Further Probing the Mechanisms Driving Projected Subtropical Decreases of Extreme Precipitation Intensity

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Abstract Regional projections of extreme precipitation intensity (EPI) are strongly influenced by regional projections of “extreme ascent,” i.e. ascending air during periods of extreme precipitation. Earlier studies have performed analysis suggesting that long-term changes in eddy length scale and vertical stability are key factors influencing extreme ascent projections, but these mechanisms have yet to be confirmed with controlled model experiments. In this study, we perform such controlled experiments using a cloud-resolving model (CRM). The selected CRM domains are two locations over the subtropical South Atlantic Ocean where global climate models consistently project weakening of extreme ascent with accordingly decreased EPI. At each study location, three pairs of 20-year maximum precipitation events are simulated with the...

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CRM, with each pair consisting of an event during the historical period (1981-2000) and an event during the future period (2081-2100), with large-scale forcings for the three pairs derived from three different members of an initial condition ensemble of the Canadian Earth System Model version 2 (CanESM2). These experiments reveal that, in both study locations, weakening of differential cyclonic vorticity advection (dCVA) is a key driver of projected decreases in extreme ascent and EPI. Weakening of dCVA is expected in accordance with hydrostatic balance because, as temperatures warm, the pressure spacing between geopotential surfaces increases. Although there is evidence that the CRM is more sensitive to dCVA changes than CanESM2, such a dCVA mechanism may nonetheless be important to consider for EPI changes in the real world.

**Keywords** extreme precipitation · atmospheric dynamics · climate change · future projections · cloud-resolving model · climate model

1 Introduction

Extreme precipitation events (EPEs) often have devastating effects on communities and livelihoods. The World Meteorological Organization (WMO) recognizes two standard definitions of extreme precipitation: (1) when precipitation exceeds a fixed threshold that is associated with a certain level of impact, and (2) when precipitation exceeds a relative threshold based on return period or percentile in a given region (WMO, 2018). Regardless of the precise definition used, the impact of EPEs has been clearly evident in infrastructure, food security and human health, with reverberating effects through entire economic systems (Masson-Delmotte et al, 2018).

Extreme precipitation led to the Alberta floods of 2013, which affected approximately 100,000 people in 29 jurisdictions and incurred approximately C$5-6 billion in damages, making it the second costliest disaster in Canadian history (Milrad et al, 2017). The Pakistan floods of 2010 resulted in over 1900 fatalities and damaged over a million homes. The World Bank estimated that this disaster cost US$9.7 billion in damages (Vaqar et al, 2011; Kronstadt et al, 2011). The record-breaking Texas floods
of May 2015 resulted from the highest 5-day precipitation accumulations over that
region in 68 years (Nie et al, 2018).

The cases highlighted above are just a few of many examples in different regions
around the world, and there is a great need to provide reliable projections of how the
intensity of such EPEs will change in the future. In a warmer climate, the available
moisture in the atmosphere is expected to increase in accordance with the Clausius-
Clapeyron relation, resulting in increased intensity of both mean and extreme precip-
itation intensity over most regions (Trenberth, 1999; Trenberth et al, 2015).

However, this simple thermodynamic explanation fails to explain many aspects of
the observational record in particular regions. Observations of extreme precipitation
show that, over recent decades, the intensity of such events is increasing more rapidly
than regional mean precipitation in most regions (Bao et al, 2017; Pfahl et al, 2017).
Intriguingly, observations show regions where mean precipitation trends are negative
but trends of extreme precipitation intensity (EPI) are positive (Alexander et al, 2006).
Furthermore, there is large spatial variability in observed EPI trends, ranging from
0% K−1 at 13°S and 11°N to above 10% K−1 at the equator and high latitudes when
EPI events are zonally aggregated (Westra et al, 2013), and there are some regions
where EPI trends are negative (Alexander et al, 2006). There is also large seasonal
variability in EPI trends. Zheng et al (2015) analyzed Australian rain gauge data
over 1966-2012 and showed that EPI has increased significantly during summer but
decreased during fall.

Global climate models (GCMs) have been crucial to untangling the physical pro-
cesses responsible for extreme precipitation. Pfahl et al (2017) analyzed 22 mod-
els participating in the Coupled Model Intercomparison Project Phase 5 (CMIP5)
and compared model output during the historical period against the Global Precip-
itation Climatology Project (GPCP) dataset. GPCP is a blend of quality-controlled
rain gauge, satellite and sounding rainfall data (Huffman et al, 1997). In general, the
simulated spatial pattern of EPEs agrees well with observations, but quantitatively,
simulated EPI shows some high bias in East Asia and tropical-to-southern Africa
and some low bias over the Americas. Models generally produce stronger EPI over
oceans compared to GPCP, but there are no ground measurements to constrain GPCP
over oceans, rendering such a comparison inconclusive. Some quantitative difference between models and observations is expected since EPEs typically occur in small scale convective clusters and such clusters are not resolved in GCMs. On the other hand, spatial patterns of EPEs are also often associated with large-scale circulation patterns, which GCMs do resolve.

Of particular interest are the future projections of GCMs. In line with thermodynamic expectations, both simplified and comprehensive GCMs project increased EPI over most of the globe (O’Gorman and Schneider, 2009a; O’Gorman and Schneider, 2009b; Pendergrass et al, 2015, 2016; Pfahl et al, 2017). However, in some regions, long-term decreases in EPI are projected. This regional variability has been linked to regional variations in projections of vertical velocity during EPEs (Pfahl et al, 2017; Tandon et al, 2018a), referred to as “extreme ascent.” The contribution of extreme ascent to EPI is often referred to as the “dynamical component” of EPI.

In addition to the regional variability of EPI projections, Pfahl et al (2017) have shown that the pattern and magnitude of the dynamical component is very different during summer than during winter. For this reason, climate change might also influence the seasonal cycle of extreme precipitation. Results of several studies indicate a possible global shift in the seasonality of extreme precipitation towards colder seasons (Rajczak et al, 2013; Pfahl et al, 2017; Brönnimann et al, 2018; Marelle et al, 2018). Because of strong seasonal variations in soil moisture and snow melt, changes in extreme precipitation seasonality can greatly exacerbate flood risk (Marelle et al, 2018). For this reason, changes in extreme precipitation seasonality can have serious consequences for various sectors such as agriculture, tourism, property insurance, hydroelectric power and water resources.

Earlier studies have performed analysis suggesting that long-term changes in the horizontal scale of vertical velocity anomalies, referred to as “eddy length,” are a key factor influencing regional extreme ascent projections (Tandon et al, 2018a,b). Projected increases in eddy length are expected to weaken the coupling between convection and the large-scale vertical velocity, which in turn weakens extreme ascent, thereby reducing the precipitation intensity. These findings were based on analysis of output from state-of-the-art fully coupled GCMs. Other studies have argued that
changes in vertical stability are a key factor influencing extreme ascent projections (Nie et al, 2020; Li and O’Gorman, 2020). To some extent, these mechanisms are related because eddy length depends on vertical stability, and eddy length is expected to change as a result of long-term changes in vertical stability (Kidston et al, 2010; Tandon et al, 2018b).

Despite the valuable insights gained from GCMs, understanding regional processes in GCMs is challenging due to the complexity of the models. Thermodynamic and dynamical coupling between adjacent atmospheric grid cells, as well as coupling between the atmosphere and the surface, makes it difficult to isolate mechanisms responsible for the projected EPI changes. Furthermore, while GCMs are capable of capturing the long-term statistics of many EPEs (Randall et al, 2007; Pierce et al, 2009), they are limited in their ability to simulate individual EPEs in the observational record, as the precise initialization and pre-conditioning required is typically not attainable with a GCMs limited spatial and temporal resolutions. Finer resolution regional models allow for controlled experimentation that can more easily isolate physical mechanisms relevant to extreme ascent in both observations and GCMs (Nie and Sobel, 2016; Nie et al, 2016b, 2018).

In this study, a dynamical downscaling approach is implemented using a cloud-resolving model (CRM) over a limited domain. Such an experimental design allows for finer control of the large scale forcings, such as the eddy length, stability and horizontal advection. We can perturb these forcings in such a way as to gain insight into the key processes responsible for changes in EPI. Insights gained from such experiments can in turn motivate further improvements in GCM parameterizations, thereby improving confidence in model projections of EPI. In this study, we focus on subtropical regions where dynamical effects are expected to drive long-term decreases in EPI (Pfahl et al, 2017; Tandon et al, 2018b; Nie et al, 2020). Improved understanding of such dynamical effects will lead to greater understanding of less dominant (but still important) dynamical effects in other regions. In contrast with earlier studies, our experiments suggest that changes in differential vorticity advection (VA) are the dominant driver of projected subtropical decreases in EPI.
This paper is organized as follows: In Section 2, we provide some additional theoretical background for understanding changes in extreme ascent. Methods are explained in section 3, including description of the modelling framework, forcing dataset and experimental design. In section 4, we present and discuss the results of our CRM experiments. Section 5 provides a summary of the key results and concluding remarks.

