Climate process chains: Examples from southern Africa

Joseph Daron
Laura Burgin
Tamara Janes
Richard G. Jones
Christopher Jack

Abstract
The climate system comprises multiple components, primarily the atmosphere, ocean and cryosphere, each incorporating physical processes that interact across scales. To help understand the behaviour of this complex system, and evaluate climate model simulations, researchers typically take a reductionist approach, focusing on individual climate processes and studying their relationships with weather and climate in different regions. While more holistic approaches, such as climate networks, have been developed to explicitly address the complexity of the climate, here we argue for the use of a new approach that accounts for multiple cross-scale process interactions, framed with respect to specific climate outcomes of societal importance. We introduce and explore the concept of “climate process chains” (CPCs), describing their potential application using examples determined for southern Africa. Building on related theoretical concepts, and through reviewing literature on climate processes and teleconnections to southern Africa, we identify candidate CPCs for two outcomes of societal interest; a regional-scale drought and local-scale heavy rainfall. Focusing on such outcomes means that CPC investigations have more relevance to climate risk management contexts, as well as providing a constraint on the exploration of climate uncertainties for a region. We argue that CPCs may help to articulate relationships amongst regionally relevant climate processes across temporal and spatial scales, and discuss their potential utility in climate research, including in the evaluation of climate models and their simulations.

KEYWORDS
teleconnections, rainfall, uncertainties, climate model evaluation

1 | INTRODUCTION

The climate system is complex, with atmosphere, ocean and cryosphere processes operating and interacting over multiple spatial and temporal scales, driven by variable external forcings and a dynamic land surface (Rial et al., 2004). In the analysis of climate variability and change for a given region, studies have often focused on individual processes and their statistical relationships (e.g., through teleconnections) with climate variables of interest (e.g., Andrews et al., 2004; Van Oldenborgh and Burgers, 2005). Such an approach has improved our understanding of the climate system, and can support assessments of the reliability of climate models (Randall et al., 2007; Kalnognomou et al., 2013). Yet alterna-
tive approaches that explicitly recognize physical interactions and causal links between different processes acting across scales are required, both to aid understanding of the present climate and in providing robust future climate information for different applications.

To demonstrate the need for considering multiple interacting processes, consider the case of an Atlantic hurricane. The outcome of interest (the hurricane) is a result of many different processes acting at multiple scales. First an atmospheric disturbance must develop that can further intensify into a tropical storm. This disturbance may originate from an African easterly wave, which itself depends on the large-scale atmospheric circulation. A combination of other factors, including the driving forcings (e.g., seasonally varying solar insolation), large-scale atmospheric and ocean conditions (e.g., humidity fields and sea-surface temperatures [SSTs]) and smaller-scale processes (e.g., mesoscale circulation), need to be conducive to the development of intense and organized convection, moisture convergence, wind intensification and pressure deepening. Every stage, from the initial disturbance to the transition into a hurricane, involves multiple processes acting across scales.

Using the above example, it is clear that a single factor (e.g., SSTs) will not be sufficient to fully describe the likelihood of occurrence for an outcome of interest; a statistical relationship between SSTs and hurricane activity can be useful for some applications but is insufficient information for making robust predictions. This can only be done by considering key drivers, and the range of relevant system state variables and processes, and their interactions at different scales. It is in this context that the concept of a climate process chain (CPC) may become useful for analysing the climate system in relation to weather and climate outcomes of interest.

In this paper, we develop the concept of CPCs and discuss their potential role in analyses of the climate system. We explore CPCs in a southern African context, drawing on research for the Future Resilience of African CitTies And Lands (FRACtAL) project.1 We focus on the outcomes of heavy rainfall and drought because of their past damaging impacts on society, their emphasis in climate policy debates, and since they have particular relevance to FRACtAL, thereby demonstrating the “bottom-up” lens (outcome first) approach to the analysis of climate processes. Recent examples of the impacts associated with these hazards include the damaging floods from heavy rainfall in northeast South Africa and southern Mozambique during February and March 2000 (Jury and Lucio, 2004) and the multi-year drought affecting the Western Cape in South Africa from 2015 to 2017, during which rainfall was consistently below average (Botai et al., 2017). Using existing literature on a range of climate drivers, processes and interactions that influence the climate of southern Africa, this paper extracts examples of CPCs for heavy rainfall and drought outcomes. We do not aim to be exhaustive in the review of literature, nor in the identification of all regionally relevant CPCs, but rather focus on those processes that have been well explored in the literature to date. In doing so, this paper aims to provide a framework for identifying and analysing CPCs with application to any weather or climate outcome across different regions of the world.

