Distinguishing southern Africa precipitation response by strength of El Niño events and implications for decision-making

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Abstract
December–February precipitation in southern Africa during recent El Niño events is studied by distinguishing circulation and precipitation responses during strong and moderate-to-weak events. We find that while both strong and moderate-to-weak El Niño events tend to dry southern Africa, the pattern and magnitude of precipitation anomalies in the region are different, with strong El Niño events resulting in rainfall deficits often less than −0.88 standardized units and deficits of only about half that for the moderate-to-weak case. Additionally, the likelihood of southern Africa receiving less than climatologic precipitation is approximately 80% for strong El Niño events compared to just over 60% for moderate-to-weak El Niño. Strong El Niño events are found to substantially disrupt onshore moisture transports from the Indian Ocean and increase geopotential heights within the Angola Low. Since El Niño is the most predictable component of the climate system that influences southern Africa precipitation, the information provided by this assessment of the likelihood of dry conditions can serve to benefit early warning systems.

1. Introduction

Despite the connection between El Niño and southern Africa precipitation, not every El Niño event has coincided with drying in the region. The historic 1997–1998 El Niño was only moderately dry in parts of southern Africa and wet in others, which Lyon and Mason (2009) conclude was due to a disruption in the teleconnection by internal atmospheric variability and not predictable. Other studies have suggested
that there might be more subtle ways to interpret the El Niño influence on southern Africa by focusing on variations between distinct El Niño events. For example, Ratnam et al (2014) show that the precipitation response in southern Africa is substantially different when one considers canonical El Niño (i.e. eastern tropical Pacific focused) events compared to El Niño Modoki (i.e. central Pacific) events, with the former capable of forcing more severe negative precipitation anomalies than the latter. Other work (e.g. Hoell et al 2015) builds on these results and shows the response in southern Africa precipitation based on a more complete suite of ENSO expressions (both warm and cold phase). Results from Hoell et al (2015) are broadly
consistent with Ratnam et al (2014), and show larger precipitation deficits with an El Niño pattern that also follows a primarily tropical eastern Pacific forcing pattern. Additionally, there is a growing body of work that suggests southern Africa summer precipitation is also related to the Subtropical Indian Ocean Dipole (SIOD) (Behera and Yamagata 2001, Reason 2001, Washington and Preston 2006), including precipitation extremes (Hoell and Cheng 2018). When ENSO and SIOD are in opposite phases, Hoell et al (2017a) show that precipitation anomalies tend to be larger because of complementary dynamical responses working to dry the region.

Clearly, the relationship between southern Africa precipitation variability and El Niño is complex, given the different flavors of El Niño, modulations with other basins, and internal atmospheric variations. However, the strong relationship between southern Africa precipitation in austral summer and ENSO provides the basis for seasonal forecasting efforts (Goddard and Dilley 2005, Yuan et al 2014). These same forecasts are also relied on by the early warning community for extrapolating societal impacts that are linked to climatic variations. For example, during 2013–2016, parts of southern Africa experienced a historic drought that the United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA) has at least partially attributed to El Niño (UNOCHA briefing note December 2016). Corresponding severe regional crop production deficits and food insecurity led to an estimate of more than 25 million people needing food aid (Funk et al 2018). Based on this recent devastation in the face of El Niño, it is appropriate to consider the sensitivity of southern Africa rainfall response to this climate mode. It is not immediately clear whether the strength of El Niño results in stronger precipitation anomalies in southern Africa when considering a regional index over the recent past. From 1920–2015, southern Africa standardized precipitation anomalies (relative to 1981–2010 climatology) are below zero for 18 of 22 observed El Niño events (figure S2). Yet, one of the strongest El Niño events (1997–1998) results in only a modest negative precipitation anomaly, while a weak event (1994–1995) results in the fifth largest negative precipitation anomaly during El Niño years. Here we seek to better identify how different strength El Niño events influence the magnitude and spatial pattern of precipitation anomalies in southern Africa. We specifically take this approach to understand how the strength of El Niño events corresponds with precipitation variability in the region because skillful ENSO forecasts that include information about projected strength can be made months in advance of their DJF peak (Barnston et al 2017, Tippett et al 2017). Broadly following the approach used by Hoell et al (2016) for the case of California precipitation and El Niño strength, we use ensembles of SST-driven atmospheric model intercomparison project (AMIP) simulations to evaluate the relevant impacts of strong versus moderate-to-weak El Niño events. We also include a discussion about how this information might be useful for the international early warning community.

