Modelling catchment inflows into Lake Victoria: regionalisation of the parameters of a conceptual water balance model

Michael Kizza, Jose-Luis Guerrero, Allan Rodhe, Chong-yu Xu and Henry K. Ntale

ABSTRACT

The goal of this study was to evaluate regionalisation methods that could be used for modelling catchment inflows into Lake Victoria. WASMOD, a conceptual water balance model, was applied to nine gauged sub-basins in Lake Victoria basin in order to test the transferability of model parameters between the basins using three regionalisation approaches. Model calibration was carried out within the GLUE (generalised likelihood uncertainty estimation) framework for uncertainty assessment. The analysis was carried out for the period 1967–2000. Parameter transferability was assessed by comparing the likelihood values of regionalised simulations with the values under calibration for each basin. WASMOD performed well for all study sub-basins with Nash–Sutcliffe values ranging between 0.70 and 0.82. Transferability results were mixed. For the proxy-basin method, the best performing parameter donor basin was Mara with four proxy basins giving acceptable results. Sio, Sondu, Gucha and Duma also performed well. The global mean method gave acceptable performance for seven of the nine study basins. The ensemble regionalisation method provides the possibility to consider parameter uncertainty in the regionalisation. Ensemble regionalisation method performed best with an average departure of 40% from the observed mean annual flows compared to 48 and 60% for proxy-basin and global mean methods, respectively.

Key words | ensemble regionalisation, generalised likelihood uncertainty estimation, Lake Victoria, proxy-basin, rainfall-runoff modelling, regionalisation

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INTRODUCTION

Modelling catchment runoff into Lake Victoria presents two major problems. The first problem is that gauged tributaries account for only about 50% of the Lake Victoria basin area. For these gauged tributaries, the problem is related to the selection of a realistic modelling framework that takes into account the limitations of data availability and quality. Uncertainties in rainfall-runoff modelling are a result of errors in both input and calibration data and also result from the simplifications that come with mathematical representation of the physical processes that govern flow generation and routing (Kundzewicz 1995; Beven & Freer 2001; Refsgaard *et al.* 2007). The proper recognition of and accounting for uncertainties is currently acknowledged as an integral part of any hydrological modelling process (Wagener & Gupta 2005). The second problem in modelling catchment inflow into Lake Victoria is related to how to make flow predictions in the ungauged tributaries using information in the gauged part. An ungauged basin is defined as one with inadequate records (in terms of both data quantity and quality) of hydrological observations to enable computation of hydrological variables of interest at the appropriate spatial and temporal scales, and to the accuracy acceptable for practical applications. Prediction of hydrologic variability in ungauged basins has been

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recognised as one of the major issues in hydrological sciences (Sivapalan et al. 2003). The lack of calibration and validation data in ungauged basins makes hydrological prediction in ungauged basins very difficult.

Large parts of the globe are ungauged and even the numbers of gauged basins are declining very fast due to factors like insufficient funding, inadequate institutional frameworks, a lack of appreciation of the worth of long term data and, sometimes, political turmoil (Sene & Farquharson 1998; Stokstad 1999; Alsdorf et al. 2007). Regionalisation of hydrologic models refers to the transfer of model parameter values from one catchment (usually gauged) to other catchments (usually ungauged or poorly gauged) (Blöschl & Sivapalan 1995; McIntyre et al. 2005; Parajka et al. 2005). In the context of conceptual water balance modelling, the aim is to transfer effective parameter values from gauged catchments to ungauged catchments. The gauged basin, from which information is to be transferred, should be similar in some way to the ungauged basin, to which the information is to be transferred (Merz & Blöschl 2004). Seibert (1999) noted that the general problem in regionalisation of model parameters is that there are usually a limited number of gauged catchments available. Modelling larger regions would increase the number of available gauged catchments but would also increase the variation in climatic, geological and physiographic characteristics resulting in additional scatter as variables change. Model parameters are usually poorly defined as almost equally good simulations may be obtained at very different locations in the parameter space (Beven & Binley 1992; Jakeman & Hornberger 1993). This parameter uncertainty may cause scatter in the relation between parameter and catchment properties and prevent them from being discovered. Nonetheless, the methods used for regionalising catchment parameters are broadly classified into three groups, namely (1) regression between individual calibrated parameters and catchment characteristics, (2) catchment spatial proximity which involves either adopting a calibrated parameter set from the nearest neighbour or interpolating calibrated parameters spatially, and (3) catchment similarity of physical properties which involves adopting a calibrated parameter set from the most physically similar catchment or interpolating calibrated parameters in similarity space. Regression methods include (a) one step regression – regional calibration (Fernandez et al. 2000; Hundecha & Bárdossy 2004; Parajka et al. 2005), and (b) multivariate regression (Abdulla & Lettenmaier 1997; Seibert 1999; Xu 1999a). Examples of catchment spatial proximity methods include (a) clustering approach (Burn & Boorman 1993; Huang et al. 2003), and (b) spatial interpolation method, for example, linear interpolation (Guo et al. 2001), kriging interpolation (Vandewiele & Elias 1995; Parajka et al. 2005) and so on. Proxy-basin method (Klemes 1986; Xu 1999b; Jin et al. 2009) is an example of a catchment similarity method whereby parameters of a gauged basin are directly applied to ungauged basins that are deemed to be similar to the gauged basin.

Regression is the most commonly applied regionalisation method whereby parameters for ungauged basins are determined by regression equations developed between the optimised parameters and catchment attributes in a set of gauged basins. However, two major limitations affect this method. First, parameters may be poorly determined and strongly interrelated, hence unstable (Beven 2006; Jin et al. 2009; Peel & Blöschl 2011). Second, some parameters may not be well estimated by regional relationships because the poor correlation between parameter values and physically measurable quantities (Abdulla & Lettenmaier 1997) which may be due to factors like equifinality (Beven & Binley 1992; Jakeman & Hornberger 1993), difficulty in deciding which physical characteristics are the most important (Parajka et al. 2005), and scatter of relationships between catchments may result in difficulties in finding the best regression form (Seibert 1999). Hundecha & Bárdossy (2004) tried to overcome the first limitation by first defining a prior for regression functions and then calibrating the parameters of the regression functions instead of model parameters themselves. However, in their application, the prior regression function couldn't be justified and the second limitation still remained. In addition, Merz & Blöschl (2004) found that methods based on spatial proximity alone performed significantly better than any of the regression methods based on catchment attributes.

Parajka et al. (2005) compared four groups of regionalisation methods (regional averages of calibrated parameters, spatial proximity techniques, regression against catchment characteristics and physical similarity techniques) using an 11 parameter semi-distributed conceptual model, calibrated to daily streamflow and snow cover, across 320 Austrian catchments. They also concluded that spatial proximity and combination physical similarity methods performed best. Similarity-based approaches, whereby the complete set of model parameters is transferred from a donor basin to an ungauged basin to which it is most similar, have an advantage that no assumptions are made about the relationship (linear or otherwise) between model parameters and catchment characteristics which is the basis of regression approaches. Kokkonen *et al.* (2003) concluded that 'where we have reason to believe that, in hydrological terms, a gauged basin resembles an ungauged basin, it might be worthwhile to adopt the entire set of calibrated parameters from the gauged basin instead of deriving quantitative relationships between basin characteristics and model parameters'. As such, the problem of estimating model parameters in ungauged basins is still a subject of investigation and there is no universal agreement of which methods work best for all conditions.

In this paper, WASMOD, a conceptual water balance model (Xu *et al.* 1996; Xu 2002), was applied to nine sub-basins in Lake Victoria basin in East Africa with the aims of (1) examining the applicability of the model to the basin as an extension of earlier work by Kizza *et al.* (2011), and (2) examining the possibility of transferring the calibrated parameter sets to the ungauged basins. This transfer is necessitated by the fact that a large part of Lake Victoria basin is ungauged or poorly gauged and yet lake water balance studies require proper accounting for catchment inflow. Three spatial similarity-based methods were tested whereby the complete set of parameters was applied, namely the proxy-basin method, global mean methods and ensemble regionalisation based on the proxy basin method.

