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Research Paper

# Water availability and agricultural demand: An assessment framework using global datasets in a data scarce catchment, Rokel-Seli River, Sierra Leone

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ABSTRACT

*Study region:* The proposed assessment framework is aimed at application in Sub-Saharan Africa, but could also be applied in other hydrologically data scarce regions. The test study site was the Rokel-Seli River catchment, Sierra Leone, West Africa.
*Study focus:* We propose a simple, transferable water assessment framework that allows the use of global climate datasets in the assessment of water availability and crop demand in data scarce catchments. In this study, we apply the assessment framework to the catchment of the Rokel-Seli River in Sierra Leone to investigate the capabilities of global datasets complemented with limited historical data in estimating water resources of a river basin facing rising demands from large scale agricultural water withdrawals. We demonstrate how short term river flow records can be extended using a lumped hydrological model, and then use a crop water demand model to generate irrigation water demands for a large irrigated biofuels scheme abstracting from the river. The results of using several different global datasets to drive the assessment framework are compared and the performance evaluated against observed rain and flow gauge records.
*New hydrological insights:* We find that the hydrological model capably simulates both low and high flows satisfactorily, and that all the input datasets consistently produce similar results for water withdrawal scenarios. The proposed framework is successfully applied to assess the variability of flows available for abstraction against agricultural demand. The assessment framework conclusions are robust despite the different input datasets and calibration scenarios tested, and can be extended to include other global input datasets.



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## 1. Introduction

### 1.1. Introduction and background

Water security is closely tied to knowledge of existing water resources and the ability to use hydro-meteorological data to quantify these resources. Water resources management and allocation has traditionally been supported by quantitative tools (such as hydrological models) to reduce the uncertainty associated with subjective decision making. However, reliable water management decisions and policy continue to be constrained by data scarcity and unreliability, typically so in African contexts (Guzinski et al., 2014).

Long term monitoring of water resources requires well established observation networks which can provide data for hydrological modelling tools, which in turn aid in robust decision making. But in sub-Saharan Africa, the classical predicament of data unavailability due to incompleteness of existing records, poorly maintained data collection infrastructure and the reluctance to distribute existing data underpins the challenge of achieving adequate hydrological characterization in many catchments.

Decisions on water use and allocation are however still being made, with resultant over-allocation between competing uses, especially so agricultural water use, which accounts for an estimated 85% of continental water consumption (Valipour, 2015). The challenge in these contexts, therefore, is how to make meaningful and sustainable water allocation decisions in the absence of conventional hydro-meteorological data.

In Ethiopia, Bossio et al. (2012) explored the implications of large scale agricultural development within a context of hydro-meteorological data scarcity, concluding that the impacts of uncontrolled water allocations are primarily an aggravation of water scarcity for smaller scale stakeholders. In Sierra Leone, typified by extreme lack of water resources information, over-allocation of water resources for a green-field biofuels project has already impacted local water resources through the depletion of local streams (Ananae and Abiwu, 2011).

The availability of freely accessible global data sets from various sources including remote sensing, interpolation of scant ground data using climate models (reanalysis data) and a maturing hydrological modelling science field are providing options for complementing scarce observation data. Wagner et al. (2009) demonstrated the application of remotely sensed data in estimation of current and future water resources in data scarce catchments in West Africa, concluding that with inclusion of uncertainty (often these datasets suffer from high uncertainties resulting from physical sensor limitations and limited spatial-temporal coverage and resolution, see Prigent, 2010; Yong et al., 2014), outputs from modelling using remotely sensed data in poorly gauged basins are useful.

In the Senegal River basin, Stisen and Sandholt (2010) evaluated remote-sensing-based rainfall products for their capability in calibrating hydrological models for water resources estimation, concluding that models calibrated and forced by satellite data inputs have Nash-Sutcliffe Efficiencies (NSE), between 0.63 and 0.87, reflecting acceptable simulation of catchment water balance components.

Presently there are many hydro-climatological and other relevant datasets available that can help with the assessment of water resources (WMO, 2012) including, for example, the Global Historical Climatology Network (GHCN) dataset (Smith and Reynolds, 2005), MSWEP (Multi-Source Weighted-Ensemble Precipitation) dataset (Beck et al., 2016), Climatic Research Unit CRU TS 2.1/3.1 (Mitchell and Jones, 2005), Global Precipitation Climatology Centre (GPCC) dataset (Schneider et al., 2011), WorldClim (Hijmans et al., 2005), and the Shuttle Radar Topography Mission (SRTM) (Jarvis et al., 2008). The TIGER-NET initiative of the European Space Agency (ESA) is also advancing the production and application of a range of relevant satellite-based information products needed for water resources management in Africa (Guzinski et al., 2014).

