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Do climate models agree on seasonal rainfall patterns and future changes over Southern Africa?

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Abstract

Understanding how rainfall will change over the southern Africa is a challenge, in part, due to large uncertainties in climate model projections. Using a large set of 201 global climate model simulations from the Coupled Model Intercomparison Project Phases 5 and 6 (CMIP5 and CMIP6) and 2018 UK Climate Projections (UKCP18), this study provides an in-depth investigation into future changes in southern African precipitation. Specifically, the spatial and temporal variation of model agreement, the intra- and inter-model uncertainties and the roles of interdecadal variability are examined. Model projections show agreement on drying over most of southern Africa in the dry season and the onset of the rainy season. Meanwhile in the main rainfall season, there is less agreement between models regarding the direction and magnitude of change over much of southern Africa, including in Zimbabwe, Mozambique, Zambia and Malawi. The range in future projections is not linked with biases in the historical climatology, and intra-model uncertainty analysis shows that multiple simulations of the same model often produce disagreeing projections in the sign of precipitation change when compared to the historical period. This highlights the importance of internal variability in influencing rainfall projections over southern Africa. For many models, this substantial interdecadal variability is greater than the projected future change. Given the large variability and uncertainty in models over southern Africa, impact and adaptation studies should consider the strong probability of both wet and dry years, and wet and dry decades, in the future.

Keywords Precipitation · Southern Africa · Climate change · Climate models · Climate variability · Climate projections

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1 Introduction

Understanding changing precipitation patterns associated with anthropogenic global warming is a key challenge in many regions of the world: southern Africa is no exception. The mechanisms driving southern Africa's climatology have been under-researched and under-evaluated, compared to other parts of the world (James et al. 2018). Precipitation observations show mixed signals in long-term trends (Douville et al. 2021) and there are many regions within southern Africa where observational data is insufficient to draw firm conclusions (Dosio et al. 2021). Furthermore, rainfall in this region is characterised by strong natural interannual to multi-decadal variability (Gaughan et al. 2016; Lüdecke et al. 2021). Climate models have shown some improvements in the representation of African precipitation over time (Almazroui et al. 2020; Tian and Dong 2020; Shongwe et al. 2015; Pinto et al. 2018) and generally show a decrease in annual mean rainfall over southern Africa in future (Douville et al. 2021). However, within the projected ensemble mean annual rainfall decline over southern Africa, there are large differences between models and seasons, which require further investigation.

This study provides a much-needed in-depth exploration of the potential contributing factors to the large range in projected seasonal rainfall in southern Africa. This includes: (a) an assessment of the temporal and spatial agreement of 201 simulations from 84 models – more than any other study to our knowledge, (b) evaluation of the intra-model agreement of models, (c) novel analysis of model families and (d) novel analysis of the role of interdecadal variability on uncertainty ranges. This represents a larger ensemble of data and deeper analysis than have been included in previous studies e.g (Dosio et al. 2021; Douville et al. 2021).

Over much of southern Africa (defined broadly as the continent south of 10°S), there is distinct rainfall seasonality, with a dry season in austral winter, June, July, August (JJA), and the primary rainy season during austral summer, December, January, February (DJF), which is vitally important for rain-fed agriculture (Archer et al. 2017; Bradshaw et al. 2022). Summer rainfall is driven by multiple processes, notably the southward migration of the tropical rainfall band (Dieppois et al. 2016), and associated with a range of weather systems including tropical lows (Howard and Washington 2020), tropical-extratropical cloud bands (Hart et al. 2010), mesoscale convective complexes (Blamey and Reason 2013), tropical cyclones (Reason and Keibel 2004) and cutoff lows (Singleton and Reason 2007). Although there is evidence that heavy precipitation extremes will increase in the region with global warming (Pohl et al. 2017), during the main rainy season (DJF), there is disagreement between climate models as to whether seasonal rainfall total is expected to increase or decrease (Dosio et al. 2019).

Climate models generally show strong agreement on drying during the austral winter dry season (Douville et al. 2021). At the onset of the rainfall season, between September and November (SON), many models suggest an ongoing trend from the recent past into the future that the rainfall season is being delayed. The physical mechanisms that could lead to a delayed onset of the rainfall season have been explored in recent research (Munday and Washington 2019; Howard and Washington 2020; Attwood et al. 2024). The Intergovernmental Panel on Climate Change (IPCC) also reports a reduction in the length of the rainy season across southern Africa by the end of this century (Dunning et al. 2018) with medium-high confidence (Douville et al. 2021). However, TAMSAT observations for the period 1985–2007 show a trend to earlier onset dates (Maidment et al. 2015; Dunning et al. 2018; Douville et al. 2021).

Therefore, important biases remain in the representation of African precipitation in climate models (Barimalala et al. 2024). In general for Africa, it has been challenging to reduce the range of future climate model projections through performance metrics (Rowell et al. 2016; Kolusu et al. 2021). The low agreement between models arguably means that a greater number of models should be included in projections to capture the full range of plausible futures. However, studies often use a subset of climate models that may not be representative of the range of potential futures that climate models project (Shiogama et al. 2021). Furthermore, the majority of studies into future projections are based on Multi-Model Ensembles (MMEs), using one realisation per model. Studies using Single Model Initial condition Large Ensembles (SMILES) and Perturbed Physics Ensembles (PPEs) suggest that these studies may not span the full range of uncertainty (Deser et al. 2020, James et al. 2014).

Therefore, there are outstanding questions regarding future rainfall change in southern Africa. In particular, would a more comprehensive analysis of modelled future changes provide additional consensus on drying during JJA and SON, or more clarity on DJF rainfall scenarios of importance for impact modellers or decision makers? There are also legitimate questions that must be addressed regarding the role of interannual to multidecadal variability in long term projections, including whether projected future changes exceed the range of interdecadal variability in the region.

This study addresses four specific research questions:

1. Where and when is there more or less agreement between Global Climate Models (GCMs) on projected rainfall changes over southern Africa?
2. Can we constrain the range of future change using observed climatologies?
3. How does the range of uncertainty in future projections vary between and within models (i.e. inter- and intra-model uncertainty)?
4. How does the magnitude of future projected changes vary over time, and compare to modelled interdecadal variability?

After detailing the data and methods used in Sect. 2, sub-sections within Sect. 3 present results addressing each of these research questions, with their implications discussed in Sect. 4.

2 Data and methods

2.1 Model data

Our analysis focuses on GCMs, which are widely used for impact analysis and provide the required forcing for Regional Climate Models (RCMs). Three GCM datasets were used: CMIP5 (Taylor et al. 2012), CMIP6 (Eyring et al. 2016) and UKCP18 (Lowe et al. 2019). We analyse historical scenarios and high emissions scenarios, Representative Concentration Pathway (RCP) 8.5 and Shared Socioeconomic Pathway (SSP) 5–8.5 (the large anthropogenic forcing in which allows us to most clearly identify climate change signals). Model simulations for the 5th and 6th Coupled Model Intercomparison Project (CMIP5 and CMIP6 respectively) were produced following a set experimental protocol. The data is freely available and was processed using ESMValTool (Righi et al. 2020) on the JASMIN data analysis facility. All model simulations for RCP8.5 in CMIP5 or SSP5-8.5 in CMIP6 with monthly precipitation output available through the Centre for Environmental Data Analysis (CEDA) Archive were processed. In total, this provided 186 simulations from 83 different models, some of which had up to 10 simulations (listed in Supplementary Table 1). We also analyse GCM simulations from the 2018 UK Climate Projections (UKCP18) produced by the Met Office Lowe et al. (2019): 15 simulations generated by perturbing physical parameters within a single model, HadGEM3–GC3.05, and run using CMIP5 forcing scenarios. These are also available through CEDA.

