Explaining monthly precipitation anomalies in northwestern South America by integrating vertical dynamics and energetics

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Abstract. In dynamically limited environments such as the coastal Northwestern South America (NWSA)~~is a critical region for monitoring El Niño-driven hydroclimatic extremes, receiving its maximum cumulative precipitation in March. Thermodynamic indices alone often fail to explain observed precipitation anomalies in this region because they neglect the limiting role of large-scale environmental dynamics. To bridge this gap, a diagnostic proxy called the~~ , thermodynamic instability (ΔT) alone is insufficient to autonomously trigger deep convection due to persistent background subsidence. The Buoyancy Work Rate (BWR) ~~is proposed, which quantifies the rate of conversion from potential to kinetic energy by coupling local thermodynamic instability (~~addresses this boundary constraint by vertically coupling ΔT ~~) with vertical motion~~ with vertical velocity (ω)~~forced by large-scale dynamics. The BWR is calculated by vertically integrating the product $-\omega\Delta T$ from the surface to the 100 hPa level. Using the PCMCI+ causal discovery algorithm, this study empirically validates the classical thermodynamic energy balance mechanism~~. A causal discovery analysis empirically verified this formulation, demonstrating that ~~precipitation in the NWSA is dynamically controlled, with ω exerting a causal influence significantly stronger than local evaporation. Validation via Tail Dependence analysis (λ_U) reveals that the BWR achieves robust asymptotic dependence ($\lambda_U \approx 0.8$) during extreme events. This robustness confirms~~ the BWR preserves the dominant causal route to precipitation over other individual thermodynamic or dynamic variables, successfully capturing the dynamic trigger required to realize convection. As a diagnostic proxy, the BWR systematically outperforms established thermodynamic indices because it explicitly quantifies the realized mesoscale atmospheric response rather than just the precursor potential. This diagnostic advantage is reinforced by an upper tail dependence analysis based on empirical copulas, which confirmed the index's ~~ability to filter out thermodynamic false positives (e.g.~~ , robustness during extreme hydroclimatic anomalies. Moreover, while isolated mid-level vertical velocity dictates instantaneous convection, its high-frequency volatility limits its utility for continuous monitoring. By integrating ΔT, the ~~2016 event) by incorporating the vertical velocity constraint. Furthermore, autocorrelation analysis indicates that the inclusion of the thermodynamic component imparts significant signal persistence to the index, stabilizing the inherently chaotic nature of pure vertical velocity. Physically, the index explains how dynamic forcing modulates precipitation outcomes across events with similar instability, resolving the contrasting impacts of the 2016, 2017, and 2023 El Niño events. Consequently~~BWR mathematically inherits the thermal inertia of the oceanic boundary conditions, imparting greater signal persistence and making it a more stable proxy for sub-seasonal operative monitoring. Ultimately, the operational value of the BWR emerges in its prognostic application. By substituting predicted precipitation anomalies from the SEAS5 model with the predicted BWR anomalies, the predictions overcome the limitations of the sub-grid parameterizations inherent in the climate model. Relying

instead on explicitly resolved mesoscale variables governed by primitive equations, the BWR ~~emerges as a physically consistent tool that offers a longer predictability horizon for monitoring sub-seasonal hydroclimatic risks~~systematically improves seasonal predictive skill during the peak of the austral summer and mitigates the forecast degradation caused by the boreal spring predictability barrier.

1 Introduction

~~The El Niño-Southern Oscillation (ENSO) is one of the main drivers of global climate variability, altering weather patterns worldwide (**??**). Northwest South America (NWSA) is a region of critical scientific importance for monitoring these events, particularly coastal El Niño events, while being exceptionally vulnerable to their hydroclimatic and socioeconomic impacts (Callahan and Mankin, 2023; Poveda et al., 2025).~~

~~Although sea surface temperature (SST) in the Niño 1+2 region possesses a known critical threshold capable of triggering deep convection (Takahashi and Martínez, 2017; Takahashi et al., 2018), SST alone has proven to be an insufficient predictor of precipitation anomalies (**?**). It has been demonstrated that above a certain SST threshold (approximately 28 °C), the direct relationship between local temperature and convection breaks down, with convective activity becoming increasingly controlled by large-scale vertical motions rather than surface fluxes alone (Lau et al., 1997; Bony et al., 1997).~~

~~Estimating precipitation anomalies remains a significant challenge, as it requires understanding~~ It is physically well-established that deep moist convection ~~, the process of vertical heat and moisture transport driving tropical climates (**?**). This process is governed by a complex interaction between local thermodynamic instability and~~ in the tropical Pacific is primarily governed by large-scale atmospheric dynamics ~~. For decades, the conventional metric for assessing this potential has been Convective Available Potential Energy (CAPE) (**?**). However, purely thermodynamic indices often yield high false-positive rates in the tropics because they quantify potential instability without accounting for the dynamic forcing required to release it (Williams and Renno, 19 . Conversely, large-scale vertical motion (ω) explains a significantly larger fraction of variance in tropical convection than local SST (Lau et al., 1997). This dynamic dominance was physically grounded by **?**, who demonstrated that~~and horizontal moisture convergence, rather than exclusively by local Sea Surface Temperature (SST) (Lau et al., 1997; Bony et al., 1997). The work of Cornejo-Garrido and Stone (1977) demonstrated that, on climatic timescales within the Walker circulation, latent heat release ~~is primarily balanced by adiabatic cooling due to vertical ascent($[\theta]_z\omega \approx Q$). This balance implies that rainfall~~ in the atmospheric column is fundamentally balanced by the adiabatic cooling induced by large-scale vertical ascent. This thermodynamic equilibrium dictates that large-scale atmospheric circulation and deep convection are inextricably coupled (Emanuel et al., 1994). Within this framework, time-mean sources of tropospheric column-integrated moist static energy must be balanced by the advective export of energy driven by divergent circulations (Neelin and Held, 1987). Consequently, the atmospheric convective response is dynamically maintained by ~~moisture convergence rather than locally fueled by surface evaporation, necessitating indices that explicitly incorporate vertical velocity~~mass and horizontal moisture convergence (Back and Bretherto
.

This ~~disconnect between thermodynamic potential and realized convection is particularly evident in the Eastern Pacific. The 2017 and 2023 Coastal El Niño events produced extreme rainfall, whereas the 2015-2016 global~~ dynamic dominance is highly evident in Northwestern South America (NWSA). The coastal subdomain between Peru and Ecuador is typically characterized by a persistent subsidence (dynamically limited environment) with a short rainy season during the austral summer. However, the disturbance of this regional circulation during strong El Niño events (e.g., 1982-1983, 1997-1998, ~~despite comparable SST magnitudes, did not produce equally severe coastal impacts (Paek et al., 2017; Sulca et al., 2017). To distinguish these regimes, indices such as the C and E indices (?) and the atmospheric $CPTICZ$ and $EPTICZ$ indices (?) were developed. However, a unified metric linking the thermodynamic potential with the dynamic realization of convection on monthly scales remains necessary.~~ 2017, and 2023) triggers extreme hydroclimatic anomalies, causing severe flooding and socio-economic impacts (Bendix, 2000; Takahashi, 2004; Callahan and Mankin, 2023; Poveda et al., 2025). Notably, not all warming events manifest similarly: the 2015-2016 global El Niño recorded historically high SSTs but failed to produce comparable extreme hydroclimatic anomalies along the NWSA coast (Paek et al., 2017). This paradox is explained by the region's physical constraints. Although local SST must exceed a specific threshold to trigger atmospheric instability (Woodman, 1999; Taka , this atmospheric instability (ΔT) is a necessary but insufficient condition for deep convection (Williams and Renno, 1993). Once the thermodynamic threshold is surpassed, control shifts predominantly to the large-scale vertical velocity (ω) (Lau et al., 1997; Bony . Convection often requires a mechanical trigger, such as the localized vertical ascent generated by the sea breeze colliding against the western Andean slope (Takahashi, 2004; Rollenbeck et al., 2022), which lifts air parcels to their Level of Free Convection (LFC) to initiate latent heat release. The ensuing mid-level ω emerges to balance this diabatic heating through adiabatic cooling (Sobel et al., 2001), stimulating further low-level horizontal convergence dictated by mass continuity (Back and Bretherto .

~~While atmospheric dynamics occur on high-frequency timescales (?), this study focuses on monthly averages to isolate robust climate signals (?). Based on the thermodynamic energy balance described by ?,~~ Despite this established dynamic-thermodynamic coupling, the ~~monthly average vertical motion serves as a robust proxy for the integrated heating of the column. Consequently, the main objective of this research was to develop, validate, and apply the Buoyancy Work Rate (~~operational assessment of precipitation has traditionally based on purely thermodynamic stability indices. E.g., the Convective Available Potential Energy (CAPE) (Emanuel et al., 1994), which evaluates the integrated atmospheric instability for an ascending air parcel from the Level of Free Convection (LFC) to the Equilibrium Level (EL). Or the Gálvez-Davison Index (GDI) (Gálvez and Davison, 2016) , which represents better tropical environments, incorporating low-to-mid tropospheric moisture availability and the stabilizing effects of trade-wind inversions. However, the GDI does not necessarily relate to regions of dynamically induced ascent or descent (WPC, 2022). In environments with persistent subsidence like the coastal subdomain, relying exclusively on thermodynamic metrics yields high false-positive rates because they cannot distinguish between active deep convection and dynamically suppressed atmospheric instability (DeMott and Randall, 2004). To overcome this limitation, the Buoyancy Work Rate (BWR) ~~index. The BWR is defined as the vertical integration of the product of~~ is proposed as a diagnostic proxy. By mathematically coupling the atmospheric instability (ΔT) directly with the vertical velocity (~~ω) and parcel buoyancy (ΔT). It should be noted that while the BWR does not carry strict units of power density (W m^{-2}) , it serves as a physical proxyproportional to the rate at~~

~~which buoyancy potential energy is converted into kinetic energy. By coupling the dynamic trigger (ω) with the thermodynamic fuel (ΔT~~ω), the BWR ~~is designed to distinguish buoyancy-driven convectionfrom mechanically forced vertical motion (where $\Delta T < 0$), providing a diagnostic of active , thermodynamically supported deep convection~~inherently incorporates the kinematic realization of convection, diagnosing active convective engines while filtering out thermodynamically unstable but dynamically suppressed environments.

~~In this study , the performance~~ The objective of this study is to evaluate the diagnostic capability, physical interpretation, and prognostic utility of the BWR ~~was rigorously evaluated against precipitation~~ index for extreme hydroclimatic anomalies in the NWSA~~from 1981 to 2025. First, Causal Discovery algorithms, specifically~~ . First, the PCMCI+ ~~(Runge, 2020) , were applied to verify the physical hypothesis that dynamics drive precipitation more strongly than local evaporation, validating the mechanism proposed by ?~~data-driven causal discovery algorithm (Runge, 2020) is used to empirically evaluate the preservation of the BWR causal route to precipitation. Second, the reliability of the ~~index during extreme events was~~ BWR during extreme hydroclimatic anomalies is assessed using the Upper Tail Dependence ~~Coefficient (λ_U) derived from Copula theory (Nelsen, 2006), determining whether the BWR maintains its coupling with precipitation during the most intense El Niño events. Finally, the predictability horizon of the index was analyzed via autocorrelation functions to determine if~~ coefficient derived from empirical copulas (Nelsen, 2006; Poulin et al., 2007). Third, an autocorrelation analysis demonstrates how the inclusion of the ~~thermodynamic component (ΔT)~~ atmospheric instability component imparts greater signal persistence to the index compared to pure vertical velocity. Finally, to evaluate its true prognostic utility, the operational prediction skill of the BWR is explicitly tested by applying the index to predicted atmospheric fields from the ECMWF SEAS5 model, assessing whether this physical translator systematically outperforms the model's direct precipitation predictions for early warning applications.

2 Data and study area

2.1 Observational~~and~~ , Reanalysis, and Forecast Data

Monthly mean air temperature (T_a), relative humidity (RH), and zonal, meridional, and vertical wind components were obtained from the ERA5 reanalysis dataset (Hersbach et al., 2020). These data were utilized for the period 1981–2025 across 27 vertical pressure levels ranging from 1000 to 100 hPa, with a spatial resolution of 0.25°. Monthly SST from ERA5 was also utilized to provide context for the identified extreme hydroclimatic events. The SST data from the ERA5 reanalysis–which strictly prescribes observation-based products such as HadISST2 and OSTIA (Hersbach et al., 2020)–were used to characterize the oceanic boundary conditions. The use of ERA5 SST, rather than an independent observational product, ensures strict thermodynamic consistency, as it represents the exact surface forcing that generated the atmospheric response (ω and ΔT) evaluated in this study.

To validate the proposed climate index, two independent high-resolution precipitation products developed specifically for the complex Peruvian topography were employed. First, the RAIN4PE product ~~(?)~~ (Fernandez-Palomino et al., 2022) was used for the 1981–2015 period. RAIN4PE is a gridded dataset that merges three data ~~sources–satellite~~ sources—satellite estimates

(CHIRPS), reanalysis data (ERA5), and ground ~~observations-corrected~~ observations—corrected via quantile mapping and validated through hydrological modeling to ensure consistency with observed streamflow and water balance closure. Second, the PISCO product (Peruvian Interpolated Data of the SENAMHI's Climatological and Hydrological Observations) (Aybar et al., 2019) was used for the 1981–2025 period. PISCO is a hybrid product developed by the National Meteorology and Hydrology Service of Peru (SENAMHI) that combines quality-controlled rain gauge records with satellite covariates (CHIRPS) using geostatistical interpolation techniques to reconstruct rainfall fields over data-scarce regions.

It is important to note that the stable version of PISCO, which incorporates both manual and automatic quality control (Aybar et al., 2019), is available only for the 1981-2016 period; consequently, the unstable version, which undergoes only automatic quality control, was utilized for the 2017-2025 period. ~~Due to RAIN4PE only having data until 2015 and the uncertainty of PISCO increasing from 2017 onwards, monthly~~

Monthly precipitation from ERA5 (Hersbach et al., 2020) ~~,~~ was used to ~~evaluate similarities among the precipitation products as a form of data triangulation to increase the credibility of precipitation anomaly behavior~~identify the area within the NWSA exhibiting the highest similarity with observational datasets, given that the proposed index is constructed entirely from ERA5 variables. Fig. 1 shows that ERA5 is ~~correlated significantly over all the domain~~ significantly correlated with RAIN4PE and PISCO ~~, being more strong near to~~ over the entire domain, being strongest near the coast between Peru and Ecuador. ~~Finally, monthly sea surface temperature (SST) from~~ This high correlation along the coastal strip is primarily due to large-scale synoptic and dynamic boundaries that global reanalyses effectively resolve, coupled with a high density of meteorological stations that enhances the reliability of PISCO and RAIN4PE in this specific subregion (Aybar et al., 2019; Fernandez-Palomino et al., 2022) .

Conversely, the correlation weakens significantly over the Andes and the Amazon basin. Over the Andes, ERA5~~was also utilized to provide context for the identified rainiest and driest events.~~'s spatial resolution is too coarse to adequately capture fine-scale orographic precipitation, systematically leading to overestimations (Insel et al., 2009; Fernandez-Palomino et al., 2022) . In contrast, regional gridded products mitigate this by incorporating local terrain elevation models and dense gauge networks. Over the Amazon basin, precipitation is largely driven by localized mesoscale convective systems and intense moisture recycling (Poveda et al., 2006), which remain challenging for ERA5's convective parameterizations to simulate accurately. This physical discrepancy is further compounded by the sparse distribution of rain gauges in the Amazon, which sharply increases the spatial interpolation uncertainty in observation-based datasets (Sun et al., 2018; Fernandez-Palomino et al., 2022).

Furthermore, to evaluate the prognostic utility of the BWR index, predicted atmospheric variables and direct precipitation outputs were obtained from the fifth generation of the ECMWF seasonal forecasting system (SEAS5) (Johnson et al., 2019). SEAS5 is an operational coupled global climate model designed for long-range predictions. Given the inherent uncertainty and chaotic nature of seasonal forecasting, this study specifically utilizes the monthly ensemble means of the real-time forecasts rather than individual deterministic members. This approach filters out high-frequency internal variability, isolating the predictable macro-scale signal required for the BWR calculation. The forecast data spans the operational period from 2017 to 2025.

