Evaluation and projections of extreme precipitation over southern Africa from two CORDEX models

Izidine Pinto¹, Christopher Lennard¹, Mark Tadross^{1,2} Bruce Hewitson¹, Alessandro Dosio³, Grigory Nikulin⁴, Hans-

Juergen Panitz⁵, Mxolisi E. Shongwe⁶

¹ Climate System Analysis Group, University of Cape Town, Private Bag X3, Rondebosch, Western Cape, South

Africa

² United Nations Development Programme (UNDP-GEF), Energy and Environment Group, New York, USA

³ European Commission Joint Research Centre (JRC), Institute for Environment and Sustainability (IES), Ispra, Italy

⁴ Rossby Centre, Swedish Meteorological and Hydrological Institute, Norrköping, Sweden

⁵ Karlsruhe Institute of Technology, Institute of Meteorology and Climate Research - Tropopshere Research, Germany

⁶ South African Weather Service and University of Pretoria, Pretoria, South Africa

1 Corresponding author address: Izidine Pinto Climate System Analysis Group, University of Cape Town (UCT),

Private Bag X3, Rondebosch, Western Cape,

South Africa

E-mail: izidinep@csag.uct.ac.za

1

Abstract

The study focus on the analysis of extreme precipitation events of the present and future climate over southern Africa. Parametric and non-parametric approaches are used to identify and analyse these extreme events in data from the Coordinated Regional Climate Downscaling Experiment (CORDEX) models. The performance of the global climate model (GCM) forced regional climate model (RCM) simulations shows that the models are able to capture the observed climatological spatial patterns of the extreme precipitation. It is also shown that the downscaling of the present climate are able to add value to the performance of GCMs over some areas and depending on the metric used. The added value over GCMs justify the additional computational effort of RCM simulation for the generation relevant climate information for regional application. In the climate projections for the end of twenty-first Century (2069-2098) relative to the reference period (1976-2005), annual total precipitation is projected to decrease while the maximum number of consecutive dry days increases. Maximum 5-day precipitation amounts and 95th percentile of precipitation are also projected to increase significantly in the tropical and sub-tropical regions of southern Africa and decrease in the extra-tropical region. There are indications that rainfall intensity is likely to increase. This does not equate to an increase in total rainfall, but suggests that when it does rain, the intensity is likely to be greater. These changes are magnified under the RCP8.5 when compared with the RCP4.5 and are consistent with previous studies based on GCMs over the region.

Keywords Extreme precipitation, CORDEX, southern Africa

1 Introduction

Increases in atmospheric greenhouse gas concentrations are expected to result not only in changes in mean climate, but also to changes in climate variability and extreme weather conditions (Seneviratne et al, 2012). Countries in southern Africa are particularly vulnerable to extreme (weather or climate) event such as droughts, floods, tropical cyclones and heat waves because of low adaptive capacity due to limited access to information, finances, technology, and capital assets. Disasters caused by extreme events in southern Africa are estimated to have caused in around US\$ 10 billion of economic losses since 1970-2012 (WMO, 2014). Thus, understanding the changes in extreme events that may occur under future climate is an important input for adaptation planning and policy making. There is increasing evidence from observed trends that extreme precipitation events are becoming more frequent and more severe (e.g. Alexander and Arblaster, 2009; Groisman et al, 2005; Donat et al, 2013). For example, Fauchereau et al (2003) identified regions of South Africa which experienced more extreme precipitation events in the later decades of the 20th Century. Groisman et al (2005) empirically assessed the observed changes of very heavy precipitation (upper 0.3% of daily precipitation events) during 1906-1997 over eastern parts of South Africa. The authors found a statistically significant increases in the frequency of very heavy precipitation. Kruger (2006) found an increase trends in the number of extreme rainfall days in the Eastern Cape, southern Free State and parts of KwaZulu-Natal. And results from climate models suggest that these trends will continue worldwide under enhanced greenhouse conditions (e.g. Kharin and Zwiers, 2000, 2005; Shongwe et al, 2009; Sillmann et al, 2013b). Mason and Joubert (1997) using a global climate model (GCM) found an increase in the magnitude of extreme daily rainfall events with return periods of 10 and 30 years over the entire southern Africa. Results were similar for changes in the frequency and intensity of precipitation extreme events of five-day duration even in areas where decreases in mean annual rainfall were simulated. Shongwe et al (2009) and Shongwe et al (2011) using an ensemble of 12 GCMs found projected increases in in heavy precipitation intensity and mean precipitation rates in east Africa, more severe precipitation deficits in the southwest of southern Africa, and enhanced precipitation further north in Zambia, Malawi, and northern Mozambique. However, robust information on changes in the characteristics of future extreme precipitation to be used at local scales remains uncertain because the spatial distribution of rain gauges is not adequate enough to allow the description of local and regional characteristics of daily precipitation. In addition to this model grid resolution are often too coarse to resolve extreme precipitation causing systems convective in nature, primarily due to dynamics and parameterizations related to their coarse spatial resolutions (Wilby and Wigley, 1997; Hudson and Jones, 2002). Thus, a regionalization process to resolve small scale weather events can improve the ability to model extreme precipitation. This is usually achieved through either statistical or dynamical downscaling (Hewitson and Crane, 1996). And in order to sample the uncertainty associated with future projections of climate, multi-model GCM/RCM/statistically downscaled ensembles are required (Hewitson et al, 2013).

In recent years, the World Climate Research Program (WCRP) Coordinated Regional Downscaling Experiment (CORDEX) (Giorgi et al, 2009) has been established in order to provide a global coordination of regional climate downscaling to explore the future climates of the defined regions, and to contribute to the information needs of climate change adaptation and impact assessment. Within CORDEX, an ensemble of RCMs for Africa, forced by ERA-Interim reanalysis has been completed at grid resolutions of 0.44 degrees (about 50 km). The first set of present-day CORDEX simulations using ERA-Interim reanalysis and GCMs at the boundaries has been analyzed in detail by Nikulin et al (2012); Endris et al (2013); Kalognomou et al (2013); Kim et al (2013); Hernandez-Diaz et al (2013); Panitz et al (2014); Gbobaniyi et al (2014), which they focused mostly on precipitation climatology. These authors confirm the ability of the RCMs to capture the broad precipitation characteristics, however biases remain and are found to be

specific to individual models, regions and seasons. Their results show that the multi-model average generally outperforms any individual simulation and that the RCMs significantly improve the precipitation climate. Klutse et al (2015) analysed some characteristics of daily rainfall and also found that the multi-model ensemble average outperforms most of the individual RCM members in terms of mean precipitation climatology, intensity, and frequency of wet days and to a lesser extent the 95th percentile. In this study we evaluate the ability of the CORDEX RCMs to simulate precipitation extremes and present the projections for the end of 21st Century over southern Africa. This study is the first one focusing on the assessment/projections of extreme precipitation using data form two CORDEX RCMs publicly available at the time of the analysis. The paper is organized as follows: section 2 gives a brief description of the models, observational dataset and methodology used. In section 3, comparisons between observed and simulated precipitation with respect to climate indices and return values and future changes are presented. In section 4, we present the conclusions.

2 Datasets

Model data

We analyse downscaled daily precipitation from two RCM simulations that were available at the time of analysis in the CORDEX project. The Rossby Center (SMHI) regional climate model (RCA4, Dieterich et al (2013)) and the Consortium for Small-scale Modeling (COSMO) Regional Climate Model (COSMO-CLM, Panitz et al (2014)) were used to downscale four GCMs from the new CMIP5 global climate projections, namely, CNRM-CM5, EC-EARTH, HadGEM2-ES, and MPI-ESM-LR. All simulations were performed at a grid resolution of 0.44°x 0.44° over the same Africa domain (see auxiliary material, Figure S1). For a more detailed description of the models the reader is referred to Dieterich et al (2013) and Panitz et al (2014). The GCMs projections are forced by the Representative Concentration Pathways (RCPs, Moss et al (2010)). The RCPs are prescribed greenhouse-gas concentration pathways throughout the 21st century, corresponding to different radiative forcing stabilization levels by the year 2100. Two RCPs are available, RCP4.5 and RCP8.5, which represent a mid and a high-level emission scenario respectively. RCP4.5 corresponds to a radiative forcing after 2100 of approximately 4.5 W/m², equivalent to ~650 ppm CO₂, which is larger than that in the SRES (Special Report on Emissions Scenarios) B1 scenario (~550 ppm) and lower than that in the SRES A1B scenario (~720 ppm). RCP8.5 corresponds to a rising radiative forcing pathway leading to 8.5 W/m² in year 2100 equivalent to ~1370 ppm CO₂ (Moss et al, 2010). Common to all simulations is the use of ERA-Interim reanalysis (Dee et al, 2011) as driving data for the period of 1989-2008 to assess the structural bias of the RCMs (e.g. Nikulin et al, 2012; Kalognomou et al, 2013).

