



Attributing observed and projected precipitation changes in Cape Town to atmospheric circulation

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Abstract. Climate models consistently project a decrease of winter rainfall over South Africa's Southwestern Cape (SWC) in the coming decades, but the magnitude of future drying is highly uncertain. Here we show that SWC winter rainfall variability and long-term changes are primarily controlled by large-scale zonal and meridional circulation. Using circulation-based driver indices tailored to the region of interest, we reconstruct observed SWC precipitation variability, capturing approximately 40% of its interannual variability. Applied to CMIP6 simulations, around 75% of the projected end-of-century precipitation decline is attributable to these dynamical relationships, and a large fraction (around 35%) of the inter-model spread can be traced back to differing driver responses to global warming across models. We further show that models struggle to realistically represent the mean-state of the identified dynamical drivers as well as their links to rainfall changes which undermines confidence in their simulated rainfall projections. Lastly, we show that observation-informed rainfall projections indicate stronger end-of-century drying than the CMIP6 multi-model median, suggesting that future winter rainfall declines in the SWC may be underestimated by model projections.

1 Introduction

From 2015 to 2017, the city of Cape Town, South Africa, experienced three consecutive years of below-average rainfall (Sousa et al., 2018), leading to a near-exhaustion of the municipal water supply – an event that became known as the “Day Zero” drought. Along socioeconomic factors amplifying its impacts (Visser, 2018; Savelli et al., 2021), the severity of the drought was shown to have been intensified by anthropogenic climate change (Otto et al., 2018).

With continuing global warming, climate models project a decline in annual mean precipitation over South Africa's Southwestern Cape (SWC) in the coming decades (Purich et al., 2013; Mahlalela et al., 2019; Doblas-Reyes et al., 2021; Seager et al., 2024; Li et al., 2025), accompanied by an increase in frequency and severity of droughts in this region (Abiodun et al., 2017; Otto et al., 2018; Naik and Abiodun, 2020; Pascale et al., 2020; Odoulami et al., 2023; Ngwenya and Simatele, 2024). However, substantial uncertainty remains in these projections, with modeled precipitation changes ranging from almost no change to a reduction of approximately 50% compared to present-day levels in global climate models (Doblas-Reyes et al., 2021). Such large inter-model uncertainties in rainfall projections hinder the proactive planning and effective implementation of measures to mitigate impacts similar to those of the Day Zero drought. Understanding the drivers of droughts and regional



25 precipitation in the SWC is critical for interpreting model uncertainty and assessing how these processes may evolve under continued warming.

The Day Zero drought sparked extensive research into the drivers of precipitation and associated teleconnections in the SWC. Unlike most other regions of South Africa where rainfall predominates in the summer months, the SWC experiences winter rainfall, with approximately 80% of its annual precipitation occurring between April and September (Conradie et al., 2022).
 30 Around 89% of this rainfall is associated with cold fronts making landfall (Burls et al., 2019). Consequently, SWC rainfall is primarily driven by factors that modulate the position of mid-latitude storm tracks, including the subtropical jet stream (Odoulami et al., 2020; Sousa et al., 2018; Mahlalela et al., 2019), the Southern Annular Mode (SAM) (Reason and Rouault, 2005), the extent of the Hadley cell (Burls et al., 2019; Taguela et al., 2025), and the position and strength of the South Atlantic High Pressure System (Sousa et al., 2018; Burls et al., 2019) – processes that are dynamically linked and reflect a coherent
 35 mode of variability in the Southern Hemisphere circulation. In addition to these dynamical drivers, SWC precipitation is known to be affected by teleconnections emerging from anomalous sea surface temperatures (SSTs) off the southwestern coast and the southeastern Atlantic (Reason and Jagadheesha, 2005), as well as moisture sources in the subtropics (Blamey et al., 2018; Ramos et al., 2019).

Despite numerous studies investigating the large-scale drivers of rainfall variability in the Southwestern Cape (SWC), most
 40 analyses of these teleconnections have focused primarily on the Day Zero drought. A more comprehensive understanding of the large-scale mechanisms governing SWC rainfall variability and changes across different timescales remains limited. However, biases in the simulation of these circulation patterns and uncertainties in their projected future changes are likely important contributors to the substantial inter-model spread in precipitation projections (Hall, 2014). Improving our understanding of how climate models represent the links between large-scale circulation and regional precipitation in the SWC is therefore critical
 45 for increasing confidence in future precipitation projections.

Previous studies have shown that many models participating in the Coupled Model Intercomparison Project Phase 6 (CMIP6) have a reasonable representation of relevant large-scale circulation features, and improvements have been documented compared to CMIP5 (Fuchs et al., 2023). For example, the seasonal cycle as well as the strength of the subtropical jet are well captured by CMIP6 models (Bracegirdle et al., 2020; Tang et al., 2024; Arias et al., 2025). Yet, substantial biases remain –
 50 most notably an equatorward bias in the SH storm tracks (Goyal et al., 2021; Priestley et al., 2023). Such positional biases can shift the simulated cyclone tracks and thereby alter precipitation patterns across the SH midlatitudes (e.g., Fuchs et al., 2023; Grose et al., 2019). Accordingly, most CMIP6 models exhibit pronounced regional precipitation biases in the SWC (Doblas-Reyes et al., 2021) as well as other regions in Southern Africa (Akinsanola et al., 2026; Kennedy-Asser et al., 2026), especially with respect to precipitation trends in the recent decades. Such biases may be related to circulation biases, although this link
 55 has not yet been formally established for the SWC.

Another challenge in simulating small-scale regional precipitation arises from the coarse spatial resolution of climate models. Previous studies have shown that frontal rainfall is highly sensitive to model resolution, and therefore climate models might not adequately resolve the relevant mechanisms (Schaffer et al., 2025). The SWC is, moreover, characterized by strong spatial heterogeneity in precipitation, as well as distinct seasonal timing and underlying physical drivers compared to surrounding



regions in South Africa (Conradie et al., 2022). Consequently, commonly used circulation metrics may not adequately capture the mechanisms most relevant to SWC rainfall variability, highlighting the need to investigate large-scale drivers beyond standard indices.

Here, we aim to develop a process-based understanding of the large-scale circulation drivers of SWC rainfall, and of how biases and uncertainties in these drivers propagate into precipitation biases and projection spread in climate models. We also quantify the contribution of the identified large-scale drivers to precipitation variability and change in the SWC on both inter-annual and multi-decadal timescales. To this end, we construct circulation-based driver indices tailored to the region and apply a multilinear regression framework to reconstruct past and future precipitation changes. Finally, we explore whether the identified relationships between large-scale circulation and precipitation can be used to estimate and constrain future precipitation projections.

2 Data and Methods

2.1 Data

For the observations, we use monthly mean rainfall data averaged over approximately 200 stations across the SWC from the South African Department of Water and Sanitation (DWS) and the South African Weather Service (SAWS). Data have been quality-controlled, gap-filled and homogeneity tested (Wolski et al., 2021). Although station records extend back to the early 19th century, coverage prior to the 1980s is sparse. Therefore, our analysis focuses on the period 1979–2018, largely overlapping with the "recent" period defined by Wolski et al. (2021), also coinciding with the satellite-era.

In addition to station data, we use monthly gridded precipitation data from the Global Precipitation Climatology Centre (GPCC) version 2025, established by the World Meteorological Organization (WMO) and operated by the German Weather Service (DWD), at a spatial resolution of 0.25° . The dataset is based on in situ rain gauge observations from approximately 6,000 to 55,000 stations, depending on the time period (Rustemeier et al., 2025).

