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Evaluation of streamflow estimates for the Rovuma River

M.R. Minihane *

University of Washington, Department of Civil and Environmental Engineering, 201 More Hall, Box 352700, Seattle, WA 98195-2700, USA

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ABSTRACT

Reliable estimates of historic streamflow are important when estimating future flows and water resources availability based on factors such as climate change, population growth, and changes in land use or land cover. Many regions across the globe have limited streamflow observations. Additional information about streamflow in these basins is critical to water resources planning and economic development strategies. In southeastern Africa, the remote Rovuma River lies on the border between Mozambique and Tanzania. There are limited historic measurements in the main tributary, the Lugenda River, and no publicly available observations from recent years. Improved knowledge of the water resources availability and seasonal and annual variability of this river will enhance transboundary river basin management discussions. A combination of methods, including index-gauge methods and a macro-scale hydrological model are used to estimate historic streamflow conditions in the Rovuma River. These methods incorporate data from remote sensing, gridded global soil data, a composite runoff dataset, and in situ observations. The hydrological model was tested in a nearby gauged basin yielding a Nash–Sutcliffe efficiency ratio of 0.8, an efficiency ratio based on mean historical streamflow by month of 0.6, an efficiency ratio based on inverse flows (sensitive to low flows) of 0.9, and a coefficient of determination equal to 0.99. In the Rovuma River, the mean and standard deviation of the index gauge-estimated mean monthly flows agree with streamflow estimates using the Variable Infiltration Capacity (VIC) hydrologic model with a 0.25 decimal degree spatial resolution. A closer look at precipitation records suggests that the model results provide a more accurate historic flow record than the index gauge methods due to small-scale precipitation events. Model inputs and results are evaluated by leveraging available regional in situ data in comparison to remote sensing data input data. Uncertainties in the streamflow estimates are high, however, additional in situ measurements can reduce these uncertainties. This combination of methods could prove useful for estimating flows in other rivers in southern Africa and other regions with intermittent or sparse streamflow observations.

1. Introduction

Sustainable development of water resources for public water supply, irrigated agriculture, or hydropower can be a powerful tool for countries seeking economic growth and improved education and public health. In some cases, the need for water resources development appears in locations that do not have a history of in situ observations of streamflow or other hydrologic parameters. Improved methods for predicting streamflow in ungauged basins could enhance these water resources planning activities.

In addition, as discussed by Milly et al. (2008) and others (e.g., Ivanović and Freer, 2009; Sivapalan and Samuel, 2009; Singh et al., 2011), the assumption that past hydrologic conditions will persist into the future is no longer valid. As such, we have the responsibility to develop tools for planning water resources under these non-stationary and uncertain conditions (Lettenmaier, 2008). While still not commonplace, water resources planning strategies can be adapted to account for a changing climate. For example, Whitely Binder et al. (2010) present state and local adaptations relevant to water supply, flood protection, drought preparedness, hydropower, agriculture, ecology, urban stormwater infrastructure, and public health. The tools we use for predicting streamflow in ungauged basins need to useful for planning under uncertain future conditions.

The Ruvuma/Rovuma River (henceforth referred to as Rovuma), which forms the border between Mozambique and Tanzania, is one of the largest undeveloped rivers in its region. The Rovuma has limited hydrologic observations throughout the basin, leading to high uncertainties of historic conditions. This presents an additional challenge in the presence of changing climate and development. The Rovuma Joint Water Commission is an international cooperative effort charged with "ensuring sustainable development and equitable utilisation of common water resources of the Rovuma/Ruvuma River basin" (http://www.icp-confluence-sadc.org/rbo/65, accessed: 09/2011). An important first step in

* Tel.: +1 650 283 7464.
E-mail address: minihane@gmail.com

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water resources planning for this basin is to establish baseline historic conditions. A hydrologic model in combination with in situ observations in the region and remote sensing data provides a plausible 10-year historic baseline of mean monthly flows in the Rovuma River. By providing an estimate of the historic conditions, this paper represents a step towards being able to carry out integrated water resources planning under non-stationary and uncertain hydrological conditions in a relatively remote basin of the Southern African Development Community (SADC) region.

1.1. Estimating streamflow in ungauged basins

Any river basin with insufficient observations for full hydrologic characterization is considered an "ungauged basin". Given spatial and temporal heterogeneities and practical limitations of historic and modern observation technologies, all river basins are ungauged to some degree. Predicting streamflow in ungauged basins has received much attention, due to both the practical need for this work as well as the academic challenge it presents. Methods for predicting streamflow in ungauged basins include regionalization of hydrologic parameters, index-gauge methods, and macro-scale hydrological models (Wagener et al., 2004; Xu and Singh, 2004).

Use of regionalized parameters in hydrologic models is common for predicting flow in ungauged basins. Regionalization methods include approaches in which model parameters or flow characteristics for the ungauged basin are estimated based on physical proximity or physical basin characteristics such as slope and soil type (Fernandez et al., 2000; Parajka et al., 2005; Cutore et al., 2006; Sanborn and Bledsoe, 2006). For example, Love et al. (2011) used a regionalization approach to develop hydrologic process understanding in their study area. Their results led to integrated water resources management recommendations for their river basin. Another regionalization approach (Yadav et al., 2007) relates model-independent streamflow indices to hydrologic response behaviors. While this approach eliminates the need for model parameter calibration, it does rely on a relatively dense regional streamflow gauging network. The generalized likelihood uncertainty estimation approach (Winsemius et al., 2009) uses a combination of hard and soft data to constrain parameter values for a lumped rainfall–runoff model and reduces some of the hard data requirements of most regionalization methods. This could be a valuable approach to apply in this basin after a few years of in situ gauging. These and other regionalization approaches outlined in the literature require more regional streamflow data than are currently available in the Rovuma River and the surrounding region. In the absence of sufficient regional hydrologic data, this study turns to alternative methods of streamflow estimation, specifically index gauge methods and a macro-scale hydrological model with regionalized parameters.