Observations

Due to scarce daily precipitation gauge datasets over Africa, few examples of work related to observed changes in extreme precipitation are available in the literature (e.g. New et al, 2006), and these observed dataset are insufficient for quantifying model biases as a consequence of limited spatial and temporal coverage of station. Gridded rainfall data based on gauge-satellite products are an alternative for evaluating climate models (e.g Shongwe et al, 2009; Sylla et al, 2013; Nikulin et al, 2012). However, discrepancies exist across different datasets as a result of stations availability, extraction algorithms, merging and interpolation techniques (Sylla et al, 2013; Nikulin et al, 2012; Kalognomou et al, 2013). Sylla et al, 2013 found that the satellite-derived precipitation dataset Global Precipitation Climatology Project

One-Degree Daily (GPCP 1DD Version 1.1, Huffman et al, 2001) and the 0.25° latitude-longitude resolution Tropical Rainfall Measuring Mission (TRMM 3B42 version 6, Huffman et al (2007) exhibit substantial systematic differences in mean rainfall and especially in frequency of wet days, intensity, and extremes as well as maximum length of wet and dry spells. And the GPCP 1DD Version 1.1 is more consistent with other observations and produces values within the range of other observational datasets. For model evaluation, we used the newer version GPCP 1DD Verion 1.2 dataset as reference available for the period 1997-2005. In addition the TRMM 3B42 version 7 available for the period 1998-2005 was also used. Our model evaluation analysis is carried out by considering a common period across the observation and the simulations (1997-2005) and the two observed dataset were remapped through bilinear interpolation to the common grid (0.44°latitude-longitude) of the models. While the climate projections are for the end of 21st Century (2069-2098) relative to 1976-2005 period.

3 Methodology

For the study of extreme weather events we used both parametric and non-parametric approach. In the non-parametric approach extreme precipitation indices were estimated from the empirical distribution of the daily data. These indices characterize moderate extreme events with re-occurrence times of a year or less (Klein Tank et al, 2009). Six indices from the Expert Team on Climate Change Detection and Indices (ETCCDI) that are based on daily precipitation were selected and these have been widely used in detection, attribution, and projection of changes in climate extremes (e.g., Alexander and Arblaster, 2009; Donat et al, 2013; Sillmann et al, 2013b). Detail of these indices are shown in Table S1 (See auxiliary material), and a full descriptive list of the indices can be found on the ETCCDI website http://etccdi.pacificclimate.org/list 27 indices.shtml. All indices are calculated on an annual basis for both historical and scenario simulations. The parametric approach based on the Extreme Value Theory (EVT) (see Coles, 2001) complements the descriptive indices in order to evaluate the intensity and frequency of rare events that lie far in the tails of the probability distribution of weather variables (e.g. events that occur once in 20 years). The EVT approach has been used in hydrology (e.g., Katz et al, 2002), atmospheric science (e.g., Palutikof et al, 1999), finance and insurance (e.g., Embrechts et al, 1997) and many other fields of applications. In this study the EVT approach follows that of Zwiers and Kharin (1998) and Kharin and Zwiers (2000). Annual precipitation maxima at the selected durations (1 day) and return periods (20 years) were estimated using the generalized extreme value (GEV) distribution. The GEV distribution parameters for each grid cell over southern Africa are estimated by the method of L-moments (LMOM) (Hosking, 1990) with the feasibility modification of Dupuis and Tsao (1998). The approach based on LMOM is less biased toward outliers present in the dataset (Hosking, 1990). To examine whether the GEV distribution is able to represent precipitation annual maxima, a standard Kolmogorov-Smirnov (KS) goodness-of-fit is applied. Since the GEV distribution parameters are estimated from the data the critical values taken from statistical tables should not be employed (von Storch and Zwiers, 1999). In this case, more appropriate estimates of the critical values are determined by parametric bootstrap procedure (e.g., Kharin and Zwiers, 2000). In this procedure 500 samples of the same size as observed or modelled series of annual maxima are generated from the fitted GEV. Further analysis on the RCMs performance considered are the added value (AV), which is defined as a measure of the difference between the large scale forcing (BC) and the downscaled RCM squared errors (e.g. Di Luca et al, 2012) and

was computed as:

$$AV = \frac{(X_{BC} - X_{OBS})^2 - (X_{RCM} - X_{OBS})^2}{Max((X_{BC} - X_{OBS})^2, (X_{RCM} - X_{OBS})^2)}(1)$$

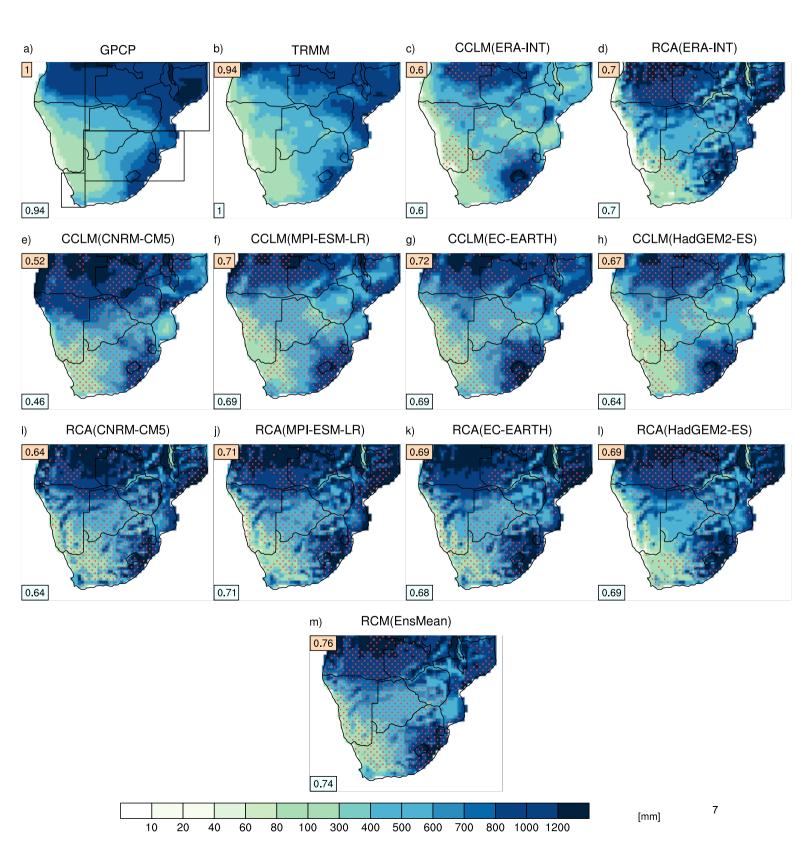
where, X_{BC} , X_{OBS} and X_{RCM} represents the index calculated from the BC (ERA-Interim or GCM), observation (GPCP), and RCMs, respectively. The normalization is introduced so that $-1 \le AV \le 1$ (e.g. Dosio et al, 2015). It is worth mentioning that for this analysis, only GPCP is used in the spatial distribution of the added value. A positive value of AV provides a measure of the added value afforded by dynamical downscaling with an RCM. Although RCMs are capable of adding value to the forcing global climate models, there is a limit to what can be corrected by the downscaling of imperfect driving conditions. For instance, Dosio et al (2015) showed that CCLM not always improves on the GCM seasonal climatology, but found that the number of consecutive wet days (i.e., daily precipitation > 1 mm) and dry days, and the number of intense precipitation events (i.e., number of rainy days when precipitation exceeds the 95 th percentile) are better reproduced by CCLM. The centered pattern correlation coefficient (PCC) is also calculated, and it indicates how well the spatial pattern is captured. Both GPCP and TRMM are used to account for uncertainties in the observed daily precipitation products.

4 Results

Simulated precipitation extreme

The spatial distribution of total annual wet-day precipitation (PRCPTOT) over southern Africa is shown in figure 1 for GPCP (fig. 1a), TRMM (fig. 1b), CCLM(ERA-INT) (fig. 1c), RCA4(ERA-INT) (fig. 1d), each of the ensemble members (fig. 1e,l) and the multi-model ensemble mean (fig. 1m). The multi-model ensemble mean is the average of the CCLM and RCA4 driven by the GCMs. The stippling in figures 1 and 2 represents areas where there is added value in the indices from the RCMs compared to the indices from ERA-Interim and GCMs for the reference period. In both observed data sets GPCP and TRMM, PRCPTOT maxima are located over the complex terrain of eastern part of South Africa, Mozambique and the northern parts domain along the Inter-tropical Convergence Zone (ICTZ). Differences can be found across the observation datasets with regard to the magnitude and spatial extent of PRCPTOT. GPCP shows higher PRCPTOT over northern Angola and northern Mozambique. The PCC exceeding 0.9 is found between GPCP and TRMM indicating a good level agreement in PRCPTOT patterns. Comparing both observed datasets with RCMs, it is found that the main features of the climatological pattern of PRCPTOT is reasonably captured. In particular the westeast gradient in precipitation totals over South Africa and the band of relatively low precipitation that stretches from Namibia in the west over Botswana to Zimbabwe. The CCLM underestimates the actual magnitude of PRCP-TOT both in ERA-Interim and individual GCM forced runs, especially over the east part of the domain. This underestimation of PRCPTOT might be caused by the misplacement of the monsoon rainbelt by the driving GCMs and an underestimation of associated rainfall intensity (Panitz et al, 2014; Dosio et al, 2015). A common tendency to overestimate PRCPTOT over the Lesotho highlands and Drakensburg areas is found in all simulations, an area that is known to be problematic for RCMs due to the complex topography (e.g. Engelbrecht et al, 2009; Kalognomou et al, 2013). The RCA4 forced by individual GCMs generally overestimate PRCPTOT over most of southern Africa, and the effect of topography is more evident in this model. Over the northwest region rainfall is overestimated and is likely influenced by the simulation of the atmospheric circulation patterns over the region (e.g. Angola low), which could lead to an increased moisture input from the Atlantic Ocean into the domain. For the pattern correlation of PRCPTOT, averaging across models gives better PCC (0.76) with observations than any individual model as a result of the cancellation of spatial errors from the individual model simulations. This limited sample suggests that the use of multi-model ensembles using different RCMs driven by different GCMs might provide an optimal approach to the provision of climate change scenarios over

