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Evaluation of ERA5 and CHIRPS Rainfall Estimates against in-situ Observations across Southeast Africa as a basis for empirical-statistical downscaling

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Abstract. Rainfall data are critical for understanding climate variability and supporting decision-making in Southeast Africa, a region with sparse and often inaccessible in-situ observations. A selection of in-situ daily rain gauge data from 1979 to 2022 from Mozambique, South Africa, Lesotho, Zimbabwe, Malawi, Tanzania, Kenya, Rwanda, Burundi and Madagascar was compared with two global gridded data products: the ERA5 reanalysis dataset from the European Centre for Medium-Range Weather Forecasts (ECMWF) and the Climate Hazards Group InfraRed Precipitation (CHIRPS) data (version 2). The comparison was conducted using root-mean-squared error (RMSE), correlation, mean bias, common principal component analysis (PCA), correlation against the NINO3.4 index, and regression-based empirical-statistical downscaling (ESD), and is a first step towards computing future downscaled rainfall projections for the region. The results indicate that ERA5 effectively captures the climatological annual cycle and large-scale annual rainfall patterns; however, discrepancies were observed between the rain gauge on one hand and ERA5 and CHIRPS on the other. In particular, the wet-day frequency was overestimated in ERA5, and the mean rainfall intensity was underestimated. A comparison between trends estimated from in-situ rain gauge data and the ERA5 reanalysis indicated inconsistent changes over Zimbabwe, Malawi, and Kenya.

1. Introduction

Climate data are crucial for understanding the climate systems and informing adaptation and mitigation decisions. Rainfall is one of the most important climate data used for assessing climate variability and change in any region. However, such assessments have been difficult due to the lack of rain gauge data in the Southeast Africa region, as a consequence of the remoteness of some regions, sparse station coverage, cessation of observation in some regions, and reduced investment in maintaining observation networks (Dinku, 2019). In areas with good weather station coverage, but for all intents and purposes, data availability is also limited by quality issues (e.g., poor accuracy, missing data, and capturing errors during digitization) (Buytaert et al., 2012; Nicholson, 2017; Nkiaka et al., 2017; Dinku, 2019).

Rainfall datasets with long-term series and of high quality are important for documenting climate change and quantifying extreme rainfall (Trenberth et al., 2003). In addition to in-situ rain gauge measurements, satellite-derived and reanalysis data are a vital source of climate information and are widely used in climate applications and assessments, such as understanding the long-term trends of rainfall and temperature in East and Southern Africa for the Intergovernmental Panel on Climate Change assessment reports (Gebrechorkos et al., 2019).

Nevertheless, Africa is facing a significant challenge due to the limited observed data, which is hampering the validation process of global models necessary for climate projections (Tapiador et al., 2017). In response to these obstacles, recent studies have chosen to evaluate gridded satellite and reanalysis products against each other, without necessarily relying on in-situ datasets (Cattani et al., 2021; Dosio et al., 2021; Randriatsara et al., 2022; Steinkopf & Engelbrecht, 2022; Assamnew & Mengistu Tsidu, 2023). Overall, they suggest that reanalysis datasets are increasingly playing an important role and can potentially be used for climate studies in areas that have space data and where the two different sources of information provide a consistent representation of the region (Gleixner et al., 2020; Cattani et al., 2021; Steinkopf & Engelbrecht, 2022).

The combination of observed, satellite and model analysis data through data assimilation provides a good spatial and temporal coverage for a detailed assessment of the past weather (Hersbach et al., 2020). In other words, where in-situ measurements remain limited, well-validated satellite and reanalysis datasets with high spatial and temporal resolution can effectively complement or compensate for the lack of ground observations (Deo, 2011; W. V. Pitman & A. K. Bailey, 2021; Vystavna et al., 2022; Kibii & Du Plessis, 2023). However, the representation of rainfall in satellite-derived products and reanalysis datasets has shown considerable inconsistencies, particularly over Southeast Africa and regions with complex topography (Maidment et al., 2017; Q. Sun et al., 2018; Beck et al., 2019). The accuracy of these products also varies significantly from one region to another, and it is therefore essential to conduct thorough assessment and validation of these datasets at the regional or local scale before applying them in climate studies or operational decision-making. One example is the use of gridded reanalysis and in-situ data as predictors and predictands, respectively, in calibrating methods for downscaling future rainfall characteristics over southeastern Africa.

The first of datasets analysed here is ERA5, which is the fifth-generation atmospheric reanalysis dataset from the European Centre for Medium-Range Weather Forecasts (ECMWF), combining historical observations with advanced modeling and data assimilation techniques to generate consistent, high-resolution estimates of numerous atmospheric, land, and ocean variables, as described by (Hersbach et al., 2020). ERA5 provides long-term temporal and spatial data for multiple climate variables. However, ERA5 assimilates a range of satellite-borne datasets with different temporal coverage, which potentially introduces inhomogeneities, particularly in the representation of the global hydrological cycle and precipitation (Dobler et al., 2024). It is often assumed that ERA5 nevertheless remains one of the most reliable alternatives to ground-based observations in data-sparse regions because it may not have been evaluated against independent local or regional data.

There have, nevertheless, been investigations of ERA5 performance in some regions, including Africa (Steinkopf & Engelbrecht, 2022), Southern Africa (Terblanche et al., 2022), West Africa (Quagraine et al., 2020; Bodjrènou et al., 2025), Iran (Izadi et al., 2021) and China (Lei et al., 2022), which generally show that ERA5 captures rainfall spatial patterns well but can overestimate or underestimate amounts in certain sub-regions (H. Sun et al., 2021).

The second analysed dataset is the Climate Hazards Center InfraRed Precipitation (CHIRPS), sometimes an alternative to ERA5, developed by the Climate Hazards Center at the University of California, Santa Barbara. It is a quasi-global (50°S–50°N), high-resolution (0.05° × 0.05°), daily rainfall dataset (Funk et al., 2015). Its higher spatial resolution and the applied methodology for incorporation of station data make CHIRPS particularly valuable for trend analysis, seasonal drought monitoring, and environmental applications, for instance across Africa (Lussana et al., 2024).

As with ERA5, there have been numerous investigations of CHIRPS accuracy worldwide, including in Cyprus (Katsanos et al., 2016), China (Bai et al., 2018; Luo et al., 2019), Northeast Brazil (Paredes-Trejo et al., 2017), South Asia (Aadhar & Mishra, 2017), East Africa (Dinku et al., 2018), East and Southern Africa (Muthoni et al., 2023). However, to our knowledge, no comprehensive assessment studies have been carried out in the Southeast Africa region regarding the accuracy of the ERA5 and CHIRPS datasets when compared with rain gauge records.

(Assamnew & Mengistu Tsidu, 2023) evaluated the performance of ERA5 reanalysis compared to its predecessor ERA-Interim in reproducing observed rainfall over East Africa, using Global Precipitation Climatology Centre (GPCC) and Climatic Research Unit (CRU) Time-Series (TS) datasets as references. ERA5 showed significant improvements, reducing wet bias by 10–12% across key seasons, especially in western Ethiopia, Sudan, South Sudan, and Uganda, attributed to improved data assimilation. Correlations between ERA5 and the reference datasets were higher than those of ERA-Interim. However, a wet bias along the Great Rift Valley persists, and ERA5's spatial correlation is slightly weaker than ERA-Interim.

More relevant to southeastern Africa, several studies have evaluated the performance of various satellite-based and reanalysis rainfall products across East and Southeast Africa. For example, (Macharia et al., 2022) evaluated four satellite precipitation products against in-situ observations over Kenya and found that the satellite remote-sensed data can complement the in-situ

data. Another study assessed rain gauge data from stations operated by the Trans-African Hydrometeorological Observatory (TAHMO) to validate three gauge-calibrated satellite rainfall products: CHIRPS, TAMSAT and GSMaP_wGauge and one satellite-only rainfall product, GSMaP over Africa. They found that satellite-derived rainfall products have notable errors, while GSMaP products produce comparable or better results at multiple time scales relative to CHIRPS and TAMSAT (Macharia et al., 2022). Furthermore, other studies (Bamweyana et al., 2021; Mulungu & Mukama, 2023) over Uganda and Tanzania, respectively, found that the CHIRPS gridded and in-situ data are highly correlated and with a modest deviation. Despite these encouraging results, satellite-based measurements remain limited by temporal gaps between successive satellite overpasses in a given location, which can affect the detection of short-duration events (Maggioni et al., 2022).

(Muthoni et al., 2023) used monthly records to evaluate the ability of three gridded precipitation products (CHIRPS-v2, CHELSA, and TerraClimate) in estimating the rain gauge observations, and compared the precipitation trends derived from these products over different elevation categories in the East and Southern Africa region. They suggested that new or higher-resolution precipitation data are not always accurate since an algorithm update can introduce artefacts or biases.

In Mozambique, three satellite rainfall products were compared with ground-based gauge data from 2001-2012 (Toté et al., 2015). The study found that Famine Early Warning Systems Network Rainfall Estimate (RFE) v2.0 and CHIRPS performed better than Tropical Applications of Meteorology using SATellite (TAMSAT) African Rainfall Climatology And Time-series (TARCAT) v2.0. blended satellite products, combining thermal infrared and passive microwave imagery, performed best in regions with complex meteorological patterns.

The evaluation of biases in these datasets is crucial for research, downscaling applications and better decisions in choosing a suitable climate dataset for regional or local investigation. Furthermore, none of the previous evaluations has addressed the data quality for their use in empirical-statistical downscaling.

