Physics and Chemistry of the Earth 100 (2017) 3–12

Contents lists available at ScienceDirect

Physics and Chemistry of the Earth

journal homepage: www.elsevier.com/locate/pce

Providing peak river flow statistics and forecasting in the Niger River basin

Jafet C.M. Andersson [a, *], Abdou Ali [b], Berit Arheimer [a], David Gustafsson [a], Bernard Minoungou [b]

[a] Swedish Meteorological and Hydrological Institute (SMHI), Folkborgsvägen 17, 601 76 Norrköping, Sweden
[b] AGRHYMET Regional Centre for Agronomy, Hydrology and Meteorology, P.O. 1011, Niamey, Niger

ARTICLE INFO

Article history:
Received 27 May 2016
Received in revised form
20 December 2016
Accepted 17 February 2017
Available online 21 February 2017

Keywords:
Decision support
Extreme discharge
Floods
Generalized extreme value distribution
Infrastructure design
Niger-HYPE

ABSTRACT

Flooding is a growing concern in West Africa. Improved quantification of discharge extremes and associated uncertainties is needed to improve infrastructure design, and operational forecasting is needed to provide timely warnings. In this study, we use discharge observations, a hydrological model (Niger-HYPE) and extreme value analysis to estimate peak river flow statistics (e.g. the discharge magnitude with a 100-year return period) across the Niger River basin. To test the model's capacity of predicting peak flows, we compared 30-year maximum discharge and peak flow statistics derived from the model vs. derived from nine observation stations. The results indicate that the model simulates peak discharge reasonably well (on average + 20%). However, the peak flow statistics have a large uncertainty range, which ought to be considered in infrastructure design. We then applied the methodology to derive basin-wide maps of peak flow statistics and their associated uncertainty. The results indicate that the method is applicable across the hydrologically active part of the river basin, and that the uncertainty varies substantially depending on location. Subsequently, we used the most recent bias-corrected climate projections to analyze potential changes in peak flow statistics in a changed climate. The results are generally ambiguous, with consistent changes only in very few areas. To test the forecasting capacity, we ran Niger-HYPE with a combination of meteorological data sets for the 2008 high-flow season and compared with observations. The results indicate reasonable forecasting capacity (on average 17% deviation), but additional years should also be evaluated. We finish by presenting a strategy and pilot project which will develop an operational flood monitoring and forecasting system based in-situ data, earth observations, modelling, and extreme statistics. In this way we aim to build capacity to ultimately improve resilience toward floods, protecting lives and infrastructure in the region.

1. Introduction

The Niger River is West Africa's largest river, with more than 100 million inhabitants within the 2.1×10^6 km^2 catchment area. The river basin extends into nine countries and spans several climate regions, from humid tropical to desert (Fig. 1). The river is an important natural resource, often key for livelihoods, especially in Mali and Niger. Substantial rainfall decreases in the Sahel have led to major disasters such as the droughts and famines of the 1970s and 1980s (Mahé et al., 2013). More recently, floods are a growing concern taking lives and damaging infrastructure; and resulting in personal tragedies, substantial repair costs and disruption of transportation (Fig. 2). Increasing flooding in recent years (e.g. in 2008 and 2016) can partly be attributed to climate variability but also to land use changes (Aich et al., 2015). The region has been designated as a particularly sensitive area for potential future climate change (Diallo et al., 2016). Better understanding of potential peak flows could contribute to improved infrastructure design, and operational flood forecasts could facilitate emergency response and thereby increase societal resilience to future floods in the region.

To be able to respond more appropriately to present and future hydrological extremes, water managers in the Niger River basin have expressed a need for an improved water information system. To this end, we recently set up the semi-distributed HYPE model (HYdrological Predictions for the Environment; Lindström et al.,

* Corresponding author.
E-mail addresses: jafet.andersson@smhi.se, aqua@jafet.org (J.C.M. Andersson).

http://dx.doi.org/10.1016/j.pce.2017.02.010
1474-7065/

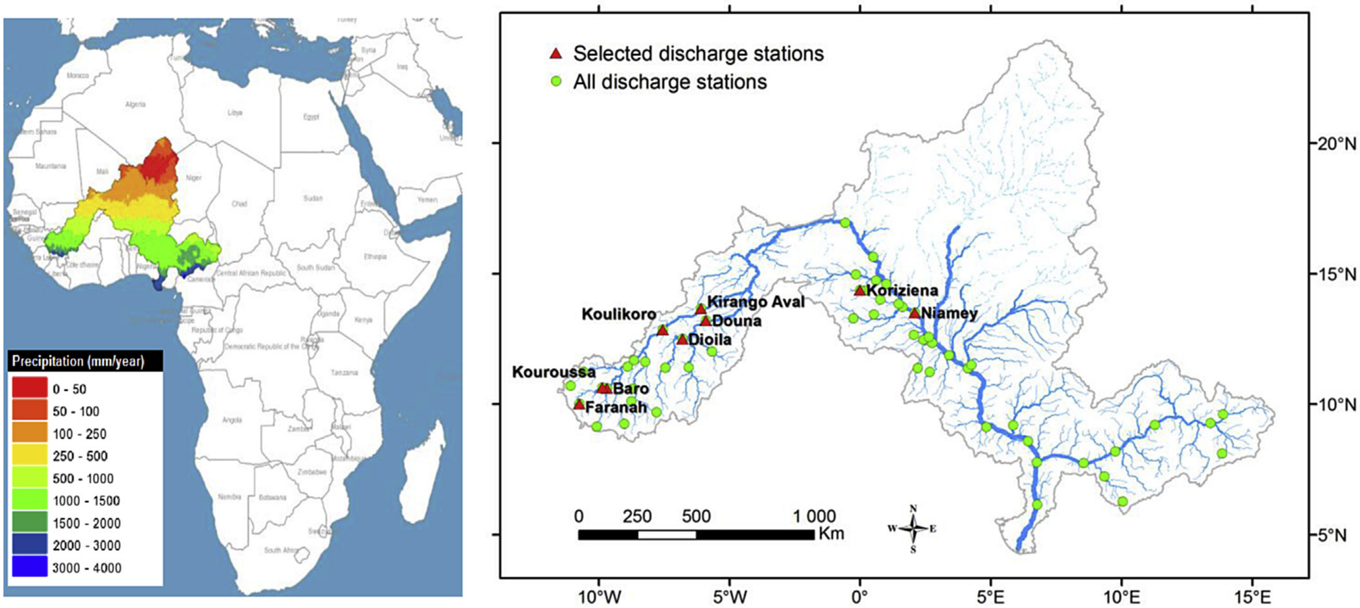

Fig. 1. Map of the Niger River basin showing (left) the mean annual precipitation and (right) all discharge stations used in calibration as well as the selected discharge stations used in the extreme value analysis.

Fig. 2. A bridge damaged by floods in the Upper Niger River basin. Photo by: Andre Kamga Foamouhoue.

2010), simulating hydrological processes on large scales, for the Niger River basin (Andersson et al., 2016, 2015). This Niger-HYPE model is here tested for practical use, i.e. to define infrastructure design variables (peak flows with various return periods) for past and future climates, and to forecast river flows.