2. Methods and data

2.1. Observations

Observations of precipitation from a variety of data sources are presented for a time period of common overlap, December–February (DJF) 1981/82–2015/16. Details for the four datasets (CRU (Harris et al 2014), GPCC (Becker et al 2013), GPCP (Adler et al 2003), and CHIRPS (Funk et al 2015)) are presented in supplementary table 1 available at stacks.iop.org/ERL/13/074015/mmedia. For consistency, we study all precipitation data on a common 1° latitude-longitude grid. Sea surface temperatures are from NOAA’s Extended Reconstructed Sea Surface Temperature, version 4 (ERSSTv4) dataset (Huang et al 2015). This dataset has monthly values on a gridded 2° latitude-longitude grid over the ocean.

2.2. AMIP data

Given the small sample size of observed El Niño events (n = 12, see table 1 and section 2.3 for description of El Niño events), we supplement the present analysis with AMIP output. In the AMIP configuration, models are forced with historic sea surface temperatures (SSTs) such that the response to El Niño, as occurred in reality, can be studied with a larger sample size and including atmospheric variability. We use three models within the full suite of AMIP simulations: CAM5 (Neale et al 2012) with n = 20 ensemble members), ECHAM5 ( Roeckner et al 2006) with n = 29 ensemble members), and GFSv2 (Saha et al 2010) with n = 50 ensemble members). For the composites showing multi-model mean AMIP data (e.g. figures 7 and 8), the composite is the average of the 99 ensemble members from all models for the same 12 El Niño years specified in table 1. Further details about each model are provided in supplementary table 2. The computation of standardized anomalies and the percent of climatology is performed for each realization for the respective model and then averaged together.

<table>
<thead>
<tr>
<th>Category</th>
<th>Years and DJF Niño 3.4 average</th>
<th>Number of events</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moderate-weak El Niño</td>
<td>1986–1987 (1.02); 1987–1988 (0.65); 1994–1995 (0.96); 2002–2003 (0.89); 2004–2005 (0.62); 2006–2007 (0.68); 2009–2010 (1.26); 2014–2015 (0.51)</td>
<td>N = 8</td>
</tr>
</tbody>
</table>

Table 1. Table categorizing El Niño events since 1981. The DJF Niño 3.4 index value is shown in parentheses. We consider two kinds of events based on the CPC designation for strength: strong events where the DJF anomaly is 1.5 °C or above and moderate-weak where the DJF anomaly is between 0.5°–1.5 °C.
2.3. El Niño composites

The NOAA CPC definition of an El Niño event is used (i.e. SST anomalies in the Niño 3.4 region (120°W–170°W and 5°S–5°N) exceed 0.5 °C anomaly for at least five consecutive three-month overlapping seasons). According to the CPC, strong El Niño events are defined when the index in the Niño 3.4 region exceeds 1.5 °C while moderate and weak events are characterized by anomalies of 1 °C–1.5 °C and 0.5 °C–1 °C, respectively. We show a summary of characteristics for strong and moderate-weak El Niño conditions in this study because there is indication that the climate response to ENSO might be dependent on the strength of the event (e.g. Lyon 2004, Hoell et al 2016). In order to retain a larger sample size in each composite, we group the moderate and weak events into a single El Niño strength category while noting that results are broadly similar when one considers moderate and weak categories separately (i.e. impacts are still higher for the strong events, lesserened for moderate events, and weakest for weak events). Table 1 provides a summary of the El Niño events considered in the present study and their strength category, as well as the observed DJF Niño 3.4 index value (computed with ERSST).

