



Seasonal Precipitation Predictability Based on Sea Surface Temperature Forecasts From a Cyclostationary Linear Inverse Model

Melissa L. Breeden¹, Andrew Hoell¹, Daniel J. Vimont², Kinya Toride^{1,3}, Weston B. Anderson⁴

¹Physical Sciences Laboratory, National Oceanic and Atmospheric Administration, Boulder CO, 80305, USA

²Department of Atmospheric and Oceanic Sciences, University of Wisconsin-Madison, Madison WI, 53716, USA

³Cooperative Institute for Research in Environmental Sciences, University of Colorado Boulder, Boulder CO, 80309, USA

⁴Department of Geographical Sciences, University of Maryland, College Park MD, 20742, USA

Correspondence to: Melissa L. Breeden (melissa.breeden@noaa.gov)

Abstract. Developing skillful seasonal precipitation forecasts remains a key challenge over many areas of the world. In this study, we test how much seasonal precipitation forecast skill can be derived from sea surface temperature (SST) forecasts from a cyclostationary linear inverse model (CSLIM) trained on observed estimates of seasonally varying predictable dynamics. Here we introduce a novel method that learns lead- and season-specific relationships between CSLIM SST forecasts and observed precipitation empirical orthogonal functions to generate precipitation forecasts up to one year in advance. Furthermore, we assess the precipitation forecast skill related to modes of SST variability, including the El Niño / Southern Oscillation (ENSO) and a long-term warming trend.

Precipitation skill generated using CSLIM SST forecasts is better than climatology for many key rainy seasons worldwide, in many cases 6-12 months in advance. A single ENSO mode, which captures most but not all ENSO variability, is the leading source of precipitation skill for several seasons such as the October-December ‘short’ rains in East Africa, the main Central America rainy season, and winter precipitation over the southeast and southwest United States. Conversely, a long-term trend accounts for most of the skill over the Sahel. West Pacific SST variability distinct from the ENSO mode contributes to skill in some cases such as the March – May ‘long’ rains in East Africa and the Middle East / Southwest Asia region. Some precipitation seasons, such as warm season southeast US precipitation, are not skillful from CSLIM SST forecasts, suggesting a limited or nonlinear relationship between SSTs and precipitation, and/or one that is hindered by seasonally unpredictable dynamics.

1 Introduction

Despite their overwhelming utility for a range of sectors such as agriculture (Ingram et al. 2002), humanitarian aid (Funk et al. 2019), emergency planning and disaster relief (Committee on Developing a U.S. Research Agenda to Advance Subseasonal to Seasonal Forecasting 2016), and water resource management (Eldadiry and Hossain 2021; Sengupta et al. 2022), generating skillful seasonal (> one month) precipitation forecasts remains a challenge for the earth system predictability community (Weisheimer and Palmer 2014; McEvoy et al. 2016; NASEM 2016; Shukla et al. 2019; Kumar and Chen 2020; Roy et al. 2020; Becker et al. 2020, 2022; Shirvani et al. 2023). Precipitation skill is often lower than 2-meter temperature skill, with relatively higher performance during periods with strong climate signals, such as the El Niño-Southern Oscillation (ENSO; McEvoy et al. 2016; Chen et al. 2017; Lenssen et al. 2020). Imperfect model representation of ENSO is a well-known feature of climate models (Joseph and Nigam 2006; Roy et al. 2019) and is consequently a source of seasonal precipitation forecast error (Williams et al. 2023), with ENSO-related errors developing within the first couple of weeks of seasonal forecasts (Beverley et al. 2023). These ENSO-related errors drive errors in the large-scale circulation and subsequently, regional temperature and precipitation.



An alternative approach to dynamical forecasts is developing statistical forecast models using sea surface temperatures (SSTs) to predict precipitation (e.g., Hastenrath 1995; Barnston et al. 1999; Giannini et al. 2000; van Oldenborgh 2005), which has benefited from including more predictors and more complex methods (Eden et al. 2015; Krikken et al. 2024). When trained on observations, these statistical approaches avoid the ENSO biases that develop in seasonal forecast models (Beverley et al. 2023). A limitation, however, is that SST indices are often used as proxies for phenomena, such as ENSO proxied by the Niño3.4 index, while ENSO variance extends beyond the Niño3.4 region. Statistical forecasts rely on the present event evolving similar to past ones, a potential setback given that no two ENSO events are the same (e.g., Wyrski 1975; Capotondi et al. 2015). However, skillful and unbiased SST forecasts can be cheaply generated with linear inverse models (LIMs), which use the observed covariance statistics between SST and, in some cases, sea surface height (SSH) anomalies to generate ensemble mean, deterministic SST forecasts (Penland 1989; Penland and Sardeshmukh 1995; Shin et al. 2021). LIMs, by construction, are devoid of mean model drift or bias and have tropical SST skill similar to that of operational dynamical forecast models such as the North American Multi-Model Ensemble (NMME; Newman et al. 2017; Shin et al. 2021).

It is unknown what degree of seasonal precipitation skill can be derived from LIM SST forecasts. In this study, we first generate SST forecasts from a seasonally-varying or ‘cyclostationary’ LIM (CSLIM; Shin et al. 2021) and subsequently train regression models between CSLIM SST forecasts and observed precipitation empirical orthogonal functions (EOFs). The CSLIM estimates the seasonally and spatially varying dynamics of a system from its lagged correlation statistics, and as such can produce forecasts that include information about the seasonal lifecycle of ENSO from its early, east Pacific pattern to its mature, central Pacific pattern captured by Niño3.4. We hypothesize that significant precipitation skill can be achieved from this method where tropical SSTs and precipitation are related, including sub-Saharan Africa (Nicholson and Entekhabi 1986; Folland et al. 1986; Ropelewski and Halpert 1989; Indeje et al. 1999; Palmer et al. 2023), the western and eastern United States (Ropelewski and Halpert 1986; Cayan et al. 1999; Yang and Delsole 2012; Nigam and Sengupta 2021; Amaya et al. 2026; Hoell et al. 2026), Central America (Waylen et al. 1994; Magaña et al. 1999; Maldonado et al. 2013), and the Middle East / southwest Asia (MESA; Barlow et al. 2002; Barlow et al. 2016; Hoell et al. 2017, 2018; Chen et al. 2018). A CSLIM can also be used to decompose SST forecasts into contributions from individual or collections of dynamical modes to isolate the influence of specific phenomena such as ENSO and long-term warming (e.g., Penland and Matrosova 2006; Vimont et al., 2022; Breeden et al. 2025). To identify sources of precipitation skill in several regions of interest, we generate precipitation forecasts using the ENSO mode, trend mode, and the remaining modes’ SST forecasts. We expect precipitation skill to be predominantly associated with the ENSO-related component of the CSLIM SST forecasts.

Section 2 describes the data and methods used to construct the CSLIM and precipitation forecasts, Section 3 presents results and Section 4 discusses the implications of this work and opportunities for future applications and research.

2 Data and Methods

This study uses monthly mean anomalies for the period 1981-2024 for training and verification of SST and precipitation forecasts. Data used include NOAA Extended Reconstructed SST V5 data provided by the NOAA Physical Sciences Laboratory (Huang et al. 2017), Ocean Reanalysis System version 5 (ORAS5) sea surface height (SSH; Copernicus Climate Change Service), and Climate Hazards Center Infrared Precipitation with Stations version 3 precipitation (CHIRPS 3.0, Funk et al. 2026; Climate Hazards Center 2025). Precipitation, SST, and SSH anomalies are calculated with respect to the 1981-2024 monthly climatology. To focus on seasonal time scales, a three-month running mean is applied to the monthly precipitation anomalies.



2.1 Cyclostationary Linear Inverse Model (CSLIM)

Following Shin et al. (2021), we train a CSLIM on SST and SSH anomalies over the period 1981-2024 to compose state vector $\mathbf{x}$, whose time evolution is modeled by the CSLIM as linear and forced by white noise (Eqns 1-3):

$$\mathbf{x} = \begin{bmatrix} SST \\ SSH \end{bmatrix} \quad (1)$$

$$\frac{d\mathbf{x}_m}{dt} = \mathbf{L}_m \mathbf{x}_m + \boldsymbol{\zeta}_m \quad (2)$$

$$\mathbf{L}_m = \ln((\mathbf{C}_m(\tau=1)\mathbf{C}_m^{-1}(\tau=0))) \quad (3),$$

where $\mathbf{L}_m$ represents the slowly-evolving, deterministic dynamics of the system, $m=1:12$ denotes each calendar month, $\boldsymbol{\zeta}_m$ is the seasonally varying stochastic white noise parameter, $\mathbf{C}_m(\tau=1)$ and $\mathbf{C}_m(\tau=0)$ are the one-month lagged and equal time covariances of $\mathbf{x}$, respectively. The key difference between ‘stationary’ LIMs (Penland and Sardeshmukh 1995) and ‘cyclostationary’ LIMs is that the latter uses unique $\mathbf{L}$ matrices for each month of the year, thereby assuming the system variance has seasonality, as opposed to training one $\mathbf{L}$ year-round, as done in stationary LIMs that assume variance is the same year-round. The homogeneous solution to Eqn 2 yields an equation for infinite ensemble mean deterministic forecasts $\hat{\mathbf{x}}_m(t+\tau)$ starting from an initial condition $\mathbf{x}_m(t)$ in calendar month m :

$$\hat{\mathbf{x}}_m(t+\tau) = \mathbf{G}_{m+\tau-1} \mathbf{G}_{m+\tau-2} \cdots \mathbf{G}_{m+1} \mathbf{G}_m \mathbf{x}_m(t) \quad (4)$$

where $\mathbf{G}_m = \exp(\mathbf{L}_m)$ propagates the state of the system in calendar month m forward one month. For example, a three-month forecast from a December initial time t would be valid in March, and would be calculated as:

$$\hat{\mathbf{x}}_{12}(t+3) = \mathbf{G}_2 \mathbf{G}_1 \mathbf{G}_{12} \mathbf{x}_{12}(t) \quad (5)$$

In the state vector, for dimension reduction, EOFs and the corresponding principal components (PCs) for SST and SSH are used to calculate $\mathbf{x}$ and forecasts of $\mathbf{x}$. The PCs of each variable are normalized by the domain root-mean-square amplitude. When $m+\tau > 12$ months, the indices for $\mathbf{L}$ and $\mathbf{G}$ start over at 1. In this CSLIM, 10 (3) EOFs representing 71% (63%) variance are employed for SST (SSH), a selection that retains enough variance for a skillful model while maintaining the expected properties of the system (Table 1; Penland and Sardeshmukh 1995). Further details regarding the CSLIM construction may be found in Shin et al. (2021). To generate cross-validated forecasts, we employ k-fold cross-validation by removing four consecutive years (9%) of the data and training unique forecast operators for each fold that are used to generate forecasts for the four years that are left out of training.

