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Multi-objective regionalisation for lake level simulation, the case of Lake Tana in the Upper Blue Nile, Ethiopia

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Abstract

The aim in this study is to simulate lake levels of Lake Tana by solving the water balance at daily time step. Since 42% of the basin is ungauged regionalisation procedures are applied. We examine the predictive capability of a regionalisation approach that combines multi-objective calibration of a simple conceptual model and multi regression analyses to establish relations between model parameters and catchment characteristics. Recently few studies are presented on lake level simulation of Lake Tana. In these studies the water balance of the lake is closed by estimation of runoff contributions from ungauged catchments. Studies partly relied on simple ad-hoc procedures of area comparison to estimate runoff from ungauged catchments. In this study a regional model is developed that relies on principles of similarity of catchments. For runoff modelling the HVB-96 model is selected while multi-objective model calibration is by a Monte Carlo procedure.

Assessment of the lake water balance was established by comparing measured to estimated lake levels. Results of daily lake level simulation show a water balance closure term of 85 mm and a relative volume error of 2.17%. Results show runoff from ungauged catchments of 527 mm per year for the simulation period 1994 to 2003 that is approximately 30% of Lake Tana stream flow inflow. Compared to previous works this closure term is smallest.

1 Introduction

During the past decades few studies on the water balance and daily lake level simulation of Lake Tana have been reported. For early work reference is made to (Conway, 1997) who studied the hydrology of the Blue Nile. For more recent work reference is made to (Kebede et al., 2006; SMEC 2008; Wale et al., 2009) who specifically focussed on the hydrology of Lake Tana basin. The objective of the latter studies was to solve the water balance of the lake by considering all inflows and outflows. Stream flow in the basin area, however, is not recorded in all catchments that drain in to the lake. A review of the above studies shows that the estimated inflows differ significantly by the selected procedures. Also assessments on the size of the ungauged area resulted in differed estimates and affected the accuracy of the lake water balance. According to (Kebede et al., 2006) the four major catchments contribute 93% of the inflow and only 7% of the lake inflow is from ungauged catchments. SMEC (2008) indicates that 29% of the lake inflow is from ungauged catchments while Wale et al. (2009) indicate that 42% of the lake inflow is from ungauged systems. It is noted that in (Kebede et al., 2006) and (SMEC, 2008) closure of the water balance was obtained by unknown stream flow inflows where any error in one of the balance terms was compensated for by the estimates of ungauged inflows. In Wale et al. (2009), however, a closure term was calculated by considering mismatches between observed and simulated lake level fluctuations to allow for objective assessment on the accuracy of the water balance.

Estimation of stream flow in ungauged basins commonly is based on principles of regionalisation which is the process of transferring information from gauged catchments to ungauged catchment (see Blöschl and Sivapalan, 1995). Merz and Blöschl (2004) describe that regionalisation approaches may be based on similarity of spatial proximity or on similarity of catchment characteristics. The rationale of the first approach is that catchments of close proximity have a similar flow regime. The rational for the second approach is that optimised model parameters are transferable to other catchments in case catchment characteristics are comparable. Transferability is based on the idea that a relation can be established between catchment characteristics and (optimised) model parameter values since, in their functioning, parameters reflect on catchment characteristics. Therefore the information that is carried by the relation can be used to estimate parameter values when catchment characteristics from the ungauged systems are known. Regionalisation may serve to simply estimate stream flow from ungauged catchments but also serves to improve the predictive capability of the selected rainfall-runoff model by assessing model uncertainty. The need to improve modeling in ungauged catchment hydrology is recognized by the International Association of

Hydrologic Sciences (IAHS) by adopting the topic as one of the core components for their 10-year Prediction in Ungauged Basins (PUB) project (see Sivapalan et al., 2003).

In Kebebe et al. (2006) and SMEC (2008) the regionalisation procedures applied are based on similarity of spatial proximity principles and on simple comparisons of catchment sizes in the Lake Tana basin area. In both studies detailed hydrological simulation using data-driven or knowledge driven modeling (see de Vos and Rientjes, 2007) was denied. We note that in (Wale et al., 2009) both regionalisation procedures are applied but the similarity of catchment characteristics approach yielded best results where closure of Lake Tana balance was as accurate as 5.0% of the annual stream flow. Results in the study must be considered most accurate when compared to results by Kebebe et al. (2006) and SMEC (2008).

The objective of this study is to further reduce the closure term of Lake Tana's water balance, to assess model parameter uncertainty and to evaluate effectiveness of a multi-objective model calibration approach to make hydrological modeling results more reliable. While the automated calibration procedure in this study is fundamentally different from the manual calibration procedure in Wale et al. (2009) also the representation of rainfall has changed by use of an additional rainfall time series and the lake evaporation estimation is now based on a more a extensive satellite based procedure.

This paper is organised as follows. Descriptions of the study area and data availability are given in Sects. 2 and 3, respectively. In Sect. 4 the hydrological model is presented. Section 5 describes the methodology that covers calibration of the rainfall-runoff model, establishing the regional model and simulation of water levels of Lake Tana. Section 6 presents and discusses the results of multi-objective model calibration, regionalisation and lake level simulation, In the final Sect. 7 conclusions are drawn.

2 Study area

Lake Tana (1786 m a.s.l.) is the source lake of the Blue Nile River and has a total drainage area of approximately 15 000 km^2, of which the lake covers around 3000 km^2.

The lake is located in the north-western highlands at 12°00′ N and 37°15′ E and receives runoff from more than 40 rivers. Major rivers feeding the lake are Gilgel Abbay from the south, Ribb and Gumara from the east and Megech River from the north. From the western side of the lake only small rivers systems drain to the lake (Fig. 1).

A Digital Elevation Model (DEM) of 90 m resolution from Shuttle Radar Topography Mission (SRTM-version 4) (http://srtm.csi.cgiar.org/) has been used to delineate the gauged and ungauged catchments. The hydro-processing tool in ILWIS software (http://52north.org/) has been used for this purpose and nineteen catchments were extracted. Stream flow records are not available for ten catchments which are ungauged (see Fig. 1). Results from catchment delineation, show that among the nine catchments seven catchments are partially gauged while catchments in the north-western part of the basin are ungauged. Nine catchments are selected for regionalisation based on the availability of runoff data from 1994 to 2003.

By its large size, Lake Tana has a large storage capacity that only responds slowly to the various processes of the hydrological cycle. Annual lake level fluctuations are approximately 1.6 m where lake level fluctuations primarily respond to seasonal influences by the rainy and the dry season. Lake levels reach maxima around September and minima around June with historic maximum and minimum water levels of 1788.02 m (21 September 1998) and 1784.46 m (30 June 2003). The only river that drains Lake Tana is the Blue Nile River (Abbay River) with a natural outflow that ranges from a minimum of 1075 Mm^3 (1984) to a maximum of 6181 Mm^3 (1964). For the period 1976–2006 the average outflow is estimated to be 3732 Mm^3/year.

3 Data availability

From the National Meteorological Agency (NMA) in Ethiopia time series of daily rainfall from seventeen stations in and close to the study area were collected for the period of 1994–2003. Also from NMA, meteorological data was collected from seven weather stations for estimation of potential evapotranspiration. Data types are daily maximum and minimum temperature, wind speed, relative humidity and sunshine hours. From the database of the Hydrology Department of Ministry of Water Resources (MoWR) daily water levels of Lake Tana and Abbay river gauging station near Bahir Dar were obtained. Daily outflow discharges from Lake Tana were obtained by a stage-discharge rating curve by the MoWR. We note that the curve was updated in (Wale et al., 2009) and is used in this study as well. Further, stream flow data from seventeen stations was collected from the MoWR in Ethiopia but only nine stations had continuous records covering the period 1994–2003. Runoff time series data were analyzed for consistency and analysis indicated that records from the smaller sub basins (Gumero, Garno and Gelda) were unreliable. We note that after screening of the stream flow data 38.3% of the Lake Tana basin is considered gauged. Catchments selected for regionalisation are Ribb, Gilgel Abbay, Gumara, Megech, Koga, Kelti.