There are also a whole range of established hydrological modelling methods that can be used in conjunction with these global datasets to provide a better assessment of needs and resources than using local data alone. However, these freely available datasets have mostly been restricted to scientific research and rarely been adopted for decision making on the ground.

Amongst other reasons, inadequate quantitative skills for analytical analysis has led to the restricted use of these datasets, as evidenced in the Nile Basin Initiative project in East Africa (Giupponi and Sgobbi, 2013). In assessing the limited uptake of remotely sensed data in Africa, Roy et al. (2010) and Kufoniyi (2009) cited the multiplicity of geospatial datasets and the resultant uncertainty as to how, when or even what dataset to deploy for decision making, as a key barrier. The lack of dependable methodologies to manipulate and extract these datasets for water resources assessment purposes underlines the challenge of applying them for decision making.

The aim of this paper is to present a simple yet effective framework which incorporates freely available remotely sensed global datasets and models that do not require sophisticated analytical capabilities, which are a barrier to the uptake of these datasets, to answer classical water resources questions in a real context in Sierra Leone where increasing agricultural, human and ecological demands, added to the pressures of climate change, calls for careful management of water resources.

### 1.2. Water quantity issues in the Rokel–Seli catchment

The Rokel-Seli has a drainage area of 8236 km$^2$ making it the third largest (in terms of size) of the nine major river systems in Sierra Leone. This watershed is of critical importance to the economy of the country, supplying water to the Bumbuna dam hydroelectric power scheme (Phase I and II) located on the upper reaches of the Rokel-Seli River, about 200 km north-east of the capital city—Freetown, as well as water for agriculture, fisheries, mining and ecological flows (World Bank, 2005).

Landsat 30 m resolution multispectral image data obtained between 2010 and 2014 shows rapidly expanding centre pivot irrigation schemes on the middle reaches of the Rokel-Seli. This activity is expected to impact the stream-flows of the river via abstraction of water. The irrigation schemes are part of the Addax Bioenergy project—a greenfield development that is used to grow sugarcane for production of bio-ethanol for export and domestic use, as well as generating electricity. It is the largest irrigation agriculture project to be developed in Sierra Leone, with a plantation size of 10,000 ha and a total project area of 14,300 ha (Africa Development Bank, 2010). Given the uneven seasonal spread of rainfall and the long and totally dry period over the catchment area, irrigation is necessary to meet crop water needs, with these demands being met by abstraction from the river flow during the driest months. This makes the Addax project significant in light of water management aspects, particularly when ensuring conjunctive water needs downstream of this project are met.

### *1.3. Objectives*

This paper aims to demonstrate that with a simple framework, it is possible to assess and quantify the availability of water resources for agricultural use within a catchment using freely available global climate datasets as well as established hydrological and crop modelling methods to supplement limited amounts of locally measured rainfall and river data. Suitably accurate and robust data are required to enable proper allocation of existing catchment water resources.

In order to demonstrate the application of the framework, we apply it to a data scarce catchment, the Rokel-Seli in Sierra Leone, which faces mounting demands from agricultural use, e.g. large scale biofuel production, mining and potable water supply for the countries capital, amongst other uses. This assessment framework should be sufficient to supply demand and river data to enable planning for sustainable water use within data-scarce catchments generally.

## 2. Assessment framework

The proposed framework (Fig. 1) consists of three stages;

(1) *Defining the area of analysis (catchment/watershed) and generating the location relevant climate variable multi-year time series for this analysis area.*

The abstraction location defines the point in the river which becomes the outflow point for the catchment area. The catchment is defined using standard drainage algorithms (available in most GIS software) using a global digital elevation model product such as the Shuttle Radar Topography Mission (SRTM DEM). The resulting catchment polygon is then used to extract the relevant climate variable time series from the chosen gridded (raster) global dataset ready for input into the next stage.

