



Subseasonal-to-seasonal predictability of the 2024 El Niño-induced Amazon drought

Prakrut Kansara¹, Benjamin Zaitchik¹, Augusto Getirana^{2,3}, Liana O. Anderson⁴, Paul Block⁵, Sujay Kumar², Carlos F. Mena^{6,7,8}, William K. Pan⁹

- 5 ¹Department of Earth and Planetary Sciences, Johns Hopkins University, Baltimore, Maryland, 21210, United States of America
²Hydrological Sciences Laboratory, NASA Goddard Space Flight Center, Greenbelt, MD, USA
³Science Systems and Applications Inc., Lanham, MD, USA
⁴National Institute for Space Research – INPE, São José dos Campos, São Paulo, Brazil
10 ⁵Department of Civil and Environmental Engineering, University of Wisconsin-Madison, Madison, WI, USA
⁶Institute of Geography, Universidad San Francisco de Quito USFQ, Quito 170901, Ecuador
⁷Galapagos Science Center, Universidad San Francisco de Quito USFQ and University of North Carolina-Chapel Hill, San Cristobal, Galapagos, Ecuador
⁸School of Biological and Environmental Sciences, Universidad San Francisco de Quito USFQ, Quito 170901, Ecuador
15 ⁹Nicholas School of the Environment and Duke Global Health Institute, Duke University, Durham, NC, USA

Correspondence to: Prakrut Kansara (pkansar3@jhu.edu)

Draft prepared for Hydrology and Earth System Sciences (HESS)

20

Abstract. The 2023–2024 Amazon drought, driven by the concurrence of an El Niño and positive sea surface temperature anomalies in the tropical North Atlantic, resulted in historically low streamflow and widespread social and ecosystem impacts. To evaluate terrestrial subseasonal-to-seasonal (S2S) predictability during this event and assess its cascading impacts on regional wildfire potential, we develop an S2S Amazon Land Data Assimilation System (Amazon-LDAS). By integrating dynamical meteorological forecasts into a high-resolution land surface and routing model, we generated 5 km daily hydrometeorological forecasts at up to a 6-month lead to evaluate the propagation of predictability from atmospheric forcings to land surface states. Results indicate that dynamical forecasts initialized at up to 3-month leads captured the drought's spatial footprint, although 1-month lead forecasts provided overall best detection. Root zone soil moisture (RZSM) forecasts demonstrated significantly high probabilistic skill with a 74% improvement over persistence forecasts, highlighting the improvement in skill due to hydrologic memory in the basin. Streamflow forecasts also showed high skill throughout the drought event at all forecast initializations. However, integrated autocorrelation analysis indicated that this statistical skill in streamflow is partially influenced by internal hydrologic memory biases. This means that the modelling framework exhibited routing sluggishness, retaining dry anomalies within the channel network longer than the retrospective baseline, which inflated



streamflow forecast metrics. Additionally, utilizing S2S RZSM forecasts as a proxy for fire risk doubled the probability of
 35 detection (POD) of fires in the arc of deforestation compared to concurrent meteorological metrics. Hydrologic memory in
 land surface and routing allows improvement of terrestrial skill in hydrometeorological forecasting at long lead times (up to 3
 months ahead) and improve the prediction of extreme event impacts on the Amazon ecosystem when accounting for intra-
 regional memory biases. Building on these findings, we provide an operational hydrometeorological outlook for October 2026
 in the context of currently developing El Niño to demonstrate the system's capacity to support early warning.

40 1 Introduction

The Amazon basin's hydroclimate is strongly modulated by large-scale ocean-atmosphere teleconnections, predominantly the
 El Niño-Southern Oscillation (ENSO) and the Atlantic Meridional Mode (AMM) (Cai et al., 2020; Ciemer et al., 2020). During
 the El Niño phase, a disruption of the Walker circulation induces anomalous air subsidence, a widespread sinking of air mass
 that suppresses deep convection, over northern South America, driving negative precipitation (P) anomalies that lead to drought
 45 conditions (Poveda et al., 2006). This drying mechanism was extensively documented during the droughts of 2005, 2010, and
 2015–2016, when basin-wide deficits exceeded 250 mm in central Amazonia, and main stem discharge at Óbidos dropped
 nearly 20% below the long-term average (Fassoni-Andrade et al., 2021; Jiménez-Muñoz et al., 2016; Marengo et al., 2011;
 Zeng et al., 2008). Recently, the exceptional 2023–2024 drought was driven simultaneously by strong El Niño and positive
 sea surface temperature (SST) anomalies in the tropical North Atlantic (Espinoza et al., 2024). This coupled atmospheric
 50 forcing severely depleted deep root-zone soil moisture (RZSM) and drove extreme surface water drawdowns; for instance, the
 Rio Negro, at the Port of Manaus, fell to its lowest stage in over 120 years of continuous observation (Fleischmann et al.,
 2025). Exacerbating these hydrological deficits, the 2023–2024 period was marked by an increased frequency of compound
 drought and heatwaves that affected half of the Amazon region, driving severe thermal spikes in river temperatures that
 exceeded the biological coping capacity of local aquatic species (Ferreira et al., 2025).
 55 Under current anthropogenic warming trends, the frequency and intensity of these hydroclimatic events are accelerating,
 creating compounding events, which increases the challenges for subseasonal-to-seasonal (S2S) predictability frameworks as
 extreme regimes become the new baseline. Observational studies demonstrate a structural lengthening of the Amazonian dry
 season, characterized by an 18% reduction of total rainfall and an accelerated depletion of hydrologic memory (Gatti et al.,
 2021). During these extended dry periods, deep RZSM, which strongly influences the partitioning of sensible and latent heat
 60 fluxes in land surface models, frequently drops to critical thresholds across southern Amazonia (Baker et al., 2009; Singh et
 al., 2024). Furthermore, future projections under coupled land-use and global warming scenarios indicate the dry season length
 in the Amazon could increase by up to 69%, accompanied by maximum daily temperature anomalies reaching 14°C higher
 than current norms by the end of this century (Bottino et al., 2024; Dutra et al., 2026a). Localized land-use changes, fires, and
 forest fragmentation compound these shifts, altering the biome's surface roughness and energy balance. By disrupting the
 65 region's intense moisture recycling, widespread deforestation amplifies runoff variability and diminishes dry-season baseflow



contributions, severely increasing the likelihood of the biome irreversibly transitioning from an energy-limited to a strictly water-limited hydrological regime (Brando et al., 2026; Costa et al., 2003).

The propagation of these hydrologic anomalies through the regional water balance drives significant socioeconomic disruptions. During the 2023–2024 event, stage heights across major tributaries, including Rio Negro and Solimões, fell to their lowest recorded levels in over a century of gauge observations (Wagner et al., 2024). Satellite observations of equivalent historical droughts demonstrate that such drawdowns can reduce seasonal surface water extent by over 3.5 million hectares (Ferreira et al., 2025; Maciel et al., 2024; Souza et al., 2020). Sudden loss of hydraulic connectivity in the rivers severely restricts inland navigation along critical economic corridors. For instance, operational draft limits along the Madeira River were reduced by up to 50% during the peak of the 2023–2024 drought. This extreme drought disrupted regional supply chains, severely restricting access to food, medicine, and markets for remote, indigenous, and riverine communities that rely entirely on river networks for transportation (Beveridge et al., 2024; Fleischmann et al., 2025). Reduced discharge during recent hydroclimatic extremes forced major hydropower facilities, such as the Santo Antônio and Jirau dams, to operate below 15% of their installed capacity (Arias et al., 2020; da Silva et al., 2025). This streamflow (Q) deficit strains the interconnected power grids of Brazil, Colombia, and Ecuador, nations where hydropower constitutes approximately 60–70% of the national energy production (Naranjo-Silva et al., 2026).

Anticipating the onset and severity of these cascading extremes requires extending predictability well beyond standard synoptic timescales. S2S forecasting systems specifically targeting the seasonal time horizon from 2–6 months can provide the actionable lead times required for operational drought and water resource management (Keating et al., 2021; Vitart et al., 2017; White et al., 2017; Yang and Block, 2023). However, season-ahead prediction of terrestrial extreme events remains challenging. Dynamical meteorological models often lose deterministic skill within 3–4 weeks (Mariotti et al., 2020; Merryfield et al., 2020). Additionally, operational global forecasting models frequently rely on generalized routing physics. For example, the Global Flood Awareness System (GloFAS) uses global parameters that may misrepresent floodplain attenuation and bidirectional river-floodplain exchanges inherent to the Amazon basin (Alfieri et al., 2013; Fleischmann et al., 2020; Paiva et al., 2013b). Regional S2S efforts address some of these limitations but face constraints from sparse in-situ assimilation data and coarse atmospheric forcings (Towner et al., 2019). Although data-driven deep learning architectures have recently achieved benchmark performance in short-term streamflow prediction, their operational application at extended lead times faces fundamental structural limitations (Kratzert et al., 2019; Nearing et al., 2024; Reichstein et al., 2019; Shen, 2018). Because these algorithms operate within the statistical bounds of their training data, they inherently struggle to extrapolate the non-stationary dynamics of out-of-distribution extremes, such as the unprecedented 2023–2024 drought. More critically for S2S applications, these models lack the explicit physical constraints required to enforce mass and energy conservation. Without strict closure of the water and energy balance, small prognostic errors in moisture accounting accumulate over consecutive weeks, ultimately decoupling the model from the deep subsurface memory needed to sustain extended lead forecasts.

Regional S2S hydrological forecast systems typically integrate dynamic meteorological forecasts, downscaling methods, and high-resolution land surface or hydrological models (Hazra et al., 2023; Li et al., 2026). This integration leverages



- 100 predictability from both meteorological boundary conditions and initialized terrestrial states. While meteorological forcings are primary drivers at extended lead times, accurately initialized deep root-zone soil moisture and surface inundation can extend forecast skill beyond the typical atmospheric predictability limit (Koster et al., 2010; Paiva et al., 2013a; Wood et al., 2016). In the tropics, precipitation forecast skill decays rapidly due to chaotic convective processes. However, the Amazon's extensive river networks and deep vegetation roots generate considerable hydrologic memory, providing an opportunity for
- 105 properly initialized hydrological models to contribute skill at 2-3 months lead time.
- Propagating land-surface memory deficits into reliable forecasts of secondary ecological disturbances, such as widespread wildfires, introduces significant nonlinearities. While physical S2S frameworks can successfully predict the elevated vapor pressure deficits (VPD) that precondition the canopy for combustion, actual fire regimes in the fragmented Amazonian biome remain heavily dictated by anthropogenic land management, notably slash-and-burn agriculture (Alencar et al., 2015;
- 110 Anderson et al., 2022; Brando et al., 2020a; Fernandes et al., 2011), and can result in substantial evapotranspiration disturbances (Ahmad et al., 2026). This fundamental decoupling between physically driven landscape flammability and stochastic human ignitions restricts the predictive limit of hydrometeorological models, confining their operational utility to projecting fire susceptibility rather than deterministic fire occurrence. However, leveraging the hydrologic memory of the system, the susceptibility to fire risk based on hydroclimate conditions can potentially be anticipated and improved.
- 115 Our primary objectives for this study are to:
- Evaluate dynamical forecast skill for hydrological variables (P, RZSM and Q) relative to persistence during a major El Niño induced drought event.
 - Assess hydrologic memory biases between retrospective land states and dynamical forecasts to evaluate the limits of land surface state initialization.
 - Assess the feasibility of leveraging S2S terrestrial predictability to forecast low flows and regional fire risk proxies under severe El Niño conditions.
- 120

2 Data and Methods

- This study develops the Amazon Land Data Assimilation System (Amazon LDAS) built using NASA's Land Information System (LIS) (Kumar et al., 2006), which is used to evaluate the terrestrial predictability of the system during the July-
- 125 September (JAS) 2024 El Niño drought as a case study. The Amazon LDAS consists of a retrospective monitoring system and a dynamical S2S forecast system. The retrospective system is utilized to establish the baseline for comparison of forecasts and generate initial land surface states for the forecast model. The following subsections detail the datasets (section 2.1), the specific configurations of the modelling pipeline (section 2.2), statistical metrics for forecast evaluation (section 2.3), method to quantify hydrologic memory (section 2.4), and framework for forecasting fire risk (section 2.5).



130 2.1 Data

2.1.1 Retrospective meteorological forcings

Baseline historical simulations are driven by the Integrated Multi-satellitE Retrievals for GPM (GPM-IMERG) V07B Final run for P (IMERG Technical documentation, 2020). Near surface meteorological forcings (downward longwave and shortwave radiation, air temperature, specific humidity, surface air pressure, and wind speed) are sourced from the NOAA Global Data
135 Assimilation System (GDAS) (Kleist et al., 2009). These forcings are acquired at 6-hourly intervals and harmonized within the Land Data Toolkit (LDT), a component of LIS for processing input forcings and parameters, to a 0.125° spatial resolution (Arsenault et al., 2018).

2.1.2 Dynamical S2S meteorological forecast forcings

Dynamically-generated meteorological fields are extracted from the NASA Goddard Earth Observing System S2S forecast
140 version 2 (GEOS-S2S v2) (Molod et al., 2020). To evaluate the JAS drought, forecasts initialized at the end of the preceding months corresponding to May 1 (3-month lead), June 1 (2-month lead), and July 1 (1-month lead) from 2001 to 2024 are used. For the initialization dates used in this study, GEOS-S2S v2 provides 9-month meteorological forecasts at a 0.5° spatial resolution for the required atmospheric variables.

2.1.3 Observational and reanalysis evaluation datasets

145 Retrospective and forecast predictions are evaluated against the Standardized Precipitation Evapotranspiration Index (SPEI) and Standardized Precipitation Index (SPI) at 1- and 3-month accumulation periods from the ECMWF Reanalysis v5 (ERA5) (Keune et al., 2025). Vertically integrated moisture divergence from ERA5 is analysed to evaluate atmospheric drivers (Hersbach et al., 2020). Fire risk areas are evaluated using the MODIS Burned Area product (MCD64A1) (Giglio et al., 2018).

2.2 Amazon land data assimilation system (Amazon-LDAS)

150 The modelling domain spans the Amazon basin from 6°N to 21°S latitude and 49°W to 82°W longitude (Figure S1). Simulations are performed at a 5 km spatial resolution on a 15-minute computational time step, aggregating sub-daily outputs to daily averages and accumulation. The system operates in an uncoupled configuration between the atmosphere and land surface.

2.2.1 Retrospective (Reanalysis) system

155 The retrospective configuration generates historical land surface states from January 1, 2001, to the present using the Noah-Multiparameterization (Noah-MP v4.0.1) land surface model (He et al., 2023; Niu et al., 2011; Yang et al., 2011). Surface runoff and subsurface drainage are routed through the Hydrological Modeling and Analysis Platform (HyMAP) utilizing a grid-to-grid kinematic wave routing scheme (Getirana et al., 2017a, b, 2025, 2012). Atmospheric fields undergo spatial



downscaling within LDT using bilinear interpolation with lapse-rate adjustments. Static physiographic fields are constrained using the SRTM DEM, STATSGO/FAO soil taxonomy, and MODIS IGBP land cover (Sulla-Menashe et al., 2019). We incorporate MODIS-derived greenness vegetation fraction (GVF) maps to capture seasonal and interannual changes (Nie et al., 2018). A 40-year offline spin-up (cycling 2001–2020 data twice) ensures equilibrium of deep soil moisture and sub-surface storage. Simulations are executed in open-loop configuration without data assimilation. Output variables are detailed in Supplementary Table S1. Daily outputs are aggregated to monthly averages for all the analysis in this study.