Satellite data was collected for the Moderate Resolution Imaging Spectro radiometer onboard the TERRA satellite (MODIS-TERRA) and from the Landsat ETM+ satellite. For the period 2000–2002, the MODIS-TERRA Images were collected from the LAADS Web site (http://ladsweb.nascom.nasa.gov/data/search.html) for estimation of lake evaporation. The land cover map was prepared by use of the Landsat ETM+ satellite and evaluated based on field data. A soil map of the major soil groups on the basin was collected from the GIS department of MoWR. Soil classification was based on (WRB, 2007) and resulted in 6 dominant soil classes. With regard to water storage capacity of Lake Tana, bathymetric relations between area-volume and elevation-volume were available through a bathymetric survey by the Faculty of Geoinformation Science and Earth observation, University of Twente, in 2005. The bathymetric relations were improved in Wale et al. (2009) by a more accurate delineation of the lake shore and are used in this study as well.

4 The HBV-96 model

For stream flow simulation the HBV-96 model has been selected that has many applications in operational and strategic water management. Applications are known for lumped model domains (see Seibert, 1997) and semi distributed model domains (see Booij, 2005) and commonly aim at simulating the rainfall-runoff relation. Examples of applications in regionalisation studies are provided by (Seibert, 1999; Merz and Blöschl, 2004; Booij, 2005, Wale et al., 2009; Deckers et al., 2010). The model is classified as a conceptual water balance based model and relies on simple approximations to simulate mass exchange processes of the hydrological cycle. Input requirements to the model are rainfall, temperature and potential evapotranspiration. In this study the HBV-96 model version (Lindström et al., 1997) is used with a simulation time step of one day. Four routines which are a precipitation accounting routine, a soil moisture routine, a quick runoff routine and a base flow routine are active and transform excess water from the soil moisture zone to local runoff (see Fig. 2).

The precipitation accounting routine defines precipitation as rainfall or snow by application of a threshold value (TT). When the actual temperature (T) is lower than this value, precipitation occurs as snow. Snowmelt and refreezing are simulated by Eqs. (1) and (2), respectively.

$$P_s = \mathrm{CFMAX}\cdot(T-\mathrm{TT}) \tag{1}$$

$$P_r = \mathrm{CFR}\cdot\mathrm{CFMAX}\cdot(\mathrm{TT}-T) \tag{2}$$

where CFMAX is a melting factor and CFR a refreezing factor.

The soil moisture routine controls the formation of direct and indirect runoff. Direct runoff occurs if the simulated soil moisture storage (SM) that is conceptualised through a soil moisture reservoir representing the unsaturated soil, exceeds the maximum soil moisture storage denoted by parameter FC. Otherwise, precipitation infiltrates (IN) the soil moisture reservoir, seeps through the soil layer or evapotranspires. The seepage through the soil layer causes indirect runoff (R) that is determined through a power relationship with parameter BETA as shown in Eq. (3) and the amount of infiltrating water and the soil moisture storage:

$$R = \mathrm{IN}\left(\frac{\mathrm{SM}}{\mathrm{FC}}\right)^{\mathrm{BETA}} \tag{3}$$

This indicates that indirect runoff increases with increasing soil moisture storage but also that indirect runoff reduces to zero in case infiltration becomes zero. Actual evapotranspiration (E_a) depends on the measured potential evapotranspiration (E_p), the soil moisture storage in the reservoir and a parameter LP which is a limit above which evapotranspiration reaches its potential value. This is shown in Eqs. (4) and (5).

$$E_\mathrm{a} = \frac{\mathrm{SM}}{\mathrm{LP}\cdot\mathrm{FC}}\cdot E_\mathrm{p} \quad \text{if} \quad \mathrm{SM} < (\mathrm{LP}\cdot\mathrm{FC}) \tag{4}$$

$$E_\mathrm{a} = E_\mathrm{p} \quad \text{if} \quad \mathrm{SM} \geq (\mathrm{LP}\cdot\mathrm{FC}) \tag{5}$$

At the quick runoff routine three components are distinguished which are percolation to the base flow reservoir, capillary transport to the soil moisture reservoir and quick runoff. Percolation is denoted through parameter PERC which is a constant percolation rate that occurs when water is available in the quick runoff reservoir. Capillary transport is a function of the maximum soil moisture storage, the soil moisture storage and a maximum value for capillary flow (CFLUX) as shown in Eq. (6).

$$R_f = \mathrm{CFLUX}\cdot\left(\frac{\mathrm{FC}-\mathrm{SM}}{\mathrm{FC}}\right) \tag{6}$$

If the yield from the soil moisture routine is higher than the percolation, water becomes available for quick flow which is shown by Eq. (7).

$$Q_q = K_f\cdot\mathrm{UZ}^{(1+\mathrm{ALFA})} \tag{7}$$

where UZ is the storage in the quick runoff reservoir, ALFA a measure for the non-linearity of the flow in the quick runoff reservoir and K_q a recession coefficient.

The slow flow of the catchment is generated in the base flow routine through Eq. (8).

$$Q_s = K_s \cdot \mathrm{LZ} \tag{8}$$

where LZ is the storage in the base flow reservoir and K_s a recession coefficient.

5 Methodology

The regionalisation approach selected for this study encompasses the following steps. First the HBV-96 model is calibrated for gauged catchments against observed discharges to establish good performing parameters sets to simulate catchment runoff. Next, relationships are established between the model parameters (MPs) and Physical Catchment Characteristics (PCCs) to develop the so called "regional model". The regional model is used to establish model parameters for ungauged catchments where MPs are defined as based on the PCCs from the ungauged catchments. Then the HBV-96 model is used to simulate the runoff from the ungauged catchments. Finally, the water balance of Lake Tana is solved by considering all inflows and outflows and the closure term is calculated by comparing observed to simulated water levels. In the following subsections a description of the procedure is presented.

5.1 Model calibration

In this study model calibration is by a Monte Carlo Simulation (MCS) procedure. MCS is a technique where numerous model simulations are executed by randomly generated model parameter values with the objective to find the best performing parameter sets. Such set yields a minimum or maximum value for selected objective function(s). Good performing parameter sets are selected for further use and unsatisfactory performing sets are denied for further use. Critical in MCS is the selection of the prior parameter space, the determination of the number of simulations to be executed and the selection of the objective function(s). For details on MCS simulation reference is made to works of Beven and Binley (1992); Harlin and Kung (1992) and Seibert (1999).

5.2 Parameter space

For selection of calibration parameters for MCS, a model sensitivity analysis is performed and literature on applications of HBV-96 is reviewed. Studies for instance by Bergström (1990); Diermanse (2001); Lidén and Harlin (2000); Seibert (1999) and Wale et al. (2009) indicate model sensitivity to selected parameters. Selection of prior parameter space for MCS is based on a sensitivity analysis and studies by (Seibert, 1997; Booij, 2005 and SMHI, 2006). In Table 1 parameter ranges for selected parameters are given.

In MCS parameter values are randomly and independently sampled from uniform distributions. Principle to the validity of MCS is that the entire parameter space is examined to allow statistical evaluation of the results. Therefore, in this study we tested the performance of the model for a systematically increased number of runs and found that after 60 000 runs model performance could not be further improved. In the procedure the 10% of the best performing parameters sets are selected for further analysis. From this subset minimum and maximum parameter values for each parameter are defined and the MCS procedure of 60 000 runs is repeated for the newly defined parameter space. The optimally performing parameter set is now defined by averaging the parameter values of the best performing 25 parameter sets. The procedure is applied to all gauged catchments and for each catchment an optimal parameter set is defined. For assessing reliability of the parameter estimates the entire MCS procedure is repeated 15 times and optimised parameter values for each of the catchments are compared. Such comparison also is for single best performing parameter sets to evaluate robustness of the procedure by comparing the averaged parameter values to the single best values.

