We thank the editor and the reviewers for insightful and constructive comments and provide answers to the comments below. The editor/reviewer comments are in normal font, our replies are in bold font. In addition to the changes requested by the reviewers and editors, the validation period has been expanded to include all of 2014. This has changed some of the results reported in the paper. Also, figures 8 and 9 in the original manuscript have been removed and replaced with a new figure showing predictive Q-Q plots. We believe that the value of figures 8 and 9 was marginal and decided to save them for the sake of compactness and readability of the manuscript.

Editor

I find the paper clear and certainly of broad international interest, the methods are correctly and soundly applied and the Authors indicated, in the lively and fruitful discussion, that they are willing and able to address all the important and constructive points raised by the Referees (whom I deeply thank for their precious input).

I believe that the importance of all the potential case studies, that is not only the specific Kavango River study basin, but all the understudied and poorly gauged catchments that may be studied with this kind of approach and open data and models provides a good motivation for the publication in HESS even if, as correctly highlighted by referees 1 and 3, scientific novelty is not the main feature of the paper.
Such motivation is particularly sustained in the most recent "guidelines" provided for the journal, given that at the last Fall EGU Publication Committee, it was proposed to add a new type of manuscript type, devoted to the description of (citing from a first draft elaborated by the Committee) "interesting and novel case studies that broaden the knowledge base in hydrology and share the underlying data and models structures" and I strongly believe that the wide interest that the adequate use of open data and open models has for all the hydrologists that attempt to study catchments located all over the world but in particular in developing countries and/or at large regional scale, may fully justify the publication of the manuscript, following a careful revision according to the Referees' suggestions.

Thank you.

In addition to the points raised by the Referees, I would also suggest to add more information on the main features of the study basin (area, elevation, …, for both the basin closed at Mohembo and the subbasin at Rundu) and also on its location in the region (widening the map shown in Fig. 1). In addition, I would move from section 2.4 to section 2.1 the description of the hydrometric measures and I would also add some details on the calibration and validation periods (are they statistically similar? do they include a variety of hydrological situations? etc). Please add the equation describing the ME used as part of the objective function.

We added an additional table (new table 1), containing the main characteristics of the various sub-basins. The hydrometric stations and sub-basins are now introduced in section 2.1 and an inset map has been added to Fig 1 showing the location of the basin on the African continent. More information was added on the calibration and validation periods in section 2.4 and the formula for the relative mean error used in the objective function was added.

Reviewer 1

General:

The paper is potentially interesting but the scientific issue/hypothesis of the paper at this moment is unclear. Besides the unclear hypothesis the manuscript does not go into the issues in enough depth. The paper maybe worthwhile to publish in HESS after improvements and added in depth analysis.

Probably, the focus of this paper is more in hydrologic engineering than hydrologic science. We do not propose a new scientific hypothesis or method. We combine different datasets and methods into an operational forecasting system for poorly gauged basins. We have extended the analysis and presentation following al reviewer comments as explained in the detailed responses below.

Detailed comments:

Abstract I doubt/am not sure if it is appropriate to highlight TIGER-NET and the funding behind the project/paper in the abstract. It is unclear what a competitive forecast is.

The reference to TIGER-NET has been removed from the abstract. "Competitive" has been replaced with "useful".

The scientific hypothesis of the paper is unclear. What scientific issue/problem is being researched? The operational goals of the TigerNET project are listed, but this is inappropriate for a scientific study. What is the added value of the work conducted and what is the relationship to work done elsewhere/previously? Or is this just another case study? As a result, a clear experimental setup to test a hypothesis is missing and the scientific contributions stay unclear.

See answer to the general comment above. The purpose of the paper is to document how we reached the operational goals of TigerNET using free, open-source and public domain data and tools and to evaluate the performance of the system. It is more than a case study, because we describe a system that can be used for any basin and just use one particular basin for demonstration purposes.

In the introduction some DA papers are being mentioned. I think in operational hydrologic DA there is not yet, a preferred method, variational approach have also been proposed by Seo et al 2003/2009 and Lee et al 2012. Some papers also try to update both the hydrologic and routing states (see e.g. Rakovec et al., 2012)=>See Liu et al. 2012 for the references for all these papers.

Our intention is not to review or judge the merits of various DA approaches. We just mention that the Kalman filter is one of the most widely used methods, which is true to our knowledge. We have expanded the discussion of combined updating of hydrologic and routing states (in the discussion section). References for variational DA approaches have been added to the introduction.

I looked at the reference (NOAA, 2014) but could not find the GFS forecast from 2006 onwards. There are only forecasts from 201208 onwards (ftp://nomads.ncdc.noaa.gov/GFS/Grid4/) are available. Therefore, it is unclear what data is being used for Figure 2 and further results. It needs to be clear which data is being used otherwise it is impossible to judge the results.

The data was downloaded from
http://nomads.ncdc.noaa.gov/data.php#hires_weather_datasets

The most recent data is online on the server, the older data is archived offline but can be ordered for FTP download. This information and a reference to the download page was added.

I also wondered why GFS is being used and not GEFS for which a hindcast exists from 1984 onwards, see ftp://ftp.cdc.noaa.gov/Projects/Reforecast2/). Especially, because in the discussion it is mentioned that no EPS is available but NOAA also provides GEFS/GENS (http://nomads.ncep.noaa.gov:9090/dods/gens) with 21 ensemble members. So this needs to be revised in the manuscript.

This has been revised in the manuscript. While the use of GEFS is an interesting perspective for future research, its implementation is beyond the scope of this revision. We have also added a discussion of GFS model changes and the need for regular re-calibration in view of changing precipitation forecasts.

Verification metrics: I think it is necessary to use persistence as reference forecast and analyse the CRPSS and maybe some other metrics (BSS, ROCS, etc) This may make clear what the source of the the skill is because the main question that remains unanswered in my opinion is where skill is coming from: updated initial conditions or bias corrected GFS forecasts or/and how important the hydrological model is especially for these short lead times.

We have added the definition of CRPS for deterministic forecasts. We have added climatology and persistence runs as benchmarks to table 6.

Reviewer 2

Summary
This study addressed a very interesting topic since it presents an operational river discharge forecasting system. This system employs meteorological forcing data from a weather forecast model (NOAA-GFS) and uses a data assimilation technique to update river discharge in real time. Although the runoff routing scheme (i.e., the Muskingum routing) and the data assimilation approach (i.e., the Kalman filter) are very simple, this study made a good attempt to combine weather forecasting output and data assimilation for flood forecasting. This operational river discharge forecasting system is successfully applied in the Kavango River, and shows the potential to assimilate remotely sensed observations. However, the manuscript may need more detailed description about forecasting experiment setups and parameter estimation. Therefore, I suggest this paper could be published after a few minor revisions.

Thank you, we will address your comments as explained below.

Comments
(1) The authors reported results for the open-loop run without assimilation, the assimilation run, and the 1–7 day ahead forecasts. I think these scenarios use different meteorological forcing data. Please correct if I miss some information. In the scenarios of 1–7 day ahead forecasts, Are the discharge observations from Rundu assimilated in real time in the forecasting system? Is the simulated discharge at the outlets of all 12 subbasins updated in the data assimilation?

Yes, the meteorological forcing is different. The open-loop, assimilation and 1-day ahead forecasting runs use 1-day ahead forecasted precipitation and temperature. The 2-day ahead forecasting run uses 1-day ahead forecasted precip and temp up to real time and then the 2-day ahead forecast. The same is done for the 3-7day forecasts. Rundu discharge measurements are assimilated in real time, or as they become available (typically a real-time delay of a few hours). And yes, the Kalman filter updates the simulated discharge at all basin outlets. These specifications have been added to the manuscript.

(2) Table 4 shows performance indicators of the forecasting system. Did you set the other scenarios of removing some observations in the data assimilation? I invite the authors present some more information about these scenarios.

Yes, in the forecasting runs, observations closer in time than the forecasting horizon have been removed. So, for instance, the 4-day ahead forecasting run only assimilates observations up to t - 4 days. This specification has been added to the manuscript.

(3) Real-time discharge observations are assimilated into the Muskingum routing scheme, and Kalman filter is used in the data assimilation. Certainly, this is very simple and efficiency. But the authors also state that the TIGER-NET project has the plan of using satellite earth observations (e.g., soil moisture), not only the in-situ observations, so the routing scheme and the Kalman filter may not meet such a big plan.

This is entirely correct and also discussed in the discussion section of the manuscript, which has been expanded in the revised manuscript.

(4) There are three parameters in the Muskingum scheme (MAK_X, MSK_CO1 and MSK_CO2, see the routing process in SWAT). They should be prescribed or estimated before simulations, because they may be influential to runoff routing in data assimilation. But the manuscript does not give any information about their estimates in Table 1.

The routing phase of the hydrologic cycle is simulated outside of SWAT in our approach to facilitate easy updating in the DA scheme. Muskingum parameters are set based on river widths, an assumed cross section geometry and channel Manning numbers (which are calibrated). These specifications have been added to the manuscript.

(5) The original meteorological forcing data from NOAA-GFS are six hourly, but the SWAT model is run at a daily time step. Did you integrate the six hourly data to daily?

Yes this is what we did. We did not run with sub-daily precipitation input. This information was added to the revised manuscript.

(6) I found the computation of persistence index (PI) in Eq. (6) is different from the expression in Bennett et al., 2013). Please check it. What is the latest available observation (Qlast) ?

Equation 6 in our paper is equivalent to equation 6.6 given in table 6 of Bennett et al, 2013. Qlast corresponds to yi-1 in the Bennett paper. We believe there is a typo in Bennett's notation as this should be ^yi-1, i.e. the hat is missing. The idea in the PI is to use the last available observation as the reference, i.e. ^yi-1 and not the average of all observations as in the NSE. Qlast is today's observation of river discharge. In the 1-day ahead forecast, there is a lag of 1 day between Qlast and the forecast, in the 7-day ahead forecast, this lag is 7 days. No changes were made in the revised version.

(7) I suggest all figures, especially Figures 5, 6, 7, 8 and 9, should be redrawn before submission. The size of the text in figures looks too small.

Yes, we agree and have changed this in the revised version.

Reviewer 3

This manuscript addressed operational forecasting in the catchment located in Africa. The topic and contents of this study will be of interest to broad ranges of the scientific and engineering community especially because they achieved improved forecasting via combination of a well-known rainfall-runoff model, SWAT, and a basic data assimilation technique, Kalman filtering on a linear routing scheme. However, no innovation is found in their methodology on data assimilation and rainfall-runoff modeling compared to their previous publications in HESS (Michailovsky and Bauer-Gottwein, 2014) and WRR (Michailovsky et al., 2013). Although their focus seems to be on "operational" applications in "poorly" gauged basins, new methodology or finding is limited for these two targets. Therefore, major revision should be required for possible publication in HESS considering following comments:

It is correct that the hydrologic-hydrodynamic modeling and DA approach is the same as in the papers mentioned above. This is also stated in the manuscript (pages 11077, 11081). The new points in this paper are

- **Combination with real precipitation forecasts from a global weather forecasting system.**
- **Operational application of the forecasting system in real time. We are issuing daily forecasts as we are writing this.**
- **Extensive evaluation of the skill of the forecasts compared to persistence and (in the revised manuscript) climatology.**

Moreover, as part of TIGER-NET, the entire system has been implemented in an open-source GIS environment (QGIS, GDAL, Python). Installation and source code are available for download from the TIGER-NET webpage.

