Estimation of flow in ungauged catchments by coupling a hydrological model and neural networks: case study

A. H. Saliha, S. B. Awulachew, J. Cullmann and Hans-B. Horlacher

ABSTRACT

The prediction of hydrological variables for ungauged basins is still a big challenge. Regionalization is the most widely used method to date, which relates parameters of watershed models to catchment characteristics. Relating catchment characteristics to watershed model parameters is too difficult for distributed hydrological models, due to the heterogeneous nature of catchments. A regional model was proposed by coupling a Kohonen neural network (KNN) and distributed Water Balance Simulation Model (WaSiM-ETH) to estimate flow in ungauged basin. KNN was used to delineate a hydrological homogeneous group based on predefined physical characteristics of catchments and WaSiM-ETH was applied to generate daily stream flow. Twenty-six subcatchments of the Blue Nile River basin, Ethiopia, were grouped into five hydrological homogenous groups, each with its own full set of optimized WaSiM-ETH parameters. In the regional model, the KNN assigned the ungauged catchment into one of the five hydrological homogenous groups. The whole set of optimized WaSiM parameters from the homogeneous group (which the ungauged river belongs to) were transferred to the ungauged river and WaSiM-ETH was used to compute the flow for this ungauged river. The regional model generally overestimated the low flow. In general, the results for validation subcatchments showed the regional model is satisfactory in transferring information from data-rich to data-poor catchments.

Key words | Blue Nile River, hydrological homogenous, Kohonen neural network, regionalization, ungauged catchment, WaSiM-ETH

A. H. Saliha (corresponding author)
Hans-B. Horlacher
Institute of Hydraulic Engineering and Technical Hydromechanics,
Technical University of Dresden,
Germany
E-mail: *alexhabte@yahoo.com*; *saliha@bafg.de*

S. B. Awulachew
International Water Management Institute,
Head, Sub Regional Office for Nile basin and East Africa,
Addis Ababa,
Ethiopia

J. Cullmann
Federal Institute of Hydrology,
UNESCO-IHP-and WMO-HWRP Secretariat,
Koblenz,
Germany

INTRODUCTION

In seeking to address the challenges of water resources and environmental degradation issues across a basin, a major difficulty is encountered with those basins for which little or no hydrometric data are available. These basins are predominantly in developing country regions, where climatic variability and basin development activities are undertaken with limited data. This frequently leads to the depletion of water resources, ecosystem degradation and poor quality of life (IAHS 2003).

Most rivers in Africa are either ungauged or have limited hydro-meteorological data due to poorly developed hydrometric networks and lack of human and financial resources to develop and maintain such networks. While the need for hydrological information for Africa is increasing, technical and human capacities are declining as the reduction in the number of meteorological stations in Africa during the last 30 years confirms (Bonifacio & Grimes 1998; Oyebande 2001).

As watershed models become increasingly sophisticated, there is a need to extend their applicability to ungauged catchments. Transfer of hydrologic characteristics of watersheds from data-rich or 'donor' catchments to data-poor environments is one of the most fundamental challenges in the field of hydrology. Sivapalan (2003) argues that the new IAHS decadal initiative on 'Predictions in Ungauged Basins' (PUB) (see Hubert *et al.* 2002) represents

doi: 10.2166/nh.2011.157

a grand challenge for the field of hydrology that forces us to deal with questions that are 'deep, grand and practical'. Sivapalan (2003) further argues that 'PUB, sans calibration, remains a difficult, unsolved problem, demanding urgent resolution and requiring significant new breakthroughs in data collection, process knowledge and understanding'.

In the past decade, there has been a significant increase in research relating to the regional calibration of watershed models to enable their use at ungauged sites. Bloschl & Sivapalan (1995), Abdulla & Lettenmaier (1997), Sefton & Howarth (1998), Xu & Singh (1998), Post & Jakeman (1999), Seibert (1999), Xu (1999), Fernandez *et al*. (2000) and Kokkonen *et al*. (2003) provide reviews of the use of regional hydrologic methods for estimating watershed model parameters at ungauged sites.

Although each previous study attempted to regionalize different watershed models, most studies to date (with the exception of Fernandez *et al*. 2000) follow the same general approaches. As stated in Fernandez *et al*. (2000), a watershed model is first calibrated to whatever climate and stream flow data are available for the region of interest. This step is followed by the application of a regional hydrologic method, which attempts to relate the optimized watershed model parameters to watershed characteristics. Even when one attempts to regionalize a very reasonable and parsimonious watershed model, results are still mixed (Post & Jakeman 1999). Schaake *et al*. (1997) further demonstrated that a very large number of watersheds are necessary to obtain a meaningful relationship between watershed model parameters and watershed characteristics. It is also too difficult, if not impossible, to find these relationships for distributed type of watershed models. Nevertheless, there is a need for distributed watershed models to take care of the spatial variability of climate, land use, soil and topographic features.

Vogel (2005) pointed out two promising approaches for regionalization. The first promising approach in data-sparse environments is to assign *a priori* values to the watershed model parameters using some generalized homogeneity classification of watersheds based on land use, soil types, climate conditions and runoff ratios. The idea is to cluster or group watersheds into 'hydrological homogeneous' regions. Another promising approach to hydrologic regionalization involves the use of hybrid methods such as in the study by Yu & Yang (2000) where cluster analysis and principal component analyses were employed to break the region into hydrological homogeneous regions. Next, drainage area was used to develop a regional flow duration curve model, which was in turn used to calibrate the watershed model at an ungauged site. Such a hybrid approach can benefit from advances relating to the definition of hydrological homogeneous regions.

Shu & Burn (2003) suggested that geographically close catchments are not necessarily homogeneous in terms of hydrological response. There are methods like L-moments technique, Ward's cluster and K-means, which are recommended by different researchers, to identify hydrological homogeneous groups. More recently, modern informatics' tools, such as the fuzzy C-means method and artificial neural networks (ANNs), have been applied to form groups and to allocate ungauged catchments to an appropriate sub-region using site characteristics (Hall & Minns 1999; Hall *et al*. 2002). These techniques may identify subregions that are not necessarily geographically contiguous. Zhang & Hall (2004) compared four methods to delineate homogenous regions based on catchment characteristics. They have applied a geographical approach (residual methods), Ward's cluster method, the fuzzy C-means method and a Kohonen neural network (KNN) to 86 sites in the Gan River Basin in China. They have found similar groupings of sites into subregions for all except the geographical approach (residual methods). However, of the three techniques, only the KNN method provides the number of groups as well as defining their membership and is therefore to be preferred. Other methods follow a trial and error procedure to obtain the number of hydrological homogeneous groups.

Despite the difficulty encountered due to limited or no hydrological data, planning and design of water resources projects must be undertaken for ungauged basins. In this paper, a regional model was proposed by combining a self-organising map (SOM) with a water-balance simulation model (WaSiM-ETH) to estimate flow in ungauged catchments of the Blue Nile (Abay) River basin in Ethiopia. In the proposed regional model, SOM/KNN was used to identify hydrological homogeneous groups based on pre-defined physical characteristic of the catchments and WaSiM-ETH was used to compute daily stream flow.

METHODOLOGY

Figure 1 presents the general framework of the proposed methodology. In the regional model, the selected watershed model (WaSiM-ETH) and self-organizing map (NeuroShell2) were coupled to estimate flow in ungauged catchments. SOM in the NeuroShell2 was trained for selected physical catchment characteristics of rivers in the case study area. The selected physical catchment characteristics, which can be derived from a digital elevation model (DEM), land use map and soil map, should also be available for ungauged catchments. These characteristics are presented to NeuroShell2 in the input layer and then propagated to the output layer. The neuron in the output layer is evaluated. The network weights are adjusted during training. This process is repeated for all patterns for a number of epochs chosen (see SOM training part of Figure 1). One output neuron is the winner. This winner neuron – in our case catchments similar to each other with respect to the selected physical catchment characteristics – has a value of 1 and all others 0, or the actual values can be extracted in the output layer. After the completion of SOM training, the number of groups (say group 1, group 2, etc.) and member of catchments in each group can be extracted from the output file. How well a Kohonen network classifies data is dependent upon how well we set the parameters such as number of epochs, neighbourhood size, initial weight and learning rate.