2.2.2 Forecast system

The forecast system shares the spatial properties, surface parameterizations, and physics configurations of the retrospective system, differing only in meteorological forcings (Figure 1). Forecasts are initialized on the first day of each month, using initial conditions from the retrospective simulation runs. For meteorological forcings, raw daily weather forecasts from the 0.5° GEOS-S2S are downscaled to 0.125° using the Ensemble Generalized Analog Regression Downscaling (En-GARD) technique (Gutmann et al., 2022; Zamora et al., 2021) (referred to as GARD in the subsequent text for brevity). Downscaling coefficients are extracted by establishing a multi-linear analog regression across nine core atmospheric variables: 2 m air temperature (T2M), zonal and 10 m meridional wind components (U10M, V10M), 2 m specific humidity (Q2M), surface pressure (PS), downward longwave and shortwave radiation (LWS, SLRSF), total precipitation (PRECTOT), and convective precipitation (CNPRCP). GARD constructs a historical analog profile from a 2001–2023 historical training data, matching distributions using quantile mapping against GPM-IMERG for P and GDAS for other meteorological variables. This technique adjusts variances and means of the target variables to match statistical distribution of the observed training data without requiring an independent post-hoc bias correction. Daily totals are disaggregated to a 6-hourly time steps using scale-factor distributions derived from reanalysis climatology to maintain diurnal cycle variability.

A hindcast (i.e., forecasts of past events) baseline (2001–2023) was generated for comparison with retrospective historical outputs. Because the operational 7-member GEOS-S2S v2 archive is only available from 2017 onward, hindcast forcing spanning 2001–2016 contain only a single ensemble member. Consequently, the derived hydrologic hindcast record matches this constraint, generating a single-member forecast prior to 2017 and a 7-member ensemble forecast post 2017. Forecast outputs are truncated at a maximum lead time of 6 months. The output variables by the forecast system matches the retrospective configuration and is provided in Supplementary Table S1. Daily forecast outputs are subsequently averaged into monthly time scale for all the analysis conducted in this paper.

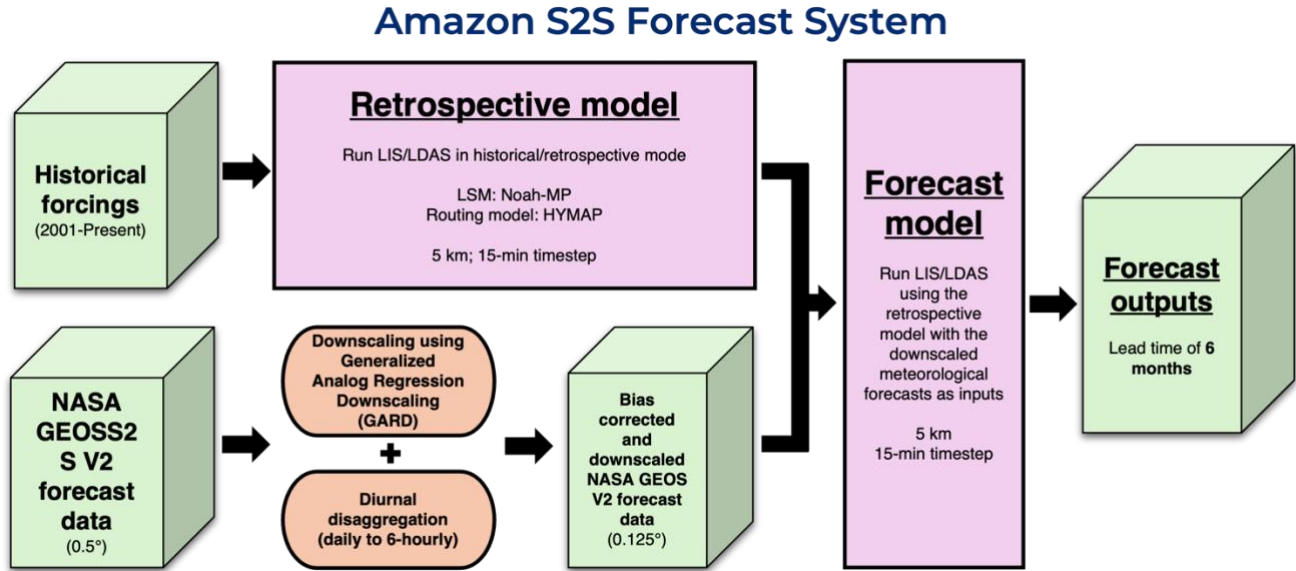


Figure 1: Schematic overview of the Amazon forecast system.

2.3 Drought detection and forecast verification metrics

Drought conditions are defined using standardized RZSM anomalies. A threshold of ≤ -2 is applied to standardized RZSM anomalies, equivalent to the D4 (exceptional drought) category defined by the U.S. Drought Monitor (Svoboda et al., 2002). Spatial agreement between the forecasted and retrospective drought extents is evaluated using the following detection metrics: probability of detection (POD), false alarm ratio (FAR), critical success index (CSI), and frequency bias (FBIAS) (Roebber, 2009). Forecasts are evaluated for deterministic and probabilistic skill, comparing the dynamical GEOS-S2S driven forecasts against a statistical anomaly persistence baseline. For each target variable, this baseline assumes that the anomaly calculated at the date of initialization remains constant throughout the 6-month forecast horizon. Deterministic skill is evaluated using the anomaly correlation coefficient (ACC) by calculating Spearman's rank correlation coefficient (Jolliffe and Stephenson, 2012) as defined by:

$$ACC(\rho) = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \quad (1)$$

where d_i is the difference between the ranks of the forecast and observed anomalies, and n is the total number of observations. ACC values range from -1 to 1, with 0 indicating no forecast skill, and 1 denoting perfect positive correlation skill and -1 showing perfect negative correlation skill. Probabilistic skill is quantified using the ranked probability skill score (RPSS), evaluating the forecast distribution across tercile categories (below normal, normal, above normal) (Weigel et al., 2007). The tercile thresholds (33.3rd and 66.7th percentiles) are calculated independently for the hindcast dataset and the retrospective dataset over the common 2001–2023 base period. The RPS is defined as:



$$RPS = \frac{1}{n} \sum_{t=1}^n \sum_{k=1}^K (\hat{P}_{t,k} - Y_{t,k})^2 \quad (2)$$

where, K denotes the number of categories, n denotes the total number of observations, $\hat{P}_{t,k}$ is the forecast probability for the k^{th} category at time t , and $Y_{t,k}$ is the historical forecast probability for the same category. Further, we define $y_{t,k}=1$ if the t^{th} observation is in category k , and $y_{t,k}=0$ otherwise. The baseline reference ranked probability score (RPS_{clim}) is defined by equal-probability climatological distribution (33.3% probability per category), representing true predictive ignorance. RPSS is derived by comparing RPS to a baseline climatological forecast (RPS_{clim}):

$$RPSS = 1 - \frac{RPS}{RPS_{\text{clim}}} \quad (3)$$

RPSS values range from $-\infty$ to 1, where 1 indicates perfect skill, and values ≤ 0 indicate no skill compared to climatology. Because standard parametric p-values are invalid in the presence of the spatial autocorrelation inherent to large hydrologic networks like the Amazon, all statistical significance testing for spatial ACC and domain-averaged RPSS is conducted using non-parametric Monte Carlo spatial permutations (Wilks, 2016). The spatial structure is randomly shuffled across 1,000 iterations to build a robust null distribution for determining field significance. All domain averages for ACC and RPSS are cosine-weighted by latitude.

2.4 Hydrologic memory quantification

Hydrologic memory is defined as the persistence of anomalies in each variable, quantified by e-folding time (Amenu and Kumar, 2005; Piles et al., 2022; Tokuda and Dirmeyer, 2026). We calculate the e-folding time across three primary variables representing the atmospheric (P), land surface (RZSM), and river flow (Q) branches of the system. The e-folding time was calculated based on anomalies for each variable for the 2001-2023 time period. The autocorrelation function, $\rho(\tau)$, of the temporal anomaly series is related to the e-folding time scale, τ_e , under the assumption of a first-order Markov process:

$$\rho(\tau) = e^{-\frac{\tau}{\tau_e}} \quad (4)$$

where $\rho(\tau)$ is the autocorrelation at lag time τ , and τ_e represents the time required for the autocorrelation to decay to $1/e$ (≈ 0.368) which represents the memory of the corresponding variable.

Systemic memory bias in the forecast system is evaluated using the integrated autocorrelation (area under the curve, AUC) to isolate whether S2S skill scores are being artificially inflated or degraded in the forecast system. While the true physical memory of the basin is established using a 12-month retrospective lagged autocorrelation, the systemic memory bias must be evaluated over identical temporal horizons. As the dynamical forecasts are constrained to a 6-month lead time, the AUC for both the forecast and the retrospective baseline is integrated up to lag $\tau=5$ months. For each of the three initializations (May, June and July), we calculate the memory bias based on the identical reference period (2001-2023) for retrospective outputs and hindcasts. The systemic memory bias is quantified as the difference in these integrated areas:



$$\text{Memory bias} = \int_0^5 \rho_{\text{hindcast}}(t)dt - \int_0^5 \rho_{\text{retrospective}}(t)dt \quad (5)$$

2.5 S2S fire risk forecasts

Hydrometeorological forecasts are converted into a predictive fire risk framework and validated against the MODIS Burned Area product (MCD64A1) aggregated from its native 500 m resolution to the 5 km Amazon-LDAS grid. First, we mask the domain to isolate ‘Climatological fire prone’ areas, defined as any 5 km pixel where the underlying 500 m MODIS data indicates an aggregate burned area exceeding 25% at least once during 2001–2023. Within this masked domain, the base climatological fire activity/burned area ($\overline{BA}$) is calculated as the mean percentage of burned area per pixel averaged across 2001–2023. Elevated fire risk (EFR) is defined as the relative departure from the climatological mean burned area:

$$EFR_{\text{obs}} = \frac{BA_{2024} - \overline{BA}}{\overline{BA}} \quad (6)$$

EFR values of greater than zero represent higher than normal fire conditions whereas EFR values less than zero represent lower than normal fire conditions. We compare this observed EFR against forecasted fire risk probabilities derived from two proxy methodologies which measures the fuel moisture rather than fuel load:

1. **Method 1 (land surface proxy):** A pixel is flagged for high fire risk if the ensemble probability of forecasting below-normal RZSM (falling into the lower tercile) exceeds 60%.
2. **Method 2 (meteorological proxy):** A pixel is flagged if the joint probability of exceedance for below-normal P (60% probability) and above-normal air temperature exceeds 60%.

Fire risk detection from these two S2S fire risk proxies is evaluated using the POD, FAR, CSI, and fractional area (% Area) detection metrics.

3 Results

3.1 Atmospheric drivers and evolution of the 2023–2024 Amazon drought

The 2023–2024 El Niño triggered a cascading, multi-year drought in the Amazon basin. Analysis of vertically integrated moisture transport (IVT) during the JAS 2024 season shows this disruption in the basin's hydrologic cycle (Figure 2). Compared to the 2001–2023 climatological mean, the 2024 IVT anomaly field exhibits a pronounced northwestward moisture divergence. Instead of penetrating deep into the basin, the easterly trade winds that typically deliver Atlantic moisture were diverted northward, driving moisture away from the basin which serves as its primary precipitation source. While El Niño typically induces dry conditions across the northern and northeastern Amazon (Kansara et al., 2025; Reboita et al., 2021), the sustained moisture deficits in 2024 were further influenced by thermodynamic anomalies in the Atlantic. Positive sea surface temperature anomalies in the tropical north Atlantic (TNA) altered the local meridional divergent circulation (the Atlantic



Hadley cell). This anomalous TNA warmth shifted the upward branch of the Hadley circulation convergence northward and away from the Amazon, inducing a persistent downward motion branch over the basin that suppressed regional convection. The temporal evolution of this atmospheric deficit is reflected in the basin averaged standardized drought indices. Both the 3-month SPI-3 and SPEI-3 indicated exceptional D4 drought conditions starting in August 2023 (Figure 3). SPEI-3 concurrently highlights the significant contribution of atmospheric thermodynamic demand (elevated vapor pressure deficit) to the drought's severity. After a brief recovery in the wet season to moderate drought conditions, the basin had dropped back into D4 conditions in JAS 2024, with the basin averaged SPI-3 dropping to a minimum of -4 in August 2024. During this period, studies reported historically low Q throughout the basin (Espinoza et al., 2024), with discharge at the Manaus gauge dropping to 12.7 m on October 26, 2023, its lowest since 1902 (Ribeiro et al., 2024).

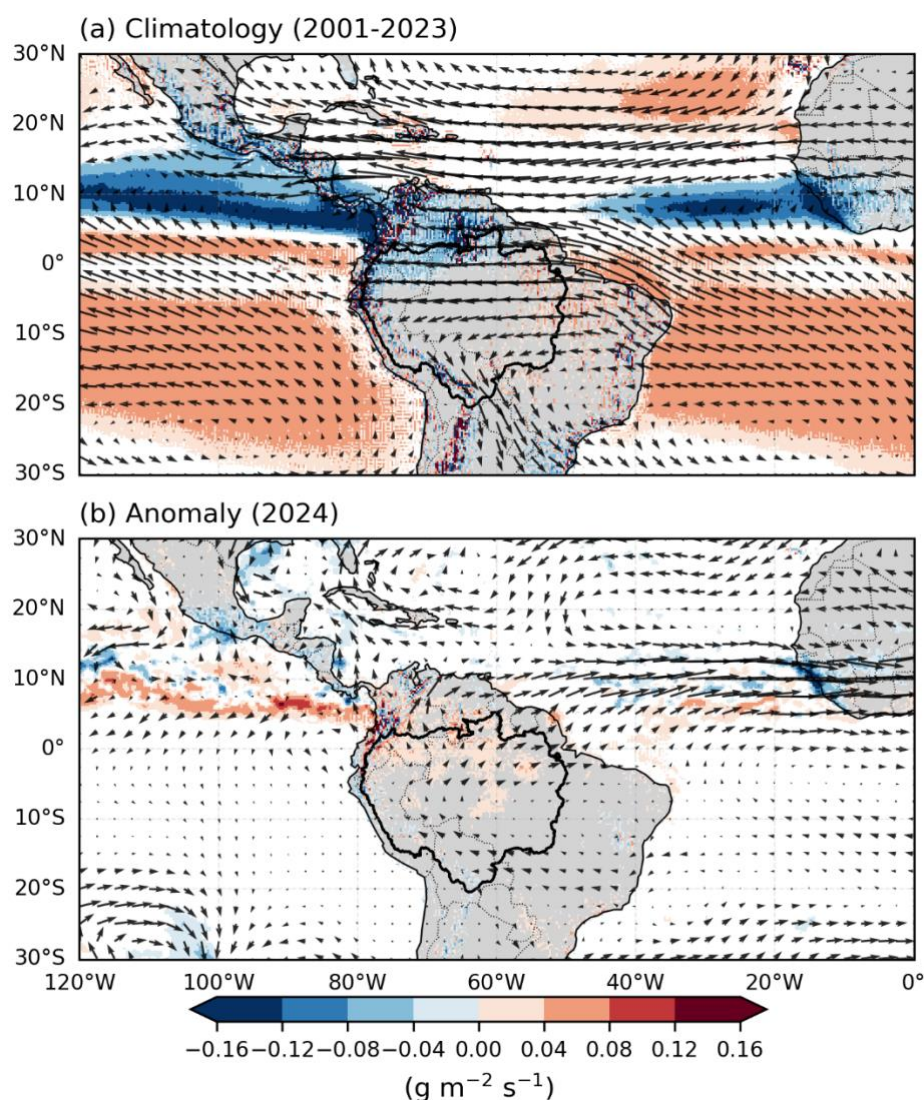


Figure 2: Vertically integrated moisture flux and divergence over the broader region around the Amazon basin. The top panel (a) shows the 2001–2023 climatological mean for the July-August-September (JAS) season, while the bottom panel (b) displays the JAS 2024 anomaly. Vector arrows indicate moisture flux direction and magnitude, and shading represents moisture divergence (positive/red) and convergence (negative/blue).

