Drivers of interannual variability of the East African “Long Rains”

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The East African Long Rains season is unusual in that its year-to-year rainfall variability is mostly insensitive to the main modes of interannual tropical sea-surface temperature (SST) variability (ENSO, Indian Ocean Dipole). Various alternative drivers of interannual variability have been described previously but remain poorly understood. Here we present an analysis of three important drivers: regional Indian Ocean SST, seasonal amplitude of the Madden–Julian Oscillation (MJO) and phase of the Quasi-Biennial Oscillation (QBO). Reanalyses and instrumental datasets are in close agreement about rainfall interannual variability across the region as a whole, which represents 30–50% of the total variance. Subregional structure of the remaining variance is far more uncertain and is not considered here. We use modern reanalyses to understand how the proposed drivers affect March–April mean. Common to all three drivers is their ability to modify the large-scale subsidence over the East African region during boreal spring. SST in the western Indian Ocean achieves this via anomalous boundary-layer heating of the lower troposphere. The MJO modifies subsidence over the region through anomalous ascent and descent. Rainfall over East Africa responds to this MJO forcing in a unidirectional way, allowing seasonal rectification and interannual modulation by seasonal MJO amplitude. Understanding the QBO’s influence is complicated by the limited number of cycles over the reanalysis period. Each driver individually has a modest effect on the Long Rains, but added together they explain 30–60% of the variance of yearly rainfall variability that affects the region as a whole. This constitutes 13–25% of the total interannual precipitation variance, depending on dataset. The mechanisms we discuss suggest priorities for model development to improve model variability over East Africa. The metrics developed here lend themselves for easy evaluation of the remote drivers in models and other datasets.

KEYWORDS
East African rainfall, Long Rains, MJO, remote drivers, teleconnections, variability

1 | INTRODUCTION

East Africa receives most of its rainfall during two rainy seasons. These seasons are often referred to as Short Rains (SR, October–December) and Long Rains (LR, March–May). Seasonal mean rainfall anomalies of the LR typically have less spatial coherency than during the SR (Camberlin et al., 2009). Unlike the SR, and unusually for tropical rainfall, the LR exhibits little consistent sensitivity to the main modes of tropical sea-surface temperature (SST) variability such as the El Niño–Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD). Various alternative drivers of interannual variability have been described previously, but remain poorly understood. Here we present an analysis of three important drivers: regional Indian Ocean SST, seasonal amplitude of the Madden–Julian Oscillation (MJO) and phase of the Quasi-Biennial Oscillation (QBO). Reanalyses and instrumental datasets are in close agreement about rainfall interannual variability across the region as a whole, which represents 30–50% of the total variance. Subregional structure of the remaining variance is far more uncertain and is not considered here.
as El Niño/Southern Oscillation (ENSO), Indian Ocean Dipole (IOD) or Atlantic SST variability (Ogallo et al., 1988; Hastenrath et al., 1993; Mutai and Ward, 2000).

Remote drivers to the LR other than SST have been described, such as phase of the Quasi-Biennial Oscillation (QBO) by Indeje and Semazzi (2000) or seasonal amplitude of the Madden–Julian Oscillation (MJO) by Pohl and Camberlin (2006b). These studies show encouraging statistical connections to LR variability in observations but much remains unclear about the mechanisms for these teleconnections. This is partly due to modelling challenges. The QBO is absent from many climate models as it requires, amongst other things, a high-top atmosphere and dissipation of upward propagating gravity waves. The latter are unresolved in climate models and require parametrization (Scaife et al., 2000; Anstey et al., 2016). Additionally, some of the processes through which the QBO is thought to modify tropical rainfall (e.g. dynamical constraints on cloud top outflow and upper-level shear: Collimore et al., 2003) would be challenging for models that use parametrized convection. The MJO has been linked to intraseasonal spells of enhanced or suppressed rainfall in East Africa, depending on MJO phase (Pohl and Camberlin, 2006a; Hogan et al., 2015). These studies have found that intraseasonal spells tend to have an east–west spatial structure in which rainfall anomalies over coastal and highland regions are out of phase. The processes for these wet/dry spells (lasting up to 3 weeks) are well-understood from these studies. It is less obvious how the amplitude of a sub-seasonal oscillation like the MJO could affect seasonal mean rainfall of the LR, but it appears to involve modification of intraseasonal characteristics such as onset or extreme events (Pohl and Camberlin, 2006b). Climate models still have problems realistically simulating the MJO, notably its amplitude and eastward propagation (Hung et al., 2013; Henderson et al., 2017). Models are therefore of limited use in advancing our understanding of how the MJO affects seasonal rainfall in East Africa.

