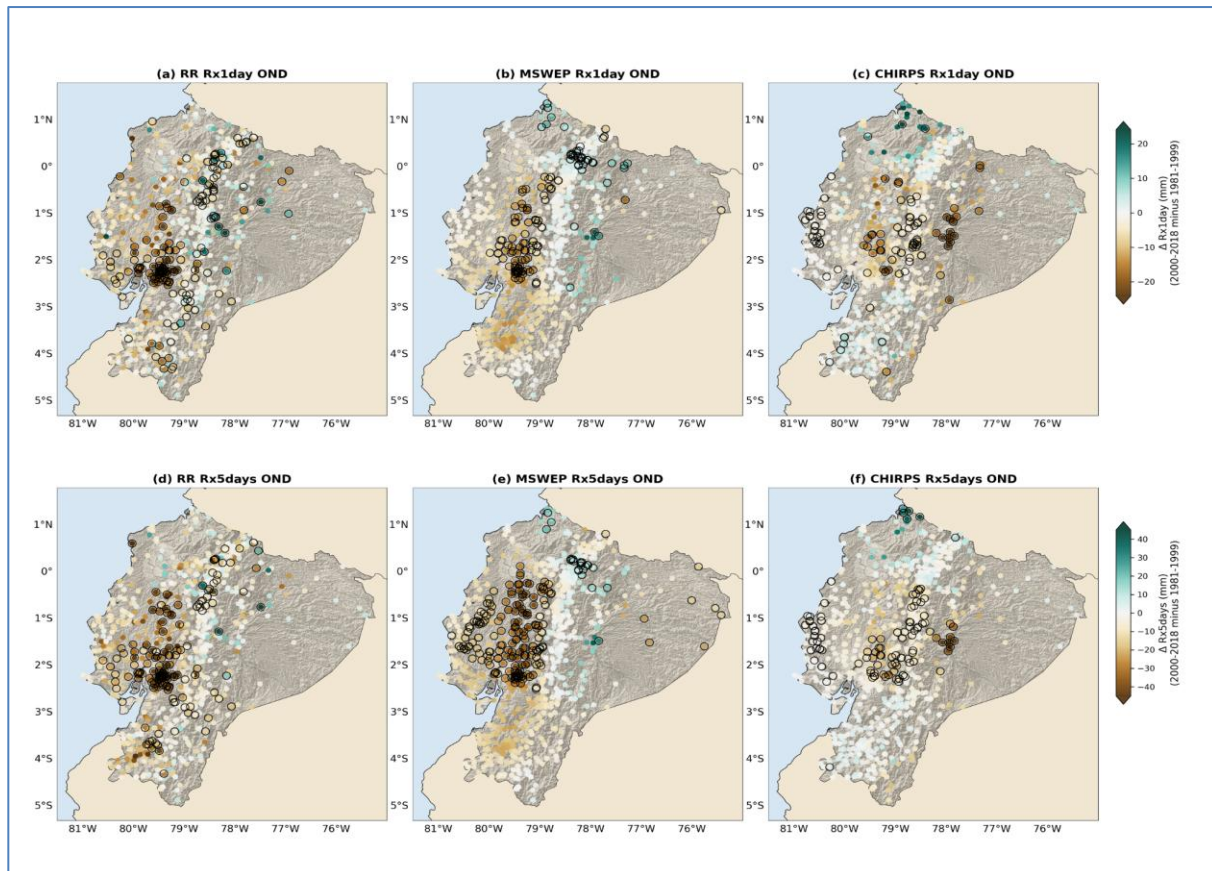
associated of the two indices; the present results reproduce the first feature but not the second, since in Ecuador wet-spell persistence shows the stronger coupling in the trimester of maximum association (Section 3.4), a difference attributable to spatial scale, as continental gridded analyses do not resolve the coastal-Andean dipole that organizes the Ecuadorian signal. Wet spells (CWD) change in a more regionally differentiated manner during the main wet season (JFM; Figs. 4d–f): MSWEP indicates a coherent shortening along the eastern Andean foothills (Fig. 4e), whereas the gauge network indicates a predominant lengthening over the northwestern Sierra and the northern Coast (Fig. 4d); wet-spell changes are therefore interpreted at the regional rather than the national scale, with the remaining trimesters shown in Supplementary Fig. S2. CHIRPS provides little constraint on this index, its Δ CWD field remaining close to zero in all trimesters (Fig. 4f; Supplementary Fig. S2), consistent with the limited sensitivity of thermal-infrared retrievals to the occurrence and persistence of low-intensity rainfall (Funk *et al.*, 2015; Section 3.7).



Figs. 5(a–f). Change in percentile-based extreme precipitation between sub-periods (2000–2018 minus 1981–1999) during OND, the only trimester in which the three datasets agree on the sign of the change (Section 3.2). (a–c) $\Delta R95p$ (mm) and (d–f) $\Delta R99p$ (mm) for RR, MSWEP and CHIRPS. Brown (green) shading denotes a decrease (increase); open black circles mark stations significant at the 5% level (Monte Carlo permutation test, 10,000 iterations). The remaining trimesters are provided in Supplementary Figures S3–S4

Changes in precipitation extremes are consistent with the spell-based results and are presented for a single trimester to permit a like-for-like comparison across indices. The percentile-based indices (R95p, R99p) and the maximum-precipitation indices (Rx1day, Rx5days) are shown for OND, the only trimester in which the three datasets agree on the sign of the change in R95p, Rx1day and Rx5days, and hence the trimester in which the post-2000 signal can be regarded as robust across independent retrieval principles. Larger changes occur in JFM, but that is also the trimester in which the thermal-infrared and merged passive-microwave products diverge most strongly (see below); the remaining trimesters are therefore documented in the Supplementary Material (Figs. S3–S6). During OND, R95p decreases significantly over both the Coastal and the Andean regions in the gauge network, MSWEP reproduces the reduction over the central Andes, and CHIRPS shows the same sign with markedly weaker amplitude (Fig. 5a–c). R99p reproduces this behaviour in the gauge network alone, with smaller amplitude and fewer significant stations, whereas the satellite products retain little signal at this more restrictive percentile (Fig. 5d–f) – consistent with the low ranking of R99p in the coupling hierarchy established in Section 3.5. The maximum-precipitation indices follow the same OND

pattern and show the closest inter-dataset agreement of the four: Rx1day and Rx5days both exhibit a dense cluster of significant decreases along the Coast in the gauge network together with a coherent reduction over the central Andes in MSWEP, with CHIRPS agreeing in sign throughout (Fig. 6). A distinct sensor-related behaviour emerges in JFM and AMJ, where CHIRPS reports widespread increases over the Andean interior that are opposite in sign to the decreases indicated by MSWEP for all four extreme indices (Supplementary Figs. S3–S6). This divergence follows the contrasting retrieval principles of the two products (Funk *et al.*, 2015; Beck *et al.*, 2017), is examined in Section 3.7, and is the reason the wet-season fields are not used to characterize the post-2000 change in the main text. Taken together, these regional tendencies contrast with the predominantly increasing heavy-precipitation indices reported for South America as a whole (Skansi *et al.*, 2013), an assessment based on a sparse station network along the tropical Andes and the Pacific coast. In the dense, homogenized network used here, all four extreme indices decrease in every trimester, indicating that western Ecuador has instead experienced a joint reduction of mean rainfall and of its interannual variance after 2000 (Fig. 3).



Figs. 6(a-f). As Figure 5, for the maximum 1-day and 5-day precipitation amounts during OND: (a-c) $\Delta Rx1day$ and (d-f) $\Delta Rx5days$ (mm). The remaining trimesters are provided in Supplementary Figures S5–S6

3.3. Shifts in the leading modes of rainfall variability and their ENSO coupling

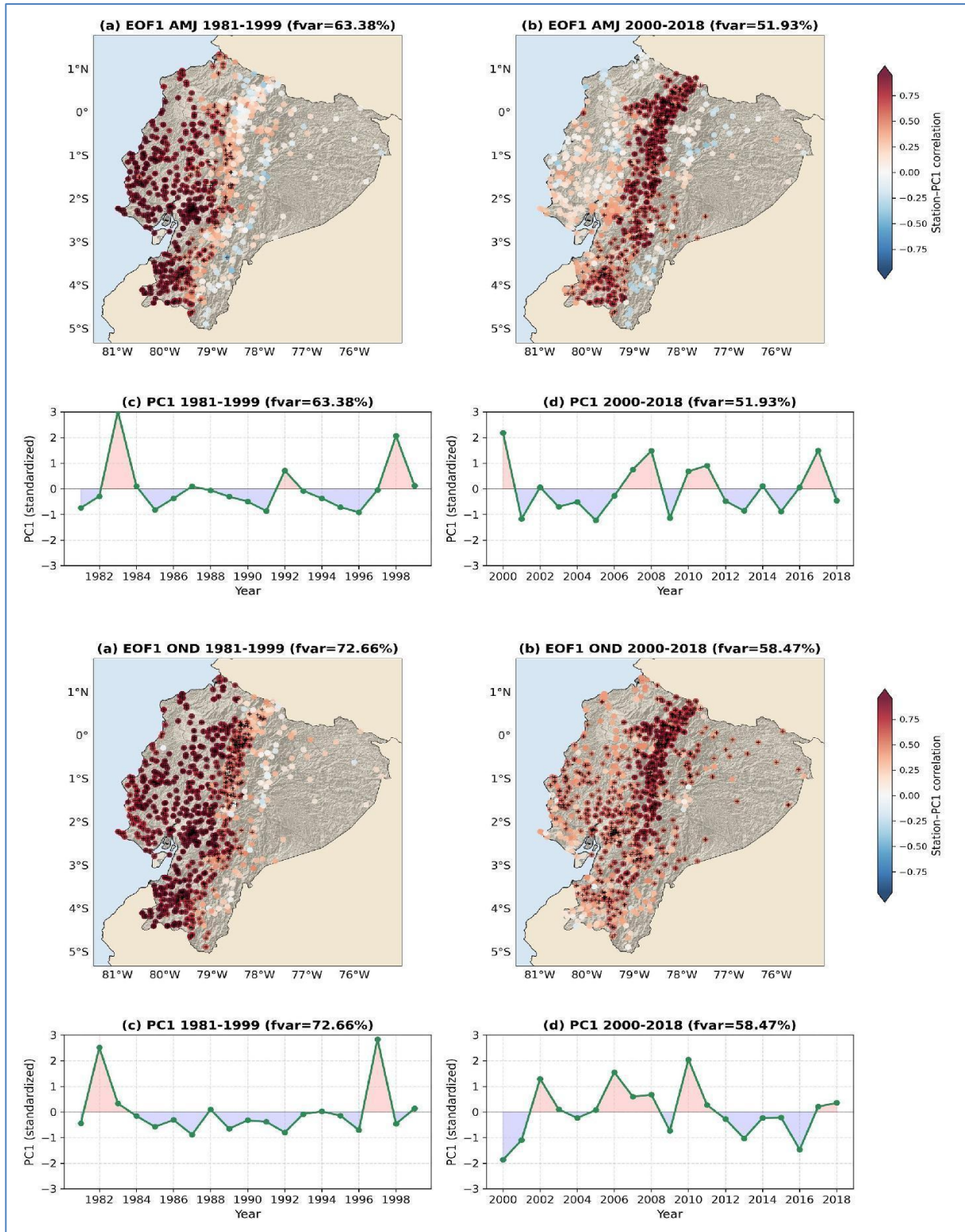
The results presented above point to substantial changes in seasonal precipitation and in the frequency of dry and wet spells and extremes after 2000. This raises the question of whether the interannual variability of rainfall - and its dominant spatial organization - also changed between the two sub-periods. To address this, the EOF analysis was performed separately for 1981–1999 and 2000–2018 for each season, and the leading modes were related to ENSO through the correlation matrix of Fig. 9.

Figs. 7 and 8 compare the leading EOF mode of seasonal precipitation (RR) between sub-periods for AMJ and OND, and for JFM and JAS, respectively. During 1981–1999, the AMJ and OND modes are coastal monopoles - loadings above 0.8 west of the Andes, with the Amazon largely decoupled - explaining 63–73% of the variance, and their PC1 series are dominated by the extreme eastern Pacific El Niño events of 1982/83 and 1997/98. This mode is the imprint of coastal El Niño conditions: anomalously warm SSTs off the Ecuadorian coast destabilize the lower troposphere and fuel

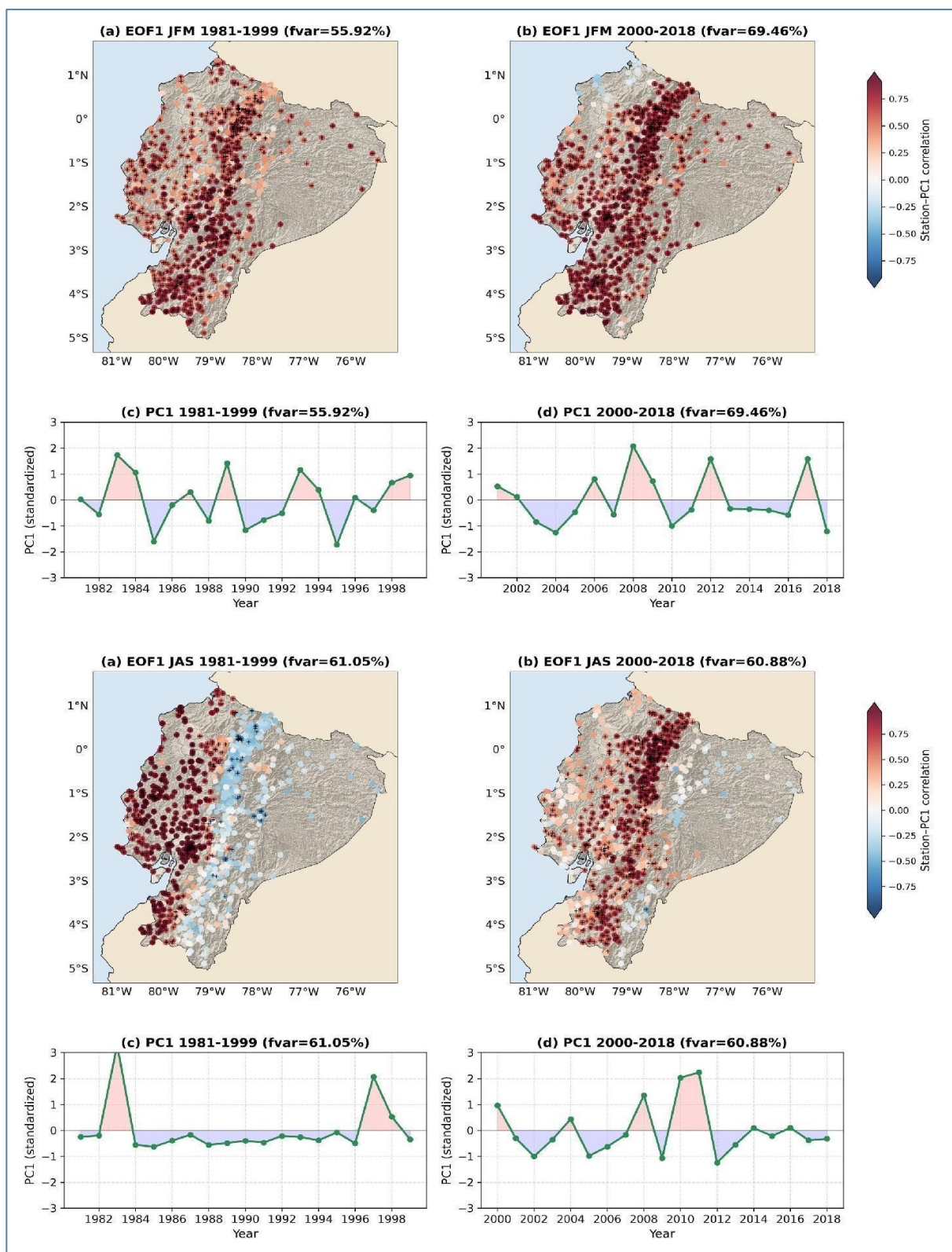
convection over the coastal plain - a local, thermodynamically driven response.