Key to understanding the climate of a region, and central to prediction of climate variations and extremes, is the application of climate models. Different climate model simulations project different future climates. One reason for such differences is the variation in numerical representation of climate processes and their interactions (e.g., Pinto et al., 2018). In order to narrow this range and establish the reliability of these projections, process-based evaluation of models is required (James et al., 2017). Process-based evaluation requires selection of one or more relevant processes. Ultimately, therefore, this paper seeks to underpin future work to advance methods for CPC-based evaluation of climate models and their simulations.

Section 2 provides a more detailed conceptual basis for the CPC concept, situated in relevant approaches from the existing literature. Section 3 extracts example CPCs for southern Africa using evidence from a review of literature on the processes and drivers of southern Africa’s climate. Section 4 expands on the potential applications of CPCs, taking examples from Section 3 to discuss their potential use. Finally, Section 5 considers the potential application of CPCs more broadly, beyond those considered only for southern Africa, and makes recommendations for further research.

2 | CLIMATE PROCESS CHAINS: THEORETICAL PERSPECTIVES

In constructing CPCs, we aim to describe how climate processes influence a particular weather or climate outcome through interactions over different temporal and spatial scales. We define a CPC as comprising a weather or climate outcome resulting from a sequence of climate processes and climate system states initiated by a driver, where each individual element in the chain has a discernible physical influence on, and/or is influenced by, an upstream element.

To further help in the definition and application of CPCs, below we set out and define those terms used in the construction of example CPCs presented in this paper:

Outcome: A weather or climate phenomena or event of interest (e.g., heavy rainfall, drought)
Climate process: A physical and dynamic element or interaction in the climate system that has a characteristic spatial and temporal scale

System state: The condition of the climate system or one of its components (e.g., atmosphere, ocean, cryosphere) at a specific time

Driver: A system state or climate process that is considered to provide the initial forcing in the context of the CPC, and evolves on a time scale relevant to the outcome of interest.

To illustrate how these terms may be applied in a CPC, we return to the Atlantic hurricane example from Section 1. In this case, the outcome of interest might be, for example, an intense land-falling hurricane in Florida. A relevant driver is an African easterly wave, in this case a climate process, altering the zonal circulation. Relevant system states include those that affect the formation, intensification and track of a hurricane—for example, the large-scale atmospheric circulation, humidity fields, Atlantic Ocean SSTs and upper-level winds. Relevant climate processes within the chain include moisture convergence, pressure deepening, wind intensification and convective processes that favour the development of intense and organized convection. The CPC would not necessarily include all of these processes and system states and could involve just a subset with causal links resulting in a hurricane, and specifically factors relevant to the intensity and track. This would then have potential as a starting point for, for example, investigating the implications of global climate change perturbing one or more of the system states or drivers. Importantly, the selection of the initial driver for the CPC is a pragmatic decision, since all drivers are themselves likely to be influenced by processes and system states upstream. An expert judgement is therefore necessary to identify a driver that is supported by current understanding and has sufficient potential causality to warrant inclusion in the CPC.

Linking physical climate system states and processes, and relating them to weather and climate outcomes, is not a new idea. Hirst and Hastenrath (1983) first introduced the concept of a “causality chain,” referring to internal causality between climate states and processes, and linking atmosphere–ocean processes to rainfall anomalies on the Angola coast. However, acknowledging that the climate system is influenced by different external forcings across time and space scales, and is known to exhibit complex nonlinear behaviour and feedbacks (Peters et al., 2004; Lenton et al., 2008), other approaches to analysing causal relationships in the climate system have emerged. These include research on climate networks, which originate from complex network theory and treat the climate as a “network of many dynamical systems” (Tsonis and Roebber, 2004). The construction of climate networks involves calculating statistical relationships between different subsystem elements operating at different scales. Climate networks quantify relationships between, for example, tropical and extra-tropical processes, and enables studies into the stability of the climate system when subject to perturbations (Tsonis and Roebber, 2004). Donges et al., 2009 state that research to construct climate networks should be embedded in the framework of synchronization in complex systems (Arenas et al., 2008), which provides a powerful paradigm to improve our understanding of (nonlinear) teleconnections in the climate system. Kretschmer et al. (2016) extended these ideas to study “causal effect networks” that assess causal relationships and time delays between different processes, applying the method to improve understanding of Arctic sea ice controls on mid-latitude circulation.

Another holistic approach to understanding climate variability is given by Pohl et al. (2018), which aims to provide a unified view of rainfall variability in southern Africa across time scales by quantifying the influence of dominant low frequency phenomena on convective regimes. This study could not include short-lived phenomena that often cause significant rainfall amounts, such as mesoscale convective complexes and cut-off lows (Favre et al., 2013). However, by ranking the importance of low-frequency modes in different synoptic regimes, it provides a useful point for further process-based understanding of the climate system.