All model data was bilinearly regridded onto a 1° x 1° spatial grid. Anomalies in monthly precipitation were calculated from a baseline of 1985–2014, selected as the final 30 years of the historical forcing period of CMIP6. CMIP5 and UKCP18 simulations were forced with historical data until 2005, followed by RCP8.5 from 2006 to 2014, however any difference between historical cumulative emissions and RCP8.5 over this period are expected to be very minor (within 1%) (Schwalm et al. 2020). The baseline 1985–2014 was preferable to an earlier period (e.g. 1975–2004) due to greater availability of observational products for comparison. For all models, 2070–2099 was taken as the end of century period.

Although the study nominally includes 84 different models, in practice a number of these will have considerable overlap in their code and structure. This could be because they are updated versions of the same model, or because models from different groups and modelling centres are using the same core code or modules. These model 'families' were identified following Kuma et al. (2023). Additionally, the CMIP models were grouped according to those models used for climate impact modelling (Lange 2021) and RCM experiments (Dosio et al. 2021): *ISIMIP2b* and *ISIMIP3b* primary groups, ISIMIP3b primary and secondary groups (here, called *ISIMIP3b all*), *CORDEX* and CORDEX-CORE (here called *CORE*). CMIP5 and CMIP6 models have multiple simulations using different initialisations or physical parameters: these are referred to as *ripf* members. The paper includes all *ripf* members available. Ensemble means or statistics (e.g. shown in maps or Hovmüller diagrams) use only one *ripf* member per model, unless explicitly noted to include *all* CMIP members. Code is available through Github (https://github.com/ATK-A/AfricaPrecipPaper.git).

2.2 Observational data

Eight observation-based precipitation products (gauge-based, satellite-based or merged) were obtained covering 6 °N to − 36 °S and 11 °W to 51 °W: CHIRPS (Funk et al. 2015), CRU (Harris et al. 2023), GPCC (Ziese et al. 2018), GPCP (Adler et al. 2003), REGEN-ALL (Contractor et al. 2020), MSWEP (Beck et al. 2017), PERSIANN-CDR (Ashouri et al. 2015) and TAMSAT (Maidment et al. 2017). Further details on these datasets are listed in Supplementary Table 2. For daily products, monthly means were calculated. All data was then regridded onto a 1° x 1° spatial grid for comparison with the model data. A 1° x 1° land-sea mask was derived from the observational data, with land taken as points where all observational datasets had data available. This mask was used for all area averaging carried out on observational or model simulation data. All spatial domains used in the analysis are defined in Supplementary Table 3.

2.3 Seasonal delineation

It is important to consider that the seasonal delineations into three-month blocks (JJA, SON, DJF and March-May; MAM) are relatively simplistic and across this region there will be significant variations around these (Wainwright et al. 2021). Other seasonal definitions have been proposed for different sub-regions within southern Africa. For example, Van Der Walt and Fitchett (2020) and Roffe et al. (2021) use October-March as the summer season, but this is defined based upon the climatology of South Africa. Additionally, previous research has effectively carried out analysis by month (Attwood et al. 2024; Hart et al. 2018). Therefore for some analysis we include month-by-month analysis to highlight when trends or patterns vary around the main seasonal breakdown and we include one figure as an example for the October-March period. However, for brevity we do not include all variations of all figures.

3 Results

Analysis in this study is carried out in four parts to address each of our research questions. First, Sect. 3.1 examines the modelled spatial and sub-annual patterns of baseline and projected rainfall change, highlighting areas of agreement or disagreement over the whole of southern Africa. In Sect. 3.2, model simulations of the baseline period are compared to observations to assess if the ensemble range can be constrained by removing models that are unrealistically biassed. In Sect. 3.3, a detailed assessment of agreement between different model ensembles and model groupings is presented, highlighting uncertainties for key sub-regions within southern Africa. In Sect. 3.4, projected changes are placed in the context of interdecadal variability, first for sub-regions before showing the implications this has for interpreting projected change over the whole of southern Africa.

3.1 Where and when is there more or less agreement between GCMs on projected rainfall changes over southern Africa?

CMIP6 models have a clear annual cycle of precipitation over southern Africa (Fig. 1a–d). In JJA there is very little rainfall over the region. In SON as the overhead sun moves southwards, rainfall increases, spreading from the Congo basin, and by DJF the rainfall maximum is reached over most of the region. During MAM, the rain belt moves northwards again. Comparable figures for CMIP5, UKCP18 and observations are shown in Supplementary Figures 1–3. Figure 2a further illustrates the seasonal migration of precipitation over southern Africa, with the rain belt moving southwards during austral summer, peaking around 15 °S in January.

The CMIP6 ensemble mean projections for the late 21st Century during JJA and SON (Fig. 1e,f) show relatively strong agreement on a drying trend over much of the region. DJF and MAM (Fig. 1g,h) have less agreement. For these months, only western southern Africa shows agreement on drying, while tropical Central and East African regions show projected wetter conditions. Eastern South Africa and southwestern Madagascar also show wetting in DJF but with less model agreement. CMIP5 shows similar but less intense spatial patterns of projected trends to CMIP6 (Supplementary Figure 1). When CMIP6 projections are

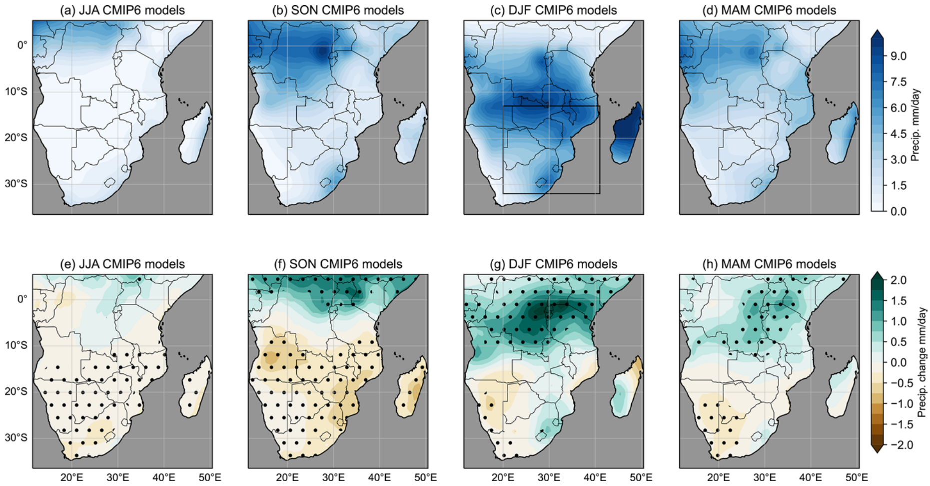


Fig. 1 CMIP6 ensemble mean seasonal precipitation for the baseline period 1985–2014 (**a-d**) and SSP5-8.5 projected change in seasonal precipitation between 1985–2014 and 2070–2099, with stippling to indicate where > 80% of models agree on the direction of change (**e-h**). Here, ensemble mean and stippling is calculated using one *ripf* simulation per CMIP6 model. Black box in (**c**) is the summer rainfall region used in subsequent figures