To analyze observed large-scale dynamics, we use ERA5 reanalysis from the European Center for Medium-Range Weather Forecasts (ECMWF) (Hersbach et al., 2020). We use ERA5 daily zonal and meridional wind aggregated data regridded to a horizontal resolution of 2.5° for the period 1979 – 2023, when high-quality satellite data is available.

We further consider simulations from the Coupled Model Intercomparison Project 6 (CMIP6), including historical runs and high-emission scenario (SSP5-8.5) simulations, covering the period 1900 – 2099. Only models providing precipitation, zonal wind, and meridional wind for both historical and future periods were selected, resulting in a total of 37 models with ensemble sizes ranging from 1 to 50 members. Model data were downloaded and regridded to a common $2.5^\circ \times 2.5^\circ$ grid using esmvaltool (Righi et al., 2020). Precipitation in the models has been averaged over the SWC defined as $18 - 20.5^\circ\text{W}$ and $31 - 33.5^\circ\text{S}$, which largely overlaps with the available rainfall station data. A list of all models used in this study, including ensemble sizes and model resolutions, is found in the supplementary material (SI Table 1).

Elevation data for the SWC is taken from the Earth TOPOgraphy (ETOPO) data from the National Centers for Environmental Information (NCEI) (Amante and Eakins, 2009).



All variables were averaged over the extended winter season (April – September). If not stated otherwise, we use 1979–2023 as reference period. For station data, which is only (publicly) available until 2018, we use 1979–2018.

95 2.2 Methods

To identify the relevant circulation patterns, we compute grid-point correlations between precipitation and zonal and meridional wind fields, and assess whether correlations differ significantly from zero using a t-test at the 90% confidence level with a false discovery rate correction (Wilks, 2016). Based on the resulting correlation patterns, we identify regions where zonal and meridional wind variability provide the greatest explanatory power for SWC precipitation. To do so, we first define broad
100 candidate regions around the areas exhibiting the strongest correlations with precipitation (see SI chapter 1). Within these boundaries, we randomly select a box, calculate area-averaged zonal or meridional wind using cosine-latitude weighting, and derive corresponding time series. These indices are then used as predictors in a multi-linear regression (MLR) model of SWC precipitation. We repeat this procedure 10^4 times and select the regions that maximize the MLR explained variance (R^2). Note that the results presented below are not sensitive to the exact location and extent of these chosen areas (see SI chapter 1).
105 Further note that all the time series used in the MLR have been detrended to remove the impact of any forced response during the reference period and standardized by mean and standard deviation. Uncertainties in the MLR coefficients are estimated by fitting a MLR (minimizing the residual sum of squares) to 80% of the data, which has been randomly selected without replacement. To obtain an estimate of the impact of internal variability on the regression coefficient, this procedure is repeated 10^4 times and the mean coefficients for the meridional and zonal wind are considered our "best estimate".
110 Similarly, uncertainty in the observed precipitation climatology and variability are estimated by randomly subsampling 70% of the precipitation data without replacement and calculating the mean and standard deviation of this subsample. Repeating this procedure 10^4 times yields a distribution with plausible values for the observed precipitation climatology and standard deviation.

3 Results

115 3.1 Observed and projected precipitation in the Southwestern Cape (SWC)

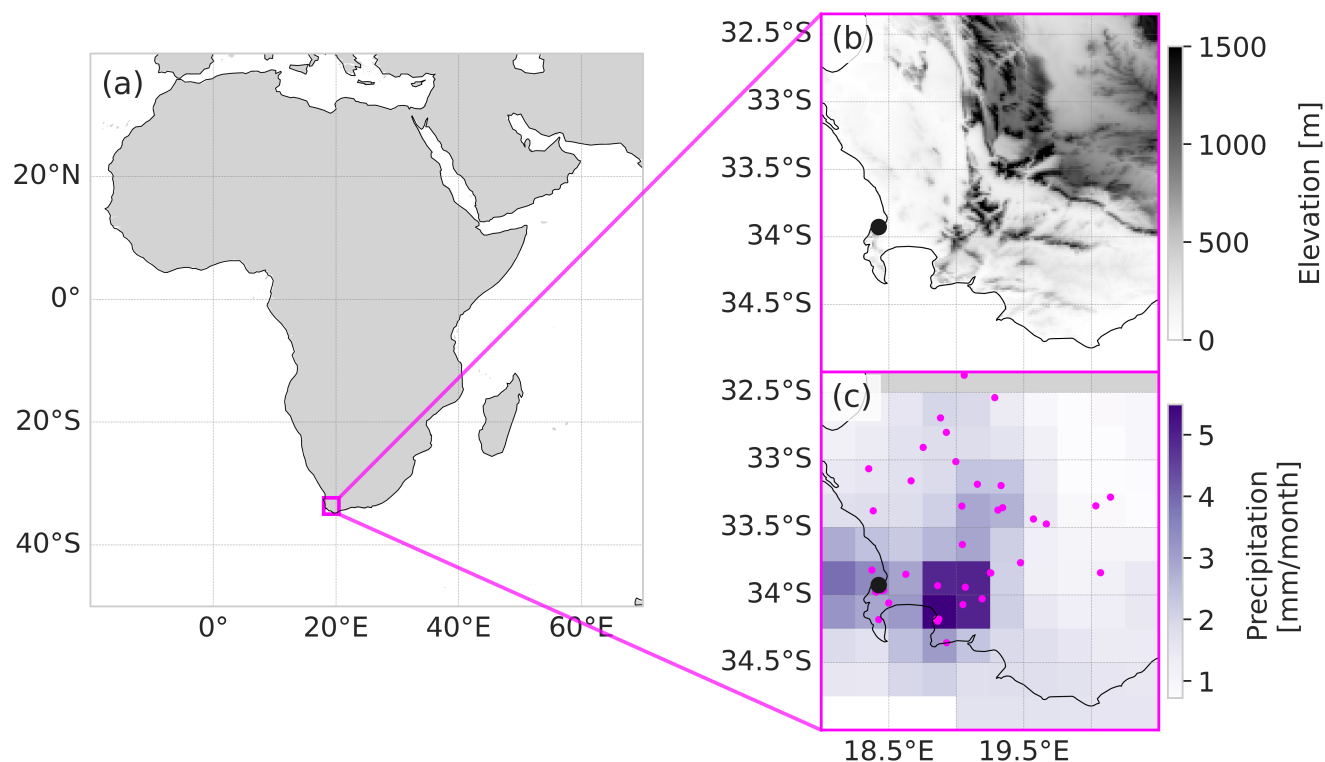


Figure 1. The study region. (a) Location of the study region defined as the Southwestern Cape (SWC). (b) Topography of the Southwestern Cape. (c) Extended-winter (April – September) precipitation climatology in GPCC from 1979 – 2023. Pink dots in (c) mark the location of the stations considered in this study. The black dot in (b) and (c) marks the location of Cape Town.

We begin by investigating observed and simulated precipitation in the SWC during the extended winter season (April – September mean), which accounts for approximately 80% of the annual precipitation in the region (Conradie et al., 2022). The study region, shown in Fig. 1a, is located at the south-western tip of the African continent and spans $2.5 \times 2.5^\circ$. It includes the city of Cape Town and is characterized by complex small-scale topography (Fig. 1b). The GPCC precipitation climatology for Cape Town and is characterized by complex small-scale topography (Fig. 1b). The GPCC precipitation climatology for the extended winter season during the reference period is presented in Fig. 1c and reveals pronounced spatial heterogeneity in rainfall across the region. In many areas, precipitation patterns closely follow the underlying topography, underscoring the importance of orographic effects and other small-scale processes in shaping regional rainfall.

