Response to Reviewer Comments (Aloysius and Saiers)

Our manuscript has benefitted from the comments and suggestions of the two reviewers. We have revised and rewritten sections of the manuscript. The comments of the reviewers are provided below in *italicized* font; our responses are in normal text. The track changes enabled version of the manuscript highlights revisions made to the manuscript.

Reviewer #1:

1) *Details are missing from the SWAT model development: version and revision of SWAT used and a table of parameters that were changed in calibration of the model (can be in SI).*

We have updated the Methods section and Supplemental Information as per the reviewer's suggestions. A table with adjusted parameters during calibration is also included in the SI (SI Table S5). We used version 488 of the model source code. We have also revised the Supplemental Figure S3 to show simulated v. observed hydrographs of all 30 gages used in calibration and validation.

2) *Was the CO2 level changed in SWAT? If so, what was it changed to; if not, why was it not changed?*

Due to the lack of information on the effect of CO_2 on the 16 land cover classes simulated, the ambient CO_2 concentration was maintained at 330 ppm throughout the simulation period. A recent study also suggest that hydrologic partitioning in tropical rainforest catchments is largely unaffected by elevated CO_2 (line 230-235).

The methods section (section 2.4) is updated accordingly.

3) *In general the figure captions need to be more detailed so that they can be stand-alone. For example, Figure 3B you should clarify if the GCM-simulated climate is the statistically downscaled and bias corrected data (similar comment for Figure S2).*

Captions of Figure 3B (lines 25-35 in "02_Aloysius_2016_figures.docx") and SI Figure S2 (SI lines 104-109) have been updated as per the reviewer's suggestion.

4) *In lines 195 and 221 you refer to the climate projection simulations going to 2099, but it does not appear this was the case so this number should be changed.*

The model simulation period is 1950-2065 (lines 198 and 230). We have updated the text accordingly.

Reviewer #2:

1) *As in the previous round of reviews, I would like to highlight that I welcome the contribution of this substantial scientific effort to investigate climate change in the Congo Basin, since it is such an important and understudied region. However, I do not believe that the authors have sufficiently addressed my previous comments, and therefore would suggest further major revisions. I think the analysis could be useful, but that the paper requires a substantial re-write to ensure that the results and their implications are represented accurately. Perhaps I can explain my points more clearly to help them to be addressed more systematically. They still center around (1) <u>model uncertainty</u>, and (2) <u>observational uncertainty</u>.*

Inadequately addressing model and observational uncertainty was a significant weakness of the manuscript. To address this issue, we have revised the methods section (lines 216-222) and added a new section "3.4 Sources of Uncertainty". This section covers both model and observational uncertainties as suggested by the reviewer. The observational uncertainties include declining gage-based precipitation observations, particularly in the equatorial region (lines 414-427) and observed runoff data (lines 428-435). We agree with the reviewer that gage-based precipitation coverage is very limited after 1990s. We have quantified the number of gage-based precipitation data that contributed to the development of historical climate observations used in the hydrological model and for statistical bias-correction. Number of gages remained at about 160 during 1950-1980 and had substantially reduced since then (Supplemental Figure S5 and S6). However, satellite-based precipitation data has been used since the 80s. We believe these multiple sources (gage and satellite-based and reanalysis) adequately capture spatial and temporal variability of precipitation in the Congo region. Additional references supporting our claim are mentioned in the main text (line 423-427).

For runoff, we used all the available gages (n = 30) during the study period. The locations of these gages adequately capture climatic, land cover and topographic variability (lines 428-435 and supplemental Figure S3).

For future projections, the largest source of uncertainty is the GCM outputs. We have discussed the potential sources in section 3.4 (lines 436-496). Suggested literature by the reviewer has been incorporated. Figures 6-8 have been revised to highlight model uncertainties. The variability in modelled runoff are presented in Table 3, which show the multi-model mean, standard deviations and fraction of model projections with increasing runoff, by region and by season.

We have revised the abstract to highlight the need to evaluate uncertainties in climate change assessment (lines 32-35)

Specific comments:

1) *First sentence in the abstract: A side point, but is this really true? Compared to other regions there is relatively little research for the Congo Basin.*

We have re-characterized the effects of climate change on CRB water resources as understudied (line 14).

2) *I do not think you can say "elucidate" since we cannot know what the variability in runoff will be I the near and mid 21s century yet.*

Changed to "explore"

3) *All models? Some models? Most models? The mean of the models? Are there any that show decrease?*

The abstract has been revised to include the mean and the range of projections (lines 20-23).

4) Here I think it would be more useful to embed the information about uncertainty into the information about projections. It is not easy to infer this from what is written, but it might be something like:

We revised the abstract according to this suggestion (lines 32-35).

5) *Unclear why this has been changed from "model consensus" to "consensus". Arguably it's important that it is just a model based consensus*

We have removed this phrase in the revised abstract.

6) *I think might and would are important here to tone down so that it is not implying that we know what will happen*

Abstract has been revised as suggested.

7) *This is a bit of a strange statement. Of course the risk attitudes of planners will influence their approach, but perhaps the scientific results can be used to imply the extent to which there is credible information for planning. Personally I think it would be OK to recommend using an approach which takes into account a range of futures, since there are so many uncertainties associated with climate information in the Congo Basin.*

The phrase "risk attitude" no longer appears in the abstract.

8) *Can you instead comment on the challenge of finding a solution that is robust to the range of projected changes?*

Addressed in section 4 (lines 501-524).

9) *Why? This is unsubstantiated and doesn't really make sense. What does it mean to say that the analyses increase the degree of confidence in using the results (since the results are based on the analysis). Suggest removing.*

Removed as suggested.

10) *In general I think it would be important to revise the text of the paper in line with these kind of edits. i.e. if referring to model results, it is important to say that they are model results, and if making inferences, to use "might" or "could" rather than "will". The use of "predict" has been changed in several cases to "project", as advised, but this has not been done consistently. I would suggest removing all references to "predict" and "forecast" when referring to long term climate projections.*

These suggestions have been adopted in the revised text.

11) *"The results presented here show a range of runoff projections under two broad assumptions, that i) individual GCM biases will cancel and that MM mean projections are more likely correct and ii) selection of GCMs that simulate mechanisms reliably is a better option for climate change assessment." However, I do not think these assumptions can be used unless they are justified. I think that both (i) and (ii) are highly questionable. There is quite a bit of work (cited in my previous round of comments) which critiques the idea of using the mean for future projections. And, on point (ii) I do agree that selecting GCMs which simulate mechanisms would be helpful, but what is meant by "mechanisms"? My understanding is that the subselection here is based on the author's previous JGR-A publication, in which models are selected based on observations of key variables like temperature and precipitation, rather than the modelled "mechanisms". Sub-selecting models using observational constraints is an approach which is often adopted, but is also questioned, particularly for regions with such high observational uncertainty. Therefore, I think that if these assumptions are to be stated they must be justified and discussed in a balanced manner which acknowledges for the readers of HESS that many climate scientists would dispute with these assumptions. Alternatively, a better approach would be to re-write the results to focus more on the range of modelled outcomes.*

These assumptions have been revised and rewritten. Section 3.4 and 4 addresses the projection uncertainties. We have provided reasoning for selection of the subset of models (lines 461-472).

12) *It would be interesting to quantify the amount of data available and comment on what is meant by "sufficient". I agree that there is more data available during the early part of the period (when I believe CRU is the only one of the datasets used to modify NCEP reanalysis – based on Sheffield et al. 2006, Table 1), however, based on Washington et al. 2013 Figure 1, there are still max 60 gauges*

contributing to CRU during this time for the whole Congo Basin, which is very few stations compared to the density of stations over e.g. UK or USA.

We have added two figures in the Supplemental Information (Figures S5 and S6) and discussed the observational data availability in section 3.4 (lines 406-427).

13) I cannot see where this discussion has been added? I think it should be discussed in the methods section. Also in results – p. 11, line 219 there is a statement about bias corrected precip from model being in agreement with observations. Wouldn't this be expected if the observations have been used to correct the model output?

The observational uncertainties are discussed in section 2.4 (lines 216-220) and section 4 (lines 408-427). Results comparing bias-corrected and observed precipitation have been revised (lines 249-251).

Simulated Hydrologic Response to Projected Changes in Precipitation and Temperature in the Congo River Basin

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Abstract

Despite their global significance, the impacts of climate change on water resources and associated ecosystem services in the Congo River Basin (CRB) have been understudied. Of particular need for decision makers is the availability of spatial and temporal variability of runoff projections. Here, with the aid of a spatially explicit hydrological model forced with precipitation and temperature projections from 25 global climate models (GCMs) under two greenhouse gas emission scenarios, we explore the variability in modeled runoff in the near (2016-2035) and mid (2046-2065) century. We find that total runoff from the CRB is projected to increase by 5% [-9%; 20%] (mean [min and max] across model ensembles) over the next two decades and by 7% [-12%; 24%] by midcentury. Projected changes in runoff from sub-watersheds distributed within the CRB vary in magnitude and sign. Over the equatorial region and in parts of northern and southwestern CRB, most models project an overall increase in precipitation and, subsequently, runoff. A simulated decrease in precipitation leads to a decline in runoff from head-water regions located in the northeastern and southeastern CRB. Climate model selection plays an important role in future projections, for both magnitude and direction of change. The multi-model ensemble approach reveals that precipitation and runoff changes under business-as-usual and avoided greenhouse gas emission scenarios (RCP8.5 vs. RCP4.5) are relatively similar in the near-term, but deviate in the mid-term, which underscores the need for rapid action on climate change adaptation. Our assessment demonstrate the need to include uncertainties in climate model and emission scenario selection during decision making processes related to climate change mitigation and adaptation.

1. Introduction

Sustainable management of water resources for food production, supply of safe drinking water, and provision of adequate sanitation~~,~~ presents immense challenges in many countries of Central Africa where the Congo River Basin (CRB) is located [*IPCC*, 2014; *UNEP*, 2011; *World Food Program*, 2014]. The economies of the nine countries that share the waters of the CRB are agriculture-based [*World Bank Group*, 2014] and, therefore, are vulnerable to the impacts of climate change. Despite the abundant water and land resources and favorable climates, the basin countries are net importers of staple food grains and are far behind in achieving Millennium Development Goals [*Bruinsma*, 2003; *Molden*, 2007; *UNEP*, 2011]. Appropriation of freshwater resources is expected to grow in the future as the CRB countries develop and expand their economies. At the same time, climate change related risks associated with water resources will also increase significantly [*IPCC*, 2014].

