Uncertainty of gridded precipitation and temperature reference datasets in climate change impact studies

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Abstract. Climate change impact studies require a reference climatological dataset providing a baseline period to assess future changes and post-process climate model biases. High-resolution gridded precipitation and temperature datasets interpolated from weather stations are available in regions of high-density networks of weather stations, as is the case in most parts of Europe and the United States. In many of the world's regions, however, the low density of observational networks renders gauge-based datasets highly uncertain. Satellite, reanalysis and merged products dataset have been used to overcome this deficiency. However, it is not known how much uncertainty the choice of a reference dataset may bring to impact studies. To tackle this issue, this study compares nine precipitation and two temperature datasets over 1145 African catchments to evaluate the dataset uncertainty contribution to the results of climate change studies. These datasets all cover a common 30-year period needed to define the reference period climate. The precipitation datasets include two gauged-only products (GPCC, CPC Unified), two satellite products (CHIRPS and PERSIANN-CDR) corrected using ground-based observations, four reanalysis products (JRA55, NCEP-CFSR, ERA-I, and ERA5) and one gauged, satellite, and reanalysis merged product (MSWEP). The temperature datasets include one gauged-only (CPC Unified) product and one reanalysis (ERA5) product.

All combinations of these precipitation and temperature datasets were used to assess changes in future streamflows. To assess dataset uncertainty against that of other sources of uncertainty, the climate change impact study used a top-down hydroclimatic modeling chain using 10 CMIP5 GCMs under RCP8.5 and two lumped hydrological models (HMETS and GR4J) to generate future streamflows over the 2071-2100 period. Variance decomposition was performed to compare how much the different uncertainty sources contribute to actual uncertainty.

Results show that all precipitation and temperature datasets provide good streamflow simulations over the reference period, but 4 precipitation datasets outperformed the others for most catchments: they are, in order: MSWEP, CHIRPS, PERSIANN, and ERA5. For the present study, the 2-member ensemble of temperature datasets provided negligible levels of uncertainty. However, the ensemble of nine precipitation datasets provided uncertainty that was equal to or larger than that related to GCMs for most of the streamflow metrics and over most of the catchments. A selection of the best 4 performing reference datasets (credibility ensemble) significantly reduced the uncertainty attributed to precipitation for most metrics, but still remained the main source of uncertainty for some streamflow metrics. The choice of a reference dataset can therefore be critical to climate

25 change impact studies as apparently small differences between datasets over a common reference period can propagate to generate large amounts of uncertainty in future climate streamflows.

1 Introduction

General Circulation Models/Earth System models (ESM) /Global Climate Models (GCMs) are the primary tools used to simulate the response of the global climate system to increases in greenhouse gas concentrations and to generate future climate

30 projections. GCMs are complex mathematical representations of the physical and dynamical processes governing atmospheric and oceanic circulations as well as the interactions with the land surface. In order to reduce the computation burden, which can be considerable, GCMs represent the earth with a grid having a relatively coarse spatial resolution (IPCC (2001)). Consequently, GCM projections cannot be used directly for fine scale climate impact studies. Statistical/empirical or dynamical downscaling techniques have thus commonly been used to address this scale mismatch. In addition, climate model outputs are

35 always biased, and the extent of these biases can be evaluated through a comparison against observations over a common reference period. A bias correction procedure is therefore generally performed in addition to the downscaling step, and biases are assumed to be invariant in time when the correction is applied to future climate projections (Velázquez et al. (2015)). Although a two-step downscaling bias correction approach is preferable in most cases, a single instance of bias correction is sometimes used to account for both scale mismatch and GCM biases. While this may be acceptable when the scale difference is small

40 (e.g., when using catchment averaged values), recent studies have shown that bias correction has limited downscaling skills (Maraun (2016)).

Statistical downscaling and bias correction approaches primarily rely on hydrometeorological observations over a historical reference period. It is therefore primordially important that the observed reference dataset represents the true climate state as closely as possible. For this task, ground stations remain the standard and most accurate/trusted source of weather data

45 (New et al. (2001); Nicholson (2013)). However, the spatial distribution of these stations varies widely across the globe, and coverage is often sparse and even deficient in many parts of the world outside of Europe and the US. Even in well-covered regions, gauge data is subject to many problems, such as missing data, precipitation undercatch and inhomogeneities related to a variety of issues such as equipment change, station relocation and land surface modifications near each station (Kidd et al. (2017); Peterson et al. (1998)).

50 In recent decades, extensive efforts have been devoted to the development and improvement of gridded global and quasi-global climate datasets to overcome the limitations of gauge stations. These datasets provide meteorological record time series with continuous spatiotemporal coverage, and typically, no missing data. However, various error sources are inherent in these datasets, thus also bringing uncertainty to the data (Voisin et al. (2008)). Thus, choosing an appropriate reference dataset for climate change impact studies is an important concern, and especially so in regions with sparse ground station coverage.

55 According to Huth (2004): "For estimates based on downscaling of General Circulation Model (GCM) outputs, different levels of uncertainty are related to: (1) GCM uncertainty or inter-model variability, (2) scenario uncertainty or inter-scenario variability, (3) different realizations of a given GCM due to parameter uncertainty (inter-model variability) and (4) uncertainty

due to downscaling methods". In most climate change impact studies, it is generally assumed that GCMs are the major source
of uncertainty (Mpelasoka and Chiew (2009); Kay et al. (2009); Vetter et al. (2017)). (Rowell (2006)) compared the effect of
60 different sources of uncertainty using the initial condition ensembles of different GCMs, GHGES and Regional Circulation
Models (RCMs) on changes in seasonal precipitation and temperature in the United Kingdom. The results indicated that the
largest uncertainty comes from the GCM choice. (Minville et al. (2008)) used ten equally-weighted climate projections derived
from a combination of five GCMs, two GHGES and the change factor approach for downscaling to investigate the uncertainty
envelope of future hydrologic variables. Their results showed that the uncertainty related to the GCM choice is dominant.
65 These results have also been confirmed by several studies (Prudhomme and Davies (2009); Nóbrega et al. (2011); Dobler et al.
(2012)). Other studies have assessed other sources of uncertainty such as Greenhouse Gases Emission Scenarios (GHGES)
(Prudhomme et al. (2003); Kay et al. (2009); Chen et al. (2011)), the downscaling method (Wilby and Harris (2006); Khan et al.
(2006)) and hydrological modeling (Bae et al. (2011); Vetter et al. (2017)). Recent studies have also looked at the uncertainty
related to the choice of the impact model (Giuntoli et al. (2018); Krysanova et al. (2018)). From these studies, a more complex
70 picture emerges, in which the main source of uncertainty may vary, depending on geographical location and metric under
study. Dataset uncertainty has been assessed in numerous studies either by direct inter-comparison between datasets (Vila et al.
(2009); Andermann et al. (2011); Romilly et al. (2011); Jiang et al. (2012); Chen et al. (2014); Prakash et al. (2018); Nashwan
and Shahid (2019)) or by using hydrological modeling (Behrangi et al. (2011); Beck et al. (2017b); Wu et al. (2018); Zhu et al.
(2018); Tarek et al. (2019)). However, to the best of our knowledge, the uncertainty of gridded datasets has not been evaluated
75 against other sources of uncertainties when performing climate change impact studies. The objective of this study is therefore
to assess the impact of the choice of a given reference dataset on the global uncertainty chain of climate change impact studies.
Since this is of particular concern to regions with sparse weather station coverage, this study is conducted over Africa.

2 Study Region and data

2.1 Study Region

2.1.1 Geographic situation

Africa is the second largest and second most-populous continent in the world. It covers a land area of about 30.3 million km^2,
including adjacent islands, which represents 6% of Earth's total surface area and 20.4% of its total land area (Mawere (2017)).
Deserts and dry lands cover 60% of its entire surface (Prăvălie (2016)). The average elevation of Africa is almost 600 m above
sea level, roughly close to the average elevations of North and South America (Atrax, 2016). Generally, higher-elevation areas
85 lie to the east and south, while a progressive decrease in altitude towards the north and west is apparent.

The African continent can be divided into 25 major hydrological basins (Karamage et al. (2018)). Generally speaking, the
main drainage for all of the continent's basins is towards the north and west, and ultimately, into the Atlantic Ocean. About 95%
of its streams are drained through permanent rivers. In some arid areas (i.e., Northwest Sahara Desert), drainage is sometimes

absent or masked by sand seas (Karamage et al. (2018)). Roughly, 60% of the African continent is drained by 10 large rivers
(Congo, Limpopo, Niger, Nile, Ogooue, Orange, Senegal, Shebelle, Volta and Zambezi) and their tributaries (Paul et al. (2014)).

2.1.2 Climate profile

Africa is the hottest continent on earth, and is the area that has seen the highest ever recorded land surface temperature (58 °C
in Libya; El Fadli et al. (2013)). The continent is characterized by highly variable climates that range from tropical to subarctic
on its highest peaks. According to the Koppen climate classification (Köppen (1900)), the northern half is mainly classified as
dry (group B) whereas the central and southern areas contain both savannah plains and dense forests with tropical and humid
subtropical climates (groups A and C) with a semi-arid climate in-between (El Fadli et al. (2013)). These wide climate ranges
are characterized by a wide variety of precipitation extremes, including droughts and floods. Droughts occur mostly in the
Sahel and in some parts of Southern Africa, whereas flooding is most prevalent in the southern and eastern regions.

2.2 Data

This project used several datasets built from climate models, observed precipitation, temperature and streamflow, as well as
catchment boundaries. These are described in the following four sub-sections.

2.2.1 General Circulation Models (GCMs)

All GCMs used in this study were part of the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al. (2012)).
Long historical climate simulations (1850–2005) and future climate projections (up to 2100 and beyond) for four Representa-
tive Concentration Pathways (RCPs) are included in the CMIP5 database.

Ten CMIP5 GCMs from 10 different modeling centers were selected for this study, as shown in Table 1. They were selected
as a subset of the GCMs used to set up the NAC^{2}H database (Arsenault et al. (2020)). The number of GCMs (10) was
selected as a compromise between having an accurate representation of GCM climate sensitivity variability and keeping the
large computational burden of this project reasonable. All GCM data was extracted over the 1983-2012 and 2071-2100 future
periods under the (RCP8.5) emission scenario.