Fig. 1: Total annual wet day precipitation (PRCPTOT) for the period 1997–2005 for (a) GPCP, (b) TRMM (1998–2005), CCLM forced by (c) ERA-Int. and different GCMs (e–h), RCA forced by (d) ERA-Int. And different GCMs (i–l) and (m) multi-model ensemble mean of CCLM and RCA4 forced by GCMs. Stippling indicates grid points where there is added value by the dynamical downscaling. Squares in (a) indicate the locations of the evaluation regions. The top left number is the PCC with GPCP and the bottom left with TRMM



Southern Africa. It is also observed that the downscaling by both CCLM and RCA4 improves the performance of the GCMs for most parts of southern Africa with the exception of the eastern region of the domain. For this particular region, GCMs produce reasonable precipitation pattern amounts as a result of overestimation of frequency of wet days (e.g. Sun et al, 2006). The RCM downscaled simulations improves the GCMs frequency of wet days (see auxiliary material, Figures S2). This supports the idea that RCM are able to resolve processes and feedbacks that operate at a subgrid scale GCM resolution (e.g. Giorgi, 1990; Di Luca et al, 2012). Although the RCMs offer some improvements in precipitation frequency compared to the driving GCMs, the best performances are captured in their ensemble mean with PCC of 0.89.

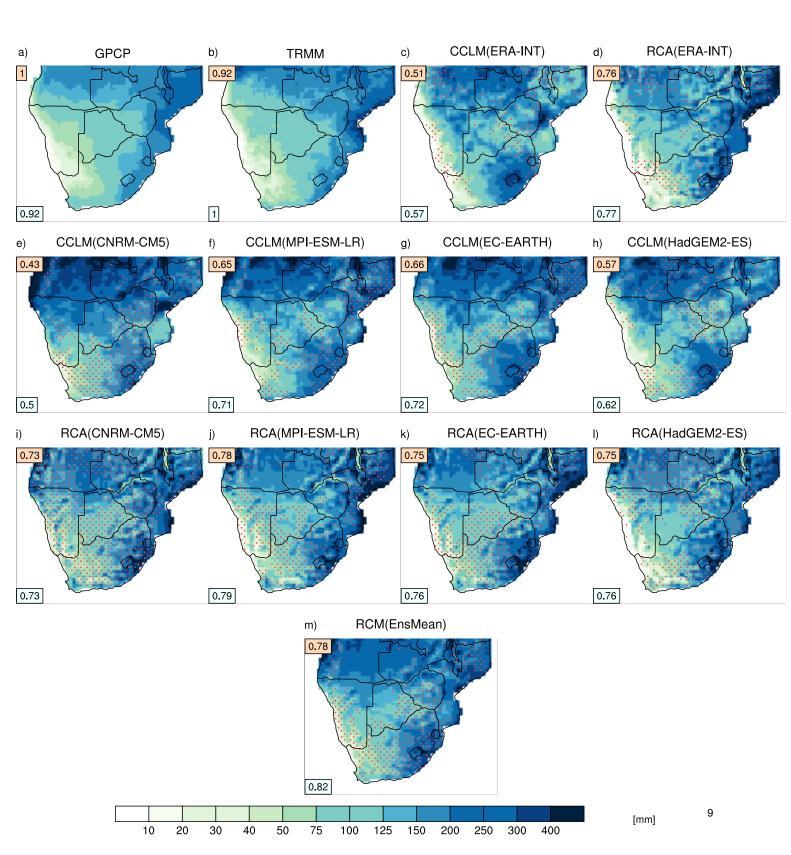
The general pattern of the maximum number of consecutive dry days (CDD) is reasonably well represented in the simulations (see auxiliary material, Figures S3). However, the magnitude of CDD is overestimated over the central areas of the domain in both RCMs forced by ERA-Interim and the downscaling does not add value for this index. This is likely because the ERA-Interim captures synoptic states associated with dry days (e.g. high pressure systems) and consequently the precipitation field reflects observed CDD, whereas the RCMs may be overly responsive to high pressure forcing during the spring and autumn seasons. However, there is still added value in the downscaled GCM data. A comparison of model ensembles with observation data shows that both CCLM and RCA are closer to the TRMM data.

The spatial distribution of heavy precipitation days (r10mm) (see auxiliary material, Figures S4) is similar to the spatial pattern of PRCPTOT. Both GPCP and TRMM indicate a good level of agreement with PCC exceeding 0.9. The r10mm events are generally underestimated/overestimated as described for PRCPTOT.

The pattern of precipitation on very wet days (R95pTOT) is similar to that of PRCPTOT, showing a decrease from east to the very dry region in the west (Fig. 2). Although the magnitude of R95pTOT is overestimated compared to GPCP and TRMM, the RCM downscaled simulation improves the GCM results except in the central parts of the domain and southern Mozambique. The ensemble mean is closer to the TRMM data (PCC=0.82) than GPCP (PCC=0.78). The spatial distribution of the maximum 5-day precipitation (RX5day) (see auxiliary material, Figures S5) and precipitation intensity (SDII) (see auxiliary material, Figures S6) are generally better represented in RCA4 than in CCLM. Both indices are overestimated over the northern parts of the domain.

Spatial patterns of the estimated 20-year return value for GPCP, TRMM, both RCMs driven by the ERA interim and ensemble mean of both RCMs driven by GCMs is shown in figure S7 in the auxiliary material. The Kolmogorov-Smirnov goodness-of-fit test indicate that at the 5% significance level, there are no rejections grid boxes. This indicates that the GEV distribution is a reasonable approximation for a distribution of annual precipitation maxima. The PCC of 0 indicate a poor level of agreement between GPCP and TRMM datasets. The magnitude of 20-year return value is generally higher in the TRMM than in GPCP. The spatial pattern from the downscaled models show a complex structure defined by local topographical conditions. The individual RCMs driven by GCMs reproduce the 20 year return values with varying magnitude. However, they show a coherent spatial distribution of precipitation extreme and there is minimal spread between the members of the ensemble driven by the same RCM. The RCMs consistently simulates maximum 20-year return values to the east of the region, whereas minima occur to the very dry region to the west. CCLM simulates maximum 20-year return values over the north of the continent which is not seen in neither the GPCP and TRMM data nor RCA4. The RCA4 forced runs are in good agreements with the observed 20-year return value estimated from the GPCP and TRMM data compared to the CCLM runs. The pattern correlation is lower compared with the pattern correlation of moderate extremes suggesting that rare extremes are not well captured by these models.

Fig. 2: Same as Fig. 1 but for annual total precipitation greater than or equal to the daily 95th percentile (R95pTOT)



A more detailed regional analysis of moderate extremes is shown in figure S8 in the auxiliary material. Regional averaging were done taking into account only grid points over land for each sub-region. Three sub-regions are used as defined in Kalognomou et al (2013) and shown here in Fig. 1a. The magnitude of extreme precipitation indices decrease from region 1 to region 3 miming the west-east gradient of the total annual precipitation over the region. Both GPCP and TRMM represent each indices with varying magnitudes. For most indices, the difference between TRMM and GPCP is not as large as the intermodel spread. For R95pTOT and RX5day both GPCP and TRMM are similar and are generally overestimated by the models except for RCA4(ERAINT) and CCLM(ERAINT) over region 3. The ensemble median of r10mm is closest to GPCP. The largest difference between GPCP and TRMM is found in region 1 for CDD, PRCPTOT and r10mm. This might be due to the dry precipitation bias on the TRMM dataset in the entire north part of southern Africa during the wet season compared to GPCP (e.g. Nikulin et al (2012)).