5.3 Objective functions

In runoff model calibration the objective commonly is to optimise parameter sets to match simulated stream flow to observed stream flow. Goodness of fit commonly is evaluated by visual inspection but also by use of objective functions that highlight selected aspects of the hydrograph such as low flows, high flows, the overall shape of a hydrograph or the rising limp of a hydrograph (see de Vos and Rientjes, 2007). Also the volumetric error is often addressed and indicates the mismatch between the volumes of runoff over the entire simulation period. In this work we selected two objective functions that indicate the overall fit of the stream flow hydrograph and the volumetric errors. For the first objective we selected the Nash-Sutcliffe (NS) efficiency criterion (Nash and Sutcliffe, 1970) and for the second objective we selected the Relative Volumetric Error (RVE). The NS objective function requires maximisation and reads:

$$\mathrm{NS} = 1 - \frac{\sum_{i=1}^{n} (Q_{\mathrm{sim},i} - Q_{\mathrm{obs},i})^2}{\sum_{i=1}^{n} (Q_{\mathrm{obs},i} - \overline{Q_{\mathrm{obs}}})^2} \tag{9}$$

where $\overline{Q_{\mathrm{obs}}}$ = mean of observed flow. NS can range between $-\infty$ and 1where the value of 1 indicates a perfect fit. NS values between 0.6 and 0.8 indicate fair to good performance. A model is said to be performed very good when values are in between 0.8 and 0.9. The RVE requires minimisation and reads:

$$\mathrm{RVE} = \left(\frac{\sum_{i=1}^{n} Q_{\mathrm{sim},i} - Q_{\mathrm{obs},i}}{\sum_{i=1}^{n} Q_{\mathrm{obs},i}} \right) \cdot 100\% \tag{10}$$

where Q_{sim} = simulated flow, Q_{obs} = observed flow, i = time step, n = total number of time steps used during the calibration. RVE may range between $-\infty$ to $+\infty$ but indicates an excellent performing model when a value of 0 is generated. An error between +5% and −5% indicates a well performing model while error values between +5% and +10% or between −5% and −10% indicate reasonable performance.

5.4 Selection of optimum parameter set

In the procedure of parameter set selection both objective functions are combined in a single objective function and performance of the model is assessed for the objective function that suggest best model performance. The procedure is after Deckers et al. (2010) where four objective functions are combined. Comparatively, in this work we excluded NS objective functions for high flows and low flows since results in Deckers et al. (2010) indicated that best performing parameter sets mostly are found by the NS or RVE objective functions. In the procedure for each parameter set both objective functions are calculated and compared. To evaluate which objective function indicates best performance, the value of each criterion was scaled over the range of objective function values by the 60 000 model runs. The NS value was scaled based on its minimum and maximum value:

$$R'_{\mathrm{NS},i,n} = \frac{R_{\mathrm{NS},i,n} - \min(R_{\mathrm{NS},i,n\mathrm{tot}})}{\max(R_{\mathrm{NS},i,n\mathrm{tot}}) - \min(R_{\mathrm{NS},i,n\mathrm{tot}})} \tag{11}$$

where R_{NS} = value for the NS criterion, i = NS value for specific catchment, n = calibration run number, $n$tot = run number.

Since RVE varies between $-\infty$ and $+\infty$ positive values as well as negative values can occur. The RVE scaling equation reads:

$$R'_{\mathrm{RVE},i,n} = \frac{\left|R_{\mathrm{RVE},i,n}\right| - \max\left|R_{\mathrm{RVE},i,n\mathrm{tot}}\right|}{\min\left|R_{\mathrm{RVE},i,n\mathrm{tot}}\right| - \max\left|R_{\mathrm{RVE},i,n\mathrm{tot}}\right|} \tag{12}$$

where R_{RVE} = value for the RVE criterion while other terms are as defined above.

After scaling of NS and RVE, the lowest value of the two was selected for each calibration run:

$$R'_{i,n} = \min\{R'_{\mathrm{NS},i,n}, R'_{\mathrm{RVE},i,n}\} \tag{13}$$

where R' = scaled value of the criteria.

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The optimum parameter set for each catchment is now determined by selecting the highest values of all selected minimum values as determined through Eq. (14):

$$R_i = \max\{\min(R'_{i,n\text{tot}})\} \tag{14}$$

It is noted that the procedure does not aim at selecting a parameter set with a highest possible objective function value but aims to select a well performing parameter set by averaging over the 25 best performing sets. This procedure aims to prevent that outliers in parameter space may cause very high objective function values. Such parameter values only have limited validity and must not be considered representative. Parameter values therefore are not suitable for establishing the regional model.

5.5 Establishing the regional model

For developing a regional model the aim is to establish hydrological relationships between MPs and PCCs. PCCs in this respect are characteristics of the catchment that relate to morphology, geometry, topography, climate, soils and land use. Selected PCCs should directly or indirectly affect the production of runoff in a catchment and as such selection is a critical step. In this work some 22 PCCs are selected from various sources. PCCs that relate to topography, geometry and the morphology of the catchments are extracted from the SRTM DEM. The PCCs under Land use and Geology and Soil are obtained from a land used and a soil map used by Wale et al. (2009). PCCs under Climate are from the meteorological data from NMS. Table 2 shows the list of PCCs selected for this study.

Knowledge on the relations between HBV MPs and the PCCs allows us to estimate MPs for ungauged catchment systems when the PCCs from these catchments are known. To set up a regional model for estimation of model parameters in ungauged catchments, regression analysis are often applied (see Bastola et al., 2008; Heuvelmans et al., 2006; Kim et al., 2008; Young, 2005; Xu, 2003, Wale et al., 2009; Deckers et al., 2010) that also is selected for this study. Relationships however should be statistically significant and hydrologically meaningful.

5.6 Regression analysis

Multiple linear regression is performed for each model parameter. Statistical significance and strength are tested to guarantee that regression equations can be used. Also the correlation (r) is tested by the t-test (Eq. 15).

$$t_{\mathrm{cor}} = \frac{|r|\sqrt{n-2}}{\sqrt{1-r^2}} \tag{15}$$

where, $t_{\mathrm{cor}} = t$ value of the correlation, $r =$ correlation coefficient, $n =$ sample size.

The following hypothesis is tested. The null hypothesis H_0 and the specific hypothesis H_1 are:

H_0: the correlation between the PCC and MPs is zero, $\rho = 0$.

H_1: the correlation between the PCC and MPs is not zero, $\rho \neq 0$

If $t_{\mathrm{cor}} > t_{\mathrm{cr}}$ the null-hypothesis is rejected (MPs are associated with PCCs in the population).

To determine the critical value t_{cr} the number of degree of freedom, df, and α, a number between 0 and 1 to specify the confident level has to be determined. In this study a significant level of α=0.1 is chosen that is applied to a two-tail test with n-2 degree of freedom. Using this information, for t_{cr} a value of 2.132 is found (critical value from t distribution table). To determine at what r value the hypothesis is rejected the test statistic is solved. An r of 0.72 was established and thus r greater than 0.72 and smaller than −0.72 results in a statistically significant relationship.

The second method applied is based on multiple regression analysis to optimize the relationship with the forward selection and with the backward removal method. Multiple linear regression is used to predict MPs from several independent PCCs. In the forward entry approach the initially established regression model that incorporates the most significant PCC is extended by entering a second independent variable in the regional model. This step is accepted if the entry statistic (i.e. significance level, α) of both independent variables is not exceeded. The statistical tools are used to select

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the independent variable that adds most significance to the relation. Additional steps are executed until the last added independent variable does not significantly contribute to the regression model. In addition to the forward entry method also the backward removal method is applied. In this method all PCCs are entered into the model. Based on the removal statistic (i.e. significance level, α) independent variables are stepwise removed from the model. The significance of the multiple linear regression equations is tested by evaluating the significance of individual coefficients and by a test of overall significance. First a hypothesis test is applied to determine if the regression equation is significant. For such test it is assumed that the error term, ε, is not correlated and normally distributed. Further the error term must have an average of zero and a constant variance. In this study these assumptions are made and two hypothesis tests are executed to evaluate statistical significance of the regression equation. Those are the null-hypothesis and the specific hypothesis. Further the strength of the determined regression equation is evaluated by the coefficient of determination, R^2.