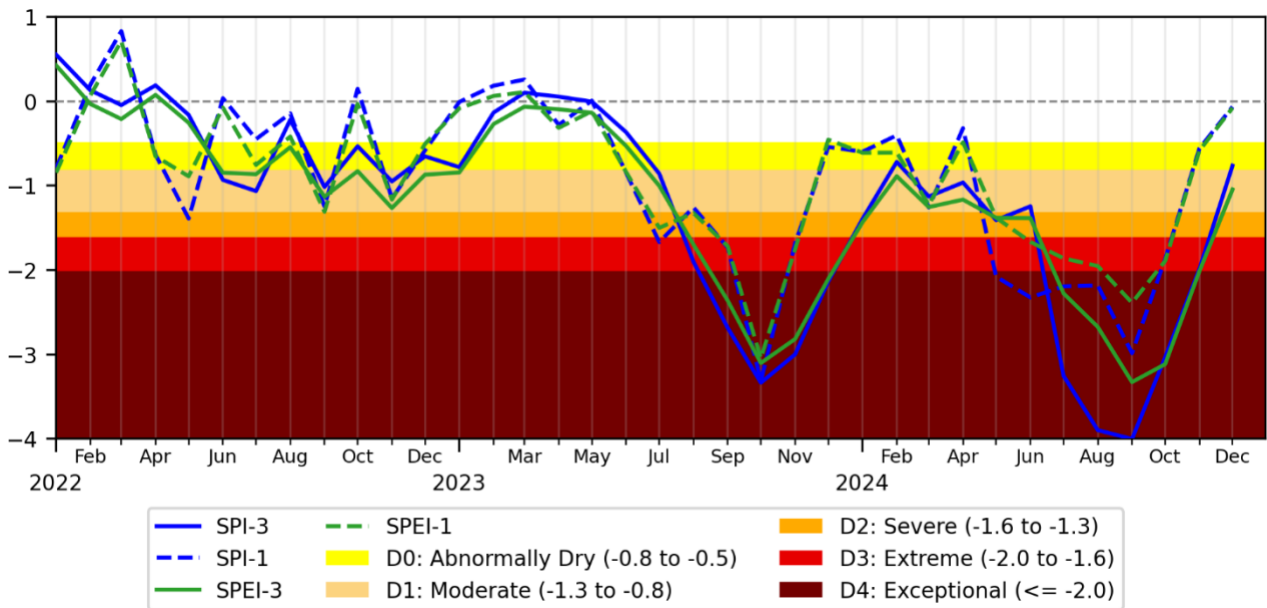


Figure 3: Basin-averaged temporal evolution of the 2023–2024 Amazon drought. Time series display the 1-month and 3-month Standardized Precipitation Index (SPI) in blue and Standardized Precipitation Evapotranspiration Index (SPEI) in green. Background shading corresponds to the U.S. Drought Monitor categorical classifications, ranging from abnormally dry (D0; yellow) to exceptional drought (D4; dark red).

3.2 Spatial extent and S2S forecast skill for drought detection

Retrospective standardized anomalies were compared against the ERA5 SPEI-3 for the JAS 2024 period to evaluate the spatial drought representation (Figure 4). The ERA5 SPEI-3 field showed that the vast majority of the Amazon basin experienced D4 conditions, with exceptions limited to the far northern boundary regions in Venezuela and localized pixels along the Andes. The retrospective RZSM anomalies indicate a similar spatial pattern of extreme deficit. Anomalies reached extreme deficits across the Negro and Solimoes subbasins, as well as the upstream reaches of the Tapajos subbasin. The northern regions being in the northern hemisphere have the dry season during December-March, potentially masking the drought effect. When evaluated against these retrospective baselines, the GEOS-S2S driven dynamical RZSM forecasts captured the large-scale drought footprint but exhibited lead-time dependent spatial biases. The 3-month lead initialization (May 1) provided the highest spatial agreement with the retrospective baseline, accurately forecasting widespread extreme conditions across the basin. However, at shorter leads of 2-month (June 1) and 1-month (July 1), a localized wet bias was observed. The analysis of

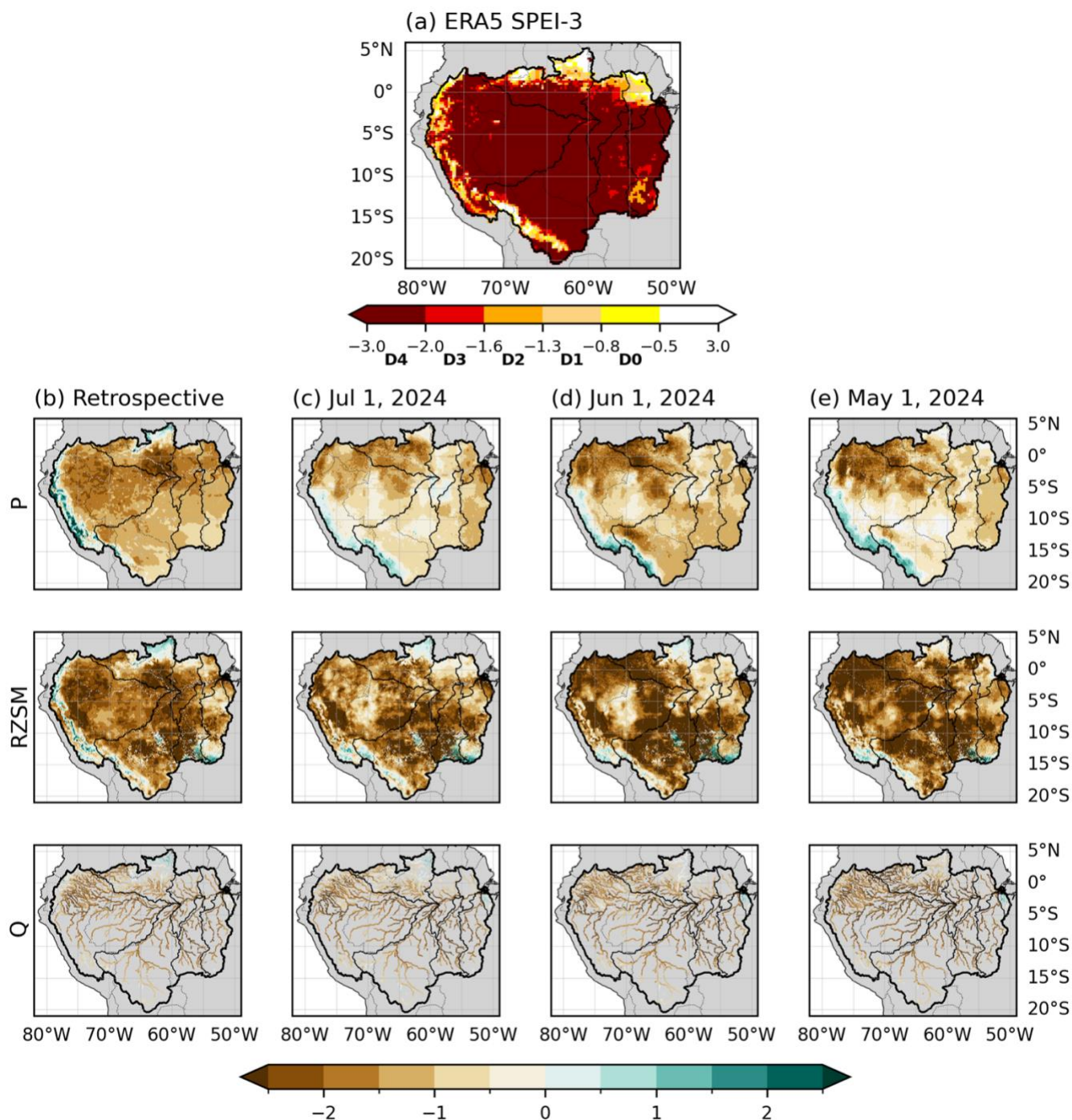


standardized anomalies of P, RZSM, and Q revealed that both the 2-month lead (June 1) and 1-month lead (July 1) initializations failed to capture the observed RZSM deficits in the central Solimoes subbasin, driven directly by a significant localized wet bias from dynamic atmospheric P forecasts. This degradation in deterministic skill at shorter lead times suggests that while the May 1 initialization successfully captured the persistent large-scale ENSO subsidence signal, the June and July atmospheric forecasts struggled to accurately resolve the localized influence of the rapid, subseasonal development of the anomalous Atlantic Hadley circulation, resulting in spurious convection. Despite localized deterministic errors, the probabilistic forecasts showed high confidence for the severity of the event, closely following the ERA5 SPEI-3 spatial extent with high probabilities (70–100%) in the below normal tercile (Figure S2).

Spatial detection skill for exceptional drought conditions (defined as standardized RZSM anomalies ≤ -2) was quantified by comparing forecasts against the retrospective baseline (Table 1). The evaluation indicates a trade-off between spatial coverage and precision as a function of lead time. The 3-month lead (May 1) initialization recorded the highest POD (0.75), capturing the largest fraction of the observed extreme drought area. However, this initialization overestimated the total drought footprint, resulting in an F-BIAS of 1.42 (a perfect F-BIAS score is 1). Conversely, the 1-month lead (July 1) initialization produced a more conservative spatial footprint. Although its POD was the lowest (0.62), influenced by the P wet bias in the central Solimoes subbasin, it demonstrated higher spatial precision. The July 1 forecasts recorded the lowest FAR (0.33) and the highest CSI (0.48), with an F-BIAS of 0.93, indicating the forecasted drought area closely aligned with the retrospective baseline.

Table 1: Drought spatial extent detection metrics comparing the retrospective and forecast RZSM anomalies ≤ -2 , capturing exceptional drought (D4) conditions across the basin. The best detection metric value across the initializations is in bold font.

Forecast initialization	Probability of detection (POD)	False alarm Ratio (FAR)	Critical success Index (CSI)	Frequency Bias (F-BIAS)
July 1, 2024	0.62	0.33	0.48	0.93
June 1, 2024	0.65	0.51	0.39	1.31
May 1, 2024	0.75	0.48	0.45	1.42

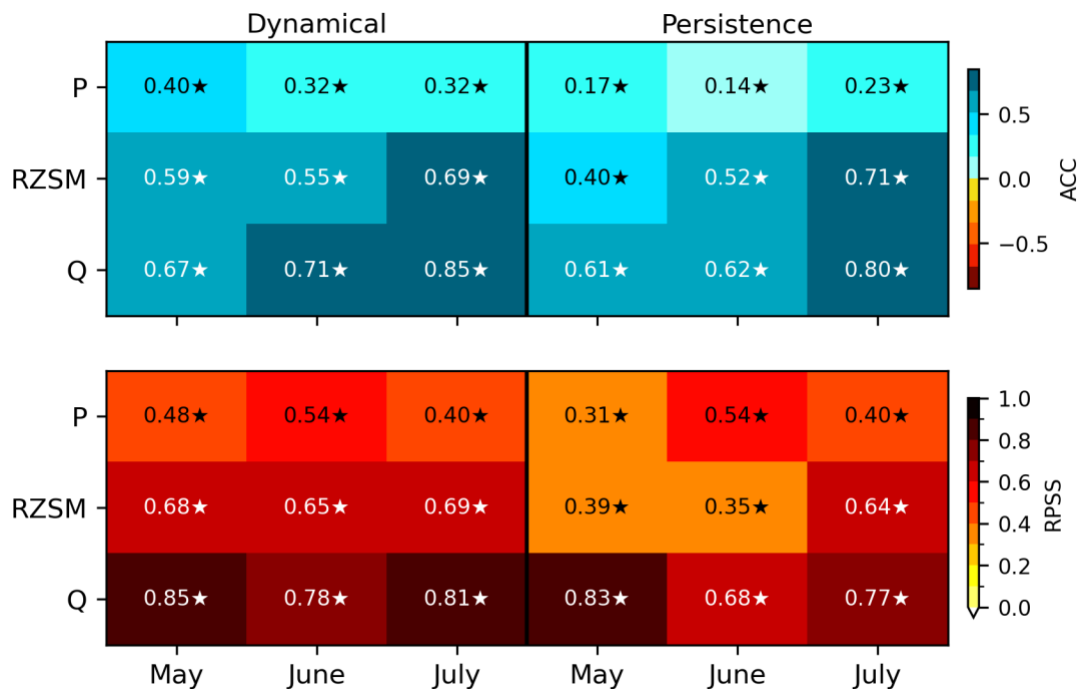


310 **Figure 4: Comparison of JAS 2024 between (a) ERA5 SPEI-3 and (b) the retrospective standardized anomalies against dynamical forecasts initialized on (c) July 1 (1-month lead), (d) June 1 (2-month lead) and (e) May 1 (3-month lead). All anomalies are computed relative to the 2001–2023 climatological baseline. Deterministic forecast anomalies are computed based on the seven-member ensemble mean.**



315 **3.3 S2S predictability in the atmospheric and terrestrial components**

The dynamical forecasts demonstrated significant deterministic (ACC) and probabilistic (RPSS) skill for the terrestrial components (RZSM and Q) across all initializations (Figure 5). As expected, P exhibited the lowest overall skill, reflecting the limited predictability beyond three to four weeks horizon. However, dynamical P forecasts provided a statistically significant improvement over persistence at the 3-month lead (May 1 initialization), where the dynamical RPSS (0.48) exceeded persistence (0.31). At shorter leads (June 1 and July 1), the probabilistic skill of the dynamical P forecast converged with persistence, yielding scores of 0.54 and 0.40, respectively. The May 1 initialization outperformed the shorter lead forecasts in both dynamical and persistence frameworks, consistent with its higher POD for the drought spatial extent. Predictability increased as the signal propagated through the hydrologic system, from P to RZSM and ultimately to Q. As the signal moved through the terrestrial components, dynamical forecast skill converged toward the persistence forecast due to the hydrologic memory of the land surface (Shukla and Lettenmaier, 2011). For RZSM, the dynamical model improved upon persistence for the May and June initializations (e.g., May RPSS 0.68 vs. 0.39). For Q, however, dynamical skill (RPSS 0.78–0.85) was only marginally higher than persistence (RPSS 0.68–0.83). At the 1-month lead (July 1), the deterministic ACC for RZSM persistence (0.71) slightly exceeded the dynamical forecast (0.69). This indicates that S2S terrestrial predictability in the Amazon during the dry season relies primarily on initial land surface conditions rather than dynamic atmospheric forcing.



330

Figure 5: Verification metrics summary for deterministic (Anomaly Correlation Coefficient; ACC) and probabilistic (Ranked Probability Skill Score; RPSS) forecasts evaluated against retrospective outputs for the JAS 2024 drought. The heatmap compares



1- to 3-month lead initializations (July 1, June 1, May 1 for 2024) across dynamical and persistence forecasts for precipitation (P), root zone soil moisture (RZSM), and streamflow (Q). Domain-averaged scores are displayed, with stars (*) denoting statistical field significance derived from Monte Carlo spatial permutations ($p \leq 0.05$).

Disaggregating this performance across the major subbasins (Figure S3) further illustrates the spatial heterogeneity of this predictability. Specifically, at the 3-month lead (May 1 initialization), the dynamical RZSM forecast shows significant probabilistic skill improvement in southeastern subbasins, such as the Tapajos (RPSS of 0.9 vs 0.12) and Xingu (0.79 vs - 0.07). Additionally, the spatial distribution of dynamical forecast RPSS exhibited intraregional variability (Figure S4). Skill in P forecasts in the central Amazon was near zero, while the northwestern and eastern parts of the basin showed higher predictability. The failure of shorter lead forecasts to capture the drought in the central basin corresponds to this lower P skill. However, hydrologic memory in RZSM and Q components filtered this atmospheric variability, maintaining high probabilistic skill across most of the basin. Exceptions occurred near the northern boundary and steep Andean gradients, where RZSM skill degraded while Q skill persisted.

