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Article (Published version)
(Refereed)

Going local: Evaluating and regionalizing a global hydrological model's simulation of river flows in a medium-sized East African basin

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ABSTRACT

Study region: The Rufiji basin, East Africa.
Study focus: Rapid advances in global hydrological model (GHM) resolution, model features, and in situ and remotely sensed datasets are driving progress towards local relevance and application. Despite their increasing use, however, evaluation of local hydrological performance of GHMs is rare. In this paper, we examine the performance of a well-known GHM (LPJmL, recently modified to ∼9 km resolution) with and without modest steps to regionalise the model. We consider the Rufiji river basin, an economically important medium-size basin in eastern Africa.
New hydrological insights for the region: Our results indicate that the unmodified GHM does provide a reasonable first approximation of spatial variability in mean flow conditions, but scores rather poorly on seasonal and inter-annual variability. For the model to achieve levels of performance indicators comparable with bespoke modelling, modifications to model inputs, additional runoff delay and wetland parameterization were required. The largest improvements are associated with adjustments in precipitation and enhanced runoff delay. With the modified version, as a proof of concept, we show that a well-known drying trend in a major tributary of the Rufiji can be explained by implementing irrigation abstractions in the model. Overall, the results suggest that with limited and fairly simple modification GHMs can be regionalised to allow their use for scenario testing and further exploration of key local processes in basins with limited observational data.

1. Introduction

Global hydrological and land surface models (further GHMs) are undergoing rapid development – ever greater computational capacity and data storage, further supported by developments in remote sensing, the availability of gridded observation datasets and meteorological forcing data, have allowed model development at higher spatial resolution covering larger areas (e.g. Flörke et al., 2013; Sutanudjaja et al., 2017). These high-resolution models, with resolutions of 5 arc-minutes (∼9 km at the equator) or higher are able to model the hydrological cycle in catchments across the whole world uniformly and systematically, including in regions for which in situ observations are scarce or where the capacity to conduct continued and detailed hydrological modelling is limited.

GHMs are now almost similar in scale – at least in spatial resolution, if not yet in process detail - to the domain of applied river

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basin hydrological studies. As GHMs increase in spatial resolution, there is more potential to interpret their results at basin and sub-basin scales, moving beyond continental and regional scale descriptions of water scarcity and climate change impacts to sectoral issues like national food security or hydropower potential, at levels of detail relevant for management applications. For example, GHM outputs are now being considered in the context of water resource management questions related to flood risk (Trigg et al., 2016; Winsemius et al., 2015) and for providing a range of hydro-meteorological services, as Jury (2017) tested for Zambia.

While there is still debate on the importance of resolution over epistemic uncertainties (Beven and Cloke, 2012; Bierkens et al., 2015; Wood et al., 2012), both proponents and sceptics agree that moving to higher resolutions will provide better opportunity to compare multi-model output against local observations and knowledge of stakeholders (Beven and Cloke, 2012; Bierkens et al., 2015). But despite their increasing use and many high-impact publications based on GHMs (Elliott et al., 2014; Gleeson et al., 2012; Schewe et al., 2014) they are generally not extensively tested for hydrological performance. Validation is often limited to comparison of monthly means at major river basin scale (e.g. Greuell et al., 2015; Langerwisch et al., 2013; Schaphoff et al., 2017a; Veldkamp et al., 2018), with individual gauge catchment areas typically greater than 5000 km^2. In a meta-analysis of applications of the VIC GHM, Melsen et al. (2016) show that, despite an increase in spatial resolution, the time interval over which the model was calibrated and validated did not change over time. Detailed process understanding, explanation of catchment-specific behaviour, and within-catchment comparative analysis are generally lacking. Calibration, shown to improve global hydrological model validation, is usually not done (Beck et al., 2017). Finally, and particularly relevant for catchments in data-scarce regions like sub-Saharan Africa, validation of GHMs is done mostly against flow observations from one global database (monthly runoff from the GRDC, http://www.bafg.de/GRDC) which could introduce bias as few station locations in the tropical to arid zones in sub-Saharan Africa are included (see, e.g., figures in Beck et al., 2017). Trigg et al. (2016) found in a comparison of flood hazard maps for Africa derived from six global models (recognising their limited validation) significant variations between flood hazard magnitudes, with important implications for model reliability and interpretation of results.

For the reasons above there is a growing need for greater focus on GHM performance at basin and sub-basin scales to assess confidence in simulation results, and to diagnose and rectify issues with model performance. We recognise that a model evaluation should reflect the model's purpose; not all developers of GHMs claim their models are suitable at the local scale or for management. Still, many studies implicitly rely on the models to do well, locally and seasonally, even if results are presented at a global scale and aggregated to annual means; estimates of hydropower generation, environmental flows conditions or sustainable (ground) water abstraction for irrigation all rely heavily on a realistic estimation of seasonality and variability in flows, at specific locations.

In this paper we take a case study approach and consider the suitability of using an established and open-source GHM, LPJmL (Schaphoff et al., 2017b), to simulate the hydrology in a mid-sized basin in East Africa, with a view to support river basin management. The Rufiji basin is the largest and most economically important river basin in Tanzania and the largest basin located within one country in eastern Africa (see Fig. 1). Many parts are remote and inaccessible, measurement locations are clustered, mainly in the central part of the basin, and frequency of observations is limited particularly at main stem locations and important tributaries in the lower part of the basin.

Previous modelling efforts on the Rufiji include a model of the Great Ruaha sub-catchment (Fig. 1) as part of a series of initiatives during the late 1990s and 2000s to understand the causes of dwindling dry season flows entering the Ruaha national park, that stopped flowing completely in 1993 (Kashaigili et al., 2006a; Lankford et al., 2004; Walsh, 2012). A recent basin scale study was conducted to support the Rufiji Basin Water Board (RBWB) in their planning of estimated water demands for hydropower production and agriculture (WREM-International, 2015). Other modelling studies in the basin are at the sub-catchment scale and include application of the PITMAN model to the Great Ruaha River catchment (Tumbo and Hughes, 2015), assessing the effects of drying events in the Usangu wetlands in the Great Ruaha River catchment using satellite radar altimetry (Kihwele et al., 2017), statistical streamflow forecasting in the Kilombero river (Yawson et al., 2005) and applying the SWAT model to assess the impact of land use changes on streamflow in the same Kilombero catchment (Leemhuis et al., 2017). Most of these models are primarily research tools. We are unaware of any description of the Rufiji basin hydrology in any global modelling study (most global studies just feature the Congo, Niger, Nile and Zambezi rivers in Africa). Part of our motivation for this study is to explore the potential opportunities of rapid advances in GHMs for developing country applications. By engaging with the global modelling community, developing country researchers and government agencies might benefit from open access code, collaborative support through networks of practice, and consistency with evolving model structure and new input datasets. Use of such models also allows replicability, comparability (with other such models) and possibly applications in ungauged basins.