One important design criteria for infrastructure located in or near water is an estimate of the potential peak flow that it is likely to experience during its lifetime. Similarly, flood warning services use peak flow statistics to judge whether a particular forecast should trigger a warning, and the severity of the situation (Arheimer et al., 2011; Thiemig et al., 2015). Such peak flow estimates are typically based on statistical extreme value analysis of historical peak flows. Several previous studies have made valuable contributions to the understanding of peak flows in the Niger River basin. They have, for example, focussed on understanding patterns and causes of historical floods (e.g. Aich et al., 2015; Descroix et al., 2012; Mahé and Paturel, 2009), on quantifying damages and loss of life due to increasing floods (Aich et al., 2016a), on projecting potential impacts of future land use and climate change on floods (e.g. Aich et al., 2016b; Roudier et al., 2014), and on evaluating a flood forecasting prototype (Thiemig et al., 2015). So far, however, little emphasis has been put on understanding the uncertainty and applicability of the extreme value analysis in the Niger basin. Uncertainties are typically assumed negligible, but if they are large it has important implications for infrastructure safety and flood warnings. In this study, we employ a structured approach to better understand the uncertainties of estimated peak flow statistics, by separating errors coming from the hydrological model and from the statistical extreme value analysis. Moreover, we apply an extreme value analysis to study potential climate change impacts on peak flows, and test the predictive capacity of the Niger-HYPE model to forecast peak flows. Finally, we describe on-going initiatives to use the model system in operational infrastructural planning for improved water security in West Africa.

In this paper, we address the following scientific questions:

- How accurately can the Niger-HYPE model simulate peak river flows?
- What are plausible peak flow magnitudes with a 10, 30, 50, and 100-year return period respectively; and how uncertain are they in different locations across the basin?
- How may climate change impact peak river flows?
- How well can the Niger-HYPE model predict the river flow 1–10 days ahead when linked to meteorological forecasts?

2. Methods

2.1. Niger-HYPE hydrological model and input data

We set up and adapted the HYPE model to the Niger River basin. The model was based on openly available data on topography (Lehner et al., 2008), land use (Arino et al., 2008), soil (Batjes, 2012; FAO et al., 2009), lakes (Lehner and Döll, 2004), reservoirs (Lehner et al., 2011), and daily air temperature and precipitation from the WFDEI dataset (Weedon et al., 2014). The Niger-HYPE model consists of 803 sub-basins of variable size averaging 2500 km^2. A tailor-made routine for simulating the floodplain dynamics of the Inner Niger Delta (IND) was employed to adapt HYPE to the Niger basin. The model parameters were regionalized based on catchment characteristics (e.g. land cover and soil type), such that identical soils, for example, use the same parameter values all over the domain. This is HYPE's approach to make predictions in ungauged basins (Sivapalan, 2003). The parameters were calibrated against 56 daily river discharge stations (Fig. 1; ABN, 2008; GRDC, 2012) as well as monthly satellite potential evapotranspiration estimates covering the basin (Mu et al., 2011). The calibration focussed on separating and refining key hydrological process on basin scale, e.g. simultaneously calibrating all gauged catchments where a particular soil dominates, and then using that value for all areas where the soil is found (including ungauged areas). The aim of the calibration was to get a satisfactory performance across the basin rather than peak performance at single discharge stations. The reason is to get a consistent model all over the basin (describing hydrological processes in a similar fashion), rather than an optimally tuned model with potentially inconsistent process descriptions in different parts of the basin. We quantified the performance using standard criteria such as the Nash-Sutcliffe Efficiency (NSE), and relative volumetric error (RE), (Donnelly et al., 2016). We evaluate the basin-scale performance by first calculating the performance criteria at each gauge, and then deriving summary statistics to quantify the performance distribution for all gauges.

All in all, this resulted in a hydrological model with satisfactory performance distribution (Table 1). The worsts gauge had NSE −16 and the best gauge had NSE 0.89, while the average volumetric deviation was ±10%. Fig. 3 illustrates the performance at two key gauges indicating reasonable predictive capacity (NSE around 0.7 in calibration and >0.4 in validation periods, respectively). The individual performance for all other gauges is available at http://hypeweb.smhi.se/nigerhype/model-performance/. This version of the model is called Niger-HYPE 2.0. More details on the model setup, refinements, calibration and validation is presented by Andersson et al. (2016).

2.2. Extreme value analysis to estimate peak flow statistics

To better understand peak flows in the basin, we here employed an extreme value analysis based on the Generalized Extreme Value distribution (GEV; Coles, 2001). In each sub-basin, the GEV was fitted to time-series of annual maximum discharge (AMAX, derived from daily discharge) by maximum-likelihood optimization of the three GEV parameters. The resulting statistical models of the annual maxima were subsequently used to derive potential peak flow magnitudes with a 10, 30, 50, and 100-year return period (statistical recurrence interval). In addition to the optimum, we calculated 95% confidence intervals of the estimated peak flow magnitudes by profiling the log-likelihood of each GEV model (Heffernan and Stephenson, 2014). In essence, the confidence interval constitutes a range of GEV parameters for which the log-likelihood is not significantly different from the optimum (at the chosen 95% significance level).

The GEV was fitted to various AMAX time-series for various purposes. Firstly, observed and simulated extremes were compared to better understand the Niger-HYPE model performance and capabilities of the GEV. To minimize the impact of missing data, only observation gauges with less than 15% missing data in the period 1980-01-01 to 2009-12-31 were identified (13 gauges). These gauges were further filtered to only include those for which the GEV fit converged, resulting in a selected set of nine discharge gauges in total (Fig. 1). To match this, the Niger-HYPE model was run for the period 1980-01-01 to 2009-12-31 (plus a warm-up period of 17 years). 30-year AMAX time-series, GEV models, and peak flow statistics were subsequently derived from the observations and the simulations, excluding the days for which the observations had missing data at each gauge. Additional analyses were carried out at the Koulikoro gauge, which has an observation record that is more than 100 years long. Here, we constructed a GEV model based on the 100-year observed AMAX (1910–2009) and another on the 30-year observed AMAX (1980–2009) and compared both models' estimate of the discharge magnitude with a 100-year return period.

Secondly, we derived peak flow statistics for the entire catchment based on a combination of the Niger-HYPE model and the selected observations. The model was again run for the period 1980–2009 but now the observations were assimilated using a daily updating scheme at each gauge, and the complete daily time series from the simulations were used to derive AMAX, GEV models, and peak flow statistics for each sub-basin.

Thirdly, we used the most recent bias-corrected climate

Table 1
Summarized distribution of model performance across the 56 daily discharge observation gauges for the period 1994 to 2009. abs() signifies the absolute value, calculated here on RE to avoid the effect that underestimation at some gauges is balanced out by overestimation at other gauges.