To diagnose sources of SST and precipitation predictability, we decompose the seasonally-varying dynamical system matrix $\mathbf{L}_m$ into eigenmodes that each have unique e-folding timescales and patterns associated with them, as done in past studies (Table 2; Shin et al. 2021; Vimont et al. 2022). These modes are seasonally-varying analogs to stationary LIM eigenmodes which have been referred to as ‘principal oscillation patterns’ or ‘empirical normal modes’ (Hasselmann 1988). Using the stationary LIM framework, Penland and Matrosova (2006) showed how ENSO variability arises from a combination of such ‘LIM eigenmodes’, while the eigenmode with the longest e-folding timescale, namely the least-damped eigenmode, represents a long-term warming trend. We isolate contributions to SST initial conditions (ICs) and CSLIM SST forecasts into three groups: the least-damped eigenmode representing a long-term trend, one mode representing ENSO variability, and a ‘remaining’ group



115 containing the rest of the modes with the shorter e-folding timescales (Table 2; Figures S1-S2). The ENSO mode was chosen based on its pattern and e-folding timescale, which is highly similar to the ENSO mode characteristics discussed in Vimont et al. 2022. To assess the precipitation skill that is associated with each group of SSTs, we use the filtered SST forecasts to generate precipitation forecasts and evaluate their corresponding skill.

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Variable	Horizontal Resolution	Domain	# EOFs used (% variance explained)
SST	2° x 2°	36°S - 24°N, 0-358°E	10 (71.13%)
SSH	1° x 1°	35.5°S - 25.5°N, 100 - 284°E	3 (63.05%)
Precipitation	1° x 1°	60°S - 60°N, 0-359°E	Varies

Table 1: Details of data used. SST and SSH are included in the CSLIM to generate SST forecasts. SST Forecasts are subsequently used to fit MLR models to forecast precipitation EOFs.

Mode	E-folding Timescale	Period	SST Grouping
1	764.5	-	Trend
2/3	20.8	34.8	ENSO
4	14.3	-	remaining
5/6	8.2	16.9	remaining
7/8	5.4	14.9	remaining
9/10	4.7	8.0	remaining
11	3.0	-	remaining
12/13	2.8	6.7	remaining

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Table 2: E-folding timescale and periods (if applicable) in months for the CSLIM Floquet modes.

2.2 Regression Model

130 Instead of using the relationship between observed SSTs and observed precipitation, as in prior studies (e.g., Hastenrath 1995; Giannini et al. 2000), here we use the relationship between *forecast* SSTs for a given month and lead time with the



observed precipitation verifying at that time. A similar approach was conducted using dynamical forecast model SSTs to predict Central American precipitation by Kowal et al. (2023). The SST forecast state vector $\hat{\mathbf{x}}$ has 13 components (Eqn 6), and the first four are used to forecast precipitation. Since precipitation contains significant fine-scale variability that is likely unrelated to SSTs and presumably less predictable, we create forecasts of the leading PCs of CHIRPS3.0 anomalies using unique regression models ($\hat{y}_e$; Eqn 7). Thereafter, the EOF patterns are used to calculate that PC's forecast in gridspace, and then the individual EOF forecasts are summed to generate the total precipitation forecast. As such, there is *no initial precipitation* information included in the precipitation forecasts. The example below is the process to generate a forecast for one lead time, and one initialization-verification pair:

$$\hat{\mathbf{x}} = [x_1, x_2, x_3, \dots, x_{13}] \quad (6)$$

$$\hat{y}_e = a_1 x_1 + a_2 x_2 + a_3 x_3 + a_4 x_4 \quad (7)$$

Where 'e' represents a given precipitation PC and the values $a_1 \dots a_4$ represent the regression coefficient that minimizes the error between the observed precipitation and the first four components of $\hat{\mathbf{x}}$ for that month and lead time. For each precipitation PC, unique regression coefficients are calculated for each lead time from 1-12 months, and each verification month. As for the CSLIM SST forecasts, k-fold cross-validation is performed for the regression coefficients. Using the first four components of $\hat{\mathbf{x}}$ yields higher precipitation skill than using all 13 components that are available (not shown). Using a single set of EOFs for both the tropics and extratropics - the full domain of CHIRPS3.0 which is global from 60S-60N - means that there are differences in the local precipitation variance explained by each EOF. To achieve the best model for a given gridpoint, we create forecasts using progressively more EOFs (i.e. the first EOF only, the first and second, first, second, and third...), evaluate the skill using progressively more EOFs at each gridpoint. For the final forecast, we use the number of EOFs that maximizes the cross-validated skill at that gridpoint.

This approach allows for regional variations in the precipitation model to reflect where local precipitation is contained within the somewhat arbitrary EOF decomposition. The distribution of the number of EOFs that maximizes skill at each gridpoint, for all verification months and lead times of one, three, and six months (Figure S3), shows that most gridpoints have the highest ACC when a small number (<10) of precipitation EOFs are used to generate the forecast. The number of EOFs used at different lead times is fairly similar for lead times of one, three, and six months, meaning that the models at different lead times are using similar amounts of precipitation variance to generate the most skillful model. This seems reasonable, as the relationships between SST and precipitation at a given location does not change from one lead time to another. Finally, the spatial distribution of the number of EOFs used shows fairly large regions with similar amounts of EOFs being used, shown for an example of OND verifications in Figure S4.

2.3 Forecast Skill Evaluation

We evaluate SST and precipitation forecast skill using mainly anomaly correlation coefficients (ACC), which measures the temporal consistency between the observed and forecast anomalies. This is done at each gridpoint and for area-averaged SST and precipitation forecasts. While the forecasts are generated using EOF-truncated anomalies, the verification SST and precipitation are not truncated, meaning they include 100% of the variance. SST skill is evaluated over the Niño3.4 (5°S - 5°N, 170°W-120°W) and Dipole Mode Index (DMI, [10°S-10°N, 50°E-70°E] - [10°S - 0°N, 90°E - 110°E]) regions to evaluate ENSO and IOD forecast skill. Precipitation skill is evaluated at each gridpoint and for forecasts area-averaged over several areas in the tropics and extratropics, including some of interest to FEWS NET: the Sahel (12°N - 22°N, 5°W - 30°E), Middle East and



170 Southwest Asia (MESA; 28°N - 42°N, 35°E - 73°E), East Africa (5°S - 10°N, 32°E - 52°E), Central America (8°N - 18°N, 75°W
- 95°W), and two skillful regions in the United States, in the southwest (30°N - 42°N, 112°W - 124°W) and southeast (30°N -
37°N, 78°W - 88°W). Skill is not shown during dry months, defined as months with less than 5% of the annual accumulated
precipitation. Since the Sahel has a precipitation trend, we also considered its skill verified against detrended precipitation.
Detrending was performed by regressing the tropical mean trend-related SST anomaly time series onto full-field precipitation
175 anomalies (Figure 12), and using the resulting regression pattern to estimate the trend-related precipitation anomaly in each
month. These anomalies were then subtracted from the unfiltered precipitation anomalies and forecasts were verified against the
resultant detrended precipitation field.

To test whether optimizing the precipitation forecasts on ACC produces skillful forecasts according to alternative skill
metrics, we calculated the root-mean-square-error (RMSE, Eqn 9) for the area-averaged forecasts for the six regions described
180 above. Since these regions have markedly different precipitation climatologies and anomaly values, we consider the RMSE
normalized by each region's standard deviation, $RMSE_{std}$:

$$RMSE_{std} = \frac{\sqrt{1/N \sum (precip - precip_f)^2}}{std(precip)} \quad (9)$$

185 2.3.1 Statistical Significance

The statistical significance of forecast skill is determined non-parametrically using bootstrapping with replacement
(Efron 1979). This process resamples a given set of values, with replacement, to determine 10000 equally plausible realizations
of a given quantity such as ACC. The confidence bounds of those bootstrapped values are determined, and for skill, if the bounds
of ACC are greater than zero - the ACC of a climatological forecast - with 95% confidence, the skill is marked as statistically
190 significant.

3 Results



3.1 CSLIM SST Forecasts

Tropical SST forecasts generated by the CSLIM and decomposed into the ENSO, trend, and remaining modes confirms that historical ENSO events are generally well-forecasted six months in advance, and that the ENSO mode accounts for most of the SST anomaly in the central tropical Pacific (Figure 1). The ENSO mode is also associated with SST anomalies in the tropical Indian Ocean, including the IOD region, consistent with past studies linking ENSO and IOD variability (e.g., Reverdin et al. 1986; Yang et al. 2015; Hoell et al. 2025). The remaining modes are associated with SST anomalies at the far western extent of the ENSO region, which together with variance in the subtropical east Pacific, somewhat resemble the Pacific Meridional Mode (PMM, Chiang and Vimont 2004; Figure 1d, Figure S1c). The trend mode contributes weakly to SST forecasts, with a transition from cooler early in the period to warmer SSTs later on, with greatest amplitude in the western Pacific and Indian Oceans (Fig. 1e). Though weak, the trend-related anomalies modulate the east-west SST gradient during ENSO events, with warm trend anomalies weakening the gradient during El Niño events and strengthening it during La Niña events. The SST anomalies from the remaining modes can oppose the SSTs from the ENSO modes, such as during the 2015-2016 El Niño event. Conversely, the 1999-2001 La Niña event involved the constructive interference of colder SSTs from both the ENSO and remaining modes. Forecasts for the 2020 - 2022 La Niña events were associated with the ENSO mode only early in the period, with the remaining modes increasingly contributing as the event continued. In contrast to events with strong ENSO mode contributions, this period of La Niña conditions was not well-forecast nine months ahead (Figure S5), given the shorter e-folding timescales of the remaining modes.

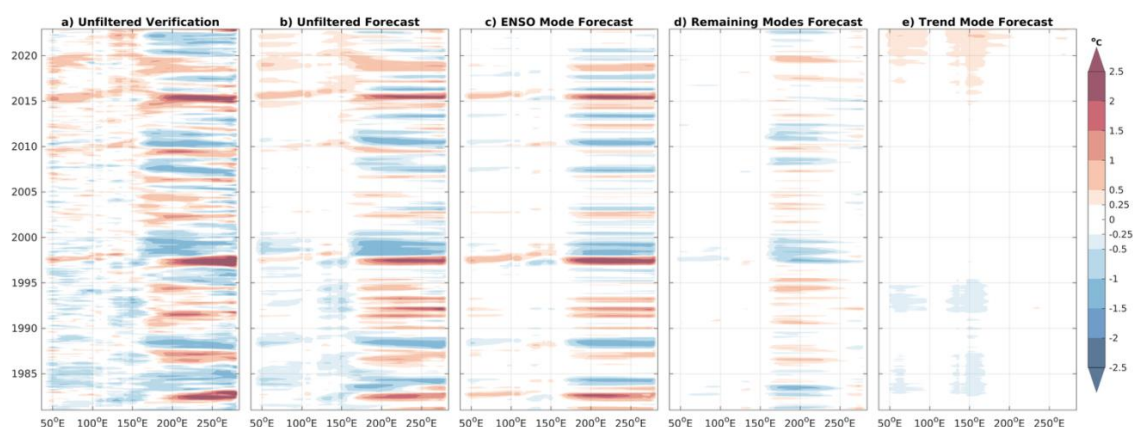
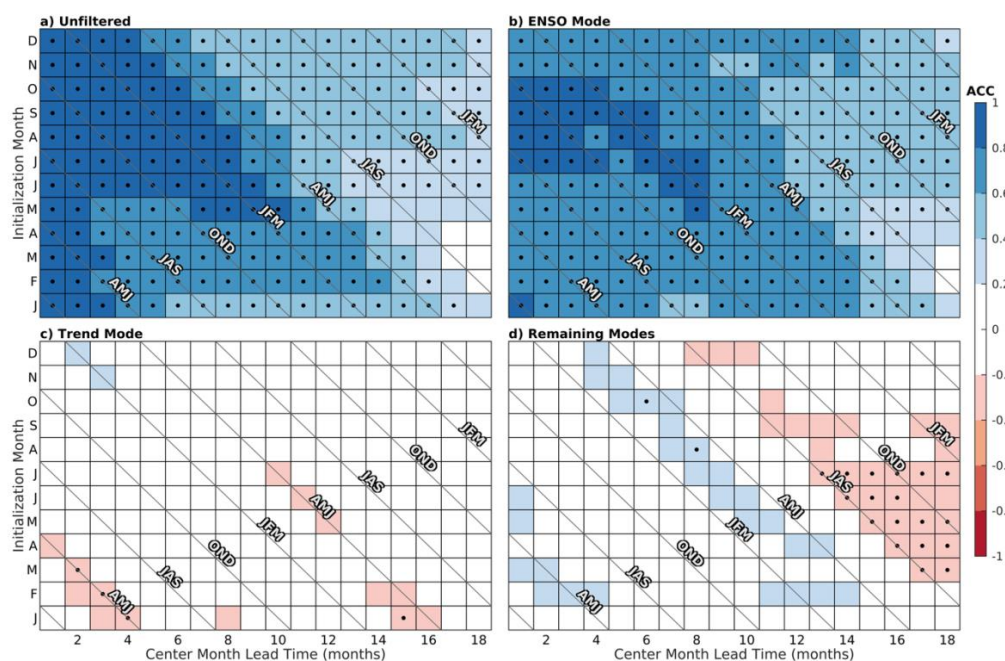