After 2000, this coastal mode is no longer the leading mode: EOF1 reorganizes toward the Andes in all seasons (explained variance falling from 63 to 52% in AMJ and from 73 to 58% in OND), with the coast contributing weakly. Concurrently, the seasons carrying an ENSO signal shift to JFM and JAS, where the Andean mode correlates negatively with the central Pacific indices (Fig. 9): warm central Pacific conditions favour dry anomalies over the highlands, consistent with a remote, dynamically driven response - a westward-displaced Walker circulation and anomalous subsidence over northwestern South America - rather than local SST forcing. The 2017 coastal El Niño still appears as a strong wet excursion (JFM, AMJ), indicating that coastal forcing remains active but no longer organizes the dominant mode of variability.

Fig. 9 summarizes the correlations between the leading principal component (PC1) of seasonal precipitation anomalies and the four Niño SST indices for both sub-periods. During 1981–1999 (Fig. 9a), significant



Figs. 7(a-d). Leading EOF mode of seasonal precipitation totals (PRCPTOT, RR) for AMJ (top block) and OND (bottom block). Each block shows the station-PC1 correlation maps for (a) 1981–1999 and (b) 2000–2018 ('+' significant at the 5% level) and the standardized PC1 series for (c) 1981–1999 and (d) 2000–2018, with the explained variance fraction (fvar) in the panel titles. The coastal monopole of 1981–1999, whose PC1 is dominated by the extreme eastern Pacific El Niño events of 1982/83 and 1997/98, is replaced after 2000 by an Andean-centred mode. The sign convention is such that positive PC1 corresponds to wet anomalies



Figs. 8(a-d). As Figure 7, for JFM (top block) and JAS (bottom block), the trimesters that carry the central Pacific ENSO signal after 2000 (cf. Figure 9)

positive correlations concentrate in the easternmost indices (Niño 3 and Niño 1+2) and occur in nearly every season: JFM (MSWEP, $r = 0.82\text{--}0.83$), AMJ (all datasets, $r = 0.63\text{--}0.85$), JAS (RR, $r = 0.84$) and OND (RR and CHIRPS, $r = 0.64\text{--}0.73$). This eastward intensification indicates that rainfall variability was dominated by eastern Pacific ENSO forcing throughout the annual cycle, consistent with canonical El Niño events.

After 2000 (Fig. 9b), this coupling reorganizes substantially: significant correlations shift toward the westernmost indices (Niño 4 and Niño 3.4), change sign, and migrate to different seasons — JFM ($r = -0.51$ to -0.65) and especially JAS ($r = -0.55$ to -0.85). Rather than an inversion of the same mode, this sign change reflects the replacement of the coastal EP mode by the CP-coupled Andean mode documented in Figs. 7 and 8. The formerly robust AMJ and OND signals largely disappear: in AMJ only two opposing cells remain significant — RR ($r = -0.56$, Niño 4) and MSWEP ($r = +0.56$, Niño 1+2) — revealing a transitional season in which the Andean CP regime and a residual coastal EP signal coexist, each dataset favouring one of them; in OND only MSWEP retains significant correlations ($r = 0.62\text{--}0.73$), tied to a coast–highlands dipolar mode that the other datasets do not rank first (Section 3.7). The eastern Pacific influence thus practically vanishes in the second sub-period, while central Pacific variability emerges as the dominant driver, with its imprint displaced toward boreal summer; the following subsections examine both regimes in detail.

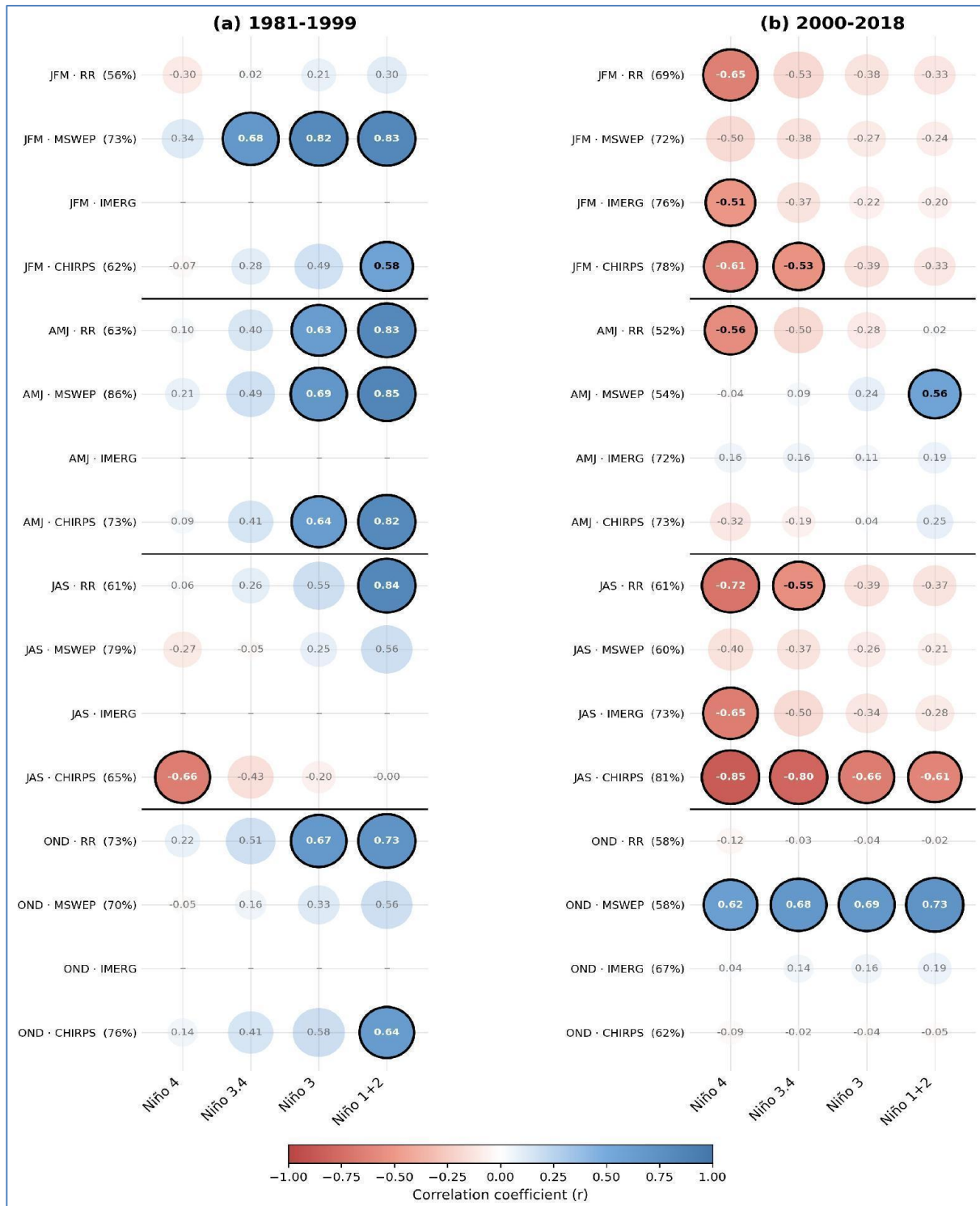
3.4. ENSO–precipitation modulation during 1981–1999 (Eastern Pacific dominance)

The results presented so far describe a change in the mean state: mean seasonal precipitation and its interannual variance decrease over western Ecuador after 2000 (Section 3.1), dry - and wet-spell persistence is redistributed between the Coast and the Andes, and the extreme-precipitation indices decrease in every trimester in the gauge network (Section 3.2). A change of this magnitude raises a further question that the preceding analysis does not address: whether the structure of interannual variability has been modified as well - that is, whether the spatial pattern that organizes year-to-year rainfall fluctuations is the same before and after 2000. To examine this, an S-mode EOF analysis was applied separately to each sub-period with the trimester held fixed, so that the leading mode (EOF1) and its principal component (PC1) for 1981–1999 can be compared directly with those for 2000–2018 for the same season and the same index (Section 2).

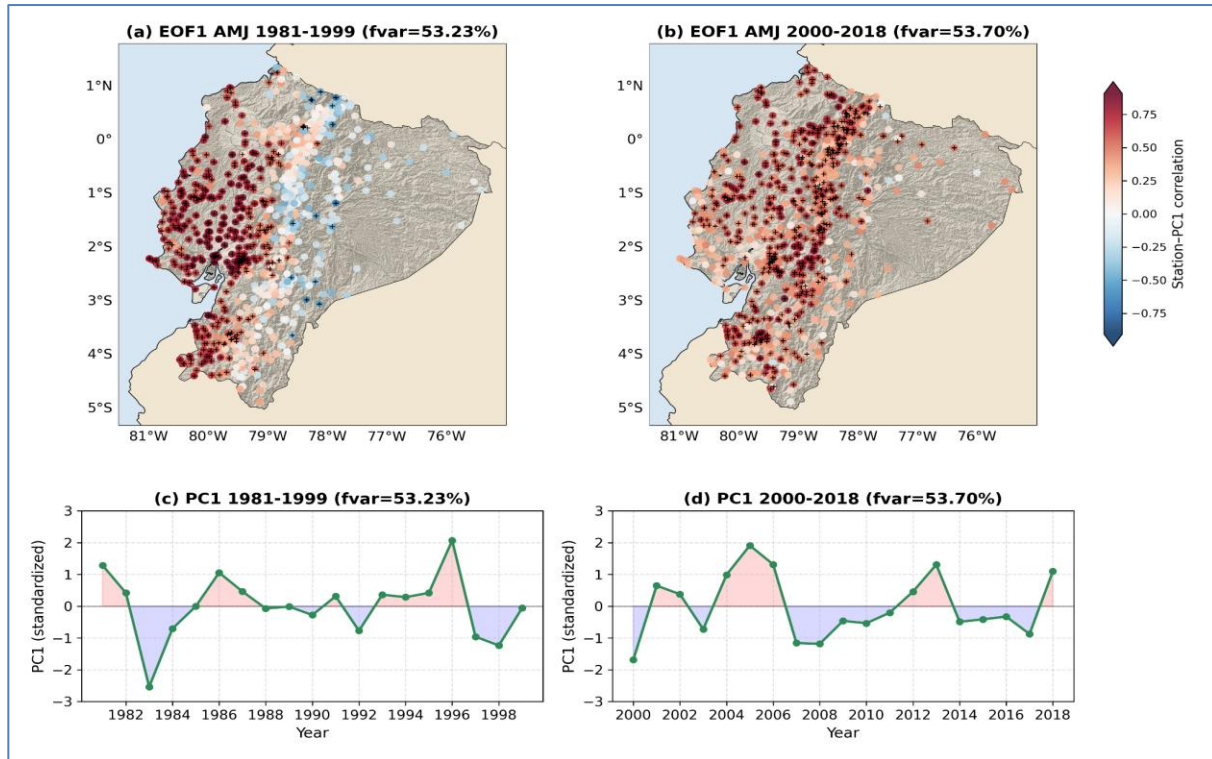
The comparison shows that the leading mode is not stationary. For seasonal accumulated precipitation (PRCPTOT), the variance explained by EOF1 falls from 63.4% to 51.9% in AMJ and from 72.7% to 58.5% in OND (Figs. 7 and 8), and the spatial pattern changes accordingly: during 1981–1999 the significant loadings form a dense monopole covering the entire Coastal plain, whereas during 2000–2018 the coastal loadings weaken and the significant stations concentrate along the inter-Andean corridor. The same reorganization characterizes the spell and extreme indices examined below - EOF1 of CWD in AMJ falls from 57.9% to 51.5% (Fig. 11) and EOF1 of Rx5days in AMJ from 58.1% to 46.0% (Fig. 12), in both cases with the significant loadings migrating from the Coast towards the Andes. CDD in AMJ is an exception in amplitude but not in structure: the explained variance is essentially unchanged (53.2% and 53.7%), yet the coastal–Andean dipole of the first sub-period is replaced by a single positive band spanning both regions (Fig. 10). The leading mode of interannual rainfall variability in present-day Ecuador is therefore both weaker and geographically displaced relative to that of the 1980s and 1990s.

Because ENSO is the dominant source of interannual rainfall variability over Ecuador, the following two subsections quantify the coupling between these leading modes and SST anomalies in the four Niño regions, first for 1981–1999 (Section 3.4) and then for 2000–2018 (Section 3.5). Each index is presented in AMJ, the trimester in which its leading mode shows the widest cross-dataset consensus with the eastern Pacific indices during 1981–1999 (Table 2), and that trimester is retained for both sub-periods, so that the two epochs are compared like for like; the remaining trimesters are provided in the Supplementary Material.