We present a stepwise approach, consisting of initial validation (assessment against three hydrological performance indicators) to examine how well the unmodified global model version performs, followed by assessment of the incremental gains from sequential adjustments to the input data, schematization of catchment areas and wetlands and limited parameter optimisation. Detailed assessments of the calibration and validation of a high-resolution GHM for a regional application of this kind are rare. We apply the latest version of LPJmL, LPJmL4 (Schaphoff et al., 2017b), at 5 min resolution. With the regionalised model, we test – as proof of concept - whether a reduction in Great Ruaha River flow, an issue of national concern and dispute (Lankford et al., 2004; Walsh, 2012), can indeed be attributed mainly to irrigation, and evaluate the influence of irrigation on flows at Stiegler's Gorge, where a major hydropower dam is planned with potentially massive impact on the floodplain ecosystem downstream (Duvail et al., 2014).
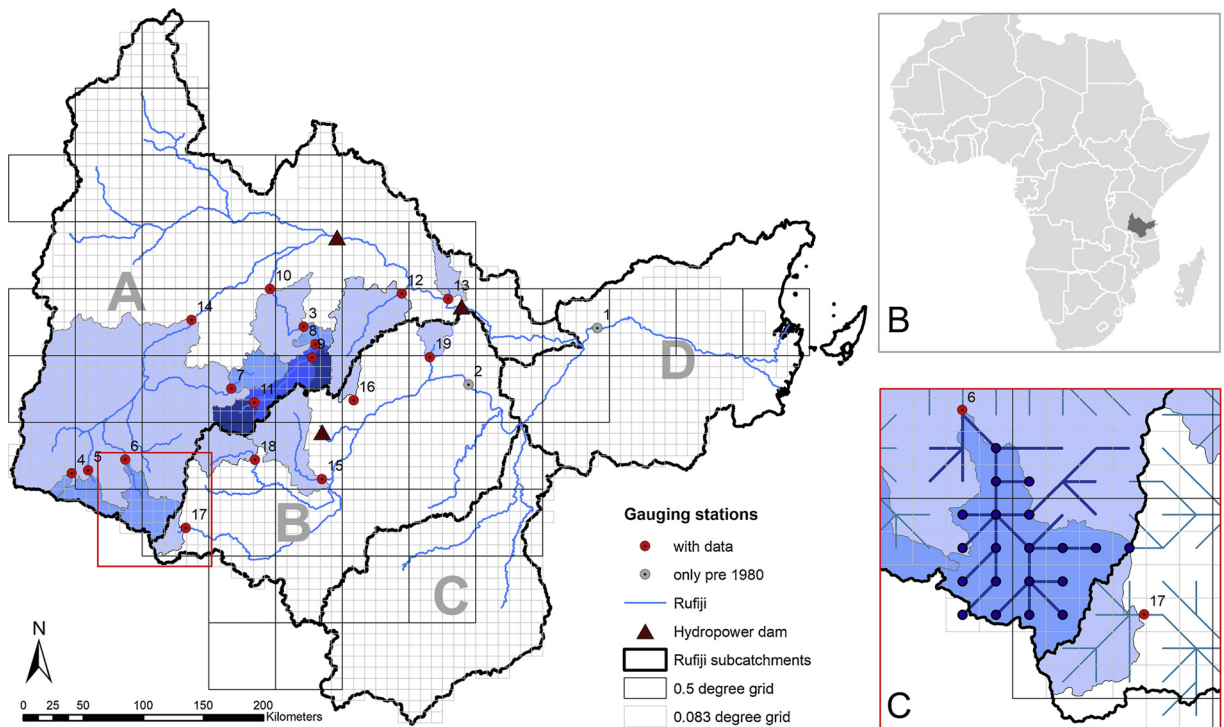
Fig. 1. Rufiji Basin overlaid with 0.5 ° (~55 by 55 km) and 0.083 ° (~9 by 9 km) grid. Flow gauging stations and their upstream areas are in blue shading, with darker shades representing nested sub-catchments (source: Rufiji Basin Water Board), with location of the basin (B) and (in C) an example of the difference between original streamflow routing according to Hydrosheds (blue lines), and the improved grid cell selection based on the sub-catchment shape (dark blue points), for the Mbarali river sub-catchment. With flow gauging stations: 1- Stiegler's Gorge, 2-Kilombero Swero, 3-Ndiuka, 4-Chimala, 5-Salimwani, 6-Mbarali, 7-Ndembera, 8-Ihimbu, 9-Mtitu, 10-Mawande, 11-Makalala, 12-Lukosi, 13-Yovi, 14-Msembe, 15-Mpanga, 16-Mgeta, 17-Ruhudji, 18-Kigogo-Ruaha (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

2. Methodology

2.1. The model – LPJmL

LPJmL (**L**und-**P**otsdam-**J**ena **m**anaged **L**and model) is a hydrology and vegetation model that is usually applied at the global scale. The model is unique in its combined representation of the dynamics of natural vegetation (Sitch et al., 2003), agricultural production (Bondeau et al., 2007; Fader et al., 2010) and hydrology (Gerten et al., 2004). It includes human impacts on the water cycle through irrigation extraction (Rost et al., 2008) and reservoir operation (Biemans et al., 2011). Evapotranspiration is calculated with the Priestley-Taylor function using downward shortwave and longwave radiation, and temperature. Unsaturated zone processes are described by a standard simple bucket-type model consisting of six soil layers, each with percolation (if soil moisture is above field capacity) and lateral drainage (if soil moisture is above saturation) Schaphoff et al. (2017b). The transport of water in the river channel is approximated by a cascade of linear reservoirs. River sections, straight lines between the midpoints of cells, are divided into homogeneous segments with a length of 10 km each, treated as a linear reservoir. River routing is calculated at a 3-hour time step with a globally constant flow velocity 1 m/s (Schaphoff et al., 2017b). This means, for our application at 5 arc minute resolution, water can travel a distance of about 8 grid cells per day so that within 10 days runoff from the furthest point in the basin would reach the outlet. This routing method excludes any floodplain or wetlands characteristics.

LPJmL is a state of the art GHM and is included in several global model inter-comparisons on hydrology and agriculture (WATERMIP by Haddeland et al. (2011), ISIMIP by Davie et al. (2013) and AGMIP by Rosenzweig et al. (2013)). LPJmL is often used to study the linkage between water and food production, and has the functionality to evaluate adaptation options related to land and water development (Biemans et al., 2013; Jägermeyr et al., 2015). The model runs at a daily time step.

Three recent improvements to the model as reported by Schaphoff et al. (2017b) enabled our testing of the model at the regional scale. First, the resolution at which the model can be applied was increased from 30 to 5′s. To match this new resolution, the schematization of the river network was updated using the Hydrosheds database (Lehner et al., 2008). Soil parameters at this resolution were derived from the Harmonized World Soil Database v1.2 (Nachtergaele et al., 2010). Second, a simple representation of groundwater was recently implemented using a linear reservoir model, similar to that of Wada et al. (2010). This allows for estimation of unsustainable groundwater use by irrigation and for delayed groundwater drainage. A single parameter (GW_{coeff})
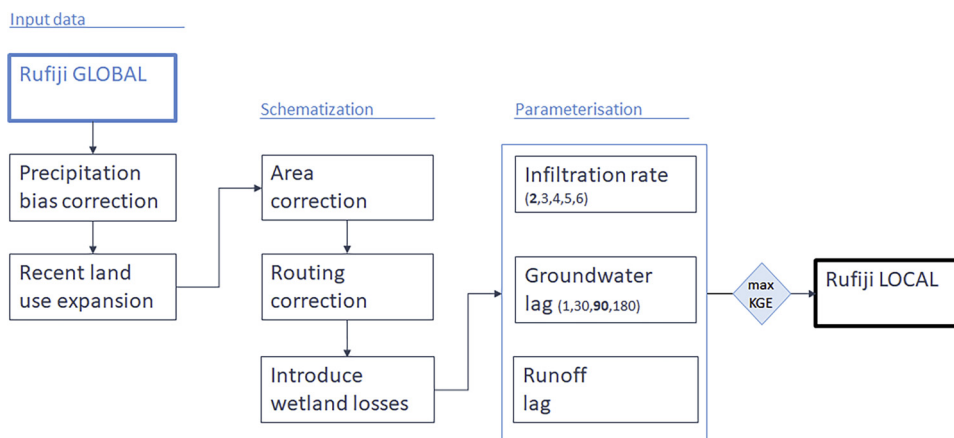
Fig. 2. Three-step model modification scheme, with modified parameter values for infiltration rate and groundwater lag (in bold the original values).

controls the lag in groundwater outflow to the surface water, by applying a linear reservoir model to the groundwater store. Third, a variable infiltration capacity parameter (*p*) has been introduced by Jägermeyr et al. (2016) on managed land use, which we also applied to the natural land use class. We used this version of the global LPJml model as our baseline (unmodified model), and the subset of results for the Rufiji catchment we call our 'Rufiji Global' model (Fig. 2).

2.2. Method: Step-wise approach and data sets

We designed a three-step approach to modify the model and achieve better performance; adjust and update essential input data using observations, improve the schematization of wetlands and explore the effects of lags in groundwater and runoff via a limited parameter sensitivity analysis (Fig. 2).

2.2.1. Input data adjustments

CHIRPS is a gridded global precipitation dataset combining cloud surface temperature with observations, at 0.05° resolution. It has been shown to compare favourably with similar global climatology products, especially in areas with complex terrain and low station densities (Funk et al., 2015) and has been tested for several regions in sub-Saharan Africa (Hessels, 2015; Toté et al., 2015). Local deviations in precipitation can, however, have a large influence on simulated flow due to the non-linear response of runoff to precipitation. Monthly CHIRPS grid cell totals were therefore compared with observed monthly precipitation data of 19 rain gauges obtained from the RBWB and the Climatic Research Unit (CRU) to obtain a first-order approximation of any bias. CHIRPS data were found to overestimate precipitation and so adjusted to correct bias on a sub-catchment basis by linear scaling, correcting for the mean percentage difference over the whole period of observation. This led to a precipitation reduction of 13% over the Kilombero River sub-catchment and 9% over the rest of the basin (Fig. 3).

The land use dataset used by LPJmL is based on MIRCA2000, a global dataset of cropping patterns of 26 major crop types for the year 2000 (Portmann et al., 2010). Major changes in land use between 2000 and 2008–2010 are reported in Tanzanian government statistics (Ministry of Agriculture of the United Republic of Tanzania, 2017a, b) as also observed by Leemhuis et al. (2017), using remote sensing. To reflect this, we adjusted the land use in LPJmL by simply applying the official estimate of percentage change to both rainfed and irrigated cropped areas in MIRCA2000, for the aggregated LPJmL crop classes (see SUPPLEMENT I), which preserved the spatial pattern of existing land use in MIRCA2000.

