Journal of Hydrology (2008) **352**, 30–49

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

Estimation of freshwater availability in the West African sub-continent using the SWAT hydrologic model

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Received 5 February 2007; received in revised form 7 August 2007; accepted 17 December 2007

KEYWORDS
Blue water;
Green water;
Prediction uncertainty;
SUFI-2;
dGen

Summary Accurate knowledge of freshwater availability is indispensable for water resources management at regional or national level. This information, however, has historically been very difficult to obtain because of lack of data, difficulties in the aggregation of spatial information, and problems in the quantification of distributed hydrological processes. The currently available estimates of freshwater availability by a few large international organizations such as FAO and UNESCO are often not sufficient as they only provide aggregated rough quantities of river discharge and groundwater recharge (blue water) at a national level and on a yearly basis. This paper aims to provide a procedure to improve the estimations of freshwater availability at subbasin level and monthly intervals. Applying the distributed hydrological model ''Soil and Water Assessment Tool'' (SWAT), the freshwater availability is quantified for a 4-million km^2 area covering some 18 countries in West Africa. The procedure includes model calibration and validation based on measured river discharges, and quantification of the uncertainty in model outputs using ''Sequential Uncertainty Fitting Algorithm'' (SUFI-2) The aggregated results for 11 countries are compared with two other studies. It was seen that for most countries, the estimates from the other two studies fall within our calculated prediction uncertainty ranges. The uncertainties are, in general, within reasonable ranges but larger in subbasins containing features such as dams and wetlands, or subbasins with inadequate climate or landuse information. As the modelling procedure in this study proved quite successful, its application for quantification of freshwater availability at a global scale is already underway. There are, however, two limitations in the West African model: (1) not all the components of the water balance model such as soil moisture or deep aquifer recharge

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0022-1694/$ - see front matter
doi:10.1016/j.jhydrol.2007.12.025

could be directly calibrated because of lack of data and (2) the full capabilities of the SWAT model could not be realized because of the lack of local water and agricultural management information.

Introduction

Freshwater availability at the global scale is an essential requirement and one of the most important challenges facing humanity at present and increasingly in the future. Other major global concerns, like food security, human health, climate change, economic development and, last but not least, regional conflicts are not exclusively but to a considerable extent related to freshwater availability. There is much ongoing research on these global topics but they are often based on imprecise estimates of the temporally and spatially unevenly distributed water resources. Beside the country-based water resources estimated by Shiklomanov (2000) on the basis of data generalization of the world hydrological network, most other studies used either climate or hydrological models. Global runoff estimates performed with existing global climate models, e.g., Nijssen et al. (2001) and Oki et al. (2001), among others, are, as stated by Döll et al. (2003), ''quite inaccurate due to their low spatial resolution, poor representation of soil water processes, and, in most cases, lack of calibration against measured discharge''. More accurate estimations, in terms of the hydrological processes, are based on global hydrological models, e.g., Alcamo et al. (2003), Arnell (1999), Vörösmarty et al. (1998), Yang and Musiake (2003) and Yates (1997), which are all raster models with a spatial resolution of 0.5° (55.7 km at the equator) and driven by monthly climatic variables (Döll et al., 2003). Probably the most sophisticated of these models is WaterGAP 2 (Alcamo et al., 2003; Döll et al., 2003) that combines a hydrological model with a water use model and calculates surface runoff and groundwater recharge based on a daily water balance of soil and canopy (Alcamo et al., 2003). The model is tuned against observed discharge at 724 gauging stations spread globally by adjusting the runoff coefficient and, in case this was not sufficient, by applying up to two correction factors, especially in snow-dominated and semiarid or arid regions (Döll et al., 2003). The main shortcomings of the freshwater estimates based on WaterGAP 2 are that (1) while it runs on a daily time step, the model is only tuned and validated against long-term annual discharge, hence, has a poor temporal resolution, (2) the application of correction factors to the modelled discharges leads to an inconsistent water balance and (3) they don't quantify the model prediction uncertainty, which could be quite large in distributed models.

Against this background the objective of our modelling work is to assess the global freshwater availability at a subbasin level and monthly intervals. The current work is based on an application to West Africa, which includes the basins of the rivers Niger, Volta, and Senegal covering a total area of 4-million km^2. For this purpose, the distributed watershed model ''Soil and Water Assessment Tool'' (SWAT, Arnold et al., 1998) was selected. SWAT is a mechanistic time-continuous model that can handle very large watersheds in a data efficient manner. The model is already used in the ''Hydrologic Unit Model for the United States'' (HUMUS) (Arnold et al., 1999; Srinivasan et al., 1998), where the entire US was simulated with good results for river discharges at around 6000 gauging stations. This study is now extended within the national assessment of the USDA Conservation Effects Assessment Project (CEAP, http://www.nrcs.usda.gov/Technical/nri/ceap/ceapgeneralfact.pdf). A more recent large-scale SWAT application included the work of Gosain et al. (2006) where 12 large river basins in India were modelled with the purpose of quantifying the climate change impact on hydrology. SWAT is recognized by the US Environmental Protection Agency (EPA) and has been incorporated into the EPA's BASINS (Better Assessment Science Integrating Point and Non-point Sources) (Di Luzio et al., 2002). We used SWAT2000 (Neitsch et al., 2002) for this project, which is linked with ArcView GIS (Di Luzio et al., 2001). A new version of the program, ArcSWAT (Winchell et al., 2007), is now available with a link to ArcGIS 9.1 with capabilities to handle larger watersheds. We are currently applying ArcSWAT to the whole of Africa. The interfaces facilitate pre- and post-processing (e.g., watershed delineation, manipulation of the spatial and tabular data), though the model itself remains independent of GIS. Another reason for choosing SWAT is its ability to perform water quality modelling, which we also plan to study next.

One of the important outputs of the model used in this study is the monthly sub-country values for both the ''blue water'' and the ''green water'' resources. Currently, the definition of blue water is generally accepted as ''the sum of the river discharge and the deep groundwater recharge''. This is in essence the water resources by the traditional hydrological and engineering definition. There exist slightly different definitions for the term green water. In this study we refer to the definition given by Falkenmark and Rockström (2006), who differentiate between the green water ''resource'' and the green water ''flow'', although we prefer the term ''storage'' instead of ''resource'' in this definition. According to their definition, ''green water storage is the moisture in the soil''. This part of the water is a renewable resource because it can potentially generate economic returns, as it is the source of the rainfed agriculture. The green water flow is composed of the actual evaporation (the non-productive part) and the actual transpiration (the productive part), commonly referred to together as the actual evapotranspiration. Applying the SWAT model, this study will quantitatively determine the volumes of the different components of water resources with consideration of the spatial and temporal variations. The results will contribute to a better understanding of the paradigm of blue and green water resources and consequently benefit the water resources planning and management.

Another important aspect of this paper is its contribution to the ongoing research on calibration and uncertainty analysis of large-scale distributed watershed models. Distributed watershed models are increasingly being called upon to investigate alternative management strategies in the areas of landuse changes, water availability/distribution, construction of waterworks, and pollution control. For this reason it is important that these models are carefully calibrated and their prediction uncertainty quantified before being used for decision making. To fulfil this demand, in recent years, researchers have come up with various uncertainty analysis techniques for watershed models. These include Bayesian inference methods such as Markov Chain Monte Carlo (Vrugt et al., 2003), Generalized Likelihood Uncertainty Estimation (GLUE) (Beven and Binley, 1992), and Parameter Solution (ParaSol) (van Griensven and Meixner, 2006), among many others. In this study, we use the program SUFI-2 (Abbaspour et al., 2004, 2007), which combines calibration and uncertainty analysis. This program is linked to SWAT in the calibration package SWAT-CUP (SWAT Calibration Uncertainty Procedures), which includes GLUE and ParaSol as well. Using SUFI-2, it was possible to handle a large number of parameters and measured data from many gauging stations simultaneously. In a comparison study Yang et al. (submitted for publication) found that SUFI-2 required much fewer simulations than other methods while producing similar Nash—Sutcliff and R^2 values when the best calibration and validation results were compared with measured data.

Materials and methods

The SWAT simulator

SWAT (Arnold et al., 1998) belongs to the group of deterministic, distributed hydrological models. It is a continuous time model and operates on a daily time step at basin scale. The main components of SWAT include weather, hydrology, sedimentation, crop growth, nutrients, pesticides, agricultural management, and stream routing. In this study, however, we focus only on the hydrologic component of SWAT, while in a later study we aim to include agricultural management to study water quality.

In SWAT the spatial heterogeneity of the watershed is taken into account, considering information from the elevation map (DEM), the soil and landuse maps. The computed runoff from each subbasin is routed through the river network to the main basin outlet by using, in our case, the Muskingum method.

The hydrologic model is based on the water balance for the four storage volumes snow, soil profile, shallow aquifer, and deep aquifer, and considers precipitation, interception, evapotranspiration, surface runoff, infiltration, percolation, and subsurface runoff. Depending on data availability, the potential evapotranspiration (PET) can be computed using different methods and we selected the Hargreaves method. Based on the PET and additional soil and landuse parameters, the actual plant transpiration and the actual soil evaporation are estimated separately. The surface runoff from daily rainfall amounts is modelled using a modification of the SCS curve number method taking into account landuse, soil type and antecedent soil moisture. The soil profile can be subdivided into multiple layers (two layers in this study) and the model considers infiltration, evaporation, plant uptake, interflow as well as up- and downward redistribution processes for each layer. A more detailed description of the model can be found in Arnold et al. (1998) and Neitsch et al. (2002).

The daily weather generator algorithm dGen

One of the most fundamental inputs to hydrological models like SWAT is weather data. SWAT requires daily data for precipitation and minimum/maximum temperature. It assigns to each subbasin the data of the nearest climate station. In many areas of the world, including West Africa, the gauging station network is not very dense, and data duration is quite short and includes many missing and often erroneous data. The weather generator program WXGEN (Sharpley and Williams, 1990) is incorporated in SWAT to simulate missing data. This program was developed for the contiguous US and fills data gaps or extends time series of daily data based on monthly statistics. The monthly statistics are, however, based on long series of daily data. Hence, the program is not useful if there are no daily data available, or the existing data are from a station far away from a specific subbasin.