2.2.2 Gridded precipitation and temperature datasets

The precipitation and temperature dataset selection was made on the basis of a high spatial resolution, daily (or better) temporal
resolution, and of the availability of at least 30 years of data covering the same time period, in order to properly define the
reference climate. Some recent datasets that provide global/near-global rainfall information at finer spatial and temporal reso-
lutions (e.g. the GPM Integrated Multisatellite Retrievals (IMERG) (Huffman et al. (2015)), and the Global Satellite Mapping
of Precipitation (GSMaP) (Okamoto et al. (2005)) were left out because their temporal coverage was too short to properly
represent the mean climate over the reference period.

According to above criteria, nine precipitation and two temperature datasets were selected for this study. The precipitation datasets include two gauged-only products, two satellite products corrected using ground-based observations, four reanalysis products and one gauge, satellite, and reanalysis merged product. The temperature datasets include one gauged-only and one reanalysis product as shown in Table 2.

2.2.3 Observed streamflow data

The Global Runoff Data Centre (GRDC) archive is arguably the most complete global discharge database providing free access to river discharge data (Fekete and Vörösmarty (2007)). The database provides streamflow records collected from 9213 stations across the globe, with an average temporal coverage of 42 years per station (Do et al. (2017)). It is operated under the World Meteorological Organization (WMO) umbrella to provide broad hydrological data to support the scientific research community. GRDC data has been widely used in various hydrological studies, such as those examining hydrological model calibrations (Milliman et al. (2008); Hunger and Döll (2008); Donnelly et al. (2010); Haddeland et al. (2011)), or as a benchmark to compare simulated streamflows (Trambauer et al. (2013); Zhao et al. (2017)).

2.2.4 Watersheds boundaries data

HydroSHEDS (the Hydrological data and maps based on the SHuttle Elevation Derivatives at multiple Scales database) is a freely available global archive, developed through a World Wildlife Fund (WWF) program, that uses a hydrologically-corrected digital elevation model to provide hydrographic information for regional and global studies (Lehner et al. (2008)). In addition, it applies a consistent methodology using Geographic Information System (GIS) technology to provide watershed polygons for more than 7000 GRDC gauging stations. Figure 1 shows watershed polygon layers at different spatial scales for the African continent. The vector layer (L5), which consists of 1145 watersheds, was chosen to be used in this study.

3 Methodology

Figure 2 presents the methodological framework for this study. A large-sample hydrological climate change impact study is performed over 1145 African catchments. It uses the standard top-down approach in a modeling chain, which consists of 10 GCMs, 2 hydrological models, 2 temperature and 9 precipitation datasets, for a total of 360 possible combinations. A single GHGES (RCP8.5), a single climate projection for each GCM and a single downscaling method (see below) are used, since the focus of this work is not on conducting a complete uncertainty chain study. The uncertainty related to the reference dataset will therefore be compared to that of the climate model ensemble and against that of both hydrological models. For each catchment, 360 30-year streamflow time series are generated for both the reference (1983-2012) and future (2071-2100) time periods. Fifty-one streamflow metrics are computed for each of these time series. An n-dimensional analysis of variance is performed to partition the uncertainty linked to the 4 groups of components of the uncertainty modeling chain.

A first set of 350 catchments were selected based on the availability of long-enough gauged streamflow series. In order to include additional catchments to allow a better spatial coverage of the African continent, an additional 795 catchments were selected and an additional regionalization step was performed to generate streamflows.

150 Both hydrological models were calibrated on all catchments for all 18 combinations of reference datasets (2 temperature datasets x 9 precipitation datasets), for a total of 41,220 independent hydrological model calibrations. The main methodological steps are described below in Figure 2.

The watershed boundaries for the African continent were extracted from the HydroSHEDS database. Streamflow records from the GRDC database were used to calibrate the hydrological models and to evaluate the hydrological modeling perfor-
155 mance. The GRDC database contains streamflow data from 1150 African stations. In this study, only 350 stations were chosen based on three criteria. First, stations should have data for the 1983-2012 study period. Second, stations that have less than five consecutive years of data during this period were excluded. Finally, all the stations should be compatible with the selected HydroSHEDS catchments. Consequently, the 1145 catchments were divided into 350 gauged and 795 ungauged catchments. The climatological data from 9 precipitation and 2 temperature datasets were then extracted for each of the 1145 catchments.

160 ## 3.1 Hydrological modeling

Given the large-scale nature of this study, distributed and physically-based models were not considered. Two lumped hydrological models, GR4J and HMETS, were selected and calibrated over each of the 350 gauged catchments. The two hydrological models have been shown to perform well in a wide range of studies and over a wide range of climate zones (Arsenault et al. (2018); Martel et al. (2017); Tarek et al. (2019); Valéry et al. (2014)).

165 ### 3.1.1 The GR4J hydrological model

The GR4J (Génie Rural à 4 paramètres Journalier) model is a four-parameter lumped and conceptual rainfall-runoff model (Perrin et al. (2003)). This model has shown overall good performance in several studies across the globe (Aubert et al. (2003); Raimonet et al. (2018); Riboust et al. (2019); Westra et al. (2014); Youssef et al. (2018)). The model requires daily precipitation, temperature and potential evapotranspiration (PET) as inputs to simulate the streamflow. The Oudin formulation (Oudin et al.
170 (2005)) was used in the present study to compute the daily PET series as it was shown to be simple and efficient.

3.1.2 The HMETS hydrological model

The HMETS hydrological model (Hydrological Model – École de technologie supérieure; Martel et al. (2017)) is more complex than GR4J, with 21 model parameters. It has four reservoirs (surface runoff, hypodermic flow from the vadose zone reservoir, delayed runoff from infiltration and groundwater flow from the phreatic zone reservoir). HMETS uses the same Oudin PET
175 formulation, but with scaling parameters to control the mass balance.

3.1.3 Hydrological model calibration

The nine precipitation and two temperature datasets were combined in their eighteen possible arrangements for analysis purposes. Due to the large number of calibrations to be performed (41,220 model calibrations), an automatic model parameter calibration approach was selected. The Covariance Matrix Adaptation Evolution Strategy (CMAES) algorithm was chosen
180   because of its flexibility and robustness (Hansen et al. (2003)). CMAES has been shown to be one of the best and fastest automatic calibration algorithms available (Arsenault et al. (2014); Yu et al. (2013)).

All 30 years were used for calibration, and no validation step was performed following the work of Arsenault et al. (2018). They showed that validation and calibration skills are not necessarily correlated, and that adding more years to the calibration dataset improves the hydrological model performance and robustness. The calibration objective function was the Kling-Gupta
185   efficiency (KGE) metric, introduced by Gupta et al. (2009) and modified by Kling et al. (2012). It is defined as a combination of equally-weighted bias, variance and correlation aggregate metrics. The KGE values theoretically range from negative infinity, implying an extremely poor performance of the model, all the way to one, suggesting a perfect performance. Pechlivanidis and Arheimer (2015) divided the KGE values into three performance groups: Bad (KGE < 0.4), Acceptable ($0.4 \leq$ KGE < 0.7) and Good (KGE $\geq$ 0.7).

190   ## 3.2 Regionalization

The transfer of hydrological information (i.e., model parameters or streamflow) from one catchment (gauged) to another (ungauged) is known as "Regionalization" (Razavi and Coulibaly (2013)). Regionalization can be conducted using two methods: 1) rainfall-runoff models/model-dependent method, which typically transfers the model parameters from one or more gauged watersheds to an ungauged watershed, and 2) hydrological model-independent methods, which transfer the streamflow directly
195   from gauged to ungauged watersheds (Razavi and Coulibaly (2013)). In this paper, the model-dependent method was applied as it has been used in several studies and has shown acceptable results (Merz and Blöschl (2004); McIntyre et al. (2005); Boughton and Chiew (2007); Cutore et al. (2007); Samaniego et al. (2010); Beck et al. (2016); Arsenault and Brissette (2014); Saadi et al. (2019)).

The three approaches, namely, the spatial proximity (S.P), physical similarity (P.S) and multi-linear regression (MLR) meth-
200   ods (Oudin et al. (2008)), have been used to estimate the model parameters in ungauged catchments. First, the three approaches were tested to find the best method to apply. Then, the best-performing precipitation-temperature datasets combination were used to feed the hydrological models and simulate the streamflow of the ungauged catchments. Based on the hydrological modeling performance on the 350 gauged catchments, the MSWEP precipitation and ERA5 temperature datasets were found to be the best combination used in computing the streamflow for the 795 ungauged catchments.

205   ## 3.3 Bias correction

In this study, the N-dimensional multivariate bias correction algorithm (MBCn) was used (Cannon (2018)). MBCn is an image processing technique extension that preserves the change projected by the between the historical and projected periods for

all quantiles of the distribution. The algorithm consists of three main steps: (1) application of an orthogonal rotation to both model and observational data; (2) correction of the marginal distributions of the rotated model data using quantile mapping, and (3) application of an inverse rotation to the results. These three steps are repeated until the model distribution matches the observational distribution. MBCn is arguably the best-performing quantile-based method available (Adeyeri et al. (2020); Meyer et al. (2019)).

3.4 Variance analysis

An n-dimensional analysis of variance was performed for the 51 streamflow metrics defined in Arsenault et al. (2020) for each of the 1145 catchments. These metrics cover a wide range of streamflow conditions: mean annual, seasonal and monthly values, distribution quantiles, as well as low- and high-flow extreme metrics. A variance was attributed to each of the four groups under study, namely, GCM, precipitation dataset, temperature dataset and hydrological model. A total of 11 variance components were computed: 4 main effect components, 6 first-order, 3 second-order, and 1 third-order interaction components.

4 Results

This section outlines the main findings of the work. Figure 3 presents the calibration results for both hydrological models using all possible combinations of the 9 precipitation and 2 temperature datasets. Each boxplot consists of 350 KGE values corresponding to the calibration result for each of the 350 selected gauged catchments. Each box extends from the 25th quantile to the 75th quantile, with the median displayed as the red line within that range. The top and bottom whiskers (where shown) represent highest and lowest values. Red crosses are considered statistical outliers.

Results show that both hydrological models perform well, but that there are important differences between datasets. HMETS performs better than GR4J, with respective overall mean KGEs of 0.58 and 0.41. All the precipitation and temperature datasets result in acceptable median KGE simulations Pechlivanidis and Arheimer (2015).