(2) *Using*: (i) *a numerical hydrology model to generate a multi-year flow time series for river flow at the location of abstraction; and* (ii) *a crop water model to generate a corresponding muti-year demand time series.*

A rainfall runoff model is used to generate a time series of river flows from the climate data (rainfall and temperature). Observed flow data that is available can be used to calibrate and validate the model parameters to the local context, then the model can be run for the full input time series. It is also important to understand the historical context for the catchment using globally available remote sensing information such as Landsat satellite images (available from the 1970's). Landsat imagery can be used to clearly identify the actual extent of any agricultural area, and since Landsat has a known predicted orbit that repeats, a unique historical record is available from these images which makes it possible to track any changes in land use from year to year since 1972 to present.

The crop model can then be used with the same climate time series together with knowledge of the planned crops and planting seasons to identify the crop water demand which will be supplemented with irrigation water (i.e. from the river abstraction). Importantly both models use the same climate data from Stage (1) as input, for consistency.

(3) *The final stage is to assess the water resource availability, annually, as well as on a seasonal and monthly basis.*

This stage should also take into account other users of the water within the catchment, as well as downstream of the abstraction. Note that the needs of the environment (fisheries, ecology etc.) should also be considered one of the "users" of the water. Flows generated from the hydrological model are assessed for their variability in light of the seasonal crop water demands. Key demand periods are identified as well as variability of available river flows during this period, which forms the assessment period. This assessment period is then repeated for different extremes, including lowest flow year, 1 in 10 year driest year, 1 in 5 driest year and 1 in 2 driest year.

While there are elements of the framework that are common to a traditional water resource assessment, the originality here is in incorporating global datasets in a consistent and transferable way. For example, any robust, low-data requirement rainfall runoff model could be used, or alternative future climate datasets could be used to drive the model and look at climate change scenarios or climate dataset sensitivity.

This framework is designed to specifically assess a poorly gauged basin with any upstream developments whose abstraction could affect demand in the lower reaches. In the following sections we describe the application study area, followed by the framework elements (data and models) chosen for our application, together with a brief description of the framework's practical application to this demonstration study case.

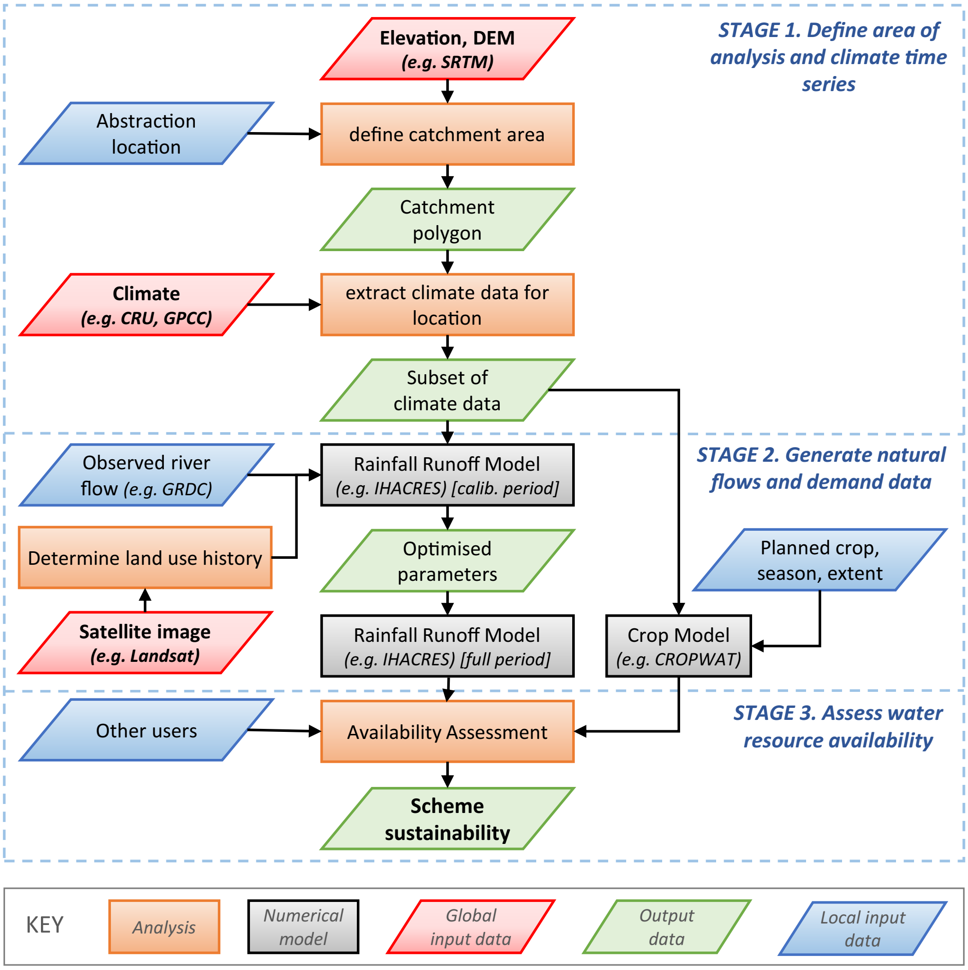


**Fig. 1.** A proposed water resources assessment framework for data scarce regions that incorporates remotely sensed data and global climate datasets.