Spatial maps of RPSS difference (Δ RPSS) evaluate the added value of dynamical meteorological forecasts over persistence (Figure 6). Monte Carlo permutations indicate that, for the May 1 initialization, both P ($\Delta\mu = +0.173$, $p < 0.001$) and RZSM ($\Delta\mu = +0.290$, $p < 0.001$) show statistically significant basin-wide improvements from the dynamical model. Q showed a marginal but statistically significant improvement ($\Delta\mu = +0.011$, $p < 0.001$). For the June 1 and July 1 initializations, dynamical Q forecasts provided no statistically significant improvement over persistence ($p = 0.746$ and $p = 1$, respectively). Regionally, May 1 dynamic P forecasts improved skill in the northeastern Amazon but reduced skill in the southern basin (Figure 6, top row). The skill reduction expanded across the central basin for the June 1 and July 1 initializations. For RZSM, the dynamical model improved skill across the eastern Amazon. The May 1 and June 1 initializations improved over persistence ($\Delta\mu = +0.29$ and $+0.305$), whereas July 1 provided only a smaller basin wide gain ($\Delta\mu = +0.047$). Spatial variability in Q skill differences was primarily confined to the northwestern basin, where the P wet bias degraded Q predictability for the May 1 and June 1 initializations relative to persistence.

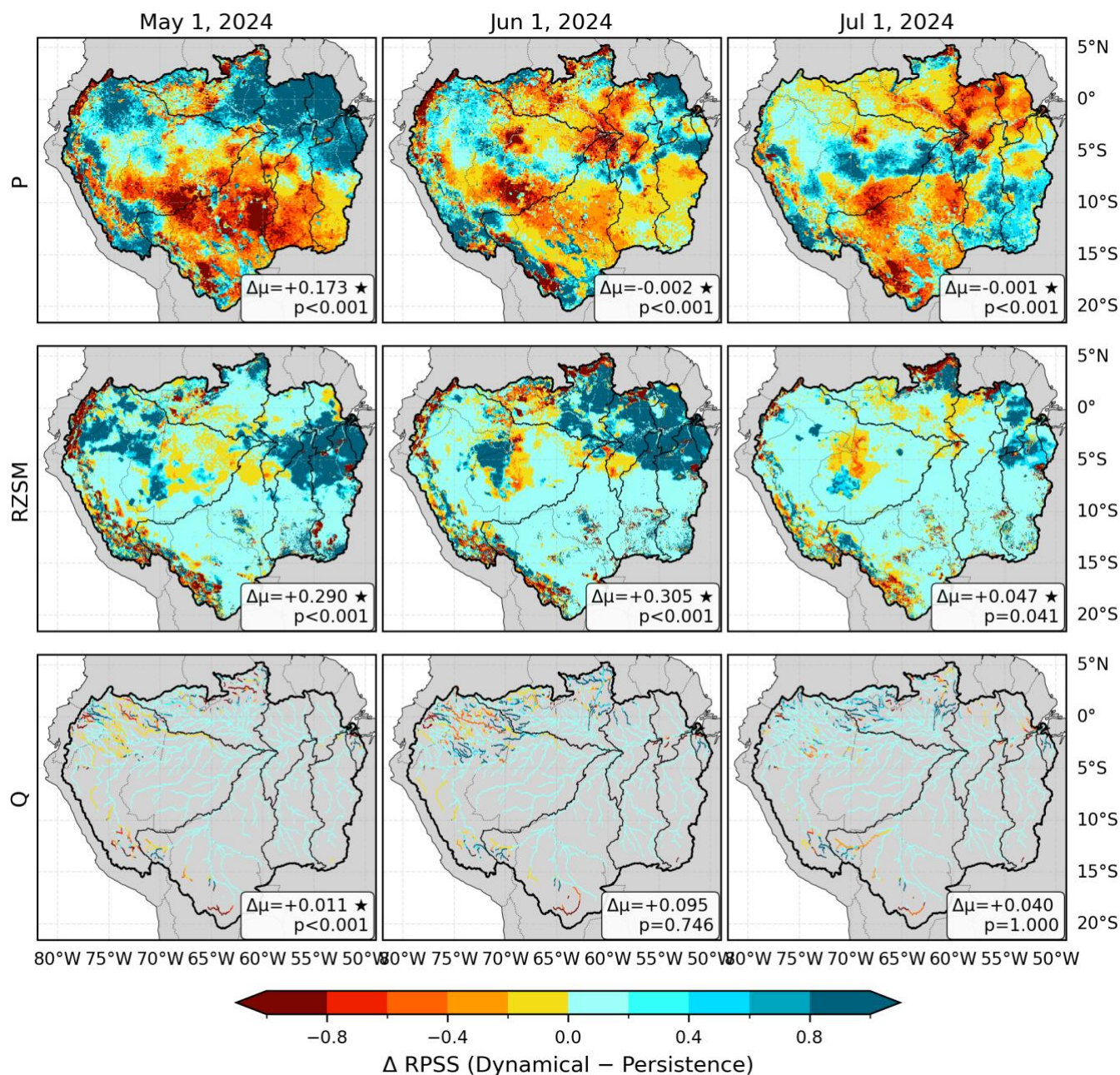


Figure 6: Spatial distribution of the difference in RPSS ($\Delta RPSS$) between the dynamical and persistence forecasts for the JAS 2024 season. Positive values (cyan/blue) indicate regions where the dynamical forecast provides added skill over persistence; negative values (yellow/red) indicate degradation by the dynamical boundary conditions. Inset text displays the basin averaged difference ($\Delta\mu$) and the Monte Carlo label permutation p-value for field significance.

3.4 Diagnosing land surface memory and its contribution to S2S forecast skill

To evaluate the sources of predictability, we analysed the hydrologic memory across the atmospheric and terrestrial components using the climatological baseline period of 2001-2023. We established the physical baseline by calculating the e-folding time scale of the retrospective model (Figure 7). Memory in P was less than one month across the domain, consistent with synoptic atmospheric time scales. Terrestrial buffering extended this memory: RZSM e-folding times in the Jupura and headwaters of Madeira subbasins were under two months, while the high Andes, and parts of Solimoes, Negro, and Madeira subbasins showed interannual memory. Within the routing network, Q e-folding times ranged from 6 to over 12 months, reflecting the routing processes of the basin's extensive soil reservoirs and channel networks (Getirana et al., 2017a; Paiva et al., 2013b).

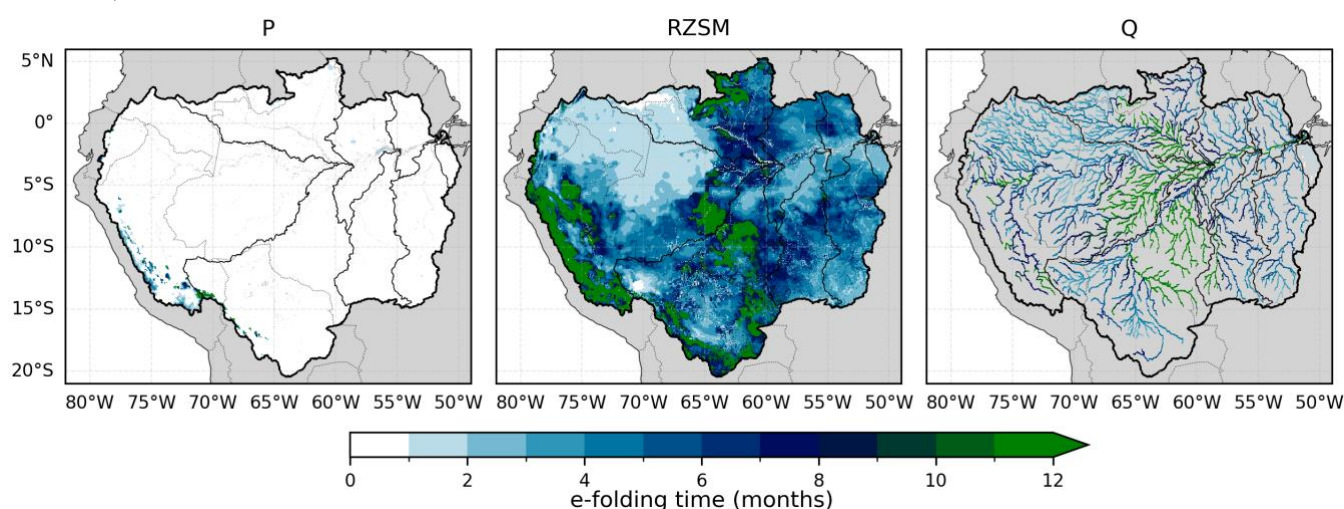
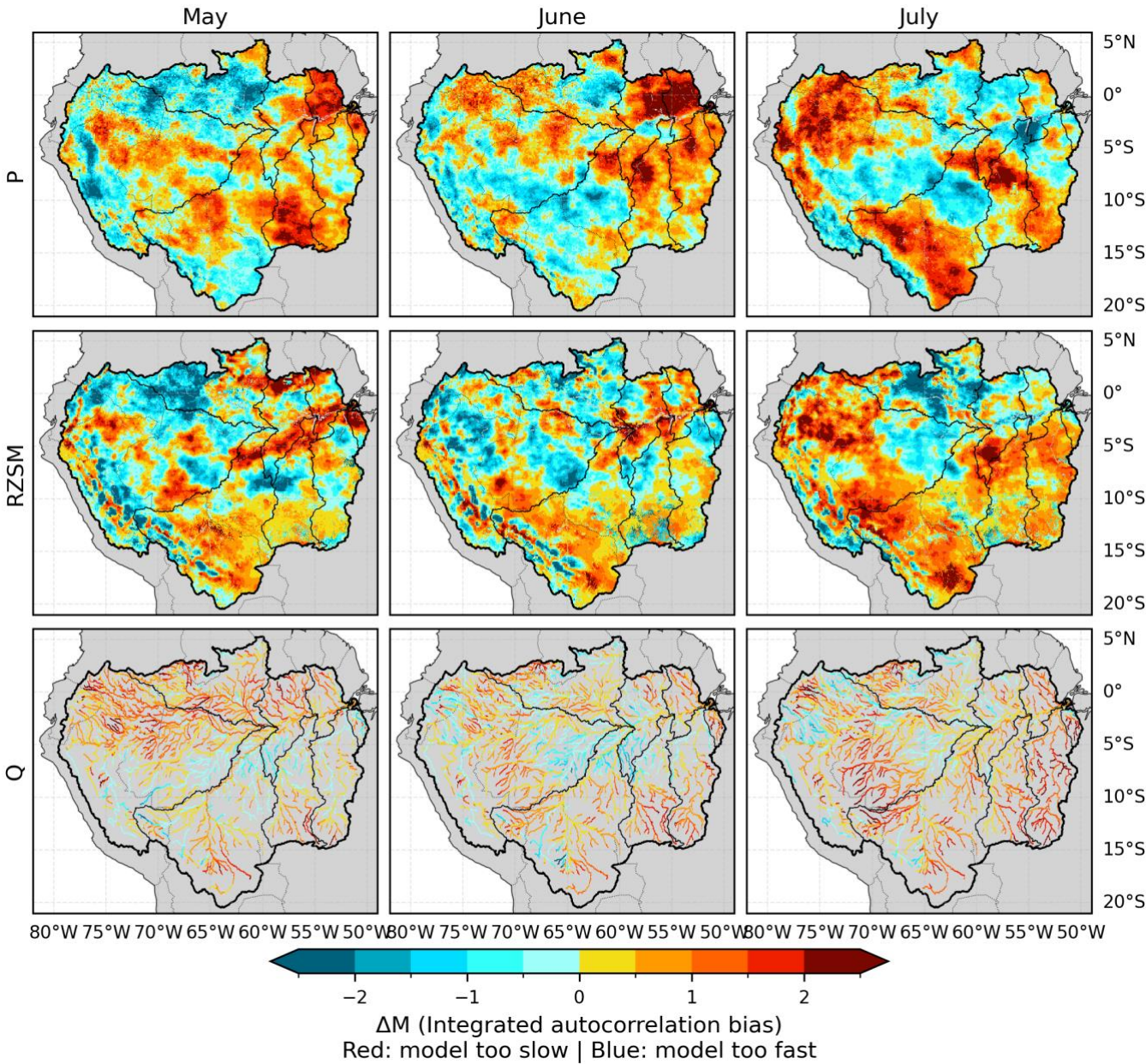


Figure 7: Spatial distribution of baseline hydrologic memory across the Amazon basin, defined by the e-folding time scale (in months) of the retrospective model. Panels illustrate the terrestrial buffering effect as water moves through the hydrologic cycle, from precipitation (left), to root zone soil moisture (center), and streamflow (right).

We compared the autocorrelation decay rates of the hindcasts against this retrospective baseline (Figure S5) averaged over 2001-2023. Based on basin averages, retrospective RZSM and Q exhibited e-folding times of approximately four months and six months, respectively. Memory in P decayed below the $1/e$ threshold in less than a month for both the models. Dynamical RZSM forecasts initialized on May 1 and June 1 aligned with the retrospective baseline. However, for the July 1 forecast exhibited an anomalously slow decay between the 1- and 4-month lags, indicating a memory bias where the land surface model retained moisture states longer than the retrospective baseline. This persistence bias was widespread in the Q routing phase. All dynamic forecast initializations exhibited slower autocorrelation decay for Q compared to the retrospective model (Figure S5, bottom row). The system prolonged the residence time of initial hydrologic states, artificially inflating forecast skill metrics during the anomaly period.



385

Figure 8: Spatial distribution of forecast memory bias, quantified as the difference in integrated autocorrelation (area under the curve, AUC) between the dynamical forecasts and the retrospective baseline (2001-2023) up to a 5-month lag. Red values indicate areas where the forecast model is sluggish (i.e., it retains anomalies for too long), while blue values indicate areas where the forecast model dissipates anomalies too rapidly.

390

We mapped the memory bias quantified as the difference in AUC up to a 5-month lag across the basin averaged over 2001-2023 to evaluate the spatial distribution of these biases (Figure 8). The memory bias varied by initialization. For RZSM initialized on May 1, the northwestern Amazon dissipated anomalies faster than the baseline (blue, accumulating a negative



bias of up to 2 months), while pixels along the main channel retained moisture longer (red). By the July 1 initialization, majority of the basin dissipated RZSM memory too slowly, except in the north central region. The fast dissipation of anomalies is concentrated in the western and northwestern subbasins, specifically the Negro and Solimoes (Figure S6), which consistently exhibit negative AUC bias across the May and June initializations.

The spatial bias in the Q network was more pronounced. For the May 1 initialization, the routing scheme was slower than the baseline across the northern Amazon, with headwater catchments retaining anomalies while the main channel dissipated them too rapidly. In the June 1 and July 1 initializations, the routing network exhibited broader kinematic sluggishness, with cumulative memory biases exceeding two months in certain headwater tributaries. The subbasin level analysis confirms that this finding applies to the entire basin rather than localized to specific channel reaches (Figure S6). This indicates that the high probabilistic skill scores for Q are partially attributable to a routing scheme that retains drought anomalies within the channel network longer than the baseline.

3.5 Forecasting low flows and fire risk from extreme drought impacts

In this section, we demonstrate the translational utility of the S2S Amazon-LDAS for predicting cascading terrestrial hazards during the 2024 extreme drought by analyzing its signal propagation into severe low flow Q anomalies and by modelling the subsequent increase in regional fire risk using both atmospheric and land surface proxies for the southern fringes of the basin.