Historical, present and near-future greenhouse gas emissions in the CRB countries constitute a small fraction of global emissions; however, the impacts of climate change on water resources are expected to be severe due to the region's heavy reliance on natural resources (e.g. agriculture and forestry) [*Collier et al.*, 2008; *DeFries and Rosenzweig*, 2010; *Niang et al.*, 2014]. The limited adaptation capacity in the CRB region is expected to cause severe water and food security challenges, which, in turn, can lead to ecosystem degradation and increased greenhouse gas emissions [*Gibbs et al.*, 2010; *IPCC*, 2014; *Malhi and Grace*, 2000].

Strategies for addressing stresses on CRB water resources, including revival of rural economies (largely agriculture based), achieving millennium development goals and environmental conservation, would benefit from detailed information on the spatial and temporal variability of water balance components under different climate projection pathways. The effect of climate change on water resources can be investigated by incorporating climate change projections (e.g. precipitation and temperature) in simulation models that reliably represent the spatial and temporal variability of CRB's hydrology. Such a framework could be applied to project changes in storage and runoff, and hence freshwater availability, under different socioeconomic pathways that affect climate trajectories.

A predictive framework of the CRB's hydrology is hindered by insufficient data and too few evaluations of models against available data [*Beighley et al.*, 2011; *Wohl et al.*, 2012]. Basin scale water budgets estimated from land-based and satellite-derived precipitation datasets reveal significantly different results, and modeled runoff shows only qualitative agreement with corresponding observations [*Alsdorf et al.*, 2016; *Beighley et al.*, 2011; *Lee et al.*, 2011; *Schuol et al.*, 2008]. *Tshimanga and Hughes* [2012; 2014] recently developed a semi-distributed hydrologic model capable of simulating runoff in CRB. This work crucially identified approaches suitable for approximating runoff generation at the basin scale, although the spatial resolution of the model predictions is rather coarse for supporting regional water management and regional-planning efforts. These regional planning efforts must take into account variablity and uncertainties stemming from climate-model selection and projected greenhouse gas emissions, but, with respect to freshwater runoff projections for the CRB, these issues have been inadequately addressed.

The goals of this study are to i) develop a spatially explicit hydrology model that uses downscaled output from general circulation models (GCMs) and is suitable for simulating the spatiotemporal variability of runoff in the CRB; ii) test the ability of the hydrological model to reproduce historical data on CRB river discharges using both observed and GCM-simulated climate fields; (iii) quantify the sensitivity and uncertainty of modeled runoff projections to GCM selection; (iv) use the hydrologic model with individual GCMs and multi-GCM ensembles to project near-term (2016-2035) and mid-term (2046-2065) changes in runoff for two greenhouse-gas emission scenarios. We focus on the runoff projections because streams and rivers will serve as the primary sources of freshwater targeted for human appropriation [*Burney et al.*, 2013; *Molden*, 2007].

We find that a hydrologic model that is forced with bias-corrected and downscaled outputs from an ensemble of 25 GCMs and two emission projects a considerable range in precipitation and runoff, and that runoff projections are highly sensitive to GCM forcing. The multi-model mean (MM, un-weighted average of all GCMs) and the select-model mean (SM, selected GCMs based on performance in the historical period and representation of certain attributes in the climate system) project a 1-3% increase in precipitation (20mm – 45mm) and a 4-9% increase in total runoff (15mm-34mm) within the CRB in the near-term (2016-2035) relative to reference period (1985-2005) for MM and SM, respectively. In the mid-term (2036-2065), on the other hand, projections are GCM and emission-scenario dependent, with the high emission

RCP8.5 scenario showing the highest increases in precipitation (2-5%, 30mm – 70mm) and runoff (7-14%, 25mm – 50mm) for MM and SM, respectively. Modeled projections also exhibit substantial inter-model variability with projected changes varying between -3% and 9% for precipitation and -12% and 24% for total runoff from the CRB between the mitigation and business-as-usual greenhouse gas emission scenarios. Regionally, both MM and SM project decreasing precipitation and runoff in parts of southern and northern headwater regions of the CRB.

2. Materials and Methods

2.1 The Congo River Basin

The Congo River Basin, with a drainage area of 3.7 million km^2, is the second largest in the world by area and discharge (Figure 1, average discharge of ~41,000 m^{3}s^{-1}) [*Runge*, 2007]. The basin extends from 9^{o}N to 14^{o}S, while the longitudinal extent is 11^{o}E to 35^{o}E. Nine countries share the water resources of the basin. Nearly a third of the basin area lies north of the equator. Due to its equatorial location, the basin experiences a range of climate regimes. The northern and southern parts have strong dry and wet seasons, while the equatorial region has a bimodal rainy season [*Bultot and Griffiths*, 1972]. Much of the rain in the northern and southern CRB occurs in Jun-Jul-Aug (JJA) and Dec-Jan-Feb (DJF), respectively. The primary and secondary rainy seasons in the equatorial region are Sep-Oct-Nov (SON) and Mar-Apr-May (MAM, see *Bultot and Griffiths* [1972] and Supplemental Information (SI) Figure S1). The mean annual precipitation is about 1,500 mm. Rainforests occupy nearly 45% of the basin and are minimally disturbed compared to the Amazon and Southeast Asian forests [*Gibbs et al.*, 2010; *Nilsson et al.*, 2005]. Grassland and savannah ecosystems, characterized by the presence of tall grasses, closed-canopy woodlands, low-trees and shrubs, occupy another 45% [*Adams et al.*, 1996; *Bartholomé and Belward*, 2005; *Hansen et al.*, 2008; *Laporte et al.*, 1998]. Water bodies (lakes and wetlands) occupy nearly 2% of the area and are concentrated mostly in the southeastern and western equatorial parts of the CRB (Figure 1). Soils of the CRB vary from highly weathered and leached Ultisols to Alfisols, Inceptisols and Oxisols [*FAO/IIASA*, 2009; *Matungulu*, 1992]. Most soils are deep and well-drained, but they are very acidic, deficient in nutrients, have low capacity to supply potassium and exhibit a low cation exchange capacity [*Matungulu*, 1992].

In order to compare regional patterns in precipitation and runoff, we divided the basin into four regions: i) Northern Congo (NC), ii) Equatorial Congo (EQ), iii) Southwestern Congo (SW), and iv) Southeastern Congo (SE). The EQ region covers most of the rainforest. The SE region consists of numerous interconnected lakes and wetlands. Most of the CRB's population is concentrated in the NC, SE and SW regions [*Center for International Earth Science Information Network (CIESIN) Columbia University et al.*, 2005].

2.2 Hydrologic model for the Congo River Basin

We used a physically based, semi-distributed watershed-scale model that operates at a daily time step [*Arnold et al.*, 1998; *Neitsch et al.*, 2011]. The hydrological processes simulated include evapotranspiration, infiltration, surface and subsurface flows, streamflow routing and groundwater recharge. The model has been successfully employed to simulate river basin hydrology under wide variety of conditions and to investigate climate change effects on water resources [*Faramarzi et al.*, 2013; *Krysanova* *and White*, 2015; *Schuol et al.*, 2008; *Trambauer et al.*, 2013; *van Griensven et al.*, 2012].

We delineated 1,575 watersheds within the CRB based on topography [*Lehner et al.*, 2008]. Watershed elevations vary between 15 m and 2,700 m with a mean value of 680 m above mean sea level. Each watershed consists of one stream section, where near-surface groundwater flow and overland flow accumulate before being transmitted through the stream channel to the watershed outlet. Watersheds are further divided into Hydrologic Response Units (HRUs) based on land cover (16 classes, *Bartholomé and Belward* [2005]), soils (150 types, *FAO/IIASA* [2009]) and topography. The runoff generated within each watershed is routed through the stream network using the variable storage routing method. The average watershed size and the number of HRUs within each watershed are 2,300 km^2 and 5, respectively. We also included wetlands and lakes as natural storage structures that regulate the hydrological fluxes at different locations within CRB (Figure 1). Detailed information is not available for the all the lakes; therefore, we incorporated the largest 16 lakes (SI Table S1).

Runoff, estimated for each HRU and aggregated at the watershed level, is generated via three pathways: overland flow, lateral subsurface flow through the soil zone and release from shallow groundwater storage. The Curve Number and a kinematic storage routing methods are used to simulate overland and lateral subsurface flows, and a nonlinear storage-discharge relationship is used to simulate groundwater contribution (see *Arnold et al.* [1998]; *Neitsch et al.* [2011] and SI). A power law relationship is employed to simulate the lake area-volume-discharge (see SI and *Neitsch et al.* [2011]). The potential evapotranspiration is estimated using the temperature-based Hargreaves method [*Neitsch et al.*, 2011]. The actual evapotranspiration is estimated based on available soil moisture and the evaporative demand (i.e. potential evapotranspiration) for the day. Additional details on model development and calibration are provided in the Supplementary Information.

2.3 Model simulation of historical hydrology with observed climate forcings

We ran the hydrology model for the period 1950-2008. Estimates of observed daily precipitation, and minimum and maximum temperatures needed to calculate potential evapotranspiration were obtained from the Land Surface Hydrology Group at Princeton University [*Sheffield et al.*, 2006]. In addition, measured monthly stream flows were obtained at 30 gage locations (Figure 1) that had at least 10 years of records [*Global Runoff Data Center*., 2011; *Lempicka*, 1971; *Vorosmarty et al.*, 1998].

The model was calibrated using observed streamflows for the period 1950-1957 at 20 locations. The number of model parameters estimated by calibration varied from 10 to 13, depending on the location of flow gages (e.g. gages with lakes within their catchment area have more parameters). The calibration involved minimizing an objective function defined as the sum-of-squared errors between observed and simulated monthly average total discharge, baseflows (estimated by applying a baseflow separation method *Nathan and McMahon* [1990]) and water yield. The Gauss-Marquardt-Levenberg algorithm as implemented in a model independent parameter estimation tool [*Doherty*, 2004] was used to adjust the fitted parameters and minimize the objective function. Parameter estimation was done in two stages. First, parameters for the watersheds in the upstream gages were estimated. Then the parameters for the downstream gages were estimated. To test the calibrated model, simulated stream flows were compared to stream flows measured at the same 20 locations, but during a period outside of calibration (i.e., 1958-2008), as well as at 10 additional locations that were not used in the calibration.

2.4 Hydrologic Simulations with Simulated Climate Forcing

Historical climate simulations for the period 1950-2005 and climate projections to 2065 for two greenhouse gas emission scenarios (Representative Concentration Pathway – RCP), mid-range mitigation emission (RCP4.5) and high emission (RCP8.5), were used to drive the hydrologic model. The RCP4.5 scenario employs a range of technologies and policies that reduce greenhouse gas emissions and stabilize radiative forcing at 4.5 W m^{-2} by 2100, whereas the RCP8.5 is a business-as-usual scenario, where greenhouse gas emissions continue to increase and radiative forcing rises above 8.5 Wm^{-2} [*Moss et al.*, 2010; *Taylor et al.*, 2012]. We used monthly precipitation and temperature outputs provided by 25 GCMs (Table 1) for the Fifth Assessment (CMIP5) of the Intergovernmental Panel on Climate Change (IPCC).