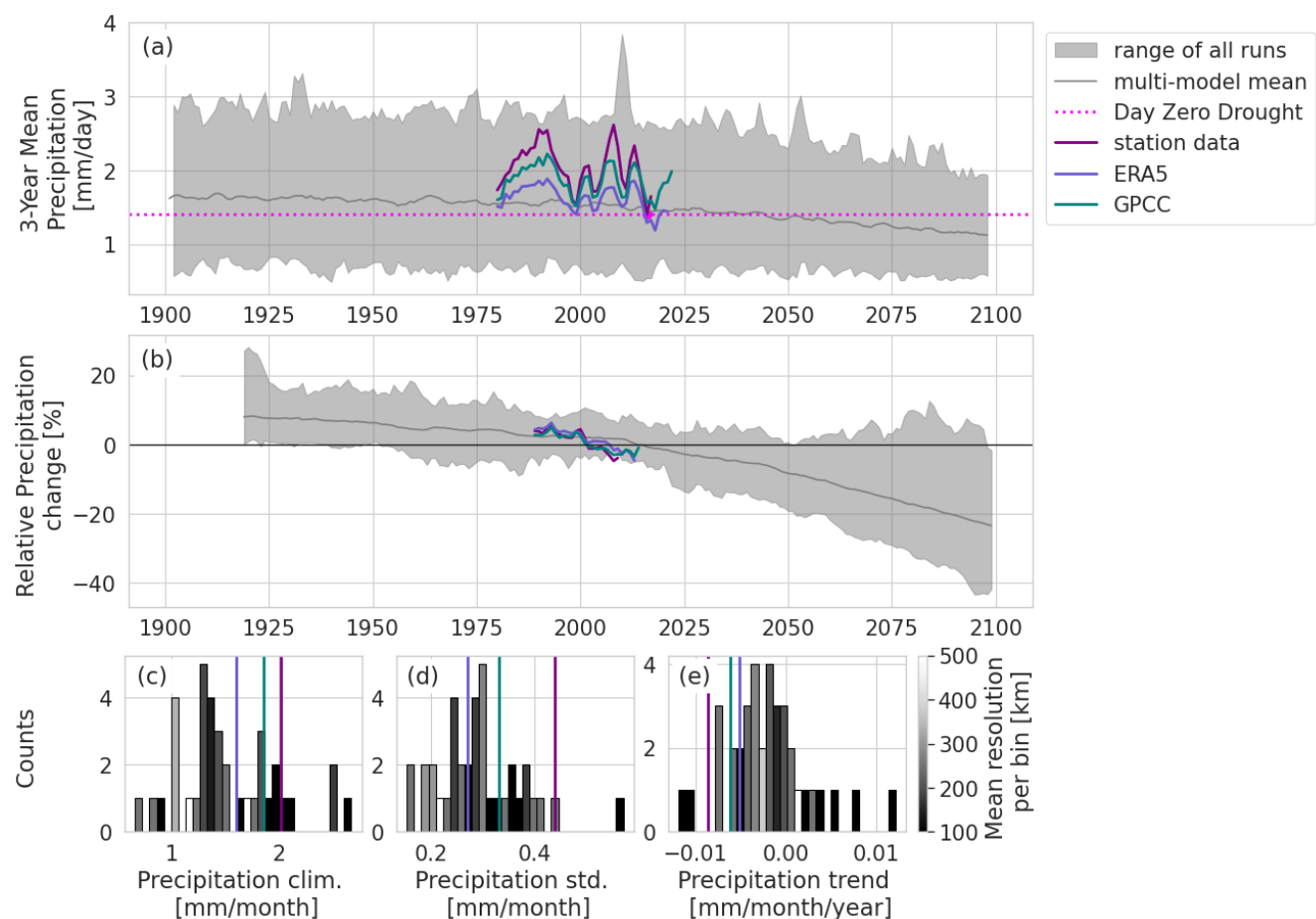


Figure 2. Observed and modeled wintertime precipitation in the Southwestern Cape (SWC). (a) Historical and future (SSP5 scenario) 3-year mean winter precipitation in CMIP6 models. The shading shows the full range of ensemble-mean CMIP6 simulations, the grey line shows the CMIP6 multi-model mean. Also shown is observational data (station data, GPCC, ERA5) as well as the 3-year mean precipitation during the "Day Zero Drought" (based on station data, pink stippled line). (b) 15-year running mean simulated precipitation changes in CMIP6 models relative to each models' 1979 – 2023 climatology, as well as observed changes relative to the same observed climatology. The shading shows again the full range of ensemble-mean CMIP6 simulations, the grey line shows the CMIP6 multi-model mean. Precipitation climatology (c), standard deviation (d), and linear trend (e) in the reference period (1979 - 2018) in CMIP6 models (histogram) as well as the 3 observational products (vertical lines). Colors of the histogram denote the mean horizontal model resolution in the respective bin. Trends in (e) have been calculated by fitting a linear trend to the 20-year running mean precipitation in the reference period.

Figure 2a shows CMIP6-simulated historical and future precipitation in the SWC, averaged using a three-year running mean to capture variability on the timescale of the "Day Zero" drought. Because our objective is to better understand precipitation biases and their underlying causes in climate models, we analyze raw, non-bias-adjusted model output. Compared to observa-



tions from station data (purple line), many models underestimate the precipitation climatology in this region in the reference period, with the multi-model mean being close to the extreme "Day Zero" drought values from station data (pink horizontal line). Since the study region only covers one to a few gridpoints in the CMIP6 models due to their coarse resolution (1 – 3°), biases in precipitation are likely linked to the small-scale processes involved in precipitation generation, particularly those linked to the region's complex topography.

Since Fig. 1a is dominated by differences in the climate models' precipitation climatology, we show precipitation changes relative to the individual models' climatology in Fig. 1b. For the coming decades, CMIP6 models consistently predict a reduction in winter mean SWC precipitation (following the high-emission scenario SSP5-8.5), with an average reduction of around 25% compared to present-day. However, while models generally agree on the sign of these precipitation changes, the magnitude of the projected decline is less certain and ranges between 0 to 50% (see Fig. 1 c, see also Fig. 10.18 in Doblas-Reyes et al. (2021)).

Figure 2c, d, and e show the CMIP6 models' precipitation climatology, variability, and trend in the reference period (1979 – 2018) compared to the three observational products (station data, GPCC, and ERA5), additionally color-coded by the models' resolutions. It can again be seen that the majority of models underestimate the precipitation climatology in the SWC (panel c). Higher-resolution models (dark bars) generally exhibit climatologies that are closer to observations, although notable exceptions remain. For precipitation variability, no clear connection between model resolution and precipitation standard deviation can be found, although models that highly underestimate precipitation variability tend to have coarse resolutions (panel d). This suggests that model resolution alone cannot fully explain the precipitation biases, and that other factors also contribute. Furthermore, panel e shows the precipitation trend over the reference period in models and observations, calculated by fitting a linear trend to the 20-year running mean precipitation. While observational datasets show a clear decline in precipitation in recent decades, this is not reflected in CMIP6 models with most models showing only moderate or opposite sign trends – independent of the models' resolution.

Figure 1a, c and d also highlight substantial differences among observational datasets in the representation of SWC precipitation climatology and variability. The station observations show the largest mean precipitation and variability, followed by the gridded GPCC dataset. In contrast, ERA5 exhibits considerably lower precipitation amounts and variability, likely underestimating both. This is probably related to the coarse resolution of the underlying model, which inadequately resolves the region's topography and associated orographic rainfall. We therefore consider ERA5 precipitation not fully suitable for the purposes of this study. Moreover, in both GPCC and ERA5 – as well as in all the CMIP6 models – the region considered includes the southeastern part of the southwestern Cape. This region usually experiences comparably little winter-time precipitation and is not covered by the station data (see Fig. 1 c), likely explaining the larger rainfall climatology and variability in the station data in comparison to gridded datasets.