Catchments in each hydrological homogeneous group were split into calibration catchments (Cali), to calibrate WaSiM-ETH model parameters using an automatic model parameter estimation method (PEST), and validation catchments (Vali) to validate the regional model (see the lower part of Figure 1). If two or more members are involved for-WaSiM-ETH model calibration, the selected members are calibrated simultaneously to generate a single set of WaSiM-ETH model parameters for a particular group. That means each hydrological homogeneous group has its own full set of optimized (after calibration and validation of the regional model) WaSiM-ETH model parameters (OWPs) which are stored in the database component of the regional model and can be retrieved for an ungauged catchment.

The trained SOM is run again for a new set of physical catchment characteristics of the ungauged catchments in the input layer (see the red broken line in Figure 1 above). The trained SOM assigns the ungauged catchments into one of the hydrological homogeneous groups formed previously, based on the similarity of the physical characteristics of the ungauged to a particular group. The regional model transfers the whole set of optimized WaSiM-ETH model parameters from the homogeneous group (which the ungauged catchment belongs to) to the ungauged river and WaSiM-ETH eventually generates daily flow for this ungauged catchment. A small program in visual basic Microsoft access environment was written to facilitate the above procedure (see Appendix, available online at http://www.iwaponline.com/nh/042/0157.pdf).

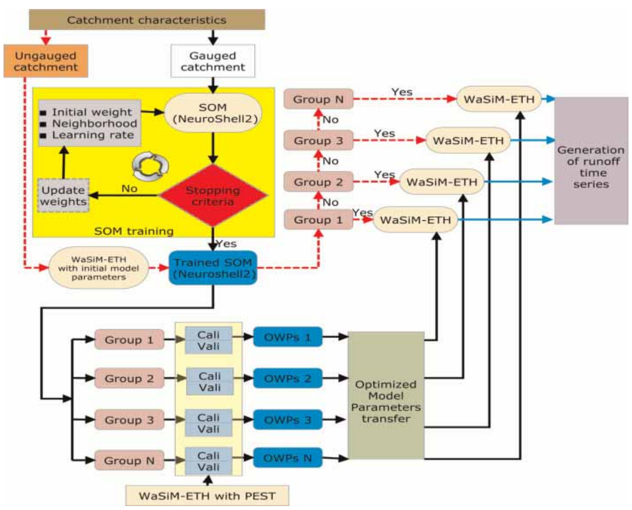

Figure 1 | General framework of the proposed regional model.

WaSiM-ETH

WaSiM-ETH (Schulla 1997) is a Water-balance Simulation Model, which has both physically based and conceptual model components. It is a distributed hydrological model that performs calculations per grid cell and per sub-basin. The spatial resolution of the grid cell can range from metres to kilometres with the highest resolution in time for modelling the hydrological process being 1 min. Because of the physical basis of many WaSiM-ETH components, the model can generally be applied to various basins in a wide range of environmental conditions all over the world (Schulla & Jasper 2000).

WaSiM-ETH uses physically based algorithms for the majority of the process descriptions, such as infiltration (which is an integral part of the soil model), estimation of saturation time, solution of the one-dimensional (1D) Richards equation for the description of the soil water fluxes in the unsaturated zone or the topographic model (TOPMODEL) approach. WaSiM-ETH has interpolation facilities for meteorological data. Depending on the availability of meteorological information, WaSiM-ETH uses different methods to compute potential evapotranspiration. Actual evapotranspiration is obtained by the respective reduction of potential evapotranspiration according to the actual soil moisture content. WaSiM-ETH routs the channel flow by means of a translation module with simple storage built in to account for diffusion. Groundwater dynamics is portrayed by a 2D module or with an optional lumped conceptual approach. WaSiM-ETH is subdivided into several submodels as depicted in Figure 2. The TOPMODEL approach for unsaturated flow and the lumped conceptual groundwater approach for saturated flow were selected for the case study area due to lack of reliable information on soil and aquifer, respectively.

For most of the submodels, WaSiM-ETH offers several alternative methods which depend on the availability of the input data to compute the same variable. A complete model description is given in Schulla & Jasper (2000). Unless otherwise stated, the following methods (which are used in this paper) are based on work by Schulla & Jasper (2000).

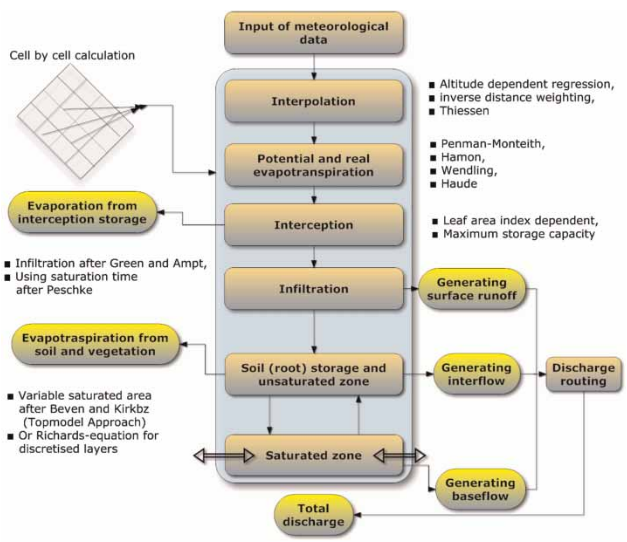

Figure 2 | Adopted WaSiM-ETH model structure (modified from Schulla & Jasper 2000).

Potential evapotranspiration

There are three possibilities in WaSiM-ETH to compute potential evapotranspiration: Penman–Monteith method (Monteith 1975; Brutsaert 1982), Wendling method (Wendling 1975) and Hamon method (in Federer & Lash 1983). In the Penman–Monteith method, many meteorological variables such as temperature, relative humidity, sunshine hour duration and wind speed are involved and this method is chosen if all variables are available for the study area. In the study area considered in this paper, where only temperature data are available as a long-time series, in the Hamon method was chosen. The default empirical constants in the Hamon method, valid for northern Switzerland and cited in Schulla & Jasper (2000), were modified accordingly to fit the case study area. For details refer to Habte *et al.* (2007).

Interception

Interception storage is defined as the storage of precipitation on vegetation and on the soil surface. A simple bucket approach is used with a capacity depending on the leaf area index, the vegetation coverage and maximum height of the water at the leaves.

Infiltration

WaSiM-ETH uses the infiltration approach described in Green & Ampt (1911) and estimation of saturation time of Peschke (1987). The time of saturation and then the accumulated infiltration are calculated until the end of the time-step. If the soil surface is saturated at the end of the time-step, in the next time-step only the accumulated infiltration will be calculated provided that the constant precipitation intensity is sufficiently high. The exceeding amount is surface runoff.