STUDY AREA AND DATA

Study area

Lake Victoria, located between latitudes 0°20′N–3°00′S and longitudes 31°40′E–34°53′E, is the largest freshwater lake in Africa and is the second largest in the world (Figure 1). The lake basin area is 194,000 km^2 and the lake surface area is about 68,800 km^2 or 35% of the basin. The lake surface

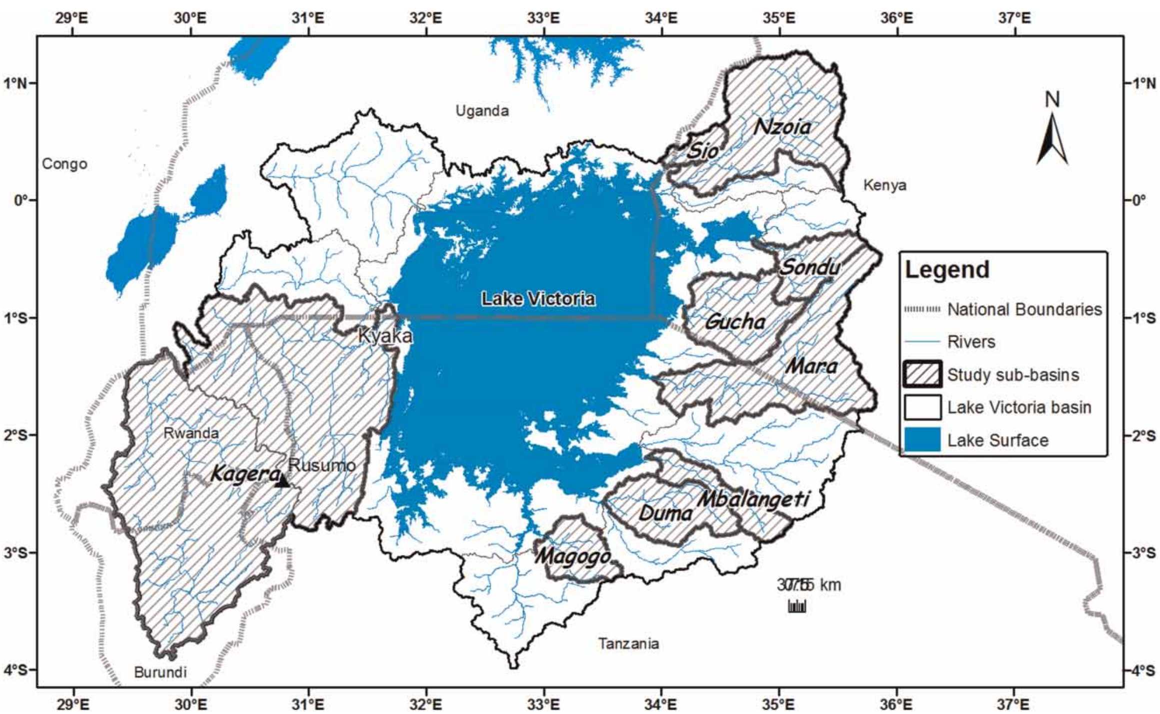

Figure 1 | Lake Victoria and the nine sub-basins studied in this paper.

area is shared between Kenya (6%), Uganda (43%) and Tanzania (51%) while its basin includes parts of Burundi and Rwanda. The altitude of the lake surface is about 1,135 m above mean sea level (a.s.l.). The basin consists of a series of stepped plateaus with an average elevation of 2,700 m a.s.l. but rising to 4,000 m a.s.l. or more in the highland areas. The lake is relatively shallow with an average depth of 45 m and maximum depth of 92 m.

Although the total volume of catchment runoff into Lake Victoria is small compared to direct rainfall on the lake surface, it has a higher variability from year to year and its impact on the water balance is significant (Piper *et al.* 1986; Tate *et al.* 2004). However, estimating catchment inflows to Lake Victoria is complicated by lack of consistent and reliable measurements of stream flow and other data (Kite 1981). Regular discharge measurements for the rivers that flow into Lake Victoria are scarce and patchy. Of the 17 major tributaries providing inflow to Lake Victoria, only five have been gauged for extended periods of time (Yin & Nicholson 1998). These are Kagera, Nzoia, Yala, Sondu and Gucha which have been estimated to account for about 50% of the total catchment inflow. Kagera River has been gauged since 1940 while the other four have been gauged since 1956. The remaining rivers have been gauged only since 1969. Since the 1980s, there has been a significant drop in the frequency and quality of discharge measurements. In some cases the discharge measurements have been abandoned altogether.

Catchment runoff contributes about 20% of the inflow into Lake Victoria with the rest being direct rainfall on the lake surface (Sene 2000; Tate *et al.* 2004). The amounts and timing of the flows in the rivers vary within the lake basin and are influenced by variations in spatial and temporal rainfall distribution as well as catchment characteristics (Sutcliffe & Parks 1999; Tate *et al.* 2004). A bimodal rainfall distribution is predominant in the basin with the main rainfall season (also called the 'long rains') occurring from March to May and a secondary rainfall season (short rains) occurring from October to December (Nicholson 1996; Conway *et al.* 2005; Kizza *et al.* 2010). However, the seasons are not fixed all across the basin and this affects the timing and amounts of the flows from the different tributaries and also accounts for the high variability in catchment runoff compared to over-the-lake rainfall. The northeastern tributaries have a prolonged rainy season with considerable amounts of rainfall received in July and August. This, coupled with the steep topography, results in fast runoff and high flow volumes to Lake Victoria (Tate *et al.* 2004). Kagera sub-basin receives high amounts of rainfall and runoff volume is high but the flow variability is modified by storage in the many lakes and wetlands where the evaporation losses are also significant. The southeastern tributaries have lower rainfall and runoff, and this makes for greater variability. The northwestern tributaries contribute less runoff because of wetland losses.

Data

The data used for this study included climate data (rainfall, potential evapotranspiration and air temperature) as well as measured discharge values. A monthly time step was used. Below is a description of the key features of the different data types.

Climate data

The rainfall data were derived from the gridded monthly dataset developed by Kizza *et al.* (2010). The dataset was interpolated using the inverse distance weighting approach from 315 point rainfall stations. The rainfall dataset covers the period 1960–2004 while the data used for this study covered the period 1967–2000 over which discharge measurements were available. During the derivation of the gridded rainfall dataset, it was noted that there was a large variation in rain gauge density around Lake Victoria basin which affects the accuracy and reliability of the interpolated rainfall (Kizza *et al.* 2010). However, the 315 stations that were used were selected from a database of more than 1,000 stations and went through a rigorous quality control process to remove erroneous data and retain only those stations that were deemed reliable and resulted in minimal errors in the resultant dataset. The point rainfall density varied considerably throughout Lake Victoria basin and therefore the uncertainties in interpolated rainfall were also expected to vary. The interpolated database had a 2 km square grid size. The gridded values were averaged over each sub-basin to compute the monthly mean areal rainfall values.

Monthly potential evapotranspiration data were obtained for 32 stations that were part of the monitoring network used by the hydrometeorological survey project of the World Meteorological Organization (WMO 1974). The station values used in this study were estimated during the WMO study using the Penman method (Penman 1948). The areal long term mean monthly potential evapotranspiration of each sub-basin were obtained using the Thiessen Polygon method based on polygons of each sub-basin that were derived from a 90 m digital elevation model (DEM) of the lake basin. The temperature data were also estimated using the Thiessen polygon method with 46 point stations across the basin.

Discharge data

Data for 18 gauging stations were obtained in the form of daily gauge heights and periodic discharge measurements for each station. The quality control tests included tests for data sufficiency and stability of the rating curves. For a station to pass the data sufficiency test we set the minimum length of daily gaugings to 4 years and the minimum number of discharge measurements to 20 measurements in 3 years. These restrictions were not ideal but they were selected iteratively to ensure that the resultant sample was large enough to support subsequent analysis. The requirement for having a stable rating curve was aimed at ensuring that only those stations with a clear relationship between gauge height and discharge were retained for analysis. This was necessitated by the fact that historical information about the stations were not available to facilitate an assessment of the causes of rating curve instability and hence no corrective measures could be carried out. At the end of the quality control process, nine discharge stations, representing about 55% of the land area of Lake Victoria basin, were retained for further analysis (Figure 1 and Table 1).