Index-gauge methods use basin characteristics or streamflow statistics of hydrologically similar basins to transform a time series of streamflow in a gauged basin to estimate flows in the ungauged basin. Time series data from a gauged (donor) site is transferred to an ungauged (receiver) site using direct scaling of the time series, regional statistics, or regression methods (Hirsch, 1979). Previous studies have shown that a combination of physical proximity and similarity in the streamflow signal are both relevant factors determining which catchment is useful for predicting streamflow for a particular ungauged basin of interest (Archfield and Vogel, 2010; He et al., 2011; Patil and Stieglitz, 2012). Due to their simplicity and, in some cases, the limited data requirements, these methods are attractive for regions with limited in situ data. One of the estimates of mean monthly flow in the Rovuma River comes from a variation of a donor–receiver streamflow estimation method. These methods are limited to historic streamflow prediction, so are insufficient for future projections under transient climate conditions.

Macro-scale hydrological models based on gridded soil, vegetation, and hydrometeorological data have been widely used to estimate streamflows around the world (e.g., Nijssen et al., 2001a; Decharme, 2007; Balsamo et al., 2011). In basins with sufficient data, these models have been calibrated to the data and the resulting parameters validated using the jackknife method (e.g., Nijssen et al., 1997; Beyene et al., 2010). However, in ungauged basins with insufficient data, parameter calibration is not feasible. As summarized by Xu and Singh (2004), parameters either are fixed based on values in the literature, interpolated from calibrated values in regional gauged catchments, estimated from physical data, or estimated from regression equations that assign parameter values based on physical characteristics. In a region in which there has been extensive previous hydrological research or data collection, scientists are able to leverage previous studies to set soil and vegetation parameters for input into their hydrological model (e.g., Ma et al., 2000). Abdulla and Lettenmaier (1997) demonstrate use of regional regression equations to assign model parameter values based on physical properties. With the parameter values, the macro-scale hydrological model performed better in humid and semi-humid regions than in arid or semi-arid regions. Nijssen et al. (2001a) estimate model parameters in ungauged (or uncalibrated) regions using physically based parameter assignment for some parameters and transferring select calibrated parameters from gauged basins in the climatic region. Their results show this parameter selection method is more effective than using only parameters based on physical properties without transferring some calibrated parameters. They also found that the transfer of calibrated parameters worked best when the transfer was limited to similar hydroclimatic regions. In the present work, an estimate of mean monthly flows in the Rovuma River is based on a macro-hydrological model with a combination of physically-based parameters and regional transfer of calibrated parameters is used in this study. This approach is particularly relevant in regions, such as the Rovuma, with sparse data such that regional regressions are not practical and there have not been sufficient studies in the region to inform parameter selection. In addition, this hydrological modeling approach can be expanded to provide future projections of streamflow based on projected climate and development conditions.

1.2. Study location

The Rovuma River lies in a 152,000 km^2 basin in sub-Saharan Africa, located in the range of $-10°$ to $-16°$ latitude and 34–41° longitude. The river forms the border between Mozambique and Tanzania with the basin lying primarily in those two countries and a small portion in Malawi (Fig. 1). The basin has a few heavily-populated areas, such as Lichinga in the southwest corner of the catchment. However, the area is generally sparsely populated with small rural populations with subsistence agriculture distributed throughout the basin. From aerial photographs, the basin is predominantly forests and open grassland areas with dispersed trees, which is consistent with remote sensing datasets. Most precipitation occurs in the small mountains in the western portion of the basin; less precipitation falls in the flatter coastal region. Temperatures typically fall in the range of 15–30 °C with lower temperatures observed during the southern hemisphere winter months. There is a strong seasonality in this region driven by heavy rains brought by seasonal movement of the Intertropical Convergence Zone (ITCZ) and strong evapotranspiration demand, particularly during the dry season. About 800–1200 mm of precipitation falls annually, mostly between November and March. The strong seasonality of the precipitation is reflected in the streamflow

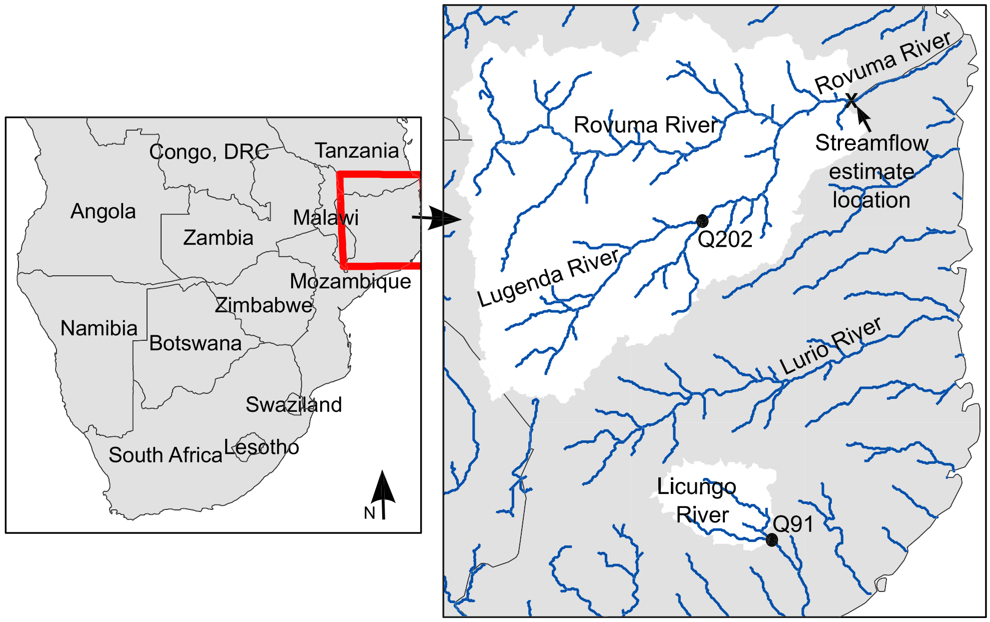

Fig. 1. Location map showing the Rovuma River, the contributing basin, and stream gauges Q202 (Lugenda) and Q91 (Licungo).

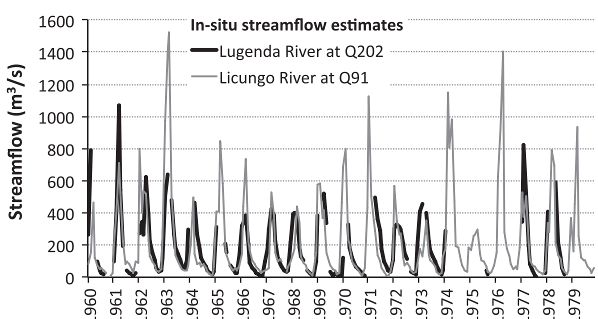

Fig. 2. In-stream estimates of streamflow at Q202 in the Lugenda tributary of the Rovuma River and at Q91 in the Licungo River between 1960 and 1979. Raw data courtesy of the Mozambique DNA.

seasonality with high flows in January through April and lower flows July through October.