5.7 Lake level simulation

For simulation of daily lake level fluctuations the following water balance equation is solved

$$\frac{\Delta S}{\Delta T} = P - E_{\text{vap}} + Q_{\text{gauged}} + Q_{\text{ungauged}} - Q_{\text{BNR}} \tag{16}$$

Where $\Delta S/\Delta T$ denotes the change in storage over time, P = Lake areal rainfall, E_{vap} = open water evaporation, Q_{gauged} = Gauged river inflow, Q_{ungauged} is Ungauged river inflow and Q_{BNR} is the Blue Nile River outflow (all terms in [Mm^3 day^{-1}]).

For estimating lake evaporation the Penman-combination equation (see Maidment, 1993) is selected where Albedo was estimated by the Surface Energy Balance System (SEBS) (see Su, 2002) that required the level 1 product from the Terra MODIS sensor. An Albedo map with a resolution of 1 km^2 was generated for Lake Tana and an average Albedo was estimated by averaging over all pixels. Meteorologic data from Bahir Dar station was used to estimate the lake evaporation. Daily rainfall over Lake Tana was estimated on daily base by spatial interpolation of gauge data from Bahir Dar, Chawhit, Zege, Deke Estifanos and Delgi station (see Fig. 1). We selected a weight power of 2 to allow representation of the relatively high spatial variability of rainfall in the basin (see Haile et al., 2009, 2010).

For calculation of stream flow from gauged systems, observed stream flow time series are directly used in the water balance. Runoff time series are screened and corrected and analysis indicated that not all time series are reliable. For instance, results indicated that some gauges were relocated over time while other gauges indicated inundation during periods of extreme rainfall. For such periods discharges are estimated by analysis of rainfall to match the pattern of the rainfall-runoff relation. The lake inflow from ungauged systems is estimated by the regionalization approach as described in Sect. 5.2.

Time series for Lake outflow by Abbay River are directly entered in the water balance equation after time series of outflow are corrected for consistency by use of a newly established stage-discharge relation in Wale et al. (2009).

In this study it is assumed that the groundwater system is decoupled from the lake and any lake leakage is ignored in the balance. We note that in (Kebede et al., 2006) lake leakage is estimated to be some 7% of the total annual lake budget. However, in Chebud and Melesse (2009), numeric groundwater modeling is applied and results indicate that lake leakage is unlikely and therefore exchange of water between the lake and the groundwater system is ignored in the balance calculations in this study.

6 Results and discussion

6.1 Gauged systems

Results of MCS are shown in Table 3. For each of the catchments objective function values for the optimized parameter set are calculated and optimal parameter sets are identified. Results of NS for calibration and validation indicate relatively high values for the 6 catchments with a highest calibration value of 0.85 for the Gilgel Abbay catchment. The results of calibration are not satisfactory for Gumero (163 km^2), Garno (98 km^2) and Gelda (26 km^2). All three catchments have low NS values (<0.41) while RVE values are relatively high. Therefore the use of these catchments is ignored when establishing the regional model. Wale et al. (2009) suggested that the time of concentration, which is defined as the time period for water to travel from the most remote point in the catchment to the outlet, is small and as such the quick runoff responses are difficult to represent at the daily simulation time step. Further, some gauging stations are not placed at the catchment outlet but at some location upstream that has easy road access. As such it is assumed that rainfall-runoff time series cannot be considered reliable.

Table 3 indicates that some parameters have relatively wide range of values as optimized for only six catchments and suggest that catchments have relatively wide range of settings that relate to catchment settings such as climate, topography and physiography. We note that the number of gauged catchments selected for regionalization is relatively small by the relatively small size of the Lake Tana basin. Most regionalisation studies aim at much larger spatial domains and rely on a much larger number of catchments. For instance, in Merz and Blöschl (2004) some 308 catchments were used; Sefton and Howarth (1998) used 60 catchments; Seibert (1999) used 11 catchments; Young (2006) used 260 catchments for the entire UK; Kokkonen et al. (2003) used 13 catchments and Deckers et al. (2010) used 48 catchments also for the UK. To evaluate to what extent the small number of catchments affected the regionalisation result is difficult and touches on the issue if large variability or relatively small variability of catchment properties favours regionalisation. In our case we assume that catchment characteristics are comparable since catchments are connected or very close to each other. Catchments, however, have different natural settings and relatively little variation implies little hydrologic diversity that in principle does not allow establishment of strong regional relationships while, on the other hand, too much variation may result in weak relationships. In this study only six catchments are available but we assume that variation of catchment properties is sufficiently guaranteed by clear differences in topographic settings and climatic settings (see e.g. Haile et al., 2009, 2010).

As described in Sect. 5.2, after finishing the first MCS calibration procedure of 60 000 runs for the posterior parameter ranges we tested the consistency of the parameter estimates by additional MCS runs. Figure 3 shows results for 15 MCS calibration runs of 60 000 each. The results indicate that in each MCS run the average of the 25 best performing parameter sets differs and therefore different optimal parameter sets are defined. Results indicate that optimal parameter sets cannot be defined uniquely but values somehow converge to an optimal value. As such the optimum parameter set is finally selected by taking the average of the 15 parameter values. Results suggest that for optimal parameter selection an extreme high number of model runs is required. We note that MCS studies often rely on less than 50 000 runs but results of this study indicate the weaknesses of such procedure. We note that the procedure of 15 MCS runs of 60 000 each is applied to all catchments and optimum parameter sets are established.

Figure 4 shows the box and whisker plots of parameters standardized by the prior range used for Monte Carlo Simulations (Gilgel Abbay catchment). The boxes depict the median and upper and lower quartiles. The whiskers show the most extreme values. The interquartile value ranges for ALFA are smallest and suggest that values are identified with consistency resulting in a stable region of solutions in parameter space. We note that box values of the upper and lower quartiles are relatively small and suggest that small ALFA values favour a good performing model. The result also suggests high model sensitivity to ALFA and thus optimum values for the calibrations runs are well defined. FC shows relatively narrow interquartile box ranges and suggest that the model is quite sensitive to changes of FC. The remaining parameters have comparatively, equally large interquantile ranges and suggest lower sensitivity as compared to ALFA and FC. Tthe whiskers indicate that distributions are not skewed and also suggest that the model is not highly sensitive. We note that ALFA is a measure for the non-linearity of the flow in the quick runoff reservoir while FC directly affects seepage flow and thus the quick runoff processes. Since both parameters affect the quick runoff behaviour of the model this suggest relatively low predictive uncertainty.

Figure 5 shows the model calibration results of catchments used for developing the regional model. In this study the model is validated for the period 2001 to 2003. Table 3 also shows the model validation results for the period 2001–2003. Results for NS values in general slightly deteriorate as compared to the calibration results. RVE values in general are somewhat higher indicating larger errors in the water balance. Errors for NS and RVE, however, are relatively small and indicate a good to satisfactory model performance.

6.2 Regionalisation

Correlations between PCCs and MPs are established to determine the significance of each relationship. In the procedure the correlation is statistically significant when the correlation coefficient is outside the critical value range of -0.72 to 0.72 (see Sect. 5.2). In Table 4 the significant correlation coefficients are highlighted.

It is assumed that by use of multiple PCCs a better relation can be established than when only one PCC is used. Therefore relations between PCCs and MPs are assessed through multiple linear regression analysis. This is done by the forward entry method and the backward removal method as described in Sect. 5.2. The established regional model is shown in Table 5 and is followed by a description of each parameter.

FC: in this study r showed positive correlation with CI and negative correlation with HI and DD. The highest correlation is with HI. The forward entry method was executed with HI as initial variable and results indicated that there was no other variable that could improve the strength of the relation. Therefore the procedure was terminated and the regression equation is determined with only HI with R^2 of 66.3%. The statistical characteristics are shown in Table 6.