averaged zonally and by month (Fig. 2b), the drying during the onset to the summer rainfall season is evident, particularly between 10 and 20 °S, with strong agreement across the models. Generally, the main DJF rainfall season shows a low ensemble mean change, due to low model agreement. The spatial pattern of projected change in precipitation is notably different in UKCP18 (Supplementary Figure 2). In DJF, UKCP18 shows an east-west contrast, with wetting in eastern regions and drying in western regions.

The multi-model ensemble plots (Figs. 1, 2a,b) conceal considerable variation between models as well as considerable precipitation biases in many CMIP models, which we illustrate by comparing regional means over the summer rainfall region from *all* CMIP5 and CMIP6 models in Fig. 2c–d. Figure 2d shows the range of future changes across CMIP5 and CMIP6. There is relatively broad model agreement on drying from May-October, but with a large range between models in the magnitude of this drying, particularly during October. During November-March, there is a huge amount of uncertainty in the model response, with little or no consensus.

Standard deviation and coefficient of variation (CV) (Fig. 3a–h) both illustrate this large variation in the magnitude of future change. Standard deviation (CV) is more likely to show larger values over wetter (drier) parts of the region. Regions that showed model consensus in the direction of change (stippling) in Fig. 1e–h also exhibit low inter-model standard deviation and CV (Fig. 3a–h). Meanwhile, both DJF and MAM have particularly low agreement, with a large CV in the projected changes over large swathes of southern Africa. Fig. 3i-l shows the percentage of models agreeing on the direction of future change in precipitation. For DJF, there is a dipole response in the number of models projecting wetting or drying over southern Africa, with Namibia and western South Africa predominantly drying and eastern South Africa, Lesotho and eSwatini predominantly wetting (Fig. 3k). The same

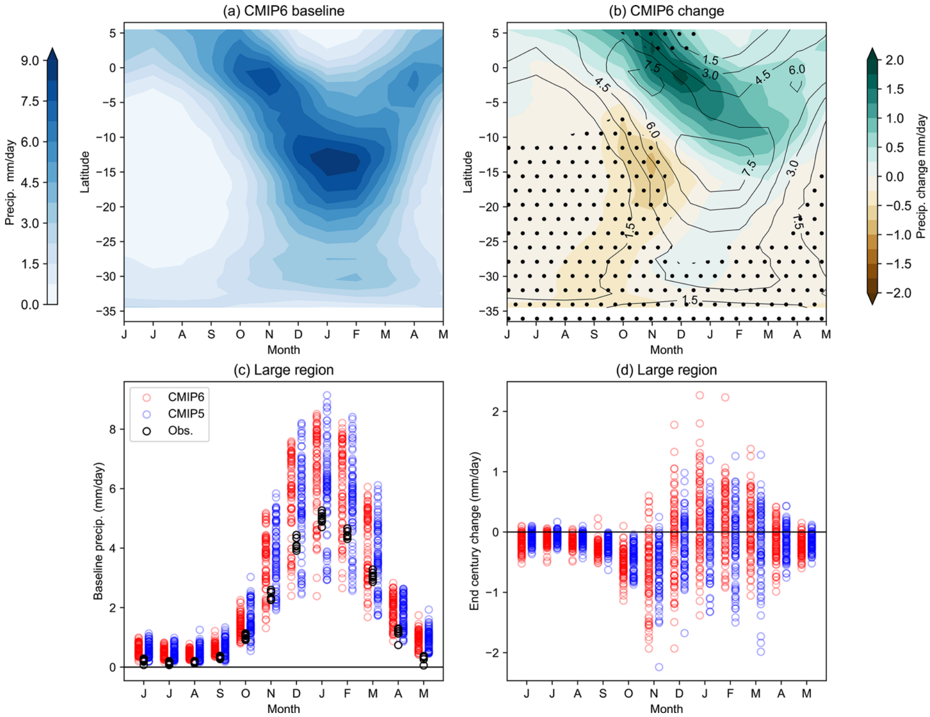


Fig. 2 Hovmüller plots showing CMIP6 ensemble monthly zonal mean precipitation (mm/day) over land for (**a**) baseline (1985–2014) and (**b**) SSP5-8.5 future (2070–2099) change (colours) from the baseline (black contours). Stippling in (**b**) shows where 80% of models agree on the direction of change. In (**a**) and (**b**), ensemble mean is calculated using one *ripf* simulation per CMIP6 model. (**c**) and (**d**) show baseline and projected change in precipitation over the region marked in Fig. 1c for each calendar month from *all* available CMIP5 and CMIP6 *ripf* simulations, with the 8 observational products marked for the baseline

figure for CMIP5 shows very similar results, indicating that there has been little change in model agreement between CMIP5 and CMIP6 (Supplementary Figure 4).

Acknowledging that the seasonal delineation we have chosen here is relatively simplistic, we also include month-by-month maps of percentage CMIP6 model agreement on direction of change in Supplementary Fig. 5. The relatively mixed signal for MAM is a result of these months being combined, with May having a much closer resemblance to JJA and March more closely resembling January and February. The widespread agreement on drying of SON is particularly pronounced in September and October, with November already having lower consensus on the direction of change, similar to DJF. Supplementary Fig. 6 shows an example of an alternative seasonal definition, October-March, which has been used for South Africa e.g (Roffe et al. 2021). Comparing this season to the rainy season that we have used (DJF), there is a slightly greater tendency for mean drying across southern Africa, with stronger agreement on drying in western parts of the domain. This is due to the inclusion of October and November that had clearer consensus on drying than DJF. However, across central and eastern regions, there is still not strong consensus on the direction of change. Therefore, there is some sensitivity in the results to seasonal definition, but disagreement on sign of change still persists for other definitions.