GCM outputs may exhibit biases in simulating regional climate. These biases, which are attributable to inadequate representation of physical processes by the models, prevent the direct use of GCM output in climate change studies [*Randall et al.*, 2007; *Salathé Jr et al.*, 2007; *Wood et al.*, 2004]. Hydrological assessments that use GCM computations as input inherit the biases [*Salathé Jr et al.*, 2007; *Teutschbein and Seibert*, 2012]. To mitigate this problem, we implemented a statistical method [*Li et al.*, 2010] to bias-correct the monthly historical precipitation and temperature fields. In brief, the method employs a quantile-based mapping of cumulative probability density functions for monthly GCM outputs onto those of gridded observations in the historical period. The bias correction is extended to future projections as well. The observed data used in the modeling and bias-correction has some limitations. That is, the number of precipitation gages decreased over the period from 1950 to 1990, and the density of the gages is sparse compared to the size of the river basin (see Section 3.4 and SI). However, we assumed that the available ground-based observations combined with satellite-based and reanalysis data adequately captured the spatiotemporal variability in precipitation. Studies by *Munzimi et al.* [2014] and *Nicholson* [2000] draw similar conclusions.

The simulated monthly precipitation and temperature values were temporally downscaled to daily values for use in the CRB hydrology model. We used the three-hourly and monthly observed historical data developed for the Global Land Data Assimilation System [*Rodell et al.*, 2004; *Sheffield et al.*, 2006] and the bias-corrected monthly simulations to generate three-hourly precipitation and temperature fields, which were subsequently aggregated to obtain daily values (see SI Methods). The hydrological model was forced with the bias-corrected and downscaled daily climate fields for the period 1950-2065. Due to the lack of information on the effect of CO_2 on the 16 land cover classes simulated, the ambient CO_2 concentration was maintained at 330 ppm throughout the simulation period. A recent study suggests that, in tropical rainforest catchments, elevated CO_2 has little impact on evapotranspiration, but results in increased plant assimilation and light use efficiency [*Yang et al.*, 2016]. A total of 50 projections (25 RCP4.5 and 25 RCP8.5 projections) were compiled and analyzed. Results of individual and multi-model means (un-weighted average of all (MM) and selected (SM) GCM simulations) for the near-term (2016-2035) and mid-term (2046-2065) projections are presented.

3. Results and Discussion

3.1 Historical simulations

Historical observations of average annual precipitation vary from 1,100 mm in the southeastern portion of the CRB to 1,600 mm in the CRB's equatorial region. We compared the GCM-simulated -annual precipitation and its inter-annual variability during the historical period with observations from 30 locations within the CRB (Figure 2). The simulated inter-annual variability among the climate models (vertical bars in Figure 2) lies within the range of the observed variability (horizontal bars in Figure 2). The linear-regression slope of 1.16 ($p < 0.001$, Figure 2) between the annual observed and the multi-model mean shows that bias-corrected precipitation is slightly over-estimated, but not significantly so. Observations of seasonal precipitation are reproduced similarly well by the GCM models (SI Figure S2 and Table S2). The good agreement between GCM-simulated and observed rainfall is expected given our bias correction of the GCM output.

We compared the simulated monthly runoff at 30 locations with observations (Figure 3A). The colored points compare observed mean annual runoff at the 30 gage locations with historical simulations (hydrological model forced with observed climate), while the vertical and horizontal bars show the modeled and observed inter-annual variability, respectively. The shades of colors (from light-green to yellow and red) reveal the model's skill in simulating the monthly flows in the historical period. The Nash-Sutcliff coefficient of efficiency (NSE), a measure of relative magnitude of residual variance compared to the monthly observed streamflow variance [*Legates and McCabe*, 1999; *Nash and Sutcliffe*, 1970], varies between 0.01 and 0.86 (color scale in Figure 3A). (The NSE ranges between negative infinity to 1, with values between 0.5 and 1 considered satisfactory [*Moriasi et al.*, 2007].) Seventeen of the 30 gages show NSE greater than or equal to 0.5. Higher NSE values at locations on both sides of the equator, particularly at major tributaries (NSE ~ 0.60, gages 1 to 8 in Figure 1 and SI Figure S3) suggest that the model reliably simulates stream flows under different climatic conditions. High NSE values also indicate that the seasonal and annual runoff simulations, including the inter-annual variability in the historical period, are in good agreement with observations. The catchment areas of the 30 gages vary between 5,000 km^2 and 900,000 km^2 (excluding the last two downstream gages) and encompass a range of land cover and climatic regions on both sides of the equator; thus the hydrology model exhibits reasonable skill in simulating runoff over a wide range of watershed conditions.

Comparison of modeled runoff forced with GCM-simulated and observed climate (Figure 3B) reveals generally acceptable runoff simulations in the CRB. The black dots and red (blue) vertical bars in Figure 3B show multi-model mean and maximum (minimum) range of inter-annual variability in the 25 historical GCM simulations. The results suggest that model-data agreement in precipitation translates to similarly acceptable runoff simulations.

Runoff patterns reflect seasonal rainfall that varies asymmetrically on either side of the equator -(see SI Figure S1). For example, the observed peak runoff at streamflow gages 2 and 6 (see Figure 1) located north and south of the equator occur near the end of the rainy seasons – during Sep-Oct and Mar-Apr, respectively (Figure 4). Augmented by flows from northern and southern tributaries (e.g. gages 1, 2, 4 and 6) and by high precipitation in the tropical equatorial watersheds during the two wet seasons (MAM and SON), the main river flows (downstream of gage 3 in Figure 1) show low variability

(Figure 4). For example, the coefficient of variation in observed (simulated) monthly flows at the basin outlet (gage 8), northern tributary (gage 2) and southern tributary (gage 4) are 0.23 (0.24), 0.77 (0.80) and 0.40 (0.48), respectively.

Regionally, runoff in the northern (NC) and southern (SW and SE) watersheds is strongly seasonal with long dry seasons, but this is not the case in the equatorial region (Figure 5). Average watershed runoff varies between 20-70 mm during dry seasons to 100-140 mm during wet seasons in the NC, SW and SE. In the equatorial region, seasonal runoff varies between 100-150mm with the highest in SON. Overall, the precipitation-runoff ratio is about 0.30 in the CRB. The accessible runoff (excluding runoff associated with flood events), which can be appropriated for human use, is about 70% of the total runoff.

3.2 Future projections in precipitation and runoff

3.2.1 Precipitation

A previous study [*Aloysius et al.*, 2016] showed that GCM projections of temperature generally increase under both emission scenarios in line with historical upward trend for Africa [*Hulme*, 2001]; however, precipitation projections contain large uncertainties. The modeled near-term (2016-2035) precipitation projections in the CRB vary between -4% and 6% with a multi-model mean (MM) change of 1% under the two emission scenarios relative to the reference period (1986-2015). Regionally, the northern CRB shows the largest annual increase in precipitation followed by southwestern and equatorial regions. However, the inter--model variability is larger than the MM in all regions, indicating greater projection uncertainties in both emission scenarios (Table 2).

The mid-term (2046-2065) projections of annual precipitation vary between -5% and 9%, with the MM of 1.7% and 2.1% for RCP4.5 and RCP8.5, respectively. More than 70% of the ensembles in both RCPs project an increase in annual precipitation in the CRB over the mid-term. The multi-model mean of all ensembles that project an increase (decrease) in precipitation is 2.7% (-2.4%) for RCP4.5 and 4.0% (-2.9%) for RCP8.5.

The GCMs project considerable spatial and seasonal variations in precipitation (Table 2 and Figure 6). However, the standard deviation of annual and seasonal projections within the four regions exceed or equal to the MM, indicating little agreement on the direction of change. The spatial patterns (Figure 6), on the other hand, show regions where modeled projections strongly agree on increasing or decreasing precipitation. For example, decreasing precipitation is projected in most of the headwater catchments in the southern and parts of northern CRB.

In general, the GCMs project decreasing precipitation in the driest parts of the southern CRB (mostly in Southeastern CRB, but portions of Southwestern as well). Under the RCP8.5 scenario, the northeastern CRB also experiences reduction in precipitation in the near-term. The areas of decreased precipitation shrink in the southeast and southwest in the mid-term; however, drying expands in parts of northern CRB under the two emission scenarios. Most GCMs (14-20) project an increase in all but the southeastern CRB.

Inter-model variability in precipitation projections are sensitive to seasons and climate region (Figure 7A-D). At monthly scale, the northern and southern regions receive less than 50mm of precipitation for at least three months, which persist in the future under both emission scenarios. The dry season is more prolonged in the southeast compared to the rest of the CRB. The inter-model variability is larger in the rainy seasons under RCP8.5, compared to RCP4.5. Larger variability under RCP8.5 highlights that GCMs may have limited skill in simulating precipitation under high greenhouse gas emissions.

3.2.2 Runoff

In general, modeled runoff increases, and its inter-annual variability within GCMs is larger during high flow periods compared to low flow periods, except in the equatorial region~~.~~ (Figure 7E-H, see Figure 1 for regions). The model projection uncertainty increases towards the middle of century, particularly under the RCP8.5 emission scenario. The temporal patterns of runoff in the near- and mid-terms are similar to the precipitation patterns, but with a time lag. As with precipitation, the monthly runoff shows prolonged periods low values in the northern and southern CRB in both projection periods. -Spatially, parts of northern, southeastern, and southwestern CRB also show reduced runoff projections relative to the reference period under both RCPs; these reductions are predominantly in the areas where fewer GCMs agree on the increase in modeled precipitation (see Figure 6 and SI Tables S3 and S4). The area of decreasing runoff expands in the northern CRB under both emission scenarios in the mid-term (see Figure 6, which shows that more models agree on decreasing precipitation in parts of northern CRB that subsequently results in decreasing runoff). Although the northern and equatorial CRB show an overall increase in precipitation, the decrease in runoff in certain parts in the northern and equatorial CRB is caused by reduction in seasonal precipitation. A larger reduction – up to 15% – in the southeastern CRB covering most of northern

Zambia is due to an overall decrease in precipitation simulated by more the half of the GCMs (see Figure 6).