3.2 Explaining historical precipitation variability

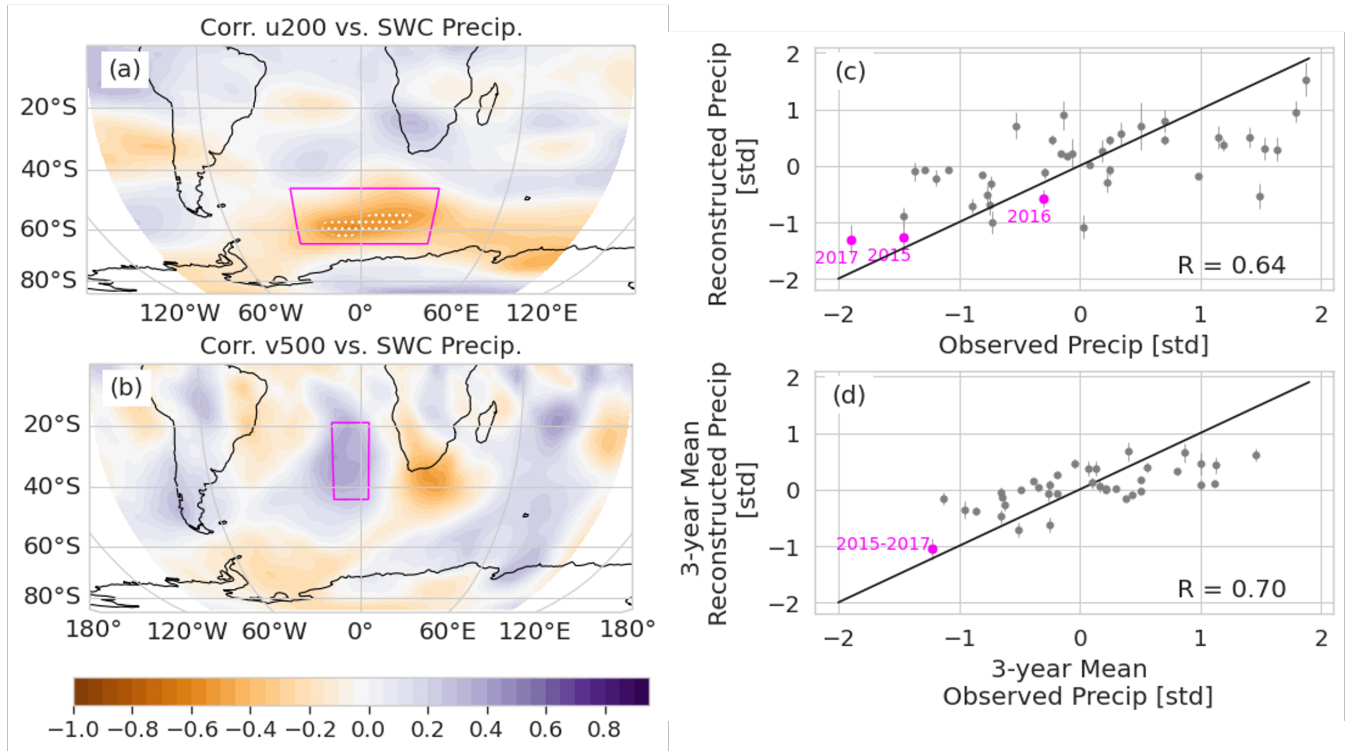


Figure 3. Links between large-scale dynamics and precipitation on interannual timescales. Correlations between observed SWC winter precipitation (station data) and (a) winter mean zonal wind at 200 hPa (u200), and (b) meridional wind at 500 hPa (v500) from ERA5. Grid-points where the correlation is significant on a 90% level according to a student t-test with applied false discovery rate are stippled in white. The pink boxes indicate the regions over which u200 and v500 indices are computed for the multiple linear regression analysis. (c) Results of the precipitation reconstruction based on the regional u200 and v200 index in comparison to the observed observation on interannual timescales, as well as for 3-year mean average precipitation (d). In panels (c) and (d), the drought zero years (2015 – 2017) are marked in pink and the black line indicates the 1-1 line.

To better understand the differences across models with respect to historical and future SWC precipitation, we aim to identify the relevant large-scale circulation patterns driving precipitation variability in this region. For this, we start by analyzing correlations between winter-mean (April – September) zonal (u) and meridional (v) wind (at 200 hPa and 500 hPa, respectively) in the Southern Hemisphere (SH) and observed regional mean precipitation in the SWC in the reference period (1979–2018). The respective variables (u and v) and altitudes (200 and 500 hPa) have been chosen based on conventions for the location of the jet stream (u200, e.g. Zolotov et al. (2018)) as well as extratropical cyclones and stationary wave pattern (v500 hPa, e.g. Emori and Brown (2005); Irving and Simmonds (2015); Goyal et al. (2022)) – circulation features that have been previously linked to SWC rainfall. For upper troposphere zonal winds (u200, Fig. 2 a), negative correlations with precipitation are mainly



present in the Southwestern Atlantic, southeast of the African continent, at latitudes of around 40°S to 70°S. This pattern mainly reflects variability in the latitudinal position of the storm tracks: an equatorward shift, i.e. reductions of the zonal wind speed in this area, is associated with precipitation increase in the SWC, while an increase in wind speeds is associated with a poleward shift of the storm track and is linked to precipitation decrease (Sousa et al., 2018). For mid-tropospheric meridional winds (v500, Fig. 2 c), we find a dipole pattern in the correlation with SWC rainfall, with positive correlations upstream of the SWC and negative correlations downstream. This pattern is consistent with anomalous northward winds to the west and southwards winds to the east of the SWC resembling cyclonic conditions usually associated with cold fronts and, thus, frontal precipitation.

To obtain a simplified representation of the dynamical patterns shown in Fig. 2a and b, we construct two circulation indices by averaging winter-mean zonal and meridional wind over the regions where their correlations with SWC precipitation are strongest (pink boxes in Fig. 1a, b). The regions are selected to maximize the explanatory power of the resulting indices (see SI chapter 1). The derived zonal wind driver is strongly correlated with both the strength and latitudinal position of the eddy-driven jet stream near the African continent (see SI Chapter 2), and is also closely linked to the position of the South Atlantic high-pressure system, which has previously been shown to influence the amount of precipitation associated with cold fronts (Burls et al., 2019). In contrast, the meridional wind index is associated with the Southern Annular Mode (SAM) and the number of fronts making landfall in the SWC (see SI Fig. S3).

We then fit a multilinear regression (MLR) model to the standardized 1-D time series obtained using the regional u200 and v500 indices as predictors of winter-mean SWC station precipitation (PR_{SWC}):

$$PR_{SWC} = -0.49 \cdot u_{200} + 0.36 \cdot v_{500}. \quad (1)$$

This way we quantify the contribution of the two drivers to winter rainfall variability in the SWC. The shown coefficients in 1 are for station precipitation as target variable. For GPCC precipitation as target variable, coefficients are smaller (-0.46 and 0.29), but comparable in magnitude.

Using this MLR model, we can predict interannual precipitation changes based on the variability of the u200 and v500 indices. Figure 1 c shows the relationship between the predicted precipitation using the MLR model and the observed precipitation (for station data, both in standardized units), revealing a high correlation of $R = 0.64$. This shows that around 40% of the winter mean precipitation variability can be explained solely by the two identified drivers. This result is somewhat surprising for the 6-month averages considered here, since rainfall driving mechanisms in the SWC typically exhibit strong seasonal dependence (Wolski et al., 2021) and include small-scale processes. Notably, the MLR model performs particularly well for years with low precipitation (including the "Day Zero" drought years marked in pink in Fig. 1 c) but struggles for some years marked by particularly high precipitation. This may reflect the shorter timescales typically associated with extreme rainfall events, which are not captured by the six-month averages analyzed here. Furthermore, during high-rainfall years, local processes and topographic influences likely play a larger role than in years characterized primarily by a lack of precipitation. For 3-year averages – the timescale of the "Day Zero" drought – the performance of the model increases ($R = 0.70$, see Fig.