BETA: in this study, BETA is negatively correlated to SHAPE and positively correlated to CROPD. As the highest correlation is with SHAPE, the forward entry method is executed including SHAPE as the initial variable. Results of the forward entry method showed that BETA is correlated with SHAPE and HI with R^2 of 96.02%. The statistical characteristics are shown in Table 6:

LP: in this study LP has significant positive correlation with HI and negative correlation with VER. The forward entry method is executed with highly correlated HI as the initial variable. This result showed that LP is correlated to HI and to LUV with R^2 of 91.1%. The statistical characteristics are shown in Table 6.

ALFA: in this study ALFA has positive correlation with VER and negative correlation with AREA, HI and AVGSLOPE. Therefore optimisation of the relation with the forward entry method is executed with variable AREA as initial variable. After adding the catchment characteristic URBAN the R^2 increased up to 95.1% and this regression equation is accepted. The statistical characteristics are shown in Table 6.

K_q: in this study K_q showed correlation with URBAN (−0.72), SAAR (0.75) and PWET (0.73). The forward entry method is executed by taking *SAAR* as the initial variable. By adding other variables the strength could not be improved and the simple relation with R^2 of 56.35% is accepted. The statistical characteristics are shown in Table 6.

Ks : in this study K_s has correlation with HI (0.77), AVGSLOPE (0.92) and VER (−0.88). The forward entry method was executed with AVGSLOPE as initial variable. The strength of the equation could not be improved by addition other variables and the simple linear relation is accepted with R^2 of 85.25%. The statistical characteristics are shown in Table 6.

PERC: in this study PERC has negative relation with AREA (−0.82), LFP (−0.74) and DD (−0.83). The forward entry method was executed by adding DD as the first variable and after including *SAAR*, R^2 increased up to 89.9%. The statistical characteristics are shown in Table 6.

CFLUX: in this study CFLUX has negative correlation with SHAPE (−0.83) and positive correlation with PDRY (0.81). Therefore optimisation of the linear relation with the forward entry method is executed with SHAPE as the initial variable. The results of the stepwise forward entry regression showed that CFLUX is correlated with SHAPE, PDRY and PET with R^2 of 99.8%. The statistical characteristics are shown in Table 6.

6.3 Performance assessment of the regional model

In most regionalisation studies, the validity of the regional model is assessed by its application to gauged catchments that are not used for establishing the regional model. In this work by the low number of gauged catchments, however, the regional model in Table 5 is used to estimate the model parameters for the gauged catchments using their PCCs. Simulate stream flow from the gauged catchments is compared to observed time series and assessments are by use of NS and RVE for the period 2001–2003. Table 7 shows the parameter values as derived from the regional model and the NS and RVE values. NS values range between 0.54 and 0.85 while RVE values range between −42 and 13.3%. For most catchments NS values are slightly lower than the results by MCS. RVE values for three catchments (i.e., Gumara, Megech, Kelti) are much larger while for the remaining three catchments RVE have similar value. In general validation results suggest fair to good performance of the regional model.

6.4 Lake level simulations

For lake level simulation all mass balance terms in Eq. (16) are solved on a daily time step and results of lake level simulations are compared to observed lake levels. As described in Sect. 5.3 for Lake evaporation a procedure is applied that combines the Penman-combination equation and a satellite based surface energy balance approach. By the approach Albedo values are estimated on a daily base and albedo ranged from 0.08 to 0.16. Averaged daily evaporation is estimated at 4.6 mm/day for the period 1992–2003 with a long-term averaged annual evaporation of 1563 mm/year. Minimum daily evapotranspiration is 2 mm/day and maximum is 6 mm/day. Daily rainfall over Lake Tana is estimated by spatial interpolation of gauge data from Bahir Dar, Chawhit, Zege, Deke Estifanos and Delgi station (Fig. 1). Inverse distance with power 2 resulted in an average lake precipitation of 1290 mm/year.

The results of lake level simulation are shown in Fig. 6 where simulated levels are compared to observed lake levels. The results indicate good match where climatic seasonality with clear dry and wet periods are well observable. Largest deviations are observed specifically during the first few and last few years of the simulation period. Obvious reasons that cause the deviations are difficult to identify and can relate to any of the water balance terms. A quantitative assessment indicates that the balance closure term is as large as 85 mm of the total lake inflow that comprised rainfall on the lake, and stream flow from gauged and ungauged catchments. This error accounts for 2.7% of the total lake inflow and is equivalent to a lake relative volume error of 2.17%. In Wale et al. (2009) the closure error was −170 mm and had a relative volume error of 5%.

Compared to the work in Wale et al. (2009) differences in the annual lake balance can be observed as indicated in Table 8. We note that refined procedures are applied in this work. For instance multi-objective model calibration by use of MCS is applied in this work, the procedure to estimate lake evaporation relies on spatially distributed albedo as input and lake rainfall is estimated by use of additional time series.

We note that there are still many sources of uncertainty and errors in the water balance but quantifying and reducing the errors is far from trivial. For instance, we assumed that lake-groundwater interaction is negligible; that for open water evaporation spatially averaged values can be used as estimated by the Penman-combination equation; that lake rainfall is sufficient accurately represented by use of spatial interpolation methods. Also we assume that the regional model is reliable although we note that only six catchments were used for establishing the regional model. This number is small when compared to regionalisation studies in literature but, to the authors, indicates the true problem of data scarcity as common in less developed countries.

7 Conclusions

This work shows that the Lake Tana water balance can be accurately represented. Compared to previous studies on Lake Tana's water balance by (SMEC, 2007; Kebede et al., 2006; Wale et al., 2009), results of this study indicate smallest error to close the water balance. In this work probably the most complete and available hydro-meteorological data set of the basin is used. Besides the use of this data set, multi-objective calibration by a Monte Carlo simulation procedure and the use of remote sensing proved to be effective when estimating the various water balance terms.

Regionalisation in this study is based on similarity of catchment characteristics principles and indicated that some 30% of inflow of Lake Tana is from ungauged systems while the area ungauged covers some 42%. The estimated stream flow is significantly lower than the results in Wale et al. (2009) and presumably is due to a number of reasons that relate to the use of additional rainfall time series, the use of an advanced model calibration procedure and the use of some different physical catchment characteristics for regionalisation.

Multi-objective model calibration by use of MCS indicated that a very large number of simulation runs must be executed. In this study a total of 15 times 60 000 runs is executed and resulted in relatively high parameter variability when single best parameter sets are defined for each of the 15 MCS runs but indicated moderate variability when averaged parameter values are used for the 25 best performing parameter sets.

Critical to the procedure of regionalisation in this work is the low number of gauged catchments. By the relatively small size of the Lake Tana basin only nine gauged catchments were available but only six catchments had stream flow time series that could be used after screening and correction. We note that in most regionalisation studies a much larger set of gauged catchments is available. Whether, however, the small set negatively affected our results is questionable since the catchments are close to each other with comparable variability of catchment settings. We presume that too large variability of PCC over a relatively small spatial domain could affect the regionalization result negatively since the assumptions and principles of similarity do not sustain. We note that validation results of the regional model in this study in general indicate fair to good performance.

The use of remote sensing for estimating lake water albedo through an energy balance approach proved to be effective. The results in this study showed spatially variable albedo values over Lake Tana but also showed time variability on daily base. The use of satellite based albedo estimates resulted in a lower estimate of Lake evaporation as compared to the study by Wale et al. (2009).

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Table 1. Prior parameter ranges.

Parameter	FC	BETA	CFLUX	LP	ALFA	K_q	K_s	PERC
Unit	(mm)	(–)	(mm)	(–)	(–)	(day^{-1})	(day^{-1})	(mm day^{-1})
Minimum	100	1	0	0.1	0.1	0.0005	0.0005	0.1
Maximum	800	4	0	1	3	0.15	0.15	2.5

Table 2. Selected physical catchment characteristics (PCCs).