Soil model TOPMODEL approach

As noted in Schulla & Jasper (2000), the modelling of the soil water-balance and of runoff generation is carried out using a modified variable saturated area approach (Beven & Kirkby 1979) extended by capillary rise and interflow. The calculation is done separately for each of the grid cells as opposed to the modelling of classes of similar indices, as in the original TOPMODEL. The base for the model is the spatial distribution of the topographic index C_s. Using this index, the potential extent of saturation areas can be estimated depending on the mean saturation deficit within the basin:

$$C_s = \ln \frac{a_t}{T_0 \tan \beta_t} \tag{1}$$

where C_s is topographic index (dimensionless), β_t is slope angle (m/m), K_s is saturated hydraulic conductivity (mm/h), a_t is specific catchment area per unit length of a grid cell (this is the area draining through 1 m of the edge of a grid cell in m^2/m) and T_0 (m^2/s) is saturated local hydraulic transmissivity ($T_0 = \int K_s \, dh$).

Surface runoff is created for each grid cell as the sum of infiltration excess along the topographic gradient towards the river. Surface runoff is routed to the sub-basin outlet by subdividing the basin into flow time zones. Flow time zones are zones of equal flow times for surface runoff to reach the sub-basin outlet. Retention is approached by applying a single linear storage to the surface runoff in the last flow time zone, with storage constant k_D:

$$Q_{D_i} = Q_{D_{i-1}} \exp(-\Delta t/k_D) + \hat{Q}_D[1 - \exp(-\Delta t/k_D)] \tag{2}$$

where Q_{D_i} is transformed surface runoff in time-step i (mm), Δt is time-step (h), $Q_{D_{i-1}}$ is transformed surface runoff in time-step $i-1$ (mm), $\hat{Q}_D$ is surface runoff in the time-step i within the lowest flow time zone (mm) and k_D is single linear recession constant for surface runoff (h).

Interflow is calculated in defined soil layers depending on suction, drainable water content, hydraulic conductivity and gradient for each grid cell separately, and then averaged over space. The TOPMODEL approach considers interflow using a conceptual approach. As for surface runoff, the interflow storage is filled dependent on the local saturation deficit. To consider retention of the interflow, a single linear storage is treated similarly as surface runoff with recession constant k_H instead of k_D in Equation (2).

The vertical flow rate (percolation) can be computed as:

$$q_v = K_{corr} k_f \exp(-S_i/m) \tag{3}$$

where q_v is vertical flow rate (mm), S_i is local saturation deficit (mm), K_{corr} is a scaling factor for considering unsaturated soils and preferred flow paths (dimensionless), m is a recession model parameter (mm) and k_f is saturated hydraulic conductivity (mm/h).

The base flow is calculated for each sub-basin as a whole:

$$\begin{aligned} Q_B &= \exp(-\gamma + \ln T_{corr}) \exp(-S_m/m) \\ &= T_{corr} e^{\gamma} e^{-S_m/m} \end{aligned} \tag{4}$$

where Q_B is base flow (mm/time-step), γ is mean topographic index (dimensionless), m is recession model parameter (mm), S_m is mean saturation deficit for a (sub-) basin (mm), and T_{corr} is transmissivities scaling factor (dimensionless).

The summation of surface runoff for actual time-step, which is the content of the lowest time zone, base flow and interflow, yields the total runoff.

The TOPMODEL soil model, which contains the most sensitive parameters (Schulla & Jasper 2000), is controlled by nine parameters (recession parameter for base flow m, correction factor for the transmissivity of the soil T_{corr}, correction factor for vertical percolation K_{corr}, single reservoir recession constant for surface runoff k_D, maximum storage capacity of the interflow storage SH_{max}, single reservoir recession constant for interflow k_H, precipitation intensity threshold for generating preferential flow into the saturated zone P_{gren}, scaling of the capillary rise/refilling of soil storage from interflow r_k and fraction of snowmelt which is surface runoff c_{melt}) and two initial conditions. The two initial conditions are the content of the interflow storage and the initial saturation deficit.

Kohonen neural network (KNN)

A hydrological homogeneous group can be defined as an open system consisting of basins that have a high degree of similarity from the point of view of hydrological characteristics and/or catchment characteristics. KNN also known as the SOM, which was introduced by Teuvo Kohonen in 1982 and is a realistic, although very simplified, model of the human brain (Kohonen 1997). SOM is a non-linear mapping technique, which has the ability to learn without being shown correct outputs in sample patterns. This means that the Kohonen network is presented with data but the correct output that corresponds to those data is not specified, unlike many other types of network. It is more efficient with pattern association and it serves as a clustering tool of high-dimensional data and for visualizing purposes. These networks are able to separate data into a specified number of categories.

SOM has been applied by many authors, including Foody (1999) and López-Rubio *et al.* (2001) for pattern recognition or classification. Cai *et al.* (1994) use standard SOM for classifying flow conditions in the unsaturated zone. Their experiments resulted in a good correspondence between the SOM classifications and visual observations. The identification of catchments may be regarded as an example of the wider problem of classification of data sets. Hall & Minns (1999) indicated the feasibility of employing a KNN for the classification of hydrological homogeneous regions. Zhang & Hall (2004) have successfully applied SOM to delineate homogenous regions based on catchment characteristics.

The architectural structure of KNNs is shown in Figure 3(a). It consists of components called input nodes or neurons and map nodes. Associated with each input node is a weight vector of the same dimension as the input data vectors that connect to each map node and a specific topological position in the map space. None of the map nodes connect to each other. The weights of the neurons are initialized either to small random values or sampled evenly from the subspace spanned by the two largest principal component eigenvectors.

Training of SOM occurs over several steps and many iterations. The weights of each node are first initialized and then a vector is chosen at random from the set of training data and

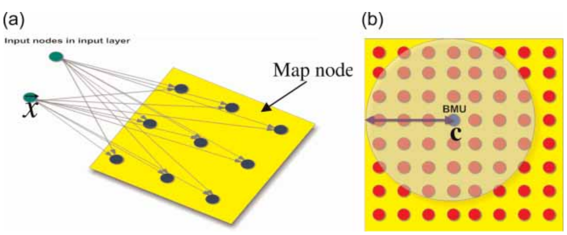

Figure 3 | (a) Structure and basic principle of rectangular topology of SOM and (b) neighbourhood radius of the BMU.

presented to the net. Every node is examined to calculate which node's weights are most like the input vector. The winning node is commonly known as the best-matching unit (BMU). The radius of the neighbourhood of the BMU is calculated. Any nodes found within this radius are deemed to be inside the BMU's neighbourhood (see Figure 3(b)). Each neighbourhood node's weights are then adjusted to make them more like the input vector. The closer a node is to the BMU, the more its weights are altered. This whole process is then repeated a large number of times.

Steps in SOM training

Generally, the SOM is trained iteratively. Each iteration k involves an unsupervised training step using a new sample vector $\vec{x}_{\mathrm{SOM}}$ and the weight vectors $\vec{m}_i$ as follows:

- Initializing the weight vectors: Prior to training, each node's weights must be initialized. Typically these initial weight vectors $\vec{m}_i$ will be set to small standardized random values.
- Search for the BMU: At each iteration k, one single sample vector $\vec{x}_{\mathrm{SOM}}(k)$ is randomly chosen from the input data set and its distance ε_i to the weight vectors of the SOM is calculated as:

$$\varepsilon_i = \|\vec{x}_{\mathrm{SOM}}(k) - \vec{m}_i\| = \sum_{j=1}^{n+m} (x^j_{\mathrm{SOM}}(k) - m^j_i)^2. \quad (5)$$

The neuron whose weight vector $\vec{m}_i$ is closest to the input vector $\vec{x}_{\mathrm{SOM}}(k)$ is the 'winner', i.e., the BMU at c (see Figure 3(b)) represented by the weight vector $\vec{m}_c(k)$, which is the smallest of the Euclidean distance.