1 d). Note that these results are not particularly sensitive to the exact location and extent of the chosen driver boxes (see SI Chapter I).

3.3 Explaining precipitation biases in models

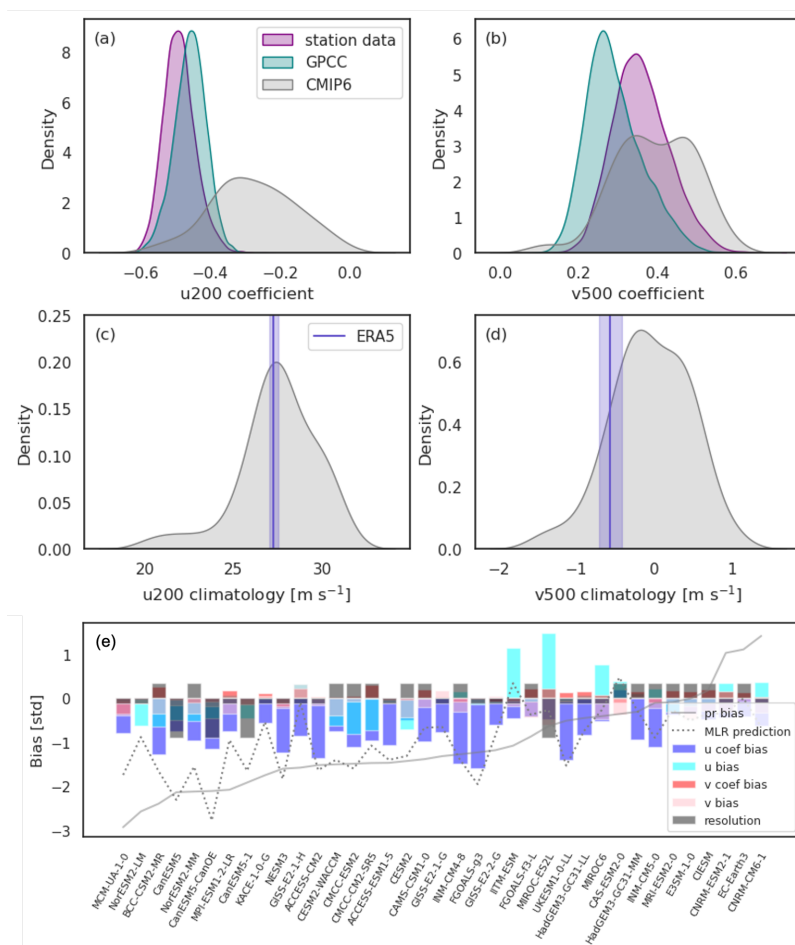


Figure 4. Evaluating model biases. Regression coefficients for zonal (a) and meridional (b) wind calculated based on observations (purple for station data and green for GPCP) as well as based on individual CMIP6 models (grey). Zonal (c) and meridional (d) wind climatologies in the reference period (1979 – 2023) in the models (grey) as well as in ERA5 (blue). Panel (e) shows the contribution of the individual models biases in zonal and meridional wind coefficients and climatologies as well as the models' resolution to mean precipitation biases. The contribution of individual biases to the precipitation offset is calculated via MLR: Biases other than the resolution are standardized by the standard deviation across models (but without removing the mean to conserve the sign of the biases). The resolution is standardized by mean and standard deviation across models. Models in panel (e) are ordered according to their precipitation mean bias in the reference period with respect to station data (illustrated by the grey line). The stippled line shows the MLR modelled bias.



Next, we assess in what way the climate models' representations of identified large-scale drivers contribute to climate models' rainfall biases in the SWC (Fig. 1 c). Following the MLR approach in Eq. 1, we fit a MLR model to precipitation variability in the reference period (1979 – 2023) in each individual CMIP6 ensemble member: For this purpose, we average zonal and meridional wind in the boxes identified in Fig. 2a and b in each model, and use these standardized indices of u200 and v500 as predictors for modeled precipitation. This yields a set of regression coefficients for u200 and v500 for every ensemble member of each model.

In Fig. 4a and b we compare these model-derived regression coefficients (grey) for u200 and v500 with those obtained from observations (purple and green for station data and GPCC, respectively). Uncertainties in the observed regression coefficients were derived via a bootstrapping approach (see Methods). On average, CMIP6 models heavily underestimate the regression coefficient for the zonal wind driver (u200) relative to observations, while on average their meridional wind coefficients are closer to observations. The driver coefficients derived from the CMIP6 models quantify how strongly a given model translates large-scale dynamical changes into regional precipitation variability, and therefore provide a measure of how well the model represents the circulation–precipitation link. Because the regions used to define the zonal and meridional wind drivers are spatially fixed, the coefficients may also be influenced by systematic circulation biases within these regions. For example, deviations of a model's zonal wind coefficient from the observed value could partly reflect positional biases in the simulated jet stream. However, the correlation between the climatological bias in zonal wind and the zonal wind coefficient is weak ($R = 0.18$, see SI Fig. S4), suggesting that jet position biases are not the primary cause of differences between coefficients in observations and CMIP6. Therefore, we conclude that coefficient biases mainly reflect differences in how models translate large-scale circulation anomalies into regional precipitation responses, rather than differences in the mean state of the circulation itself. We therefore argue that models with smaller coefficient biases provide a more realistic representation of the physical processes governing SWC precipitation.

Next, we turn to the representation of the identified drivers' climatologies in climate models. Figure 4c shows that the bulk of CMIP6 models represents zonal wind in the respective box reasonably well. However, there are some notable exceptions of models heavily underestimating the zonal wind driver (u200). This, again, is likely due to their equatorward jet stream bias. Moreover, almost all models simulate a too weak or reversed meridional wind in the respective box (see 4d). A comparison of the spatial climatologies for both zonal and meridional wind in CMIP6 and observations can be found in the supplementary material (SI Fig. S5).

Finally, we examine to what extent model biases in the large-scale drivers – both their climatological mean state (Fig. 4c, d) and their regression coefficients (Fig. 4a ,b) – result in precipitation biases in the SWC. To quantify the contributions of the individual biases to the overall precipitation bias, we again use a regression framework using the mean state biases of u200 and v500 (δu_{200} and δv_{500}), the biases in the u200 and v500 coefficients ($\delta u_{200,coef}$ and $\delta v_{500,coef}$, as well as the models' horizontal resolutions (res) as predictors. Individual biases have been standardized by the inter-model spread but without removing the mean to conserve the sign of the biases. This results in the following MLR:

$$\delta PR = -0.48 \cdot \delta u_{200} - 0.19 \cdot \delta v_{500} - 0.41 \cdot \delta u_{200,coef} + 0.14 \cdot \delta v_{500,coef} - 0.38 \cdot res. \quad (2)$$



In Fig. 4e, we plot the contributions of the individual biases to the mean precipitation offset, with models ordered along the x-axis by their precipitation climatology: models on the left are drier than observed, models on the right wetter. Among the metrics considered, a clear link is present between the models' precipitation climatology and the bias in the zonal regression coefficient (blue bars), as well as the zonal mean state bias (turquoise bars). Contributions of the meridional wind driver to the overall precipitation biases are smaller but non-zero. Moreover, the models' resolution contributes heavily to the models' precipitation mean state bias (regression coefficient -0.38).