In recognition of climate system complexity, including nonlinearities and feedbacks, we do not seek to replace such approaches with the study of CPCs. There may be contexts in which they are inappropriate, even considering multiple CPCs. Rather, we aim to develop a complementary approach that can be applied in those cases where dominant “chains” are known to affect climate outcomes. Additionally, unlike climate networks and other methods described above, CPCs describe conceptual models rather than analytical models. CPCs are intended to guide the development and application of further analytical models and procedures (see Section 4).

The study of CPCs has synergies with the attribution of extreme climate events (Otto et al. 2015; Trenberth et al., 2015; Stott et al. 2016). Otto et al (2015) discuss the application of attribution methods in an African context. While they note the challenges arising from studying a region with poor long-term observations and substantial climate variability, there exist strong correlations between rainfall in parts of Africa and remote SSTs, providing a basis for conducting attribution studies (Hoerling et al., 2006, Funk et al. 2013, Wolski et al., 2014). A key challenge for attribution studies is demonstrating causality between processes, particularly for processes influenced by feedbacks. Developing a conceptual framework for articulating CPCs may help in
investigations of the causal mechanisms that influence weather and climate events of interest, noting the requirement for complementary approaches that can test and demonstrate causality between specific links in a CPC.

The CPC approach is also related to other emerging approaches that describe responses to future climate change using “storylines” and “narratives.” Zappa and Shepherd (2018) present storylines of atmospheric circulation change, aiming to provide a new way for describing uncertainty in future climate projections and impacts for regions. They focus on Europe and analyse output of CMIP5 models, relating combinations of remote drivers to different climate responses (e.g., precipitation in the Mediterranean) using a pattern scaling approach. Alternatively, Dessai et al. (2018) use expert elicitation to generate six narratives of plausible changes in long-term summer monsoon precipitation over a river basin in India (Figure 1). One narrative describes reduced moisture availability and a weaker flow towards southern India resulting in reduced monsoon precipitation. In this case, several other underlying processes are known to be relevant (e.g., cooling of SSTs in the Arabian Sea and weakening of the Westerly Jet). The authors acknowledge that these climate processes are interconnected, but they did not elicit the causal links between them. Similarly, the storyline approach of Zappa and Shepherd (2018) relates plausible changes in large-scale remote drivers to regional responses, though they do not describe the full causal pathways for particular outcomes. The concept of CPCs may therefore complement the narrative approach described by Dessai et al. (2018) and the storyline approach of Zappa and Shepherd (2018), by effectively providing causality hypotheses based on current understanding, and helping to articulate the cross-scale links between processes and system states relevant to these characterisations of uncertainty in future climate projections.

3 CLIMATE PROCESS CHAINS IN SOUTHERN AFRICA

To develop a general framework for articulating and applying CPCs, we first determine example CPCs for the outcomes of heavy rainfall and drought in southern Africa. After briefly describing the main features of the southern African climate, we present three example CPCs determined from a review of current peer-reviewed literature. The processes included are not exhaustive but are found to feature most prominently in the literature; their relationships with other climate processes and outcomes are relatively well understood. In Section 4, we further discuss ways in which these CPC examples may be applied in practice.

Our region of focus, southern Africa, stretches from Angola and Zambia in the north to the southern tip of South Africa at 35°S. The climate across the region varies substantially, with arid conditions in the west, Mediterranean conditions in the south-west and humid subtropical conditions in the north and east. Tropical, extra-tropical and mid-latitude processes all influence the region’s climate, with many remote processes driving annual and decadal climate variability (e.g., El Nino Southern Oscillation—ENSO) (Daron, 2014).

Most of southern Africa primarily receives rainfall during austral summer (December to February), due to the southward migration of the tropical rainfall belt driven by the location of maximum solar insolation. The southwest primarily receives rainfall in winter (June to August) and the south coast experiences rainfall in all seasons, with small peaks in spring and autumn. Winter rainfall results

![FIGURE 1 Climate process “narratives” for the Indian Summer Monsoon; reproduced from Dessai et al. (2018) [Colour figure can be viewed at wileyonlinelibrary.com]](image-url)
predominantly from temperate frontal systems embedded in the westerlies (Tyson and Preston-Whyte, 2000), enhanced by orographic and coastal influences, with contributions from other westerly disturbances, such as cut-off lows (Favre et al., 2013).

The neighbouring oceans have a major influence on the region’s climate (e.g., Cook et al., 2004; Lutjeharms, 2007; Rouault et al., 2009; Favre et al., 2016; Hoell et al., 2017). Moisture supply to southern Africa principally originates from the Indian Ocean and is transported by easterly trade winds in the lower troposphere (e.g., Nicholson, 2000). In general, SSTs around southern Africa play a modulating role (Klutse et al., 2016) and are highly variable due to the proximity of the Agulhas, Benguela and Antarctic circumpolar currents (Shannon et al., 1990; Cook, 2000; Rouault et al., 2009). The Agulhas and Benguela currents exert a stronger control on southern African rainfall during austral summer in non-ENSO years and times of Subtropical Indian Ocean Dipole (SIOD) and ENSO phase alignment (Reason and Smart, 2015; Hoell et al., 2017).