METHODS

The model and parameter estimation approach

WASMOD, a lumped conceptual rainfall-runoff model (Xu *et al.* 1996; Xu 2002), was used in the current study. The model is used for simulating streamflow from rainfall and can be operated at different time scales. The concept of the model is that the actual rainfall is split into a fraction that evaporates and a fraction that is active rainfall and contributes to the fast flow and the slow flow ('base flow'). The adopted WASMOD version has four parameters that control potential evapotranspiration, actual evapotranspiration, slow flow and fast flow (Table 2). Before rainfall contributes to the soil storage as 'active' rainfall, a part is subtracted and added to the loss by evapotranspiration (Xu 2003). The soil water storage contributes to evapotranspiration e_t, to the fast flow component f_t and to the slow flow s_t. Parameter

Table 1 | Characteristics of the study sub-basins. Lake and swamp areas are expressed as percentages of each sub-basin's area. The mean basin slope is expressed as the slope measured between points 10% and 85% along the main stream from the outlet. MAF is the mean annual flow computed from gauge measurements, MAR is the mean annual rainfall as an areal average over the basin and PET is the annual basin potential evapotranspiration

Basin	Area (km^2)	MAF (mm/year)	MAR (mm/year)	PET (mm/year)	Temp (°C)	Lakes area (%)	Swamp area (%)	Mean Basin Slope (%)	Mean Elevation (m a.s.l.)	Number of years of observed data available
Sio	1,275	236	1,490	1,593	22.9	–	–	1.9	1,254	24
Nzoia	12,630	269	1,315	1,616	18.5	–	0.1	3.9	1,898	9
Sondu	3,448	378	1,422	1,309	17.4	–	–	5.5	2,039	18
Gucha	6,616	189	1,383	1,483	21.4	–	0.2	4.1	1,603	16
Mara	13,497	98	1,239	1,724	20.3	–	2.7	3.8	1,725	16
Mbalang et	3,269	212	1,198	1,840	21.7	–	6.4	1.6	1,466	6
Duma	5,380	116	1,172	1,858	22.5	0.4	5.2	1.5	1,466	4
Magogo	3,273	165	1,007	1,935	22.5	2.4	6.5	1.1	1,206	4
Kagera-Rusumo	30,696	228	1,130	1,197	18.8	1.2	4.0	9.3	1,679	9

Table 2 | WASMOD variables and their equations

Variable controlled	Parameter (units)	Equation	
Potential evapotranspiration	$a_1(^{\circ}\mathrm{C}^{-1})$	$ep_t = [1 + a_1(c_t - c_m)]ep_m$	(1)
Actual evapotranspiration	$a_2(-)$	$e_t = \min\left[ep_t\left(1 - a_2^{w_t/ep_t}\right), w_t\right]$	(2)
Slow flow	$a_3(\mathrm{month}^{-1})$	$s_t = a_3(sm_{t-1})^2$	(3)
Fast flow	$a_4(\mathrm{mm}^{-1}\ \mathrm{month})$	$f_t = a_4 sm_{t-1} n_t$	(4)

where ep_m is the monthly long term potential evapotranspiration; c_t and c_m are monthly mean temperature and long term mean temperature, respectively; $w_t = r_t + sm_{t-1}$ is the available water; sm_{t-1} is a available storage (non-negative); $n_t = r_t - ep_t(1 - e^{-r_t/ep_t})$ is the effective rainfall with r_t as the rainfall in a given month.

a_1 is used to convert long term average monthly values to actual values of monthly potential evapotranspiration and can be eliminated from the model if potential evapotranspiration data are available or are calculated using other methods. Parameter a_2 determines the actual evapotranspiration that is an increasing function of potential evapotranspiration and available water. Smaller values of a_2 result in high evaporation losses at all moisture states. The slow flow parameter a_3 controls the proportion of runoff that appears as 'base flow'. Higher values of a_3 produce a greater proportion of 'base flow'. Values are expected to be higher in forest areas than in open fields and in sandy than clayey soils. The fast flow parameter a_4 increases with degree of urbanisation, average basin slope and drainage density. Lower values are expected for catchments dominated by forest. The inputs used for WASMOD model in the current study included monthly values of rainfall, temperature and mean monthly potential evapotranspiration, which were readily available for the catchments. Monthly runoff and other water balance components were the outputs. The time period used for this study was 1967–2000 of which the first 3 years (1967–1969) were set aside as the warm-up period.

The applicability of WASMOD to the region was assessed in an earlier study by testing it on Nzoia sub-basin (Kizza *et al.* 2011), one of the catchments in the current study. In that study, WASMOD was shown to produce acceptable results for the sub-basin. Model assessment for Nzoia study was carried out within the GLUE (generalised likelihood uncertainty estimation) framework (Beven & Binley 1992; Beven 2006) in order to carry out parameter estimation using set performance criteria and assess predictive uncertainty for the Nzoia sub-basin using WASMOD model. Performance was assessed using the Nash–Sutcliffe coefficient (Nash & Sutcliffe 1970), Average Relative Interval Length (Jin *et al.* 2010) and the percentage of observations bracketed by simulations. The Nash–Sutcliffe efficiency (NS) was computed from log-transformations of both measured and simulated flow. For a NS threshold of 0.6, the percentage of observations bracketed by simulations was 74%, the average relative interval length was 0.93 while the maximum NS value was 0.87. The residuals were shown to be homoscedastic, normally distributed and nearly independent. When the NS threshold was increased to 0.8, percentage of observations bracketed by simulations decreased to 54% with an improvement of average relative interval length to 0.5. As such the model was shown to be a viable candidate for application in Lake Victoria basin.

In the current study, model assessment was carried out for the nine selected sub-basins within a GLUE framework (Beven 2006) following the same procedure as described in (Kizza *et al.* 2011). GLUE is a methodology based on Monte Carlo simulation for estimating the predictive uncertainty associated with environmental models. For each catchment, Monte Carlo simulations were carried out using uniformly sampled parameter spaces. In uniform sampling, the model simulation is reflected by the shape of the response surface. Initial model runs were made to select the feasible ranges for each parameter. These were expected to be changing as flow generation characteristics vary around Lake Victoria basin. In total, 400,000 model runs were carried out for each catchment. The selection of the number of model runs was done in tandem with constraining of the parameter ranges to ensure that the parameter space was well sampled. All parameter sets that resulted in NS values higher than 0 were retained for possible consideration as behavioural (having acceptable performance) under calibration.

The behavioural threshold was selected such that the percentage of observation contained within limits of the simulations of the behavioural parameter sets (POBS) was higher than 80%. The likelihood of parameter sets with a NS value less than the behavioural threshold was set to zero. The minimum number of parameter sets to include in the behavioural set was set to 10% of the simulations that had NS values higher than 0 while the maximum number was set to 5,000. The requirement for minimum number of parameter sets was to ensure that the sample size was large enough for subsequent analysis. The requirement for maximum number of parameter sets was to take into account the fact that, given the uncertainties in input, model and discharge, it may not be possible to achieve the POBS requirement of 80% for some basins. The NS value corresponding to a POBS of 80% was taken as the behavioural threshold in calibration. The parameter set that resulted in maximum NS value for each sub-basin was selected as representing the best model performance for the sub-basin and was used for applying the proxy-basin and global mean regionalisation methods. NS values were converted into likelihoods by (i) rescaling them to ensure that simulations that were considered un-acceptable were given a likelihood of 0 and (ii) normalising to ensure that the sum of all likelihoods was unity.

Regionalisation methods

Three regionalisation approaches tested on the study sub-basins were namely the proxy basin method, the global mean method, and the ensemble regionalisation method. The methods were selected because of the small number of study sub-basins which meant that detailed assessments of parameter and catchment characteristics were unlikely to be robust and could lead to misleading results.

Proxy basin method

The proxy-basin method is a two step approach to regionalisation whereby parameter transferability is first cross-checked over two sub-basins in the region of interest before direct application to ungauged basins in the same region (Jin *et al.* 2009). The method is based on the presumption that, in a hydrologically and climatically homogeneous region based on spatial proximity, one would expect the parameters of basins in the region to be similar as climate and catchment conditions only vary smoothly over space. A proxy-basin test (Xu & Singh 2004) was carried out to examine the transferability of parameter values by calibrating parameters on one basin and then validating them on the other basins. Only if the proxy-basin tests gave acceptable results would the model be considered to be geographically transferable.

Global mean method

The rationale behind the global mean method is that, in conceptual hydrological models, the physical attributes of a catchment are represented by parameters and so the average attributes are represented by mean parameters. Three types of global mean were computed and applied on each of the sub-basins by assuming that they are ungauged. The first global mean method tested was the computation of arithmetic mean value of each parameter which assumes homogeneity in characteristics of the sub-basins and would work best in situations where the differences in individual parameter values do not vary considerably across the region. The second method was the computation of area weighted mean values that takes into account the area of each sub-basin. The rationale for this method is that sub-basins with a large area contain more attribute information than small ones and this should be highlighted in the averaging of parameters (Jin *et al.* 2009). The third global mean method was the computation of Thiessen weighted mean values aimed at interpolating to take into account each sub-basin's position and density. This method is an attempt to account for the variation of sub-basin attributes in space by giving more weight to sub-basins in a regional center or in sparse areas (with fewer gauged basins) compared to sub-basins in a regional margin or in a dense area.