Both temperature datasets perform very similarly across all combinations, with ERA5 generally slightly outperforming CPC. Figure 3 clearly shows that most of the variability seen originates from the precipitation datasets. Four precipitation datasets are ahead of the field. They are, in order of performance: the merged product MSWEP, followed by the two satellite datasets; CHIRPS and PERSIANN, and the ERA5 reanalysis dataset. The gauge-based precipitation datasets (e.g., GPCC and CPC), and the ERA-I reanalysis follow with a similar performance. Finally, the CFSR and JRA55 reanalysis are the worst-performing products for hydrological model calibration.

Table 3 presents the main results of the analysis of variance for the 2071-2100 period for the gauged catchments. It shows the relative variance for all main effect and first-order interactions of the four components of uncertainty under study, and for 6 streamflow metrics. The variance originating from second- and third-order interactions are summed up and presented in the last row. Results show that most of the variance consistently comes from 5 sources, for all 6 streamflow metrics. They are: precipitation datasets (P), GCMs, hydrological models (HM), interactions between precipitation datasets and GCMs (P-GCM), as well as interactions between precipitation datasets and hydrological models (P-HM).

Table 3 indicates that both the precipitation datasets and GCMs are the main contributors to variance, including through interactions (P-GCM). The hydrology models also generate some uncertainty, and in particular, through interaction with the precipitation datasets. All metrics exhibit a similar pattern, with the exception of the low-flow metric (QQ5), where precipitation, hydrological models and their interaction components (P-HM) are dominant, and for which GCM uncertainty is minimal. In almost all cases, the five highlighted components represent approximately 85% of the total variance. The average amount of variance introduced by both temperature datasets is less than 0.25% for all 6 different streamflow metrics.

To show cross-catchment variability, Figure 4 shows boxplots of the relative variance attribution results for the 5 main contributors to variance, as identified in Table 3, and for the same 6 streamflow metrics. The results are also decomposed into three parts: all 1145 catchments (A), as well as the 350 gauged (G) and 795 ungauged (U) catchments, in order to ensure that the regionalization process does not introduce undesirable effects on the results.

Figure 4 shows that the response of the gauged and ungauged catchments is very similar across all variance components and streamflow metrics, and that no major variance artifact is introduced by the regionalization step. Consequently, all further results will only be shown for all 1145 catchments, with no differentiation made between the gauged and ungauged ones.

The results show that there is considerable across-catchment variability, as shown by the extent of the boxplots, with GCM and P-GCM interaction being the most important, and most variable contributors to variance. As was shown in Table 3, the low-flow metric displays a pattern that is much different from the other five metrics, with HM being important and GCM, being the lowest. There is a relatively large difference between the two metrics representing high flows (Q95 and Q1X). While GCM dominates the former, a much larger part of the uncertainty is transferred to the precipitation dataset (P and P-GCM) for the latter.

In order to study the impact of spatial variability, Figure 5 presents the spatial distribution of the relative variance attribution for the five main contributors to variance of Table 3 and all 6 streamflow metrics. Mean Q, Winter Q, QX1 and QQ95 display somewhat similar spatial patterns. Summer Q and QQ5 metrics display somewhat similar spatial patterns. The largest precipitation uncertainty (P and P-GCM interactions) is found in the northern parts of Sub-Saharan Africa, between 0 and 30 °N. GCM uncertainty appears to be larger all around the coastlines of Africa. Hydrological model uncertainty is strongest for QQ5, but spatial patterns are fairly consistent across all 6 streamflow metrics. GCM uncertainty is strongly different for both Summer Q and Winter Q, likely because of the monsoon pattern. Above 20°N, there is generally less than 100 mm of total annual precipitation, and some level of care should therefore be taken when analyzing results in relative contribution to variance.

In other words, a variance analysis of a metric with very little absolute variance could be misleading. Consequently, Figure 6 displays the standard deviation of the 360 streamflow values computed for each streamflow metric and for each watershed. The streamflow value for each metric is normalized per unit area to allow for a comparison of large and small watersheds in the same figure. Not surprisingly, the results demonstrate a larger variance along the equatorial band, where precipitation is largest. This pattern is particularly clear for the QQ95 high-flow metric. The catchment database is, however, large enough to show some catchments which exhibit a large variance, even in arid regions above 20°N and below 20°S.

Since some precipitation datasets are clearly better than others based on the hydrological model calibration results, it may not
275 be entirely fair to compare precipitation uncertainty to GCM uncertainty. To investigate this further, the uncertainty contribution
obtained when using all 9 precipitation datasets is compared to that of 3 sub-ensembles, as presented in Table 4. While ensemble
4 is composed of the clearly best-performing datasets for model calibration, the main goal here is to investigate the impact of
dataset selection, not the definition of a credibility ensemble, as will be further discussed later.

Figure 7 presents the boxplots of percentages of variance for each catchment, for the five main contributors to variance for all
280 4 precipitation dataset ensembles of Table 4. Unsurprisingly, it shows that reducing the size of the precipitation ensemble results
in a consistent decrease in the variance attributed to precipitation. Most of this reduction in variance comes from the P-GCM
interaction term, although there is also a noticeable decrease in the main effect P component. The lost precipitation variance is
transferred mostly to GCMs, and to a lesser extent, to hydrological modeling. The exception is the low-flow QQ5, where most
of the variance is transferred to HM. Most of the drop observed is obtained by dropping the five worst precipitation datasets,
285 as no significant difference is observed between precipitation ensembles 3 and 4. Even in a reduced ensemble, precipitation
datasets still provide between 10 to 20% of median variance, and more than 30% for the low-flow metric (QQ5) when taking
into account the main effect and first-order interaction term.

Figure 8 presents the spatial distribution of the relative variance attribution for each of the 6 streamflow metrics after in-
cluding only the four best overall precipitation datasets (Ensemble 4 of Table 4). This is the same as Figure 5, but with a
290 reduced precipitation ensemble. Results outline that GCM uncertainty is the dominant source of uncertainty when using the
reduced precipitation ensemble, with the exception of the low-flow metric, for which precipitation uncertainty remains dom-
inant. There are, however, significant interactions between GCM and precipitation for all metrics, especially in the northern
half of the continent. Otherwise, the observed spatial patterns are similar to the ones presented in Figure 5.

5 Discussion

295 Defining a reference climate dataset is an important but difficult task. A reference climate dataset is used as a benchmark for
monitoring environmental changes and correcting climate model biases of future climate projections to assess future impacts of
a changing climate. Data from weather stations is still mostly considered to be the most accurate representation of the current
climate, despite suffering from several important issues, such as precipitation undercatch and inhomogeneities (Peterson et al.
(1998)). To allow for regular data coverage and remove missing data, it is now common practice to interpolate station data
300 onto a regular grid. Such gridded datasets greatly simplify the processing of meteorological data for environmental studies at
the regional, continental and global scales. However, even in regions with a good weather station coverage, gridded datasets
using the same underlying data differ due to the different interpolation methods (Essou et al. (2016)), and typically see an
increase in the number of wet days and a decrease in the frequency of extreme events (Ensor and Robeson (2008)). In regions
with scarce weather station coverage (such as Africa), interpolation becomes extrapolation, and is therefore potentially highly
305 unreliable. In such cases, environmental studies have had to rely on additional sources of data, such as satellite and atmospheric
reanalysis for environmental studies. Several inter-comparison studies have been done (e.g., Beck et al. (2017b); Essou et al.

(2017)), including over Africa (Satgé et al. (2020); Dembélé et al. (2020)). These studies outline a complex picture in which performance depends on scale, climate and data source, and for which no dataset consistently outperforms all of the others. Because of this, in data-sparse regions such as Africa, there is not only no commonly agreed upon reference dataset, but even

310   no agreement on the optimal source of climate data (e.g., satellite vs. reanalysis), and different environmental studies have used completely different datasets. This is particularly problematic for climate change impact studies since there is no knowledge on how dataset uncertainty may propagate in the typical hydroclimatic modeling chain. The results presented in this study attempt to answer this question by comparing dataset uncertainty to other sources of uncertainty, such as that derived from GCMs.

Results show that most of the dataset uncertainty originates from precipitation. Temperature displays much smaller spatial

315   and temporal variability than precipitation, and can therefore be a lot more reliably interpolated using the adiabatic lapse rate to account for elevation and terrain orientation in mountain areas. Precipitation interpolation is a much more challenging problem, which explains why most dataset intercomparison work has focused on this variable. Based on KGE performance over a common reference period, all nine precipitation datasets performed adequately in terms of hydrological modeling performance, but some clearly performed much better than others. This is in agreement with the results of Beck et al. (2017b) and Beck et al.

320   (2019). The uncertainty contribution of datasets to future streamflow uncertainty was first evaluated using all 9 precipitation datasets, in conjunction with 2 temperature datasets, a sample of 10 GCMs and two hydrological models, for a total of 360 possible element combinations. While this is a relatively large sample, not all sources of uncertainty were accounted for. In particular, GHGES, downscaling and bias correction were not included in the analysis. In comparison, the North American Climate Change and Hydroclimatology Dataset (NAC^{2}H) database (Arsenault et al. (2020)) offers 16,000 combinations al-

325   lowing examining future streamflow uncertainty. In this regard, the relative variance contribution of the climate dataset is best examined in comparison to that of GCMs, the most studied source of climate change impact uncertainty. Results outline the important, and in some cases, dominant contribution of the precipitation dataset to the overall uncertainty of future streamflows. For all 6 streamflow metrics presented here, the precipitation dataset uncertainty was comparable and sometimes larger than that of GCMs.

330   Uncertainty contribution was then studied by retaining subsets of precipitation datasets, eliminating the least performing ones with respect to the chosen KGE metric. This follows the concept of a credibility ensemble based on carefully selecting the best/most robust components of the hydroclimatic modeling chain, in order to obtain the most credible uncertainty range (e.g., Brissette et al. (2020); Giuntoli et al. (2018); Maraun et al. (2017)). Results demonstrate a large decrease in contribution to uncertainty for 5 of 6 streamflow metrics. The precipitation dataset remained the largest contributor to uncertainty for the

335   low-flow metric, and still accounted for 10 to 20% of the total variance for the other metrics. Most of the decrease in uncertainty was obtained by dropping the worst-performing datasets, rather than keeping the best-performing ones.

The results presented here indicate that hydrological model uncertainty is relatively small, with the exception of the low-flow metric. These results should be taken with caution because only two hydrological models were used, and also because they both share the same potential evapotranspiration (PET) formula. For climate change impact studies, the climate sensitivity of

340   PET is now thought to be an important source of uncertainty for impact studies (Clark et al. (2016); Brissette et al. (2020)),

and the importance of hydrological model uncertainty has been outlined in many studies (Vetter et al. (2017); Krysanova et al. (2018); Giuntoli et al. (2018)). It is therefore likely that the contribution of hydrological models is underestimated here.