2.2.2. Schematization correction

While the Hydrosheds database provides a detailed river flow routing at 5′ resolution (Lehner et al., 2008), at the scale of small sub-catchments - for which we evaluate the model performance - small deviations in area can be significant for the total runoff (see Fig. 1C for an example of the Mbarali River sub-catchment). We first corrected for the difference in area between the gridded Hydrosheds grid and the official sub-catchment shapefiles (from the Rufiji Basin Water Board), applying a simple correction factor to simulated runoff per sub-catchment (see SUPPLEMENT; sub-catchments smaller than approximately 10,000 km^2 show large errors in area). In a second step, we corrected for any spatial deviations due to errors in the routing scheme, aggregating only the simulated runoff of gridcells within the shape of each sub-catchment. As a result, we overrule the LPJmL routing from this step onwards, and instead calculate flow in a post processing procedure using gridcell runoff as input (using the program *R*).

A third correction accounted for wetland evaporative losses which are not explicitly modelled by LPJmL. We applied a loss factor for wetlands upstream of the Makalala flow observation point in the Little Ruaha River sub-catchment, for the well-known Usangu wetlands upstream in the Great Ruaha sub-catchment (upstream of point 14, at the confluence of multiple tributaries, in Fig. 1A) and for the Kilombero wetland system, to calibrate simulated mean annual flows to within a 10% deviation of observed flows at
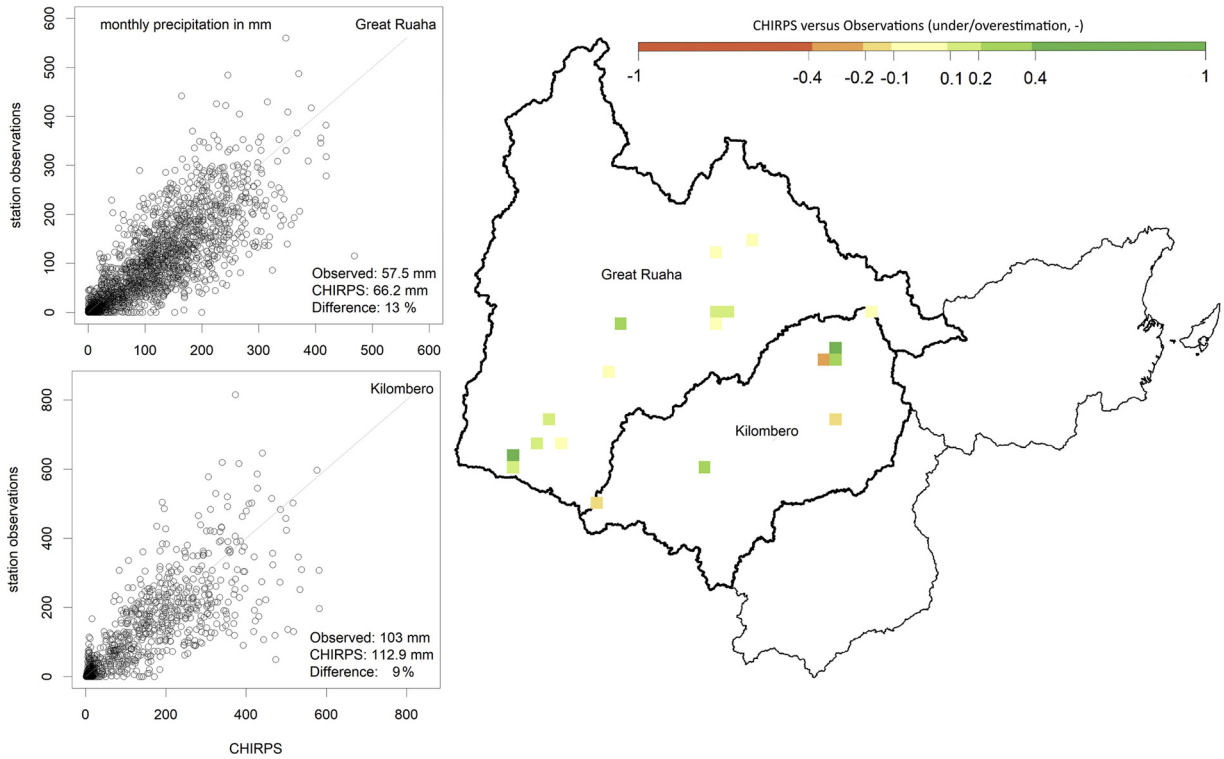
Fig. 3. Comparison of monthly CHIRPS precipitation versus observations at meteorological stations for the Great Ruaha and Kilombero sub-catchments (sources for observations: RBWB and Climatic Research Unit (CRU)). Inlays show the station location, with the colour scale representing the over- or underestimation of CHRIPS grid cell precipitation versus station data at that location (monthly values, over the period 1980–2015).

measurement points just downstream of these wetlands (Makalala for the Little Ruaha wetland, Msembe for the Usangu wetland, and Kilombero Swero for the Kilombero wetland). The Usangu wetlands are known to delay flow (Kashaigili et al., 2006a), which was approximated by adding a lag of one month to all flow leaving the wetlands at any one time. We applied the same delay to the Kilombero and Makalala wetlands.

2.2.3. Parameter sensitivity and optimization

Our aim was to use the original model parameters as far as possible with minimal adjustments, but enough to achieve an acceptable simulation of monthly flow characteristics. We therefore limited our calibration to a simple sensitivity analysis on two model parameters; the infiltration capacity parameter (p; varied from 1–6, with 2 being default and 6 leading to the highest in-filtration; see eq 1) and a groundwater drainage lag recently introduced in LPJmL ($GWcoeff$; varied from 1, 90, 180 to 270 days). The infiltration rate (q_{inf}, in mm/day) depends on the current soil water content of the first layer as follows:

$$q_{inf} = prir \times \sqrt[p]{1 - \frac{SW - W_{pwp}}{W_{sat} - W_{pwp}}}$$

(1)

where $prir$ is daily rain and applied irrigation water, W_{sat} is the soil water content at saturation and W_{pwp} the soil water content at wilting point, and SW the total actual soil water content of the first layer in mm. The surplus water that does not infiltrate is assumed to generate surface runoff. The groundwater coefficient (GW_{coeff}, in days) defines the period over which a certain amount of seepage into the groundwater component at day i (in days) contributes to groundwater drainage at time t (in days):

$$q_{drain_t} = \sum_{i=t-GW_{coeff}}^{t} \frac{q_{seep_i}}{GW_{coeff}}$$

(2)

where q_{drain} is the amount of groundwater drainage with q_{seep} the amount of seepage at time, *i (in days)*. A higher GW_{coeff} means that seepage is spread out over a longer time period, buffering peaks in drainage and, if GW_{coeff} is high enough, leading to a higher base flow.

In addition, we added a surface water lag parameter to the total runoff of LPJmL in post-processing based on an initial assessment of observed hydrographs; one which splits the monthly runoff (surface runoff, lateral runoff and groundwater drainage) into an immediate component without lag, a component with a one month lag, and a tail component lagged for the five consecutive months. This was implemented to solve some of the limitations of a simple bucket type model which does not capture the intricacies of

subsurface drainage (see, e.g., the Kilombero subcatchment study by Lyon et al., 2015). Such a lag might also capture some of the delay due to storage in surface waters affected by the detail of small-scale topography in reality, which global river routing models tend to misrepresent (Yamazaki et al., 2011). We applied the lag parameters uniformly over the whole basin, rather than varying them by sub-catchment, since we had no information on their spatial distribution.

Other parameters (notably soil parameters) were updated to latest available data, but not calibrated. Standard crop parameters were used, for which the planting and harvesting dates have recently been improved and validated for East Africa (Waha et al., 2013, 2012).

2.3. Model performance assessment indicators

Daily observed flow data were obtained from the RBWB. A total of 57 stations have been installed over the past decades in the Rufiji basin, but only a few have recorded consistently and during recent years (RWBO, 2013). Sixteen stations provided some data for 1980–2010, for which results are shown, out of which eight were selected to optimize the parameters, those with long data series, covering various parts of the basin (see Fig. 1). Simulated flows were compared with observations at a monthly time-step, after aggregating the daily data to monthly averages. When more than three days in a month were missing, the complete month was removed which led to a reduction of approximately 5% of the data. For comparison of annual time series, only years with data for all months were included.

