A Methodological Approach to Assess the Co-Behavior of Climate Processes over Southern Africa

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ABSTRACT

The study develops an approach to assess co-behavior of climate processes. The regional response of precipitation and temperature patterns over southern Africa to the combined roles (co-behavior) of El Niño–Southern Oscillation (ENSO), Antarctic Oscillation (AAO), and intertropical convergence zone (ITCZ) is evaluated. Self-organizing maps (SOMs) classify circulation patterns over the subcontinent, and principal component analysis (PCA) is used to identify related patterns across the data. The tropical rain belt index (TRBI), a measure of the ITCZ, is generally in phase with the AAO but mostly out of phase with ENSO. The phases of AAO may enhance or suppress ENSO impact on the location and distribution of regional precipitation and temperature over the region. This understanding of the co-behavior of large-scale processes is important to assess the impact these processes collectively have on precipitation and temperature, especially under future climate forcings.

1. Introduction

A regional climate is typically conditioned by a number of climate processes operating on multiple spatial and temporal scales. Evaluating the regional response to the collective co-behavior of these processes is thus central to understanding a region’s climate variability. Most especially for southern Africa, where there is no dominant large-scale driver, this is important. The regional climate variability of southern Africa is influenced by multiple processes such as the migration of the tropical rainfall belt [also referred to as intertropical convergence zone (ITCZ)], which influences the intensity and timing of rainfall through the seasons (Nicholson 2000; Suzuki 2011), and El Niño–Southern Oscillation (ENSO), which influences the timing and spatial distribution of rainfall (Dieppois et al. 2015; Meque and Abiodun 2015). Additionally, there are also relevant small-scale processes that modulate the impact of such large-scale processes. An example is the effect of mountain winds and convection on rainfall (Houze 2012). Variability of these large-scale processes, and their interactions across spatial and temporal scales ranging from global and decadal through to regional and subdaily, leads to regional climate variability and extreme events (Frei et al. 2006; IPCC 2012; Mason and Jury 1997; Meehl and Tebaldi 2004; Nicholson 2000; Stocker et al. 2013).

Earlier studies have dealt with how individual processes influence regional climate variability and change (see Hope et al. 2006; Hoell et al. 2017; Manatsa et al. 2017; Pohl et al. 2010; Suzuki 2011; Sheridan and Lee 2012). However, there arises a challenge when we want to examine the combined influence of these processes on regional climate. It becomes increasingly complex due to the nonlinearity of the climate system, which then implies that the combined impact of individual climate processes is not merely that of their linear combinations. For example, recent studies have focused on the relevance of the impact of cross–time scale interactions of multiple climate drivers on improving the predictive skills of extreme rainfall (Munoz et al. 2015), establishing a framework for considering the influence of cross–time
scale interactions in establishing weather types using coupled circulation models (Munoz et al. 2017) and exploring the predictability of weather type variability over Maritime Continent using $k$-means clustering algorithm (Moron et al. 2015).

The concept of co-behavior in this study is defined as an interaction between two or more large-scale climate processes that have an influence on regional weather and climate. Hence our ability to develop methodologies to address collective co-behavior of important climate processes will aid in understanding the nature of these interactions and will improve robustness of seasonal and interannual predictions to accurately present the regional information and consequently address regional climate change.

The aim of the present study is to develop a methodology to examine co-behavior through identifying and examining its influence on precipitation and temperature. However, we do not examine dynamical processes behind surface rainfall and temperature responses, which is beyond the scope of the present study. The next subsection provides a brief review of the southern African climate while identifying the influence of important large-scale processes on the regional climate. Section 2 explains the data and methods adopted for the study. The results are presented and discussed in section 3 with a summary and conclusions in section 4.