Projected changes in extreme precipitation

In this section, the ensemble mean of the downscaled projected changes for the end of 21st century of precipitation-based indices are discussed. Changes that are not significant at the 5% significance level are indicated by stippling. The significance of the changes was tested with a Student-t test. Changes in moderate extremes under RCP4.5 and RCP8.5 are shown in Fig. 3 and 4, respectively. There are significant decreases in annual PRCPTOT projected over most of South Africa, southern Botswana and Zimbabwe under the RCP4.5 scenario. Under RCP8.5 the projected magnitude of the decrease is greater and covers a wider spatial area that also includes Namibia, Angola and Mozambique. In general, the maximum number of CDD is projected to increase over the entire subcontinent with longer dry spells projected over Namibia, Botswana, northern Zimbabwe and southern Zambia. Increases in CDD over southern Africa were also found in Giorgi et al (2014) for the period of 2071-2100 compared to 1976-2005. Reductions in PRCPTOT together with increases in CDD have implications for seasonal precipitation onset in southern Africa (e.g. Tadross et al, 2005) and is likely to have negative impacts in agriculture, particularly in the areas of traditional rain-fed agriculture and water resources. The R95pTOT and RX5day indices generally increase over the northern region of the domain but decrease in the south western parts of South Africa. R10mm are projected to decrease in most of southern Africa. Across most of southern Africa a significant increases in SDII is projected fot both scenarios with the spatial extent and magnitude greater under RCP8.5.

The ensemble median of the projected changes in rare extreme precipitation (20- year return values) for the late 21st Century for both RCPs is shown if Figure S9 (see auxiliary material). The significance of projected changes is evaluated using the non-parametric Wilcoxon signed rank test, which tests whether the multimodel median change is zero. Changes that are not significant at the 5 ì significance level are indicated by stippling in the maps of projected changes. A general increase in the magnitude of the 20 year extreme precipitation event is projected over the central and eastern parts of southern Africa and a decrease over western parts of South Africa and central and southern Namibia. This pattern of change in extreme precipitation is projected consistently across both scenarios although the magnitude of increases are generally higher under RCP8.5 in areas where the change is positive. However, these changes are not statistically significant over southern Africa. The projected increases in return periods imply more frequent recurrence and less time between extreme events.

Fig. 3: Projected multi-model mean changes in moderate extreme events for the period of 2069–2098 under RCP4.5 emission scenario, relative to the reference period 1976–2005. Stippling indicates grid points with changes that are not significant (5 % significance level using t-test)

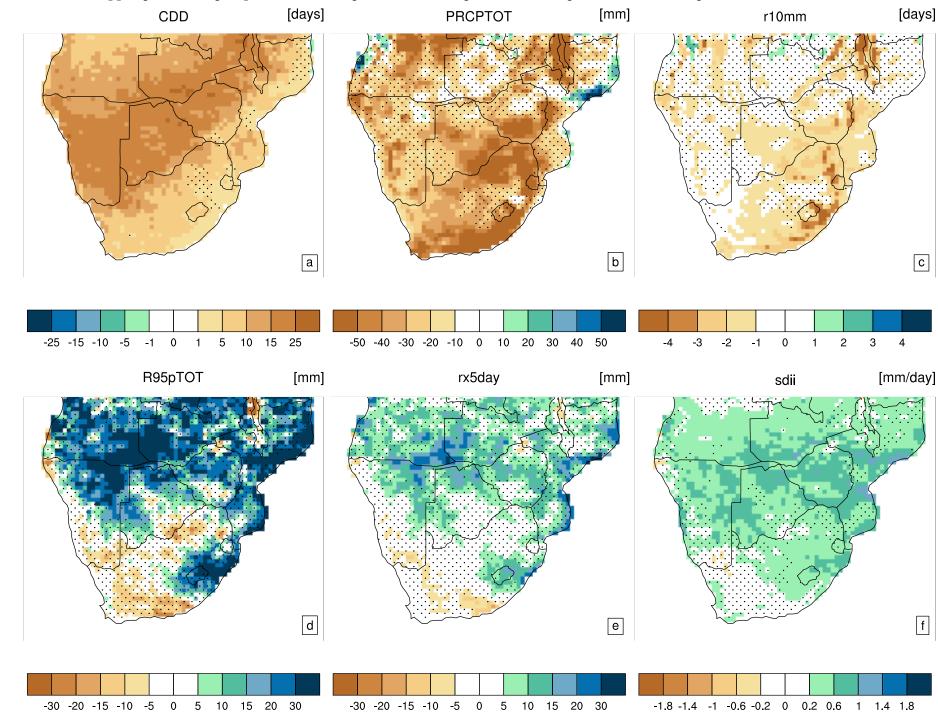
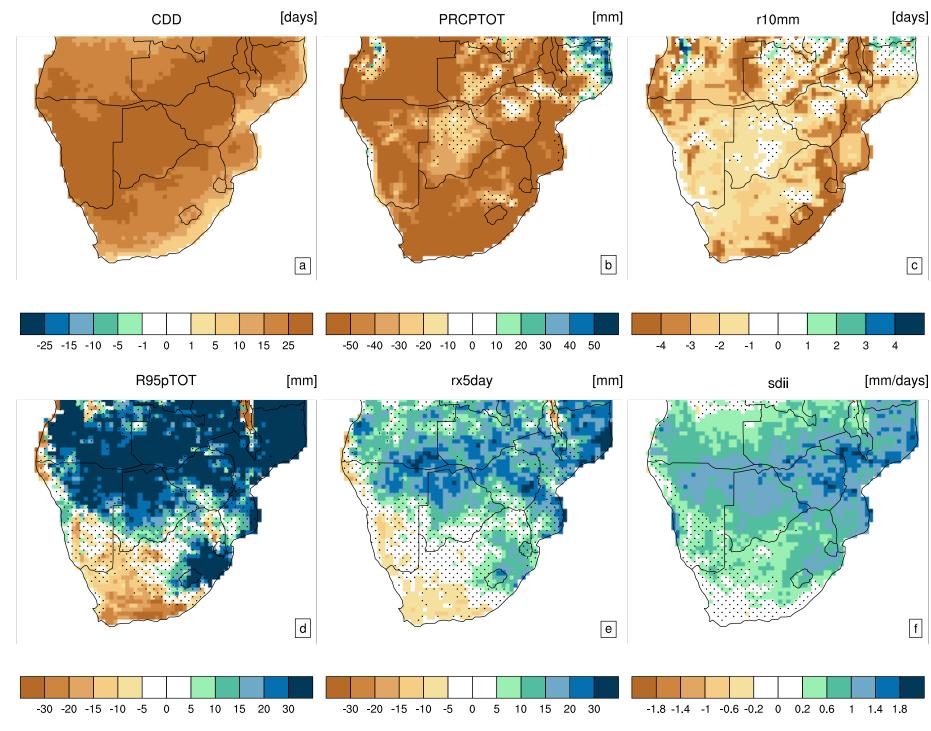
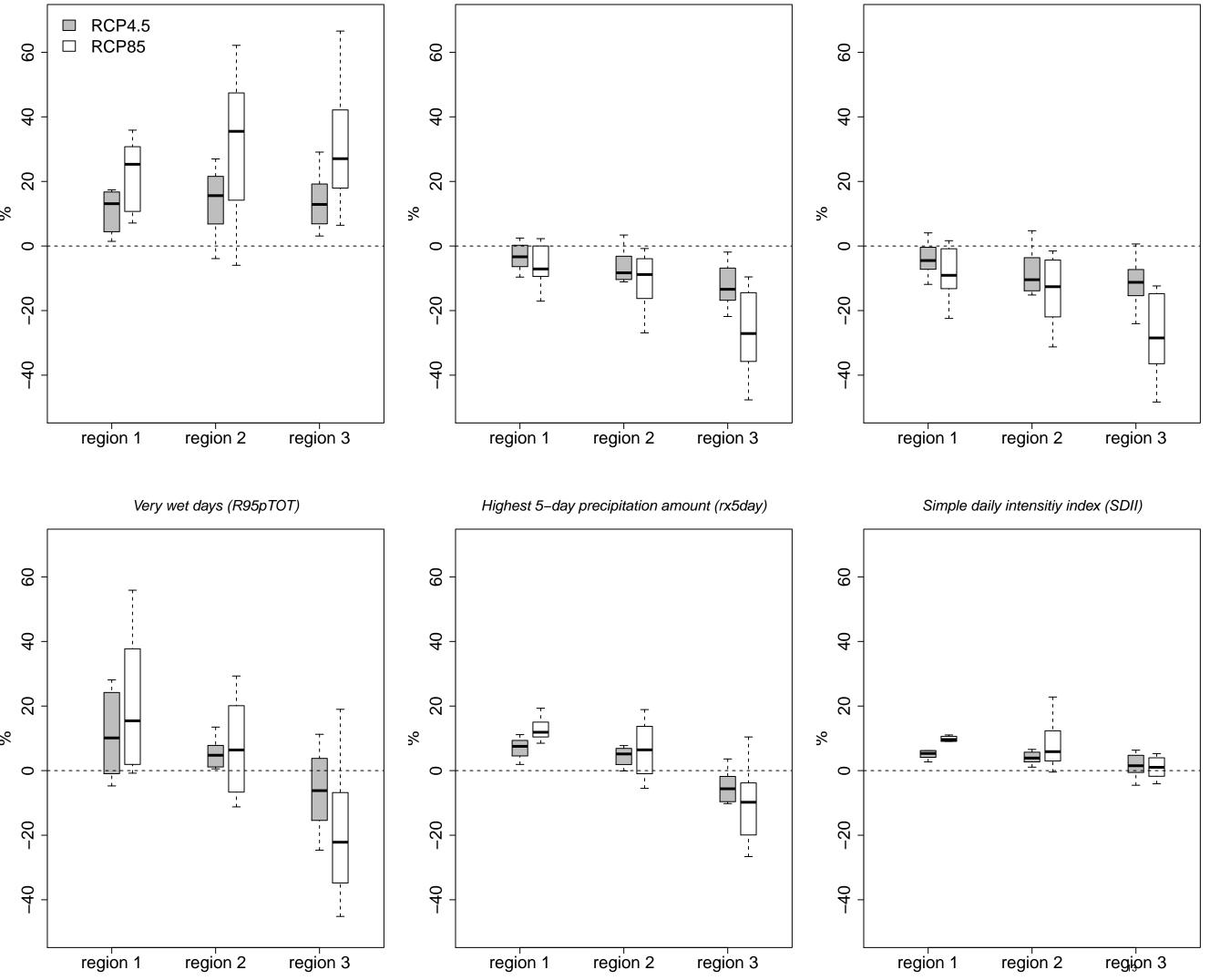