Our incomplete understanding of what controls LR variability makes it difficult to improve the low skill of seasonal forecasts of LR compared to the SR in initialised coupled models (Batté and Déqué, 2011). On longer time-scales the LR has a well-documented drying trend since the late 1970s (e.g. Liebmann et al., 2014). This drying appears to contradict the projected wetting under global warming in Coupled Model Intercomparison Project phase 5 (CMIP5) models (Rowell et al., 2015). Much work is still required to understand the reasons for the drying trend, particularly as models do not necessarily display a realistic sensitivity of LR to remote forcing by SST (Liebmann et al., 2014; Phillipon et al., 2015). A better understanding of how remote drivers can influence the LR would be helpful to further our understanding of the LR drying trend and implications for future projections. Local (e.g. land–atmosphere) processes may also play an important role but here we focus on remotely forced variability. The wider context of variability in the LR at various time-scales (days to decades) is described by Nicholson (2017).

The purpose of the present study is twofold: (a) to quantify the combined effect of multiple remote drivers on interannual LR variability in various observations and reanalyses, and (b) to clarify the processes through which these drivers modify East African rainfall. Following the literature we explore remote drivers from tropical SST, MJO and QBO. For (b) we require a model to provide a physically consistent relation between remote drivers and the dynamical processes that modify LR precipitation locally. Here we use observation-constrained reanalyses rather than free-running general-circulation model (GCM) experiments to understand processes in (b). Reanalyses have the advantage of retaining an atmospheric state close to observed, including the full spectrum of tropical variability which most CMIP5 models underestimate (Hung et al., 2013). The disadvantage of using modern reanalyses is that we are limited to the satellite period (1979 to present), i.e. fewer years to analyse than typically available from multi-century GCM experiments. To test dependency of our results on the dataset we use three reanalysis sets. Where possible we also use instrumental records to corroborate what is found in reanalyses.

The layout of this article is as follows. Data and methods are described in section 2. In section 3 we describe aspects of the mean state over East Africa relevant to the interannual variability. Remote drivers to East African LR are described in section 4; their mechanisms are analysed in section 5. Conclusions are presented in section 6.

2 | DATA AND METHODS

2.1 | Datasets

In this study we use a combination of reanalyses and instrumental data. The main reanalysis dataset we use is Modern Era Retrospective analysis for Research and Applications (MERRA2: Gelaro et al., 2017). It spans the period 1980 to present. We also use National Centers for Environmental Prediction (NCEP2: Kanamitsu et al., 2002) and ECMWF ERA-Interim (ERAI: Dee et al., 2011) reanalyses to account for uncertainty in reanalyses. To account for the uncertainty in instrumental precipitation and SST observations we used multiple datasets. For monthly mean precipitation we work with two datasets from different data sources: Global Precipitation Climatology Project (GPCP) version 2.3 (Adler et al., 2003, for 1979 to present) which is a blend of satellite estimates and rain-gauge measurements; and University of Delaware land precipitation version 4.01 (UDEL: Willmott and Matsuura, 2001, for 1901–2014) using only gauge data. For monthly mean SST we use Hadley Centre global sea-Ice coverage and Sea-Surface Temperature (HadISST1: Rayner et al., 2003, for 1870 to present) and National Oceanic and Atmospheric Administration (NOAA) Optimum Interpolation SST v2 (Reynolds et al., 2002, for
Rainfall variability metric

We need to define a suitable LR variability metric though which the effect of remote drivers on the region can be quantified. Climatological rainfall varies substantially across the region and a regional rainfall variability metric should not be dominated by the wettest parts. An additional complication, already mentioned in the introduction, is that seasonal mean rainfall variability itself varies at subregional scale. To account for this spatial heterogeneity of the LR variability we use empirical orthogonal eigenfunction (EOF) analysis (e.g. von Storch and Zwiers, 2002). EOFs were calculated for precipitation over land points in instrumental observations and reanalyses: GPCP, UDEL, MERRA2 and ERAI. EOF1 is shown in Figure 1. Rainfall variability during May is known to be only weakly connected to that during March and April (Mutai and Ward, 2000; Camberlin and Phillipon, 2002) and we limit our analysis to March–April mean rainfall.

The first EOFs from the different datasets are shown in Figure 1. They are very similar in spite of the diverse nature of the data (gauge, satellite, reanalyses). In all datasets EOF1 is an anomaly of the same sign across most of the region with opposite and weaker loadings in the far southeast and northwest. GPCP lacks some regional detail compared to the other datasets, e.g. the higher loading in the mountainous centre of the domain. This is part due to its coarse resolution and perhaps part to the difficulty satellites have with observing warm orographic rainfall (Adler et al., 2003; Dinku et al., 2011). Variance explained by EOF1 ranges from 28 to 49% and is well separated from EOF2 in all datasets using North’s rule-of-thumb (North et al., 1982). Temporal correlation between the first principal component (PC1) of the various datasets is also high (see Table 1). PC1 peaks in the extreme dry years that affected the region such as 1984 and 2011. Given the good agreement between datasets for EOF1 we use PC1 as our LR variability index in this study. The strong agreement between EOF1 and is well separated from EOF2 in all datasets using North’s rule-of-thumb (North et al., 1982). Temporal correlation between the first principal component (PC1) of the various datasets is also high (see Table 1). PC1 peaks in the extreme dry years that affected the region such as 1984 and 2011. Given the good agreement between datasets for EOF1 we use PC1 as our LR variability index in this study. The strong agreement between EOF1 and