Processes affecting southern African climate

The processes affecting the climate of southern Africa have been well documented (see Buckle 1996; Chase and Meadows 2007; Tyson and Preston-Whyte 2000), and we describe some of the main processes below to provide a context for the paper. Southern Africa, defined here as region bounded to the north by latitude $10^\circ$S, to the south by $35^\circ$S, to the west by $25^\circ$E, and the east by $45^\circ$E, consists primarily of arid or semiarid climatic regions (Fig. 1). The domain was selected in order to include relevant atmospheric climate processes occurring immediately around the subcontinent such as the subtropical high pressure system inland; baroclinic disturbances in the midlatitudes leading to Rossby waves over the southwestern and southern parts of the region; a barotropic, quasi-stationary subtropical easterly wave of low pressure over the interior linking up with midlatitude westerlies; and ridging highs eastward from South Atlantic to the south Indian Oceans (see Hart et al. 2010; Lennard and Hegerl 2015; Schulze and Maharaj 2007; Taljaard 1996).

Atmospheric controls of regional climate variability in the region include regional processes such as the tropical temperate troughs (TTT) and the tropical rainfall belt migration, which have been identified as important drivers of precipitation over the subcontinent. The former has been known to contribute substantially to heavy precipitation in summer over the region (Hart et al. 2010; Lennard et al. 2013; Macron et al. 2014; Ratna et al. 2014), while the position of the latter controls the intensity and timing of moisture flow across the African continent (Nicholson 2000; Suzuki 2011). Westerly waves bring cold fronts from the South Atlantic Ocean to the western and southern parts of the country during winter (Makarau and Jury 1997; Tyson and Preston-Whyte 2000). Additionally, the South Atlantic and south Indian high pressure systems advect dry air and warm moist air respectively to the western and eastern parts of the country and potentially control the latitudinal movement of midlatitude westerly waves poleward or equatorward (DeBlander and Shaman 2017).

Teleconnection processes also influence southern African rainfall variability, for example, ENSO teleconnection (Camberlin et al. 2001; Engelbrecht et al. 2013; Fauchereau et al. 2003; Hulme et al. 2001; Jury and Freiman 2002; Lennard et al. 2013; Meque and Abiodun 2015). The region generally experiences dryer
positive TRBI is associated with higher rainfall intensities within the tropical rain belt.

We further analyze the co-behavior of these indices on surface temperature and rainfall variability in the region. We use temperature data from Climatic Research Unit (CRU-TS v4.01; Harris et al. 2014), and precipitation data from Climate Hazards Infrared Precipitation with Stations (CHIRPS; Funk et al. 2015), which is known to give a good representation of the rainfall regimes across the region (Dunning et al. 2016).

b. Methods

The study uses self-organizing maps (SOMs; Kohonen 2001) to characterize regional circulation variability, and principal component analysis (PCA; see Abdi and Williams 2010; Jolliffe 2002; Wilson et al. 1992) to explore co-behavior of climate processes and regional circulation variability. Figure 2 shows a schematic diagram of the phases of methods employed in this study.

We use the SOM to produce 12 characteristic 700-hPa anomaly fields circulation patterns over the study period 1980–2013 (see below for more detail on the SOM technique). Daily 700-hPa anomaly fields are used to train a 12-node SOM, after which each day in the study period is mapped to one of the 12 circulation patterns. From this, a 3-month frequency of occurrence of each synoptic type is determined. The 3-month frequencies (using a centered moving average 3-month window) are used to construct a monthly time series matrix of each synoptic type’s frequencies. The moving average window serves as a low-pass filter to eliminate short-term trends and highlight longer-term trends.

This matrix is augmented with additional columns for climate indices for ENSO, AAO, and TRBI. PCA is then used to identify the dominant modes of independent variability within the augmented matrix. Using the N-Rule test (Peres-Neto et al. 2005), which is based on randomization and assessment of significance at 90% confidence level, three principal components (PCs) were retained for the analysis. This allows for an exploration of the frequency of occurrence of synoptic types in relation to the co-behavior of the conditioning large-scale drivers represented by the indices. The PCA loadings indicate the relation between the frequency of occurrence of synoptic types and the conditioning by the three large-scale processes.