Fig. 4: Same as Fig. 3, but for RCP8.5 emission scenario





Regional summaries of the projected changes by the end of 21st Century (2069-2098) for the three sub-regions on annual basis are are shown in Fig. 5. These figures show the model agreement on the sign of the change, and is assessed on the basis of the interquartile model spread (boxes) which correspond to an agreement on sign amongst at least 75% of models (Sillmann et al, 2013b). The percentage of median changes of all indices are almost the same for regions 1 and 2 and the interquartile model spread is generally smaller in RCP4.5 compared to RCP8.5 probably due to different climate sensitivity in the models and feedback mechanisms. There is a general agreement on the sign of change of all indices independent of the region considered. Increases in CDD are projected in all regions followed by decreases in PRCPTOT and r10mm. Increases in R95pTOT, Rx5day and SDII are projected over region 1 and 2. Higher amount of change in PRCPTOT is found in region 3 together with decreases in R95pTOT, Rx5day and no change in median SDII.

5 Summary and conclusions

Using an ensemble of regional climate models from the CORDEX project we analysed climate projections in terms of precipitation extremes across southern Africa. The ensemble consists of two regional climate models, namely RCA4 and CCLM4.8 forced by the ECMWF ERA-Interim reanalysis as perfect boundary conditions and four different GCMs. Our results are a comparison between a possible future climate (2069-2098) under the RCPs 4.5 and 8.5 with present (1975-2005) climate conditions. Comparisons of both observed data sets, GPCP and TRMM reveal that substantial differences exists between them. For moderate extremes we found that both observed show high level of agreement. On the contrast, for rare extreme there is no agreement between them and this adds a strong element of uncertainty in the model validation. Validation of the downscaled GCM and reanalysis ERA-Interim realizations under present conditions shows that the RCMs simulate the climatology of extreme precipitation over southern Africa reasonably well. Although the relative performance of an individual model may depend on the choice of the reference dataset. As a result of error cancellation between the different models, the ensemble mean of both RCMs driven by all GCMs compares better with observations than individual ensemble members, a phenomena found in many other studies (e.g Nikulin et al, 2011; Sillmann et al, 2013a). Extreme precipitation simulated by RCMs is found to be determined by the model physics and parameterizations rather than the large scale forcing provided by the driving GCMs. Also the downscaling of GCMs with the RCMs reduces biases across in certain regions which implies an added value through the downscaling, especially in areas of strong topographical forcing.

The multi-model ensemble projections suggest that changes in the characteristics of precipitation over southern Africa region can be expected by the end of the 21st Century. We find a decrease in total annual mean precipitation but an increase in the magnitude of extreme precipitation events. Increases in CDD are accompanied by increases in R95pTOT, suggesting that dry spell duration becomes longer, but precipitation may be more extreme when it occurs. These changes are accompanied by a consistent inter-model agreement on the sign of the change. In addition the magnitude 20-year return period precipitation events are projected to increase over most regions of southern Africa. This suggests rising flood risk for the region, with implications for disaster management, development planning and local livelihoods. The radiative forcing (RCP) affects the magnitude of change in extreme events and to a lesser degree expands the spatial extent of patterns of these changes. The spatial distribution of changes in extreme precipitation events are largely in line with previous studies based on coarser-resolved models (e.g Sillmann et al, 2013b). It should be noted that the projected changes that are not classified as statistically significant may still be senstive to changes in radiative forcing given that (1) determining statistical significance is dependent on choice of analysis methods and (2) it is not clear that changes in precipitation that are not significant will have no detectable impact, because of different

levels of sensitivity of each sector or system (McSweeney and Jones, 2012). The results presented here give an overview of the changes in extreme precipitation projected by the CORDEX multimodel ensemble and motivates for further investigation to explore reasons for these changes.

Acknowledgements We are grateful to the Water Research Commission financial support from the Project K5-2240. We would like to thank the regional downscaling groups for producing and making available their model data. We also thank two anonymous reviewers for their helpful comments.

References

Alexander L, Arblaster J (2009) Assessing trends in observed and modelled climate extremes over Australia in relation to future projections. *Int. J. of Climatol.* 29, 417–435

Coles S (2001) An Introduction to Statistical Modeling of Extreme Values. Springer Series in Statistics, London, UK

Dee D, Uppala S, Simmons A, Berrisford P, et al (2011) The era-interim reanalysis: Configuration and performance of the data assimilation system. *Quart. J. Roy. Meteor. Soc.* 137, 553–597

Di Luca A, de Elía R, Laprise R (2012) Potential for added value in precipitation simulated by high-resolution nested regional climate models and observations. *Climate Dyn.* 38,1229-1247

Dieterich C, Schimanke S, Wang S, Väli G, Liu Y, et al. (2013) Evaluation of the SMHI coupled atmosphere-ice-ocean model RCA4 NEMO. Report Oceanography 47 p 80

Donat M, Alexander L, Yang H, Durre I, Vose R et al (2013) Updated analyses of temperature and precipitation extreme indices since the beginning of the twentieth century: The hadex2 dataset. *J. Geophys. Res. Atm.* 118,2098-2118

Dosio A, Panitz HJ, Schubert-Frisius M, Lüthi D (2015) Dynamical downscaling of CMIP5 global circulation models over CORDEX-Africa with COSMO-CLM: evaluation over the present climate and analysis of the added value. *Climate Dyn* 44, 2637-2661

Dupuis D, Tsao M (1998) A hybrid estimator for generalized pareto and extreme-value distributions. Communications in Statistics-Theory and Methods 27:925–941

Embrechts P, Klüppelberg C, Mikosch T (1997) Modelling extremal events for insurance and finance, vol 33. Springer Verlag

Endris HS, Omondi P, Jain S, Lennard C, Hewitson B, et al (2013) Assessment of the performance of CORDEX regional climate models in simulating east african rainfall. *J. Climate* 26,8453-8475

Engelbrecht F, McGregor J, Engelbrecht C (2009) Dynamics of the conformal-cubic atmospheric model projected climate-change signal over southern Africa. *Int. J. Climatol.* 29, 1013-1033

Fauchereau N, Trzaska S, Rouault M, Richard Y (2003) Rainfall variability and changes in southern africa during the 20th century in the global warming context. *Nat. Hazards* 29,139-154

Gbobaniyi E, Sarr A, Sylla MB, Diallo I, Lennard C, Dosio A, et al (2014) Climatology, annual cycle and interannual variability of precipitation and temperature in CORDEX simulations over west africa. *Int. J. Climatol.* 34,2241-2257

Giorgi F (1990) Simulation of regional climate using a limited area model nested in a general circulation model. *J. Climate* 3,941-964

Giorgi F, Jones C, Asrar G (2009) Addressing climate information needs at the regional level: the cordex framework. WMO Bulletin 58, 175

Giorgi F, Coppola E, Raffaele F, Diro G, Fuentes-Franco R et al (2014) Changes in extremes and hydroclimatic regimes in the CREMA ensemble projections. *Climatic Change* 125,39-51

Groisman P, Knight R, Easterling D, Karl T, Hegerl G, Razuvaev V (2005) Trends in intense precipitation in the

climate record. J Climate 18,1326-1350

Hernandez-Diaz L, Laprise R, Sushama L, Martynov A, Winger K, Dugas B (2013) Climate simulation over CORDEX Africa domain using the fifth-generation canadian regional climate model (CRCM5). *Climate Dyn* 40, 1415-1433

Hewitson B, Daron J, Crane R, Zermoglio M, Jack C (2013) Interrogating empirical statistical downscaling. *Climatic Change* 122, 539-554

Hewitson BC, Crane RG (1996) Climate downscaling: Techniques and application. Climate Res. 7,85-95

Hosking JRM (1990) L-moments: Analysis and estimation of distributions using linear combinations of order statistics. Journal of the Royal Statistical Society Series B (Methodological) 52,105-124

Hudson DA, Jones RG (2002) Regional climate model simulations of present-day and future climates of southern africa. Tech. rep., Hadley Centre Technical Note 39, Hadley Centre for Climate Prediction and Research, Met Office, Bracknell, U.K.