2. Data and methods

2.1. Data sources

Data sources include in situ observations, remote sensing data, assimilation of multiple datasets, and regionalization of model parameters. Many of the datasets have been published globally or for a large portion of the globe, so while the results need to be locally evaluated, the methods and data sources are widely applicable.

2.1.1. In situ observations

In recent years, hydrologic observations in Northern Mozambique have been sporadic, but they were more consistent between 1950 and 1970. Recently, the Mozambique government has reinvigorated hydrologic monitoring efforts to enhance water resources planning in the region.

The Directorate National de Agua (DNA) and the Instituto National de Meteorologia, Moçambique provided data from the Lugenda River (a tributary of the Rovuma) and the Licungo River (Fig. 2) and some precipitation measurements from the region. The streamflow gauge on the Lugenda has sporadic observations from 1960 through 1982 while the gauge on the Licungo, which is located on a bridge along a well-maintained road, has had regular observation-based streamflow estimates from the 1950s through the present day. There are no public records of in situ streamflow observations in the main channel of the Rovuma. The in situ observations in the Lugenda and Licungo provide a basis to assess streamflow estimates obtained using the methods described for this study. Table 1 provides a summary of some basin characteristics of the Licungo, Lugenda, and Rovuma basins.

In addition, in situ observations of precipitation and evaporation are available for a few locations in or near the basin of interest. These local observations are not extensive enough to provide direct input to the hydrologic model. Rather, a comparison of the in situ observations and model precipitation input and simulated evapotranspiration informs the interpretation of model results.

2.1.2. Historic gridded composite runoff fields

Mean annual flow and seasonality of the Rovuma are estimated using the composite runoff fields published by the University of New Hampshire Institute for the Study of Earth Ocean and Space

Table 1
Summary basin characteristics for the Rovuma River, Lugenda River (above Q202), and Licungo River (above Q91) basins.

	Rovuma (no gauge)	Lugenda (Q202, Rovuma tributary)	Licungo (Q91)
Mean elevation (range)	620 m (0–1845 m)	720 m (290–1765 m)	570 m (125–1866 m)
Area	151,200 km^2	40,300 km^2	20,200 km^2
Annual precipitation (TMPA, 1998–2008)	980 mm/yr	1030 mm/yr	1290 mm/yr

and the Global Runoff Data Center (Fekete et al., 2002). This dataset (referred to henceforth as "composite runoff") includes historic mean runoff by month published at 30-min spatial resolution for 6 continents, excluding Antarctica. The runoff estimates are based on a combination of in situ observations and output from a water balance model. The runoff is based on a historic period prior to 2000 (actual historic period length varies by location with data availability) and is averaged by month across the entire period of record. This results in annual and 12 monthly estimates of mean runoff for each 30-min grid cell. Although the derived flows are not naturalized, that is not a limitation for this work since there is not extensive development in the Rovuma and Licungo basins.

2.1.3. Hydrometeorologic data (precipitation, temperature, wind speed)

There is not sufficient in situ precipitation data to provide inputs to the hydrological model, so a gridded precipitation product based on a combination of remote sensing and land based precipitation estimates is used instead. Precipitation is estimated from the Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis (TMPA) research product (Huffman et al., 2007). This precipitation dataset is provided on 3-h intervals at 0.25° spatial resolution for the region between 50 °S and 50 °N. The precipitation values are derived from a combination of passive microwave data from low earth orbit satellites; infrared data from geosynchronous earth orbit satellites; the TRMM combined instrument estimate, which incorporates data from the Microwave Imager on TRMM with data from the precipitation radar for calibration (TRMM product 2B31; Haddad et al., 1997); and monthly rain gauge analysis from both the Global Precipitation Climatological Center (GPCC) Global Precipitation Climatology Project (GPCP; Adler et al., 2003) and the GPCC Assessment and Monitoring System (Xie and Arkin, 1996). Prior to 2000, the infrared data was not available and supplemental data from GPCP (Huffman et al., 2001) was incorporated into the TMPA dataset for that period.

Wind speed and daily maximum and minimum temperature are taken from the National Centers for Environmental Prediction-Department of Energy (NCEP-DOE) Atmospheric Model Intercomparison Project (AMIP-II) reanalysis (Kanamitsu et al., 2002). The National Oceanic & Atmospheric Administration (NOAA) Earth System Research Laboratory provides this reanalysis product through their website (http://www.esrl.noaa.gov/psd/). The University of Washington Land Surface Hydrology Group provided the processed TMPA and NCEP–DOE data for use in the hydrologic model.

2.1.4. Soil and vegetation data and related model parameters

Soil and vegetation properties impact how water is partitioned into evapotranspiration, surface flow, and subsurface soil moisture. Since the Rovuma basin and the surrounding region lacks in situ information about soils and vegetation, a combination of remote sensing data, global datasets, and transfer of hydrologic parameters from calibrated basins is used to estimate model parameters. The University of Washington Land Surface Hydrology Group prepared the baseline soil and vegetation files used in this analysis.

The soil parameters were derived according to the process described by Nijssen et al. (2001a,b) except that the soil texture and bulk density values are based on the updated 2009 FAO Harmonized World Soil Database (FAO/IIASA/ISRIC/ISS-CAS/JRC 2008). Using this method, soil parameters, such as porosity, saturated hydraulic conductivity, and the unsaturated hydraulic conductivity curve, were assigned based on combining the FAO soils data and predictive relationships described by Cosby et al. (1984). A subset of soil hydrologic parameters, including the infiltration capacity parameter, the saturated hydraulic conductivity, and the soil depth, was then modified according to the calibration and parameter transfer process described by Nijssen et al. (2001a) and summarized here. The specified soil hydrologic parameters were calibrated over 9 large river basins globally. The calibrated parameters were then transferred to other basins based on climatic zone. They found that using the calibrated parameters rather than the uncalibrated values improved the model performance in the uncalibrated basins that were tested. Therefore, this soil parameter data is used as a starting point for the Rovuma and Licungo study area.