Ensemble regionalisation

In practice, many combinations of parameter values will result in similar or equally acceptable model performance.

This is the equifinality problem (Seibert 1999; Beven & Freer 2001; Wagener & Wheater 2006) and arises from over-parameterisation of models, data limitations and faults within the model and leads to high uncertainties in the model predictions. As such, a single optimum parameter set may not have the best transfer capability during regionalisation studies (Buytaert & Beven 2009). Therefore, this study also investigated the possibility that other acceptable parameter sets for a given sub-basin can have better transfer capabilities than the best performing parameter sets for each sub-basin as defined by the parameter set having maximum NS. The goal was to test the transfer properties of acceptable parameter sets from one sub-basin to other sub-basins in the study area. The following procedure was used for ensemble regionalisation.

For each candidate sub-basin for parameter donation, all behavioural parameter sets under calibration were selected. The remaining eight sub-basins were then grouped in terms of the closeness of their hydrological response to the donor sub-basin. The grouping was carried out by using the donor sub-basin parameter sets to simulate flow in the rest of the sub-basins and organising them in descending order of number of parameter sets that continue to be behavioural. The regionalisation performance was then tested by using the donor sub-basin parameter sets to carry out simulations for the remaining sub-basins in sequential order, starting with the most closely related sub-basin. At each stage, the likelihood of parameter sets that resulted in NS efficiencies less than the threshold value were set to zero and such parameter sets were dropped from subsequent steps. The process was continued until the number of behavioural parameter sets dropped to zero.

Success in ensemble regionalisation was based on the number of sub-basins that could be simulated using the parameter sets of a given donor sub-basin with acceptable performance. Parameter sets that continued performing well for most study sub-basins were said to be robust and it was assumed that they would be more likely to perform well when applied to ungauged basins. The minimum number of sub-basins that had to be successfully simulated was set to three for a given donor sub-basin's parameter set to be considered to be robust.

RESULTS

Model performance

Visual and statistical comparisons were carried out to evaluate the modelling results for the gauged sub-basins. Table 3 shows the maximum NS values for each sub-basin and their associated parameter values. The lowest NS value was 0.71 for Kagera-Rusumo and the highest was 0.83 for Sondu. Generally a NS of 0.6 is considered as a threshold for streamflow simulations (Moriasi *et al.* 2007). Therefore, the model can be said to have a good performance in Lake Victoria basin. In terms of variability of the parameter sets having maximum NS over all sub-basins, the narrowest range was in the range of values of parameter a_2 that controls actual evapotranspiration while the widest range was in the values of parameter a_3 that controls slow flow. The minimum value of parameter a_2 was 0.30 while the maximum was 0.9 giving a range of just 0.6 or a variation of 120% about the mean parameter value. On the other hand the minimum value of parameter a_3 was 1.1×10^{-5} while the maximum value was 152.3×10^{-5} or a variation of 330% about the mean parameter value. It has been shown in Kizza *et al.* (2011) that for Nzoia sub-basin, WASMOD is most sensitive to parameters a_2, a_3 and a_4 and their specification is more important for model performance. Therefore, similarity between these three parameters (a_2, a_3 and a_4) between any two sub-basins is a good first indicator of the possibility for one sub-basin being a parameter donor for another. While general inferences from Table 3

Table 3 | Maximum NS values and their associated parameter values. The parameter units are shown in Table 2

Basin	Max NS	$a_1 \times 10^{-2}$	$a_2 \times 10^{-1}$	$a_3 \times 10^{-4}$	$a_4 \times 10^{-4}$
Sio	0.78	0.186	2.736	1.565	38.379
Nzoia	0.81	6.686	5.982	3.603	14.196
Sondu	0.83	13.911	3.820	12.398	24.952
Gucha	0.79	10.897	3.576	4.314	16.669
Mara	0.75	23.620	4.476	2.656	7.914
Mbalanget	0.77	32.761	8.438	0.247	2.391
Duma	0.76	30.785	3.576	0.549	47.622
Magogo	0.76	22.935	4.414	15.239	41.371
Kagera-Rusumo	0.70	2.765	8.842	0.110	0.146

are hard, parameter a_2 does not vary considerably between the study sub-basins while parameters a_1, a_3 and a_4 are more variable and they are expected to be critical for the success of any regionalisation scheme.

In terms of the percentage of observed flow bounded by simulations (POBS), Nzoia and Mbalanget sub-basins had the best performance with POBS values in excess of 90% (Table 4). In terms of the threshold NS values, Sondu had the best performance with an NS threshold of 0.69 while Kagera-Rusumo did not perform very well. A lower threshold NS value implies a more peaked variation of one or more parameter(s) while a lower POBS may indicate uncertainties in the observed flow data. Only Sio sub-basin did not meet the POBS requirement of 80% but a value of 79.4% for 5,000 parameter sets was considered good enough.

For visual comparison, Figure 2 shows the hydrographs for both measured and simulated flow including the 90% confidence interval of the simulated flow for three sub-basins from different parts of Lake Victoria basin. For each sub-basin, the 90% confidence interval was estimated from the range of likelihood weighted simulations for each time step based on the approach outlined in Beven & Freer (2001) and Kizza *et al.* (2011). The plots emphasise the differences in flow generation in different parts of the Lake Victoria basin from the wet and humid northeast (represented by Nzoia sub-basin), to the drier southeast (represented by Duma sub-basin). In all cases, there was good agreement between measured and simulated flows for all sub-basins. The mean flows were quite well estimated

Table 4 | Model calibration results for the nine study sub-basins. POBS is the percentage of observations bracketed by behavioural simulations. Threshold NS is the minimum Nash–Sutcliffe value of the parameters included in the behavioural set

Basin	POBS (%)	Threshold NS	Number of parameter sets
Sio	79.4	0.54	5000
Nzoia	94.1	0.55	4357
Sondu	85.0	0.69	4234
Gucha	83.7	0.58	2344
Mara	80.5	0.50	3712
Mbalanget	93.8	0.46	1948
Duma	81.8	0.51	2120
Magogo	80.0	0.58	1953
Kagera-Rusumo	80.0	0.44	1808

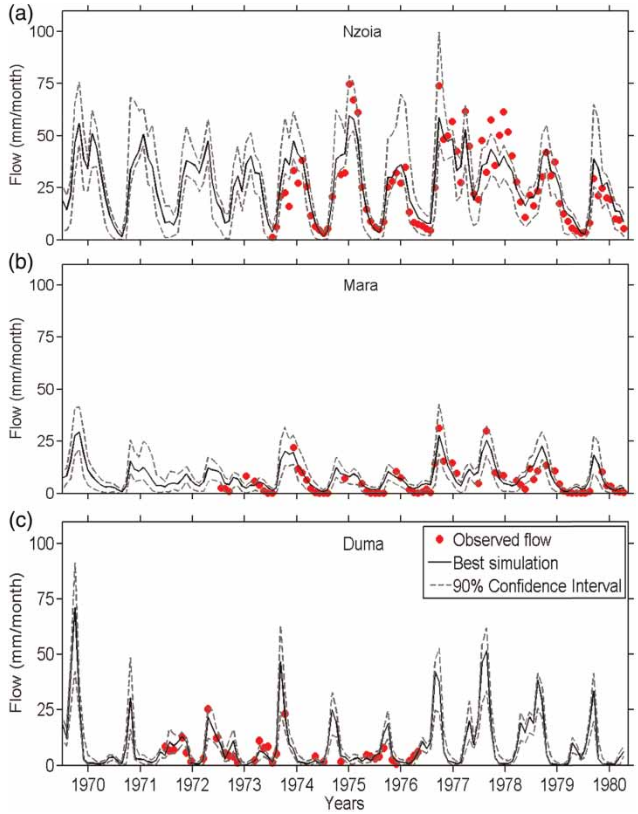

Figure 2 | Calibration results for three selected sub-basins in different parts of Lake Victoria basin, namely: (a) Nzoia, (b) Mara and (c) Duma. The 'best simulation' is based on the parameter set having maximum NS.

while the low and high flows were sometimes poorly captured by the model though, in most cases, the measured values fall within the confidence interval. The values of measured flow that fall outside the 90% confidence interval used here may reflect uncertainty sources that are not directly dealt with in this study, but are also due to the constraint placed on the behavioural parameter sets of having at least 80% of the observations bracketed by simulations. An assessment was also carried on whether the model was able to capture known significant hydrological events within the Lake Victoria basin. Periods of anomalously high rainfall have been documented in the Lake basin that are driven by forcing mechanisms like El Niño/southern oscillation, sea surface temperature anomalies, quasi biennial oscillation and other factors (Nicholson 1996; Indeje & Semazzi 2000; Indeje *et al.* 2000; Mistry & Conway 2003). El Niño years are usually associated with above normal rainfall amounts in the short rainfall season of the

Lake Victoria basin causing widespread flooding. Towards the end of 1997 and early 1998, the region received extremely high rainfall amounts that caused severe flooding of rivers and also a rise in lake level. While the dataset used in this study had no measured flows for 1997 and 1998, WASMOD model was able to capture the high rainfall signal as extremely high discharge for 1998 for all the study sub-basins (Table 5).

