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Comparison of gridded datasets for the simulation of streamflow in Africa

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Abstract. In recent decades, many parts of the African continent have experienced high precipitation variability with periodic drought and flood events. However, the network of streamflow gauges is too sparse in most countries to adequately capture these variations. In addition, no observed reference climatological dataset exists to adequately represent precipitation and temperature changes within all topographic and climatic zones. Consequently, the use of global gridded datasets needs to be considered. This paper aims to use the different available gridded datasets as inputs to a hydrological model to evaluate dataset performance. Nine precipitation and two temperature gridded datasets are used to this effect. The precipitation datasets include two gauged-only products, two satellite products corrected using ground-based observations, four reanalysis products and one merged product of gauge, satellite, and reanalysis. The two temperature datasets include one gauged-only and one reanalysis product. The ten precipitation and two temperature datasets were combined in their 18 possible arrangements for analysis purposes. Each combination was used to force the HMETs lumped hydrological model. The model parameters were calibrated individually for each combination against the streamflow records of 850 African catchments. The Kling-Gupta Efficiency (KGE) was used to evaluate the simulation performance. Results show that both temperature datasets performed equally well. Large differences were however observed between precipitation datasets. The MSWEP merged-product was the best-performing precipitation dataset, followed by CHIRPS satellites and ERA5 reanalysis products, respectively. The performance of both gauged-only datasets (CPC and GPCC) was inferior, outlining the limitations of extrapolating information in data-sparse regions.

Keywords: precipitation datasets, gridded datasets, reanalysis products, streamflow simulation, hydrological modeling, African catchments.

1. Introduction

Ground meteorological stations are considered the most accurate source of climate data, as they offer physical record of data in a specified area. However, stations may suffer from many limitations such as missing measurements or short temporal coverage [1]. In recent decades, many regions have experienced high variability in precipitation with periodic drought and flood events [2-5]. However, the spatial coverage of station networks is not sufficient to adequately represent these changes within all topographic and climatic



zones [4]. In addition, a gradual but steady decrease in the number of weather stations with long record listed in the Global Historical Climatology Network (GHCN) has started in the early 1990. To resolve all these problems, a large effort has been put into producing global gridded meteorological datasets. Such datasets provide continuous spatial and temporal coverage and, typically, with no missing data.

Over recent decades, several precipitation products have been produced with different spatial and temporal characteristics. These datasets differ in terms of data sources (gauge, radar, satellite, reanalysis or combinations thereof), spatial resolution (0.05° to 2.5°), spatial coverage (continental to global), temporal scale (30 minutes to annual) and temporal coverage (from 1 to several years). Several studies addressed the importance of evaluating these datasets to stand on their advantages and limitations. Most studies quantified the accuracy of these products through a direct comparison against data from weather stations [6-11], while others assessed the performance indirectly using a hydrological model to compare against observed streamflow [12-16].

2. Study Area

In this study, the African continent was chosen as the main research area. Africa is considered the second largest continent with an area of 30.3 million km^2 covering about 20% of the global land area [17]. Africa is considered to be the hottest continent on Earth. The northern half is mostly covered by drylands and desert, while the central and southern parts contain savanna and rainforests [18]. Based on the combination of temperature, precipitation and evapotranspiration, Africa can be divided into four main climatic zones; 1) arid and semi-arid, 2) tropical, 3) equatorial, and 4) temperate [19].

3. Data and Methods

3.1 Data

For many African regions, observed meteorological data are not easily available, either due to the lack of weather stations or the high fees to access the data. Most studies in Africa therefore depend on using satellite-derived data as a reference dataset [20-23]. Hence, this paper aims to evaluate the performance of other several types of gridded datasets over a large set of hydrologically heterogeneous watersheds. The dataset performance is assessed through their ability as generating accurate streamflow through the use of a hydrological model.