2 The Quasigeostrophic Omega Equation

Complementary to various numerical modelling tools, the quasigeostrophic omega (QG\(\omega\)) equation provides an especially useful framework for analyzing mechanisms relevant for extreme ascent. The QG\(\omega\) equation combines the quasigeostrophic vorticity, thermodynamic and continuity equations into a form that allows computation of the vertical pressure velocity, \(\omega\), from the instantaneous three-dimensional geostrophic flow field (Holton and Hakim, 2012). The QG\(\omega\) equation, including a diabatic forcing term, can be written as

\[
\frac{\partial \sigma}{\partial x} \nabla^2 \omega = -\frac{1}{f_0} \nabla^2 \text{Adv}(\omega) - \frac{R}{p f_0} \nabla^2 \text{Adv}(T) - \frac{R}{p f_0} \nabla^2 Q, \tag{1}
\]

where \(p\) is pressure, \(\sigma\) is the dry static stability, \(f_0\) is the reference value of the Coriolis parameter (\(f\)), \(\nabla^2\) is the horizontal Laplacian operator, \(R\) is the gas constant for dry air, \(\zeta\) is the geostrophic absolute vorticity, \(T\) is temperature and \(Q\) is the diabatic heating. Here, \(\text{Adv}(\cdot) = -u_g \partial_x (\cdot) - v_g \partial_y (\cdot)\) is the horizontal geostrophic advection operator, where \(u_g\) and \(v_g\) are the horizontal geostrophic winds in the \(x\) (zonal) and \(y\) (meridional) directions, respectively. The dry stability is given by \(\sigma = -(RT/p) \partial_x \ln \theta\), where \(\theta\) is potential temperature. The geostrophic vorticity is given by \(\zeta = f_0^{-1} \nabla^2 \phi + f\), where \(\phi\) is the geopotential.

The horizontal and vertical curvature of \(\omega\) will typically be opposite in sign to \(\omega\). (Consider, for example, a vertical velocity anomaly that is localized in the horizontal, and parabolic over the depth of the troposphere.) Thus for ascending motion (\(\omega < 0\), the left-hand side (LHS) of (1) is positive. One key effect of the Laplacian is that \(\omega\) responds to spatially averaged gradients of the forcing terms rather than localized
gradients. As a result, in synoptic scale motions, $\omega$ is representative of uplift taking place in a column of air rather than small plumes.

The QG$\omega$ equation has three forcing terms on its right-hand side (RHS). The first forcing term is the differential VA. When VA is increasing with height [$\frac{\partial}{\partial p} \text{Adv}(\zeta) < 0$], referred to as differential cyclonic vorticity advection (dCVA), that implies that at a given location, the relative vorticity is increasing more at higher levels compared to lower levels, which implies that the curvature of height surfaces is increasing at higher levels more than at lower levels. This in turn implies that height levels are getting closer in pressure, which in the absence of other forcings implies ascending motion ($\omega < 0$). This physically intuitive result is mathematically clear from (1) for $\frac{\partial}{\partial p} \text{Adv}(\zeta) < 0$.

The second term on the RHS of (1) is the Laplacian of temperature advection (TA). If there is warm air advection [$\text{Adv}(T) > 0$] that is spatially localized, then $\nabla^2 \text{Adv}(T) < 0$, which in the absence of other forcings implies $\omega < 0$. The last term on the RHS is the diabatic heating term, which is primarily convective heating on the time scales of an EPE. If the convective heating anomaly is positive and localized, then $\nabla^2 Q < 0$, so convective heating will force upward motion. On the LHS of (1), the key parameter is static stability ($\sigma$). For a given positive forcing, smaller values of $\sigma$ imply a less stable atmosphere and accordingly larger (more negative) values of $\omega$.

The QG$\omega$ equation can be solved numerically with just a single forcing term from the RHS of (1) to obtain the particular $\omega$ solution associated with that forcing. Because the QG$\omega$ equation is linear, the total $\omega$ solution is just the sum of the three particular solutions, i.e.

$$\omega = \omega_\zeta + \omega_T + \omega_Q,$$

(2)

where $\omega_\zeta$ is the solution with only differential VA forcing applied, $\omega_T$ is the solution with only TA forcing applied and $\omega_Q$ is the solution with only diabatic forcing applied (Nie and Sobel, 2016).
Assuming $\omega$ has wavelike structure with horizontal length scale $L$ (where $L$ is an inverse wavenumber), then the Laplacian in (1) can be replaced by $-1/L^2$, yielding

$$\partial_p \omega_E - \frac{\sigma \omega_E}{f_0 L_E^2} = - \frac{1}{f_0} \partial_p \text{Adv}(\zeta_E) + \frac{R}{p f_0^2 L_E^2} \text{Adv}(T_E) + \frac{RQ_E}{p f_0^2 L_E^2}. \tag{3}$$

Here, the subscript $E$ indicates values computed on days of extreme precipitation, which is our focus in this study. Nie and Sobel (2016) performed scaling analysis of this equation and showed that the Rossby radius of deformation ($L_R = \Pi \sqrt{\sigma/f_0}$, where $\Pi$ is a representative vertical pressure scale of motion) provides a useful scale against which to determine the dominant balances in (3). Such analysis reveals that for large eddy lengths ($L_E > L_R$), the dominant balance is between the first term on the LHS and the first term on the RHS, reflecting a state in which the large-scale circulation is decoupled from convection and vertical velocity is determined entirely by differential $V_A$. In such a regime, we expect an increase in eddy length to increase the advective time scale of a precipitating weather system, thus increasing the accumulated precipitation (e.g., Dwyer and O’Gorman, 2017).

Conversely, for small eddy lengths ($L_E < L_R$), convection and the large-scale circulation are strongly coupled, and the dominant balance is between adiabatic ascent, temperature advection and diabatic heating (Nie and Sobel, 2016). Tandon et al (2018b) have presented evidence suggesting that GCM-projected changes in subtropical extreme ascent are mostly driven by changes in diabatic heating, in accordance with the fact that subtropical $L_E$ is small compared to $L_R$, suggesting that contributions from differential $V_A$ are weak. In such a regime, we expect an increase in eddy length to reduce coupling between convection and the large scale circulation, thus reducing the strength of extreme ascent.

In other words, the influence of eddy length on precipitation depends on the degree of coupling between convection and the large-scale circulation. In the strongly-coupled regime, we expect an $L_E$ increase to decrease EPI, and in the weakly-coupled regime, we expect an $L_E$ increase to increase EPI. Nie and Sobel (2016) performed model experiments showing that for values of $L_E$ approaching $L_R$, coupling between convection and the large scale vertical velocity is especially strong. In this strongly-coupled regime, as air rises, diabatic heating in the mid-troposphere acts to reduce
the vertical stability at upper levels, resulting in deeper convection, stronger vertical motion, and longer, more intense precipitation events.

3 Data and Methodology

3.1 Cloud resolving model configuration

Our experiments utilize the column quasigeostrophic (CQG) framework, which relies on the QG$\omega$ equation for wave-like disturbances (Nie and Sobel, 2016; Tandon et al, 2018a). In this formulation, coupling between convection and the large-scale vertical velocity is parameterized in terms of the eddy length ($L$) of the large-scale vertical velocity, as schematically depicted in Fig. 1.

![CQG Framework Diagram](image)

**Fig. 1** Schematic diagram of the column quasigeostrophic (CQG) framework used in this study.

In this study, the CQG framework is implemented in a specific CRM called the System for Atmospheric Modeling (SAM) (Khairoutdinov and Randall, 2003) with the details of the implementation described in (Nie et al, 2018). SAM is a non-hydrostatic anelastic model, and we run it with a timestep of 10 s over a 128 km by 128 km domain with 2 km horizontal resolution and doubly periodic lateral boundaries. At such resolution, the CRM explicitly resolves convection within the domain.
The model has 64 vertical levels with spacing ranging from 75 m near the surface to 500 m in the free troposphere.

At each time step, the horizontally averaged diabatic heating produced by the CRM is fed into the QG$\omega$ equation along with imposed horizontal advection of temperature and absolute vorticity taken from a GCM. (The GCM forcing data are described in more detail below.) These large-scale forcings are applied evenly across the CRM domain. The QG$\omega$ equation is then solved for the large-scale vertical velocity, which is used to compute large-scale temperature and moisture tendencies at every level, which are fed back into the CRM. In this way, the CRM captures coupling between convection and the large-scale vertical velocity, a key process that is missing in most previous dynamical downscaling studies.