During 1981–1999, the leading modes of several precipitation indices are strongly modulated by eastern Pacific ENSO variability. The PC1 of consecutive dry days (CDD) in AMJ correlates negatively with Niño 1+2 ($r = -0.68$ in RR and -0.75 in CHIRPS; $p < 0.01$; MSWEP directionally consistent), and the corresponding loading map (Fig. 10a) indicates that warm eastern Pacific anomalies were associated with reduced dry-spell persistence over the Coastal region, the western Andean slopes and the inter-Andean valleys. A stronger and fully consistent signal is found for consecutive wet days (CWD) in the same trimester, whose leading mode shows the highest positive correlation of the entire analysis ($r = +0.83$ in RR; $r_{\text{max}} = +0.87$ in CHIRPS; $p < 0.001$; Fig. 11a). Likewise, the PC1 of maximum five-day cumulative precipitation (Rx5days) in AMJ is robustly correlated with Niño 1+2 ($r = +0.81$ in RR, with full cross-dataset consensus in Table 2; 58.1% of the variance explained; p



Figs. 9(a&b). Correlation between the leading principal component (PC1) of trimestral precipitation totals and the four Niño SST indices, for (a) 1981–1999 and (b) 2000–2018. Rows are grouped by trimester (JFM, AMJ, JAS, OND) and, within each trimester, by dataset (RR, MSWEP, IMERG, CHIRPS; IMERG is available for 2000–2018 only); columns run from the central (Niño 4) to the eastern (Niño 1+2) Pacific. Circle size and colour give the correlation coefficient (blue positive, red negative) and black outlines mark correlations significant at the 1% level (Monte Carlo permutation test, 1,000 permutations). The percentage in each row label is the variance explained by EOF1. Comparison of the two panels shows the three components of the post-2000 reorganization discussed in Section 3.5: the migration of significance from the eastern to the central Pacific columns, the reversal from positive to negative correlations, and the displacement of the most strongly coupled trimester from AMJ to JAS



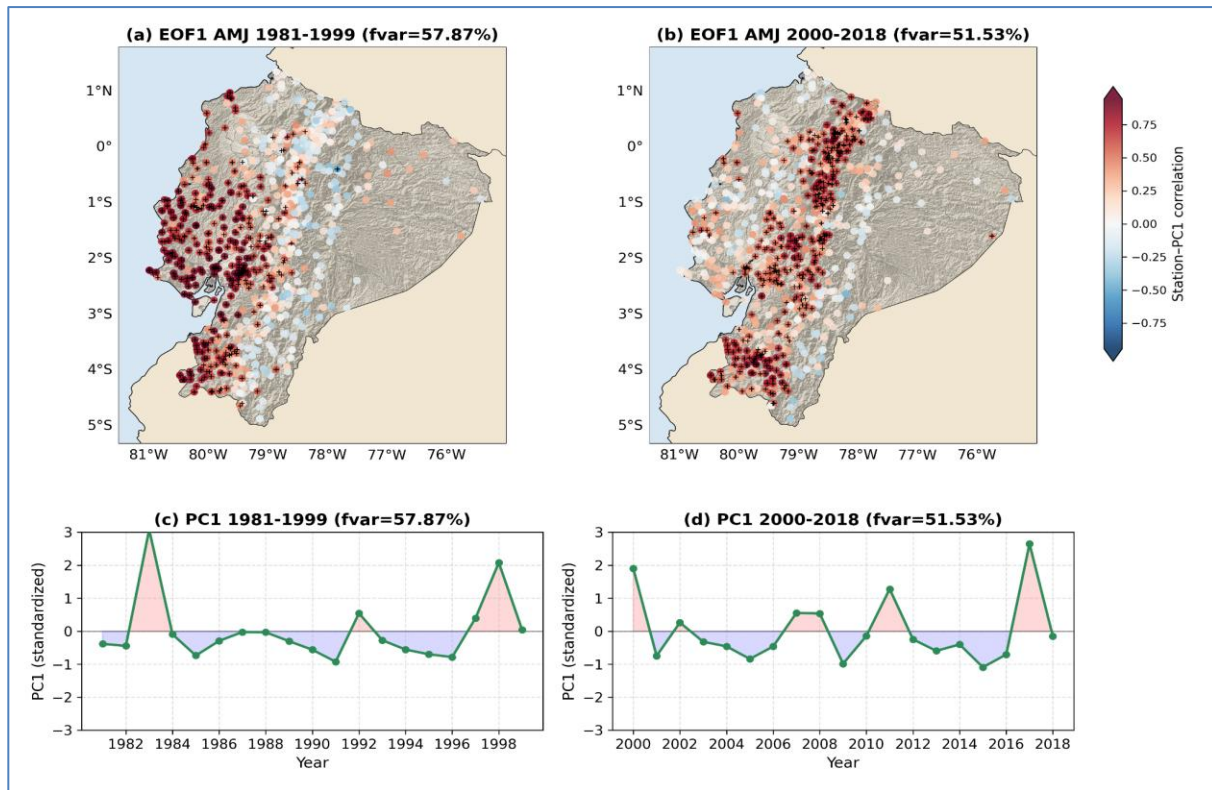
Figs. 10(a-d). Leading mode of interannual variability of the maximum number of consecutive dry days (CDD) in AMJ for the rain-gauge network (RR), computed separately in each sub-period. (a, b) Correlation between the CDD series of each station and PC1 for 1981–1999 and 2000–2018, respectively; crosses mark stations significant at the 5% level. (c, d) Standardized PC1 series for the same sub-periods. The fraction of variance explained by EOF1 is indicated in each panel title, AMJ is the trimester in which the CDD leading mode is most strongly coupled to eastern Pacific SST during 1981–1999 (Section 3.4); the remaining trimesters are provided in the Supplementary Material (Figures S7–S9)

TABLE 2

Regression and significant correlation between El Niño indices and the PC1 of climatic indices using rainfall data from Observation, MSWEP, IMERG, and CHIRPS.

Climate Index (PC1)	Period	Niño 4				Niño 3.4				Niño 3				Niño 1+2			
		JFM	AMJ	JAS	OND	JFM	AMJ	JAS	OND	JFM	AMJ	JAS	OND	JFM	AMJ	JAS	OND
CDD		—	—	—	—	—	-1	—	—	-1	-1	—	—	-1	-2 (F10)	-1	-1
CWD		-1	—	—	—	-1	+1	—	—	-1	+3	—	+1	—	+3 (F11)	+1	+2
R95p	1981-1999	+2	-1	—	—	+2	+1,-1	—	+1	+3	+2	—	+1	+3	+2	+1	+1
R99p		+1	-1	—	—	+3	+1,-1	—	+1	+3	+2	+1	+1	+3	+2	+1	+1
Rx1day		+1	-1	—	—	+1,-1	+1,-1	—	—	+2,-1	+2,-1	—	+1	+2,-1	+2	+1	+1
Rx5days		+1	—	—	—	+2	+1	—	—	+2	+2	—	+1	+2	+3 (F12)	+1	+1
CDD		—	—	+1 (F10)	—	—	—	+1	-1	—	—	—	-1	—	—	—	-1
CWD		-3 (F11)	—	-2	—	-1	-1	-2	—	—	—	-1	—	—	—	—	—
R95p	2000-2018	-1	—	-1	—	—	—	—	+1	—	—	—	+1	—	—	—	+1
R99p		—	—	-1	-1	—	—	—	-1	—	—	—	-1	—	—	—	-1
Rx1day		—	—	—	—	+1	—	—	—	+1	—	—	—	+1	+1	—	—
Rx5days		-1	-1	-1 (F12)	—	-1	—	-1	—	—	—	-1	—	—	—	-1	—

Cell values indicate the number of datasets (RR, MSWEP, CHIRPS and, from 2000 onwards, IMERG) in which the PC1–Niño correlation is statistically significant at the 1% level (Monte Carlo test). Positive numbers indicate positive correlation; negative numbers indicate negative correlation; combined entries (e.g., +2,-1) mean some datasets show positive and others negative significant correlations. “—” means no dataset reaches significance. Cells highlighted in light green correspond to the configurations shown in Figures 10–12 of the main text.



Figs. 11(a-d). As Figure 10, for the maximum number of consecutive wet days (CWD) in AMJ. Positive PC1 values correspond to longer wet spells. The remaining trimesters are provided in the Supplementary Material (Figures S10–S12)

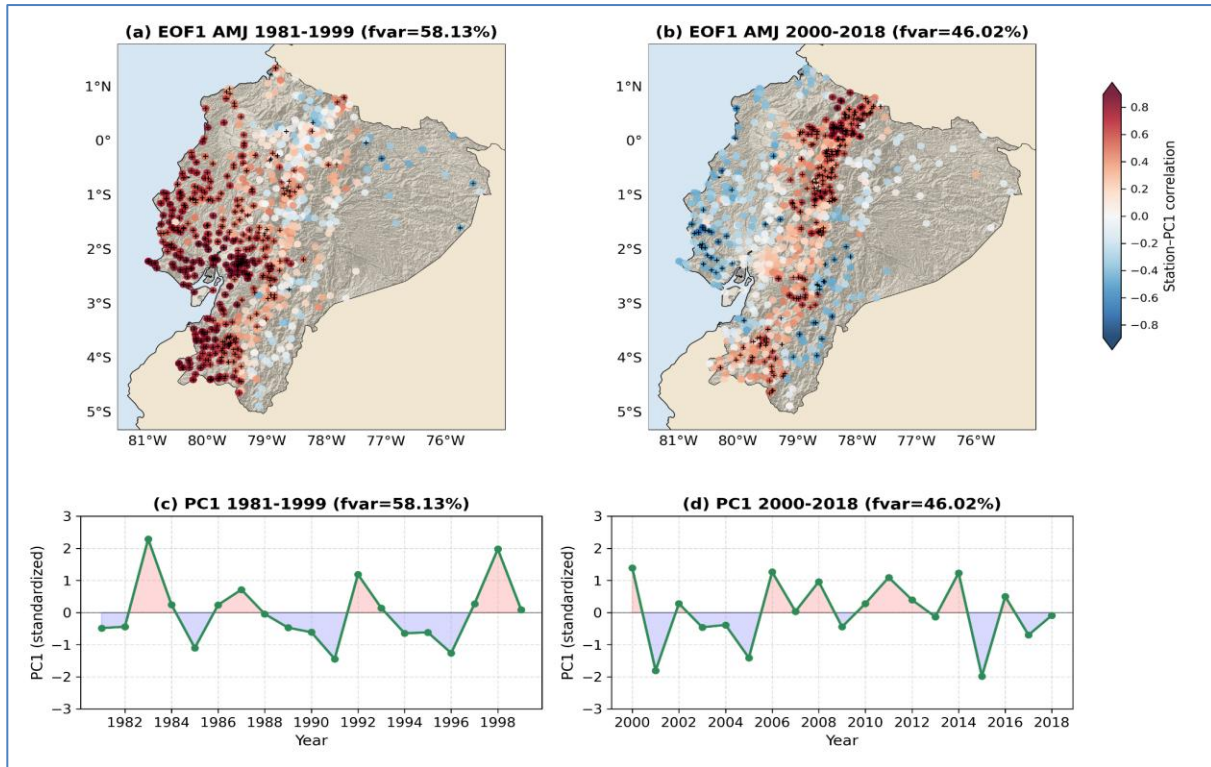
< 0.001 ; Fig. 12a), its loading pattern indicating intensified extreme rainfall over the Coastal plain and southwestern lowlands during canonical El Niño events; the coupling during OND, the trimester of the second Andean rainfall maximum, remains significant but weaker ($r = +0.72$; Supplementary Fig. S15). Taken together, these results show that before 2000 eastern Pacific ENSO variability coherently modulated both the persistence of wet and dry spells and the magnitude of extreme precipitation across mainland Ecuador.

Table 2 reveals several additional significant configurations during 1981–1999 that complement the three main figures of this sub-period and reinforce the eastern Pacific dominance hypothesis. The PC1 of CWD shows full cross-dataset consensus (+3) in AMJ $\times$ Niño 1+2 (Fig. 11) and AMJ $\times$ Niño 3, and remains strong (+2) in OND $\times$ Niño 1+2, indicating that wet-spell persistence in Ecuador was coherently modulated by eastern Pacific SST anomalies across multiple seasons and Niño boxes. The percentile-based extremes behave similarly, with R95p and R99p reaching full positive consensus (+3) with the easternmost indices (Niño 3 and Niño 1+2) in JFM. In contrast, single-day extremes (Rx1day) reveal a marked dataset dependence during the wet season: the gauge network (RR) and MSWEP show positive correlations with the eastern indices in AMJ (RR: $r = +0.67$ and $+0.83$

at Niño 3 and Niño 1+2; MSWEP up to $+0.86$) and JFM, whereas CHIRPS instead exhibits significant negative correlations over the same trimesters ($r = -0.60$ to -0.71 in AMJ). This split reflects the Andean, deep-convective mode preferentially captured by CHIRPS as opposed to the coastal extreme signal captured by RR and MSWEP, and is revisited in Section 3.7 as a matter of dataset sensitivity to short-duration extremes. The same contrast underlies the opposite signs reported for CHIRPS and MSWEP in JFM and AMJ in Section 3.2 (Supplementary Figs. S3–S6), indicating that it is a systematic property of the retrieval rather than a feature of any single index.