3.1.1 Precipitation gridded datasets

Gridded datasets can be classified as a function of their data source. Gauge-based gridded datasets are obtained by interpolating the information measured at a small scale (typically a point measurement at a weather station) and mapped onto a predefined spatial and temporal resolutions grid. However, variation in gauge types or instrument replacements affect error characteristics on the long-term records. In addition, observations are affected by systematic biases from evaporation and wind effect or due to, for example, elevation placement of gauges in mountainous regions [24].

A different approach to measure precipitation is using ground weather radars, as it partially addresses the issue of rain gauge coverage. Moreover, it provides much larger spatial coverage to measure precipitation than the point measurements provided by gauges. However, radar coverage is limited to developed regions that have a high population. In addition, they sense the real rainfall rate at a certain observational level above ground. Therefore, the presence of weather stations is required for the calibration and correction processes [25].

Nowadays, satellite products are available at the global scale and can cover large areas at high spatial and temporal resolutions and near real time coverage. They are mainly suitable for rainfall estimation in the tropics and data sparse regions. However, satellites are relatively insensitive and generally miss a significant quantity of light precipitation and tend to fail over snow and ice-covered surfaces [26]. Some studies evaluated the uncertainties of these datasets and showed that high resolution satellite products perform better when bias corrected using gauge observations [27, 28].

Retrospective-analysis / reanalysis systems are vital sources of data in weather and climate studies. A typical reanalysis system consists of two main components, the forecast model and the data assimilation system. The role of the data assimilation system is to integrate observed databases of many sources of observations with the numerical weather forecast models to produce consistent gridded datasets [29]. Although reanalysis are not

Table 1. The selected global gridded datasets

	Short name	Data Source	Spatial Resolution	Spatial Coverage	Temporal Resolution	Temporal Coverage
<i>1- Precipitation datasets</i>						
1	CPC Unified	Gauge	0.50°	Global	Daily	1979 - Present
2	GPCC	Gauge	1.0°	Global	Daily	1979 - 2016
3	PERSIANN-CDR	Gauge, Satellite	0.25°	60°N - 60°S	6 hours	1983 - 2012
4	CHIRPS	Gauge, Satellite	0.05°	50°N - 50°S	Daily	1981 - Present
5	NCEP-CFSR	Reanalysis	0.50°	Global	6 hours	1979 – 2010
6	ERA-Interim	Reanalysis	0.75°	Global	3 hours	1979 – 8/2019
7	ERA5	Reanalysis	0.25°	Global	hourly	1979 – 2017
8	JRA-55	Reanalysis	0.5625°	Global	3 hours	1959 - Present
9	MSWEP V1.0	Gauge, Satellite, Reanalysis	0.25°	Global	3 hours	1979 - 2015
<i>2- Temperature datasets</i>						
1	CPC Unified	Gauge	0.50°	Global	Daily	1979 - Present
2	ERA5	Reanalysis	32 Km.	Global	hourly	1979 - 2017

direct observations, they provide analyzed variables in areas where stations are minimal [30]. Overall, no single precipitation product could be considered ideal for measuring precipitation. In fact, all precipitation products tend to miss a significant volume of rainfall [12].

As discussed earlier, there is now a rather large number of gridded datasets from stations, satellites, reanalysis or a combination thereof. However, not all those datasets can be used for climate change impact studies. Appropriate datasets would have the following desirable characteristics: 1) spatial resolution (between 0.05° to 1°); 2) daily scale or finer temporal resolution, 3) long temporal coverage (~ 30 years), and 4) all datasets should cover approximately the same time interval. Based on those criteria, ten precipitation and two temperature gridded datasets were chosen in this study as shown in 'table 1'. The precipitation datasets include two gauged-only products (GPCC and CPC), two satellite products corrected using ground-based observations (CHIRPS and PERSIANN), four reanalysis products (JRA55, NCEP-CFSR, ERA-Interim and ERA5) and one merged product of gauge, satellite, and reanalysis (MSWEP).