The multi-model mean of total runoff from the CRB shows an increase of 5% (±6%, one standard deviation, n = 25) and 7% (±8%) in the near- and mid-terms under both RCPs relative to the reference period (1986-2005). Annual Runoff in the equatorial region, which receives the highest precipitation, is projected to increase by up to 5% (±7%) in the near-term to 6% (±8%) and 7% (±9%) in the mid-term for RCP4.5 and RCP8.5, respectively. The increases are greater in the secondary rainy season (MAM) than the primary (SON, Figure 7 B and F). Monthly runoff projections show that the majority of the ensembles project an increase in the equatorial CRB, with the RCP8.5 ensembles exhibiting larger variability (Figure 7F).

Runoff that can be appropriated for human use is generated mostly in the northern, southeastern and southwestern CRB, which at present varies from 130mm/year in the southeastern CRB to 250-400mm/year in the northeastern and southwestern CRB. Runoff is projected to increase in all three of these regions. However, the inter-model variability is greater than twice the MM in nearly all the regions and during all four seasons (Figure 8 and Table 3). In most cases, the largest uncertainties are in non-rainy seasons and under high emission RCP8.5 scenario (e.g. DJF in the northern CRB, Figure 8B, and JJA in the southeastern CRB, Figure 8H).

3.3 Variability in accessible flows

Only part of the runoff may be appropriated for human use. In the CRB, the accessible runoff (AF), excluding runoff associated with flood events, is about 70%. The

AF is largely under-utilized, but its appropriation is expected to increase in the future, mostly in the populated areas of northern, southwestern and southeastern CRB. We present the uncertainty associated with GCM and scenario selection by quantifying seasonal and inter-model variability in AF at eight major tributaries (identified in Figure 1) that drain watersheds across a range of climatic regions on both sides of the equator (Figure 9). Modeled AF exhibits substantial inter-model spread in the near-term and widens in the mid-term (SI Figure S5). The inter-model variability is larger during high flow periods compared to low flow periods.

Following the general pattern of increasing precipitation and runoff in the northern and southwestern watersheds, we find that AF increases with greater model agreement in tributaries that drain these watersheds (e.g. gages 1, 2 and 6 in Figure 9). A closer look at tributaries in the northern and southwestern CRB reveals better agreement of increased AF during low flow periods compared to high flow periods (compare gages 1, 2, 6 and 7 in Figure 9). In contrast, tributaries that drain southeastern watersheds exhibit greater variability in modeled AF with majority of the ensembles projecting a reduction (e.g. gages 4 and 5 in Figure 7). Overall, the AF in the main tributary (gages 3 and 8) is projected to increase, partly due to the contributions from the northern and southwestern tributaries. The decrease in modeled precipitation and AF in the southeastern CRB appears to have marginal effect on downstream flows in the main river.

The spatial and temporal variations in the projected AF have consequences for water resources development and management. For example, the uncertainty in projections of the AF near the proposed Grand Inga Hydropower project (near gage 8, *Showers* [2009]) is low compared the projections near the proposed trans boundary water diversion in the southeast (near gage 5, *Lund et al.* [2007]). Reductions in high and low flows in streams in the southeastern region will have implications to aquatic life, channel maintenance and lake and wetland flooding.

3.4 Sources of uncertainty

Climate model outputs under the two emission scenarios used in this study provide an opportunity to assess a range of future projections that could potentially resolve wide variations in results and, hence, uncertainties in modelled projections for the CRB. The uncertainties can be broadly categorized into i) observational uncertainty, particularly the sparse and declining network of precipitation and stream flow gages and ii) model uncertainty, which, in GCMs, include model structure, model initialization, parameterization and climate sensitivity – the response of global temperature to a doubling of CO_2 in the atmosphere relative to pre-industrial levels. We used only one hydrological model, which is also a source of uncertainty. However, variation in climate signals between GCMs and emissions scenarios, particularly precipitation projections, may be a larger source of uncertainty than the choice of hydrology model [*Thompson et al.*, 2014; *Vetter et al.*, 2016].

The climate data used for bias-correction and for historical hydrologic simulations has its own uncertainties. Gage-based, satellite derived data and reanalysis outputs are used to develop the historical observations [*Sheffield et al.*, 2006]. Precipitation gages were more numerous at the beginning of the simulation period and declined in number toward the end of the 20th century [*Mitchell and Jones*, 2005; *Washington et al.*, 2013]. Available gage data varied both spatially and temporally (SI Figure S6 and S7). For example, the equatorial region – nearly a third of CRB – had about 70 rain gages through early 1990s, but only 10% of these were functioning by 2005 (SI Figure S5). The southeastern and parts of northern CRB also had good rainfall-gage coverage, which has similarly decreased since the 1990s [*Mitchell and Jones*, 2005]. However, satellite-based and sparsely distributed gage data has been used to demonstrate that spatiotemporal distribution of precipitation can be sufficiently described in the CRB region [*Munzimi et al.*, 2014; *Nicholson*, 2000; *Samba et al.*, 2008]. We assume that, even with these limitations, the available historical data are adequate to model the hydrology of the CRB.

In addition to climate data, observed runoff data are another limitation that could restrict proper validation of hydrological models. However, we utilized a time period (1950-1959) when the CRB had maximum coverage of both precipitation and runoff data to calibrate and validate the hydrology model (for example see evidence in *L'vovich* [1979]). Where available, we used additional runoff data to further validate model outputs in the historical period. The runoff gage locations are distributed within the CRB (see Figure 1) such that they adequately capture climatic, land cover and topographic variability.

For future projections, the largest sources of uncertainty arise from the GCMs and emission scenarios. GCMs do not consistently capture observed rainfall seasonality and heavy rainfall in regions of the central CRB, and in most cases do not show key features such as seasonality and heavy rainfall regions of central CRB [*Aloysius et al.*, 2016; *Washington et al.*, 2013]. The biases in the GCM-simulated precipitation, particularly in the tropical regions, have been attributed to multiple factors including poorly resolved physical processes such as the mesoscale convection systems, inadequately resolved topography due to the coarse horizontal resolution and inadequate observations to constrain parameterization schemes. These limitations are unavoidable in the current set CMIP5 projections. We assume that the number of GCM outputs used in our work, and the bias-correction method, which maintains key statistical properties in the original GCM outputs (see *Aloysius et al.* [2016] and *Li et al.* [2010]), adequately captures the uncertainties in GCM and emission scenarios. Based on monthly precipitation climatology, *Aloysius et al.* [2016] found no significant shift in seasonality in modeled future precipitation projections.

The range of projections presented here for the two emission scenarios also highlight the uncertainties planners would encounter when making climate-related decisions. For example, broader agreement on increase in runoff in parts of the CRB would help make robust decisions, whereas weaker agreement in the southern CRB calls for greater scrutiny of regional climate. Generally, the MM approach reduces the uncertainty because averaging tend to offset errors across models. However, one could also ask whether this approach work with fewer models.

Washington et al. [2013] and *Siam et al.* [2013] presented evidence that evaluating atmospheric moisture flux which are modulated by wind patterns and humidity, and soil water balance are better ways to diagnose GCM performance in data scarce regions like the CRB. *Balas et al.* [2007], *Hirst and Hastenrath* [1983] and *Nicholson and Dezfuli* [2013] have shown that sea surface temperature (SST) anomalies in the Atlantic and Indian ocean sectors could partly explain precipitation in the CRB region. Along the same lines, *Aloysius et al.* [2016] identified five models as suitable candidates. We examined this subset of GCM projections (M6, M7, M18, M23 and

M24), which we refer to as the select model average, or SM (see refs. *Giorgetta et al.* [2013]; *Good et al.* [2012]; *Jungclaus et al.* [2013]; *Meehl et al.* [2013]; *Siam et al.* [2013]; *Voldoire et al.* [2012]; *Yukimoto et al.* [2006] and *Aloysius et al.* [2016] for further comparison of GCM performance). -By evaluating seasonal atmospheric moisture and soil water balance in 11 CMIP5 GCMs in the CRB and Nile River basin regions, *Siam et al.* [2013] identified M7, M18 and M24 as good candidates for climate change assessment.

Focusing on the northern, southeastern and southwestern CRB, where human appropriation of runoff is expected to increase, we find that the magnitude of annual projections (both precipitation and runoff) in SM are more than twice that of MM in the northern region. The extent of drying in the south is concentrated in the southeastern upstream watersheds in both MM and SM, although the magnitude of decrease is smaller in SM (SI Table S3 and S4).

From the viewpoint of water resources for human appropriation, the changes by seasons are also important. Future changes and uncertainties in modeled seasonal runoff averaged over the four regions are presented Figure 8. In comparison with the CRB projections, the uncertainties in sub-regions are larger. Nearly all the MM and SM projections show an increase in runoff in all the four seasons; however, there is substantial inter-model variability. The uncertainties increase under the high emission RCP8.5 scenario during the mid-century. Considering the southeastern region as an example, under RCP8.5 emission scenario, uncertainties reported as one inter-model standard deviation in the mid-term are ±20%, ±27%, ±26% and ±13%, respectively for DJF, MAM, JJA and SON seasons, and are greater than the MM and SM. Further, the deviation of uncertainty within the sub-regions of CRB increases under high emission RCP8.5 scenario. For example, the inter-model projection ranges are larger in the northern and southeastern CRB (Figure 8 B and H) compared to the equatorial and southwestern CRB (Figure 8 D and F). Finally, the uncertainty assessment presented here represents climate model uncertainty arising from emission scenarios, different response to the same external forcing, different model structures and parameterization schemes. While these uncertainties in projections pose challenges for robust decision making, they also provide insights into where further research might be most valuable.

4. Conclusions

From the point of view of climate change adaptation related to water resources, agriculture, and ecosystem management, the challenge faced by CRB countries is recognizing the value of making timely decisions in the absence of complete knowledge. In some settings, climate change presents opportunities as well as threats in the CRB. The projected increases in accessible runoff imply new opportunities to meet increasing demands (e.g. drinking water, food production and sanitation), while the enhanced flood runoff would pose new challenges (e.g. flood protection and erosion control). On the other hand, water managers could face different challenges in the southeast where precipitation and runoff are projected to decrease.

GCM-related variability in regional climate projections could be constrained by a subset of models based on attributes that modulate large-scale circulations (see *Knutti and Sedlacek* [2013] and *Masson and Knutti* [2011]). This approach is particularly useful because regions like the CRB lack complete coverage of observational data but the mechanisms that moderate the climate system, particularly precipitation, are fairly well understood [*Hastenrath*, 1984; *Nicholson and Grist*, 2003; *Washington et al.*, 2013]. Yet, the span in rainfall predictions among the MM, SM, and individual GCMs suggest that, despite the advances in climate modeling, significant uncertainties in precipitation projections for CRB persist.