Figure 1: Time-longitude cross section of SST anomalies averaged from 5° S - 5° N for a) the unfiltered verification SST, b) unfiltered six-month SST forecast, c) six-month ENSO mode SST forecast, d) six-month remaining modes SST forecast, and e) six-month trend mode SST forecast.

Tropical SST skill produced by the CSLIM is high, including notable Niño3.4 and DMI skill representing ENSO and the IOD, respectively (Figures 2-3). Skill is greatest for forecasts verifying in JFM-FMA seasons, with ACC > 0.8 up to ten months in advance for May initializations and remaining significant 18 months ahead. This timing aligns with when ENSO is amplifying to maturity, while forecasts initialized from January to April when ENSO is often decaying or transitioning are less skillful, with ACC decreasing after 2-3 month lead times. Niño3.4 skill is dominated by the ENSO mode, with minimal skill from the trend, and smaller contributions to skill from the remaining modes that are weakly positive in year one and negative in year two (Figure 2b-d). The ENSO mode skill, by comparison, remains more constant with lead time, with ACC > 0.6 extending

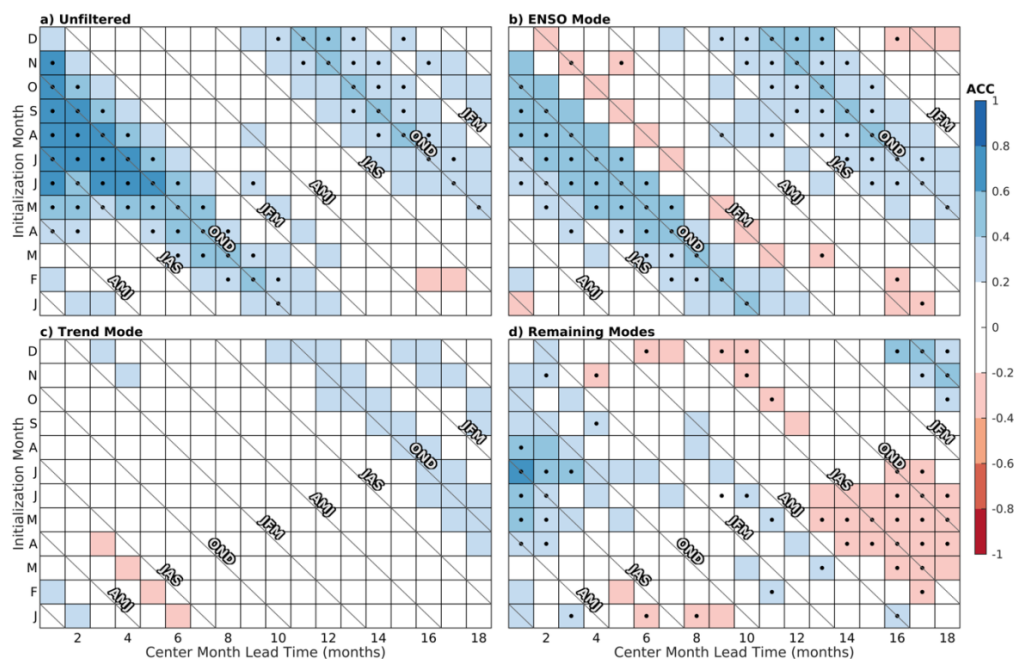


to longer lead times than the unfiltered forecasts (c.f., Fig. 2a, b). This means that modes with shorter e-folding time are not contributing to ENSO prediction and actually hinder its prediction at longer lead times.



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Figure 2: Niño3.4 ACC generated by the CSLIM, as a function of lead time (horizontal axis) and initialization month (vertical axis), with the middle month of each season indicated. Forecast verification seasons are indicated by the diagonal lines and their respective labels. Black stippling marks where ACC is statistically significant from zero with 95% confidence.



230 **Figure 3:** As in Figure 2 but for the DMI representing IOD variability.

In contrast to Niño3.4 skill, DMI skill is only significant for forecasts verifying from ASO to NDJ seasons, when IOD events are amplifying and reaching their peak intensity (Figure 3). DMI skill is a function of both lead time and initialization month, with greatest ACC observed mainly for shorter lead times, though with higher skill remaining for lead times up to 9-10 months for OND verifications. Consistent with past studies linking ENSO and IOD variability (Klein et al. 1999; Krishnamurty and Kirtman 2000; Wang et al. 2016), IOD skill is associated with the ENSO mode, which contributes to skill from September to December and accounts for all skill at longer lead times, including significant skill in year two (Fig. 3b). The trend mode does not contribute notably to IOD skill, which is unsurprising since it is associated with basin-wide Indian Ocean warming (Figure S2). However, the remaining SST modes do contribute to IOD skill, earlier in the year and for shorter lead times than the ENSO mode, mainly for short-term forecasts made from May to August (Figure 3d). Thus, the full CSLIM DMI skill arises due to the combined effect of the ENSO and remaining modes. It is possible that some of the IOD skill from the remaining modes is due to remaining ENSO variability, or that it arises from non-ENSO IOD variability. Indeed, prior modeling work has found that IOD events can develop during summer and early fall in the absence of ENSO variability (Huang and Shukla, 2007; Wang et al. 2016), coinciding with when IOD skill from the remaining modes is greatest.

245 3.2 SST-Derived Precipitation Skill

Precipitation forecast skill derived from CSLIM SST forecasts is significant during many seasons world-wide (Figure 4). We first consider the spatial distribution of ACC for a six-month lead time, noting that in similar areas skill remains significant nine months in advance (Figure S6). Forecasts verifying in JFM are skillful over the southwestern and southeastern US, northern South America, and southern Africa, where ENSO teleconnections are known to be active (Figure 4a). A large area



from central and eastern Europe spanning eastward into Asia also has skill at this time, as well as southeast China, and parts of the Maritime Continent and northern Australia. Forecasts verifying in AMJ have high skill over East Africa, MESA, and northwest Europe, while skill declines over the US (Figure 4b). Southeast Asia precipitation is highly skillful, while the Maritime Continent less so, likely due to ENSO often transitioning at this time of year.

Forecasts verifying in JAS are most skillful during the main rainy season in the Sahel, most notably from central Mali to western Sudan, as well as over southern Mexico, Central America and northern South America (Figure 4c). Significant and high skill ($ACC > 0.5$) in the Sahel is interesting since North Atlantic (north of 25°N) and Mediterranean SSTs are not explicitly included in the CSLIM, but are regions where SSTs have long been linked to Sahel precipitation (Palmer et al. 1986; Gaetani et al. 2010; Li et al. 2016). Elsewhere, skill is somewhat scattered but still notable over the Missouri River Basin in the US, the Maritime Continent, parts of Asia, and northern Democratic Republic of the Congo. Finally, forecasts verifying in OND are highly skillful over east, central and parts of southern Africa, and southwest Asia, which are both regions affected jointly by ENSO and the IOD (Figure 4d; Figure 3). Significant skill is observed across much of southern Central America and South America, the southeast US and northern Mexico, and the Maritime Continent and northern Australia, many regions that are affected by ENSO, which is often amplifying to maturity during OND, and likely contributing to the high amplitude and large spatial extent of precipitation skill evident in this season.

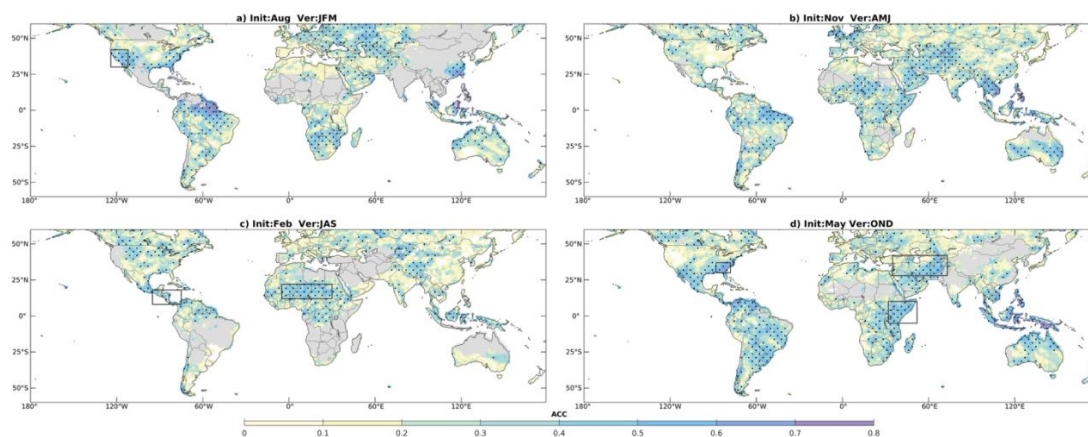


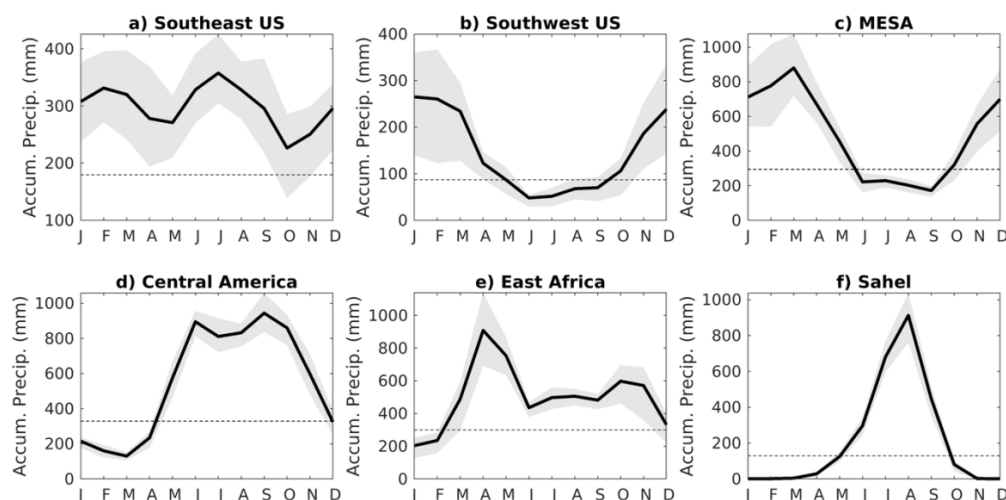
Figure 4: ACC of 6-month precipitation forecasts verifying in a) JFM b) AMJ, c) JAS and d) OND seasons. ACC that is statistically significant with 95% confidence is marked with black stippling. Gray shading indicates seasons in which each of the three months contributes to $<5\%$ of annual accumulated precipitation, and white areas indicate locations where ACC is less than zero. Verification is 3-month running mean CHIRPS3.0 precipitation. The black boxes indicate the regions over which precipitation forecasts are averaged and their skill evaluated in Figures 6-11.