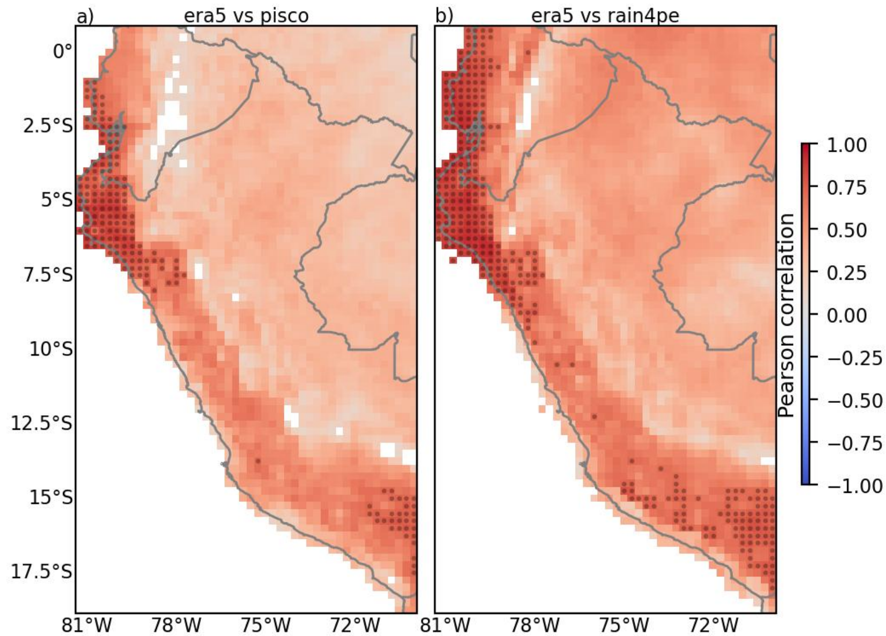

Figure 1. Pearson correlation (R) at the 95% confidence level between monthly precipitation anomaly from ERA5 and PISCO (a) for 1981–2025, and RAIN4PE (b) for 1981–2015. Only pixels with significant R (p-value<0.05) are shown, the gray points represent R>0.7. The blue (red) shaded colors indicate negative (positive) values of R. Anomalies were calculated taking the 1981–2015 median as climatology for all datasets.

2.2 Study area: The NWSA and the coastal coupling zone

Two domains of interest were defined: the broader NWSA region (~~18.95° S–1.95° N, 81.95~~81.6° W–67.05° W, 18.95° S–1.5° N) and a specific coastal subdomain adjacent to the Niño 1+2 region (81.25° W–78.5° W, 8° S–0.75° N) (Fig. 2).

The ~~selection of this coastal subdomain is physically motivated by the energy balance framework proposed by ?. This area typically lies beneath the descending~~ coastal subdomain NWSA (Fig. 2b) is typically located under the regional branch of the Walker circulation, characterized by ~~strong subsidence and thermal inversion~~ persistent subsidence and trade-wind-driven coastal upwelling that suppresses convection. ~~Consequently, it serves as an ideal natural laboratory to verify the hypothesis that precipitation anomalies are driven by the dynamic interruption of this subsidence (adiabatic cooling via vertical motion ,~~ This stability is reinforced by the mid-level easterly flows, which, upon crossing the Andes, descend, forcing a dry leeward subsidence on the coastal strip (Quispe, 2018; Rollenbeck et al., 2022), but this subsidence weakness during the short austral summer. However during El Niño events, this subsidence regime collapses: the South Pacific Anticyclone migrates southward, upwelling weakens, and warm sea surface temperatures (SST) invert the low-to-mid-level flows into anomalous westerlies below 5 km (Douglas et al., 2009), generated by the sea breeze colliding against the western Andean slope (Takahashi, 2004; Rollenbeck et . This westerly moisture advection around 600 hPa becomes essential to organize convective systems and couple them with the second band of the ITCZ (Aliaga-Nestares et al., 2023; Rivas Quispe et al., 2024), while low-level sea breezes force windward orographic ascent that helps air parcels reach their level of free convection (Horel and Cornejo-Garrido, 1986; Goldberg et al., 1987; Bendix . Physically, this dynamically limited region operates as a thermodynamic switch governed by Strict Quasi-Equilibrium (SQE) dynamics: during dry months, the SQE is decoupled and net vertical motion (ω) ~~rather than by local surface evaporation, as the region acts as a boundary zone between stable and unstable regimes~~fluctuates without producing rain; but once the SST exceeds the critical ∼26°C threshold (Woodman, 1999; Takahashi and Dewitte, 2016; Jauregui and Takahashi, 2018), the inversion breaks and the system enters a rigidly coupled SQE regime, where ω and the latent heat of precipitation feed each other in a contemporaneous, bidirectional loop (Cornejo-Garrido and Stone, 1977; Emanuel et al., 1994).

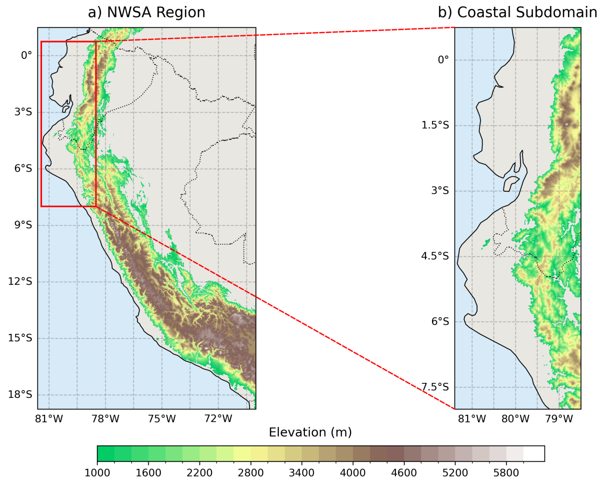

Figure 2. Study domains: the broader NWSA region (a) (81.6° W–67.05° W, 18.95° S–1.5° N) and the coastal subdomain (b) (81.25° W–78.5° W, 8° S–0.75° N).

Figure 3 presents the precipitation climatology (~~1981–2015~~1981–2025) from PISCO averaged over this coastal subdomain. It is observed that March constitute the rainiest month; this seasonal peak represents a critical coupling window ~~where~~ when dynamic relaxation (weakening of trade winds) and ~~thermodynamic~~ atmospheric instability (SST warming) come into phase, facilitating the development of deep convection (Takahashi, 2004; Poveda et al., 2006; Adachi et al., 2018; Peng et al., 2024).

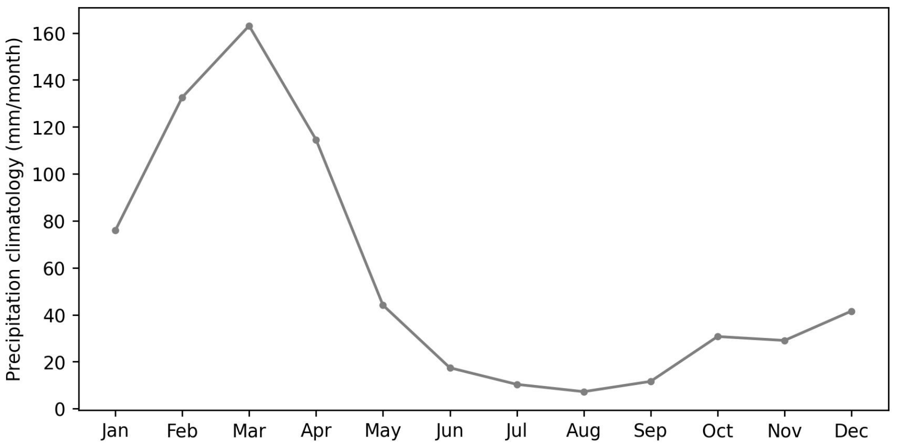

Figure 3. Precipitation climatology as the ~~1981–2015 median~~ 1981–2025 mean from ~~ERA5~~ PISCO averaged over the ~~NWSA next to 1+2 El Niño region~~coastal subdomain.

3 Methodology

3.1 Identification of ~~Rainiest and Driest Events~~ extreme hydroclimatic anomalies as Diagnostic Case Studies

To characterize the distinct vertical atmospheric configurations associated with extreme hydroclimatic anomalies, a set of representative case studies was identified. Monthly precipitation was averaged over the coastal NWSA ~~region adjacent to Niño 1+2~~ subdomain (Fig. 2b), and anomalies were calculated from the PISCO dataset relative to the 1981–2015 climatological ~~median. Two arbitrary thresholds~~mean. Two thresholds, corresponding to the 5th and 95th percentiles, were defined solely for event selection purposes: anomalies below ~~-60 mm month^{-1}~~ 5th percentile were used to detect significant dry events, and anomalies above ~~80 mm month^{-1}~~ 95th percentile were used to detect extreme rainy events. It is important to clarify that these thresholds were applied exclusively to select events for physical diagnosis (e.g., analyzing vertical structure) and were not utilized to calibrate or derive the formulation of the proposed index.

To determine the spatial core of these anomalies, the vertical motion field was analyzed through latitudinal and longitudinal cross-sections (see Figs. 10 and 9 in Section 4). The longitude of 80° W and latitude of 5° S were identified, approximately, as the axes of maximum vertical ascent over the coastal ~~domain~~subdomain. This geometric characterization allowed for the identification of subsidence and convective layers, as well as the specific pressure levels where convection was initiated and suppressed during the selected case studies.

3.2 Buoyancy Work Rate (BWR) formulation

The formulation of the BWR is physically grounded in the thermodynamic energy balance of the Walker circulation described by ~~?~~Cornejo-Garrido and Stone (1977), which posits that on climatic timescales, latent heat release ~~(Q)~~ is primarily balanced by adiabatic cooling due to vertical motion~~$(-\omega\partial\theta/\partial p)$~~. Consequently, an index capable of ~~estimating precipitation~~ explaining precipitation anomalies in this region must explicitly couple the ~~dynamic trigger~~ atmospheric instability with the dynamic forcing (vertical velocity) ~~with the thermodynamic fuel (buoyancy)~~required to overcome the persistent background subsidence.

First, the dew point temperature (T_d) was calculated from relative humidity following Bolton (1980). Using surface T_d and air temperature (T_a), the parcel temperature path was computed and compared against the environmental temperature profile to yield the parcel buoyancy (ΔT) for every grid point. To construct the index, the product of vertical velocity (ω) and parcel buoyancy (ΔT) was analyzed.

The Buoyancy Work Rate (BWR) is defined as the vertical integration of this product from the surface to 100 hPa with respect to the natural logarithm of pressure ($d\ln P$), as shown in Eq. (1).

$$BWR = -\int_{sfc}^{100} \omega \Delta T \, d\ln P \tag{1}$$

In this integration, only layers exhibiting positive buoyancy ($\Delta T > 0$) and upward motion ($\omega < 0$) were included. This constraint ensures that the index specifically quantifies the rate at which potential energy is converted into kinetic energy during deep convection, filtering out stratiform or forced ascent in stable environments.

~~It is acknowledged that the BWR serves as a diagnostic proxy proportional to the rate of work performed by buoyancy , rather than a strict physical quantity of energy flux density (W m^{-2}), due to~~ To understand this diagnostic formulation, it is instructive to mathematically and conceptually contrast the BWR with CAPE. CAPE is defined as the ~~combination of kinematic and thermodynamic units. However~~vertical integral of parcel buoyancy from the level of free convection to the equilibrium level (Emanuel, 1994). It strictly evaluates the precursor thermodynamic potential energy available for convection, remaining mathematically blind to whether a dynamic trigger actually exists to overcome background subsidence (Fu et al., 1999; DeMott and Randall . In contrast, the BWR is formulated by integrating the product of thermodynamic instability (ΔT) and vertical velocity (ω) across the atmospheric column. Rather than measuring stored static potential, this hybrid formulation ~~is proposed to capture the non-linear interaction between large-scale dynamics and local instability , which neither variable alone can fully represent~~explicitly quantifies the realized rate of kinetic energy conversion. By mathematically coupling buoyancy with mesoscale kinematic ascent, the BWR imposes a strict physical constraint: it systematically penalizes and zeroes out environments that possess massive thermodynamic instability (high CAPE) but remain mechanically suppressed by persistent subsidence ($\omega > 0$).

3.3 Validation framework

To evaluate the physical robustness and predictive utility of the BWR, a multi-tiered validation framework was implemented, moving from causal verification to statistical comparative evaluation.

3.3.1 Causal discovery and physical drivers

To ~~verify the physical hypothesis that large-scale dynamics (ω) exert a stronger control on precipitation than local surface fluxes, the~~ causally evaluate the proposed Buoyancy Work Rate (BWR) index and its diagnostic validity for precipitation anomalies in the coastal NWSA, a causal discovery analysis was conducted using monthly time series for the 1981–2025 period. The PCMCI+ ~~causal discovery~~ algorithm (Runge, 2020) was applied to navigate this framework. Unlike its predecessor, PCMCI+ is specifically designed to discover both time-lagged and contemporaneous (lag-0) causal relationships in highly autocorrelated time series. This capability is fundamentally required for this study, as the macro-scale dynamic and thermodynamic interactions governing precipitation at monthly timescales occur predominantly at lag-0. ~~This method,~~

The methodology operates through two core phases. First, a lagged condition-selection step (based on the PC algorithm~~and~~) is executed to iteratively estimate the lagged parents of each variable. This step filters out spurious autocorrelations and drastically reduces the dimensionality of the conditioning sets. Second, the algorithm applies the Momentary Conditional Independence (MCI) ~~tests, allows for the identification of causal directions and time-lagged links from observational data, filtering out spurious correlations~~test to evaluate the remaining lagged and contemporaneous links. Crucially, the MCI test evaluates the conditional independence between two variables by simultaneously conditioning on the estimated past of both variables. By explicitly optimizing these conditioning sets, the MCI test isolates the true causal signal from the inherent background noise induced by strong autocorrelation, yielding a highly calibrated estimate of the partial correlation (causal strength).

The causal analysis was performed using time series of monthly standardized anomalies~~averaged over land pixels within the NWSA adjacent to Niño 1+2 (81.25° W–78.5° W, 8° S–0.75° N). The variables included in the network were~~ , and the statistical robustness of the inferred causal links was evaluated using a bagging bootstrapping procedure with 3,000 samples. To accurately represent the land-atmosphere interaction, precipitation was averaged strictly over the land pixels of the coastal NWSA subdomain. In contrast, local evaporation, ~~precipitation, and~~ vertical velocity at 500 hPa (ω_{500}), and parcel buoyancy ($\Delta T_{700-400}$) as atmospheric instability proxy were averaged over the entire coastal NWSA bounding box (incorporating $\sim$21% oceanic area) to capture the regional atmospheric boundaries. SST averaged over the Niño 1+2 region was set as an exogenous boundary condition. To facilitate the physical interpretation of the causal links, the signs of vertical velocity and evaporation were inverted ($-\omega_{500}$ and $-E$, respectively) prior to input, ensuring that positive values strictly indicate upward mass and upward moisture fluxes. The 500 hPa level was specifically selected because it typically corresponds to the level of maximum vertical mass flux in the tropical troposphere~~; according to the energy balance framework of ?~~, ω at this mid-tropospheric level serves as the most robust proxy for the column-integrated adiabatic cooling required to balance convective latent heat release. ~~Additionally, parcel buoyancy averaged between 700 and 400 hPa ($\Delta T_{700-400}$)and the BWR index were included, with Sea Surface Temperature (SST) averaged over the Niño 1+2 region set as a boundary condition. Contemporaneous links (lag-0) were explicitly permitted in the~~

In our reference causal network (7a), we utilize the PCMCI+ ~~setup; this configuration was necessary to capture rapid atmospheric interactions, such as the thermodynamic triggering of convection, that occur on timescales faster than the monthly~~

~~sampling resolution of the dataset.~~ algorithm restricted to contemporaneous relationships (Runge, 2020). The relationship between atmospheric dynamics and precipitation is dominated by a simultaneous circularity known as the convergence feedback (Back and Bretherton, 2005). Because a purely contemporaneous algorithmic configuration cannot resolve the temporal sequence to isolate the portion of the variance where large-scale dynamics perturbed the environment prior to the onset of deep convection (Fu et al., 1999), we explicitly break this statistical circularity by imposing directional physical link assumptions. By doing so, we enforce a strict physical hierarchy that imposes the mesoscale dynamics as the boundary condition that authorizes or restricts convection, isolating this mesoscale environmental forcing from local and sub-grid scale convective processes (Lau et al., 1997; Bony et al., 1997). This theoretically grounded causal network serves exclusively as a physical baseline to evaluate whether our proposed BWR index successfully preserves the mesoscale thermodynamic and dynamic signals governing precipitation.