3.1.2 Temperature gridded datasets

Land surface temperature is a key variable for meteorological monitoring and forecasting services [31]. It is also a key variable for climate and hydrological studies. In hydrological modelling, the air temperature is the

key driving variable for the evapotranspiration and snowmelt processes. Hence, accurate temperature data is a vital issue. However, the lack of adequate gauge network can result in improper estimates of temperature. Therefore, temperature gridded datasets are also crucial in many fields. Temperature products are generally thought to be less complex than precipitation datasets due to its much smaller spatial and temporal variability. Therefore, much fewer studies have compared and evaluated the uncertainty of using different temperature datasets. On this study, two temperature datasets have been included: the gauge-based CPC dataset, and the ERA5 reanalysis.

3.1.3 Observed streamflow data

Streamflow records from the Global Runoff Data Centre (GRDC) were used to calibrate the hydrological models and evaluate the hydrological modelling performance. The GRDC database has streamflow data from 1150 African stations. In this study, 850 stations were chosen based on two criteria. First, stations should have data during the 1983-2012 study period. Second, stations that have less than three years of consecutive data during this period were excluded. The spatial distribution of these stations is shown in 'figure 1'.

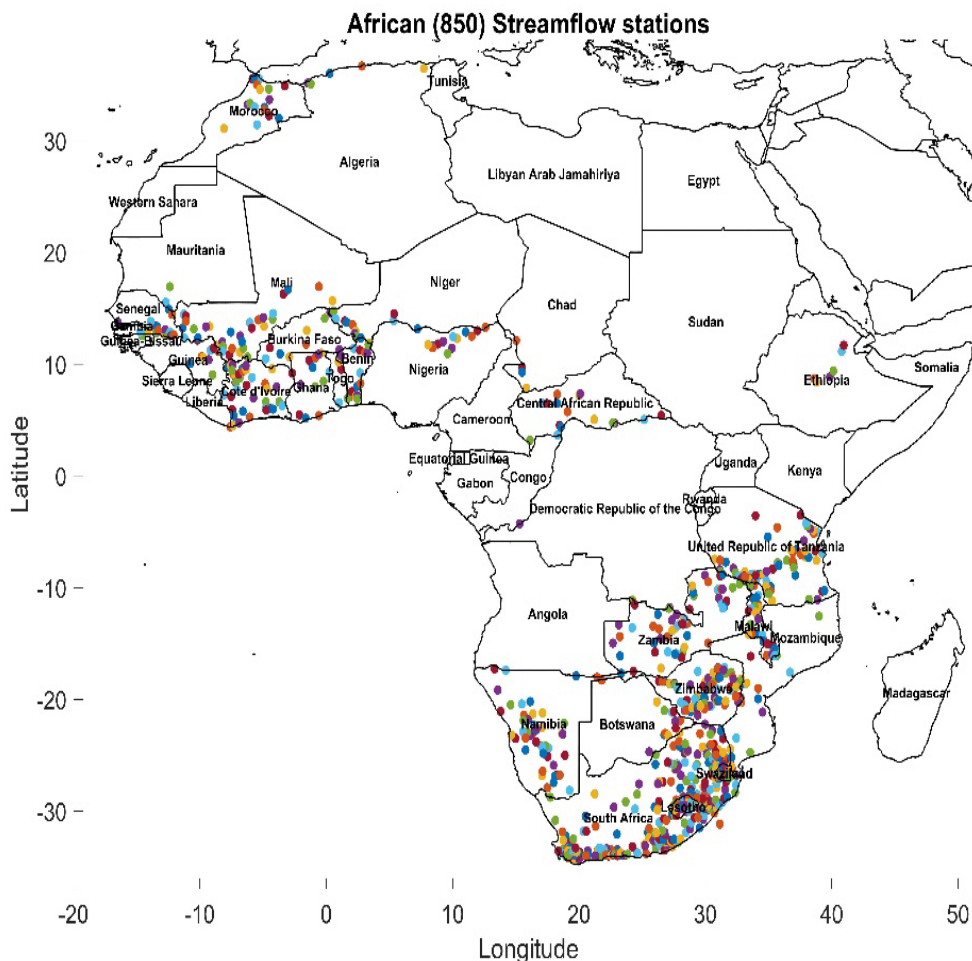


Figure 1. Spatial distribution of the African 850 streamflow stations

3.2 Hydrological model

In this study, the use of a distributed model was discarded due to the scale of the study. The lumped hydrological model HMETs [32] was used to evaluate the performance of the various climate datasets. This model has shown an overall good performance in a wide range of climates and hydrological studies [32-34]. The model requires daily precipitation, temperature and potential evapotranspiration (PET) as inputs. The Oudin's temperature-based formula [35] was used to calculate PET as it has shown an overall good performance and robustness on large-scale hydrological studies [36].