Insolation in the CRM varies with the diurnal cycle, but the daily mean insolation is held fixed to its daily mean value at the beginning of the simulation period. (We performed tests with seasonally varying insolation, and our results were not affected.) Surface temperature, $T_s$, is prescribed. Horizontally averaged potential temperature and moisture are nudged toward prescribed GCM-derived time-varying vertical profiles of temperature and specific humidity, with a nudging timescale of six hours. Fully interactive radiation is applied within the CRM, updating at every model time step. For the CRM radiation scheme, we use the same ozone profile as is used in the driving GCM, corresponding to the average ozone concentration over the month during which the simulated EPE occurs.

3.2 CanESM2 forcing data

SAM is forced with large scale temperature, moisture, geopotential height and wind fields derived from output of the Canadian Earth System Model version 2 (CanESM2, Arora et al, 2011). CanESM2 is a fully-coupled earth system model developed by the Canadian Centre for Climate Modelling and Analysis (CCCma). The atmospheric component of CanESM2 is a spectral model employing T63 triangular truncation, corresponding to approximately $2.8^\circ \times 2.8^\circ$ horizontal resolution, with 35 vertical levels.
The CanESM2 output came from a 50-member ensemble simulating the historical (1950-2005) and future (2006-2100) periods. The future portion of the simulation follows the high-emission representative concentration pathway 8.5 (RCP8.5) scenario. RCP8.5 combines assumptions about high population growth and relatively low income growth with modest rates of technological and energy improvements, leading to high greenhouse gas (GHG) emissions in the absence of climate change mitigation policy (Riahi et al, 2011). This CanESM2 ensemble was generated from five historical runs initialized in 1850, each of which was branched in 1950 into ten ensemble members obtained by applying perturbations to the initial atmospheric state. Thus, this large ensemble samples five different ocean initial states and fifty different atmospheric initial states. In the model output archive, these ensemble members are organized into five “ensemble groups” labelled r1 through r5, corresponding to each of the five historical runs initialized in 1850, and within each of these ensemble groups, the ten atmosphere-perturbed runs are labelled r1 through r10. Taking an average of multiple ensemble members acts to reduce noise associated with internal climate variability. We use output from only one model (CanESM2) both because of the large number of ensemble members available and the availability of all required output variables. Future work will assess whether the mechanisms we identify are applicable to other models.

The specific CanESM2 output fields used to force the CRM forcing are as follows:

Monthly mean surface air temperature is used for the prescribed surface temperature.

Daily and 6-hourly output of air temperature ($T$), wind ($u$), specific humidity ($q$) and geopotential height ($\phi/g$, where $g$ is the acceleration due to gravity) are used. The 6-hourly data are archived on model sigma levels, and these are linearly interpolated to pressure levels required by the CRM. Following Nie and Sobel (2016), we use 6-hourly output to compute the horizontal advective forcings required by the CRM. These advective forcings include QG VA [Adv($\zeta$)], QG TA [Adv($T$)] and QG moisture advection [Adv($q$)]. Even though moisture advection does not appear in the QG equation (1), it can influence EPI by modifying the amount of moisture in a given column.
Daily CanESM2 output is used to construct vertical profiles of potential temperature and moisture, which are additional large-scale forcings required by the CRM. All time-varying forcings are supplied to the CRM at the same temporal resolution as the CanESM2 output, and the CRM linearly interpolates these forcings in time. The surface boundary condition is prescribed as the seasonal mean of monthly surface air temperature, averaged over the 20-year epoch of interest (1981-2000 for the historical period and 2081-2100 for the future period). Here, the long-term seasonal average is taken including only the month containing the EPE of interest. We have also tested running the CRM with daily varying SST corresponding to the precise dates surrounding the EPE, and our results were not substantially different.

Eddy length is computed from CanESM2 output following essentially the same procedure as in Tandon et al (2018a):

1. On a given day of extreme precipitation at location \((x, y)\), we compute the anomaly of daily mean \(\omega\) at 850 hPa with respect to the monthly climatology during the relevant epoch.

2. We then compute the zonal and meridional e-folding distances of this \(\omega\) anomaly relative to \((x, y)\), applying linear interpolation between grid point centres.

3. We divide the e-folding distances by \(0.19 \times 2\pi\) to obtain the zonal and meridional scales of the corresponding waves, \(L_x\) and \(L_y\) respectively, expressed as inverse wavenumbers. As shown by Barnes and Hartmann (2012), this factor arises from the fact that the e-folding distance of a cosine wave is 0.19 times its wavelength.

4. We combine \(L_x\) and \(L_y\) to obtain an effective eddy length, \(L_E = (L_x^{-2} + L_y^{-2})^{-1/2}\).

5. We multiply \(L_E\) by an adjustment factor in order to maintain the numerical stability of the CRM. (We further explain this step below.)

The second-last step in this procedure is a refinement of the procedure used in Tandon et al (2018b), who use \(L_E = \sqrt{L_x^2 + L_y^2}\). While the latter is a heuristically reasonable approach, it is not mathematically consistent with how zonal and meridional wavenumbers are typically combined. The two approaches produce similar results for the eddy lengths considered in this study.
Different methods have been suggested for computing eddy length relevant for the QG\(\omega\) equation. For example, Dai and Nie (2020) compute eddy length based on geopotential height anomalies, and they obtain results that are larger than the eddy lengths computed from the \(\omega\) field. Our argument for computing eddy length based on the \(\omega\) field is that \(\omega\) is the field being solved for in the QG\(\omega\) equation (3). The assumption that solutions to the QG\(\omega\) equation have wavelike structure means that the eddy length on the LHS of equation (3) corresponds to the \(\omega\) field. It is also reasonable to assume, as we do, that the forcing terms have the same eddy length as \(\omega\), in which case the eddy lengths on the LHS and RHS of (3) are equal. Alternatively, one can allow for the possibility that the forcing terms have different eddy lengths from \(\omega\) (e.g., Li and O’Gorman, 2020).

To give an example of the eddy length computation, for one CanESM2 ensemble member at one of our study locations (26.51°S, 2.83°W), we obtained \(L_{E0} = 149\) km during the historical period, and we obtained \(L_{E} = 473\) km during the future period. (We use the “0” subscript hereafter when referring to values during the historical period.) We attempted to prescribe these eddy length values in the CRM, but such small horizontal eddy lengths created numerical instability in the CRM owing to unrealistically strong updrafts. Such numerical instability is not surprising, as CanESM2 parameterizes convection, and sensitivity of the GCM convection scheme to large-scale forcing may be very different to the sensitivity of a CRM to the same large-scale forcing.

In order for the CRM to run without numerical instability, we increase the eddy length by a factor of 3-6 compared to its CanESM2-derived value. This adjustment is applied to both the historical and future \(L_{E}\) values so that \(\delta\frac{L_{E}^2}{L_{E0}^2}\) in the CRM runs matches \(\delta\frac{L_{E}^2}{L_{E0}^2}\) in the GCM runs. (We use \(\delta\) hereafter when referring to “climatic changes” between the historical and future periods.) The specific adjustment factor for each experiment is provided in Table 1. Since some of the events investigated in this study have spatial scales that are close to the spatial resolution of CanESM2, their realism is questionable. It is nonetheless worthwhile to investigate the mechanisms driving such EPEs as a way to further assess the realism of EPEs in GCMs and point to possible model improvements.
3.3 Model experiments

We have constructed specific CRM experiments based on the results of Tandon et al (2018b), who have examined regional variability of extreme precipitation projections in the CanESM2 large ensemble. Fig. 2a shows the CanESM2-derived composite climatic change of the 10-year maximum of daily precipitation ($\delta P_E/P_{E0}$), normalized by the zonal mean climatic change of annual mean surface temperature, as presented by Tandon et al (2018b). Fig. 2b shows the dynamical part of EPI change, isolated by linearly decomposing changes in the vertical moisture advection and isolating a term associated with changes in extreme ascent. [See Tandon et al (2018b) and references therein for details.] As mentioned earlier, there are widespread regions of projected weakening of extreme ascent, especially in the subtropics. Tandon et al (2018b) obtained very similar results when considering projected changes in 20-year maximum EPI.

We have chosen two locations in the subtropical South Atlantic (indicated by stars in Fig. 2b) as our study locations. These are locations where weakening of extreme ascent is especially strong, providing some confidence that a clear mechanism will emerge in these locations. Because both of these locations are over ocean, we also avoid possible complications of land surface interactions. This approach allows us to build up our basic knowledge of mechanisms in a simpler physical setting, which will help inform future investigations of EPE mechanisms over land regions.