To evaluate whether our results are heavily impacted by the location of the boxes used to define the two drivers, we again turn to the full spatial pattern and calculate spatial correlation patterns linking the two wind components to precipitation over the SWC in CMIP6 models, analogous to the observations in Fig. 2a and b. The comparison of correlation patterns in CMIP6 and observations and related discussion is presented in SI chapter 5, revealing that models underestimate the links between u200 and precipitation independent of the location of the chosen box.

In summary, CMIP6 models generally fail to realistically simulate the relationship between zonal wind changes and precipitation and exhibit substantial biases in both the meridional and zonal mean state. Therefore, we conclude that correctly capturing the the climatology of the identified meridional and zonal wind drivers and their links to precipitation is crucial for a model to realistically reproduce precipitation climatology and variability in the SWC.

3.4 Explaining future precipitation changes

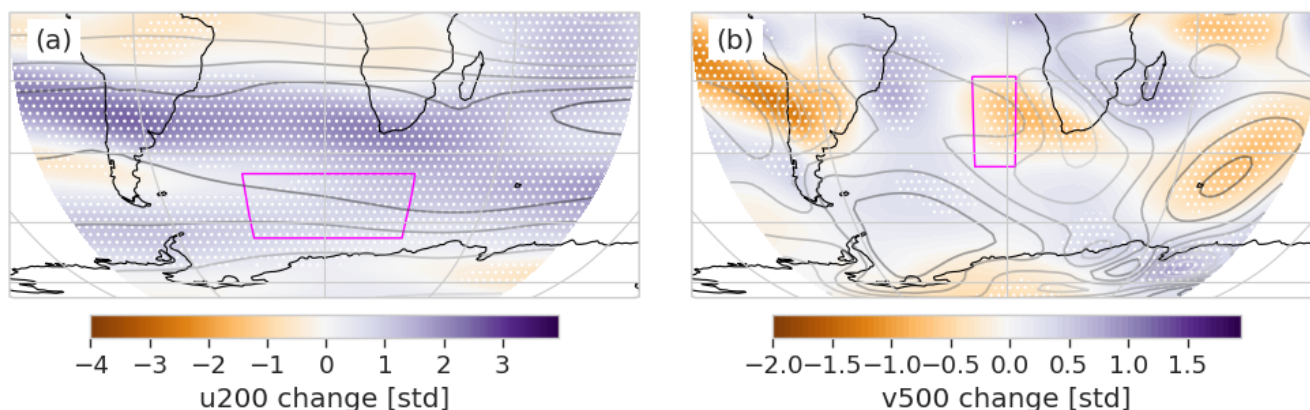


Figure 5. Projections of circulation changes. CMIP6 multi-model mean end-of-century (2080 - 2099) changes in (a) zonal wind at 200 hPa, as well as (b) meridional wind at 500 hPa compared to the 1979 – 2023 reference climatology in standardized units in a high-emission scenario (SSP5-8.5). Stippled areas show regions where 80% of the models agree on the sign of changes. Contours in (a) and (b) show the multi-model mean climatology of u200 and v500, respectively, over the reference period.

Having established two driver indices (u200 and v500) of interannual rainfall variability in the SWC, we investigate how these driver fields change in the coming decades using CMIP6 simulations under a high-emission scenario (SSP5-8.5). As shown in Fig. 5, CMIP6 models generally agree on the sign of the changes in meridional and zonal wind within the identified regions



(white stippling in pink boxes). Models consistently project a strengthening in zonal wind southwest of the African continent. This intensification is consistent with enhanced upper-tropospheric warming in the tropics, which increases the meridional temperature gradient and, following thermal-wind balance, strengthens zonal winds in the subtropics and midlatitudes as well as the polar flank of the jet stream (Mindlin et al., 2025, e.g.). In contrast, meridional wind in the identified region (pink box in Fig. 5 b) is projected to weaken Overall, projected meridional wind changes exhibit a wave pattern across the SH midlatitudes, with zonally alternating decreases and increases between 20°S and 40°S. This pattern can be explained by the dependence of stationary waves on the strength of the background flow (i.e. the jet stream); An increase in zonal wind impacts the wave number and thus the stationary wave pattern (Tuel et al., 2021; Patterson et al., 2021). In addition, changes in Rossby wave sources might also play a role (Patterson et al., 2021). The resulting meridional wind changes resemble anticyclonic conditions over Southern Africa, which are associated with reduced precipitation.

To evaluate to what extent the end-of-century changes in large-scale drivers lead to precipitation changes, we apply the MLR model as defined in Eq. 1 and plug in projected end-of-century (2080 – 2099) changes in u_{200} (Δu_{200}) and v_{500} (Δv_{500}) for each model (using the regression coefficients resulting from fitting the model to observed (station) interannual variability). This approach yields a reconstruction of regional precipitation changes (ΔPR_{SWC}) based solely on projected changes in the two wind indices. The resulting scatterplot with the MLR-reconstructed end-of-century precipitation changes plotted against modeled precipitation changes across CMIP6 models are shown in Fig. 6a in standardized units (standardized by individual models' climatology). The high correlation ($R = 0.58$) indicates that around one third of the inter-model spread in projected rainfall changes can be attributed to uncertainties in future wind responses to global warming. This distributions of the reconstructed end-of-century precipitation changes are also shown in Fig. 6b in purple, alongside the raw model output (grey) and the MLR reconstructed if based on GPCC instead of station data (green).

The MLR reconstruction highlights that a substantial fraction of the future precipitation change is dynamically driven through changes in the zonal and meridional winds. Decomposing the dynamical precipitation projections into their zonal and meridional components ($-0.49 \cdot \Delta u_{200}$ and $0.36 \cdot \Delta v_{500}$) reveals changes in zonal wind as the dominant driver of future precipitation changes, in accordance with the larger overall projected changes in this driver. Taken together, dynamical changes account for over 68% of the projected precipitation changes on a multi-model mean.

Precipitation changes not explained by changes in u_{200} and v_{500} are likely linked to thermodynamic impacts on precipitation changes. To reproduce the full extend of modeled future precipitation changes using the MLR approach, we fit a linear regression to the residual precipitation (i.e. the amount of projected precipitation changes which is not explained by changes in u_{200} and v_{500}) using global mean temperature change (ΔGMT) as predictor:

$$PR_{res} = -0.06 \cdot \Delta GMT + 0.26. \quad (3)$$

This term represents both thermodynamic impacts as well as potential dynamical changes not accounted for by our two large-scale scale drivers. Figure 6 b shows the end-of-century MLR reconstruction of precipitation when accounting for both