3.2.1 Sources of Regional Precipitation Skill

Next we consider the lead-and season-dependent skill of the area-averaged precipitation forecasts for the six regions outlined in Figure 4. The seasonality and accumulated precipitation in these regions (Figure 5) highlight the differences in seasonality and variability of precipitation in these areas. The southeast US receives precipitation year-round, with relative peaks around JFM and JJA, while southwest US precipitation peaks during the cold season, with the greatest year-to-year variability of any region (Figure 5a-b). The cold-season MESA precipitation season peaks from November to March, with notable spread from year to year (Figure 5c). The less-variable Central America rainy season occurs from May to November, with peak precipitation in June and September (Figure 5d). The long (MAM) and short (OND) rains in East Africa are evident, as well as relatively lower but still appreciable precipitation from June to September (Figure 5e). The Sahel rainy seasons is unimodal, displaying



280 minimal variance and a dry season with no precipitation accumulation from November – March and peak precipitation occurring June - September (Figure 5f).



285 **Figure 5: Monthly accumulated precipitation averaged over the black boxes in Figure 4. The thick black line is the 1981-2024 monthly mean accumulation, and gray shading indicates the interquartile range. Precipitation must exceed the value shown by the black dotted line to account for more than five percent of the total annual accumulation.**

The skill of area-averaged precipitation forecasts derived from SST forecasts is often high and statistically significant during key rainy seasons in all regions (Figures 6-11). To identify sources of precipitation skill in the regions of focus, we generated precipitation forecasts using the unfiltered regression weights and SST forecast component associated with either the ENSO mode, trend mode, or remaining modes. The verification is the same for all sets of forecasts, and is the 100% variance CHIRPS3.0 field. The normalized RMSE of the area-averaged forecasts decreases (higher skill) for the same regions and seasons for which ACC is greatest, meaning that the high ACC is also associated with lower amplitude errors of the forecasts (Figure S7). When normalized RMSE exceeds one standard deviation, the forecasts are worse than climatology, which is observed predominantly when the forecasts also do not have significant ACC. Thus, either metric highlights similar lead times and regions as having notable skill. Consequently, we focus on ACC hereafter.

Southeast and Southwest United States

Southeast US precipitation forecasts verifying between OND-DJF are highly skillful, with exceeding 0.6 ACC six months in advance and longer in some cases (Figure 6). Conversely, skill for spring and summer precipitation in this region is largely negligible, suggesting precipitation is not as linearly predictable using tropical SST forecasts to the same extent as during the cool season. Consistent with past studies linking precipitation in the southeast US to ENSO variability (e.g., Ropelewski and Halpert 1987), the ENSO mode contributes predominantly to peak skill, with ACC exceeding 0.4-0.6 even a year in advance during boreal winter (Figure 6b). For some lead time - verification pairs at longer lead times, using only the ENSO mode yields more skillful forecasts than using the full ICs. The trend mode contributes negligibly to precipitation skill in this area except for a weak, variably significant impact in some seasons (Figure 6c). The remaining modes contribute some skill for forecasts initialized between March and August, more often for lead times between 1-7 months and a range of verification seasons (Figure



6d). As such, the high skill of the unfiltered forecasts is explained predominantly by the ENSO mode peaking in boreal winter and marginally the remaining modes boosting skill during a range of seasons.

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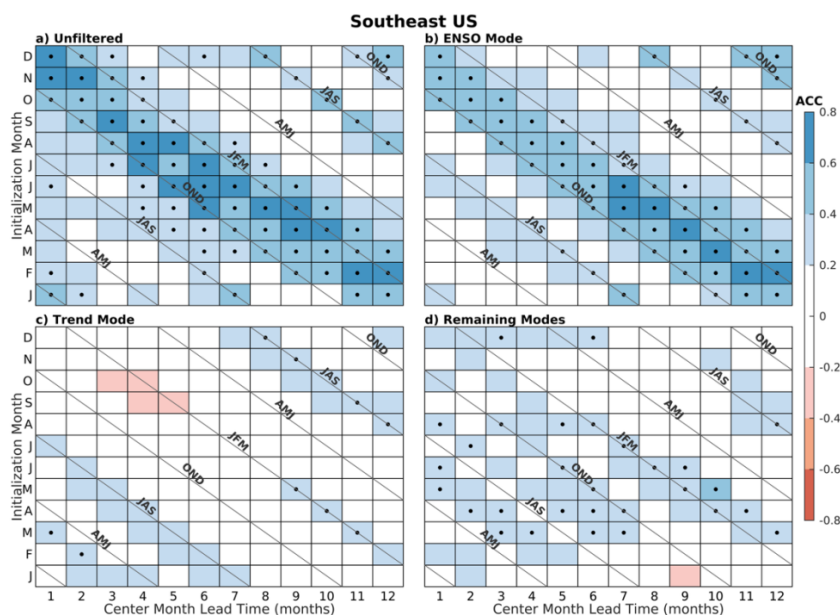


Figure 6: ACC of area-averaged precipitation forecasts for the southeast US using a) unfiltered SSTs, b) ENSO mode SSTs, c) trend mode SSTs, and d) remaining modes SSTs. Black dots indicate statistically significant skill with 95% confidence. Gray areas indicate dry months.

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Southwest US precipitation skill is greatest for lead times up to eight months in advance verifying during the DJF - AMJ seasons, while there is negligible skill observed earlier in the season during boreal fall (Figure 7). As observed for the southeast US, ENSO mode SSTs account for most of the unfiltered skill, although the significant DJF-JFM skill from lead times 9-12 months is not observed, while some weak skill is observed from the remaining modes, suggesting that both the ENSO and remaining modes contribute to the total long-lead skill in this region. We note that the timing within the boreal cold season during which the ENSO mode contributes to precipitation skill differs between the eastern and western US, with the east having greatest skill from OND - DJF and the west from DJF - FMA. These differences likely reflect unique, regional interactions between ENSO, the mean flow, and high-frequency synoptic variability.

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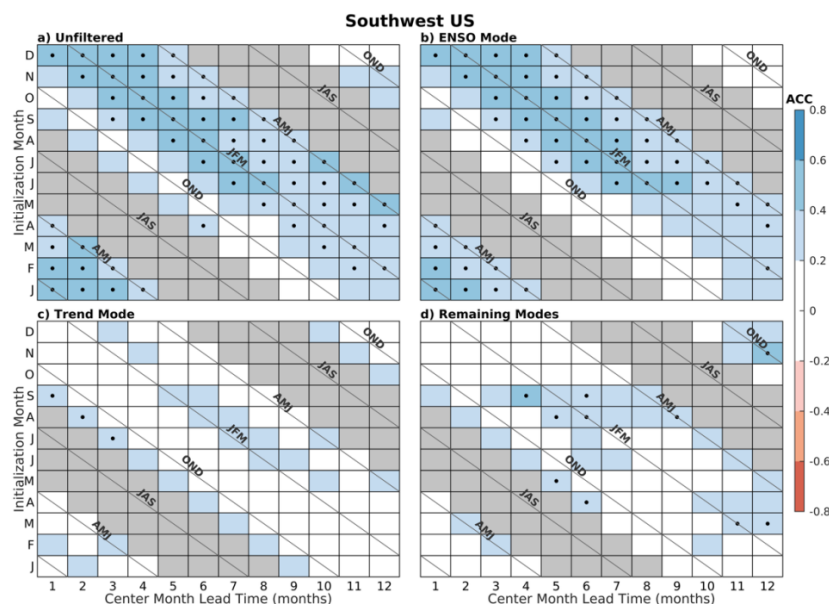


Figure 7: As in Figure 6 but for southwest US precipitation forecasts.

Middle East and Central Asia (MESA)

MESA forecasts are skillful for the start of the wet season, with forecasts for OND exceeding 0.4 ACC up to nine months ahead, meaning they are initialized the prior February (Figure 8). There is a distinct skill minimum for forecasts verifying in DJF and JFM while forecasts for MAM and AMJ are skillful even 10-12 months in advance, which coincides with two peak precipitation months, March and April (Figure 5c). The ENSO mode strongly contributes to skill early and late in the cold season, with a secondary contribution at similar times of year from the remaining modes, particularly from lead times 1-7 (Figure 8b, d). OND skill from the remaining modes is only evident at shorter lead times while MAM skill is significant up to eight months ahead. Skill from the trend mode SSTs is low and insignificant at all times (Figure 8c). Thus, total MESA skill can be understood as coming from a variety of modes with differing e-folding timescales represented by the ENSO and remaining modes.

Consistent with the timing when ENSO-precipitation links diminishes in this region (Hoell et al. 2015; Breeden et al. 2023), the minimum in unfiltered skill in DJF - JFM seasons arises from coincident decreases in skill from the ENSO and remaining modes. Given the broadband nature of ENSO, the ENSO mode may not capture all ENSO variability. This means that contributions to skill from the remaining modes are not guaranteed to be distinct from ENSO variability, although it is most likely a combination. Indeed, the remaining modes contribute to SST variance in the far western extent of the ENSO region (Figure S1), but whether this is non-ENSO variability, or a part of ENSO with a faster decay time, requires additional testing beyond the scope of this study. Regardless, the reliance of precipitation predictability on both the ENSO and remaining modes could make MESA forecasting more difficult for seasonal forecast models, as several aspects of SST variability must be well-simulated as opposed to just one, as observed in other regions (e.g., the southwest US).