Group	PCC	Description and unit
Morphology, Topography	AREA	Catchment area [km^2]
	LFP	Longest flow path [km]
	MDEM	DEM mean [m]
	HI	Hypsometric integral [–]
	AVGSLOPE	Average slope of catchment [%]
	SHAPE	Catchment shape [–]
	CI	Circularity index [–]
	EL	Elongation ratio [–]
	DD	Drainage Density [m/km2]
Land use	CROPD	Cultivated Dominantly [%]
	CROPM	Cultivated Moderately [%]
	GL	Grassland[%]
	URBAN	Urban [%]
	FOREST	Forest [%]
Geology and Soil	LEP	Leptosol area [%]
	NIT	Nitosol area [%]
	VER	Vertisol area [%]
	LUV	Luvisol area [%]
Climate	SAAR	Standard annual average rainfall [mm]
	PWET	Mean precipitation wet season (Jun to Sep) [mm]
	PDRY	Mean precipitation dry season (Oct to May) [mm]
	PET	Mean annual evapotranspiration [mm]

Table 3. Optimized model parameters for gauged catchments (1994–2000).

	Ribb	Gilgel Abbay	Gumara	Megech	Koga	Kelti	Gumero	Garno	Gelda
FC	309	434	349	193	730	196	469	221.25	141.14
BETA	1.23	2.08	1.31	1.56	1.34	1.60	1.10	2.58	1.20
LP	0.73	0.63	0.87	0.71	0.42	0.62	0.26	0.23	0.86
ALFA	0.31	0.24	0.25	0.29	0.41	0.28	1.08	0.27	0.51
KF	0.07	0.08	0.03	0.03	0.07	0.03	0.03	0.10	0.003
KS	0.10	0.09	0.07	0.09	0.05	0.10	0.13	0.11	0.15
PERC	1.09	1.02	1.44	1.47	1.63	1.53	2.32	1.61	1.41
CFLUX	0.60	1.09	0.72	0.79	0.74	0.83	0.39	1.35	1.00
				Calibration					
NS	0.78	0.85	0.72	0.61	0.67	0.66	0.16	0.33	0.41
RVE %	−1.61	−0.35	−2.44	2.91	−0.06	−2.00	18.51	34.02	−23.16
				Validation					
NS	0.87	0.85	0.79	0.51	0.65	0.67	–	–	–
RVE %	3.55	−2.32	−9.87	2.87	−9.83	−5.30	–	–	–

Table 4. Correlation matrix between model parameters and PCCs for 6 selected catchments; significant correlation coefficients are highlighted and in bold.

	FC [mm]	BETA [–]	LP [–]	ALFA [–]	KF [1/d]	KS [1/d]	PERC [mm/d]	CFLUX [mm/d]
AREA	−0.18	−0.01	0.49	**−0.77**	0.13	0.62	**−0.82**	0.07
LFP	−0.17	−0.15	0.53	−0.51	0.25	0.52	**−0.74**	−0.16
MDEM	0.04	−0.58	0.33	−0.64	−0.11	0.66	−0.51	−0.51
HI	**−0.81**	−0.03	**0.77**	**−0.76**	−0.44	**0.77**	−0.44	−0.07
AVGSLOPE	−0.30	−0.48	0.39	**−0.75**	−0.31	**0.92**	−0.52	−0.45
SHAPE	0.65	**−0.90**	−0.42	0.12	−0.29	−0.04	0.43	**−0.83**
CI	**0.78**	−0.37	−0.55	0.58	0.37	−0.46	0.28	−0.37
EL	0.54	−0.59	−0.32	0.59	−0.01	−0.48	0.57	−0.66
DD	**−0.74**	0.23	0.64	−0.35	0.30	**0.77**	**−0.83**	0.06
CROPD	−0.39	**0.77**	−0.04	0.35	0.10	−0.36	0.20	0.69
CROPM	0.47	−0.71	0.03	−0.52	−0.22	0.27	−0.16	−0.55
GL	−0.18	−0.54	0.36	−0.19	0.08	0.61	−0.42	−0.67
URBAN	−0.53	−0.19	0.42	−0.71	**−0.72**	0.59	−0.05	−0.13
FOREST	0.67	−0.61	−0.60	0.47	0.20	−0.09	0.23	−0.63
LEP	−0.50	−0.36	0.20	−0.23	−0.59	0.57	0.14	−0.44
NIT	0.26	−0.31	−0.56	0.26	−0.49	−0.16	0.69	−0.26
VER	0.65	0.07	**−0.73**	**0.81**	0.18	**−0.88**	0.71	0.09
LUV	0.04	0.40	0.30	0.15	0.37	−0.55	−0.08	0.38
SAAR	0.45	0.52	−0.31	0.12	**0.75**	−0.29	−0.42	0.62
PWET	0.45	0.39	−0.21	0.07	**0.73**	−0.24	−0.46	0.49
PDRY	0.41	0.69	−0.45	0.20	0.71	−0.36	−0.31	**0.81**
PET	−0.13	−0.11	−0.23	−0.09	−0.59	0.13	0.43	−0.05

Table 5. The regional model.

Regression equation	R^2
$\mathrm{FC}=\beta_0+\beta_1\cdot \mathrm{HI}$	66.3%
$\mathrm{BETA}=\beta_0+\beta_1\cdot\mathrm{SHAPE}+\beta_2\cdot \mathrm{HI}$	96.02%
$\mathrm{LP}=\beta_0+\beta_1\cdot\mathrm{HI}+\beta_2\cdot \mathrm{LUV}$	91.1%
$\mathrm{ALFA}=\beta_0+\beta_1\cdot\mathrm{AREA}+\beta_2\cdot \mathrm{URBAN}$	95.1%
$K_q=\beta_0+\beta_1\cdot \mathrm{SAAR}$	56.35%
$K_s=\beta_0+\beta_1\cdot \mathrm{AVGSLOPE}$	85.25%
$\mathrm{PERC}=\beta_0+\beta_1\cdot\mathrm{DD}+\beta_2\cdot \mathrm{SAAR}$	89.9%
$\mathrm{CFLUX}=\beta_0+\beta_1\cdot\mathrm{SHAPE}+\beta_2\cdot\mathrm{PDRY}+\beta_3\cdot \mathrm{PET}$	96.27%

Table 6. Statistical characteristics of the regionalized model parameters.

	Coefficient	*p*-value	t_{cal}	Std error	R^2
FC=$\beta_0+\beta_1\cdot$ HI					
β_0	3520.82	0.0351	3.1317	1124.26	66.3%
β_1	−6651.21	0.0487	−2.8032	2372.70	
BETA=$\beta_0+\beta_1\cdot$SHAPE$+\beta_2\cdot$ HI					
β_0	7.551	0.0100	5.85	1.2918	96.02%
β_1	−8.544	0.0429	−3.39	2.5233	
β_2	−0.036	0.0034	−8.50	0.0043	
LP=$\beta_0+\beta_1\cdot$HI$+\beta_2\cdot$ LUV					
β_0	−2.2435	0.0258	−4.13	0.5432	91.1%
β_1	5.8697	0.0133	5.27	1.1141	
β_2	0.0027	0.0471	3.26	0.0008	
ALFA= $\beta_0+\beta_1\cdot$AREA$+\beta_2\cdot$ URBAN					
β_0	0.45233	0.0003	18.63	0.02428	95.1%
β_1	−0.00009	0.0251	−4.17	0.00002	
β_2	−0.73650	0.0341	−3.71	0.19865	
$K_q=\beta_0+\beta_1\cdot$ SAAR					
β_0	−0.06555	0.3095	−1.16	0.05636	56.35%
β_1	0.00009	0.0855	2.27	0.00004	
$K_S=\beta_0+\beta_1\cdot$ AVGSLOPE					
β_0	0.0187	0.2093	1.49	0.0125	85.25%
β_1	0.0018	0.0086	4.81	0.0004	
PERC= $\beta_0+\beta_1\cdot DD+\beta_2\cdot$ SAAR					
β_0	7.4926	0.0088	6.11	1.2266	89.9%
β_1	−0.0128	0.0192	−4.61	0.0028	
β_2	−0.0005	0.0864	−2.52	0.0002	
CFLUX= $\beta_0+\beta_1\cdot$SHAPE$+\beta_2\cdot$PDRY$+\beta_3\cdot$ PET					
β_0	−0.2184	0.2689	−1.52	0.1441	96.27%
β_1	−0.0082	0.0021	−21.86	0.0004	
β_2	0.3867	0.0019	22.63	0.0171	
β_3	0.0007	0.0184	7.28	0.0001	

Table 7. Assessment of the regional model for gauged catchments (2001–2003).