Having a longer period to analyse LR variability processes (i.e. before 1979) would clearly be helpful. We explored the possibility of using NCEP (Kalnay et al., 1996) which starts in 1948, but found its leading LR EOFs for years 1979–2016 to be rather different from those in Figure 1. Furthermore, its PC1 was uncorrelated with that from the other datasets including NCEP2. We concluded that interannual rainfall variability over East Africa in NCEP is very different from that in modern reanalyses, even after 1979 when NCEP assimilates satellite data.

By focussing on EOF1/PC1 we implicitly restrict the analysis here to LR anomalies that affect the region as a whole. Such anomalies are arguably the most important from a socio-economic point and understanding their origins is clearly of great importance. Nevertheless this leaves

### Table 1

|                 | GPCP | UDEL | MERRA2 | ERAI | NCEP2 |
|-----------------|------|------|--------|------|-------|
| GPCP            | 1    | 0.94 (0.79) | 0.88 (0.13) | 0.83 (0.43) | 0.76 (0.33) |
| UDEL            | 1    | 0.83 (0.22) | 0.78 (0.29) | 0.67 (0.37) |       |
| MERRA2          | 1    | 0.74 (0.22) | 0.71 (0.16) |       |       |
| ERAI            | 1    | 0.58 (0.16) |       |       |       |
| NCEP2           | 1    |       |       |       |       |

Correlation between datasets is calculated over the common period 1982–2014. Correlations in bold are significant at the 5% level.
50–70% of the subregional rainfall variance unaccounted for. Unfortunately the uncertainty in the spatio-temporal features of this remaining variance is large between the various datasets (cf. PC2 correlations in Table 1). It is therefore not clear how one could use the reanalyses to understand this remaining variability with great confidence. Finally, since our focus is interannual variability, all data in this article are linearly de-trended to remove the signal of the LR decadal drying trend.

3 | MEAN STATE

It helps our discussion of the remote drivers in sections 4 and 5 if we first show the time-mean atmosphere circulation and moisture budget in the region. We show the mean circulation from MERRA2 in March–April in the lower troposphere in Figure 2. The circulation is characterised by the northeast and southeast trades converging towards the region. Where the trades meet the orography (white lines) there is strong ascent (purple colours). Otherwise there is large-scale descent (red colours) extending south and west from the Indian Ocean over most of the lower terrain in East Africa. The northeast trades bring relatively dry air (low relative humidity, cyan contours) to the region, the southeast trades more-humid air.

The vertical structure of the circulation is shown in northeast–southwest transects along the main slopes of the highlands (Figure 3). During March there is large-scale subsidence of relatively dry air into the lower troposphere. In the boundary layer, northward flow of relatively moist air moistens the region. During April the low-level northward flow strengthens giving much greater penetration of humid air in the boundary layer and lower troposphere than in March. During April there is also a reduction of large-scale subsidence of dry air in the mid-troposphere. Humidity gradients are reduced in April.

The effects of the circulation on the moisture budget can be seen in moisture tendency terms along the same transect (Figure 4). The strong humidity gradients and subsidence in March (cf. Figure 3a) cause a large drying effect by the resolved dynamics (Figure 4, top left). Turbulent mixing across the boundary layer (Figure 4, top centre) balances the drying by the resolved dynamics. Moisture converted into precipitation by the microphysics and convection schemes appears as a loss, i.e. drying the atmosphere (Figure 4, top right). During March the moisture divergence by the resolved dynamics in the lower troposphere acts as a brake on precipitation. Low-level moisture convergence moistens the boundary layer that supports the turbulent mixing of moisture. During April (Figure 4, bottom row) the importance of moisture divergence above the boundary layer by the large-scale dynamics is reduced and a closer balance is achieved by turbulent mixing (acting as a moisture source above the boundary layer) and microphysics that generates rainfall. This dominance of subsidence and convergence in the lower troposphere for rainfall over East Africa is comparable to what Yang et al. (2015) show for the mean seasonal cycle in ERAI.