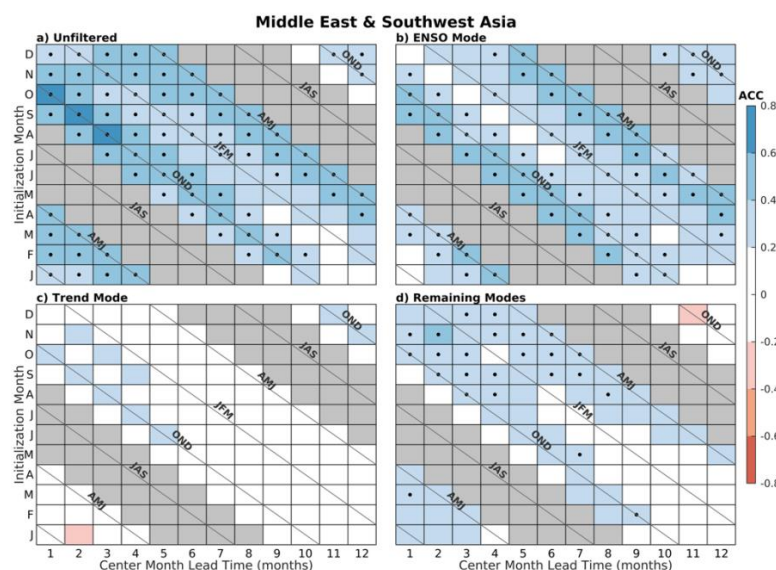


Figure 8: As in Figure 6 but for MESA precipitation forecasts.

Central America

350 Forecasts for the rainy season in Central America are most skilful for JAS – OND seasons, with significant $ACC > 0.4$ observed 6-9 months in advance and the greatest skill observed during ASO (Figure 9a). Some skill is significant even 9-12 months ahead, though low in amplitude. Conversely, skill for earlier in the season, AMJ-MJJ, is much lower and only significant one month ahead, which coincides with when there is lower skill from the ENSO mode (Figure 9b). The trend mode contributes weakly and intermittently to skill in JAS and OND, but not the seasons in-between (Figure 9c), while skill from the residual modes is significant mainly for 1-2 month lead times between MJJ-SON seasons. Overall, including information from the trend and remaining modes does produce better skill than just using the ENSO mode SSTs (c.f., Figure 9a, 9b), except for late season, long-lead forecasts, when ENSO mode skill is higher than the unfiltered forecasts. The lower unfiltered skill at these instances is related to negative skill associated with the residual modes. Thus, while the bulk of Central America precipitation predictability is associated with the ENSO mode, there are important modulations by other modes, which enhance skill at shorter lead times but degrade skill at longer lead times.

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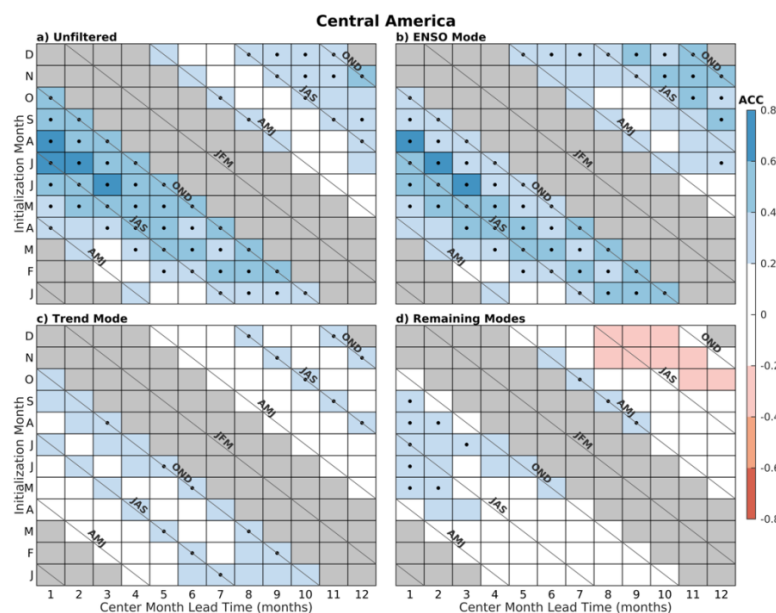


Figure 9: As in Figure 6 but for Central America precipitation forecasts.

East and West Africa

The East Africa OND / short rains season is well-forecasted even 8-9 months in advance, with ACC remaining above 0.4, while forecasts verifying during the MAM season have lower skill significant for lead times 3-5 months (Figure 10). Lower skill in MAM for East Africa compared to OND has also been observed in seasonal forecast models (Young and Klingaman, 2020), while we do find that AMJ skill is higher than MAM and significant even 12 months in advance. OND skill is attributed exclusively to the ENSO mode, and forecasts using just this component are actually more skillful than the unfiltered forecasts for most lead times (Fig. 10b), which is surprising since the regression weights were optimized for the full ICs, not the ENSO mode component. The joint ENSO and IOD predictability associated with the ENSO Mode during OND (Figures 2-3) presumably contributes to enhanced predictability at this time of year. This is in contrast to MAM-AMJ seasons, when precipitation skill is associated mainly with the more rapidly-decaying remaining modes and only a marginal contribution from the ENSO mode in MJJ (Figure 10d). In fact the ENSO mode negatively contributes to skill in this season at shorter lead times, with better skill achievable up to eight months ahead from only using the remaining modes instead of the unfiltered ICs (c.f., Figure 10a, d). Given where the remaining modes contribute to SSTs (Figure 1d, Figure S1), it seems the MAM rains are more linked to SST variability in the far western Pacific than the central/east Pacific SST variability associated with the ENSO mode. Forecasts generated using the trend mode are mostly not skillful except for weak skill at long lead times in some seasons (Figure 10c).

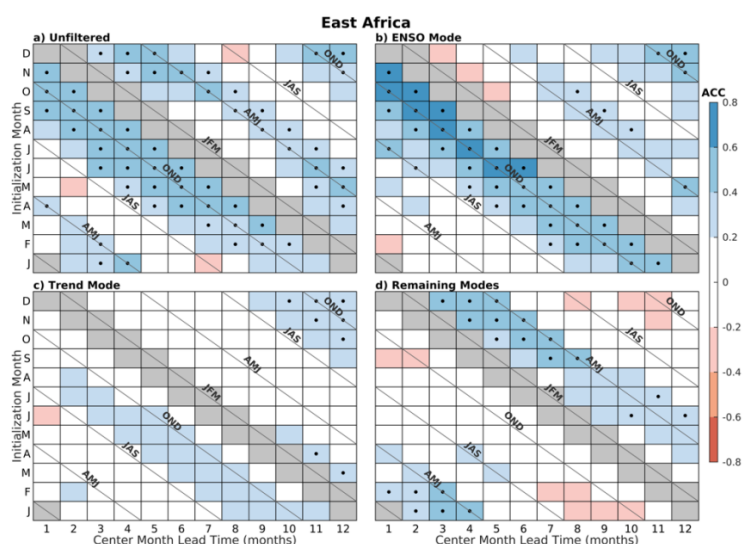


Figure 10: As in Figure 6 but for East Africa precipitation forecasts.

The Sahel has similar skill, 0.4-0.6 ACC, from all initialization months and lead times for verifications during the entire rainy season from June to September (Figure 11). This region is unique in that its precipitation skill can mostly be explained by the trend mode SSTs, while skill associated with the ENSO mode is mainly significant for initializations the prior October - November and is lower than the trend-related skill. The remaining modes are not associated with skill in this region at any time, with weak and statistically insignificant skill in all instances. Given the upward trend in Sahel precipitation over the period used here (e.g., Spat et al. 2025), it is unsurprising that the trend contributes to skill. ENSO teleconnections to Sahel precipitation have also been documented but with some dependence on the period of record used for analysis (Folland et al. 1986; Janicot et al. 1995; Pomposi et al. 2020).

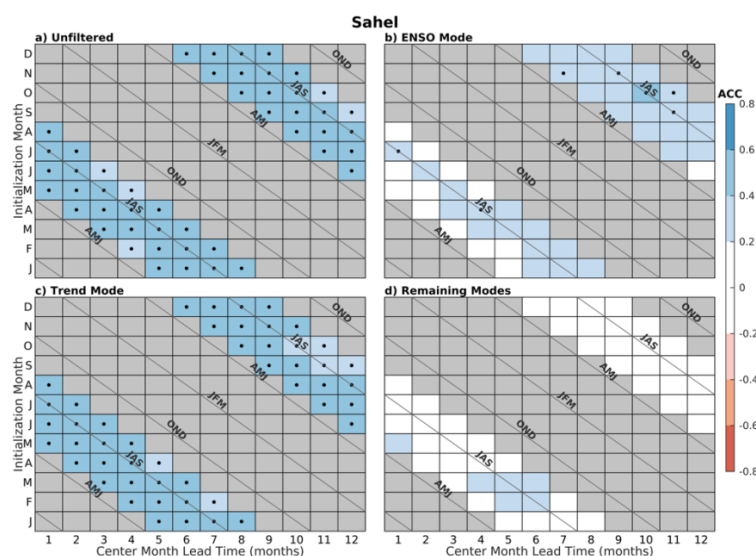


Figure 11: As in Figure 6 but for Sahel precipitation forecasts.



It is possible that the presence of a trend in Sahel precipitation obscures non-trend skill, as has been noted for temperature-related variables (e.g., Risbey et al. 2021; Breeden et al. 2025). To test this, we detrended the area-averaged Sahel June - September precipitation anomalies used for forecast verification and reevaluated the unfiltered and ENSO Mode derived forecasts (Figures 12-13). The positive sign of the trend time series is associated with enhanced precipitation over the Sahel, related to enhanced easterly IVT indicating a strengthening of the African Easterly Jet and enhanced moisture flux convergence (Figure 12; Gbode et al. 2021). When verified against the detrended precipitation, the skill of forecasts generated using the unfiltered SST forecasts disappears (Figure 13a), implying that these forecasts learned mainly trend-related information. Conversely, the skill of forecasts generated using the ENSO mode SSTs is slightly higher and more significant than the same forecasts verified against precipitation including the trend (c.f. Figure 13b, Figure 11c). Skill at shorter lead times, however, is still insignificant, a result that does not depend on the verification precipitation. Thus, for this case, removing the trend from verification slightly increases the estimate of ENSO mode precipitation skill, while the timing remains the same. Finally, while Sahel-averaged precipitation is more influenced by the trend, there are sub-regional areas with skill from the ENSO mode, such as southwest Niger and eastern Mali (Figure S8).

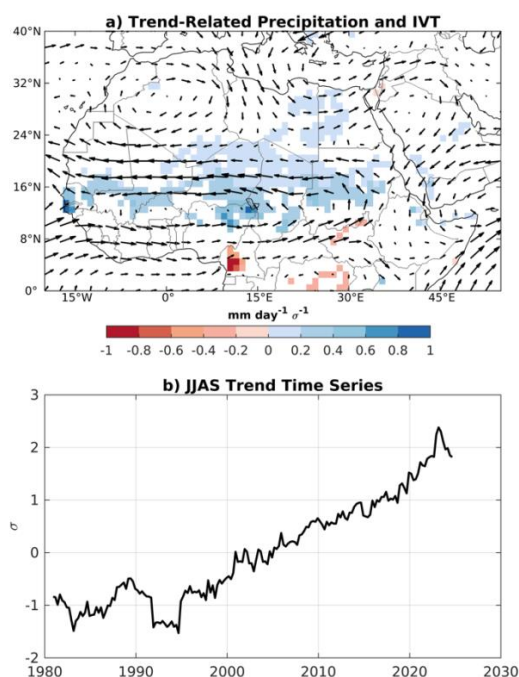


Figure 12: (a) Jun-Jul-Aug-Sept (JJAS) regression between global tropics area-averaged trend-related SST anomalies (panel b) and full-field precipitation anomalies (color shading; statistically significant values with 95% confidence only) and ERA5 horizontal vertically integrated water vapor transport (vectors) at each gridpoint.