1. Methodology for operational forecasting
Even though values of this manuscript could be found in terms of "engineering", they didn't present any advanced method required for operational setting. Without innovation for these main keywords, this study could be mere applications using modeling techniques, developed by themselves in the previous publications, and operational input forcing. Therefore, I strongly suggest authors would provide additional methodology or analysis on operational applications for readers to have more confidence and understanding on their approach. For example, rainfall forecasts could be analyzed for varying lead times. If significant bias exists in operational forecasts, authors should re-think additional treatment such as bias correction or pre-processing, which shouldn't be remained as future study in such a case.

This basin is un-gauged in terms of precipitation. We do not have access to long-term in-situ precipitation records from any place in the basin. The "true" precipitation is therefore unknown. In order to address this issue, we compared NOAA-GFS with FEWS-RFE and we actually do implement a static bias correction (see section 3.1). We have added an analysis of rainfall forecasts for varying lead times (see right-hand panel of figure 2).

2. Data assimilation
2.1 It is interesting that the study utilizes the AR1-type model and runoff correlation matrix in the model noise specification. However, the impacts of the noise specification were not clearly verified in the manuscript. Please clarify how the error specification would affect the performance of discharge forecasts with additional evidence and analysis.

Four additional forecasting scenarios have been added with varying model error and observation error specifications.

2.2 Although authors used several probabilistic measures such as coverage, sharpness, ISS, and CRPS, it was hard to find analysis on appropriateness of probabilistic forecasts. As DA is expected to reduce uncertainty range, only comparison between DA and open-loop could not justify appropriateness of probabilistic forecasts. It is recommended that authors should add evaluation and analysis of probabilistic forecasts based on their uncertainty assumption on observation and simulation (10% of standard deviation of discharge uncertainty seems to be underestimation especially in poorly gauged basins as well as in high-flow seasons). An additional measure such as predictive Q-Q plot could be useful to assess appropriateness of the probabilistic forecast.

We have added persistence and climatology benchmarks to table 6. We have included an experiment with higher assumed observation error. We have added q-q plots for forecasted flows in Figure 8.

2.3 Description on DA procedure is not enough for readers to understand and reproduce this study. Authors should revise the manuscript with additional description and equations about how noise specification would be applied and updated in Kalman filtering equations.

As the reviewer states above, the modeling and DA methodology is equivalent to what has been published in earlier papers. We therefore kept this part very short and referenced the existing papers. No changes were made.

2.4 Please clarify how the error model is applied in DA if observation is missing. It is not clear how confidence interval is estimated in open-loop simulations, either.

If no observations are available, the Kalman filter update equations are simply not applied, i.e. the model is propagated without updating. The AR1 error model for the runoff will still produce a model spread (confidence interval). In the open-loop simulations, there are no observations available, i.e. the model is run without any updating whatsoever. This specification has been added to the manuscript.

3. Methodology for poorly gauged basins There is no doubt that the study area is a poorly gauged basin. But, there is no technical treatment or analysis for poorly gauged basins in the manuscript, although authors might think public-domain input forcing and models are solutions. Therefore, the current title could confuse readers who are finding new methodology for data-sparse regions. I wonder if it is proper to use the term “poorly gauged basins” in the title with the present content.

We are unsure how to address this comment. In principle, this system can run with no or minimal feed of in-situ data, which is a typical situation in many African river basins (the target region of TIGER-NET). For many of these basins (Zambezi, Chari-Logone, Kavango etc.) there presently do not exist any operational forecasting systems and the presented methodology can fill this gap and provide a first solution. No changes were made to the manuscript.

4. Revision of abstract
4.1 As an anonymous reviewer addressed, description on funding body in the abstract is not desirable especially because this manuscript covers limited parts of this project. Referencing the website in the middle of the manuscript might be enough to show relationships of this study with the entire project.

Reference to funding agency has been removed from the abstract.

4.2 I couldn’t find any evidence supporting the sentence “the value of the forecasts is greatest for intermediate lead times between 4 and 7 days”. In the contrary, the accuracy of forecasts seem to degenerate gradually according to increasing lead times.

The support for this statement is in table 6. This discussion has been significantly extended in the revised manuscript.

5. Terminology
The authors used the term “hydrodynamic model” to indicate the Muskingum routing scheme, which might be different from general usage. As my limited knowledge, the hydrodynamic models usually refer to simulation models to represent the motion of the flow by momentum and continuity equations. I don’t think the Muskingum routing scheme belongs to a range of hydrodynamic models. Instead, river routing scheme, as the authors used in their previous publications, would be a better term to indicate the Muskingum scheme through the manuscript.

The term “hydrologic-hydrodynamic modeling” is used in parts of the literature to refer to models addressing both the land phase and the channel flow phase of the runoff process. The Muskingum routing scheme solves a strongly simplified version of the full 1D Saint Venant equations for channel flow. We have adapted the terminology to avoid any potential misunderstanding.

6. Formulation of objective function
The authors included NSE and ME (Eq. (2)) in the objective function. However, ME varies in wider ranges compared to NSE. Please justify how two measures could be used having similar influence.

We realize that this has not been accurately reported in the paper: ME in Equation 2 is the mean error expressed as a fraction of the mean observed flow, i.e. the normalized relative error. The term 1-NSE and the normalized relative error have similar magnitude and thus a similar influence in the SCE objective function. This information has been added to the revised version of the paper.

7. Figure 7
It would help readers to understand discharge forecast more clearly to add hyetographs of (catchment-averaged) forecast input forcing for each lead time in Fig. 7.

Hyetographs were added to figure 7.

Operational river discharge forecasting in poorly gauged basins: the Kavango River Basin case study

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Abstract

Operational probabilistic forecasts of river discharge are essential for effective water resources management. Many studies have addressed this topic using different approaches ranging from purely statistical black-box approaches to physically-based and distributed modelling schemes employing data assimilation techniques. However, few studies have attempted to develop operational probabilistic forecasting approaches for large and poorly gauged river basins. The objective of this study is to develop open-source software tools to support hydrologic forecasting and integrated water resources management in Africa. We present an operational probabilistic forecasting approach which uses public-domain climate forcing data and a hydrologic-hydrodynamic model which is entirely based on open-source software. Data assimilation techniques are used to inform the forecasts with the latest available observations. Forecasts are produced in real time for lead times of 0 to 7 days. The operational probabilistic forecasts are evaluated using a

selection of performance statistics and indicators and the performance is compared to persistence and climatology benchmarks. The forecasting system delivers useful forecasts for the Kavango River, which are reliable and sharp. Results indicate that the value of the forecasts is greatest for intermediate lead times between 4 and 7 days.

Introduction

Operational probabilistic hydrological modelling and river discharge forecasting is an active research topic in water resources engineering and applied hydrology (Pagano et al., 2014). Sharp and reliable forecasts of river discharge are required over a range of forecasting horizons for flood and drought management. A state of the art river discharge forecasting system consists of a weather forecast or an ensemble of weather forecasts (Cloke and Pappenberger, 2009), a hydrologic-hydrodynamic modelling system and a data assimilation approach to inform the forecasts with all available in situ and remote sensing observations. Alternatively, in the absence of resources, data and computing power, simpler solutions can be implemented which disregard more and more of the physics and rely on past observations to parameterize black-box type models such as, for instance, artificial neural networks (Maier et al., 2010).

Many studies have shown that operational hydrological models can benefit from the assimilation of in-situ or satellite remote sensing observations. Different techniques and approaches have been presented (Liu et al., 2012). They differ both in terms of the type of data that are assimilated to the models, the assimilation algorithms used and in terms of the assimilation strategy, i.e. which model components, states and/or parameters are updated. Some hydrological data assimilation studies update the internal states of rainfall-runoff models (e.g. Clark et al., 2008; Pauwels and De Lannoy, 2009) while other approaches focus on updating the hydrodynamic parts of the model (Biancamaria et al., 2011; Neal et al., 2009) or combinations of rainfall-runoff and routing state variables (e.g.

Rakovec et al., 2012). One of the most popular algorithms used in hydrologic data assimilation is the ensemble Kalman filter (e.g. Clark et al., 2008). Alternatively, the particle filter (Moradkhani et al., 2005) can be used, which does not require the assumption of Gaussian model errors. Variational data assimilation has also been used in a number of hydrologic studies (e.g. Seo et al., 2009, 2003). Some studies use filtering approaches where the gain is determined heuristically from offline simulations and then used operationally in forecasting mode (Madsen and Skotner, 2005). As pointed out by Liu et al., 2012, despite the large body of literature on hydrologic data assimilation, few studies evaluate the benefit of data assimilation for actual forecasting and practical application of data assimilation by operational agencies is rare.

In many river basins the performance of operational hydrological modelling and forecasting is limited because in-situ observations of precipitation and river discharge are scarce or unavailable. This is also the case for many of Africa’s large river basins which are poorly gauged (e.g. Zambezi, Volta, Congo). Consistent, long-term and spatially resolved in-situ observations of precipitation and river discharge are unavailable for large portions of Africa. Moreover, the number of operational meteorological stations and river discharge stations has been decreasing consistently around the world since the 1970s (Fekete and Voeroesmarty, 2007; Peterson and Vose, 1997). Remote sensing techniques have the potential to fill critical data gaps in the observation of the global hydrological cycle. All major components of the water balance, except river discharge, can now be estimated based on various types of remote sensing data. However, the available techniques are still limited by coarse spatial and temporal resolution as well large and/or poorly understood error characteristics (Tang et al., 2009). From a management perspective one of the most important components of the hydrological cycle is river discharge. Extremely high flows in rivers cause flooding which can have severe consequences in terms of fatalities and economic damage. Low flows cause conflicts in the allocation of scarce water resources between economic sectors and/or the environment. Therefore, in many river basins there is a need for hydrological models to provide operational estimates of river discharge based on remotely sensed observations and limited available in-situ measurements.

The TIGER-NET project addresses the demand for free, up-to-date and spatially resolved water information for the African continent. The project is funded by the European Space Agency (ESA) and aims to support integrated water resources management in Africa by (i) providing access to ESA Earth observation (EO) data, (ii) developing an open-source Water Observation and Information System (WOIS) and (iii) implementing capacity building actions in collaboration with African partner institutions (Guzinski et al., 2014).

The WOIS includes a hydrological modelling component, which supports long-term scenario analysis (e.g. impact of climate change, deforestation etc.) as well as operational probabilistic forecasting. The specific objective for the operational modelling capability is to provide reliable and sharp probabilistic forecasts of river discharge over time horizons of up to one week. In addition to hydrological modelling, WOIS includes functionality for operational flood monitoring, basin characterization at high (~30 m) and medium (~1 km) spatial resolutions and derivation of other products requiring EO data processing and analysis (Guzinski et al., 2014). It was designed for use in African organizations, where budgetary and technical constraints often limit the use of EO data for integrated water resources management. Therefore, WOIS is based purely on free, open-source software components and was created as an easy to use tool for both capacity building and operational use. Among the partner institutions engaged in the TIGER-NET project is the Namibian Ministry of Agriculture, Water and Forestry. The Ministry has an interest in forecasting the discharge of the Kavango River.