4 | TELECONNECTIONS AND THEIR JOINT EFFECTS ON THE LONG RAINS

Previous studies have described links between individual remote drivers and LR. However, as pointed out by Nicholson (2017), these studies often use different datasets and periods, making it difficult to assess the combined effect of multiple drivers. In this section we first describe the presence of three important drivers (MJO, SST and QBO) individually in a number of reanalysis and observational datasets (sections
4.1 Tropical SST

We calculated linear correlations between de-trended March–April mean tropical SST and LR PC1 in the various datasets. For reanalyses we used their native SST, for OBS1 HadISST and for OBS2 Reynolds SST. In all datasets there are weak but significant correlations to SST in the western Indian Ocean of about 0.4 (Figure 5). Correlation in the Indian Ocean is most extensive in MERRA2 and OBS2, least in OBS1. Weak correlations are seen throughout the tropical oceans (eastern Indian Ocean, Maritime Continent,
tropical central and eastern Pacific) but there is clearly less agreement among the datasets. HadISST/UDEL show similar correlations in the northwest Indian Ocean (NWIO) over an extended period (1960–2014, not shown) but they are less extensive than those during the satellite era in Figure 5. The correlations from Figure 5 are similar to those in Ogallo et al. (1988) for boreal spring (their fig. 7).

Variability from the Indian Ocean Dipole (IOD) is weak during boreal spring and its peak occurs in boreal autumn (Saji et al., 1999; Saji and Yamagata, 2003). There is clearly no sign of the IOD in the SST teleconnection patterns of Figure 5, consistent with previous studies, e.g. Ogallo et al. (1988). However, we noticed weak positive correlation between March–April mean SST in the NWIO and the IOD of the preceding November/December (0.3 for MERRA2 and HadISST). This suggests that SST anomalies in the NWIO may be partly associated with remnants of a decaying IOD.

4.2 | MJO

To clarify the dependence of the LR on the MJO in MERRA2 we calculated daily Real-time Multivariate MJO (RMM1,2) indices for the MJO, following Wheeler and Hendon (2004). In this method daily mean fields of outgoing long-wave radiation (OLR) and zonal winds at 200 and 850 hPa (averaged between 15°S and 15°N) are projected onto the first two multivariate EOFs. These projections are referred to as RMM1,2 that jointly describe the intraseasonal oscillation. In the western hemisphere the main contribution to RMM1,2 comes from zonal winds as the contribution from OLR is small outside the Indian Ocean.

We constructed phase diagrams of the MJO during February–March for the six wettest and six driest LR years (Figure 6). During dry years (Figure 6a) the MJO is more than twice as likely to be inactive (i.e. lie inside the bold unit circle) than during wet years (Figure 6b). This is consistent with Pohl and Camberlin (2006b) LR who found a positive correlation of 0.67 between MJO amplitude and MAM rainfall in rain-gauge data, mainly over the highland region. It is clear from Figure 6 that the greatest difference between dry and wet years occurs for MJO phases 8, 1 and 2 and to a lesser extent phase 7. Median amplitude (circle segments) during phases 8–2 co-varies with LR variability, with stronger (weaker) than normal amplitude of active MJO during wet (dry) LR years. However, it is not only the amplitude of MJO active phases that changes in these composites. The probability of the MJO being active in the first place roughly doubles for phases 7–1 (small numbers in Figure 6). Changes for phases 3–6 between wet and dry years are more modest.

By construction the RMM1,2 representation reduces the MJO to two-dimensional phase space. To determine the spatial extent of MJO activity in boreal spring and identify changes during wet/dry LR years we applied wave-number-frequency filtering in an MJO window (Wheeler and Kiladis, 1999) to MERRA2 (Figure 7). We use a filtering window of 30–96 days, zonal wave-number
1–5. Following Kiladis et al. (2009), filtering was applied to the full fields and not separately to their (anti-)symmetrical components. Mean variance of OLR (Figure 7a, colours) is highest in the Indian Ocean and Maritime Continent (near the warmest mean SST), while variance of 200 hPa zonal winds (U200) is more homogeneous but with a maximum over the east Pacific (Figure 7b). Averaged over the six wettest years there is an increase in OLR variance compared to the six driest years in the Indian and North Pacific Oceans, i.e. where the mean variance is highest. Changes in U200 variance are weaker, with some reduction along the Equator during wet years compared to dry years (Figure 7b).

Given the pivotal role of the mid-tropospheric vertical velocity for the LR (section 3) we calculated its MJO-filtered variance. There is maximum variance in the Indian Ocean and west Pacific Ocean collocated with maxima of OLR variance (Figure 7c). This suggests a coupling between variability of convection and the resolved (large-scale) vertical circulation at MJO spatial and temporal scales. The maximum decreases eastward in the central Pacific but there is another maximum just north of the Equator. This latter band is collocated with the mean maritime intertropical convergence zone (ITCZ) (red line in Figure 7c) and stretches from the central Pacific and Atlantic to East Africa. This maximum is also evident in MJO-filtered diabatic heating but only at mid-tropospheric levels and not in the upper troposphere (not shown). This explains why it is absent from OLR (Figure 7a). During wet years, MJO-filtered variance of \( \omega \) increases compared to dry years in the regions of maximum mean variance, stretching from the west Pacific to East Africa. These results show that the increased amplitude of the MJO in wet years compared to dry years (Figure 6) is mainly caused by increased variance of OLR and diabatic heating that result in increased variance of \( \omega \) along the main ITCZ.