The vegetation data used to parameterize the model were derived from the University of Maryland Global Land Cover Facility 1 km dataset (Hansen et al., 2000) as described by Su et al. (2005) and Nijssen et al. (2001b). Leaf area index for each vegetation type is from Myneni et al. (1997). The leaf area index for each vegetation type varies by month but is constant year-to-year. Vegetation data are specified on a 0.25° grid; multiple vegetation types can be assigned to a fraction of each grid cell. Up to 100% of the cell can be assigned vegetation types and any unassigned percent is assumed to be bare soil. Evaporation is calculated for any bare soil fraction of a grid cell.

2.2. Streamflow estimation methods

This study employs two methods of streamflow estimation for the Rovuma River using multiple data sources. These methods include an index-gauge method and a macro-scale hydrologic model.

2.2.1. Streamflow estimation methods using in-stream observations

When two basins are hydrologically similar, flow measurements from one are sometimes used to predict flows in the other. While scientists and engineers are still working on how to answer the question of hydrologic similarity (McDonnell and Woods, 2004; Wagener et al., 2007), some relevant characteristics include precipitation (seasonality and quantity), soil classification, vegetation, land use, slope, catchment size, and the ratio of precipitation to evaporative demand, among other factors (Corduas, 2011). In the case of using an index gauge to directly transfer the scaled time series of streamflow or streamflow statistics to another basin, the similarity of the streamflow patterns of the two basins is the most relevant factor. The question is often: which of several basins is the most hydrologically similar to the basin of interest. In our study region, only the Licungo basin has regular observations during the period of interest, 1999–2008, so the question gets turned around. Is the Licungo basin hydrologically similar enough to the Rovuma basin that it can serve as an index gauge?

In the absence of a large number of potential donor catchments, a simple comparison of precipitation and streamflow in the two catchments demonstrates the plausibility of using the Licungo as

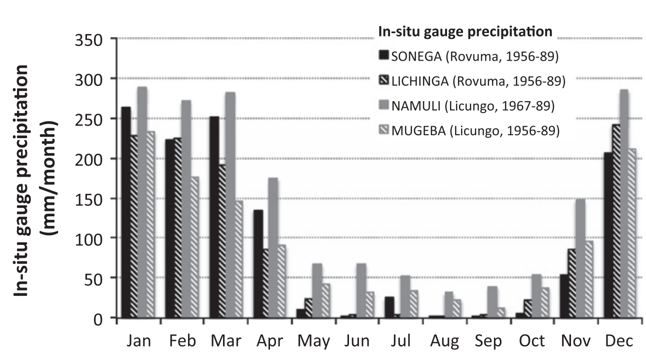

Fig. 3. Monthly averaged in situ precipitation observations in the Rovuma River basin (black solid and stripes) and the Licungo River basin (grey solid and stripes). Years for which data were accessible and used for this figure are included for each location in the legend. Raw data courtesy of the Mozambique DNA.

a donor catchment for estimating flows in the Rovuma River. Fig. 3 shows monthly-averaged in situ precipitation measurements taken at two locations in the Rovuma River basin and at two locations in the Licungo River basin. The two basins have similar seasonal precipitation patterns and total mean monthly precipitation values. While this is only cursory comparison, it suggests that a gauge in the Licungo might be an appropriate index gauge for streamflow estimates in the Rovuma River. Additional comparisons of seasonality of precipitation and runoff are presented in Section 3.

When evaluating index gauge methods for this region, Minihane (in preparation) used statistical regression (Vogel and Stedinger, 1985), drainage area ratio, mean historical streamflow by month, and annual and monthly flow ratios to estimate flows in the at Q202 in the Lugenda River using observations in both the Lugenda River (Q202) and the Licungo River (Q91). Minihane found that, for these gauges, the mean annual flow ratio (MFR) outperformed the other methods considered in the study. MFR had a relatively low bias (18%) and the highest Nash–Sutcliffe efficiency ratio of the methods tested (0.8). Therefore, the Licungo streamflow record is combined with the MFR method to estimate historic mean monthly streamflow in the Rovuma River.

Using the MFR (Eq. (1)), the observation-based Licungo streamflow record time series, $Q_{91}(t)$, and mean annual flow, $\overline{Q_{a,91}}$, and estimates of mean annual flow in the Rovuma, $\overline{Q_{a,R}}$, are combined to provide an estimate of a time-series of historic Rovuma flows.

$$Q_R(t) = Q_{91}(t)\frac{\overline{Q_{a,R}}}{\overline{Q_{a,91}}} \quad (1)$$

To implement the MFR method, the time series of in situ monthly streamflow estimates in the Licungo River at Q91 is scaled by the ratio of the mean annual flows in the Rovuma and Licungo Rivers to produce a time series of mean monthly flow estimates in the Rovuma River. In the absence of in situ observations in the main channel of the Rovuma River, the mean annual streamflow is estimated using the composite runoff dataset described in Section 2.1. The results of the MFR method, and other index-gauge methods, are limited to time frames of the available observations. In this case, the MFR method provides estimates of historical mean monthly flows in the Rovuma River. Future projections are not possible without the use of additional tools, such as climate and weather projection datasets and an appropriate hydrological model.

2.2.2. Macro-scale hydrologic model

The Variable Infiltration Capacity (VIC) semi-distributed macro-scale hydrologic model (Gao et al., in preparation; Liang et al., 1994; Nijssen et al., 1997) was selected for this work due to its versatility for streamflow estimation, climate impacts, and as a decision support tool. For example, VIC has been used for 10-day flood forecasting (Voisin et al., 2011), seasonal streamflow forecasting (Bohn et al., 2010), climate impacts on streamflow for a variety of regional studies (Beyene et al., 2010; Elsner et al., 2010), and to estimate potential impacts of climate change on hydropower supply in the Pacific Northwest (Hamlet et al., 2010) and in the Nile River basin (Beyene et al., 2010).

Other hydrologic models are also likely to be useful in this region. One example is the Pitman hydrology model (Pitman, 1973), which has been used successfully in many basins throughout the SADC region (Hughes et al., 2006; Ndiritu, 2009; Kapangaziwiri et al., 2009). The Pitman model has some advantages over other models in that there is an active regional user group and recent applications have explicitly considered model uncertainties. The Pitman model can be used both to evaluate historic hydrologic conditions and to provide water resources decision support for development under uncertain conditions (Kapangaziwiri et al., 2009). The Pitman model uses a monthly time step. Since daily precipitation variability is important for some water resources applications, particularly flood forecasting, VIC was chosen over the Pitman model.