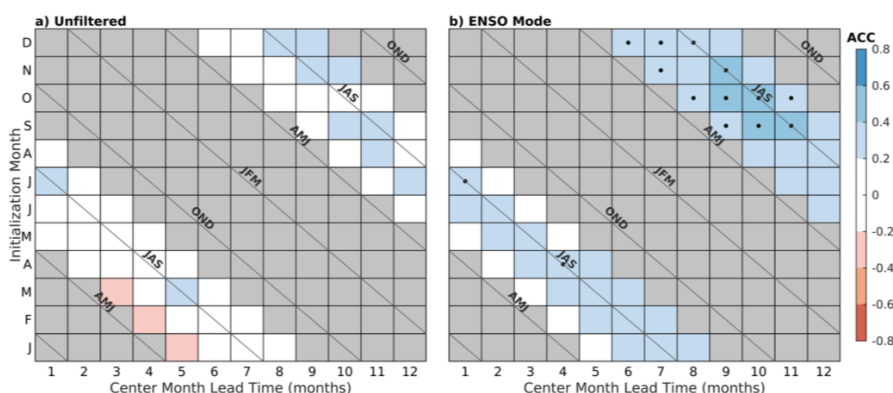


Figure 13: ACC of Sahel precipitation verified against *detrended* precipitation anomalies and regression models trained using a) unfiltered SST forecasts and b) ENSO Mode-related SST forecasts.

415 4 Discussion and Conclusions

This study introduces a novel approach to address an old question: how much precipitation predictability is attainable from SSTs? ENSO is predictable well into year two, while dynamical model precipitation forecast skill often drops off much more rapidly, on the order of a few months. Here we find that using CSLIM SST forecasts can produce skillful precipitation forecasts up to a year in advance in some regions, such as the Sahel, MESA, and East Africa short rains. Consequently, there is an opportunity for improvement in seasonal precipitation forecasts compared to what is currently realized by dynamical forecast models (McEvoy et al. 2016; Becker et al. 2022). To identify sources of precipitation skill, we generated precipitation forecasts using dynamically filtered components of the SST forecasts to isolate relationships between precipitation and ENSO, trend, and remaining modes of SST variability. As hypothesized, the ENSO mode - and the attendant IOD predictability in boreal fall (Figure 3b) - contributes predominantly to skill in most areas and does so at different times of year in different locations. This highlights the importance of understanding how ENSO uniquely interacts with the regional background environment and higher-frequency variability to affect local precipitation predictability. Furthermore, though not investigated here, precipitation forecasts of opportunity are likely related to ENSO events in many areas, suggesting that the predictability during individual events may be even higher than the unconditional skill that we considered.

Precipitation skill in the southeast and southwest US is greatest during the boreal cold season and is associated predominantly with the main ENSO mode, with secondary skill contributions from the PMM-like remaining modes (Figures 6,7). The MESA region has notable skill at the start and end of the wet season with a skill minimum in JFM, driven by coincident changes in skill from ENSO and remaining modes (Figure 8). In Central America, precipitation is more predictable in the middle and end of the rainy season compared to early in the season, timing that is driven by skill variations from the ENSO mode, while the trend and remaining modes also contribute to skill at shorter lead times. Tropical North Atlantic (TNA) SSTs have a greater impact on Central America precipitation early in the season (Spence et al., 2004; Alfaro et al., 2016; Maldonado et al., 2017), apparently coinciding with when there's a weaker influence of ENSO. While TNA SSTs are included in the domain of the CSLIM, it is possible their impact is dwarfed by the covariance of tropical Pacific SSTs, obscuring Atlantic-Central America precipitation teleconnections. Higher skill for OND rains in East Africa than for MAM rains found by Shukla et al. (2019) may be related to the ENSO mode, being a source of precipitation predictability in the former, but not the latter, seasons. This ENSO-precipitation relationship is consistent with past work deriving precipitation forecasts in this region from SSTs and SST forecasts



(Colman 2021). Conversely, the remaining modes contribute mainly to MAM precipitation skill, consistent with prior work linking the 'Western V SST Gradient' to MAM precipitation (Funk et al., 2023) and potentially, the prevalence of the PMM at this time of year. Sahel rainfall predictability is unique in having only a limited contribution from the ENSO mode, with skill mainly associated with the long-term trend (Figure 11). While there is some dependence of ENSO skill on detrending the verification precipitation (Figure 13), skill from both perspectives is greatest for longer lead times from 9-12 months and lower for shorter lead times, reasons for which are not immediately clear but merit further investigation.

Given the broadband nature of ENSO (e.g., Penland and Matrosova 2006), we emphasize that the remaining modes may be capturing far west Pacific SST variability that includes ENSO variance not captured by the ENSO mode. However, there are clear differences in skill where some areas, such as southeast US, only need ENSO mode information to realize the unfiltered skill, while others – including East Africa and MESA - have skill associated with both the ENSO and remaining modes. These differences shed light on which aspects of tropical SST / ENSO variability need or need not be correctly simulated by forecast models to achieve the greatest possible precipitation skill in these regions. As prior work has found climate models that have notable errors simulating the western extent of ENSO events (e.g., Beverley et al. 2023), they might be related to errors representing the remaining modes. Future work could diagnose the representation of the SST modes considered here in seasonal forecast models to shed further light on their biases and impacts on regional precipitation forecast errors.

The application of LIMs/CSLIMs to seasonal prediction has previously been confined to variables that are slowly evolving enough to be included directly into the state vector, which are most often temperature based (e.g., PS95, Alexander et al. 2012; Newman et al. 2017; Breeden et al. 2025). This study uses regression models between SST forecasts and observed precipitation to leverage the unbiased and skillful CSLIM SST forecasts to predict seasonal precipitation. This approach is a computationally cheap but effective means by which seasonal forecasts for additional rapidly-decorrelating variables could be generated, provided they have a usable relationship to tropical SSTs. Since no information about the precipitation initial conditions is included in the forecasts, this method can be employed with any available SST forecast, provided a long enough hindcast period is available to train relationships with precipitation. A small number of precipitation EOFs generate the best forecasts in key regions and times of year (Fig. S3), highlighting the benefit of developing relationships between the large-scale component of precipitation and SSTs, as opposed to fitting models to unfiltered, local precipitation. While EOF truncation is not the only option for this task, it does appear effective for isolating the component of precipitation that is most closely related to SSTs and thus more predictable.

Next steps to improve this baseline approach for precipitation forecasts could include trying more sophisticated models than MLR, improving skill by adding new predictors, and using methods to optimize the number of predictors as well as the predictands. Seasonal mean precipitation may not be the best indicator for agricultural applications, given the high impact that poorly-timed dry spells can have on vegetation despite above-average seasonal totals. Whether seasonal outlooks for precipitation characteristics that are more impactful to agriculture, such as precipitation intermittency or precipitation start of season, can be generated with this method remains to be determined. Furthermore, the application to forecasting the demand side of drought rather than the supply-side represented by precipitation, by using targets such as evapotranspiration or the evaporative demand drought index, could be a fruitful extension of the method introduced herein.

Data Availability

All data used in this study are publicly available. ERSSTv5: <https://psl.noaa.gov/data/gridded/data.noaa.ersst.v5.html>, ORAS5 SSH: <https://cds.climate.copernicus.eu/datasets/reanalysis-oras5?tab=overview>, CHIRPS3.0:



<https://www.chc.ucsb.edu/data/chirps3>, ERA5: <https://cds.climate.copernicus.eu/datasets/derived-era5-single-levels-daily-statistics?tab=download>.

Supplement link

Link to supplemental material will be included here:

485 Author contributions

MLB conducted analysis, generated all figures and wrote the text. AH secured funding, provided guidance on analysis, and provided comments on the text in the manuscript. DJV provided some initial code and edits to the text in the manuscript. KT and WBA provided edits to the text in the manuscript.

Competing interests

490 One of the authors is a member of the editorial board of Weather and Climate Dynamics.

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Review statement

505 References

Alexander, M. A., Shin, S.-I., and Battisti, D. S.: The influence of the trend, basin interactions, and ocean dynamics on tropical ocean prediction, *Geophys. Res. Lett.*, 49, e2021GL096120, <https://doi.org/10.1029/2021GL096120>, 2022.



- Alfaro, E. J., Hidalgo, H.G. and Mora, N.: Prediction of MJ rainfall season using CCA models. *Topicos Meteorologicos* y2194
510 *Oceanograficos*, 15, 5–19, 2016.
- Amaya, D. J., Wei, H.-H., Newman, M., Barsugli, J., and Yeager, S.: Seasonal precipitation skill in current climate forecast models is due to initial tropical conditions alone, *J. Appl. Meteor. Climatol.*, <https://doi.org/10.1175/JAMC-D-25-0235.1>, 2025.
- 515 Barnston, A. G., Glantz, M. H., and He, Y.: Predictive skill of statistical and dynamical climate models in SST forecasts during the 1997–98 El Niño episode and the 1998 La Niña onset, *Bull. Am. Meteorol. Soc.*, 80, 217–244, [https://doi.org/10.1175/1520-0477\(1999\)080<0217:PSOSAD>2.0.CO;2](https://doi.org/10.1175/1520-0477(1999)080<0217:PSOSAD>2.0.CO;2) 1999.
- Becker, E. J., Kirtman, B. P., L’Heureux, M., Muñoz, Á. G., and Pegion, K.: A decade of the North American Multimodel
520 Ensemble (NMME): Research, application, and future directions, *Bull. Am. Meteorol. Soc.*, 103, E973–E995, <https://doi.org/10.1175/BAMS-D-20-0327.1>, 2022.
- Beverley, J., Newman, M., and Hoell, A.: Rapid development of systematic ENSO-related seasonal forecast errors, *Geophys. Res. Lett.*, 50, e2022GL102249, <https://doi.org/10.1029/2022GL102249>, 2023.
525
- Breeden, M. L., Hoell, A., Albers, J. R., and Slinski, K.: The monthly evolution of precipitation and warm conveyor belts during the central southwest Asia wet season, *Weather Clim. Dynam.*, 4, 963–980, <https://doi.org/10.5194/wcd-4-963-2023>, 2023.
- Breeden, M. L., Hoell, A., Worsnop, R. P., Albers, J. R., Hobbins, M., Robinson, R. M., and Vimont, D. J.: Seasonal
530 Predictability of Vapor Pressure Deficit in the western United States, *Weather Clim. Dynam.*, 6, 1443–1459, <https://doi.org/10.5194/wcd-6-1443-2025>, 2025.
- Cayan, D. R., Redmond, K. T., and Riddle, L. G.: ENSO and hydrologic extremes in the western United States, *J. Climate*, 12, 2881–2893, [https://doi.org/10.1175/1520-0442\(1999\)012<2881:EAHEIT>2.0.CO;2](https://doi.org/10.1175/1520-0442(1999)012<2881:EAHEIT>2.0.CO;2), 1999.
535
- Chen, L., van den Dool, H., Becker, E., and Zhang, Q.: ENSO precipitation and temperature forecasts in the North American Multimodel Ensemble: Composite analysis and validation, *J. Climate*, 30, 1103–1125, <https://doi.org/10.1175/JCLI-D-15-0903.1>, 2017.
- 540 Chen, X., Wang, S., Hu, Z., Zhou, Q., and Hu, Q.: Spatiotemporal characteristics of seasonal precipitation and their relationships with ENSO in Central Asia during 1901–2013, *J. Geogr. Sci.*, 28, 1341–1356, <https://doi.org/10.1007/s11442-018-1529-2>, 2018.
- Chiang, J. C. H. and Vimont, D. J.: Analogous Pacific and Atlantic meridional modes of tropical atmosphere–ocean variability, *J. Climate*, 17, 4143–4158, <https://doi.org/10.1175/JCLI4953.1>, 2004.
545
- Climate Hazards Center: Infrared Precipitation with Stations version 3, CHIRPS3 Data Repository [data set], <https://doi.org/10.15780/G2JQ0P>, 2025.