- Determining the BMU's local neighbourhood: After the BMU has been determined, the next step is to calculate which of the other nodes are within the BMU's neighbourhood. All these nodes will have their weight vectors altered/updated in the next step. A unique feature of the Kohonen learning algorithm is that the area of the neighbourhood reduces over time. This can be accomplished by making the radius of the neighbourhood converge over time. The convergence depends on the function of the neighbourhood radius $\sigma(k)$. A common choice is an exponential decay described by Ritter *et al.* (1992).

$$\sigma(k) = \sigma(0)e^{-k/k_{\max}} \tag{6}$$

- Adjusting the weights: If a node is found to be within the neighbourhood then the weight vector of this node and the BMU are updated. The rule for updating the weight vector of unit i is given by:

$$\vec{m}_i(k+1) = \vec{m}_i(k) + \alpha_s(k)h_{ci}(k)[\vec{x}_{\text{SOM}}(k) - \vec{m}_i(k)] \tag{7}$$

where k denotes the iteration step of a training procedure, $\alpha_s(k)$ is the learning rate at step k and $h_{ci}(k)$ is the so-called neighbourhood function which is valid for the actual BMU at c; it is a non-increasing function of k and of the distance d_{ci} of unit i from the BMU at c. The Gaussian function is widely used to describe this relationship:

$$h_{ci}(k) = e^{-d_{ci}^2/2\sigma^2(k)} \tag{8}$$

where σ is the neighbourhood radius at iteration k and $d_{ci} = \|\vec{r}_c - \vec{r}_i\|$ is the distance between map units c and i on the map grid. The neighbourhood radius σ corresponds to the neighbourhood relationship N_i.

The learning rate $\alpha_s(k)$ should also vary with the increasing number of training steps as indicated in Equation (6). Kohonen (2001) suggested starting at an initial value $\alpha_s(0)$ with a value close to 1 and then to decrease gradually with an increasing number of training steps k.

The cooperation between neighbouring neurons – a unique feature of the SOM algorithm – ensures a fast convergence and a high accuracy in approximating functional relationships. Even though the exponential decays described in Equations (7) and (8) for the neighbourhood radius $\sigma(k)$ and the learning rate $\alpha_s(k)$ are purely heuristic solutions, they are adequate for a robust formation of the self-organizing map (Kohonen 2001).

NeuroShell2, which use the KNN module to process a data file through a trained neural network to produce the network's classifications for each pattern in the file, was selected to cluster hydrological homogeneous groups in the case study area. The SOM network used in NeuroShell2 is a type of unsupervised network, which has the ability to learn without being shown correct outputs in sample patterns. These networks are able to separate data into a specified number of categories.

CASE STUDY: BLUE NILE (ABAY) RIVER BASIN

The area of the Abay basin is about 200,000 km^2 and the total perimeter is 2,440 km. The basin is located in the centre and west of Ethiopia, as shown in Figure 4. It lies approximately between latitude 7°45′N and 12°46′N and longitude 34°06′E and 40°00′E, is generally rectangular in shape and extends about 400 km from north to south and about 550 km from east to west. It accounts for almost 17.1% of Ethiopia's land area and about 50% of its total average annual runoff (BCEOM *et al.* 1999). The Abay River rises in the centre of the catchments and develops

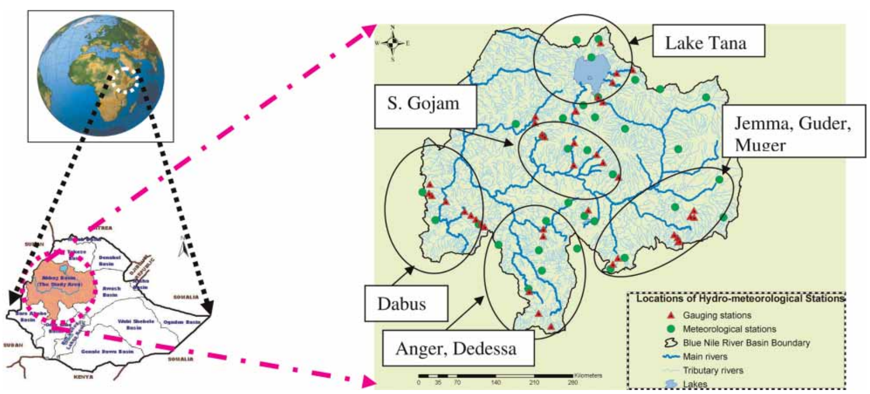

Figure 4 | Location of the hydro-meteorological stations in the study area.

its course in a clockwise spiral in a deep gorge, collecting tributaries along its 922 km length from Lake Tana to the Sudan border. The elevation of the basin ranges from 490 m a.s.l. at the Sudan border to 4,230 m a.s.l. at the summit of mountain Guna. Annual rainfall varies between about 800 and 2,220 mm, with a mean of about 1,420 mm. High rainfall is found in the southern part of the basin where it persists over a relatively long period (April–October). A second area of relatively high rainfall lies on the centre of the basin and has a shorter, more pronounced wet season. In the east, rainfall is relatively low but follows a bimodal pattern with peaks in April/May and July/September. Rainfall generally declines towards the northwest over the eroded hills and plains. The mean temperature of the basin is 18.5 °C, with mean minimum and maximum daily temperature of 11.4 and 25.5 °C, respectively. Average annual potential evapotranspiration is estimated to be 1,310 mm (BCEOM *et al.* 1999).

Rainfall–runoff model simulation

Almost all operational gauging stations of tributaries of the Abay river basin (see Figure 4) are located along the main road from Addis Ababa, capital city of Ethiopia, to different routes of cities of Bahir Dar, Gondor, Jimma and Assosa and are located upstream of the main rivers, which capture a small portion of the sub-basin flow. From an accessibility point of view, their locations are best. From the hydrological point of view, however, some of the gauging stations are located on unstable section of the river. For some gauging stations, the carrying capacities of the channel are limited to hold above-average flows. Such phenomena such as deposition of debris and siltation on the vertical staff gauge and inadequacy of tandem vertical staff gauge to measure low flows were observed during field visits to gauging stations in the Lake Tana sub-basin. The quality of measured hydrometric data from such gauging stations is questionable. Detailed assessments and recommendations of the gauging stations in the Blue Nile river basin can be found in BCEOM *et al.* (1999).

There are more than 100 gauging stations in the Blue Nile river basin that have daily runoff records. However, 7 years (1993–1999) of daily runoff records from 40 gauging stations can be collected from the Ethiopian Ministry of Water Resources for this study. Additional daily runoff data for some gauging stations in Anger and Dedessa sub-basins (1986–1993) and Lake Tana sub-basin (1986–2005) were collected from the same Ministry. About nine gauging stations in the Dabus subcatchment, which has different surface water hydrology from the rest of the rivers in the Blue Nile river basin, were excluded from this regionalization technique. After checking their homogeneity and the consistency of the runoff data series, only runoff time series from 26 gauging stations were of relatively good quality and were selected for regionalization. Daily precipitation, daily maximum and daily minimum temperatures from 33 meteorological stations were collected for the same period from Ethiopian National Meteorological Service Agency.

To check the performance of the model to generate daily stream flow for gauged rivers in the case study area, WaSiM-ETH was applied at a spatial resolution of 90×90 m^2. The hydro-meteorological data, land use and soil data were prepared as per the format of the WaSiM-ETH through Arc-GIS and Tanalys. The snow accumulation component was disabled, as there is no snow in the study area.

With the exception of c_{melt} (fraction of snowmelt model parameter), which is not valid for the case study area, the remaining eight model parameters of the soil model of TOPMODEL-approach were calibrated intensively by coupling WaSiM-ETH to the automatic parameter estimation package PEST. PEST is a non-linear model-independent parameter estimation tool that uses two approaches. The standard method uses the Gauss–Marquardt–Levenberg (GML) algorithm. This method is fast and stable as it switches between the steepest gradient. The drawback of this method is that it might become 'stuck' in local minima, depending on the surface of the error and the start values for the optimization run. The second approach available in PEST is the global Shuffled Complex Evolution-University of Arizona (SCE-UA) search algorithm (Duan *et al.* 1992). This algorithm is capable of finding the global minimum of the objective function. However, it requires substantially more effort in terms of computer processing unit (CPU) time. The second approach was embedded in WaSiM-ETH for the case study area considered in this study.