VIC is a semi-distributed hydrology model that calculates evapotranspiration, soil moisture storage, baseflow, and runoff for each simulation grid cell at each simulation time step. For this work, the VIC model was run in the water and energy balance mode to simulate energy and moisture fluxes for each 0.25° grid cell for 3-h time steps. The alternative mode is the water-balance mode, which is typically used to save computation time for large simulations. Since this study was not computationally intensive, the more accurate water and energy balance mode was used. There are other processes that can be included in VIC simulations, such as snow transport and frozen soil, but were not included for this study since they are not critical processes for this basin (temperatures usually stay above 10 °C and are often much higher). Baseflow and runoff for each grid cell and time step are routed through the main channel system using a streamflow routing model (Lohmann et al., 1996, 1998). The output of the routing model represents the flow estimates for the Rovuma River near the point where the river discharges to the sea and in the Licungo River at the gauging station Q91.

In the model, soil properties are assumed constant for each grid cell, but vegetation parameters are assigned the percent of the grid cell that they cover. The baseline model parameters are described in Section 2.1. Parameter values were not calibrated to streamflows in the Licungo, Lugenda, or Rovuma Rivers. However, the soil depths were changed to allow for a deeper soil and increased evapotranspiration, which is consistent with expected hydrologic conditions in the region and calibrated soil values elsewhere in Africa (Beyene et al., 2010; Voisin, *personal communication 2010*). Descriptions of the daily hydrometeorologic forcings for the VIC model, including precipitation, wind, and daily maximum and minimum temperatures, are also described in Section 2.1.

The model was run for the period 1998–2008. Due to the strong seasonality of the region, a brief model spin-up period of a single year was sufficient to remove any impact of initial conditions. Thus, results from 1999 to 2008 were used in the analysis. The model was run for the entire region that includes the Licungo and Rovuma Rivers. Basin delineations were based on the U.S. Geological Survey HYDRO1K dataset (http://webgis.wr.usgs.gov/globalgis/metadata_qr/metadata/hydro1k.htm; accessed 09/2011). Runoff and baseflow that contributed to streamflow was routed to the main channel using the routing model described by Lohmann et al. (1996, 1998). The results include daily streamflow estimates at the points of interest in the Licungo and Rovuma Rivers. While the model was run for a historic period for this study, estimates of potential future flows can be made using hydrometeorologic forcing data from downscaled global circulation models or regional climate models.

3. Results

3.1. Comparisons of seasonal runoff patterns

The use of index gauge methods, such as the mean flow ratio, depends on hydrologic similarity between the basin of interest (Rovuma River basin) and the index gauge basin (Licungo River basin). Since streamflow observations are available in only one of these two rivers, and many of the precipitation and streamflow observations and runoff estimates that are available are for different time frames, the average monthly runoff and streamflow by month is used to better understand hydrologic similarity of these basins.

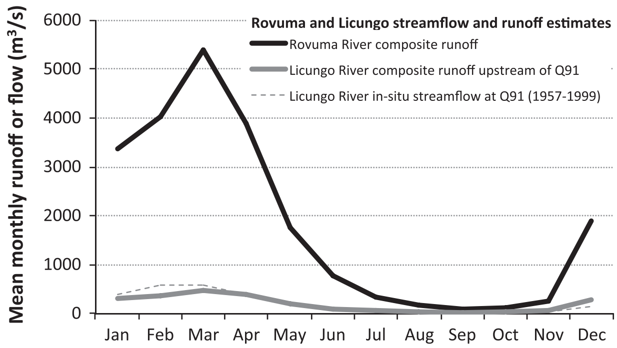

Fig. 4. UNH–GRDC runoff estimates for the Rovuma River basin and the Licungo River basin and in situ estimates at Q91 in the Licungo River.

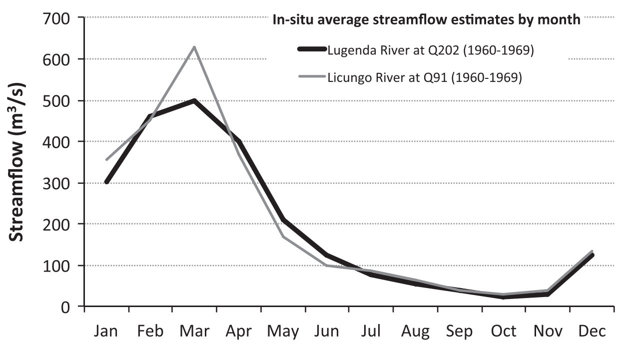

Fig. 5. Mean monthly observed flows averaged over 1960–1969 for the Licungo River at gauge Q91 and the Lugenda River (Rovuma tributary) at gauge Q202. Mean annual flows for this period were 205 m^3/s at Q91 and 195 m^3/s at Q202. Raw data courtesy of the Mozambique DNA.

Monthly climatologies from the composite runoff dataset averaged over the Rovuma and Licungo Rivers (Fig. 4) show that the two basins have similar seasonality, though the peak mean monthly runoff is much larger for the Rovuma basin, as is expected since the basin is so much larger. For comparison, monthly climatologies from the in situ streamflow estimates in the Licungo River at Q91 are also included in Fig. 4. A qualitative comparison confirms that the composite runoff values are similar to the in situ observations, though the peak in mean monthly values appears earlier for the in situ data.

The gridded composite runoff dataset (Fig. 4) suggests that streamflow in these basins follow similar seasonal patterns. In addition, comparison of monthly climatologies from in situ flow estimates in the Licungo River at Q91 and in the Lugenda tributary to the Rovuma River at Q202 for the period 1960–1969 (Fig. 5) confirm similar seasonal trends in the two basins. Note that some flow estimates are missing for the Q202 gauge for this period (see full observation record for Q202 in Fig. 2).

3.2. Using observations in the Licungo River to assess model performance

Since in situ observations in the main channel of the Rovuma River are not available, and observations in the tributaries do not coincide with the modeling period, it is difficult to quantify the accuracy of the model results. However, a comparison of simulated streamflow with observations in the Licungo River is used to evaluate the utility of the model processes and parameter estimation methods in this region. The observed and simulated streamflows follow the same seasonal patterns and, in many years, the same interannual variability pattern (Fig. 6). The simulated mean monthly flows are often higher during the wet season and have a significant positive bias (~20%) when averaged over the 10-year period as compared to the observations. Water resources planners will want to consider this positive bias, along with the observation that the peak simulated flow is as much as three times greater than the in situ observations, when utilizing this model and these regionalized parameters in the Rovuma River.