3.5. ENSO–precipitation modulation during 2000–2018 (Central Pacific dominance)

By contrast, during 2000–2018 the dominant ENSO–precipitation relationships in Ecuador shift toward central Pacific (Niño 4) variability, consistent with the post-2000 changes in ENSO behaviour reported in the literature (Ashok *et al.*, 2007; Yeh *et al.*, 2009). During the dry season (JAS), the PC1 of CDD is positively correlated with Niño 4 in the in situ network and directionally consistent across MSWEP and CHIRPS ($r = +0.71$ in RR; $p < 0.001$; Fig. 10), indicating that warm anomalies in the central Pacific are associated with longer dry spells over



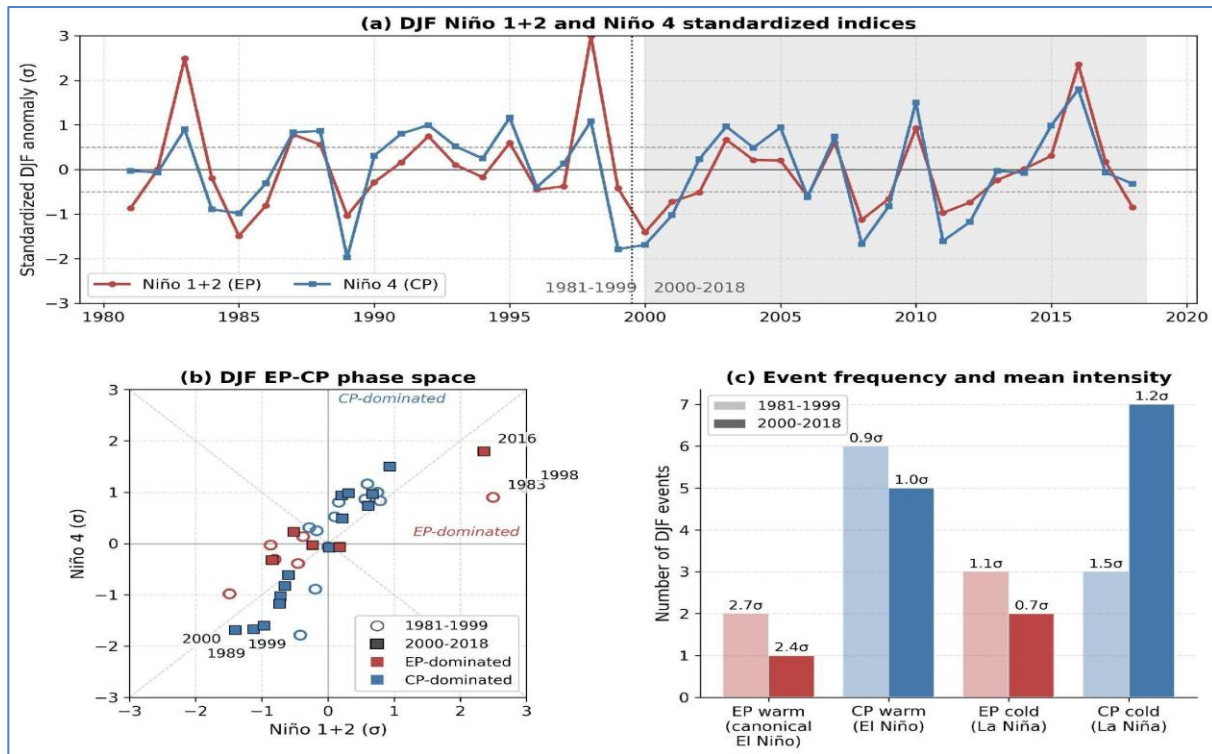
Figs.12(a-d). As Figure 10, for the maximum 5-day cumulative precipitation (Rx5days) in AMJ. Positive PC1 values correspond to positive Rx5days anomalies. AMJ is the trimester in which the Rx5days leading mode shows the strongest eastern Pacific coupling and full cross-dataset consensus during 1981–1999 (Table 2, Section 3.4); the remaining trimesters are provided in the Supplementary Material (Figures S13–S15)

the Coastal region, the western Andean slopes and the southern Sierra. The PC1 of CWD during the main wet season (JFM) shows a consistent negative correlation with Niño 4 across three datasets ($r = -0.59$ in RR, -0.58 in MSWEP and -0.59 in IMERG; $p < 0.01$; Fig. 11), indicating that central Pacific warming shortens wet spells in the rainy season. The PC1 of Rx5days remains coupled to the central Pacific with reversed sign relative to the pre-2000 period, showing significant negative correlations in JAS (CHIRPS: $r = -0.60$ to -0.70 across all four Niño boxes; $p < 0.01$; Fig. 12) and in JFM (RR: $r = -0.61$ and -0.55 at Niño 4 and Niño 3.4). Although the agreement between datasets is weaker than before 2000, the consistent negative sign across sources supports the robustness of the shift toward central Pacific-dominated modulation.

Table 2 also reveals additional significant configurations during 2000–2018 that complement the three main figures of the post-2000 sub-period. A particularly novel feature is the emergence of a full cross-dataset negative consensus for the PC1 of CWD in JFM $\times$ Niño 4 (-3 across RR, MSWEP and IMERG; Fig. 11), together with a -2 consensus in JAS: central Pacific warming during the wet and dry seasons is now associated with shorter wet spells, a configuration absent before

2000. Dry spells (CDD) mirror this behaviour, turning positive with Niño 4 in JAS. The very wet-day index R95p retains an OND signal only in MSWEP, whose coast–highlands dipole (Section 3.3) yields positive correlations ($r = +0.52$ to $+0.57$), while the other datasets show no significant OND coupling. Beyond the CWD case, full cross-dataset consensus becomes rare in 2000–2018, in contrast with 1981–1999, and the total number of statistically significant cells drops markedly in the post-2000 half of Table 2. This loss of coherence - together with the shift toward central Pacific indices - suggests that the ENSO–precipitation modulation in Ecuador has not only reorganized but also become weaker and more dataset-dependent, consistent with the documented reduction in canonical El Niño amplitude after 2000 (Yeh *et al.*, 2009; Capotondi *et al.*, 2015; Hu *et al.*, 2017).

Finally, comparing across indices reveals that the strength of the post-2000 central Pacific coupling depends on the temporal organization of rainfall. Indices tied to persistence and multi-day accumulation - wet and dry spells (CWD, CDD) and the five-day maximum (Rx5days) - retain a significant central-Pacific-negative signal, whereas the single-day maximum (Rx1day) becomes essentially decoupled from ENSO after 2000, its only significant correlations being a positive, eastern-type



Figs.13(a-d). ENSO regime shift around 2000. (a) Standardized and detrended DJF anomalies of the Niño 1+2 (eastern Pacific, EP; red) and Niño 4 (central Pacific, CP; blue) indices, 1981–2018; dashed lines mark the $\pm 0.5\sigma$ event threshold and the shaded area highlights the 2000–2018 sub-period. (b) DJF anomalies in EP–CP phase space; colour indicates the dominant index (red EP, blue CP), open (filled) symbols denote 1981–1999 (2000–2018), and the strongest events are labelled. (c) Number of DJF events per sub-period (light: 1981–1999; solid: 2000–2018), classified by the dominant index and phase; values above the bars give the mean event intensity (mean $|z|$ of the dominant index)

cluster in the high-resolution IMERG record during JFM ($r = +0.64$ to $+0.70$), attributable to the 2015/16 El Niño, the only EP-dominated warm event of the recent sub-period (Section 3.6), and an isolated coastal cell in AMJ (MSWEP, $r = +0.48$ at Niño 1+2). The percentile-based extremes fall in between, with R95p retaining scattered significance and the rarer R99p losing it almost entirely. This yields a hierarchy of coupling strength in the recent period ($\text{CWD} \approx \text{PRCPTOT} > \text{Rx5days} \approx \text{R95p} > \text{R99p} > \text{Rx1day}$) with a direct implication for predictability: what remains potentially predictable from the central Pacific in present-day Ecuador is the seasonal persistence and accumulation of rainfall, rather than its daily peak intensity.

These changes are summarized in Table 2 and displayed in full in Fig. 9, which gives the correlation between PC1 and the four Niño indices for every trimester, dataset and sub-period. Read together, the two panels indicate that the reorganization has three distinct components rather than one. The first is the shift in the Pacific region responsible for the coupling, from the eastern indices (Niño 3 and Niño 1+2) before 2000 to the central index (Niño 4) afterwards. The second is a reversal of sign: significant correlations are positive throughout the

first sub-period, warm eastern Pacific anomalies being associated with wetter conditions, and predominantly negative in the second, warm central Pacific anomalies now being associated with drier conditions. The third - least apparent in a season-by-season reading of the individual figures - is a redistribution across the annual cycle. During 1981–1999 the coupling is significant in all four trimesters and is strongest in AMJ ($r = +0.85$ with Niño 1+2 for seasonal totals and $+0.87$ for wet-spell persistence). During 2000–2018 that same trimester retains virtually no significant coupling, whereas JAS, marginal in the first sub-period, becomes the most strongly coupled trimester of the year ($r = -0.85$ with Niño 4 for seasonal totals and -0.62 for wet-spell persistence). The trimester through which ENSO exerts its influence on Ecuadorian rainfall has therefore moved from the wet season towards the dry season at the same time as the source region moved from the eastern to the central Pacific. This seasonal displacement is why Sections 3.4 and 3.5 examine each index in a different trimester in each sub-period, while Figs. 10–12 hold the trimester fixed: the former follows the season in which the coupling is strongest, the latter isolates the change in spatial structure from the annual cycle. It also carries a practical implication - a seasonal forecast calibrated on the pre-

2000 relationship would target both the wrong predictor and the wrong time of year.

3.6. ENSO regime shift around the year 2000

This shift in the ENSO–precipitation relationships takes place against a broader change in ENSO behaviour around the year 2000 (Fig. 13). The eastern Pacific is represented here by Niño 1+2 rather than by Niño 3, the box more commonly used in the EP–CP literature, because Niño 1+2 covers the ocean adjacent to the Ecuadorian coast and is the index through which the pre-2000 rainfall coupling is expressed (Section 3.4); repeating the classification with Niño 3 leaves the result unchanged in its essentials - eastern Pacific events decline from seven to three, central Pacific events rise from eight to eleven, and the increase is again carried entirely by the cold phase, which doubles from three to six (Supplementary Fig. S16). The DJF series of the two standardized indices (Fig. 13a) show that the two extreme eastern Pacific events of the record, 1982/83 and 1997/98, have no equivalent after 2000: the only EP-dominated warm event of the recent sub-period, 2015/16, reached a comparable amplitude (2.4σ against a mean of 2.7σ for the earlier pair) but carried a strong central Pacific signature (Fig. 13b). Central Pacific cold events, by contrast, rise from three to seven and become the most frequent ENSO category of the recent sub-period, whereas central Pacific warm events remain essentially unchanged in number (six and five; Fig. 13c). Because each category contains only a few events, these counts are presented as a description of the record rather than as a statistical test of a change in frequency. Fig. 13 characterizes the forcing rather than the rainfall response, which is documented in Figs. 9–12; read together, the two are consistent with a picture in which the disappearance of the extreme eastern Pacific events accompanies the loss of the coastal, EP-forced mode of variability, and the increased incidence of central Pacific cold events accompanies the emergence of the CP-linked Andean mode. This regime change is consistent with the interdecadal shift widely documented in the literature (Ashok *et al.*, 2007; Yeh *et al.*, 2009; McPhaden *et al.*, 2011; Capotondi *et al.*, 2015; Cai *et al.*, 2018).

3.7. Dataset limitations and cross-dataset robustness

Several limitations of the precipitation datasets deserve explicit consideration. While RR is based on quality-controlled, homogenized and gap-filled in situ observations (Guijarro, 2016), the rain-gauge network is not uniform across the country: station density is substantially higher over the Coastal and Andean regions and lower over the Amazon basin, and the number of available stations varies year by year. This non-uniform

sampling can affect both the spatial coherence of the EOF loading maps and the empirical determination of percentile-based extreme indices (R95p, R99p) at individual stations. CHIRPS combines satellite estimates with station observations, and its skill in capturing localized extreme events may be limited where rain-gauge inputs are sparse (Geleta and Deressa, 2020), which is consistent with the relatively low number of statistically significant stations for R99p in CHIRPS (Supplementary Fig. S4). MSWEP also blends multiple sources and produces a smoother representation of small-scale extremes than the in situ record. These dataset-specific sensitivities should be considered when interpreting the cross-dataset consistency of the results: where the three datasets agree both in direction and significance, the inferred ENSO–precipitation relationships can be considered robust, whereas dataset-specific signals - particularly for extreme indices - should be interpreted with caution.

4. Conclusions

This study examined the modulation of rainfall variability and its implications for seasonal predictability in mainland Ecuador using multiple observational and satellite precipitation datasets over the period 1981–2018. The consistency among datasets supports the robustness of the identified large-scale precipitation patterns captured by the leading EOF mode (PC1), while regional differences highlight the influence of complex topography and dataset-specific sensitivities.

The analysis reveals a general tendency toward shorter wet spells and a reduction in several extreme precipitation indices across key regions and seasons, particularly during OND and JFM. These changes indicate a modification of rainfall characteristics rather than a uniform increase or decrease in total precipitation, with potential implications for hydrological impacts such as floods and droughts, especially in coastal and Andean regions.

A central result of this study is that the ENSO–precipitation relationship over mainland Ecuador is non-stationary in three respects at once, as summarized in Table 2 and displayed in full in Fig. 9. First, the basin from which the influence originates changes: significant correlations with the eastern indices (Niño 3 and Niño 1+2) fall from 84 to 17 of the cells examined, a reduction of 80%, while those with the central index (Niño 4) double from 10 to 21. Second, the sign of the relationship reverses: 81% of the significant correlations are positive during 1981–1999 and only 26% during 2000–2018, so that the anomalies formerly accompanying wetter conditions are now associated with drier ones. Third, the

part of the annual cycle through which ENSO acts is displaced. During 1981–1999 more than three quarters of the significant coupling (78%) occurs jointly in JFM and AMJ; during 2000–2018 that concentration reverses, JAS and OND accounting for 64% of the coupling, JAS becoming the most coupled trimester and AMJ retaining almost none (five of fifty-three significant cells). The influence of ENSO on Ecuadorian rainfall has therefore migrated from the first half of the calendar year to the second, at the same time as its source moved from the eastern to the central Pacific and its sign reversed.

The practical consequence is that a statistical seasonal forecast calibrated on the pre-2000 record would fail on three counts simultaneously: it would draw on the wrong predictor region, expect the wrong sign of response, and target the wrong part of the year. Potential predictability has not disappeared – it has moved. In the recent sub-period it resides in the persistence and multi-day accumulation of rainfall (CWD, PRCPTOT and Rx5days) forced from the central Pacific during the second half of the year, whereas the single-day maximum (Rx1day) has become effectively ENSO-decoupled and is not predictable from SST anomalies in any Niño region. In the context of a changing climate, as emphasized by IWM-8, these results argue for recalibrating seasonal prediction schemes for Ecuador on the recent record rather than on the full historical period, and for monitoring the central Pacific indices as the operative predictors.

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Conflicts of interest

We have no conflicts of interest to disclose.

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Supplementary Material

This document contains four sections. Section S1 provides the full mathematical formulation of the S-mode Empirical Orthogonal Function (EOF) analysis used throughout the manuscript. Section S2 presents Supplementary Figures S1–S6 with the between-sub-period differences of the ETCCDI indices in the trimesters not shown in the main text (Figures 4–6). Section S3 presents Supplementary Figures S7–S15 with the period-comparison EOF analyses of CDD, CWD and Rx5days for the trimesters not shown in Figures 10–12. Section S4 presents Supplementary Figure S16, which repeats the ENSO regime classification of Figure 13 with Niño 3 as the eastern Pacific index.

S1. Empirical Orthogonal Function (EOF) analysis: formulation

S1.1. Notation and data preparation

For each combination of precipitation dataset (RR, MSWEP, CHIRPS and, for the 2000–2018 sub-period, IMERG), climatic index (PRCPTOT, CDD, CWD, R95p, R99p, Rx1day, Rx5days), trimester (JFM, AMJ, JAS, OND) and sub-period (1981–1999 or 2000–2018), the analysed variable is arranged as a data matrix

$$Y \in \mathbb{R}^{N \times ns} \quad (S1.1)$$

where the rows index the $N = 19$ years of the corresponding sub-period and the columns index the ns stations retained by the analysis (up to 1,061 for RR; equivalent locations sampled at the nearest grid point for MSWEP, CHIRPS and IMERG). Missing values are excluded on a case-by-case basis; the residual fraction of missing daily values in RR after the Climatol homogenization is below 0.1%.