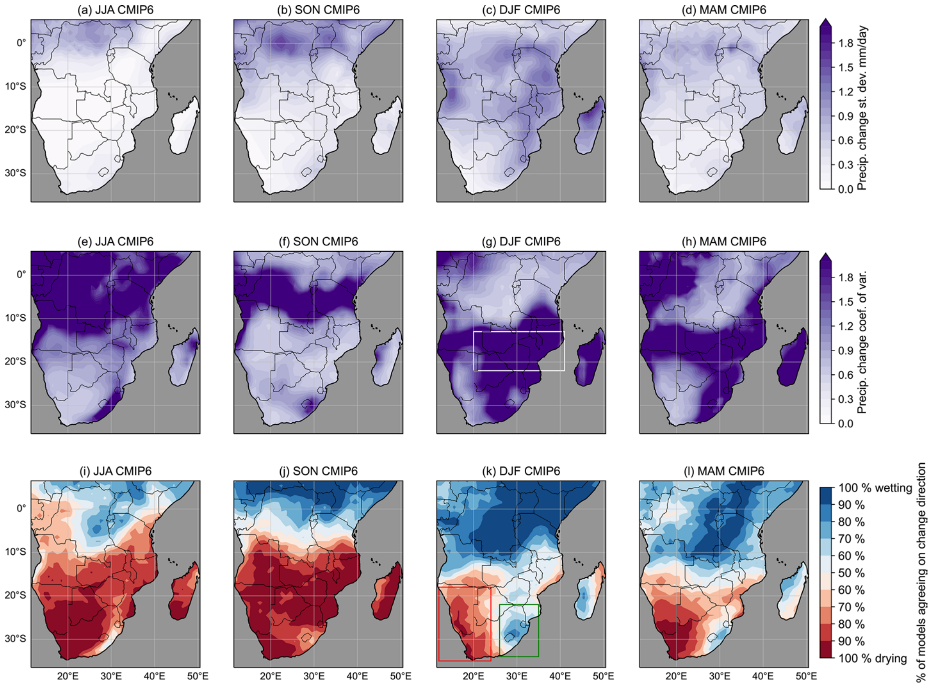


Fig. 3 CMIP6 ensemble statistics for precipitation change by the end of the 21st Century in SSP5-8.5, showing inter-model standard deviation (**a-d**) and coefficient of variation (**e-h**) in precipitation change; and percentage of models agreeing on direction of change (wetting or drying; **i-l**). The white box in (**g**) shows a particularly uncertain northeastern region (hereafter 'northeastern' region), while the boxes in (**k**) show a dipole response between the western and eastern regions. Here, ensemble statistics are calculated using one *ripf* simulation per CMIP6 model

Using Fig. 3 we identify three sub-regions for further analysis. The northeastern part of the summer rainfall region (white box in Fig. 3g) exhibits particularly high standard deviation and CV values, plus low agreement on direction of change in DJF. The bipolar response in terms of ensemble agreement on direction of change in DJF is represented by the red and green boxes in Fig. 3k. In the next sections, we explore the model (dis)agreement in greater depth to address the second and third research questions for these different sub-regions and seasons.

3.2 Can we constrain the range of future change using observed climatologies?

The results in Sect. 3.1 highlighted the diversity in model behaviour across CMIP models, which presents a challenge in synthesising where or when there is consensus on projected change. It is important to assess the simulated precipitation of individual models to understand if certain models or groups of models behave in similar ways and if the model range can be constrained by observations.

Looking first at model biases relative to observations, for JJA in Fig. 2c, none of the observational products shows more than 0.2 mm/day of rainfall, while many of the models show a wet bias with up to 1.1 mm/day. During the wetter months, many of the models again overestimate rainfall, with a modelled range in January of 2.4–9.1 mm/day, compared to observed values of ~5.0 mm/day. The wettest models therefore overestimate rainfall relative to observations by over 80%. Supplementary Figure 7 and 8 illustrate that in many places almost all models are outside of the range of observational products.

We next consider if there is a relationship between the baseline and future precipitation change. Figure 4 shows how *all* individual simulations from the three ensembles compare in terms of baseline and projected change in seasonal rainfall for the summer rainfall, western, and eastern regions, indicating that there is little correlation between the baseline precipitation and projected change. There is evidence of heteroscedasticity (the range of projected changes increases with a larger precipitation baseline), which combines with a slightly negative correlation for JJA and SON in the summer rainfall region. However, there is considerable noise and for DJF (for any region) and MAM (for the summer rainfall region) there is little or no correlation. It is again illuminating to see how the models' baseline precipitation compares with the range in the observational datasets (vertical grey band).

Model biases and the lack of relationship suggest it could be challenging to constrain the range of future changes based on evaluation against observations. It could be argued that those models whose baseline rainfall falls within the observed range are the most trustworthy. If this were applied as a constraint, it would reduce the range of future projections substantially, although projections for DJF and MAM would still show no agreement on

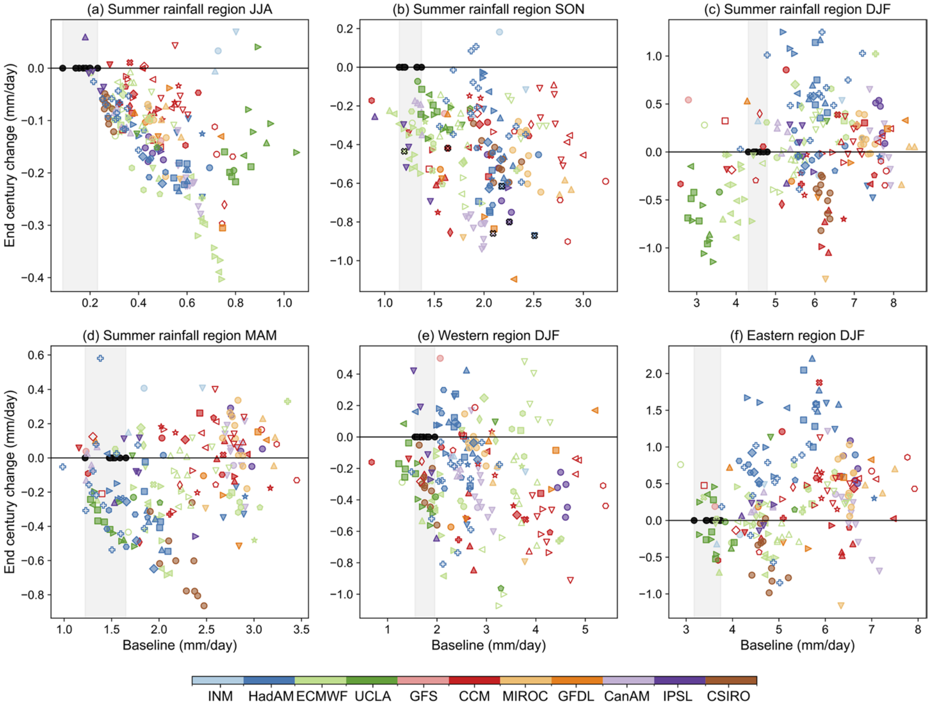


Fig. 4 CMIP5 and CMIP6 1985–2014 baseline and projected change by 2070–2099 in precipitation over the four seasons for the summer rainfall region and DJF for the western and eastern regions, in RCP8.5/SSP5-8.5. Each model is coloured according to its model family. The 8 observational products for the baseline period are shown by the black dots, with vertical shading showing the range. A full legend showing which marker represents which model is available in supplementary figure 10

increasing or decreasing precipitation. It is also noteworthy that no models are within the observational range for all regions and seasons.