Criteria	Min	1st Quartile	Median	3rd Quartile	Max
RE, %	−40	−11	−1	8	38
abs(RE), %	0	4	10	21	40
NSE	−16	0.1	0.38	0.58	0.89

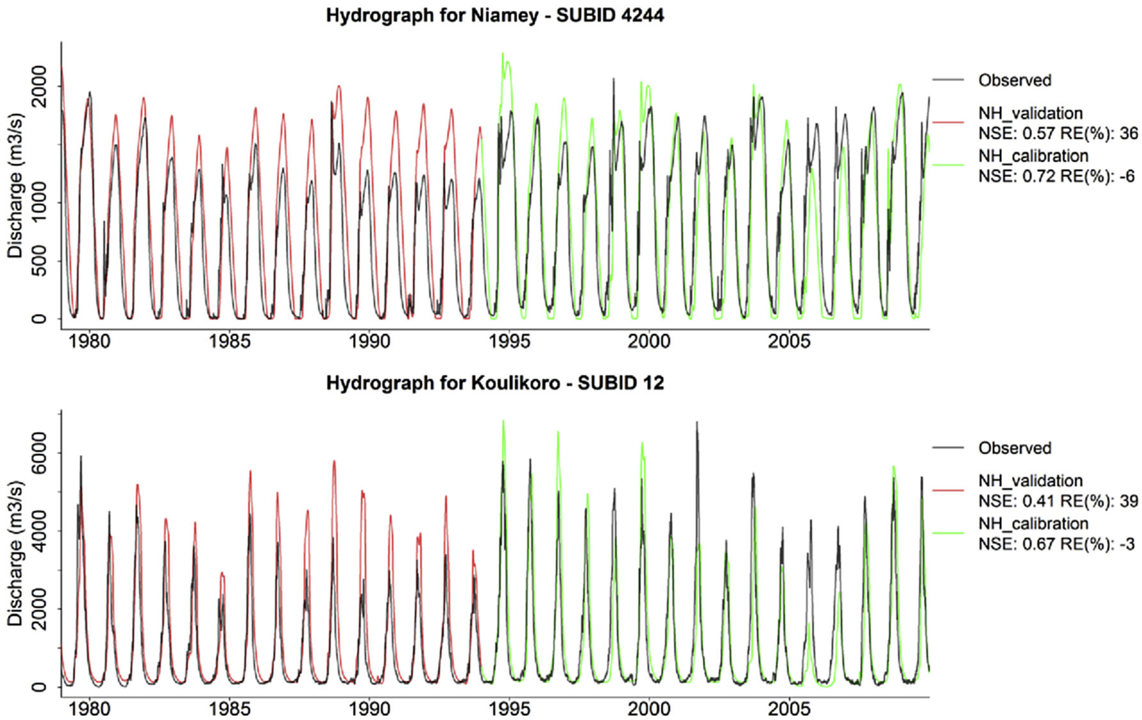

Fig. 3. Observed and simulated discharge at the Niamey station (top) and the Koulikoro station (bottom) during the calibration period (green, 1994–2009), and validation period (red, 1979–1993). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

projections from the COordinated Regional climate Downscaling Experiment (CORDEX) for the Middle-East North Africa (MENA) domain (Table 2) to drive the Niger-HYPE model from 1951 to 2100 (Andersson et al., 2014). We then derived 30-year AMAX time-series and peak flow statistics projected for the end of the century (2070–2099) and compared these with peak flow statistics of a reference climate period (1971–2000) for each sub-basin.

The data analysis was carried out with the R software (R Core Team, 2016) and the packages HYPEtools (Capell et al., 2014), extRemes (Gilleland and Katz, 2011), ismev (Heffernan and Stephenson, 2014), maptools (Bivand and Lewin-Koh, 2014), sp (Pebesma and Bivand, 2005), lattice (Sarkar, 2008), and latticeExtra (Sarkar and Andrews, 2013).

2.3. Hydrological forecasting

To test the forecasting capacity of the model we combined Niger-HYPE with short-term meteorological forecasts from the ECMWF (European Centre for Medium-Range Weather Forecasts) Integrated Forecasting System (IFS), version 33r1 (ECMWF, 2009). As an example, we focussed on the 2008 high-flow season because significantly higher peak discharge were observed for this year than on average in many locations (e.g. 5360 $m^3 s^{-1}$ vs. 3500 $m^3 s^{-1}$ at Koulikoro). We produced 1 to 10-day-ahead forecasts for each day between 2008-08-01 and 2009-09-30 (i.e. 61 days of forecast initialization, each with predicted discharge 10 days into the future). To initialize the model up until the beginning of each forecasting day (e.g. 2008-08-01), we ran Niger-HYPE with the reference WFDEI meteorological dataset (representing the best available historical weather data, and to which the model was calibrated). Subsequently, we forecasted the river discharge 10 days ahead using the ECMWF forecasts (e.g. from 2008-08-01 to 2008-08-10). We focussed the evaluation on the Koulikoro station, which is located on the main branch of the Niger River near Bamako (city population 1.8 million in 2009), and upstream of the flood-sensitive IND. To analyze the forecasts we calculated the percentage deviation ("forecast error") relative to observed discharge and relative to a reference simulation. The reference simulation constitutes the Niger-HYPE model driven with the WFDEI dataset for the forecasted days. It was used to separate out the meteorological forecasting error from the total forecasting error (the latter also includes error due to incorrect hydrological states at initialization).

3. Results & discussion

3.1. Observed and simulated peak flows

The Niger-HYPE model adequately captures the maximum

Table 2
Characteristics of the climate change projections used in this study. See Andersson et al. (2014) and Nikulin et al. (2012) for more details.

Ensemble name	Climate Change scenario	Global Climate Model	Regional Climate Model	Bias correction
MB4	RCP 4.5	EC-Earth CNRM-CM5 GFDL-ESM2M	RCA4 for MENA-CORDEX domain	DBS
MB8	RCP 8.5	EC-Earth CNRM-CM5 GFDL-ESM2M	RCA4 for MENA-CORDEX domain	DBS

discharge observed during the period 1980–2009 at the selected discharge stations (Fig. 4). The correlation is high, indicating that the model captures the main hydrological processes differentiating the gauges (catchment area, precipitation, evaporation etc.). The largest deviations were obtained for the gauges Baro, Douna and Kirango Aval, while the best performance was obtained at Koulikoro, Niamey and Dioila. On average the model overestimated the maximum discharge by 20%, and in only two cases underestimated the peak. This deviation could be due to model error (e.g. underestimation of evaporation), or could be due to errors in the observations (peak flows are generally difficult to monitor accurately). Provided peak observations are adequate, utilizing the Niger-HYPE outputs for infrastructure design would typically provide an additional level of caution toward the risk of floods.

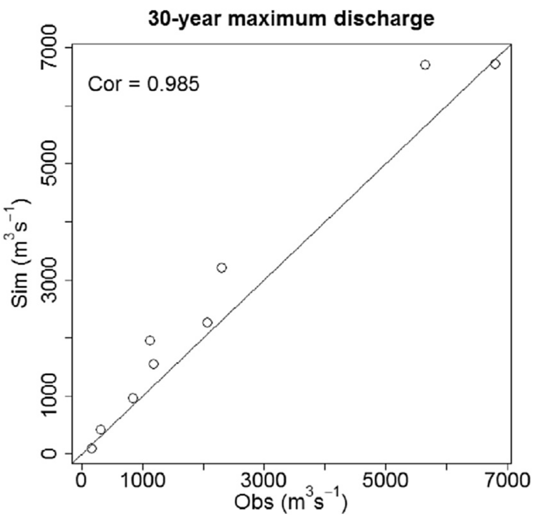

Fig. 4. 30-year maximum discharge as observed vs. as simulated by Niger-HYPE for the selected discharge stations (1980–2009). Each point represents one gauging station.

Similarly, peak flow statistics derived from GEV models fitted to Niger-HYPE simulated discharge match quite well peak flow statistics derived from observed discharge (Fig. 5, Fig. 6), and are not significantly different in a statistical sense (p-values >0.7 based on a Student's t-test). As the return period increases the deviation increases slightly, but the differences are minor. Peak flow statistics based on Niger-HYPE are generally higher in magnitude and more widespread than those based on observations. The mean deviation is only 8%, but at a given location the deviation can be as large as −45% to +59%. Deviations are typically negative in sub-basins with relatively small discharge and positive at locations with relatively large discharge; possibly due to underestimated precipitation in mountain areas and underestimated evaporation from the river in the lower reaches. Given the similarity of these results to those based on pure Niger-HYPE outputs (Fig. 4), we attribute these differences to the Niger-HYPE model rather than to the GEV models.