In this study, the monthly climate statistics provided by the Climatic Research Unit (CRU) were used to generate the daily data required to run SWAT. CRU provides complete monthly global data at 0.5° grids for the time-period 1901—1995 (Mitchell and Jones, 2005; New et al., 2000). Using the CRU monthly values for precipitation, minimum and maximum temperature and the number of wet days per month, Schuol and Abbaspour (2007) developed a semi-automated daily weather generator algorithm dGen, to obtain the required daily inputs. dGen is based on SIMMETEO (Geng et al., 1986), a procedure that works based on monthly climatic summaries unlike many other generators that use daily measured values. Researches have shown that the performance of SIMMETEO is rather similar to the generators based on daily measured values (Hartkamp et al., 2003; Soltani and Hoogenboom, 2003), indicating the potential applicability of the monthly CRU data.

To use dGen, the 0.5° climate grids are first overlaid with the subbasin shape-file of the SWAT model and then the values are aggregated in order to obtain one value per month for each subbasin. This step is performed using an automated procedure in ArcGIS 9.1. Schuol and Abbaspour (2007) showed that in data scarce regions simulations using generated weather data were superior to simulations using the available poor quality measured data.

The conceptual basis of SUFI-2

The program SUFI-2 was used for calibration and uncertainty analysis. In SUFI-2, parameter uncertainty accounts for all sources of uncertainties such as uncertainty in driving variables (e.g., rainfall), conceptual model, parameters, and measured data. The degree to which all uncertainties are accounted for is quantified by a measure referred to as the *P-factor*, which is the percentage of measured data bracketed by the 95% prediction uncertainty (95PPU). The 95PPU is calculated at the 2.5% and 97.5% levels of the cumulative distribution of an output variable obtained through Latin-hypercube sampling. As all forms of uncertainties are reflected in the measurements (e.g., discharge), the parameter uncertainties generating the 95PPU account for all uncertainties. Breaking down the total uncertainty into its various components is of some interest, but quite difficult to do, and as far as the authors are aware, no reliable procedure yet exists. Another measure quantifying the strength of a calibration/uncertainty analysis is the so called *R-factor*, which is the average thickness of the 95PPU band divided by the standard deviation of the measured data. SUFI-2, hence seeks to bracket most of the measured data (large *P-factor*, maximum 100%) with the smallest possible value of *R-factor* (minimum 0).

The concept behind the uncertainty analysis of the SUFI-2 algorithm is depicted graphically in Fig. 1. This Figure illustrates that a single parameter value (shown by a point) leads to a single model response (Fig. 1a), while an uncertain parameter (shown by a line) leads to the 95PPU illustrated by the shaded region in Fig. 1b. As parameter uncertainty increases, the output uncertainty also increases (not necessarily linearly) (Fig. 1c). Hence, SUFI-2 starts by assuming a large parameter uncertainty (within a physically meaningful range), so that the measured data initially falls within the 95PPU, then decreases this uncertainty in steps while monitoring the *P-factor* and the *R-factor*. In each step, previous parameter ranges are updated by calculating the sensitivity matrix (equivalent to Jacobian), and equivalent of a Hessian matrix, followed by the calculation of covariance matrix, 95% confidence intervals of the parameters, and correlation matrix. Parameters are then updated in such a way that the new ranges are always smaller than the previous ranges, and are centred around the best simulation (for more detail see Abbaspour et al., 2004, 2007). The goodness of the fit and the degree to which the calibrated model accounts for the uncertainties are assessed by the above two measures. An ideal situation would lead to a *P-factor* of about 100% and an *R-factor* near zero. When acceptable values of *R-factor* and *P-factor* are reached, then the parameter uncertainties are the desired parameter ranges. Further goodness of fit can be quantified by the R^2 and/or Nash–Sutcliff (NS) coefficient between the observations and the final best simulation.

If initially a set of parameter ranges cannot be found where the 95PPU brackets most of the data, for example, if the situation in Fig. 1d occurs with the parameter uncertainties at physically meaningful limits, then the problem is not one of parameter calibration and the conceptual model must be re-examined.

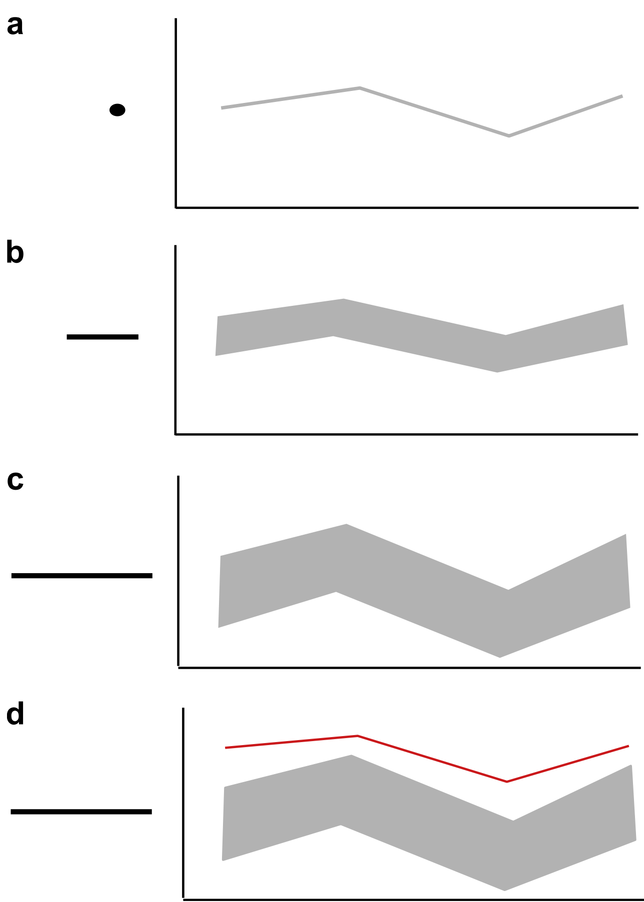

Figure 1 A conceptual illustration of the relationship between parameter uncertainty and prediction uncertainty.

Description of the modelled area

The modelled basin in West Africa (Fig. 2) covers an area of 4-million km^2, which equals about one-seventh of Africa. Since the late sixties, West Africa suffers from an ongoing drought and it is estimated that the flow of West African rivers declined in some places by more than 50% compared to the previous wet period mainly due to a continuous reduction in precipitation (Servat et al., 1997). Within these vulnerable regions the decrease of perennial rivers often goes together with increasing social conflicts (between and within countries) over water availability and supply (Ashton, 2002). Using the reported water availability estimates from FAO (1995) and population prediction figures, Yang et al. (2003) estimated that by the year 2030 four countries in West Africa (Burkina Faso, Niger, Nigeria and Togo) will experience water scarcity (defined as available water less than 1500 m^3 capita^{-1} year^{-1}. For these reasons, a proper assessment of the actual water availability and seasonal and yearly variations in West Africa is of great importance to various studies that are based on these values. In addition, it is also an interesting case study from a technical modelling and calibration point of view as it covers a large climatic and landuse variety in a region with comparably scarce data, which is typical for a large part of the world.

The largest basins within the area are those of the rivers Niger (2.2 million km^2 including the arid sections), Volta (0.4 million km^2), and Senegal (0.4 million km^2). The Niger is the third-longest river in Africa (about 4100 km) and 11 nations share the total basin which is characterized by a great variability in climate, topography and land cover (Shahin, 2002). The springs of the Niger are in the very wet Fouta–Djallon highlands (>2000 mm year^{-1}) at the Guinea–Sierra Leone border, an area that is less than 300 km from the Ocean. The river flows north-east, traverses the interior plateau and just before the great Niger Inland Delta (NID) in Mali the important tributary Bani River joins. The Inland Delta at the arid southern edge of the Sahara is one of the largest riverine floodplains in the world. It depends fully on the upstream supply and covers an area of up to

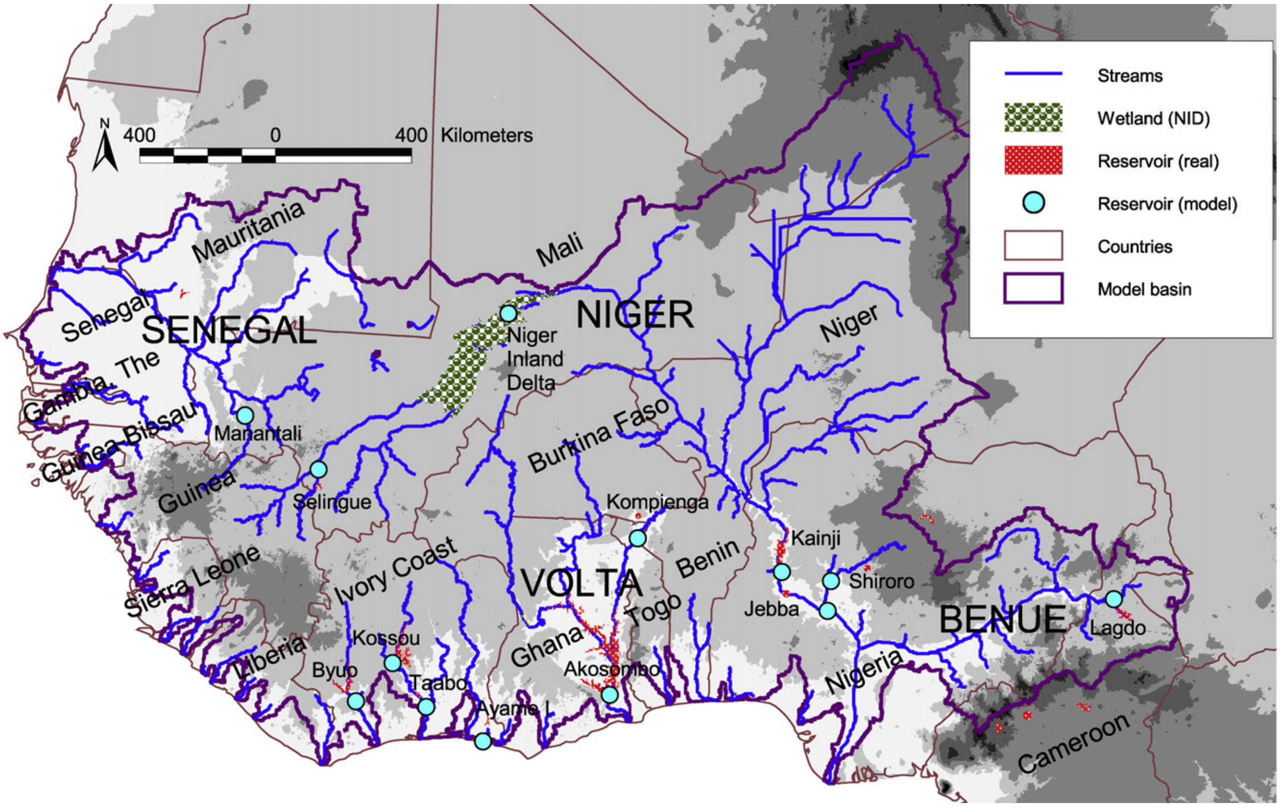

Figure 2 The modelled area in West Africa including the location of the Niger Inland Delta and of the reservoirs with a storage capacity greater than 1 km^3. The shading represents elevation.