We applied three basic hydrological indicators:

- Overall performance: Kling-Gupta model Efficiency (KGE). KGE is a comprehensive metric, a weighted average of the Pearson product-moment correlation coefficient, the ratio between the mean of the simulated values and the mean of the observed ones, and variability ratio, which is computed using the standard deviation of simulated and observed. Kling-Gupta efficiencies range from -Infinity to 1. The closer to 1, the more precise the model is. The two selected model parameters (p and GW_{coeff}) were optimised on the mean KGE for the eight selected measurement locations. KGE is a useful overall metric, and suitable as an environmental flow indicator, as environmental flow requirements often depend on effective representation of both low flows and high flows;
- Low flows: log-transformed Nash-Sutcliffe model Efficiency (LogNSE). By taking the log of simulated and observed before calculating the NSE, the influence of (missing) peak flows - is reduced and more emphasis is placed on the base flow (the criticism of the standard NSE is that it is overly sensitive to the magnitude and timing of peak flows (e.g., Schaefli and Gupta, 2007). LogNSE is a useful model performance indicator when one is interested in using a model to assess irrigation water availability during the low flow period.
- Volume Errors: Relative Volume Errors (RVE). RVE gives an indication of whether the overall water balance is reasonably well simulated and is a useful indicator for assessing hydropower production with a model, as total water availability is important when dam storage can buffer seasonality.

2.4. Study area – Rufiji Basin

The basin, approximately 177,420 km^2 in size, includes a marked elevation range (from sea level to 2960 m), encompassing both dry and tropical climate zones as a result of a large gradient in total precipitation, which ranges from 500 mm per year to more than 1500 mm per year (see Fig. 6a for the spatial pattern). Precipitation is highly seasonal with a mix of uni- and bi-modal maxima together with a complex hydrology including several major wetland systems, expanding irrigation and several hydropower reservoirs. Similar to other river basins in sub-Saharan Africa the basin is experiencing rapid socio-economic change and it also comprises a large part of a region earmarked for ambitious agricultural expansion, the Southern Agricultural Growth Corridor of Tanzania. The Rufiji produces roughly half of Tanzania's river flow, supplies water for 4.5 million people and generates 80% of the country's hydro-power (464 MW at three hydropower sites, almost 50% of the total combined national hydro-thermal power capacity) (WREM-International, 2015). High development potential involves critical trade-offs between the water, energy, agriculture and conservation sectors.

3. Results

3.1. Step wise model improvement – seasonal patterns

The global model performs rather poorly for all gauging stations, and all three indicators, in the unmodified 'global' run. Table 1 shows the performance per gauging station, for the period 1981–2010, with Fig. 4 highlighting the eight selected sub-catchments, showing a step-wise improvement in seasonal flow as modifications are applied. Fig. 5 shows a Taylor diagram, a further graphical refinement of the KGE indicator used to select the parameters. The original GHM overestimates both absolute flow volume and seasonality, underscoring a need for adjustment to input data and model specification to produce a simulation performance that is satisfactory for exploring scenarios.

There is no single adjustment that improved both volume and seasonality, for all sub-catchments. The correction of precipitation input reduced simulated flow significantly in all sub-catchments, but did little to improve the indicators that describe seasonality, the KGE and logNSE. Adjustments in routing and sub-catchment area also have a strong effect, however, the direction of change differed between sub-catchments. For example, the Mbarali sub-catchment (see Fig. 1 for locations of gauging sites and sub-catchments) was

Table 1

performance statistics per station, for monthly time series, 1981–2010. Red resembles a poor indicator score, yellow reasonable, and green good. Step 3 involves limited parameter optimisation. With official station code, and (in brackets) the numbering as in Fig. 1 (the asterix indicate the 8 selected stations used for the parameter optimisation). Flows are in m³/s. (For interpretation of the references to colour in this Table legend, the reader is referred to the web version of this article.)

	Flow obs	metric	sim. GLOBAL	sim. rainfall	sim. land use	sim. area	sim. routing	sim. wetland	sim. LOCAL
Great Ruaha									
Mbarali at Igawa	12.4	KGE	-0.1	0.38	0.37	0.7	0.71	0.71	0.76
*1KA11 (6)		logNSE	0.1	-0.81	-0.71	-1.1	-0.69	-0.69	0.43
		RVE	73	31	31	-11	2	2	-3
Chimala at Chitekelo	2.6	KGE	-0.09	0.38	0.37	0.65	0.65	0.65	0.62
*1KA7A (4)		logNSE	-0.06	-0.27	-0.23	-0.4	-0.4	-0.4	0.54
		RVE	83	37	39	-8	-9	-9	-11
Great Ruaha at Salimwani	12.0	KGE	0.32	0.5	0.5	0.19	0.24	0.24	0.21
1KA8A (5)		logNSE	0.12	-0.32	-0.22	-0.79	-0.1	-0.1	0.52
		RVE	53	15	16	-40	-32	-32	-33
Ndembera at Ilongo	5.8	KGE	0.37	0.6	0.61	0.54	0.57	0.57	0.73
*1KA15A (7)		logNSE	0.07	-0.65	-0.55	-0.55	0.07	0.07	0.65
		RVE	42	10	10	19	19	19	16
Great Ruaha at Msembe	50.4	KGE	-1.58	-0.77	-0.79	-0.83	-0.44	0.61	0.64
*1KA59 (14)		logNSE	-0.42	-0.35	-0.33	-0.33	-0.79	0.28	0.61
		RVE	212	138	140	143	101	20	11
Lukosi River at Mtandika	20.6	KGE	-3.77	-2.89	-2.87	-1.97	-1.78	-1.78	-0.79
1KA37A (12)		logNSE	-7.62	-14.96	-14.67	-15.79	-18.46	-18.46	-4.86
		RVE	139	92	92	58	50	50	41
Yovi river at Yovi	3.1	KGE	-0.53	0.15	0.15	0.08	0.2	0.2	0.3
1KA38A (13)		logNSE	-0.49	-0.36	-0.34	-0.36	-0.4	-0.4	-0.21
		RVE	137	70	70	77	62	62	54
Little Ruaha									
Little Ruaha at Makalala	3.7	KGE	-1.41	-0.69	-0.68	-1.14	-1.12	0.54	0.73
*1KA32A (11)		logNSE	-0.17	-0.04	-0.03	-0.13	-0.14	0.5	0.64
		RVE	152	93	93	123	121	11	9
Little Ruaha at Ihimbu	16.0	KGE	-1.58	-0.88	-0.86	-0.12	-0.14	0.31	0.69
*1KA21A (8)		logNSE	-0.69	-1.77	-1.59	-1.83	-6.19	-6.22	-0.52
		RVE	136	78	77	34	28	7	3
Little Ruaha at Ndiuka	20.3	KGE	-1.84	-1.13	-1.11	-0.33	-0.33	0.13	0.59
*1KA2A (3)		logNSE	-0.37	-1.05	-0.94	-1.06	-4.13	-4.07	-0.04
		RVE	140	84	83	40	33	14	11
Mtitu at Mtitu	3.5	KGE	-0.56	-0.18	-0.17	-1.41	-1.14	-1.14	-0.34
1KA22 (9)		logNSE	-3.24	-11.72	-10.47	-8.45	-13.76	-13.76	-2.12
		RVE	31	2	2	59	42	42	38
Little Ruaha at Mawande	21.7	KGE	-2	-1.22	-1.21	-0.74	-0.64	-0.27	0.2
1KA31 (10)		logNSE	-0.13	-0.26	-0.21	-0.18	-1.53	-1.49	0.40
		RVE	182	120	119	90	78	59	52
Kilombero									
Ruhudji river below Kifung'a	5.9	KGE	-0.61	-0.19	-0.22	0.56	0.55	0.55	0.82
*1KB18 (17)		logNSE	-0.11	-0.69	-0.57	-0.9	-1.58	-1.58	0.25
		RVE	87	53	55	-1	-4	-4	-5
Mpanga River	37.9	KGE	-0.04	0.17	0.17	-0.03	0.22	0.22	0.64
1KB8B (15)		logNSE	-2	-3.91	-3.81	-3.36	-3.01	-3.01	-0.68
		RVE	12	-7	-7	4	-5	-5	-6
Ruaha Kigogo	8.6	KGE	-2.77	-2.01	-2.01	-1.57	-0.8	-0.8	-0.29
1KB31 (18)		logNSE	-2.56	-1.91	-1.9	-1.55	-1.19	-1.19	-0.33
		RVE	180	126	126	103	59	59	63
Kilombero at Swero	443.2	KGE	0.48	0.71	0.71	0.72	0.65	0.86	0.66
1KB17 (2)		logNSE	0.34	0.33	0.34	0.34	0.03	0.55	0.62
		RVE	38	15	15	14	13	-14	-14

oversized in the Hydrosheds delineation and the area correction improved simulation of flow volumes. In the Chimala sub-catchment the adjustment of area and routing of upstream runoff reduced flow volume below observed values, thereby leading to a worse performance. This, however, was a helpful finding as it uncovered errors elsewhere; specific discharge, i.e. volume of flow per unit of area, was likely too low which could have been a result of an underrepresentation of precipitation in this small sub-catchment represented by just a couple of grid cells including a steep elevation gradient.