In Sections 3.1–3.3, we articulate three example CPCs, determined using evidence from the existing literature. After outlining the results of relevant studies, we construct diagrams to represent the CPCs, showing how the drivers, system states, processes and outcomes of interest relate to each other (see Section 2 for definitions). Further explanatory text is provided to demonstrate how altered system states act as drivers to affect the outcome of interest through the CPC.

3.1 Example 1: ENSO and drought

The influence of the ENSO phenomenon on regional climate characteristics of southern Africa, and its significant impact on rainfall variability in the region, has been widely studied (e.g., Dyer, 1979; Lindesay, 1988; Lindesay and Vogel, 1990; Goddard and Graham, 1999; Reason et al., 2000; Fauchereau et al., 2009). Warm phases of ENSO (El Nino) typically invoke a southwest–northeast dipole pattern consisting of positive rainfall anomalies in equatorial eastern Africa and areas of coastal southern Africa, and negative rainfall anomalies across much of southern Africa south of 15°S (Nicholson and Kim, 1997; Goddard and Graham, 1999; Cook, 2001). During an El Nino event, there is typically an anomalous northwards shift in maximum rainfall (Ropelewski and Halpert, 1987) associated with the tropical rainfall belt (Klutse et al., 2016). When the tropical rain belt is north of the equator, the climate of southern Africa typically experiences an intensification of the mean meridional Hadley circulation (a low-latitude overturning circulation) (Cook, 2001), anomalous high pressure producing mid-tropospheric descent (Driver and Reason, 2017), and increased incoming solar radiation and temperatures due to less cloud cover (Mason and Jury, 1997). This results in a tendency towards increased dry spell frequency and severe seasonal droughts (Lindesay, 1988; Reason et al., 2000; Usman and Reason, 2004; Boulard et al., 2013).

Model simulations forced solely by Pacific SST variability are unable to sufficiently capture the observed rainfall response to ENSO in southern Africa (Goddard and Graham, 1999; Reason and Jagadheesha, 2005). However, models forced by both Indian and Pacific Ocean SSTs are better able to depict the climate of eastern and southern Africa (Reason and Jagadheesha, 2005; Hoell et al., 2017). There is debate on precisely how SST variability in the Indian Ocean propagates to southern Africa (Mason and Jury, 1997; Copey et al., 2006; Fauchereau et al., 2009). It is suggested that the spatial structure of rainfall anomalies over southern Africa is dependent on SSTs within the Indian Ocean (Nicholson 1997; Nicholson and Kim, 1997; Nicholson, 2003), while the amplitude of the anomaly is modulated by a large-scale atmospheric response characteristic of Rossby waves (Cook, 2001). In addition, the phasing of ENSO with the SIOD, an SST pattern in the subtropical Indian Ocean, is linked to changes in regional southern African climate. When the SIOD and ENSO are in opposite phases, the SIOD compliments the ENSO atmospheric response to strengthen the associated Rossby waves and results in anomalously reduced rainfall over southern Africa beyond that noted for ENSO alone (Hoell et al., 2017). Conversely, when SIOD is positive and in phase with ENSO, then their atmospheric responses often interfere with one another and the impact on rainfall anomalies in southern Africa is reduced (Hoell et al., 2017).

A recent study of three strong El Nino events has described how three key regional pressure systems, the Angola Low, the Botswana High and the south Indian Ocean high pressure (SIHP) system, modulate the response of southern Africa’s climate to ENSO (Blamey et al., 2018). The Angola Low and the SIHP drive moisture convergence into the region and the Botswana High produces subsidence that leads to reduced convection. Variations in their strength and position have therefore been linked to rainfall anomalies in southern Africa (Cook et al., 2004; Reason et al., 2006; Driver and Reason, 2017; Munday and Washington, 2017; Crétat et al., 2018). The combination of the anomalies in these systems and their dominance at particular times contributes to the characteristics found for individual ENSO events. For example, it is widely believed that an anomalously strong Angola Low, coupled with high SSTs in the western Indian Ocean and eastern subtropical South Atlantic Ocean, were partly responsible for reducing the impact of El Nino during the intense 1997/1998 ENSO event, resulting in near-normal seasonal rainfall (Reason and Jagadheesha, 2005; Lyon and Mason, 2009; Hoell et al., 2017; Blamey...
et al., 2018). Créat et al. (2018) additionally found that the Indian Ocean modes of variability provided favourable background conditions for the development of the anomalous Angola Low. On examination of the strong 2015/2016 El Nino, Blamey et al. (2018) report that a much stronger Botswana High was present at the start of the austral summer than in other El Nino events. They also note that SIHP was weaker during 2015/2016 resulting in less moisture transport from the subtropical south Indian Ocean into the continent.