80,000 km^2 (450 km length) of which 10,000—45,000 km^2 are potentially inundated by a crowded network of channels, swamps and lakes (Shahin, 2002). The Inland Delta is of great importance for the hydrology of the Niger as seepage and evaporation within the wetland result in a flow loss of more than 50% and in addition the peak discharge is delayed by about two months (Fig. 3). After the Inland Delta the river flows to the east before it bends to the south-east. The large potential contributing area from the north-east (about 1 million km^2) is extremely dry and is of almost no importance for the Niger water supply. The Benue River is the most important tributary of Niger and joins it at about 600 km from the river mouth which lies in a great delta. The natural river flow is influenced by quite a few reservoirs, of which the biggest ones are the Kainji, the Shiroro, the Lagdo and the Selingue with 15.0, 7.7, 7.0 and 2.2 km^3 storage capacities, respectively.

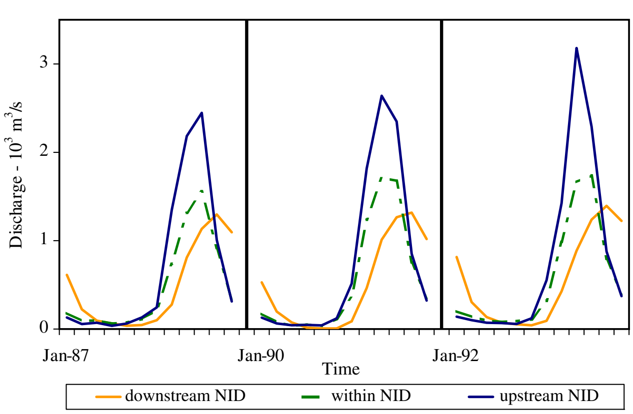

Figure 3 Observed discharge within, up- and downstream of the Niger Inland Delta for three selected years with available data.

The second most important river in West Africa is the 1800-km long Senegal River. The Bafing is the main supplier of the Senegal River with its source at the wet Fouta Djallon highland in which the rivers Niger and Gambia also originate. After the confluence with Bakoye, the river is called Senegal and flows north-west bound through areas with constantly decreasing precipitation. Of great importance is the Manatali dam with a reservoir storage capacity of 11.3 km^3.

The basin of the 1600 km long river Volta is shared by five riparian countries. The Black and the White Volta are the two main upper branches and originate from the open plateaus of Burkina Faso, an area with Sahelian climate and an annual precipitation of below 500 mm. The Volta flows mainly southward through areas with steadily increasing precipitation and has a strong seasonal runoff pattern. The Akosombo Dam, about 60 km upstream of the river mouth, forms the Lake Volta, which has a surface area of 8500 km^2 and a storage volume of 150 km^3.

Data compilation

The West African SWAT model was constructed using globally and in most cases freely available information.

(i) Digital elevation model (DEM) was constructed from the US Geological Survey's (USGS) public domain geographic database HYDRO1k (http://edc.usgs.gov/products/elevation/gtopo30/hydro/index.html), which is derived from their 30″ digital elevation model of the world GTOPO30. HYDRO1k has a consistent coverage of topography at a resolution of 1 km.

(ii) Digital stream network was also taken from the USGS' HYDRO1k database. It is derived from the flow accumulation layer for areas with an upstream drainage area greater than 1000 km^2.

(iii) Soil map was produced by the Food and Agriculture Organization of the United Nations (FAO, 1995). Almost 5000 soil types at a spatial resolution of 10 km are differentiated and some soil properties for two layers (0–30 cm and 30–100 cm depth) are provided. Further soil properties (e.g., particle-size distribution, bulk density, organic carbon content, available water capacity, and saturated hydraulic conductivity) were obtained from Reynolds et al. (1999) or by using pedotransfer functions implemented in the model Rosetta (http://www.ars.usda.gov/Services/docs.htm?docid=8953).

(iv) Landuse (or land cover) map was constructed from the USGS Global Land Cover Characterization (GLCC) database (http://edcsns17.cr.usgs.gov/glcc/glcc.html). This map has a spatial resolution of 1 km and 24 classes of landuse representation. The parameterization of the landuse classes (e.g., leaf area index, maximum stomatal conductance, maximum root depth, optimal and minimum temperature for plant growth) is based on the available SWAT landuse classes and literature research.

(v) Monthly weather statistics at a resolution of 0.5° were obtained from the Climatic Research Unit (CRU, http://www.cru.uea.ac.uk/~timm/data/index-table.html) data-sets TS 1.0 (wet days per month) and TS 2.0 (precipitation per month, average minimum and maximum temperature). Daily weather values were generated based on CRU data using the dGen described above. Daily station data provided by the National Climatic Data Centre (NCDC, 1994, 2002) were used for verification of the generated rainfall and temperature values (Schuol and Abbaspour, 2007).

(vi) Wetlands and reservoir data were mainly extracted from the Global Lakes and Wetlands Database (GLWD, Lehner and Döll, 2004). Beside the location, it comprises also some attribute data (e.g., storage capacity of the reservoirs) which was also complemented by internet research.

(vii) River discharge data were obtained for calibration purposes from the Global Runoff Data Centre (GRDC, http://grdc.bafg.de).

Model setup

The model parameterization was derived using the ArcView GIS interface for SWAT (Di Luzio et al., 2001), which provides a graphical support for the disaggregation scheme and thus facilitates the data handling. The first step is to divide, based on the DEM and the stream network, the whole watershed into subbasins. Requiring a minimum drainage area of 10,000 km^2 and including some additional outlets at available discharge gauging stations, resulted in a total of 292 subbasins. The parameterization of the stream reaches and the subbasin geomorphology (e.g., area, slope, elevation distribution, stream length) is done automatically by the interface. The next step is the landuse and soil input, overlay, and characterization for each subbasin which is again performed with the help of the interface. It would be possible to further differentiate HRUs (areas with a unique soil–landuse combination) within each subbasin but due to the large-scale nature of the problem and the consequently long computational time, we decided to consider only the dominant landuse and soil type within each subbasin.

The simulation time-period was from 1966 to 1995, where the first five years (1966–1970) were used as warm up period and not included in the analysis.

SWAT allows inclusion of wetlands and reservoirs in the model but their parameterization was quite difficult because of the limited available information. While initially reservoirs and wetlands were neglected in the model setup, we later included the largest reservoirs (storage volume greater than 1 km^3, Table 1) and the Niger Inland Delta and parameterized them based on the following available information. The values for the storage volume and the reservoir surface area filled to the emergency spillway as well as the year since they became operational were obtained

Table 1 Properties of the West African reservoirs which are included in the SWAT model

Name	River	Year	Long (°)	Lat (°)	Surface area (km^2)	Storage volume (km^3)
Akosombo	Volta	1981	0.11	7.63	7490.7	150.00
Kossou	Bandama	1972	−5.68	7.55	1566.0	27.68
Kainji	Niger	1968	4.56	10.43	1414.0	15.00
Byuo	Sassandra	1980	−6.98	6.64	988.9	8.30
Lagdo	Benoue	1972	13.97	8.88	585.9	7.70
Manantali	Bafing	1988	−10.34	13.14	477.0	11.27
Jebba	Niger	1984	4.75	9.25	360.0	1.00
Shiroro	Kaduna/Dinya	1984	6.91	9.97	312.0	7.00
Kompienga	Kompienga	1987	0.63	11.16	220.0	2.00
Selingue	Sankarani	1982	−8.17	11.50	172.7	2.17
Ayame I	Bia	1959	−3.21	5.73	160.2	1.10
(Taabo)	Bandama	1979	−5.15	6.30	143.1	2.32

from GLWD-1 (Lehner and Döll, 2004). In addition, it was assumed that the volume at the principal outlet equals 75% and the surface area equal 90% of the emergency spillway values. In order to simulate the outflow, SWAT also needs a definition of the starting and the ending month of the non-flood season, which was obtained based on a rough analysis of the existing runoff hydrographs and precipitation patterns within the reservoir region. It was further assumed that the reservoirs were controlled and the management goal was to guarantee at least a certain outflow during the whole year. We also defined the minimum daily outflow for each month depending on the average total runoff and an analysis of the downstream gauging stations. The number of days to reach the target storage was set to 90. In SWAT, a wetland is handled as an impoundment within the subbasin and wetlands on the main channel network are treated as reservoirs. For this reason we included at the downstream end of the Niger Inland Delta an artificial reservoir and parameterized it in such a way that the basic simulated outflow pattern resembles the observed one. Especially the minimum daily outflows for the different months were adjusted to the long-term observed average. After this, the model setup was complete allowing initial simulations.

Model application

After setting up the model, the important and challenging next step is the calibration and validation procedure. For this purpose we initially calibrated the model based on annual river discharge, and then based on monthly values at 64 stations within the West Africa basin. Only very few of the available stations have data for every month of the 25-year simulation period and therefore it was inevitable to include different time-periods for calibration at different stations. The available data were always split into equal time-periods for calibration (more recent data) and validation (prior data). Furthermore only stations with at least three years of monthly available data were included. The initial annual calibration helped to identify the important processes and parameters, but the main calibration is done using monthly data.

The objective function was formulated as the 64-station-average of the Nash–Sutcliff (NS) coefficients between the monthly measured (Q_m) and the simulated (Q_s) discharges. The NS coefficient was selected as it is one of best available fit estimators and one of the most preferred evaluation methods for monthly comparison in hydrological and especially SWAT studies (Coffey et al., 2004).

$$g = \frac{1}{64}\sum_{i=1}^{64}\left(1 - \frac{\sum_{i=1}^{n}(Q_m - Q_s)^2}{\sum_{i=1}^{n}(Q_m - \overline{Q})^2}\right) \tag{1}$$

As already mentioned, it is not feasible to include all (thousands) parameters in the calibration procedure and therefore a pre-selection and aggregation is inevitable. The initial pre-selection is based on literature research and previous SWAT studies (among others: Lenhart et al., 2002; Muleta and Nicklow, 2005; White and Chaubey, 2005). Further information on sensitive parameters were obtained applying a combination of Latin-hypercube and one-factor-at-a-time sampling strategy (van Griensven et al., 2006). This global sensitivity analysis approach has the advantage of being quite fast compared to similar procedures and as a result one does not obtain an absolute measure of the sensitivity but rather a ranked order of the parameters. We assessed the sensitivity at each of the 64 runoff stations and averaged the rank. Table 2 shows the 10 most sensitive parameters according to this analysis.