Rather than providing a narrow pathway for decision-making, our results, for the first time for CRB, provide a framework to i) assess implications under various climate model assumptions and uncertainties, ii) characterize and expose vulnerabilities and iii) provide ways to guide the search for impact-oriented and actionable policy alternatives, as emphasized by *Weaver et al.* [2013]. Projections and associated uncertainties vary widely by region within the CRB, and therefore diverse but robust planning strategies might be advisable within the river basin. We emphasize that projections provided here could be considered as part of the process of incorporating multiple stressors into climate change adaptation and engaging stakeholders in the decision making process.

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Simulated Hydrologic Response to Projected Changes in Precipitation and Temperature in the Congo River Basin

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Figures in the main text

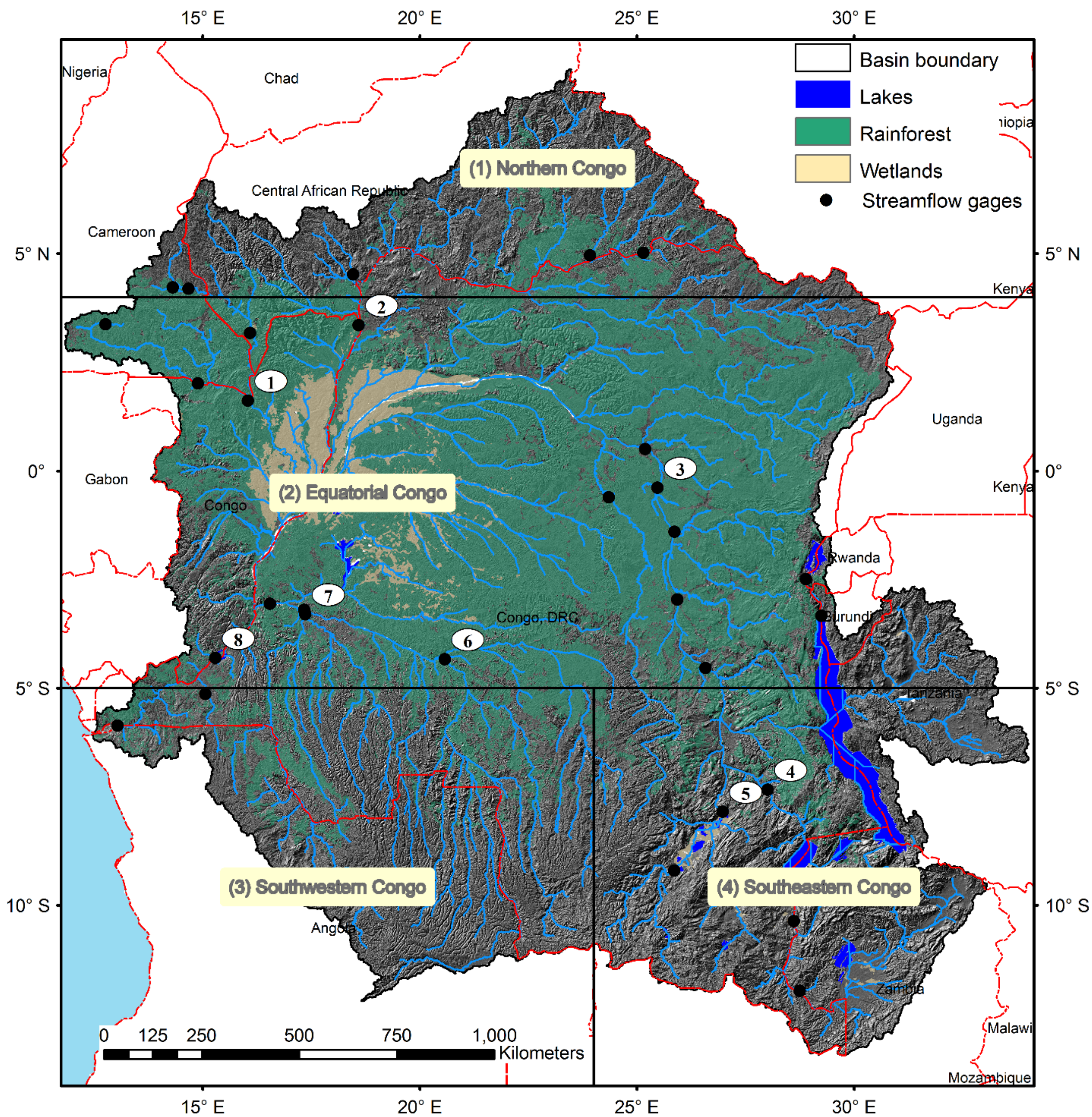

Figure 1 Congo River Basin: the river basin boundary, the extent of the rainforest, locations of lakes and wetlands, and the locations of streamflow gages are shown.

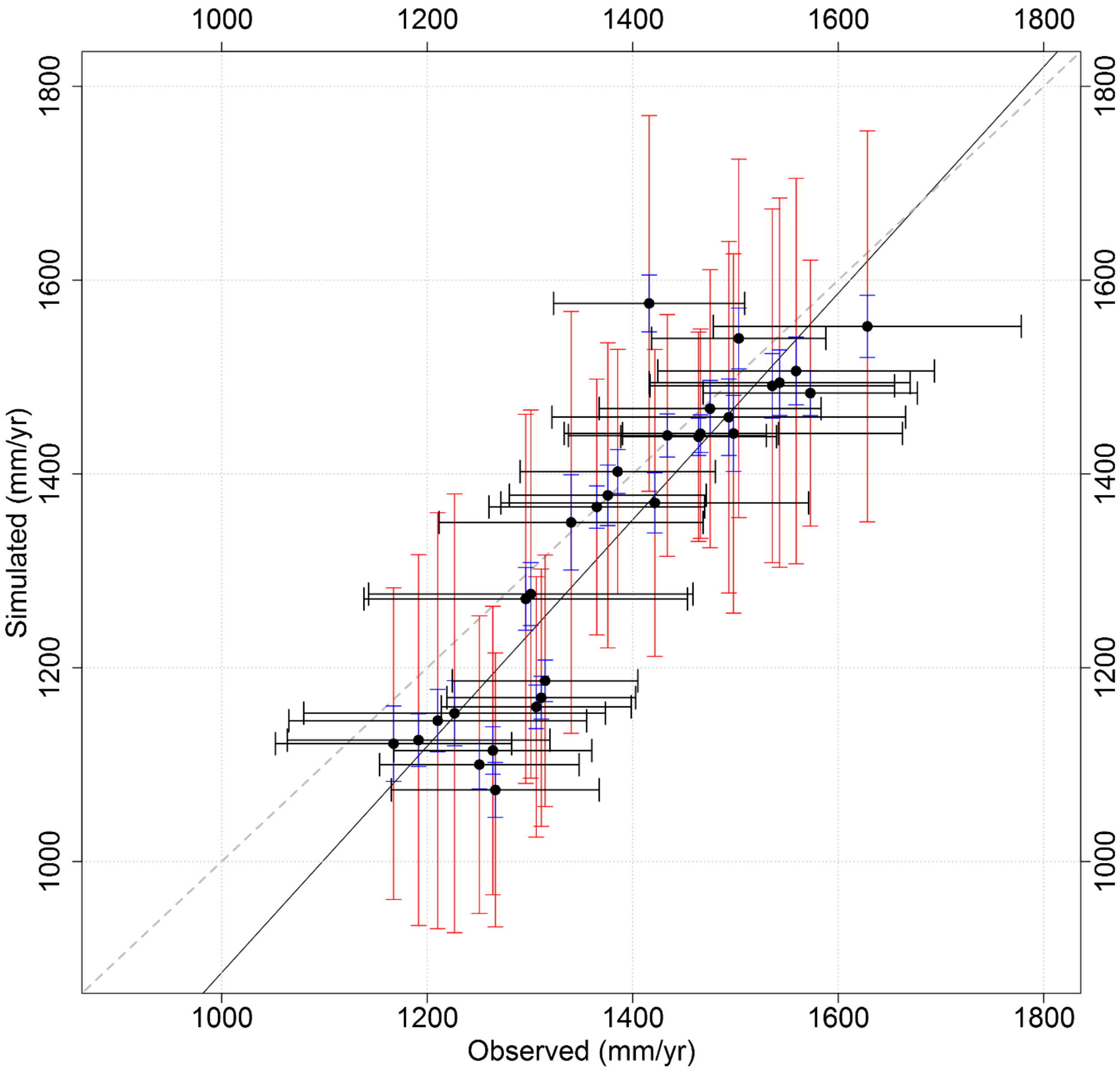

Figure 2 Comparison of observed and bias-corrected GCM-simulated average annual precipitation for 30 catchments with stream-flow gages (shown in Figure 1) in the historical period (1950-2005). Y-axis values are statistically downscales GCM-simulated precipitation. Black dots compare multi-model means with observed precipitation, black horizontal bars show observed inter-annual variability (± one standard deviation), and red (blue) vertical bars show maximum (minimum) range of modeled inter-annual variability (± one standard deviation) within the 25 climate model outputs. The black line is linear regression fit between observed and multi-model mean of simulated precipitation ($y = 1.16 \pm 0.204x - 283.4, p < 0.001, R^2 = 0.825$); parameter bounds are 95% confidence interval.