The calibration of the model was assessed by comparing measured and model output discharge at the selected gauged rivers using coefficient of determination (R^2) and the Nash–Sutcliffe (N–S) efficiency criteria (Nash & Sutcliffe 1970) given by:

$$\text{N–S} = 1 - \frac{\sum_i (Q_{\text{sim},i} - Q_{\text{obs},i})^2}{\sum_i (Q_{\text{obs},i} - \bar{Q}_{\text{obs}})^2} \tag{9}$$

where $Q_{\text{sim},i}$ is the simulated discharge at time-step i, $Q_{\text{obs},i}$ is the observed discharge at time-step i and $\bar{Q}_{\text{obs}}$ is the mean observed discharge.

The model performance was compared with the soil water assessment tool SWAT2005 and the HBV (Hydrologiska Byråns Vattenbalansavdelning) model. Shimelis *et al.* (2008) have applied the SWAT2005 hydrological model for prediction of stream flow in the Lake Tana sub-basin. The model was calibrated and validated using Sequential Uncertainty Fitting (SUFI-2), Generalized Likelihood Uncertainty Estimation (GLUE) and Parameter Solution (ParaSol) algorithms. Wale *et al.* (2009) have used the HBV to map a relationship between rainfall and runoff and to regionalize the HBV model parameters to the Lake Tana sub-basin. Table 1 presents the performance of WaSiM-ETH, SWAT2005 and HBV model for the same case study area.

Although it is difficult to conclude that WaSiM-ETH performed better than the other two models due to the differences in calibration and validation periods, it is evident from Table 1 and Figure 5 that WaSiM-ETH performed well in both calibration and validation periods. Figure 5 depicts time series of observed and simulated (WaSiM-ETH model) daily flow at Gilgel Abay River gauging station during calibration and validation periods. Results of the performance of WaSiM-ETH for other rivers in the case study area can be found in Habte *et al.* (2007).

Identification of hydrological homogeneous groups

Physical catchment characteristics which are also available for ungauged catchments, such as catchment area (km^2), dominant land use (%), dominant soil type (%), slope (%), longest distance from the most upstream to the outlet of river (km), weighted average topographic index, weighted average elevation (m) and shape of the catchment were selected to identify hydrological homogeneous groups (see Figure A1 for description). This information was extracted from a 90 m × 90 m grid DEM using ARC-GIS.

The physical characteristics of the selected catchments were imported to NeuroShell2. Sixteen neurons that include catchment area (km^2), slope (%), longest distance from the most upstream point to outlet of the catchment (km), dimensionless weighted topographic index, weighted average elevation (m), dimensionless shape of the catchment, five dominant soil types (%) and five dominant land uses (%) were presented in the input layer of the KNN. The number of neurons (number of similar groups or clusters) in the

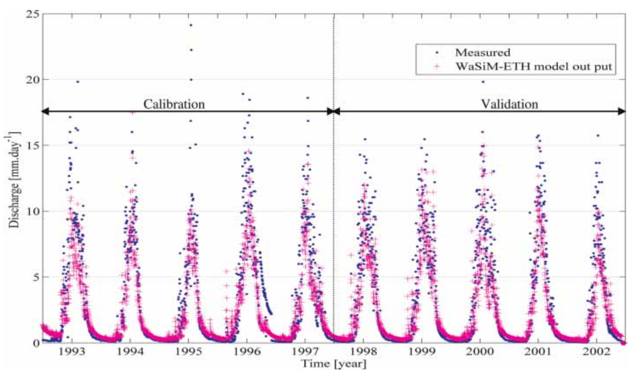

Figure 5 | Gilgel Abay observed and simulated daily discharge for calibration and validation period.

Table 1 | Performance of the WaSiM-ETH, the HBV and the SWAT2005 hydrological models for two rivers in the Lake Tana sub-basin (cal: calibration; val: validation)

	Gilgel Abay				Gumera			
	N–S		R^2		N–S		R^2	
Models	Cal	Val	Cal	Val	Cal	Val	Cal	Val
WaSiM-ETH	0.79	0.78	0.80	0.78	0.73	0.70	0.72	0.71
HBV	0.85	0.77	–	–	0.72	0.80	–	–
SWAT2005 using ParaSol	0.73	0.71	0.80	0.78	0.61	0.61	0.71	0.70

rectangular topology of the output layer was first taken as 14 (and is decided by the program as it progresses).

Initial neighbourhood size and initial weight were taken as 13 and 0.5, respectively. The number of epochs was increased from 1,000 to 10,000. The neighbourhood size was decreasing with learning until during the last training event i.e. when the neighbourhood size became zero. At this time only the winning neuron's weights were changed and the learning rate became very small, which indicates that clusters have been defined.

RESULTS AND DISCUSSION

Following the procedure and initial parameters in NeuroShell2, the selected 26 subcatchments were grouped into five hydrological homogeneous groups (see Figure 6). Accordingly, four rivers (Main Belles, Uke, Great Anger and Dedessa near Dembi) were clustered into group 1. Donder, Ardy, Andassa, Buno Bedele, Belo and Guder rivers were grouped under group 2. Most rivers in South Gojam sub-basin of the Blue Nile River (Birr, Temcha, Dura, Lower Fetta, Fetta rivers and Neshi River in Fincha sub-basin) were pooled together in group 3. Most rivers in Lake Tana sub-basin (Gilgel Abay, Koga, Gumera, Gilgel Beles river in Beles sub-basin and Chemoga river in South Gojam sub-basin) were clustered in group 4. Group 5 comprised rivers in the Muger sub-basin (Muger, Alelitu, Sibilu rivers) and rivers in Jemma sub-basin (Robi Jida and Robi Gumero rivers).

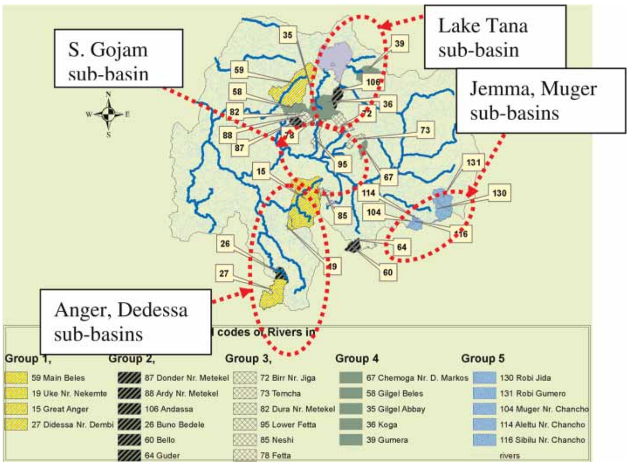

Figure 6 | Five hydrological homogeneous groups in the case study area.

The regional model was validated; validation catchments in each group had flow data that had not been involved in the calibration of the model. The regional model performance is evaluated by Nash–Sutcliffe (N–S) and coefficient of determination (R^2) efficiency criteria between observed and simulated flows. Table 2 depicts optimized regional model parameters for groups 1–5.

Tables 3–5 show the results of the proposed regional model. The shaded catchment(s) in the tables were used as calibration catchments for each group and the remaining catchments were used as validation catchments. The validation periods are different for different validation catchments, depending on the availability of runoff data. In the same tables, daily runoff was aggregated into 10-day and monthly time-steps. An improvement of regional model performance was observed from daily to 10 days and then to monthly time-steps. This is mainly due to the fact that the sum of plus and minus errors in the daily time-steps were significantly reduced in the aggregation process. For visual inspection, Figures 7–9 show daily measured and regional model output for selected validation catchments in each group.