To investigate the regional precipitation and temperature response under different combined teleconnection and circulation states, 3-month periods are identified where the score of each of the three retained PCs identified by the PCA exceeds plus or minus one standard deviation in different combinations (details

2. Data and methods

a. Data

For the classification of circulation patterns over southern Africa domain we used geopotential height data at 700-hPa from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA-Interim (Dee et al. 2011) with a grid resolution of 0.75° for the period 1980–2013. The 700-hPa level is chosen over other levels because it effectively captures both tropical and mid-latitude synoptic weather systems, such as easterly waves, westerly waves, subtropical high pressures, and continental low pressures over the region (e.g., Bartman et al. 2003).

We use three indices that describe and analyze the state and changes in ENSO, AAO, and ITCZ intensity. For ENSO, we use the multivariate ENSO index (MEI; Wolter and Timlin 1993, 1998), which accounts for changes in both atmospheric and oceanic fields and best describes the coupled nature of the phenomenon. We also use AAO index constructed by projecting the daily 700-hPa height anomalies poleward of 20°S onto the leading pattern of the AAO (see Thompson and Wallace 2000). This index was obtained from KNMI Climate Explorer (ftp.cpc.ncep.noaa.gov/cwlinks). The intensity of the ITCZ is characterized using the tropical rain belt index (TRBI), which is an index based on methodology used by Nikulin et al. (2012). The reader is referred to Nikulin et al. (2012) for further reading.

Reason et al. 2010; Lennard and Hegerl 2015; Mason and Jury 2014). In our study of co-behavior, we analyze three of the important processes that govern the southern African regional climate, ENSO, AAO, and intensity of ITCZ. It is worth mentioning that other processes could have equally been used, but for the purposes of exploring the methodology we focus on processes that are well known and described in literature and have relatively convenient established indices describing their variability.

To investigate the regional precipitation and temperature response under different combined teleconnection and circulation states, 3-month periods are identified where the score of each of the three retained PCs identified by the PCA exceeds plus or minus one standard deviation in different combinations (details
Plus or minus one standard deviation is selected as a threshold for considering each PC to be a “strong” driver of the regional climate. As each PC relates to the indices of large-scale processes, this assists in evaluating the co-behavior role in conditioning the regional climate response on seasonal time scales. Precipitation and temperature anomalies are then calculated for each of the subperiods for each grid cell using the CHIRPS and CRU-TS v4.01 datasets. Standard bootstrapping with replacement (details below) is used to determine the standard error of this anomaly and anomalies that exceeded the 90th percentile of the error estimate are deemed statistically significant.

1) SELF-ORGANIZING MAP

The SOM is a form of artificial neural network (Kohonen 1982, 2001) and may be thought of as a topologically sensitive clustering technique that has been used in studying synoptic climatology (Hewitson and Crane 2002; Lee 2017; Richardson et al. 2003; Sheridan and Lee 2012). The method aids in objectively classifying archetypal circulation patterns (nodes) over a region and quantifying the frequency of occurrence of each node. The strongest attribute of SOM is that it preserves relationships between weather states by maintaining the data as a continuum while presenting both the basic and transitional patterns as an array making classified patterns readily understood and visualized, which is a challenge in other methods (Rousi et al. 2015). For a more detailed explanation of the workings of SOM, the reader should see Lennard and Hegerl (2015). The SOM is randomly initialized with different SOM node sizes while being trained with the daily 700-hPa geopotential height anomalies of ERA Interim data and after testing the different sizes for the SOM, a 12-node SOM size was selected as it was found to adequately represent the generalized synoptic circulation patterns over the region. Other studies (Mackellar et al. 2010; Tadross et al. 2005) have also successfully used a 12-node SOM to determine circulation patterns for the region. The SOM produced 12 archetypal 700-hPa patterns and each day in the training dataset is then mapped to one of these nodes thereby generating corresponding frequency mappings for each node. These nodal mappings are then grouped seasonally to aid in understanding the seasonal variability of the 700-hPa field.