3. Results

3.1. Observed correlation with SSTs

Figure 1 shows the correlation of southern Africa precipitation averaged over 10°–40°E and 15°S–35°S for the four data sources and local SSTs for DJF 1981/82–2015/16. Robust ENSO-like teleconnection patterns are shown, consistent with prior studies. Correlation between the southern Africa precipitation index and SSTs in the Indian Ocean are in contrast weak (absolute value less than 0.35). Some significant correlations are identified in the southern Atlantic, consistent with other work (Reason et al 2006), including the positive correlation centered around 0° and ~40°S and the negative correlation off the west coast of southern Africa around 25°S. Overall the tropical Pacific is most strongly correlated with the precipitation indices, exceeding r = 0.5. Figure 2 shows historical correlations between DJF Niño 3.4 SSTs and precipitation over southern Africa. Much of the region, including the land stretching across the 20°S latitude band as well as along the eastern coast, shows statistically significant correlation with the Niño 3.4 index. Note that correlations have also been tested for field significance (following methods outlined by Livezey and Chen (1982), see supplementary figure S3).

3.2. DJF SSTs and southern Africa precipitation during strong and moderate-weak El Niño

Figure 3 shows the difference in DJF SST anomalies for the two composites defined in table 1: strong El Niño and moderate-weak El Niño. Consistent with the composites’ design, there is greater warming in the Niño 3.4 region (indicated by the black box) in the strong composite compared to the moderate-weak composite. The difference between the two composites is significant and extends throughout the entire eastern to central tropical Pacific. Maps of each composite SST anomaly spatial pattern are shown in supplementary figure 4 and indicate a tendency for the strong events to have a more eastern Pacific location contrasted with a more central Pacific position for the moderate-weak events. This is not unlike the contrast of eastern Pacific and El Niño Modoki and their impacts on southern Africa precipitation explored in Ratnam et al (2014) (see their figures 1(b) and (c)), or the distinction between Johnson’s (2013) type 3 and type 4 El Niño, analyzed by Hoell et al (2016).
Figure 4. Standardized precipitation anomalies (baseline period 1981–2010) for strong events (left column) and moderate-weak events (right column) in the different datasets. Contours are from $-1.54$ to $1.54$ by $0.22$. The zero contour is shown in the thick black line.

Further discussion of the corroboration of our results with these prior works is in later sections.

Notably, there are few other regions of the ocean that display significantly different anomalies for the strong and moderate-weak composite. The northern portion of the Indian Ocean (north of about 20°N) is warmer and the southwest Indian Ocean extending around the southern Africa peninsula to the southeast Atlantic is cooler in the strong El Niño composite. Yet these differences are not significant and are much smaller compared to the difference in the Niño 3.4 region. This includes areas previously studied for links with southern Africa precipitation variability—the Indian Ocean Dipole region (Saji and Yamagata 2003, Manatsa et al 2012, 2012, areas outlined by the green boxes) and the subtropical Indian Ocean Dipole region (Behera and Yamagata 2001, Reason 2001, Washington and Preston 2006, areas outlined by the blue boxes). While we cannot rule out the influence of these oceanic regions in the resulting precipitation patterns explored, we find strong evidence for a control on the regional circulation patterns consistent with the strength of the El Niño events (see figures 6 and 7 below). A more comprehensive study of the impacts of
each of these regional SST forcings is beyond the scope of this paper.