One of our study locations is 26.5107°S, 2.8125°W, hereafter referred to as “S27” (black star in Fig. 2), and the other location is 18.1389°S, 19.6875°W, hereafter referred to as “S18” (green star in Fig. 2). At each of these locations, we have selected three members of the CanESM2 ensemble which show projected decreases in 20-year maximum EPI. Given the effort involved in setting up each CRM experiment, the number of CRM experiments is limited compared to the size of the CanESM2 ensemble. However, this limitation is offset by the fact that we select only CanESM2 ensemble members with decreasing EPI in the study locations. This approach exploits the knowledge that the CanESM2 ensemble mean EPI projections are negative in the study locations. Rather than relying on many CRM experiments to filter internal vari-
Fig. 2 (a) Composite climatic change in 10-year maximum of daily precipitation and (b) its dynamical part normalized by zonal mean climatic change in surface temperature, computed from the CanESM2 large ensemble (adapted from Tandon et al, 2018b). See Tandon et al (2018b) for details of these calculations. The stars indicate the locations used for the dynamical downscaling experiments in the current study. The black star corresponds to the “S27” study location, and the green star corresponds to the “S18” study location.

ability, we can essentially pre-filter the internal variability by selecting CanESM2 ensemble members whose EPI projections resemble the ensemble mean projections, thus requiring fewer CRM experiments to produce clear results.

Table 1 describes the CanESM2 EPEs examined with our CRM experiments. Case names are constructed starting with the study location name (e.g. S27 or S18), followed by the CanESM2 ensemble group label, followed by the epoch (“Hist” for historical, “Fut” for future). “GCM” is appended to the case name when examining CanESM2 output directly; otherwise it is assumed that the case is a CRM experiment driven by an ensemble member in the indicated ensemble group of CanESM2.
As we use only one CanESM2 ensemble member from a given ensemble group, the ensemble group number provides a distinctive label for each case, and the specific CanESM2 ensemble member number used for each case is also provided in Table 1 for reference. For example, the S27r1-Hist case is the CRM experiment in the S27 location driven by ensemble member r4 in ensemble group r1 of CanESM2. When considering ensemble means, the ensemble group number is omitted (e.g., “S27-Hist”).

Table 1 Descriptions of the GCM (CanESM2) simulations examined in this study. The eddy length adjustment factor is applied to the GCM-diagnosed eddy length in order to maintain numerical stability of the CRM. See text for additional details.

| Case Name         | Ensemble Group | Ensemble Member | Location            | 20-Year Max Eddy Length [km] | EPE Date          | Eddy Length Adjustment Factor |
|-------------------|----------------|----------------|---------------------|----------------------------|------------------|-------------------------------|
| S27r1-Hist-GCM    | r1             | r4             | 26.51°S, 2.83°W     | 149                        | 24 September 1997 | 5.5                           |
| S27r1-Fut-GCM     | r1             | r4             | 26.51°S, 2.83°W     | 473                        | 30 September 2094 | 5.6                           |
| S27r2-Hist-GCM    | r2             | r6             | 26.51°S, 2.83°W     | 149                        | 1 July 1982       | 4.3                           |
| S27r2-Fut-GCM     | r2             | r6             | 26.51°S, 2.83°W     | 231                        | 2 April 2093      | 4.3                           |
| S27r5-Hist-GCM    | r5             | r10            | 26.51°S, 2.83°W     | 177                        | 29 June 1982      | 3.2                           |
| S27r5-Fut-GCM     | r5             | r10            | 26.51°S, 2.83°W     | 146                        | 12 April 2082     | 3.2                           |
| S18r2-Hist-GCM    | r2             | r6             | 18.14°S, 8.44°W     | 193                        | 10 May 1981       | 5.8                           |
| S18r2-Fut-GCM     | r2             | r6             | 18.14°S, 8.44°W     | 177                        | 19 June 2092      | 5.8                           |
| S18r4-Hist-GCM    | r4             | r6             | 18.14°S, 8.44°W     | 255                        | 13 May 1982       | 4.4                           |
| S18r4-Fut-GCM     | r4             | r6             | 18.14°S, 8.44°W     | 161                        | 16 June 2084      | 4.4                           |
| S18r5-Hist-GCM    | r5             | r10            | 18.14°S, 8.44°W     | 198                        | 31 March 1987     | 3.6                           |
| S18r5-Fut-GCM     | r5             | r10            | 18.14°S, 8.44°W     | 134                        | 28 September 2087 | 3.6                           |

As mentioned above, all six EPE pairs selected from CanESM2 produce projected decreases in EPI. However, Table 1 shows that these pairs produce a range of eddy length changes. Two out of the three pairs of S27 cases produce projected increases in eddy length, and all three pairs of S18 experiments produce decreases in eddy length. Thus, the cases we have selected explore a range of possible mechanisms for projected EPI decreases, in addition to the eddy length convective coupling mechanism discussed by Tandon et al (2018b). (See discussion of this mechanism in Section 2.) It should be noted, however, that for 10-year maximum EPEs, change in eddy length in the S18 study location increases when composited over the full 50-
member CanESM2 ensemble (Tandon et al, 2018b). Thus, the eddy length decreases produced by the three ensemble members selected in the current study likely results from internal variability rather than externally-forced climate change. We will discuss the implications of these details further below.

To visualize our case selection process, Fig. 3 shows timeseries of annual maximum of daily precipitation from CanESM2 over the S27 location during the historical (black) and future (red) periods, corresponding to the S27r1-Hist-GCM and S27r1-Fut-GCM cases. Comparison of the two timeseries shows that the 20-year maximum of daily precipitation (within the green triangles) is reduced by about 33% in the future period compared to the historical period. Such a strong decrease is in stark contrast with the increase in EPI over most other regions, and thus these S27r1 cases are suitable choices for further investigation of the dynamical mechanisms responsible for projected EPI decrease.

**Fig. 3** Timeseries of annual maximum daily precipitation over the S27 study location in CanESM2 ensemble group 1 ensemble member 4 during the (a) historical period (1981-2000) and (b) future period (2081-2100). The green triangles indicate the 20-year maximum events chosen for our CRM experiments. See the text for additional details.
Using the CanESM2 forcing fields derived as described in Section 3.2, we run the CRM for both the historical and future cases. For each GCM case identified in Table 1, a corresponding CRM experiment is performed, and these cases are accordingly named S27r1-Hist, S27r1-Fut, S27r2-Hist, S27r2-Fut, S27r5-Hist, S27r5-Fut, S18r2-Hist, S18r2-Fut, S18r4-Hist, S18r4-Fut, S18r5-Hist and S18r5-Fut. In each case, we run the model for 10 days with only the temperature and moisture profiles applied, which allows the CRM to reach a state of radiative-convective equilibrium. Thereafter, the additional CQG forcings \([\text{Adv}(\zeta), \text{Adv}(T), \text{Adv}(q)]\) are turned on, beginning 15 days before the EPE and continuing until 15 days after the EPE.

4 Results and Discussion

Much of our presentation will focus on the ensemble average of the three CRM experiments performed in each study location, shown in Table 2 and subsequent figures. For reference, Table 3 shows results of the individual CRM ensemble members, along with results from the individual GCM ensemble members for comparison. We will refer to this table at various points when the results of individual ensemble members merit special attention.

Table 2 Ensemble mean results of the CanESM2 and CRM simulations examined in this study.

| Historical Case | Future Case | \(P_E\) (Hist) \([\text{mm d}^{-1}]\) | \(P_E\) (Fut) \([\text{mm d}^{-1}]\) | \(\delta P_E/P_E0\) | \(\delta T_{E,E}\) | \(\delta P_E/P_E0/\delta T_{E,E}\) |
|-----------------|-------------|---------------------------------|---------------------------------|----------------|----------------|----------------|
| S27-Hist-GCM    | S27-Fut-GCM | 27.73                           | 13.27                           | -52.10         | 4.3            | -12.12         |
| S27-Hist        | S27-Fut     | 54.51                           | 36.59                           | -32.90         | 4.3            | -7.65          |
| S27-Hist        | S27-\(\Delta\)L | 54.51                           | 60.20                           | 10.4           | 4.3            | 2.42           |
| S27-Hist        | S27-\(\Delta\)Stab | 54.51                           | 56.74                           | 4.10           | 4.3            | 0.95           |
| S27-Hist        | S27-\(\Delta\)Adv | 54.51                           | 27.11                           | -50.3          | 4.3            | -11.70         |
| S18-Hist-GCM    | S18-Fut-GCM | 19.35                           | 3.86                            | -80.10         | 0.43           | -186.28        |
| S18-Hist        | S18-Fut     | 38.84                           | 31.17                           | -19.75         | 0.43           | -45.92         |
| S18-Hist        | S18-\(\Delta\)L | 38.84                           | 30.86                           | -20.55         | 0.43           | -47.78         |
| S18-Hist        | S18-\(\Delta\)Stab | 38.84                           | 34.44                           | -11.33         | 0.43           | -26.35         |
| S18-Hist        | S18-\(\Delta\)Adv | 38.84                           | 34.89                           | -10.17         | 0.43           | -23.65         |
Table 3 Results for every ensemble member of CanESM2 and the CRM examined in this study. As discussed in the text, the timing of EPEs in the CRM experiments sometimes preceded that of the GCM experiments by 1-2 days. In these cases, we shifted the CRM timeseries later by the number of days indicated in the “Timing Adjustment” columns to facilitate comparison of EPI between different cases.