We now provide an example CPC (Figure 2) showing one response pathway between the state of the climate system in the equatorial Pacific to seasonal rainfall in southern Africa. Alternative CPCs related to the outcome of interest can be used in combination—for example, CPCs that further elucidate the role of the Angola Low. The CPC given can be used to consider the effect of an ENSO event by connecting anomalies in the Walker Circulation and equatorial Pacific SSTs through each climate process and system state in the CPC across spatial and temporal scales. In this example: Weakening/reversing of Walker Circulation -> Positive ENSO (El Nino) conditions in the Pacific -> Eastward propagation of Rossby Wave -> Eastward shift of surface convergence over Indian Ocean -> Reduced moisture advection towards continent - > Increased subsidence over continent - > Increased temperature and reduced moisture over southern Africa -> Reduced convection -> Reduced rainfall. The magnitude of rainfall reductions—and therefore the prevalence for drought—would depend on the strength of the driver and the modulating influence of the downstream processes and systems states.

3.2 | Example 2: Indian Ocean variability and heavy rainfall

Variability in the Indian Ocean is one of the dominant drivers of climate variability in southern Africa. In addition to the SIOD (Section 3.1), the Indian Ocean Dipole (IOD) is a pattern of SST variability, characterized by warmer (cooler) than average temperatures in the equatorial western Indian Ocean during a positive (negative) phase, with reversed SST anomalies in the eastern part of the basin (Saji et al., 1999). These SST variations force wide-ranging teleconnections through modifications to zonal winds, moisture fluxes and rainfall patterns over eastern and southern Africa (Behera et al., 2005; Hoell et al., 2017). However, as discussed in the previous section, there is debate on the role of Indian Ocean SSTs in propagating teleconnection signals from the tropical Pacific to southern Africa (Mason and Jury, 1997; Copsey et al., 2006; Fauchereau et al., 2009). The SIOD also additionally affects the likelihood of heavy rainfall events in eastern parts of southern Africa through its influence on the dominant pressure systems that control the advection of moisture in the summer months (Reason, 2001). Through this effect, positive SIOD conditions are related to intense extra-tropical cyclones and the formation and location of the leading mode of summer rainfall variability known as tropical-temperate troughs (TTTs) (Reason, 2002; Fauchereau et al., 2009).

TTTs are manifestations of tropical-extra-tropical interactions and are visible as prominent cloud bands oriented from north-west to south-east (Washington and Todd, 1999; Behera and Yamagata 2001). TTTs cause substantial intra-seasonal and interannual rainfall variability through variations in their frequency, position and intensity (Hart et al., 2013) and are frequently responsible for flooding during late summer (Barclay et al., 1993). TTTs develop through interactions between synoptic scale mid-latitude waves and meso- to micro-scale convection in the tropics (Barclay et al., 1993). Their location coincides with a zone of moisture convergence supplied by strong fluxes from the Indian and Atlantic Oceans (Todd and Washington, 1999). Mid-latitude transient perturbations, interpretable as Rossby waves, are also a necessary component for TTT formation through their role in enabling large-scale instability and favourable conditions for convection (Vigaud et al., 2009; Hart et al., 2013; Macron et al., 2014). Following their formation, TTTs tend to propagate eastward (Vigaud et al., 2009; Macron et al., 2014) often causing extreme rainfall events in the affected regions (Hart et al., 2013).
Figure 3 shows how SSTs in the subtropical Indian Ocean can be related to heavy rainfall events in the east of southern Africa through a CPC. As in the previous example, we can use this to consider the effect of perturbations to system states (i.e., drivers in this context) and translate this to the outcome of interest through other links in the CPC. For example: Positive SIOD event consists of warm SSTs in the western subtropical Indian Ocean and relatively cool SSTs in the east -> Reduced atmospheric pressure yielding low pressure anomalies over the southwest Indian ocean -> Modified zonal winds, leading to convergence at the surface and divergence of winds at higher altitudes -> Increased evaporation -> Increased moisture advection towards Mozambique and eastern South Africa -> Interactions with TTTs -> Increased frequency and intensity of heavy rainfall events.