2) ROTATED PCA

PCA is a multivariate statistical technique used in identifying the dominant phases of variance within data that consists of several generally related variables. PCA is used as it reduces the dimensionality of large datasets while maintaining its interpretability and preserving information (Abdi and Williams 2010; Jolliffe 2002; Jolliffe and Cadima 2016; Wilson et al. 1992). PCA aids in revealing the hidden structure of a dataset (Shlens 2005) by computing new variables called principal components (usually containing coefficients of correlation or loadings) obtained as linear...
combinations of the original variables. The principal component axis may be rotated to facilitate the interpretation of the components by maximizing the variance of the rotated squared loadings.

In this study, PCA is used to examine the interrelations that may exist among climate processes and the circulation patterns identified through the SOM by reducing the dimensions of the data into its simplest form to establish the relationship with minimal change in fundamental structure of data (see Abdi and Williams 2010). The N-Rule test is used to determine the number of components to retain in the PCA (Peres-Neto et al. 2005). The Psych package from R programming software is used here. This package uses eigenvalue decomposition and returns the loadings for components of a correlation matrix. Component loadings are produced by rescaling the eigenvectors by finding the square root of the eigenvalues. The principal components are varimax rotated.

3) Evaluating regional precipitation and temperature response, and assessing significance

In assessing the significant differences in average regional precipitation and temperature from the long-term average (anomalies), we use a bootstrapping approach. The approach, which is a resampling method, assumes the unknown cumulative distribution function of a sample (in this instance, precipitation and temperature series) can be estimated reasonably by the empirical cumulative distribution function (see Efron and Tibshirani 1994). This normally highlights the fact that the empirical density function approximates the population density function (Xu 2006).

On the above premise, we bootstrapped with replacement each precipitation and temperature anomaly subsample representing PC scores exceeding the thresholds described to construct empirical distributions of the mean anomalies. We then constructed 10,000 randomized composites from the anomalies and a statistical significance for each grid cell determined from the resampled distribution. Anomalies greater than the 90th percentile or lower than the 10th percentile of the resample distribution were calculated and deemed significant (see Brown 2018). These are then used to characterize precipitation and temperature uncertainty in obtained results.

3. Results and discussion

a. SOM mapping of geopotential height at 700 hPa

The circulation patterns of geopotential height at 700-hPa are shown in Fig. 3. To the leftmost part of the SOM, (i.e., nodes 1–2–5–9), we identify passing midlatitude frontal systems that cause rains over the southwestern parts of South Africa during winter (wet winter states). However, under these same conditions, the strong high pressure (also known as the Kalahari high) of the interior suppresses convection and typically results in dry conditions (dry summer; see Tyson and Preston-Whyte 2000). The circulation in the rightmost part of the SOM (nodes 4–8–12), representing disturbances in the easterly flow caused by interactions between the ITCZ and the warm, humid easterly wave, forces the semipermanent subtropical high to migrate south due to continental heating. These conditions allow warm air masses to converge humid air over the interior leading to rainfall in the region during summer (wet summer).

The frequency of circulation patterns across the SOM shows a characteristically even distribution across the nodes (Fig. 4). Seasonally, nodes 1–2–5–9 occur primarily in winter (JJA) days and accounted for 17%, 14.8%, 14.9%, and 15.5%, respectively, of the total days of occurrence in each of those nodes. Nodes 4–8–12 are also mostly associated with summer (DJF) days accounting for 16%, 18%, and 13% of the total days of occurrence. Nodes 3 and 6 accounted for 12% and 9.5% of the total days of occurrence which were predominantly spring (SON) days whereas in nodes 10 and 11 they accounted for 12% and 14% of the total days of occurrence and were predominantly autumn (MAM) dominated days. Node 7 occurs in both summer (DJF) and spring (SON) with both accounting for 9.5% of the days of occurrence.