- Colman, A.: Skilful long-lead hybrid predictions of the East African short-rains season, *Int. J. Climatol.*, 42, 4097–4110, 550 <https://doi.org/10.1002/joc.7486>, 2022.
- Copernicus Climate Change Service: ORAS5 global ocean reanalysis monthly data from 1958 to present, Copernicus Climate Change Service (C3S) Climate Data Store (CDS) [data set], <https://doi.org/10.24381/cds.67e8eeb7>, 2021.
- Eden, J. M., van Oldenborgh, G. J., Hawkins, E., and Suckling, E. B.: A global empirical system for probabilistic seasonal climate prediction, *Geosci. Model Dev.*, 8, 3947–3973, <https://doi.org/10.5194/gmd-8-3947-2015>, 2015.
- Efron, B.: Bootstrap methods: Another look at the jackknife, *Ann. Statist.*, 7, 1–26, <https://doi.org/10.1214/aos/1176344552>, 1979.
- 560 Eldardiry, H. and Hossain, F.: The value of long-term streamflow forecasts in adaptive reservoir operation: The case of the high Aswan Dam in the transboundary Nile River basin, *J. Hydrometeorol.*, 22, 1099–1115, <https://doi.org/10.1175/JHM-D-20-0241.1>, 2021.
- 565 Folland, C., Palmer, T., and Parker, D.: Sahel rainfall and worldwide sea temperatures, 1901–85, *Nature*, 320, 602–607, <https://doi.org/10.1038/320602a0>, 1986.
- Folland, C. K., Owen, J. A., Ward, N. M., and Coleman, A. W.: Prediction of seasonal rainfall in the Sahel region using empirical and dynamical methods, *J. Forecast.*, 10, 21–56, <https://doi.org/10.1002/for.3980100104>, 1991.
- 570 Funk, C., and coauthors: Recognizing the Famine Early Warning Systems Network: Over 30 years of drought early warning science advances and partnerships promoting global food security, *Bull. Am. Meteorol. Soc.*, 100, 1011–1027, <https://doi.org/10.1175/BAMS-D-17-0233.1>, 2019.
- 575 Funk, C., Fink, A. H., Harrison, L., Segele, Z., Endris, H. S., Galu, G., et al.: Frequent but predictable droughts in East Africa driven by a Walker circulation intensification, *Earth's Future*, 11, e2022EF003454, <https://doi.org/10.1029/2022EF003454>, 2023.
- Funk, C., Peterson, P., Harrison, L. et al. The Climate Hazards Center Infrared Precipitation with Stations, Version 3. *Sci Data* 13, 718, <https://doi.org/10.1038/s41597-026-07096-4>, 2026.
- 580 Gaetani, M., Fontaine, B., Roucou, P., and Baldi, M.: Influence of the Mediterranean Sea on the West African monsoon: Intraseasonal variability in numerical simulations, *J. Geophys. Res.*, 115, D24115, <https://doi.org/10.1029/2010JD014436>, 2010.
- Gbode, I. E., Ogunjobi, K. O., Dudhia, J., Ajayi, V. O., and Liu, C.: Impacts of global warming on West African monsoon rainfall: Downscaling by pseudo global warming method, *Atmos. Res.*, 249, 105334, 585 <https://doi.org/10.1016/j.atmosres.2020.105334>, 2021.



Giannini, A., Kushnir, Y., and Cane, M. A.: Interannual variability of Caribbean rainfall, ENSO, and the Atlantic Ocean, *J. Climate*, 13, 297–311, [https://doi.org/10.1175/1520-0442\(2000\)013<0297:IVOCRE>2.0.CO;2](https://doi.org/10.1175/1520-0442(2000)013<0297:IVOCRE>2.0.CO;2), 2000.

590

Giannini, A., Saravanan, R., and Chang, P.: Oceanic forcing of Sahel rainfall on interannual to interdecadal time scales, *Science*, 302, 1027–1030, <https://doi.org/10.1126/science.1089357>, 2003.

Hasselmann, K.: PIPs and POPs: The reduction of complex dynamical systems using principal interaction and oscillation patterns, *J. Geophys. Res.*, 93, 11015–11021, <https://doi.org/10.1029/JD093iD09p11015>, 1988.

595

Hastenrath, S.: Recent advances in tropical climate prediction, *J. Climate*, 8, 1519–1532, [https://doi.org/10.1175/1520-0442\(1995\)008<1519:RAITCP>2.0.CO;2](https://doi.org/10.1175/1520-0442(1995)008<1519:RAITCP>2.0.CO;2), 1995.

600 Hoell, A., Shukla, S., Barlow, M., Cannon, F., Kelley, C., and Funk, C.: The forcing of monthly precipitation variability over southwest Asia during the boreal cold season, *J. Climate*, 28, 7038–7056, <https://doi.org/10.1175/JCLI-D-14-00757.1>, 2015.

Hoell, A., Barlow, M., Cannon, F., and Xu, T.: Oceanic origins of historical southwest Asia precipitation during the boreal cold season, *J. Climate*, 30, 2885–2903, <https://doi.org/10.1175/JCLI-D-16-0519.1>, 2017.

605

Hoell, A., Barlow, M., Xu, T., and Zhang, T.: Cold season southwest Asia precipitation sensitivity to El Niño–Southern Oscillation events, *J. Climate*, 31, 4463–4482, <https://doi.org/10.1175/JCLI-D-17-0456.1>, 2018.

610 Hoell, A., Breeden, M. L., Worsnop, R. P., Robinson, R., Agel, L., Anderson, W., Barlow, M., Jayanthi, H., McNally, A., Shukla, S., Slinski, K., Verdin, J., and Zaheer, F.: An unexpected outcome followed an apparent seasonal forecast of opportunity and prolonged drought in southwest Asia, *Int. J. Climatol.*, 45, e8851, <https://doi.org/10.1002/joc.8851>, 2025.

615 Hoell, A., Robinson, R., Hobbins, M., Breeden, M. L., Worsnop, R. P., and Guerrero, E.: The relationship between the El Niño–Southern Oscillation and extensive wildfire area burned in contiguous United States geographic area Coordination centers, *J. Geophys. Res.-Atmos.*, 131, e2025JD045436, <https://doi.org/10.1029/2025JD045436>, 2026.

Huang, B., Thorne, P. W., Banzon, V. F., Boyer, T., Chepurin, G., Lawrimore, J. H., Menne, M. J., Smith, T. M., Vose, R. S., and Zhang, H.-M.: NOAA Extended Reconstructed Sea Surface Temperature (ERSST), Version 5, NOAA National Centers for Environmental Information [data set], <https://doi.org/10.7289/V5T72FNM>, 2017.

620

Huang, B. and Shukla, J.: Mechanisms for the interannual variability in the tropical Indian Ocean. Part II: Regional processes, *J. Climate*, 20, 2937–2960, <https://doi.org/10.1175/JCLI4169.1>, 2007.

625 Indeje, M., Semazzi, F. H. M., and L. J. Ogallo: ENSO signals in East African Rainfall Seasons, *International Journal of Climatology*, 20: 19–46, 1999.



Ingram, K. T., Roncoli, M. C., and Kirshen, P. H.: Opportunities and constraints for farmers of west Africa to use seasonal precipitation forecasts with Burkina Faso as a case study, *Agric. Syst.*, 74, 331–349, [10.1016/S0308-521X\(02\)00044-6](https://doi.org/10.1016/S0308-521X(02)00044-6), 2002.

630 Janicot, S., Moron, V., and Fontaine, B.: Sahel droughts and ENSO dynamics, *Geophys. Res. Lett.*, 23, 515–518, <https://doi.org/10.1029/96GL00246>, 1996.

Joseph, R. and Nigam, S.: ENSO evolution and teleconnections in IPCC’s twentieth-century climate simulations: Realistic representation?, *J. Climate*, 19, 4360–4377, <https://doi.org/10.1175/jcli3846.1>, 2006.

635

Klein, S. A., Soden, B. J., and Lau, N.: Remote sea surface temperature variations during ENSO: Evidence for a tropical atmospheric bridge, *J. Climate*, 12, 917–932, [https://doi.org/10.1175/1520-0442\(1999\)012<0917:RSSTVD>2.0.CO;2](https://doi.org/10.1175/1520-0442(1999)012<0917:RSSTVD>2.0.CO;2), 1999.

Kowal, K. M., Slater, L. J., García López, A., and Van Loon, A. F.: A comparison of seasonal rainfall forecasts over Central America using dynamic and hybrid approaches from Copernicus Climate Change Service seasonal forecasting system and the North American Multimodel Ensemble, *Int. J. Climatol.*, 43, 2175–2199, <https://doi.org/10.1002/joc.7969>, 2023.

Krishnamurthy, V. and Kirtman, B. P.: Variability of the Indian Ocean: Relation to monsoon and ENSO, *Q. J. R. Meteorol. Soc.*, 129, 1623–1646, <https://doi.org/10.1256/qj.01.166>, 2003.

645

Kumar, A. and Chen, M.: Understanding skill of seasonal mean precipitation prediction over California during boreal winter and role of predictability limits, *J. Climate*, 33, 6141–6163, <https://doi.org/10.1175/JCLI-D-19-0275.1>, 2020.

650 Lenssen, N. J. L., Goddard, L., and Mason, S.: Seasonal forecast skill of ENSO teleconnection maps, *Weather Forecast.*, 35, 2387–2406, <https://doi.org/10.1175/WAF-D-19-0235.1>, 2020.

Li, L., et al.: North Atlantic salinity as a predictor of Sahel rainfall, *Sci. Adv.*, 2, e1501588, <https://doi.org/10.1126/sciadv.1501588>, 2016.

655 Maldonado, T., Alfaro, E., Fallas-López, B., and Alvarado, L.: Seasonal prediction of extreme precipitation events and frequency of rainy days over Costa Rica, Central America, using Canonical Correlation Analysis, *Adv. Geosci.*, 33, 41–52, <https://doi.org/10.5194/adgeo-33-41-2013>, 2013.

660 Maldonado, T., Alfaro, E., Rutgersson, A. and Amador, J.A.: The early rainy season in Central America: the role of the tropical North Atlantic SSTs. *International Journal of Climatology*, 37(9), 3731–3742. <https://doi.org/10.1002/joc.4958>, 2017.