3.3 | Example 3: Southern Annular Mode and winter rainfall

The Southern Annular Mode (SAM), also referred to as the Antarctic Oscillation (AAO), has been linked to winter rainfall characteristics in South Africa, particularly over the Western Cape (Reason and Jagadheesha, 2005; Reason et al., 2002; Reason and Rouault, 2005; Gillet et al. 2006; Weldon and Reason, 2014). The SAM is a measure of the poleward extent of the circumpolar westerlies around the Antarctic continent, which play an important role in mid- to high-latitude atmospheric circulation in the southern hemisphere (Kidson, 1988; Thompson and Wallace, 2000; Reason et al., 2006). It is linked to Western Cape winter rainfall through its influence on the subtropical jet and extra-tropical cyclones that pass through the region (Reason and Rouault, 2005).

Extra-tropical cyclones dominate day-to-day weather variability in the mid-latitudes and are associated with strong winds, precipitation and temperature changes (Ulbrich et al., 2009). Changes in the intensity of the cyclones or location of their tracks strongly impact regional climate variations (Chang et al., 2012). The Western Cape of South Africa...
shows substantial interannual and interdecadal variability in winter rainfall which is largely supplied by cold fronts associated with extra-tropical cyclones (Reason et al., 2002). The interannual variability of cyclone tracks is strongly influenced by the position and strength of the subtropical and subpolar jets, which control moisture supply to the cyclones. A stronger equatorwards shifted jetstream is associated with wet winters and a weaker polewards shifted jetstream during dry winters in the Western Cape (Reason and Rouault, 2005).

An important region of cyclogenesis is found in the southwest Atlantic upstream of the Western Cape (Jones and Simmonds, 1993; Reason et al., 2002). Warmer SSTs in the southwest Atlantic favour increased cyclogenesis and cool SSTs in the central southwest Atlantic act to conserve potential vorticity and shift the track of the cyclones equatorward. The Agulhas Current retroflection region supplies large amounts of heat to the atmosphere to the area south of the Western Cape (Walker, 1990; Reason, 2001) and combined with warm SST anomalies can lead to more intense cyclones over the landmass (Reason et al., 2002).

Figure 4 shows how the circumpolar winds in the Antarctic defining the SAM can be related to winter rainfall in the Western Cape region of South Africa. For example: Negative SAM meaning a greater equatorward extent of the circumpolar westerlies -> Shifted meridional circulation -> Equatorward shift in the subtropical jet location over the South Atlantic -> Increased moisture flux from the subtropical Atlantic -> Enhanced moisture supply to cold fronts moving towards South Africa -> Increased rainfall and a higher risk of wet winters in the western Cape region with associated heavy rainfall events.

## 4 | USING CPCs IN CLIMATE RESEARCH AND APPLICATIONS

Having presented three example CPCs for southern Africa, in this section, we use them as a basis for discussing potential applications. We discuss three ways in which CPCs can be used: (1) to support assessments of climate model reliability, (2) for use in attribution studies and (3) to explore sources of uncertainties across scales. For the first two applications we refer to example 2—Indian Ocean variability and heavy rainfall (see Section 3.2)—which has particular relevance to FRAC TAL cities in the eastern parts of southern Africa, most notably Maputo (Mozambique) but also Blantyre (Malawi), Lusaka (Zambia), Harare (Zimbabwe), Johannes burg and Durban (South Africa). In Maputo, the FRAC TAL project has worked with city partners and identified flooding, resulting from heavy rainfall and coastal inundation, as one of the three primary climate risks facing the city. For the third application we refer to example 3—SAM and winter rainfall (see Section 3.3)—which has relevance to another FRAC TAL city, Cape Town (South Africa).

### 4.1 Assessing climate model reliability

Many studies relate single drivers of regional climate variability (e.g., ENSO) to specific climate responses (e.g., seasonal rainfall in southern Africa), including those cited in this paper. Yet it is also well understood that these single driver-response studies have limited value for explaining the physical processes involved (though they sometimes suggest “atmospheric pathways” through which their influence is mediated) and are therefore insufficient for assessing climate models and making robust statements about future climate change. Having defined the CPC concept and provided examples, we now outline how CPCs might be used for assessing climate models.

We propose that CPC investigations can be used to help identify novel metrics needed to assess model reliability and understand differences in model behaviour, thus supporting efforts for process-based evaluation of models. Such studies have been argued to be especially important in Africa where model development lags other regions (James et al., 2017). Below we outline a number of steps that would be necessary in applying CPCs to help assess climate model reliability. Where multiple CPCs are relevant to an outcome, steps 2–8 below should be repeated for each CPC.