These results provide important clues for the mechanism of how the MJO affects LR and this will be explored in detail in section 5. For simplicity we will in the remainder of this section use the mean RMM1,2 amplitude over all phases as an index to quantify the effect of the MJO on the LR. In MERRA2 we find that correlation between LR PC1 and MJO SST QBO MLR

|        | MJO | SST | QBO | MLR |
|--------|-----|-----|-----|-----|
| MERRA2 | 0.51| 0.47| −0.42| 0.77|
| ERAI   | 0.30| 0.51| −0.38| 0.69|
| NCEP2  | 0.46| 0.23| −0.34| 0.55|
| OBS1   | 0.52| 0.30| −0.49| 0.71|
| OBS2   | 0.42| 0.39| −0.45| 0.70|

4.3 | QBO

We use the standard definition of equatorial zonal winds at 30 hPa as an index of the QBO. Indeje and Semazzi (2000)
suggested the LR has both an instantaneous and a lagged response to the QBO. A lagged response is consistent with the time it can take for mid-stratospheric equatorial wind anomalies from the QBO to descend to the tropopause: up to half a year (Huesmann and Hitchman, 2001). At zero lag we found no correlation between LR variability and the QBO in MERRA2. From various lags strongest correlation in MERRA2 is with the QBO index averaged over the preceding September–October–November (SON), $-0.42$. The mean QBO from SON was then used in all other datasets. Correlation is also negative in all other datasets (wet LR conditions follow an easterly QBO in SON). This difference in correlation between OBS and reanalyses could be a consequence of the convective parametrizations used in the reanalyses. These schemes do not necessarily incorporate all processes by which the QBO is thought to modify convective rainfall in the Tropics (Collimore et al., 2003) which would reduce the QBO’s influence. We noticed that the SON QBO index is very weakly correlated with the MJO amplitude index from section 4.2 in all datasets (typically around $-0.2$) which is not significant at the 10% level. There have been several recent studies that show a connection between the seasonal amplitude of the MJO during boreal winter and the QBO (e.g. Yoo and Son, 2016; Marshall et al., 2017). The relevant timings for the EALR discussed here are somewhat different from those in these studies and we have not explored this.

### 4.4 Joint effects

To quantify how much of the interannual variability in LRPC1 can be explained by the combined drivers of sections 4.1–4.3 we use multiple linear regression (MLR):

\[
\text{LRPC1}'(t) = a_0 + \sum_{n=1}^{3} b_n x_n(t). \tag{1}
\]

Here the $a$ and $b$ are linear regression coefficients obtained by a least-squares fit; $x_n$ are the driver time series used as independent variables in the MLR using the results from sections 4.1 to 4.3: area-averaged SST in the northwest Indian Ocean ($55-80^\circ$E, $5-20^\circ$N), MJO (RMM1,2) amplitude and QBO index. The three drivers are not significantly correlated with each other at the 5% level. In Figure 8d we show the actual LRPC1 series used as dependent variable in the MLR (black curve) and that of LRPC1', obtained by the MLR, i.e. the result from the fit (green curve). Correlation between LRPC1 and LRPC1' is 0.77 which is significant at the 5% level. This strong correlation underlines the importance for the Long Rains of the three drivers considered here. Most extreme wet and dry years (blue and red dots) are reproduced by the MLR regression (Equation (1)), which implies the drivers played a role in forcing the anomalies in those years. However, there are also some misses (e.g. 1984 and 2007).

For comparison we also show the three single linear regressions between LRPC1 and each of the individual drivers (Figure 8a–c). When the single linear regressions of Figure 8a–c are compared to the MLR of Figure 8d we can infer the contributions from individual drivers to an anomaly, e.g. the dry anomaly in 2000 has contributions from all drivers (mainly weak MJO and cold Indian Ocean SST), the wet anomaly in 1997 is mainly from easterly QBO and strong MJO, and opposed by (cold) Indian Ocean SST.