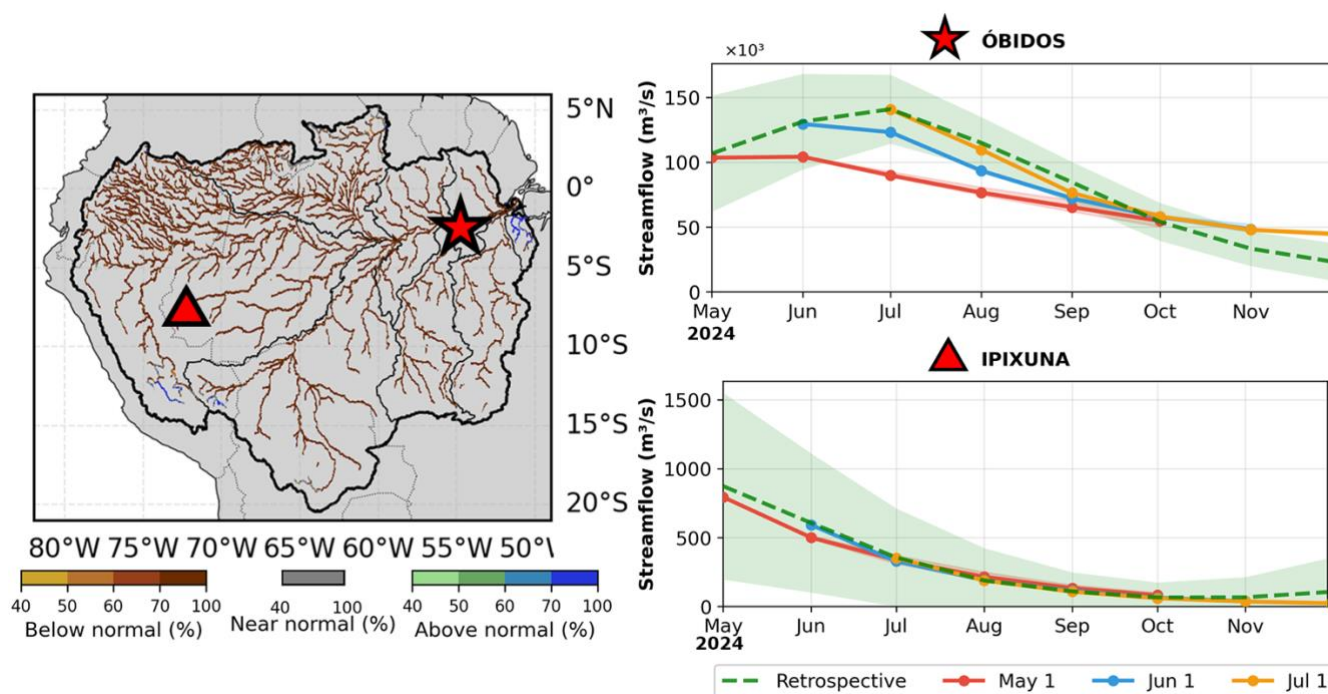


Figure 9: Streamflow (Q) forecasts during the JAS 2024 drought. Left panel shows the tercile probability map from the July 1 initialization showing the highly probable below normal tercile probabilities across the Amazon stream network. Right panel shows time series of Q near the basin outlet (Óbidos), contrasting the retrospective baseline against the dynamical forecasts initialized on



May 1, June 1, and July 1 and corresponding time series for a headwater location (Ipixuna), showing the rapid response to the atmospheric deficit are shown. The green shaded area for retrospective data shows the ± 1 climatological standard deviation.

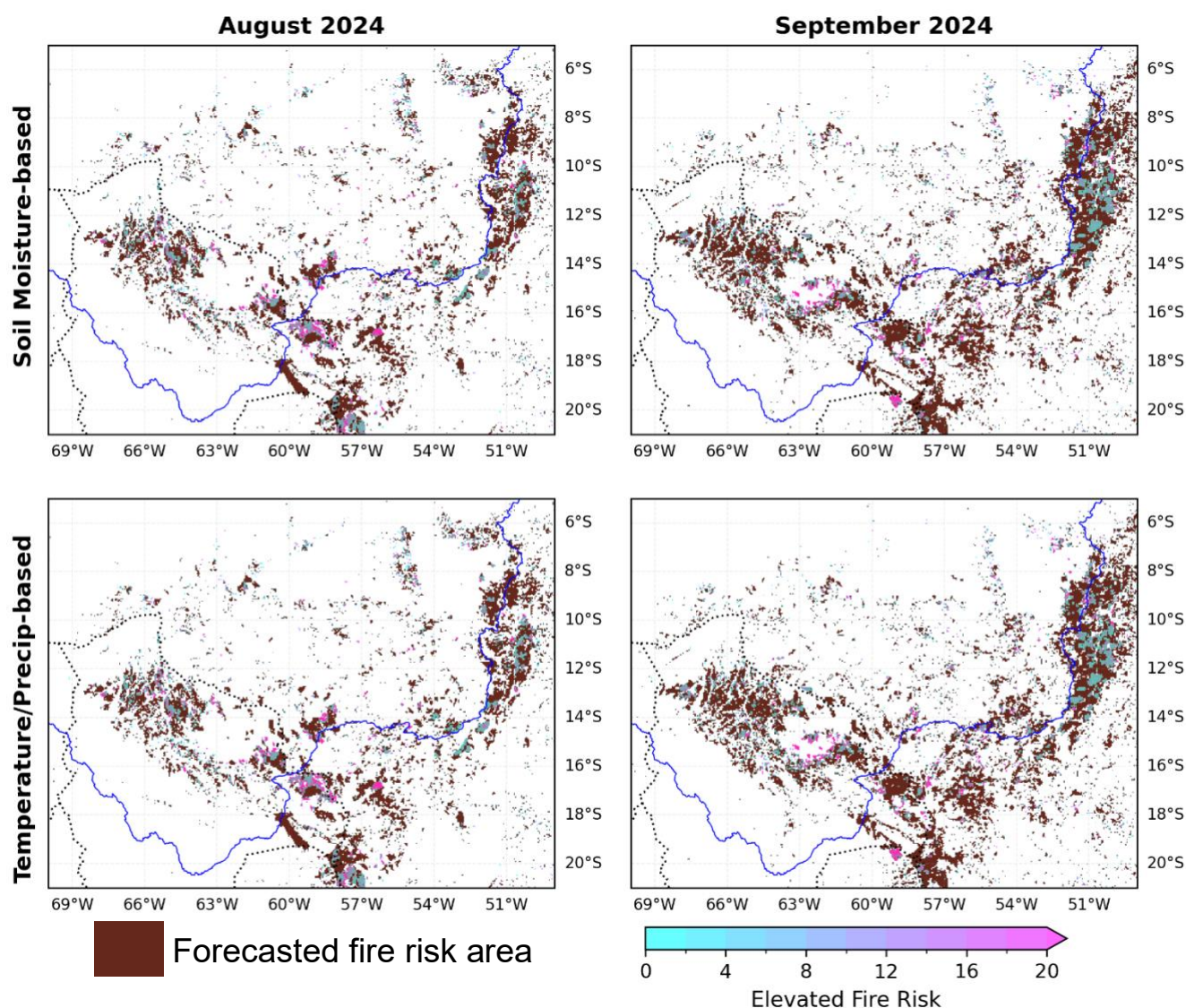
3.5.1 Streamflow routing and low-flow characterization

415 Categorical probabilistic forecasts initialized on July 1 indicated below normal flow conditions across the Amazon stream network for the JAS 2024 season (Figure 9). River channels of Strahler order 3 or higher were predominantly in the below normal tercile, excluding isolated northern tributaries. We compared forecasted Q against the retrospective baseline at a headwater catchment location (Ipixuna) and the integrated basin outlet (Óbidos). At Ipixuna, Q declined steadily from May to October. All forecast initializations captured this rapid decline, aligning with the retrospective baseline. Conversely, the
 420 integrated response at Óbidos highlighted the routing limitations identified in Section 3.5. The retrospective baseline showed Q at Óbidos did not decline substantially until July, due to routing lag of upstream deficits. Longer lead forecasts (May 1 and June 1) exhibited an early dry bias, predicting main channel drying 2 months prior to the retrospective baseline before converging in October. This suggests that the headwater routing sluggishness retained baseflow upstream, amplifying the simulated drought signal at the outlet prematurely. The magnitude of the event was captured across the basin, with Q declining
 425 by 28% at Ipixuna and 40% at Óbidos relative to the climatological mean.

3.5.2 Forecasted fire risk in the Arc of deforestation

Extreme hydrometeorological deficits led to increased fire activity across the arc of deforestation. We modeled forecasted fire risk using two methodologies: an atmospheric proxy (concurrent temperature/precipitation (T/P) extremes), and a land surface proxy (RZSM deficits). We only quantify the fuel moisture component of fire risk. The analysis was constrained to
 430 climatological fire-prone areas defined by historical MODIS burned area data (2001–2023) (Figure S7). We overlaid the binary fire risk forecasts with the observed elevated fire risk for August and September 2024 (Figure 10). Extreme RZSM deficits (probability of below normal soil moisture $> 60\%$) served as a better proxy for sustained hydrometeorological deficit. Within the climatological fire prone areas, 332,621 sq. km (70%) exhibited elevated fire risk in August, expanding to 421,868 sq. km (64% of the active domain) in September, historically the peak month for fire activity in the arc of deforestation (Aragão et al., 2018).
 435

Detection metrics (Table 2) indicate the land surface (RZSM) proxy outperformed the atmospheric (T/P) proxy. The RZSM proxy-based fire risk yielded higher PODs (0.75 vs. 0.31 in August; 0.70 vs. 0.38 in September). Because RZSM integrates the long-term atmospheric deficits, it better represents the terrestrial deficit. The atmospheric T/P method captures transient weather conditions but does not account for pre-conditioned landscape susceptibility. Both methodologies produced a high
 440 FAR (> 0.75), which reduced the CSI. This high FAR is expected, as hydrometeorological models predict deficits and fire potential rather than stochastic anthropogenic or lightning induced ignition events (Hantson et al., 2016). The higher CSI of the RZSM method indicates that land surface memory provides a more reliable foundation for S2S fire risk early warning systems than atmospheric metrics alone.



445 **Figure 10: Spatial evaluation of forecasted fire risk overlaid on MODIS-derived elevated fire risk within the Arc of Deforestation for August and September 2024 based on July 1, 2024 forecast initialization. The top row displays the forecast derived from the land surface proxy (RZSM), while the bottom row displays the forecast derived from the atmospheric proxy (T/P). Dark brown pixels indicate forecasted high risk, which are evaluated against the observed elevated risk gradient (cyan to magenta).**

450



Table 2: Detection metrics for forecasted fire risk in the Arc of Deforestation evaluated against the MODIS burned area product for August and September 2024. The RZSM proxy relies on soil moisture deficits, while the T/P proxy relies on concurrent temperature/precipitation extremes.

	Method 1: SM		Method 2: T/P	
	Aug	Sep	Aug	Sep
Probability of detection (POD)	0.75	0.7	0.31	0.38
False alarm ratio (FAR)	0.75	0.77	0.82	0.78
Critical success index (CSI)	0.24	0.21	0.13	0.16
Area sq. km. (%)	332,621 (70)	421,868 (64)	201,664 (43)	238,663 (36)

4 Discussion

4.1 Sources of predictability and the role of initial conditions

The evolution of the 2023–2024 Amazon drought demonstrates a predictability gradient across the terrestrial hydrologic cycle. Consistent with atmospheric internal variability, P predictability decays rapidly, resulting in low deterministic skill beyond sub-monthly timescales (Vitart et al., 2017). However, at 1- to 3-month leads, the dynamical forecasts mostly outperformed persistence, particularly for RZSM. This extended skill depends on the implicit bias correction within the GARD downscaling architecture. By maintaining statistical consistency with Amazonian climatology, GARD reduces the mean-state drift common in raw dynamical boundary conditions (Gutmann et al., 2022). The terrestrial components of Amazon-LDAS act as a low-pass filter, where Noah-MP and HyMAP integrate high-frequency atmospheric variability into slowly evolving RZSM and Q states (Thomas L. Delworth; Syukuro Manabe, 1988). Because these terrestrial reservoirs control hydrologic memory, the reliability of S2S hydrologic forecasts beyond a 1-month horizon is primarily governed by the accuracy of the initialized land surface state (Koster et al., 2025).

4.2 Forecast model memory bias and equifinality

Although the dynamical framework yielded high ACC and RPSS for hydrological variables, the integrated autocorrelation (AUC) analysis for the 2001-2023 period identified underlying memory biases (Figure 6). The routing sluggishness observed in the July 1 hindcasts highlights an equifinality issue: the forecasting system can achieve elevated statistical skill through non-physical persistence (Beven, 2006). Because Amazon-LDAS uses identical static physiographic parameters (e.g., STATSGO/FAO soils, MODIS IGBP land cover) for both the retrospective and forecast system, this divergent memory structure isolates the effect of non-linear hydrologic parameterizations interacting with atmospheric forcing errors. Differences in forecasted P intensity or dry-spell frequency alter modeled infiltration and runoff partitioning. As noted by (Niu et al., 2011),



these variations can trap moisture anomalies or accelerate drainage relative to the physical baseline. Relying on static soil maps and fixed rooting depths limits the representation of dynamic plant-water adaptations, such as deep taproot extraction and subsurface heterogeneity during moisture deficits (Fan et al., 2017). Consequently, when forced with S2S boundary conditions, these static parameterizations can increase modeled hydrologic residence times, retaining drought anomalies in the channel network longer than observed hydrodynamics support.

4.3 Hydrometeorological vulnerability vs. realized ignition in stochastic fire risk

Applying these S2S hydrometeorological outputs to evaluate regional fire risk in the arc of deforestation highlights the distinction between physical Earth system predictability and stochastic human activity. Utilizing land surface proxies (RZSM) instead of atmospheric proxies (temperature and P) doubled the POD for elevated fire risk (e.g., 0.75 versus 0.31 in August). However, this improvement coincided with a FAR exceeding 75%. This high FAR reflects the separation between hydrometeorological vulnerability and realized ignition. In managed landscapes such as the arc of deforestation, ignitions are primarily anthropogenic, associated with agricultural slash-and-burn practices (Brando et al., 2020b). S2S framework identifies the spatial extent of hydrometeorological deficits, which serves strictly as a proxy for fuel moisture. However, forecasting active fires requires localized ignition triggers and fuel load, neither of which is explicitly accounted for in the framework. Therefore, validating continuous physical vulnerability metrics against discrete occurrence datasets, such as the MODIS burned area product, inherently yields a high FAR. Methodological constraints also affect these detection metrics. Using monthly-averaged forecasts smooths short-term peaks in vapor pressure deficit that can increase rapid fire spread (Brando et al., 2014). Additionally, the static proxy used here does not incorporate fragmentation edges or historical hot-pixel trends, which amplify localized fire risk non-linearly (Anderson et al., 2022; Cochrane, 2003). Furthermore, utilizing a static land cover map within the rapidly changing arc of deforestation represents a structural limitation for accurately relating physical drought to fire risk based on fuel moisture. Incorporating data assimilation to improve the initialized land surface states by incorporating dynamic land cover could substantially reduce FAR. For example, previous studies have demonstrated that assimilating leaf area index improves the model's representation of vegetation sensitivity to hydroclimatic extremes and accurately alters the portioning of post fire water fluxes (Kumar et al., 2022, 2021), thereby providing a more dynamic and realistic boundary condition for susceptibility assessments.

Despite these constraints, S2S land surface forecasts provide a physically based indicator of heightened fire vulnerability conditioned on antecedent hydrologic deficits (Dutra et al., 2026b). Compared to static historical fire risk maps, these dynamic forecasts offer a distinct advantage for proactive resource allocation, specifically by identifying regions where severe hydrometeorological anomalies threaten to accelerate fire spread. Because El Niño-induced droughts and their associated fire potential can be predicted at lead times of up to six months (Di Giuseppe et al., 2024), integrating S2S outlooks into operational planning can enable agencies to preposition suppression assets in emergent hotspots. This anticipatory approach can reduce the substantial economic and social costs inherent to reactive emergency response (Valente and Laurini, 2023).



4.4 Operational outlook: Forecasting the impacts of the 2026 El-Niño

Given the high probability of a new El Niño event developing in late 2026, we applied the Amazon-LDAS system to forecast the hydrometeorological conditions for October 2026. We deliberately present this outlook in the discussion section to focus on the operational utility of the S2S Amazon-LDAS system rather than present them as actual results, as these forecasts are not yet validated and are being regularly updated. Using a 5-month lead (initialized on June 1, 2026), we forecast the deterministic standardized anomalies and categorical tercile probabilities for P, RZSM, and Q (Figure 11).