1. Identify candidate CPCs through reviewing physical understanding and/or analysis of observations
2. For each CPC, articulate characteristic time and spatial scales for each process (e.g., zonal atmospheric circulation—hours to days, and hundreds to thousands of kilometres)
3. Identify meteorological variables/indices to characterize each link in the chain (e.g., zonal atmospheric circulation—mean 850 hPa winds, or SSTs in the Indian Ocean defined by an SIO D index)
4. Decide on observational, reanalysis and model data sets to conduct assessments, that have the appropriate variables and sufficient resolution to represent the CPC elements
5. Identify instances of the relevant outcome/events in the data sets being used in the analysis (e.g., heavy rainfall events in a specific location)
6. Using the variables/indices defined in steps 2 and 3, work backwards from each event and quantify the characteristic variables/indices (for relevant temporal/spatial scales) for each CPC link
7. Compile CPC “event sets”—that is, collate data relevant to all outcomes/events identified
8. Assess characteristics of CPCs (e.g., joint statistical distributions) and compare across observations, reanalyses and model datasets
If the statistical characteristics of the CPCs differ between different data sets, this provides a basis for diagnosing model errors and explaining the differences in simulations, otherwise not captured through single process evaluations. Future work planned in the FRACtAL project will adopt and test this approach for application to newly available high-resolution regional climate model simulations across Africa; known as the CP4-Africa data set (Stratton et al., 2018). Ultimately, this work may provide improved assessments of confidence in model projections of future climate.

4.2 | Use in attribution studies

An important application of extreme event attribution is to understand the extent to which global climate change or regional climate variability was responsible for a specific damaging event. In the case of the former, it would provide evidence for increasing efforts to mitigate future emissions or to increase the protection of people or systems impacted by the event. In the case of the latter, it may provide evidence for the need for improved impact-based forecasting systems and related insurance services to be put in place to cover losses from the event.

The use of CPCs in this context would be to isolate those processes and system states that could clearly be influenced by global climate change. This would inform a targeted analysis of event attribution experiments, focusing on quantifying the influence of global climate change as opposed to other possible external drivers (e.g., volcanic eruptions) or internal variability of the climate system. The application of CPCs in this way has parallels with the “storyline approach” to attribution discussed by Shepherd (2016), which is “anchored in a physically based causal narrative” and analyses the various factors influencing specific events.

In the case of example 2, the general warming of the oceans would clearly affect (increase) the process of evaporation and moisture advection; however, the implications for the gradient in SSTs or the formation of TITs are not so clear. This would imply that extreme event attribution experiments should focus on whether and how climate change has influenced these system states (i.e., SSTs in the subtropical Indian Ocean) or processes (e.g., evaporation over the subtropical Indian Ocean) and in particular, linked to assessment of model reliability, the level of confidence that simulated changes in these are robust.

4.3 | Exploring sources of uncertainties across scales

Uncertainty around future projected changes in regional or local climate variables is often identified as a barrier to effective adaptation decision-making. While various approaches to decision-making under uncertainty have been developed and applied, concurrent efforts to better quantify the uncertainty in projected changes continue to be critically important. CPCs can facilitate this process in two ways.

First, building on the approach described in Section 4.1, CPCs can help interrogate climate model ensembles such as the most recent coordinated by the Coupled Model Intercomparison Project, CMIP5. This could involve identifying models that demonstrate realistic simulation of the processes/system states in the chain, which would increase confidence in their projected changes of a particular outcome of importance. Alternatively, it could be used to exclude models from an ensemble that fail to adequately capture the observed CPC dynamics and so removing implausible projections from the ensemble (e.g., McSweeney et al., 2015; Gallo et al., 2018). While model exclusion on this basis will necessitate subjective decisions around thresholds of “adequate,” all model exclusion or weighting approaches involve subjective decisions whether around the criteria for weighting and/or the thresholds for exclusion. The advantage of using the CPC framing is that the model evaluation explicitly targets the relevant processes for a particular outcome across multiple scales. Other approaches (Coppola et al., 2010; Räisänen et al., 2010; Weigel et al., 2010) typically focus on local model performance, or global scale performance. The CPC approach typically identifies multiple climate features of relevance ranging from local scales through to global teleconnection scales.

Second, CPCs can assist in disaggregating uncertainty at the local decision scale. Uncertainty is well recognized to consist of various components that dominate over different time scales. The primary components are natural internal variability (an inherent property of the climate system), model uncertainty and scenario uncertainty (Hawkins and Sutton, 2009). Methods exist to quantify these components and they clearly demonstrate that internal variability tends to dominate over shorter time horizons (10–20 years), model uncertainty dominates on medium time frames (20–60 years) and beyond that scenario uncertainty dominates (Hawkins and Sutton, 2009). However, these analyses are often based on a single spatial scale and single climate variable. CPCs offer the potential to begin to describe how different components of uncertainty may dominate at different scales through the chains of processes leading to the area and variables of interest.