| Historical Case | Future Case | Timing Adjustment | $P_{E0}$ (Hist) [mm d$^{-1}$] | $P_{E}$ (Fut) [mm d$^{-1}$] | $\delta P_{E}/P_{E0}$ [%] | $\delta T_{SE}$ [K] | $\delta P_{E}/P_{E0}/\delta T_{SE}$ [% K$^{-1}$] |
|-----------------|-------------|-------------------|--------------------------|--------------------------|----------------------|------------------|------------------------------------|
| S27r1-Hist-GCM  | S27r1-Fut-GCM | +1d | 28.02 | 17.22 | -38.5 | 3.3 | -11.7 |
| S27r1-Hist      | S27r1-Fut   | +1d | 61.54 | 45.06 | -26.8 | 3.3 | -8.1  |
| S27r1-Hist      | S27r1-ΔL    | +1d | 61.54 | 72.35 | 17.6  | 3.3 | 5.3   |
| S27r1-Hist      | S27r1-ΔStab.| +1d | 61.54 | 67.13 | 9.1   | 3.3 | 2.8   |
| S27r1-Hist      | S27r1-ΔAdv  | none | 61.54 | 22.86 | -62.9 | 3.3 | -19.1 |
| S27r2-Hist-GCM  | S27r2-Fut-GCM | +1d | 23.64 | 12.55 | -46.9 | 4.9 | -9.6  |
| S27r2-Hist      | S27r2-Fut   | +1d | 71.26 | 52.11 | -26.9 | 4.9 | -5.5  |
| S27r2-Hist      | S27r2-ΔL    | +1d | 71.26 | 81.09 | 13.8  | 4.9 | 2.8   |
| S27r2-Hist      | S27r2-ΔStab.| +1d | 71.26 | 75.78 | 6.3   | 4.9 | 1.3   |
| S27r2-Hist      | S27r2-ΔAdv  | +1d | 71.26 | 30.72 | -56.9 | 4.9 | -11.6 |
| S27r5-Hist-GCM  | S27r5-Fut-GCM | +1d | 30.52 | 10.06 | -67.0 | 4.7 | -14.3 |
| S27r5-Hist      | S27r5-Fut   | +1d | 30.75 | 12.59 | -59.1 | 4.7 | -12.6 |
| S27r5-Hist      | S27r5-ΔL    | none | 30.75 | 27.18 | -11.6 | 4.7 | -2.5  |
| S27r5-Hist      | S27r5-ΔStab.| none | 30.75 | 27.33 | -11.1 | 4.7 | -2.4  |
| S27r5-Hist      | S27r5-ΔAdv  | +1d | 30.75 | 27.74 | -9.8  | 4.7 | -2.1  |
| S18r2-Hist-GCM  | S18r2-Fut-GCM | none | 38.9 | 3.7 | -90.5 | 1.8 | -50.2 |
| S18r2-Hist      | S18r2-Fut   | +1d | 28.53 | 40.24 | 41.0  | 1.8 | 22.8  |
| S18r2-Hist      | S18r2-ΔL    | none | 28.53 | 28.16 | -1.3  | 1.8 | -0.5  |
| S18r2-Hist      | S18r2-ΔStab.| none | 28.53 | 26.39 | -7.5  | 1.8 | -4.2  |
| S18r2-Hist      | S18r2-ΔAdv  | +2d | 28.53 | 42.12 | 47.6  | 1.8 | 26.4  |
| S18r4-Hist-GCM  | S18r4-Fut-GCM | none | 8.67 | 5.07 | -41.6 | 0.9 | -46.2 |
| S18r4-Hist      | S18r4-Fut   | +2d | 48.41 | 11.44 | -76.4 | 0.9 | -84.9 |
| S18r4-Hist      | S18r4-ΔL    | none | 48.41 | 38.98 | -19.5 | 0.9 | -21.7 |
| S18r4-Hist      | S18r4-ΔStab.| none | 48.41 | 46.22 | -4.5  | 0.9 | 5.0   |
| S18r4-Hist      | S18r4-ΔAdv  | +2d | 48.41 | 8.43  | -82.6 | 0.9 | -91.8 |
| S18 r5-Hist-GCM | S18 r5-Fut-GCM | none | 10.49 | 2.82 | -73.1 | -1.4 | 52.2  |
| S18 r5-Hist     | S18 r5-Fut  | none | 39.57 | 41.84 | 5.7   | -1.4 | 4.1   |
| S18 r5-Hist     | S18 r5-ΔL   | none | 39.57 | 25.51 | -35.5 | -1.4 | 25.4  |
| S18 r5-Hist     | S18 r5-ΔStab.| none | 39.57 | 30.70 | 22.4  | -1.4 | 16.0  |
| S18 r5-Hist     | S18 r5-ΔAdv | +2d | 39.57 | 54.13 | 36.8  | -1.4 | 26.3  |
As mentioned earlier, all six pairs of ensemble members show climatic weakening of EPI. Interestingly, for one ensemble member pair (S18r5), the future EPE occurs at a cooler temperature than the historical event, likely related to the fact that the future and historical events occur in different seasons (see Table 1). This result gives a sense of the range of behaviour sampled by our ensemble, and we will discuss additional details of individual ensemble members below.

4.1 Model Evaluation

Having identified the cases of interest from the GCM, simulations have been performed to assess how well the CRM reproduces the selected cases. Three pairs of experiments have been simulated over each study location, with each pair of simulations in each location driven by a different ensemble member of CanESM2. Fig. 4 shows the comparison between the ensemble mean CRM cases in the S27 location (red) and the corresponding GCM cases (blue) for the historical (panel a) and future (panel b) periods. (See also Table 2.) All of the CRM precipitation presented in this study is horizontally averaged over the CRM domain. Quantitatively, the CRM overestimates the GCM precipitation in both the historical and future simulations. Nonetheless, the CRM qualitatively captures the decrease in EPI between the historical and the future periods. The S27r5-Hist and S27r5-Fut cases show especially close quantitative agreement with CanESM2 (Table 3).

Further examining individual ensemble members, we found that the peak precipitation in some CRM experiments occurred 1-2 days earlier than in the GCM. Such a difference in timing is not surprising, as the GCM parameterizes convection whereas the CRM explicitly resolves convection. Khairoutdinov and Randall (2003) also noted a precipitation timing mismatch of approximately one day when evaluating SAM against observations. Our focus in this study is on EPI rather than the precise timing of EPEs. Thus, to facilitate comparison of EPI across different experiments, we have shifted the CRM timeseries if necessary so that the timing of maximum precipitation matches that of CanESM2. The specific time shift applied to each run is shown in Table 3.
The CRM exhibits similar behaviour at the S18 location (Fig. 5) compared to the S27 location. That is, the CRM generally overestimates the EPI compared to CanESM2, but the CRM still captures the climatic decrease in EPI. (See also Table 2.) However, individual ensemble members show a range of behaviour. In particular, the S18r2 and S18r5 CRM experiments produce increases in EPI, in contrast to the decreases produced by CanESM2 (Table 3). These contrasts notwithstanding, the ability of the CRM ensemble mean to capture the projected EPI decreases in CanESM2 provides reassurance that our downscaling framework is reasonable for examining extreme precipitation mechanisms.
4.2 Isolation Runs

To investigate the mechanisms responsible for the changes in EPI, we have performed “isolation runs” in which a subset of the CRM’s large-scale forcings were taken from future projections while all other forcings were derived from historical simulations. In other words, in each isolation run, we have applied a climatic change to only a subset of the large-scale CRM forcings, while holding all other large-scale forcings fixed to those used in the historical simulations. In doing so, we isolate the effect of changes in just one or a few of the large-scale forcings.