Additional analyses at the Koulikoro gauge provide insights into the adequacy and uncertainty of the GEV model (Fig. 7). From a century perspective, it is clear that the last 30 years analyzed

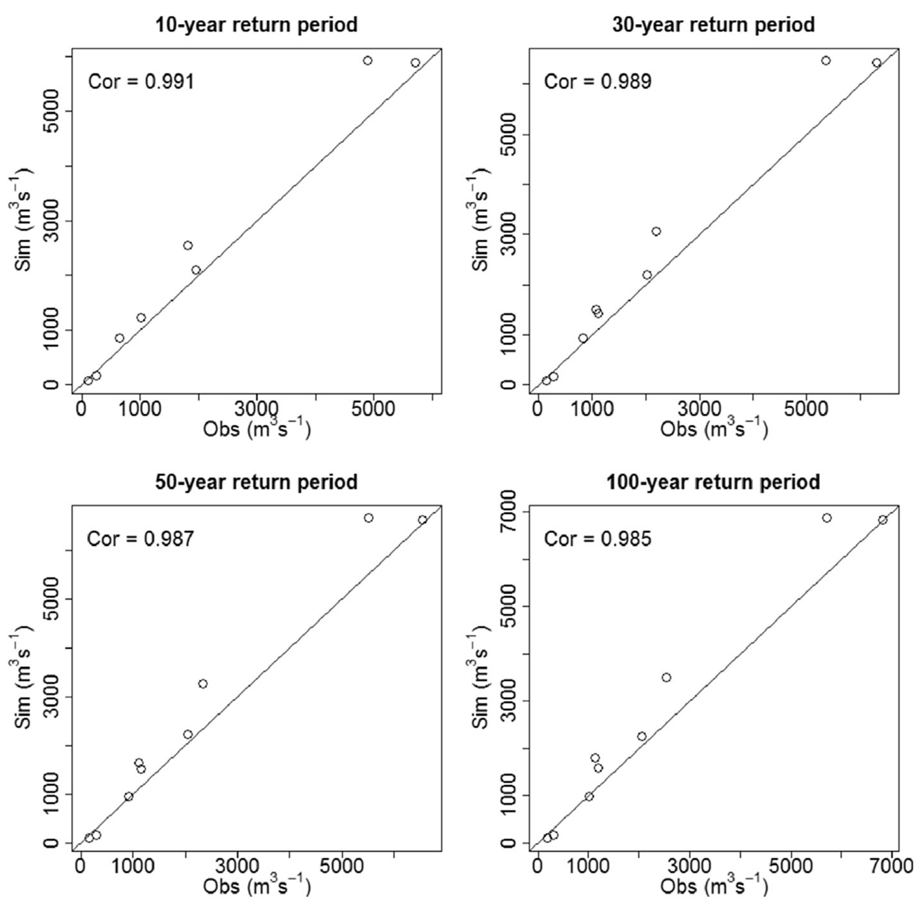

Fig. 5. Scatterplots of peak flow magnitudes with a 10, 30, 50 and 100-year return period, respectively, using GEV models fitted to annual maximum discharge time series for the period 1980–2009 based on observed vs. simulated discharge (using Niger-HYPE).

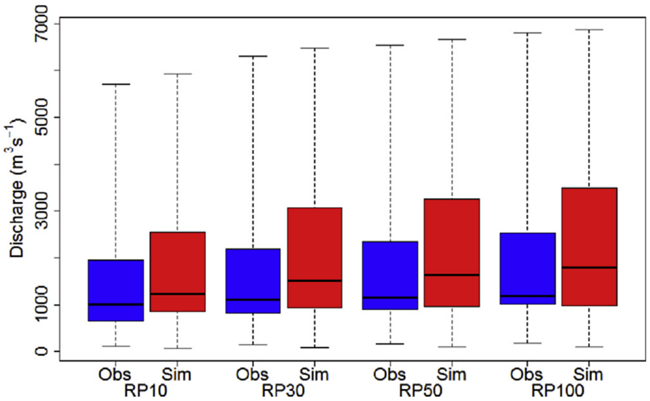

Fig. 6. Boxplot of peak flow magnitudes with a 10, 30, 50 and 100-year return period, respectively, using GEV models fitted to annual maximum discharge time series for the period 1980–2009 based on observed vs. simulated discharge (using Niger-HYPE). Note: the whiskers extend to cover the entire data range.

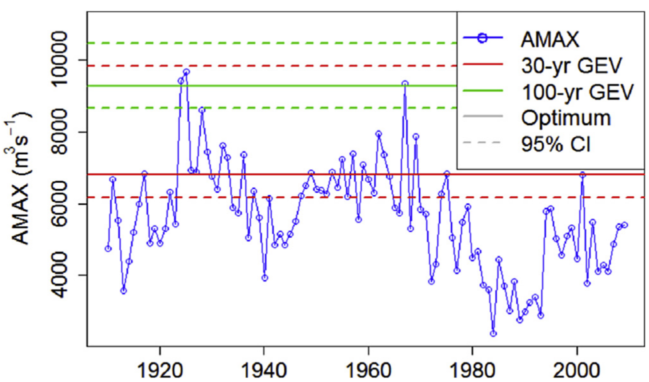

Fig. 7. 100 years of annual maximum discharge (AMAX) at the Koulikoro gauge and the estimated discharge magnitude with a 100-year return period based on GEV models fitted to 30 years (red, 1980–2009) and 100 years (green, 1910–2009) of observed data respectively. Solid horizontal lines indicate the optimum GEV fit and dashed lines the 95% confidence intervals (CI). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

represent a dry–to–average period without any major century-peaks. As a consequence the optimum GEV fitted to 30 years of data underestimates the discharge magnitude with a 100-year return period (20 years had higher AMAX during the last century). However, the confidence interval is quite large and covers the century peaks (0 years have AMAX higher than the top of the confidence interval). So it appears in this case that the GEV based on 30-year AMAX can be used for infrastructure design even when extrapolating to longer return periods if the uncertainty band is taken into account. In other situations this may not be the case since GEV extrapolation is typically very uncertain.

The GEV model fitted to the full 100 years of AMAX provides a good approximation of the discharge magnitude with a 100-year return period already at the optimum GEV fit (3 years have AMAX higher during the last century), and also a narrower confidence interval that extends well beyond the highest observed discharge. A plausible reason is that the longer time-series contains larger climatic variability. Hence, analyzing longer AMAX time-series is preferable if the data is available. However, since this is rarely the case in this region, the 30-year GEV model with confidence intervals constitutes a more widely applicable approach with acceptable results. Infrastructure should thus be designed with consideration of the GEV uncertainty band to be on the safe side. This analysis also illustrates the need to maintain observation stations with long records (at least at some locations), and to extend meteorological reanalyses of the past further back in time.

The selected observation gauges covers the Upper Niger, the Bani River, the IND, and Middle Niger (Fig. 1). Hence the conclusions from this evaluation do not necessarily apply to the Lower Niger or the Benue River.