Each column (station) is centered and scaled by its own temporal mean and standard deviation, and its linear trend is removed:

$$Y^*_{\{t,i\}} = (Y_{\{t,i\}} - \mu_i - a_i \cdot t) / \sigma_i \quad (S1.2)$$

where μ_i and σ_i are the temporal mean and standard deviation of station i , and $a_i \cdot t$ is its ordinary-least-squares linear trend. This anomaly matrix Y^* is the input to the SVD.

S1.2. Singular Value Decomposition and S-mode PCA

The Y^* matrix is decomposed by Singular Value Decomposition (Wilks, 2019):

$$Y^* = U \Sigma V^T \quad (S1.3)$$

with U of size $N \times r$, $\Sigma = \text{diag}(\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r \geq 0)$ of size $r \times r$ and V of size $ns \times r$, where $r = \min(N - 1, ns)$. This decomposition is mathematically equivalent to the eigendecomposition of the temporal covariance matrix

$$C = (N - 1)^{-1} Y^{*T} Y^* = V \Lambda V^T, \Lambda = \Sigma^2 / (N - 1), \quad (S1.4)$$

and to the eigendecomposition of the alternative dispersion matrix $(N - 1)^{-1} Y^* Y^{*T}$. Because we compute PCs from the standardized anomaly matrix, we adopt the S-mode formulation (Björnsson and Venegas, 1997; Hannachi *et al.*, 2007), in which the eigenvectors describe spatial patterns and the principal components describe their temporal evolution.

S1.3. Principal components, loadings and explained variance

The k -th standardized principal component is

$$PC_k(t) = \sqrt{N - 1} \cdot U_{\{t,k\}} \quad (S1.5)$$

so that $\text{Var}[PC_k] = 1$ by construction. The associated fraction of variance explained is

$$fvar_k = \sigma_k^2 / \sum_{j=1..r} \sigma_j^2 \quad (S1.6)$$

& appears in the title of every panel of Figures 7–12 & in the row labels of Fig. 9. The leading mode ($k=1$) accounts, across the analyses reported in the manuscript, for approximately 44–86% of the interannual variance of the corresponding index. Only the leading mode is analysed in the manuscript, its separation from higher-order modes being guaranteed by the criterion of Section S1.6.

S1.4. Sign convention

The sign of the k -th mode ($U_{\{\cdot,k\}}$, $V_{\{\cdot,k\}}$) is a free choice of the decomposition. We impose the physical convention that positive PC values correspond to positive (wet) anomalies of the analysed variable:

$$sign(V_{\{i,k\}}) \text{ chosen so that } \sum_i V_{\{i,k\}} > 0 \quad (S1.7)$$

This convention is applied identically to every combination (dataset, index, trimester, sub-period), so that the PC series and the loading maps of Figures 7–12 are physically comparable across panels. For dry indices (CDD), positive PC values correspond to longer dry spells (i.e., dry-anomaly excursions), consistent with the same rule applied to their own values.

S1.5. Homogeneous correlation maps & significance

The spatial loading map shown in Figs. 7–12 is the *homogeneous correlation map*, i.e., the Pearson correlation between the standardized station series $x_i(t) = Y^*_{\{i,t\}}$ and the principal component $PC_k(t)$:

$$\rho_{\{i,k\}} = \text{Corr}[x_i(t), PC_k(t)] = \lambda_k \cdot V_{\{i,k\}} / \text{std}(x_i) \quad (S1.8)$$

For the standardized anomaly matrix Y^* used here, $\text{std}(x_i) = 1$ and $\rho_{\{i,k\}} = \sigma_k \cdot V_{\{i,k\}} / \sqrt{N-1}$. Values are bounded in $[-1, 1]$ and directly interpretable as the fraction of a station's standardized variability captured by mode k .

Stations reaching the analytical Student t threshold at the 95% two-sided confidence level are highlighted in the loading maps with a '+' marker. For $N-2 = 17$ degrees of freedom, the threshold is

$$|\rho| > t_{\{0.05, 17\}} / \sqrt{t_{\{0.05, 17\}}^2 + N - 2} \approx 0.456 \quad (S1.9)$$

The same numerical threshold is used consistently across Figs. 7 through 12, since all EOF analyses share $N = 19$ years within each sub-period.

The correlations between the PC series and the four Niño SST indices summarised in Figure 9 (correlation

matrix) and in Table 2 are additionally tested with a non-parametric Monte Carlo permutation test in which the yearly values of the PC are randomly shuffled 1,000 times and the empirical significance level is set to $\alpha = 0.01$ (Wilks, 2019). This complementary test is more conservative than the analytical Student t threshold applied to the individual loading maps and is the criterion used for the cross-dataset consensus codes in Table 2.

S1.6. North et al. (1982) separability criterion and truncation

Following North et al. (1982), the sampling error on the k -th eigenvalue of a covariance matrix estimated from N independent realisations is approximately

$$\delta\lambda_k \approx \lambda_k \sqrt{(2/N)} \quad (S1.10)$$

and two consecutive modes are considered separable, in the sense that their patterns are not mixed by sampling noise, when their eigenvalue difference exceeds the sum of the two sampling errors:

$$\lambda_k - \lambda_{k+1} > \delta\lambda_k + \delta\lambda_{k+1} \quad (S1.11)$$

We evaluated (S1.11) for the first two modes of every analysis presented in the main text. In every case in which the leading mode is displayed (Figures 7 to 12), $\lambda_1 - \lambda_2$ comfortably exceeds $\delta\lambda_1 + \delta\lambda_2$, so that the leading pattern is well separated from PC2 and its interpretation is not affected by mode-mixing. Consequently, only the leading mode is presented in the main text; higher-order modes are not shown.

S1.7. Software and reproducibility

All EOF analyses in this study were computed with the S-mode formulation described above, using Python 3 (NumPy for the SVD, pandas for the temporal alignment of stations, xarray and Cartopy for the geospatial handling and plotting). Correlation and Monte Carlo significance tests were computed with SciPy. The station homogenization was performed in R with the Climatol 3.0 package (Guijarro, 2016).

S2. Between-sub-period changes in ETCCDI indices (Figs. S1–S6)

S2.1. Overview

Figs. 4, 5 and 6 of the main text show the between-sub-period differences (2000–2018 minus 1981–1999) of six ETCCDI indices. Figure 4 presents each spell index in the season in which it is physically informative (CDD in

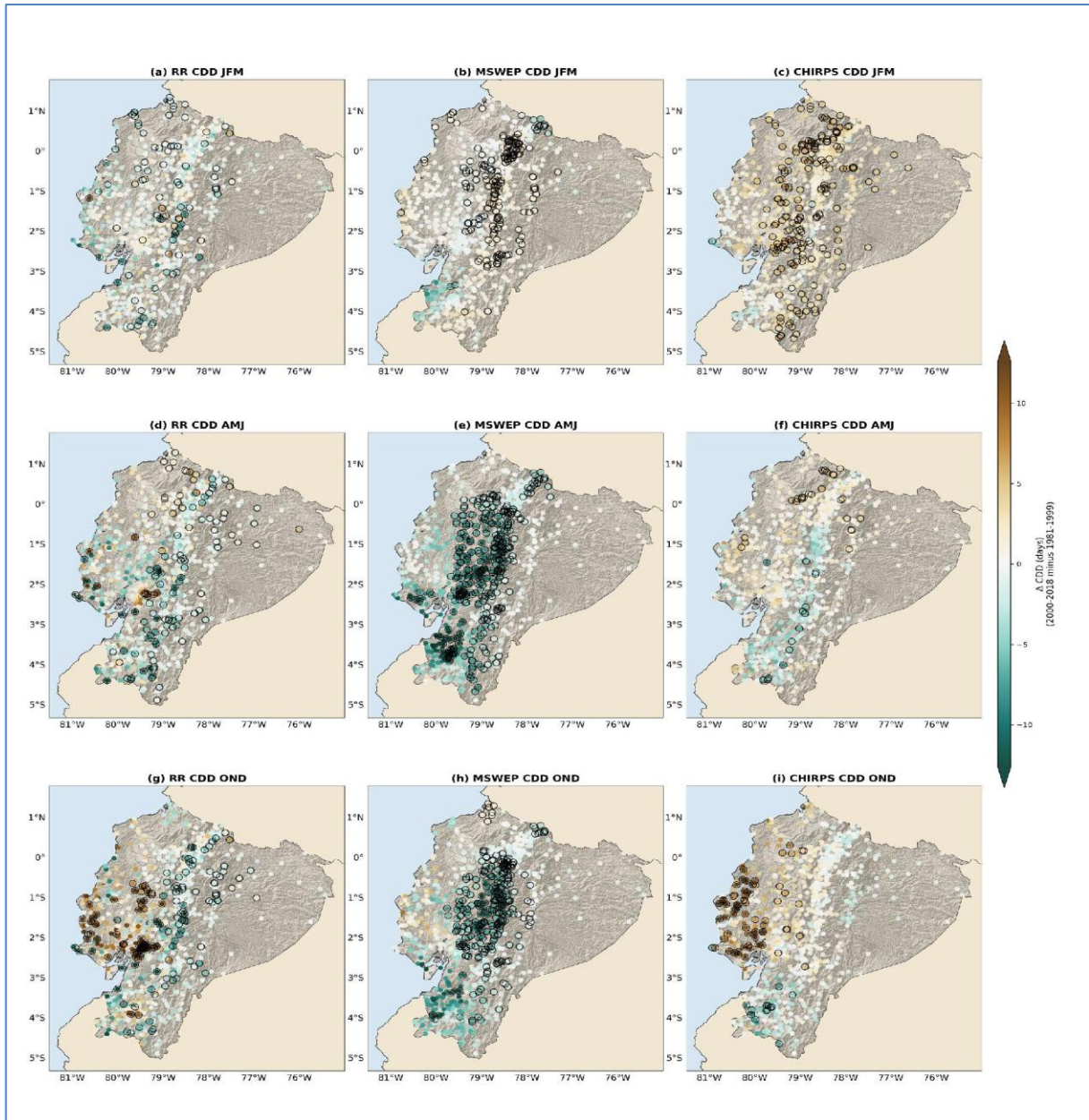


Fig. S1. ACDD (remaining trimesters)

As Figure 4 (top row) of the main text, for the change in the maximum number of consecutive dry days (CDD, days) between 2000–2018 and 1981–1999 during (a–c) JFM, (d–f) AMJ and (g–i) OND, for the rain-gauge network (RR), MSWEP and CHIRPS. Brown (green) shading denotes a tendency toward longer (shorter) dry spells; open black circles mark stations significant at the 5% level (Monte Carlo permutation test, 10,000 iterations). Colour limits are symmetric per figure.

JAS, CWD in JFM), while Figures 5 and 6 present the four extreme indices in OND, the only trimester in which the three datasets agree on the sign of the change (Section 3.2). This section provides the same maps for the remaining trimesters, produced with an identical pipeline

(Monte Carlo permutation test, 10,000 iterations, open black circles marking stations significant at the 5% level; identical basemap, panel layout and colour convention as in the main text). Supplementary Figures S1–S6 are cited in Section 3.2 of the main text.

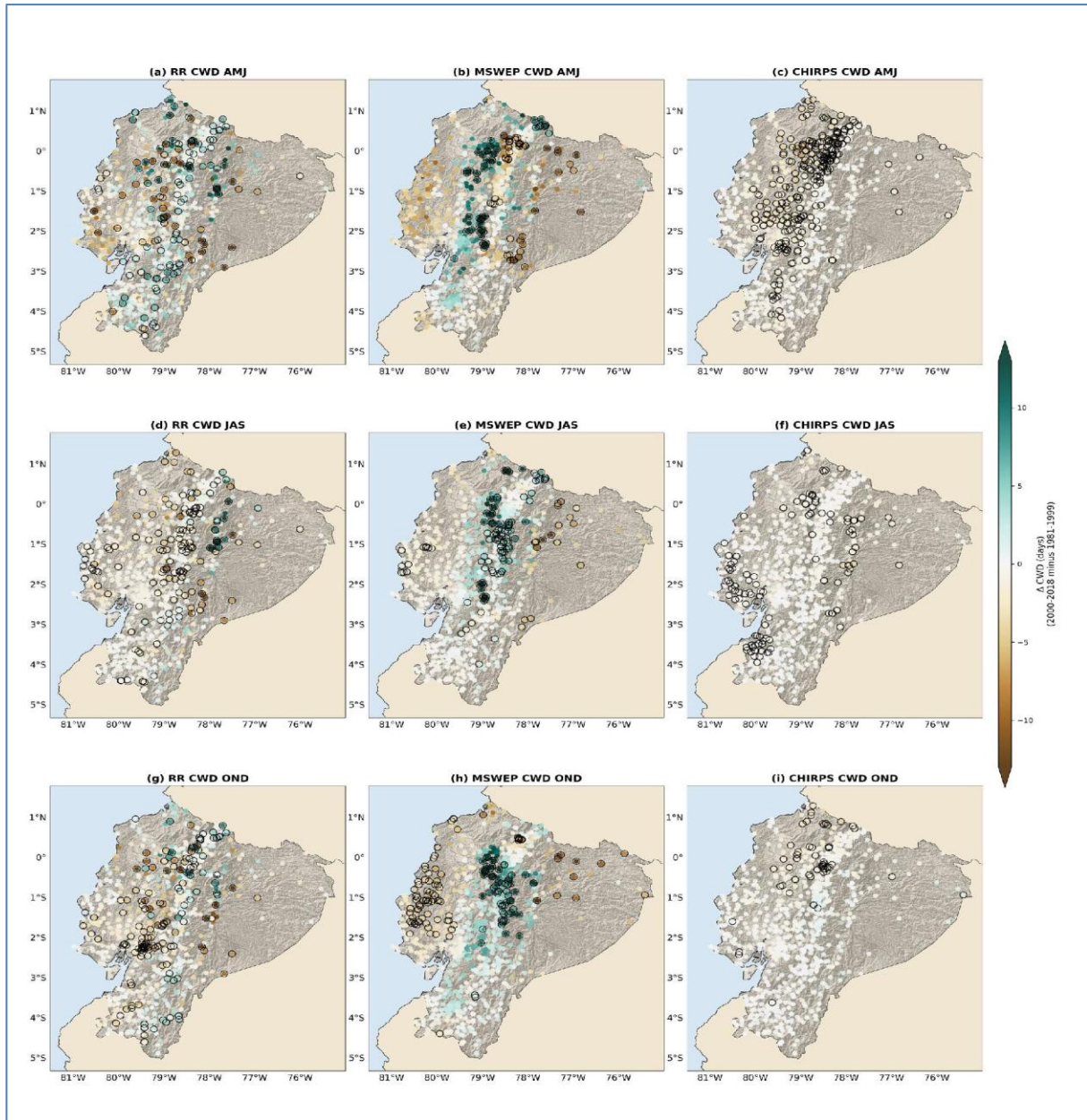


Fig. S2. Δ CWD (remaining trimesters)