This paper aims to evaluate and compare in-situ daily rain gauge data from Mozambique, South Africa, Lesotho, Zimbabwe, Malawi, Tanzania, Kenya, Rwanda, Burundi and Madagascar with the ERA5 reanalysis dataset and CHIRPS blended dataset. We begin by assessing how well ERA5 and CHIRPS datasets reproduce the spatial patterns of annual and seasonal rainfall totals across Southeast Africa, in this case in terms of their coherent variability. We then examine the annual rainfall cycle and evaluate how the ERA5 and CHIRPS data capture the El Niño-Southern Oscillation (ENSO) teleconnection to Southeast African rainfall. Therefore, the primary strength of the present study, compared to previous research in the region, lies in its broader spatial coverage, use of a substantially larger number of in-situ observations, and analysis of longer time-series data. In addition, much of the in-situ rain gauge data presented here has never been published before.

2. Data and Methods

2.1. The Study Area

The study area encompasses east and southern Africa countries, a region characterised by highly variable topography, temperature, vegetation and climatic conditions, ranging from coastal lowlands to inland highlands. This area includes countries such as Mozambique, South Africa, Lesotho, Zimbabwe, Malawi, Tanzania, Kenya, Rwanda, Burundi, and Madagascar, shown in Figure 1, each with unique topographical features, including the Great Rift Valley.

Rainfall patterns in the region is highly variable in space and time and are influenced by a range of factors including complex variation in topography, the presence of inland water bodies, and major climate systems such as the Indian Ocean Dipole (IOD), El Niño-Southern Oscillation (ENSO), various air masses, South Indian Ocean Convergence Zone (SICZ) and the Intertropical Convergence Zone (ITCZ) (Nicholson & Kim, 1997; Cook, 2000; Blamey & Reason, 2013; Barimalala et al., 2018, 2020; Mpungose et al., 2022; Manhique et al., 2023; Mawren et al., 2023; Lim Kam Sian et al., 2024).

The northern parts of the study area, particularly Kenya, Rwanda, Burundi, and the northern highlands of Tanzania, generally experience a bimodal rainfall regime, with the long rains occurring from March to May (MAM) and the short rains from October to December (OND). June–August forms an additional significant wet season due to moisture influx from the Congo Basin for Rwanda and western Kenya. Despite these broad patterns, rainfall seasonality exhibits considerable spatial and interannual variability across the region (Camberlin & Philippon, 2002; Liebmann et al., 2014; Yang et al., 2014; Nicholson, 2017).

In contrast, regions such as central, western, and southern Tanzania, along with Malawi, Zambia, Mozambique, Zimbabwe, Lesotho, and the southeastern and northeastern parts of South Africa, generally experience a unimodal rainfall pattern. In these areas, the rainy season typically spans from October to April, though it is marked by considerable spatial and temporal variability (Masih et al., 2014; Mberego & Gwenzi, 2014; Nicholson, 2017; Muthoni et al., 2019; Manhique et al., 2023; Frank & Sarth, 2024).

The region is highly vulnerable to extreme weather and climate events, such as tropical cyclones, droughts, and floods, which have profound impacts on agriculture, water resources, people safety and overall livelihoods (Reason & Keibel, 2004; Mavume et al., 2010; Fitchett & Grab, 2014; Manhique et al., 2015; Blamey et al., 2018; Kebacho, 2021; Manhique et al., 2021; Umutoni et al., 2021; Thoithi et al., 2022; Funk et al., 2023; Kimutai et al., 2024; Chichava et al., 2024).

2.2. Data

2.2.1. Observation Dataset

The in-situ rain gauge data used in the evaluation of ERA5 and CHIRPS datasets are presented in **Fig. 1,** which shows a map of the locations of a selection of station data shared between the national meteorological services of South Africa, Lesotho, Mozambique, Zimbabwe, Malawi, Tanzania, Kenya, Burundi, Rwanda and Madagascar. The daily rain gauge measurements from southeastern Africa have been collected over the period 1979-2022 by the respective national meteorological services. The selection presented here was shared within the partners of the Coordinated Regional Downscaling Experiment (CORDEX) flagship pilot study (FPS) Southeast Africa, and aggregated to statistics to provide parameters describing the shape of statistical curves for the daily rainfall over the rainy season for the respective hydrological years. In this case, the annual wet-day frequency and wet-day mean precipitation are two key parameters for probability curves that describe the daily rainfall characteristics, as explained in (Benestad et al., 2019). A comparison on a day-to-day basis is beyond the scope of this paper and not so meaningful if there are substantial differences on an annual basis, and daily information is derived from parameters describing the statistical properties for annual samples, as in (Benestad et al., 2025). Furthermore, these raw rain gauge measurements may lack systematic quality control and homogenization. Such processes are handled independently by national meteorological services using ClimSoft and/or R-Instat, leading to potential inconsistencies across countries. The evaluation presented here, nevertheless, provides a sort of quality control by assessing the station group behaviour in addition to their similarity with gridded data on an individual station basis. In addition, publicly available data from the daily global historical climate network (GHCND) (Menne et al., 2012) were collected and compared with the data presented in **Fig. 1**, and there was a close agreement for matching locations in the two data sources. The annual aggregation was done for October 1st to September 30th of the subsequent year to capture respective rain seasons within the same hydrological year.

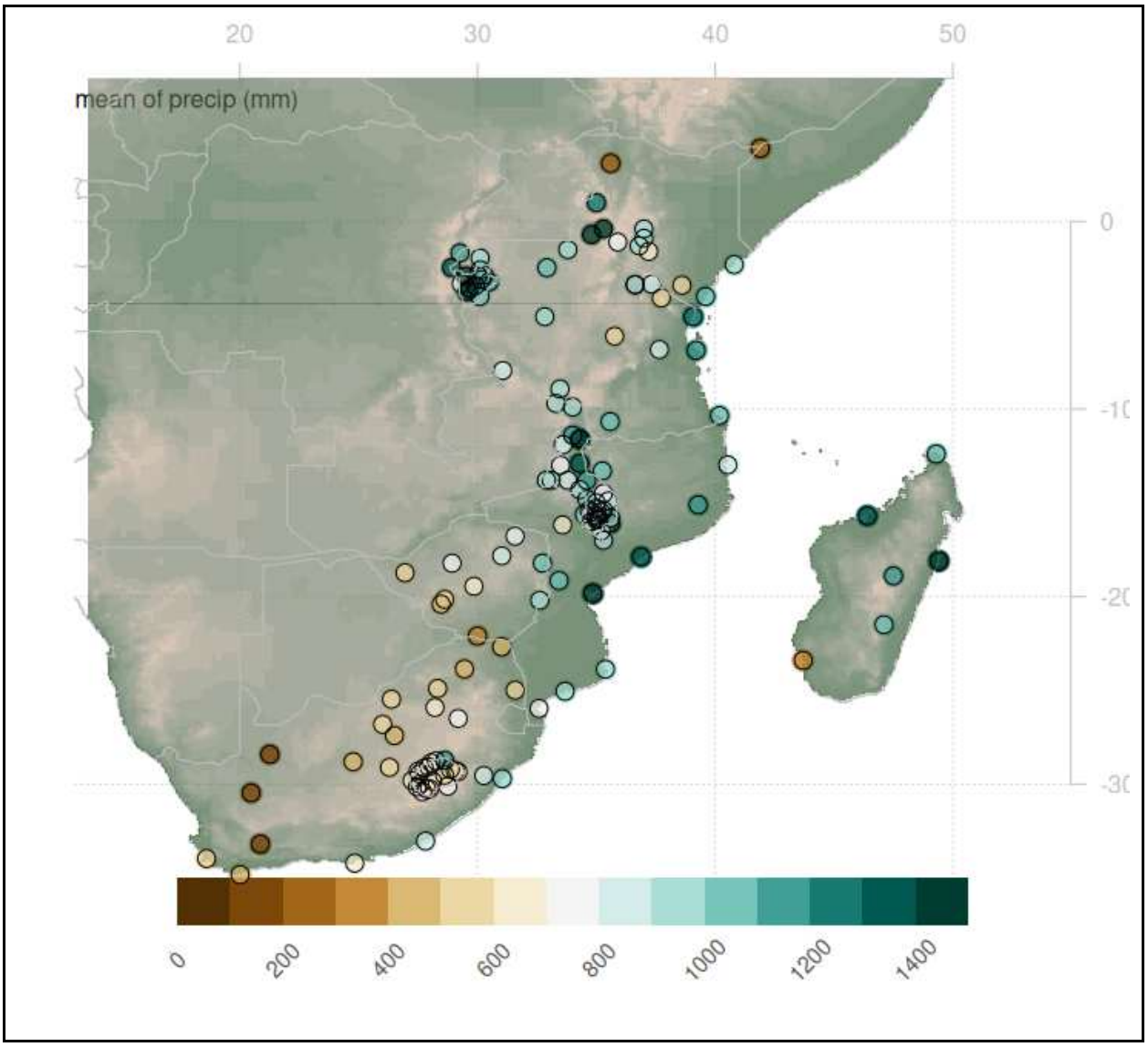


Fig.1. The location of daily rain gauge measurements involved in the data evaluation study and compared with corresponding data from the ERA5 reanalysis and CHIRPS data sets. The colours indicate the mean annual total rainfall collected at the different rain gauges.