3.3.2 ~~Analysis of extremes and predictability~~

~~Standard correlation metrics often underestimate performance during extreme events. Therefore, the Upper Tail Dependence Coefficient (λ_U) was calculated using empirical copulas (Nelsen, 2006). Following the methodology of Poulin et al. (2007), λ_U was calculated across varying quantile thresholds to assess asymptotic dependence without imposing parametric assumptions. This approach allows for the evaluation of the robustness of the BWR during extreme precipitationevents (~~The second causal network was evaluated by introducing the BWR index. It must be clarified that the BWR evaluated in this network is not the simplified product of $-\omega_{500}$ and $\Delta T_{700-400}$, but rather the strict vertical integration defined in Eq. 1. In addition, the mid-level vertical velocity ($-\omega_{500}$) and the atmospheric instability ($\Delta T_{700-400}$) were explicitly removed from the algorithm to prevent deterministic collinearity. It is important to note that our objective with this network is not to discover the drivers of precipitation, as these have been extensively documented by previous works [e.g., ~~strong El Niño years). Furthermore, to evaluate the signal memory and potential predictability horizon of the index compared to its individual components, autocorrelation functions were computed. For both the tail dependence and autocorrelation analyses, the time series utilized were the monthly standardized anomalies of the BWR, ω_{500}, and $\Delta T_{700-400}$, averaged spatially over the land pixels of the NWSA adjacent to Niño 1+2.~~ Lau et al. (1997); Woodman (1999); Takahashi (2004)], but rather to assess whether the BWR index acts as a causal driver of precipitation. Because the algorithm was restricted to contemporaneous relationships, we imposed two directional physical link assumptions (from SST to -E, and from SST to BWR). These constraints dictate that while a statistical relationship might not necessarily exist between these variables, if one is detected, it must follow this physically grounded direction. This approach breaks the simultaneous statistical circularity of the system.

3.3.2 Statistical comparative evaluation with established indices

The diagnostic skill of the BWR was compared with established indices previously tested in the region: the Convective Available Potential Energy (CAPE) ~~(?)~~ (Emanuel, 1994) and the Gálvez-Davison Index (GDI) ~~(?)~~(Gálvez and Davison, 2016), both evaluated for the NWSA by ~~?; and~~ Rivas Quispe et al. (2024); as well as the asymmetric (I_a) and double ITCZ (I_d) indices proposed by ~~?~~Yu and Zhang (2018), assessed by ~~?.~~

~~Performance~~ Aliaga-Nestares et al. (2023). However, this comparison must be interpreted under a strict physical distinction. While indices such as CAPE and the GDI solely quantify the thermodynamic potential for convection based on precursor conditions, the BWR is designed to explicitly measure the realized mesoscale atmospheric response. This fundamental asymmetry arises because the BWR incorporates mesoscale vertical velocity (ω), thereby directly capturing the ascending motion physically coupled with precipitation. Bearing this distinction in mind, their diagnostic performance was evaluated using the spatial distribution of the Pearson correlation coefficient (R) ~~and Root Mean Square Error (RMSE)~~ between the indices and three precipitation products (ERA5, PISCO, RAIN4PE) for the 1981–2015 period.

Given that the evaluated indices and precipitation products possess disparate physical ~~units and scales(e.g., J kg^{-1} for CAPE versus mm month^{-1} for precipitation)~~dimensions and scales, all time series were converted to standardized anomalies ~~prior to the calculation of RMSE and scatterplot generation~~ strictly for the generation of scatterplots and temporal series to ensure comparable ~~magnitudes~~variance visualization. Finally, to evaluate performance specifically over the coastal ~~region adjacent to Niño 1+2~~subdomain, indices and precipitation were averaged over land pixels within the ~~domain defined by 81.25° W–78.5° W and 8° S–0.75° N~~subdomain defined (Fig. 2b). Scatterplots and time series were analyzed to identify regimes where the BWR offers advantages or limitations compared to purely thermodynamic or precipitation-based indices.

3.3.3 Analysis of extremes, signal persistence, and predictive capability

Standard correlation metrics often underestimate performance during extreme events. Therefore, the Upper Tail Dependence Coefficient (λ_U) was calculated using empirical copulas (Nelsen, 2006). Following the methodology of Poulin et al. (2007), λ_U was calculated across varying quantile thresholds to assess asymptotic dependence without imposing parametric assumptions. This approach allows for the evaluation of the robustness of the BWR during extreme hydroclimatic anomalies (e.g., strong coastal El Niño years).

Furthermore, to evaluate the diagnostic memory and signal persistence of the index compared to its individual components, autocorrelation functions were computed. To maintain strict spatial consistency across the validation framework, the monthly standardized anomalies of the atmospheric predictors (BWR, ω_{500}, and $\Delta T_{700-400}$) were averaged over the entire coastal subdomain, whereas precipitation anomalies were strictly averaged over the land pixels.

Finally, while the application of the BWR to historical reanalysis data serves strictly as an explanatory diagnostic proxy, its true prognostic utility was evaluated to establish its predictive capability. The BWR was computed using predicted meteorological fields from the ECMWF SEAS5 model for its operational period (2017–2025). The predictive skill of these predicted BWR anomalies, quantified via Pearson correlation against PISCO anomalies, was then compared directly against the skill of the SEAS5 model's native precipitation predictions. This framework tests whether predicting the mesoscale atmospheric response (BWR) systematically outperforms the model's internal precipitation parameterization schemes for early warning applications.

4 Results

4.1 BWR Performance and diagnostic skill

To quantify the skill of the BWR relative to established indices, the spatial distribution of the Pearson correlation coefficient (R) was analyzed (Fig. 4). ~~The BWR and CAPEexhibited the strongest correlations specifically~~ A clear spatial divergence emerges: while CAPE, GDI, and the BWR all exhibit positive correlations over the NWSA~~region adjacent to Niño 1+2. However, the performance of CAPE was spatially inconsistent, showing~~ , the BWR and CAPE display stronger correlations than the GDI in the coastal subdomain (Fig. 2b). However, their performance diverges significantly over the Amazon basin and eastern Andes. In these continental regions, the GDI maintains slightly higher positive correlations than the BWR, whereas CAPE collapses, exhibiting non-significant or ~~even negative correlationsover the Amazon. This suggests that while thermodynamic potential is necessary, it is not a sufficient condition for precipitation in continental regimes where dynamic forcing varies independently. The GDIshowed significant correlations across the entire domain but with lower magnitudes ($R \leq 0.7$)compared to the BWR in the coastal zone. The indices I_a and I_d (Figs. A1 4) demonstrated the poorest performance, likely due to their reliance on precipitation gradients rather than direct convective physics~~significantly negative correlations.

This divergence reflects the fundamental physical differences in how each index interacts with varying convective regimes. Along the dynamically limited coastal region, deep convection is a rare, binary process governed by large-scale subsidence. When this dynamic suppression relaxes and coincides with local surface warming, the boundary layer rapidly destabilizes (Takahashi, 2004). Because coastal precipitation is strictly governed by this synchronized activation of surface instability and dynamic lifting, the BWR and CAPE capture the convective variance more accurately than the GDI, whose heavy reliance on mid-tropospheric moisture makes it slightly less sensitive to the boundary-layer triggers of this specific regime.

Conversely, the Amazon basin and eastern Andes constitute a thermodynamically abundant regime governed by Mesoscale Convective Systems (MCS), orographic lifting, and intense local moisture recycling (Poveda et al., 2006). Here, CAPE systematically fails because it evaluates raw potential energy. As demonstrated by Fu et al. (1999), maximum instability occurs during the spring transition, when intense surface heating generates high CAPE, but convection is suppressed by Convective Inhibition (CIN). During the peak wet season, extensive cloud shading and convective consumption actively destroy this instability despite high precipitation volumes (DeMott and Randall, 2004). This out-of-phase relationship generates the negative correlations for CAPE at the monthly timescale. In contrast, the GDI and BWR remain positively correlated because they do not rely solely on raw buoyancy. The GDI incorporates mid-tropospheric moisture, which remains persistently high during the rainy season, giving it a slight diagnostic advantage over the continent. While the BWR is rescued from the thermodynamic phase-shift by its vertical velocity (ω) component, its correlation is slightly weaker than the GDI over the eastern Andes. This physically occurs because the macro-scale ω cannot fully resolve the fine-scale orographic lifting or the localized MCS dynamics that dominate Andean precipitation, whereas the GDI's moisture fields provide a more continuous spatial proxy in complex terrain.

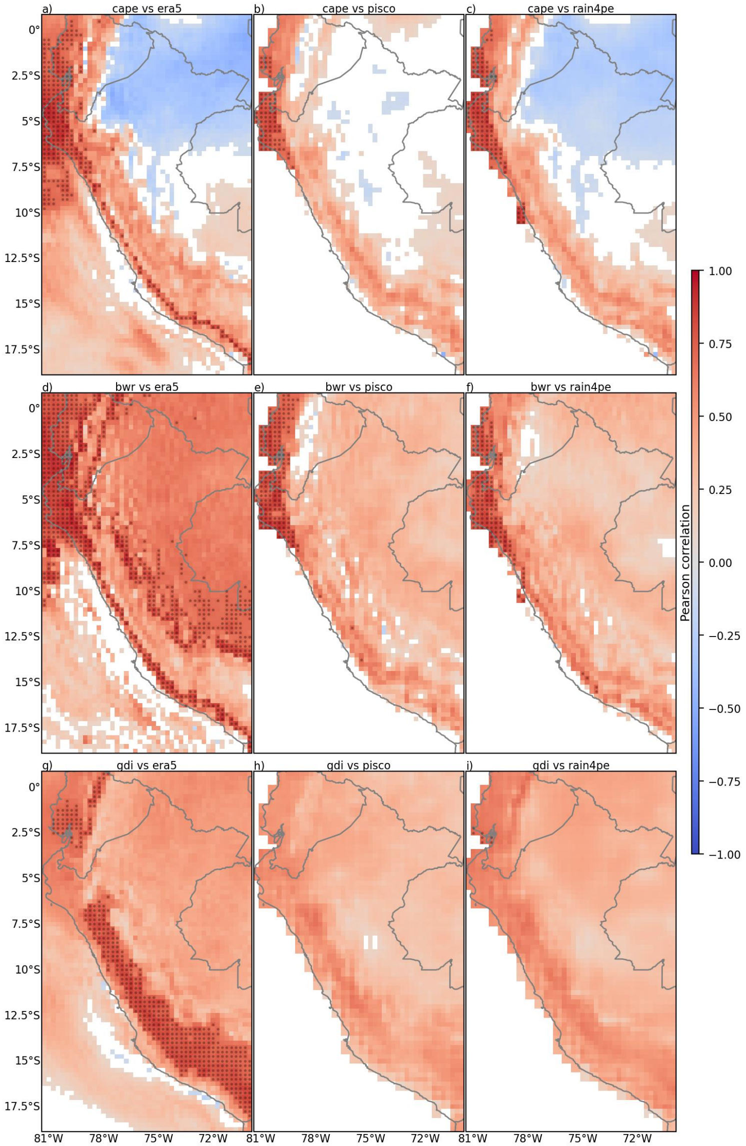

Figure 4. Pearson correlation (R) maps at the 95% confidence level between monthly anomalies of convective indices (rows) and precipitation datasets (columns) for the 1981–2015 common period. The indices (rows) are (a-c) CAPE, (d-f) BWR, (g-i) GDI, (h-l) Ia, and (m-o) Id. The precipitation datasets (columns) are (a, d, g) ERA5, (b, e, h) PISCO, and (c, f, i) RAIN4PE. Shading is shown only for significant correlations (p-value < 0.05). Red (blue) indicates positive (negative) R values. Gray points highlight strong correlations ($R > 0.7$). Anomalies were calculated taking the 1981–2015 median as climatology.

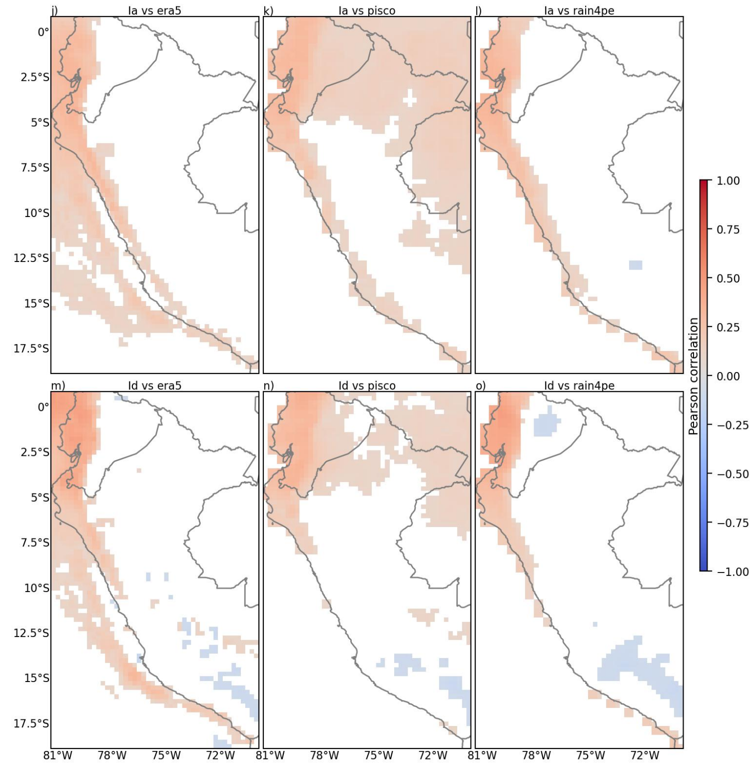

Figure 4. (Continued).

~~The Root Mean Square Error (RMSE) maps (Fig. ??) further corroborate these findings, with the BWR minimizing error along the coast, although higher errors persist in the eastern Andes, a common challenge for reanalysis-based indices over complex topography.~~

Focusing on the critical coastal ~~domain (NWSA adjacent to Niño 1+2~~subdomain (Fig. 2b), the standardized scatterplots (Fig. 5) reveal that the BWR achieves the highest linear association and lowest dispersion among all evaluated indices. Unlike I_a and I_d, which show little relation to the intensity of anomalies, the BWR scales proportionally with precipitation magnitude~~without requiring bias correction.~~ . While the BWR calculation requires surface dewpoint temperature (~~Td~~T_d), which is ~~strongly coupled to SST boundary conditions~~ tightly constrained by local oceanic boundary conditions (e.g., Niño 1+2 SST), the GDI fundamentally requires mid-tropospheric humidity ~~, which~~ (Gálvez and Davison, 2016). This distinction is critical because free-tropospheric moisture is highly sensitive to sub-grid convective parameterization schemes and remote advection, leading to substantial inter-model spread ~~in the tropics and biases at climatic timescales (John and Soden, 2007; Han et al., 2022)~~and systematic biases in climate models (John and Soden, 2007; Han et al., 2022). Unlike surface ~~variables, which are well-constrained by oceanic boundary conditions, humidity in the free troposphere exhibits relative biases often exceeding 50-100~~and boundary-layer variables, whose variance is physically anchored by local SSTs via the Clausius-Clapeyron relationship (John and Soden, 2007), mid-level humidity in climate models inherits significant uncertainty. Consequently, metrics dependent on free-tropospheric moisture could inherit more uncertainty for climate monitoring compared to surface-constrained proxies.

The temporal evolution of the indices (Fig. 6) highlights specific strengths. The BWR outperformed other indices in capturing the magnitude of the extreme 1983 and 1998 El Niño events. For the 1998 event, the index aligned closely with precipitation observations, helping to resolve discrepancies between PISCO and RAIN4PE products. In the recent 2023 Coastal El Niño, all indices and ERA5 precipitation peaked in March-April; however, the PISCO product exhibited a sudden and physically unexplained decline in April. To validate the positive anomalies diagnosed by the BWR and ERA5 during this period, independent official climatological reports were consulted. Specifically, the National Meteorological and Hydrological Service of Peru (SENAMHI, 2023) and the Ministry of Agriculture and Livestock of Ecuador (MAG, 2023) documented significant positive rainfall anomalies along the northern Peruvian and southern Ecuadorian coasts during April 2023. Furthermore, during the 2024 dry event, PISCO showed a contradictory positive anomaly peak in April, whereas BWR, CAPE, and ERA5 precipitation consistently indicated negative anomalies ~~. These discrepancies suggest potential inconsistencies in the automatic quality control of the PISCO dataset for the post-2017 period, reinforcing the value of the BWR~~ according with observational monthly reports (SENAMHI, 2024; ERFEN, 2024). This independent observational consensus supports the physical consistency of the BWR, highlighting its value as a robust ~~independent diagnostic toolwhen observational networks are uncertain.~~ diagnostic tool.