The forecasted conditions for October 2026 contrast with the 2024 event. The 2024 drought developed following a prolonged El Niño established in August 2023, resulting in cumulative atmospheric and extreme hydrological deficits. Conversely, the October 2026 forecast models a developing El Niño during the late dry season. The June 1 initialization predicts a spatial dipole rather than a basin-wide deficit. Deterministic anomalies indicate drying concentrated in the northern, central, and eastern Amazon, regions that have historically been sensitive to early shifts in the Walker circulation. Meanwhile, the southern basin is projected to retain positive moisture anomalies. The probabilistic forecast supports this distribution, indicating a 70-100% probability of below-normal conditions in the north and central basin, and a high probability of above-normal conditions in the south. Because RZSM serves as a better proxy for fire risk (Section 3.5.2), this spatial dipole suggests regional variations in fire potential. The projected above-normal moisture states across the southern Amazon, including portions of the arc of deforestation, may suppress late-season fuel load, thereby reducing ignition potential in those specific areas for the 2026 fire season. However, these operational projections must be contextualized by the model limitations identified in Sections 3.4 and 4.2. Dynamical forecasts exhibit specific spatial memory biases, meaning the forecasted above-normal Q in the southern basin may be temporally extended by sluggishness in streamflow forecasts.

To support decision-making, these forecasts are distributed through a publicly accessible dashboard developed in collaboration with practitioner partners. However, operational deployment must contextualize these forecasts within the structural limitations identified in this study as the forecast system can provide reliable information at actionable lead time for localized disaster preparedness.

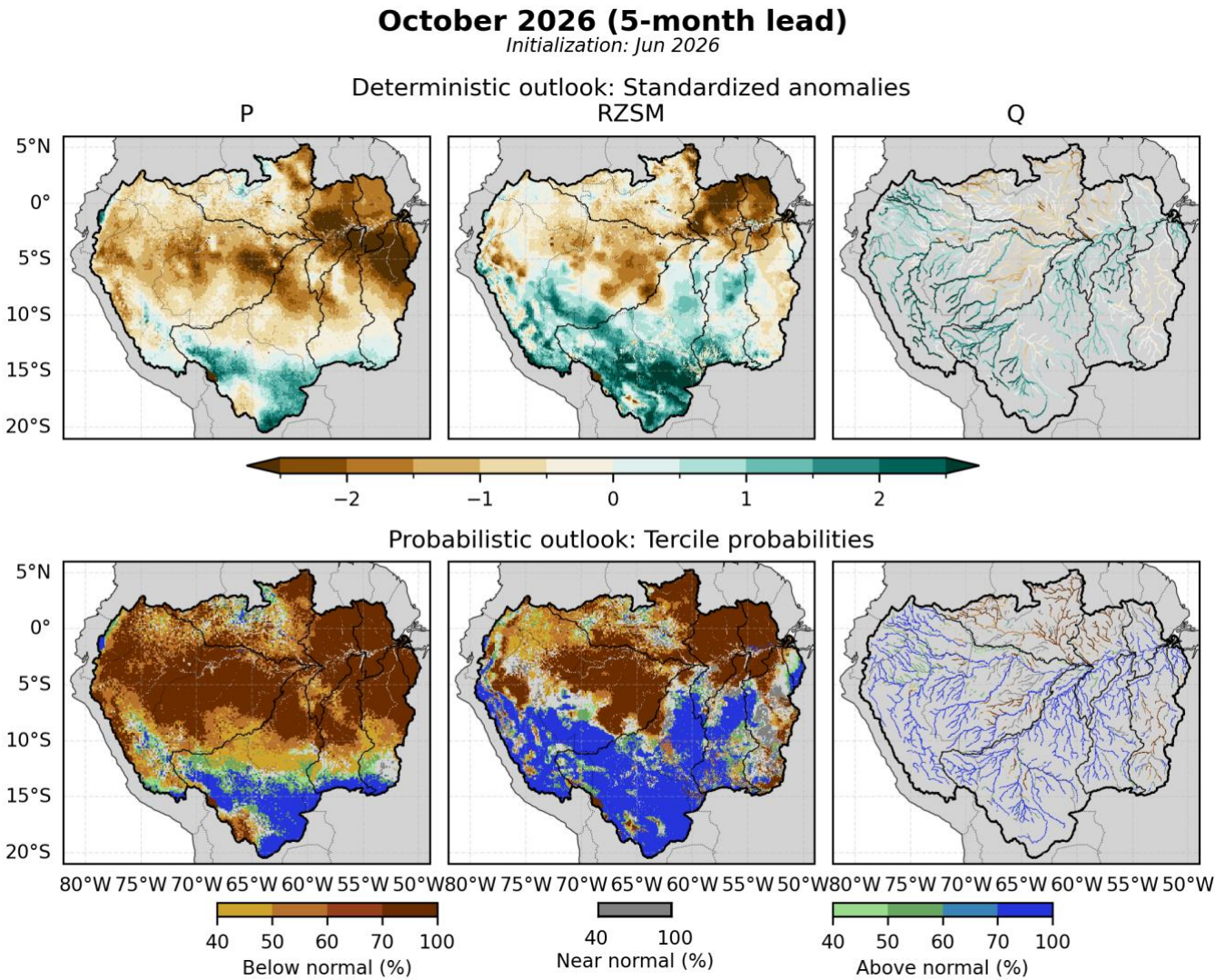


Figure 11: Hydrometeorological forecast outlook for October 2026 (6-month lead), derived from the June 1, 2026 initialization. The top panel displays the deterministic ensemble mean forecast of standardized anomalies for precipitation (P), root zone soil moisture (RZSM), and streamflow (Q). The bottom panel illustrates the corresponding probabilistic forecast, indicating the probability (percentage) of each variable falling into the below normal (brown), near normal (gray), or above normal (blue/green) tercile categories.

5 Conclusions

This study described and evaluated the Amazon-LDAS subseasonal-to-seasonal (S2S) forecasting framework (5 km spatial resolution, utilizing Noah-MP and HyMAP) during the JAS 2024 drought. By partitioning predictability between dynamic atmospheric boundary forcings and terrestrial initial conditions, we quantified the influence of hydrologic memory biases on statistical forecast skill at 1- to 3-month leads. Our evaluation highlights three primary findings:



- The 3-month lead (May 1) initialization captured the broadest spatial footprint of exceptional drought ($POD = 0.75$) but overestimated the total spatial extent ($FBIAS = 1.42$). The 1-month lead (July 1) reduced the POD to 0.62 while optimizing spatial precision, yielding the lowest FAR (0.33), the highest CSI (0.48), and a near-perfect $FBIAS$ (0.93). For RZSM, dynamical forecasts systematically outperformed persistence, increasing the basin-averaged $RPSS$ from 0.39 to 0.68 at the 3-month lead ($\Delta\mu = +0.29$).
- Integrated autocorrelation (AUC) analysis over the baseline period of 2001-2023 demonstrated that high streamflow predictability ($RPSS$ 0.78–0.85) is due to bias in runoff partitioning and kinematic routing sluggishness rather than dynamical atmospheric skill. Dynamical streamflow forecasts offered negligible improvement over persistence at the 1- and 2-month leads. Specifically, the forecast model retained dry anomalies up to 2 months longer than the physical retrospective baseline in headwater catchments, artificially inflating apparent forecast skill during the prolonged deficit.
- Utilizing S2S RZSM deficits as a proxy for terrestrial hydrometeorological deficit improved the detection of elevated fire risk in the arc of deforestation compared to concurrent atmospheric thresholds (temperature and precipitation). The RZSM proxy increased the POD from 0.31 to 0.75 in August and from 0.38 to 0.70 in September. While the FAR remained above 0.75 due to the stochastic nature of anthropogenic ignitions, the RZSM metric physically integrates long-term atmospheric moisture deficits to establish an improved threshold for hydrometeorological vulnerability.

Advancing S2S hydrometeorological prediction requires moving beyond atmospheric bias correction to explicitly calibrating land surface memory parameters. The spatial inconsistencies in soil moisture dissipation and prolonged channel routing residence times observed here indicate that fixed parameterizations (e.g., static rooting depths and physical soil properties) constrain model hydrodynamics under extreme boundary forcing. Correcting these structural routing biases is necessary for operational centers to transition from high statistical skill scores to physically reliable, extended-lead terrestrial forecasts. From a practical standpoint, the Amazon LDAS S2S framework represents a valuable operational tool, particularly for western Amazonian nations (e.g. Ecuador, Peru, and Colombia) where the integration of S2S predictions remains limited.

Code and data availability

Codes are available on GitHub: [link to be provided upon publication, or reviewer request]

Model outputs (including downscaled GEOS2S v2 meteorological forecasts) and evaluation datasets used in this study are available through the JHU Data Archive [link to be provided upon publication, or reviewer request]

Note to reviewers: the latest operational probabilistic forecasts can be visualized on the public dashboard (<https://hydroclimate.shinyapps.io/amazonhydroviewer/>), but we do not intend to include that link in the paper as it may not be permanently available.



Supplement link

Supplementary document attached.

Author contributions

BZ and PK conceptualized the idea for manuscript. PK conducted the analysis and prepared the manuscript. BZ, AG, LA, PB, SK, CM, and WP reviewed and edited the manuscript draft.

580 Competing interests

The authors declare that they have no conflicts of interest relevant to this study.

Disclaimer

585 Copernicus Publications remains neutral with regard to jurisdictional claims made in the text, published maps, institutional affiliations, or any other geographical representation in this paper. While Copernicus Publications makes every effort to include appropriate place names, the final responsibility lies with the authors. Views expressed in the text are those of the authors and do not necessarily reflect the views of the publisher.

Acknowledgements

590 We would like to thank Kris Su (qsu4@jhu.edu) for developing dashboard to visualize the operational forecasts. Computing resources supporting this work were provided by the NASA High-End Computing (HEC) Program through the NASA Center for Climate Simulation (NCCS) at NASA Goddard Space Flight Center.

L.O.A. acknowledges funding from the National Council for Scientific and Technological Development (CNPq) projects CAPOEIRA (#443849/2024-2) and Productivity scholarship (#307364/2025-9) and support from The Natural Environment Research Council (NERC AMAZON SOS-NE/X019055/1).



595 Financial support

This research was supported by funding from NASA (Award numbers 80NSSC23K0248 and 80NSSC22K1137) and NIH (Award number: R01AI151056).

References

- Ahmad, S. K., Holmes, T. R., Kumar, S. V., Lahmers, T. M., Konapala, G., Getirana, A., Nie, W., Liu, P. W., Hain, C. R.,
 600 Locke, K. A., and Libonati, R.: Evapotranspiration declines prolonged by deforestation and fire in South American biomes,
 Nat. Geosci., <https://doi.org/10.1038/s41561-026-01981-8>, 2026.
- Alencar, A. A., Brando, P. M., Asner, G. P., and Putz, F. E.: Landscape fragmentation, severe drought, and the new Amazon
 forest fire regime, *Ecological Applications*, 25, 1493–1505, <https://doi.org/10.1890/14-1528.1>, 2015.
- Alfieri, L., Burek, P., Dutra, E., Krzeminski, B., Muraro, D., Thielen, J., and Pappenberger, F.: GloFAS-global ensemble
 605 streamflow forecasting and flood early warning, *Hydrol. Earth Syst. Sci.*, 17, 1161–1175, <https://doi.org/10.5194/hess-17-1161-2013>, 2013.
- Amenu, G. G. and Kumar, P.: Interannual Variability of Deep-Layer Hydrologic Memory and Mechanisms of Its Influence on
 Surface Energy Fluxes, 2005.
- Anderson, L. O., Burton, C., dos Reis, J. B. C., Pessôa, A. C. M., Bett, P., Carvalho, N. S., Junior, C. H. L. S., Williams, K.,
 610 Selaya, G., Armenteras, D., Bilbao, B. A., Xaud, H. A. M., Rivera-Lombardi, R., Ferreira, J., Aragão, L. E. O. C., Jones, C.
 D., and Wiltshire, A. J.: An alert system for Seasonal Fire probability forecast for South American Protected Areas, *Climate
 Resilience and Sustainability*, 1, <https://doi.org/10.1002/cli2.19>, 2022.
- Aragão, L. E. O. C., Anderson, L. O., Fonseca, M. G., Rosan, T. M., Vedovato, L. B., Wagner, F. H., Silva, C. V. J., Silva
 Junior, C. H. L., Arai, E., Aguiar, A. P., Barlow, J., Berenguer, E., Deeter, M. N., Domingues, L. G., Gatti, L., Gloor, M.,
 615 Malhi, Y., Marengo, J. A., Miller, J. B., Phillips, O. L., and Saatchi, S.: 21st Century drought-related fires counteract the
 decline of Amazon deforestation carbon emissions, *Nat. Commun.*, 9, <https://doi.org/10.1038/s41467-017-02771-y>, 2018.
- Arias, M. E., Farinosi, F., Lee, E., Livino, A., Briscoe, J., and Moorcroft, P. R.: Impacts of climate change and deforestation
 on hydropower planning in the Brazilian Amazon, *Nat. Sustain.*, 3, 430–436, <https://doi.org/10.1038/s41893-020-0492-y>,
 2020.
- 620 Arsenault, K. R., Kumar, S. V., Geiger, J. V., Wang, S., Kemp, E., Mocko, D. M., Beaudoin, H. K., Getirana, A., Navari, M.,
 Li, B., Jacob, J., Wegiel, J., and Peters-Lidard, C. D.: The Land surface Data Toolkit (LDT v7.2) - A data fusion environment
 for land data assimilation systems, *Geosci. Model Dev.*, 11, 3605–3621, <https://doi.org/10.5194/gmd-11-3605-2018>, 2018.
- Baker, I. T., Prihodko, L., Denning, A. S., Goulden, M., Miller, S., and Da Rocha, H. R.: Seasonal drought stress in the amazon:
 Reconciling models and observations, *J. Geophys. Res. Biogeosci.*, 114, <https://doi.org/10.1029/2007JG000644>, 2009.
- 625 Beven, K.: A manifesto for the equifinality thesis, in: *Journal of Hydrology*, 18–36,
<https://doi.org/10.1016/j.jhydrol.2005.07.007>, 2006.