The reduction and one-month delay in flow by the wetland factor for the Little Ruaha above Makalala, improved flow estimates for the immediate downstream location of Makalala, and for locations further downstream along the Little Ruaha. Wetland losses of 50% of flow were required to bring RVE within 10% of observations. For Usangu, in the Great Ruaha River, assumed losses of 35% were sufficient to bring the RVE at Msembe within 10% of observations. This loss in flow translates into an area-specific loss over the Usanga plains (~ 4480 km², Kashaigili et al. (2006b)) of 2.5–3 mm/day, during and just after the wet season when the plains are flooded or saturated (January-June). This corresponds well with the evapotranspiration deficit over this area as calculated by LPJmL (monthly averages vary between 2.3 and 4 mm/day for the period January-June), a deficit that could be considered an approximation of potential, additional wetland evapotranspiration. For the Kilombero wetlands, no additional losses were imposed as this would have led to further underestimation of flows. Limited available observations of questionable quality (Kilombero Swero observations
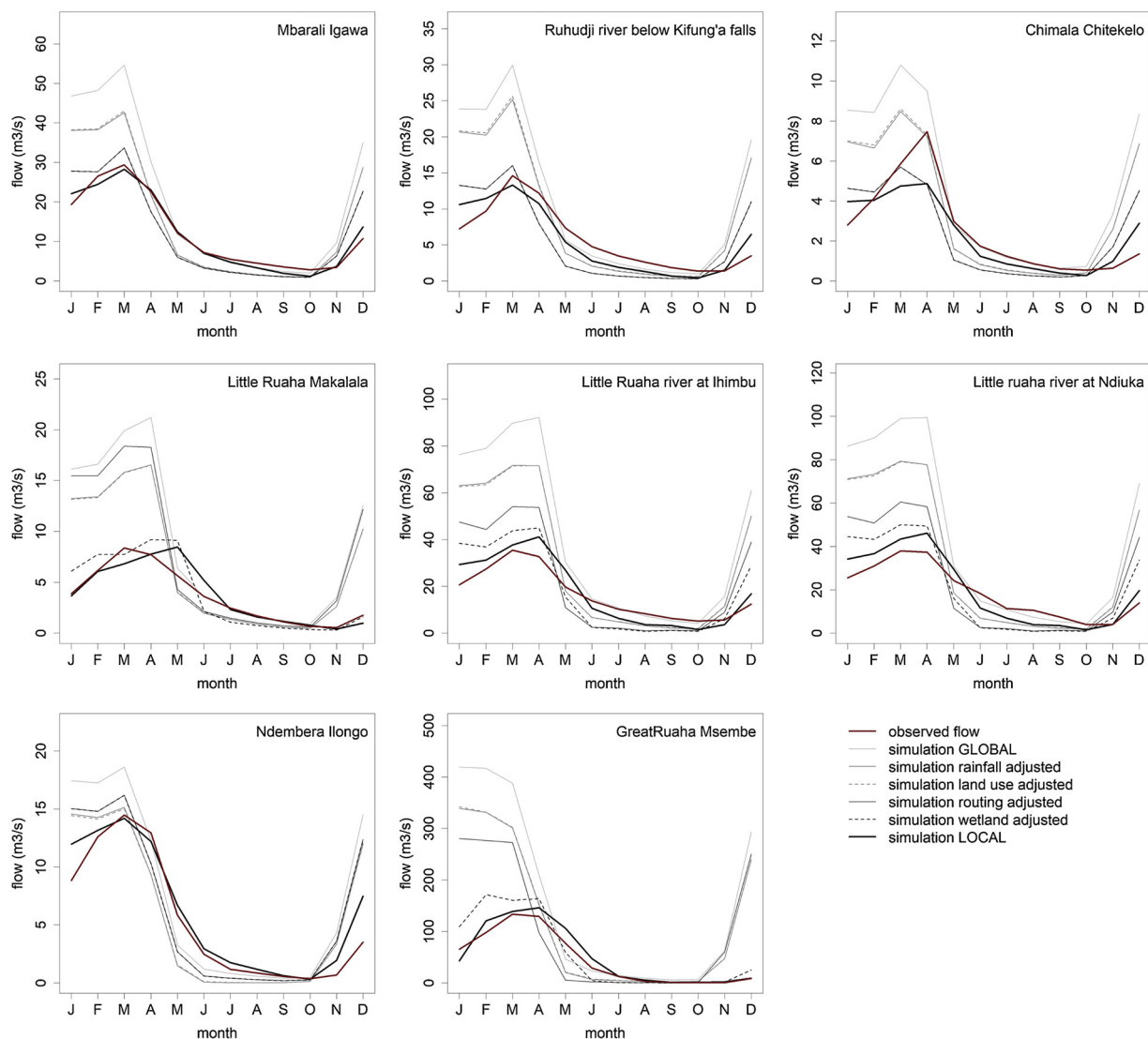
Fig. 4. Observed versus simulated seasonal runoff pattern for eight sub-catchments selected to optimise parameters (improvements are incremental and applied cumulatively).

only overlap three years with our simulation period, with several data gaps especially during the wet season) complicate deriving a loss factor based on the RVE. Lower losses than for the other wetlands could be expected, though, as in this wetter part of the basin the difference between actual (and simulated) soil evapotranspiration and potential evapotranspiration is relatively modest during the wet season.

Land use adjustments had only a very small effect, with changes in runoff due to updated vegetation cover very limited, and increased irrigation demand (due to change in crop water requirements) hardly visible. Partly this is due to the order in which improvement steps have been introduced; it is only after the seasonality of flow has been improved that by introducing a greater lag through the parameter optimization which leads to more base flow, allowing irrigation demand to be met in months when precipitation is mostly absent. Reductions in flow in the dry seasons as a result of introducing irrigation, improved model performance especially at Msembe, which lies downstream of the major rice growing area in the Great Ruaha sub-catchment. Fig. 6 c shows the concentration of irrigation in the western, drier part of the basin where large commercial farms are fed by runoff from the neighbouring hills. We simulated an irrigation water demand for the basin of 2.2 BCM per year, similar to that reported in the river basin management plan (2.4 BCM per year; WREM-International (2015)).

The introduction of a uniform lag in surface water runoff was most effective in improving the seasonality, which greatly improved the logNSE and KGE indicators. Optimal values were a lag of one month for 35% of flow, and further delay of another 15% of flow, equally divided over the next consecutive five months. Interestingly, the infiltration parameters and groundwater lag coefficient gave best results for selected stations when kept at their original values. Our final modified 'local' model, LPJmL$_{local}$, matches both the total monthly volumes and seasonality of the observations at the eight selected sub-catchments rather well, with the initial
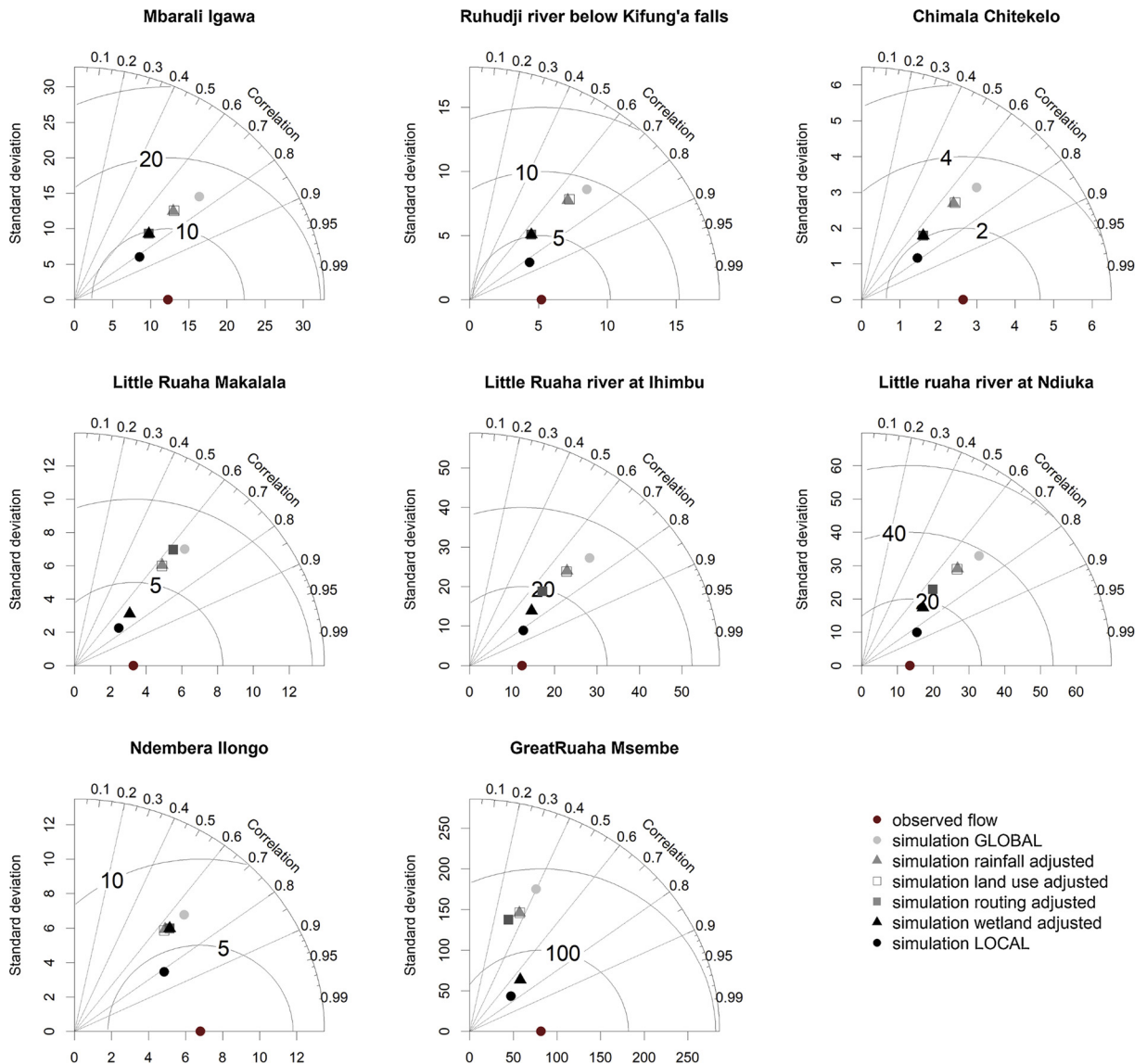
Fig. 5. Taylor diagrams for selected sub-catchments, showing cumulative model improvement in terms of the Pearson correlation coefficient, the root-mean-square error (RMSE) error, and the standard deviation.