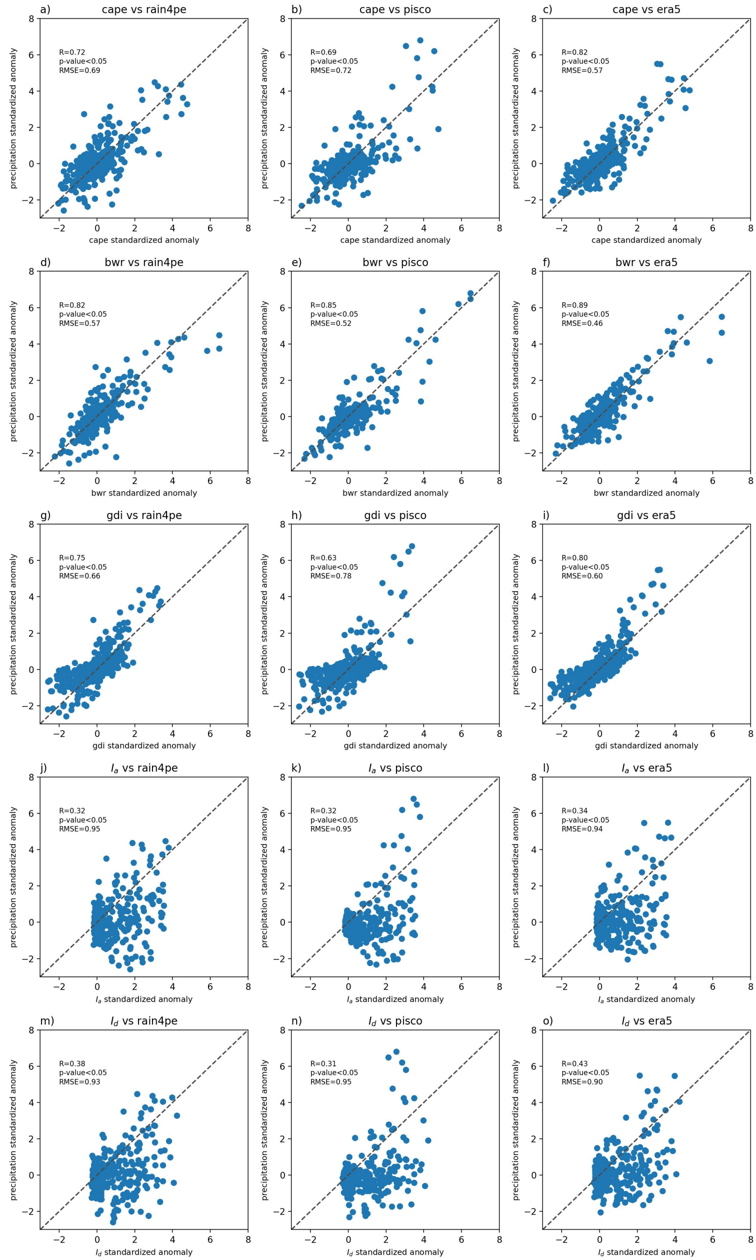

Figure 5. Scatterplots between convective indices and precipitation datasets over the NWSA adjacent to Niño 1+2. Scatterplots comparing monthly standardized anomalies of CAPE (a-c), BWR (d-f), GDI (g-i), (h-l) Ia, and (m-o) Id against standardized precipitation anomalies from ERA5 (left column), PISCO (middle column), and RAIN4PE (right column). All data are spatially averaged over the NWSA adjacent to Niño 1+2. The Pearson correlation coefficient (R) ~~, RMSE~~ and the significance at the 95% confidence level (p-value < 0.05) are shown in each panel. The diagonal dashed line is the identity function.

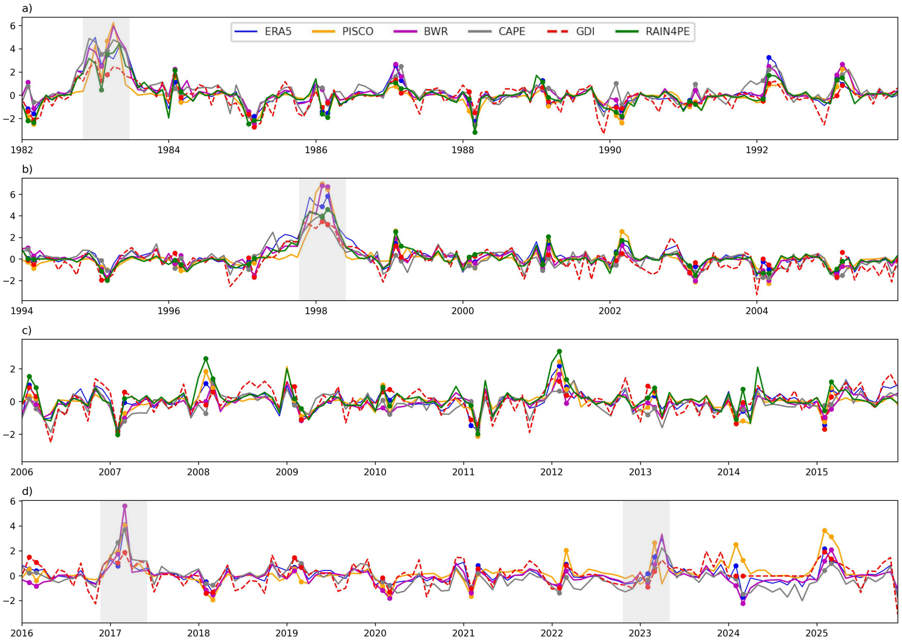

Figure 6. Time series of monthly standardized anomalies of convective indices, such as CAPE (gray), BWR (magenta), and GDI (dashed red), and standardized precipitation from ERA5 (blue), PISCO (orange), and RAIN4PE (green). All data are spatially averaged over the ~~NWSA adjacent to Niño 1+2~~ coastal subdomain (Fig. 2b) for the period 1981–2025. The RAIN4PE dataset is only available for 1981–2015. Anomalies were calculated taking the 1981–2015 median as climatology. Circle markers indicate February and March of every year.

4.2 Causal discovery of precipitation in the NWSA

~~To determine the primary physical drivers governing precipitation anomalies in~~ Figure 7a presents the reference causal network, constrained by the physical link assumptions described in Section 3.3.1. Although the causal directionality was a priori imposed to break the simultaneous circularity, the algorithm quantified the strength of these conditional dependencies. Such as, the ~~NWSA adjacent to~~ SST over Niño 1+2 ~~on monthly timescales, a causal discovery analysis was conducted using the PCMCI+ algorithm . This approach allows for going beyond statistical correlation to identify directional dependencies and quantify the relative strength of thermodynamic versus dynamic forcing.~~

~~Initially, an agnostic approach was adopted, implementing the algorithm without imposing strict structural assumptions regarding the relationships between vertical velocity at 500 hPa (ω_{500}) , local evaporation, and precipitation (Fig. 7a). The results reveal a clear hierarchy in the drivers of precipitation. The causal link from ω_{500} to precipitation is the dominant feature of the network~~ and the mesoscale vertical velocity ($-\omega_{500}$) exert a strong control over atmospheric instability ($\Delta T_{700-400}$) [MCI: ~~-0.59~~0.73] ~~, exhibiting a causal strength nearly three times greater than that of local evaporation~~ and precipitation [MCI: ~~-0.22~~0.61]~~.~~

~~Causal graphs without BWR (a) and with BWR (b). Red (blue) colors indicate direct (inverse) relationship. Arrows indicate the causal directions. Labels in middle of arrows indicate MCI values and confidence of the 3000 bootstrap samples. All variables were averaged over (81.25° W–78.5° W, 8° S–0.75° N), except SST, which was averaged over Niño 1+2 region.~~

~~Regarding the surface flux, the negative causal link between evaporation and precipitation must be interpreted in the context of the sign convention, where negative values indicate upward moisture flux. Thus, this relationship implies that positive precipitation anomalies are associated with increasingly negative surface latent heat flux anomalies (i.e., enhanced local evaporation). This behavior is consistent with the seasonal cycle of the NWSA region: unlike the open tropical ocean where deep convection is quasi-permanent and cloud shading can suppress evaporation (negative feedback), the NWSA is largely controlled by large-scale subsidence, with precipitation restricted to the austral summer. Consequently, on an annual basis, periods of higher precipitation coincide with periods of higher surface moisture supply. However, the significantly lower magnitude of the evaporation link compared to~~ ~~ω_{500}~~ ~~confirms that while local surface fluxes provide necessary moisture, they are not the sufficient or primary trigger for convection. Deep convection in this region is fundamentally controlled by the relaxation of large-scale subsidence (dynamic forcing), validating the focus on vertical velocity for the proposed index~~, respectively.

Building upon this ~~established dynamic control, a second causal analysis was performed to evaluate the structural coherence of the proposed Buoyancy Work Rate (BWR) index~~ reference, the second causal network (Fig. 7b) ~~. In this setup, physical link assumptions were introduced to test the dependence of BWR on its constituent components~~illustrates the system after the introduction of the BWR index. The resulting causal ~~architecture confirms that parcel buoyancy (~~~~ΔT~~~~) is causally driven by SST variations MCI: +0.75, reflecting the thermodynamic preconditioning of the boundary layer by the ocean.~~

~~Additionally, the causal influence of SST on local evaporation observed in the network is physically attributable to thermodynamic adjustments. The warming of the ocean surface heats the overlying air, which is subsequently transported via horizontal advection toward the coastal continent. This increase in air temperature induces a decrease in relative humidity, thereby generating a moisture deficit that enhances the upward evaporation flux from the surface to the atmosphere in an attempt to restore thermodynamic equilibrium. Furthermore,~~ ~~ω_{500}~~ ~~and~~ ~~ΔT~~ ~~are identified as independent parents converging on the BWR node. Notably, even when the BWR is introduced into the network, the dynamic signal remains robust,~~ network confirms the preservation of the mesoscale thermodynamic and dynamic signals governing precipitation. Most importantly, the BWR index ~~exhibits a causal association with~~ maintains a direct, robust causal link to precipitation [MCI: ~~0.28that is stronger than the local evaporation signal MCI: -0.23in the multi-variable graph. This validates the BWR formulation as a physical integrator that effectively couples the dominant dynamic trigger with the thermodynamic fuel.~~ 0.60, with a confidence of 95.9

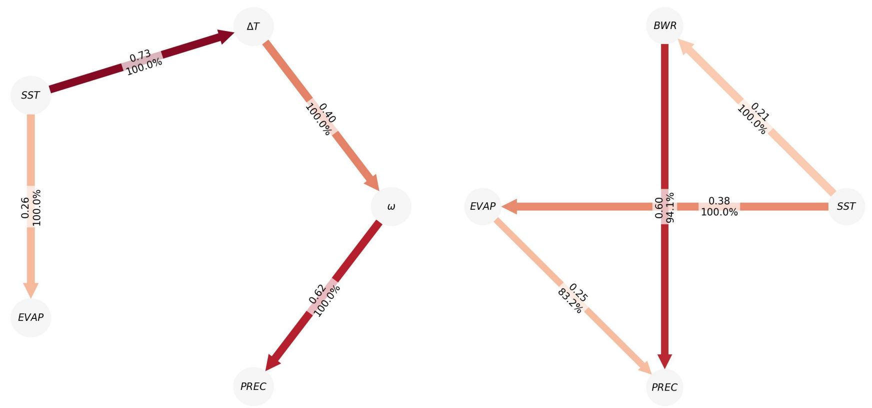

Figure 7. Causal networks without BWR (a) and with BWR (b). Red (blue) colors indicate direct (inverse) relationship. Darker (lighter) colors represent stronger (weaker) causal links. Arrows indicate the causal directions. Labels in middle of arrows indicate MCI (causal strength) values and their confidence of the 3000 bootstrap samples. All variables were averaged over the coastal subdomain (Fig. 2b), except precipitation, which was averaged only continentally, and SST, which was averaged over Niño 1+2 region. ω_{500} and E values were inverted

4.3 Physical mechanisms during ~~rainiest and driest events~~extreme hydroclimatic anomalies

To characterize the atmospheric conditions associated with extreme hydroclimatic anomalies, ~~the March precipitation anomaly was analyzed~~ March precipitation anomalies were analyzed over the coastal subdomain (Fig. 8)~~over the NWSA adjacent to Niño 1+2 region~~. Based on the thresholds defined in ~~Sect.~~ Section 3.1, the ~~years~~ rainiest (1983, 1993, 1998, 2002, 2017, 2022, 2023, and 2025~~were identified as the rainiest events, whereas~~) and driest (1982, 1985, 1988, 2003, 2011, and 2018~~were classified as the driest. These extremes are generally associated with~~) events were identified. As established in previous studies, these extreme precipitation responses are fundamentally governed by coastal El Niño and La Niña ~~phases, as evidenced by the~~ events, evidenced by SST anomalies in the Niño 1+2 region (Takahashi, 2004; Takahashi et al., 2018; Peng et al., 2024) (Fig. A2). ~~Specifically, positive SST anomalies characterize the rainiest years, while negative anomalies typically prevail during the driest ones. A notable exception is March 2022, which exhibited cool conditions up to 4° S front the coast, despite being a rainy event~~Within this set, the 1998 and 2017 events are of particular interest as they encompass distinct oceanic dynamics driving similar precipitation extremes: while 1998 represents a canonical basin-wide extreme El Niño (Takahashi, 2004), 2017 manifested as a highly localized extreme coastal El Niño, characterized by intense warming strictly confined to the far-eastern Pacific despite weak La Niña conditions in the central basin (Takahashi et al., 2018; Peng et al., 2024). Additionally, the 2016 event was included ~~in the analysis due to the~~ as a contrasting case study because, despite prevailing strong global El Niño conditions, ~~despite its lack of extreme coastal precipitation, to serve as a contrasting case study~~it lacked an extreme hydroclimatic response along the coast compared to the 1983 or 1998 events (Paek et al., 2017; Sanabria et al., 2019). This deviation underscores the notable influence that internal atmospheric variability can exert in altering regional teleconnections during distinct El Niño flavors (Huang et al., 2026).

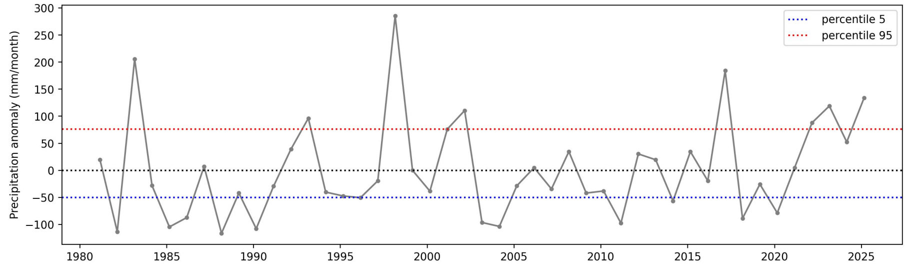

Figure 8. Monthly precipitation anomaly time series in March from PISCO, taking the ~~1981–2015 median~~ 1981–2025 mean as climatology, averaged over the ~~NWSA next to 1+2 El Niño region~~coastal subdomain. ~~Points~~ Precipitation above ~~(~~the 95th percentile and below ~~) horizontal red (blue) dotted line~~ the 5th percentile are considered as ~~rainiest (driest)~~ extreme hydroclimatic events.

4.3.1 ~~Precipitation spatial distribution~~ Cross-section analysis in the ~~NWSA~~coastal subdomain

~~The spatial footprint of the anomalies reveals distinct regimes (Fig. ??) in the NWSA adjacent to Niño 1+2. In the rainiest events, positive anomalies extended across nearly the entire domain, stimulating deep convection~~ During the 1998 and 2017 events, anomalous onshore westerly winds—driven by enhanced sea-breeze circulations—prevailed in the lower troposphere (Fig. ~~??b,e,f,g,k,m,n,o) .~~

~~However, the 2016 event (Fig. ??j) exhibited a decoupling between global conditions and local impacts, dominated by anomalies ranging from slightly positive to negative. That event had a stronger signal in the Central Pacific (CP) than in the Eastern Pacific (EP), where maximum warming was confined to the Niño 3.4 region rather than the far eastern Pacific (?). Physically, this configuration shifts the ascending branch of the Walker Circulation westward, forcing a compensatory subsidence limb over the NWSA which inhibits rainfall (Sulca et al., 2017; Paek et al., 2017).~~

~~Precipitation anomaly distribution, taking the 1981–2015 median as climatology, from PISCO for the rainiest and driest events identified in Sect. 4. The blue (red) shaded colors indicate negative (positive) values of precipitation.~~

~~This mechanism was particularly evident in 2016. Sulca et al. (2017) noted that the "atmospheric bridge", which typically teleconnects equatorial warming to the South American coast, was not established. The Intertropical Convergence Zone (ITCZ) showed limited southward displacement, and the ascending motion remained anchored to the Central Pacific. Consequently, the descending branch of the Walker Circulation did not shift sufficiently eastward to be replaced by ascent over the coast, leaving the region under stable, dry air (Paek et al., 2017). This "out-of-phase" response resulted in moisture deficits, contrasting with the surplus observed during Eastern Pacific events like 1983 or 1998 (Sanabria et al., 2019).~~

~~In contrast, the 2017 event was driven by a localized relaxation of the trade winds and sudden coastal warming (approx. 29~~10f,k) (Takahashi, 2004; Rollenbeck et al., 2022). The collision of this flow against the western Andean slope near 80° ~~C), triggered not by remote Kelvin waves but by atmospheric teleconnections (Rossby wave trains) originating from deep convection in the western Pacific (Echevin et al., 2018; ?; ?). This highlights the sensitivity of the region to distinct atmospheric forcing mechanisms.~~ W generated strong surface convergence. Consistent with the convergence feedback (Back and Bretherton, 2005)

, this near-surface forcing sustained a deep vertical ascent core extending from the surface up to 300 hPa. Finally, this convective column was ventilated in the upper troposphere ($\sim$ 200 hPa) by easterly winds that induced strong divergence, completing the vertical circulation.