Based on these requirements, this study has four specific objectives:

1. Development of a robust and simple probabilistic river discharge forecasting system for poorly gauged river basins, based solely on open source software and public-domain data.
2. Informing the forecasting system with in-situ discharge observations in real time.
3. Operational demonstration of the system for the Kavango River case study.
4. Comprehensive evaluation of the operational probabilistic forecasts using a selection of performance statistics and indicators as well as comparison with persistence and climatology benchmarks.

The entire system has been implemented in an open-source GIS environment (QGIS, GDAL, Python). Installation and source code are available for download from the TIGER-NET webpage (www.tiger-net.org).

Materials and Methods

Study Area

The Kavango River originates in the highlands of central Angola and flows south to the border between Angola and Namibia. The Cuito River joins the Kavango River just before the river enters into Namibia's Caprivi Strip. It terminates in the Okavango Delta, a large wetland system in Northern Botswana (Milzow et al., 2009). An overview of the basin is provided in Figure 1. The basin is located on the Southern fringes of the inter-tropical convergence zone. A strong south-to-north precipitation gradient is observed. The climate is highly seasonal and large inter-annual variations are typical, which are controlled by a number of climate time scales (McCarthy et al., 2000; Wolski et al., 2014). The Kavango River is an important resource for all riparian countries and forms the basis of many people's livelihoods (Kgathi et al., 2006). While water scarcity and water allocation between economic sectors and the environment have been in focus for some time, flood risk has recently become a major concern because the northern part of Namibia has experienced increased magnitude and frequency of flooding events since 2008 (Wolski et al., 2014). Water managers need accurate and reliable forecasting tools to deal with both floods and droughts.

Three hydrological modelling efforts have been reported in the literature for the Kavango River basin. Folwell and Farqhuarson, 2006 used the Global Water Availability Assessment (GWAVA) model to assess climate change impacts in the basin. Hughes et al., 2011, 2006 calibrated a Pitman model for the basin and were able to reproduce in-situ observations satisfactorily. Milzow et al., 2011 developed a SWAT (Soil and Water Assessment Tool) model of the Kavango basin and calibrated the model with water levels from radar altimetry, soil moisture from Envisat-ASAR and total water storage change from GRACE.

Long-term in-situ observations of river discharge are available from two hydrometric stations in the basin, Rundu and Mohembo (Figure 1). Table 1 summarizes the main characteristics of the Kavango river basins and the two sub-basins contributing to the stations Rundu and Mohembo.

Hydrologic and hydrodynamic modelling

The modelling approach implemented in this study consists of a hydrologic (rainfall-runoff) model which is coupled to a simple routing model for channel flow. A one-way coupling between the two model compartments is implemented, i.e. once runoff has entered the river channel, the water cannot move back into the land phase of the hydrological cycle.

We use the well-known SWAT hydrological model, version 2009 (Gassman et al., 2005; Neitsch et al., 2011) for rainfall-runoff modelling. SWAT is a semi-distributed, physically based hydrological model which operates at a daily time step. The river basin is divided into a number of sub-basins. Each sub-basin is in turn divided into hydrological response units (HRU), which are defined as portions of the sub-basin with similar terrain slope, land use and soil type. The Kavango SWAT model consists of 12 subbasins with outlets located at the confluences of major tributaries as well as at in-situ discharge station locations (Figure 1).

The hydrodynamic model used in this study is a simple Muskingum routing scheme, which is implemented outside of the SWAT simulator to allow efficient updating in the data assimilation scheme. Muskingum parameters are computed from river widths, assumed cross section geometry and channel Manning numbers (which are calibration parameters). The river is divided into 12 primary individual river reaches. The primary reaches are further sub-divided if required to meet the numerical stability criteria of the Muskingum routing scheme (Chow et al., 1988). The hydrodynamic model state vector consists of the simulated discharges in each individual reach. In the Muskingum routing scheme, the model operator propagating the discharge forward in time is linear, i.e. the simulated discharges at time step *t+1* are a linear function of the simulated discharges at time step *t* and the runoff forcings at time steps *t* and *t+1*:

$$\mathbf{q}^{t+1} = \mathbf{A}\mathbf{q}^{t} + \mathbf{B}\mathbf{r}^{t} + \mathbf{C}\mathbf{r}^{t+1} \quad (1)$$

In this equation, **q** is the vector of simulated discharges and **r** is the vector of runoff forcings, **A**, **B** and **C** are linear operators which depend on the configuration of the river channels and network connectivity and the superscripts indicate time steps. For details on the implementation of the Muskingum routing scheme the reader is referred to Chow et al., 1988 and Michailovsky et al., 2013.

Input data

SWAT requires the following input datasets: elevation, land cover, soil type and climate forcings. The elevation dataset is used for automatic watershed and river network delineation as well as for the determination of terrain slope. We use the ACE2 (Altimeter Corrected Elevation, version 2, Berry et al., 2010) global elevation dataset at a resolution of 30 arc-seconds. The parameterization of vegetation processes in the SWAT model is based on the land cover input dataset. We use the USGS Global Land Cover Characterization (GLCC) dataset, version 2.0 with a spatial resolution of 1 km (USGS, 2008). The soil dataset forms the basis for parameterizing soil hydraulic processes in SWAT. We use the FAO/UNESCO digital soil map of the world and derived soil properties, revision 1, with a spatial resolution of 5 arc-minutes (FAO-Unesco, 1974). Look-up tables translating GLCC land cover classes and FAO/UNESCO soil types into SWAT parameters have been developed by the WaterBase project (George and Leon, 2007).

The model is forced with daily precipitation and daily minimum and maximum temperature from the National Oceanic and Atmospheric Administration's Global Forecast System (NOAA-GFS) which provides up to seven days of forecast at a six hourly temporal resolution and 0.5 degree spatial resolution (NOAA, 2014). Real-time and recent historical forecasts can be downloaded from the NOMADS server (http://nomads.ncdc.noaa.gov/data.php#hires_weather_datasets, last accessed: 14.01.2015). Historical forecasts older than a few months have to be ordered for FTP download. NOAA-GFS data was aggregated to daily precipitation prior to its use in the hydrological model. For historical simulation periods and model calibration, forcing time series consisting of the 1-day ahead forecasts are used. In operational mode, long-term forecasts are successively replaced with short-term forecasts as time proceeds. In order to assess the performance of the NOAA-GFS precipitation forecast for the Kavango region, the 1-day ahead forecasts were compared to FEWS-RFE rainfall estimates (Herman et al., 1997). FEWS-RFE was previously found to be one of the most accurate remote sensing precipitation products for Africa (Milzow et al., 2011; Stisen and Sandholt, 2010).

Calibration and validation of the hydrologic-hydrodynamic model

Calibration and validation of the hydrologic-hydrodynamic model were performed against observed in situ river discharge using a split-sample approach. The years 2005-2011 were used for calibration, while the years 2012-2014 served as validation period. Mean observed flows in the validation period are higher than in the calibration period (Table 2). After a series of dry years in the beginning of the century, the region has experienced much higher amounts of precipitation and river flow since 2008 (Wolski et al., 2014). In order to ensure a balanced representation of both wet and dry years in the calibration period, we had to use a major portion of the entire data record for calibration and could only reserve three years for validation. Particularly for the station Mohembo, only very few observations are available in the validation period (Table 2). The objective function which was minimized in the calibration was formulated as

$$\varphi = (1 - NSE)^2 + RME^2$$
$$RME = \frac{1}{\overline{Q_{obs}}} \frac{1}{n} \sum_{i=1}^{n} (Q_i - Q_{obs,i}) \quad (2)$$

where *NSE* is the Nash-Sutcliffe model efficiency (Nash and Sutcliffe, 1970) and *RME* is the relative water balance error (relative mean error). The symbols Q and Q_{obs} denote simulated and observed river discharge, respectively, n is the number of available discharge observations and the overbar indicates temporal averaging. This formulation ensured a reasonable trade-off between fitting the observed hydrographs and matching the observed water balance of the catchment. A sequential calibration strategy was implemented: First, the subcatchments upstream of Rundu were calibrated using Rundu observations and subsequently the subcatchments between Rundu and Mohembo were calibrated using Mohembo observations.

Calibration was performed using the model-independent parameter estimation programme PEST (Doherty et al., 2014). Because of the strongly non-linear response of the SWAT rainfall-runoff model, global derivative-free search strategies are the preferred option for calibration of SWAT models (Arnold et al., 2012). We use the shuffled complex evolution (SCE) algorithm (Duan et al., 1992) which performs a global search over the entire allowed parameter space. The SCE algorithm is included in the PEST package (SCEUA_P).

The selection of calibration parameters was the result of an iterative procedure including extensive sensitivity analysis and repeated trial model runs. The final selection was based on the following principles: (i) spatial variation of vegetation and soil parameters is determined by the input datasets and should be left unchanged during calibration. The corresponding SWAT parameters were either not changed at all or multiplied with a global factor. (ii) The water balance of the rainfall-runoff model should be maintained. Therefore the fraction of the recharge entering the deep aquifer was set to zero. (iii) SWAT groundwater parameters are highly uncertain a priori but at the same time very sensitive. Enough spatial variation in groundwater parameters must be allowed in order to reproduce the various recession time scales in the observed hydrographs. (iv) SWAT has two threshold values of the shallow groundwater storage, one controlling the onset of baseflow and one controlling the onset of phreatic evapotranspiration. The absolute magnitudes of the two threshold values are less important because they mainly control the length of the required model warm-up period. However, the difference between these two threshold values has significant control over the water balance of the catchment: If the baseflow threshold is below the phreatic ET threshold, more water will leave the catchment as baseflow and less as actual ET and vice versa. In order to reduce parameter correlation and non-uniqueness, the baseflow threshold was generally fixed at 100 mm in the Kavango SWAT model.

Table 3 provides an overview of the calibration parameters and their allowed ranges. For the groundwater parameters, spatial variation was allowed between the Rundu and Mohembo regions, the upstream and downstream catchments within each region and the high slope and low slope portions of the land surface. This resulted in a total number of 19 calibration parameters for the Rundu region and 20 calibration parameters for the Mohembo region. We chose 8 complexes in the SCE calibration run and the number of complexes remained the same throughout the run. Both the number of parameter sets in each complex and the number of evolution steps before complex shuffling were set to 39 and 41 for the Rundu and Mohembo regions respectively. The convergence criterion was set to a relative improvement of the best objective function of 1% over 10 shuffling loops. A total of 50000 model runs were allowed, however the calibration converged after 14711 and 18373 model runs for the Rundu and Mohembo regions respectively. After completion of the SCE run, the evolution of the parameter values over the course of the shuffling loops was evaluated. All parameter values converged to a stable solution away from the a priori parameter bounds.

Assimilation strategy

The objective of data assimilation is to combine, at each point in time, the model-based estimate of the state of the system as well as the most recent observations of the state, in order to produce the best possible estimate of the current and future states, taking into account the respective uncertainties of simulated states and observations. The assimilation strategy chosen in this study consists of updating the simulated discharge in the Muskingum routing model only, because the objective was to generate probabilistic river discharge forecasts with lead times of up to 7 days. Updates of the rainfall-runoff model states would probably improve long-term forecasts significantly but may have limited effect on forecasts with short lead times in large basins such as the Kavango basin. Moreover, updating the rainfall-runoff model would require ensemble-based assimilation approaches. For the intended user group of the TIGER-NET products, simplicity and efficiency are key criteria.