Table 2 | Optimized WaSiM-ETH model parameters

	Optimized regional model parameters							
Group	m (10^{-2})	T_{corr} (10^{-5})	K_{corr} (10^{3})	k_D (10^{2})	SH_{max}	k_H (10^{1})	P_{gren}	r_k
Group 1	5.78	0.149	1.46	2.02	3.6	1.09	10	0.01
Group 2	8.93	0.92	0.09	3.73	58	3.68	10	1
Group 3	6.57	7.21	0.25	1.06	20	2.75	10	0.5
Group 4	4.28	6.49	4.81	4.96	5.8	0.94	1.26	1
Group 5	3.81	0.45	2.36	0.70	1.22	11.4	10	1

Table 3 | Regional model performance for subcatchments in group 1 and group 2

	Regional model performance R^2 (N–S)		
	Daily	10-day	Monthly
Group 1			
Uke	0.82 (0.60)	0.85 (0.62)	0.88 (0.62)
D. Nr. Demb	0.69 (0.55)	0.79 (0.70)	0.83 (0.71)
Great Anger	0.83 (0.72)	0.87 (0.75)	0.89 (0.75)
Main Beles	0.57 (0.59)	0.74 (0.74)	0.80 (0.79)
Group 2			
Donder	0.74 (0.65)	0.83 (0.85)	0.93 (0.89)
Ardy	0.63 (0.50)	0.89 (0.73)	0.92 (0.79)
Andassa	0.50 (0.46)	0.80 (0.64)	0.85 (0.70)
Buno Bedele	0.77 (0.75)	0.79 (0.75)	0.82 (0.78)
Bello	0.68 (0.60)	0.76 (0.70)	0.82 (0.77)
Guder	0.73 (0.67)	0.80 (0.70)	0.85 (0.71)

Table 4 | Regional model performance for subcatchments in group 3 and group 4

	Regional model performance R^2 (N–S)		
	Daily	10 days	Monthly
Group 3			
Birr Nr. Jiga	0.53 (0.51)	0.71 (0.66)	0.83 (0.78)
Temcha	0.59 (0.56)	0.81 (0.78)	0.88 (0.82)
Dura	0.75 (0.61)	0.82 (0.77)	0.85 (0.80)
L. Fetta	0.73 (0.70)	0.85 (0.82)	0.89 (0.87)
Neshi	0.59 (0.52)	0.62 (0.55)	0.68 (0.55)
Fetta	0.76 (0.70)	0.89 (0.77)	0.95 (0.81)
Group 4			
Chemoga	0.63 (0.44)	0.80 (0.48)	0.89 (0.52)
G. Beles	0.70 (0.60)	0.88 (0.80)	0.91 (0.80)
G. Abay	0.81 (0.80)	0.90 (0.86)	0.93 (0.91)
Koga	0.59 (0.56)	0.72 (0.70)	0.78 (0.80)
Gumera	0.72 (0.67)	0.82 (0.76)	0.86 (0.90)

In group 1, daily runoff records (1985–1999) for river Uke were used during the calibration process; the remaining rivers Dedessa near Dembi, Great Anger and Main Beles were used as validation catchments for this group. Their R^2 value ranges from 0.51 to 0.83, from 0.74 to 0.87 and from 0.80 to 0.89 for daily, 10-day and monthly time-steps, respectively.

In group 2, daily runoff records (1987–1999) for rivers Buno Bedele and Donder, which are geographically not close to each other, were calibrated simultaneously and

Table 5 | Regional model performance for subcatchments in group 5

	Regionalized model performance R^2 (N–S)		
	Daily	10 days	Monthly
Group 5			
Robi Jida	0.61 (0.52)	0.85 (0.55)	0.92 (0.60)
Robi Gumero	0.69 (0.44)	0.89 (0.50)	0.95 (0.77)
Muger Nr Chancho	0.58 (0.45)	0.74 (0.49)	0.83 (0.65)
Aleltu Nr Chancho	0.62 (0.52)	0.81 (0.57)	0.88 (0.59)
Sibilu Nr. Chancho	0.74 (0.59)	0.81 (0.75)	0.85 (0.50)

four other rivers in the same group were used as validation catchments. The R^2 values of the validation catchment range from 0.50 to 0.73, from 0.70 to 0.80 and from 0.82 to 0.85 for daily, 10-day and monthly time-steps, respectively.

In group 3, daily records (1993–1999) for rivers Fetta and Birr near Jiga, which are located south of Lake Tana sub-basin, were calibrated simultaneously. The remaining four rivers in the same group were reserved for validation of the regional model. Validation rivers in this group are geographically close to each other and their R^2 values range from 0.53 to 0.73, from 0.62 to 0.85 and from 0.65 to 0.89 for daily, 10-day and monthly time-steps, respectively.

In group 4, daily records (1993–2005) for rivers Gilgel Abay and Gumera, which are located in Lake Tana sub-basin, were calibrated simultaneously. Gilgel Abay has a relatively long dataset of good quality and demonstrated the best R^2 value. The coefficient of determination of the validation rivers in this group range from 0.59 to 0.70, from 0.72 to 0.88 and from 0.78 to 0.91 for daily, 10-day and monthly time-steps, respectively.

In group 5, daily records (1995–1999) of Robi Gumero and Sibilu near Chancho Rivers, which are located in the eastern part of the Blue Nile river basin, were calibrated simultaneously. The remaining three catchments were used as validation catchments and their R^2 values range from 0.58 to 0.62, from 0.74 to 0.89 and from 0.83 to 0.92 for daily, 10-day and monthly time-steps, respectively. The regional model was validated for validation catchments in group 5 only from 1995 to 1999, due to a lack of hydro-meteorological data.

As can be seen from Tables 3–5, the results for rivers in groups 1–4 are better than those of the results of rivers in group 5. This is mainly due to the existence of a large

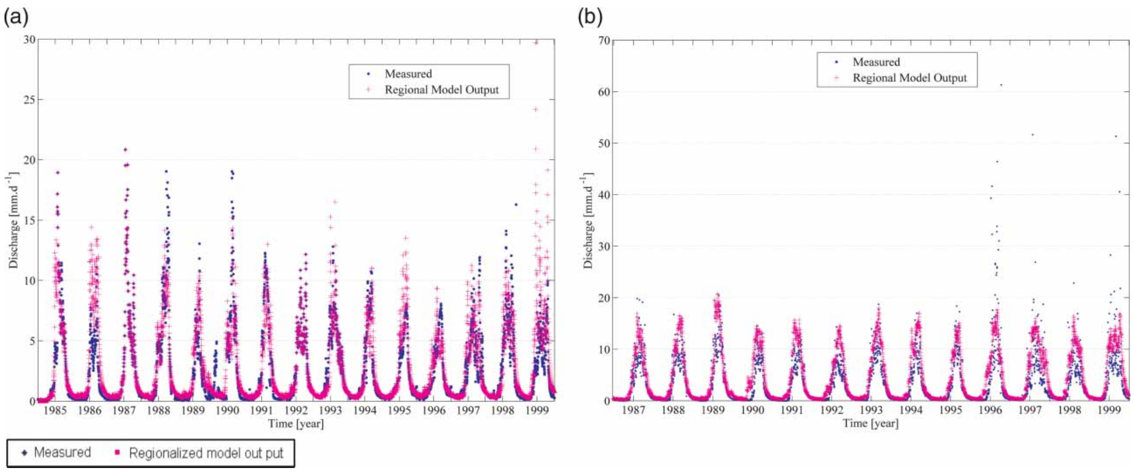

Figure 7 | (a) Measured and regionalized model out put of Dembi river (validation of group 1) and (b) measure and regionalized model out put of Ardy river (validation of group 2).