As Figure 4 (bottom row) of the main text, for the change in the maximum number of consecutive wet days (CWD, days) between 2000–2018 and 1981–1999 during (a–c) AMJ, (d–f) JAS and (g–i) OND, for RR, MSWEP and CHIRPS. Green (brown) shading denotes a tendency toward longer (shorter) wet spells; open black circles mark stations significant at the 5% level (Monte Carlo permutation test, 10,000 iterations)

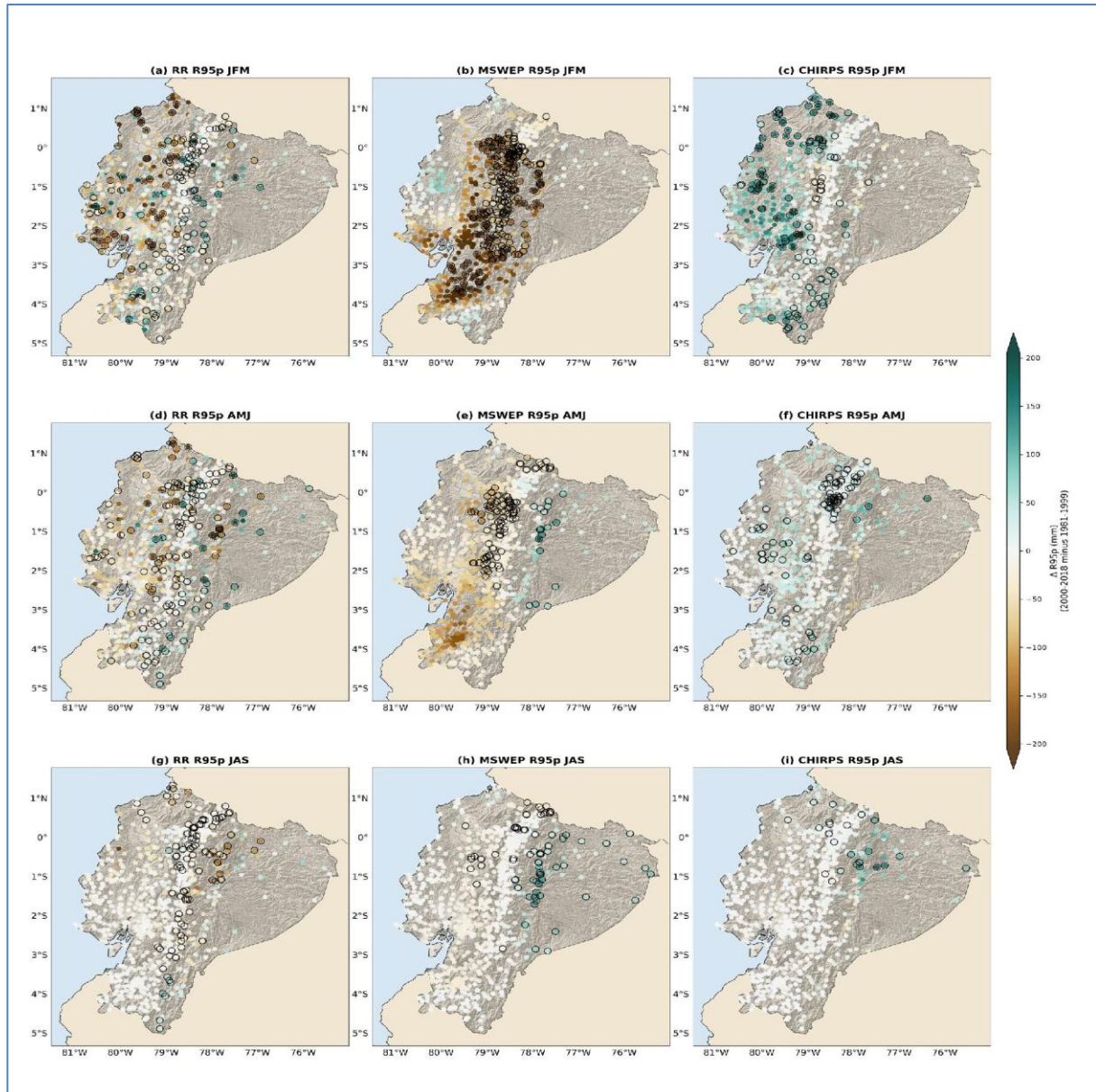


Fig. S3. $\Delta R95p$ (remaining trimesters)

As Figure 5 of the main text, for the change in the very-wet-day precipitation total ($R95p$, mm) between 2000–2018 and 1981–1999 during (a–c) JFM, (d–f) AMJ and (g–i) JAS, for RR, MSWEP and CHIRPS. Green (brown) shading denotes a wetter (drier) contribution from very wet days; open black circles mark stations significant at the 5% level (Monte Carlo permutation test, 10,000 iterations)

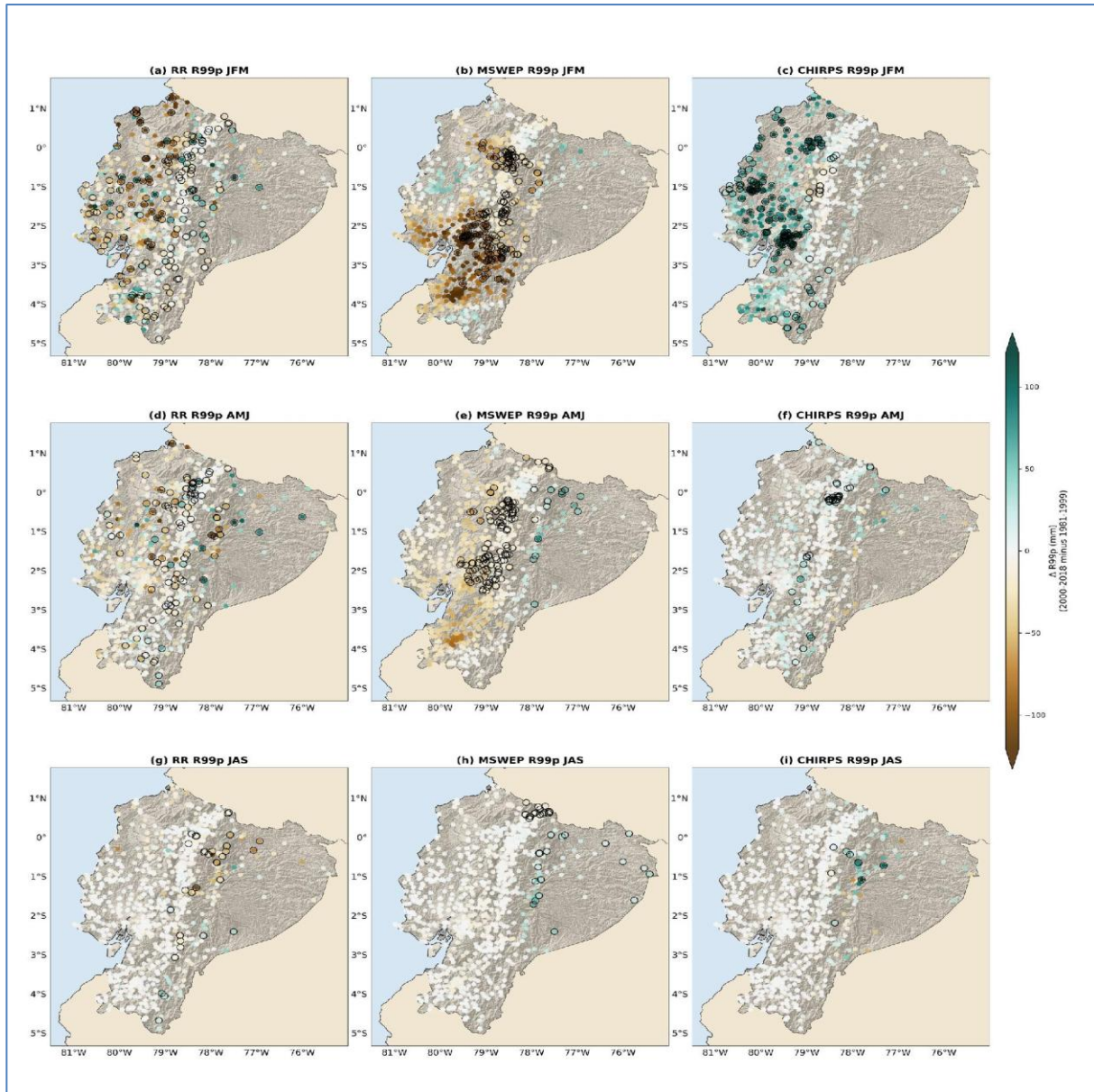


Fig. S4. $\Delta R99p$ (remaining trimesters)

As Figure 5 of the main text, for the change in the extremely-wet-day precipitation total ($R99p$, mm) between 2000–2018 and 1981–1999 during (a–c) JFM, (d–f) AMJ and (g–i) JAS, for RR, MSWEP and CHIRPS. Convention and significance criterion as in Figure S3

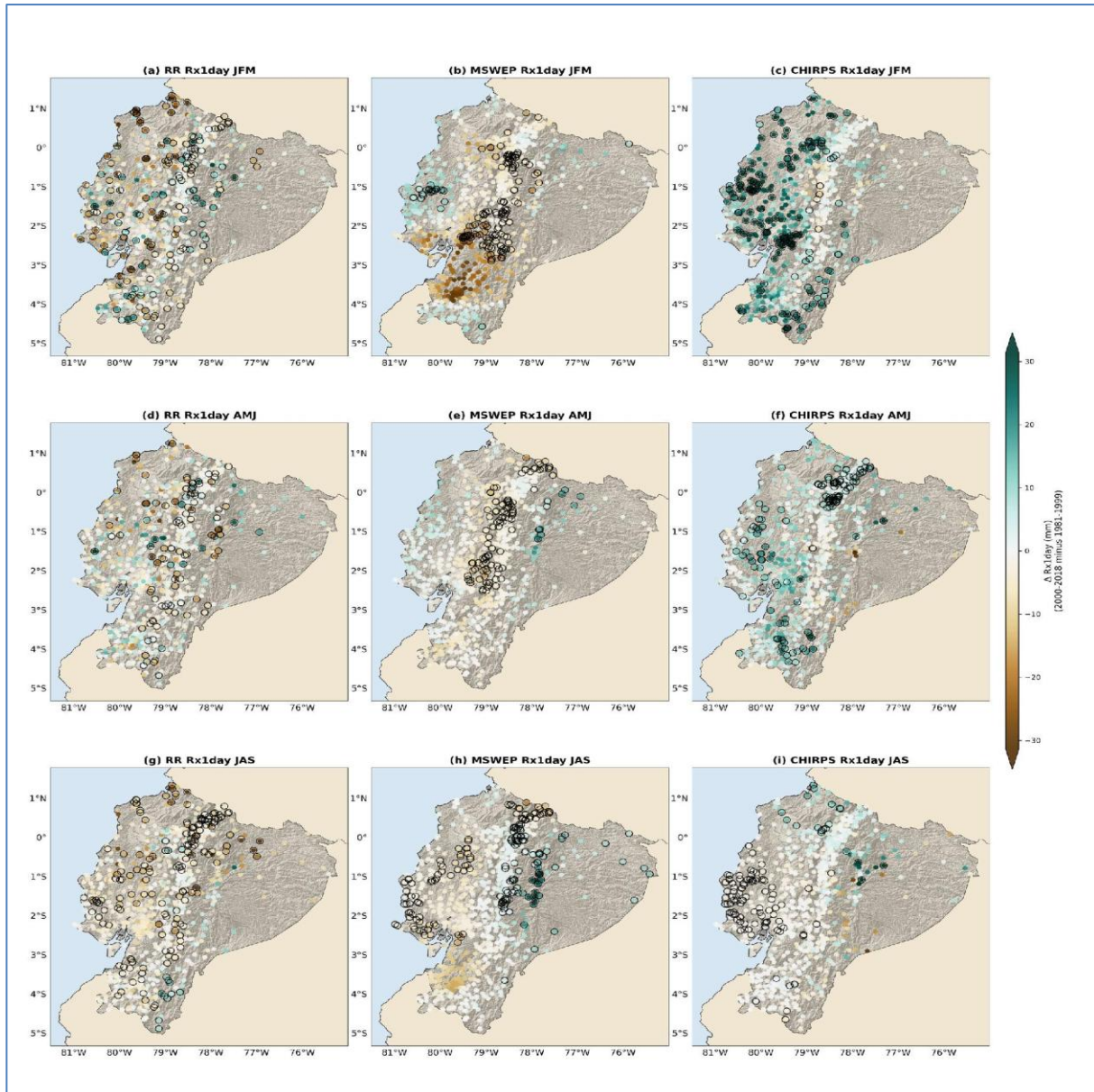


Fig. S5. $\Delta Rx1day$ (remaining trimesters)

As Figure 6 (top row) of the main text, for the change in the maximum 1-day precipitation ($Rx1day$, mm) between 2000–2018 and 1981–1999 during (a–c) JFM, (d–f) AMJ and (g–i) JAS, for RR, MSWEP and CHIRPS. Green (brown) shading denotes an increase (decrease) in the single-day maximum; open black circles mark stations significant at the 5% level (Monte Carlo permutation test, 10,000 iterations).