Observed in-situ discharge at the station Rundu was assimilated to the model in the operational runs. Because the Muskingum routing operator is linear and the measurement operator is linear too, we could use the standard Kalman filter for state updating, since it is the optimal sequential assimilation method for linear dynamics (Kalman, 1960). The Kalman filter simultaneously updates discharge at all basin outlets. If instead of river discharge, water level measurements from space-borne or ground-based instruments are assimilated, the measurement operator becomes non-linear and the extended Kalman filter can be used (Michailovsky et al., 2013). The reader is referred to the literature (e.g. Jazwinski, 1970) for a detailed discussion of the Kalman filter equations and to Michailovsky et al., 2013 for a detailed description of the assimilation approach.

Description of the model error

Runoff is assumed to be the dominant source of error in the routing model. While the routing model parameters, which depend on reach geometries and Manning's friction factors, are uncertain, runoff uncertainty can be expected to be much more significant due to the error in the NOAA-GFS rainfall forcing as well as structural deficiencies and/or parameterization errors in the SWAT model. In order to find a reasonable representation of the model error, the magnitude, auto-correlation and spatial cross-correlation of the runoff error had to be assessed. No direct measurements of runoff are available within the river basin. To derive an operational error model, we assume, in the baseline experiment, that magnitude and autocorrelation of the relative runoff error are the same as magnitude and autocorrelation of the relative model residuals at the available in-situ discharge stations:

$$\mathbf{w_t} = \frac{(\mathbf{Q_{sim,t}} - \mathbf{Q_{obs,t}})}{\mathbf{Q_{obs,t}}} \tag{3}$$

where w_t is the relative model residual (-), $Q_{sim,t}$ is the modelled discharge at the in-situ discharge station at time step t and $Q_{obs,t}$ is the in-situ discharge as time step t. The autocorrelation of the residuals was assumed to be represented by a first order autoregressive (AR1) model:

$$w_t = \delta w_{t-1} + \varepsilon_t \tag{4}$$

where δ is the AR1 parameter and ε is a sequence of white Gaussian noise with a spatial covariance *Q'*. Due to the correlated meteorological inputs the runoff forcing error was assumed to be spatially correlated between the various subcatchments of the model. In the baseline experiment, we assume that the spatial correlation of the runoff forcing error is equivalent to the spatial correlation of the runoff forcing itself. The correlation matrix of the runoff inputs was computed and Q' was set to:

$$\mathbf{Q}' = \mathbf{C}\,\sigma(\epsilon)^2 \quad (5)$$

where **C** is the runoff correlation matrix and $\sigma(\epsilon)^2$ is the variance of the white noise component of the AR1 model. The auto-correlated runoff error state was integrated in the Kalman filter updating scheme by augmenting the model state vector with the correlated noise term (Jazwinski, 1970; Michailovsky et al., 2013). This ensures persistence of assimilation benefits in time.

The major source of error in in-situ discharge observations is the rating curve, which is used to transform readings of river stage into river discharge. Rating curves are particularly unreliable for extreme flow rates and, depending on the channel characteristics, the rating curve changes over time and requires frequent updating. In the absence of detailed information on the in-situ measurement procedure, we assumed the measurement error to be uncorrelated in time and proportional to the discharge. In the baseline experiment, the relative error was assumed to be 10 %, which is a typical value for in-situ discharge derived from rating curves (Di Baldassarre, 2009) and comparable to other hydrologic data assimilation studies (e.g. Clark et al. 2008).

In order to evaluate the impact of model error and observation error specifications on the performance of the probabilistic discharge forecasts, four additional forecasting experiments were conducted. Table 4 presents an overview of the experiments. In the baseline experiment, the autocorrelation of the relative runoff error was set equal to the autocorrelation of the relative model error at Rundu (0.9942), as described above. The magnitude of the relative runoff error was set to 4.38%, which is the same as the relative model error at Rundu. The spatial correlation of relative runoff error was set equal to the spatial correlation of runoff and the relative observation error was set to 10%. In experiment 1, the autocorrelation of the runoff error was set equal to the autocorrelation of the spatially aggregated runoff (0.9934) while the other specifications are the same as in the baseline run. In experiment 2, the spatial correlation of the runoff error was set to zero and all other specifications are as in the baseline run. In experiment 3, the runoff error specifications are the same as in the baseline and the relative observation error was set to 20%. Finally, in experiment 4, the white noise component of the relative runoff error was increased from 4.38% to 6% and all other specifications are as in the baseline run.

Operational forecasting and performance evaluation

Operational forecasts have been issued at the daily basis for the validation period and supplied to Namibia's Ministry of Agriculture Water and Forestry for web-based dissemination. A set of criteria were used to assess the performance of the probabilistic river discharge forecasts. Performance assessment was done separately for the open loop model and the 0 to 7-day forecasting horizons. The criteria assess the performance of the central model forecast, as well as the reliability and sharpness of the probabilistic forecasts. The following criteria were used to assess the performance of the central model forecast: Nash-Sutcliffe model efficiency (NSE), root-mean square error (RMSE), mean error (ME) and persistence index. The persistence index (PI, Bennett et al., 2013) is defined analogous to the NSE:

$$PI = \frac{\frac{1}{n}\sum_{i=1}^{n}(Q_i - Q_{obs,i})^2 - \frac{1}{n}\sum_{i=1}^{n}(Q_i - Q_{last})^2}{-\frac{1}{n}\sum_{i=1}^{n}(Q_i - Q_{last})^2} \quad (6)$$

where n is the number of forecasted observations, Q are the forecasts, Q_{obs} are the observations and Q_{last} is the latest available observation before the forecasted observation. While the NSE uses the average of the observations as the benchmark (i.e. a forecast that performs as good as the long-term average of the available observations scores an NSE of 0), the PI uses the last available observation as the benchmark (i.e. a forecast that performs as good as the latest available observation scores a PI of 0).

Reliability and sharpness of the probabilistic forecasts were assessed with the coverage of the 95% confidence interval (i.e. percentage of observations that fall within the predicted nominal 95% confidence interval), the sharpness of the 95% confidence interval (width of predicted 95% confidence interval), the Interval Skill Score (ISS) of the 95% confidence interval as well as the continuous ranked probability score (CRPS). The ISS is defined according to Gneiting and Raftery, 2007 as:

$$ISS_\alpha = \sum_{i=1}^{n} iss_\alpha\left(l_i, u_i, Q_{obs,i}\right)$$

$$iss_\alpha(l, u, Q_{obs}) = \begin{cases} (u-l) & \text{if} \quad l < Q_{obs} < u \\ (u-l) + 2/\alpha\,(l-x) & \text{if} \quad Q_{obs} < l \\ (u-l) + 2/\alpha\,(x-u) & \text{if} \quad Q_{obs} < u \end{cases} \tag{7}$$

where α is the level of the confidence interval (0.05 in our case), l is the lower and u the upper bound of the confidence interval.

The CRPS is a verification tool for probabilistic forecasts and can be interpreted as the area between the cumulative distribution function of the forecast and the cumulative distribution function of the observation, which is a Heaviside step function. The CRPS thus compares the full distribution function of the forecast with the observation and not only selected confidence intervals. For normally distributed forecasts, a closed-form expression for the CRPS exists (Gneiting et al., 2004):

$$\begin{aligned} CRPS &= \frac{1}{n}\sum_{i=1}^{n} crps(Q_{obs,i}, Q_i, \sigma_i) \\ crps(Q_{obs}, Q, \sigma) &= \sigma\left[\frac{Q_{obs}-Q}{\sigma}\left(2\Phi\left(\frac{Q_{obs}-Q}{\sigma}\right)-1\right) + 2\phi\left(\frac{Q_{obs}-Q}{\sigma}\right) - \frac{1}{\sqrt{\pi}}\right] \end{aligned} \tag{8}$$

where σ is the standard deviation of the probabilistic forecast, Φ is the cumulative distribution function and ϕ the probability density function of the standard normal distribution. For a deterministic forecast, the CRPS is equivalent to the mean absolute error (Boucher et al., 2011; Schellekens et al., 2011). This allows for a systematic and objective comparison between deterministic and probabilistic forecasts.

The performance of operational forecasts was compared to two benchmark forecasts which can be produced with minimal effort: persistence and climatology. Persistence forecasts the flow as equal to the last available observation, while climatology forecasts the flow as equal to the historical average flow for this day of the year.

Results

Comparison of precipitation products

Comparison of the FEWS-RFE and NOAA-GFS precipitation products showed large deviations between the two products. Figure 2 shows a double mass plot for the average precipitation over the entire Kavango River catchment for the period 2005-2012. Obviously, there is a significant bias and the timing of precipitation events is inconsistent too, as evidenced by the wiggles in the double mass curve. The FEWS-RFE product is based on both satellite observations and in-situ gauging stations, while NOAA-GFS is derived from a global weather model. Moreover, FEWS-RFE has been shown to perform well in previous studies on the African continent (Milzow et al., 2011; Stisen and Sandholt, 2010). We therefore assume that the FEWS-RFE product is closer to the unknown true precipitation than NOAA-GFS and bias correct the NOAA-GFS data to match the long-term average precipitation for both products. A spatially and temporally constant precipitation correction factor of 0.67 was therefore used throughout the study. Figure 2 also presents a quantitative comparison of the NOAA-GFS precipitation forecasts for various forecasting horizons. As a general trend, the longer the forecasting horizon, the lower the predicted precipitation compared to the 1-day ahead forecasts. These effects are particularly pronounced for the rainy seasons 2008/2009 and 2011/2012. However, for the most recent years, the double mass plots show slopes close to unity. We therefore did not implement variable bias correction for the different forecasting horizons. Because the NOAA-GFS system is continuously updated and modified (process parameterization, spatial resolution etc.), performance of precipitation forecasts should be regularly checked during operational application of the hydrologic forecasting system. Changes in the quantitative precipitation forecasts may require adjustments in the bias correction and/or recalibration of the hydrological model.

Clearly, the quality of the precipitation forcing is a critical issue, which has significant control over the performance of the forecasting system. Within the TIGER-NET framework, we are dependent on public domain datasets and NOAA-GFS was the only free source of operational weather forecasts for the African continent available to the project. Potentially, model performance could be improved if NOAA-GFS data was corrected dynamically, for instance by continuously benchmarking it against real-time or near real-time precipitation products such as FEWS-RFE or TRMM-3B42 (Huffman et al., 2007) for the recent past and estimating a time-variable bias correction. An even better solution would be to merge NOAA-GFS data with in-situ precipitation data. However, no operational dataset of in-situ precipitation observations is available for this part of Africa.

Performance of the calibrated model

Table 3 provides an overview of the calibrated parameter values. All parameter values are physically reasonable and calibrated parameter values do not stick to the bounds of a-priori parameter intervals.