## 3. Study area

The Addax Bioenergy project is an example of a biofuels development and is within the Rokel-Seli basin. The project has a plantation size of 10,000 ha that is used to grow sugarcane for the production of bio-ethanol for export and domestic use (Africa Development Bank, 2010). It is located near the town of Makeni in the Bombali district, Sierra Leone (Fig. 2a) and is approximately 160 km north east of the capital, Freetown. The project draws its water requirements from the nearby Rokel-Seli River which has a total catchment area of 8236 km$^2$ catchment (Fig. 2b), and is experiencing rapidly expanding water needs for agricultural, potable, mining and ecological water supply. The catchment area of the river at the Addax offtake is 5367 km$^2$. A large part of the flow in the Rokel-Seli is generated in the upper catchment above the Bumbuna dam (catchment area 3803 km$^2$). As there are some historical flow data at the dam location but not at the Addax site, for this exercise, we will scale the flows from the Bumbuna dam outlet to incorporate additional runoff generated between Bumbuna and the Addax outtake, and consider this as the river flow arriving at the Addax site. A simple relative catchment area ratio of 1.41 was used for the scaling. Between the dam and the Addax offtake, there are also other water abstractors (below the dam but upstream of the Addax offtake) specifically Magbass Sugar and the Tonkolili iron ore mine, for which no water use data were available for this study. For this study we will only assess the abstraction from the Addax site, but ideally a complete water resource assessment would require the conjunctive use of all the river users. This study can be considered a first step in this process in order to illustrate the application of the framework methodology. The application of the framework in this catchment could be easily extended to cover other abstractors if the abstraction data becomes available or can be estimated.

The Addax sugarcane estates, established between 2010 and 2013, are irrigated during the dry season (November–May). They are clearly visible on recent Landsat 8 ETM+ images obtained on 15 April, 2014 (Fig. 3a).

In the Makeni area of Sierra Leone, rainfall averages around 2914 mm per annum (long term mean from 1921 to 2013, Ministry of Water Resources, 2015). Spread evenly over a year, this would be sufficient for growing a crop of sugarcane,

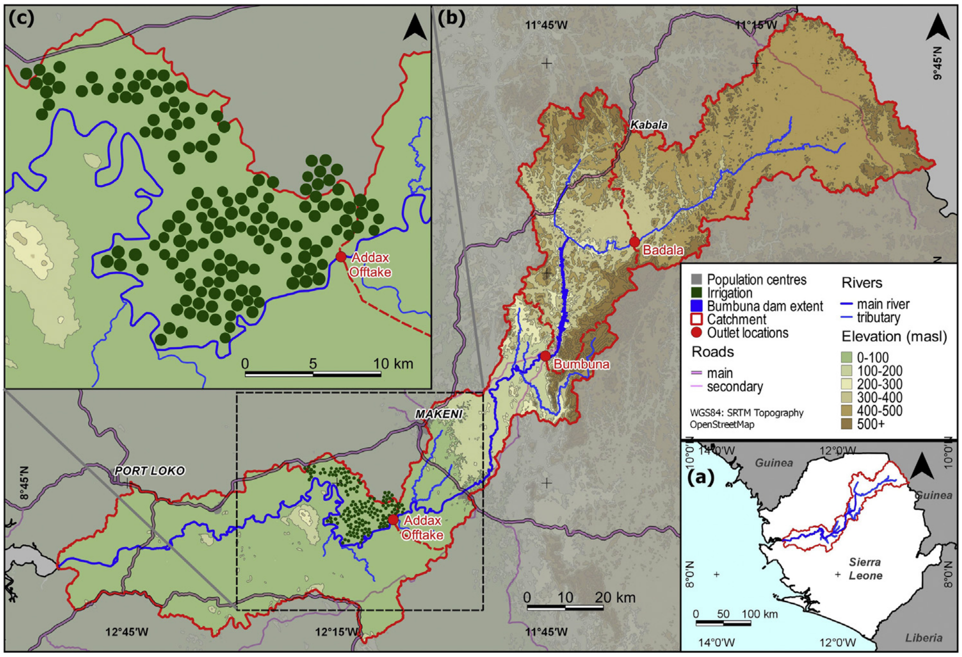


**Fig. 2.** Study catchment location, (a) catchment location within Sierra Leone, (b) main catchment, with sub catchments, (c) detail of irrigation centre pivot locations.