overestimation of flow of more than 100% reduced to, on average, only 4% and KGE values increased to, on average, 0.7. LogNSE, representing low flow conditions, improved but only to moderate levels (0.4, on average), mainly because of overestimation of low-flows in the Little Ruaha sub-catchment.

Of the other stations in Table 1, some - measuring flows from small upstream sub-catchments like the Mtitu, Ruaha Kigogo and Yovi – perform poorly. Fig. 4 also shows there is a trade-off in performance between sub-catchments, especially during the months November till February, with some requiring a stronger seasonality (e.g. the Little Ruaha river stations) while others would improve with lower peak flows during the rainy season (e.g. Chimala River at Chitekelo). If parameters would be calibrated per sub-catchment, rather than for the basin as a whole, better performances would be achieved, but such a differentiation in parameter values should preferably be guided by sub-catchment specific process understanding.

3.2. Simulation of monthly and annual flow time series

Monthly time series for the 1981–2010 period show in more detail the match between simulated and observed (Fig. 6). While LPJmL$_{local}$ does well in reproducing the overall pattern, some peaks, e.g. in the Mbarali Igawa catchment in 1992, are missed. The high flows during the 1997–1998 El Niño event are visible in several sub-catchments, indicating that the basin was mainly influenced by wet conditions more typical of the East African response to El Niño, rather than the dry/normal conditions more typical of
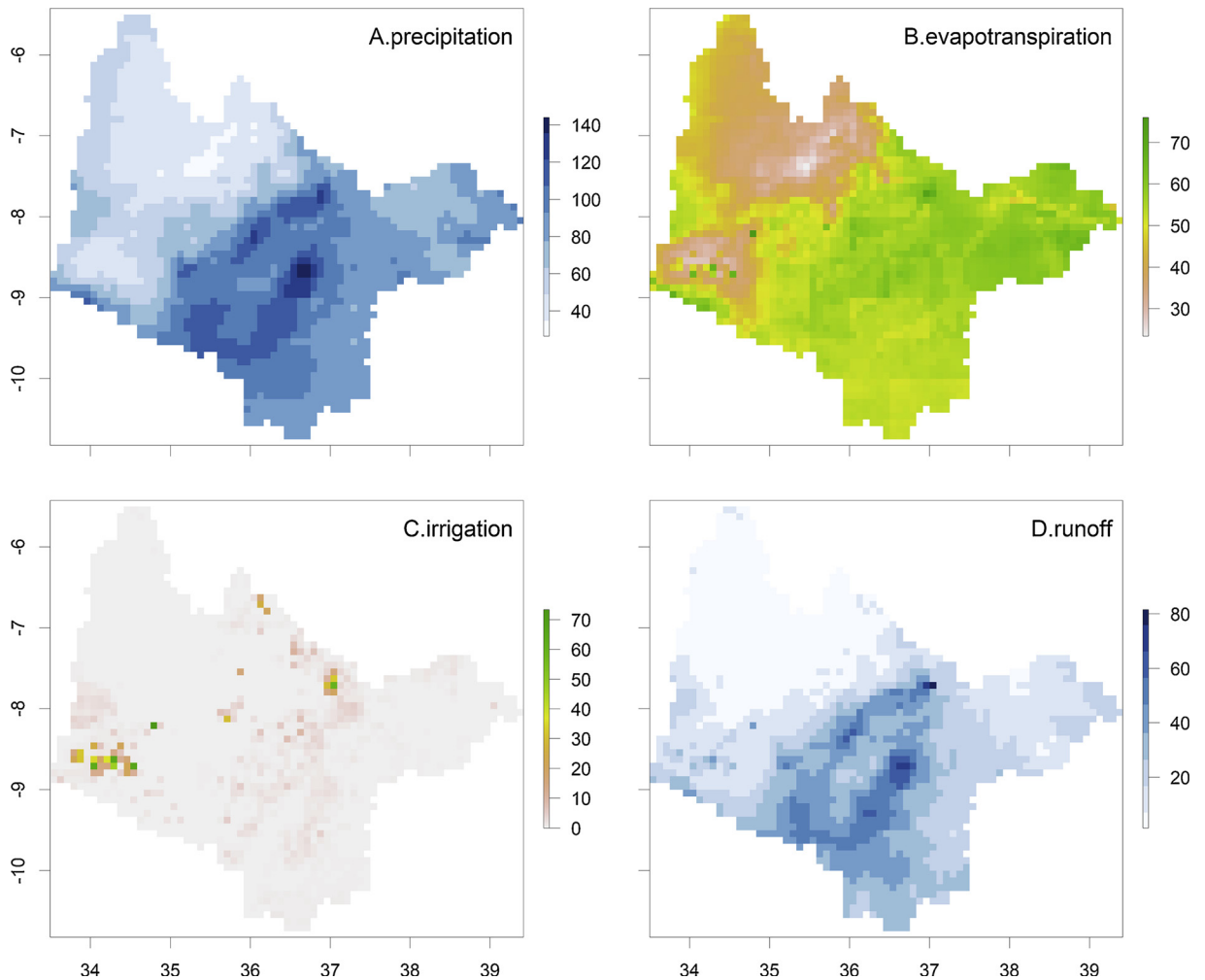
Fig. 6. Spatial pattern of precipitation and simulated evapotranspiration, applied irrigation and runoff, in mm/month as a grid cell average over the period 1981–2010.

southern Africa. Recent low flow years in 2000, 2003 and 2006 are well captured by the model.

Observed flows at Msembe for 1997–1998 are shown dotted (Fig. 7) and have been excluded from the evaluation. While flows in the Great Ruaha were reported higher during this year (e.g. by citizen observer; www.theruahanotes.com/great-ruaha-river), the extremity of values - more than 10 times the average flow - is difficult to explain. Upstream catchments (Mbarali, Ndembera, Salimwani) did record higher flows during this El Niño year, but not to this extent. Equally, precipitation measurements at Msembe, and other stations close by, show an increase during the rainy season but only a modest one. Extrapolation of the rating curve, with which water levels are translated into flows, to such an extremes is prone to errors (e.g., Di Baldassarre and Montanari, 2009) and they are of limited accuracy beyond the range for which they were established, which suggests these observations should be used with caution.