Model residuals were analysed and tested for normality and autocorrelation. Figure 5 summarizes the results of the model error analysis for the station Rundu. Figure 5a plots the relative error of the hydrologic-hydrodynamic model versus the observed discharge. Obviously, the relative error is not independent of discharge; it is higher for low discharge than for high discharge. The Q-Q plot in Figure 5b shows that the empirical distribution of model errors significantly deviates from a normal distribution. The empirical distribution of the model errors is narrower than the normal distribution and a larger portion of the data is clustered around the mean. The correlogram in Figure 5c shows highly significant auto-correlation of the model errors. Figure 5d shows the residual model errors (ε) after application of the AR1 model (equation 4), plotted against the observed discharge. This distribution looks more even than the distribution of the primary model residuals in Figure 5a. A test for normality using the Q-Q plot shows significant deviations and again a narrower distribution than the normal distribution (Figure 5e). Temporal correlations have been effectively removed from the model errors and no significant correlations remain as shown in Figure 5f. We conclude from this analysis that the relative error of the hydrologic-hydrodynamic model can be reasonably represented with an AR1 model. The time correlation of the AR1 model is δ=0.9942 on the daily time step. The random error contribution is ε=0.0438. As explained in the methods section, we assume, in the baseline experiment, that the same AR1 model parameters can represent the relative error of the runoff forcing and we use this result to parameterize the model error in the Kalman filter assimilation scheme.

Discharge forecasting and data assimilation

Table 5 reports the performance statistics for the probabilistic model runs. We report results for the open-loop run without assimilation, the assimilation run ("now-casting") as well as the 1-7 day ahead forecasts. The various forecasting horizons use different precipitation forcings (forecasts available at the simulated issue date) and in-situ data are assimilated up to simulated issue date. We only assimilate data from the station Rundu, because (i) no real-time observations are available for Mohembo and (ii) this enables us to assess the effect of upstream assimilation on a downstream station. The indicators are reported for both in-situ stations and for the calibration and the validation period. We are well aware that the observations in the calibration period have been used already for model calibration and are now used again for assimilation. Still, we feel that it is useful to present the statistics for information. Figure 6 shows the open-loop and assimilation run for the station Rundu during calibration and validation periods. We first assess the performance of the probabilistic open-loop run. Generally, the chosen error model seems to be appropriate. The forecasts produced by the open-loop run are reliable; the coverage of the nominal 95% confidence interval does not fall below 84% at any of the stations during any of the periods. However, the open-loop forecasts are not very sharp, as evidenced by the wide confidence intervals in Figure 6. This results in a relatively high ISS score.

The assimilation run is much sharper for all stations and periods but we observe a significant loss of reliability in the validation period. This can again be explained by the relatively low number of observations, particularly at the station Mohembo during the validation period as well as relative over-sampling of the high-flow period. ISS scores of the forecasting runs are much lower than for the open-loop run, which indicates massive improvement. The 1-7 day ahead forecast runs show degrading performance for increasing lead times. However, even the 7-day ahead forecast generally has a lower ISS than the open-loop run, except for Rundu during the validation period. Clearly, the central forecast is better for all lead times than the central run in the open-loop simulation. All three indicators (NSE, RMSE and ME) show significant improvement. Coverage decreases rapidly with increasing lead time for the station Rundu but is more or less independent of lead time for the station Mohembo. This can be explained by the routing time lag between the two stations.

Improvements due to assimilation of Rundu data travel down to Mohembo and are still visible at this station after many days. For the station Rundu, increased sharpness is over-compensated by loss of reliability, which leads to increasing ISS scores with increasing lead time. For the validation period, only the 0-3 ahead forecasts are better than the open-loop run, if evaluated with the ISS score.

Table 6 summarizes the performance of the operational forecasts produced in the different forecasting experiments for the validation period and the station Rundu. Results are reported for the baseline and experiments 1, 3 and 4. Experiment 2 produced results that are very similar to the baseline results and those are therefore not separately reported. Table 6 also includes the performance indicators for the persistence and climatology benchmarks.

Experiment 4 generally shows the best performance. According to the CRPS score, the forecasts are superior to the open-loop run for all forecasting horizons. Forecasts are also better than the persistence benchmarks for forecasting horizons between 4 and 7 days. For forecasting horizons between 1 and 6 days, the model outperforms the climatology benchmark. The persistence index indicates that the forecasting system performs worse than the persistence benchmark. However, it is important to note that the PI does not assess the quality of probabilistic forecasts in terms of sharpness and reliability but only takes the central forecast into account and compares two deterministic predictions.

Figure 7 graphically presents the forecasts produced in experiment 4 for the station Rundu during the validation period and Figure 8 shows predictive quantile-quantile plots for these forecasts.

Discussion

The presented approach for the generation of probabilistic river discharge forecasts is simple and robust and designed to work in data-sparse and poorly gauged basins. A key factor for the performance of the system is the rainfall forcing. While the NOAA-GFS rainfall can produce reasonably reliable and sharp forecasts for the Kavango River, the product should be further compared against other operational precipitation products. A promising avenue for future research may be dynamic bias correction using other precipitation or soil moisture products. From Table 6, we conclude that extending the forecast lead time beyond 7 days could add value to the system, because CRPS scores are still well below the open-loop score at 7 day lead time and comparison with CRPS of persistence indicates break-even at around 4 days. NOAA-GFS does actually provide forecasts up to 16 days into the future. However, the spatial resolution is reduced by a factor of 2 for forecasting horizons beyond one week. It may nevertheless be valuable to explore the use of more long-term weather forecasts. To further improve the reliability and sharpness of the forecasts, an ensemble of weather forecasts should be used to drive the forecasting system (Cloke and Pappenberger, 2009). One potential source of free ensemble weather forecasts for the African continent is the Global Ensemble Forecasting System (GEFS, http://www.emc.ncep.noaa.gov/?branch=GEFS).

As in other hydrologic data assimilation studies (e.g. Clark et al., 2008), parameterization of the model error is a fundamental issue for the performance of the assimilation scheme. Generally, model error terms can be added to the forcings, the states, and the parameters of a model. Here, we assign all model error to the runoff forcing and quantify magnitude and auto-correlation of the error based on the comparison of simulated and observed river discharge. Unlike other authors, we do not apply error terms to the states and parameters of the routing model, because we assume that these error contributions are minor compared to the runoff error. While this approach is robust and efficient, it clearly represents a strong simplification of reality. It is clear that the simple Muskingum routing model has significant structural error, for instance due to the fact that floodplains and surface water / groundwater interactions are not simulated.

Comparison of the various forecasting experiments shows that assumptions about the model and observation errors have a large impact on the performance of the forecasting system. The magnitude of the relative runoff error is particularly sensitive, as evidenced by the improved performance of experiment 4 compared to the baseline. It is reasonable to assume a higher relative error for the runoff than the relative error computed from the model residuals at Rundu, because the routing model has a smoothing effect on the runoff response. Experiment 3 and the baseline show a comparable performance in terms of CRPS. Basically the higher assumed observation error in experiment 3 results in predictions that are less sharp but more reliable. Comparison of experiment 1 and baseline results shows that even small differences in the assumed autocorrelation of the runoff error result in significant differences in the forecast performance. Higher error autocorrelation leads to increased sharpness, but lower reliability. CRPS indicates that experiment 1 forecasts marginally outperform the baseline forecasts. Experiment 2 results are very close to the baseline, because the spatial correlation of runoff between the different subcatchments is low, due to the variable hydrologic characteristics of the subcatchments. Predictive Q-Q plots for experiment 4 (Figure 8) indicate significant deviations of the empirical distribution of normalized forecast errors from the normal distribution.

As is common for studies dealing with probabilistic river discharge forecasting, we find that our probabilistic forecasts are over-reliable during low flow periods and under-reliable during high-flow periods. This issue can be addressed by separating the total runoff forcing generated by the SWAT model into its components, i.e. overland flow, interflow and baseflow, and developing separate error representations for the various runoff components. However, given the sparse availability of in-situ observations in the basins, it may be difficult to find robust parameters for these error representations.

We generally observe weaker performance of the forecasting system in the beginning of the rainy season, i.e. after the long dry season during the onset of the annual high-flow season. This may be due to deficiencies in the precipitation forecasts and/or due to weaknesses in the representation of hydrological processes in the SWAT model. It appears that in reality, the first rains in the early rainy season already lead to increased river flow, while in the model, these precipitation events are completely absorbed in the various simulated hydrological storage compartments.

In this study, focus has been on the final output of the modelling chain, i.e. river discharge. However, SWAT simulates a multitude of intermediate states and fluxes in the land phase of the hydrological cycle, which could be analysed and compared to observations, if such observations were available. There is an obvious opportunity to inform the modelling system with other types of in-situ and remote sensing observations such as radar altimetry, soil moisture and total water storage from time-variable gravity (Milzow et al., 2011). However, if such data were to be formally assimilated to the modelling system, an ensemble approach would have to be chosen because of the highly non-linear responses inherent in the SWAT model. Many studies have addressed ensemble-based streamflow forecasting with lumped-conceptual or distributed hydrological models. Rakovec et al., 2012 found that rainfall-runoff model states were less sensitive compared to routing states in their hydrologic data assimilation study with the Ensemble Kalman Filter and suggested time lags between the rainfall-runoff model states and streamflow response as the likely reason. Alternative updating strategies that use several previous time steps instead of the last time step only (e.g. Ensemble Kalman Smoother) can potentially solve these problems. Other recurring issues in such studies are high computational demand, and model error parameterization (e.g. Clark et al., 2008).

Conclusions

We have presented an operational probabilistic river discharge forecasting system for poorly gauged basins which relies exclusively on public-domain, open-source software and data. The forecasting system is specifically adapted to the conditions prevailing in many African basins, such as weak in-situ monitoring infrastructure, budget constraints for operational monitoring and management as well as weak institutional capacity. We demonstrated the performance of the forecasting system for the Kavango River and obtained encouraging results. Zero to 7-day ahead probabilistic forecasts produced by the system are sharp and reliable. The results indicate that forecasting horizons could be extended to more than seven days, if suitable weather forecasting products can be made available. The system may also benefit from ingestion of other types of in-situ or remotely sensed observations such as radar altimetry and soil moisture. The TIGER-NET project and its Water Observation and Information System (WOIS) provide an ideal platform to combine remote sensing observations and hydrological models to generate accurate estimates of hydrological states as well as sharp and reliable forecasts for operational water resources management.

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Tables

Table 1: Characteristics of the Kavango River basin and the Rundu and Mohembo sub-basins

Sub-basin	Catchment area (km^2)	Mean elevation (mamsl)	Mean annual precipitation (bias-corrected 1-day ahead NOAA-GFS, mm)
Kavango	162050	1320	847
Rundu	101520	1341	843
Mohembo	60530	1286	853

Table 2: Model performance for calibration and validation periods. Numbers in brackets are percent of mean observed flow.

In-situ station	NSE (-)	RMSE (m^3/s)	ME (m^3/s)	Mean of observations (m^3/s)	No. of simulated observations
Calibration Period (2005-2011)					
Rundu	0.73	105.6 (42.5%)	-5.4 (-2.2%)	248.4	2440
Mohembo	0.69	97.1 (32.8%)	6.8 (2.3%)	295.9	1935
Validation Period (2012-2014)					
Rundu	0.74	94.6 (35.0%)	-55.0 (-20.6%)	249.0	572
Mohembo	0.33	144.0 (30.7%)	-119.0 (-25.4%)	469.1	46

Table 3: Model calibration parameters. Subcatchment IDs for the various regions: r = 2+3+5+6+7+9+10; m = 1+4+8+11+12; ru = 2+3; rd = 5+6+7+9+10; mu = 1; md = 4+8+11+12; ruh = HRUs in region ru with terrain slope above 2%; rul = HRUs in region ru with terrain slope below 2%; rdh = HRUs in region rd with terrain slope above 2%; rdl = HRUs in region rd with terrain slope below 2%; muh = HRUs in region mu with terrain slope above 2%; mul = HRUs in region mu with terrain slope below 2%; mdh = HRUs in region md with terrain slope above 2%; mdl= HRUs in region md with terrain slope below 2%.