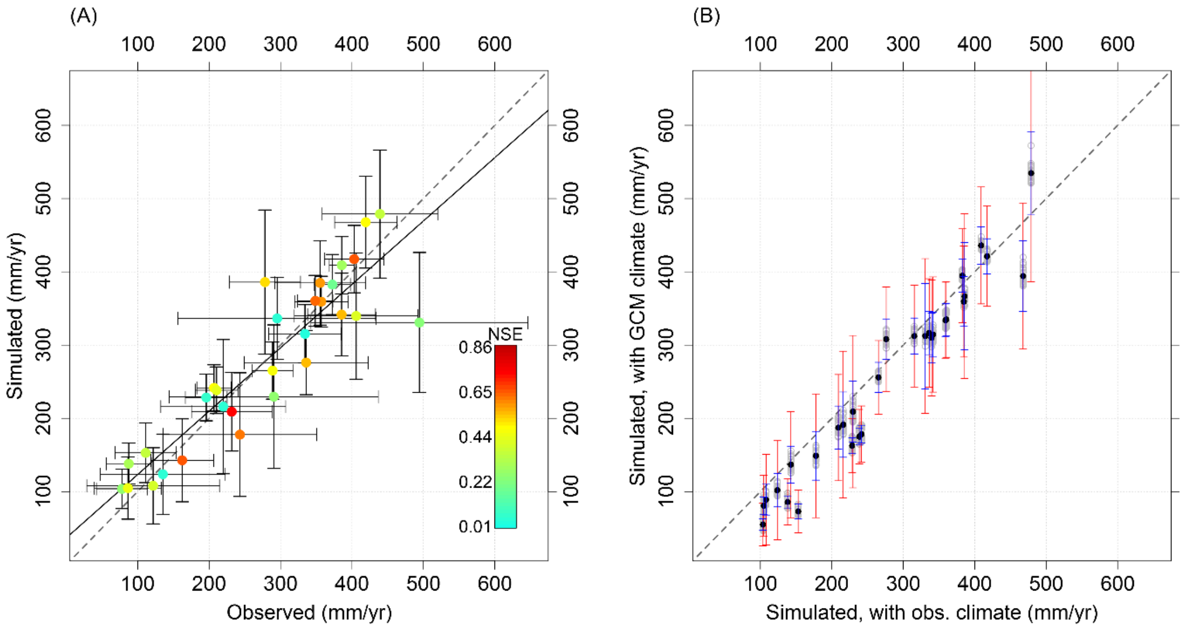

Figure 3. Comparison of observed and simulated annual runoff at the 30 streamflow gage locations (shown in Figure 1). (A) Historical simulations with observed climate: the positions of the colored dots compare annual values of observed and simulated historical runoff; the dots' colors (see legend) show the Nash-Sutcliff coefficient of efficiency (NSE) of observed vs. simulated monthly stream flows; and the black horizontal and vertical bars show observed and modeled inter-annual variability (± one standard deviation), respectively. The black line is linear regression fit between annual simulated and observed runoff ($y = 0.865 \pm 0.158x + 36.63, p < 0.001, R^2 = 0.82$), parameter bounds are the 95% confidence interval. (B) Simulations in the historical period with GCM-simulated climate: black dots show the multi-model mean; red (blue) vertical bars show modeled (forced with GCM-simulated historical climate) maximum (minimum) inter-annual variability (± one standard deviation) within the 25 simulations; and gray circles show multi-year mean of individual GCM simulations. The gray dotted lines in A and B are 1:1 line. The GCM-simulated forcings are statistically downscaled and bias-corrected.

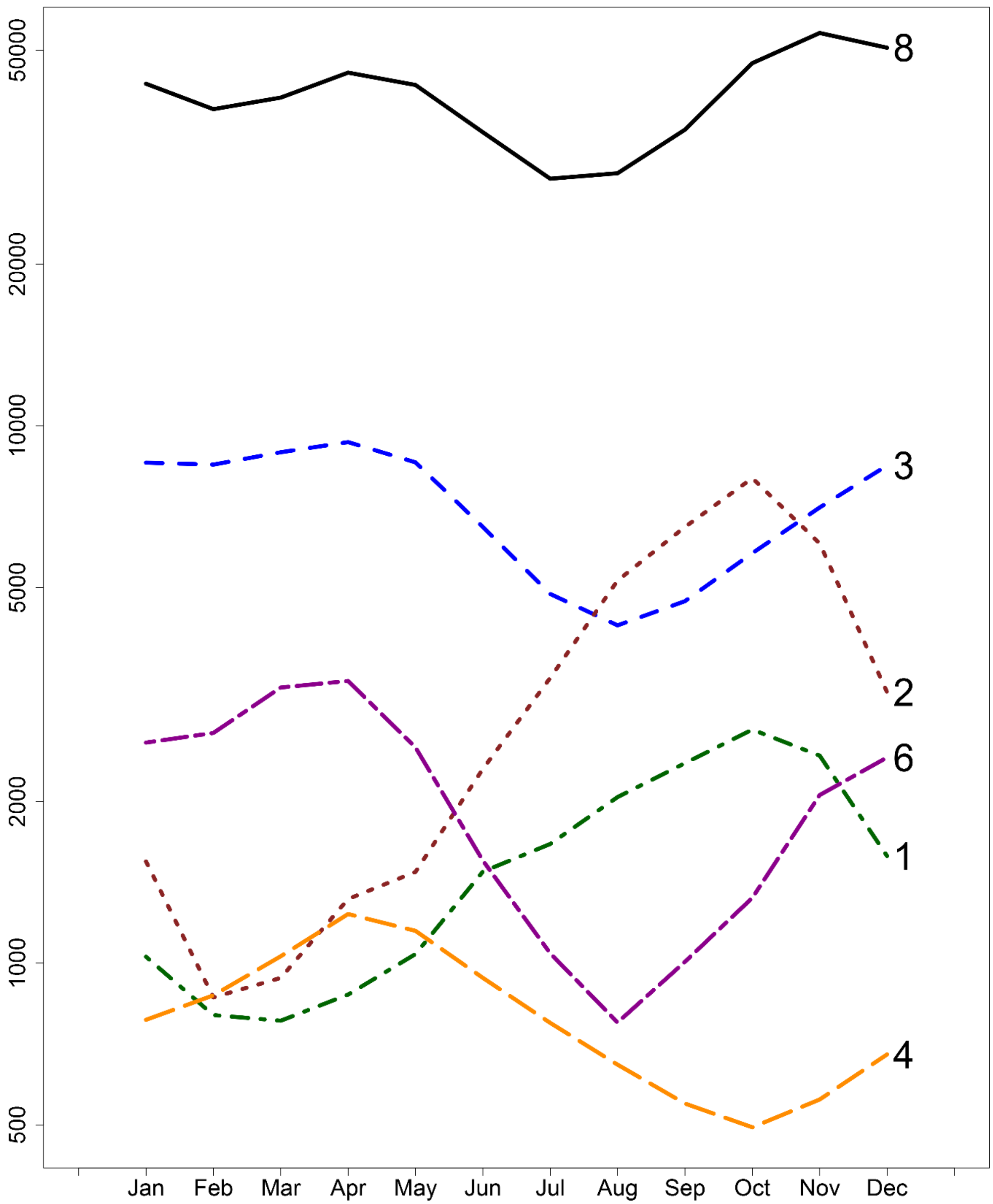

Figure 4 Mean monthly flows at selected tributaries in the CRB. Flows are in m^3/s and gage numbers are identified in Figure 1. Monthly values are based on simulated flows (forced with observed precipitation) for the period 1950-2005.

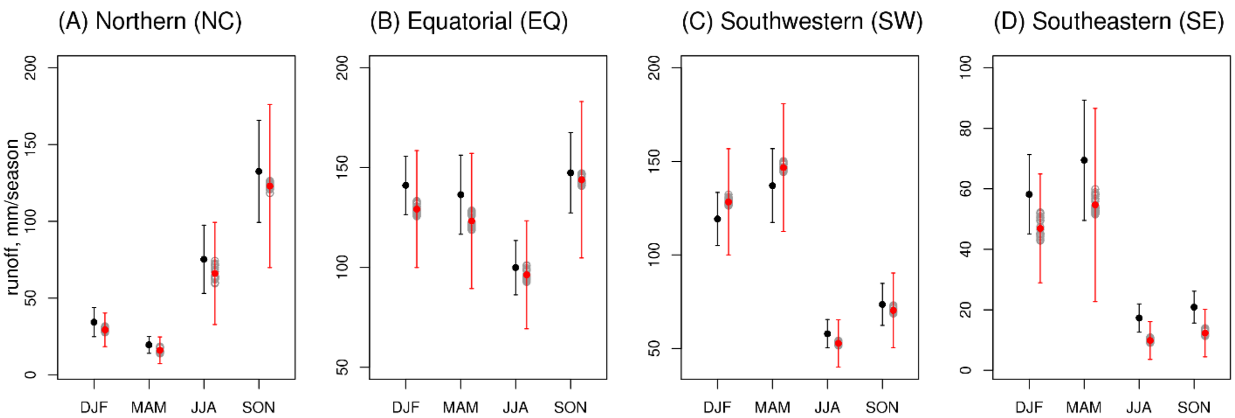

Figure 5 Seasonal variation in runoff in (A) Northern, (B) Equatorial, (C) Southwestern and (D) Southeastern Congo River Basin. Black dots and vertical bars show the modeled inter-annual variability forced with observed climate, red dots show the multi-model mean forced with GCM-simulated climate, red vertical bars show the maximum range of inter-annual variability within the 25 models and the grey open circles show the mean of individual models in the historical period, 1950-2005. Y-axis scale is different for each plot.