To verify if these results could have arisen by chance we test the null-hypothesis that the variance explained by the MLR of Figure 8d is indistinguishable from that due to random correlations between uncorrelated time series. We ran a 10,000
 FIGURE 8  EALR and its relation to three drivers (1982–2014). In (a–c) each driver time series is regressed individually onto LRPC1 (heavy black curve). The “predicted” LRPC1 time series obtained from this regression is shown by thin green line, its correlation with the actual LRPC1 is shown in the panel legends. (a) March–April mean Indian Ocean SST averaged over 5–20°N, 55–80°E, (b) February–March mean (RMM1,RMM2) MJO amplitude, (c) QBO during SON of the preceding year, and (d) multiple linear regression of three drivers from (a) to (c) onto LRPC1. Blue circles (red squares) denote the six wettest (driest) EALR years in MERRA2 used in the composites of Figures 6 and 7 [Colour figure can be viewed at wileyonlinelibrary.com]

sample Monte Carlo test of MLR, in which three random time series of 33 elements (i.e. corresponding to 2014–1982) were fitted to a fourth random series. All data were drawn from a uniform distribution. The 99th percentile of the distribution of explained variances in the Monte Carlo test was 23%. The variance explained by MLR of Figure 8d (59%) is therefore highly significant ($p$-value $< 10^{-4}$) and we reject the null-hypothesis. Note that we caution against using this MLR as a prediction tool for regional precipitation because that would require more rigorous cross-validation. We use the MLR not as a prediction tool but to evaluate past rainfall variability and its forcing by multiple drivers in various datasets in a consistent manner, as advocated by Nicholson (2017).

We have calculated the simple and multiple linear regressions in the other datasets to check the MERRA2 results (Table 2). Correlation of the MLR using all three drivers is significant in all datasets, be they instrumental or reanalysis. This supports the notion of a robust link between drivers and rainfall, independent of dataset. In spite of the heterogeneous nature of the underpinning datasets there is general agreement about the amount of variance explained by the three drivers, between 30 and 60% of the total variance. Among the reanalyses noticeable differences are weak (strong) sensitivity to SST in NCEP2 (MERRA2) and weak sensitivity to the MJO in ERAI.

5 MECHANISMS OF TELECONNECTIONS

In section 3 it was shown that large-scale subsidence of dry air acts as a brake on precipitation in the region. We found in MERRA2 that in wet years there is a weakening of the northeast trades and reduction of the subsidence over the western
Indian Ocean and East Africa (not shown). Dry years have opposite circulation anomalies. In the following subsections we describe how individual drivers control rainfall by modifying this large-scale subsidence. For this analysis it is helpful to maximise the number of years in this analysis so we use the full period from MERRA2 (1980–2017), rather than the common period 1982–2014 that we used in section 4 to compare the various datasets.

5.1 | SST

The link between Indian Ocean SST and LR variability occurs via the large-scale subsidence over the region. The leading mode from maximum covariance analysis (von Storch and Zwiers, 2002) between SST and vertical velocity consists of basin-wide, monopole structures (Figure 9). In these, warm SSTs heat the boundary layer (not shown) and force anomalous ascent over the region. This anomalous ascent opposes large-scale subsidence by the mean circulation (solid contours in Figure 9b) reducing its drying effect on the region. The opposite (anomalous descent, more drying) occurs with cold SST anomalies. The SST pattern of this first maximum covariance mode (Figure 9a) projects strongly onto the SST teleconnection field of Figure 5c. The teleconnection from Indian Ocean SST to the LR thus arises simply as the leading-order response by the atmosphere to boundary-layer heating driven by regional SST variability in boreal spring. As pointed out in section 4.1 and evident from Table 2, this driver to the LR is particularly strong in MERRA2 and weak in NCEP2, indicating uncertainty in sensitivity in the reanalyses.

5.2 | MJO

As mentioned in the introduction the key question here is how periodic forcing by the MJO at sub-seasonal time-scales is rectified onto seasonal mean LR anomalies? Strong MJO events are known to cause dry or wet spells depending on their phase. These spells last up to 3 weeks and one would expect that, considering many years, these MJO-forced rainfall anomalies would cancel out over the length of a season. Also, as shown by Pohl and Camberlin (2006a), the spatial structure of these spells has east–west antisymmetry that would reduce the net effect over the region as a whole, as measured by EOF1.

The answer lies in the way the MJO modifies the mean circulation over the region. It was shown in section 3 that moisture divergence through large-scale subsidence over the region acts as a brake on precipitation. Vertical velocity anomalies associated with the MJO, if strong enough, could modify (weaken or strengthen) this subsidence and therefore rainfall.