	FC	BETA	LP	ALFA	K_q	K_s	PERC	CFLUX	NS [−]	RVE [%]
Ribb	298	1.17	0.71	0.29	0.055	0.098	1.10	0.62	0.85	−1.3
Gilgel Abbay	333	1.99	0.72	0.25	0.086	0.084	1.13	1.10	0.83	0.1
Gumara	307	1.48	0.83	0.28	0.057	0.079	1.40	0.71	0.75	−22.8
Megech	201	1.54	0.70	0.29	0.031	0.085	1.52	0.79	0.54	13.3
Koga	659	1.32	0.41	0.43	0.068	0.061	1.63	0.75	0.65	−1.1
Kelti	437	2.45	0.72	0.39	0.072	0.054	1.18	1.06	0.53	−42.0

Table 8. Lake Tana water balance components simulated for the period 1994–2003.

Water balance components	mm/year	MCM/year
Lake areal rainfall	+1347	+4104
Gauged river inflow	+1254	+3821
Ungauged river inflow	+527	+1605
Lake evaporation	−1563	−4762
River outflow	−1480	−4508
Closure term	+85	+260

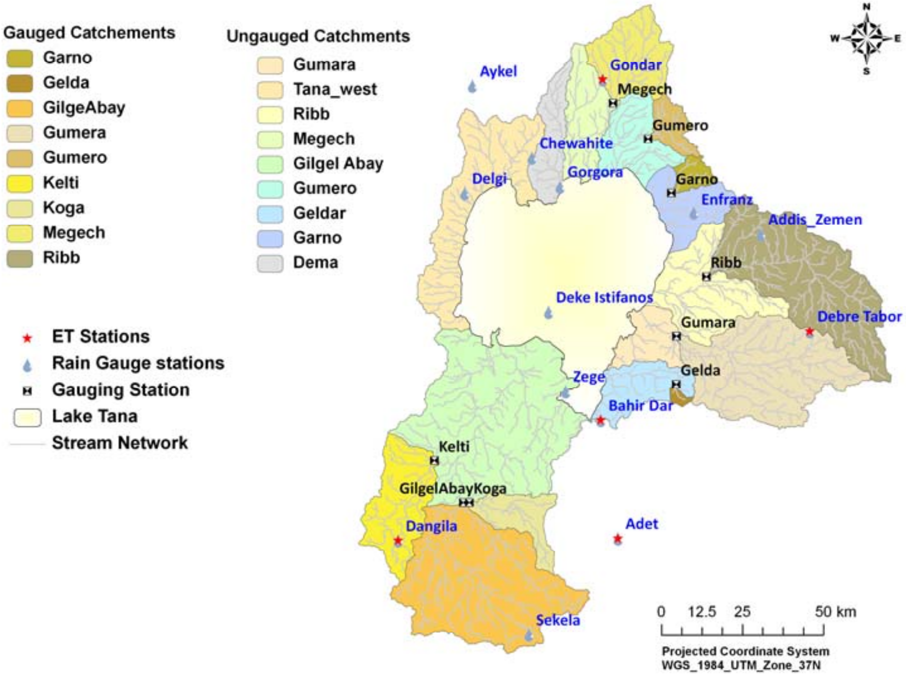

Fig. 1. Gauged and ungauged catchments in the Lake Tana basin. Weather and gauge stations are indicated.

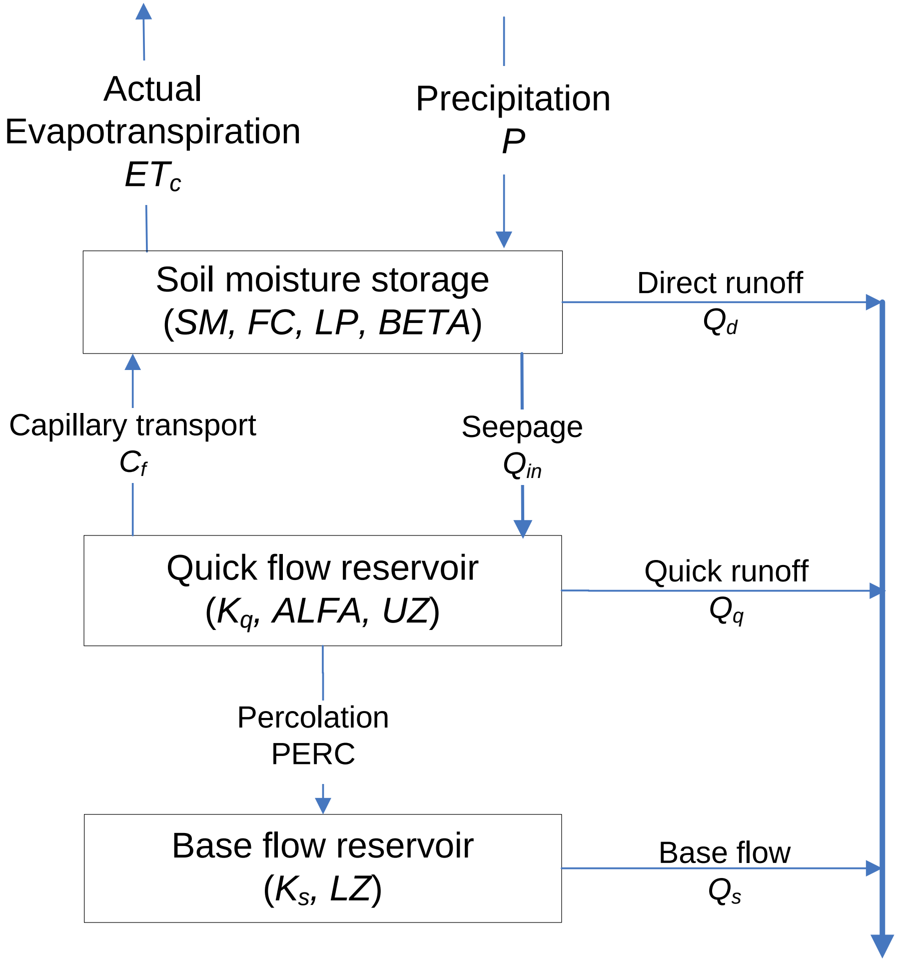

Fig. 2. A diagram of the HBV-96 approach (modified after Lindström, 1997).

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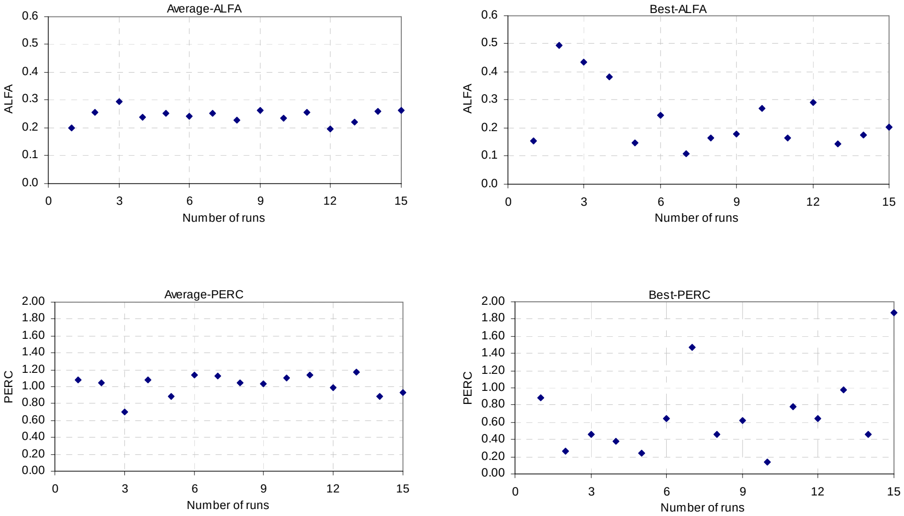

Fig. 3. Left hand side shows the average parameter values the 25 best performing parameter sets for ALFA and PERS for each MCS run of 60 000 runs each. The right hand side shows single best parameter values.