The selection of this set of rain gauge observations was based on the availability of long time series with relatively few data gaps, given that the comparison will be conducted region-wise and hence, datasets from one country would benefit the neighbouring ones. To deal with missing daily data needed for the annual statistics, two different strategies were used for estimating annual total rainfall: (1) taking the sum of daily precipitation for years with a minimum of 300 valid data points, and (2) taking the daily mean precipitation for years with a minimum of 300 valid data points and multiplying by 365.25 days. These estimates are expected to differ according to whether missing data involve dry periods or the rainy seasons, and we

compared them to see if the results were sensitive to the choice of method of aggregation. If the missing data only represent dry days, then the sum will give a correct number for the annual rainfall, but if the missing data are from any random day in the year (dry or wet), then the mean value times the number of days may give a better estimate of the annual rainfall sum. Our tests suggested that the differences were negligible.

The estimation of mean annual cycle ("climatology") involved the mean monthly rainfall totals for each respective calendar month over the 1979-2022 period. It involved estimating the mean value, e.g. all days in January over 1979-2022, and minor gaps of missing data therefore have little effect on the estimated climatology. For comparison, the same days with missing data in the in-situ rain gauge measurements are set to missing in ERA5 and CHIRPS when estimating the climatology. The mean annual rainfall was mainly less than 2000 mm/year, except in Toamasina on the east coast of Madagascar, Bukoba in Tanzania, as well as in Kericho and Kisii in Kenya, all located in the western and northern parts of Lake Victoria, respectively. This calculation of climatology was also applied to the wet-day frequency (using a threshold of 1 mm/day to distinguish between dry and wet days) and the wet-day mean precipitation.

2.2.2. Global Reanalysis Datasets

We used annual (October-September) aggregated rainfall taken from the ERA5 (Hersbach et al., 2020) for comparison with local rain gauge data. Monthly mean ERA5 data had been downloaded from the Copernicus climate data store (CDS), and we used bilinear interpolation to extract the precipitation dataset at the nearest grid point of the rain gauge geographical locations. Monthly mean values from ERA5 were multiplied by 30 to estimate total rainfall. Since ERA5 data from Copernicus C3S was in mm/day rather than mm/month, we multiplied it by the number of days to make it comparable. While this did not give an exact monthly estimate, it was close enough for all intents and purposes. For comparison with the rain gauge data, we removed the months and years where corresponding rain gauge measurements had gaps of missing data.

We also compared the annual rainfall statistics from ERA5, interpolated to the same coordinates as the rain gauge stations, with corresponding data from ERA5-Land (Copernicus Climate Change Service, 2019; Muñoz-Sabater et al., 2021) and found that the two datasets matched closely at the same coordinates as the rain gauge stations. Since ERA5-Land has a higher spatial resolution, and is tougher to process due to its sheer volume, and ERA5 will be used as a predictor for subsequently training the methods for empirical-statistical downscaling and computing future local rainfall projections for the region, we based our evaluation on ERA5 rather than ERA5-Land. ERA5-Land is less suitable as a predictor than ERA5 since it's less similar to the output of global climate models and is only defined over land.

The rain gauge data were also compared with the gridded CHIRPS version 2 dataset, which comprises satellite and in situ data (Suliman et al., 2024). CHIRPS uses the climatological dataset CHPclim, 0.05° resolution satellite imagery, and available in situ station data to create gridded rainfall time series.

2.3. Methods

Daily local observations were collected in the R environment and aggregated into seasonal and annual statistics using the R-package 'esd' (Benestad, Abdelakder Mezghani, et al., 2015) available from https://github.com/metno/esd. The evaluation of the data sets involved a comparison between the respective climatologies of the different sites and their interannual variations in terms of annual rainfall totals, wet-day frequency, and wet-day mean precipitation. An evaluation of the climatology provides information about how well the model used to produce the reanalysis, and CHIRPS, capture the most important processes affecting variations in the rainfall. The reason for including wet-day frequency and wet-day mean precipitation in the evaluation is that they are two key parameters that describe various statistical properties of daily rainfall, such as the probability for heavy 24-hr rainfall (Benestad et al., 2019). While these statistics were aggregated on an annual basis, they nevertheless provide information about the statistical properties of daily rainfall. We also carried out an evaluation involving principal component analysis (PCA) (Benestad, Chen, et al., 2015) for representing coherent the group characteristics of the annual rainfall of all stations collectively, and used multiple regression applied to the PCA principal components representing annual rainfall totals against the leading 7 principal components of empirical orthogonal functions (EOFs) for the annual rainfall derived from the ERA5 reanalysis to gauge the similarity of the two data sets. This regression-based evaluation is equivalent to the calibration of empirical-statistical downscaling (ESD), and provides a means for comparing the spatial structure of variations (covariance) as well as temporal variations. In this case, we use diagnostics from empirical-statistical downscaling to evaluate the match between annually aggregated statistics from the set of in-situ rain gauge station series on the one hand and the large-scale rainfall from ERA5 on the other. In other words, this evaluation is a first step towards downscaling regional climate projections for rainfall over southeastern Africa, and the aspects addressed here are relevant for that. We excluded CHIRPS from this part of the evaluation because it is not intended to use it as a predictor for such projections. ERA5 is a more appropriate choice because it bears more similarities to the global climate models to which the ESD is applied, since it involves an atmospheric model.

We evaluate ERA5 and CHIRPS against local rain gauge measurements from national meteorological services, data which, to the best of our knowledge, still need to be published in scientific peer-reviewed literature. This evaluation differs from previous efforts, as here our goal is to prepare the data for empirical-statistical downscaling, where statistical models are calibrated against local rain gauge data, and statistical downscaling relies on long-term, high-quality observations to establish a robust statistical relationship (Tang et al., 2016).

To compare the mean annual cycle of the combined set of station records in an aggregated fashion, the average of total rainfall estimates for each 12 calendar months (January-December) were estimated from both the rain gauges and from corresponding ERA5 and CHIRPS precipitation data interpolated to the same coordinates. These three sets of climatology were subsequently combined in a series so it had 36 data points for each site rather than 12, and a PCA was then applied to these combined annual cycle estimates for all locations. The mean annual cycle in the rain gauge data, CHIRPS, and ERA5 were evaluated by comparing the first 12 data points with the last two subsets of corresponding 12 data points representing CHIRPS and ERA5,

respectively, and this method is referred to as 'common PCA', similar to 'common EOFs' presented in (Barnett, 1999; Benestad et al., 2023). This mathematical technique emphasises the group behaviour of the selected stations by comparing their spatio-temporal covariance structure with similar information derived from CHIRPS and ERA5 through bilinear interpolation to the same coordinates, rather than the skill at individual locations. In other words, common PCAs provide information about the similarity of the variability of the whole set of in-situ and interpolated time series rather than an evaluation on a station to station basis. An additional motivation for using common PCA to evaluate the data is the intended use of PCA to represent the predictands in future downscaling of rainfall over southeastern Africa, as in (Benestad et al., 2025).

The comparison of the rain gauge data against corresponding information from CHIRPS and ERA5 also involved more traditional testing methods, such as a Taylor diagram, scatter plot, correlation estimates, root-mean-squared error (RMSE), and mean biases.

3. The Results

There are many different aspects worth considering when it comes to rainfall, but the evaluation of the match between ERA5, CHIRPS and rain gauge data was limited here to the most salient features. The first and most important question is whether the different data sources describe a similar rainfall climatology, in this case, quantified in terms of the mean seasonal variations in rainfall. Another question is whether there is a correspondence between the year-to-year variations in the rainfall estimated from the rain gauge measurements, ERA5 and CHIRPS.

3.1. The mean annual cycle

The mean annual cycle in rainfall recorded by the rain gauge measurements and from the nearest grid point of CHIRPS and ERA5 were compared on a station-to-station basis as well as using a common PCA applied to the mean value for each of the 12 calendar months.

Fig.2 shows some examples of the mean annual cycle in rainfall for a small selection of locations, and both the rainfall climatology of ERA5 and CHIRPS tend to match that of the in-situ rain gauges. However, there were some exceptions, such as Warmbad Towoomba in South Africa and Fianarantsoa in Madagascar, where both ERA5 and CHIRPS indicated higher rainfall in January-March. These only represent a small sample of cases, and to see the climatology of the combined group of stations, we computed common PCAs for all the station climatologies.