Parameter	Description and unit	Lower bound	Calibrated value		Upper bound
CN2_m	Multiplier on the SCS curve number for moisture condition II (dimensionless)	0.6	r	0.63	1.2
			m	0.65	
ESCO	Soil evaporative compensation factor (dimensionless)	0.5	r	0.95	1
			m	0.80	
EPCO	Plant uptake compensation factor (dimensionless)	0.5	r	0.89	1
			m	0.92	
CH_N1	Manning's n for tributary channels ($sm^{-1/3}$)	0.02	r	0.185	0.2
			m	0.023	
CH_N2	Manning's n for main reaches ($sm^{-1/3}$)	0.02	r	0.023	0.2
			m	0.104	
GW_DELAY	Groundwater delay (days)	30	ru	81.3	120
			rd	43.4	
			mu	101.6	
			md	112.8	
ALPHA_BF	Base flow recession constant (dimensionless)	0.05	ruh	0.676	1
			rul	0.177	
			rdh	0.221	
			rdl	0.730	
			muh	0.846	
			mul	0.264	
			mdh	0.161	
			mdl	0.080	
GW_REVAP	Groundwater re-evaporation coefficient (dimensionless)	0	ruh	0.81	1
			rul	0.90	
			rdh	0.68	
			rdl	0.53	
			muh	0.75	
			mul	0.86	
			mdh	0.90	
			mdl	0.26	
REVAPMN	Threshold depth of water in shallow aquifer for re-evaporation to occur (mm)	0	ruh	103	200
			rul	29	
			rdh	75	
			rdl	31	
			muh	15	
			mul	100	
			mdh	97	
			mdl	26	
LOSS_11	Fractional loss from the Kavango River between Rundu and Mohembo, due to evaporation, infiltration and abstraction (dimensionless)	0	0.011		0.2

Table 4: Overview of the different forecasting experiments

Experiment	Autocorrelation of relative runoff error	Relative runoff error	Spatial correlation of relative runoff error	Relative observation error
Baseline	Same as autocorrelation of model error at Rundu (0.9942)	4.38%	Same as spatial correlation of runoff	10%
Experiment 1	Same as autocorrelation of total runoff (0.9934)	4.38%	Same as spatial correlation of runoff	10%
Experiment 2	Same as autocorrelation of model error at Rundu (0.9942)	4.38%	Zero	10%
Experiment 3	Same as autocorrelation of model error at Rundu (0.9942)	4.38%	Same as spatial correlation of runoff	20%
Experiment 4	Same as autocorrelation of model error at Rundu (0.9942)	6%	Same as spatial correlation of runoff	10%

Table 5: Performance of the operational model in the calibration and validation periods

Period	In-situ station	Run	NSE (-)	RMSE (m^3/s)	ME (m^3/s)	Cove-rage (%)	Sharp-ness (m^3/s)	Interval Skill Score (m^3/s)	Mean of predicted observations (m^3/s)	No. of predicted obser-vations
Calibration Period (2005-2011)	Rundu	Open-Loop	0.73	105.6	-5.4	90.0	423.5	654.9	248.4	2440
		Assimilation	0.99	22.9	-0.9	88.6	54.1	147.1	248.4	2440
		1-day ahead	0.98	29.2	-0.3	86.7	64.4	196.3	248.5	2440
		2-day ahead	0.97	36.5	0.5	85.8	75.6	250.8	248.7	2439
		3-day ahead	0.95	44.0	1.3	84.5	86.7	307.5	248.9	2438
		4-day ahead	0.94	51.2	2.2	83.6	97.2	362.0	249.1	2437
		5-day ahead	0.92	57.9	3.1	83.3	106.9	415.2	249.3	2436
		6-day ahead	0.90	64.1	4.0	82.6	115.8	465.5	249.4	2435
		7-day ahead	0.88	69.9	4.9	81.9	124.0	511.5	249.6	2434
	Mohembo	Open-Loop	0.69	97.1	6.8	93.3	478.2	638.1	295.9	1935
		Assimilation	0.93	45.1	-11.3	93.3	154.5	251.2	295.9	1935
		1-day ahead	0.93	45.2	-11.2	93.3	154.5	251.7	295.9	1935
		2-day ahead	0.93	45.1	-11.1	93.4	154.6	249.3	296.0	1934
		3-day ahead	0.93	45.0	-11.0	93.4	154.7	246.9	296.0	1933
		4-day ahead	0.93	44.9	-10.9	93.5	154.8	244.7	296.1	1932
		5-day ahead	0.93	44.8	-10.8	93.5	154.9	242.4	296.2	1931
		6-day ahead	0.93	44.8	-10.6	93.4	155.2	240.2	296.3	1930
		7-day ahead	0.93	45.0	-10.4	93.3	155.5	238.4	296.4	1929
Validation Period (2012-2014)	Rundu	Open-Loop	0.74	94.6	-55.0	83.9	224.6	515.9	249.0	572
		Assimilation	0.97	31.7	-0.5	81.8	43.6	265.7	249.0	572
		1-day ahead	0.96	39.3	0.5	78.8	49.3	351.4	252.5	556
		2-day ahead	0.94	47.3	1.5	75.9	54.9	442.4	254.1	547
		3-day ahead	0.92	54.8	2.3	74.6	60.1	527.4	254.0	544
		4-day ahead	0.89	61.6	3.1	72.4	65.1	609.9	254.2	540
		5-day ahead	0.87	67.5	3.7	70.8	69.9	687.6	254.9	534
		6-day ahead	0.86	72.3	4.2	69.5	74.2	750.4	254.8	531
		7-day ahead	0.84	76.0	4.4	69.0	78.2	799.6	254.4	529
	Mohembo	Open-Loop	0.33	144.0	-119	93.5	498.4	686.7	469.1	46
		Assimilation	0.92	48.4	-9.0	80.4	176.3	206.5	469.1	46
		1-day ahead	0.92	48.7	-7.6	81.8	178.3	209.5	478.9	44
		2-day ahead	0.92	49.0	-8.0	82.2	177.3	208.2	473.4	45
		3-day ahead	0.92	49.9	-7.4	81.8	178.5	210.6	480.4	44
		4-day ahead	0.91	51.2	-7.5	79.5	178.6	213.6	481.4	44
		5-day ahead	0.91	52.3	-6.9	79.5	178.9	218.0	481.1	44
		6-day ahead	0.91	52.7	-7.8	76.6	176.4	233.0	464.2	47
		7-day ahead	0.92	52.1	-8.4	79.2	175.2	255.7	449.0	48

Table 6: Performance indicators for the forecasts issued for the station Rundu in the validation period, excluding model "warm-up" periods

Run	NSE (-)	RMSE (m^3/s)	Cove-rage (%)	Sharp-ness (m^3/s)	Interval Skill Score (m^3/s)	Persistence index (-)	CRPS (m^3/s)	No. of predicted obser-vations
Benchmarks								
Persistence, 1-day ahead	1.00	10.3					6.3	556
Persistence, 2-day ahead	0.99	18.4					12.1	547
Persistence, 3-day ahead	0.98	26.7					17.6	544
Persistence, 4-day ahead	0.97	34.7					23.2	540
Persistence, 5-day ahead	0.95	42.6					28.5	534
Persistence, 6-day ahead	0.93	50.2					33.6	531
Persistence, 7-day ahead	0.91	57.4					38.5	529
Climatology	0.82	78.5	100	346.1	346.1		28.2	580
Baseline								
Open-Loop	0.74	94.6	83.9	224.6	515.9		40.0	572
Assimilation	0.97	31.7	81.8	43.6	265.7		13.1	572
1-day ahead	0.96	39.3	78.8	49.3	351.4	-13.7	16.7	556
2-day ahead	0.94	47.3	75.9	54.9	442.4	-5.6	20.3	547
3-day ahead	0.92	54.8	74.6	60.1	527.4	-3.2	23.8	544
4-day ahead	0.89	61.6	72.4	65.1	609.9	-2.1	27.1	540
5-day ahead	0.87	67.5	70.8	69.9	687.6	-1.5	30.1	534
6-day ahead	0.86	72.3	69.5	74.2	750.4	-1.1	32.7	531
7-day ahead	0.84	76.0	69.0	78.2	799.6	-0.8	34.9	529
Experiment 1								
Open-Loop	0.74	94.6	89.9	295.6	473.0		38.4	572
Assimilation	0.98	25.8	87.6	49.5	189.4		10.0	572
1-day ahead	0.97	33.9	84.5	57.7	261.2	-9.9	13.4	556
2-day ahead	0.95	42.6	83.4	66.2	339.7	-4.4	16.9	547
3-day ahead	0.93	50.9	82.2	74.2	416.1	-2.7	20.4	544
4-day ahead	0.90	58.5	81.5	81.8	485.6	-1.8	23.7	540
5-day ahead	0.88	65.2	80.9	89.1	549.1	-1.3	26.8	534
6-day ahead	0.86	70.5	79.5	95.6	599.5	-1.0	29.4	531
7-day ahead	0.85	74.7	78.8	101.5	635.6	-0.7	31.6	529
Experiment 3								
Open-Loop	0.74	94.6	91.3	315.5	464.8		38.1	572
Assimilation	0.96	39.2	85.8	74.9	261.1		15.6	572
1-day ahead	0.94	46.1	83.8	82.2	323.1	-19.2	18.7	556
2-day ahead	0.92	53.2	82.8	89.2	385.9	-7.3	21.8	547
3-day ahead	0.90	59.7	81.6	95.7	441.1	-4.0	24.6	544
4-day ahead	0.88	65.7	81.1	101.9	493.5	-2.6	27.2	540
5-day ahead	0.86	70.9	80.9	108.0	539.4	-1.8	29.7	534
6-day ahead	0.84	75.1	80.0	113.4	571.2	-1.2	31.7	531
7-day ahead	0.83	78.5	79.6	118.5	595.9	-0.9	33.3	529
Experiment 4								
Open-Loop	0.74	94.6	95.3	432.2	525.3		38.6	572
Assimilation	0.99	20.5	91.1	55.6	141.6		7.7	572
1-day ahead	0.98	29.0	89.4	67.5	202.4	-7.0	10.8	556
2-day ahead	0.96	38.4	88.5	80.1	269.0	-3.4	14.3	547
3-day ahead	0.94	47.7	88.6	92.1	335.2	-2.2	17.8	544
4-day ahead	0.91	56.2	87.8	103.6	397.8	-1.6	21.1	540
5-day ahead	0.89	63.8	86.5	114.4	454.0	-1.2	24.2	534
6-day ahead	0.87	69.8	85.7	123.9	497.8	-0.9	26.8	531
7-day ahead	0.85	74.6	85.6	132.7	531.6	-0.7	29.0	529