We first consider the effect of changing just the eddy length. (See Section 3.2 for details on how eddy length is computed.) Fig. 6a shows the comparison over the S27 location of the eddy length isolation run S27-ΔL (yellow) with the S27-Hist (blue) and S27-Fut (red) simulations of the CRM. This experiment shows that the change in eddy length alone causes an increase in EPI. (See also Table 2.) Since the ensemble mean eddy length increases (see Table 1), this result suggests that the effect of eddy length on advective timescale is dominating over the convective coupling effect. (See Section 2 for discussion of these concepts.)
Over the S18 location, eddy length change in isolation produces a decrease in EPI (Fig. 7a and Table 2), indicating that changes in eddy length may contribute to decreased EPI in the middle of the subtropical dry zone. Since the ensemble mean eddy length decreases over the S18 location (see Table 1), this result suggests that the eddy length effect arises from changes in advective timescale, as was the case over the S27 location. This effect of eddy length is apparent in the individual ensemble members as well. In every case, the eddy length change in isolation causes a change in EPI of the same sign as the change in eddy length (see Tables 1 and 2), indicating that the change in the advective timescale is likely the mechanism at work. These results contrast with the analysis of Tandon et al (2018b), which suggests that sign of EPI changes in the subtropics are opposite to those of eddy length changes, indicating that the convective coupling effect is dominant. It is also worth reiterating, as mentioned above, that the eddy length decreases in the three S18 ensemble members likely reflect internal variability in CanESM2. Thus, we can expect that with
additional CRM experiments using more CanESM2 ensemble members, the contribution of eddy length to projected EPI over S18 would more closely resemble the eddy length contribution over S27.

Fig. 7 As in Fig. 6 but over the S18 study location.

Next we consider the effect of changing only surface temperature and vertical stability. Over the S27 location (Fig. 6b), this S27-∆Stab run (yellow) produces a slight increase in EPI in contrast with the EPI decrease produced when all forcings are changed (red). Over the S18 location, however (Fig. 7b), the S18-∆Stab run produces a decrease in EPI, albeit weaker than the decrease produced by S18-∆L (Fig. 7a; see also Table 2). This result suggests that the effect of vertical stability change may depend on the location, in agreement with the GCM output analysis of Nie et al (2020).

Now we consider the effect of changing just the horizontal advective forcings. In these isolation experiments, we change the vorticity, temperature and moisture advection while holding all other forcings fixed. Over S27 (Fig. 6c), advection changes (yellow) produce a strong decrease in EPI in contrast with the increases produced by the other isolation runs. (See also Table 2.) This result clearly indicates that changes in
horizontal advection are the dominant driver of EPI changes in this location. Over the
S18 location (Fig. 7c), advection changes (yellow) also produce a decrease in EPI, but
this effect is weaker than the the effect of eddy length change (Fig. 7a) and compara-
tible to the effect of stability change (Fig. 7b; see also Table 2). However, as mentioned
above, it is reasonable to expect that if simulations were performed with additional
ensemble members, changes in horizontal advection would dominate over changes in
eddy length. Furthermore, the dominant effect of eddy length change over S18 can
be understood as working together with the effect of horizontal advection: because
eddy length decreases in these experiments, the advective timescale decreases, which
reduces the accumulated precipitation. (See Section 2 for theoretical background.)

All of the individual ensemble members at location S27 show decreases in EPI in
response to horizontal advection changes, but not all of the S18 ensemble members
behave this way (Table 3). However, the two S18 ensemble members that produce EPI
increases in response to horizontal advection changes also show EPI increases when
all forcings are changed, thus further establishing the dominant role of horizontal
advection. Stated another way, two of the S18 CRM ensemble members produce EPI
changes that are opposite in sign to the CanESM2 changes, and this disagreement
is due to effects of horizontal advection. This result suggests that the CRM may be
responding more strongly to horizontal advection than the GCM, and this sensitivity
may influence the sensitivity of the CRM to other forcings such as eddy length. The
reason for the contrasting sensitivity to horizontal advection is unclear.

4.3 Dominant role of vorticity advection

To gain further insight, we have conducted additional experiments to isolate the ef-
teffects of the individual advective forcings [Adv(T), Adv(ζ), Adv(q)]. EPI with per-
turbed TA is quantitatively comparable to the historical EPI over both the S27 (Fig. 8)
and S18 (Fig. 9) locations. These results suggest that changes in TA alone do not
appear to influence the decrease of EPI in these locations. Changes in moisture ad-
vection produce an increase in EPI over S27 (Fig. 8b) but a small decrease over S18
(Fig. 9). However, changes in differential VA alone produce strong decreases in EPI
over both S27 (Fig. 8c) and S18 (Fig. 9c). In combination with the results of our other isolation runs (Figs. 6-7), we can conclude that changes in differential VA are a key driver of EPI decrease in the study locations.

**Fig. 8** Comparison of daily precipitation timeseries for CRM experiments isolating individual horizontal advective forcings over the S27 location. (a) S27-Hist (blue), S27-Fut (red) and S27-AdvT, isolating the temperature advection effect (yellow). (b) S27-Hist (blue), S27-Fut (red) and S27-Advq, isolating the moisture advection effect (yellow). (c) S27-Hist (blue), S27-Fut (red) and S27-Advζ, isolating the vorticity advection effect (yellow). The day of the extreme precipitation in the GCM ("simulation day 6") lies between the vertical dotted lines.

This result agrees with the findings of Nie et al (2020), who conducted analysis of output from GCMs participating in CMIP5. Nie et al (2020) found substantial contribution of large-scale advective forcings to subtropical decreases in EPI, although, as mentioned above, they also found substantial contributions of vertical stability changes in some locations.

To further illuminate the dynamics responsible for the EPI changes, we can linearly decompose the contributions of each large-scale forcing to \( \omega \), as detailed in Section 2. Fig. 10 shows vertical profiles of \( \omega_\zeta \), \( \omega_T \) and \( \omega_Q \) for each simulation day.
Fig. 9 As in Fig. 8 for the S18 study location.

in the S27-Hist and S27-Fut experiments. Fig. 10a shows that during the EPE, $\omega_\zeta$ is strongly negative in the upper troposphere, reiterating its key role in generating extreme precipitation. Furthermore, the negative $\omega_\zeta$ anomaly in S27-Fut (Fig. 10b) is much weaker compared to $\omega_\zeta$ in S27-Hist, further establishing its role in weakening EPI. Based on the QG $\omega_\zeta$ equation (1), such a reduction of $\omega_\zeta$ would result from $\partial_p \text{Adv}(\zeta)$ becoming less negative (i.e. weaker dCV A) during the EPE. (See Section 2 for additional theoretical background.)

Comparing the first and second rows of Fig. 10, we see that $\omega_\zeta$ anomalies are almost an order of magnitude larger than $\omega_T$ anomalies. This result contrasts with the common expectation of partial cancellation between TA and differential VA (Trenberth, 1978), which is often applicable in the middle troposphere. The reason for the overwhelming dominance of $\omega_\zeta$ over $\omega_T$ requires further investigation, but it may relate to horizontal temperature gradients being relatively weak in the subtropics compared to the extratropics.

Comparing the first and third rows of Fig. 10, we find that $\omega_\zeta$ anomalies are also much larger than $\omega_Q$ anomalies. However, the $\omega_Q$ anomalies are also larger than the
Fig. 10 Vertical pressure velocity associated with (a,b) vorticity advection, $\omega_\zeta$, (c,d) temperature advection, $\omega_T$, and (e,f) diabatic heating, $\omega_Q$, for the (a,c,e) S27-Hist experiments and (b,d,f) S27-Fut experiments. Red dashed lines in each panel mark the beginning and end of the day of extreme precipitation. For clarity, $\omega_T$ and $\omega_Q$ are plotted on a scale that is a factor of ten smaller than for $\omega_\zeta$. $
abla_\zeta$ anomalies, so $\omega_Q$ appears to play a more significant role than $\omega_T$. Furthermore, the climatic decreases of $|\omega_\zeta|$ and $|\omega_Q|$ are both approximately 50%. This correspondence between fractional changes might explain why Tandon et al (2018b) are able to explain fractional EPI changes in terms of diabatic heating changes, without considering differential VA changes. It is possible that the subtropical EPI changes in CanESM2 could have also been explained by differential VA changes, although it also appears (as mentioned above) that CanESM2 is less sensitive to horizontal advective forcing than the CRM.

Over the S18 study location (Fig. 11), $\omega_\zeta$ is an order of magnitude larger than $\omega_T$, and it is also somewhat larger than $\omega_Q$, qualitatively resembling the S27 results. However, in contrast with S27, $\omega_\zeta$ and $\omega_Q$ over S18 are the same order of magnitude, and the climatic fractional decrease of $|\omega_Q|$ (approximately 50%) is larger than that of
4.4 Role of large-scale circulation changes

Our results above beg the question: what is responsible for these large changes in differential VA? This question motivates some additional analysis of the vertical velocity in CanESM2 during the EPEs of interest. Fig. 12 shows vertical profiles of extreme ascent in CanESM2 over the study locations averaged over the same ensemble members used to force the CRM experiments. The magnitude of $\omega$ is smaller in CanESM2 than in the CRM (Figs. 10-11). This contrast corresponds with the fact...
that EPI in the CRM is also greater than in CanESM2 (Figs. 4-5), which as mentioned above, is likely because the CRM is more sensitive to horizontal advective forcing than CanESM2.