Within the modelled basin we have seven different landuse classes and seven different soil texture classes (Table 3). Many important SWAT parameters like the curve number, the available water capacity or the bulk density are closely related to texture and the parameter values change accordingly. For this reason a combined calibration of them is not advisable. Based on these analyses, we determined 55 parameters (13 global parameters, 2 parameters with a separate value for each landuse and 4 parameters with a separate value for each texture, i.e., available water storage capacity for sandy loam soils and for sandy clay loam soils) which were included in the more in-depth sensitivity analysis as part of the SUFI-2 calibration procedure. The parameter disaggregation noticeably increased the total number of parameters to be calibrated. To decrease the number of parameters, we on the one hand included

Table 2 The 10 most sensitive parameters based on the approach of van Griensven et al. (2006)

Parameter name	Definition	Avg. sens. rank – incl. obs. values	Avg. sens. rank – without obs. values
CN2	SCS runoff curve number [–]	1	1
ESCO	Soil evaporation compensation factor [–]	2	2
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur [mm H_2O]	5	3
SOL_AWC	Soil available water storage capacity [mm H_2O/mm soil]	6	5
GW_REVAP	Groundwater 'revap' coefficient [–]	9	6
RCHRG_DP	Deep aquifer percolation fraction [–]	9	7
SOL_Z	Soil depth [mm]	9	7
SURLAG	Surface runoff lag coefficient [days]	3	8
SOL_K	Soil conductivity [mm/h]	13	9
CH_K2	Effective hydraulic conductivity in the main channel [mm/h]	10	11

Table 3 Soil texture and land use distribution within the modelled basin

Texture	% area	Landuse	% area
Clay	0.8	Barren or sparsely vegetated	15.9
Clay—loam	2.0	Dryland cropland and pasture	0.5
Loam	25.1	Cropland/woodland mosaic	4.5
Loamy—sand	6.3	Evergreen broadleef forest	2.3
Sand	8.7	Grassland	13.5
Sandy—clay—loam	31.4	Savannah	56.8
Sandy—loam	26.0	Shrubland	6.6

only the ''dominant'' texture and landuse types (Fig. 3), and on the other hand neglected the apparently insensitive ones.

Similar to other studies, e.g., Butts et al. (2004), we included a measured discharge uncertainty of 10% in the analysis of the *P-factor*. Many streams in West Africa are intermittent and in order to capture the dry periods, we allowed an additional absolute measured discharge uncertainty of 0.1 m^3/s.

Results and discussion

Model calibration and uncertainty measures

Table 4 has a listing of the parameters in the last iteration of SUFI-2 and their uncertainty ranges. Based on the two SUFI-2 stopping criteria — the *P-factor* and the *R-factor* — it was decided that a further reduction in parameter uncertainty is not reasonable. In average 62% (out of a perfect 100%) of the measured monthly runoff values at the 64 calibration stations could be bracketed by the 95PPU and the average *R-factor* was 0.88 (out of a perfect 0, but quite reasonable around 1). Fig. 4 shows detailed pictures of these two criteria for both, the calibration and the validation periods. Dark squares mark stations with more than 80% of the measured data bracketed and the check-mark signifies an *R-factor* below one, which signifies a narrow 95PPU band. Ten stations fulfil these strong requirements for the calibration period and 8 fulfil them for the validation period. A somewhat less stringent model quality requirement — *P-factor* > 60% and *R-factor* < 1.3 — is fulfilled for more than half of the stations for both the calibration and the validation period.

The goal of the optimization procedure was to maximize the average of the NS-coefficients at the calibration stations. The NS of the ''best'' simulation (the ''best'' parameter set) of the last iteration step are shown in Fig. 5. One

Table 4 The 16 SWAT model parameters included in the final calibration and their initial and final ranges

Parameter name	Definition	Initial parameter range	Final parameter range
CN2_GRAS	Curve number for grassland (—)	35—76/40—87[a]	43—57/49—65[a]
CN2_SAVA	Curve number for savannah (—)	33—72/38—84/41—90[a]	46—55/54—65/57—70[a]
SOL_BD_SCL	Moist soil bulk density (g/cm^3)	−0.50—0.50[b]	−0.35—0.05[b]
SOL_AWC_L	Soil available water storage capacity for the soil texture type ''loam'' (mm H_2O/mm soil)	−0.50—0.50[b]	−0.03—0.25[b]
SOL_AWC_SCL	Soil available water storage capacity — texture type ''sandy—clay—loam'' (mm H_2O/mm soil)	−0.50—0.50[b]	−0.30—0.10[b]
SOL_AWC_SL	Soil available water storage capacity — texture type ''sandy-loam'' (mm H_2O/mm soil)	−0.50—0.50[b]	0.10—0.40[b]
ALPHA_BF	Baseflow alpha factor (days)	0.00—1.00	0.25—0.80
ESCO	Soil evaporation compensation factor (—)	0.00—1.00	0.15—0.50
SURLAG	Surface runoff lag coefficient (days)	0.0—10.0	0.3—3.0
GWQMN	Threshold depth of water in the shallow aquifer required for return flow (mm H_2O)	0—1000	150—700
REVAPMN	Threshold depth of water in the shallow aquifer for 'revap' or percolation to the deep aquifer (mm H_2O)	0—500	30—200
GW_REVAP	Groundwater 'revap' coefficient: regulates the movement of water from the shallow aquifer to the root zone (—)	0.02—0.20	0.03—0.09
GW_DELAY	Groundwater delay time: lag between the time that water exits the soil profile and enters the shallow aquifer (days)	0—100	10—50
RCHRG_DP	Deep aquifer percolation fraction (—)	0.00—1.00	0.40—0.65
MSK_CO1	Calibration coefficient that controls impact of the storage time constant for normal flow (—)	0.0—10.0	3.0—7.0
MSK_CO2	Calibration coefficient that controls impact of the storage time constant for low flow (—)	0.0—10.0	1.0—3.5

[a] Ranges vary depending on the hydrologic soil group within one land use type.
[b] Relative change of the parameter value.

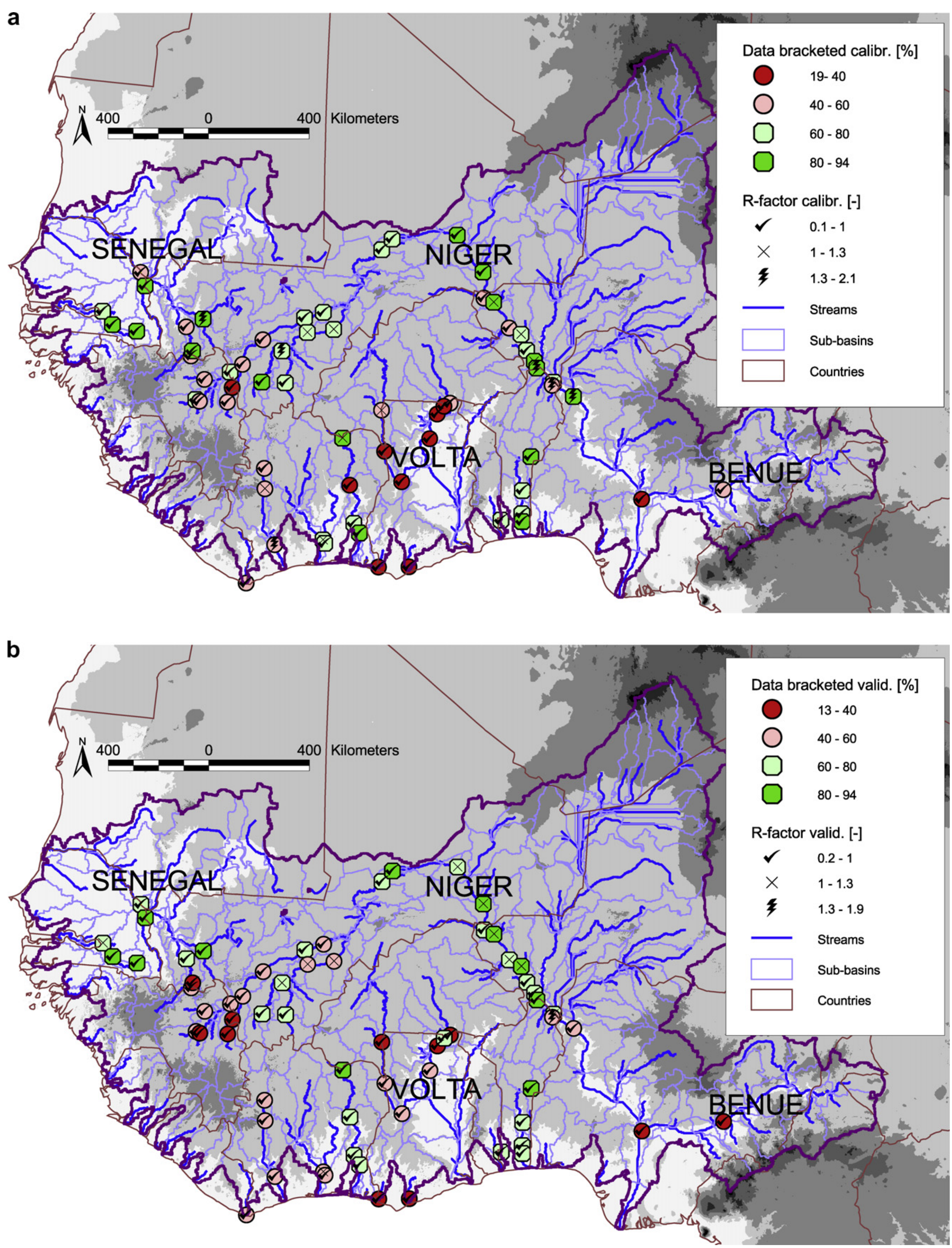

Figure 4 Measured monthly runoff data bracketed by the 95% prediction uncertainty and the *R-factor* of the monthly (a) calibration and (b) validation at all 64 stations.