Figures

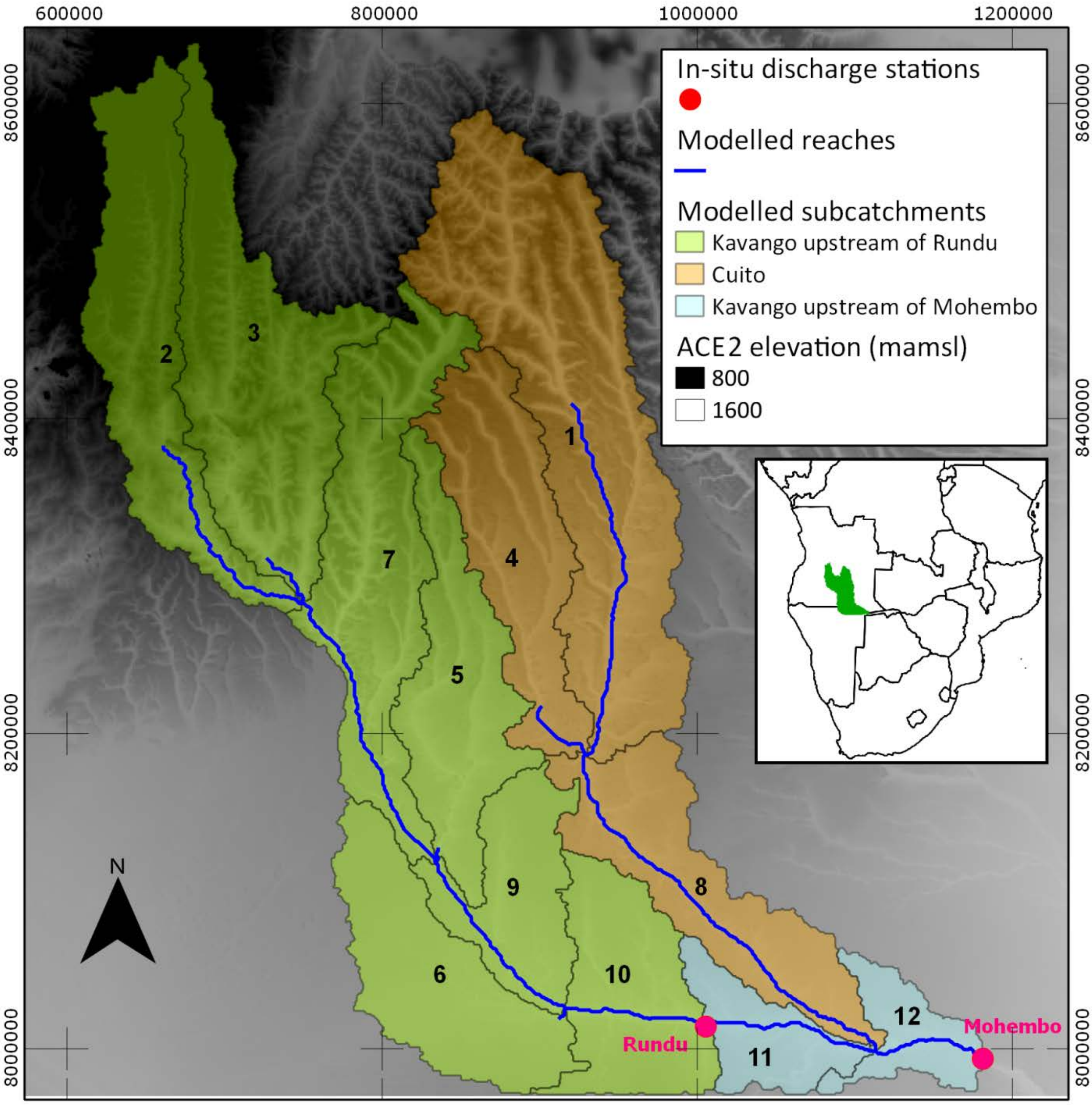

Figure 1: Basemap for the Kavango River Basin with location of in-situ discharge stations. The coordinate system is UTM 33S, WGS84 datum. Inset map shows the location of the basin in Southern Africa.

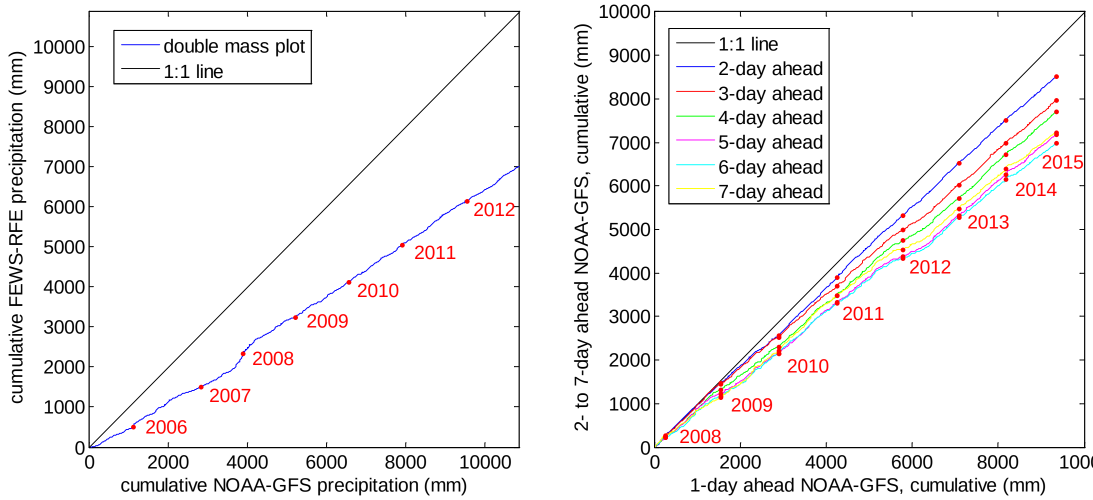

Figure 2: Left: Double mass plot of the FEWS-RFE and NOAA-GFS precipitation products averaged over the entire Kavango River basin. Right: Double mass plots of the 1-day ahead forecasted NOAA-GFS precipitation and the 2-7 day ahead forecasted NOAA-GFS precipitation averaged over the entire Kavango River basin.

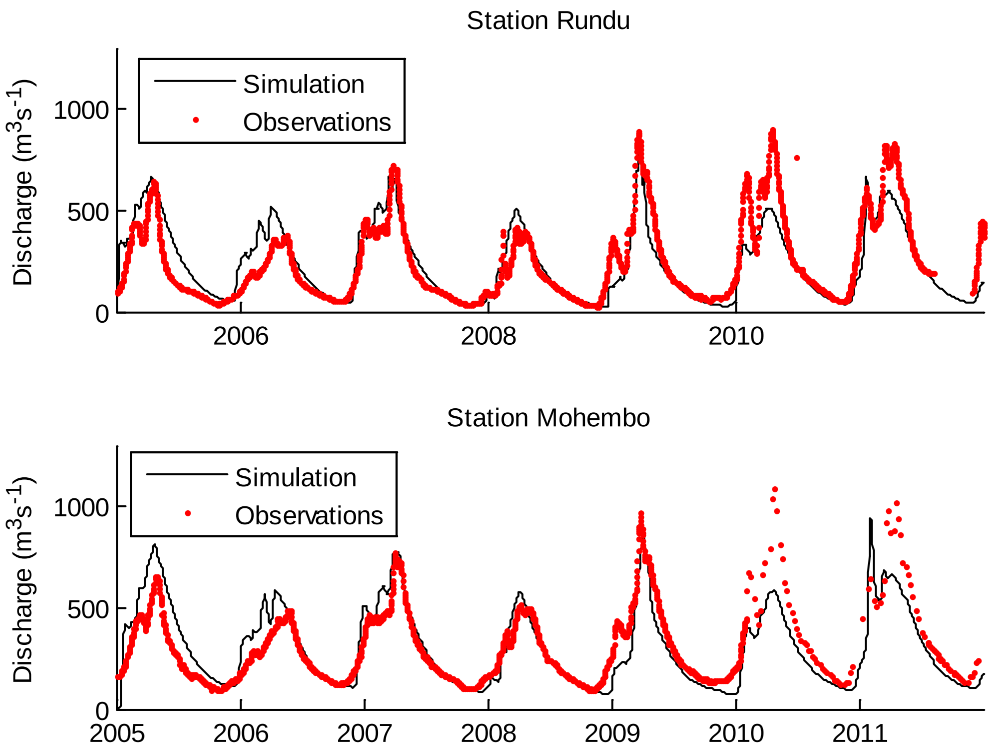

Figure 3: Observed (red dots) and simulated (black lines) hydrographs for the calibration period for Rundu (top) and Mohembo (bottom).

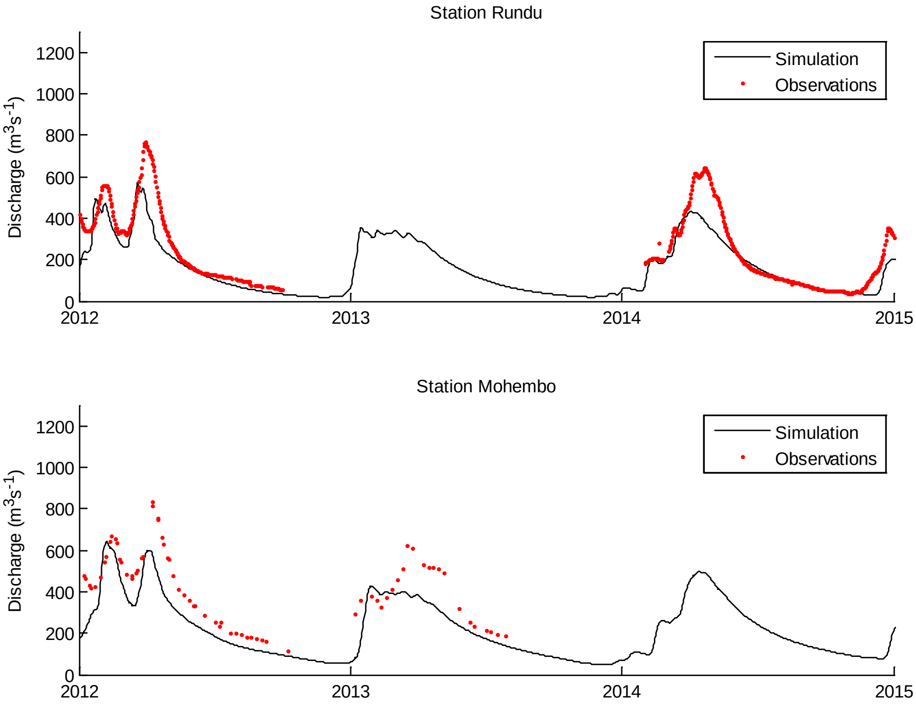

Figure 4: Observed (red dots) and simulated (black lines) hydrographs for the validation period for Rundu (top) and Mohembo (bottom).