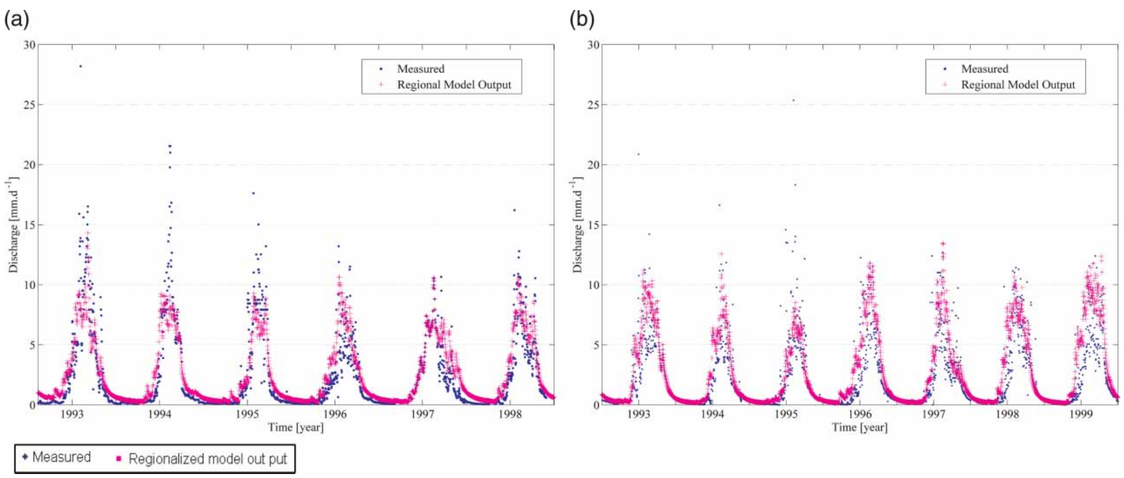

Figure 8 | (a) Measured and regional model out put of Lower Fetta river (validation of group 3) and (b) Measured and regional model out put of Gilgel Belles river (validation of group 4).

number of meteorological stations (temperature and rainfall) for rivers in groups 1–4.

For the sake of comparison, the regional model was applied to gauged and ungauged catchments in the Lake Tana sub-basin (see Figure 6) to estimate total flow to Lake Tana. The estimated mean annual total inflow to Lake Tana of this study was compared with other studies by SMEC (2007), Gieske *et al*. (2008) and Wale *et al*. (2009). SMEC (2007) and Gieske *et al*. (2008) have estimated inflow from the ungauged catchment as the rest term of the water balance of Lake Tana; in this research and that of Wale *et al*. (2009), a regional model has been developed.

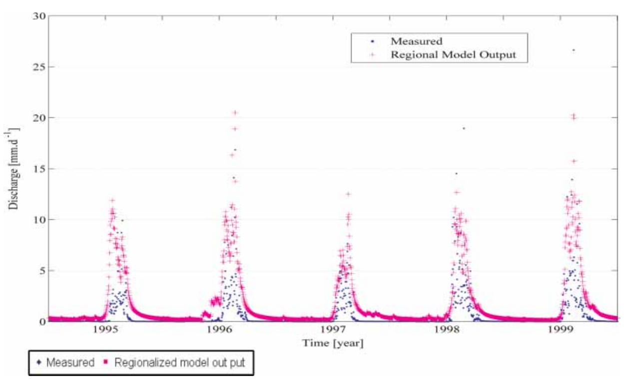

Figure 9 | Measured and regional model out put of Robi Jiga river (validation of group 5).

Wale *et al.* (2009) regionalized HBV-IHMS rainfall–runoff model parameters with catchment characteristics by using single and multiple regressions for tributary rivers in the Lake Tana sub-basin, Ethiopia. They calibrated the rainfall–runoff model and formed regional models for runoff data series from 1993 to 2000 for Ribb, Gumera, Gilgel Abay, Megech and Kiliti rivers. They have validated their regional model for the same five rivers for runoff time series from 2001 to 2003.

The mean annual total inflow to Lake Tana by SMEC (2007), Gieske *et al.* (2008), Wale *et al.* (2009) and results of our proposed regional model are 5028, 5487, 6699 and 6523×10^6 m^3, respectively.

CONCLUSIONS

Daily, 10-day and monthly stream flow were estimated using a regional model which combine KNNs and WaSiM-ETH. By using KNNs with pre-defined physical catchment characteristics of 26 selected subcatchments of the Blue Nile river basin, five hydrological homogeneous groups were formed. A set of optimized WaSiM-ETH model parameters for each group were obtained by calibrating one or more subcatchments from each group using an automatic model calibration method. The whole set of optimized WaSiM-ETH model parameters were then transferred to ungauged catchments. Except for subcatchments in group 5, results confirmed that subcatchments that are geographically close to each other did not necessarily belong to the same hydrological homogeneous group.

The performance of WaSiM-ETH to map a relationship between rainfall and runoff was compared with HBV and SWAT2005 models and gave reasonable results.

The regional model needed only temperature, rainfall, land-use and soil maps and a DEM, which are easily obtainable for ungauged catchments. The regional model generally overestimated the low flow part of the hydrograph. For most selected subcatchments of the Blue Nile river basin, the regional model performed better over the 10-day and monthly time-step than the daily time-step.

The datum of zero flow (H_0) of most rating curves and a smaller number of meteorological stations in some parts of the study area could be taken as one reason for the regional model's overestimation of the lower part of the hydrograph. The value of H_0 corresponds to zero discharge in the stream, which is a hypothetical parameter to fit the rating curve and cannot be measured in the field. It is observed that in some gauging stations in the Dedessa subcatchments where the datum correction H_0 is above 0.5, the rating curve implied zero flow for some months whereas, in reality, there were substantial amounts of flow during those months.

Results of the proposed regional model were compared with the results from other methods applied to the Lake Tana sub-basin to estimate total flow (from gauge and ungauged rivers in the Lake Tana sub-basin) and the proposed regional model gave reasonable results. The proposed regional model can therefore be applied to each proposed artificial reservoir and to Lake Tana in the case study area to estimate flow.

Results could be improved with longer hydro-meteorological datasets of good quality from a large number of meteorological stations in the study area. Our proposed regional model could be used for any river basin following the steps described in this paper. In general, the validation performance showed that the proposed regionalization technique is quite satisfactory in transferring information from data-rich catchments to data-poor catchments or ungauged catchments, vital for any water resources development activities in the basin.

ACKNOWLEDGEMENTS

The authors wish to thank the Ethiopian Ministry of Water Resources and Ethiopian National Meteorological Service Agency for providing the necessary data for the case studies considered in this paper. The authors would also like to thank ArbaMinch University, Ethiopian Ministry of Water Resources, German Technical Cooperation (GTZ) and Challenge Program on Water and Food (CPWF) of the International Water Management Institute project for their financial support.

REFERENCES

Abdulla, F. A. & Lettenmaier, D. P. 1997 Development of regional parameter estimation equations for a macro-scale hydrologic model. *Journal of Hydrology* **197**, 230–257.

BCEOM and associates 1999 Abay River Integrated Development Master Plan Project. Phase 2, Section II, Vol III: Water Resources: Part 1: Climatology and Part 2: Hydrology.

Beven, K. J. & Kirkby, M. J. 1979 A physically based variable contributing area model of basin hydrology. *Hydrology Science Bulletin* **24** (1), 43–69.