Table 5 | Simulated mean annual flows (1970–2000) for the study sub-basins compared to simulations for 1998. All units are mm/year

Basin	Mean	1998
Sio	224	340
Nzoia	287	436
Sondu	372	516
Gucha	191	468
Mara	97	318
Mbalanget	195	357
Duma	124	326
Magogo	161	421
Kagera-Rusumo	228	332

The percentage increase in annual flow for 1998 over the long term mean annual flow varied from 39% for Sio to 230% for Mara averaging slightly over 108% for all study sub-basins. Other years of heavy rainfall include 1970, 1976, and 1989 and these signals were also captured in most of the sub-basins.

An important requirement of any hydrological model is the correct representation of the flow frequency which is useful for many applications, including reservoir and lake sedimentation studies, in-stream flow assessments and flood frequency analysis (Castellarin *et al*. 2004). Streamflow frequency is usually represented using a flow duration curve (FDC) which provides the percentage of time (duration) streamflow is exceeded over a historical period. The FDCs for the study sub-basins were prepared by plotting simulated and observed flow data against the fraction of time a given flow amount was exceeded (Figure 3). There was a close match between measured and simulated FDCs for most of the sub-basins. The only significant exception was for Nzoia where the high measured and simulated flows did not match. In an earlier study by Kizza *et al.* (2011), this

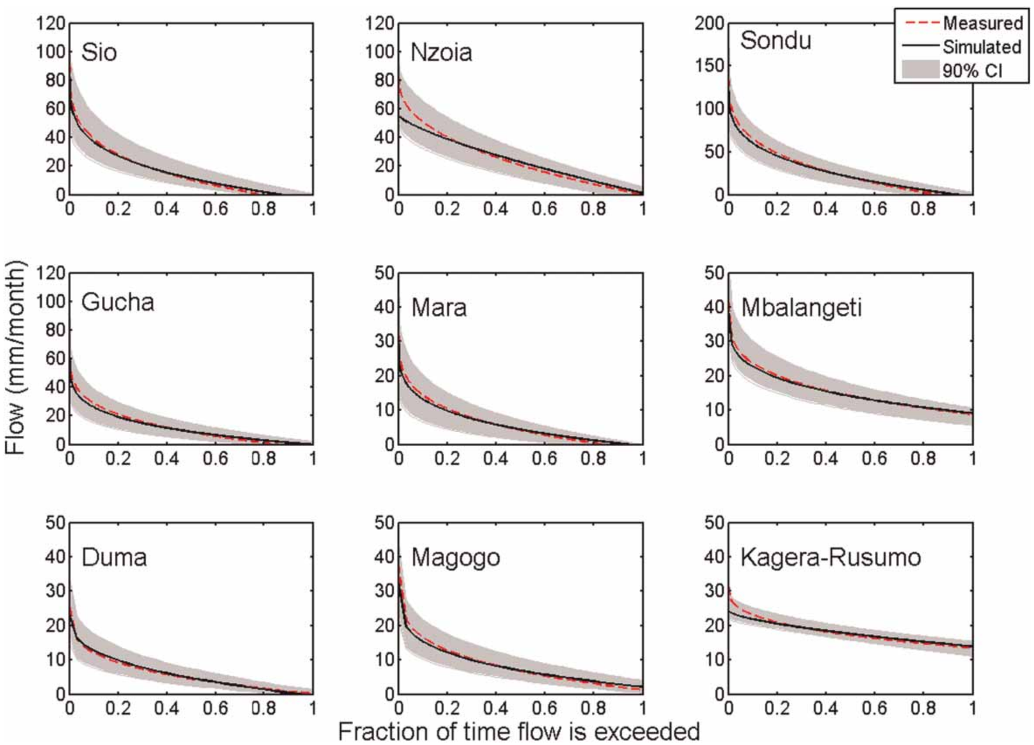

Figure 3 | Flow duration curves for observed and simulated flow. CI stands for confidence interval. Note the different scales on the *y*-axes.

problem for Nzoia was addressed by applying a log- transformation to measured and simulated flows before computing the NS measure. However, initial simulations showed that log-transformation did not improve the simulations of the rest of the basins. Additionally, uncertainties in the medium to high flows were generally higher than the uncertainties for the low flows. This is an expected feature of flow in the region since routine field measurements are generally not carried out during high flow and flooding conditions and their estimation involves extrapolation of the rating curve. For a direct comparison of the catchment characteristics in terms of response of each sub-basin to rainfall input, a single FDC for all study sub-basins was prepared and is reproduced in Figure 4. Steep FDCs are associated with a more peaky hydrograph while FDCs of base flow-dominated rivers tend to be flatter (Wagener & Wheater 2006). By this classification, the base-flow dominated study sub-basins are Kagera-Rusumo, Mbalanget and, to some extent, Nzoia while the rest have much smaller base flow components. It was also noted that the steep FDCs tend to intersect the x-axis meaning that they are dry some months of the year. Figure 4 also shows a great diversity of the flow regime in the Lake Victoria basin, which increases the difficulty in parameter transfer study and partly results in low accuracy in the regionalisation results in some cases as described in the following section.

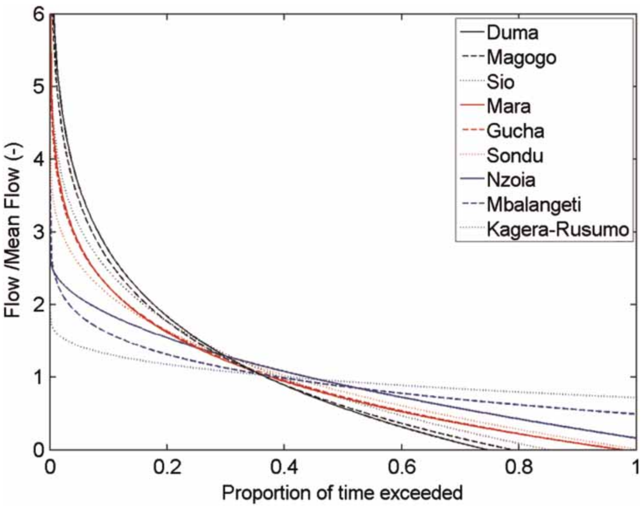

Figure 4 | Comparison of simulated FDCs for the study sub-basins. For each sub-basin the y-values were obtained by dividing the flow values by the mean of all flow values for the sub-basin. For clarity, the legend entries are arranged in the order of the respective plots as they appear in the figure close to the y-axis.

Proxy-basin method

The performance of transferring the various parameter sets varied significantly in Lake Victoria basin (Table 6). The NS from transferring the parameters of the northeastern sub-basins of Sio, Nzoia, Sondu, Gucha and Mara were the highest while the parameters of the southeastern sub-basins of Mbalangeti, and Magogo showed limited performance. Duma sub-basin also showed a good

Table 6 | Proxy basin test results. The dashed fields mean that the model performance for that proxy basin was very poor, i.e. NS was less than 0 and was considered a failure