The selection of the best-performing precipitation dataset was evaluated over a reference period using the single metric of the KGE criterion. This criterion is considered to be a good metric as it weighs bias, correlation and RMSE between simulation

345   and observations, all rightfully considered to be important attributes of a good hydrological simulation. There are, however, many other metrics that could have been chosen to perform this comparison, some of which might be even more important for specific applications such as floods. For example, the JRA55 and CFSR reanalyses were at the bottom of the list of the best-performing datasets presented here. However, in other studies, JRA55 was shown to provide the best reanalysis (Odon et al. (2019)), while CFSR was successfully used for precipitation modeling (Khedhaouiria et al. (2018)). Clearly, the results

350   presented in this paper should only be used as intended (i.e., to study uncertainty related to the choice of a reference climate dataset), and not as a judgment of the absolute performance of each dataset. As mentioned earlier, it is important to keep in mind that all of the datasets used in this paper generate adequate streamflow simulations.

It is recommended that reference dataset uncertainty be included in climate change impact studies, and especially so in regions with a sparse network of weather stations. We believe that climate dataset uncertainty can be minimized for most

355   streamflow metrics using a careful validation and selection of the best-performing ones. A dataset ensemble should nonetheless be retained to assess the sensitivity of the impact study to the choice of a reference dataset. As is the case for most other elements of the hydroclimatic modeling chain of future climate change impacts, there is 'no free lunch' in the sense that there is no single recipe, which will be applicable in all cases. Climate dataset performance is spatially-dependent, as shown here and other studies, and will depend on the criteria used to assess said performance. In addition, the relative uncertainty contribution also

360   depends on the catchment location and streamflow metric under study. The importance of first-order interactions in variance analysis, and especially of interactions between precipitation datasets with GCMs and with the hydrology models testify to the complex nature of the propagation of uncertainties in the hydroclimatic modeling chain. The use of an appropriate credibility climate dataset ensemble is therefore more than likely to be catchment-related and metric-dependent, and some minimum level of upstream validation would be needed to select the best components.

365   ## 6   Conclusions

The main objective of this study was to assess the uncertainty related to the choice of a reference dataset against that of other sources of uncertainty in climate change impact studies. This was achieved by performing a large-sample hydrological climate change impact study over 1145 African catchments. The study used 9 precipitation and 2 temperature datasets, along with 10 GCMs and 2 hydrological models, for a total of 360 possible combinations. Temperature dataset-related uncertainty was

370   minimal; with a median relative contribution to uncertainty, less than 0.25% for all 6 presented streamflow metrics. On the other hand, the nine precipitation dataset ensembles generated a future uncertainty equal to or larger than that related to GCMs. Using a reduced ensemble of the best-performing precipitation datasets systematically reduced the precipitation dataset uncertainty, but still accounted for 10 to 20% of the total variance for 5 of the 6 streamflow metrics, and still remained the main source

of uncertainty for the low-flow metric. The main conclusion of this study is that the choice of a climate reference dataset can
375 induce significant uncertainty in climate change impact studies, at least in regions with a sparse weather station coverage.

Code and data availability. The NAC^{2}H climate and streamflow data was downloaded from the NAC^{2}H database, available here: https://osf.io/s97cd/ (Arsenault et al. (2020)).

The GRDC streamflow data can be downloaded from the Global Runoff Data Centre, available here: https://portal.grdc.bafg.de/applications/public.html?publicuser=PublicUser#dataDownload/Home.

380 ERA-Interim data are available through the ECMWF servers at: https://apps.ecmwf.int/datasets/data/interim-full-daily/ (Dee et al. (2011)).

ERA5 data is available on the Copernicus Climate Change Service (C3S) Climate Data Store: https://cds.climate.copernicus.eu/#!/search?text=ERA5&type=dataset (Hersbach and Dee (2016)).

JRA55 datasets are available on the Research Data Archive: https://rda.ucar.edu/datasets/ds628.0/ (Kobayashi et al. (2015)).

NCEP datasets can be downloaded from The NCAR Research Data Archive, available here: https://rda.ucar.edu/datasets/ds093.1/#!access
385 (Saha et al. (2010)).

MSWEP data are available through the PCA servers at: https://platform.princetonclimate.com/PCA_Platform/mswepRetro.html (Beck et al. (2017a)).

The CHIRPS satellite dataset can be downloaded from the Climate Hazards Center: https://www.chc.ucsb.edu/data/chirps (Funk et al. (2015)).

390 The CPC and GPCC datasets can be downloaded from The NOAA Physical Sciences Laboratory (PSL), available here: https://psl.noaa.gov/data/gridded/tables/precipitation.html (Chen et al. (2008); Schneider et al. (2018)).

The Coupled Model Intercomparison Project Phase 5 (CMIP5) data can be downloaded from the World Climate Research Programme (WCRP) at: https://esgf-node.llnl.gov/search/cmip5/ (Taylor et al. (2012)).

The HMETS hydrological model is available on the Matlab File Exchange:
395 https://www.mathworks.com/matlabcentral/fileexchange/48069-hmets-hydrological-model (Martel et al. (2017)).

Finally, the GR4J model and Cemaneige snow module are made available by the IRSTEA: https://webgr.irstea.fr/en/models/ (Perrin et al. (2003)).

Author contributions. MT performed all of the computing work, including all datasets and GCMs download, hydrological modelling and
400 calibration. He performed most of the analysis and wrote the main sections of the paper. FB contributed to experiment design and data analysis and provided multiple edits to the document. RA, provided expertise on the catchment database and parallel computing.

Competing interests. The authors declare that they have no conflict of interest.

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References

Adeyeri, O., Laux, P., Lawin, A., and Oyekan, K.: Multiple bias-correction of dynamically downscaled CMIP5 climate models temperature projection: a case study of the transboundary Komadugu-Yobe river basin, Lake Chad region, West Africa, SN Applied Sciences, 2, 1–18, 2020.

410 Andermann, C., Bonnet, S., and Gloaguen, R.: Evaluation of precipitation data sets along the Himalayan front, Geochemistry, Geophysics, Geosystems, 12, 2011.

Arsenault, R., B., F., C., J., D., G., G., and Q: NAC2H: The North-American Climate Change and hydroclimatology dataset, Water Resources Research, 2020.

Arsenault, R. and Brissette, F. P.: Continuous streamflow prediction in ungauged basins: The effects of equifinality and parameter set selection

415 on uncertainty in regionalization approaches, Water Resources Research, 50, 6135–6153, 2014.

Arsenault, R., Poulin, A., Côté, P., and Brissette, F.: Comparison of stochastic optimization algorithms in hydrological model calibration, Journal of Hydrologic Engineering, 19, 1374–1384, 2014.

Arsenault, R., Brissette, F., and Martel, J.-L.: The hazards of split-sample validation in hydrological model calibration, Journal of hydrology, 566, 346–362, 2018.

420 Aubert, D., Loumagne, C., and Oudin, L.: Sequential assimilation of soil moisture and streamflow data in a conceptual rainfall–runoff model, Journal of Hydrology, 280, 145–161, 2003.

Bae, D.-H., Jung, I.-W., and Lettenmaier, D. P.: Hydrologic uncertainties in climate change from IPCC AR4 GCM simulations of the Chungju Basin, Korea, Journal of Hydrology, 401, 90–105, 2011.

Beck, H. E., van Dijk, A. I., De Roo, A., Miralles, D. G., McVicar, T. R., Schellekens, J., and Bruijnzeel, L. A.: Global-scale regionalization

425 of hydrologic model parameters, Water Resources Research, 52, 3599–3622, 2016.

Beck, H. E., Van Dijk, A. I., Levizzani, V., Schellekens, J., Gonzalez Miralles, D., Martens, B., and De Roo, A.: MSWEP: 3-hourly 0.25 global gridded precipitation (1979-2015) by merging gauge, satellite, and reanalysis data, Hydrology and Earth System Sciences, 21, 589–615, 2017a.

Beck, H. E., Vergopolan, N., Pan, M., Levizzani, V., Van Dijk, A. I., Weedon, G. P., Brocca, L., Pappenberger, F., Huffman, G. J., and Wood,

430 E. F.: Global-scale evaluation of 22 precipitation datasets using gauge observations and hydrological modeling, Hydrology and Earth System Sciences, 21, 6201, 2017b.

Beck, H. E., Pan, M., Roy, T., Weedon, G. P., Pappenberger, F., Van Dijk, A. I., Huffman, G. J., Adler, R. F., and Wood, E. F.: Daily evaluation of 26 precipitation datasets using Stage-IV gauge-radar data for the CONUS, Hydrology and Earth System Sciences, 23, 207–224, 2019.

Behrangi, A., Khakbaz, B., Jaw, T. C., AghaKouchak, A., Hsu, K., and Sorooshian, S.: Hydrologic evaluation of satellite precipitation

435 products over a mid-size basin, Journal of Hydrology, 397, 225–237, 2011.

Boughton, W. and Chiew, F.: Estimating runoff in ungauged catchments from rainfall, PET and the AWBM model, Environmental Modelling & Software, 22, 476–487, 2007.

Brissette, F., Arsenault, R., and Chen, J.: The potential pitfalls of hydrological climate change impact studies, Geophysical Research Letters, 2020.

440 Cannon, A. J.: Multivariate quantile mapping bias correction: an N-dimensional probability density function transform for climate model simulations of multiple variables, Climate dynamics, 50, 31–49, 2018.

Chen, J., Brissette, F. P., and Leconte, R.: Uncertainty of downscaling method in quantifying the impact of climate change on hydrology, Journal of hydrology, 401, 190–202, 2011.

Chen, M., Shi, W., Xie, P., Silva, V. B., Kousky, V. E., Wayne Higgins, R., and Janowiak, J. E.: Assessing objective techniques for gauge-based analyses of global daily precipitation, Journal of Geophysical Research: Atmospheres, 113, 2008.

Chen, S., Liu, H., You, Y., Mullens, E., Hu, J., Yuan, Y., Huang, M., He, L., Luo, Y., Zeng, X., et al.: Evaluation of high-resolution precipitation estimates from satellites during July 2012 Beijing flood event using dense rain gauge observations, PloS one, 9, 2014.