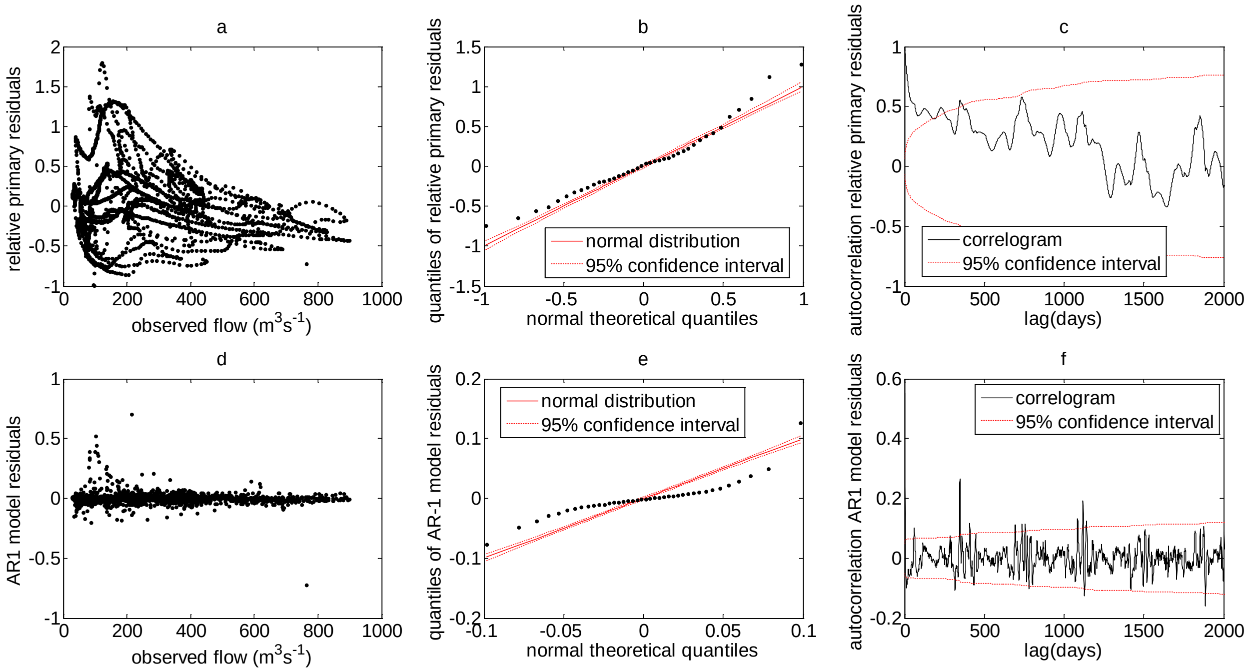

Figure 5: a) Relative error of the hydrologic-hydrodynamic model vs observed discharge. b) Q-Q plot of the relative errors shown in a). c) Correlogram of the relative errors shown in a). d) Relative errors of hydrologic-hydrodynamic model after removal of the time-correlated part plotted vs observed discharge. e) Q-Q plot of the relative errors shown in d). f) Correlogram of the relative errors shown in d).

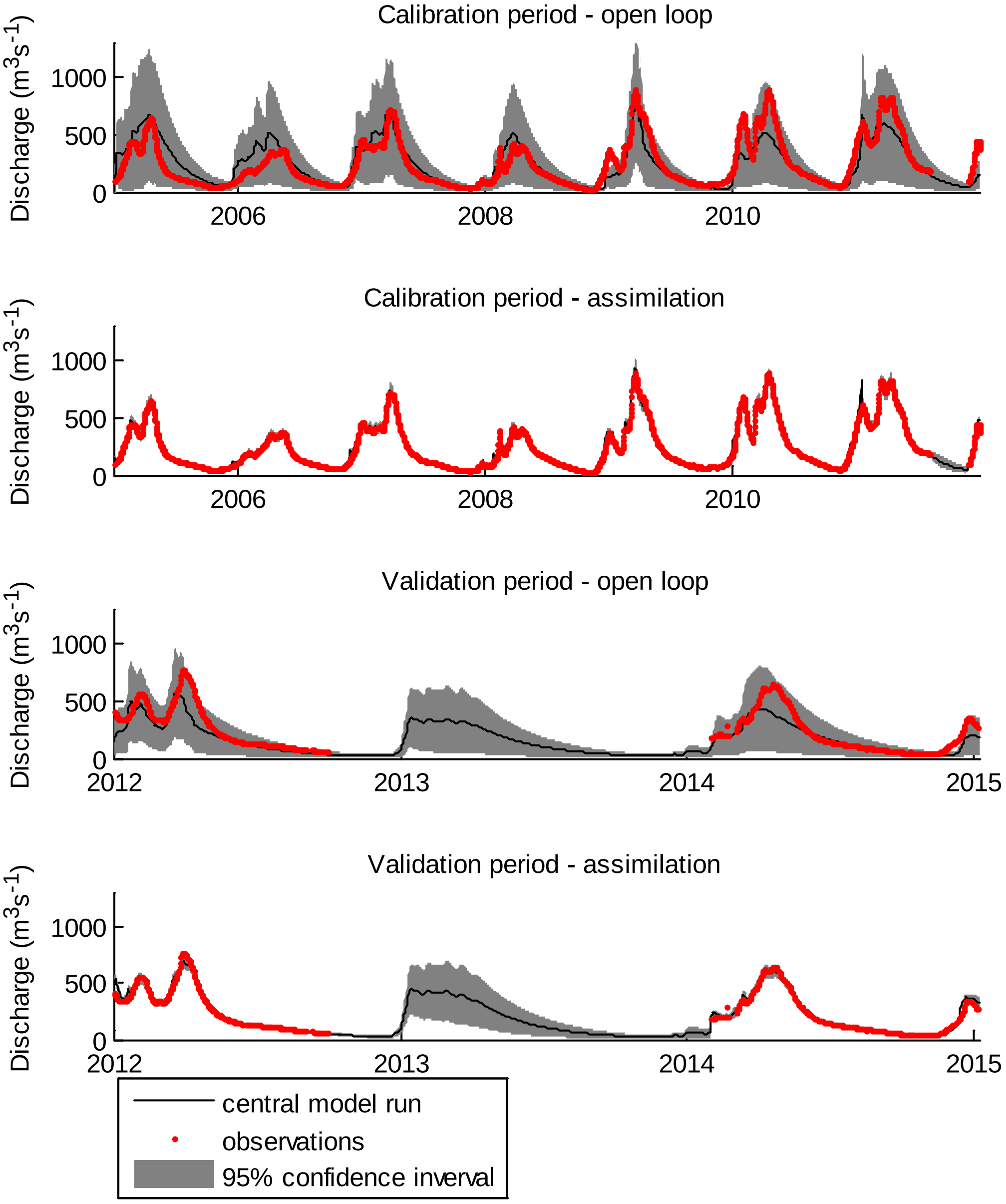

Figure 6: Probabilistic simulation of river discharge in the open-loop and assimilated run for the calibration and the validation periods for the station Rundu.

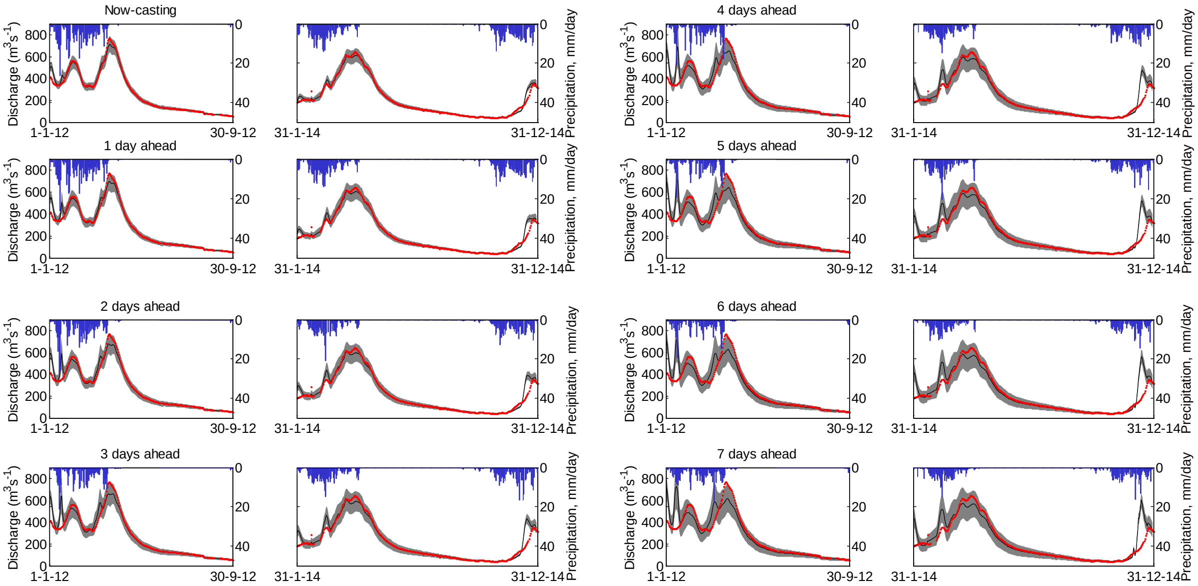

Figure 7: Performance of the 0-7 day ahead probabilistic forecasts in the validation period at Rundu station for experiment 4. The black solid line is the central forecast. Grey shading indicates the 95% confidence interval of the forecast and red dots are observations. Blue bars indicate daily forecasted precipitation from NOAA-GFS.

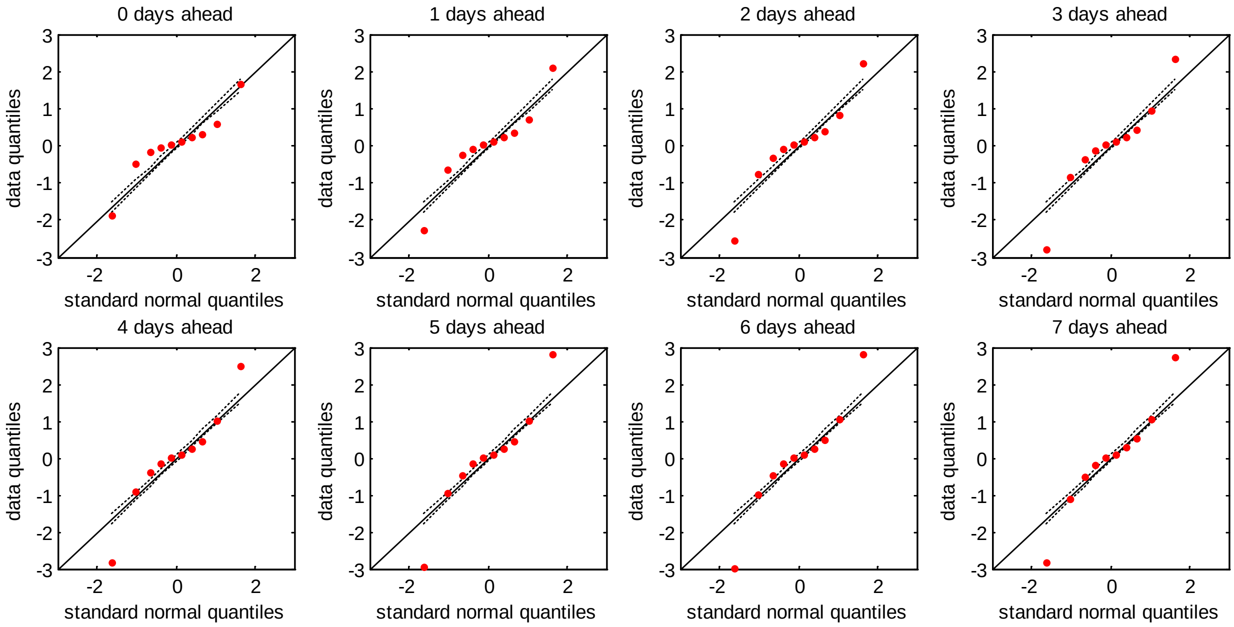

Figure 8: Predictive Q-Q plots for the station Rundu and the validation period for experiment 4.