b. Rotated PCA

To analyze the co-behavior between the seasonal SOM frequencies and the climate indices, we applied PCA. The PCA loadings and explained variance for the three retained PCs are presented in Table 1 below. The first rotated principal component (hereafter called PC1) accounted for 30% of the explained variance of the data across the period examined. MEI, AAO, and TRBI show weak correlations with PC1, while strong correlations are seen across the SOM node loadings. PC1 is strongly negatively correlated with the summer synoptic states on the right hand side of the SOM and strongly positively correlated with winter synoptic states suggesting that PC1 is capturing the seasonal cycle. The MEI is negatively correlated with AAO and TRBI on the second rotated principal component (hereafter called PC2). However, MEI dominates PC2 by exhibiting a strong positive correlation (0.72), AAO exhibits a weak negative correlation of −0.09, and TRBI exhibits a moderate negative
correlation of $-0.32$ in Table 1, suggesting that this component is largely an ENSO response. This component also accounted for 19.8% of the explained variance. Consequently, the strong positively correlated MEI points to an increase in dry summer states (winter circulation) and a decrease in wet summer states (summer circulation). The moderate negative correlation of PC2 with TRBI ($-0.32$) is likely explained by the tendency for positive MEI (El Niño) to suppress regional convection (see Dieppois et al. 2015; Cook 2001). The third rotated principal component (PC3) is dominated by a positively correlated AAO, a weak MEI, and a positively weak TRBI, which suggests this component is largely an AAO mode. An increase in both dry and wet summer states is associated with these conditions. This component also accounted for 12.6% of the explained variance across the data also shown in Table 1. In the first two components, AAO and TRBI are found to be out of phase with MEI whereas this is not the same for the third component.

c. Links between climate processes, regional precipitation, and temperature

In this section, we investigate how circulation patterns identified by the SOM influences the distribution of precipitation and temperature over the SRR, WRR, and ARR of southern Africa by considering their composite anomalies. Figures 5 and 6 show precipitation and temperature composite anomalies when PC1, PC2, and PC3 are in positive (when scores are greater than 1 standard deviation) and negative (when scores are less than $-1$ standard deviation) phases. To ascertain the potential influence of each phase on regional precipitation and temperature we examine the variations in their spatial distribution. To reduce redundancy, we only mention areas of statistical significance for the sake of summary, discussion and interpretation.
From Fig. 5a we note that both positive and negative phases of PC1 produce very weak and largely statistically insignificant precipitation anomalies. This is to be expected as the anomalies are calculated relative to month of the year in which the positive or negative phase events occurred and PC1 is strongly dominated by the seasonal cycle. As the method of calculating anomalies removes the seasonal cycle from the observations we expect and observe very weak anomalies for PC1. However, we only record significant precipitation anomalies (although negative) for the east of SRR, particularly northern Mozambique when PC1 is in positive phase (Fig. 5a).

For PC2 in positive phase (Fig. 5b), we see dryness in SRR and to the north of WRR. Since PC2 is largely an ENSO response as shown in our PCA, we suggest here that the positive phase of ENSO (El Niño) is largely responsible in suppressing convective systems, such as the south Indian Ocean convergence zone (SIOCZ), due to the weakening of convergence zones during El Niño events as a result of changes in the Walker circulation (Dieppois et al. 2015; Mason and Jury 1997; Reason et al. 2000) and its effect is particularly strong in the SRR. Again, the wetness in central parts of SRR could be attributed to the negative phase ENSO (La Niña) enhancing convective systems (Fig. 5e), leading to wetter and cooler than normal conditions in SRR (see Trujillo and Thurman 2011). When PC3, which is also seen largely as the AAO response, is in a positive phase, the central parts of SRR and the east of ARR

| PC1 [MEI = −0.10, AAO = 0.06, TRBI = 0.07(30.0%)| |
|---|---|---|---|
| 0.87 | 0.74 | 0.16 | −0.46 |
| 0.83 | 0.23 | −0.53 | −0.66 |
| 0.62 | −0.17 | −0.76 | −0.71 |

| PC2 [MEI = 0.72, AAO = −0.09, TRBI = −0.32(19.8%)] | |
|---|---|---|---|
| 0.09 | 0.09 | −0.23 | −0.70 |
| 0.27 | 0.48 | −0.06 | −0.58 |
| 0.56 | 0.81 | 0.25 | −0.34 |