Huffman G, Adler R, Bolvin D, Gu G, Nelkin E, et al (2007) The TRMM multisatellite precipitation analysis (TMPA): quasiglobal, multiyear, combined-sensor precipitation estimates at fine scales. *J. Hydro.* 8,38-55

Huffman GJ, Adler RF, Morrissey MM, Bolvin DT, Curtis S, Joyce R, McGavock B, Joel Susskind (2001) Global precipitation at one-degree daily resolution from multisatellite observations. *J. Hydro*. 2,36-50

Kalognomou EA, Lennard C, Shongwe M, Pinto I, Favre A, et al (2013) A diagnostic evaluation of precipitation in CORDEX models over southern africa. *J. Climate* 26, 9477-9506

Katz R, Parlange M, Naveau P (2002) Statistics of extremes in hydrology. Advances in water resources 25,287-1304

Kharin VV, Zwiers FW (2000) Changes in the extremes in an ensemble of transient climate simulations with a coupled atmosphere–ocean GCM *J. Climate* 13,3760-3788

Kharin VV, Zwiers FW (2005) Estimating extremes in transient climate change simulations. J. Climate 18,1156-1173

Kim J, Waliser DE, Mattmann CA, Goodale CE, Hart AF, Zimdars PA, et al (2013) Evaluation of the CORDEX-Africa multi-RCM hindcast: systematic model errors. *Climate Dyn* 42, 1189-1202

Klein Tank AM, Zwiers FW, Zhang X (2009) Guidelines on analysis of extremes in a changing climate in support of informed decisions for adaptation. WCDMP-72,WMO-TD 1500

Klutse NAB, Sylla MB, Diallo I, Sarr A, Dosio A, Diedhiou A, et al (2015) Daily characteristics of west african summer monsoon precipitation in cordex simulations. *Theor Appl Climatol* 1-18

Kruger A (2006) Observed trends in daily precipitation indices in South Africa: 1910-2004. *Int. J. Climatol.* 26,2275-2285

Mason S, Joubert A (1997) Simulated changes in extreme rainfall over southern Africa. Int. J. Climatol 17,291-301

McSweeney CF, Jones RG (2012) No consensus on consensus: the challenge of finding a universal approach to measuring and mapping ensemble consistency in GCM projections. *Climatic Change* 1-13

Moss R, Edmonds J, Hibbard K, Manning M, Rose S, van Vuuren D, et al (2010) The next generation of scenarios for climate change research and assessment. *Nature* 463,747-756

New M, et al (2006) Evidence of trends in daily climate extremes over southern and west Africa. *J. Geophys. Res.* 111:D14,102

Nikulin G, Kjellström E, Hansson U, Strandberg G, Ullerstig A (2011) Evaluation and future projections of temperature, precipitation and wind extremes over Europe in an ensemble of regional climate simulations. *Tellus A* 63,41-55

Nikulin G, Jones C, Giorgi F, Asrar G, Büchner M, Cerezo-Mota R, et al (2012) Precipitation climatology in an ensemble of CORDEX-Africa regional climate simulations. *J. Climate* 25,6057-6078

Palutikof J, Brabson B, Lister D, Adcock S (1999) A review of methods to calculate extreme wind speeds. Meteorological Applications 6,119-132

Panitz HJ, Dosio A, Büchner M, Lïthi D, Keuler K (2014) COSMO-CLM (CCLM) climate simulations over CORDEX-Africa domain: analysis of the ERA-Interim driven simulations at 0.44 and 0.22 resolution. *Climate Dyn* pp 1–24

Seneviratne SI, Nicholls N, Easterling D, Goodess C, Kanae S, et al (2012) Changes in climate extremes and their impacts on the natural physical environment. Managing the risks of extreme events and disasters to advance climate change adaptation pp 109–230

Shongwe M, Van Oldenborgh G, Van Den Hurk B, De Boer B, eta al (2009) Projected changes in extreme precipitation in Africa under global warming. Part 1: Southern Africa. *J. Climate* 22,3819-3837

Shongwe ME, van Oldenborgh GJ, van den Hurk B, van Aalst M (2011) Projected changes in mean and extreme precipitation in africa under global warming, Part II: East africa. *J. Climate* 25,3718-3733

Sillmann J, Kharin V, Zhang X, Zwiers F, Bronaugh D (2013a) Climate extremes indices in the CMIP5 multimodel ensemble: Part 1. Model evaluation in the present climate. *J. Geophy. Res. Atm.* 118,1716-1733

Sillmann J, Kharin V, Zwiers F, Zhang X, Bronaugh D (2013b) Climate extremes indices in the CMIP5 multimodel ensemble: Part 2. Future climate projections. *J. Geophy. Res. Atm.* 118,2473-2493

von Storch H, Zwiers FW (1999) Statistical Analysis in Climate Research, vol 95. Cambridge University Press

Sun Y, Solomon S, Dai A, Portmann RW (2006) How often does it rain? J. Climate 19,916-934

Sylla M, Giorgi F, Coppola E, Mariotti L (2013) Uncertainties in daily rainfall over Africa: assessment of gridded observation products and evaluation of a regional climate model simulation. *Int. J. Climatol.* 33,1805-1817.

Tadross M, Hewitson B, Usman M (2005) The interannual variability of the onset of the maize growing season over south africa and zimbabwe. *J. Climate* 18,3356-3372

Wilby RL, Wigley T (1997) Downscaling general circulation model output: a review of methods and limitations. Progress in Physical Geography 21,530-548

WMO (2014) Atlas of Mortality and Economic Losses from Weather, Climate and Water Extremes 1970-2012

Zwiers FW, Kharin VV (1998) Changes in the Extremes of the Climate Simulated by CCC GCM2 under CO2 Doubling. *J. Climate* 11,2200-2222

References

Alexander L, Arblaster J (2009) Assessing trends in observed and modelled climate extremes over Australia in relation to future projections. *Int. J. of Climatol.* 29, 417–435

Coles S (2001) An Introduction to Statistical Modeling of Extreme Values. Springer Series in Statistics, London, UK

Dee D, Uppala S, Simmons A, Berrisford P, et al (2011) The era-interim reanalysis: Configuration and performance of the data assimilation system. *Quart. J. Roy. Meteor. Soc.* 137, 553–597

Di Luca A, de Elía R, Laprise R (2012) Potential for added value in precipitation simulated by high-resolution nested regional climate models and observations. *Climate Dyn.* 38,1229-1247

Dieterich C, Schimanke S, Wang S, Väli G, Liu Y, et al. (2013) Evaluation of the SMHI coupled atmosphere-ice-ocean model RCA4 NEMO. Report Oceanography 47 p 80

Donat M, Alexander L, Yang H, Durre I, Vose R et al (2013) Updated analyses of temperature and precipitation extreme indices since the beginning of the twentieth century: The hadex2 dataset. *J. Geophys. Res. Atm.* 118,2098-2118

Dosio A, Panitz HJ, Schubert-Frisius M, Lüthi D (2015) Dynamical downscaling of CMIP5 global circulation models over CORDEX-Africa with COSMO-CLM: evaluation over the present climate and analysis of the added value. *Climate Dyn* 44, 2637-2661

Dupuis D, Tsao M (1998) A hybrid estimator for generalized pareto and extreme-value distributions. Communications in Statistics-Theory and Methods 27:925–941

Embrechts P, Klüppelberg C, Mikosch T (1997) Modelling extremal events for insurance and finance, vol 33. Springer Verlag

Endris HS, Omondi P, Jain S, Lennard C, Hewitson B, et al (2013) Assessment of the performance of CORDEX regional climate models in simulating east african rainfall. *J. Climate* 26,8453-8475

Engelbrecht F, McGregor J, Engelbrecht C (2009) Dynamics of the conformal-cubic atmospheric model projected climate-change signal over southern Africa. *Int. J. Climatol.* 29, 1013-1033

Fauchereau N, Trzaska S, Rouault M, Richard Y (2003) Rainfall variability and changes in southern africa during the 20th century in the global warming context. *Nat. Hazards* 29,139-154

Gbobaniyi E, Sarr A, Sylla MB, Diallo I, Lennard C, Dosio A, et al (2014) Climatology, annual cycle and interannual variability of precipitation and temperature in CORDEX simulations over west africa. *Int. J. Climatol.* 34,2241-2257

Giorgi F (1990) Simulation of regional climate using a limited area model nested in a general circulation model. *J. Climate* 3,941-964

Giorgi F, Jones C, Asrar G (2009) Addressing climate information needs at the regional level: the cordex framework. WMO Bulletin 58, 175

Giorgi F, Coppola E, Raffaele F, Diro G, Fuentes-Franco R et al (2014) Changes in extremes and hydroclimatic regimes in the CREMA ensemble projections. *Climatic Change* 125,39-51

Groisman P, Knight R, Easterling D, Karl T, Hegerl G, Razuvaev V (2005) Trends in intense precipitation in the

climate record. J Climate 18,1326-1350

Hernandez-Diaz L, Laprise R, Sushama L, Martynov A, Winger K, Dugas B (2013) Climate simulation over CORDEX Africa domain using the fifth-generation canadian regional climate model (CRCM5). *Climate Dyn* 40, 1415-1433

Hewitson B, Daron J, Crane R, Zermoglio M, Jack C (2013) Interrogating empirical statistical downscaling. *Climatic Change* 122, 539-554

Hewitson BC, Crane RG (1996) Climate downscaling: Techniques and application. Climate Res. 7,85-95

Hosking JRM (1990) L-moments: Analysis and estimation of distributions using linear combinations of order statistics. Journal of the Royal Statistical Society Series B (Methodological) 52,105-124

Hudson DA, Jones RG (2002) Regional climate model simulations of present-day and future climates of southern africa. Tech. rep., Hadley Centre Technical Note 39, Hadley Centre for Climate Prediction and Research, Met Office, Bracknell, U.K.