	Parameter donating basins								
Proxy basins	Sio	Nzoia	Sondu	Gucha	Mara	Mbalanget	Duma	Magogo	Kagera- Rusumo
Sio		0.06	0.33	0.65	0.51	–	0.37	–	–
Nzoia	0.33		0.65	0.36	0.27	0.55	0.56	0.57	0.02
Sondu	0.68	0.71		0.68	0.58	0.39	0.68	0.73	0.13
Gucha	0.71	–	0.27		0.75	–	0.33	–	–
Mara	0.49	–	–	0.70		–	–	–	–
Mbalanget	–	0.10	–	–	–		–	–	–
Duma	0.16	–	0.13	0.36	0.41	–		–	–
Magogo	–	0.50	0.40	–	–	0.24	0.02		–
Kagera-Rusumo	–	–	–	–	–	–	–	–	
Average	0.47	0.34	0.36	0.55	0.50	0.40	0.39	0.65	0.07
Minimum	0.16	0.06	0.13	0.36	0.27	0.24	0.02	0.57	0.02
Maximum	0.71	0.71	0.65	0.70	0.75	0.55	0.68	0.73	0.13

performance as a donor. The parameters of Kagera at Rusumo were very dissimilar compared with the other parameters and their transferability was not possible. The dissimilarity of the Kagera-Rusumo sub-basin with other basins can be seen clearly from the flow duration curves shown in Figure 4. Parameters from Mara sub-basin provided the best transfer performance with four proxy-basins giving NS performance measures of 0.4 and above. Parameters for Sio and Gucha sub-basins performed well for three proxy-basins while parameters for Nzoia, Sondu and Magogo perfomed well for only two proxy basins each. Parameters for Sio, Gucha, Mara and Duma also produced the best mean performances in the proxy basins with average NS values of above 0.5. An assessment was also carried out on performance of each proxy basin in terms of how many donor parameter sets produced acceptable performance when applied to the input of the proxy basin. Sondu sub-basin, having the FDC in the middle of the wide ranges of nine FDCs (Figure 4), performed best as it produced NS values of above 0.4 with six of the donor parameter sets and an average NS value of 0.57. This was followed by Nzoia which produced acceptable performance with four donor parameter sets producing NS values that were higher than 0.4 but the average was only 0.41. Sio, Gucha, Mara and Magogo produced acceptable performance ($NS > 0.4$) for two parameter sets but the average NS values were only 0.4, 0.51, 0.59 and 0.29, respectively.

In terms of forward and reverse transferability performance, where parameter sets of one sub-basin are tested on a sub-basin and vice versa, the best performance was between Nzoia and Sondu and also between Gucha and Mara which produced NS values higher than 0.7 for the forward and reverse computations. However, it is important to note that Nzoia is geographically adjacent to Sondu and Gucha is also adjacent to Mara. Additionally, other sub-basin pairs that are not adjacent to each other also produced acceptable performances. These included Sio and Gucha, Sio and Mara, Nzoia and Magogo as well as Sondu and Magogo which all gave NS values above 0.4 for the forward and reverse computations.

Neglecting the results for Kagera-Rusumo, average efficiency losses (EL), which is the difference between calibration NS and proxy-basin NS, varied between 0.24 for Gucha and 0.44 for parameter sets of Nzoia and Mbalanget. The minimum efficiency loss was 0.05 for the parameter transfer between Mara and Gucha. Closely related was an efficiency loss of 0.05 for Gucha when using Mara parameters. This result points to a strong transfer performance between the two sub-basins. Based on EL values, the best performances were for parameter sets of Sio, Gucha, Mara, Duma and Magogo for which average EL values where less than 0.3, although Magogo parameters only produced acceptable performance with two sub-basins.

Global mean method

Results from modelling with the global mean of estimating regional parameter sets (Table 7) showed that the best performance was for the four northeastern sub-basins of Sio, Nzoia, Sondu, Gucha and Mara with NS measures above 0.4 each for the arithmetic global mean estimation method. There were slight variations in the results for area-weighted and Thiessen interpolation methods but the general performance variation was the same as that of the arithmetic mean method. The parameter set for Kagera-Rusumo was not used in the estimation of global mean values for any of the three methods used as it was very different from the rest and would bias the results. The arithmetic mean method for computing global mean performed slightly better with mean NS value of 0.48 compared to the area weighting and Thiessen interpolation methods which gave NS mean values of 0.41 and 0.47, respectively. This performance is also shown in the estimates for efficiency losses that take the same trend. The best performance of the global mean method was for Nzoia basin with an NS value of 0.68 for the arithmetic mean method. Nzoia also produced the lowest efficiency loss at 0.14. For Nzoia, the NS values for the other two methods were also high at 0.64 and 0.54 for area-weighted and Thiessen interpolation methods, respectively. In terms of station by station performance for each of the three methods, the results were mixed. The arithmetic mean method performed best for Sio and Duma sub-basins. The Thiessen interpolation method performed best for Nzoia, Sondu and Mbalanget sub-basins

Table 7 | NS and EL (efficiency loss) values from application of three global mean estimation methods. The NS values for Magogo sub-basin were less than 0 and are not reproduced here

		Method for computing average					
		Arithmetic		Area weighted		Thiessen interpolated	
Basin	Calibration results (NS)	NS	EL	NS	EL	NS	EL
Sio	0.78	0.45	0.32	0.39	0.39	0.45	0.33
Nzoia	0.81	0.64	0.17	0.54	0.27	0.68	0.14
Sondu	0.83	0.61	0.22	0.51	0.32	0.64	0.19
Gucha	0.79	0.51	0.29	0.51	0.28	0.49	0.31
Mara	0.75	0.41	0.34	0.44	0.31	0.38	0.37
Mbalanget	0.77	0.32	0.45	0.13	0.64	0.33	0.44
Duma	0.76	0.39	0.37	0.34	0.42	0.36	0.40
Magogo	0.76	–	–	–	–	–	–
Average	0.78	0.48	0.31	0.41	0.37	0.47	0.31

while the area-weighted method performed best for Gucha and Mara sub-basin.

Ensemble regionalisation

Table 8 shows the number of parameter sets from each basins (acting as a donor) that continued performing well when applied sequentially to other basins. All parameter sets that resulted in likelihood values less than the set threshold were dropped from the subsequent analysis stage. By producing acceptable performance for five sub-basins, parameter sets for Mara and Duma sub-basins had the best ensemble transfer performance (Table 8). Nzoia, Sondu, Mbalanget and Magogo parameter sets had low performance and produced acceptable results for only two basins each. In terms of number of times a given basin performs well given the donor basin, both Nzoia and Sondu had the highest number of times over all stages at seven, followed by Gucha and Duma at two times, while Magogo had the lowest at only two. Sondu sub-basin was the most closely related to the different parameter donor sub-basins for stage 1 application with close relationship to five of the eight donors while Nzoia (two donors) and Gucha (one donor) were the other two.

For hydrologically homogeneous basins, the response surface should not be greatly modified during regionalisation. This modification was checked by computing the percentage reduction in number of parameter sets at each stage. For stage 1, Duma had the lowest loss of parameter sets in transferring to Sondu at 1% of all calibration parameter sets not meeting the behavioural

Table 8 | Results of ensemble regionalisation for different parameter donor basins. The number of parameter sets that were acceptable at each stage are shown in brackets and only these were carried on to the subsequent stage

Parameter donor basin	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5
Sio (5000)	Sondu (4730)	Gucha (2516)	Duma (438)	Mara (51)	–
Nzoia (4357)	Sondu (4164)	Magogo (1248)	–	–	–
Sondu (4234)	Nzoia (198)	Magogo (11)	–	–	–
Gucha (2344)	Sondu (1895)	Sio (826)	Mara (139)	Duma (5)	–
Mara (3712)	Gucha (3473)	Sondu (2912)	Sio (1435)	Duma (245)	Nzoia (40)
Mbalanget (1948)	Nzoia (1875)	Sondu (1443)	–	–	–
Duma (2120)	Sondu (2091)	Nzoia (1246)	Sio (434)	Gucha (267)	Mara (5)
Magogo (1953)	Sondu (1184)	Nzoia (435)	–	–	–

criteria while Sondu had the highest loss in transferring to Nzoia at 95%. Other donor basins that had low losses of parameter sets at stage 1 included Nzoia (4%), Mbalanget (4%), Sio (5%) and Mara (6%). Generally, the parameter losses at stage 1 were low, averaging 22%. At stage 2, Mara had the lowest loss in number of parameter sets at 16% of all stage 1 parameter sets not meeting the behavioural criteria while Sondu had the highest loss at 95%. The average loss of parameter sets at stage 2 was 51% while the losses for stages 3, 4 and 5 were 85%, 77% and 95%, respectively. The modification of Mara sub-basin parameter distributions for the different regionalisation stages are shown in Figure 5 as projections of the weighted and rescaled likelihood functions onto single parameter axes. In addition to the reduction in number of parameter sets from one stage to the next, it can be seen that the distributions become more peaky. In addition, the parameter values having maximum likelihood keep on changing from one stage to the next and the widths on the *x*-axes keep on narrowing.