- Beveridge, C. F., Espinoza, J. C., Athayde, S., Correa, S. B., Couto, T. B. A., Heilpern, S. A., Jenkins, C. N., Piland, N. C., Utsunomiya, R., Wongchuig, S., and Anderson, E. P.: The Andes–Amazon–Atlantic pathway: A foundational hydroclimate system for social–ecological system sustainability, *Proc. Natl. Acad. Sci. U. S. A.*, 121, <https://doi.org/10.1073/pnas.2306229121>, 2024.
- Bottino, M. J., Nobre, P., Giarolla, E., da Silva Junior, M. B., Capistrano, V. B., Malagutti, M., Tamaoki, J. N., de Oliveira, B. F. A., and Nobre, C. A.: Amazon savannization and climate change are projected to increase dry season length and temperature extremes over Brazil, *Sci. Rep.*, 14, <https://doi.org/10.1038/s41598-024-55176-5>, 2024.
- Brando, P. M., Balch, J. K., Nepstad, D. C., Morton, D. C., Putz, F. E., Coe, M. T., Silvério, D., Macedo, M. N., Davidson, E. A., Nóbrega, C. C., Alencar, A., and Soares-Filho, B. S.: Abrupt increases in Amazonian tree mortality due to drought-fire interactions, *Proc. Natl. Acad. Sci. U. S. A.*, 111, 6347–6352, <https://doi.org/10.1073/pnas.1305499111>, 2014.
- Brando, P. M., Soares-Filho, B., Rodrigues, L., Assunção, A., Morton, D., Tuchsneider, D., Fernandes, E. C. M., Macedo, M. N., Oliveira, U., and Coe, M. T.: The gathering firestorm in southern Amazonia, 2020a.
- Brando, P. M., Soares-Filho, B., Rodrigues, L., Assunção, A., Morton, D., Tuchsneider, D., Fernandes, E. C. M., Macedo, M. N., Oliveira, U., and Coe, M. T.: The gathering firestorm in southern Amazonia, 2020b.
- Brando, P. M., Barlow, J., Macedo, M. N., Silvério, D. V., Ferreira, J. N., Maracahipes, L., Anderson, L., Morton, D. C., Alencar, A., Paolucci, L. N., Jacobs, S., Stouter, H., Randerson, J., Flores, B. M., Starinchak, B., Coe, M., Pires, M. M., Rattis, L., Armenteras, D., Artaxo, P., Ordway, E. M., Trumbore, S., Staver, C., Berenguer, E., Menor, I. O., Maracahipes-Santos, L., Potter, N., Spracklen, D. V., and Uribe, M.: Annual Review of Environment and Resources Tipping Points of Amazonian Forests: Beyond Myths and Toward Solutions, 53, <https://doi.org/10.1146/annurev-enviro-111522>, 2026.
- Cai, W., McPhaden, M. J., Grimm, A. M., Rodrigues, R. R., Taschetto, A. S., Garreaud, R. D., Dewitte, B., Poveda, G., Ham, Y. G., Santoso, A., Ng, B., Anderson, W., Wang, G., Geng, T., Jo, H. S., Marengo, J. A., Alves, L. M., Osman, M., Li, S., Wu, L., Karamperidou, C., Takahashi, K., and Vera, C.: Climate impacts of the El Niño–Southern Oscillation on South America, <https://doi.org/10.1038/s43017-020-0040-3>, 1 April 2020.
- Cierner, C., Rehm, L., Kurths, J., Donner, R. V., Winkelmann, R., and Boers, N.: An early-warning indicator for Amazon droughts exclusively based on tropical Atlantic sea surface temperatures, *Environmental Research Letters*, 15, <https://doi.org/10.1088/1748-9326/ab9cff>, 2020.
- Cochrane, M. A.: Fire science for rainforests, 2003.
- Costa, M. H., Botta, A., and Cardille, J. A.: Effects of large-scale changes in land cover on the discharge of the Tocantins River, Southeastern Amazonia, *J. Hydrol. (Amst.)*, 283, 206–217, [https://doi.org/10.1016/S0022-1694\(03\)00267-1](https://doi.org/10.1016/S0022-1694(03)00267-1), 2003.
- Dutra, D. J., Jones, C., Betts, R. A., Ferreira, I. J. M., Aragão, L. E. O. C., Mataveli, G., Leão, H., Domingos, B. I., Cabral, B. F., Fearnside, P. M., Graça, P. M. L. A., Yanai, A. M., Silva-Junior, C. H. L., de Medeiros, T. P., Dalagnol, R., Braga, D., Peripato, V., Burton, C., and Anderson, L. O.: Dry-Season Water Deficits in the Southwestern Amazon Under High Emissions, *International Journal of Climatology*, <https://doi.org/10.1002/joc.70331>, 2026a.



- 660 Dutra, D. J., Ferreira, I. J. M., Rodrigues, É. T., Braga, D., Izidoro, B., Mataveli, G., de Aragão, L. E. O. e. C., and Anderson, L. O.: Intensification of drought-associated wildfires challenges actions for Amazonia's sustainable development, *Perspect. Ecol. Conserv.*, <https://doi.org/10.1016/j.pecon.2026.02.013>, 2026b.
- Espinoza, J. C., Jimenez, J. C., Marengo, J. A., Schongart, J., Ronchail, J., Lavado-Casimiro, W., and Ribeiro, J. V. M.: The new record of drought and warmth in the Amazon in 2023 related to regional and global climatic features, *Sci. Rep.*, 14, 665 <https://doi.org/10.1038/s41598-024-58782-5>, 2024.
- Fan, Y., Miguez-Macho, G., Jobbágy, E. G., Jackson, R. B., and Otero-Casal, C.: Hydrologic regulation of plant rooting depth, *Proc. Natl. Acad. Sci. U. S. A.*, 114, 10572–10577, <https://doi.org/10.1073/pnas.1712381114>, 2017.
- Fassoni-Andrade, A. C., Fleischmann, A. S., Papa, F., Paiva, R. C. D. de, Wongchuig, S., Melack, J. M., Moreira, A. A., Paris, A., Ruhoff, A., Barbosa, C., Maciel, D. A., Novo, E., Durand, F., Frappart, F., Aires, F., Abrahão, G. M., Ferreira-Ferreira, J., 670 Espinoza, J. C., Laipelt, L., Costa, M. H., Espinoza-Villar, R., Calmant, S., and Pellet, V.: Amazon Hydrology From Space: Scientific Advances and Future Challenges, <https://doi.org/10.1029/2020RG000728>, 1 December 2021.
- Fernandes, K., Baethgen, W., Bernardes, S., Defries, R., Dewitt, D. G., Goddard, L., Lavado, W., Lee, D. E., Padoch, C., Pinedo-Vasquez, M., and Uriarte, M.: North Tropical Atlantic influence on western Amazon fire season variability, *Geophys. Res. Lett.*, 38, <https://doi.org/10.1029/2011GL047392>, 2011.
- 675 Ferreira, V., Buras, A., Zscheischler, J., Mahecha, M., and Rammig, A.: Evaluating the 2023-2024 record dry-hot conditions in the Amazon in the context of historical compound extremes, *Environmental Research Letters*, 20, <https://doi.org/10.1088/1748-9326/ade550>, 2025.
- Fleischmann, A., Rabelo, R., Tregidgo, D., Benitz, T., Viana, F. M. F., de Lima Franco, D., Hercos, A., Maranhão, L., Bicudo, T., Camelo, P., Costa, A. V. L., da Silva Costa, J., Lopes, J. C., Oler, J. R. L., Pedro, J. P. B., Corrêa Pereira, H., dos Santos 680 Silva, P., Torralvo, K., Xavier, R., Zumak, A., Custódio, Lady, Torres Gonçalves, A. C., de Meireles Lima, B., Gomes, M. C. R. L., Bandeira, M., da Silva Coelho, Y. K., da Costa, D. G., Franca, F. M. S., Hymans, D., Lopes, K. G. D., Mendel, B., de Mello Mendes, D. M., Mendes, R., Nascimento, R., Paim, F. P., Pinto, A. C., Prestes, A., Sarmiento, C. G., Silva, A. C. F. B., Silva, F. P., Marmontel, M., and do Amaral, J. V.: Unprecedented social-ecological impacts of the 2023 extreme drought in the central Amazon, *Sci. Rep.*, 15, <https://doi.org/10.1038/s41598-025-25125-x>, 2025.
- 685 Fleischmann, A. S., Paiva, R. C. D., Collischonn, W., Siqueira, V. A., Paris, A., Moreira, D. M., Papa, F., Bitar, A. A., Parrens, M., Aires, F., and Garambois, P. A.: Trade-Offs Between 1-D and 2-D Regional River Hydrodynamic Models, *Water Resour. Res.*, 56, <https://doi.org/10.1029/2019WR026812>, 2020.
- Gatti, L. V., Basso, L. S., Miller, J. B., Gloor, M., Gatti Domingues, L., Cassol, H. L. G., Tejada, G., Aragão, L. E. O. C., Nobre, C., Peters, W., Marani, L., Arai, E., Sanches, A. H., Corrêa, S. M., Anderson, L., Von Randow, C., Correia, C. S. C., 690 Crispim, S. P., and Neves, R. A. L.: Amazonia as a carbon source linked to deforestation and climate change, *Nature*, 595, 388–393, <https://doi.org/10.1038/s41586-021-03629-6>, 2021.
- Getirana, A., Kumar, S., Giroto, M., and Rodell, M.: Rivers and Floodplains as Key Components of Global Terrestrial Water Storage Variability, *Geophys. Res. Lett.*, 44, 10,359–10,368, <https://doi.org/10.1002/2017GL074684>, 2017a.



- Getirana, A., Peters-Lidard, C., Rodell, M., and Bates, P. D.: Trade-off between cost and accuracy in large-scale surface water
 695 dynamic modeling, *Water Resour. Res.*, 53, 4942–4955, <https://doi.org/10.1002/2017WR020519>, 2017b.
- Getirana, A., Kumar, S. V., Yoon, Y., Arsenault, K. R., and Geiger, J. V.: The HyMAP-3 Hydrodynamic Model, 2025.
- Getirana, A. C. V., Boone, A., Yamazaki, D., Decharme, B., Papa, F., and Mognard, N.: The hydrological modeling and
 analysis platform (HyMAP): Evaluation in the Amazon basin, *J. Hydrometeorol.*, 13, 1641–1665,
<https://doi.org/10.1175/JHM-D-12-021.1>, 2012.
- 700 Giglio, L., Boschetti, L., Roy, D. P., Humber, M. L., and Justice, C. O.: The Collection 6 MODIS burned area mapping
 algorithm and product, *Remote Sens. Environ.*, 217, 72–85, <https://doi.org/10.1016/j.rse.2018.08.005>, 2018.
- Di Giuseppe, F., Vitolo, C., Barnard, C., Libertá, G., Maciel, P., San-Miguel-Ayanz, J., Villaume, S., and Wetterhall, F.: Global
 seasonal prediction of fire danger, *Sci. Data*, 11, <https://doi.org/10.1038/s41597-024-02948-3>, 2024.
- Gutmann, E. D., Hamman, J. J., Clark, M. P., Eidhammer, T., Wood, A. W., and Arnold, J. R.: En-GARD: A Statistical
 705 Downscaling Framework to Produce and Test Large Ensembles of Climate Projections, *J. Hydrometeorol.*,
<https://doi.org/10.1175/JHM-D-21>, 2022.
- Hantson, S., Arneth, A., Harrison, S. P., Kelley, D. I., Colin Prentice, I., Rabin, S. S., Archibald, S., Mouillot, F., Arnold, S.
 R., Artaxo, P., Bachelet, D., Ciais, P., Forrest, M., Friedlingstein, P., Hickler, T., Kaplan, J. O., Kloster, S., Knorr, W., Lasslop,
 G., Li, F., Mangeon, S., Melton, J. R., Meyn, A., Sitch, S., Spessa, A., Van Der Werf, G. R., Voulgarakis, A., and Yue, C.:
 710 The status and challenge of global fire modelling, *Biogeosciences*, 13, 3359–3375, <https://doi.org/10.5194/bg-13-3359-2016>,
 2016.
- Hazra, A., McNally, A., Slinski, K., Arsenault, K. R., Shukla, S., Getirana, A., Jacob, J. P., Sarmiento, D. P., Peters-Lidard,
 C., Kumar, S. V., and Koster, R. D.: NASA’S NMME-based S2S hydrologic forecast system for food insecurity early warning
 in southern Africa, *J. Hydrol. (Amst.)*, 617, <https://doi.org/10.1016/j.jhydrol.2022.129005>, 2023.
- 715 He, C., Chen, F., Barlage, M., Yang, Z. L., Wegiel, J. W., Niu, G. Y., Gochis, D., Mocko, D. M., Abolafia-Rosenzweig, R.,
 Zhang, Z., Lin, T. S., Valayamkunnath, P., Ek, M., and Niyogi, D.: Enhancing the Community Noah-MP Land Model
 Capabilities for Earth Sciences and Applications, *Bull. Am. Meteorol. Soc.*, 104, E2023–E2029,
<https://doi.org/10.1175/BAMS-D-23-0249.1>, 2023.
- Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers,
 720 D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., De Chiara,
 G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L.,
 Healy, S., Hogan, R. J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., de Rosnay, P.,
 Rozum, I., Vamborg, F., Villaume, S., and Thépaut, J. N.: The ERA5 global reanalysis, *Quarterly Journal of the Royal
 Meteorological Society*, 146, 1999–2049, <https://doi.org/10.1002/qj.3803>, 2020.
- 725 IMERG Technical documentation: https://gpm.nasa.gov/sites/default/files/document_files/IMERG_doc_190909.pdf, last
 access: 25 January 2020.



- Jiménez-Muñoz, J. C., Mattar, C., Barichivich, J., Santamaría-Artigas, A., Takahashi, K., Malhi, Y., Sobrino, J. A., and Schrier, G. Van Der: Record-breaking warming and extreme drought in the Amazon rainforest during the course of El Niño 2015-2016, <https://doi.org/10.1038/srep33130>, 8 September 2016.
- 730 Jolliffe, I. T. . and Stephenson, D. B. .: Forecast verification : a practitioner's guide in atmospheric science, John Wiley & Sons, 304 pp., 2012.
- Kansara, P., Zaitchik, B., Getirana, A., and Anderson, L.: Identifying and Accounting for Spatial Biases in Subseasonal to Seasonal Precipitation Forecasts in the Amazon Basin, *J. Hydrometeorol.*, <https://doi.org/10.1175/JHM-D-25>, 2025.
- Keating, C., Lee, D., Bazo, J., and Block, P.: Leveraging multi-model season-ahead streamflow forecasts to trigger advanced
 735 flood preparedness in Peru, *Natural Hazards and Earth System Sciences*, 21, 2215–2231, <https://doi.org/10.5194/nhess-21-2215-2021>, 2021.
- Keune, J., Di Giuseppe, F., Barnard, C., Damasio da Costa, E., and Wetterhall, F.: ERA5–Drought: Global drought indices based on ECMWF reanalysis, *Scientific Data* , 12, <https://doi.org/10.1038/s41597-025-04896-y>, 2025.
- Kleist, D. T., Parrish, D. F., Derber, J. C., Treadon, R., Wu, W. S., and Lord, S.: Introduction of the GSI into the NCEP global
 740 data assimilation system, *Weather Forecast.*, 24, 1691–1705, <https://doi.org/10.1175/2009WAF2222201.1>, 2009.
- Koster, R. D., Mahanama, S. P. P., Yamada, T. J., Balsamo, G., Berg, A. A., Boisserie, M., Dirmeyer, P. A., Doblas-Reyes, F. J., Drewitt, G., Gordon, C. T., Guo, Z., Jeong, J. H., Lawrence, D. M., Lee, W. S., Li, Z., Luo, L., Malyshev, S., Merryfield, W. J., Seneviratne, S. I., Stanelle, T., Van Den Hurk, B. J. J. M., Vitart, F., and Wood, E. F.: Contribution of land surface initialization to subseasonal forecast skill: First results from a multi-model experiment, *Geophys. Res. Lett.*, 37,
 745 <https://doi.org/10.1029/2009GL041677>, 2010.
- Koster, R. D., Lim, Y., Lee, E., and Kolassa, J.: Investigations into the Subseasonal Predictability of Soil Moisture and Streamflow, <https://doi.org/10.1175/JHM-D-25>, 2025.
- Kratzert, F., Klotz, D., Shalev, G., Klambauer, G., Hochreiter, S., and Nearing, G.: Towards learning universal, regional, and local hydrological behaviors via machine learning applied to large-sample datasets, *Hydrol. Earth Syst. Sci.*, 23, 5089–5110,
 750 <https://doi.org/10.5194/hess-23-5089-2019>, 2019.
- Kumar, S., Getirana, A., Libonati, R., Hain, C., Mahanama, S., and Andela, N.: Changes in land use enhance the sensitivity of tropical ecosystems to fire-climate extremes, *Sci. Rep.*, 12, <https://doi.org/10.1038/s41598-022-05130-0>, 2022.
- Kumar, S. V., Peters-Lidard, C. D., Tian, Y., Houser, P. R., Geiger, J., Olden, S., Lighty, L., Eastman, J. L., Doty, B., Dirmeyer, P., Adams, J., Mitchell, K., Wood, E. F., and Sheffield, J.: Land information system: An interoperable framework for high
 755 resolution land surface modeling, *Environmental Modelling and Software*, 21, 1402–1415, <https://doi.org/10.1016/j.envsoft.2005.07.004>, 2006.
- Kumar, S. V., Holmes, T., Andela, N., Dharssi, I., Vinodkumar, Hain, C., Peters-Lidard, C., Mahanama, S. P., Arsenault, K. R., Nie, W., and Getirana, A.: The 2019–2020 Australian Drought and Bushfires Altered the Partitioning of Hydrological Fluxes, *Geophys. Res. Lett.*, 48, <https://doi.org/10.1029/2020GL091411>, 2021.