~~Regarding the driest events, negative anomalies dominated the domain~~ Concurrently with the onshore westerlies, the alongshore circulation exhibited a collapse of the climatological southerly winds (Takahashi, 2004). This relaxation permitted the intrusion of anomalous low-level northerly winds (Fig. ~~??a,c,d,h,i,l). These events were associated with coastal La Niña conditions (Fig. A2a,c,d,h,i,l), characterized by enhanced coastal upwelling and cooler-than-average Sea Surface Temperatures (SST) that stabilize the marine boundary layer and suppress convective activity. Specifically, the years 1996, 2007, and 2011 correspond to well-documented periods of significant meteorological drought in the region. ? identified severe rainfall deficits in the northern Peruvian coast during these years, mechanically linked to the strengthening of the South Pacific Anticyclone and the resulting intensification of the southeasterly trade winds. Furthermore, ? highlighted that the 2010-2011 La Niña event caused widespread hydrological deficits across the Andean and coastal catchments, severely impacting water availability for agriculture. These dry anomalies are consistent with the suppression of the seasonal southward migration of the ITCZ, which remains north of the equator during La Niña phases, depriving the NWSA of its primary source of deep convection during the austral summer (Sulca et al., 2017).~~

4.3.2 ~~Cross-section analysis in the NWSA adjacent to Niño 1+2~~

~~The vertical structure of the atmosphere reveals a distinct dynamic signature for the rainiest events. Consistent air ascent was observed around 80° W and 5° S in the middle to upper troposphere (Figs. 10 and 9), with the most intense vertical motion occurring during the 1998 El Niño and the 2017 Coastal El Niño. Notably, subsidence was observed in the planetary boundary layer (PBL) for all these rainiest cases. This suggests that the air parcels had to overcome a low-level inhibition barrier to reach the level of free convection, highlighting the necessity of strong dynamic forcing to breach this cap. Conversely, the driest events were characterized by weak ascent near the PBL but dominant subsidence in the middle to upper troposphere around 80~~10f,k), consistent with the coastal dynamics described by Echevin et al. (2018) and Peng et al. (2019). Rather than a passive feature, these northerly flows acted as the primary driver for the coastal Bjerknes feedback (Peng et al., 2019) and the subsequent activation of the ITCZ southern branch (Takahashi and Martínez, 2017). Kinematically, this activation was captured as a robust convergence zone strictly confined between 6° ~~W and 5~~S and 3° S, ~~effectively capping any shallow convection.~~ which matches the established latitudinal limits of the active southern ITCZ band (Huaman and Takahashi, 2016). Finally, to balance this massive low-level mass convergence, the upper troposphere (200–100 hPa) responded with strong meridional divergence, effectively evacuating the ascending air northward and southward away from the convective core.

~~The~~ In contrast, the 2016 ~~event provides a critical counter-example. Although weak ascent was present near the PBL around 5° S~~ event showed a vertical descent core directly over the peak of the Andes (Fig. 9j). This subsidence was mechanically forced by upper-tropospheric convergence (~300 hPa) induced by anomalous westerly winds—a teleconnection strictly consistent with the Central Pacific El Niño pattern identified by Sulca et al. (2017)—coupled with mid-level convergence (700–500 hPa) driven by easterly winds. This severe mid-level subsidence capped the atmospheric instability, keeping the region under stable, dry air as the descending branch of the Walker circulation failed to shift sufficiently eastward (Paek et al., 2017). As consequence of this mid-level subsidence, the low-level convergence were neutralized, which can be identified as the absence of both northerly winds (Fig. 9j) and ~~80° W~~ westerly sea-breeze (Fig. 10j), ~~it was overlaid by significant subsidence in the middle troposphere. This mid-level suppression explains the neutralization of potential rainfall despite the favorable large-scale context. In sharp contrast, the 2017 event, which was dynamically uninhibited, produced extreme rainfall in the northern Peruvian departments of Piura, Tumbes, and Lambayeque, exceeding historical records in several locations (??).~~

~~Longitudinal cross-section of the resultant vector between the anomalies of ω and zonal wind at 5° S for the rainiest and driest events identified in Sect. 4. The blue (red) shaded colors indicate negative (positive) values of ω. The ω vector was multiplied by -20 to increase its scale and to get upward (downward) arrows with the air ascent (descent). Anomalies were calculated taking the 1981–2015 median as climatology.~~

~~Latitudinal cross-section of the resultant vector between the anomalies of ω and meridional wind at 80° W for the rainiest and driest events identified in Sect. 4. The blue (red) shaded colors indicate negative (positive) values of ω. The ω vector was multiplied by -20 to increase its scale and to get upward (downward) arrows with the air ascent (descent). Anomalies were calculated taking the 1981–2015 median as climatology.~~ driving the severe moisture deficit and downward motion characteristic of this out-of-phase event (Sanabria et al., 2019).

4.3.2 ~~Vertical structure analysis~~

~~The interaction between thermodynamics and dynamics is quantified in~~ To explicitly quantify how the dynamic constraints modulate the local thermodynamic potential, we examine the vertical profiles of ΔT, ω, and ~~the~~ their product $-\omega\Delta T$ at the convective core ~~(80~~boundary (79.75° W, 5° S~~) (Fig. 11). The positive area enclosed by the $-\omega\Delta T$ profile represents the Buoyancy Work Rate (BWR).~~

~~For the rainiest events , a consistent pattern of sustained deep tropospheric ascent was observed, aligning with the cross-section analysis. Notably,the~~ ; red star in Fig. 10f). Consistent with the deep convergence described previously, the extreme wet events of 1998 ~~El Niño exhibited the strongest BWR integral, followed by the~~ and 2017 ~~Coastal El Niño, which surpassed even the 1983 event in terms of dynamic intensity. Crucially, while the parcel buoyancy~~ exhibit a fully coupled atmospheric column. In these cases, atmospheric instability (ΔT) remains robust from 600 to 200 hPa and perfectly synchronizes with the maximum dynamic ascent ($-\omega$), yielding peak $-\omega\Delta T$ values between 500 and 400 hPa (Fig. 11f,k). Conversely, the 2016 profile captures the exact top-down suppression identified in the cross-sections. Although substantial instability (ΔT) ~~values were comparable across 1983, 1998, and 2017, the primary discriminator was the magnitude of the vertical velocity (ω) . This implies that the troposphere in 1998~~ and ~~2017 provided significantly stronger dynamic forcing than in 1983. Although the 1983 air parcels required less energy to overcome Convective Inhibition (CIN), the resulting BWR was lower due to weaker upward motion. This underscores that warm SSTs~~ localized ascent exist aloft (400–200 hPa), a severe layer of subsidence ($\omega > 0$) centered at 600 hPa physically severs the column, neutralizing the surface-to-upper-level connection and preventing deep convection (Fig. ~~A2)provide the necessary thermodynamic potential (Takahashi and Martínez, 2017), but the intensity of the event is modulated by the dynamic response (Echevin et al., 2018).~~

~~Conversely~~11j). Furthermore, the driest events ~~were dynamically characterized by significant~~ are systematically characterized by intense mid-level subsidence ~~($\omega > 0$~~ around 600 hPa~~). This suppression is consistent with a strengthened descending~~ . This persistent suppression is driven by the descending regional branch of the Walker Circulation (Sulca, 2021) and the stabilizing effect of negative SST anomalies ~~, which enhance~~ (Fig. A2), which strengthen the coastal inversion (Rudloff et al., 2025). ~~Even in the absence of local~~ Ultimately, these vertical profiles confirm that while warm SSTs provide the necessary thermodynamic potential (Takahashi and Martínez, 2017), the convective outcome is strictly dictated by the mid-level dynamic response (Peng et al., 2019). Crucially, even without local oceanic cooling, teleconnected subsidence ~~from Central Pacific forcing can induce similar drying effects (Takahashi and Dewitte, 2016; Sulca et al., 2017)~~forced by Central Pacific warming can impose identical drying effects by capping the atmospheric column (Sulca et al., 2017; Paek et al., 2017).

As demonstrated by the contrasting outcomes of the 1998, 2017, and 2016 events, monitoring surface warming and low-level kinematics is insufficient to diagnose precipitation in dynamically limited regions like the NWSA. The mid-level dynamic environment (ω) ultimately dictates the convective response, either authorizing deep ascent or neutralizing the atmospheric column through subsidence. While this three-dimensional physical dependency is already recognized in the literature, routinely evaluating it requires complex, multi-level cross-sectional analysis. This highlights the practical need for a unified metric that explicitly couples the local thermodynamic potential with the mesoscale dynamic constraint. Consequently, the vertically integrated positive area of this product defines the BWR (Fig. 11), which acts as an explanatory proxy that could be useful for simplified monitoring and diagnosis, e.g. for using in a similar way as a stream-function (although not similar in its mathematical nature), condensing the complex 3D convective state into a rapidly interpretable 2D field.

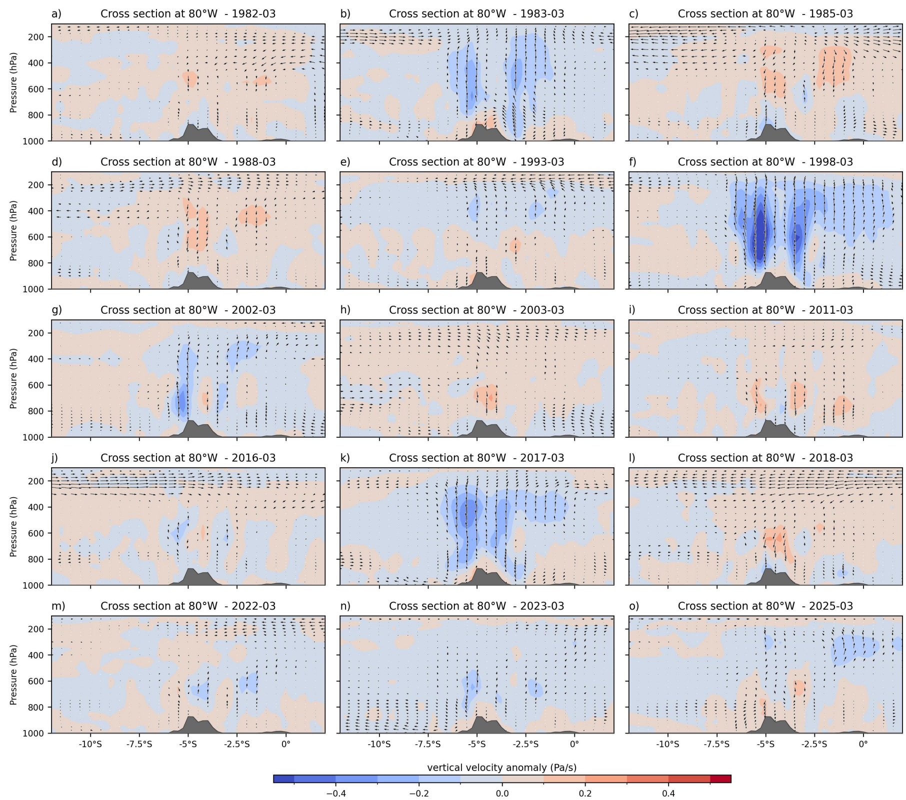

Figure 9. Latitudinal cross-section of the resultant vector between the anomalies of ω and meridional wind at 80° W, spanning from 12° S to 2° N, for the extreme hydroclimatic anomalies identified in Section 4. The blue (red) shaded colors indicate negative (positive) values of ω. The ω vector was multiplied by -20 to increase its scale and to get upward (downward) arrows with the air ascent (descent). Anomalies were calculated taking the 1981–2025 median as climatology.

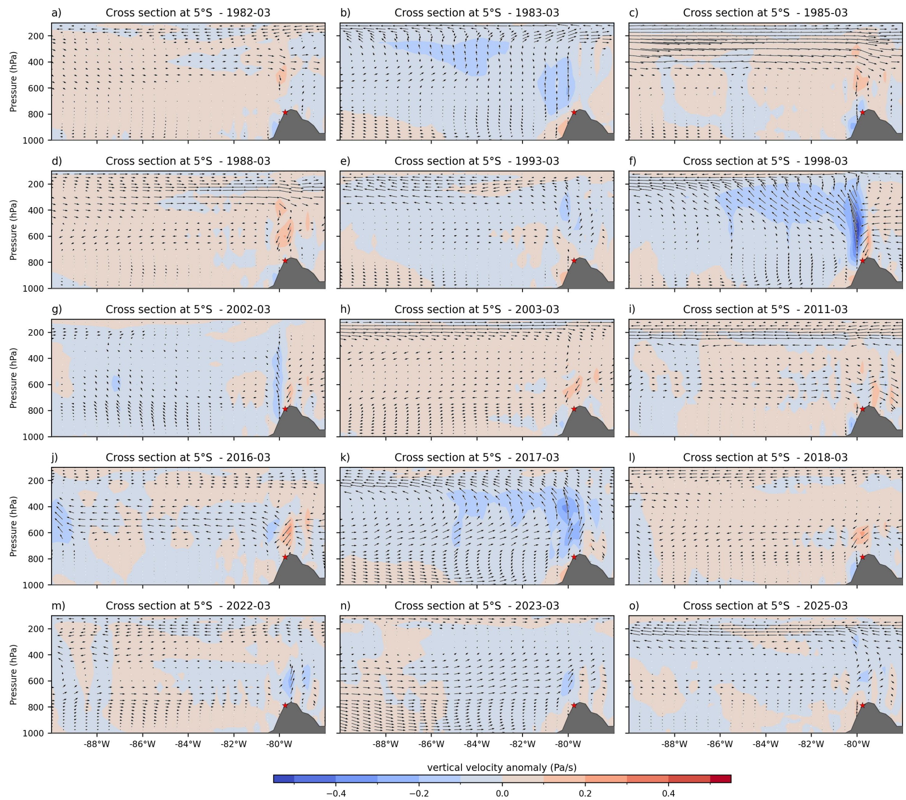

Figure 10. Longitudinal cross-section of the resultant vector between the anomalies of ω and zonal wind at 5° S, spanning from 90° W to 78° W, for the extreme hydroclimatic anomalies identified in Section 4. The blue (red) shaded colors indicate negative (positive) values of ω. The ω vector was multiplied by -20 to increase its scale and to get upward (downward) arrows with the air ascent (descent). Anomalies were calculated taking the 1981–2025 median as climatology. Red star represents the longitude of the boundary between the ascent core and the descent core of the 1998 event.