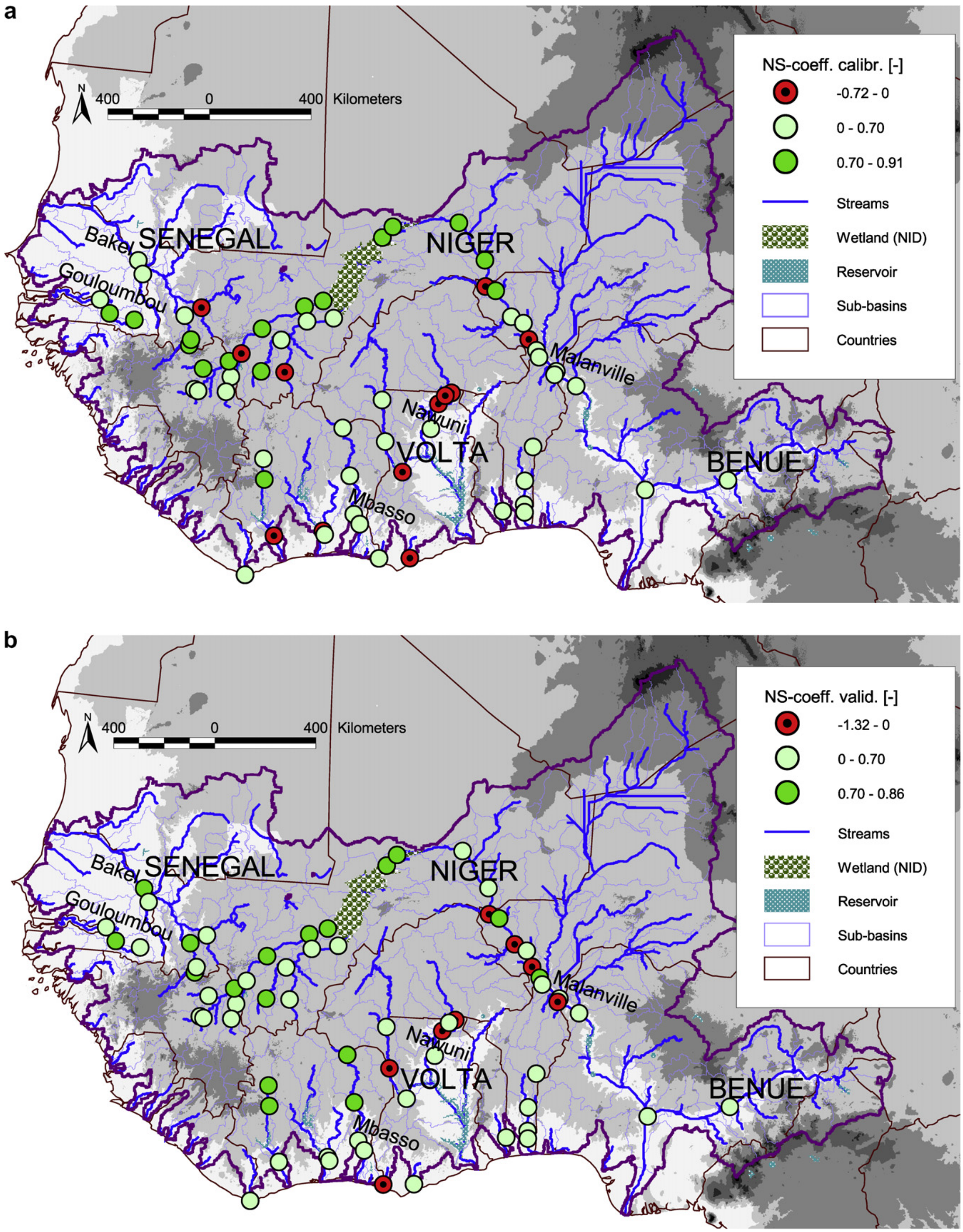

Figure 5 Nash—Sutcliff coefficient of the ''best'' simulation of the monthly runoff for (a) the calibration and (b) the validation period at all 64 stations.

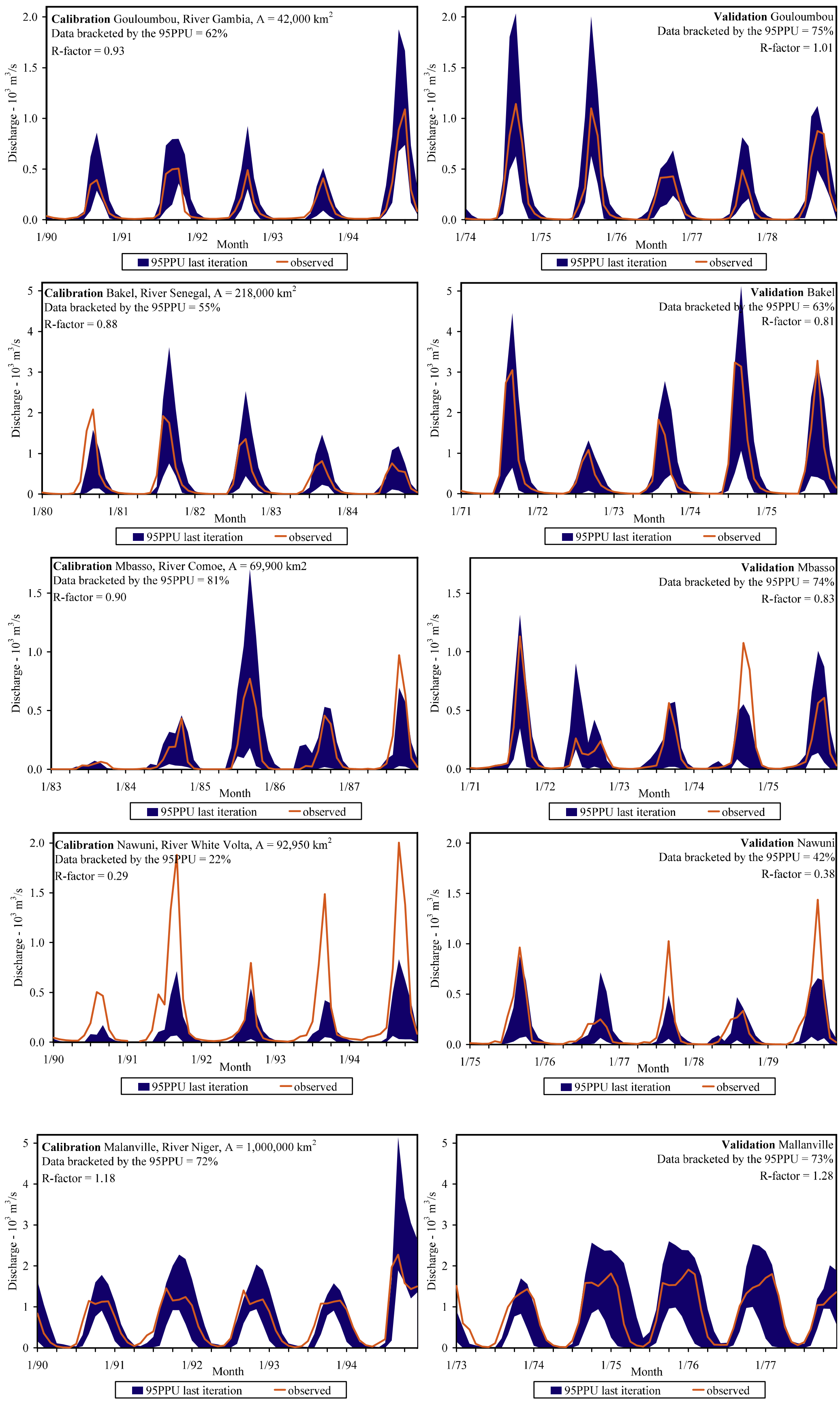

Figure 6 Extracts of the monthly calibration and validation results for five selected stations showing the 95% prediction uncertainty intervals along with the measured discharge.

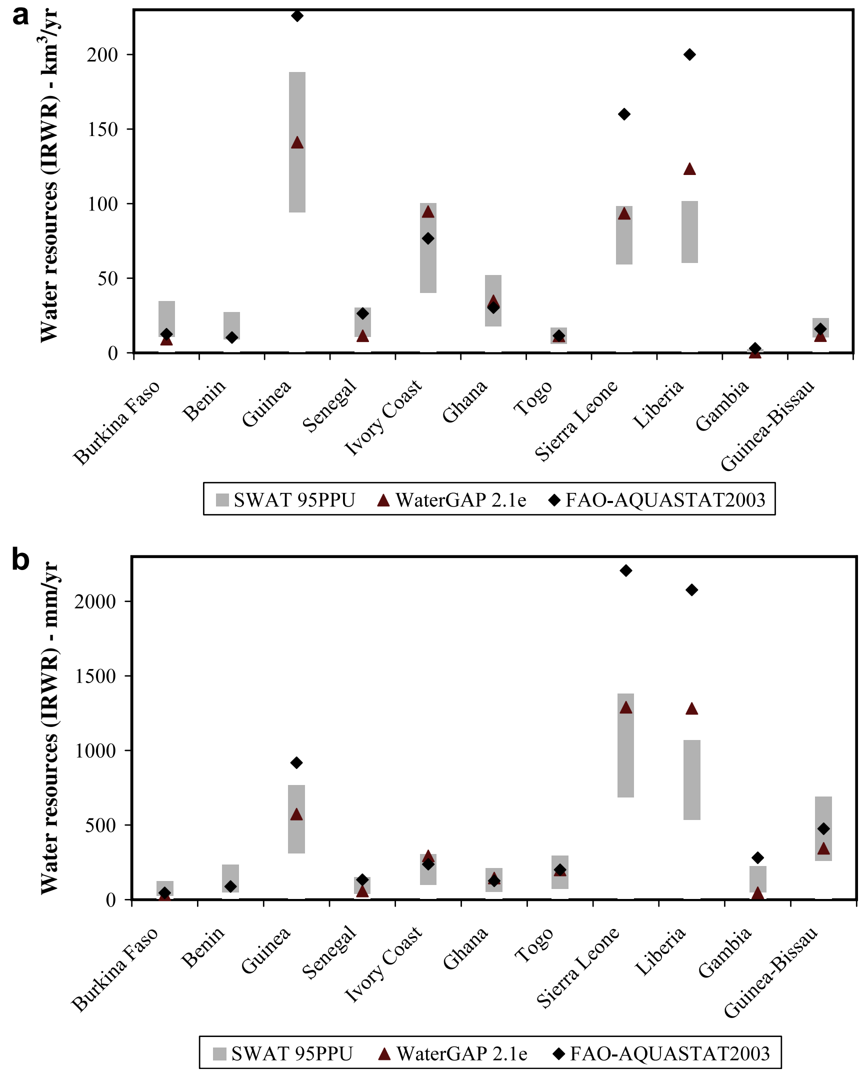

Figure 7 Comparison of the computed 95PPU intervals for the annual average (1971–1995) of the internal renewable water resources (IRWR) for selected countries with the results from the FAO assessment and the Water GAP model in (a) km^3 year^{-1} and (b) mm year^{-1}.

quarter of the included stations have a NS greater than 0.7 — which can be regarded as very good for such a large-scale study. Only 12 out of the 64 stations have a negative NS for the calibration and 8 for validation periods, which indicates a poor model performance for these stations. Actually, a NS below zero indicates that the mean value of the observed discharge would have been a better prediction than the model result. Poorly simulated stations are mainly located at the Upper Volta and at rather small Niger tributaries. Especially in the Volta catchment we clearly underestimated the average runoff. The reasons might be manifold — from underestimated precipitation to the dominant soil type which is different from the three most frequent types and therefore whose attributes are not explicitly calibrated.