Nonetheless, the CanESM2 $\omega$ profiles (Fig. 12) reveal, as expected, clear climatic weakening of extreme ascent, which is responsible for the decreased EPI in both study locations. Interestingly, there are also clear changes in the vertical structure of the vertical velocity: the peaks of the extreme ascent profiles are in the lower troposphere (700-900 hPa) during the historical period and in the mid-troposphere (around 500 hPa) during the future period. Together with these changes, there is a weakening of the vertical gradient of $\omega$ in the lower troposphere, indicating a weakening of horizontal convergence at low levels, which points to a possible link with other large-scale circulation changes.

Figure 13 shows the spatial structure of the CanESM2 $\omega$ and $P$ fields during the EPEs of interest. Comparing Fig. 13a and b, we once again see a clear weakening of extreme ascent, as we did in Fig. 12. However, for such a dramatic change in the
vertical velocity, we do not see a dramatic change in the horizontal spatial structure of the vertical velocity anomalies. In particular, the $\omega$ anomalies have a northeast-southwest elongation that does not dramatically change from the historical to future period. The fact that the spatial pattern of the $\omega$ anomalies does not change dramatically suggests that it is unlikely that a spatial shift of the large-scale circulation, such as Hadley Cell expansion and poleward shifting of the subtropical jets, is responsible for the weakening of the vertical velocity, as has been suggested in earlier studies (Lu et al, 2014; Pfahl et al, 2017; Norris et al, 2020).

![Fig. 13 CanESM2 precipitation (shading) and $\omega$ at 700 hPa (contours) during EPEs over the (a,c) S27 and (b,d) S18 study locations during the (a,b) historical and (c,d) future periods. The stars indicate the study locations. The fields have been averaged over the same ensemble members used for the CRM experiments.](image)

We see more dramatic changes in circulation spatial structure when examining individual ensemble members. For example, the spatial structure of extreme ascent in S27r5-Fut-GCM is dramatically different from that in S27r5-Hist-GCM (not shown). This finding likely reflects the fact that the EPE occurs in June during the historical...
period and April during the future period, and the location of the Hadley Cell edge is very different in these two seasons. However, such seasonal differences are not consistent across all ensemble members, and so such spatial changes in the large-scale circulation are not evident in the ensemble mean.

These results suggest that factors other than spatial circulation shifts are responsible for the changes in $\omega$ and differential VA. One possible explanation arises from considering the change in pressure thickness as the atmosphere warms. Neglecting the effect of moisture on the gas constant, we can express hydrostatic balance as

$$\frac{\partial \phi}{\partial \ln p} = -RT. \quad (4)$$

Thus, an increase in temperature produces an increase in pressure spacing between geopotential surfaces. We can expect such a change to have a direct effect on differential VA because QG vorticity depends on the horizontal curvature of geopotential surfaces. Furthermore, if $\omega$ changes then mass conservation requires that the $\omega$ change be non-uniform in space (e.g., weaker ascent in one location requires weaker descent in another location), which requires that the horizontal curvature of geopotential surfaces must change as well.

With these constraints in mind, an increase in pressure spacing between geopotential surfaces requires the circulation to advect geopotential disturbances whose positive curvature is reduced more at upper levels compared to lower levels, which implies a greater reduction in cyclonic vorticity at upper levels compared to lower levels (i.e. weaker dCVA), which in turn implies weaker ascent. Thus, weakening of dCVA (which is a key driver of decreased EPI in our CRM experiments) is a natural consequence of warming, and it does not require a spatial shift in the large-scale circulation.

5 Summary and Conclusion

We have conducted dynamical downscaling experiments using a CRM driven by CanESM2 output in order to examine the dynamical mechanisms influencing projected subtropical decreases of EPI. The CRM reproduces an ensemble mean de-
crease in EPI over the subtropical South Atlantic Ocean that is in qualitative agree-
ment with CanESM2 projections. In our CRM experiments, vertical stability change
is not the dominant driver of projected decrease in EPI, although it does contribute
to decreased EPI over the S18 study location. This finding agrees with the analysis
of Nie et al (2020), who found that vertical stability change contributes to projected
decrease of EPI in some subtropical locations.

Over both study locations, weakening of dCV A is a key driver of the ensemble
mean EPI changes. Over the S18 study location, this decreased dCV A combines with
decreased eddy length to produce the projected decrease in EPI. Furthermore, over
S18, decreased eddy length on its own contributes a stronger EPI decrease than dCV A
weakening. However, decreased eddy length over S18 is likely a result of internal cli-
mate variability, and we expect CRM experiments with additional ensemble members
to show that dCV A weakening is the dominant effect over both study locations.

Weaker dCV A is expected because, as temperatures warm, hydrostatic balance
requires the pressure spacing between geopotential levels to increase, which in turn
implies greater weakening of cyclonic vorticity at upper levels compared to lower
levels. Such a change does not require a horizontal spatial shift in the large-scale cir-
culation, and we do not see evidence that such spatial shifts are playing a significant
role in generating the EPI changes in our experiments, in contrast with suggestions
in earlier studies (Lu et al, 2014; Pfahl et al, 2017; Norris et al, 2020).

Although the role of dCV A is clear in our CRM experiments, it appears that the
CRM used in this study has high sensitivity to horizontal advective forcing compared
to CanESM2. So the mechanisms of EPI change found in our CRM experiments may
not fully reflect mechanisms in GCMs, and this is a topic in need of further investiga-
tion. Nonetheless, our results do highlight a clear dynamical mechanism of possible
importance to future changes in EPI. Given the established role of VA in observed
subtropical EPEs (e.g., de Vries et al, 2018; Ma et al, 2019; de Vries, 2021), our re-
sults motivate further examination of its role in future EPI changes. With additional
controlled modelling experiments over a variety of regions (especially land regions,
which we have not considered here), we aim to build up a level of mechanistic under-
Standing that can be used to further assess climate models and improve confidence in regional projections of extreme precipitation.

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References

Alexander LV, Zhang X, Peterson TC, Caesar J, Gleason B, Klein Tank AMG, Haylock M, Collins D, Trewn B, Rahimzadeh F, Tagipour A, Rupa Kumar K, Revadekar J, Griffiths G, Vincent L, Stephenson DB, Burn J, Aguilar E, Brunet M, Taylor M, New M, Zhai P, Rusticucci M, Vazquez-Aguirre JL (2006) Global observed changes in daily climate extremes of temperature and precipitation. Journal of Geophysical Research: Atmospheres 111(D5), DOI https://doi.org/10.1029/2005JD006290

Arora VK, Scinocca JF, Boer GJ, Christian JR, Denman KL, Flato GM, Kharin VV, Lee WG, Merryfield WJ (2011) Carbon emission limits required to satisfy future representative concentration pathways of greenhouse gases. Geophysical Research Letters 38(5), DOI https://doi.org/10.1029/2010GL046270

Bao J, Sherwood SC, Colin M, Dixit V (2017) The robust relationship between extreme precipitation and convective organization in idealized numerical modeling simulations. Journal of Advances in Modeling Earth Systems 9(6):2291–2303, DOI https://doi.org/10.1002/2017MS001125
Brönnimann S, Rajczak J, Fischer EM, Raible CC, Rohrer M, Schär C (2018) Changing seasonality of moderate and extreme precipitation events in the Alps. Natural Hazards and Earth System Sciences 18(7):2047–2056, DOI https://doi.org/10.5194/nhess-18-2047-2018

Dai P, Nie J (2020) A global quasigeostrophic diagnosis of extratropical extreme precipitation. Journal of Climate 33(22):9629 – 9642, DOI https://doi.org/10.1175/JCLI-D-20-0146.1

Dwyer JG, O’Gorman PA (2017) Changing duration and spatial extent of midlatitude precipitation extremes across different climates. Geophysical Research Letters 44(11):5863–5871, DOI https://doi.org/10.1002/2017GL072855

Holton JR, Hakim GJ (2012) An Introduction to Dynamic Meteorology, 5th edn. Elsevier

Khairoutdinov MF, Randall DA (2003) Cloud resolving modeling of the ARM summer 1997 IOP: Model formulation, results, uncertainties, and sensitivities. Journal of the Atmospheric Sciences 60(4):607–625, DOI https://doi.org/10.1175/1520-0469(2003)060 ⟨0607:CRMOTA⟩2.0.CO;2

