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Oceanic Influences that have Lingered Rain

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Abstract

The October Through December "short rains" (OND) in East Africa show significant interannual variability. Long-range rainfall forecasts can help with preparation and readiness for such situations since drought and flooding are not uncommon occurrences. Although statistical models based on Sea Surface Temperature (SST) precursors are still extensively employed, and seasonal forecasts based on dynamical models are beginning to gain traction, it is crucial to comprehend the advantages and disadvantages of such models. Here, we define a straightforward statistical forecast model that may be used to provide light on the processes that connect SSTs and rainfall over time and space, as well as the reasons why these models occasionally fall short. The August states of the El Nio-Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD) predict roughly 40% of the variability in brief rains from 1950 to 2020 in our model, which is a linear regression. Forecasting mistakes can be connected linearly to initial positive (negative) ENSO and IOD conditions in August for too-wet (too-dry) forecasts. Changes in the IOD between August and OND serve as a mediator in the link to the initial IOD state, illuminating a possible physical mechanism for prediction busts. We also find asymmetry and nonlinearity: the range and variance of OND forecast errors are higher in August when ENSO and/or the IOD are positive than when the SST indices are negative.

Keywords:GHACOF • Precipitation • (CHIRPS) • Rainfall • Atlantic

Introduction

In some years with significant forecast busts, such as the dry 1987 season during a severe El Nio, for which the model inaccurately predicts plentiful rainfall, upfront changes of predictions conditioned on starting SSTs would have helped, but they would have made the situation worse. Floods and droughts have a substantial influence on lives and livelihoods in East Africa due to the region's high level of climate variability [1-3]. The "brief rains" in the boreal fall in particular exhibit significant interannual variability, with extreme impacts from both flooding and drought. The National Meteorological and Hydrological Services (NMHS) of 11 nations, from Sudan in the north to Tanzania in the south, collaborated with the Intergovernmental Authority on Development (IGAD) Climate Prediction and Applications Centre (ICPAC) to develop the GHACOF forecasts. The GHACOF projections were previously the result of a secret "consensus" process that used statistical regression models, dynamical forecast models, and "analog years" based on the present tropical SST anomalies (mainly ENSO and the IOD). It is unfortunate that the consensus procedure "tends to over-forecast the near-normal category of rainfall" which under-predicts lower- and upper-tercile events.

Although there is an understandable hesitation to completely accept dynamical models, the creation of the forecasts has gradually developed in recent years to ameliorate this difficulty towards being based on 'objective' dynamical model projections \5^/To identify those climate states that are (and are not) a good indication of forthcoming climate variability, we specifically aim to understand how well ENSO and IOD, which are present at the time of the late August GHACOF, can predict OND rains. We do this by using a linear regression model to relate ENSO and IOD to rainfall and factors that characterize the Walker circulation over the Indian Ocean, based on reanalysis data from 1950 to 2020. We next use the reanalysis-based linear model's flaws as a diagnostic tool to shed light on the connection between the August SSTs, the OND Walker circulation, and the brief rains. As a potential source of inaccuracies, changes in the SST forcing between the prediction time in August and the OND are examined. Additionally, we investigate the association between precursor SST conditions in August and OND forecast mistakes to see if any conditions can a priori (upfront) predict the level of uncertainty in a seasonal forecast. The ECMWF monthly forecasting algorithm has a systematic conditional short-showers bias dependent on the starting IOD state, which we previously demonstrated using a similar methodology. The monthly mean data from 1950 to 2020 from the ERA5 reanalysis are utilized throughout. Precipitation, SST, the vertical velocity at 500 hPa (w500; positive upwards), and zonal wind at 850 hPa are the factors that are examined (u850). SSTs for ERA5 are determined from separate databases. The SST and precipitation data from ERA5 are linearly detrended to account for trends for the research period. The data for the remaining variables are not detrended because they show less consistent patterns. There are datasets for precipitation that are based on both direct observations and satellite-derived data, like the Climate Hazards Infrared Precipitation with Stations (CHIRPS) dataset. In East Africa, a comparison of ERA5 with CHIRPS has shown that ERA5 is marginally wetter than CHIRPS in October and November, especially close to the equator. The drying trend in ERA5 is likewise more pronounced than in CHIRPS from the 1980s onward, but it seems to be more of an issue in Central Africa than in our target region. Nevertheless, we detrend the data first to eliminate any erroneous ERA5 precipitation patterns from our research.