After inclusion of the large reservoirs, and especially of the wetland, the model improved significantly. This is apparent in the good model performance at the Niger stations downstream of the wetland (Figs. 4 and 5) capturing the striking observed peaks, discharge decrease, and delay within the Niger Inland Delta (Fig. 3).

While we could show comparisons of the observed runoff with the ''best'' simulated runoff as it is done in many other studies, we believe that this is not appropriate as it is the result of only one of many similarly good simulations. More meaningful is it to show the 95% model prediction uncertainty (95PPU) intervals of the last iteration. In Fig. 6 we show the 95PPU of the discharge simulation together with the observed discharges at five representative stations located at different rivers and with relatively large catchments: Gouloumbou/River Gambia, Bakel/River Senegal, Mbasso/River Comoe, Nawuni/River White Volta and Malanville/River Niger. For reasons of clarity we extracted in each case five years of the calibration and five years of the validation period. Apart from the Nawuni station the results look for both the calibration and the validation period similarly good and the inter- and intra-annual variations are nicely represented. The timing of the annual peaks fits in general quite well but the uncertainty interval at peaks is in many cases — for example in the wet year 1985 at the Mbasso station — extremely large. While the general trend

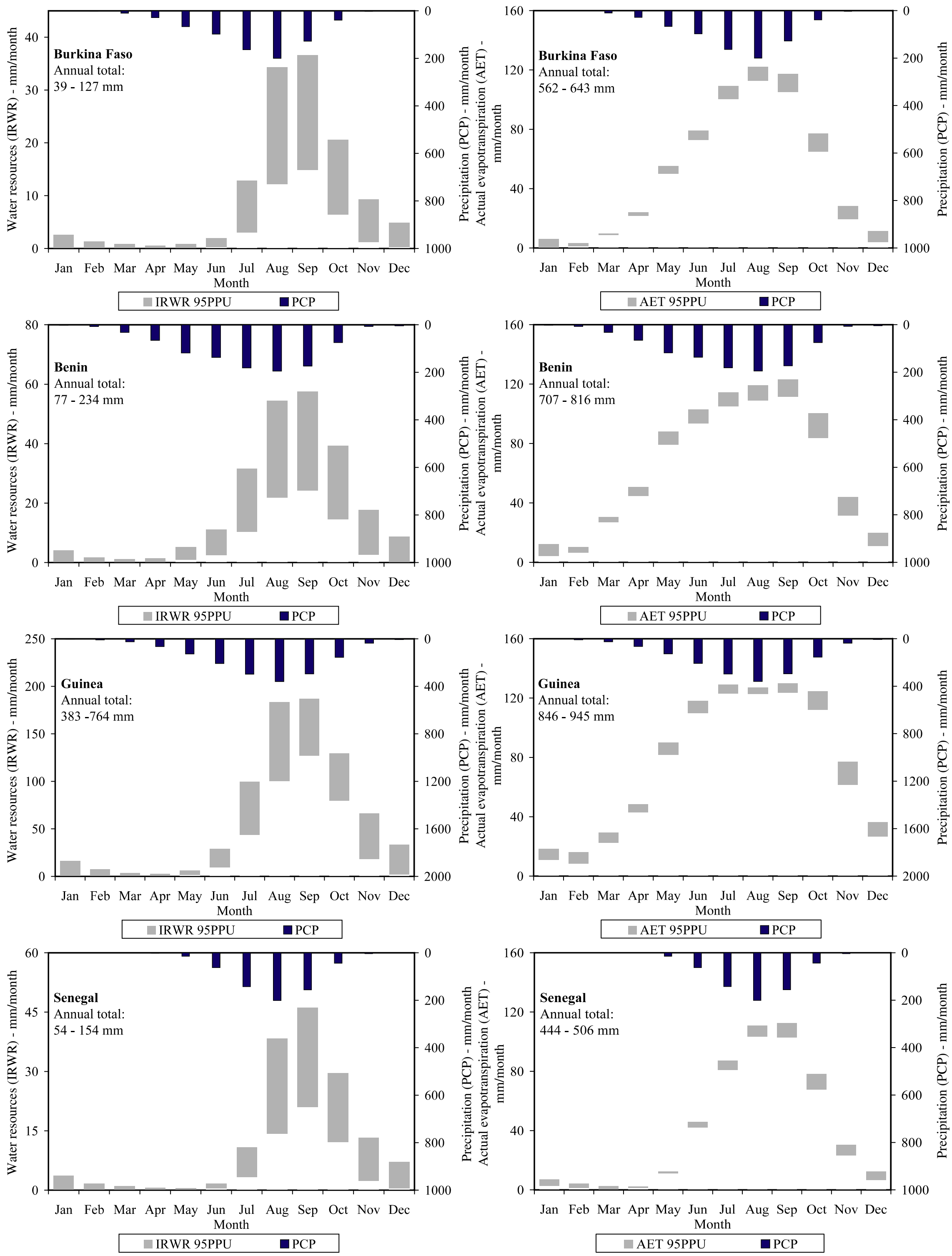

Figure 8 Average (1971—1995) monthly 95PPU intervals of the internal renewable water resources (IRWR, blue water) and the actual evapotranspiration (AET, green water flow) for eight selected countries in West Africa.

of the simulated discharge at the Nawuni station at the River Volta is fairly consistent with the observed one, the underestimation of discharge especially for wet years is quite large.

The 95PPUs are the combined outcome of the uncertainties in the conceptual model, the parameters and also the input data. In SUFI-2 these uncertainty sources are not separately evaluated but attributed as a total model uncertainty to the parameters and are visualized through the final parameter ranges and hence through the model output ranges. Each hydrological model suffers from conceptual model uncertainties and this is particularly true for large watershed models where many processes (natural or man-made) may not be represented in the models. In

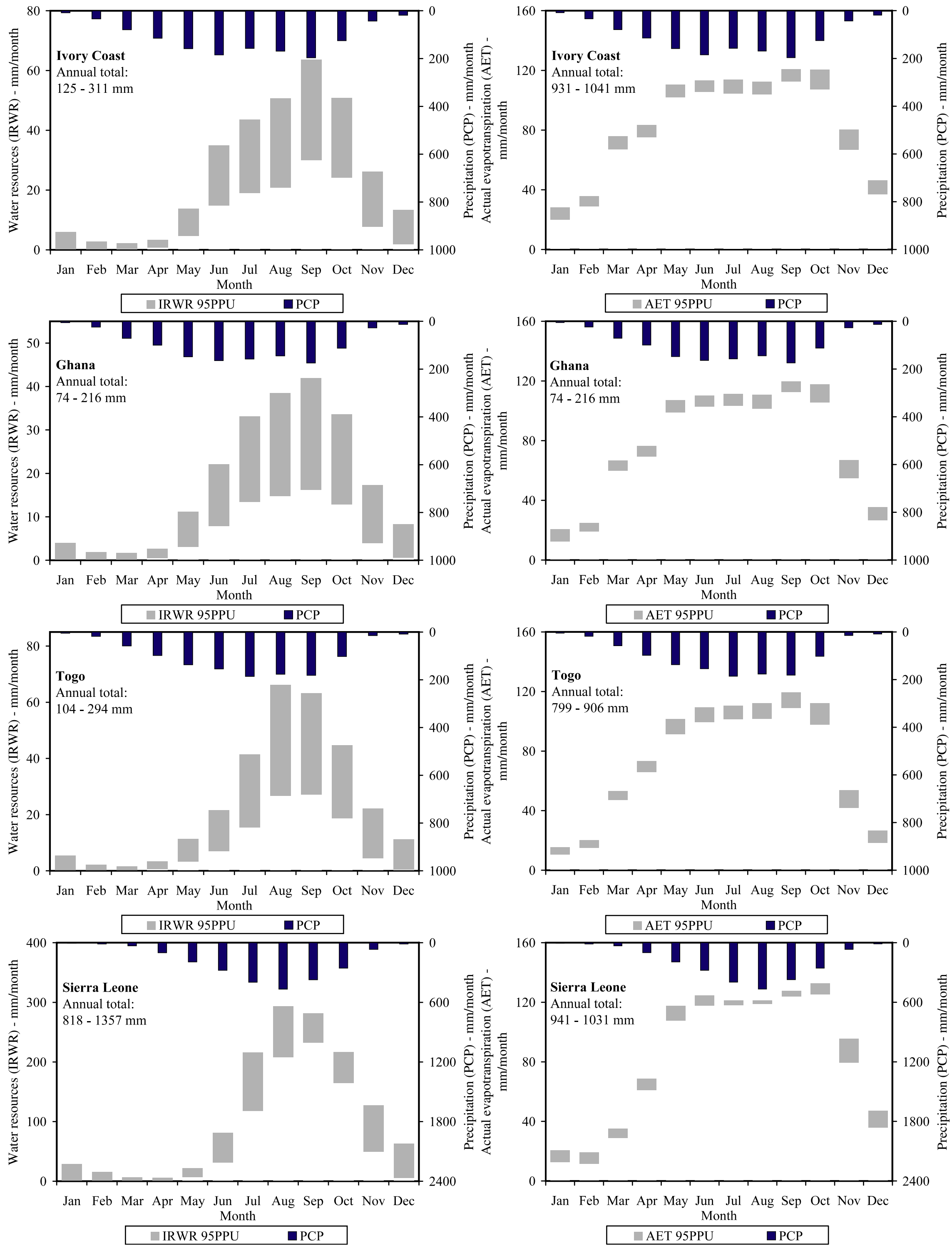

Figure 8 (*continued*)

this study, these regions are clearly identified through the quantification of the two uncertainty measures: *R-factor* and *P-factor* (e.g., Nawumi station on White Volta River, Fig. 6). Studies that show only one best model output have to be treated with caution. The use of ''best parameter set'' or the ''best simulation'' in other studies could lead to misleading results. For this reason, we believe that the scientific robustness of any modelling results requires showing the effect of the uncertainties. In general, the model performance, as represented by the *P-factor* and the *R-factor*, is quite reasonable in all stations. Large uncertainties are, however, seen in regions with reservoirs, wetlands, or regions with inadequate climate or landuse representations.