3.2. Basin-wide peak flows

Fig. 8 illustrates the GEV method applied to the entire river basin, as well as the spatial variation of the GEV uncertainty. Generally, the GEV method is applicable across the hydrologically active part of the river basin. This is a promising result since most infrastructure is located and constructed in this part of the basin. In contrast, the GEV models fail (typically due to non-convergence) in most of the dry areas of the Sahara Desert where river flow is normally zero and extremely rare. Hence, the GEV approach is

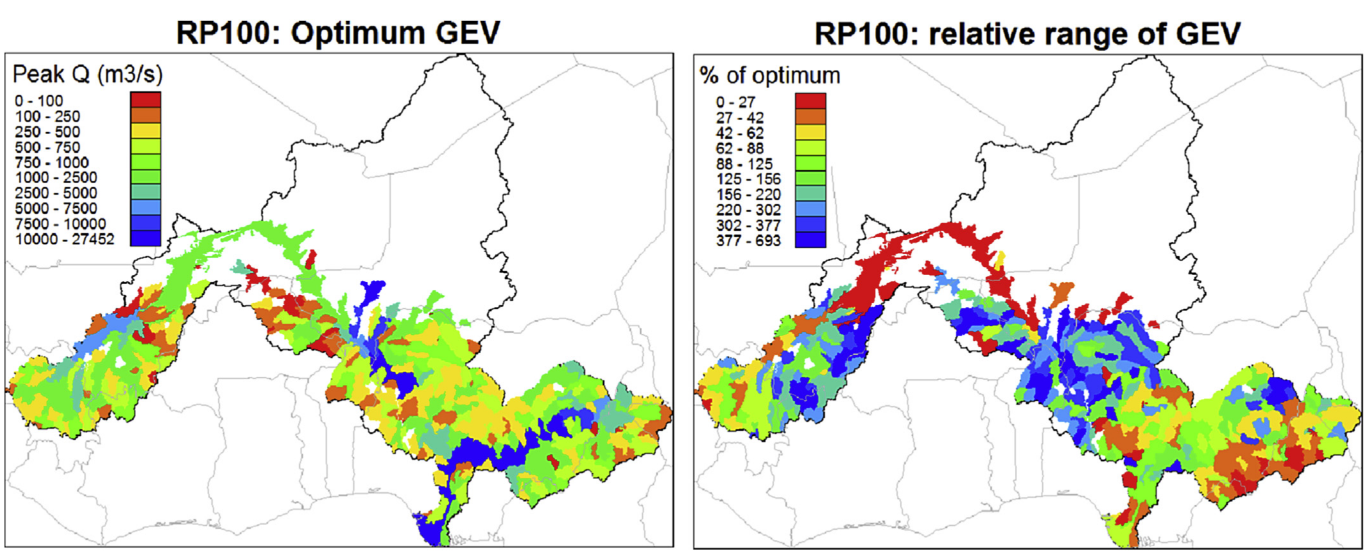

Fig. 8. Peak flow magnitudes with a 100-year return period for the hydrologically active part of the Niger River basin: (left) peak flow magnitudes at the optimum GEV fit, (right) range of the 95% confidence interval relative to the magnitude of the optimum GEV fit (i.e. uncertainty due to the statistical model).

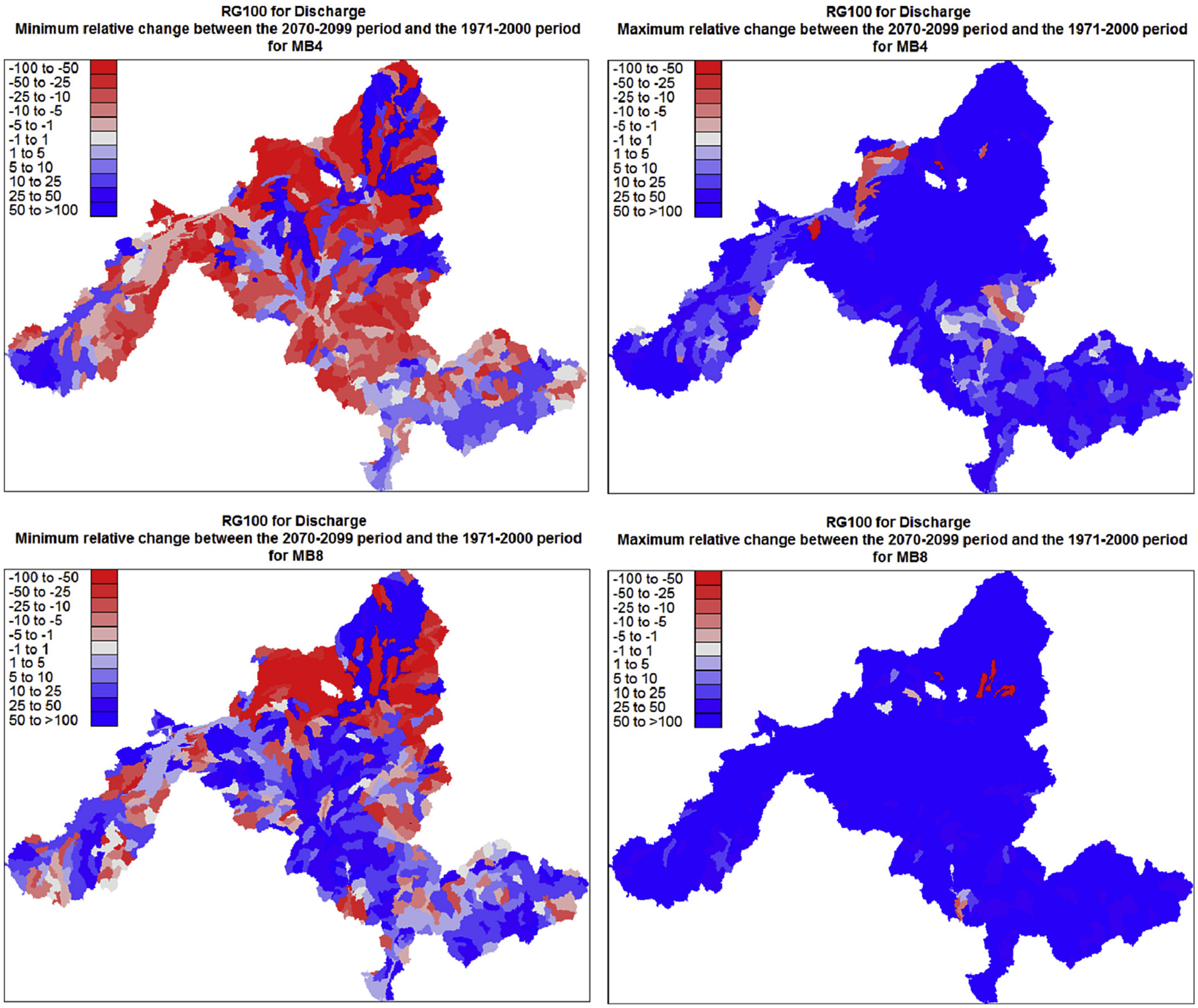

Fig. 9. Projected percentage changes in the magnitude of peak flows with a 100-year return period between 1971-2000 and 2070–2099. The figures illustrate the uncertainty range due to variability between climate models by showing the maximum (right) and minimum (left) of the RCP4.5 (top, MB4) and RCP8.5 (bottom, MB8) projection ensembles.

unlikely to be useful for designing infrastructure aimed at alleviating the risk of flash floods in such areas. The highest peak flow magnitudes with a 100-year return period were obtained along the main branch of the Upper Niger River (near Bamako) and along the Benue River in Nigeria. The GEV uncertainty is generally quite large, typically spanning more than 100% of the peak flow magnitude obtained with the optimum GEV parameters. The GEV uncertainty is relatively small (<50%) in the Cameroon highlands and downstream of the IND, probably due to the buffering capacity of the IND evening out inter-annual variability in the AMAX time-series. In contrast, the highest uncertainty (>300%) was obtained for the drier Sahelian parts of the basin (the east of the IND, the Burkina Faso tributaries, and the Niger-Nigeria borderlands).