3.3 Hydrological model calibration

As will be detailed in the following section, the nine precipitation and two temperature datasets were combined in their 18 possible arrangements for analysis purposes and the hydrological model parameters were calibrated for each catchment and each dataset combination. The 15300 calibrations to be performed (9 precipitation datasets x 2 temperature datasets x 850 catchments) required the application of an automatic model parameter calibration method. For this study, the CMAES algorithm was applied because of its flexibility [37]. Moreover, it is considered as one of the best auto-calibration algorithms for hydrological modelling [38].

The Kling-Gupta Efficiency (KGE) calibration objective function was used to evaluate the simulation performance. KGE is a modified version of the Nash-Sutcliffe Efficiency (NSE) metric that was introduced by Gupta [39] and modified by Kling [40]. It is defined as a combination of three elements; correlation, bias and variability as shown in 'equation 1'. Pearson's correlation coefficient used to represent the correlation component (r), the ratio of estimated and observed means used to calculate the bias component (β) and the ratio of the estimated and observed coefficients of variation represent the variability component (γ).

$$KGE = 1 - ((r - 1)^2 + (\beta - 1)^2 + (\gamma - 1)^2)^{1/2} \quad (1)$$

The theoretical value for KGE to be equal 1 means that there is a perfect fit between the observed and simulated flows. Generally, KGE values above 0.6 are considered good.

4. Results and discussion

4.1 Analysis of precipitation and temperature

'Figure 2' presents mean annual temperature over the 1983-2012 period for the two selected temperature datasets.

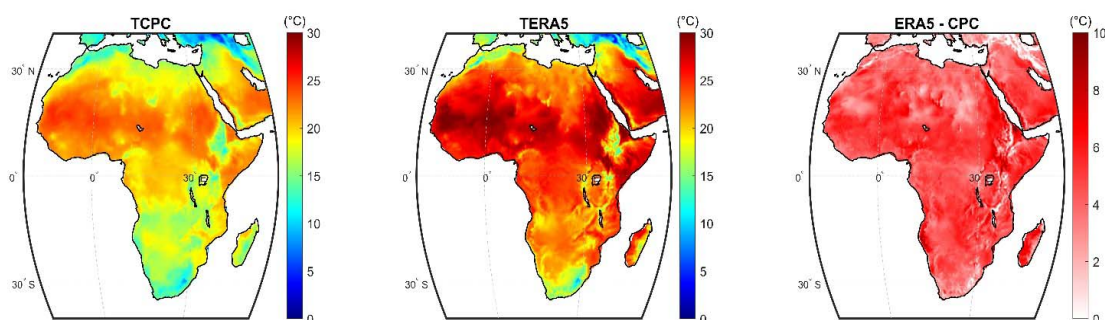


Figure 2. Mean annual temperature for the two datasets and the bias between them

Both datasets display the same temporal patterns. ERA5 is however significantly warmer than CPC with a typical warm bias of 5-6 degrees over most of Africa. This difference is very large and can potentially affect

evapotranspiration. However, the specific calibration of the hydrological model to each dataset has the potential to take this into account.

To better present the differences between the datasets, the bias in the mean annual precipitation was calculated between each individual dataset and the average of all datasets. Results are shown in 'Figure 3'. The average here is considered as the reference benchmark. Since all the gridded datasets have different spatial resolution, the datasets were first interpolated to the finest grid scale. A red color indicates that the dataset is wetter than the average, while the blue color indicates it is dryer. Results show important differences between the different precipitation datasets. All the datasets are generally similar in the desert and semi-desert regions but large differences are obvious in the tropical western and central regions.