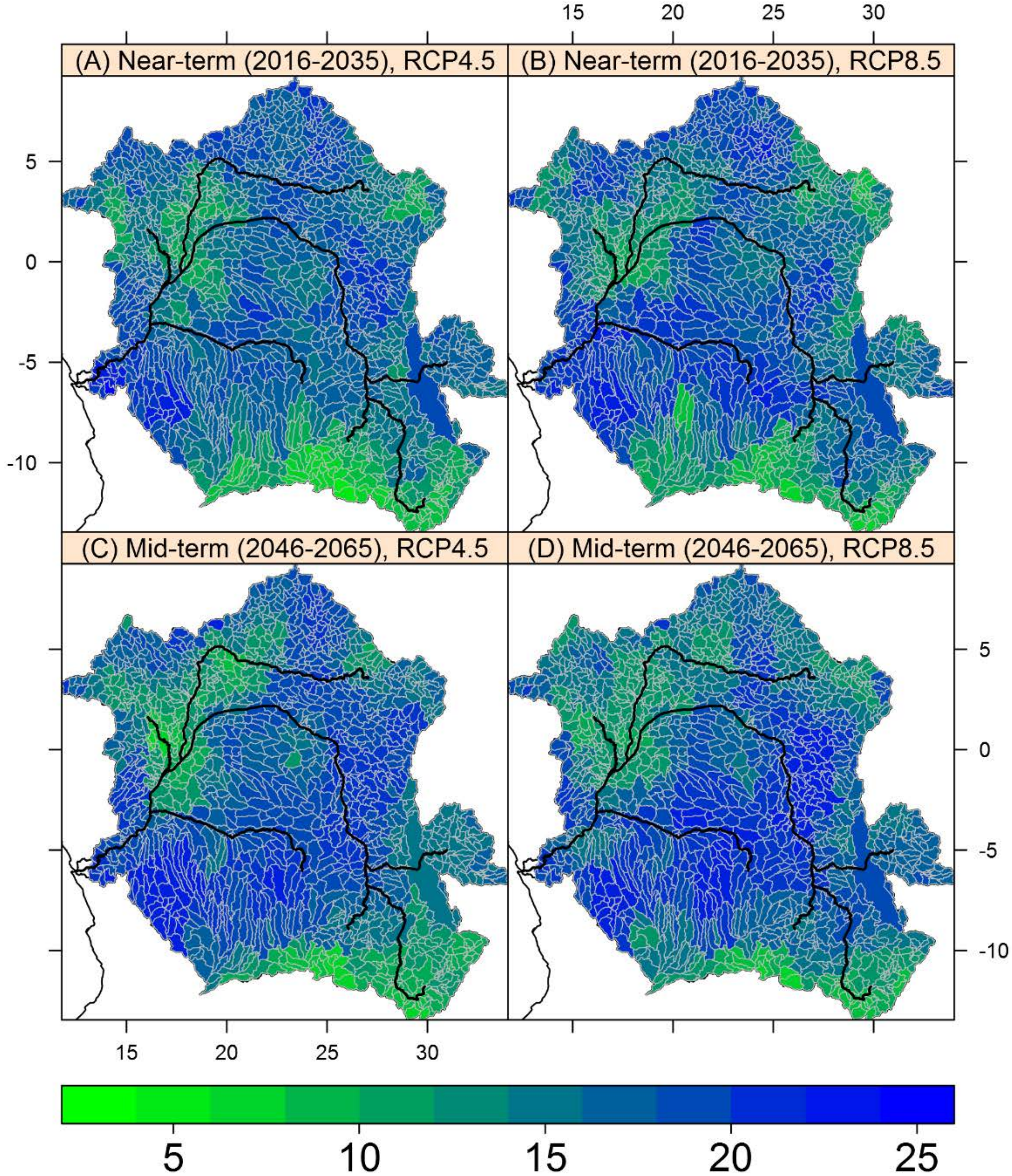

Figure 6 Number of climate model outputs that projects an increase in precipitation in the (A) near-term, 2016-2035, RCP4.5, (B) near-term RCP8.5, (C) mid-term, 2046-2065, RCP4.5 and (D) mid-term RCP8.5. Number of modeled precipitation outputs used is 25. Main rivers and lakes are also shown.

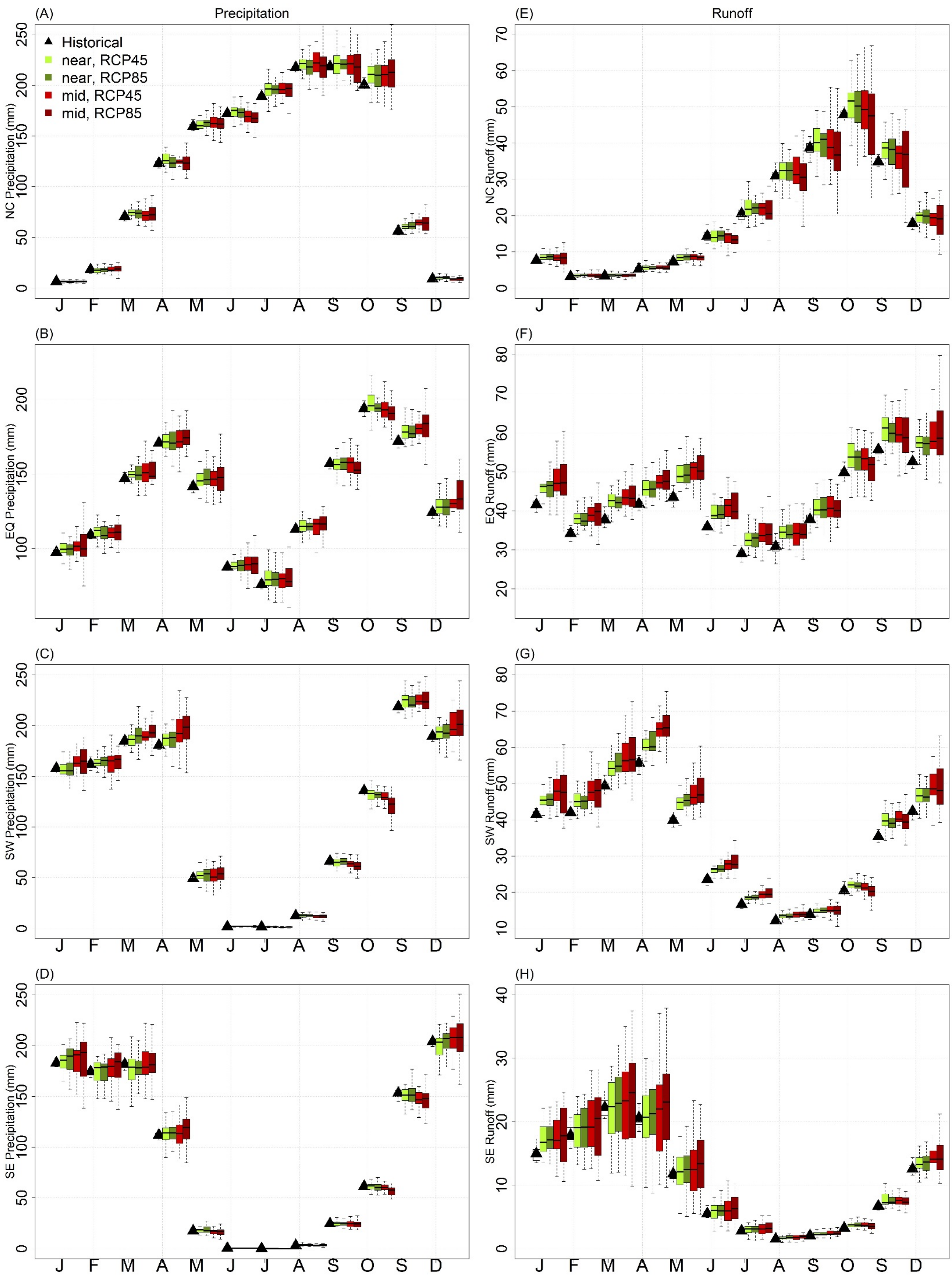
(A)
Precipitation
Historical
near, RCP45
near, RCP85
mid, RCP45
mid, RCP85
NC Precipitation (mm)
(E)
Runoff
NC Runoff (mm)
(B)
EQ Precipitation (mm)
(F)
EQ Runoff (mm)
(C)
SW Precipitation (mm)
(G)
SW Runoff (mm)
(D)
SE Precipitation (mm)
(H)
SE Runoff (mm)
J F M A M J J A S O S D

Figure 7 Monthly variation of precipitation (A-D) and runoff (E-H) in the four regions shown in Figure 1. Box-and-whiskers for each month shows the inter-model variability for the historical period (black), near-term RCP4.5 (light green), near-term RCP85 (dark green), mid-term RCP4.5 (red) and mid-term RCP8.5 (brown). The upper and lower end of the boxes show the 75th and 25th quartiles, the mid bar in each box shows the median, and the outer lines cover approximately 90% of the values. The multi-model mean value for the reference period is shown as triangles for clarity. All values are in mm/month. NC – northern, EQ – equatorial, SE – southeast and SW – southwest, see Figure 1 for locations.

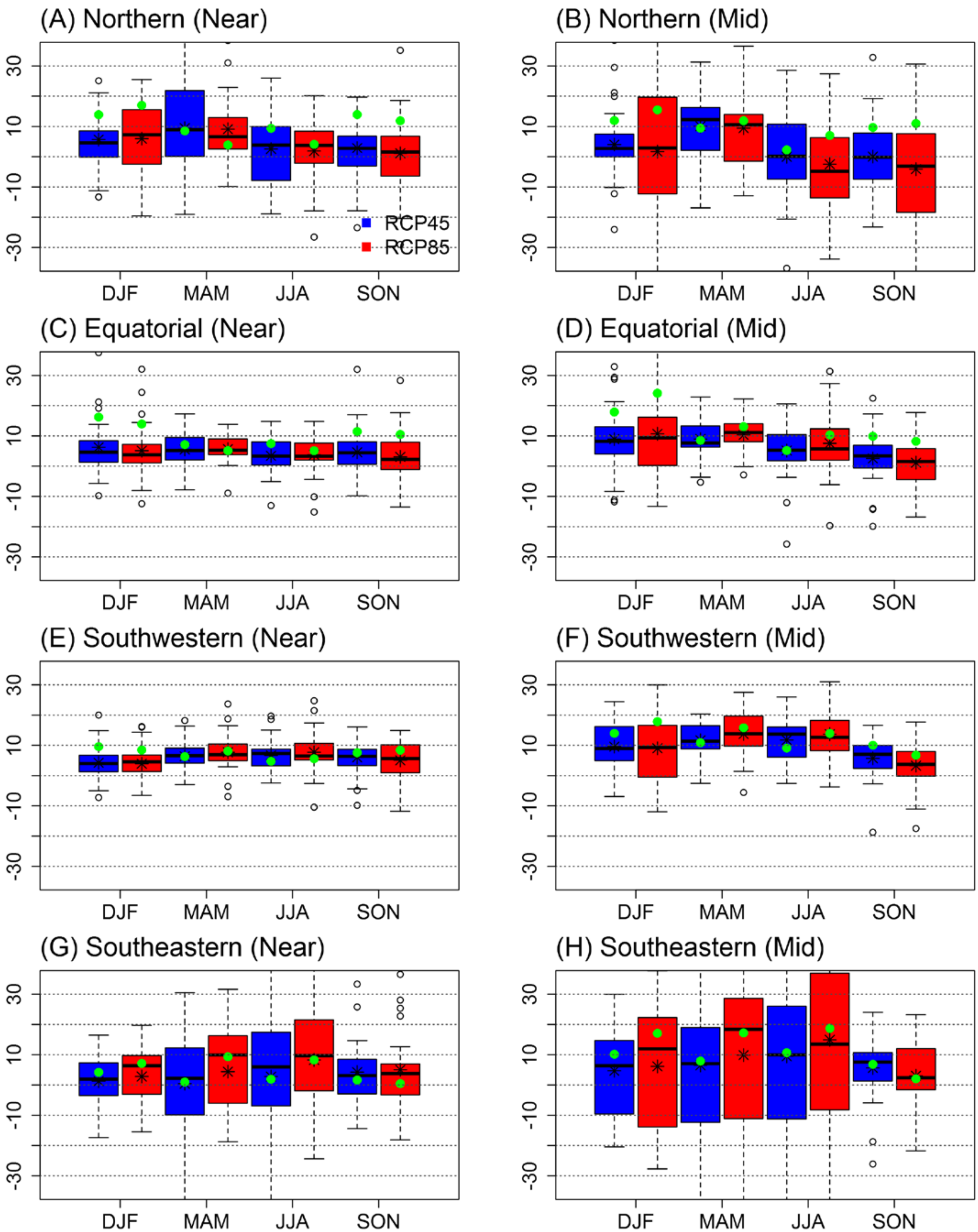

Figure 8 Seasonal runoff projections (as percent relative to the reference period 1986-2005) for the near-term (2016-2035) and mid-term (2046-2065) projection period for northern (A-B), equatorial (C-D), southwestern (E-F) and southeastern

(G-H) regions. Boxes show the 25th and 75th percentiles, the horizontal line within the boxes show median value and the whiskers mark the 5th and 95th percentiles. The multi-model mean (asterisks) and the select-model mean (green dots) are also shown. The y-axis range is limited to show the smaller boxes. Y-axis values are in percentages.