Simulation of annual flows is reasonable, with the exception of Chimala at Chitekelo, the smallest sub-catchment evaluated, and the Little Ruaha at Ihimbu (Table 2). Reasons for lower KGE are different in each sub-catchment. In Mbarali, for example (Fig. 8), especially the last three years (2008–2010) are simulated drier than observed, but it is unclear why, as both observed rainfall and the CHIRPS rainfall product used in the hydrological model seem to correspond well and signal average or below average precipitation during these years. A possible explanation could be the influence of isolated cloud bursts on runoff, not picked up by satellite, in this small catchment in a hilly region. More generally, fewer data points in the annual time series - with years omitted completely if a single month was missing - means that a single outlier year will strongly affect the performance indicators. This explains partly the low values for Little Ruaha at Ihimbu, where two wet outliers, not observed in the neighbouring downstream point at Ndiuka, strongly influence the KGE value. Limited resources, a vast catchment and difficult road conditions complicate data collection, especially during the rainy season.
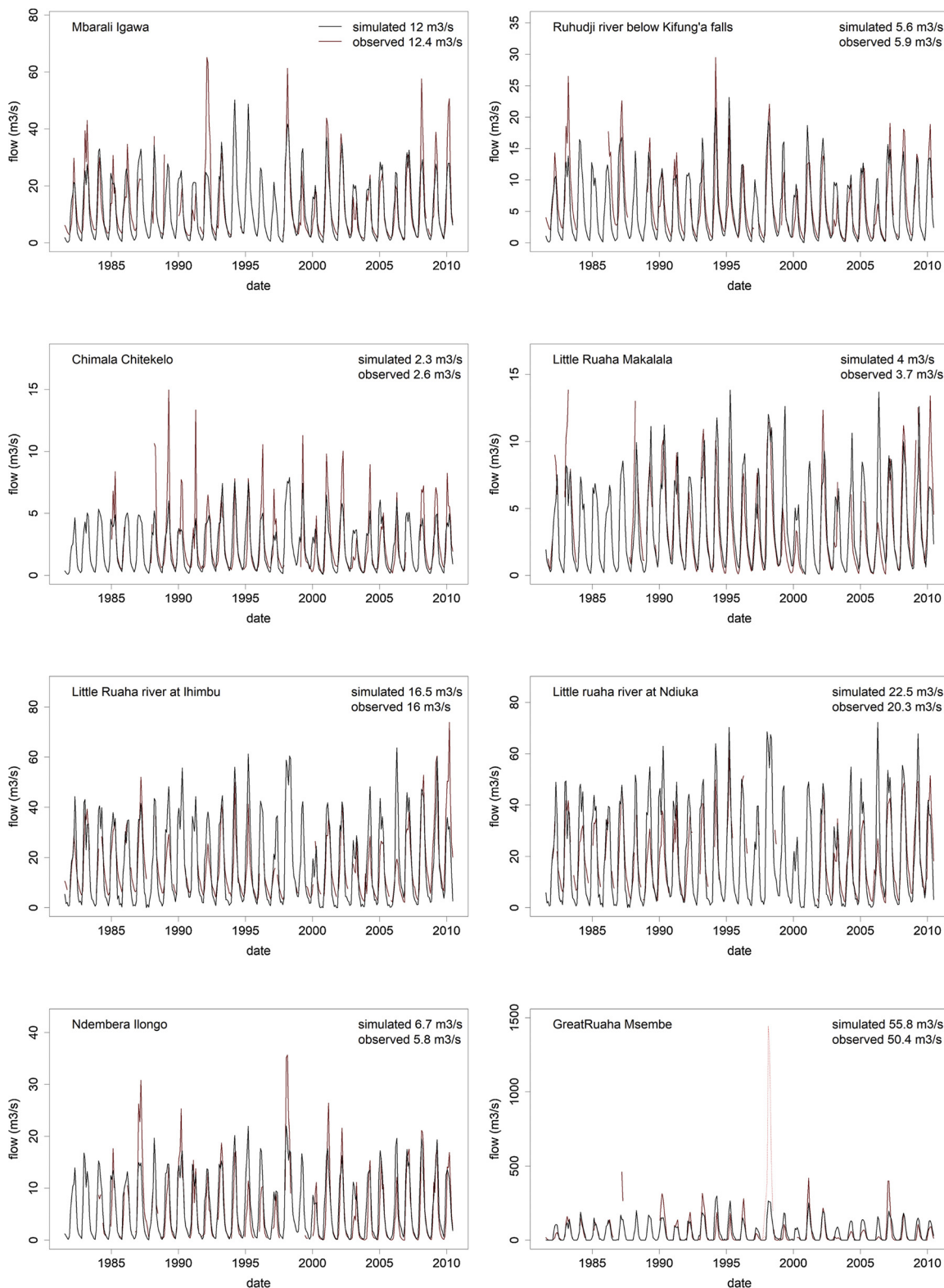
Fig. 7. Time series of simulated (black) and observed (red) for selected sub-catchments (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Table 2

Mean annual flow KGE at selected locations.

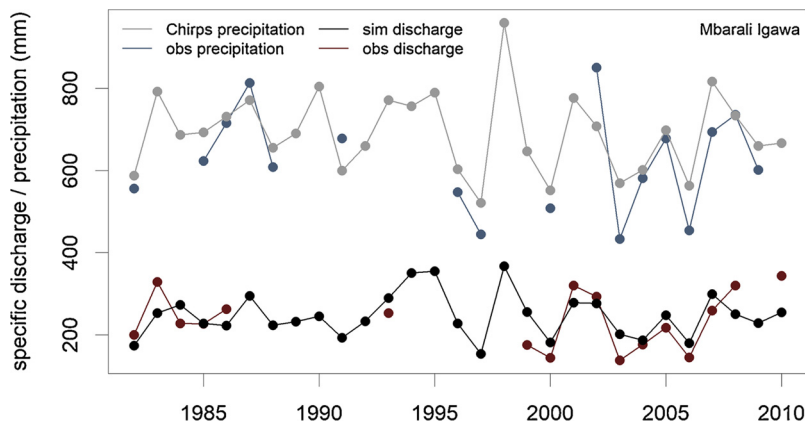| station	KGE
Mbarali river at Igawa	0.48
Ruhudji river	0.54
Chimala river at Chitekelo	0.12
Little Ruaha river at Makalala	0.33
Little Ruaha river at Ihimbu	−0.03
Little Ruaha river at Ndiuka	0.47
Ndembera river at Ilongo	0.49
Great Ruaha river at Msembe	0.31

Fig. 8. Comparison of Mean annual flow for Mbarali sub-catchment, expressed as specific discharge, simulated and observed, with precipitation based on CHIRPS and station data (with years defined as from July till June to capture the complete rainy season).

3.3. Irrigation expansion affecting downstream flows

An improved local hydrology-vegetation model provides an opportunity to evaluate the interaction between upstream water abstractions for irrigation and downstream flow. Causes of reduced dry season flows since the beginning of the 1990s in the Great Ruaha River have long been contentious (because of their role in the Ruaha National Park). Increased abstraction from rice cultivation in the upstream regions has been suggested to be the main cause, but disagreement about the effect of climate variability or the contribution of the expanding and non-stationary Usangu wetland to reduced flows (Lankford et al., 2004) remains.

Fig. 9 shows pre-1980 observed flow variation (mean, and 0.25–0.75 quantile range) and the 1981–2010 observed seasonality, which indicates flows have diminished at the end of the long rains, in April-May, and into the low flow season. Historically, flow could be observed year round at Msembe (the main gauging site below Usangu wetland), dropping in November, but still enough to maintain a basic ecosystem function, e.g. providing water for wildlife in the Ruaha National Park and surrounding areas. In only two months, in 1980, did average monthly flows drop below 1 m³/s. In the last decades, since 1981, flow has reduced to almost zero from September onwards leaving the Great Ruaha River (almost) dry for months on end. The LPJmL$_{local}$ model reproduces well this reduced flow during the 1981–2010 period. Switching off irrigation in the model brings back a pattern that matches the historic observed flows reasonably well, though flows in January and February seem to be slightly overestimated. Similar to historic observations, the model shows that no/low flows are extremely rare under natural flow conditions, without water abstractions.

Further downstream, at Stiegler's Gorge, is the site of one of the largest hydropower schemes currently in the planning and development stage in Africa. The irrigation extraction of 2.2 BCM per year has only a modest effect on flows at this location. Here, close to the delta, the Rufiji has increased to a large river with an annual flow of about 35 BCM, although this fluctuates from less than 20 BCM to more than 40 BCM per year (note that the observed series at this critical point in the basin stops in 1978). A median monthly reduction in flow at Stiegler's due to irrigation abstractions of 4.5% was simulated with the model (25 percentile = 2.6%, 75 percentile = 7.8% reduction) and only in two months over the whole 30 years' time series did simulated flow drop below 100 m³/s at Stiegler's Gorge, partly due to upstream irrigation abstractions. If, however, upstream demand for irrigation more than triples to 7.6 BCM in 2030, as suggested by the basin water resources development plan (WREM-International, 2015), irrigation is likely to have a much more significant effect on downstream water availability, especially in dry years.