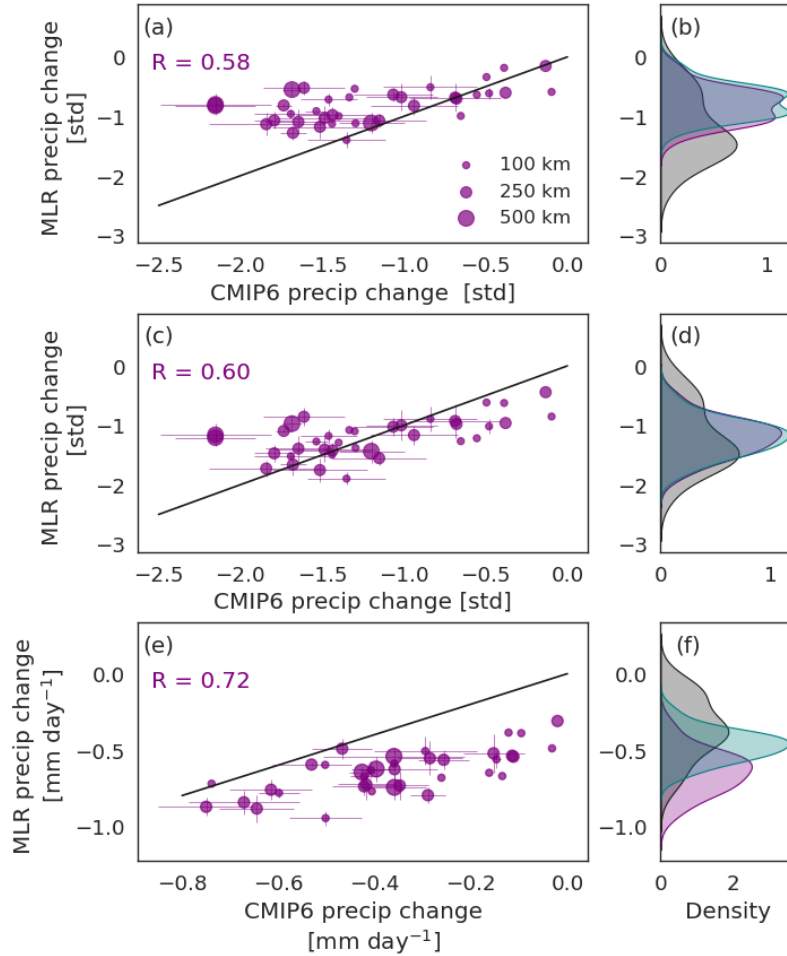


Figure 6. Projected precipitation changes. (a) Projected end-of-century precipitation changes as predicted by the MLR model ($\Delta PR = -0.49 \cdot \Delta u_{200} + 0.36 \Delta \cdot v_{500}$) in standardized units against CMIP6 model projections of precipitation changes. The black line indicates the 1:1 line. The size of the markers show the horizontal nominal resolution of each model. The resulting distribution of MLR projected precipitation changes based on station data (pink) and the raw model output (grey) are shown in (b). In addition, the green distribution shows MLR projections with coefficients calculated based on GPCC. (c) Shows the MLR projections after adjusting for GMT changes (by fitting the residual in (a) against GMT changes, $\Delta PR = -0.49 \cdot \Delta u_{200} + 0.36 \cdot \Delta v_{500} - 0.06 \cdot \Delta GMT + 0.26$). (d) is analogous to (b) for GMT-adjusted projections. (e) shows MLR precipitation projection in physical units based on the station data precipitation variability ($\Delta PR = \sigma_{obs} \cdot (-0.49 \cdot \Delta u_{200} + 0.36 \cdot \Delta v_{500} - 0.06 \cdot \Delta GMT + 0.26)$). (f) is analogous to (b) and (d).

dynamical drivers as well as GMT changes. Resulting distributions for the MLR reconstruction based on station data (purple) and GPCC (green) are shown in Fig. 6 d.



To this point, we have reconstructed projected precipitation changes only in standardized units. However, for interpretation and policy relevance, it is essential to express these changes in physical units, which can be done by multiplying the standardized changes with the observed precipitation standard deviation (σ_{obs}), i.e.

$$\Delta PR_{phys} = \Delta PR \cdot \sigma_{obs}. \quad (4)$$

The MLR projection translated in physical units (based on station-based precipitation variability) shows a large correlation with the CMIP6 precipitation changes ($R = 0.72$). Notably, the mean of the MLR reconstructed precipitation changes is larger (i.e. more negative) than the raw model output. This reflects the higher precipitation variability in observations compared to CMIP6 models (see Fig. 2d). When using GPCC-based coefficients and standard deviation, the MLR reconstruction still shows a larger precipitation decline than the CMIP6 distribution, but less extreme than the station-based approach due to the smaller precipitation variability in GPCC (see Fig. 6f). Hence, the use of observed variability to translate the dynamical projections from standardized into physical units functions as a bias-correction step accounting for the models' underestimated rainfall variability (Mindlin et al., 2025). This way, we can derive an observation-informed dynamical precipitation projection. Distributions for dynamically projected absolute rainfall changes derived this way are shown in Fig. 6f.

3.5 What can we learn from this about future precipitation changes?

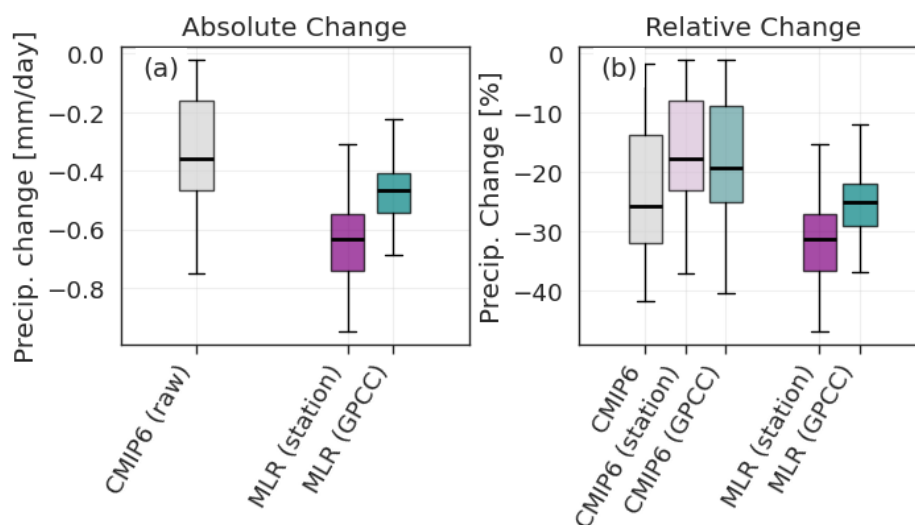


Figure 7. Summary of precipitation projections. (a) Projected absolute end-of-century precipitation changes (SSP5-8.5) simulated by CMIP6 models (grey), as well as precipitation changes projected by the MLR approach based on station data (purple) and GPCC (green). (b) Precipitation changes simulated by CMIP6 models relative to the models' climatology (grey), station data (light purple), and GPCC (light green), as well as relative precipitation changes derived from the MLR approach based on station data (purple) and GPCC (green) coefficients and climatology.



In the previous chapters, we have shown that upper troposphere zonal and mid-troposphere meridional wind can be leveraged to reconstruct precipitation variability across timescales using a simple multilinear regression approach, enabling precipitation projections that are independent of the climate models' precipitation output. Figure 7 summarizes the end-of-century precipitation projections for the SWC discussed above, including the raw model output (grey), and the MLR projection based on observed precipitation variability (station data and GPCC), shown in absolute (b) and relative (c) units. Relative changes are computed with respect to the precipitation climatology in the reference period (1979 – 2023). For the CMIP6 projected changes, relative changes based on the individual models' climatologies (grey, analogous to Fig. 2 b), as well as relative changes based on the observed station data (light purple) and GPCC (light green) are shown. For the MLR based estimates, relative changes are based on the climatologies of the respective observational product (station data in purple and GPCC in green).

Based on the multi-model median, CMIP6 projected precipitation changes indicate a precipitation decline of $-0.36 \text{ mm day}^{-1}$ (with a 5th – 95th percentile of -0.69 to $-0.08 \text{ mm day}^{-1}$), corresponding to a relative median decline of -25.8% . The station-based MLR projection yields a median precipitation change of $-0.63 \text{ mm day}^{-1}$ (-0.88 , $-0.39 \text{ mm day}^{-1}$), corresponding to around -31.4% (-43.4 , -19.3%). If based on GPCC, the MLR projection yields precipitation changes of $-0.47 \text{ mm day}^{-1}$ and -25.0% for median absolute and relative precipitation changes, respectively. Taken together, these observation-informed estimates suggest precipitation median declines that are around 1.3 – 1.75 larger than the raw CMIP6 multi-model median precipitation changes. The MLR reconstructions therefore suggest that precipitation declines in the SWC may be substantially larger than suggested by unfiltered ensemble means of raw CMIP6 model output in absolute terms, at least under the high-emission scenario (SSP5) considered here. For relative changes, however, all estimates yield similar results, suggesting a precipitation decline of around 25-30% compared to the recent historical period.