Huffman G, Adler R, Bolvin D, Gu G, Nelkin E, et al (2007) The TRMM multisatellite precipitation analysis (TMPA): quasiglobal, multiyear, combined-sensor precipitation estimates at fine scales. *J. Hydro*. 8,38-55

Huffman GJ, Adler RF, Morrissey MM, Bolvin DT, Curtis S, Joyce R, McGavock B, Joel Susskind (2001) Global precipitation at one-degree daily resolution from multisatellite observations. *J. Hydro*. 2,36-50

Kalognomou EA, Lennard C, Shongwe M, Pinto I, Favre A, et al (2013) A diagnostic evaluation of precipitation in CORDEX models over southern africa. *J. Climate* 26, 9477-9506

Katz R, Parlange M, Naveau P (2002) Statistics of extremes in hydrology. Advances in water resources 25,287-1304

Kharin VV, Zwiers FW (2000) Changes in the extremes in an ensemble of transient climate simulations with a coupled atmosphere–ocean GCM *J. Climate* 13,3760-3788

Kharin VV, Zwiers FW (2005) Estimating extremes in transient climate change simulations. J. Climate 18,1156-1173

Kim J, Waliser DE, Mattmann CA, Goodale CE, Hart AF, Zimdars PA, et al (2013) Evaluation of the CORDEX-Africa multi-RCM hindcast: systematic model errors. *Climate Dyn* 42, 1189-1202

Klein Tank AM, Zwiers FW, Zhang X (2009) Guidelines on analysis of extremes in a changing climate in support of informed decisions for adaptation. WCDMP-72,WMO-TD 1500

Klutse NAB, Sylla MB, Diallo I, Sarr A, Dosio A, Diedhiou A, et al (2015) Daily characteristics of west african summer monsoon precipitation in cordex simulations. *Theor Appl Climatol* 1-18

Kruger A (2006) Observed trends in daily precipitation indices in South Africa: 1910-2004. *Int. J. Climatol.* 26,2275-2285

Mason S, Joubert A (1997) Simulated changes in extreme rainfall over southern Africa. Int. J. Climatol 17,291-301

McSweeney CF, Jones RG (2012) No consensus on consensus: the challenge of finding a universal approach to measuring and mapping ensemble consistency in GCM projections. *Climatic Change* 1-13

Moss R, Edmonds J, Hibbard K, Manning M, Rose S, van Vuuren D, et al (2010) The next generation of scenarios for climate change research and assessment. *Nature* 463,747-756

New M, et al (2006) Evidence of trends in daily climate extremes over southern and west Africa. *J. Geophys. Res.* 111:D14,102

Nikulin G, Kjellström E, Hansson U, Strandberg G, Ullerstig A (2011) Evaluation and future projections of temperature, precipitation and wind extremes over Europe in an ensemble of regional climate simulations. *Tellus A* 63,41-55

Nikulin G, Jones C, Giorgi F, Asrar G, Büchner M, Cerezo-Mota R, et al (2012) Precipitation climatology in an ensemble of CORDEX-Africa regional climate simulations. *J. Climate* 25,6057-6078

Palutikof J, Brabson B, Lister D, Adcock S (1999) A review of methods to calculate extreme wind speeds. Meteorological Applications 6,119-132

Panitz HJ, Dosio A, Büchner M, Lïthi D, Keuler K (2014) COSMO-CLM (CCLM) climate simulations over CORDEX-Africa domain: analysis of the ERA-Interim driven simulations at 0.44 and 0.22 resolution. *Climate Dyn* pp 1–24

Seneviratne SI, Nicholls N, Easterling D, Goodess C, Kanae S, et al (2012) Changes in climate extremes and their impacts on the natural physical environment. Managing the risks of extreme events and disasters to advance climate change adaptation pp 109–230

Shongwe M, Van Oldenborgh G, Van Den Hurk B, De Boer B, eta al (2009) Projected changes in extreme precipitation in Africa under global warming. Part 1: Southern Africa. *J. Climate* 22,3819-3837

Shongwe ME, van Oldenborgh GJ, van den Hurk B, van Aalst M (2011) Projected changes in mean and extreme precipitation in africa under global warming, Part II: East africa. *J. Climate* 25,3718-3733

Sillmann J, Kharin V, Zhang X, Zwiers F, Bronaugh D (2013a) Climate extremes indices in the CMIP5 multimodel ensemble: Part 1. Model evaluation in the present climate. *J. Geophy. Res. Atm.* 118,1716-1733

Sillmann J, Kharin V, Zwiers F, Zhang X, Bronaugh D (2013b) Climate extremes indices in the CMIP5 multimodel ensemble: Part 2. Future climate projections. *J. Geophy. Res. Atm.* 118,2473-2493

von Storch H, Zwiers FW (1999) Statistical Analysis in Climate Research, vol 95. Cambridge University Press

Sun Y, Solomon S, Dai A, Portmann RW (2006) How often does it rain? J. Climate 19,916-934

Sylla M, Giorgi F, Coppola E, Mariotti L (2013) Uncertainties in daily rainfall over Africa: assessment of gridded observation products and evaluation of a regional climate model simulation. *Int. J. Climatol.* 33,1805-1817.

Tadross M, Hewitson B, Usman M (2005) The interannual variability of the onset of the maize growing season over south africa and zimbabwe. *J. Climate* 18,3356-3372

Wilby RL, Wigley T (1997) Downscaling general circulation model output: a review of methods and limitations. Progress in Physical Geography 21,530-548

WMO (2014) Atlas of Mortality and Economic Losses from Weather, Climate and Water Extremes 1970-2012

Zwiers FW, Kharin VV (1998) Changes in the Extremes of the Climate Simulated by CCC GCM2 under CO2 Doubling. *J. Climate* 11,2200-2222

Supplementary material

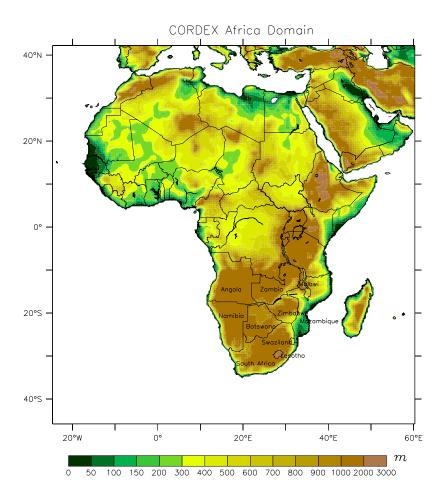


Fig. S1 The CORDEX-Africa domain and southern Africa countries names

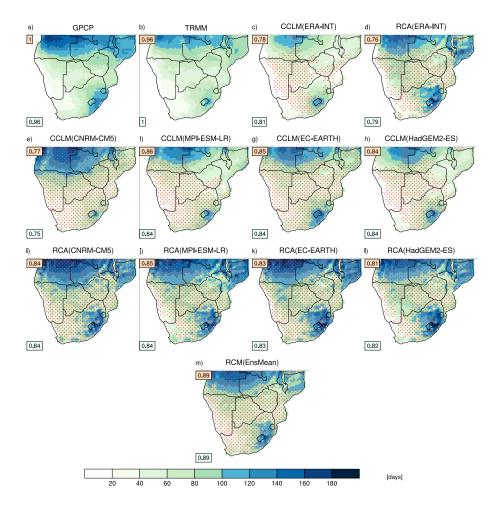
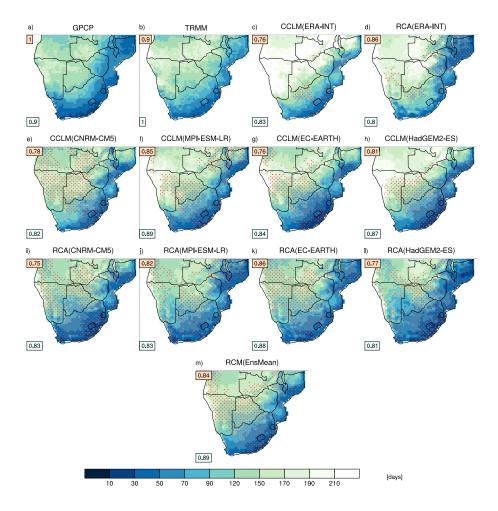
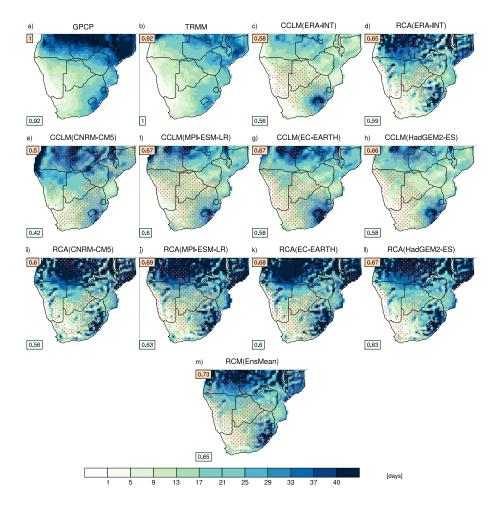