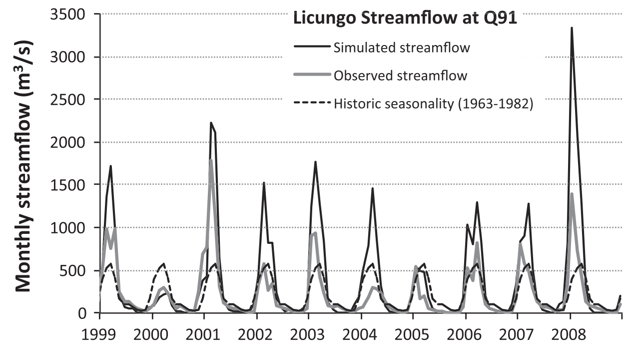

Fig. 6. Simulated and observed streamflow estimates for the Licungo River at gauge Q91. Historic seasonal mean monthly flows (by month) are shown for comparison. Raw data for streamflow observations are courtesy of the Mozambique DNA.

While qualitative evaluation of "goodness of fit" is useful, it is also helpful to have a quantitative metric for comparison. The Nash–Sutcliffe efficiency (E_{NS}; Eq. (2)) is a widely used efficiency ratio for characterizing how well streamflow estimates predict observations.

$$E_{NS} = 1 - \frac{\Sigma(Q_{obs}(t) - Q_{est}(t))^2}{\Sigma(Q_{obs}(t) - \overline{Q_{obs}})^2} \tag{2}$$

where $Q_{obs}(t)$ is the time series of observed flows (L^3/T), $Q_{est}(t)$ are estimated or simulated flows (L^3/T), and $\overline{Q_{obs}}$ is the long-term average of the observed monthly flows (L^3/T). E_{NS} has been criticized as a weak and/or flawed indicator for a variety of reasons (e.g., McCuen et al., 2006). Some authors have proposed alternative streamflow estimation indicators (Lettenmaier, 1984; Yilmaz et al., 2008). Even with limitations, E_{NS} is still widely used in practice, particularly in combination with other indicators such as percent bias and root mean square error (Makungo et al., 2010).

A minor modification to the conventional Nash–Sutcliffe efficiency ratio uses mean historical streamflow by month as the basis for comparison rather than the long-term mean. This modification was proposed by Garrick et al. (1978) and is particularly relevant in regions such as northern Mozambique that experience a strong seasonality. Using this idea, an alternate measure of goodness of fit (EALT; Eq. (3)) is proposed as a simple modification to the more common ENS.

$$E_{ALT} = 1 - \frac{\Sigma(Q_{obs}(t) - Q_{est}(t))^2}{\Sigma(Q_{obs}(t) - Q_s(i))^2} \tag{3}$$

where $Q_s(i)$ is the historic seasonal flow (L^3/T) by month and i ranges from 1 to 12, indicating January through December. E_{ALT} provides a quantitative comparison between the simulated streamflow and the historic seasonal streamflow (rather than a single mean value as in E_{NS}).

Interpretation of E_{ALT} is analogous to interpretation of E_{NS}. When the value is less than zero, the historic seasonality is closer to the observations than the simulated streamflow. When the value is greater than zero, the model provides an improvement over the historic streamflow seasonality. Values closer to one indicate improved model performance. While this indicator is still subject to other limitations associated with E_{NS}, it does represent an improvement and is a simple modification that is relevant and useful in tropical regions with strong seasonality.

Another concern with both E_{NS} and E_{ALT} is that the results can be overwhelmed by high flow errors and might not reflect how well the model represents streamflow during low flow months. As an added metric, I have included an efficiency ratio based on inverse of the streamflow values (E_{INV}; Eq. (4)). This metric focuses on the lower flow periods and is less sensitive to errors in high flow estimates (Pushpalatha et al., 2012). This metric is interpreted in a similar way to E_{NS} and E_{ALT}; the values range from negative infinity to an ideal value of one.

$$E_{INV} = 1 - \frac{\Sigma(1/Q_{obs}(t)) - 1/(Q_{est}(t))^2}{\Sigma(1/Q_{obs}(t)) - 1/(Q_s(i))^2} \tag{4}$$

The 20-year period of 1963–1982 was used to calculate the historic seasonality in the Licungo River for comparison with the simulated streamflow. The dashed line in Fig. 6 provides a qualitative comparison of using the historic seasonality (1963–1982) versus the model results to approximate observed Licungo flows at Q91 for the simulation period of 1999–2008. For the simulation period 1999–2008, $E_{ALT} = 0.6$, indicating that the model performed better than the historic seasonality. In addition, $E_{NS} = 0.8$, $E_{INV} = 0.9$, and the coefficient of determination (R^2) = 0.99, showing that all these metrics indicate that the VIC model results represent an improvement over the historic seasonality and mean value, especially during low flow periods.

When using remote sensing data, it can be informative to compare that data with local, in situ observations. Fig. 7 provides a comparison of average monthly precipitation for three ground-based precipitation gauges in the Licungo basin and the TMPA mean basin precipitation estimate. While the time periods for each dataset are not identical, this demonstrates that the TMPA precipitation estimates are of the same order of magnitude with similar seasonal patterns compared to the in situ estimates. This comparison suggests that either TMPA underestimates precipitation slightly in the Licungo basin, or the period for the Licungo observations (1998–2003) was wetter on average than TMPA period (1998–2008). Since the seasonal patterns and magnitudes are consistent with observations in the region, TMPA appears appropriate for use in this study. This is consistent with more comprehensive comparisons between in situ gauges and TMPA precipitation data in Eastern Africa (Li et al., 2008) and the Zambezi River basin (Liechti et al., 2012).