- 760 Li, B., Hazra, A., McNally, A., Slinski, K., Shukla, S., and Anderson, W.: Skills in sub-seasonal to seasonal terrestrial water storage forecasting: insights from the FEWS NET land data assimilation system, *Hydrol. Earth Syst. Sci.*, 30, 1097–1115, <https://doi.org/10.5194/hess-30-1097-2026>, 2026.
- Maciel, D. A., Lousada, F., Fassoni-Andrade, A., Pacheco Quevedo, R., Barbosa, C. C. F., Paule-Bonnet, M., and Novo, E. M. L. de M.: Sentinel-1 data reveals unprecedented reduction of open water extent due to 2023-2024 drought in the central Amazon basin, *Environmental Research Letters*, 19, <https://doi.org/10.1088/1748-9326/ad8a71>, 2024.
- 765 Marengo, J. A., Tomasella, J., Alves, L. M., Soares, W. R., and Rodriguez, D. A.: The drought of 2010 in the context of historical droughts in the Amazon region, *Geophys. Res. Lett.*, 38, <https://doi.org/10.1029/2011GL047436>, 2011.
- Mariotti, A., Baggett, C., Barnes, E. A., Becker, E., Butler, A., Collins, D. C., Dirmeyer, P. A., Ferranti, L., Johnson, N. C., Jones, J., Kirtman, B. P., Lang, A. L., Molod, A., Newman, M., Robertson, A. W., Schubert, S., Waliser, D. E., and Albers, J.: Windows of opportunity for skillful forecasts subseasonal to seasonal and beyond, *Bull. Am. Meteorol. Soc.*, 101, E608–E625, <https://doi.org/10.1175/BAMS-D-18-0326.1>, 2020.
- 770 Merryfield, W. J., Baehr, J., Batté, L., Becker, E. J., Butler, A. H., Coelho, C. A. S., Danabasoglu, G., Dirmeyer, P. A., Doblaser-Reyes, F. J., Domeisen, D. I. V., Ferranti, L., Ilynia, T., Kumar, A., Müller, W. A., Rixen, M., Robertson, A. W., Smith, D. M., Takaya, Y., Tuma, M., Vitart, F., White, C. J., Alvarez, M. S., Ardilouze, C., Attard, H., Baggett, C., Balmaseda, M. A., Beraki, A. F., Bhattacharjee, P. S., Bilbao, R., De Andrade, F. M., DeFlorio, M. J., Díaz, L. B., Ehsan, M. A., Fragkoulidis, G., Grainger, S., Green, B. W., Hell, M. C., Infanti, J. M., Isensee, K., Kataoka, T., Kirtman, B. P., Klingaman, N. P., Lee, J. Y., Mayer, K., McKay, R., Mecking, J. V., Miller, D. E., Neddermann, N., Ng, C. H. J., Ossó, A., Pankatz, K., Peatman, S., Pegion, K., Perlwitz, J., Recalde-Coronel, G. C., Reintges, A., Renkl, C., Solaraju-Murali, B., Spring, A., Stan, C., Sun, Y. Q., Tozer, C. R., Vigaud, N., Woolnough, S., and Yeager, S.: Current and emerging developments in subseasonal to decadal prediction, *Bull. Am. Meteorol. Soc.*, 101, E869–E896, <https://doi.org/10.1175/BAMS-D-19-0037.1>, 2020.
- 780 Molod, A., Hackert, E., Vikhliayev, Y., Zhao, B., Barahona, D., Vernieres, G., Borovikov, A., Kovach, R. M., Marshak, J., Schubert, S., Li, Z., Lim, Y. K., Andrews, L. C., Cullather, R., Koster, R., Achuthavarier, D., Carton, J., Coy, L., Friere, J. L. M., Longo, K. M., Nakada, K., and Pawson, S.: GEOS-S2S Version 2: The GMAO High-Resolution Coupled Model and Assimilation System for Seasonal Prediction, *Journal of Geophysical Research: Atmospheres*, 125, <https://doi.org/10.1029/2019JD031767>, 2020.
- 785 Naranjo-Silva, S., Barros-Enriquez, J. D., Avemañay-Morocho, A. M., Amaya-Jaramillo, C. D., Socasi-Gualotuña, M. S., and Escobar-Segovia, K.: Assessing Climate Change Impacts on Ecuador’s Hydropower Under Representative Concentration Pathway Scenarios to 2060, *Sustainability (Switzerland)*, 18, <https://doi.org/10.3390/su18104989>, 2026.
- Nearing, G., Cohen, D., Dube, V., Gauch, M., Gilon, O., Harrigan, S., Hassidim, A., Klotz, D., Kratzert, F., Metzger, A., Nevo, S., Pappenberger, F., Prudhomme, C., Shalev, G., Shenzen, S., Tekalign, T. Y., Weitzner, D., and Matias, Y.: Global prediction of extreme floods in ungauged watersheds, *Nature*, 627, 559–563, <https://doi.org/10.1038/s41586-024-07145-1>, 2024.
- 790



- Nie, W., Zaitchik, B. F., Rodell, M., Kumar, S. V., Anderson, M. C., and Hain, C.: Groundwater Withdrawals Under Drought: Reconciling GRACE and Land Surface Models in the United States High Plains Aquifer, *Water Resour. Res.*, 54, 5282–5299, <https://doi.org/10.1029/2017WR022178>, 2018.
- 795 Niu, G. Y., Yang, Z. L., Mitchell, K. E., Chen, F., Ek, M. B., Barlage, M., Kumar, A., Manning, K., Niyogi, D., Rosero, E., Tewari, M., and Xia, Y.: The community Noah land surface model with multiparameterization options (Noah-MP): 1. Model description and evaluation with local-scale measurements, *Journal of Geophysical Research Atmospheres*, 116, <https://doi.org/10.1029/2010JD015139>, 2011.
- Paiva, R. C. D., Collischonn, W., Bonnet, M. P., De Gonçalves, L. G. G., Calmant, S., Getirana, A., and Santos Da Silva, J.:
 800 Assimilating in situ and radar altimetry data into a large-scale hydrologic-hydrodynamic model for streamflow forecast in the Amazon, *Hydrol. Earth Syst. Sci.*, 17, 2929–2946, <https://doi.org/10.5194/hess-17-2929-2013>, 2013a.
- Paiva, R. C. D., Buarque, D. C., Collischonn, W., Bonnet, M. P., Frappart, F., Calmant, S., and Bulhões Mendes, C. A.: Large-scale hydrologic and hydrodynamic modeling of the Amazon River basin, *Water Resour. Res.*, 49, 1226–1243, <https://doi.org/10.1002/wrcr.20067>, 2013b.
- 805 Piles, M., Munoz-Mari, J., Guerrero-Currieses, A., Camps-Valls, G., and Rojo-Alvarez, J. L.: Autocorrelation Metrics to Estimate Soil Moisture Persistence from Satellite Time Series: Application to Semiarid Regions, *IEEE Transactions on Geoscience and Remote Sensing*, 60, <https://doi.org/10.1109/TGRS.2021.3057928>, 2022.
- Poveda, G., Waylen, P. R., and Pulwarty, R. S.: Annual and inter-annual variability of the present climate in northern South America and southern Mesoamerica, *Palaeogeogr. Palaeoclimatol. Palaeoecol.*, 234, 3–27, <https://doi.org/10.1016/j.palaeo.2005.10.031>, 2006.
- 810 Reboita, M. S., Ambrizzi, T., Crespo, N. M., Dutra, L. M. M., Ferreira, G. W. de S., Rehbein, A., Drumond, A., da Rocha, R. P., and Souza, C. A. de: Impacts of teleconnection patterns on South America climate, *Ann. N. Y. Acad. Sci.*, 1504, 116–153, <https://doi.org/10.1111/nyas.14592>, 2021.
- Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., and Prabhat: Deep learning and process
 815 understanding for data-driven Earth system science, *Nature*, 566, 195–204, <https://doi.org/10.1038/s41586-019-0912-1>, 2019.
- Ribeiro, J. M., Wongchuig, S., and Zhao, S. Y.: The Drought of Amazonia in 2023–2024, *Am. J. Clim. Change*, 2024, 567–597, <https://doi.org/10.4236/ajcc.2024.133026>, 2024.
- Roebber, P. J.: Visualizing multiple measures of forecast quality, *Weather Forecast.*, 24, 601–608, <https://doi.org/10.1175/2008WAF2222159.1>, 2009.
- 820 Shen, C.: A Transdisciplinary Review of Deep Learning Research and Its Relevance for Water Resources Scientists, <https://doi.org/10.1029/2018WR022643>, 1 November 2018.
- Shukla, S. and Lettenmaier, D. P.: Seasonal hydrologic prediction in the United States: Understanding the role of initial hydrologic conditions and seasonal climate forecast skill, *Hydrol. Earth Syst. Sci.*, 15, 3529–3538, <https://doi.org/10.5194/hess-15-3529-2011>, 2011.



- 825 da Silva, L. J., Parente, V., de Jesus, J. O. N., Oliveira Esquerre, K. P., Sahin, O., and de Araujo, W. C.: Pumped Hydro Storage in the Brazilian Power Industry: A Sustainable Approach to Expanding Renewable Energy, Sustainability (Switzerland), 17, <https://doi.org/10.3390/su17051911>, 2025.
- Singh, C., Van Der Ent, R., Fetzer, I., and Wang-Erlandsson, L.: Multi-fold increase in rainforest tipping risk beyond 1.5-2 °C warming, Earth System Dynamics, 15, 1543–1565, <https://doi.org/10.5194/esd-15-1543-2024>, 2024.
- 830 Souza, C. M., Shimbo, J. Z., Rosa, M. R., Parente, L. L., Alencar, A. A., Rudorff, B. F. T., Hasenack, H., Matsumoto, M., Ferreira, L. G., Souza-Filho, P. W. M., de Oliveira, S. W., Rocha, W. F., Fonseca, A. V., Marques, C. B., Diniz, C. G., Costa, D., Monteiro, D., Rosa, E. R., Vélez-Martin, E., Weber, E. J., Lenti, F. E. B., Paternost, F. F., Pareyn, F. G. C., Siqueira, J. V., Viera, J. L., Neto, L. C. F., Saraiva, M. M., Sales, M. H., Salgado, M. P. G., Vasconcelos, R., Galano, S., Mesquita, V. V., and Azevedo, T.: Reconstructing three decades of land use and land cover changes in Brazilian biomes with Landsat archive and earth engine, Remote Sens. (Basel), 12, <https://doi.org/10.3390/RS12172735>, 2020.
- Sulla-Menashe, D., Gray, J. M., Abercrombie, S. P., and Friedl, M. A.: Hierarchical mapping of annual global land cover 2001 to present: The MODIS Collection 6 Land Cover product, Remote Sens. Environ., 222, 183–194, <https://doi.org/10.1016/j.rse.2018.12.013>, 2019.
- Svoboda, M., Lecomte, D., Hayes, M., Heim, R., Gleason, K., Angel, J., Rippey, B., Tinker, R., Palecki, M., Stooksbury, D., 840 Miskus, D., and Stephens, S.: THE DROUGHT MONITOR, 2002.
- Thomas L. Delworth; Syukuro Manabe: clim-1520-0442_1988_001_0523_tiopeo_2_0_co_2, J. Clim., 1988.
- Tokuda, D. and Dirmeyer, P. A.: On the Comparison of Multiple Types of Soil Moisture Memory, J. Hydrometeorol., <https://doi.org/10.1175/JHM-D-24-0149.1>, 2026.
- Towner, J., Cloke, H. L., Zsoter, E., Flamig, Z., Hoch, J. M., Bazo, J., De Perez, E. C., and Stephens, E. M.: Assessing the performance of global hydrological models for capturing peak river flows in the Amazon basin, Hydrol. Earth Syst. Sci., 23, 3057–3080, <https://doi.org/10.5194/hess-23-3057-2019>, 2019.
- 845 Valente, F. and Laurini, M.: A spatio-temporal analysis of fire occurrence patterns in the Brazilian Amazon, Sci. Rep., 13, <https://doi.org/10.1038/s41598-023-39875-z>, 2023.
- Vitart, F., Ardilouze, C., Bonet, A., Brookshaw, A., Chen, M., Codorean, C., Déqué, M., Ferranti, L., Fucile, E., Fuentes, M., Hendon, H., Hodgson, J., Kang, H. S., Kumar, A., Lin, H., Liu, G., Liu, X., Malguzzi, P., Mallas, I., Manoussakis, M., Mastrangelo, D., MacLachlan, C., McLean, P., Minami, A., Mladek, R., Nakazawa, T., Najm, S., Nie, Y., Rixen, M., Robertson, A. W., Ruti, P., Sun, C., Takaya, Y., Tolstykh, M., Venuti, F., Waliser, D., Woolnough, S., Wu, T., Won, D. J., Xiao, H., Zaripov, R., and Zhang, L.: The subseasonal to seasonal (S2S) prediction project database, Bull. Am. Meteorol. Soc., 98, 163–173, <https://doi.org/10.1175/BAMS-D-16-0017.1>, 2017.
- 855 Wagner, F. H., Favrichon, S., Dalagnol, R., Hirye, M. C. M., Mullissa, A., and Saatchi, S.: The Amazon's 2023 Drought: Sentinel-1 Reveals Extreme Rio Negro River Contraction, Remote Sens. (Basel), 16, <https://doi.org/10.3390/rs16061056>, 2024.



- Weigel, A. P., Liniger, M. A., and Appenzeller, C.: The discrete Brier and ranked probability skill scores, *Mon. Weather Rev.*, 135, 118–124, <https://doi.org/10.1175/MWR3280.1>, 2007.
- 860 White, C. J., Carlsen, H., Robertson, A. W., Klein, R. J. T., Lazo, J. K., Kumar, A., Vitart, F., Coughlan de Perez, E., Ray, A. J., Murray, V., Bharwani, S., MacLeod, D., James, R., Fleming, L., Morse, A. P., Eggen, B., Graham, R., Kjellström, E., Becker, E., Pegion, K. V., Holbrook, N. J., McEvoy, D., Depledge, M., Perkins-Kirkpatrick, S., Brown, T. J., Street, R., Jones, L., Remenyi, T. A., Hodgson-Johnston, I., Buontempo, C., Lamb, R., Meinke, H., Arheimer, B., and Zebiak, S. E.: Potential applications of subseasonal-to-seasonal (S2S) predictions, <https://doi.org/10.1002/met.1654>, 1 July 2017.
- 865 Wilks, D. S.: “The stippling shows statistically significant grid points”: How research results are routinely overstated and overinterpreted, and what to do about it, <https://doi.org/10.1175/BAMS-D-15-00267.1>, 1 December 2016.
- Wood, A. W., Hopson, T., Newman, A., Brekke, L., Arnold, J., and Clark, M.: Quantifying Streamflow Forecast Skill Elasticity to Initial Condition and Climate Prediction Skill, *J. Hydrometeorol.*, 17, 651–668, <https://doi.org/10.1175/JHM-D-14-0213.1>, 2016.
- 870 Yang, G. and Block, P.: Enhancing Season-Ahead Streamflow Forecasts with GCMs, Climate Indices, and Their Interactions, *J. Water Resour. Plan. Manag.*, 149, <https://doi.org/10.1061/jwrmd5.wreng-6067>, 2023.
- Yang, Z. L., Niu, G. Y., Mitchell, K. E., Chen, F., Ek, M. B., Barlage, M., Longuevergne, L., Manning, K., Niyogi, D., Tewari, M., and Xia, Y.: The community Noah land surface model with multiparameterization options (Noah-MP): 2. Evaluation over global river basins, *Journal of Geophysical Research Atmospheres*, 116, <https://doi.org/10.1029/2010JD015140>, 2011.
- 875 Zamora, R. A., Zaitchik, B. F., Rodell, M., Getirana, A., Kumar, S., Arsenault, K., and Gutmann, E.: Contribution of Meteorological Downscaling to Skill and Precision of Seasonal Drought Forecasts, *J. Hydrometeorol.*, 22, 2009–2031, <https://doi.org/10.1175/JHM-D-20-0259.1>, 2021.
- Zeng, N., Yoon, J. H., Marengo, J. A., Subramaniam, A., Nobre, C. A., Mariotti, A., and Neelin, J. D.: Causes and impacts of the 2005 Amazon drought, *Environmental Research Letters*, 3, <https://doi.org/10.1088/1748-9326/3/1/014002>, 2008.