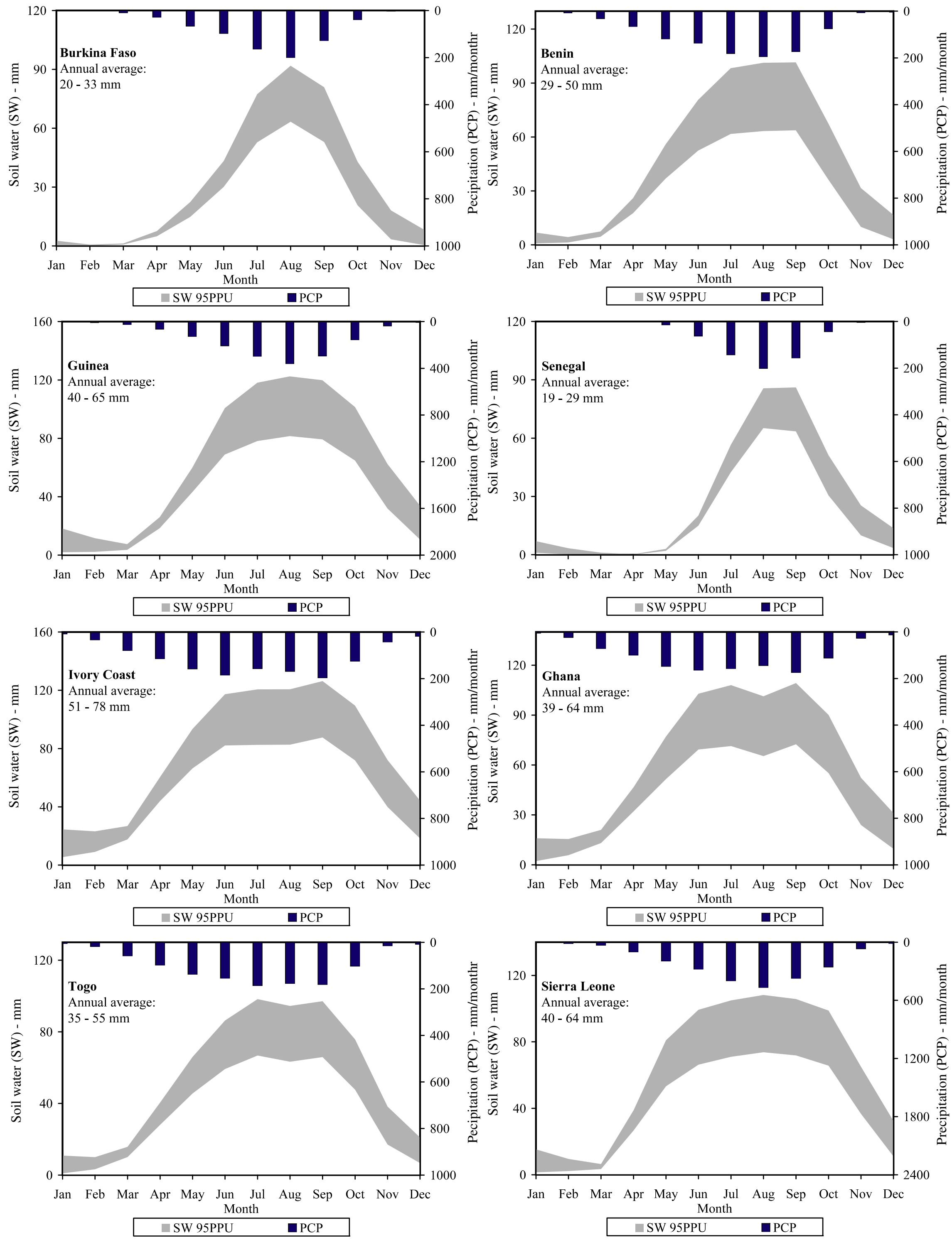

Figure 9 Average (1971—1995) monthly 95PPU intervals of the soil water (SW, green water storage) for eight selected countries in West Africa.

Country-based quantification of blue and green water resources

Although by now the paradigm of blue and green water has been widely accepted by the water resource and management communities, a quantitative determination of the volumes of the different water components at the country level with monthly interval has not been available in the literature. In order to avoid confusion, we will first introduce and define some commonly used terminologies in the water resources literature.

The term *internal renewable water resources* (IRWR) is calculated as the sum of *water yield* (SWAT parameter WYLD: total amount of water leaving the area and entering the main channels during a time period) and *deep aquifer recharge* (SWAT parameter DA_RCHG: the amount of water from the root zone that recharges the deep aquifer). By definition, this is the *internal blue water*. *Actual evapotranspiration* (AET) is the amount of water released to the atmosphere through a combination of evaporation from soil and water bodies and transpiration from vegetation. *Soil water* (SW) is the amount of water in the soil profile at the end of a time-period. We also adhere to the definition of Falkenmark and Rockström (2006) who differentiate between the *green water storage* and *green water flow*. In the above, IRWR and AET constitute water flow, while SW is water storage. It is important to differentiate between flow and storage so that proper terms are added together in calculating fresh water resources.

Often, the degree of the detail and accuracy of the above variables is not sufficient for a rigorous analysis of the issues concerned and for providing a reliable information basis for water resources planning and management.

Table 5 The average precipitation (model input) and the 95PPU intervals for the components of freshwater availability in 11 selected countries in West Africa

Country	Area (10^3 km^2)	Precipitation (km^3 year^{-1})	Blue water (km^3 year^{-1})	Green water flow (km^3 year^{-1})	Green water storage (km^3)
Burkina Faso	274.2	201.9	10.5—34.6	153.8—175.9	5.6—9.1
Benin	112.6	116.4	9.0—27.3	82.4—95.1	3.4—5.8
Guinea	245.9	390.6	94.2—188.1	208.2—232.5	9.9—16.0
Senegal	196.2	123.5	10.7—30.4	87.4—99.6	3.8—5.8
Ivory coast	322.5	415.1	40.2—100.3	300.1—335.5	6.3—25.2
Ghana	239.5	273.8	17.7—51.9	208.1—232.2	9.4—15.4
Togo	56.8	65.4	6.0—16.9	45.8—51.9	2.0—3.1
Sierra-Leone	71.7	159.1	59.3—98.4	68.3—74.8	2.9—4.6
Liberia	111.4	211.6	60.4—101.7	113.6—123.0	6.0—7.9
Gambia	11.3	8.3	0.8—2.4	5.4—6.3	0.2—0.3
Guinea-Bissau	36.1	44.9	10.3—23.1	22.3—25.3	1.2—1.9

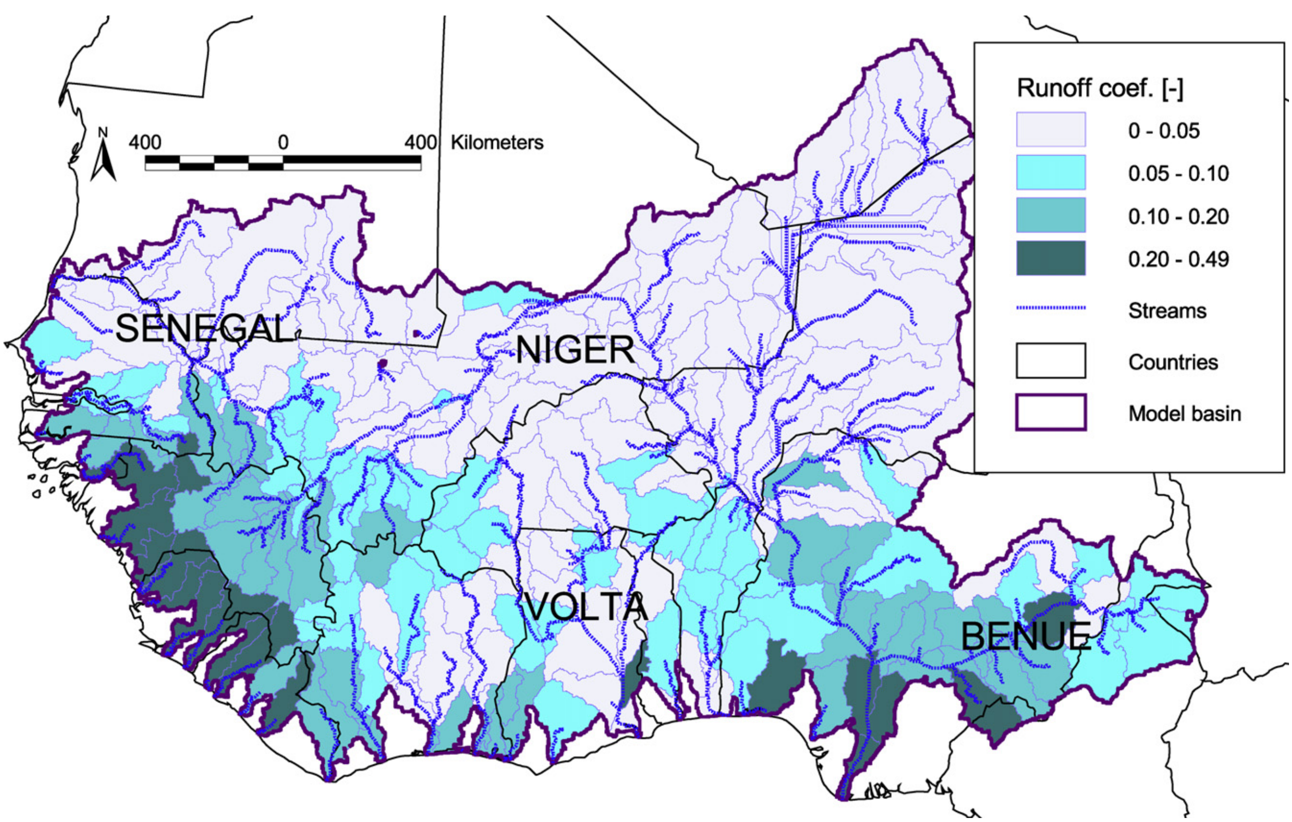

Figure 10 The average (1971—1995) runoff coefficient for the Western Africa sub-continent model at a subbasin level.