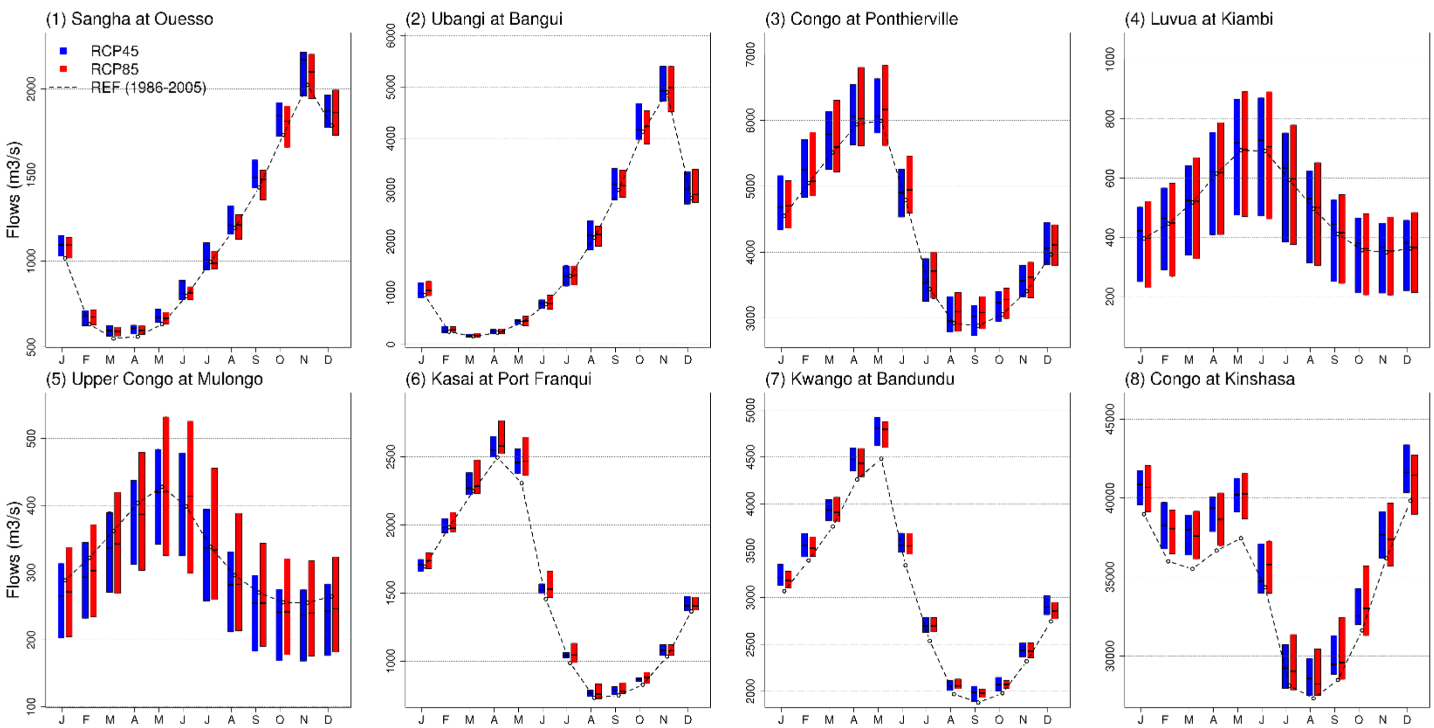

Figure 9 Accessible streamflow hydrographs in the near-term at selected locations shown in Figure 1A. Blue (red) bars show the inter-model variability. Dotted black line shows the hydrograph in the reference period (1986-2005). Figure numbers 1-8 coincide with the gage numbers in Figure 1.

Tables in the main text

Table 1 Global Climate Models whose outputs are used in this study. Further details about comparison of model outputs and key references for GCMs are given in Aloysius et al., 2016.

Model Number	Model Name
M1	ACCESS1-3
M2	bcc-csm1-1
M3	BNU-ESM
M4	CanESM2
M5	CCSM4
M6	CESM1-CAM5
M7	CNRM-CM5
M8	CSIRO-Mk3-6-0
M9	EC-EARTH
M10	FIO-ESM
M[11-13]*	GISS-E2-H*
M[14-16]*	GISS-E2-R*
M17	HadGEM2-CC
M18	HadGEM2-ES
M19	INM-CM4
M20	IPSL-CM5A-LR
M21	MIROC5
M22	MIROC-ESM

M23	MPI-ESM-LR
M24	MRI-CGCM3
M25	NorESM1-M

* These climate models provide outputs from three different physics ensembles. We treat each a separate model.

Table 2 Multi-model mean of projected changes in precipitation (%) in the four regions within the Congo River Basin (see Figure 1) for the near-term (2016-2035) and the mid-term (2046-2065) relative to the reference period of 1986-2005. The regions are identified in Figure 1. The standard deviation values across the 25 GCM-simulations are provided in parenthesis. DJF: Dec-Jan-Feb, MAM: Mar-Apr-May, JJA: Jun-Jul-Aug and SON: Sep-Oct-Nov.

	Northern (NC)		Equatorial (EQ)		Southwestern (SW)		Southeastern (SE)	
	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5
Near future (2016-2035)								
Annual	1.6 (3.0)	1.3 (2.9)	1.3 (2.9)	1.1 (2.7)	1.3 (2.3)	1.5 (2.6)	-0.4 (3.7)	0.1 (4.2)
DJF	3.3 (13.3)	5.4 (21)	2.0 (4.9)	1.4 (4.7)	1.6 (3.2)	1.8 (4.0)	-0.3 (3.7)	0 .04 (4.8)
MAM	1.4 (4.5)	1.1 (3.7)	0.5 (2.9)	0.8 (2.8)	1.5 (4.2)	2.5 (5.2)	-0.5 (7.8)	0.9 (8.3)
JJA	1.3 (3.3)	0.4 (4.2)	1.3 (4.2)	1.3 (4.7)	-0.7 (14.6)	-0.3 (15.7)	19.6 (32.0)	18.7 (31.6)
SON	2.3 (4.6)	2.3 (4.7)	1.7 (4.1)	1.1 (4.0)	0.9 (3.6)	0.2 (3.8)	-0.6 (5.4)	-1 (4.8)
Mid-term (2046-2065)								
Annual	1.6 (3.8)	1.2 (4.9)	1.7 (3.4)	2.4 (3.9)	2.9 (2.9)	3.3 (4.0)	0.2 (5.4)	0.3 (7.4)
DJF	1.1 (15.2)	3.9 (18.8)	3.5 (6.3)	5.3 (9.4)	4.8 (5.1)	5.4 (7.4)	1.5 (6.4)	1.4 (9.6)
MAM	0.9 (4.4)	0.6 (5.4)	1.5 (3.5)	2.4 (3.5)	4.1 (5.1)	6.9 (5.8)	0.4 (9.6)	2 (11.0)
JJA	0.6 (4.3)	0.1 (5.5)	0.7 (5.8)	2.2 (7.3)	-6.1 (14.8)	-5.9 (19)	6.7 (30.6)	9.7 (32.0)
SON	3.4 (6.2)	2.9 (7.3)	1.3 (4.0)	0.6 (4.1)	-0.3 (4.2)	-2.5 (4.6)	-3.2 (5.2)	-4.6 (5.8)

Table 3 Multi-model mean of projected changes in runoff (%) in the four regions within the Congo River Basin for the near-term (2016-2035) and the mid-term (2046-2065) relative to the reference period of 1986-2005. The regions are identified in Figure 1. The standard deviation values across the 25 GCM-simulations are provided in parenthesis. The asterisks (*) show the degree of agreement that projected runoff > 0 in more than 50% of the ensembles. DJF: Dec-Jan-Feb, MAM: Mar-Apr-May, JJA: Jun-Jul-Aug and SON: Sep-Oct-Nov.

	Northern (NC)		Equatorial (EQ)		Southwestern (SW)		Southeastern (SE)	
	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5
Near future (2016-2035)								
Annual	3.6 (12.1)	2.5 (11.2)	5.0 (7.0)*	4.3 (6.7)*	5.6 (4.8)*	6.0 (5.4)*	1.4 (12.8)	4.2 (12.1)
DJF	5.7 (13.3)	6.0 (14.1)	6.2 (9.8)*	5.1 (9.5)*	4.2 (6.1)*	3.9 (6.4)*	1.3 (9.3)	2.8 (9.8)
MAM	9.4 (15.0)*	9.1 (11.1)*	5.5 (6.3)*	5.7 (4.9)*	6.3 (5.1)*	7.7 (6.3)*	0.4 (18.4)	4.4 (17.3)
JJA	2.6 (12.1)	1.9 (10.2)	3.4 (6.3)*	3.8 (6.9)*	6.7 (5.5)*	7.7 (7.1)*	2.8 (20.7)	8.3 (19.6)
SON	2.8 (13.5)	1.1 (13.3)	4.6 (9.1)*	3.1 (9.4)	6.0 (6.4)*	5.0 (6.4)*	4.3 (10.7)	5.0 (12.6)
Mid-term (2046-2065)								
Annual	1.2 (15.4)	-2.0 (17.1)	6.3 (8.1)*	7.2 (8.5)*	9.9 (5.9)*	10.4 (8.2)	6.1 (18.8)	8.3 (20.6)
DJF	4.0 (18.0)	1.7 (21.9)	8.9 (11.2)*	10.7 (14.7)*	9.6 (7.9)*	9.0 (12.4)	4.7 (14.9)	6.2 (20.3)
MAM	10.1 (13.4)*	9.5 (17.1)	8.9 (7.1)*	10.3 (6.2)*	11.7 (6.1)*	13.7 (8.0)*	6.5 (26.2)	9.9 (26.6)
JJA	-0.02 (14.5)	-2.5 (15.8)	5.2 (9.8)*	7.5 (11)*	11.8 (7.1)*	13.7 (8.6)*	9.5 (25.9)	14.9 (25.7)
SON	0.04 (17.7)	-4.1 (19.4)	2.5 (9.3)*	1.1 (8.5)	5.7 (7.2)*	3.3 (7.7)	5.6 (11.2)*	3.1 (12.6)