Clark, M. P., Wilby, R. L., Gutmann, E. D., Vano, J. A., Gangopadhyay, S., Wood, A. W., Fowler, H. J., Prudhomme, C., Arnold, J. R., and Brekke, L. D.: Characterizing uncertainty of the hydrologic impacts of climate change, Current Climate Change Reports, 2, 55–64, 2016.

Cutore, P., Cristaudo, G., Campisano, A., Modica, C., Cancelliere, A., and Rossi, G.: Regional models for the estimation of streamflow series in ungauged basins, Water resources management, 21, 789–800, 2007.

Dee, D. P., Uppala, S. M., Simmons, A., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M., Balsamo, G., Bauer, d. P., et al.: The ERA-Interim reanalysis: Configuration and performance of the data assimilation system, Quarterly Journal of the royal meteorological society, 137, 553–597, 2011.

Dembélé, M., Schaefli, B., van de Giesen, N., and Mariéthoz, G.: Suitability of 17 rainfall and temperature gridded datasets for largescale hydrological modelling in West Africa, Hydrology and Earth System Sciences Discussions, pp. 1–39, 2020.

Do, H. X., Westra, S., and Leonard, M.: A global-scale investigation of trends in annual maximum streamflow, Journal of hydrology, 552, 28–43, 2017.

Dobler, C., Hagemann, S., Wilby, R., and Stätter, J.: Quantifying different sources of uncertainty in hydrological projections in an Alpine watershed, Hydrology and Earth System Sciences, 16, 4343–4360, 2012.

Donnelly, C., Dahné, J., Rosberg, J., Strömqvist, J., Yang, W., and Arheimer, B.: High-resolution, large-scale hydrological modelling tools for Europe, IAHS Publ, 340, 553–561, 2010.

El Fadli, K. I., Cerveny, R. S., Burt, C. C., Eden, P., Parker, D., Brunet, M., Peterson, T. C., Mordacchini, G., Pelino, V., Bessemoulin, P., et al.: World Meteorological Organization assessment of the purported world record 58 C temperature extreme at El Azizia, Libya (13 September 1922), Bulletin of the American Meteorological Society, 94, 199–204, 2013.

Ensor, L. A. and Robeson, S. M.: Statistical characteristics of daily precipitation: comparisons of gridded and point datasets, Journal of Applied Meteorology and Climatology, 47, 2468–2476, 2008.

Essou, G. R., Arsenault, R., and Brissette, F. P.: Comparison of climate datasets for lumped hydrological modeling over the continental United States, Journal of hydrology, 537, 334–345, 2016.

Essou, G. R., Brissette, F., and Lucas-Picher, P.: The use of reanalyses and gridded observations as weather input data for a hydrological model: Comparison of performances of simulated river flows based on the density of weather stations, Journal of Hydrometeorology, 18, 497–513, 2017.

Fekete, B. M. and Vörösmarty, C. J.: The current status of global river discharge monitoring and potential new technologies complementing traditional discharge measurements, IAHS publ, 309, 129–136, 2007.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., et al.: The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes, Scientific data, 2, 1–21, 2015.

Giuntoli, I., Villarini, G., Prudhomme, C., and Hannah, D. M.: Uncertainties in projected runoff over the conterminous United States, Climatic change, 150, 149–162, 2018.

Gupta, H. V., Kling, H., Yilmaz, K. K., and Martinez, G. F.: Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling, Journal of hydrology, 377, 80–91, 2009.

Haddeland, I., Clark, D. B., Franssen, W., Ludwig, F., Voß, F., Arnell, N. W., Bertrand, N., Best, M., Folwell, S., Gerten, D., et al.: Multimodel estimate of the global terrestrial water balance: setup and first results, Journal of Hydrometeorology, 12, 869–884, 2011.

Hansen, N., Müller, S. D., and Koumoutsakos, P.: Reducing the time complexity of the derandomized evolution strategy with covariance matrix adaptation (CMA-ES), Evolutionary computation, 11, 1–18, 2003.

Hersbach, H. and Dee, D.: ERA5 reanalysis is in production, ECMWF newsletter, 147, 5–6, 2016.

Huffman, G. J., Bolvin, D. T., Braithwaite, D., Hsu, K., Joyce, R., Xie, P., and Yoo, S.-H.: NASA global precipitation measurement (GPM) integrated multi-satellite retrievals for GPM (IMERG), Algorithm Theoretical Basis Document (ATBD) Version, 4, 26, 2015.

Hunger, M. and Döll, P.: Value of river discharge data for global-scale hydrological modeling, 2008.

Huth, R.: Sensitivity of local daily temperature change estimates to the selection of downscaling models and predictors, Journal of Climate, 17, 640–652, 2004.

IPCC: Working Group I: The Scientific Basis, Third Assessment Report of the Intergovernmental Panel on Climate Change. New York, Cambridge Univ. Press, 2001.

Jiang, S., Ren, L., Hong, Y., Yong, B., Yang, X., Yuan, F., and Ma, M.: Comprehensive evaluation of multi-satellite precipitation products with a dense rain gauge network and optimally merging their simulated hydrological flows using the Bayesian model averaging method, Journal of Hydrology, 452, 213–225, 2012.

Karamage, F., Liu, Y., Fan, X., Francis Justine, M., Wu, G., Liu, Y., Zhou, H., and Wang, R.: Spatial relationship between precipitation and runoff in Africa, Hydrology and Earth System Sciences Discussions, pp. 1–27, 2018.

Kay, A., Davies, H., Bell, V., and Jones, R.: Comparison of uncertainty sources for climate change impacts: flood frequency in England, Climatic change, 92, 41–63, 2009.

Khan, M. S., Coulibaly, P., and Dibike, Y.: Uncertainty analysis of statistical downscaling methods, Journal of Hydrology, 319, 357–382, 2006.

Khedhaouiria, D., Mailhot, A., and Favre, A.-C.: Daily precipitation fields modeling across the great lakes region (Canada) by Using the CFSR reanalysis, Journal of Applied Meteorology and Climatology, 57, 2419–2438, 2018.

Kidd, C., Becker, A., Huffman, G. J., Muller, C. L., Joe, P., Skofronick-Jackson, G., and Kirschbaum, D. B.: So, how much of the Earth's surface is covered by rain gauges?, Bulletin of the American Meteorological Society, 98, 69–78, 2017.

Kling, H., Fuchs, M., and Paulin, M.: Runoff conditions in the upper Danube basin under an ensemble of climate change scenarios, Journal of Hydrology, 424, 264–277, 2012.

Kobayashi, S., Ota, Y., Harada, Y., Ebita, A., Moriya, M., Onoda, H., Onogi, K., Kamahori, H., Kobayashi, C., Endo, H., et al.: The JRA-55 reanalysis: General specifications and basic characteristics, Journal of the Meteorological Society of Japan. Ser. II, 93, 5–48, 2015.

Köppen, W.: Versuch einer Klassifikation der Klimate, vorzugsweise nach ihren Beziehungen zur Pflanzenwelt, Geographische Zeitschrift, 6, 593–611, 1900.

Krysanova, V., Donnelly, C., Gelfan, A., Gerten, D., Arheimer, B., Hattermann, F., and Kundzewicz, Z. W.: How the performance of hydrological models relates to credibility of projections under climate change, Hydrological Sciences Journal, 63, 696–720, 2018.

Lehner, B., Verdin, K., and Jarvis, A.: New global hydrography derived from spaceborne elevation data, Eos, Transactions American Geophysical Union, 89, 93–94, 2008.

Maraun, D.: Bias correcting climate change simulations-a critical review, Current Climate Change Reports, 2, 211–220, 2016.

Maraun, D., Shepherd, T. G., Widmann, M., Zappa, G., Walton, D., Gutiérrez, J. M., Hagemann, S., Richter, I., Soares, P. M., Hall, A., et al.: Towards process-informed bias correction of climate change simulations, Nature Climate Change, 7, 764–773, 2017.

Martel, J.-L., Demeester, K., Brissette, F. P., Arsenault, R., and Poulin, A.: HMET: a simple and efficient hydrology model forteaching
520   hydrological modelling, flow forecasting and climate change impacts, The International journal of engineering education, 33, 1307–1316, 2017.

Mawere, M.: Theorising development in Africa: Towards building an African framework of development, Langaa RPCIG, 2017.

McIntyre, N., Lee, H., Wheater, H., Young, A., and Wagener, T.: Ensemble predictions of runoff in ungauged catchments, Water Resources Research, 41, 2005.

525 Merz, R. and Blöschl, G.: Regionalisation of catchment model parameters, Journal of hydrology, 287, 95–123, 2004.

Meyer, J., Kohn, I., Stahl, K., Hakala, K., Seibert, J., and Cannon, A. J.: Effects of univariate and multivariate bias correction on hydrological impact projections in alpine catchments, Hydrology and Earth System Sciences, 23, 1339–1354, 2019.

Milliman, J. D., Farnsworth, K., Jones, P., Xu, K., and Smith, L.: Climatic and anthropogenic factors affecting river discharge to the global ocean, 1951–2000, Global and planetary change, 62, 187–194, 2008.

530 Minville, M., Brissette, F., and Leconte, R.: Uncertainty of the impact of climate change on the hydrology of a nordic watershed, Journal of hydrology, 358, 70–83, 2008.

Mpelasoka, F. S. and Chiew, F. H.: Influence of rainfall scenario construction methods on runoff projections, Journal of Hydrometeorology, 10, 1168–1183, 2009.

Nashwan, M. S. and Shahid, S.: Symmetrical uncertainty and random forest for the evaluation of gridded precipitation and temperature data,
535   Atmospheric Research, 230, 104 632, 2019.

New, M., Todd, M., Hulme, M., and Jones, P.: Precipitation measurements and trends in the twentieth century, International Journal of Climatology: A Journal of the Royal Meteorological Society, 21, 1889–1922, 2001.

Nicholson, S. E.: The West African Sahel: A review of recent studies on the rainfall regime and its interannual variability, ISRN Meteorology, 2013, 2013.

540 Nóbrega, M., Collischonn, W., Tucci, C., and Paz, A.: Uncertainty in climate change impacts on water resources in the Rio Grande Basin, Brazil, Hydrology and Earth System Sciences, 15, 585, 2011.

Odon, P., West, G., and Stull, R.: Evaluation of Reanalyses over British Columbia. Part II: Daily and Extreme Precipitation, Journal of Applied Meteorology and Climatology, 58, 291–315, 2019.

Okamoto, K., Ushio, T., Iguchi, T., Takahashi, N., and Iwanami, K.: The global satellite mapping of precipitation (GSMaP) project, in:
545   Proceedings. 2005 IEEE International Geoscience and Remote Sensing Symposium, 2005. IGARSS'05., vol. 5, pp. 3414–3416, IEEE, 2005.