Here we have only explored observational constraints using the observed rainfall climatology. There are many other precipitation metrics that could be used to explore constraints, such as onset dates, variability and extremes indices. Previous research with CMIP5 has demonstrated that it is very challenging to constrain projections using such indices (Rowell et al. 2016), in part because none of the models perform well for all metrics. Evaluation of processes associated with rainfall has also struggled to constrain CMIP ensembles over Africa (James et al. 2018, 2020; Barimalala et al. 2024). This suggests that any observational constraints should be applied cautiously. JJA is potentially a more straightforward case, since for many models the magnitude of projected drying exceeds the observed rainfall for the recent baseline period (Supplementary Fig. 9).

A monthly breakdown for the summer rainfall region (Supplementary Figure 10) shows interesting variations at the start and end of the broader rainfall season. In September, the models more closely resemble those in JJA than they do the SON mean, meanwhile May has the broadest observational range, which many models lie within. For the core rainfall season, DJF, individually assessing the months does not provide any further clarity or consensus within the models: all individual months also have little or no relationship, with change spanning zero.

3.3 How does the range of uncertainty in future projections vary between and within models?

Having identified in Sect. 3.2 that constraining the range in model projections based upon historical observations remains challenging, it is vital to consider the origin of the uncertainty range in model projections. Specifically, we wish to consider if certain models, model groups or families have more variability than others within the ensembles studied here.

In Fig. 4, model simulations from the same family, as defined by Kuma et al. (2023), have the same colour, while *ripf* simulations from exactly the same model have the same marker shape. Across the seasons and regions, it is possible to see examples of clustering both by individual model and by model family. For example, in terms of the baseline precipitation, the CanAM family (lilac) are clearly split into a grouping of CanESM2 (upward triangles) and CanESM5(−CanOE) (downward triangles and circles). Some model families show a wider spread: for example, the UCLA family (dark green) has clustering of variants of GISS-E2, but the related MRI models (downward triangles and pentagons) behave quite differently in terms of baseline and/or future change in precipitation.

Taking the summer rainfall region in DJF, it can be seen that some model families largely or exclusively respond in a given direction, for example the UCLA and CSIRO models exhibit drying. However, although many of the HadAM models show the largest wetting trends and likely contribute a positive pull to the overall CMIP ensemble mean, not every HadAM model shows wetting. The overall spread in the projections in terms of wetting vs. drying cannot be attributed purely to certain opposing families of models.

Clustering of models by family has implications for how models are used: models that are nominally described as independent and come from different modelling groups may in fact be very similar in terms of both their underlying code and behaviour. This could be an issue if model consensus is taken to infer likelihood of a future change. The analysis here suggests for rainfall over southern Africa, this is unlikely to be a serious issue. Families that generally cluster strongly such as CSIRO and UCLA contain limited models that are unlikely to be mistaken for being independent (i.e. GISS- variants are clearly related). On the other hand, model families with the largest number of members from diverse institutions, such as CCM and ECMWF, show large spread across this season with no clear sign of clustering. An initial exploration of clustering using DBSCAN (Schubert et al. 2017) (not shown) indicates that statistically identified clusters are not clearly correlated with the model families shown in Fig. 4.

Inter-model and intra-model spread in the model simulations is further summarised in Fig. 5. It shows how the single *ripf* ensemble members (denoted 'CMIP6') used in producing the multi-model statistics in Figs. 1–3 (except Fig. 2c,d) compare with *all* available *ripf* ensemble members in the CMIP6 archive shown in Fig. 4 (denoted 'CMIP6 all'), and likewise for CMIP5. It also shows the typical intra-model spread due to different initial conditions or perturbed parameters for models with more than 5 *ripf* ensemble members and variability between models used in climate impact modelling and RCM experiments.

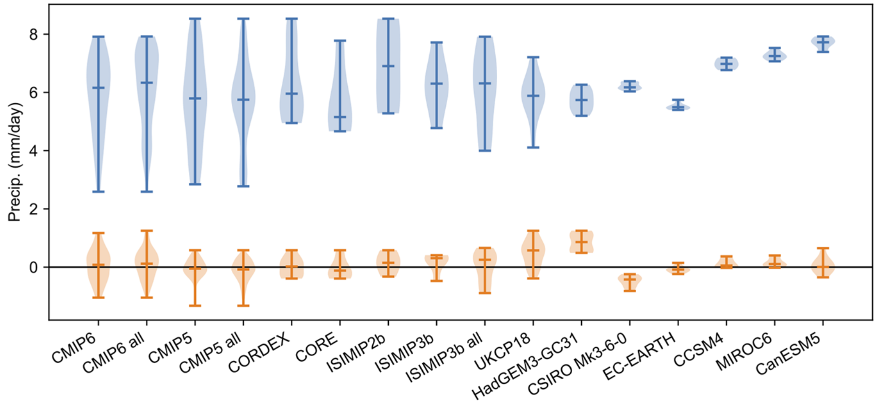
Focusing first on the projected change in CMIP6 results, the ranges shown reflect the findings from Figs. 1–3: for the summer rainfall region, the median of the projections is near zero, with models showing both increases and decreases in precipitation. Meanwhile, for the western (eastern) region, the median response is drying (wetting), with the majority of the distribution lying below (above) zero. It is notable that, for every region, the range in projected change spans both positive and negative values, highlighting that it is not possible to summarise the information into a unidirectional change statement for the region, which creates a communication challenge. This includes the northeastern region, which had a similar pattern to Fig. 5a but with wider ranges (not shown).

Comparing CMIP6 with CMIP5, there is little difference in the median future change response, however, the distributions are different. For all regions, the CMIP6 range extends further towards wetting and the CMIP5 range extends further towards drying. Comparing the single realisations from CMIP5 and CMIP6 (one *ripf* member per model) with the full ensembles *CMIP6 all* and *CMIP5 all,* it appears that single realisations can broadly capture the ranges for both baseline and projected change.

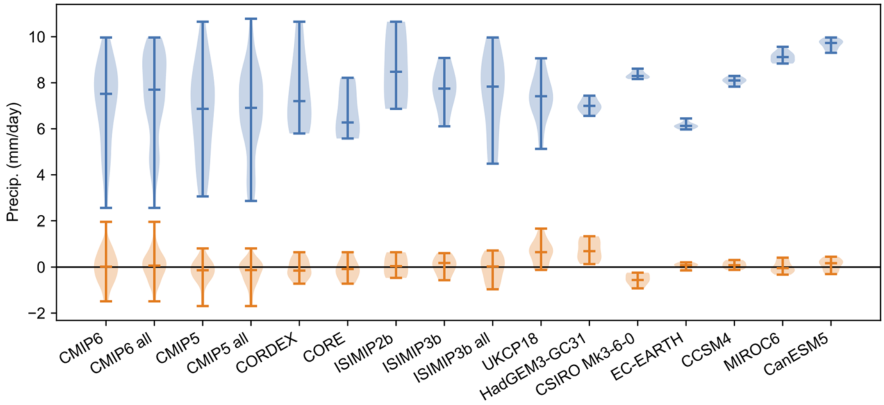
The subsets of models used for climate impact assessments *ISIMIP2b*, *ISIMIP3b* and *ISIMIP3b all*, and the driving GCMs used in *CORDEX* and *CORE*, generally show reduced ranges in baseline precipitation and projected change compared to *CMIP6* and *CMIP5*. The RCMs used within *CORDEX* and *CORE* may respond differently from their driving GCMs (Dosio et al. 2019), however it is important to consider that studies relying solely on these models may not be sampling the full range of future precipitation changes. This is particularly true for DJF: for MAM, JJA and SON (Supplementary Fig. 11), the subsets capture a range closer to the full ensembles.