4. Discussion

"Everywhere and locally relevant" has been posed as the ultimate aim of global hydrological modelling (Bierkens et al., 2015). In this paper we examined the performance of a well-known GHM – LPJmL – for a medium-sized basin in eastern Africa, the Rufiji basin.
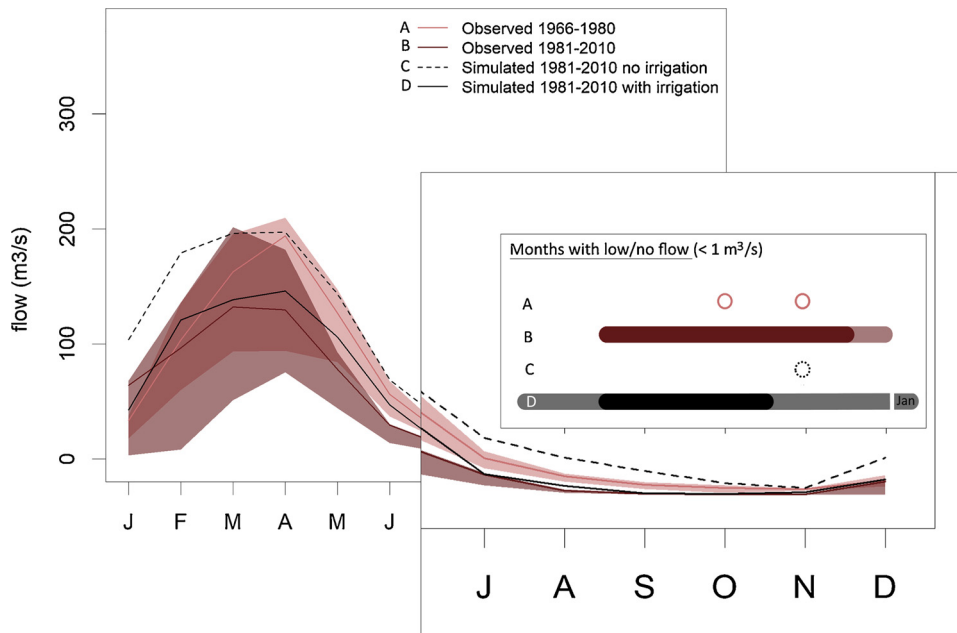
Fig. 9. Historic and present-day observed flow seasonality (with mean and 0.25-0.75 quantile range) compared to simulated flow, with and without irrigation abstractions. Inlay shows months with flows below 1 m³/s. Historically (pre 1981) no/low flow months occurred only on two occasions (A), which is matched by the simulation without irrigation abstractions (as in C; only one month of flows lower than 1 m³/s. Open circles, representing single months in the data series). Post 1981, low flow occurred annually, lasting for several months. Darker shades represent the mean period of no/low flows and lighter shading the 0.25 quantile period, i.e. length of no/low flows at the driest 25 percent of years, with observed (B) roughly matching the simulation with irrigation (D).

The rather poor performance of the original model in its global configuration is not surprising given the complex hydrology (multiple wetlands systems, seasonal inundation) of the basin, the steep gradients in elevation and precipitation, and the limited schematization of delayed runoff and groundwater processes in LPJmL. It is a hard target to hit with an uncalibrated global model. Our study finds that for scenario analysis or water management applications, further calibration and validation against observed discharge is required (as also mentioned by Hattermann et al., 2017).

Our study does provide several suggestions for what could be relatively simple but effective steps in the regionalization of a GHM like LPJmL that uses global input data. The first step considered input data and precipitation adjustment, using a comparison of global remote sensed input data against local observations, was most effective in achieving a good simulation of the annual water balance. More advanced methods to correct precipitation than used in this paper could be applied, e.g. through elevation informed interpolation of station data, rather than using a single sub-catchment based adjustment factor. The adjustments made are relatively modest (and not uncommon in this scale of hydrological modelling), but due to the non-linear nature between precipitation and runoff they lead to large changes in simulated flows and hence the high model sensitivity to bias in input data. In the case of the Rufiji local data on catchment areas was important for some sub-catchments, particularly small ones in areas of high precipitation.

Second, introducing lags in surface water runoff, one representing site-specific processes (in our case wetlands) and one compensating for general limitations to process description, schematization and parameterization, was essential to reproduce the observed seasonal pattern of flow. For the Rufiji, due to almost total lack of information on wetlands in the Kilombero and Makalala and limited data on those in the Usanga plains, adding the most basic functions of such wetlands through a delay of 1 month and a loss as a fraction of flow was felt to be a reasonable compromise between rigour and practice. Specific losses for Usanga corresponded well with the evapotranspiration deficit during the rainy season, providing some confidence in the approach. More advanced methods, like treating them as a non-linear storage reservoir with variable evapotranspiration based on surface water level and vegetation development could potentially lead to a better simulation of surface water losses and flow delay. Several alternatives have recently been described and tested (Pereira et al., 2017; Yamazaki et al., 2011) but were considered beyond the scope of this study as they would require a major reconfiguration of LPJmL. The non-site specific lag introduced, represented those delays in soil and surface water not explicitly included in process description or parameterisation. The soil module with the local parameterisation derived from the harmonized soil database appeared to react particularly rigid, separating water in the soil column mainly between fast surface runoff and slow groundwater discharge, with no intermediate lateral flow. A more catchment-specific schematization of soil layers (not available for the Rufiji but possibly available for other basins) might improve separation between fast runoff and medium to slow lateral and deep drainage. In the context of optimizing a conceptual two-parameter model over a large number of catchments, Mouelhi et al., (2006) found the 'exchange with the outside of the basin' (e.g. our wetland losses) and the routing storage capacity the most important parameters, followed by the soil moisture storage capacity (similar to our lag parameters).

Third, whilst trying to stay as close to the original GHM, it was useful to examine the effects of adjusting some model parameters

considered critical for key characteristics of observed flows (we found the lag parameters to be most critical). Issues of equifinality, e.g. between groundwater lag and surface water lag parameters, could be further explored. Guiding this process with local understanding of sub-catchment-specific processes could allow calibration by sub-catchment, rather than for the basin as a whole. However, taking this too far begins to replicate development of a bespoke model, which is not the purpose of this study. Including more GHMs, targeting the same catchment/s would make an interesting opportunity for cross-comparison.

After improvements, the LPJmL model performed well in simulating average annual flows, monthly time series and seasonal patterns, and reasonably well in simulating observed inter-annual variability. Whilst we note that some fairly important assumptions have been made to arrive at the final model version, these are not unprecedented in this scale of hydrological modelling, particularly in areas such as the Rufiji that are very data sparse. The simulation performance is adequate to use the model for exploring the effects of recent environmental change, future scenarios and sensitivity analysis; for example, we show that depletion of flows, especially during the dry season, in the Great Ruaha River during recent decades can be largely accounted for by increased irrigation abstractions. Critical data requirements for further model development include information on wetland characteristics (this would allow a stronger focus on simulation of daily flow characteristics, but is some way off given the present data situation), and in situ measurements of precipitation and discharge, specifically for downstream major tributaries Kilombero and Luwegu, and the Rufiji main stem.

A key question that remains is whether it is worth adjusting a global model to apply it to a medium-sized basin. The time spent improving LPJmL (in the order of months) for just one basin most probably equals the time that would have been spent setting up a designated hydrological model like SWAT. Many of the steps have required and benefitted from local sources of data and existing reports on the hydrology and environment in the basin. However, as GHMs improve (resolution and schematization) fewer local adjustments may be required, they could be more targeted and the adjustment time greatly reduced, using lessons learned from studies such as this. In large developing countries with data sparse regions and few long-duration, good-quality flow records, application of a regionalised GHM would have significant benefits to allow consistent modelling of multiple basins, and opportunities for local researchers to link with global research networks and access open source models.

5. Conclusions

Our study contains a dual message: whilst the GHM under consideration (LPJmL), in its original configuration, does provide a first approximation of Rufiji hydrology, capturing much of the spatial variation in rainfall and evapotranspiration leading to varying flows at different locations, for it to do well at the local scale and to be accurate enough to explore sensitivities and scenarios, various catchment specific modifications are needed. Stepwise implementation of relatively simple modifications revealed the most important step to improve flow volumes was precipitation adjustment. To improve seasonality, introducing a lag in surface water runoff was the most effective measure.

Local sources of in situ data and information on the hydrology and environment have been essential for the regionalisation process, but there remain critical data requirements for further model development. This modified version of a GHM is robust enough to explore water management questions such as assessment of the impact of climate or land use changes on hydropower or irrigation plans. We show – as a proof of concept - that a reduction in the Great Ruaha River flow can be explained by increased irrigation, but that the influence of irrigation (based on the area under irrigation in 2010) on flows much further downstream at Stiegler's Gorge, where large hydropower infrastructure is planned, is modest. Projected demand from irrigation expansion will, though, constitute a more considerable proportion of annual flow.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ejrh.2018.10.007.

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