Since the CHIRPS period begins in 1981, using ERA5 precipitation data gives us an analysis window of 31 years. We calculated the Empirical Orthogonal Functions of East African precipitation for both datasets to assess the differences between ERA5 and CHIRPS. The interannual correlation between the first principal components was 0.97 in the overlapping period between 1981 and 2020. (Note that while CHIRPS is only specified over land, we included maritime grid points in the calculation of the ERA5-based EOFs.) On the aggregated temporal and spatial dimensions examined here, ERA5 and CHIRPS produce very similar results, despite undoubtedly existing disparities on the local scale and daily periods. The NINO3.4 index (also known as N34 from now on), which is computed as area-averaged SST anomalies from 170°W to 120°W and between 5°S and 5°N, and the IOD Dipole Mode Index (also known as DMI from now on), which is calculated as the difference between area-averaged SST anomalies in the western (50°E to 70°E and 10° S to 10°N) and eastern (90°E to 110°E) [5-7]. The N34 and DMI time series were then normalized, and the detrending was completed after the indices had been calculated. The geographic distribution of the lagged connection between PC1 and tropical SSTs in August. The oppositely signed correlations in the two IOD zones are consistent with a positive lagged connection with DMI. The correlations within the NINO3.4 region are positive. N34 (r=0.56) and DMI (r=0.55) are both strongly lag-correlated with PC1 in index form in August. Although there are hints of strong connections in regions other than the N34 and DMI, such as the Atlantic, the two indices seem to account for a sizable portion of the interannual correlations. The detrended August SST indices are shown in a normalized interannual time. Some years, such as the significant El Nio incidents of 1972 and 1997 and the La Nia events of 1998 and 2010, both indexes have high values with the same sign. Other years, like 2019, have strong ENSO conditions but huge absolute DMI values. The time series for PC1 and its (leave-one-out) forecast PC1, where are applied. The magnitudes of the significant coefficients are identical.

The correlation between PC1 and PC1 is 0.64, and even though this may be a minor overestimation of the real skill (because the EOFs were not computed out-of-sample the strong and significant correlation shows significant prediction capacity on the seasonal time series. The two SST indices on August, 1month-2 months before the start of the rainy season, account for about 40% of the interannual variability of the first principal component of OND rainfall, according to the high and significant correlation, which shows significant predictive power on the seasonal time scale. In contrast, the N34 coefficient c1 is somewhat bigger than the DMI coefficient c2 for the August SST indices. The zero-lag correlation with OND rainfall is stronger for DMI than for N34. We now look into how the indices' functions alter when the starting SST state is derived from various months. The relative relevance of N34 about DMI is at its highest for initial states in July before declining (with in mind that the IOD peaks in September-November). The N34 coefficient is non-significant for October starting states, showing that the IOD directly affects East African rainfall at short delays. In other words, the same linear models that forecast SST, vertical velocity, and low-level zonal wind anomalies in the regions where these variables are connected with East African rainfall also fail to predict these variables when the linear East African rainfall prediction model fails. According to one interpretation of this finding, the Walker circulation in OND and consequently the rainfall in East Africa are typically predicted by the SST indices in August quite accurately, but the OND rainfall prediction fails when the Walker circulation deviates from the anticipated response to the August SSTs. What can cause an OND Walker circulation reaction to August SSTs that wasn't expected, and consequently, a mistake in the rainfall prediction using August SST indices? We explore this option in more detail in the following section. Another possibility is that the SSTs in the Indian Ocean change significantly between August and OND, which could result in a different SST forcing than that anticipated by the linear model.

We have demonstrated in the sections above that the August DMI values are associated with both the rainfall forecast error and the DMI. We now demonstrate that DMI fully mediates the lag impact of August DMI using the mediation analysis framework from Section 2.5. For the sake of completeness, we point out that DMI and N34 have a significant link with a correlation coefficient of 0.28; however, since N34 has no discernible influence, N34 is not a viable mediator. We should also mention that we looked into whether DMI may mediate August N34's delayed effect, but it cannot. About 40% of the interannual variance of an East African short rains index, which again accounts for more than half of the spatial and temporal OND rainfall variance in the region, is explained by a linear prediction model based on ENSO and IOD states in August. Even while the N34 index in August is a reliable prediction of rainfall in OND, the IOD index DMI in OND completely mediates this impact.

The linear model's great predictive ability is consistent with other studies, and we have now verified the conclusion for a lengthy 70-year record Given that linear regression models are still often utilized in East Africa, it's critical to understand why and when they fall short. Because of this, the remaining analysis makes use of this linear model, and particularly its errors, as a tool to investigate the dynamical relationships between August SSTs and OND rainfall across time and space, as well as to determine whether it is possible to forecast errors a priori based on initial SSTs.

Conclusion

Through a Walker circulation across the Indian Ocean, tropical SSTs in August are connected to the East African brief rains in OND. We looked into the relationships between the errors of linear prediction models for vertical velocity, low-level zonal wind, and tropical SST and errors of similarly constructed linear prediction models for rainfall. This strategy is justified by the fact that regions with positive error correlations show where the other variables 'convey' the lagged effects of the SSTs on rainfall. When the linear model predicts too much rainfall, a too-strong Walker circulation is concurrently projected, and when the model predicts too little rainfall, a too-weak Walker circulation is predicted.

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