The intra-model ranges for ensembles from individual models are typically 10–20% of the CMIP inter-model range for the baseline period. For the projected change, the intra-model range is relatively larger, with some models showing around 50% of the range in the CMIP ensembles. It is hard to draw out many consistent variations between the individual models shown in Fig. 5, although the HadGEM3–GC31 models (note this includes both HadGEM3–GC31-LL and HadGEM3–GC31-MM) have a tendency towards increased precipitation while CSIRO Mk3-6–0 is prone to drying trends across all regions. With the exception of the eastern region, UKCP18 has a larger spread in both baseline and projected

(a) Summer rainfall region DJF



(b) Western region DJF



(c) Eastern region DJF

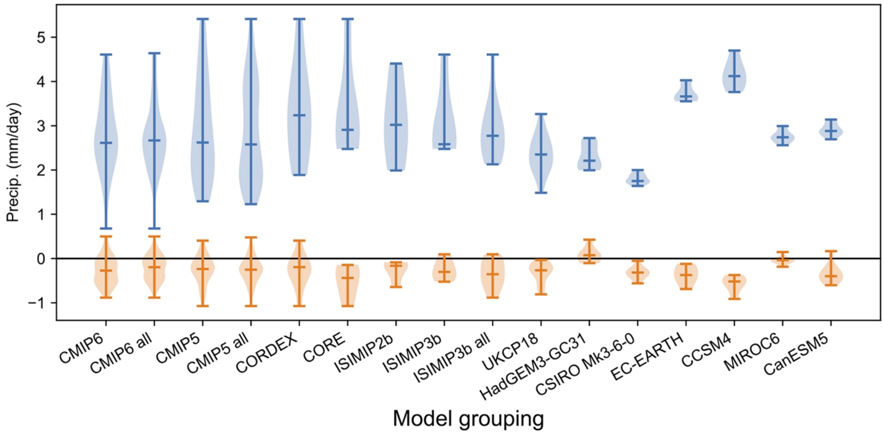


Fig. 5 Ranges of DJF baseline precipitation and projected change over three regions for different subsets in the model ensemble, including CMIP6 and CMIP5 (1 simulation per model and *all* simulations), UKCP18 and HadGEM3-GC31, and 5 models which had more than 5 *ripf* members. The colours indicate the baseline 1985-2014 (blue) and future change by 2070-2099 in RCP8.5/SSP5-8.5 (orange) and the width of the shading gives an indication of the ensemble distribution. Central horizontal lines show the median value, with upper and lower horizontal lines showing the full range

changes than the HadGEM3–GC31 models, reflecting both the larger size of this ensemble and the effort made in the development of that ensemble to capture a wide range of perturbed physics conditions.

These relatively large precipitation ranges between simulations from the same model suggest a potential role for interdecadal variability in modelled rainfall over this region, warranting further examination of longer-term temporal variability in the final section of our analysis.

3.4 How does the magnitude of future projected changes vary over time, and compare to modelled interdecadal variability?

Supplementary Figure 12 shows time series of observed precipitation over the summer rainfall region, smoothed with a 20-year running mean. Since the 1980s, there is generally drying in SON and wetting in DJF and MAM. However, this is not part of a long-term trend and long periods of wetter and drier conditions during the 20th Century are observed. Analysis of long-term variability in historical model simulations based on standard deviation of smoothed time series (Supplementary Figure 13), suggests that many models have similar or larger long-term variability than CRU or GPCC. Therefore, it is important to consider the range of interdecadal variability within climate model projections on these longer timescales, which could be skewing the projected changes. It is possible that when calculating future change between two climatological periods (as in Figs. 1–5) the magnitude of projected change could be biased by either the baseline and/or future period capturing a peak or trough in interdecadal variability.

Climate stripes for CMIP simulations illustrate the variations within a smoothed timeseries for the 21st Century (Fig. 6) . It is striking to note the diversity in model behaviour, with some models remaining within the historic range of variability (shown by hatching) throughout the entire 21st Century, while others very quickly move into future rainfall regimes that are outside the range in the modelled past. The DJF season has the most divergent range of signals across the ensemble. Similar plots were generated for other regions and seasons (Supplementary Figure 14). For JJA and SON, they show agreement on drying, with the change signal exceeding historical variability by the 2050s in most models. For MAM, many more models lie within the range of historic variability for the entire future period. Many models do not exceed the range of historic variability until the second half of the 21st Century. Therefore, near-term changes might be expected to be within the historic range and, depending on the emissions scenario, even the future changes at the end century might not greatly exceed those that have been observed throughout the 20th Century.

Often, we examine consensus in rainfall projections in terms of the direction of change (as in Fig. 1,3), however this can conceal agreement between models on minimal change or continued variability in future. To further examine future projections through the lens of past variability, model years are categorised by when projected end of century precipitation lies in either the upper, middle or lower tercile of the 1901–2000 modelled precipitation (Fig. 7). In this figure, if there were no change in future climate relative to past climate and the end of century were typical in terms of natural variability, ~ 33% of model years would lie in each tercile and shading would be mainly white.

For JJA, over the majority of the southern African rainfall region, many future model years (shown in green) lie in the lower, drier tercile, and few (shown in pink) lie in the