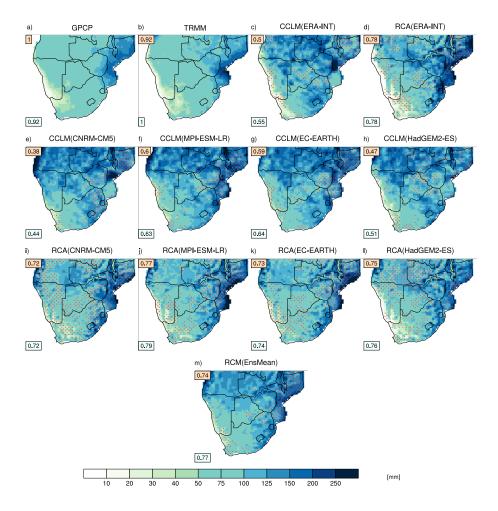
Fig. S2 Annual precipitation frequency for the period 1998-2006 for (a) GPCP, CCLM forced by (b) ERA-Int. and different GCMs (e-h), RCA forced by (c) ERA-Int. and different GCMs (i-l) and (e) multimodel ensemble mean of CCLM and RCA4 forced by GCMs. The numbers in the bottom right corner show the pattern correlation. Stippling indicates grid points where there is added value by the dynamical downscaling.



 $Fig. \ S3 \ \ \text{Same as Figure S2 but for maximum number of consecutive dry days (CDD)}.$



 $\textbf{Fig. S4} \ \ \text{Same as Figure S2 but for heavy precipitation days (r10mm)}.$



 $\textbf{Fig. S5} \ \ \text{Same as Figure S2 but for maximum 5 day precipitation (RX5day)}.$

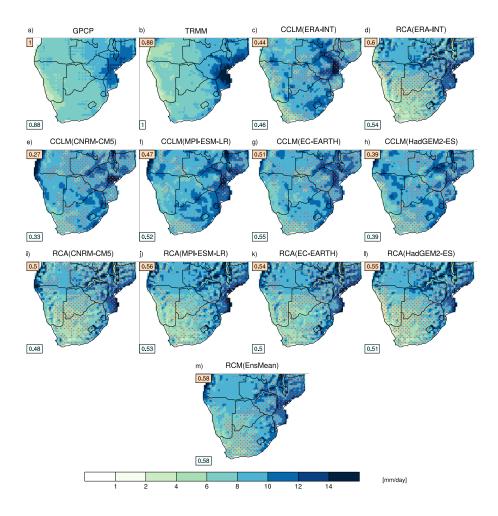
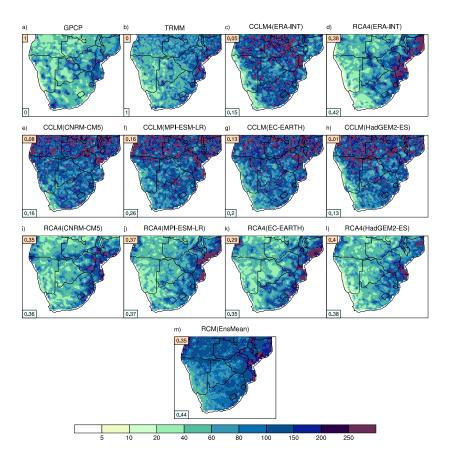


Fig. S6 Same as Figure S2 but for single daily precipitation intensity (SDII).



 $\begin{tabular}{ll} \textbf{Fig. S7} & 20-year \ return \ values \ of annual maximum \ daily \ precipitation \ (P_{20}) \ for \ the \ period \ 1997-2006 \ for \ (a) \ GPCP, \ (b) \ TRMM \ (1998-2005), \ CCLM \ forced \ by \ (c) \ ERA-Int. \ and \ different \ GCMs \ (e-h), \ RCA \ forced \ by \ (d) \ ERA-Int. \ and \ different \ GCMs \ (i-l) \ and \ (m) \ multi-model \ ensemble \ mean \ of \ CCLM \ and \ RCA4 \ forced \ by \ GCMs. \end{tabular}$

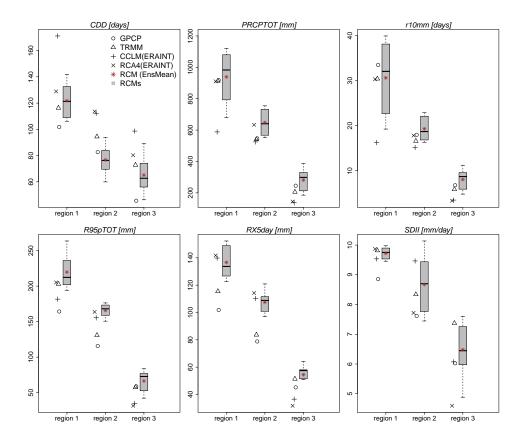


Fig. S8 Box-and-whisker plots for precipitation indices calculated from CCLM and RCA4 forced by GCMs. The boxes indicate the interquartile model spread (range between the 25th and 75th quantiles), the black solid marks within the boxes show the multimodel median and the whiskers indicate the full intermodel range. GPCP, TRMM, CCLM(ERAINT) and RCA4(ERAINT) are indicated in different shapes

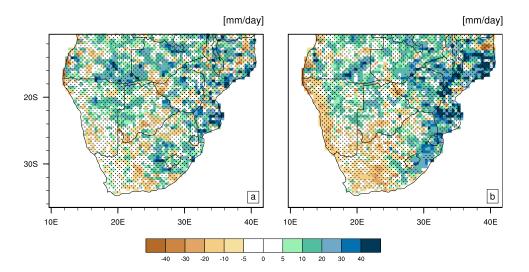


Fig. S9 Projected multimodel mean changes in 20-yr return values for maximum daily precipitation for the period of 2069-2098 under (a) RCP4.5, (b) RCP8.5 emission scenario, relative to the reference period 1976-2005. Stippling indicates grid points with changes that are not significant at the 5% significance level.

 $\textbf{Table S1} \ \ \text{Definitions of the indices of precipitation extremes used in this study.}$

Label	Index Name	Index definition	Units
R10mm	Heavy precipitation days	Number of days (per year) with precipitation amount ≥ 10 mm. Let	days
		PR_{ij} be the daily precipitation amount on day i in period j . Count the	
		number of days where $PR_{ij} \ge 10 \text{ mm}$	
CDD	Consecutive dry days	Maximum (annual) number of consecutive dry days. Let PR_{ij} be the	days
		daily precipitation amount on day i in period j . Count the largest number	
		of consecutive days where PR_{ij} ; 1 mm	
Rx5day	Highest 5-day precipita-	Maximum (annual) precipitation sums for 5-day interval. Let PR_{kj} be	mm
	tion amount	the precipitation amount for the 5 day interval ending k , period j . Then	
		maximum 5 day values for period j are: RX5day $_j$ = max (PR $_{kj}$)	
SDII	Simple daily intensity in-	Annual average precipitation from wet days. Let PR_{wj} be the daily pre-	mm/day
	dex	cipitation amount on wet days, $PR \ge 1$ mm in period j. If W represents	
		number of wet days in j, then: SDIIj = $(\sum_{w=1}^{W} PR_{wj})/W$	
R95 _p TOT	Very wet days	Annual total precipitation from days with PR \geq 95th percentile of the	mm
		distribution of daily precipitation amounts at days with 1 mm or more	
		precipitation in the 1976-2005 baseline period. Let PR_{wj} be the daily	
		precipitation amount on a wet day w (PR ≥ 1 mm) in period i and let	
		$PR_{wn}95$ be the 95th percentile of precipitation on wet days in the base-	
		line period (1976-2005). If W represents the number of wet days in the	
		period, then: $R95p_j = \sum_{W=1}^{W} PR_{wj}$, where PR_{wj} ; $PR_{wn}95$	
PRCPTOT	Total wet-day precipita-	Annual total precipitation from wet days. Let PR_{ij} be the daily precipi-	mm
	tion	tation amount on day i in period j . If I represents the number of days in	
		j , then: PRCPTOT $j = \sum_{i=1}^{J} PR_{ij}$	