Standardized precipitation anomaly maps for the strong and moderate-weak El Niño composites are next shown in figure 4. The standardization is completed by dividing anomalies with the climatologic (i.e. 1981–2010) standard deviation. Overall, there are larger precipitation deficits during strong El Niño events compared with moderate-weak El Niño events. The differences between strong and moderate-weak composites are similar across datasets, which builds confidence in the robustness of the patterns. Specifically, in the strong composite, the standardized precipitation anomalies are often in excess of $-0.88$ standardized units. In contrast, a much smaller subset of countries show negative precipitation anomalies in the moderate-weak El Niño composite, with rates that are of a much smaller magnitude (deficits of mostly $-0.44$ to $-0.88$ standardized units). Additionally, the moderate-weak anomaly pattern appears to be centered on the $18^\circ$S latitude band and have an east-west orientation, thus showing a fundamentally different spatial pattern than in the strong composite, where the largest precipitation deficits are tilted along the eastern-most part of the region. When precipitation anomalies for the two composites are tested using a left-sided student’s $t$-test (testing whether precipitation anomalies in the strong composite are significantly lower than in the moderate-weak composite), differences are significant only in portions of Mozambique, Zambia, Zimbabwe, and South Africa, implying that these countries should be especially vigilant in the case of forecasted strong El Niño (figure S5). While the strong composite has fewer events ($n = 4$) than the moderate-weak composite ($n = 8$), the reduction in strength of precipitation anomaly and location differences remain when considering only the top four strongest moderate-weak events (figure S6) and are thus not due to averaging.

Figure 5 shows standardized precipitation anomaly maps for the same composites calculated using each ensemble member from the different AMIP models. There are some biases evident within the model precipitation signature, including a southward and westward shift to the maximum precipitation anomalies in the strong composite compared to their location in the observational datasets. This is consistent with similar spatial biases in the precipitation climatology and standard deviation for each model (figures S7(a)–(b)). Note also that the precipitation anomalies are not as strong in the AMIP model ensemble. Even in the strong El Niño composite, the maximum negative anomalies are only approximately $-1$ standardized units, with much of the domain showing even weaker rates between $-0.2$ to $-0.6$ standardized units. The same bias can be seen for the moderate-weak El Niño composite with rates only reaching about $-0.2$ standardized units (note difference in color scale). While noting these discrepancies, it is encouraging that the overall weakening of the precipitation anomaly during strong versus moderate-weak El Niño events is captured in the multi-model ensemble mean, both in magnitude and spatial extent. Furthermore, the correlation structure in the individual AMIP models and observations are similar (figure S7(c)), as are the spatial precipitation patterns (with a northeast tilt in the strong case in both models and observations and a more east-west orientation for the moderate-weak composite). This motivates us to continue to explore aspects of the precipitation distribution with the AMIP output and reach conclusions regarding the distribution of precipitation for the two composites, a task that would not be feasible with the observations alone.

![Figure 5](image.png)
Figure 6. DJF simulated precipitation probability density functions (top) and cumulative distribution functions (bottom) made using output from all ensemble members (three models total) events from 1981–2016. The blue curve indicates the climatologic distribution; the red curve indicates the distribution for strong El Niño; and the yellow curve indicates the distribution for moderate-weak El Niño. The average observed precipitation (GPCP) for the two composites is shown as vertical lines along the bottom of the pdfs. The pdfs were constructed using Matlab. The pdfs are based on the normal kernel function, and use a normal kernel smoother. The pdfs are produced by evaluating the density estimate at every 100 points covering the range of the data (here 0%–200%). A kernel smoothing window with a bandwidth of four kernels is used to smooth the pdfs.