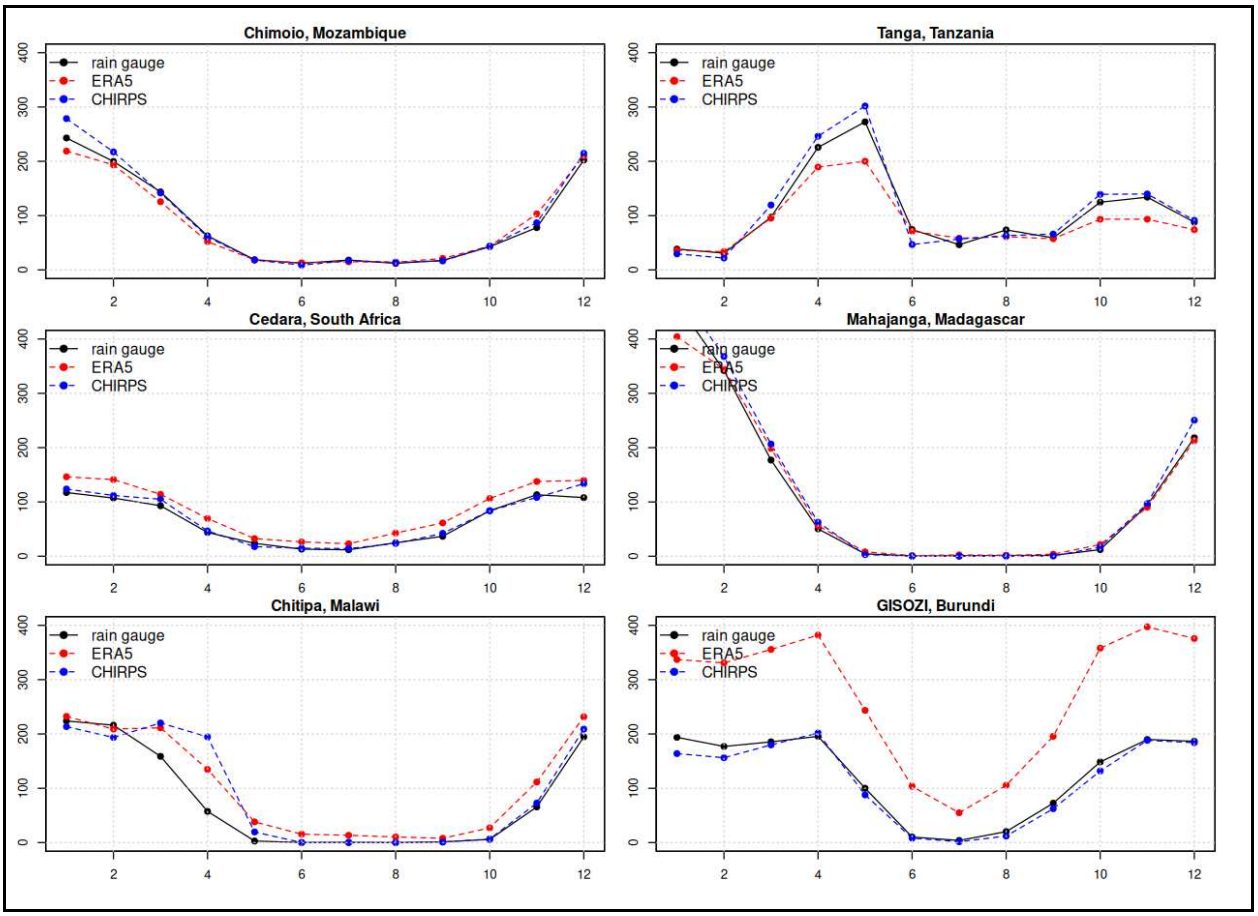


Fig. 2. Some examples of mean seasonal variations for a small selection of locations. In many cases, there is a close match between the climatology in ERA5 (red), CHIRPS (blue), and rain gauge data, but there are also some locations with large differences. This example shows some examples where there was a good match between the rain gauges and the gridded data, and some of the cases where there was a mismatch. The zero line for CHIRPS was caused by the lack of valid data over the sea. The Tanga station in Tanzania is an example from a region with bimodal rainfall regime (MAM and OND).

Fig.3 shows that the mean rainfall for each calendar month was similar for most sites, as the leading common PCA explained 81% of the total variance. In other words, most station data had a similar character in their climatology, but there were also some deviations from this. The evaluation indicated a closer match between the annual rainfall totals from CHIRPS than ERA5, and the results also indicated that the most pronounced seasonal variations in the rainfall are found around Malawi and that the rainy season starts in October and lasts until April, the following year. There were some sites with differences in the measured annual cycle and corresponding annual cycle interpolated from ERA5, but these were isolated cases and did not indicate any regional character, as they did not cluster geographically.

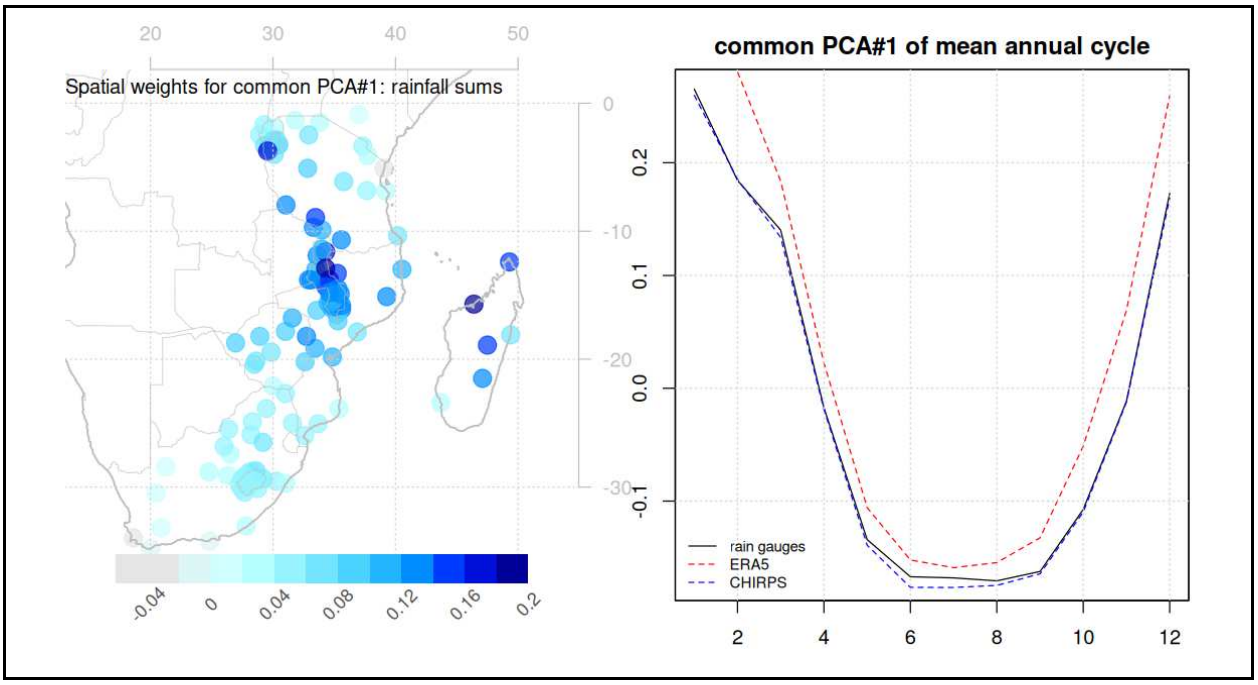
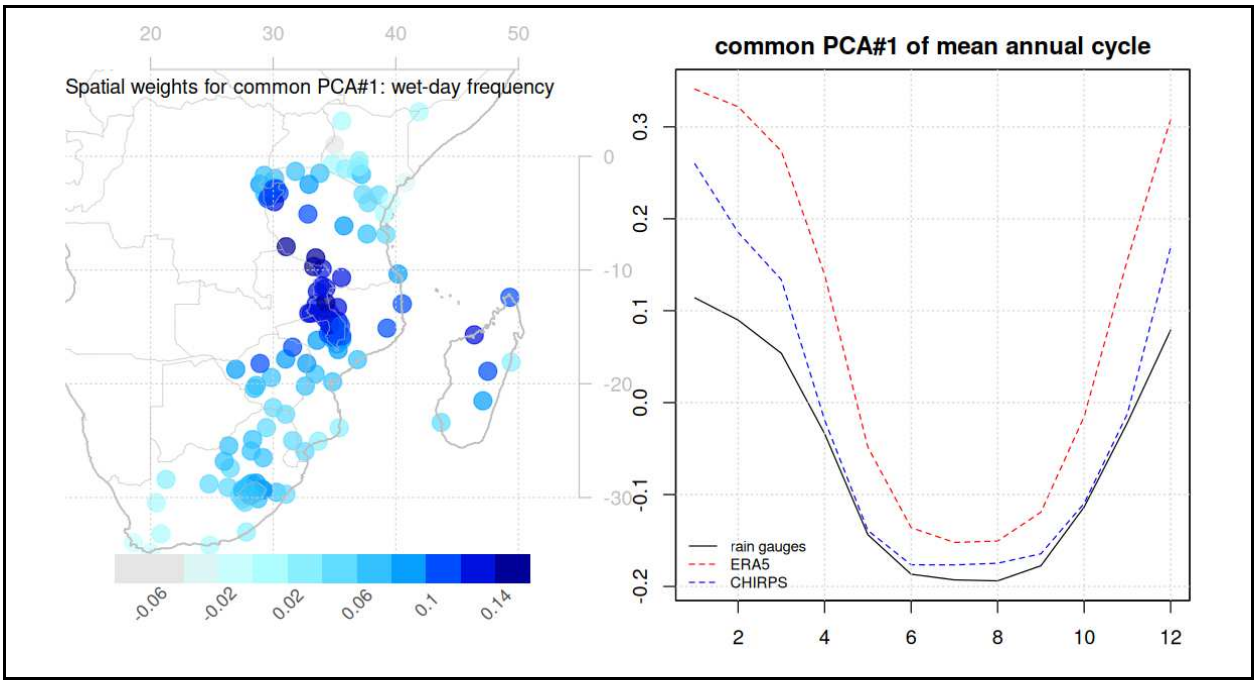


Fig. 3. The leading PCA for the joint mean seasonal in *monthly rainfall* from rain gauge data and corresponding coordinates in ERA5 and CHIRPS explained 81% of the total variance and was most pronounced around Malawi and parts of Madagascar, as indicated with the dark blue symbols in the left-hand panel. Deeper blue colours for the points highlight the locations with stronger weights (variance) connected with the curves shown in the right-hand panel. The temporal evolution of the monthly rainfall from the two data sources was also similar throughout the year.