McEvoy, D. J., Huntington, J. L., Mejia, J. F., and Hobbins, M. T.: Improved seasonal drought forecasts using reference evapotranspiration anomalies, *Geophys. Res. Lett.*, 43, 377–385, <https://doi.org/10.1002/2015GL067009>, 2016.

665 National Academies of Sciences, Engineering, and Medicine (NASEM): Next generation earth system prediction: Strategies for subseasonal to seasonal forecasts, National Academies Press, 2016.



Newman, M. and Sardeshmukh, P. D.: Are we near the predictability limit of tropical Indo-Pacific sea surface temperatures?, *Geophys. Res. Lett.*, 44, 8520–8529, <https://doi.org/10.1002/2017GL074088>, 2017.

670

Nicholson, S. E. and Entekhabi, D.: The quasi-periodic behavior of rainfall variability in Africa and its relationship to the southern oscillation, *Arch. Meteorol. Geophys. Bioclimatol. Ser. A*, 34, 311–348, <https://doi.org/10.1007/BF02257765>, 1986.

Nigam, S. and Sengupta, A.: The full extent of El Niño's precipitation influence on the United States and the Americas: The suboptimality of the Niño 3.4 SST index, *Geophys. Res. Lett.*, 48, e2020GL091447, <https://doi.org/10.1029/2020GL091447>, 2021.

675

O'Reilly, C. H., MacLeod, D., Befort, D. J., Shepherd, T. G., and Weisheimer, A.: Evaluating seasonal forecast improvements over the past two decades, *Q. J. R. Meteorol. Soc.*, 152, e70036, <https://doi.org/10.1002/qj.70036>, 2026.

680

Palmer, T.: Influence of the Atlantic, Pacific and Indian Oceans on Sahel rainfall, *Nature*, 322, 251–253, <https://doi.org/10.1038/322251a0>, 1986.

Palmer, P. I., Wainwright, C. M., Dong, B., et al.: Drivers and impacts of Eastern African rainfall variability, *Nat. Rev. Earth Environ.*, 4, 254–270, <https://doi.org/10.1038/s43017-023-00397-x>, 2023.

685

Penland, C.: Random forcing and forecasting using principal oscillation pattern analysis, *Mon. Weather Rev.*, 117, 2165–2185, [https://doi.org/10.1175/1520-0493\(1989\)117<2165:RFAFUP>2.0.CO;2](https://doi.org/10.1175/1520-0493(1989)117<2165:RFAFUP>2.0.CO;2), 1989.

Penland, C. and Matrosova, L.: Studies of El Niño and interdecadal variability in tropical sea surface temperatures using a nonnormal filter, *J. Climate*, 19, 5796–5815, <https://doi.org/10.1175/JCLI3951.1>, 2006.

690

Penland, C. and Sardeshmukh, P. D.: The optimal growth of tropical sea surface temperature anomalies, *J. Climate*, 8, 1999–2024, [https://doi.org/10.1175/1520-0442\(1995\)008<1999:TOGOTS>2.0.CO;2](https://doi.org/10.1175/1520-0442(1995)008<1999:TOGOTS>2.0.CO;2), 1995.

695

Pomposi, C., Kushnir, Y., Giannini, A., and Biasutti, M.: Toward understanding the occurrence of both wet and dry Sahel seasons during El Niño: The modulating role of the global ocean, *J. Climate*, 33, 1193–1207, <https://doi.org/10.1175/JCLI-D-19-0219.1>, 2020.

Reverdin, G., Cadet, D., and Gutzler, D.: Interannual displacements of convection and surface circulation over the equatorial Indian Ocean, *Q. J. R. Meteorol. Soc.*, 112, 43–67, <https://doi.org/10.1002/qj.49711247104>, 1986.

700

Risbey, J. S., et al.: Standard assessments of climate forecast skill can be misleading, *Nat. Commun.*, 12, 4346, <https://doi.org/10.1038/s41467-021-23771-z>, 2021.

705



- Ropelewski, C. F. and Halpert, M. S.: Global and regional scale precipitation patterns associated with the El Niño/Southern Oscillation, *Mon. Weather Rev.*, 115, 1606–1626, [https://doi.org/10.1175/1520-0493\(1987\)115<1606:GARSPP>2.0.CO;2](https://doi.org/10.1175/1520-0493(1987)115<1606:GARSPP>2.0.CO;2) 1987.
- Ropelewski, C. F., and M. S. Halpert: Precipitation Patterns Associated with the High Index Phase of the Southern Oscillation. *J. Climate*, 2, 268–284, [https://doi.org/10.1175/1520-0442\(1989\)002<0268:PPAWTH>2.0.CO;2](https://doi.org/10.1175/1520-0442(1989)002<0268:PPAWTH>2.0.CO;2), 1989.
- Roy, I., Gagnon, A. S., and Siingh, D.: Evaluating ENSO teleconnections using observations and CMIP5 models, *Theor. Appl. Climatol.*, 136, 1085–1097, <https://doi.org/10.1007/s00704-018-2536-z>, 2019.
- Roy, T., He, X., Lin, P., Beck, H. E., Castro, C., and Wood, E. F.: Global evaluation of seasonal precipitation and temperature forecasts from NMME, *J. Hydrometeorol.*, 21, 2473–2486, <https://doi.org/10.1175/JHM-D-19-0095.1>, 2020.
- Seager, R., Ting, M., Alexander, P., Liu, H., Nakamura, J., Li, C., and Newman, M.: Ocean-forcing of cool season precipitation drives ongoing and future decadal drought in southwestern North America, *npj Clim. Atmos. Sci.*, 6, 1, <https://doi.org/10.1038/s41612-023-00461-9>, 2023.
- Sengupta, A., Singh, B., DeFlorio, M. J., Raymond, C., Robertson, A. W., Zeng, X., Waliser, D. E., and Jones, J.: Advances in subseasonal to seasonal prediction relevant to water management in the western United States, *Bull. Am. Meteorol. Soc.*, 103, E2168–E2175, <https://doi.org/10.1175/BAMS-D-22-0146.1>, 2022.
- Shin, S.-I., Sardeshmukh, P. D., Newman, M., Penland, C., and Alexander, M. A.: Impact of the annual cycle on ENSO variability and predictability, *J. Climate*, 34, 171–193, <https://doi.org/10.1175/JCLI-D-20-0291.1>, 2021.
- Shirvani, A., Landman, W. A., Barlow, M., and Hoell, A.: Evaluation of the forecast skill of North American Multi-Model Ensemble for monthly and seasonal precipitation forecasts over Iran, *Int. J. Climatol.*, 43, 1141–1166, <https://doi.org/10.1002/joc.7900>, 2023.
- Shukla, S., Roberts, J., Hoell, A., et al.: Assessing North American multimodel ensemble (NMME) seasonal forecast skill to assist in the early warning of anomalous hydrometeorological events over East Africa, *Clim. Dynam.*, 53, 7411–7427, <https://doi.org/10.1007/s00382-016-3296-z>, 2019.
- Simpson, I. R., et al.: Confronting Earth System Model trends with observations, *Sci. Adv.*, 11, eadt8035, <https://doi.org/10.1126/sciadv.adt8035>, 2025.
- Spät, D., Biasutti, M., and Voigt, A.: Extreme sahelian rainfall continues to rise despite stable storm frequency, *Geophys. Res. Lett.*, 52, e2025GL115942, <https://doi.org/10.1029/2025GL115942>, 2025.
- Spence, J.M., Taylor, M.A. and Chen, A.A.: The effect of concurrent sea-surface temperature anomalies in the tropical Pacific and Atlantic on Caribbean rainfall. *International Journal of Climatology*, 24(12), 1531–1541. <https://doi.org/10.1002/JOC.1068>, 2004.



Touré, A. K., Fall, C. M. N., Diakhaté, M., Wane, D., Rodríguez-Fonseca, B., Ndiaye, O., Diop, M., and Gaye, A. T.: Predictability of intra-seasonal descriptors of rainy season over Senegal using global SST patterns, *Atmosphere*, 13, 1437, <https://doi.org/10.3390/atmos13091437>, 2022.

750

van Oldenborgh, G. J., Balmaseda, M. A., Ferranti, L., Stockdale, T. N., and Anderson, D. L. T.: Did the ECMWF seasonal forecast model outperform statistical ENSO forecast models over the last 15 years?, *J. Climate*, 18, 3240–3249, <https://doi.org/10.1175/JCLI3420.1>, 2005.

755 Wang, H., Murtugudde, R., and Kumar, A.: Evolution of Indian Ocean dipole and its forcing mechanisms in the absence of ENSO, *Clim. Dynam.*, 47, 2481–2500, <https://doi.org/10.1007/s00382-016-2977-y>, 2016.

Waylen, P.R., Quesada, M.E. and Caviedes, C.N.: The effects of El Niño–Southern Oscillation on precipitation in San José, Costa Rica. *International Journal of Climatology*, 14(5), 559–568. <https://doi.org/10.1002/JOC.3370140506>, 1994.

760

Webster, P. J., Moore, A. M., Loschnigg, J. P., and Leben, R. R.: Coupled ocean-atmosphere dynamics in the Indian Ocean during 1997–98, *Nature*, 401, 356–360, <https://doi.org/10.1038/43848>, 1999.

Weisheimer, A. and Palmer, T. N.: On the reliability of seasonal climate forecasts, *J. R. Soc. Interface*, 11, 20131162, <https://doi.org/10.1098/rsif.2013.1162>, 2014.

765

Williams, N. C., Scaife, A. A., and Screen, J. A.: Underpredicted ENSO teleconnections in seasonal forecasts, *Geophys. Res. Lett.*, 50, e2022GL101689, <https://doi.org/10.1029/2022GL101689>, 2023.

770 Wu, Y. and Tang, Y.: Diagnosing seasonal forecast skill of the Indian Ocean Dipole mode using model analogs, *J. Atmos. Ocean. Technol.*, 40, 1037–1047, <https://doi.org/10.1175/JTECH-D-22-0106.1>, 2023.

Wyrski, K.: El Niño—The dynamic response of the equatorial Pacific Ocean to atmospheric forcing, *J. Phys. Oceanogr.*, 5, 572–584, [https://doi.org/10.1175/1520-0485\(1975\)005<0572:ENTDRO>2.0.CO;2](https://doi.org/10.1175/1520-0485(1975)005<0572:ENTDRO>2.0.CO;2), 1975.

775

Yang, X. and DelSole, T.: Systematic comparison of ENSO teleconnection patterns between models and observations, *J. Climate*, 25, 425–446, <https://doi.org/10.1175/JCLI-D-11-00175.1>, 2012.

Yang, Y., Xie, S., Wu, L., Kosaka, Y., Lau, N., and Vecchi, G. A.: Seasonality and predictability of the Indian Ocean Dipole mode: ENSO forcing and internal variability, *J. Climate*, 28, 8021–8036, <https://doi.org/10.1175/JCLI-D-15-0078.1>, 2015.

780

Young, H. R. and Klingaman, N. P.: Skill of seasonal rainfall and temperature forecasts for East Africa, *Weather Forecast.*, 35, 1783–1800, <https://doi.org/10.1175/WAF-D-19-0061.1>, 2020.