Figure 7. Ensemble mean sea level pressure anomalies (baseline period 1981–2010; mb, colors) and 850 mb horizontal wind anomalies (m/s, vectors) for each of the three models employed and for the different composites.
3.3. Precipitation distribution for strong and moderate-weak El Niño

Precipitation sensitivity to El Niño strength is next explored by constructing probability density functions (pdfs) and cumulative distribution functions (cdfs) for each of the composites. Each pdf and cdf (figure 6) is constructed by considering each ensemble member from all models for the years comprising the composite. There is a clear shift in the pdf of both the strong El Niño composite precipitation and the moderate-weak El Niño composite precipitation compared to the climatologic curve, representing a higher frequency of lower than climatologic precipitation rates during both types of El Niño events. Note that the shift is much larger for the strong El Niño composite, indicating that the probability of receiving less than climatologic precipitation is greater when El Niño is stronger. The shifts in model precipitation distribution with strength of El Niño are similar to the observed precipitation rates for the composite of each event (shown in vertical lines along the x-axis). During the strong El Niño years, the precipitation rate was only 85% of the climatology compared to the moderate-weak El Niño years when average precipitation was 94% of the climatologic rate. These differences remain when only the top four moderate-weak events are studied and are thus not due to the different sample sizes of the two composites (figures S8–S9).

Consistent with the shifts in the pdfs, the cdfs detail the probability of above and below normal (i.e. climatologic) rainfall for the different strength El Niño events. Across all ensemble members, there is once more a clear shift in the probabilities of drier than normal conditions. During moderate-weak El Niño events, the probability of below normal precipitation is just above 0.6; this probability jumps to almost 0.8 in the case of strong events.

4. Atmospheric response during strong and moderate-weak El Niño

We note that the pdf of precipitation response with the strength of El Niño events for individual models is completed based on its own climatology. Therefore, the resulting probability and frequency shown in figure 6 is unaffected by the individual model biases relative to observations, as the change in response is shown relative to each model’s own climatology.
Figure 9. NMME forecast skill (shown in terms of correlation) for DJF SST forecasts 1982–2010 for 0 to 5 months lead-time.

(Reason and Jagadheesha 2005) and modeling (Cook 2000) studies have shown a weakening of the heat low due to El Niño forcing, resulting in disruption of moisture transports poleward. The reduced strength of the Angola Low shown in the present study coincides with less moisture advection into the region from the southeast Atlantic via northwesterlies, represented here by the anomalous easterly flow around 16°S, stronger for the strong composite. The elevated surface heights appear to be a barotropic response stretching from the surface to 200 mb, and are thought to be associated with the barotropic atmospheric Rossby waves propagating eastward from the east Pacific forcing region (Hoell et al. 2016). These circulation changes combine with anomalous westerly flow off the southeast coast of southern Africa that is opposite to the main (easterly) supply of moisture from the western Indian Ocean (Lyon and Mason 2006) and work overall to divert moisture from the region, consistent with the stronger precipitation anomalies (see also supplementary figure 10). In contrast, in the moderate-weak El Niño composite these features are less distinct, or the precipitation deficit.

5. Discussion and use in decision-making

The above results indicate a difference in the likelihood of southern Africa receiving below climatologic precipitation for a given El Niño year. This is particularly true in parts of the countries of Zimbabwe, Mozambique, southern Africa, and Botswana where the correlation with ENSO is strong and the largest differences in precipitation exist between strong and moderate-weak El Niño. Based on the results from AMIP simulations, during both strong and moderate-to-weak El Niño events the probability of receiving less than climatologic rainfall is greater than 50%, with an approximately 80% chance in the case of a strong El Niño, and only approximately a 60% chance in the case of a moderate-weak El Niño. This finding is similar to studies that distinguish different precipitation responses in southern Africa related to El Niño or El Niño Modoki events (Ratnam et al. 2014) and the super-position of ENSO with the subtropical Indian Ocean dipole (Hoell et al. 2015). The results here do not contradict the above results but rather provide an additional framing of information about southern Africa precipitation variability for use in short-term decision-making. It should be noted, however, that the AMIP ensemble may under-represent the full magnitude of the ENSO teleconnection. For eastern southern Africa, one finds a strong empirical negative relation to Niño3.4 SSTs (R² = 0.53, Funk et al. 2016), and consistently large negative standardized anomalies (figure 4). While our sample of strong El Niños is small (n = 4), 75% of these events were associated with severe droughts.
(1982/83, 1991/92 and 2015/16) in reality, even though the response is much more muted in the AMIP ensemble explored here.