Overall, the reanalysis (middle row) are wetter over the intertropical zone, with ERA5 being much closer than the other three considered reanalysis. The CPC gauge-based dataset is much drier than all other datasets. The large differences between both gauge-based datasets (CPC and GPC) outline the complexity of interpolating in data-spare regions. Differences between the other datasets are comparatively smaller. In the absence of any reliable reference datasets, it is difficult to interpret the differences observed here. While an outlier dataset (e.g. CPC) may lead to suspicion, the limitations associated with each dataset does not allow for any firm conclusion. This is why hydrological modeling is used as an indirect validation method in this study. Even though streamflow gauges records do contain errors[41], in the context of this study, they are considered as the most reliable source for validation of the precipitation and temperature datasets.

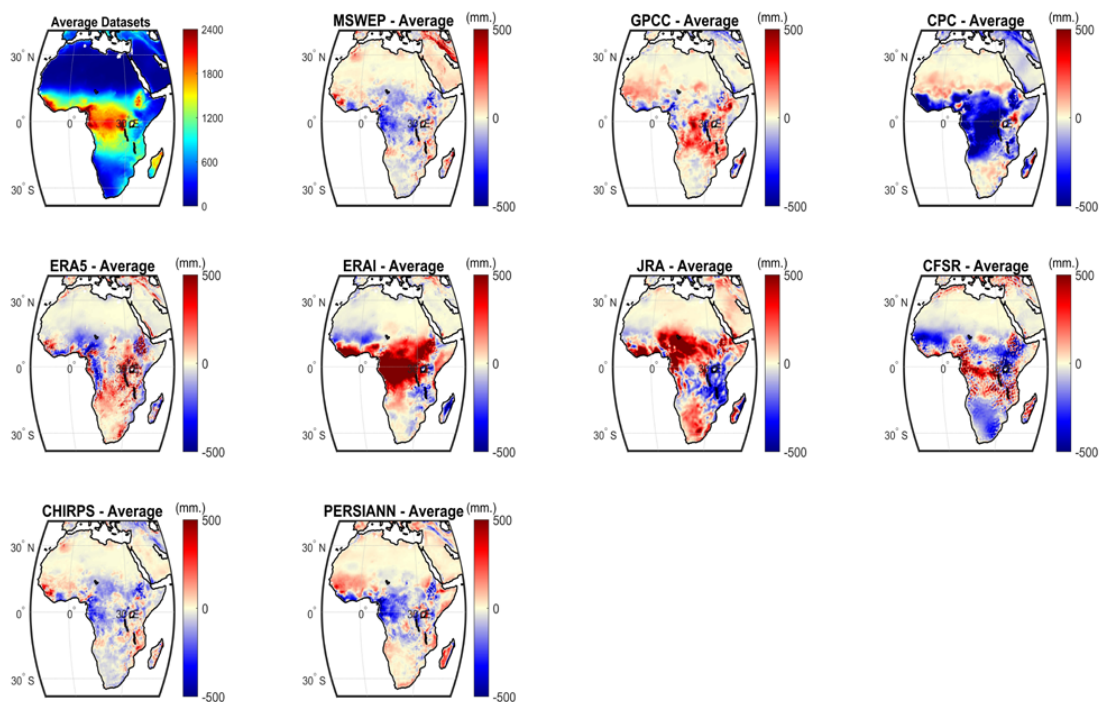


Figure 3. Mean annual precipitation for the average of the all datasets (top left) and the bias from the average

4.2 Hydrological model simulations

This section presents the results obtained from the hydrological modelling simulations. 'figure 4' shows the distribution of KGE scores for each of the 18 combinations of precipitation (9 sets) and temperature (2 sets). Each boxplot in 'figure 4' contains the KGE scores of all of the catchments in this study.