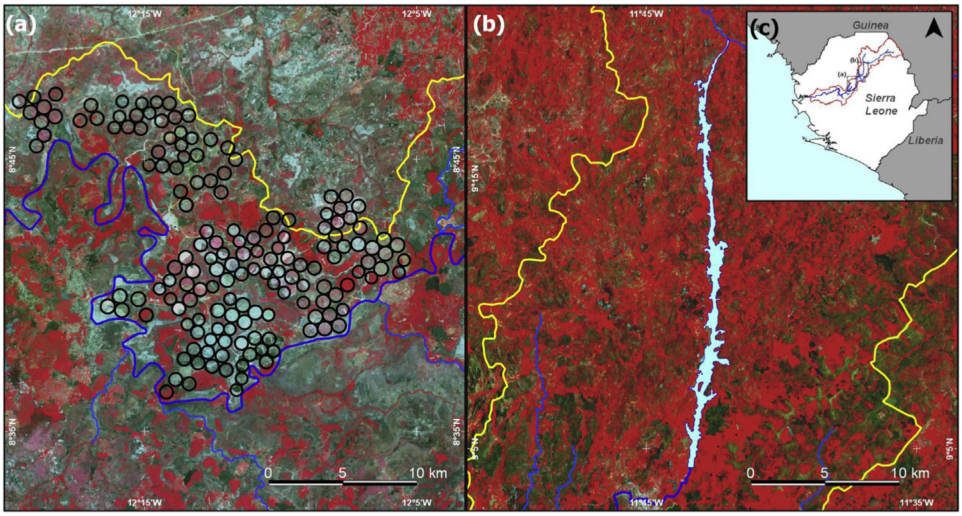


**Fig. 3.** Landsat 8 false colour image (Bands 5,4,3), 15 April, 2014, (a) detail of irrigation centre pivot locations, black circles are planned locations, yellow line is the catchment boundary, (b) Bumbuna reservoir extent, blue outline shows maximum extent—January 2013, (c) Locations within Sierra Leone. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

which typically requires 1500–2500 mm (FAO, 2014). However, given the uneven spread of the rain throughout the year (Fig. 4), irrigation has to be carried out in the dry season.

Given Sierra Leone's fast growing population, urbanisation and industrialisation, competition for the water resources of the Rokel-Seli could lead to unplanned demands from the river and this could compromise future and existing projects reliant on the river's stream flow. Over allocation of water resources, due to inadequate information on the catchment's water resource availability, could lead to unsustainable use of water, as well as possible environmental degradation. Indeed, Akiwumi (1997) highlighted many of these competing demands were already present before the recent mining and agricultural expansion within the catchment.

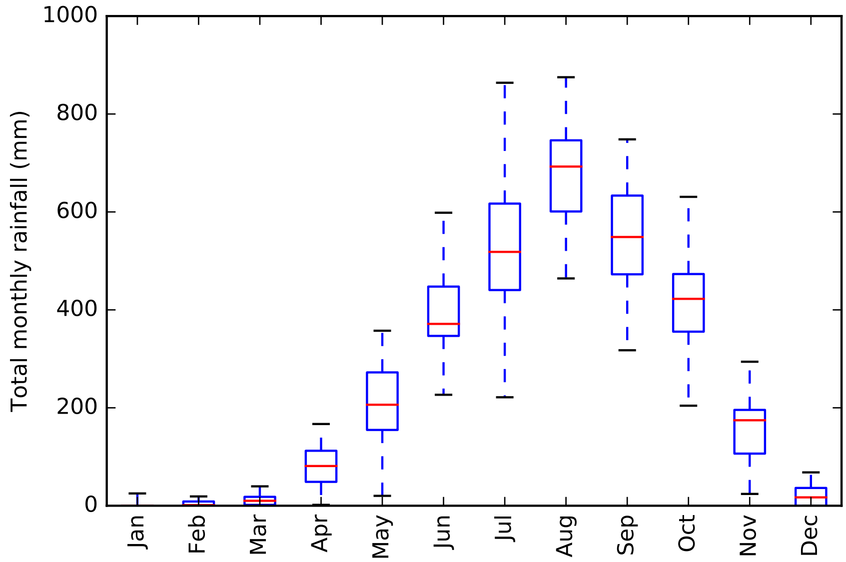


**Fig. 4.** Mean monthly rainfall at Makeni, 1921–1994. The blue box extends from the lower to upper quartile values of the data, with a red line at the median value. The black whiskers extend from the box to show the range of the data. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