| PC3 [MEI = 0.09, AAO = 0.40, TRBI = 0.22(12.6%)] | |
|---|---|---|---|
| −0.03 | 0.29 | −0.81 | −0.01 |
| −0.20 | 0.50 | −0.58 | −0.30 |
| −0.30 | 0.07 | −0.21 | −0.36 |
are marginally wet (Fig. 5c). On the other hand, WRR is wet while central parts of SRR are dry when PC3 is in negative phase (Fig. 5f). This in previous studies has been attributed to the reduction in the typical subsidence over the interior of the region as a result of weaker South Atlantic and south Indian subtropical anticyclones shifting frontal systems northward (see Reason and Rouault 2005).

For spatial distribution of temperature associated with PC1 (Figs. 6a,d), we identify warming in SRR when in positive phase. Again, although SRR, WRR, and ARR are warm during PC2 (Fig. 6b) positive phase, we find SRR much warmer when compared to WRR and ARR. We also identify that SRR and ARR are cold when PC2 is in negative phase (Fig. 6e). With PC3 in positive phase, WRR and ARR appear to be warm showing an east to west gradient (Fig. 6c). WRR and ARR are however cold when PC3 is in negative phase (Fig. 6f). The conditions in PC2 and PC3 are quite typical of ENSO and AAO individual influence over the subcontinent as mentioned earlier.

d. Analyzing co-behavior

In the next step we evaluate co-behavior by assessing the eight possible combinations that may likely influence regional precipitation and temperature based on the PCs identified from the rotated PCA. These combinations are realized by the mixing of the alternating phases of PC1, PC2, and PC3 and the results presented.

If we focus on significant dry conditions in the SRR in Figs. 7d and 7g, we see that these dry conditions are regionally extensive (Fig. 7d) under dry summer conditions (PC1 > 1 std), El Niño (PC2 > 1 std), and positive AAO (PC3 > 1 std). If AAO is strongly negative (Fig. 7g) the dry pattern becomes more northerly, suggesting that AAO is moderating the regional precipitation response to El Niño.

Similarly, if we focus on significant wet conditions in the SRR (Figs. 7a,f), we see that summer conditions
(PC1 > 1 std), La Niña (PC2 < −1 std), and negative AAO (PC3 < −1 std) are associated with broad wet conditions across central and northern parts of the region. If AAO shifts to positive (PC3 > 1 std) then this wet region is concentrated more in the east while northern Namibia and southern Angola are only marginally wetter. Again, this suggests that the AAO is moderating the regional precipitation response to ENSO, in this case under La Niña conditions.

For significant wet conditions in the WRR (Fig. 7c), we find areas around the southwestern Cape of South Africa marginally wet under winter conditions (PC1 < −1 std), positive AAO (PC3 > 1 std), and La Niña (PC2 < −1 std).

Additionally, focusing on significant warm conditions in the SRR (Figs. 8b, d, g), we see the center/north of the region is anomalously warm and the southwestern areas are cool (though not statistically significantly) under summer conditions (PC1 > 1 std), El Niño (PC2 > 1 std), and positive AAO (PC3 > 1 std) in Fig. 8d. The AAO shifting to negative (Fig. 8g) shifts the center of the warm anomaly westward and is concentrated around southern Angola with Zimbabwe and northern Botswana. With El Niño and a negative AAO phase co-behaving (Fig. 8b), most parts to the west of the subcontinent are warm spreading from the south to the north. In totality, this is similar to the precipitation response, which suggests that the AAO does moderate the El Niño temperature responses as well when they co-behave.

A positive AAO co-behaving with La Niña in winter is the only identified condition where all the rainfall regions are cold.

4. Summary and conclusions

The study develops a methodology to objectively identify co-behavior between climate processes and drivers of the southern African regional climate. We developed a PCA based on indices of seasonal circulation types, ENSO, AAO, and the ITCZ and the resulting loadings were associated with characteristic circulation patterns. Composites of precipitation and temperature for the first three components of the PCA...
were then produced and statistical significance at each grid cell determined.