The skill of NMME mean forecasts for DJF sea surface temperature is shown in figure 9, indicating that there is high correlation (and thus skill) in predicting SSTs in the eastern tropical Pacific as early as July (5 months lead time). It is this component of the system that we wish to exploit in the present study and provide additional information about. As El Niño is developing, practitioners can begin to allocate resources and efforts to assist in planning for a rainfall season with reduced precipitation. The results presented here indicate that the probability of this occurring is higher if the forecasts continue to indicate a strong El Niño.

Of course, southern Africa displays considerable precipitation variability with drivers that are not limited to ENSO forcing (Behera and Yamagata 2001, Reason 2001, Washington and Preston 2006, Manatsa et al 2012, Hoell et al 2016, among others) and seasonal forecasts are far from perfect in terms of predicting any given season’s rainfall. Still, additional information regarding the probability of southern Africa precipitation characteristics based on the largest single driver of variability (i.e. ENSO) can be beneficial for managing drought risks. The knowledge that a strong El Niño event can significantly shift the distribution of regional precipitation would be useful for regional climate agencies such southern Africa Development Community Climate Services Centre (www.sadc.int/sadc-secretariat/services-centres/climate-services-centre/) that are tasked with providing early warning of the climate outlook in this region to support decision making needs of regional/national/international stakeholders. Strong El Niño-based early warning can be made well in advance of changes in the Indian or Atlantic Ocean that while important, are less potentially predictable and therefore more difficult to prepare for. Earlier and more confident warning of a looming drought could help with decisions having to do with seed planting, labor market, fisheries, municipal water management, reservoir and hydropower management, as well as trigger for and deployment of food-aid and relief efforts.

6. Conclusions

Southern Africa precipitation variability has been shown to correlate strongly with SSTs in the eastern tropical Pacific, characteristic of El Niño, and seasonal forecasts for the region are most skillful during ENSO years (Archer et al 2017). Previous studies have pointed to subtle differences in precipitation response to different patterns of El Niño forcing, specifically Modoki or non-Modoki events (Ratnam et al 2014). Others have shown how anomalies in basins besides the Pacific may help to exacerbate or mitigate some of the changes expected due to El Niño (Hoell et al 2015, 2016). Here, we consider how DJF southern African precipitation is sensitive to the strength of El Niño events (strong or moderate-weak). We make this designation to provide additional information about drought-related risks based on the most predictable component within the climate system.

Our results show a difference in both the magnitude and spatial pattern of precipitation anomalies for strong compared to moderate-weak El Niño events. These differences are linked to disruption of moisture supply to the area and a weakening of the strength of the Angola Low, behavior that is more apparent in the stronger El Niño events. Based on AMIP simulations, our results indicate that strong El Niño events increase the probability of a seasonal accumulation lower than average by about 20% more than a moderate-weak El Niño event. This additional information about both the distribution of precipitation during different strength El Niño events and the illustration of precipitation anomalies in space has particular relevance for users of climate information in southern Africa. Because El Niño can be forecast with some skill up to 5 months in advance, preparedness measures can begin in earnest well in advance of the timing of maximum precipitation declines and socio-economic losses.

There are limitations to the present study, particularly because there are so few El Niño events over which to study observed precipitation variations. One way we attempt to build confidence in our results is to employ multiple lines of observational evidence and show the consistency in precipitation changes over various time intervals (see supplementary material). Still, the samples sizes are small enough that determining the distributions from observations alone would be difficult, and thus we turn to the AMIP simulations to increase the sample size. While each model shows some bias in terms of the precipitation response, the overall agreement between characteristics of the model precipitation and observations is reassuring.

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