Oudin, L., Hervieu, F., Michel, C., Perrin, C., Andréassian, V., Anctil, F., and Loumagne, C.: Which potential evapotranspiration input for a lumped rainfall–runoff model?: Part 2—Towards a simple and efficient potential evapotranspiration model for rainfall–runoff modelling, Journal of hydrology, 303, 290–306, 2005.

550 Oudin, L., Andréassian, V., Perrin, C., Michel, C., and Le Moine, N.: Spatial proximity, physical similarity, regression and ungaged catchments: A comparison of regionalization approaches based on 913 French catchments, Water Resources Research, 44, 2008.

Paul, J. D., Roberts, G. G., and White, N.: The African landscape through space and time, Tectonics, 33, 898–935, 2014.

Pechlivanidis, I. and Arheimer, B.: Large-scale hydrological modelling by using modified PUB recommendations: the India-HYPE case, Hydrology and Earth System Sciences, 19, 4559–4579, 2015.

Perrin, C., Michel, C., and Andréassian, V.: Improvement of a parsimonious model for streamflow simulation, Journal of hydrology, 279, 275–289, 2003.

Peterson, T. C., Easterling, D. R., Karl, T. R., Groisman, P., Nicholls, N., Plummer, N., Torok, S., Auer, I., Boehm, R., Gullett, D., et al.: Homogeneity adjustments of in situ atmospheric climate data: a review, International Journal of Climatology: A Journal of the Royal Meteorological Society, 18, 1493–1517, 1998.

Prakash, S., Kumar, M. R., Mathew, S., and Venkatesan, R.: How accurate are satellite estimates of precipitation over the north Indian Ocean?, Theoretical and Applied Climatology, 134, 467–475, 2018.

Prăvălie, R.: Drylands extent and environmental issues. A global approach, Earth-Science Reviews, 161, 259–278, 2016.

Prudhomme, C. and Davies, H.: Assessing uncertainties in climate change impact analyses on the river flow regimes in the UK. Part 2: future climate, Climatic Change, 93, 197–222, 2009.

Prudhomme, C., Jakob, D., and Svensson, C.: Uncertainty and climate change impact on the flood regime of small UK catchments, Journal of hydrology, 277, 1–23, 2003.

Raimonet, M., Thieu, V., Silvestre, M., Oudin, L., Rabouille, C., Vautard, R., and Garnier, J.: Landward perspective of coastal eutrophication potential under future climate change: The Seine River case (France), Frontiers in Marine Science, 5, 136, 2018.

Razavi, T. and Coulibaly, P.: Streamflow prediction in ungauged basins: review of regionalization methods, Journal of hydrologic engineering, 18, 958–975, 2013.

Riboust, P., Thirel, G., Le Moine, N., and Ribstein, P.: Revisiting a simple degree-day model for integrating satellite data: implementation of SWE-SCA hystereses, Journal of hydrology and hydromechanics, 67, 70–81, 2019.

Romilly, T., G., G., and M.: Evaluation of satellite rainfall estimates over Ethiopian river basins, Hydrology and Earth System Sciences, 15(5), 1505, 2011.

Rowell, D. P.: A demonstration of the uncertainty in projections of UK climate change resulting from regional model formulation, Climatic Change, 79, 243–257, 2006.

Saadi, M., Oudin, L., and Ribstein, P.: Random Forest Ability in Regionalizing Hourly Hydrological Model Parameters, Water, 11, 1540, 2019.

Saha, S., Moorthi, S., Pan, H.-L., Wu, X., Wang, J., Nadiga, S., Tripp, P., Kistler, R., Woollen, J., Behringer, D., et al.: The NCEP climate forecast system reanalysis, Bulletin of the American Meteorological Society, 91, 1015–1058, 2010.

Samaniego, L., Bárdossy, A., and Kumar, R.: Streamflow prediction in ungauged catchments using copula-based dissimilarity measures, Water Resources Research, 46, 2010.

Satgé, F., Defrance, D., Sultan, B., Bonnet, M.-P., Seyler, F., Rouché, N., Pierron, F., and Paturel, J.-E.: Evaluation of 23 gridded precipitation datasets across West Africa, Journal of Hydrology, 581, 124 412, 2020.

Schneider, U., Becker, A., Finger, P., Meyer-Christoffer, A., and Ziese, M.: GPCC Full Data Monthly Product Version 2018 at 0.5°: Monthly land-surface precipitation from rain-gauges built on GTS-based and historical data, Global Precipitation Climatology Centre, 2018.

Tarek, M., Brissette, F. P., and Arsenault, R.: Evaluation of the ERA5 reanalysis as a potential reference dataset for hydrological modeling over North-America, Hydrology and Earth System Sciences Discussions, pp. 1–35, 2019.

Taylor, K. E., Stouffer, R. J., and Meehl, G. A.: An overview of CMIP5 and the experiment design, Bulletin of the American Meteorological Society, 93, 485–498, 2012.

Trambauer, P., Maskey, S., Winsemius, H., Werner, M., and Uhlenbrook, S.: A review of continental scale hydrological models and their suitability for drought forecasting in (sub-Saharan) Africa, Physics and Chemistry of the Earth, Parts A/B/C, 66, 16–26, 2013.

Valéry, A., Andréassian, V., and Perrin, C.: 'As simple as possible but not simpler': What is useful in a temperature-based snow-accounting routine? Part 2–Sensitivity analysis of the Cemaneige snow accounting routine on 380 catchments, Journal of hydrology, 517, 1176–1187, 2014.

Velázquez, J. A., Troin, M., Caya, D., and Brissette, F.: Evaluating the time-invariance hypothesis of climate model bias correction: implications for hydrological impact studies, Journal of Hydrometeorology, 16, 2013–2026, 2015.

Vetter, T., Reinhardt, J., Flörke, M., van Griensven, A., Hattermann, F., Huang, S., Koch, H., Pechlivanidis, I. G., Plötner, S., Seidou, O., et al.: Evaluation of sources of uncertainty in projected hydrological changes under climate change in 12 large-scale river basins, Climatic Change, 141, 419–433, 2017.

Vila, D. A., De Goncalves, L. G. G., Toll, D. L., and Rozante, J. R.: Statistical evaluation of combined daily gauge observations and rainfall satellite estimates over continental South America, Journal of Hydrometeorology, 10, 533–543, 2009.

Voisin, N., Wood, A. W., and Lettenmaier, D. P.: Evaluation of precipitation products for global hydrological prediction, Journal of Hydrometeorology, 9, 388–407, 2008.

Westra, S., Thyer, M., Leonard, M., Kavetski, D., and Lambert, M.: A strategy for diagnosing and interpreting hydrological model nonstationarity, Water Resources Research, 50, 5090–5113, 2014.

Wilby, R. L. and Harris, I.: A framework for assessing uncertainties in climate change impacts: Low-flow scenarios for the River Thames, UK, Water resources research, 42, 2006.

Wu, Z., Xu, Z., Wang, F., He, H., Zhou, J., Wu, X., and Liu, Z.: Hydrologic evaluation of multi-source satellite precipitation products for the upper Huaihe River Basin, China, Remote Sensing, 10, 840, 2018.

Youssef, H., Simon, G., Younes, F., Ghani, C., and Vincent, S.: Rainfall-Runoff modeling in a semi-arid catchment with presence of snow. The Rheraya wadi case study (Marrakech, Morocco), EGUGA, p. 5214, 2018.

Yu, X., Bhatt, G., Duffy, C., and Shi, Y.: Parameterization for distributed watershed modeling using national data and evolutionary algorithm, Computers & Geosciences, 58, 80–90, 2013.

Zhao, F., Veldkamp, T. I., Frieler, K., Schewe, J., Ostberg, S., Willner, S., Schauberger, B., Gosling, S. N., Schmied, H. M., Portmann, F. T., et al.: The critical role of the routing scheme in simulating peak river discharge in global hydrological models, Environmental Research Letters, 12, 075 003, 2017.