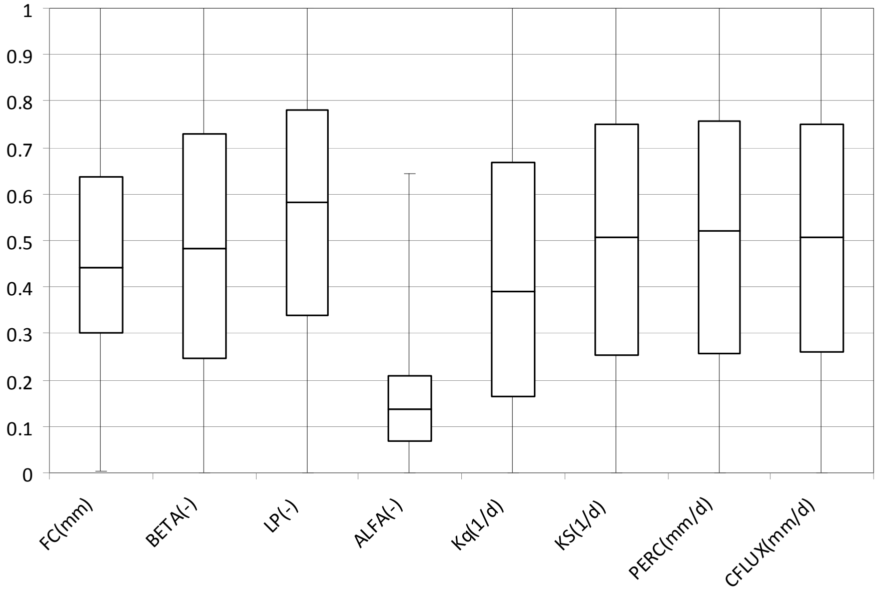

Fig. 4. Box and whisker plots of parameters standardized by the prior range used for Monte Carlo Simulations (Gilgel *Abbay* catchment). The boxes depict the median and upper and lower quartiles. The whiskers show the most extreme values.

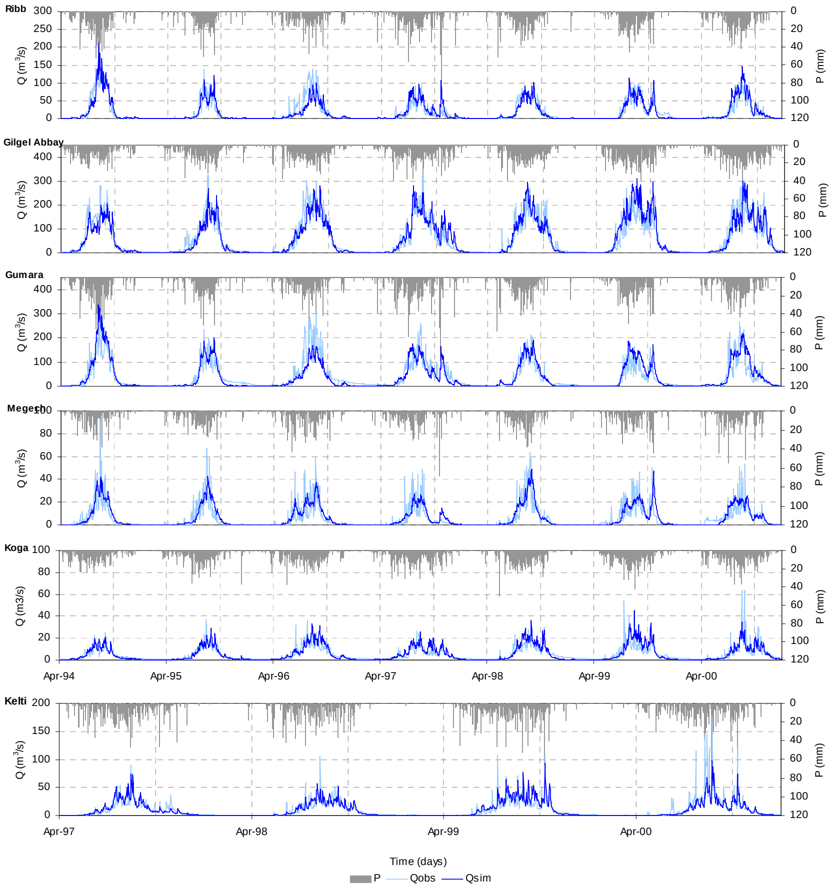

Fig. 5. Model calibration results of Ribb, Gilgel Abbay, Gumara, Megech, Koga (1994–2000) and Kelti (1997–2000) catchments.

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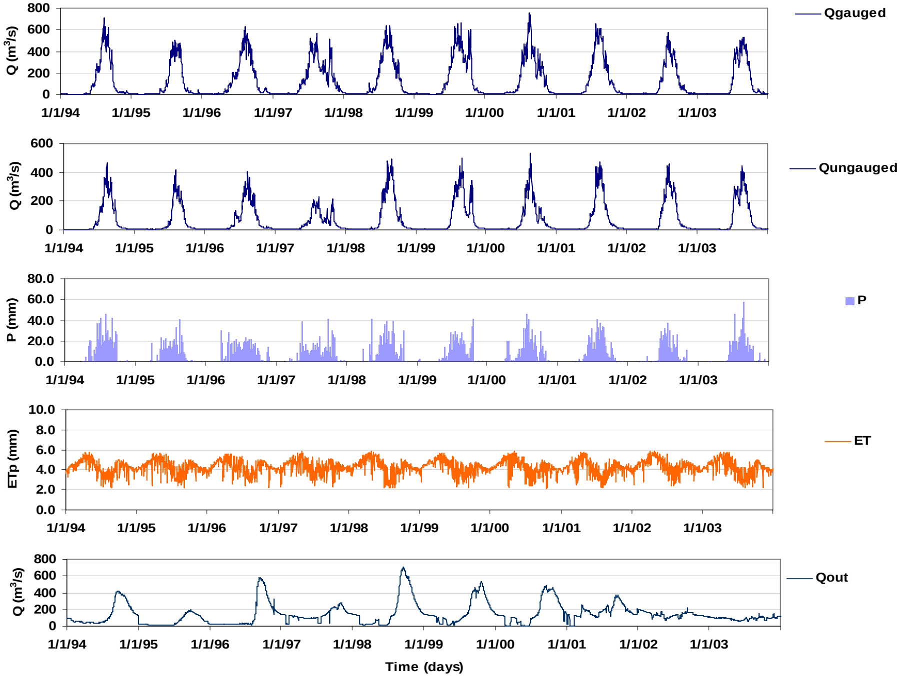

Fig. 6. Daily estimates of water balance terms of Lake Tana.

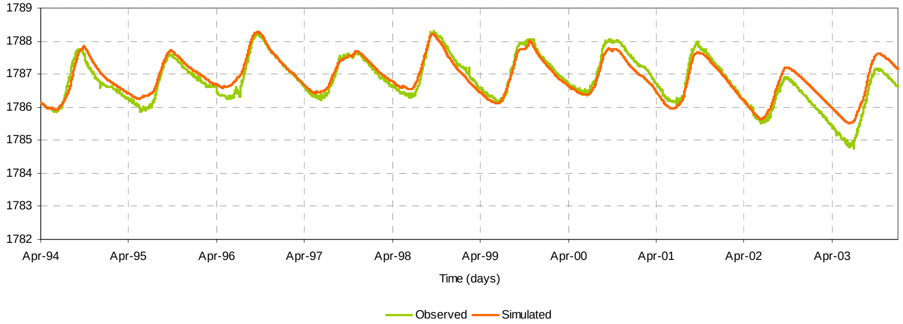

Fig. 7. Comparison of simulated to observed lake levels.