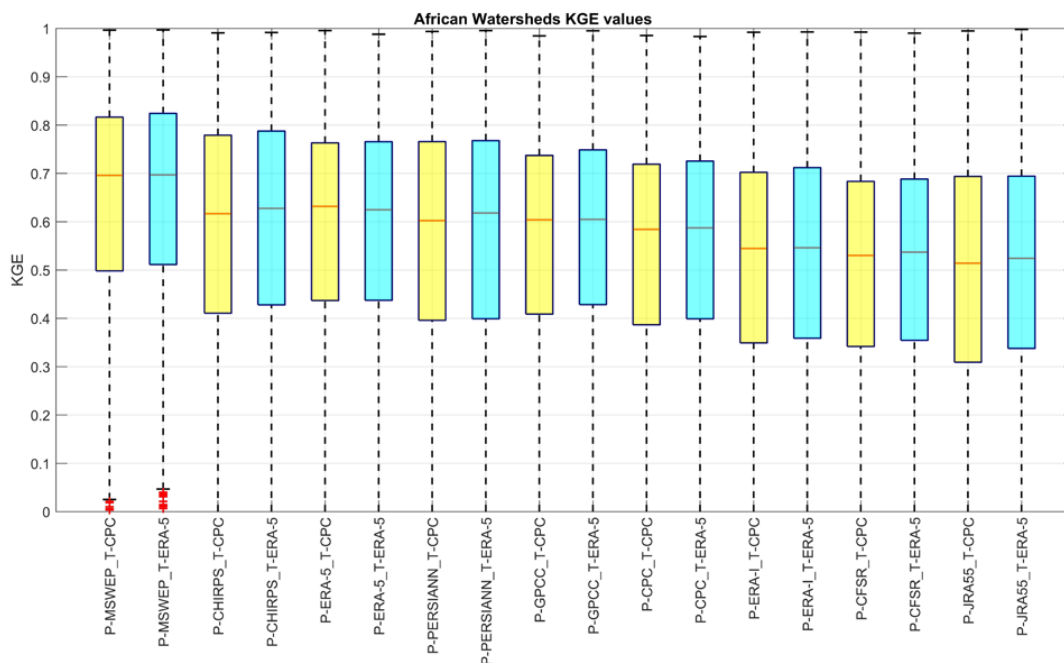


Figure 4. KGE boxplots for nine precipitation and two temperature datasets

Many conclusions can be drawn from 'figure 4'. Both temperature datasets perform very similarly across all precipitation datasets, although ERA5 gives very small but consistently better results. Most of the differences observed in 'figure 4' therefore originate from the precipitation datasets.

All precipitation datasets result in acceptable KGE median value larger than 0.5, showing they can all be used for hydrological modeling. There are however large differences with some datasets clearly outperforming others. The CPC and GPCC gauge-based datasets are outperformed by five datasets. The MSWEP merged-product is quite clearly the best-performing precipitation dataset, followed by the CHIRPS satellite and the ERA-5 reanalysis datasets. The ERA-I, CFSR and JRA reanalysis are the least-performing datasets in this study.

In order to study the impact of spatial variability, 'figure 5' present the spatial distribution of KGE values for all nine precipitation datasets used in conjunction with ERA5 temperature.