While the MLR reconstructions exhibit a smaller uncertainty ranges compared to the CMIP6 modeled precipitation changes, it is important to note that the estimates shown in Fig. 7 do not include uncertainties in the observation-based MLR coefficients or uncertainties in the observed standard deviation (for Fig. 7 b). A bootstrapping approach accounting for all known uncertainties is therefore used to explore the upper and lower limits of the MLR-based estimates (see SI Fig. S6).

All MLR-based estimates shown in Fig. 7 are informed by historical precipitation observations, i.e. they are based on historical precipitation variability and climatology, as well as ERA5 historical zonal and meridional wind. The MLR reconstructions are, however, subject to two key limitations: (1) the assumption of stationarity in the processes governing precipitation across timescales, and (2) a strong dependence of the results on observed precipitation variability, which is limited by observational quality and record length, and differs across observational datasets. Considering potential non-stationarities, e.g. due to the occurrence of tipping points, is especially important since the driver regions considered here are spatially fixed, which is in contrast to the expected spatial changes in the drivers, e.g. the poleward movement of the jet stream. However, the eddy-driven jet is expected to change by less than 5° (Mindlin et al., 2025) – little in comparison to the large regions chosen for the MLR. Further, forced circulation responses often project strongly onto the modes of variability, suggesting that dynamical processes, such as latitudinal shifts of the jet stream, operate similarly on interannual and long-term timescales (Shepherd, 2014). In addition, the empirical consistency of our results across timescales points towards approximate stationarity of the involved processes. The quality of the station data used here has been thoroughly investigated by Wolski et al. (2021) and the coverage



of rainfall stations in the SWC with over 200 stations is deemed sufficient, even when accounted for the heterogeneous landscape and small-scale topography of the region. However, the results are subject to the short observational record for which reliable data is available (less than 40 years), emphasizing the importance of continued long-term regional rainfall monitoring. Moreover, results differ across observational products, although the projections shown in Fig. 7 are mostly consistent across different datasets.

Given these limitations, namely the assumption of stationarity and the short length of the observational datasets, the MLR-derived distributions in Fig. 7 should not be taken at face value as quantitative estimates. They are better interpreted as an indication that CMIP6 precipitation projections may be affected by biases in the representation of the associated large-scale drivers, and as a starting point for further model evaluation.

4 Discussion and Conclusions

We have shown that large-scale indices tailored to the region of interest can be useful in explaining and attributing historical and future precipitation changes. In case of the Southwestern Cape, we have shown that the two identified drivers of zonal and meridional circulation explain around 40% of the interannual precipitation variability in the observations (Fig. 3). Further, biases in the representation of these drivers translate to precipitation biases in the CMIP6 models (Fig. 4). We showed that around 68% of the modeled end-of-century precipitation decline can be attributed to changes in zonal and meridional wind drivers. Moreover, around one third of the spread in precipitation projections across climate models is caused by uncertainties in wind changes with climate change (Fig. 6).

To assess which important large-scale or regional drivers of SWC precipitation remain unaccounted for in the MLR reconstruction, we analyze correlations between the residual precipitation variability and previously identified drivers for the reference period, including regional-scale sea surface temperatures (SSTs) and hemispheric teleconnections (e.g. Indian Ocean Dipole (IOD), see SI chapter S2). Most interestingly, the residual precipitation, defined as the difference between the MLR reconstructed and observed precipitation – and thus the precipitation variability not explained by the MLR model – shows strong correlations with local sea SSTs west of the South African coast. Such correlations are consistent with earlier studies suggesting that local SST anomalies may modulate the intensity of rain-bearing storms reaching the SWC (Reason et al., 2002) – a process not captured by the large-scale meridional and zonal wind drivers in our MLR model.

Similar approaches to attribute and explain trends and variability to remote drivers have been previously applied in different contexts. For example, Mindlin et al. (2025) used a regression approach to derive dynamical reconstructions of historical changes in the Southern Hemisphere eddy-driven jet and attributed these changes to several large-scale (dynamical and thermodynamical) drivers. Further, for the Northern Hemisphere Mediterranean region, Zappa et al. (2015) used a similar regression approach to link zonal wind over northern Africa to precipitation in the Mediterranean region. Consistent with our findings for the SH, Zappa et al. (2015) show that CMIP5 models struggle to reproduce the regression coefficients derived from observations. They further show that changes in zonal wind explain 85% of Mediterranean end-of-century precipitation changes. This is comparable to the 68% of SWC precipitation changes we attribute to changes in zonal and meridional wind.



However, for the NH Mediterranean, Zappa et al. (2015) find that 80% of the inter-model spread of future precipitation projections can be explained by uncertainties in zonal wind changes – compared to the 35% of model uncertainty attributable to wind changes for the SWC. These differences could be due to the large region analyzed by Zappa et al. (2015) (the whole NH Mediterranean) compared to the small area (SWC) considered here. Hence, small-scale processes and their parametrization in models likely play a larger role in the SWC than uncertainties in large-scale processes. Moreover, in contrast to our regression approach based on standardized units, Zappa et al. (2015) base their regression on absolute values. Therefore, their regression coefficients reflect not only the models' ability in translating wind changes into rainfall changes, but also potential model biases in the precipitation variability itself. In addition, several studies use hybrid dynamical-statistical approaches to reconstruct precipitation from large-scale drivers. For example, Nicolì et al. (2025) reconstruct wintertime precipitation in the NH Mediterranean from the North Atlantic Oscillation and local sea surface temperatures, showing that such hybrid approaches can enhance predictability on decadal timescales.

Finally, we conclude that since the models exhibit substantial biases in the large-scale drivers analyzed here and additionally underestimate precipitation changes associated with wind variability on interannual timescales, they may also underestimate future precipitation changes. Although our estimates based on large-scale drivers already provide some evidence that absolute precipitation decreases could exceed those projected by CMIP6 models for a high emission scenario, this hypothesis requires further validation. Importantly, the MLR estimates are themselves derived from simulated changes in large-scale drivers and therefore depend on climate models realistically capturing trends in these drivers. However, in the NH midlatitudes, climate models have been shown to struggle to reproduce observed trends in large-scale circulation patterns over the recent historical period, leading to substantial regional biases in simulated precipitation trends (Blackport and Fyfe, 2022; Gu et al., 2026). Further improving our understanding of the representation of large-scale circulation changes and their hydrological impacts therefore remains essential for increasing confidence in future precipitation projections and ultimately mitigate drought-related impacts.

Code and data availability. Rainfall data from GPCC can be downloaded from the DWD homepage (https://opendata.dwd.de/climate_environment/GPCC/html/gpcc_precipitation_analysis_monthly_v2025_doi_download.html). ERA5 and CMIP6 data can be downloaded from the Climate Data Storage: <https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels?tab=overview> and <https://cds.climate.copernicus.eu/datasets/projections-cmip6?tab=download>. The code used for analysis and data pre-processing can be found here: https://github.com/marinafriedel/CT_precip_paper.git.

Author contributions. M.F. and M.K. conceived the study. M.F. analyzed and interpreted the results with extensive input from M.K. and B.H.. M.F. wrote the paper with input from all authors.

Competing interests. The authors declare no competing interests.



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