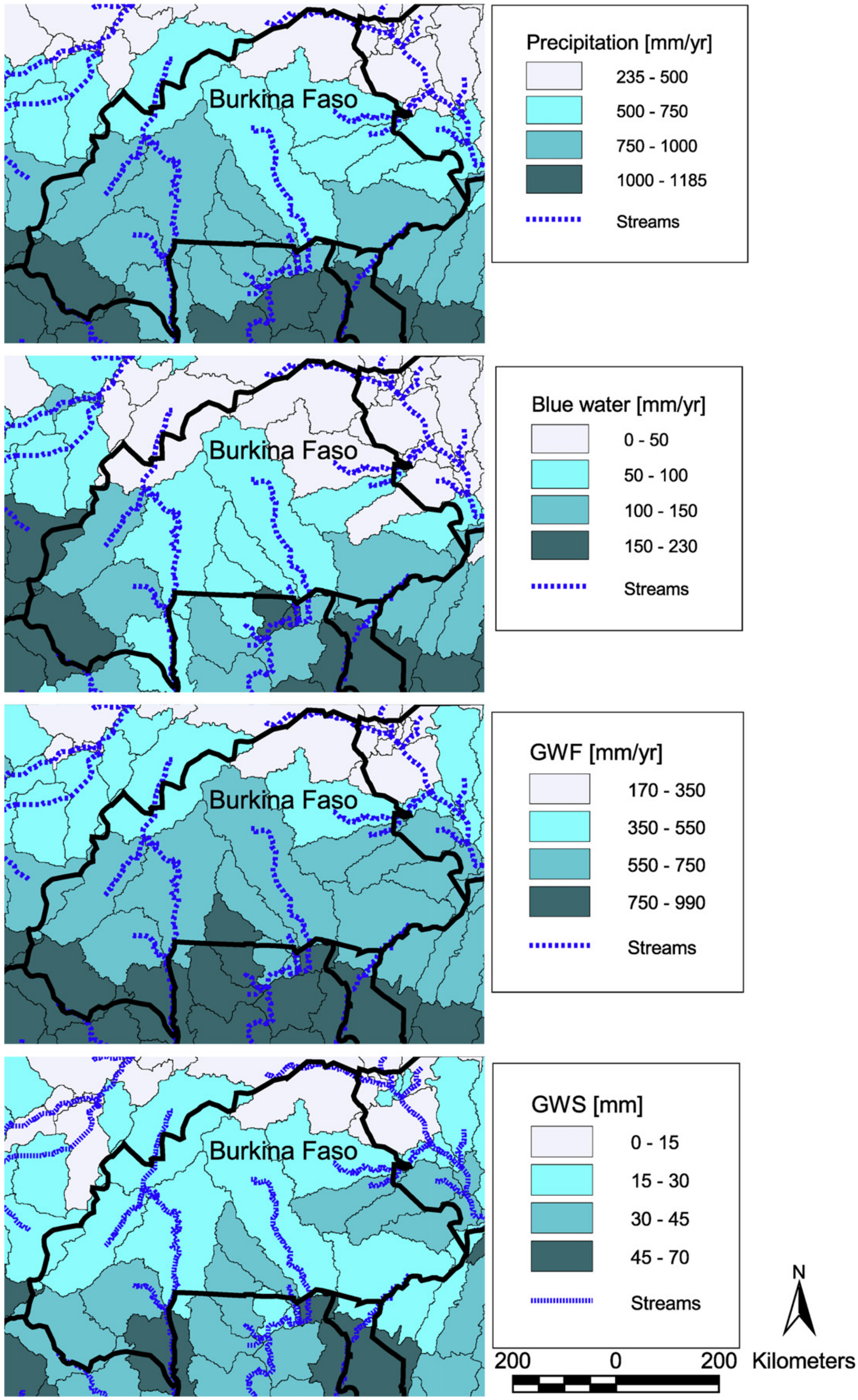

Figure 11 Average (1971—1995) regional differences of the annual precipitation, the blue water and the green water flow (GWF) as well as the average green water storage (GWS) in Burkina Faso.

With the current modelling work, we are able to provide an improved information basis in this regard.

In Fig. 7 the computed annual average (from 1971 to 1995) of the IRWR is presented for selected countries within the modelled area. The units are given in both $km^3\ year^{-1}$ and $mm\ year^{-1}$. For some of the countries the modelled area does not cover the entire land surface of the country, especially, the coastal region. Hence, a number of small watersheds (below the threshold of 10,000 km^2) were not included in the model. In these cases we linearly extrapolated the IRWR for the modelled area to the total area. Results for countries with a significant land area in another major watershed (e.g., Nigeria, Mali, and Niger) are not shown, but could be estimated for certain regions. For the purpose of comparison and model verification, in Fig. 7 we also show the results of two other global IRWR assessments: (1) WaterGAP 2.1e (long-term average 1961–95, no water use), where the results were produced for the 2005 Environmental Sustainability Index calculation (Esty et al., 2005), and (2) FAO (2003), where long-term averages are reported from multiple sources and years. The calculated 95PPU of the IRWR cover the WaterGAP and FAO values in most countries. In general, the WaterGAP results, which are also model results, are closer to our estimates and only for Liberia there seems to be an obvious incongruity. The smaller estimate might be due to a variety of reasons, but the most probable is that the country area covered in this study equals only to two-third of the total area and the regions missed are located at the sea with above-average rainfall and runoff. In addition we had no observed runoff data within Liberia, which could be used for calibration and validation and the dominant landuse is quite different from the major landuse classes within the modelled basin. In general the 95PPU intervals are large but looking at the difference between the WaterGAP and the FAO single-value estimates, the ranges seem to be quite realistic representation of the existing uncertainties.

In Fig. 8 we present the monthly average (from 1971 to 1995) 95PPU of the IRWR and the AET (green water flow) aggregated for eight selected countries. For a better inter-country comparison we give the values in mm per month and show also the monthly precipitation. In general, the uncertainty ranges of the average monthly IRWR are quite large and this is especially true for the wet months. The spatial heterogeneity of the annual IRWR pattern across the countries is quite significant. Also, it can be seen that in the months after the rainy period there is still a remarkable contribution to the total IRWR from the baseflow and groundwater recharge components. In contrast to the IRWR, the uncertainty ranges of the average monthly AET are clearly smaller. This is in part due to the fact that only one parameter (ESCO) controls AET, while all calibrated model parameters affect IRWR. Interestingly, the uncertainty ranges of the AET are not larger for higher volumes as it is the case for the IRWR.

The uncertainty range of the SW (green water storage) within the uniform 1-m thick soil layer in different countries is shown in Fig. 9. The 95PPU ranges (averaged over 25 years) are in general narrower than that of the IRWR and the annual pattern is similar to the precipitation pattern. The graphs show the differences in the long-term average and the maximum soil water in different countries, as well as the periods where plant-available soil–water is negligible. As an example, Senegal has insignificant green water resource in half of the year. A direct validation of the modelled soil water was not possible as suitable soil water observations for the region of interest were not available.

In the present modelling framework we were able to calculate the ranges for both blue and green water components of freshwater availability per sub-country basis. The next question is how to appropriately present the quantity of total water resources availability in a country. It has widely been agreed that the water resource data containing only blue water component are not appropriate for representing the total water resource (Rockström and Gordon, 2001; Gerten et al., 2005; Falkenmark and Rockström, 2006). Green water must be taken into account as it is crucially important for sustaining ecosystem services and rainfed agriculture. There is, however, an ambiguity as to what constitutes the green water of a country. As this definition may differ in different studies, the present work provides enough detail for various definitions and interpretations of green water, and hence, totals water resources in general. In Table 5, we present for 11 countries the average annual precipitation together with the 95PPU intervals of the average annual blue water (IRWR) and the green water flow (AET), as well as the long-term average green water storage (SW). It is seen that the sum of green water flow and the internal blue water (minus the water used for irrigation, which was not considered in this study for being negligible in the region) are roughly equal to the total precipitation. Therefore, ultimately, the ''total potential water resource'' of a country is the amount of precipitation falling on that country. The ''total actual water resource'', however, is smaller than the potential as not all the precipitation can be beneficially used for generating economic return, e.g., precipitation that falls on desert areas. For this reason, to better quantify the actual water resources one could use a more practical spatial resolution in assessing the water resources as adapted in this study.

With the modelling approach outlined here, we are able to show a more detailed regional picture. For example, Fig. 10 shows the runoff to rainfall ratio (runoff coefficient) for the Western Africa sub-continent at a subbasin level. Also, in Fig. 11, it is shown that for a larger country like Burkina Faso, the intra-country differences can be very distinctive, while the use of country averages of the freshwater availability in advanced studies may be deceptive.

Conclusions

Based on globally available data only, we successfully implemented and calibrated the SWAT model for water quantity investigations in the 4-million km^2 area in West Africa. Considering the scale and especially also the data scarcity, the results are very satisfying and provide notable insight into the freshwater availability and the associated uncertainties in this vulnerable region. An important improvement in the model setup was the change from the use of the poor quality measured weather data to the use of daily generated data based on monthly climate grids. Furthermore the applied parameter optimization and uncertainty analysis procedure SUFI-2, with the multi-site, was very efficient not only in terms of localizing an optimum parameter range but also in terms of the necessary number of simulations. A program using a relatively small number of simulations to perform calibration and uncertainty analysis was essential for such a computationally extensive model.

While we successfully included the major wetland (Niger Inland Delta) and the largest reservoirs, there are still many other influencing processes which were neglected (e.g., further reservoirs, water use, irrigation) or simplified (e.g., assigning the dominant soil and landuse to represent the whole subbasin, and using generated daily precipitation and temperature) due to the limited available information. Given all uncertainties in the model input, the parameters, and especially in the conceptual model, the presentation of the results as the 95% prediction uncertainty is quite logical. Expressing freshwater availability as one number could be quite misleading. In addition to annual averages, we also provide monthly information on the blue water, the green water flow, and the green water storage at subbasin level. These variables are necessary for many advanced studies, e.g., food security, virtual water flow, and strategic water planning and management. As only river discharges were calibrated and validated, we emphasize that other outputs presented in this study, such as soil moisture, have to be treated with the appropriate care. However, we believe that the estimated uncertainties are a reliable representation of the real situation.

This study is part of a larger project to assess the global freshwater availability. The West Africa study showed that the model SWAT and the selected calibration procedure is applicable to very large areas and provides reliable results. In the next step, the ArcGIS version of SWAT (Olivera et al., 2006; Winchell et al., 2007) will be used to develop a continental model.

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