We analyze the large-scale circulation types over the subcontinent as a proxy to understanding the influence of co-behavior. Results show the SOM was effective in capturing the dominant circulation patterns leading to the identification of the seasonal evolution patterns. Circulation types represented in nodes 1–2–5–9 are

FIG. 7. Composite precipitation anomaly patterns associated with eight possible combinations of positive and negative phases for retained PCs. Stippling denotes grid cells not statistically significant at 90% level. At the lower right corner is the number of data points and the corresponding percentage that contributed to each combination.

FIG. 8. As in Fig. 7, but for composite temperature anomaly.
primarily associated with winter (wet conditions for the WRR and ARR) and dry conditions over the interior of the SRR. Conversely, circulation types in nodes 4–8–12 represent weak high pressure systems and are associated with summer and precipitation over the SSR.

From the PCA analysis, we associate PC1 with the seasonal cycle as the loading matrix correlates strongly with winter (positive correlation) and summer (negative correlation) circulation types. The loading matrix of PC2 is identified as largely an ENSO response with strong MEI index loading on the matrix and moderate negative TRBI pointing to the expected suppression of convection under warm ENSO conditions. PC3 appears to be largely representing the variability of AAO and to a smaller extent the TRBI.

The PCA enables us to further examine the influence of individual teleconnective drivers on precipitation and temperature over the SRR, WRR, and ARR. We identified already established associations in literature, for instance the influence of a strongly negative AAO on precipitation in the WRR (PC3) and the ENSO influence on temperature and precipitation (PC2) in the SRR validating the strengths of the developed methodology.

Addressing our primary objective, combining the different combinations and variability of our retained PCA components, we are able to analyze the co-behavior of teleconnective drivers on regional precipitation and temperature. Results show conditions in SRR to be extensively dry and warm when El Niño episodes co-behave with a strongly positive AAO during summer. However, when AAO shifts to strongly negative in summer conditions, the dry pattern is more northerly and warming peak shifts westward. Broadly wet conditions persist in the SRR and parts of the ARR when La Niña episodes co-behave with a strongly negative AAO during summer. Conversely, a shift in AAO to strongly positive drives wet conditions in central and northern parts of the SRR although peak conditions are centered to the east.

We demonstrate that the WRR is both marginally wet and cold, with ARR only cold and the SRR much colder to the west when La Niña episodes co-behave with a strongly positive AAO during winter. However, during summer, this co-behavior enhances wet conditions in central to northern parts of the WRR. While further investigation would be required, Pohl et al. (2010) identifies a slowdown in the subtropical jet speed as a result of the combined effect of positive phase of the AAO and La Niña which may lead to rain-causing synoptic systems. During winter, a co-behavior of El Niño and a strongly negative AAO augments very warm conditions in the SRR while both the WRR and ARR are moderately warm.

Despite our analysis of co-behavior between drivers of climate over the study region, it must be noted that there are additional regional circulation features such as the Angola low, Botswana high, the subtropical south Indian high pressure system together with local soil moisture feedbacks and local topographic effects, particularly of the escarpment, that may modulate the local response to these co-behaving systems (Mackellar et al. 2010; Blamey et al. 2018). Although the large-scale processes and their co-behavior studied here establish the environment for the surface responses in rainfall and temperature, these additional drivers of local variability in the region may modulate the effect of the large-scale forcing. However, it is beyond the scope of this study to investigate these relationships.

In conclusion, the methods developed in this study have demonstrated that the impact of co-behaving climate processes may be analyzed. The method identified already established relationships over the subcontinent and further identified significant relationships between different phases of ENSO, AAO, and ITCZ with precipitation and temperature distribution across the southern African region. The methodology developed aims to underpin future work to advance the study of co-behavior of climate processes relevant to any given region. The present method can also be used to analyze climate drivers at multiple time scales. This type of analysis is essential for climate model evaluation and in subsequent studies we will assess how well co-behavior is captured in climate models and how co-behavior may change in future climate scenarios.

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