Although applicable, some GEV models do not provide robust results in certain sub-basins. The Dallol Bosso valley provides a case in point. The valley is the topographic drainage outlet of the Sahara Desert into the Niger downstream of Niamey. It contains a well-developed drainage network but typically lacks enough rainfall to support river flows. The peak flow magnitude with a 100-year return period estimated from the GEV model is in the same range for Dallol Bosso as that of the Benue River, and much larger than the Niger river itself at Niamey, which is clearly wrong. Hence, the basin-wide application of the GEV method needs to be further refined to better handle inappropriate GEV models. Additionally, infrastructure design for specific areas should analyze the GEV model in more detail before using the basin-wide results (e.g. with GEV diagnostics and profiling tools).

Future research in this direction could for example (i) explore the potential determinants of GEV confidence limits (e.g. AMAX variability, error variance or catchment characteristics), (ii) refine the GEV uncertainty estimates (e.g. based on different optimization methods), or (iii) use alternative extreme value analysis methods (perhaps employing a peak-over-threshold approach based on the General Pareto distribution).

3.3. Potential impacts of climate change

A changed climate will probably have notable impacts on the region (Aich et al., 2016b; Andersson et al., 2014). One expected change is a speed-up of the hydrological cycle with faster evaporation and more intense precipitation during shorter periods. The net effect on peak flows depend on the intricate interplay between these factors and the available hydrological storage components, land use change, runoff flow paths etc. The most recent climate change projections indicate that there is a large uncertainty regarding how peak flows may change in the future (Fig. 9). In most cases it is not even clear whether peak magnitudes will increase or decrease, although increases dominate. Consistent increases were obtained in some areas: in parts of Guinea, in the Benue River basin and in the Lower Niger (toward the Atlantic Ocean). Changes in the Sahara are again very uncertain. No areas displayed consistent decreases in peak flows. In the future, a larger ensemble of climate models and hydrological models could perhaps clarify if increases or decreases are more likely.

3.4. Forecasting discharge

As a first test of short-term hydrological forecasting with the Niger-HYPE model, we carried out an experiment for the high-flow season of the year 2008 at Koulikoro (Fig. 10). On average, the forecasted discharge magnitudes deviated from observations by 17% during the 2008 high-flow season (range: −38% to +33%). Typically, the further the forecast extended into the future, the larger the error (exemplified by the increasing inter-quartile range in the top-left Fig. 11). The median 2-day-ahead forecast error was −2%, whereas the median 10-day-ahead forecast error was +10%. Still, some 2-day-ahead forecasts deviated more than 30% from observations. The forecast errors fluctuate in line with the error of the reference simulation (lower-left Fig. 11), i.e. the forecasting errors primarily originate from the hydrological state at initialization (correlation = 0.8). Removing the error due to initialization, the forecast error due to the meteorological forcing is negligible for the first two days ahead, whereas the 10-day-ahead forecasts range from −25% to +10% centred around −3% (top-right Fig. 11). The largest errors due to meteorological forecasts were obtained during August 2008 (lower-right Fig. 11). This could be due to a simpler prognosis situation during September (e.g. more stable conditions with less rainfall).

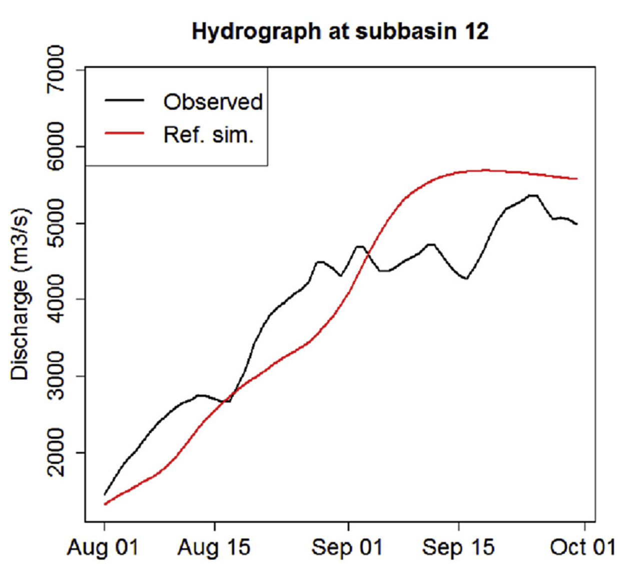

Fig. 10. River discharge at the Koulikoro station during 2008 in the period leading up to the peak, as observed in the field and as simulated with the reference Niger-HYPE simulation.

3.5. Strategy for operational flood monitoring and forecasting

A potential approach to improve forecasts is to assimilate various observations in the model during initialization to more accurately represent the current state of the hydrological system. In addition to real-time discharge observations, satellite remote sensing data have a large potential to monitor floods and to improve initialization of flood forecasting models through assimilation. A major problem for application in operational flood forecasting is the high demand on the user side regarding data processing and data access capabilities, which can be a real issue in areas with limited or unstable internet access. In a recently started European Space Agency project called Thematic Exploitation Platform for Hydrology we will develop and evaluate an operational flood monitoring and forecasting system operated in a cloud environment, tailored to users' needs, integrating in-situ data, earth observation (EO) data and modelling (https://hydrology-tep.eo.esa.int/). The overall aim of the project is to facilitate access and exploitation of water related EO data. However, in the context of the Niger River basin, the aim is to develop a pilot service for operational flood forecasts and historical analyses on various timescales based on the Niger HYPE model (climatological timescales as well as short-term, medium-term and seasonal forecasts). EO data on flooded area and water level based on the Sentinel-1 satellite will be assimilated in the model, to improve monitoring of current flood situation and model initialization for the coming forecast periods. The pilot service will be evaluated for recent (2016) and historical flooding events.

This and other initiatives are part of our vision to improve societal resilience toward floods and droughts in Africa by building capacity among regional experts to operationalize a system capable of providing quantitative water and climate information on both short and long time-scales in order to protect lives and infrastructure through e.g. operational forecasts and alerts.