The analysis of the Licungo River streamflows for the simulation period shows that the structure, parameters, and hydrometeorologic drivers used in the model are useful for estimating flows in the Licungo River at Q91. This combination of indicators demonstrates the utility of applying the hydrologic model to river basins

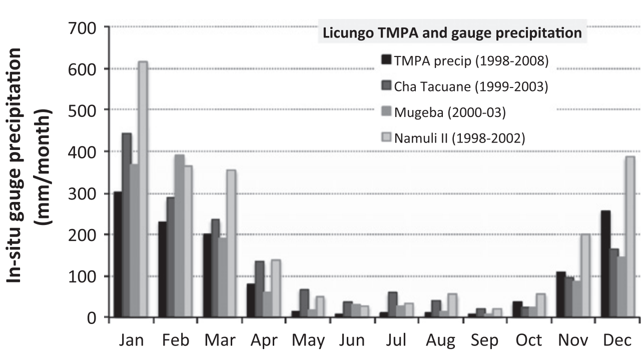

Fig. 7. In-situ precipitation gauge data for three locations in the Licungo River basin for the available times overlapping the simulation period and basin-averaged TMPA precipitation data for the entire simulation period. Raw data for in situ observations courtesy of the Mozambique DNA.

in this region with the parameters and hydrometeorologic forcings described. Depending on data availability and local knowledge, vegetation and soil parameter files can be modified further based on local datasets, ground-based observations, or more updated remote sensing data. With minor modifications (such as those made to the soil parameter file), this methodology is likely to be effective elsewhere in Sub-Saharan Africa.

3.3. Rovuma River flow estimates

The goal of this work is to demonstrate a useful methodology that provides a historic time-series of mean monthly flows in the Rovuma River. Streamflow estimates for the Rovuma River using two different approaches are provided for the location noted in Fig. 1, close to where the Rovuma discharges to the sea. Basic summary statistics of estimated Rovuma River streamflow (Table 2) demonstrate similarities between results from the MFR and the numerical model. The 10-year mean monthly flow estimates for the Rovuma River from both the model and the MFR have comparable means and standard deviations. In addition, the model-simulated mean annual flow in the Rovuma is very close to the composite runoff estimate of mean annual flow. The composite runoff estimates are provided for comparison; the mean annual flow estimate from the MFR method is based on the composite runoff data and is therefore a similar magnitude.

Over the 10-year period, the mean monthly flow estimates from both the VIC macro-scale hydrologic model and the MFR estimates are similar in magnitude and seasonality (Fig. 8). However, there are a few years for which the differences in method results stand out. Specifically, in early 2001, the MFR estimate is much higher than the simulated flow; in early 2007, the opposite is true. This discrepancy can be explained through precipitation records, and is addressed in Sections 4 and 5.

3.4. Simulated runoff ratio in the Rovuma River basin

In the humid tropics, streamflow typically shadows seasonal precipitation patterns with a slight delay due to basin response times. Fig. 9 shows the simulated Rovuma streamflow for 1999–2008 in black with grey lines that represent 20%, 40%, and 70% of the basin-average precipitation, calculated using an area-averaged precipitation and shown with a 1-month time lag. The grey lines effectively shows what the mean monthly streamflow would look like if all months had 20%, 40%, or 70% runoff ratio, respectively. The 20% and 70% runoff ratios are shown because they bracket the simulated precipitation and 40% is included because it is equal to the simulated mean annual runoff ratio for the 10-year period. Simulated streamflow follows the same seasonality as the precipitation with a lag due to travel times (1 month time lag was included in precipitation average) and the size of the basin. At the beginning of the wet season each year, there is very little streamflow; precipitation (and therefore streamflow) increases throughout the wet season. The monthly runoff ratio is often close to the long term mean of 40%, but the runoff ratio is higher during wet years and lower during dry years. This is expected since once the ground is saturated, additional precipitation contributes directly to surface flow, increasing the percent of precipitation that contributes to runoff. This demonstrates that the simulated streamflow is consistent with expectations given general understanding of hydrologic processes in the region.

3.5. Seasonal comparison of Rovuma River basin hydrology

Since the various sources of hydrologic data and streamflow estimates available in the Rovuma River basin span a wide range of time periods, average values by month can provide a basis for

Table 2
Basic statistics of annual and mean monthly estimated streamflows for the Rovuma River.

	VIC modeled flows (1999–2008)	MFR estimated flows (1999–2008)	UNH–GRDC estimated runoff (historical period, pre-2000)
Annual flow estimates			
Mean	22,365 m^3/s	22,630 m^3/s	22,053 m^3/s
Standard deviation	10,460 m^3/s	8078 m^3/s	–
Coefficient of variation	0.4	0.5	–
Mean monthly flow estimates			
Mean	1864	1866 m^3/s	1838 m^3/s
Standard deviation	2698	2657 m^3/s	1873 m^3/s
Coefficient of variation	1.4	1.4	1.0

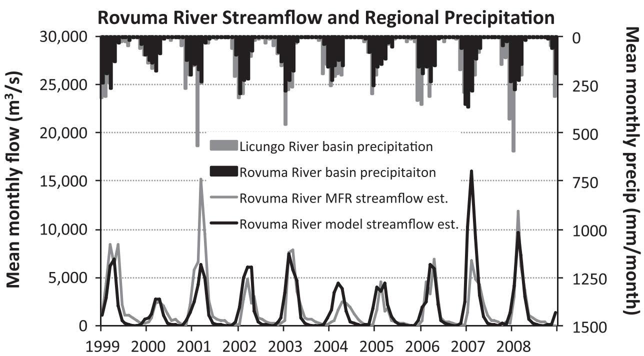

Fig. 8. Rovuma River monthly streamflow estimates and basin-average precipitation in the Rovuma basin and the Licungo (index gauge) basin. Rovuma flow estimates from both the hydrological model (solid black) and the MFR with Q91 as the index gauge (solid grey) are shown in the left axis. The basin-average TMPA precipitation (model input) in the Rovuma (black) and the Licungo above gauge Q91 (grey) for the simulation period 1999–2008 are shown on the right axis, positive downwards.

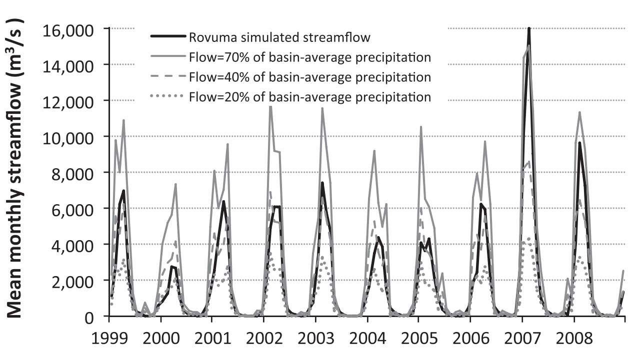

Fig. 9. Simulated Rovuma streamflow (black lines), 1999–2008, with grey solid and dashed lines indicating runoff ratio values of 20%, 40% and 70% (percent of basin-averaged precipitation with 1 month time lag included).