DISCUSSION

Three different regionalisation approaches were applied to nine sub-basins in Lake Victoria basin. Local calibration for each of the sub-basins was carried out with WASMOD model within the GLUE framework. The regionalisation approaches were all based on transfer of locally calibrated parameter sets to 'ungauged' sub-basins. Regionalisation performance between the sub-basins was assessed using the NS likelihoods and visual inspection of the resulting FDCs. For regionalisation methods to be successful it is necessary that: (1) the number of free parameters should be limited so that the physical meaning for each parameter is maintained; (2) if the model has many parameters, a sensitivity study is needed so that the least sensitive parameters can be fixed using the knowledge about the model and the study region; and (3) the geographic and climatic conditions of the study region are similar (Xu 2003). The proxy-basin method was applied by selecting the parameter set having maximum NS for each sub-basin and using the parameter

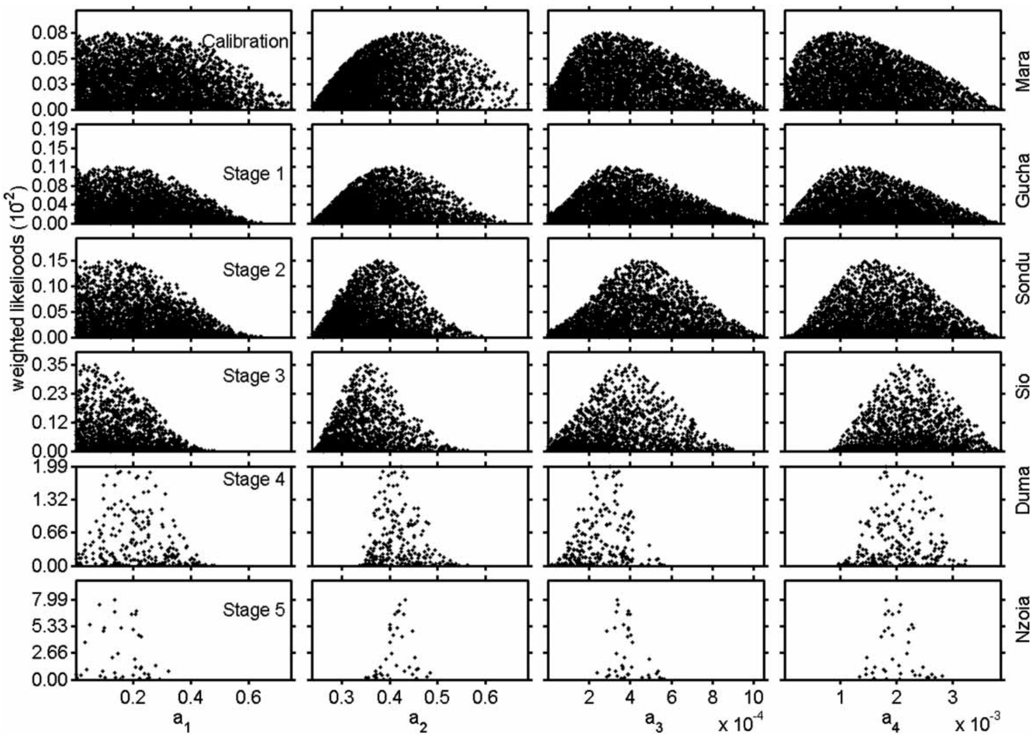

Figure 5 | Dotty plots showing the posterior parameter sets for the selected likelihood function as projections onto single parameter axes. The parameter set donor basin is Mara (top row) and the subsequent rows represent the continued performance for the different stages of regionalisation. For each stage, only the acceptable parameter sets are retained for the next regionalisation step.

set to simulate flow in the remaining eight sub-basins. The global mean method was applied by computing a mean parameter set using three different methods namely; arithmetic mean, area-weighted mean and Thiessen interpolated mean. The third method was one that recognises the existence of equifinality on model prediction whereby many different parameter sets can result in modelling results that are almost equally as good. This ensemble regionalisation approach was applied by using all behavioural parameter sets of one basin at a time (the donor basin) to simulate flow in the remaining sub-basins in a sequential order. The parameter sets that continued giving acceptable results for most of the sub-basins were considered as robust and it was postulated that they could possibly continue performing robustly when applied to ungauged sub-basins.

Results showed varying degrees of similarity between the sub-basins. Kagera-Rusumo sub-basin was the most dissimilar to the others and produced no useful results for any of the methods. The poor performance of Kagera-Rusumo sub-basin for all regionalisation methods was noted to be because of its different hydrological regime compared to the other sub-basins. The flow in Kagera sub-basin is considerably attenuated by the numerous lakes and swamps. Before the Rusumo gauging station, Kagera River flows through more than 20 lakes with a total surface area in excess of 367 km^2 while swamps cover an extra 1,237 km^2 which provide substantial storage thus changing the flow timing and amount at the exit (Table 1).

For the proxy-basin method, parameters of the northeastern sub-basins of Sio, Nzoia, Sondu, Gucha and Mara provided better transfer capability than the southeastern sub-basins of Mbalanget and Magogo. The performance of Duma sub-basin as a parameter donor was also good. As such the northeastern sub-basins can generally be said to be hydrologically similar and their parameter sets can be used for ungauged sub-basins in this region. However, the low levels of parameter transferability for the southeastern sub-basins may be due to deficiencies in input and calibration data which affect the identifiability of parameters. As an example of differences in data quality, the south eastern sub-basins had an average of only 6 years of observed discharge for calibration compared to 18 years for the north eastern sub-basins (see Table 1). This pattern of performance was also reflected in the results of global mean method where the northeastern sub-basins outperformed the southeastern sub-basins. The arithmetic mean method of global mean estimation was slightly better than the area weighting and Thiessen interpolation methods. In average terms, the global mean method was better than the proxy basin method.

All global mean estimation methods resulted in seven of the study sub-basins having NS coefficients of 0.3 and above while the best performing parameter set for proxy basin method was that of Gucha sub-basin which produced acceptable performance for five. This was a surprising result, given the generally poor performance of global mean method in some other studies (Merz & Blöschl 2004; Parajka *et al*. 2005). However, Jin *et al*. (2009) found that the performances of global mean and proxy-basin regionalisation methods where quite similar when applied to Dongjiang Basin in southern China. The differences in regionalisation performance can also be explained in terms of the differences in sub-basin flow duration curves (Figure 4). Mbalanget and Kagera-Rusumo sub-basins had the most dissimilar flow duration curves and also showed poor regionalisation performance. The Nzoia and Magogo sub-basins also showed limited performance as parameter donor basins. These observations suggest that catchment heterogeneity may have been partially responsible for the cases where regionalisation did not perform well. However, owing to the limited sample size, statistical homogeneity tests could not be carried out. In addition, the problems of limited availability and quality of data in the Lake Victoria basin were apparent in the study.

In terms of the regionalised flow duration curves, most of the measured flow FDCs were well produced by the regionalisation methods as shown by the generally good reproduction of the shapes of the measured flow FDCs (Figure 6). The regionalisation approaches generally resulted in under-estimation of the high flows and over-estimation of the lower flows due to the effect of averaging in parameter values and also due to degradation in performance. The impact of this over- and under-estimation was more pronounced for the global mean method for which the effect of averaging was more pronounced. Figure 7 shows the measured, calibrated and regionalised mean monthly flow estimates, including the areal rainfall and the calibrated actual evapotranspiration estimates. Similar results are

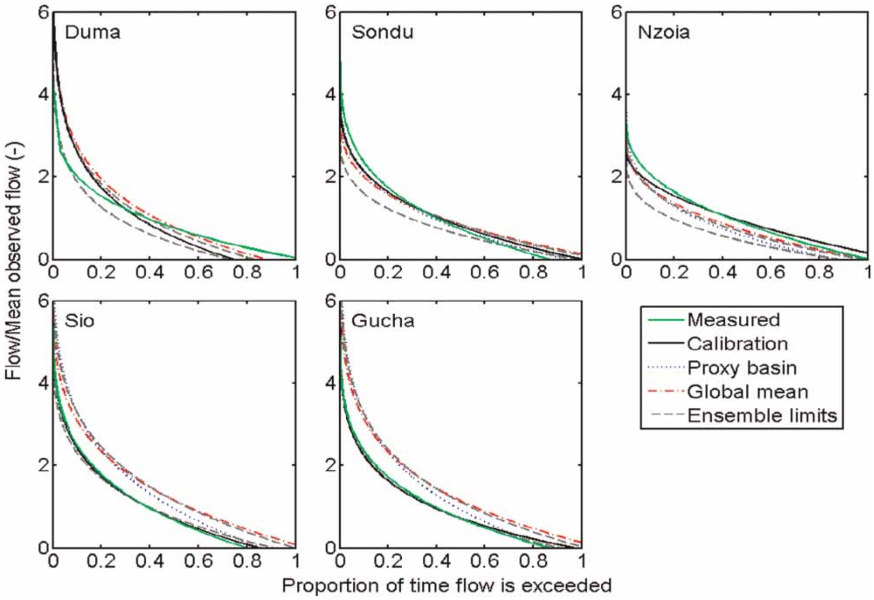

Figure 6 | Regionalised flow duration curves together with flow duration curves for measured and calibrated flow for five selected sub-basins. Proxy basin and ensemble results are based on transferring Duma parameter sets. Global mean estimates are based on the arithmetic mean of all parameter sets.

summarised as mean annual flows in Table 9. All methods were able to reproduce the mean monthly variations and differences were only in flow volumes. From Table 9, the percentage departures was estimated as the difference between estimated and observed mean annual flow for each regionalisation method as a ratio of the mean observed value.