Zhu, H., Li, Y., Huang, Y., Li, Y., Hou, C., and Shi, X.: Evaluation and hydrological application of satellite-based precipitation datasets in driving hydrological models over the Huifa river basin in Northeast China, Atmospheric Research, 207, 28–41, 2018.
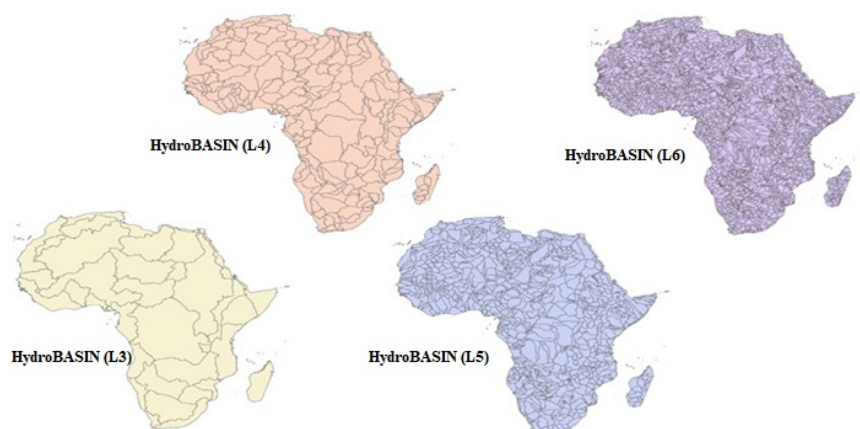
Figure 1. Sample of the different vector layers of watersheds on the African continent. Each layer has a different number of watersheds, depending on the required scale.
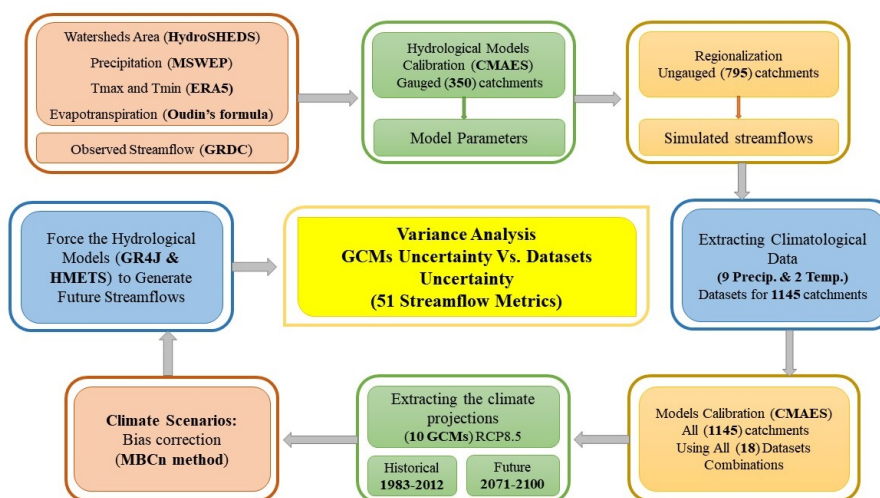
Figure 2. Overview of the various methodological steps implemented in this study.
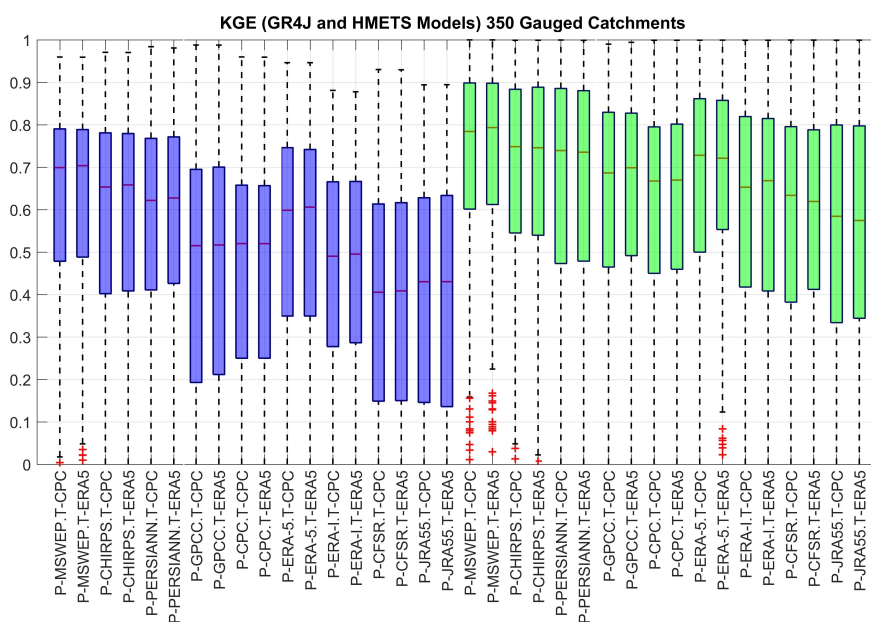
Figure 3. KGE calibration values using the 18 possible combinations of precipitation and temperature datasets, for both hydrological models (GR4J in blue and HMETS in green) for each of the 350 selected gauged catchments.
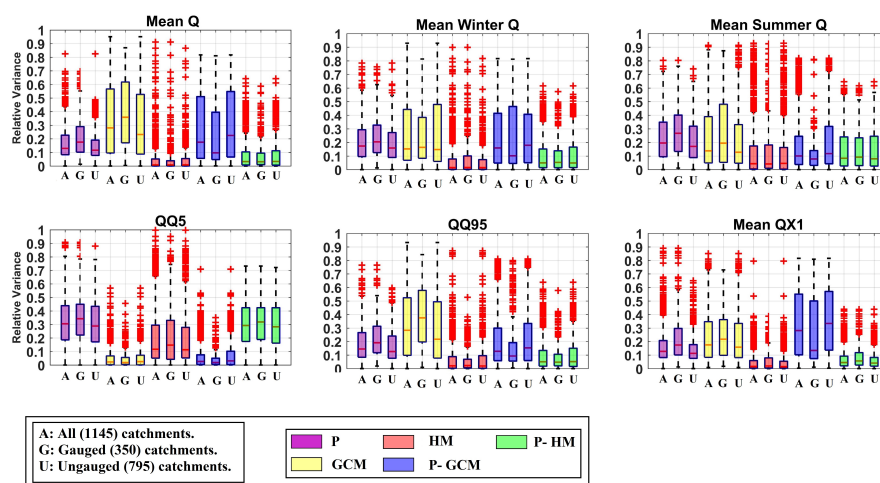
Figure 4. Boxplots of the relative variance attribution results for the five main contributors to overall variance (P, GCM, HM, P-GCM and P-HM) and 6 streamflow metrics. Relative variance is shown for all 1145 catchments: (A), 350 gauged (G) and 795 ungauged (U) catchments.
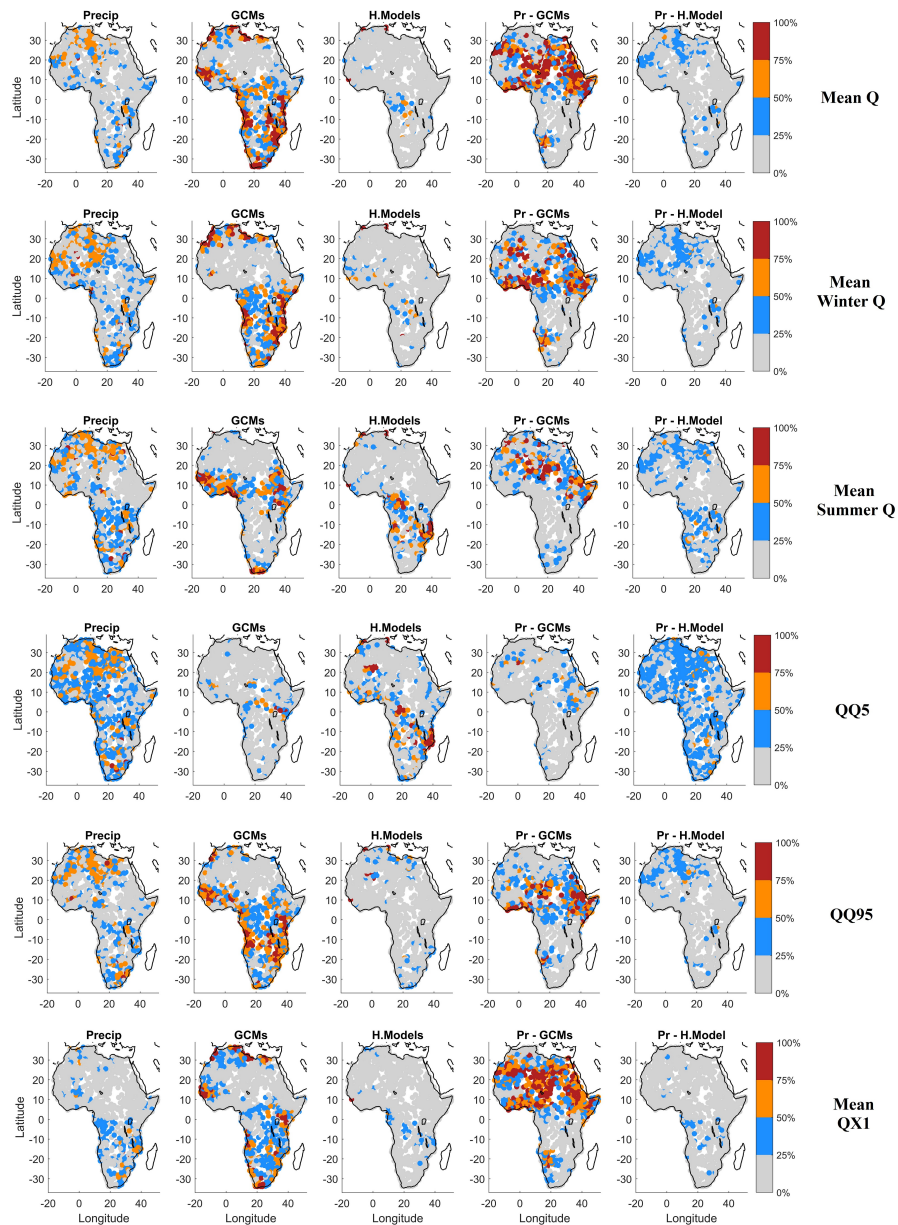
Figure 5. Spatial distribution of the five main contributors to variance for each of the 6 streamflow metrics.
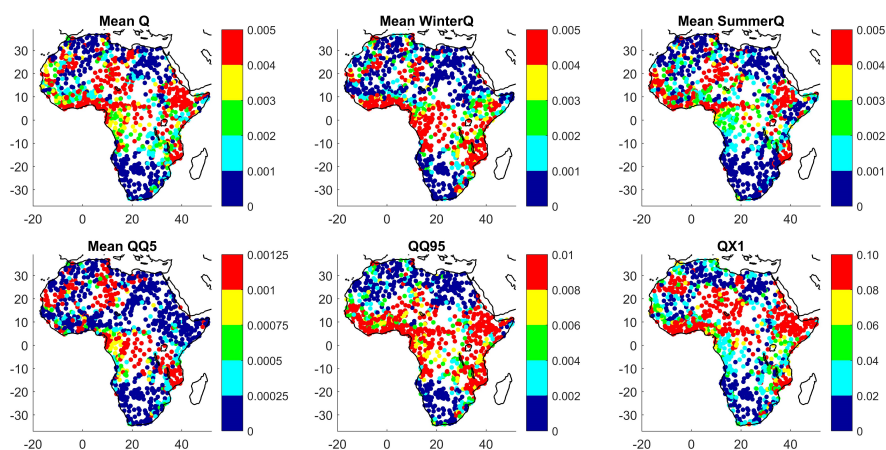
Figure 6. Standard deviation of discharge per unit area (in m^3/sec/km^2), constructed from 360 values for each catchment and streamflow metric.
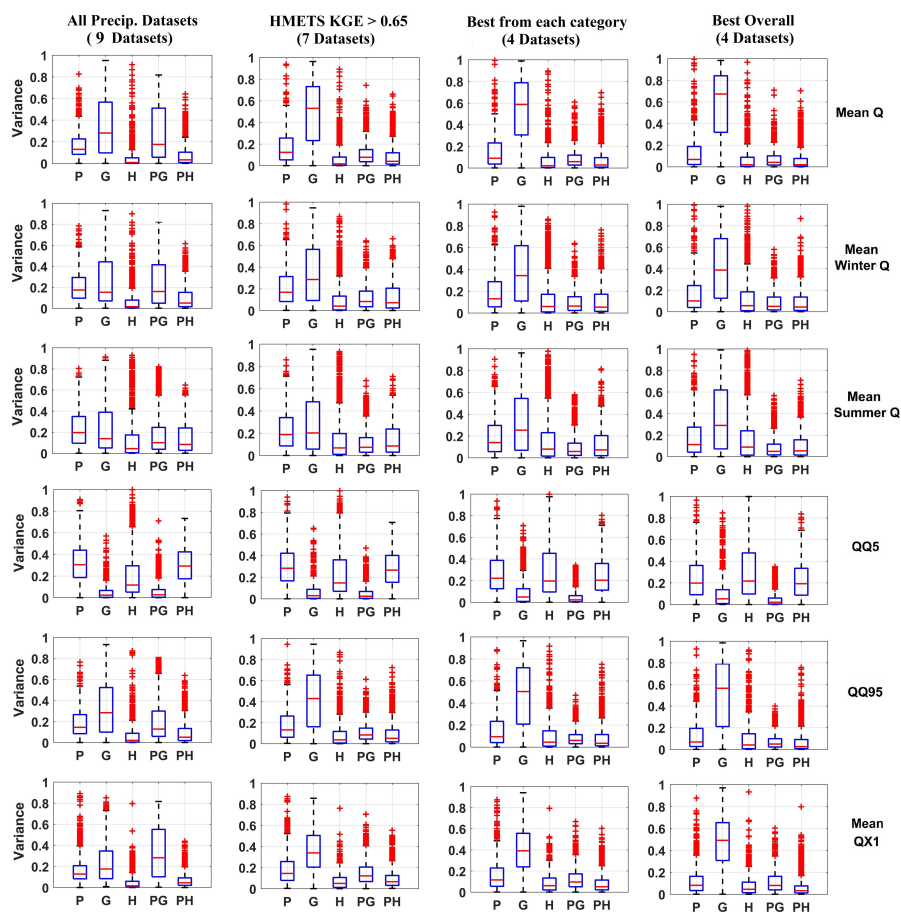
Figure 7. Boxplots of the five main components of the variance attribution: precipitation (P), GCMs (G), hydrological models (H), interaction between precipitation datasets and GCMs (PG) and interaction between precipitation datasets and hydrological models (PH). Columns represent the four precipitation ensembles of Table 4, while rows represent the 6 hydrological indices investigated in this study.
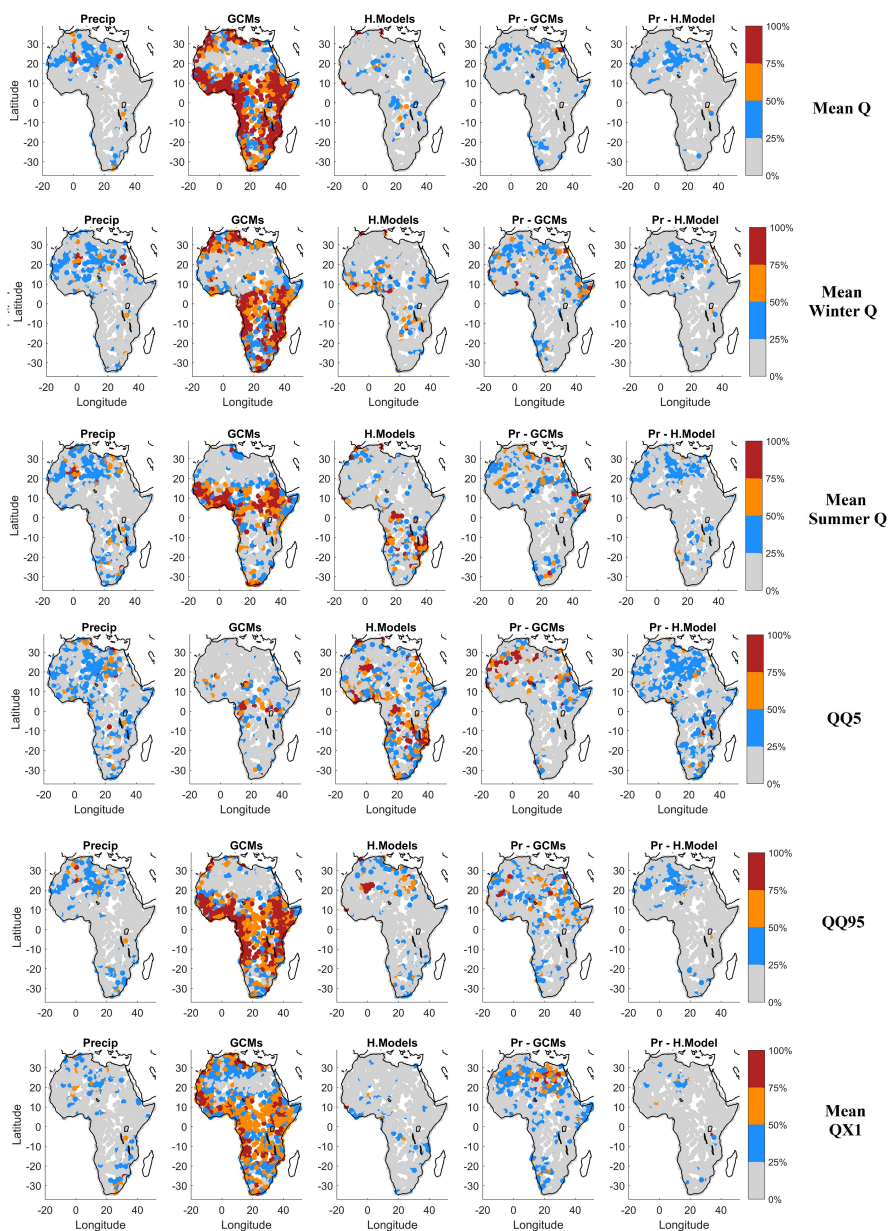
Figure 8. Spatial distribution of the five main contributors to variance for each of the 6 streamflow metrics, using the 4 best precipitation datasets (Ensemble 4 of Table 4).