4.3.2 BWR anomaly analysis

~~The~~ Building upon the vertical diagnoses from Section 4.3.1, the spatial distribution of the ~~Buoyancy Work Rate (BWR)~~ BWR anomalies (Fig. 12) ~~provides a comprehensive synthesis of the thermodynamic and dynamic interactions governing the extremes. For the rainiest events (e.g. , 1983, 1998, 2017, 2023), positive BWR anomalies dominate the NWSA domain adjacent to Niño 1+2. This spatial coherence confirms that the strong vertical ascent identified in the cross-section analysis (Sect. 4.3.2) was spatially coupled with positive buoyancy ($\Delta T > 0$) , effectively converting potential energy into kinetic energy~~ maps the explicitly realized atmospheric response. As established in tropical dynamics (Cornejo-Garrido and Stone, 1977; Emanuel et al., 1994) , large-scale vertical ascent (ω) and precipitation are inextricably coupled; diabatic heating from deep convection is fundamentally balanced by the adiabatic cooling induced by large-scale vertical motion. However, there is a critical physical distinction: while precipitation represents the localized thermodynamic output, ω represents the divergent circulation required to advectively export column-integrated moist static energy, dynamically maintaining the convective system (Neelin and Held, 1987). Consequently, by mathematically incorporating ω, the BWR is not a redundant empirical metric of precipitation, but an explicit physical quantification of the three-dimensional convective engine. In dynamically limited regions like the NWSA, where atmospheric instability (ΔT) is a necessary but insufficient condition for deep convection ~~. The intensity of the positive BWR signal in~~ (Williams and Renno, 1993), this formulation is crucial. It physically discriminates actively coupled convective environments from those that are thermodynamically unstable but dynamically suppressed (Lau et al., 1997; Bony et al., 1997; DeMott and Randall, 2004) . During the extreme wet events positive BWR anomalies dominated the coastal domain (Fig. 12b,e,f,g,k,m,n,o), being stronger in the 1998 and 2017 ~~is particularly pronounced along the coastline, mirroring the extreme precipitation patterns observed in Fig. **??** and the intense vertical profiles of $-\omega\Delta T$ discussed in Sect. **??**.~~

events, confirming the effective conversion of potential energy into kinetic energy. Conversely, the ~~driest~~ extreme dry events are characterized by widespread negative BWR anomalies (~~blue shading) across the domain (~~Fig. 12a,c,d,h,i,l). ~~Mechanistically, this negative signal arises from the stable configuration described in Sect. 4.3.1: cooler SSTs, during coastal La Niña, induce thermodynamic stability ($\Delta T < 0$) , while the strengthening of the South Pacific Anticyclone forces large-scale subsidence ($\omega > 0$). Consequently, the atmospheric heat engine is effectively shut down, preventing the release of any residual instability.~~

~~The diagnostic value of the BWRis most evident in the analysis of~~ The practical necessity of differentiating the localized thermodynamic output (precipitation) from the mesoscale mechanism of energy conversion (captured by the BWR) is empirically demonstrated by the 2016 event (Fig. 12j). ~~Despite being classified as a strong Global~~ During this strong Central Pacific El Niño~~with positive SST anomalies in the Pacific, the NWSA region exhibits neutral to slightly negative BWR anomalies. This aligns with the findings in Sect. 4.3.1, where the "atmospheric bridge" failed to establish. The BWR correctly captures the decoupling mechanism: although the thermodynamic potential might have been marginally favorable due to global warming, the imposed subsidence from the Walker Circulation's descending branch (ω>0, as seen in Fig. 10j and Fig. 9j) inhibited the conversion of energy. This contrast confirms that BWR is a more robust proxy for local hydroclimatic impacts than SST indices alone, as it integrates the necessary dynamic trigger for precipitation~~, intense surface warming generated a high thermodynamic potential ($\Delta T > 0$), warning an extreme hydroclimatic event. However, the observed precipitation anomaly was near zero. While analyzing precipitation merely quantifies this lack of localized response (the effect), the BWR physically diagnoses the cause of the failure. Consistent with the vertical profiles from Section 4.3.1, the index yielded neutral to negative anomalies because it mathematically captured the structural decoupling of the atmospheric column: the atmospheric instability was neutralized by the mid-level subsidence ($\omega > 0$) imposed by the displaced Walker Circulation (Paek et al., 2017). Because atmospheric instability is a necessary but insufficient condition for deep convection (Williams and Renno, 1993), the BWR successfully filtered out this false positive. By explicitly diagnosing the dynamically suppressed environment, the BWR proves to be a more comprehensive diagnostic proxy for regional convection than isolated thermodynamic fields or precipitation outputs. Furthermore, for a more comprehensive diagnosis, it would be useful to overlay the divergent component of the wind or mid-level wind streamlines over the BWR anomaly maps, as this would explicitly visualize the 3D coupling between the vertical convective engine captured by the index and the mesoscale horizontal circulation.

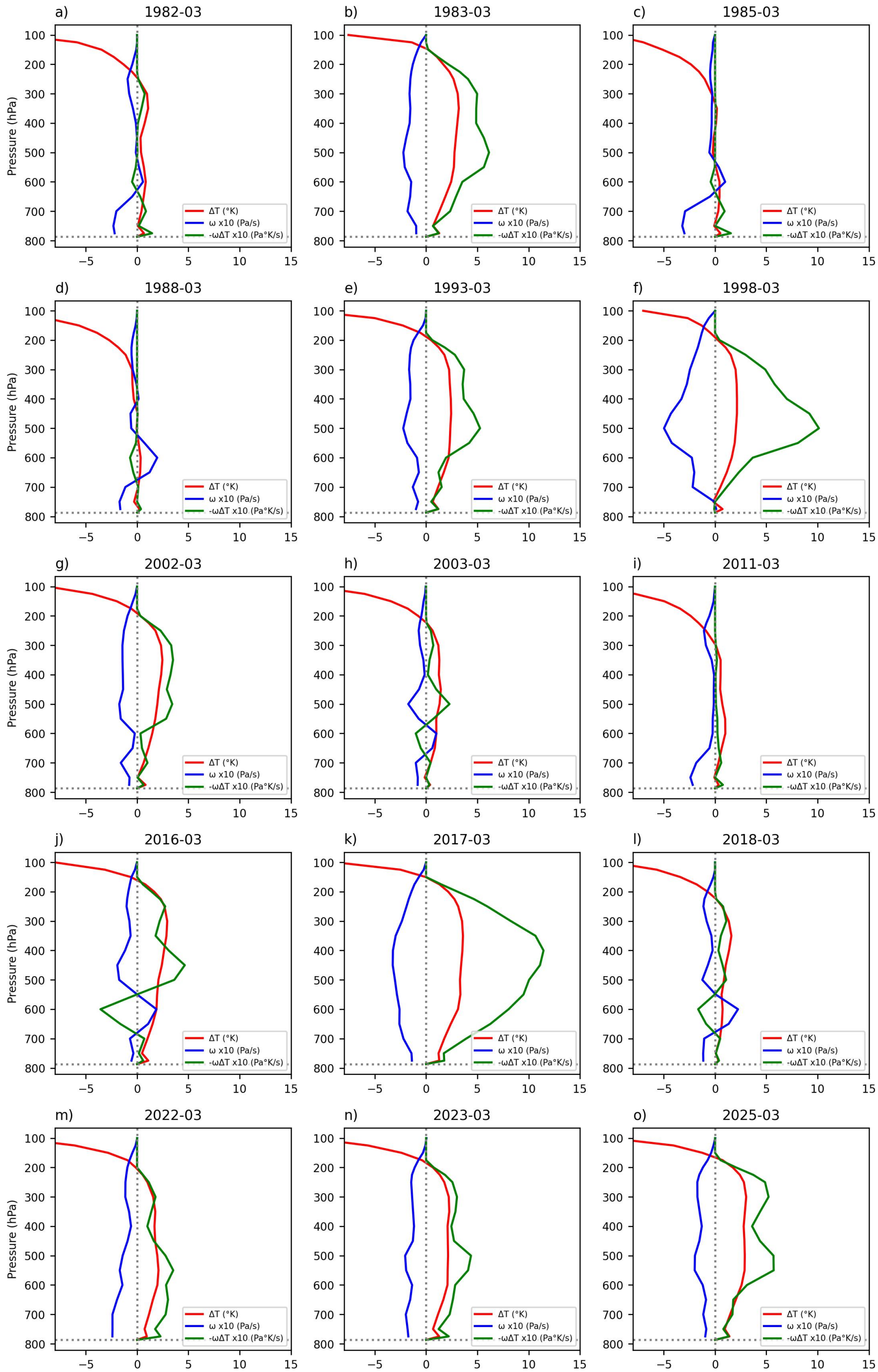

Figure 11. Profiles of ΔT (red), ω (blue) and $-\omega\Delta T$ (green) at (~~80~~79.75° W,5° S) for the ~~rainiest and driest events~~ extreme hydroclimatic anomalies identified in ~~Sect.~~ Section 4. The ~~LCL, LFC and EL dotted horizontal lines represent the lifting condensation level, the level of free convection and the equilibrium level respectively. The~~ ω was multiplied by 10 to increase its scale. The horizontal dotted line shows the equivalent altitude of that point in pressure units. All variables share the same horizontal numerical axis.

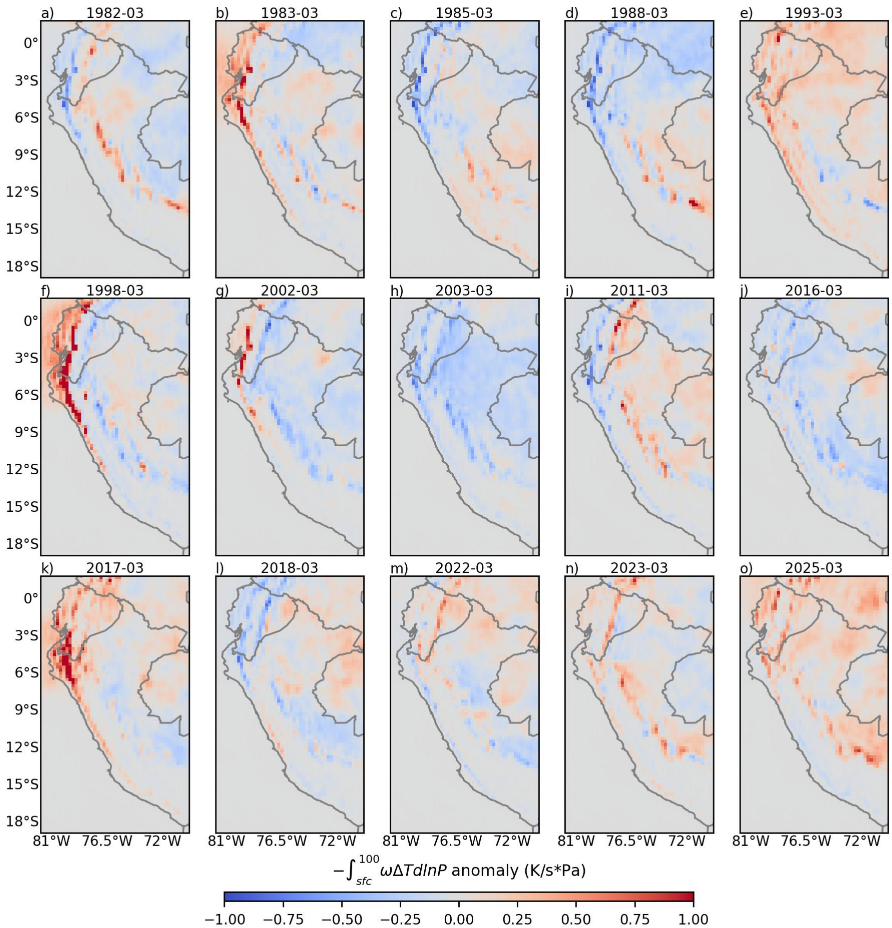

Figure 12. BWR anomaly, taking the ~~1981–2015~~ 1981–2025 median as climatology, for the ~~rainiest and driest~~ extreme hydroclimatic events identified in ~~Sect.~~ Section 4. The blue (red) shaded colors indicate negative (positive) ~~values~~ anomalies of BWR.~~Positive (negative) values indicate favorable (unfavorable) conditions for deep convection.~~

4.4 Validation of extremes and signal persistence

To rigorously evaluate the robustness of the BWR ~~and its constituent components~~ during critical hydroclimatic phases, ~~a Tail Dependence~~ an Upper Tail Dependence (λ_U) analysis was conducted using empirical ~~Copulas on the standardized anomalies~~copulas. This approach ~~allows for the quantification of~~ quantifies the conditional probability that precipitation exceeds a high quantile given that the predictor index also exceeds the same quantile, providing a measure of asymptotic dependence essential for risk assessment.

~~The Upper Tail Dependence Coefficient (λ_U) profiles reveal a clear hierarchy in the physical drivers of extreme precipitation (Fig. 13 and ??). Consistent with the energy balance mechanism described by ?, vertical velocity at 500 hPa (ω_{500}) exhibits~~

~~the strongest and most stable asymptotic dependence with precipitation, reaching λ_U values near 0.9 for the highest quantiles (Fig. **??**). This confirms that large-scale dynamic ascent is the primary sufficient condition for extreme rainfall events in the NWSA.~~

~~Analysis of the extreme dependence structure between BWR index and precipitation anomalies in the NWSA adjacent to Niño 1+2. **(a)** Scatterplot of pseudo-observations (uniform ranks) in the empirical copula space. The dashed red lines indicate the 0.90 quantile threshold; points in the upper-right quadrant represent concurrent extreme events. **(b)** The empirical Upper Tail Dependence Coefficient (λ_U) as a function of the quantile threshold (u).~~

~~The BWR index also demonstrates strong asymptotic dependence, peaking near 0.8 at the 97.5th percentile (Fig. 13). However, a slight decrease in performance is observed in the extreme tail compared to pure ω_{500}. To understand this divergence, the thermodynamic component (ΔT, averaged 700–400 hPa) was analyzed independently (Fig. **??**). It was found that ΔT exhibits asymptotic independence (λ_U decreases as quantiles increase), implying that extreme parcel buoyancy does not linearly translate to extreme precipitation without dynamic support. Consequently, the thermodynamic term acts as a slight dampening factor on the BWR at the most extreme percentiles, likely reflecting cases where dynamic forcing is strong enough to drive heavy rainfall even in environments of moderate thermodynamic instability.~~

The copula space visualization (Fig. 13, left) exhibits a cross-like structure. While the main diagonal confirms the primary physical coupling~~(positive correlation)~~, the anti-diagonal reveals ~~the presence of~~ regime mismatches in moderate conditions (e.g., ~~dry ascent or~~ false positives). However, the ~~Upper Tail Dependence Coefficient (λ_U)~~ analysis (Fig. 13, right) demonstrates that this noise fades in the extremes. The λ_U coefficient ~~actually~~ increases for higher quantiles, peaking near 0.8 at the 97.5th percentile. This confirms strong asymptotic tail dependence: while the index may produce ~~false alarms~~ noise during moderate anomalies, it becomes a highly reliable ~~predictor~~ diagnostic proxy specifically for the most extreme, potentially disastrous precipitation events~~(e.g., strong El Niño years)~~.

~~Furthermore, the λ_U for local evaporation and SST in 1+2 Niño region (not showed) remains consistently low (~ 0.5 and ~ 0.2, respectively) and does not increase for extreme quantiles. This lack of tail dependence provides further empirical evidence rejecting local moisture recycling as a driver of extremes, reinforcing the hypothesis that moisture convergence driven by dynamics is the dominant mechanism.~~

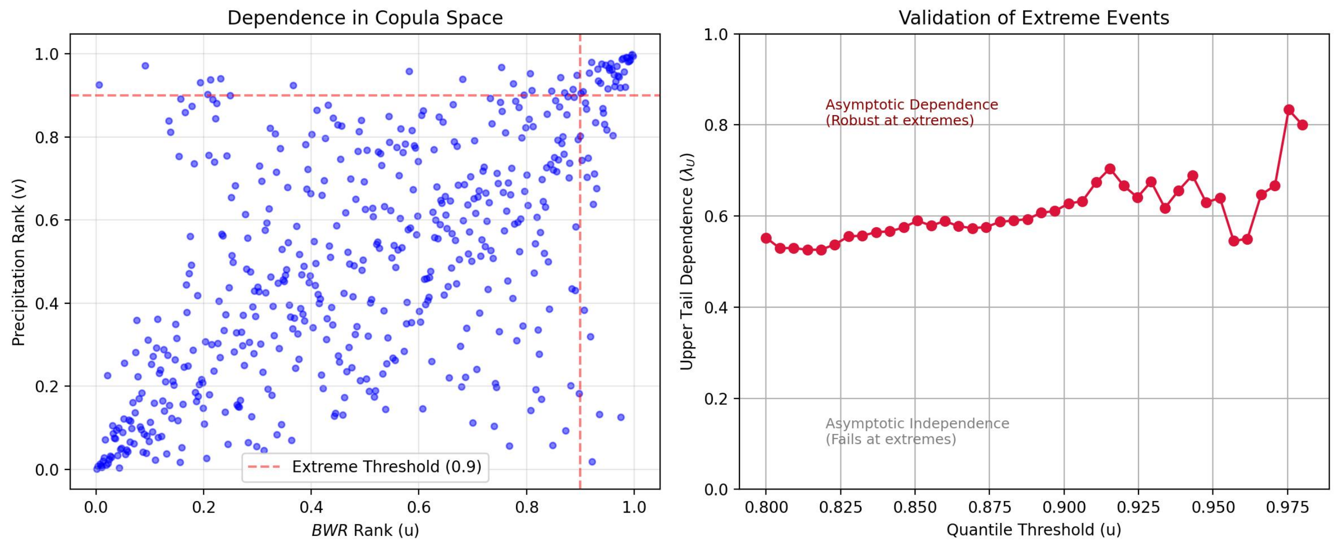

Figure 13. Analysis of the extreme dependence structure between BWR index and precipitation anomalies in the NWSA adjacent to Niño 1+2. **(a)** Scatterplot of pseudo-observations (uniform ranks) in the empirical copula space. The dashed red lines indicate the 0.90 quantile threshold; points in the upper-right quadrant represent concurrent extreme events. **(b)** The empirical Upper Tail Dependence Coefficient (λ_U) as a function of the quantile threshold (u).