Kidston J, Dean SM, Renwick JA, Vallis GK (2010) A robust increase in the eddy length scale in the simulation of future climates. Geophysical Research Letters 37(3):n/a–n/a, DOI https://doi.org/10.1029/2009GL041615

Kronstadt KA, Pervaze AS, Vaughn B (2011) Flooding in Pakistan: Overview and issues for congress. environmental stress in Pakistan and U.S. interests. Internet, URL https://www.everycrsreport.com/reports/R40926.html

Li Z, O’Gorman PA (2020) Response of vertical velocities in extratropical precipitation extremes to climate change. Journal of Climate 33(16):7125 – 7139, DOI https://doi.org/10.1175/JCLI-D-19-0766.1
36 M. A. Thabo Mpanza, Neil F. Tandon

Lu J, Ruby Leung L, Yang Q, Chen G, Collins WD, Li F, Jason Hou Z, Feng X (2014) The robust dynamical contribution to precipitation extremes in idealized warming simulations across model resolutions. Geophysical Research Letters 41(8):2971–2978, DOI https://doi.org/10.1002/2014GL059532

Ma T, Wu G, Liu Y, Jiang Z, Yu J (2019) Impact of surface potential vorticity density forcing over the Tibetan Plateau on the South China extreme precipitation in January 2008. Part I: Data analysis. Journal of Meteorological Research 33(3):400–415

Marelle L, Myhre G, Hodnebrog Ø, Sillmann J, Samset BH (2018) The changing seasonality of extreme daily precipitation. Geophysical Research Letters 45(20), DOI https://doi.org/10.1029/2018GL079567

Masson-Delmotte V, Zhai P, Pörtner HO, Roberts D, Skea J, Shukla PR, Pirani A, Moufouma-Okia W, Péan C, Pidcock R, et al (2018) IPCC. 2018: Summary for policymakers. In: Global warming of 1.5°C. an IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty. URL https://www.ipcc.ch/sr15/chapter/spm/

Milrad SM, Lombardo K, Atallah EH, Gyakum JR (2017) Numerical simulations of the 2013 Alberta flood: Dynamics, thermodynamics, and the role of orography. Monthly Weather Review 145(8):3049–3072, DOI https://doi.org/10.1175/MWR-D-16-0336.1

Nie J, Sobel AH (2016) Modeling the interaction between quasigeostrophic vertical motion and convection in a single column. Journal of the Atmospheric Sciences 73(3):1101–1117, DOI https://doi.org/10.1175/JAS-D-15-0205.1

Nie J, Shaevitz DA, Sobel AH (2016b) Forcings and feedbacks on convection in the 2010 Pakistan flood: Modeling extreme precipitation with interactive large-scale ascent. Journal of Advances in Modeling Earth Systems 8(3):1055–1072, DOI https://doi.org/10.1002/2016MS000663

Nie J, Sobel AH, Shaevitz DA, Wang S (2018) Dynamic amplification of extreme precipitation sensitivity. Proceedings of the National Academy of Sciences
115(38):9467–9472, DOI https://doi.org/10.1073/pnas.1800357115
Nie J, Dai P, Sobel AH (2020) Dry and moist dynamics shape regional patterns of extreme precipitation sensitivity. Proceedings of the National Academy of Sciences 117(16):8757–8763, DOI https://doi.org/10.1073/pnas.1913584117
Norris J, Chen G, Li C (2020) Dynamic amplification of subtropical extreme precipitation in a warming climate. Geophysical Research Letters 47(14):e2020GL087200, DOI https://doi.org/10.1029/2020GL087200
O’Gorman PA, Schneider T (2009a) The physical basis for increases in precipitation extremes in simulations of 21st-century climate change. Proceedings of the National Academy of Sciences 106(35):14,773–14,777, DOI https://doi.org/10.1073/pnas.0907610106
O’Gorman PA, Schneider T (2009b) Scaling of precipitation extremes over a wide range of climates simulated with an idealized GCM. Journal of Climate 22(21):5676 – 5685, DOI https://doi.org/10.1175/2009JCLI2701.1
Pendergrass AG, Lehner F, Sanderson BM, Xu Y (2015) Does extreme precipitation intensity depend on the emissions scenario? Geophysical Research Letters 42(20):8767–8774, DOI https://doi.org/10.1002/2015GL065854
Pendergrass AG, Reed KA, Medeiros B (2016) The link between extreme precipitation and convective organization in a warming climate: Global radiative-convective equilibrium simulations. Geophysical Research Letters 43(21):11,445–11,452, DOI https://doi.org/10.1002/2016GL071285
Pfahl S, O’Gorman PA, Fischer EM (2017) Understanding the regional pattern of projected future changes in extreme precipitation. Nature Climate Change 7(6):423–427, DOI https://doi.org/10.1038/nclimate3287
Pierce DW, Barnett TP, Santer BD, Gleckler PJ (2009) Selecting global climate models for regional climate change studies. Proceedings of the National Academy of Sciences 106(21):8441–8446, DOI https://doi.org/10.1073/pnas.0900094106
Rajczak J, Pall P, Schär C (2013) Projections of extreme precipitation events in regional climate simulations for Europe and the Alpine Region. J Geophys Res Atmos 118(9):3610–3626, DOI https://doi.org/10.1002/jgrd.50297
Randall D, Wood R, Bony S, Colman R, Fichefet T, Fyfe J, Kattsov V, Pitman A, Shukla J, Srinivasan J, Stouffer R, Sumi A, Taylor K (2007) Climate change 2007: The physical science basis. contribution of Working Group I to the fourth assessment report of the Intergovernmental Panel on Climate Change. Internet, URL http://web.crc.losrios.edu/~larsenl/ExtraMaterials/IPCC4/ar4-wg1-chapter8.pdf

Riahi K, Rao S, Krey V, Cho C, Chirkov V, Fischer G, Kindermann G, Nakicenovic N, Rafaj P (2011) RCP 8.5—a scenario of comparatively high greenhouse gas emissions. Climatic Change 109(1-2):33–57, DOI https://doi.org/10.1007/s10584-011-0149-y

Tandon NF, Nie J, Zhang X (2018a) Strong influence of eddy length on boreal summertime extreme precipitation projections. Geophysical Research Letters 45(19):10,665–10,672, DOI https://doi.org/10.1002/2018GL079327

Tandon NF, Zhang X, Sobel AH (2018b) Understanding the dynamics of future changes in extreme precipitation intensity. Geophysical Research Letters 45(6):2870–2878, DOI https://doi.org/10.1002/2017GL076361

Trenberth KE (1978) On the interpretation of the diagnostic quasi-geostrophic omega equation. Monthly weather review 106(1):131–137

Trenberth KE (1999) Atmospheric moisture recycling: Role of advection and local evaporation. Journal of Climate 12(5):1368–1381, DOI https://doi.org/10.1175/1520-0442(1999)012⟨1368:AMRROA⟩2.0.CO;2

Trenberth KE, Fasullo JT, Shepherd TG (2015) Attribution of climate extreme events. Nature Climate Change 5(8):725–730, DOI https://doi.org/10.1038/nclimate2657

Vaqar A, Khan MAA, Shakeel R, Zuhair M, Amir P (2011) National economic and environmental development study: The case of Pakistan. MPRA Paper 30942, University Library of Munich, Germany, URL https://ideas.repec.org/p/pra/mprapa/30942.html

de Vries AJ (2021) A global climatological perspective on the importance of Rossby wave breaking and intense moisture transport for extreme precipitation events. Weather and Climate Dynamics 2(1):129–161, DOI https://doi.org/10.5194/wcd-2-129-2021
de Vries AJ, Ouwersloot HG, Feldstein SB, Riemer M, El Kenawy AM, McCabe MF, Lelieveld J (2018) Identification of tropical-extratropical interactions and extreme precipitation events in the Middle East based on potential vorticity and moisture transport. Journal of Geophysical Research: Atmospheres 123(2):861–881, DOI https://doi.org/10.1002/2017JD027587

Westra S, Alexander LV, Zwiers FW (2013) Global increasing trends in annual maximum daily precipitation. Journal of Climate 26(11):3904–3918, DOI https://doi.org/10.1175/JCLI-D-12-00502.1

WMO (2018) Guidelines on the definition and monitoring of extreme weather and climate events. Task team on the definition of extreme weather and climate events. DOI https://doi.org/10.1109/CSCI.2015.171

Zheng F, Westra S, Leonard M (2015) Opposing local precipitation extremes. Nature Climate Change 5(5):389–390, DOI https://doi.org/10.1038/nclimate2579