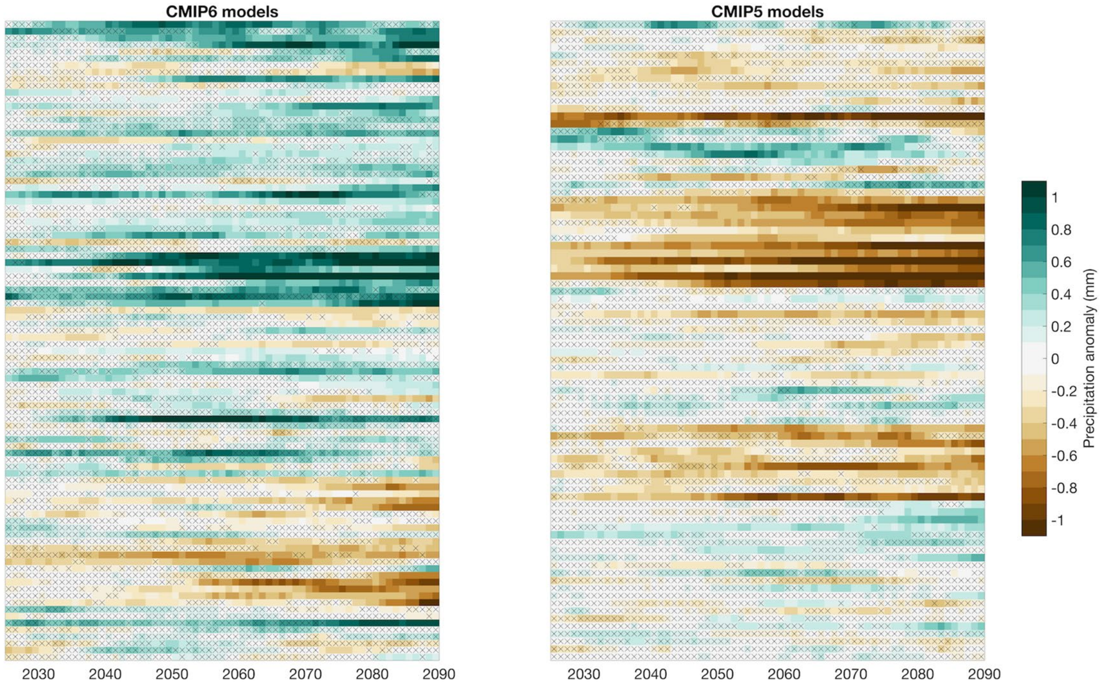


Fig. 6 Stripes plot showing the future change in 20-year running mean of precipitation relative to the 1985–2014 baseline over the summer rainfall region for DJF (magnitude of change indicated by colour shading, with time progressing along x-axis). All CMIP5 RCP8.5 and CMIP6 SSP5-8.5 ensemble members that had complete time series back to 1901 were included (individual rows for each model on y-axis). For each given model, years that lie within the range of modelled historic minimum and maximum precipitation (i.e. the minimum and maximum from the 20-year running mean for the period 1901–2000) are hatched.

upper, wetter tercile; indicating that the drying is associated with a shift toward more below normal years. In SON, over a large proportion of the domain, the majority of model years lie in the middle tercile, and there are very few in the upper tercile. Eastern South Africa is an exception, showing many model years below normal. This indicates that the drying in SON is associated with a reduction in 'above normal' years, and an increase in 'normal' years over much of the domain, and 'below normal' years over eastern South Africa. In DJF and MAM, the colours are more muted, indicating less change, or less consistent change across the ensemble – changes in one model can cancel out changes in another model in this figure. In general, for most of the summer rainfall region during DJF, there are many future model years within the middle tercile, and fewer in the lower and upper terciles, with the exception of eastern South Africa, which shows more above normal years in future. Displaying the data in this way, rather than focussing on a binary of wetting or drying in future, highlights that models show many 'normal' years in future climate.

Analysis of modes of variability in global sea surface temperatures (SST) could explain some of this variability. Observations (CRU, GPCC and HadSST; Kennedy et al. 2019) show a statistically significant negative correlation between precipitation over the summer rainfall region and SST in the tropical Pacific and Indian oceans (Supplementary Fig. 15). This is consistent with El Niño Southern Oscillation (ENSO) and (Southern) Indian Ocean Dipole being drivers of rainfall in this region. This result is robust to using raw or detrended observational data.

In contrast, maps of correlation and statistical significance in a selection of CMIP6 models show varying signals between the past and future periods, between different models (Supplementary Figure 16) and within the ensemble of CanESM5 (Supplementary Figure 17). Only CNRM-ESM2-1 and NorESM2-MM show statistically significant negative correlations in the Niño 3.4 region for both the past and future, but these models show many other statistically significant correlations that are inconsistent with each other. CanESM5 members show very different correlation patterns, diverging and insignificant patterns for the Niño 3.4 region and nowhere that 7 or more out of the 10 members have a statistically significant relationship. These complex relationships between modelled precipitation over southern Africa and global SSTs show that understanding the mechanisms driving the internal variability is not straightforward, requiring further research, including simulation-by-simulation investigation beyond the scope of this paper.

4 Discussion and conclusions

Changes in southern African precipitation could have huge implications for societies, economies, and ecosystems. In this paper we undertook an in-depth analysis of all-season rainfall change in 201 GCM simulations, which to our knowledge is the largest set of models analysed. This complements and builds upon previous literature that has investigated future change in southern African rainfall (Munday and Washington 2019; Pohl et al. 2017; Pinto et al. 2018), using smaller subsets of models or a specific season. In agreement with previous studies, we find that most models agree on future change in JJA and SON, when the majority of southern Africa is projected to dry and exhibit a delayed onset of the rainfall period (Dunning et al. 2018; Wainwright et al. 2021). As highlighted previously (Munday and Washington 2019), model projections diverge for the main rainy season (DJF) and we

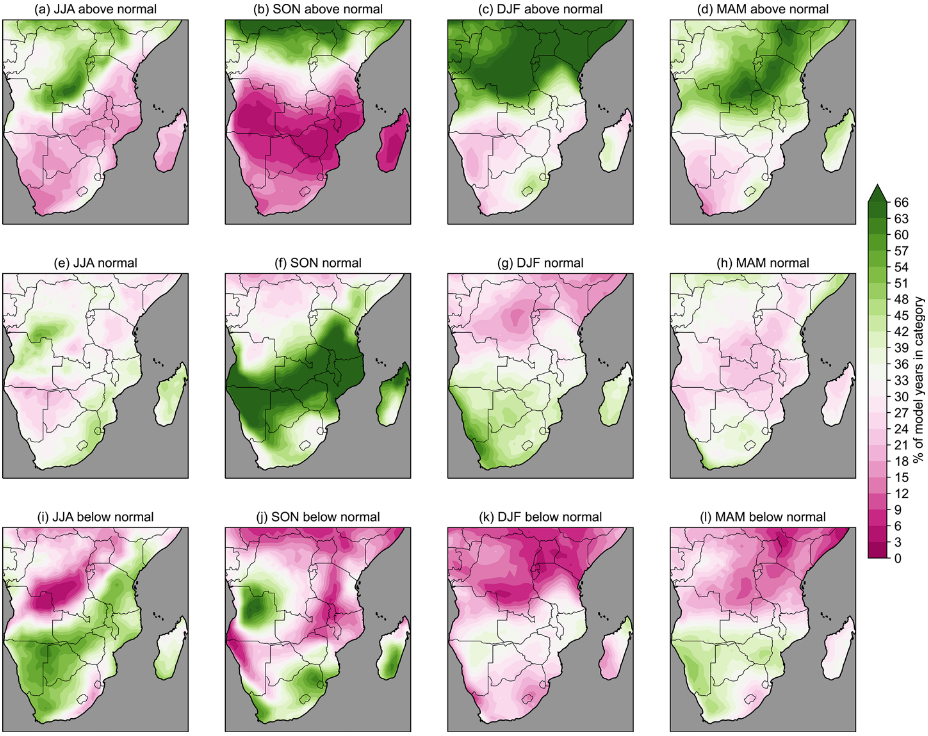


Fig. 7 Maps showing percentage of model years for the period 2070-2099 that have seasonal precipitation within each tercile of the 1901-2000 precipitation, for the upper/wetter tercile **(a-d)**, the middle tercile **(e-h)** or lower/drier tercile **(i-l)**. Here, one ripf simulation per CMIP6 model is used forced with SSP5-8.5. Tercile bounds are calculated for each model individually.

explore this further to identify where there is more or less agreement. For the end of the 21st Century many models show a drying trend in western South Africa and Namibia, and wetting in eastern South Africa, Lesotho, and eSwatini. However, over large parts of southern Africa (Zimbabwe, Mozambique, Zambia, Malawi, Madagascar) model projections for the end of the 21st Century are split, with some suggesting it will get wetter, and some suggesting it will get drier. In MAM there is again divergence between model projections, with the exception of the dry western southern Africa region which is, as in other seasons, generally projected to get drier.