While large-scale dynamic ascent (ω_{500}~~serves as the superior diagnostic for~~) alone might dictate instantaneous extremes, its utility for continuous monitoring is limited by its chaotic nature. This was assessed through a signal persistence analysis (Fig. 14). A rapid decorrelation was observed for ω_{500} (blue line), which loses significant memory after short lags. In contrast, by integrating ΔT ~~(red line) exhibits high persistence, inheriting the thermal inertia of the SSTs. Crucially~~, the BWR (green line) ~~demonstrates a predictability horizon significantly longer than that of pure~~ ~~ω_{500}~~~~. By integrating the thermodynamic component, the BWR~~ mathematically inherits the thermal inertia of the oceanic boundary conditions. This integration effectively "anchors" the volatile dynamic signal to the slower-evolving ~~boundary conditions~~thermodynamic state, yielding a predictability horizon significantly longer than that of pure ω_{500}. Thus, the BWR represents a physical trade-off: it sacrifices a marginal fraction of diagnostic precision at the extreme tail (compared to pure ω) to gain substantial signal stability and predictive ~~memory~~capability, rendering it a ~~more~~ highly practical tool for sub-seasonal to seasonal operative monitoring.

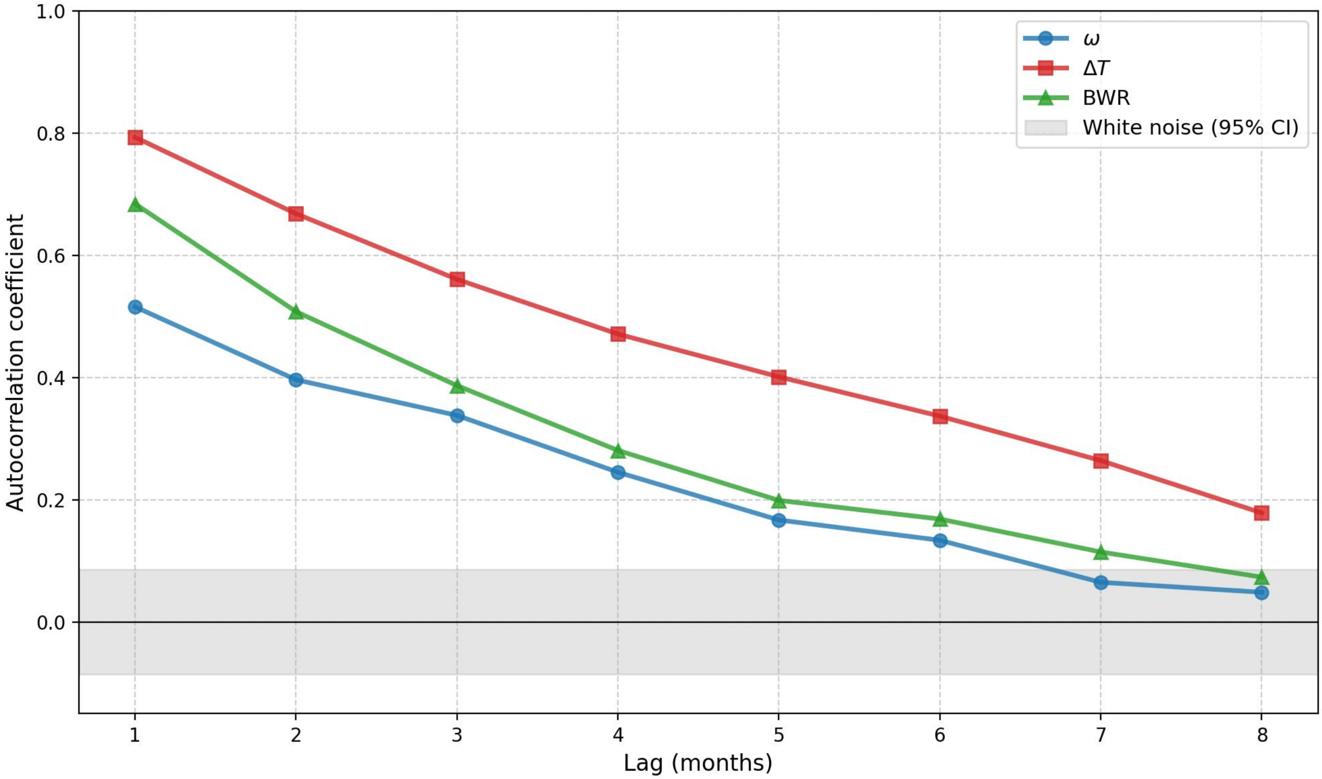

Figure 14. Analysis of signal persistence ~~and predictability horizons~~ for the physical components of the BWR index. The plot displays the autocorrelation function (ACF) for vertical velocity (ω, blue), parcel buoyancy 400-700 hPa average (ΔT, red), and the BWR index (green) up to a lag of 8 months. The gray shaded area indicates the 95% confidence interval for a white noise process ($\pm 1.96/\sqrt{N}$).

4.5 Predictive skill of the predicted BWR anomalies

During the peak of the rainy season (February–April), BWR anomaly predictions initialized in November and December exhibit a consistent improvement in predictive skill ($\Delta R \approx 0.1$ to 0.2) compared with precipitation anomalies predicted by the ECMWF SEAS5 model (Fig. 15). Predicting precipitation anomalies in the NWSA during this critical hydroclimatic period is inherently complex due to the interaction between large-scale moisture convergence and the steep Andean topography (Garreaud, 2009; Trachte, 2018). Climate models often exhibit significant biases in these dynamically limited regimes because they rely on sub-grid convective parameterizations to generate local precipitation (Insel et al., 2009; Fernandez-Palomino et al., 2022). By substituting direct precipitation outputs with the BWR, the diagnosis circumvents these microphysical uncertainties. Instead, the BWR leverages the explicitly resolved large-scale vertical dynamics (ω) and thermodynamics (ΔT), which are governed by primitive equations and simulated with substantially greater fidelity by models (John and Soden, 2007; Emmenegger et al., 202 .

Furthermore, the BWR demonstrates a significant advantage for extended-lead predictions initialized in May, targeting the austral spring (October–November). At these 5- to 6-month lead times, the BWR anomalies yield marked correlation improvements ($\Delta R > 0.3$). This indicates that the BWR effectively retains predictive skill across the boreal spring predictability barrier. Because the BWR integrates the maesoscale atmospheric energetic conversion rather than relying on parameterized local rainfall, it provides a more robust and persistent proxy for the atmospheric state, confirming its operational utility for sub-seasonal to seasonal forecasting.

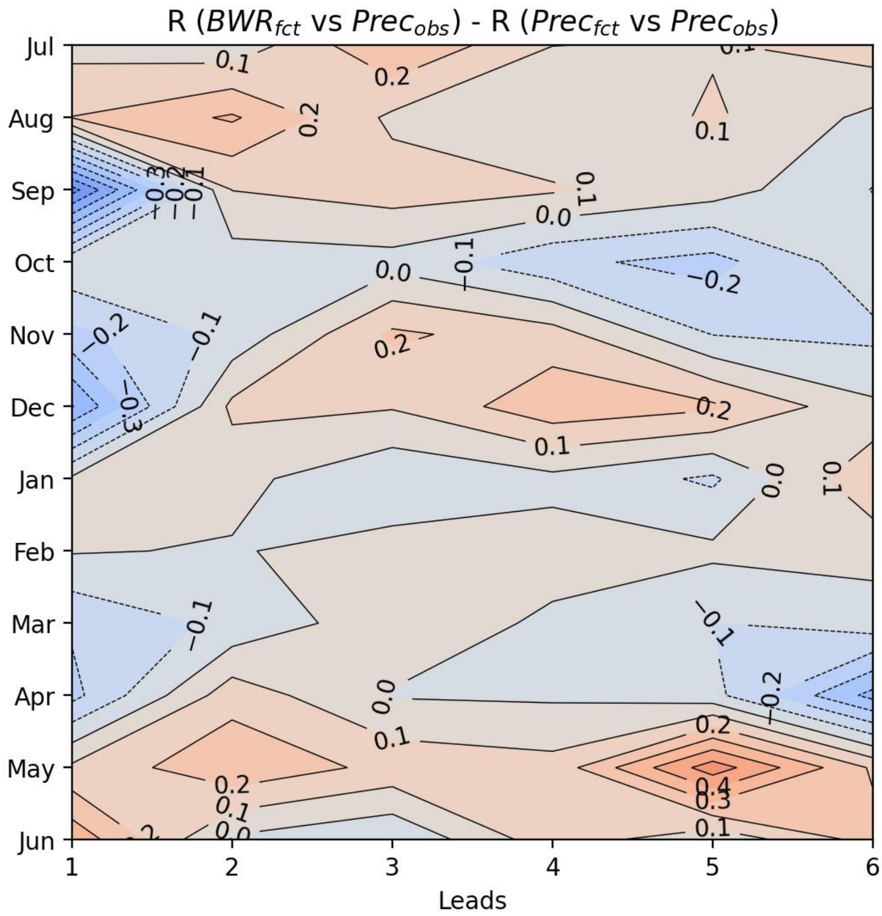

Figure 15. Predictive skill of BWR anomalies predicted up to a lead of 6 months. Shaded colors in red (blue) and contours with $\Delta R > 0$ ($\Delta R < 0$) represent better (worse) BWR predictive skill compared to the precipitation anomalies predicted by the SEAS5 model for the 2017–2025 operational period, using the PISCO dataset as the observational reference. The Y-axis represents the initial condition of the prediction.

5 Discussion

~~The Dynamic vs. Thermodynamic Control of Precipitation~~

5.1 The Dynamic vs. Thermodynamic Control of Precipitation

~~The results obtained in this study provide robust empirical verification for the physical energy balance mechanism proposed by ? for the tropical atmosphere. Through the application of Causal Discovery (PCMCI+)and Tail Dependence analysis, a clear~~

~~hierarchy in the drivers of precipitation over the NWSA was established, distinguishing between the roles of thermodynamic potential and dynamic forcing.~~

~~It was demonstrated that while Sea Surface Temperature (SST) acts as a strong exogenous driver of parcel buoyancy (~~The causal networks evaluated in Section 4.2 empirically support the physical hierarchy preserved by the BWR index, whose causal route to precipitation significantly dominates over other variables. This dominance is explained by the background dynamics of the region: although it is well established that local SST must exceed a specific threshold to trigger atmospheric instability (Woodman, 1999; Takahashi, 2004; Jauregui and Takahashi, 2018), in dynamically limited environments such as the coastal subdomain, this atmospheric instability (ΔT) ~~, as evidenced by the high causal strength in the PCMCI+ network, thermodynamic destabilization alone is insufficient to explain the variability of precipitation anomalies. The analysis of extremes revealed that ΔT exhibits asymptotic independence with respect to precipitation (Fig. **??**), implying that extremely unstable environments do not linearly translate into extreme rainfall in the absence of a lifting mechanism. This limitation explains the "false positives" observed in purely thermodynamic indices (e.g., CAPE) over the Amazonian region (Fig. 4a-c), where high instability frequently coexists with convective inhibition.~~

~~Conversely, large-scale vertical motion (~~is a necessary but insufficient condition for deep convection (Williams and Renno, 1993). Once the thermodynamic threshold is surpassed, control shifts predominantly to the mesoscale vertical velocity (ω) ~~was identified as the dominant control. The PCMCI+ analysis revealed that the causal effect of ω on precipitation is approximately three times stronger than that of local evaporation. Furthermore,~~ (Lau et al., 1997; Bony et al., 1997). Specifically, convection requires a mechanical trigger, such as the localized vertical ascent generated by the sea breeze colliding against the western Andean slope (Takahashi, 2004; Rollenbeck et al., 2022). This forced ascent lifts the air parcel to its Level of Free Convection (LFC), initiating latent heat release. Consequently, mid-level ω ~~was the only variable to exhibit strong asymptotic dependence ($\lambda_U \approx 0.9$) during extreme events. Physically, this confirms that on climatic timescales, the release of latent heat (Q) in the NWSA is primarily balanced by adiabatic cooling associated with vertical ascent ($[\theta]_z\omega$), rather than by radiative cooling or local surface fluxes (**?**Lau et al., 1997).~~ emerges to balance this diabatic heating through adiabatic cooling (Sobel et al., 2001), which, dictated by mass continuity, stimulates further low-level horizontal convergence, generating a circular causality known as convergence feedback (Back and Bretherton, 2005). By mathematically abstracting this dynamic mechanism, the BWR acts as a coherent physical integrator that successfully couples vertical velocity with atmospheric instability without losing the causal route to precipitation.

~~The hypothesis that monthly precipitation anomalies are fueled significantly by local surface evaporation was critically challenged by the findings. The weak and physically secondary causal link observed between evaporation and precipitation, combined with the lack of tail dependence, suggests that the moisture sustaining deep convection is imported via dynamic moisture convergence rather than supplied by local recycling. This supports the notion that the NWSA operates under a "dynamically limited" regime rather than a "moisture limited" one~~The BWR index mathematically abstracts this exact dynamic mechanism to operate in the dynamically limited environment of the coastal subdomain through the product of $-\omega$ and ΔT. This mathematical formulation acts as a physical constraint: the bidirectional feedback is only quantitatively realized when dynamic ascent ($-\omega > 0$) coincides with thermodynamic instability ($\Delta T > 0$). If the atmospheric column remains mechanically suppressed by the background subsidence ($\omega > 0$), the index zeroes out values, explicitly capturing the inability of local buoyancy to autonomously initiate the convective feedback loop.

~~This dynamic control explains the hydroclimatic decoupling observed during Central Pacific~~ The interaction between this thermodynamic potential and its dynamic realization fully explains the divergent regional responses observed during different El Niño ~~events, such as in 2016. Despite the presence of positive SST anomalies (Fig. A2j) and high thermodynamic potential,~~ flavors. While SST controls atmospheric instability, while SST gradients drive low-level horizontal convergence (Lindzen and Nigam, 1987) . However, there are situations characterized by spatial and extensively homogeneous high SST values across the Pacific but with low SST gradients. This configuration translates into weak or null local convergence, as absolute high SSTs alone cannot force deep convection without the vertical ascent provided by spatial gradients (Lau et al., 1997; Sanabria et al., 2019) (e.g., the 2015-2016 El Niño). Conversely, asymmetric or high SSTs confined over smaller areas, such as the Niño 1+2 region (e.g., the ~~precipitation response was neutralized by mid-tropospheric subsidence (Fig.11j). Consequently, indices that rely solely on surface boundary conditions or thermodynamic profiles fail to capture the suppression of convection by the remote Walker circulation.By contrast, the dominant role of ω justifies the formulation of the BWR as an index thatexplicitly requires the coupling of the dynamic trigger with the thermodynamic fuel~~2017 and 2023 coastal El Niño events), generate strong SST gradients (Bony et al., 1997; Echevin et al., 2018; Aliaga-Nestares et al., 2023; Peng et al., 2024) that, initially, result in weak convergence, but when the convergence feedback is activated the convergence becomes stronger (Back and Bretherton, 2005), seamlessly converting thermodynamic potential into the extreme hydroclimatic anomalies physically diagnosed by the BWR.

5.2 Advantages of BWR as a physical diagnostic proxy

~~Based on the hierarchy of physical drivers established in Sect. 4.2, the Buoyancy Work Rate (BWR) is proposed as a physical diagnostic proxy that integrates the essential components of the atmospheric energy cycle. While purely thermodynamic indices (e. g. , CAPE) quantify the potential energy available and kinematic indices (e.g. ,~~In dynamically limited environments like the NWSA coast, relying exclusively on thermodynamic indices yields high false-positive rates. As established by Williams and Renno (1993) , thermodynamic instability (ΔT) is a necessary but insufficient condition for deep convection. When the regional Walker circulation imposes persistent subsidence, the atmospheric column remains mechanically suppressed despite intense surface warming. By mathematically coupling the thermodynamic potential with the vertical velocity (ω~~) quantify the motion, the BWR represents the interaction between them.~~), the BWR acts as an explicit physical filter. It systematically zeroes out or yields negative values in thermodynamically unstable but dynamically suppressed environments, providing a selective diagnosis that purely thermodynamic predictors fail to capture (DeMott and Randall, 2004).