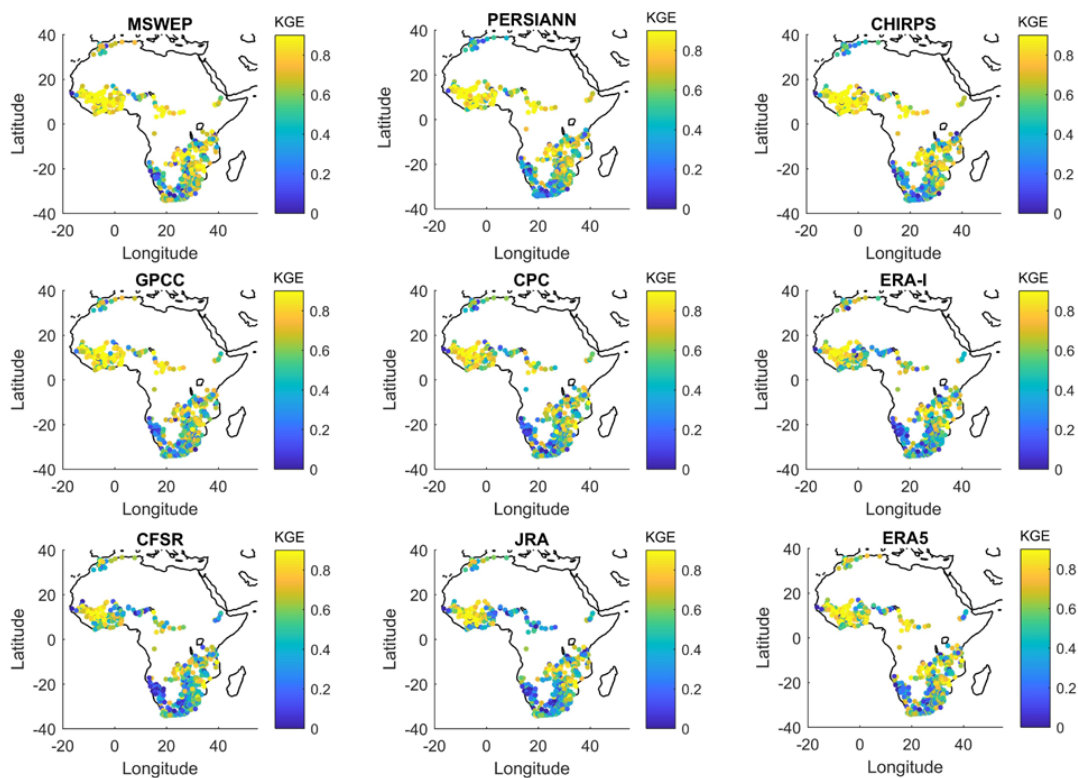


Figure 5. Spatial distribution of Kling-Gupta efficiency metrics for nine precipitation datasets and ERA5 temperature datasets

The spatial patterns are consistent for all precipitation datasets. Hydrological modelling performance is general quite good everywhere with the exception of South Africa. This could either be due to less reliable streamflow records in this region or more likely to the hydrological model difficulties in dealing with the arid climate of south Africa. Rainfall-runoff models have long been known to have difficulties in such climates [42].

5. Conclusion

The main objective of this study was to evaluate the performance of nine precipitation and two temperature datasets to simulate streamflows of 850 African catchments over the 1983-2012 period. The MSWEP merged-product dataset was clearly the best performing one, followed by CHIRPS and ERA5 products, respectively. The performance of both gauged-only datasets (CPC and GPCC) was inferior, outlining the limitations of extrapolating point-based measurement in data-sparse regions. Both temperature datasets performed similarly.

6. Acknowledgements and data access

This study was partly funded by the National Science and Engineering Research Council of Canada and the Egyptian Armed Forces (Ministry of Defense).

The CPC, GPCC and NCEP datasets can be downloaded from the Earth System Research Laboratory (ESRL), available here: <https://www.esrl.noaa.gov/psd/data/gridded/tables/precipitation.html>

ERA-Interim, ERA5 and JRA55 dataset are available on the Research Data Archive: <https://rda.ucar.edu/datasets/ds628.0/>

The GRDC streamflow data can be downloaded from the Global Runoff Data Centre, available here: https://www.bafg.de/GRDC/EN/Home/homepage_node.html;jsessionid=814972125050CA97A6F1CE67230E5CE6.liv_e21303.

MSWEP data are available through the PCA servers at: https://platform.princetonclimate.com/PCA_Platform/mswepRetro.html.

CHIRPS satellite dataset can be downloaded from the Climate Hazards Center: <https://www.chc.ucsb.edu/data/chirps>

Finally, the HMETS hydrological model is available on the MATLAB File Exchange: <https://www.mathworks.com/matlabcentral/fileexchange/48069-hmets-hydrological-model>.

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