The assessment of the mean annual cycle indicated that the seasonal rainfall from most of the rain gauge measurements matched corresponding statistics based on ERA5, but there were also some exceptions, as seen in **Fig.2**. These results provide a basis for concluding that ERA5 nevertheless gives an approximate description of the rainfall climatology over southeast Africa in terms of monthly rainfall totals for most sites, although there were some exceptions such as Gizosi in Burundi. CHIRPS also indicated a similar climatology as the rain gauge data, and matched the in-situ data also for sites such as Gizosi.

As the purpose of this evaluation was to explore possibilities for using ERA5 as a predictor for empirical-statistical downscaling of statistics derived from rain gauge data, similar to (Benestad et al., 2025), we extended the analysis shown in **Fig.3** to the large-scale wet-day frequency (f_w) and the mean intensity (μ). **Fig.4** shows an evaluation of the climatology of the wet-day frequency, which indicates that ERA5 generates too frequent daily rainfall over extensive parts of southeast Africa and especially around Malawi.



288 **Fig.4.** Same as **Fig.3**, but for the wet-day frequency (f_w). These results indicate a reduced agreement between the two data sources. The
289 estimates from ERA5 and CHIRPS suggest systematically more rainy days than those based on the daily rain gauge measurements.

290 A similar analysis for the mean intensity in **Fig.5** suggests that the climatological intensity is too weak. Since the mean
291 precipitation is approximately the product of the frequency and intensity (mean(x) = f_w μ, but due to the threshold of 1 mm/day,
292 it is not exact when there are many drizzle days), the two biases cancel each other and yield an average that seems to correspond
293 with the total rainfall. CHIRPS indicated a closer match to the in-situ data in all of these evaluations, but CHIRPS is not as
294 appropriate a predictor for empirical-statistical downscaling as ERA5, which is generated from atmospheric models. The
295 higher scores for CHIRPS do not provide a validation for subsequent downscaling of the rainfall statistics because it has less
296 in common with global climate models, but is included here as an independent source of evaluation of the in-situ and ERA5
297 data.

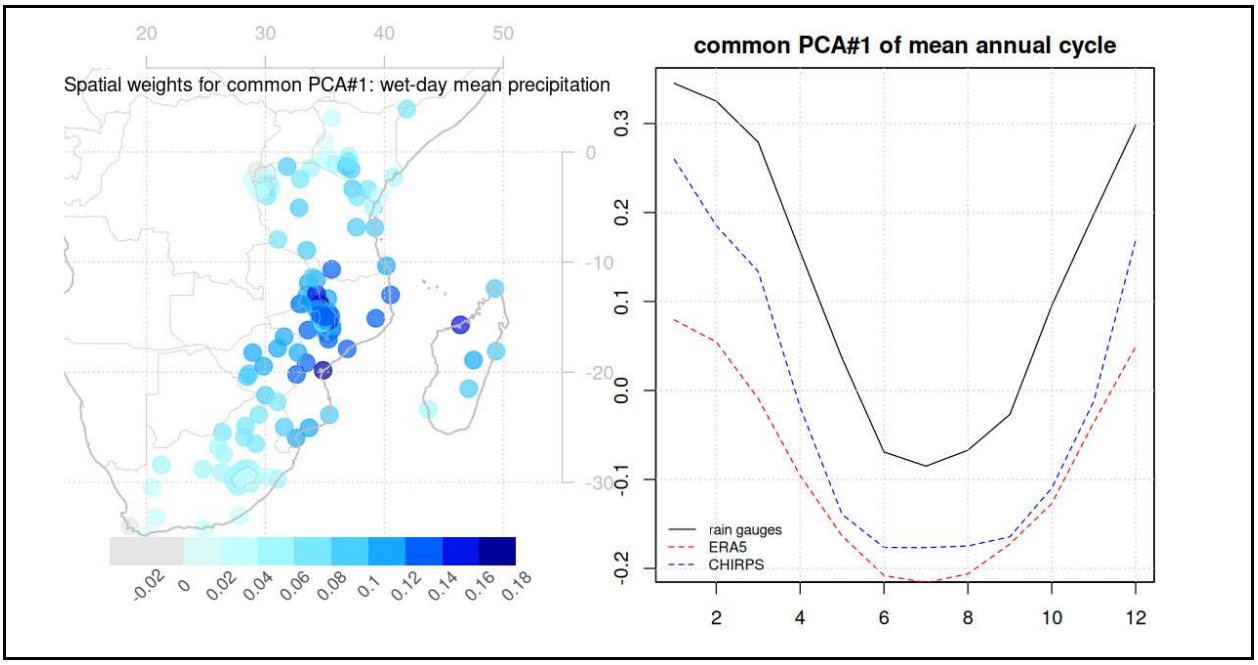


Fig.5. Same as **Fig.3**, but for wet-day mean precipitation (μ), which also indicates a reduced agreement between the two data sources. Estimates of μ from ERA5 and CHIRPS are systematically lower than those based on the daily rain gauge measurements.

3.2. Annual rainfall statistics

Fig.6 shows a Taylor diagram estimated for the annual rainfall from the rain gauges and CHIRPS, and ERA5, with a substantial scatter of results. There was a close match between the three sources of annual rainfall estimates for some locations, but there were also substantial differences at others. Furthermore, the maps in **Fig.7** indicate that the year-to-year annual rainfall from rain gauge measurements matched well the rainfall from CHIRPS and ERA5 interpolated to the same coordinates at some sites (correlation above 0.8), but there were also other sites with low correlation. Some of the mismatch between CHIRPS, ERA5 and local measurements was associated with systematic offsets, as indicated by both the root-mean-square-error (RMSE) and mean bias shown in **Fig.7**.

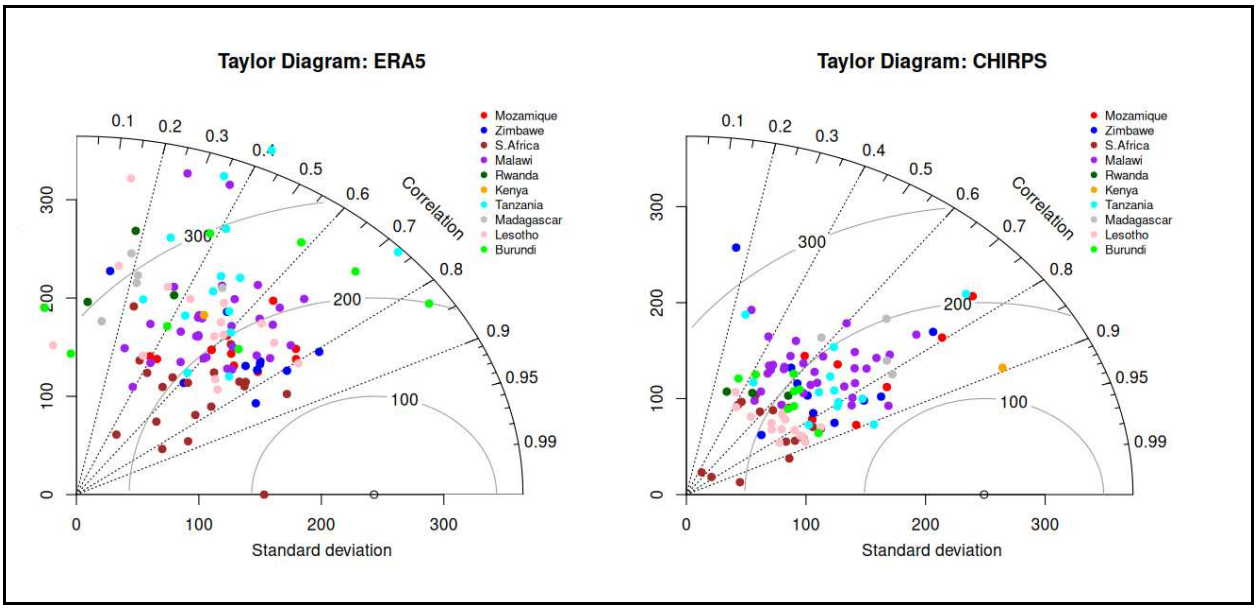


Fig.6. A Taylor diagram indicating the match between the rain gauge data ERA5 (left) and CHIRPS (right), for October-September annual rainfall.

The calibration of an empirical-statistical downscaling (ESD) model, based on stepwise multiple regression, provided a basis for comparing annual rainfall data from the ERA5 reanalysis with corresponding estimates from the rain gauges (**Fig.8**). This evaluation included a cross-validation (Wilks, 2006) of the stepwise multiple regression between the leading PCA, representing 62% of the variance of the annual rainfall from the rain gauges from southeastern Africa, and the 7 leading modes of EOFs holding annual rainfall from the ERA5 data.