Based on mean of these departures over the five basins shown in Table 9, the ensemble regionalisation method performed best with an average departure of 21% from the observed mean annual flows compared to local calibration results that had a departure of 5%. The mean departures for proxy-basin and global mean methods were 23% and 26%, respectively. The ensemble regionalisation method provides the possibility to consider parameter uncertainty in the regionalisation. Alternative ensemble regionalisation approaches have been used in the past with a similar aim of being able to account for uncertainties in parameters or other uncertainties. Buytaert & Beven (2009) outlined an approach how to transform model parameters between a gauged and an ungauged catchment using an iterative process, in which a model structure was applied successively to gauged catchments. In the study, they generated parameters for a given donor catchment and then used the model ensemble to predict the discharge of the other catchments, after applying a stochastic parameter transformation to account for the uncertainty in the model migration. The parameter transformation was then evaluated and improved before further application. Using a case study in the Ecuadorian Andes, they showed that accurate predictions could be made for predicted basins and they could also gain knowledge about model behaviour and potential model limitations.

McIntyre *et al*. (2005) applied an approach to regionalisation of conceptual rainfall-runoff models using ensemble modelling and model averaging to 127 catchments in the United Kingdom. They found that using the parameters of the 10 gauged catchments most similar to the ungauged catchment provided generally the best results and performed significantly better than the regression method, especially for predicting low flows. They also noted that the ensemble of candidate models provided an indication of uncertainty in ungauged catchment predictions, although this was not a robust estimate of possible flow ranges, and frequently failed to encompass flow peaks. Owing to the smaller dataset used in the current study, the comparatively better performance of ensemble regionalisation is regarded as a

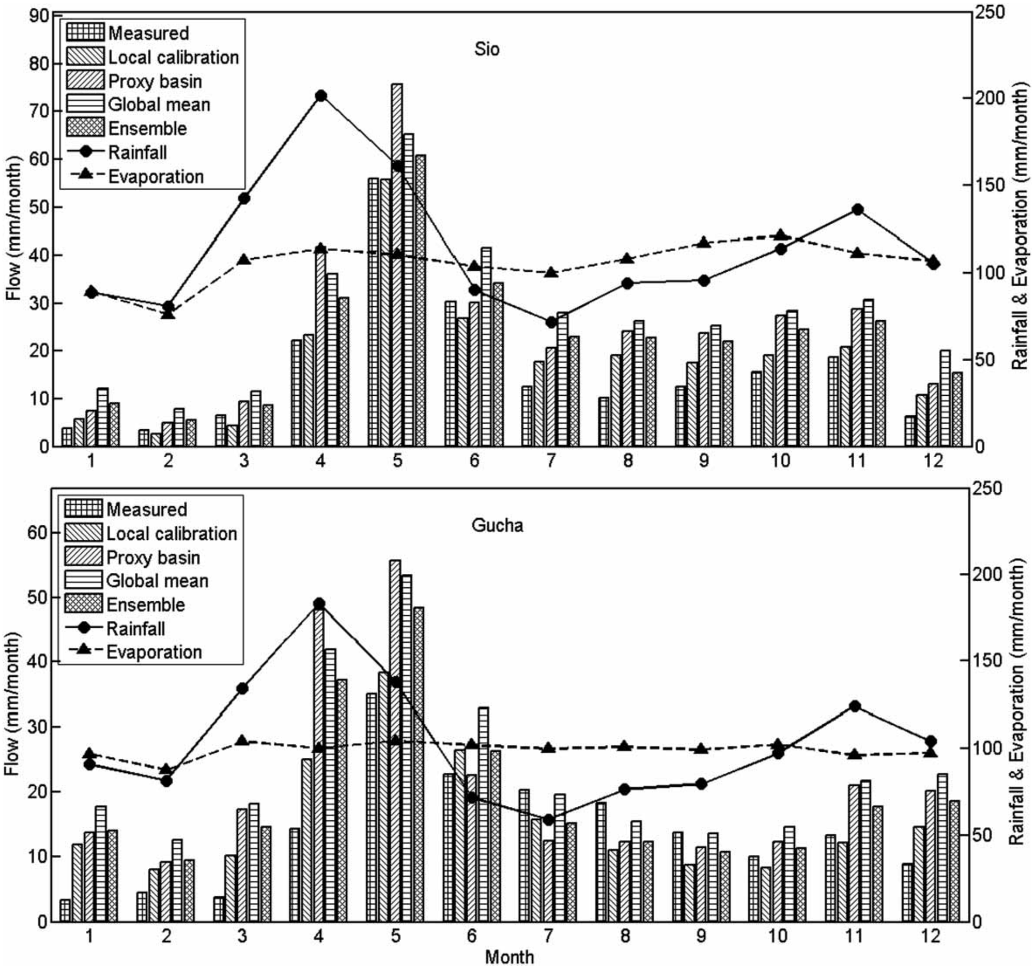

Figure 7 | The mean monthly flow estimates for Sio sub-basin (above) which had the best performance for global mean method and Mara sub-basin (below) which had the best performance when the calibrated Duma sub-basin parameters were used. Evaporation values are calibration estimates.

Table 9 | Mean annual flow (mm/year) estimates for the three regionalisation methods compared with estimates from local calibration. Proxy basin results are based on the parameter set for Gucha sub-basin. The differences between the calibration and regionalisation mean estimates and the measured flow are shown in brackets

Sub-basin	Measured	Local calibration	Proxy basin	Global mean	Ensemble method
Duma	116	124 (7%)	124 (7%)	150 (30%)	113 (1%)
Sondu	378	371 (1%)	350 (7%)	375 (0%)	331 (12%)
Nzoia	269	287 (6%)	209 (22%)	236 (11%)	192 (28%)
Sio	236	223 (5%)	307 (30%)	333 (41%)	283 (20%)
Gucha	189	190 (0%)	256 (35%)	284 (50%)	235 (24%)
Mean departure from measured flow		3%	23%	26%	21%

good indication of the strength of such methods over traditional regionalisation approaches. The ensemble regionalisation method used in the current study is a similarity based method that involves transferring all robust parameter sets from the donor basin to ungauged basins, without the need to make assumptions about the relationship between model parameters and catchment characteristics. Other studies have also found similarity based methods better to be better than regression methods (Kokkonen *et al.* 2003; Parajka *et al.* 2005; Hundecha *et al.* 2008).

CONCLUSIONS

From the above analysis, the following conclusions are pertinent. Application of WASMOD within a GLUE framework for modelling the Lake Victoria sub-basins produced good results with model performances of above 0.7 for the NS coefficient and also in terms of reproduction of the observed flow duration curves of observations.

The selected regionalisation approaches produced mixed results with acceptable performance in some parts of the Lake Victoria basin while the performance was poor in other parts. In particular, sub-basins in the northeastern part of the basin had generally good performance while sub-basins in the southeast did not generally produce good performance. The reason for this was partly due to variations in data quality but could also be attributed to variations in climate and catchment characteristics. The relatively good performance of the global mean method was noted as applying it would simplify the estimation of flow in ungauged sub-basins.

Use of area weighted and Thiessen polygon methods instead of arithmetic means did not significantly improve on the results of global mean method. This may be due to the limited number of sub-basins considered in this study but may also be due to an inherent feature of the basin where parameter values of WASMOD vary smoothly over the basin.

The study emphasises the fact that limitations in data can seriously constrain any efforts in regionalisation modelling. Collection of additional data in the Lake Victoria basin sub-basins would be very helpful as more advanced regionalisation techniques can then be tested.

The acceptance of equifinality by considering parameter uncertainty in the regionalisation process can result in the identification of parameter sets with better transferability characteristics and also the estimation of conditional confidence intervals. The regionalisation approaches that were tested in this study could be useful for testing other models that are intended for use under similar conditions. Additional testing of the models would be necessary to demonstrate their applicability.

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