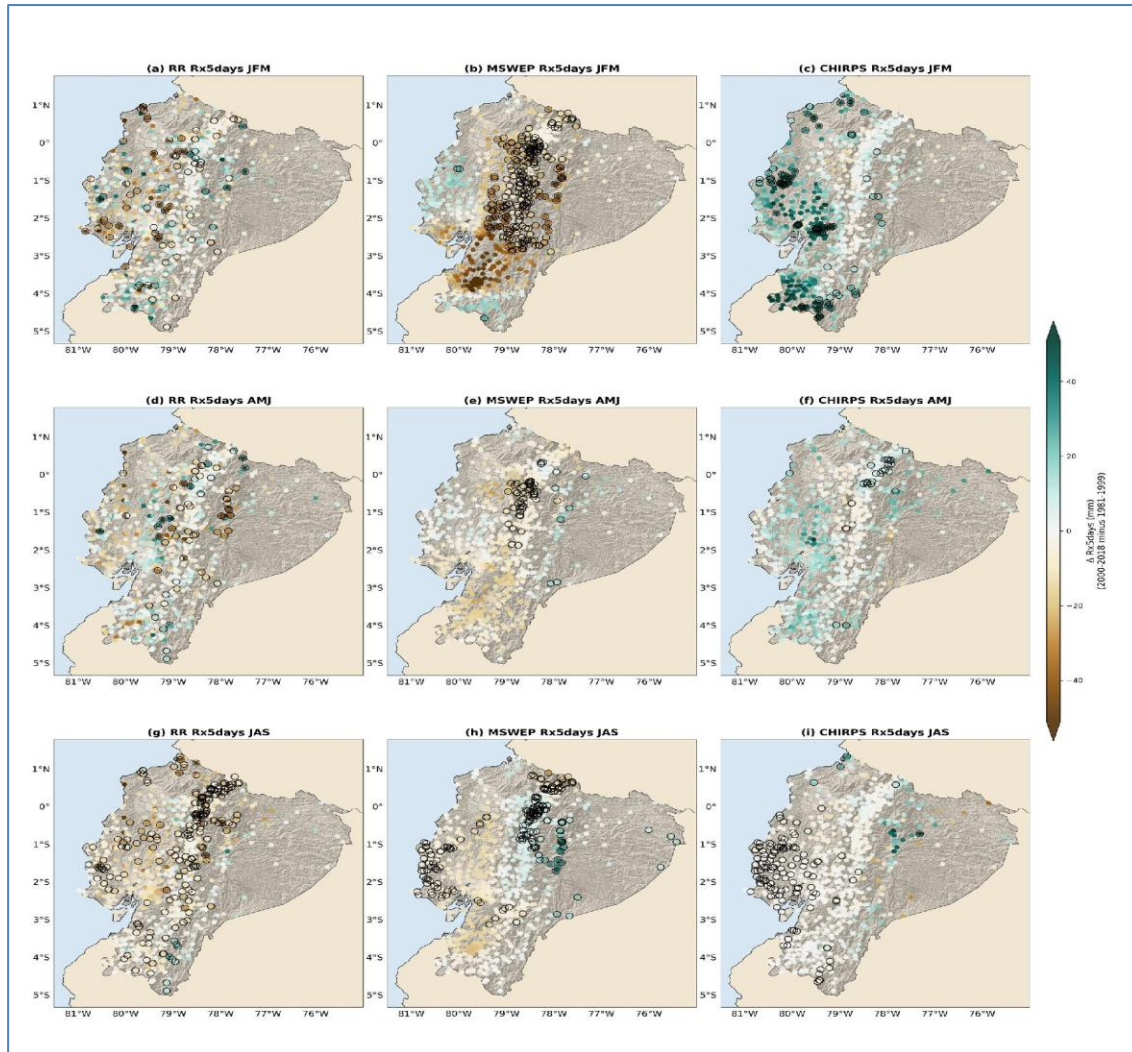


Fig. S6. $\Delta Rx5days$ (remaining trimesters)

As Figure 6 (bottom row) of the main text, for the change in the maximum 5-day cumulative precipitation ($Rx5days$, mm) between 2000–2018 and 1981–1999 during (a–c) JFM, (d–f) AMJ and (g–i) JAS, for RR, MSWEP and CHIRPS. Convention and significance criterion as in Figure S5.

S3. Period-comparison EOF analysis (Figures S7–S15)

S3.1. Overview

Section 3.3 of the main text compares the leading mode of interannual variability (EOF1) and its principal component (PC1) between the two sub-periods, with the trimester held fixed so that 1981–1999 and 2000–2018 are compared like for like. Figures 10, 11 and 12 of the main text present this comparison for the rain-gauge network (RR) in AMJ, the trimester in which each index shows the widest cross-dataset consensus with the eastern Pacific indices during 1981–1999 (Table 2 of the main text). This section provides the same comparison for the remaining

trimesters of those three indices, computed with an identical procedure (S-mode EOF on the standardized station–year matrix, PC1 sign convention and significance criterion described in Section S1). Supplementary Figures S7–S15 are cited in Sections 3.4 and 3.5 of the main text and in the captions of Figures 10–12.

In every panel, the map shows the correlation between each station series and PC1 of the corresponding sub-period (the homogeneous correlation map, Section S1.5); crosses mark stations significant at the 5% level under the analytical Student *t* threshold. The lower panels show the standardized PC1 series, and the fraction of variance explained by EOF1 is given in each panel title.

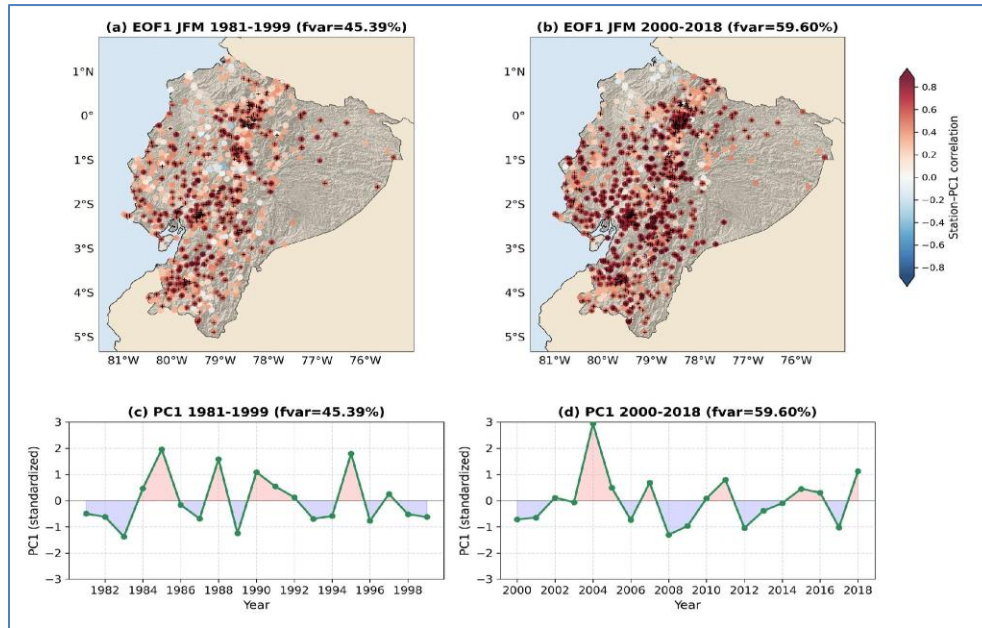


Fig. S7. EOF1/PC1 of CDD in JFM (RR)

Leading mode of interannual variability of the maximum number of consecutive dry days (CDD) in JFM for the rain-gauge network (RR), computed separately in each sub-period. (a, b) Correlation between the CDD series of each station and PC1 for 1981–1999 and 2000–2018, respectively; crosses mark stations significant at the 5% level. (c, d) Standardized PC1 series for the same sub-periods. The fraction of variance explained by EOF1 is indicated in each panel title. Figure 10 of the main text shows the same analysis for AMJ, the trimester in which the CDD leading mode shows the widest cross-dataset consensus with the eastern Pacific indices during 1981–1999 (Table 2).

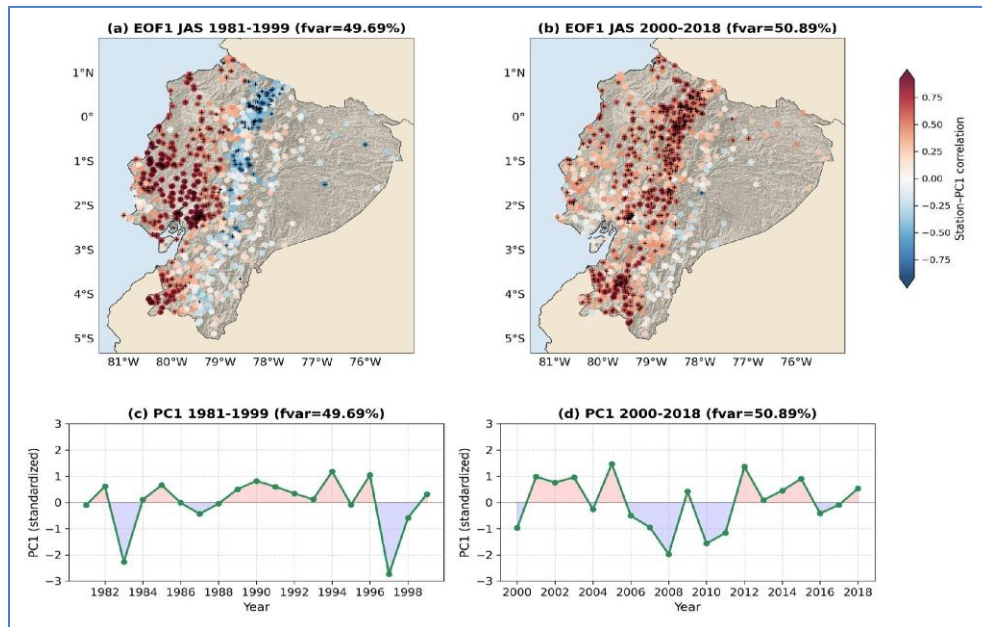


Fig. S8. EOF1/PC1 of CDD in JAS (RR)

As Figure S7, for JAS.

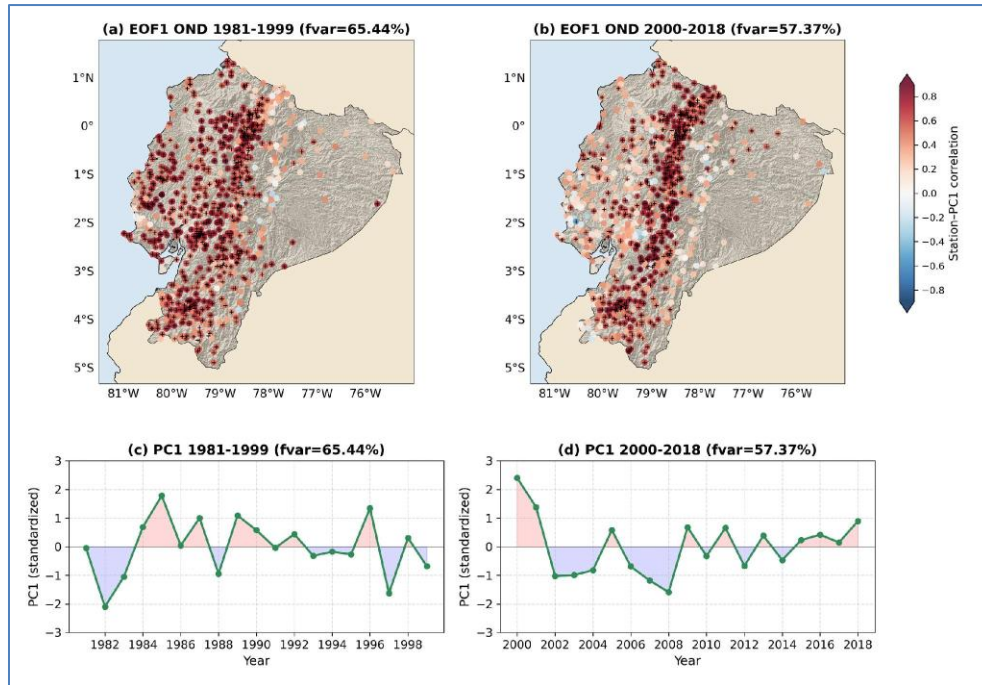


Fig. S9. EOF1/PC1 of CDD in OND (RR)

As Figure S7, for OND.

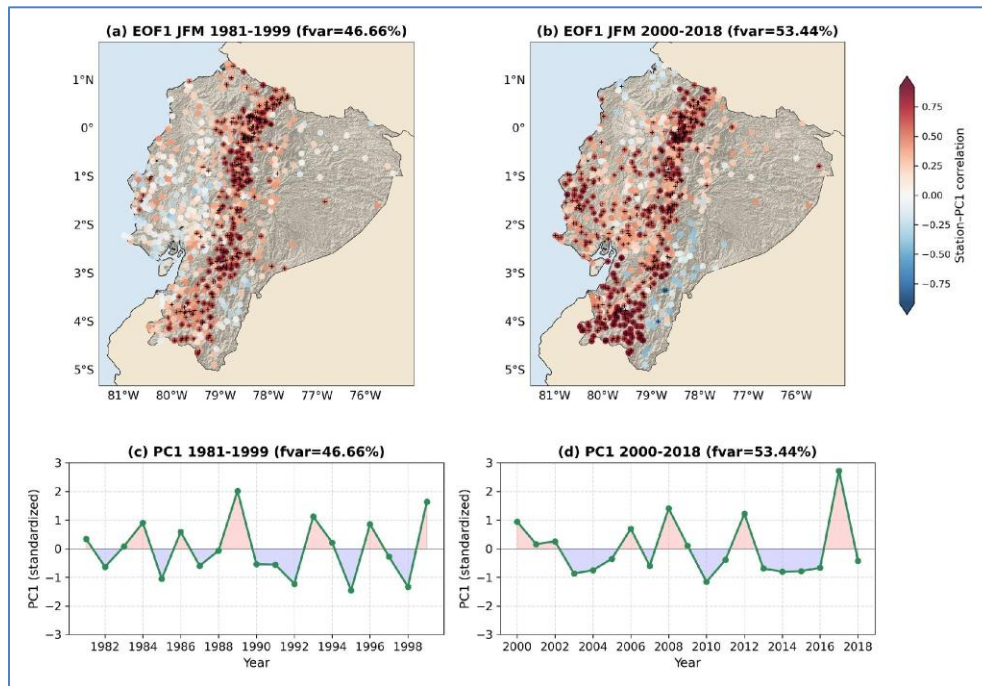


Fig. S10. EOF1/PC1 of CWD in JFM (RR).

As Figure S7, for the maximum number of consecutive wet days (CWD) in JFM. Figure 11 of the main text shows the same analysis for AMJ.