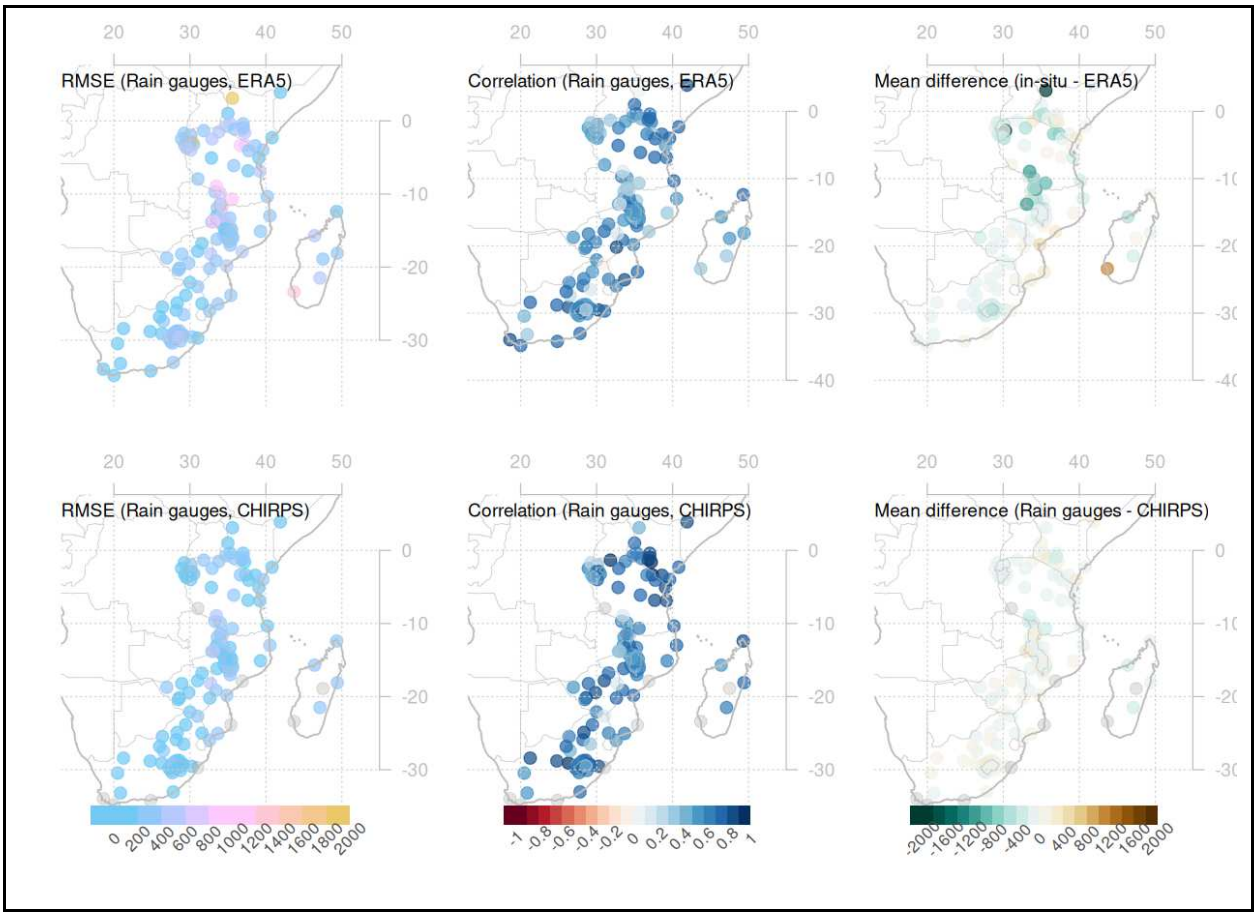


Fig.7. The root-mean-square-error (RMSE), correlation and mean difference between annual rainfall estimated from rain gauge measurements and interpolated from ERA5 (upper) and CHIRPS (lower).

The geographical weights of the predictand (the leading PCA) had a similar geographical distribution as the ERA5-based predictor pattern associated with the best fit. The two represent the same variable but at different spatial scales (upper left panel), and a good match between the two should also show similar geographical distributions. The correlation of the cross-validation was 0.76 (upper right panel), indicating a moderately good match between the rain gauge data and the reanalysis, albeit with differences between individual rain gauge records. Also, the reproduction of the leading PC from this calibration exercise that used detrended data gave results that closely matched the predictand, but with a somewhat different long-term trend (lower panel).

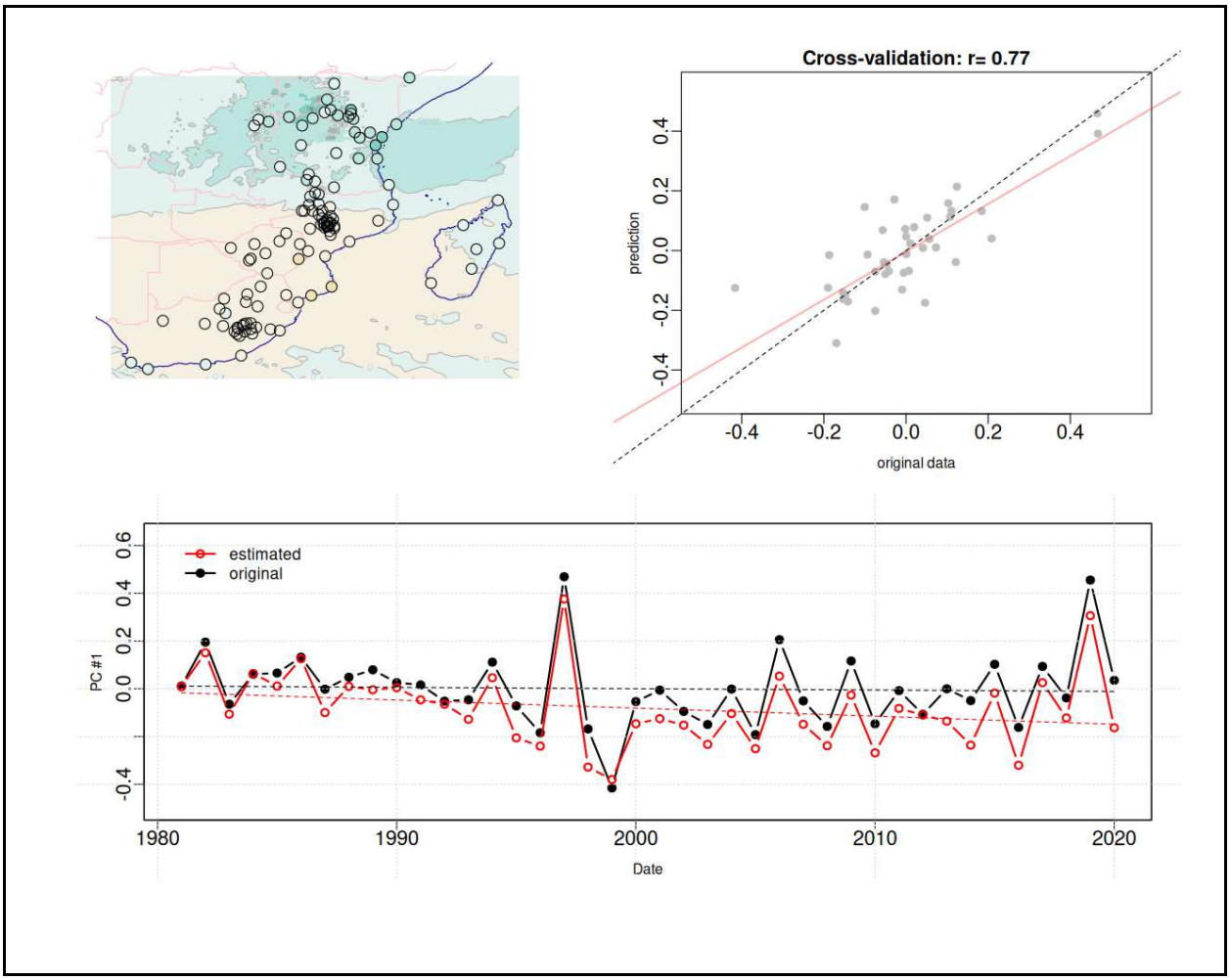


Fig.8. An evaluation based on the calibration of empirical-statistical downscaling between in-situ annual rainfall from rain gauges and ERA5 reanalysis and multiple regression, showing both spatial patterns of weights for predictand (symbols) and predictor (background map in the upper left panel) of leading PCA, cross-validation correlation associated with the leading mode and a comparison between the first principal component (upper right panel) and an estimated time series where the calibration was carried out on detrended data and the trend was added back to the input of the regression model for prediction purposes.

3.4. Precipitation trends

We estimated the relative trends in the annual rainfall derived from the rain gauge data and from the same locations in ERA5 and CHIRPS in a more traditional fashion, as opposed to the diagnostics provided by the empirical-statistical downscaling exercise shown in **Fig. 8**. Therefore, **Fig.9** shows how well the trends match on a regional basis between the in-situ rain gauge data, ERA5 and CHIRPS, whereas **Fig.8** only shows an aggregated comparison between in-situ data and ERA5. The analyses shown in **Fig.9** indicate geographical variations in how the rainfall tendency has changed over the 1981-2019 time period

when all of them had data. They indicate changes towards generally drier climates in the south and parts of Madagascar, but wetter conditions over parts of the tropical region. There are some inconsistencies in the trends, and it is interesting to note that there are opposite trends at nearby sites on the different sides of Lake Malawi and Lake Victoria. Furthermore, ERA5 indicates pronounced drying over northern Tanzania, Rwanda and southern Kenya, and differs from the analysis based on in-situ data and CHIRPS for the same locations. The trend estimates based on CHIRPS (right panel) exhibit a geographical distribution that matches the in-situ rain gauge data (left panel) more closely than ERA5. A correlation analysis between the local trend estimates of the in-situ data and CHIRPS gives a score of 0.47, as opposed to a correlation of 0.13 with ERA5. The geographical distribution of the trend estimates for ERA5 and CHIRPS, on the other hand, has a correlation coefficient of 0.49.