Table 1. List of chosen GCMs, research centres and spatial resolutions.

No.	Models	Research Center	Spatial Resolution
1	BCC-CSM1-1	Beijing Climate Center, China Meteorological Administration, China	2.79° x 2.81°
2	BNU-ESM	College of Global Change and Earth System Science, Beijing Normal University, China	2.79° x 2.81°
3	CanESM2	Canadian Center for Climate Modeling and Analysis, China	2.79° x 2.81°
4	CCSM4	National Center of Atmospheric Research, USA	0.94° x 1.25°
5	CMCC-CESM	Centro Euro-Mediterraneo per I Cambiamenti Climatici, Italy	3.44° x 3.75°
6	CNRM-CM5	National Center of Meteorological Research, France	1.40° x 1.40°
7	FGOALS-g2	LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences, China	2.79° x 2.81°
8	INMCM4	Institute for Numerical Mathematics, Russia	1.5° x 2.0°
9	MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan	1.40° x 1.40°
10	MRI-CGCM3	Meteorological Research Institute, Japan	1.12° x 1.125°

Table 2. The selected global gridded datasets.

No.	Short Name	Data Source	Spatial Resolution	Spatial Coverage	Temporal Resolution	Temporal Coverage
			1- Precipitation datasets			
1	CPC Unified	Gauge	0.5°	Global	Daily	1979- Present
2	GPCC	Gauge	1.0°	Global	Daily	1982- 2016
3	PERSIANN-CDR (V1R1)	Gauge, Satellite	0.25°	±60° Lat.	6 hourly	1983- 2012
4	CHIRPS V2.0	Gauge, Satellite	0.05°	±50° Lat.	Daily	1981- Present
5	NCEP-CFSR	Reanalysis	0.5°	Global	6 hourly	1979- 2012
6	ERA-Interim	Reanalysis	0.75°	Global	3 hourly	1979- 8/2019
7	ERA5	Reanalysis	0.25°	Global	hourly	1979- 2017
8	JRA-55	Reanalysis	0.5625°	Global	3 hourly	1959- Present
9	MSWEP V1.2	Gauge, Satellite, Reanalysis	0.25°	Global	3 hourly	1979- 2015
			2- Temperature datasets			
1	CPC Unified	Gauge	0.5°	Global	Daily	1979- Present
2	ERA5	Reanalysis	0.25°	Global	hourly	1979- 2017

Table 3. Mean percentage of variance for 6 streamflow metrics for 1145 catchments. All main effects (P, GCM, temperature (T), and HM) and first-order interactions are shown in rows 3 to 12. The last row sums up the second- and third-order elements contribution to variance. QQ5 and QQ95 are respectively the 5th and 95th quantiles of streamflow distribution. QX1 is the 30-year mean of the annual daily maximum streamflow value. These rows written in **bold font** outline the main contributors to variance.

	Mean relative variance (%)						
	Mean Q	Winter Q	Summer Q	QQ5	QQ95	QX1	Average
P	**21.62**	**24.12**	**28.54**	**34.38**	**23.17**	**22.36**	*25.70*
GCM	**39.71**	**24.93**	**27.29**	**4.39**	**39.56**	**25.82**	*26.95*
T	0.17	0.12	0.09	0.02	0.15	0.04	0.09
HM	**5.18**	**8.43**	**19.99**	**21.96**	**5.59**	**5.50**	*10.11*
P-GCM	**21.55**	**25.19**	**10.20**	**3.42**	**16.01**	**26.33**	*17.12*
P-T	0.02	0.01	0.02	0.01	0.02	0.01	0.015
P-HM	**7.38**	**9.72**	**14.69**	**31.12**	**8.17**	**8.78**	*12.31*
GCM-T	0.01	0.01	0.006	0.0018	0.017	0.005	0.008
GCM-HM	1.30	2.13	1.44	1.36	2.49	3.49	2.04
T-HM	0.0087	0.0098	0.0069	0.0041	0.0189	0.0058	0.009
Others	2.78	5.20	3.46	2.99	4.60	7.58	4.43

Table 4. List of ensemble of precipitation datasets.

Ensemble no.	Number of precipitation datasets	Rationale for selection	Datasets included	Datasets excluded
1	9	All 9	All	None
2	7	Mean KGE $\geq$ 0.65	MSWEP, GPCC, CPC, CHIRPS, PERSIANN ERA5 and ERA-I	CFSR and JRA55
3	4	Best of each category (merged, satellite, gauge, and reanalysis)	MSWEP, CHIRPS, GPCC and ERA5	CPC, PERSIANN, ERA-I, CFSR and JRA55
4	4	Best (4)	MSWEP, CHIRPS, PERSIANN and ERA5	CPC, GPCC, ERA-I, CFSR and JRA55