We investigated historical biases in the models, which are often suggested as a constraint on future projections. In general, most models are wet biased over much of southern Africa for all seasons, as has been the case since CMIP3, despite some small improvements (Tian and Dong 2020). This wet bias has been linked to representation of the Angolan Low (Munday and Washington 2017), topography and moisture transport (Munday and Washington 2018; Barimalala et al. 2024; Dosio et al. 2019). So, can the model biases be used to constrain future projections? For JJA, arguably yes. We find that most models start from a wet baseline, with 70% or more of CMIP6 projecting drying that is – in absolute terms – larger than the current climatology. Analysis on a monthly basis shows there are some variations within seasons, for example more models lie within the observational range for May, while

June and September also have a wet baseline. However, for other seasons, it is more difficult to apply an observational constraint, and there is little or no relationship between historical climatologies and future change. Furthermore, even if only those models with climatologies within the observed range were considered, the future projections would still span zero, with some models showing increases and some showing decreases in precipitation. This resonates with previous research in which performance metrics were unable to reduce the range of future projections over Africa (Rowell et al. 2016).

To better understand the large divergence in climate model projections (especially for DJF), we compared ranges from different models, different runs from the same model, and different model families. In many cases calculating the inter-model range based upon a single ensemble member from each model in CMIP5 or CMIP6 will largely capture similar variability to using all available ensemble members and this would be a suitable compromise if computing resources are limited. However, intra-model uncertainty is still considerable, with individual models exhibiting up to 10–20 and 50% of full ensemble variability for the baseline and change respectively. This result is based upon only relatively small samples of simulations with single models, the largest being UKCP18 with 15 simulations. Large ensembles with single models (SMILES) could provide further insights (Deser et al. 2020; Lehner and Deser 2023; Monerie et al. 2024). Meanwhile, families of models (Kuma et al. 2023) show some evidence of clustering, but this is scale and variable dependent. In some cases, models from the same family, particularly large families such as CCM and ECMWF, still show a large range of future projections. It is understandable that many studies leverage simulations and data from CORDEX and ISIMIP, given the potential benefits of having higher resolution or bias corrected results. From an academic perspective, this may be adequate, however in the case of making an adaptation or policy decision, our results suggest it is advisable to consider other models outside of these subsets, as for certain sub-regions, they may only capture a fraction of the variability.

The large intra-model uncertainty suggests an important role for internal variability and prompted investigation into interdecadal variability and relationships with global SST patterns. Observed datasets show prolonged wetter and drier periods during the 20th Century. Many models show similar or larger interdecadal variability to observations, and for some models and seasons this variability is of a comparable magnitude to projected changes by the end of the 21st Century. This highlights the importance of variability over time as a key feature, which might help us better understand model projections, in agreement with Monerie et al. (2024). When examining changes for the end of the 21st Century and focusing on a binary distinction between wetting and drying, we find strong disagreement between climate models over large parts of southern Africa during DJF and MAM. However, at least part of this divergence between models is due to interdecadal variability, and in fact there might be more agreement between models that both wetter and drier periods can be expected in future, as well as many 'normal' years.

It is also worth highlighting that our analysis is limited to high emissions scenarios. If we were to investigate additional mitigation scenarios we might find even more evidence of variability over unidirectional change. It is important that climate change adaptation planning has an emphasis on managing variability: the models analysed here suggest that wet and dry years, and wet and dry periods could continue throughout the twenty-first century. In the absence of clear consensus on the direction of change during DJF and MAM, it may be more productive to focus on managing variability than preparing for long term change in mean rainfall. From a research perspective, given the importance of internal variability, continuing to build a better empirical and conceptual understanding of the large-scale teleconnections and drivers in this region will be important, for example the role of the Angola Low variability in driving moisture transport into the region (Monerie et al. 2024), or changes in variability of and southern African response to ENSO (Steinkopf and Engelbrecht 2025).

In summary, we have provided new information on agreement in modelled precipitation changes and highlighted the importance of natural variability for the region in different seasons. We find strong agreement between models that JJA is likely to get drier, although it may not lead to substantial impacts in this already very dry season. For SON, we also find strong model agreement on future drying: in many models this is larger than interdecadal variability and it is consistent with a recent drying in observational datasets. Process-based model evaluation and comparison with recent trends has indicated plausible mechanisms to explain the SON drying (Munday and Washington 2019, Howard and Washington 2020, Attwood et al. 2024), and further investigation should focus on whether these drivers of recent trends are consistent with model responses. For DJF and MAM, agreement on wetting and drying signals are limited to specific regions and, over much of southern Africa, the dominant signal is perhaps interdecadal variability, which is pronounced in many models and evident in past observations.

To conclude, it is very important that potential changes in rainfall during these seasons are understood, with summer in particular a key season for livelihoods, economy and food and water security. Given the challenge of taking many model simulations into account, it is tempting for impacts and adaptation work to focus on either the model consensus, or a small subset of models. This paper suggests that such an approach, if not applied carefully, could lead to maladaptation. Consensus may be due to model families or corresponding internal variability rather than a consistent forced response. A sub-set of models (selected for ISIMIP, CORDEX, or another project) may only capture a reduced range of signals. Research to investigate the physical processes and driving mechanisms behind both variability and change could help identify plausible futures, ruling out models shown to be behaving in physically implausible ways (Rowell et al. 2016; Pinto et al. 2018; Daron et al. 2019). Our analysis of model families suggests that model groupings could be used to direct such analyses. In the meantime, for much of this region, it is necessary to plan for both wetter and drier conditions (Siderius et al. 2021), due to the range of uncertainty and the significant internal, multi-annual variability in precipitation.

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Author contributions AKA: primary analysis, figure production and initial text draft. RAJ: project conception, supervision of analysis, text editing. JD: data and result interpretation, text editing. AC: data and result interpretation, text editing. CDJ: data and result interpretation. PW: data and result interpretation. RGJ: data and result interpretation.

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Data availability All datasets analysed during the current study are publicly available. CMIP and UKCP18 model data is available from https://archive.ceda.ac.uk. Links to observational datasets are provided in the Supplementary Material.

Declarations

Ethics approval and consent to participate Not applicable (This article does not contain any studies with human or animal participants performed by any of the authors).

Consent for publication All authors consent to the publication. For the purpose of open access, the authors have applied a Creative Commons Attribution (CC BY) licence to any Author Accepted Manuscript version arising from this submission.

Competing interests The authors report there are no competing interests to declare.

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