To isolate the vertical velocity ($\omega$) signal associated with the MJO we applied wave-number-frequency filtering to 3-hourly $\omega$ fields using the same method as in section 4.2. We calculate composites of these filtered fields during active MJO phases only (i.e. RMM1,2 amplitude >1) from 30 days before to 90 days after each active MJO event. Years 1980 and 2017 were excluded to avoid the influence from temporal padding that was applied to the start and end of the time series for the filtering. We calculated meridional means of all composites and show them as a function of longitude and lag (Figure 10). We show results at 700 hPa (i.e. close to the strongest moisture gradients (Figure 4); results are very similar between 500 and 700 hPa. For brevity we only show phases 7, 8, 1 and 2, as these were found in section 4.2 to be particularly important to the LR. Mean composites for these phases have a strong signature over East Africa/western Indian Ocean (30–90°E). Strongest ascending anomalies (negative $\omega$) occur at a wide range of non-zero lead/lags, from –30 to +60 days, depending on MJO phase. There is an obvious link between these anomalies of $\omega$ and regions of suppressed/enhanced convective activity usually associated with the different MJO phases. For example in phase 7 at lag 0, $\omega$ is positive. This coincides with suppressed convection over the eastern Indian Ocean typical of phase 7. The magnitude of $\omega$ composites is largest between 60° and 150°E and the composite signal weakens during propagation over the eastern Pacific.

From Figure 10 we see that there is a wide time window over which $\omega$ anomalies from the various MJO phases pass over East Africa. This poses a problem when trying to
understand the effect of the MJO on rainfall as it would be non-trivial to composite daily-mean diagnostic fields against MJO phases (e.g. as in Hogan et al., 2015). We have instead chosen to use linear regression, in which we regress daily precipitation data against daily mean MJO-filtered \( \omega \) averaged over East Africa (region shown by red box in Figure 11). This allows us to capture both instantaneous and delayed effects from all MJO phases. Regressions are calculated separately for when there is MJO-filtered ascent \((\omega < 0)\) or descent \((\omega > 0)\). To exclude noise from the filtered data not associated with an active MJO event we only use the data from the strongest 25% of positive and negative \( \omega \) (549 days for the period considered, 1981–2016).

In Figure 11 we show the regression of daily mean precipitation against MJO-filtered \( \omega \) when there is ascent (left column) or descent (right column). There is a striking asymmetry in the sensitivity of precipitation anomalies to the magnitude of MJO-filtered \( \omega \). During times of ascent there is widespread sensitivity over the region, implying that stronger ascent gives stronger precipitation anomalies. In contrast, during times of descent there is little sensitivity, apart from parts of western Somalia with reduced rainfall during descent. When precipitation is split into its convective (middle row) and large-scale (bottom row) components the regressions show that the greatest contribution comes from the large-scale precipitation over the orographic slopes. In these regions most rainfall occurs when the easterly flow is forced over the orography. This process is found to become stronger when there is additional ascent coming from the MJO. The lack of sensitivity to magnitude of MJO descent suggests that the mean orographic lift is strong enough to overcome the effect from any descent forced by the MJO. The sensitivity of convective precipitation during ascent is weaker but more extensive and covers most of the region. The asymmetry of sensitivity to MJO ascent/descent is again striking. Stronger descent does not lead to increased reduction in convective rainfall, whereas increased MJO ascent does cause stronger convective rainfall. In the latter case MJO ascent could cause enough weakening of the subsidence by the resolved flow against which the convective (parametrized) updraughts have to lift surface parcels of moist air. This would allow more convective precipitation. The lack of sensitivity during MJO descent implies that stronger net subsidence is not a limiting factor for convective rainfall.

This different sensitivity to positive and negative \( \omega \) explains the link between seasonal mean rainfall and MJO. In years with stronger than normal MJO activity (stronger positive and stronger negative \( \omega \)) this leads to net strong positive rainfall anomalies (Figure 11a,c,e). We need to keep in mind that the MJO-filtered \( \omega \) signals that reach East Africa originate from different phases and have different non-zero lags (Figure 10). They are therefore not directly comparable to the MJO composites by Pohl and Camberlin (2006a) or Hogan et al. (2015). In years with average MJO activity (positive and negative \( \omega \) anomalies of average amplitude crossing East Africa) the magnitude of wet anomalies is smaller than during strong MJO years. In years with weaker than normal MJO activity the rainfall anomalies are weakly positive or even completely absent, and therefore give a dry anomaly compared to normal MJO years.

We also calculated regressions between MJO-filtered \( \omega \) and precipitation in ERAI and NCEP2. These reanalyses also have an asymmetry of precipitation during MJO ascent and descent, with regression patterns broadly similar to MERRA2. The fact that the asymmetry occurs in
all reanalyses implies that it is a robust result that does not depend critically on the difference in the underlying models (resolution, orography, convection scheme, etc.).

5.3 | QBO

Based on our results from section 4.3 we calculated monthly mean composites of wind and humidity fields following QBO westerly minus easterly phase in SON up to April, i.e. 5 months’ lag. QBO westerly or easterly phases are defined as wind speed anomalies greater than 5 m/s. Because of its multi-annual period there are not many realisations of the QBO in the period covered by MERRA2 and the other reanalyses: between 1980 and 2016 there are 17 westerly and easterly phases using this definition. We found the composite differences of westerly minus easterly QBO to have a pronounced zonal structure (with zonal wave-number 1–2) which confirms the notion that, although the QBO’s stratospheric winds themselves may be virtually zonally symmetric, the response of the tropical troposphere to the QBO is not. Zonal gradients of tropical SST (Nie and Sobel, 2015) and tropopause height (Collimore et al., 2003) are likely contributing factors to this zonal dependence of the tropospheric response.