For example, referring to example 3 (Section 3.3), in the case of winter rainfall over south-western South Africa, internal variability at the local scale (order of 200 km) makes identifying historical trends difficult and may dominate the range of climate model projected outcomes over short to medium time frames. However, model uncertainty may
dominate projected changes in an upstream process such as the migration of subtropical jet, and hence we could decompose the range of outcomes into a component which is influenced mainly by internal variability and a component that is influenced mainly by climate model formulation. In this instance, applying a process-based assessment of how well these upstream processes are represented in the climate models (as explored in Pinto et al., 2018) could constrain the latter component of the projected changes.

Recent studies are beginning to use the language of CPCs to relate uncertainties in climate projections to processes at different scales. Rowell and Chadwick (2018) examine the causes of regional climate projection uncertainties in seasonal rainfall over eastern Africa. In considering the impacts of anthropogenic forcing the authors identify “a process chain from initial CO₂ impact of altered radiative forcing, to global-scale responses, and then regional-scale responses,” which ultimately impacts on rainfall.

5 | DISCUSSION AND CONCLUSIONS

The CPC concept presented here is not a fundamentally new idea but it has not been previously defined or readily applied in different areas of climate science. To help determine a framework for the application of CPCs in different contexts, we focused on three examples extracted from literature describing climate processes and their interactions in southern Africa. The example CPCs presented in Section 3 do not explain all of the factors relevant to the outcomes of interest, namely regional-scale drought and localized heavy rainfall events. Indeed these outcomes are likely to be influenced by more than one CPC, and multiple CPCs should be considered in applications. We also do not claim that the CPCs presented are proven to be dominant for the stated outcomes; they were selected only as examples and warrant further investigation using observational and model data sets. However, since they were based on current understanding from prior studies, we do believe that they provide a suitable starting point for subsequent CPC investigations.

The entry point for determining and articulating CPCs may differ depending on the context. It can initially derive from physical understanding, analysis of observations, or even representation in models. However, in all cases a CPC should be physically plausible—that is, consistent with current understanding of how processes interact with system states—and assessed using different data sets. If a model is not able to capture a CPC, this could mean either the model is inadequate or that the CPC articulation is flawed. CPCs can be refined by drawing on multiple lines of evidence, but in attempting to simplify how the complex climate system evolves there will always be a risk that the CPC is describing “apparent” relationships and not the reality of how the climate system works.

We recognize that the CPC approach has limitations. In particular, singular “chains” do not, by their definition, allow for feedbacks. Since feedbacks between climate processes are known to be critically important in many instances (e.g., in cold climates where snow and ice feedbacks have first order impacts), the CPC approach could have limited realism and therefore potentially limited value in application. In other cases, where feedbacks exist but are less important, a judgement is needed to determine the most appropriate ordering of components in the CPC; it may be appropriate to identify one or more additional CPCs to account for such feedbacks. Furthermore, the CPC concept is premised on the idea that specific dominant chains exist—that is, individual chains that link processes across scales and explain large parts of the driver-to-response relationships. How to determine a dominant CPC for a given region and outcome of interest is a non-trivial task, and relies on exploiting existing knowledge of the regional climate system. Nevertheless, there may be value in testing hypotheses about the dominance of different CPCs in a specific context to help improve our physical understanding of the climate.

In extending the work presented here, important next steps include further exploration of the example CPCs provided for southern Africa, in both observed and model data sets, as well as considering alternative CPCs for different outcomes and regions of interest. Ultimately, CPC investigations aim to complement other approaches in assessing confidence in climate models, both for use in attribution studies examining past events and for evaluating the robustness of future climate projections. In aiming to advance methods for CPC-based evaluation of climate models, it is important to provide clear examples of how this can be done and the added value it provides to conventional evaluation approaches. Examples should also address the challenges of assessing CPC representation in downscaled regional model simulations which rely on global models at their boundaries.

An alternative way forward is to use CPCs as a starting point for more qualitative studies to consider the effects of climate variability and change for specific regions and outcomes of interest. They may have value in complementing climate process narrative approaches (Dessai et al., 2018, see Section 2) to help articulate physical relationships and causal pathways that connect climate drivers and climate processes across different scales.

In this paper we have developed an initial framework for describing and using CPCs. In doing so, we aim to improve methods for understanding the results of climate modelling studies and the ability of climate models to provide robust information about past and future changes in climate. We note, however, that there are limitations with the CPC
approach and therefore we do not suggest that CPC investigations necessarily replace existing or newly emerging process-based approaches. Rather they offer an additional line of enquiry to help in climate model evaluation, extreme-event attribution, and uncertainty quantification, and moreover as a general conceptual framing for articulating multi-scale climate processes as they impact a given region. We cannot expect CPCs to fully account for the complex behaviour of the climate system, but they may offer a practical tool for simplifying and navigating the complexity.

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ENDNOTE

1 http://www.fractal.org.za/

ORCID

Joseph Daron https://orcid.org/0000-0003-1917-0264
Richard G. Jones https://orcid.org/0000-0002-0904-3141

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