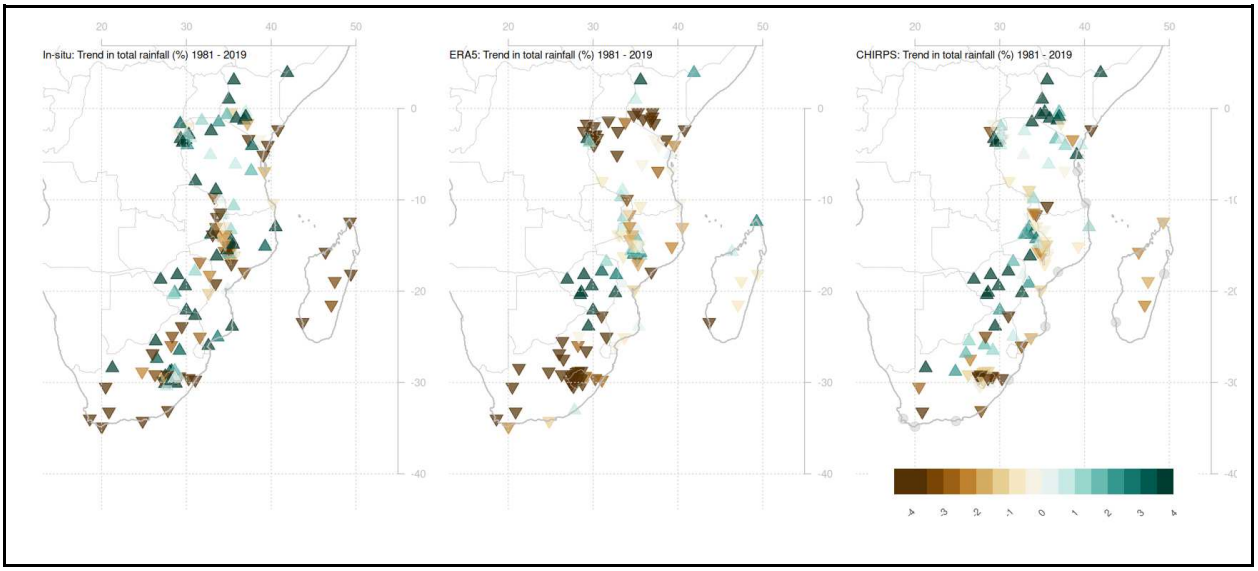


Fig.9. A trend analysis of the annual rainfall totals over the 1981-2019 period. All panels show trend analyses for the same years.

Historical trends provide a valuable baseline for projections of how the future climate may unfold, and since the strengthening of the greenhouse effect and global warming have been going on for decades already, they are likely to point towards what to expect for the future, unless there are tipping points that may take the evolution into new directions.

3.5. Teleconnections of Southeast African rainfall as an additional evaluation

Geographical variations in teleconnections to El Niño Southern Oscillation (ENSO) can also provide some information about local rain gauge data, as outliers may indicate suspect data. In this case, the evaluation employs a different benchmark than ERA5 and CHIRPS, providing an independent test case in addition to those presented above. **Fig.10** shows the correlation between annual rainfall totals and the NINO3.4 index, suggesting a large-scale pattern with both dry and wet conditions in connection with El Niño years. There were only a few anomalies where one site indicated an opposite effect from ENSO than

the surrounding sites, such as South Africa. However, in general, the correlation pattern confirms the well-established north-south contrast with wet rainy season in the northern parts with years coinciding with El Niño (positive values for the NINO3.4 index) and dry rainy seasons in the south. This pattern is reversed with dry rainy seasons in the northern part of the region and wet in the south during La Niña conditions (negative values for the Niño3.4 index).

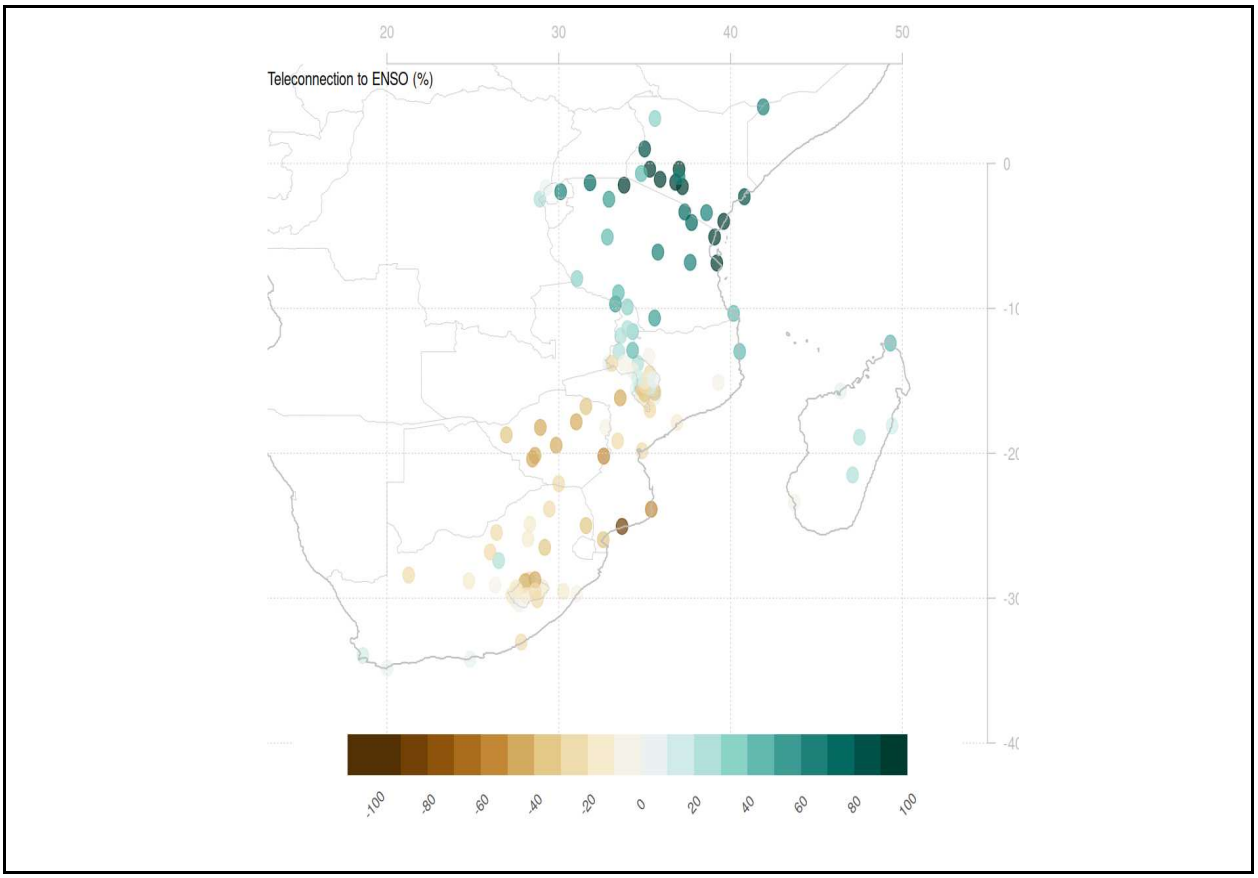


Fig.10. Weights from a regression analysis of October-September annual rainfall from in-situ rain gauge data against the NINO3.4 index over the 1981-2020 period, indicating dry El Niño years over southern Mozambique, Zimbabwe, Lesotho, Malawi, and parts of South Africa and opposite in the northern part of the region.

Fig.11 shows a comparison between the mean annual rainfall aggregated from the in-situ rain gauge data (symbols) and ERA5 (shown on the map). There was a general consistency in the large-scale geographical distribution seen in the two data sources. However, there were also sites where the rain gauges indicated higher rainfall than ERA5 and vice versa. A similar comparison between the in-situ annual rainfall and CHIRPS also gave similar patterns, but there were some exceptions where the local rain gauges indicated wetter conditions than CHIRPS, especially for regions around Lake Victoria. A comparison between

ERA5 and CHIRPS indicated that ERA5 had substantially higher rainfall than CHIRPS in spotted regions around Lake Victoria, Lake Tanganyika, and Lake Malawi.

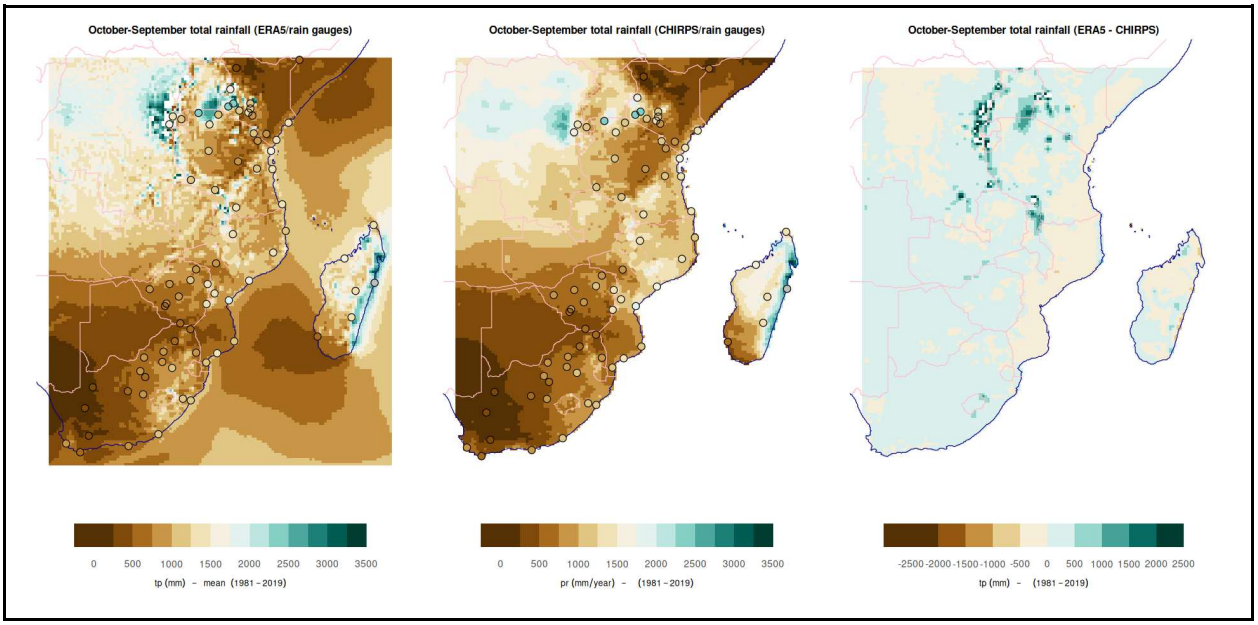


Fig.11. A comparison of the October-September annual rainfall totals (mm) in ERA5 and the rain gauges over the period 1979-2020 (left). The middle panel shows the corresponding comparison with the CHIRPS data, and the left panel shows the mean difference between ERA5 and CHIRPS.