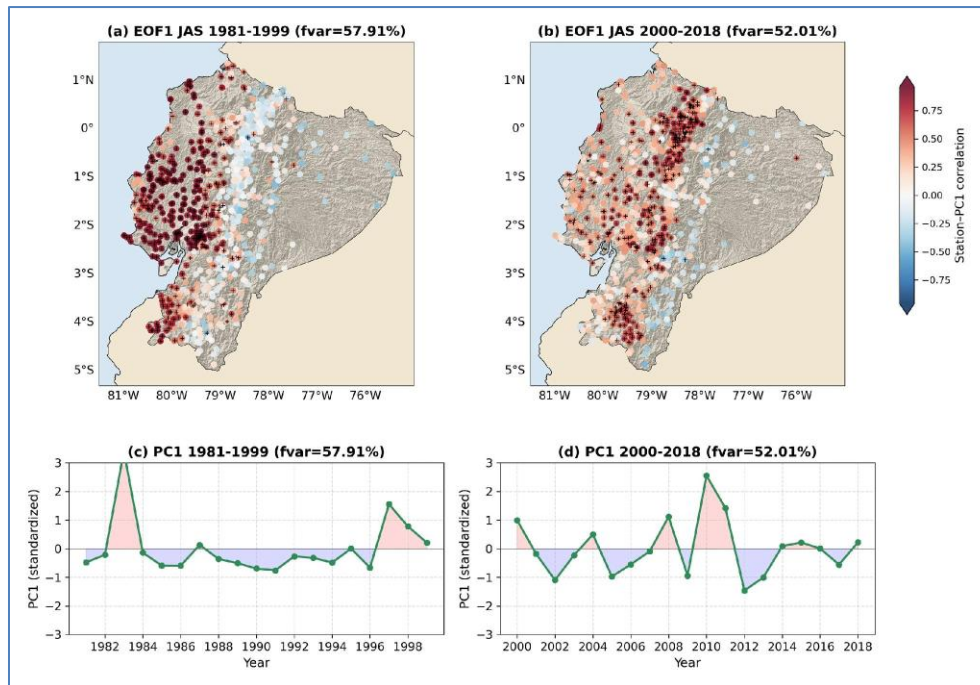


Fig. S11. EOF1/PC1 of CWD in JAS (RR).

As Figure S10, for JAS.

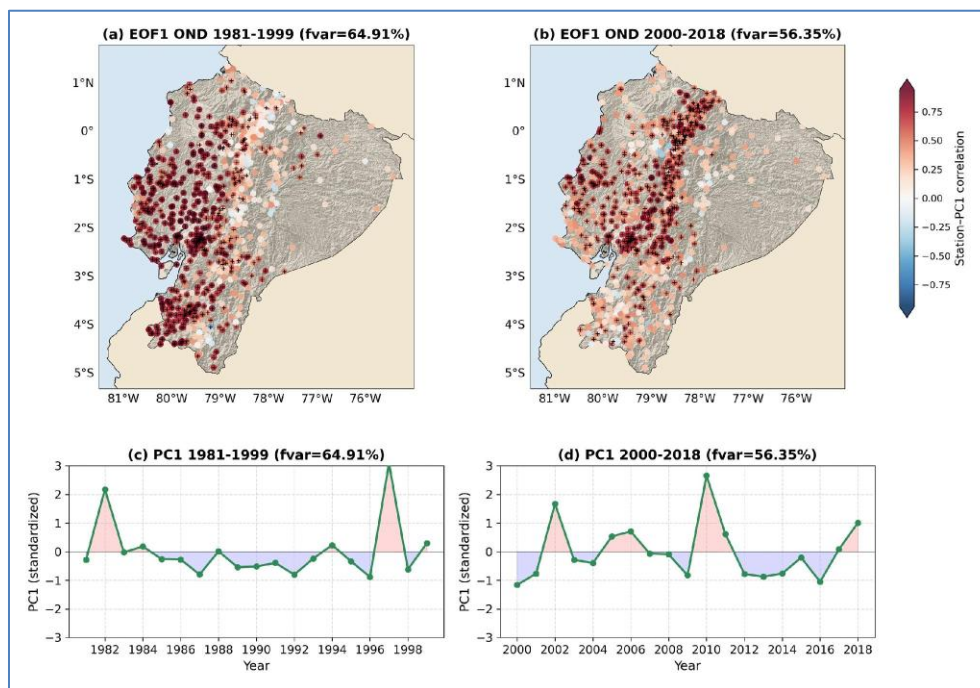


Fig. S12. EOF1/PC1 of CWD in OND (RR)

As Figure S10, for OND.

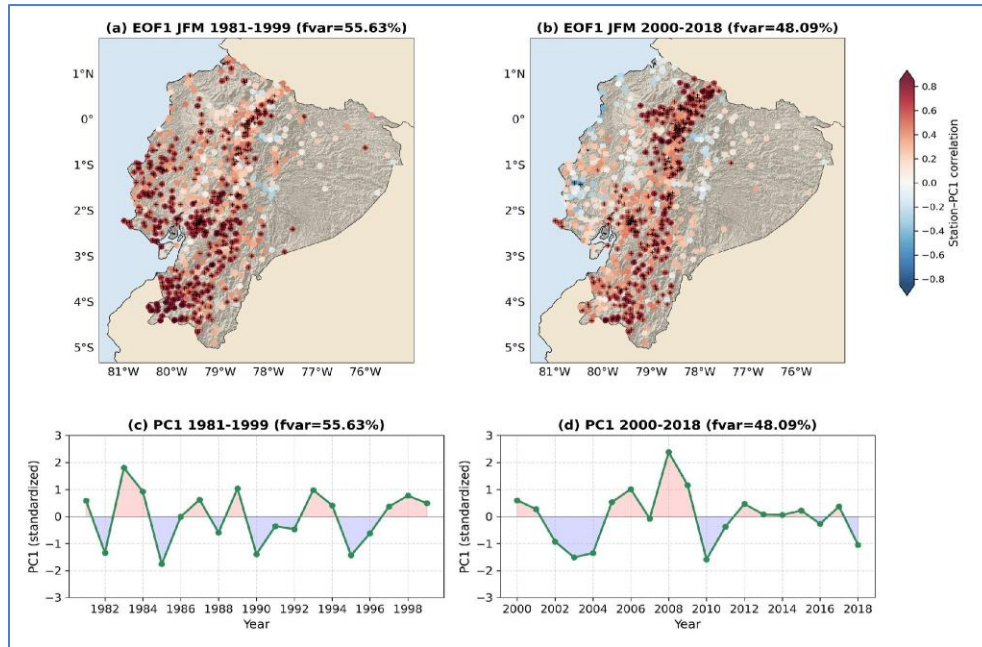


Fig. S13. EOF1/PC1 of Rx5days in JFM (RR)

As Figure S7, for the maximum 5-day cumulative precipitation (*Rx5days*) in JFM. Figure 12 of the main text shows the same analysis for AMJ, the trimester in which the *Rx5days* leading mode shows the strongest eastern Pacific coupling and full cross-dataset consensus during 1981–1999 (Table 2).

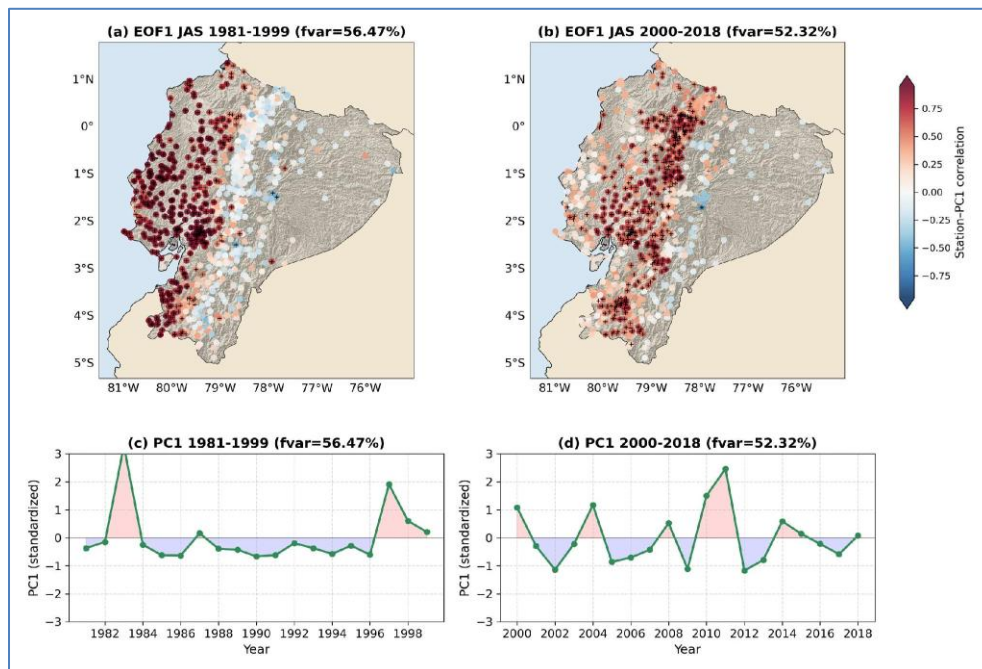


Fig. S14. EOF1/PC1 of Rx5days in JAS (RR)

As Figure S13, for JAS.

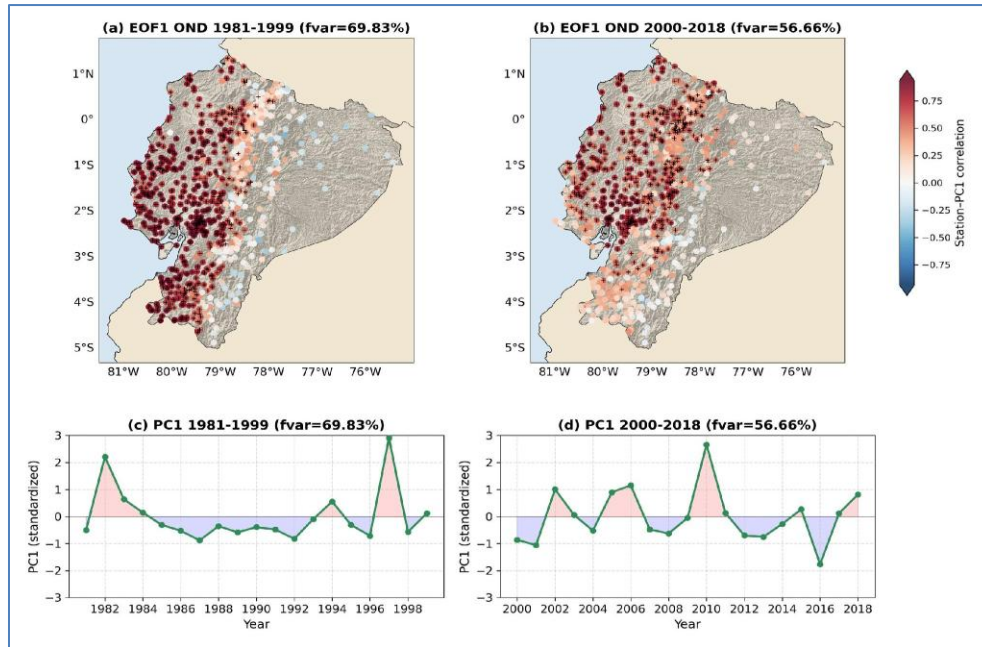


Fig. S15. EOF1/PC1 of Rx5days in OND (RR)

As Figure S13, for OND.

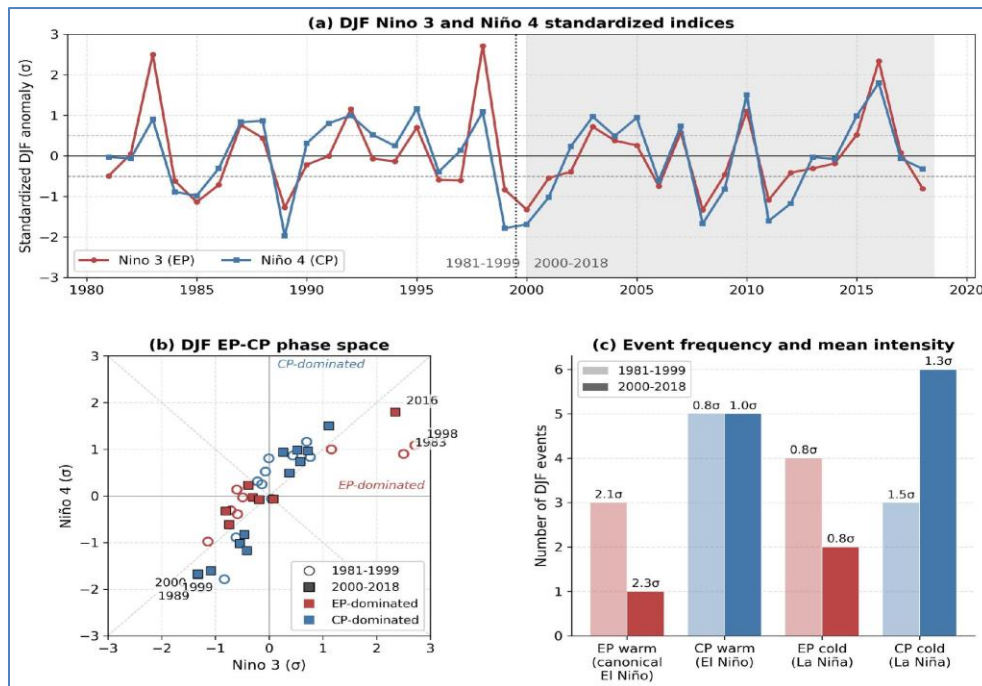


Fig. S16. ENSO regime shift with Niño 3 as the eastern Pacific index

As Figure 13 of the main text, but with the eastern Pacific represented by Niño 3, the box conventionally used in the EP-CP literature, instead of Niño 1+2, the box adjacent to the Ecuadorian coast used in the main text. (a) DJF standardized Niño 3 and Niño 4 series; (b) DJF EP-CP phase space, with the dominant index giving the colour and the two sub-

periods distinguished by open and filled symbols; (c) number of DJF events per sub-period and category, with the mean intensity of each category above the bars. Events are classified as in Figure 13. The qualitative result of Figure 13 is unchanged: eastern Pacific events decline (seven to three, against five to three with Niño 1+2), central Pacific events increase (eight to eleven, against nine to twelve), the increase is carried entirely by the cold phase (three to six, against three to seven) and central Pacific warm events remain unchanged (five and five, against six and five). The two extreme eastern Pacific events of 1982/83 and 1997/98 remain the largest of the record under either index. The choice of eastern box therefore does not drive the conclusions of Section 3.6.

S4. Sensitivity of the ENSO regime classification to the eastern Pacific index (Fig. S16)

Section 3.6 of the main text characterizes the change in ENSO behaviour around the year 2000 using Niño 1+2 as the eastern Pacific index and Niño 4 as the central Pacific index. Niño 1+2 was chosen because it covers the ocean adjacent to the Ecuadorian coast and is the index through which the pre-2000 rainfall coupling is expressed (Section 3.4). Because the EP-CP literature conventionally uses Niño 3 for this purpose, the classification has been repeated with Niño 3 in place of Niño 1+2; the result is given below.

Supplementary References

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