Bloschl, G. & Sivapalan, M. 1995 Scale issues in hydrological modelling: a review. *Hydrological Processes* **9**, 251–290.

Bonifacio, R. & Grimes, D. I. F. 1998 *Drought and Flood Warning in Southern Africa*. IDNDR Flagship Programme Forecasts and warnings, UK National Coordination Committee for the IDNDR. Thomas Telford, London, UK.

Brutsaert, W. 1982 *Evaporation into the Atmosphere*. Kluwer Academic Publishers, Dordrecht.

Cai, S., Toral, H., Qiu, J. & Archer, J. S. 1994 Neural network based objective flow regime identification in air-water two phase flow. *The Canadian Journal of Chemical Engineering* **72**, 440–445.

Duan, Q., Sorooshian, S. & Gupta, V. 1992 Effective and efficient global optimization for conceptual rainfall-runoff models. *Water Resources Research* **28** (4), 1015–1031.

Federer, C. A. & Lash, D. 1983 *BROOK – A Hydrologic Simulation Model for Eastern Forests*. Water Resources Research Center, University of New Hampshire, USA.

Fernandez, W., Vogel, R. M. & Sankara Subramanian, A. 2000 Regional calibration of a watershed model. *Hydro. logyScience Journal* **45** (5), 689–707.

Foody, G. M. 1999 Applications of the self-organizing feature map neural network in community data analysis. *Ecology Modelling* **120**, 97–107.

Gieske, A., Wale, A. W., Getachew, H. A., Alemseged, T. H. & Rientjes, T. 2008 Non-linear parameterization of Lake Tana's flow system. In *Hydrology and Ecology of the Nile River Basin under Extreme Condition*s (W. Abtew & A. M. Melesse eds.). Proceedings of the Workshop, Addis Abeba, National Science Foundation, USA, pp. 128–145.

Green, W. H. & Ampt, G. A. 1911 Studies on Soil Physics: I. The flow of air and water trough soils. *Journal of Agricultural Sciences* **4**, 1–24.

Habte, A., Cullmann, J. & Horlacher, H. B. 2007 Application of WaSiM Distributed Water Balance Simulation Model to the Abay River Basin. *FWU Water Resources Publications* **6**, 1613–1045.

Hall, M. J. & Minns, A. W. 1999 The classification of hydrological homogeneous regions. *Journal of Hydrology Science* **44** (5), 693–704.

Hall, M. J., Minns, A. W. & Ashrafuzzaman, A. K. M. 2002 The application of data mining techniques for the regionalization of hydrological variables. *Hydrology and Earth Systems Sciences* **6** (4), 685–694.

Hubert, P., Schertzer, D., Takeuchi, K. & Koide, S. (eds.) 2002 *PUB Communications. IAHS Decade for Prediction in Ungauged Basins*. Brasilia, 20–22 November, http://www.cig.ensmp.fr/~iahs/index.html.

IAHS 2003 Decade on predictions in ungauged basins (PUB). *Hydrological Sciences Journal* **48** (6), 857–880.

Kohonen, T. 1997 *Self-Organizing Maps*. 2nd edition, Springer, Berlin.

Kohonen, T. 2001 *Self-Organizing Maps*. Vol. 30. Springer Series in Information Sciences. 3rd edition, Springer-Verlag, Berlin and Heidelberg.

Kokkonen, T. S., Jakeman, A. J., Young, P. C. & Koivusalo, H. J. 2003 Predicting daily flows in ungauged catchments: model regionalization from catchment descriptors at the Coweeta Hydrologic Laboratory, North Carolina. *Hydrological Processes* **17**, 2219–2238.

López-Rubio, E., Muñoz-Pérez, J. & Gómez-Ruiz, J. A. 2001 Invariant pattern identification by self-organising networks. *Pattern Recognition Letters* **22**, 983–990.

Monteith, J. L. 1975 *Vegetation and the Atmosphere, vol. 1: Principles*. Academic Press, London.

Nash, J. E. & Sutcliffe, J. V. 1970 River flow forecasting through conceptual models. Part 1–A discussion of principles. *Journal of Hydrology* **10**, 282–290.

Oyebande, L. 2001 Water problems in Africa: How can sciences help? *Hydrology Science Journal* **46** (6), 947–961.

Peschke, G. 1987 Soil moisture and runoff components from a physically founded approach. *Acta Hydrophysica* **31** (3/4), 191–205.

Post, D. A. & Jakeman, A. J. 1999 Predicting the daily stream flow of ungauged catchments in S.E. Australia by regionalizing the parameters of a lumped conceptual rainfall-runoff model. *Ecological Modelling* **123**, 91–104.

Ritter, H., Martinetz, T. & Schultzen, K. 1992 *Neural Computation and Self-Organizing Maps: An Introduction*. Addison-Wiley, Reading, MA.

Schaake, J. V., Duan, Q., Koren,, V. I. & Cong, S. 1997 Regional parameter estimation of land surface parameterizations for GCIP large-scale area southwest. Paper presented at 13th Conference on Hydrology, American Meteorology Society, Long Beach, Calif, February.

Schulla, J. 1997 Hydrologische Modellierungvon Flussgebieten zur Abschätzung der Folgen von Klimaänderungen. Diss ETH 12018, Verlag Geographisches Institut ETH Zürich, 187S.

Schulla, J. & Jasper, K. 2000 *Model Description WaSiM-ETH (Water Balance Simulation Model ETH)*. ETH-Zurich, Zurich.

Sefton, C. E. M. & Howarth, S. M. 1998 Relationships between dynamic response characteristics and physical descriptors of catchments in England and Wales. *Journal of Hydrology* **211**, 1–16.

Seibert, J. 1999 Regionalization of parameters for a conceptual rainfall-runoff model. *Agricultural and Forest Meteorology* **98–99**, 279–293.

Shimelis, G. S., Srinivasan, R. & Dargahi, B. 2008 Hydrological modelling in the Lake Tana Basin, Ethiopia using SWAT model. *The Open Hydrology Journal* **2**, 49–62.

Shu, C. & Burn, D. H. 2003 Spatial patterns of homogenous pooling groups for flood frequency analysis. *Hydro. Sci. J.* **48** (4), 601–618.

Sivapalan, M. 2003 Prediction in ungauged basins: a grand challenge for theoretical hydrology. *Hydrological Processes* **17**, 3163–3170.

SMEC 2007 *Hydrological Study of The Tana-Beles Sub-Basins (part 1)*. Snowy Mountains Engineering Corporation, Australia, 77.

Vogel, R. M. 2005 Watershed models. In: *Regional Calibration of Watershed Models* (V. P. Singh & D. K. Frevert, eds.). CRC Press, pp. 47–71.

Wale, A., Rientjes, T. H. M., Gieske, A. S. M. & Getachew, H. A. 2009 Ungauged catchment contributions to Lake Tana's water balance. *Hydrological Processes* **23**, 3682–3693.

Wendling, U. 1975 Zur messung und schätzung der potentiellen verdunstung. *Zeitschrift für Meteorologie* **25** (2), 103–111.

Xu, C.-Y. 1999 Estimation of parameters of a conceptual water balance model for ungauged catchments. *Water Resource Management* **13**, 353–368.

Xu, C.-Y. & Singh, V. P. 1998 A review of monthly water balance models for water resource investigations. *Water Resources Manageent* **12**, 31–50.

Yu, P.-S. & Yang, T.-C. 2000 Using synthetic flow duration curves for rainfall-runoff model calibration at ungauged sites. *Hydrological Processes* **14**, 117–133.

Zhang, J. & Hall, M. J. 2004 Regional flood frequency analysis for the Gan-Ming River basin in China. *Journal of Hydrology* **296**, 98–117.

First received 15 December 2009; accepted in revised form 29 September 2010. Available online June 2011