4. Conclusions

Key conclusions from this research are that:

- The Niger-HYPE model adequately simulates 30-year maximum discharge (on average overestimating by 20%). Similar results were obtained for all investigated peak flow statistics. Hence, utilizing the Niger-HYPE outputs for infrastructure design would typically provide an additional level of caution toward the risk of floods (but not everywhere).
- The peak flow magnitude based on statistical extreme value analysis (GEV) is not one fixed value for a given return period and location in the Niger basin, but rather an uncertain range. It varies asymmetrically depending on several factors including the length of the time series available, the period analyzed, and the parameterization of the GEV statistical model.
- A 30-year GEV model is capable of representing the 100-year peak at Koulikoro but only if the confidence interval is taken into account. As a precaution, infrastructure ought to be designed with consideration of the GEV uncertainty band. If longer time series are available to construct the GEV models, the peak flow statistics will likely have a narrower uncertainty band.
- Peak flow statistics can be derived with the GEV method for the hydrologically active part of the Niger River basin where most infrastructure is located and constructed (but not in the dry areas). The GEV uncertainty is generally quite large and varies substantially across the basin. Hence, the uncertainty should be taken into account to ensure safe infrastructure design.
- Climate change will probably affect extremes, but available projections provide very uncertain results so far in the Niger

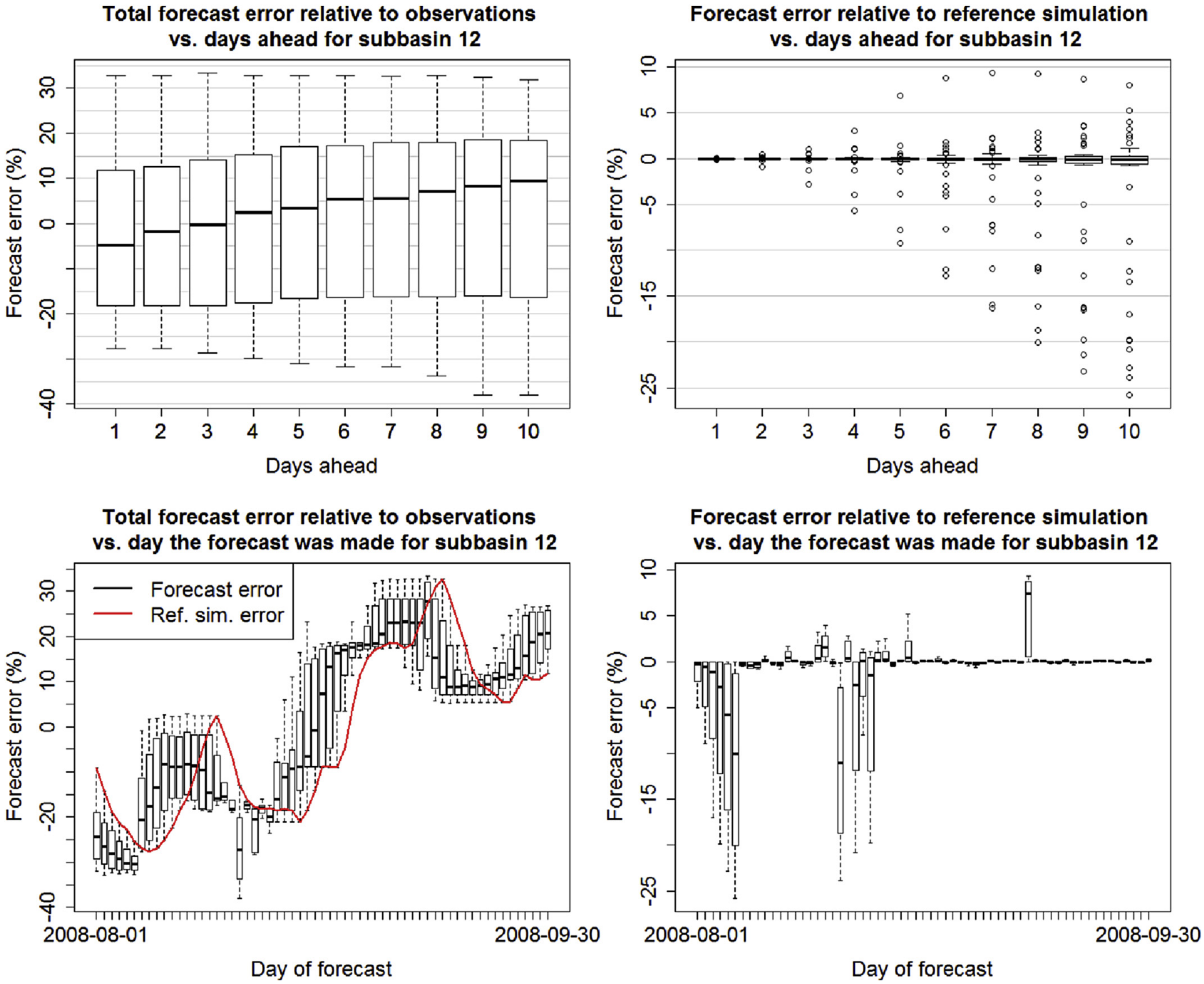

Fig. 11. Forecast error at Koulikoro (left) relative to observed discharge, and (right) relative to the reference Niger-HYPE simulation (used for initialization), plotted against (top) the number of forecasted days ahead, and (bottom) the day the forecast was made. The range within a given day-ahead category originate from differences between initialization dates (N = 61, top), whereas the range for a given day of forecast originate from differences between all forecasted days ahead (N = 10, bottom).

River basin. Some areas display consistent increases in peak flow statistics.

- Short-range hydrological forecasts with the Niger-HYPE model driven by ECMWF meteorological forecasts show some potential. The average deviation from observations was 17% at the Koulikoro station during the 2008 high-flow season. This compares well with the national target within operational forecasting in Sweden, which is 15%. Most of the forecast error in the Niger trial originated from incorrect initial hydrological states. Assimilation of real-time observations could potentially improve the model initialization and hence the hydrological forecasts.
- More results from the model are available at http://hypeweb.smhi.se/nigerhype

Acknowledgements

We are grateful for the financial support of this research from Swedish International Development Cooperation Agency (Sida), the Swedish Research Council (VR), the European Union (EU), and the European Space Agency (ESA) through a number of projects including “Building resilience to floods and droughts in the Niger River basin – hydrological predictions for sustainable water use and climate change adaptation” (Sida: SWE-2011-182, VR: 348-2013-6303), IMPACT2C (EU FP7, 282746), and the Hydrology-TEP (ESA, AO/1-7870/14/I-NB). We would also like to acknowledge fruitful interactions with a large number of institutions and individuals in Africa.

References

ABN, 2008. Niger-HYCOS Hydrological Information System [WWW Document]. http://nigerhycos.abn.ne/ (accessed 2012-03-01).

Aich, V., Koné, B., Hattermann, F., Paton, E., 2016a. Time series analysis of floods across the Niger River basin. Water 8, 165. http://dx.doi.org/10.3390/w8040165.

Aich, V., Liersch, S., Vetter, T., Andersson, J., Müller, E., Hattermann, F., 2015. Climate or land use?—attribution of changes in river flooding in the Sahel Zone. Water 7, 2796–2820. http://dx.doi.org/10.3390/w7062796.

Aich, V., Liersch, S., Vetter, T., Fournet, S., Andersson, J.C.M., Calmanti, S., van Weert, F.H.A., Hattermann, F.F., Paton, E.N., 2016b. Flood projections within the Niger River Basin under future land use and climate change. Sci. Total Environ.