~~A fundamental advantage of the BWR is its capacity to act as a physical filter for "regime mismatches. " In the NWSA adjacent to the Niño 1+2 region,~~Furthermore, the BWR provides diagnostic capabilities that extend beyond observing precipitation anomalies. In atmospheric fluid dynamics, the ~~atmosphere is directly influenced by the local eastern limb of the Walker circulation, characterized by a persistent subsidence branch that suppresses deep convection despite high surface thermodynamic potential. By mathematically coupling these terms (Eq. 1)~~conversion of available potential energy to kinetic energy requires the ascending of warm air and the descending of cold air. For the NWSA coast, this conversion mechanism has been specifically documented within the Lorenz energy cycle framework by Aliaga-Nestares et al. (2023). By computing the product of temperature anomalies (ΔT) and vertical ascent ($-\omega$), the BWR functions as a direct two-dimensional proxy for this three-dimensional energy conversion. Therefore, the BWR explicitly quantifies the intensity of the convective forcing engine, whereas precipitation merely records the subordinated thermodynamic output.

Further, while the mid-level vertical velocity (ω) ultimately dictates the convective outcome, its high-frequency variability and rapid decorrelation limit its utility as an isolated monitoring index. The NWSA coastal climate is strongly constrained by the SST, which evolves slowly due to the ocean's large heat capacity and acts as a boundary condition for deep convection (Takahashi, 2004; Jauregui and Takahashi, 2018). By integrating ΔT, the BWR ~~yields near-zero values when high instability coexists with dynamic inhibition. This selectivity explains the superior diagnostic skill~~ mathematically inherits this oceanic thermal inertia. The resulting hybrid index retains the rigorous dynamic constraint of ω required to prevent false positives, while acquiring the temporal stability of the oceanic forcing, making it an optimal proxy for sub-seasonal operative monitoring.

Finally, beyond its diagnostic utility, the operational advantage of the BWR ~~in the coastal domain compared to purely thermodynamic predictors, which fail to capture the suppression of convection by the remote dynamic forcing of the Walker circulation~~becomes evident when applied to climate models for seasonal predictions. In topographically complex regions like the NWSA, climate models systematically exhibit biases because they rely on sub-grid convective parameterizations to estimate localized precipitation (Garreaud, 2009; Insel et al., 2009; Trachte, 2018; Fernandez-Palomino et al., 2022). By substituting native precipitation outputs with the BWR, the forecast circumvents these microphysical uncertainties. The index evaluates the large-scale vertical dynamics (ω) and thermodynamics (ΔT), which are governed by primitive equations and explicitly resolved with higher accuracy by the models (John and Soden, 2007; Emmenegger et al., 2024). Consequently, the BWR retains predictive skill at extended lead times and mitigates the forecast degradation caused by the boreal spring predictability barrier. By calculating the mesoscale atmospheric energy conversion rather than relying on parameterized rainfall, the BWR provides a physically robust proxy for operational predictions.

5.3 Physical limitations and interpretation of errors

It is acknowledged that the BWR, in its current formulation using ~~pressure~~ vertical velocity (ω in Pa s^{-1}), does not possess strict units of power density (W m^{-2}). However, ~~it functions as a proxy~~ its mathematical formulation ($-\omega\Delta T$) is directly proportional to the ~~rate of conversion of Available Potential Energy (APE) into Kinetic Energy (~~generation term of Kinetic Energy (KE) ~~within the atmospheric column. This formulation is physically grounded in the framework of **?**, where the generation of kinetic energy maintains the circulation against dissipation. Therefore, the BWR provides a more direct measure of the intensity of~~ from Available Potential Energy (APE) in the ~~"atmospheric heat engine" driving regional variability than precipitation anomalies alone, which are influenced by local moisture recycling and microphysical efficiency.~~

~~From a monitoring perspective, the hybrid nature of the index offers a significant advantage over the use of pure vertical velocity. Although ω was identified as the primary control for precipitation extremes (Sect. 4.4), its signal is inherently chaotic and exhibits rapid decorrelation, limiting its utility for sub-seasonal monitoring. The autocorrelation analysis demonstrated that~~

~~the inclusion of the thermodynamic component (ΔT) effectively transfers the thermal inertia of the ocean boundary conditions (SST) to the index . This confers a "thermal memory" to the BWR, resulting in a signal that remains physically consistent with the dynamic control required by the **?** mechanism, yet is sufficiently stable on monthly timescales to be utilized in early warning applications~~Lorenz energy cycle (Lorenz, 1955; Michaelides, 1987). By capturing the upward motion of warm air and the downward motion of cold air (Aliaga-Nestares et al., 2023), the index functions as a kinematic quantification of the energy conversion rate within the atmospheric column.

5.4 ~~Physical limitations and interpretation of errors~~

Despite the robust performance of the BWR during extreme events, significant limitations exist in moderate convective regimes, as evidenced by the dispersion observed in the copula space (~~Sect.~~ Section 4.4). ~~A primary limitation of the BWR formulationis the exclusion of~~ These limitations stem directly from the index's simplified formulation. First, the BWR lacks an explicit humidity term~~and an entrainment parameter~~. The index assumes that the product $-\omega\Delta T$ ~~is proportional to the generation of kinetic energy and subsequent rainfall. However, this holds strictly true only in environments where the moisture supply is sufficient to reach saturation and release latent heat~~ leads to latent heat release (Q)~~.~~

~~In~~ , consistent with the tropical energy balance where Q is primarily balanced by adiabatic cooling (Cornejo-Garrido and Stone, 1977) . However, in cases of "dry ascent," where strong dynamic lifting occurs in a moisture-starved environment, ~~the BWR may yield high positive values that do not translate into precipitation. This physical decoupling likely explains the false positives observed in the lower-right quadrant of the dependence plot. This limitation is consistent with the energy balance of **?**, where the term Q is assumed to be balanced by adiabatic cooling ($[\theta]_z\omega$). If the air is too dry,~~ Q is limited by moisture availability rather than vertical motion. Consequently, the BWR ~~measures~~ yields false positives, measuring the intensity of the circulation's "engine" but not ~~necessarily~~ the efficiency of its output.

~~Furthermore, "false negatives" (low BWR, high precipitation) were observed, particularly along the eastern slopes of the Andes and in transition zones. These discrepancies are attributable to two factors. First,~~ Second, because the BWR is integrated from the surface to 100 hPa to strictly isolate deep convection~~; therefore,~~ , it systematically generates false negatives for precipitation driven by shallow convection or warm rain processes~~—~~, which do not involve deep tropospheric ascent~~—is systematically underestimated. Second, precipitation driven by~~ . Third, the current formulation lacks a high-frequency spatial filter. At native grid resolutions, the ω field inherently convolves the large-scale background dynamics with localized kinematic responses. While filtering the smaller horizontal scales in ω would isolate the large-scale environment to formulate a more transparent metric of precursor conditions leading eventually to precipitation anomalies, the current unfiltered index operates fundamentally as a diagnostic proxy of the realized convective state. Future efforts to further optimize the BWR will explore the application of spatial filters to the ω field.

Consequently, the translation of the BWR to other tropical latitudes imposes strict physical boundaries. Over continental regimes like the Amazon basin (Fig. 4), deep convection is primarily constrained by convective inhibition (CIN) (Fu et al., 1999) . Because the BWR evaluates dynamic forcing and positive buoyancy without accounting for the energy required to overcome CIN, its diagnostic correlation decreases significantly in these environments. Furthermore, over the eastern slopes of the Andes, precipitation is frequently driven by localized mechanical orographic lifting ~~can occur~~ under conditions of weak large-scale ω ~~or moderate instability, mechanisms that are not fully resolved at the resolution of the reanalysis data~~ (Trachte, 2018). These highly localized mechanical processes are unresolved at the spatial resolution of current global reanalysis data (Insel et al., 2009; Fernandez , which physically exacerbates the generation of false negatives.

Beyond the tropics, the application of the BWR becomes physically inconsistent. In the midlatitudes and subtropics, atmospheric dynamics are predominantly governed by baroclinic instability, frontal lifting, and strong Coriolis forcing (Sobel et al., 2001) . Applying the BWR directly to extratropical regimes misrepresents the fundamental energy conversion processes driving precipitation in those latitudes. Finally, it must be reiterated that the BWR is ~~a climatic diagnostic proxy and~~ fundamentally a diagnostic proxy of the macro-scale convective environment, not a direct measure of precipitation physics. ~~Unlike complex convective parameterization schemes, the BWR was designed to monitor the macroscopic state of the local branch of the Walker circulation between Peru and Ecuador.~~ The Tail Dependence analysis confirms that while ~~these limitations introduce~~ the index's simplified formulation introduces noise during moderate conditions, ~~the influence of dry entrainment and shallow processes becomes~~ these limitations become secondary during extreme ~~El Niño events. In such regimes, the massive moisture supply and~~ events, where intense dynamic forcing ~~render the BWR a highly reliable indicator for disaster risk management~~and boundary-layer instability strictly dominate the atmospheric response.

6 Conclusions

~~This study introduced and validated the Buoyancy Work Rate (BWR) as a physical diagnostic proxy for monitoring hydroclimatic extremes in Northwestern South America (NWSA). By integrating vertical dynamics with thermodynamic instability , the BWR addresses the limitations of traditional indices in regions where dynamic inhibition frequently decouples potential energy from precipitation. The main conclusions are:~~

~~**Dynamic control of precipitation:**~~ ~~The~~ In dynamically limited environments such as the coastal NWSA, thermodynamic instability (ΔT) alone is insufficient to autonomously trigger deep convection due to persistent background subsidence. The BWR addresses this boundary constraint by vertically coupling ΔT and vertical velocity (ω). The causal discovery analysis (PCMCI+) empirically verified ~~the energy balance mechanism described by **?**~~this formulation, demonstrating that ~~vertical velocity (ω) exerts a stronger causal influence on monthly precipitation than local evaporation. This confirms that precipitation in the NWSA is dynamically limited rather than moisture-limited during extreme events.~~

~~**Filtering of decoupled regimes:** Comparative evaluation using scatterplots and correlation maps revealed that purely thermodynamic indices (e.g., CAPE or GDI) produce inconsistent signals during regimes of subsidence-capped instability, frequently showing high values associated with low precipitation anomalies (e.g., during the 2016 El Niño). The BWR effectively filters out these "thermodynamic false positives" by incorporating the vertical velocity constraint, yielding a more robust diagnostic for moisture-deficit events.~~

~~**Robustness in extremes:**~~ ~~The~~ the BWR preserves the dominant causal route to precipitation over other individual thermodynamic or dynamic variables, capturing the dynamic trigger required to realize convection. Furthermore, the upper tail dependence analysis ~~of the BWR components revealed that while thermodynamic instability (ΔT) exhibits asymptotic independencefrom extreme precipitation, the coupled BWR index achieves robust asymptotic dependence ($\lambda_U \approx 0.8$). This indicates that the BWR captures the non-linear coupling required for extreme rainfall, filtering out cases where dynamic forcing is insufficient despite high instability~~based on empirical copulas confirmed the index's robustness during climate extremes. While isolated thermodynamic variables exhibit asymptotic independence, the BWR demonstrates strong asymptotic tail dependence, proving to be a highly reliable diagnostic specifically for the most extreme hydroclimatic events.

~~**Predictability and monitoring:** The integration of the thermodynamic component (~~As a diagnostic proxy, the BWR systematically outperforms established thermodynamic indices because it explicitly quantifies the realized mesoscale atmospheric response rather than just the precursor potential. Furthermore, while isolated mid-level vertical velocity dictates instantaneous convection, its high-frequency volatility limits its utility for monitoring. By integrating ΔT~~) confers significant signal persistence to the BWR, anchoring the chaotic variability of vertical motion to the thermal memory of the ocean boundaries. This characteristic makes the BWR a more stable and practically useful tool~~ , the BWR mathematically inherits the thermal inertia of the oceanic boundary conditions. This integration imparts greater signal persistence to the index, making it a slightly more stable proxy for sub-seasonal ~~monitoring than kinematic variables alone.~~ operative monitoring.

~~Future work should focus on integrating a moisture entrainment parameter to resolve the limitations in moderate regimes and exploring the application of the BWR to other tropical regions dominated by the Walker circulation~~Ultimately, the operational value of the BWR emerges in its prognostic application. By substituting predicted precipitation anomalies from SEAS5 with the predicted BWR anomalies, the predictions slightly overcome the limitations of the sub-grid parameterization inherent in the model. Relying instead on explicitly resolved mesoscale variables governed by primitive equations, the BWR systematically improves seasonal predictive skill during the peak of the austral summer and mitigates the forecast degradation caused by the boreal spring predictability barrier.

Appendix A

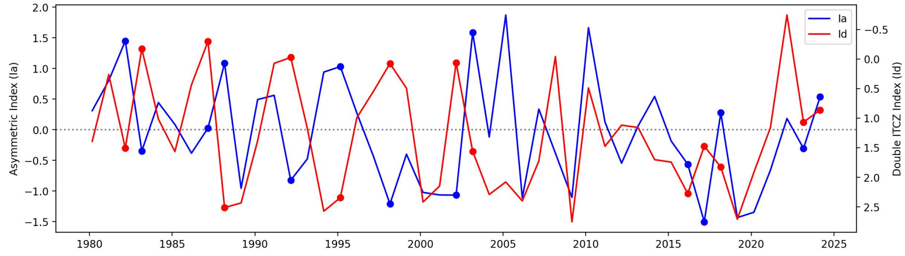

Figure A1. Time series of the March Ia and Id indices for the period 1981–2025 taking the same areas proposed by ~~?~~ Aliaga-Nestares et al. (2023).

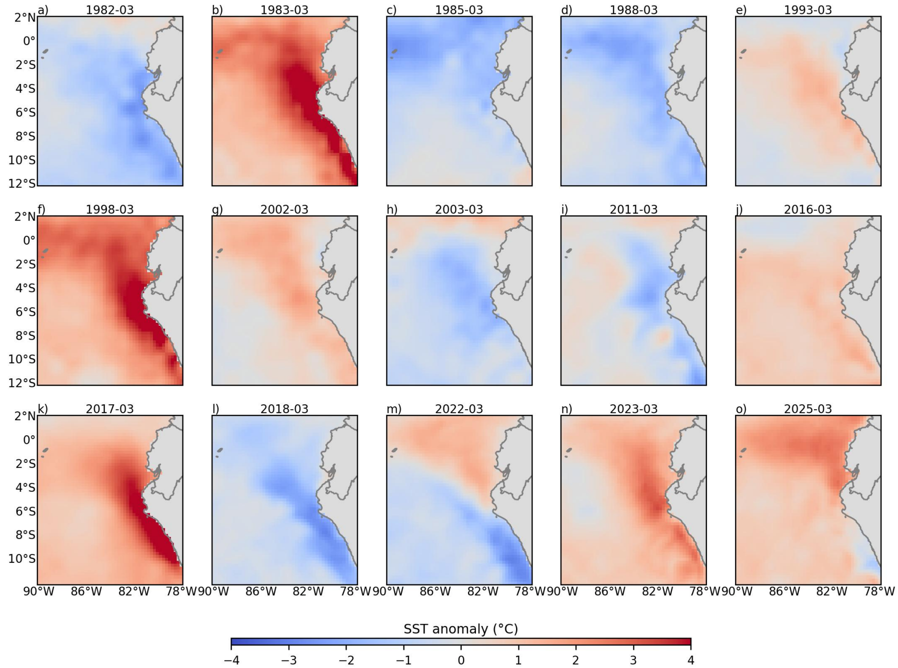

Figure A2. ~~Spatial distribution of RMSE in mm month^{-1}~~ SST anomaly over the Niño 1+2 region from ERA5 for the ~~common period 1981–2015. Anomaly precipitation was estimated using linear regression based on five convective indices: CAPE (a-c), BWR (d-f), GDI (g-i), (h-l) Ia, and (m-o) Id~~extreme hydroclimatic events identified in Section 4. The ~~RMSE was calculated by comparing the estimates against three precipitation anomaly products: ERA5 (left column), PISCO~~ blue (~~middle column~~red) ~~, and RAIN4PE~~ shaded colors indicate negative (~~right column~~positive) anomalies of SST. ~~Values are only displayed for pixels with a significant regression ($p < 0.05$)~~Taking the 1981–2025 median as climatology.

~~(Continued).~~

~~NWSA adjacent to Niño 1+2 area (81.25° W–78.5° W, 8° S–0.75° N).~~

~~SST anomaly from ERA5 for the rainiest and driest events identified in Sect. 4 over the Niño 1+2 region. The blue (red) shaded colors indicate negative (positive) values of SST.~~

~~Same as Fig. 13, but for the ω at 500 hPa.~~

~~Same as Fig. 13, but for the 400–700 hPa ΔT.~~

Code and data availability. PISCO V2.1 dataset is available at https://iridl.ldeo.columbia.edu/SOURCES/.SENAMHI/.HSR/.PISCO/index.html; RAIN4PE at https://datapub.gfz-potsdam.de/download/10.5880.PIK.2020.010enouiv/; ERA5 reanalysis and SEAS5 data at https://cds.climate.copernicus.

Author contributions. All authors designed the study, analyzed and interpreted the results, and wrote and reviewed the manuscript.

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