We show composites for zonal and vertical winds and relative humidity during April (Figure 12). In this month the (westerly minus easterly) QBO composite difference has a zonal wave-number-1 structure, with anomalous descent and drying in much of the eastern hemisphere and near the date-line and opposite anomalies over the Atlantic and eastern Pacific. Over East Africa and the western Indian Ocean there is anomalous descent and drying. This reinforces subsidence by the mean state and therefore causes additional drying, similar to cold basin-wide SST anomalies in the northwest Indian Ocean (cf. section 5.1 and Figure 9). The subsidence caused by the QBO appears connected to that near the Maritime Continent with ascent over the Atlantic. Unfortunately the sample size of 17 events is insufficient to explore how the stratospheric anomalies from the QBO set up the pattern of Figure 12, as its evolution is very noisy. Long climate model experiments could offer a larger sample, but until the models become better at representing the QBO and its effect on
tropical convection, understanding this sensitivity of the LR will remain difficult.

6 | CONCLUSIONS AND DISCUSSION

Interannual variability of the Long Rains (LR) that affects the entire East African region is well-captured by both instrumental and reanalysis precipitation datasets from 1979 to present. This supports the notion that a robust signal exists in these datasets and that the processes causing this variability are captured by modern reanalyses. Critically, this demonstrates that the reanalyses exhibit a credible interaction between drivers of the rainfall variability (be they remote or local) and the local response to these drivers that generates the rainfall over the region as a whole. There is less agreement between the datasets about interannual rainfall variation at subregional scale and we have not investigated this.

An important feature of mean climate in the region is subsidence in early spring. We found that, on average, subsidence of relatively dry air acts as to suppress precipitation over the region during March and April. Turbulent mixing of moisture from the boundary layer provides the main moisture source for precipitation. Remote drivers exert their influence on rainfall in the region by modifying the subsidence. Disruption of this subsidence in boreal spring by interannual tropical SST variability is difficult when, unlike in autumn, forcing from IOD and ENSO (both phase-locked to the annual cycle) is typically weak or in decline. However, warm regional SST in the western Indian Ocean, strong MJO activity in February–March and easterly QBO during the preceding autumn are all able to reduce subsidence to some extent and increase LR rainfall. The opposite occurs for cold SST, reduced MJO activity and westerly QBO. Total interannual rainfall variance explained by these drivers is about 60% in MERRA2. Our metrics for quantifying these drivers of the LR can be readily applied to model evaluation.

The effect of Indian Ocean SST occurs via direct boundary-layer heating but that of the MJO is more subtle. During wet LR years the MJO often has stronger amplitude and a stronger convective component over the tropical eastern Pacific and Atlantic than normal. Accompanying this stronger convection are increased vertical velocity anomalies, both positive and negative, which propagate eastward with the MJO. We found that when these MJO-forced vertical velocities reach East Africa, stronger negative (i.e. upward) anomalies cause stronger increase in rainfall. In contrast, rainfall in East Africa is insensitive to the magnitude of positive (downward) velocity anomalies when these reach the region. This unidirectional response to the MJO allows a net effect of quasi-periodic MJO forcing such that strong MJO activity causes a wet signal. Weaker than normal MJO activity reduces the importance of this process of weakened large-scale subsidence during MJO ascent. This will lead to dry anomalies in seasonal rainfall.

The vertical velocity anomalies that reach East Africa stem from different MJO phases and reach the region at different lead/lags, relative to times of MJO active phase, from −15 to 30 days. This explains the relevance of the MJO amplitude in February–March for the LR. Instantaneous compositing of precipitation against MJO phase would not pick up the complete seasonal response in the region to MJO forcing.
Model improvements along these lines will obviously benefit sub-seasonal-to-seasonal predictions for the region. Yet there are implications, too, for longer-term predictions and projections. For these longer time-scales additional “slow” drivers become important for East Africa (Rowell et al., 2015). If slow drivers project onto “fast” (interannual) drivers then this offers an efficient mechanism for slow drivers to alter mean rainfall. We have found no evidence to suggest that the drivers we discuss have contributed to the recent decadal decline of the LR, but this may change in a warmer world. For example, let us assume slow drivers increase probability of strong MJO events in the future (Arnold et al., 2015; Chang et al., 2015). Projections with a climate model that does not account for the link between MJO and Long Rains precipitation (as described in section 5.2) will miss one of the processes for rainfall change over the region. Improving representation of interannual drivers will therefore help to reduce model uncertainty in longer-term predictions and projections.

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