4. Discussion

The comparison between the in-situ rain gauge data within the project *CORDEX FPS southeast Africa*, GHCND, ERA5, ERA5-land and CHIRPS suggests an overall consistency, but also that there are sites with differences. The correlation between the leading PCAs of rain gauge data and ERA5 suggests that it may be possible to use the local data as predictand and ERA5 as the predictor for training empirical-statistical downscaling models. Furthermore, the results of the analysis presented herein suggest that all these data sources may provide a useful basis for the evaluation of regional climate models. We also introduce some novel evaluation techniques, such as common PCA and diagnostics from empirical-statistical downscaling and show their merit in giving an impression of bulk similarities in addition to scores on an individual station basis.

As mentioned earlier, this analysis focused on the local in-situ rain gauge data and ERA5 because they are important for empirical-statistical downscaling and computing future local rainfall projections. The CHIRPS (Funk et al., 2015) and ERA5-Land data sets are not as relevant as a predictor for empirical-statistical downscaling because they are less similar to GCM output than ERA5. The reanalyses and GCM results are both computed by atmospheric models, and for predictors of empirical-

statistical downscaling, the focus is on large scales that the atmospheric models manage to mimic. It is nevertheless informative to include CHIRPS and ERA5-Land in the comparison to judge whether the reason for the differences between ERA5 and in-situ data is due to errors in the in-situ rainfall measurements of the ERA5 reanalysis. One explanation for the differences between ERA5 and CHIRPS, however, is that the representation of rainfall in ERA5 and CHIRPS is a prognostic variable in the former that has not been directly used in the assimilation to impose the observed state onto the numerical model, whereas the CHIRPS data have been a synthesis of satellite observations and rain gauge measurements. When local rainfall data have been used to generate the gridded product, it is not surprising to find a good match when comparing the two, but for ERA5, on the other hand, a good match implies that the reanalysis has used high-quality satellite observations to initialise the model, and it has captured well the processes responsible for rainfall generation in its prognosis. If the use of the data is for providing the best description of the local rainfall, then one should use the data that is closer to the in-situ data, but when it is being used as a predictor for downscaling, it is an advantage if the data is closer to the representation provided by the global atmospheric models such as those used to produce the reanalyses.

It is expected that the statistics from in-situ rain gauge measurements and precipitation generated by numerical models differ because the respective numbers represent slightly different realities. Whereas the in-situ data are collected by cylinders with a standard diameter of 20 cm, the grid-size of ERA5 is 0.25 degrees (24-27 km depending on the latitude) and represents the average rainfall over a much larger area. Hence, the mismatch in wet-day frequency and mean intensity between in-situ measurements and reanalysis may be explained by the larger box size in ERA5, especially if the rain-producing phenomena generally involve local small-scale convection that tends to be captured over a larger area but misses a nearby point-size rain gauge collection. This mismatch may also have an effect on the representation of the number of days with heavy rainfall according to the formula presented by (Benestad et al., 2019).

One implication of these results is that the similarity between local in-situ rain gauge data and ERA5 can provide a basis for using them for calibrating empirical-statistical downscaling methods, albeit with limitations due to an imperfect match. Scatter plots between annual rainfall for all locations combined with corresponding data from ERA5, however, indicated only a moderate correlation of 0.4, partly due to a poor correspondence for some locations. However, a closer correspondence was found when the same comparison was applied to CHIRPS (correlation 0.81).

The spatial maps of the evaluation scores RMSE, correlation, and mean biases in **Fig.7** reveal some single sites with different values (green colour) than the surrounding sites, e.g. over western Kenya, Burundi, Malawi, Zimbabwe and South Africa. Their different reproduction of rainfall may explain a weaker total score. For instance, ERA5 and CHIRPS slightly overestimate rainfall over a large part of Tanzania, but underestimate in a few areas over northeastern parts of Tanzania and Kenya. The mean biases appear to be weaker in the southern parts of southeastern Africa.

This study also included an independent form of evaluation by comparing the in-situ rain gauge data against the NINO3.4 index to see if they reproduced the well-established teleconnection. The correlations exhibited a north-south contrast between

dry and wet conditions in El Niño years, but there were also single outliers which did not follow this pattern, such as Bothaville - Balkfontein in South Africa, and some sites in Malawi, consistent with (Blamey & Reason, 2023). The rain in these locations may be connected more to a mid-latitude climate, similarly affected by frontal systems such as Cape Town, Cape Agulhas and Cape St. Francis.

The difference in trend estimates from the in-situ rain gauges and ERA5 is a concern, especially when these data subsequently will be used as a basis for empirical-statistical downscaling of GCMs to make local climate projections. Both ERA5 and in-situ data indicate drying trends in southern regions, but inconsistencies arise in Zimbabwe, Malawi, Kenya, northeastern Mozambique, and Madagascar. CHIRPS trends align more closely with in-situ data (correlation in terms of site-based trends was 0.42) than ERA5 (correlation 0.13).

The mismatch in the trends of annual rainfall is also visible in the lower panel of **Fig. 8**, but since the calibration of the downscaling method is done with de-trended data (Benestad, 2002), the projected future changes hinge on the results from the GCMs. Nevertheless, one concern is whether a lack of observations from Africa and changes in the satellite-based observations over time have a degrading effect on the ERA5 quality, which is underscored by some suspicious features in ERA5 data over Africa reported by (Benestad et al., 2024).

For climate monitoring and projections, ERA5 is a useful tool but requires cautious interpretation due to local discrepancies and trend uncertainties, emphasising the need for enhanced in-situ networks and further validation to improve reanalysis reliability in Southeast Africa. (Terblanche et al., 2022) found a wet bias in ERA5 with a consequence for the timing of individual events, but also that ERA5 reproduced both large-scale trends and seasonal variability reasonably well over South Africa.

5. Summary and Conclusions

We evaluated ERA5 reanalysis and the CHIRPS blended data against in-situ rain gauge measurements from southeast Africa and found a good agreement for many locations, but there were also some exceptions with different climatology, interannual variations and long-term trends.

ERA5 accurately captures the climatological annual cycle and large-scale annual rainfall patterns, with a leading common PCA mode explaining 81% of the variance and most pronounced weights around Malawi. However, discrepancies appear to exist at some sites, with ERA5 overestimating wet-day frequency and underestimating rainfall intensity, though these biases offset to yield a more reasonable mean precipitation estimate.

ERA5 is a valuable substitute for precipitation analysis in southeast Africa, effectively capturing the annual cycle and large-scale rainfall patterns in data-scarce regions. Its performance is comparable to in-situ data for climatological studies, with strong potential for climate monitoring and projection. However, limitations include overestimation of wet-day frequency, underestimation of rainfall intensity, and inconsistencies in trend estimates at local scales, particularly in areas like Zimbabwe

and Malawi. CHIRPS, incorporating in-situ data, shows stronger correlations with rain gauges, suggesting it may be more reliable for certain applications.

Code availability

The code that supports the findings of this study is openly available in Figshare (Benestad, 2025) at https://doi.org/10.6084/m9.figshare.28943465.v2.

Data availability

The meteorological and hydrological data analyzed in this study were obtained from the respective National Meteorological and Hydrological Services of Mozambique, South Africa, Lesotho, Zimbabwe, Malawi, Tanzania, Kenya, Rwanda, Burundi, and Madagascar. Due to third-party restrictions, these data are not publicly available and must be requested directly from the relevant national authorities.

Author contributions

BJN: Conceptualization, Methodology, Software, Data curation, Investigation, Validation, Formal analysis, Supervision, Funding acquisition, Visualization, Project administration, Resources, Writing - original draft, Writing - review & editing; **REB:** Conceptualization, Investigation, Funding acquisition, Writing - original draft, Methodology, Validation, Visualization, Writing - review & editing, Software, Formal analysis, Project administration, Data curation, Supervision, Resources; **CLV:** Data curation, Validation, Formal analysis, Writing - original draft, Writing - review & editing, Investigation; **POS**: Data curation, Formal analysis, Validation, Investigation, Writing - original draft, Writing - review & editing; **PA**: Investigation, Validation, Data curation, Formal analysis, Writing - original draft, Writing - review & editing; **ILM**: Data curation, Formal analysis, Validation, Investigation, Writing - original draft, Writing - review & editing; **VM**: Data curation, Formal analysis, Validation, Investigation, Writing - original draft, Writing - review & editing; **RL**: Investigation, Validation, Formal analysis, Writing - original draft, Writing - review & editing, Data curation; **HIM**: Data curation, Formal analysis, Validation, Investigation, Writing - original draft, Writing - review & editing.

Conflict of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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