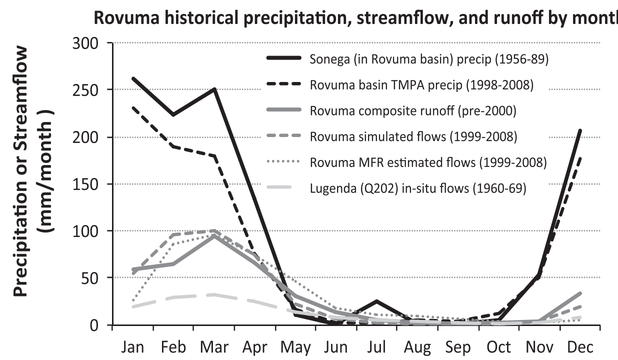

Fig. 10. Rovuma basin precipitation, streamflow, and runoff estimates by month. Streamflow and in situ precipitation estimates are for the locations specified, runoff and TMPA basin precipitation are basin-average values. Raw data for in situ observations are courtesy of the Mozambique DNA. Data availability by year is provided parenthetically in the legend.

comparing streamflow results to other hydrologic data in the region. Specifically, in situ data for the Rovuma River basin (precipitation and tributary streamflows) is for a different time period than the composite runoff data and the simulated and index-gauge estimated streamflow. However, a qualitative comparison of the data summarized by monthly means demonstrates that seasonal patterns of model inputs and estimated streamflow in the Rovuma basin are consistent with observations (Fig. 10). For example, precipitation seasonality for the TMPA dataset matches the historic in situ observations. The in situ precipitation observations are from Sonega, which is in the wetter portion of the basin, so the basin-average TMPA precipitation is slightly lower than the observations, as expected. The precipitation values are greater than the streamflow estimates and the streamflow peaks later in the wet season than the precipitation does. The various Rovuma River streamflow estimates lie in a narrow range with similar seasonality. The Rovuma flow estimates using the hydrologic model and MFR are both consistent with an annual runoff ratio around 0.4 with the peak flows delayed in comparison to peak precipitation. The observations in the Lugenda River (tributary of the Rovuma River, at station Q202) reflect the same seasonality as the estimated Rovuma flows, with lower magnitudes since it includes runoff from only a fraction of the Rovuma basin.

4. Discussion

4.1. Utility of the annual mean flow ratio (MFR) method and the macro-hydrologic model

The mean flow ratio (MFR) reflects hydrologic conditions specific to the index gauge and thus the method is only as effective as the similarity in streamflow signals of the donor and receiver basins. The hydrological model is only useful if the correct processes are represented and appropriate parameters (e.g., soil properties) and inputs (e.g., precipitation) are used. In this case, practitioners and researchers can find a balance between the simplicity of the MFR method and the relative complexity of the regionalized macro-hydrologic numerical model.

A comparison of precipitation in the two basins (Fig. 8) provides the basis for explaining the discrepancies between the MFR and simulated streamflows in the Rovuma. In early 2001, during the wet season, the precipitation in the Licungo basin upstream of gauge Q91 was particularly high compared to precipitation in the Rovuma basin, whereas the opposite was true in 2007. Localized tropical storms might have caused some of the precipitation differences between these two basins during this 10-year period. In 2001, relatively high precipitation in the Licungo basin led to higher streamflow. Since the MFR method scaled the observed Licungo flows by the historical mean annual flow ratio, the MFR estimates for the Rovuma River were also relatively high that year. Since the

Rovuma basin did not experience the same high precipitation event(s), the simulated streamflow was smaller than that calculated using MFR. In 2007, high precipitation in the Rovuma basin lead to higher flows. Since the Licungo did not experience the same relatively high precipitation, the MFR flow estimates for the Rovuma are lower than expected, assuming the precipitation record is accurate.

While the MFR provides a comparable set of summary statistics of historical mean monthly flows (Table 2), the simulated flow estimates provide an improvement because they directly reflect hydrologic inputs for the Rovuma basin. Therefore, while the MFR method is a useful quick first-look at a basin's mean flow behavior in this region, a more sophisticated tool, such as a hydrological model that includes localized precipitation estimates, will be more useful for water resources decision support in this region. In addition, the hydrologic model approach can be extended to include future streamflow projections based on changes in climate and land use conditions.

4.2. Uncertainties related to simulated and in situ streamflow estimates

Published literature discusses uncertainties related to both in-stream flow estimates and hydrologic modeling uncertainties (Wagener et al., 2003; Ajami et al., 2007). Engineering problems inherently incorporate some level of risk, so the idea of planning under uncertainty is not new. For water resources planning in ungauged basins, infrastructure investments are most likely to be well spent if some of the uncertainties can be reduced. Specifically, in this case, the estimates of mean monthly streamflow are highly uncertain in the Rovuma River and potentially have a significant positive bias. In situ observations during multiple flow regimes (high, medium, low) will be critical to reducing uncertainty prior to water resources development in the Rovuma River basin.

5. Conclusions

This work establishes a baseline estimate of historic flows for the Rovuma River along the border of Mozambique and Tanzania. Water resources planners can extend the tools and results described here to support flood forecasting, seasonal forecasting for agriculture and drought, hydropower potential, water supply, reservoir operations, and climate impacts on all of these sectors. The numerical model and parameters were evaluated using in situ observations in a nearby basin (Licungo River at Q91) with $E_{NS} = 0.8$, $E_{ALT} = 0.6$, $E_{INV} = 0.9$, $R^2 = 0.99$, demonstrating the utility of the VIC model and methods described here. While both the simple index gauge method (MFR) and the macro-scale hydrologic model yield similar average mean monthly flow rates over the study period, the hydrologic model better reflects basin conditions and is more flexible as a decision-support tool. Uncertainties associated with estimating streamflow without in situ discharge measurements are significant. Measures to reduce this uncertainty prior to constructing water resources infrastructure in the region are likely to enhance project planning in the region. Estimation of flow in the main channel of the Rovuma (upstream or downstream of the confluence with the Lugenda tributary), particularly during high flow months, would provide valuable information for water resources planners interested in developing regional water resources for economic and health benefits.

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