562, 666–677. http://dx.doi.org/10.1016/j.scitotenv.2016.04.021.
Andersson, J.C.M., Andersson, L., Arheimer, B., Bosshard, T., Graham, L.P., Nikulin, G., Kjellström, E., 2014. Experience from Assessments of Climate Change Effects on the Water Cycle in Africa. Paper no. 82, in: Symposium Proceedings of the Fifteenth WaterNet/WARFSA/GWP-SA Symposium - IWRM for harnessing socio economic development in Eastern and Southern Africa, Lilongwe, Malawi, pp. 1–13.
Andersson, J.C.M., Arheimer, B., Traoré, F., Gustafsson, D., Ali, A., 2016. Process refinements improve a hydrological model concept applied to the Niger River basin. Hydrol. Process (submitted for publication).
Andersson, J.C.M., Pechlivanidis, I.G., Gustafsson, D., Donnelly, C., Arheimer, B., 2015. Key factors for improving large-scale hydrological model performance. Eur. Water 49, 77–88.
Arheimer, B., Lindström, G., Olsson, J., 2011. A systematic review of sensitivities in the Swedish flood-forecasting system. Atmos. Res. 100, 275–284. http://dx.doi.org/10.1016/j.atmosres.2010.09.013.
Arino, O., Bicheron, P., Achard, F., Latham, J., Witt, R., Weber, J.-L., 2008. GLOBCOVER the Most Detailed Portrait of Earth. Esa Bull.-Eur. Space Agency, pp. 24–31.
Batjes, N.H., 2012. ISRIC-WISE Derived Soil Properties on a 5 by 5 Arc-minutes Global Grid (Ver. 1.2) (No. 2012/01). ISRIC - World Soil Information, Wageningen, The Netherlands.
Bivand, R., Lewin-Koh, N., 2014. Maptools: Tools for Reading and Handling Spatial Objects.
Capell, R., Andersson, J., Gustafsson, D., 2014. HYPEtools: Tools for Processing and Analysing Files from the Conceptual Rainfall-runoff Model HYPE. SMHI, Norrköping, Sweden. https://github.com/rcapell/HYPEtools.
Coles, S., 2001. An Introduction to Statistical Modeling of Extreme Values, Springer Series in Statistics. Springer London, London.
Descroix, L., Genthon, P., Amogu, O., Rajot, J.-L., Sighomnou, D., Vauclin, M., 2012. Change in Sahelian Rivers hydrograph: the case of recent red floods of the Niger River in the Niamey region. Glob. Planet. Change 98–99, 18–30. http://dx.doi.org/10.1016/j.gloplacha.2012.07.009.
Diallo, I., Giorgi, F., Deme, A., Tall, M., Mariotti, L., Gaye, A.T., 2016. Projected changes of summer monsoon extremes and hydroclimatic regimes over West Africa for the twenty-first century. Clim. Dyn. 47, 3931–3954. http://dx.doi.org/10.1007/s00382-016-3052-4.
Donnelly, C., Andersson, J.C.M., Arheimer, B., 2016. Using flow signatures and catchment similarities to evaluate the E-HYPE multi-basin model across Europe. Hydrol. Sci. J. 61 (2), 255–273. http://dx.doi.org/10.1080/02626667.2015.1027710.
ECMWF, 2009. IFS Documentation CY33r1 [WWW Document]. http://www.ecmwf.int/en/forecasts/documentation-and-support/changes-ecmwf-model/ifs-documentation (accessed 2017-03-02).
FAO, ASA II, ISRIC, ISS-CAS, JRC, 2009. Harmonized World Soil Database (Version 1.1). FAO and IIASA, Rome, Italy.
Gilleland, E., Katz, R.W., 2011. New software to analyze how extremes change over time. Eos 92, 13–14.
GRDC, 2012. The GRDC world-wide repository of river discharge data and associated metadata. Glob. Runoff Data Cent. Fed. Inst. Hydrol. BfG Kobl. Ger. [WWW Document] http://www.bafg.de/GRDC/ (accessed 2012-02-01).
Heffernan, J.E., Stephenson, A.G., 2014. Ismev: an Introduction to Statistical Modeling of Extreme Values.
Lehner, B., Döll, P., 2004. Development and validation of a global database of lakes, reservoirs and wetlands. J. Hydrol. 296, 1–22. http://dx.doi.org/10.1016/j.jhydrol.2004.03.028.
Lehner, B., Liermann, C.R., Revenga, C., Vörösmarty, C., Fekete, B., Crouzet, P., Döll, P., Endejan, M., Frenken, K., Magome, J., Nilsson, C., Robertson, J.C., Rödel, R., Sindorf, N., Wisser, D., 2011. High-resolution mapping of the world's reservoirs and dams for sustainable river-flow management. Front. Ecol. Environ. 9, 494–502. http://dx.doi.org/10.1890/100125.
Lehner, B., Verdin, K., Jarvis, A., 2008. New global hydrography derived from spaceborne elevation data. Eos 89, 93 doi: 200810.1029/2008EO100001.
Lindström, G., Pers, C., Rosberg, J., Strömqvist, J., Arheimer, B., 2010. Development and testing of the HYPE (Hydrological Predictions for the Environment) water quality model for different spatial scales. Hydrol. Res. 41, 295–319. http://dx.doi.org/10.2166/nh.2010.007.
Mahé, G., Lienou, G., Descroix, L., Bamba, F., Paturel, J.E., Laraque, A., Meddi, M., Habaieb, H., Adeaga, O., Dieulin, C., Chahnez Kotti, F., Khomsi, K., 2013. The rivers of Africa: witness of climate change and human impact on the environment. Hydrol. Process 27, 2105–2114. http://dx.doi.org/10.1002/hyp.9813.
Mahé, G., Paturel, J.-E., 2009. 1896–2006 Sahelian annual rainfall variability and runoff increase of Sahelian Rivers. Comptes Rendus Geosci. 341, 538–546. http://dx.doi.org/10.1016/j.crte.2009.05.002.
Mu, Q., Zhao, M., Running, S.W., 2011. Improvements to a MODIS global terrestrial evapotranspiration algorithm. Remote Sens. Environ. 115, 1781–1800. http://dx.doi.org/10.1016/j.rse.2011.02.019.
Nikulin, G., Jones, C., Giorgi, F., Asrar, G., Büchner, M., Cerezo-Mota, R., Christensen, O.B., Déqué, M., Fernandez, J., Hänsler, A., van Meijgaard, E., Samuelsson, P., Sylla, M.B., Sushama, L., 2012. Precipitation climatology in an ensemble of CORDEX-Africa regional climate simulations. J. Clim. 25, 6057–6078. http://dx.doi.org/10.1175/JCLI-D-11-00375.1.
Pebesma, E.J., Bivand, R.S., 2005. Classes and Methods for Spatial Data in R. R News 5.
R Core Team, 2016. R: a Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.
Roudier, P., Ducharne, A., Feyen, L., 2014. Climate change impacts on runoff in West Africa: a review. Hydrol. Earth Syst. Sci. 18, 2789–2801. http://dx.doi.org/10.5194/hess-18-2789-2014.
Sarkar, D., 2008. Lattice: Multivariate Data Visualization with R. Springer, New York.
Sarkar, D., Andrews, F., 2013. latticeExtra: Extra Graphical Utilities Based on Lattice.
Sivapalan, M., 2003. Prediction in ungauged basins: a grand challenge for theoretical hydrology. Hydrol. Process 17, 3163–3170. http://dx.doi.org/10.1002/hyp.5155.
Thiemig, V., Bisselink, B., Pappenberger, F., Thielen, J., 2015. A pan-African medium-range ensemble flood forecast system. Hydrol. Earth Syst. Sci. 19, 3365–3385. http://dx.doi.org/10.5194/hess-19-3365-2015.
Weedon, G.P., Balsamo, G., Bellouin, N., Gomes, S., Best, M.J., Viterbo, P., 2014. The WFDEI meteorological forcing data set: WATCH Forcing Data methodology applied to ERA-Interim reanalysis data. Water Resour. Res. 50, 7505–7514. http://dx.doi.org/10.1002/2014WR015638.