## 4. Data and methods

This study utilises a mix of freely available global datasets; including remotely sensed data (Landsat ETM+), interpolated climate data (CRU TS 2.1, GPCC) and a lumped hydrological model appropriate to a data scarce context, to conduct an assessment of long-term water resource availability in a catchment. The same hydro-meteorological data is also applied to a crop demand model to determine catchment crop water demands and finally, catchment water availability is assessed. The application of these data and methods to the study catchment follows the generalised framework already presented.

### *4.1. Hydro-meteorological data-sets*

In the absence of sufficient local data, global climate data sets can be used to derive the hydro-meteorological data for the catchment, including monthly rainfall and temperature for the study area. The CRU TS 2.1 (Mitchell et al., 2004) and Global Precipitation Climatology Centre (GPCC) (Schneider et al., 2011) data that were used in this study are examples of freely available global climate data sets. The CRU TS climate dataset contains interpolated average data from climate models and stations over a spatial grid of 30 arc minutes (roughly 50 km) of the necessary climatic variables (temperature and precipitation) for the period 1901–2002. Each grid cell of the CRU TS 2.1 data set has data values that are interpolated from historically observed station data. In this study, data from the grid cells covering the catchment area were extracted using the catchment extent in a Geographical Information System (GIS).

The GPCC Full Data Reanalysis product provides monthly global land-surface precipitation based on 67,200 stations world-wide that feature record durations of 10 years or longer. In this study, monthly precipitation totals on a regular grid with a spatial resolution of $0.5^\circ \times 0.5^\circ$ latitude by longitude were used. The temporal coverage of this dataset ranges from January 1901 until December 2010 and is recommended for global and regional water balance studies, calibration/validation of remote sensing based rainfall estimations and verification of numerical models (National Centre for Atmospheric Research Staff, 2015).

To test the robustness of global datasets for modelling and analysis of water requirements, we also ran the assessment framework using available locally observed rainfall—which having considerable data gaps therefore limited our model time period to 1961–1994. This model period could be extended to the full period for the global datasets, but for clarity and consistency of comparison we restricted these to the same time period available from the observed rain gauge.

### *4.2. Stream flow*

Some observed stream flow data was critical for this study as it is the key data required to calibrate the rainfall runoff model flow output. Monthly data was obtained from the Global Runoff Data Centre (GRDC, 2011). The stage of the River Seli has been recorded in the past at gauges installed at Bumbuna and Badala stations (Fig. 2) in the 1970s as part of a UNDP program (World Bank, 2005). However, the only available and reliable observed stream flow data available from the GRDC at the time of this study was from the Bumbuna gauging station, covering a period of 3 years (1976–1979). Given the extensive

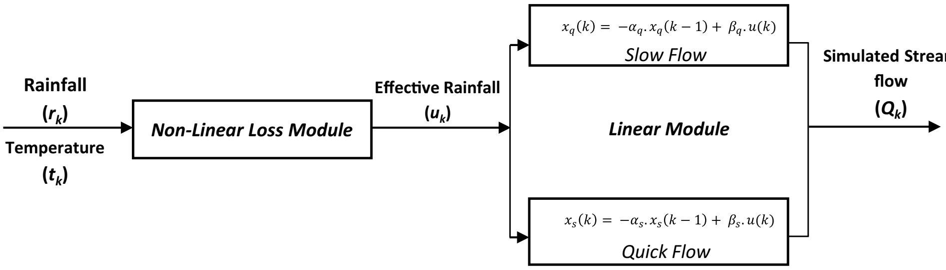


**Fig. 5.** IHACRES model schematic showing the two main modules.

gaps in the GRDC data from Badala, only the data from the Bumbuna gauging station, with just 4 gaps between January 1976 and March 1979, was usable. Missing data was filled-in using linear interpolation, with filled gaps representing only 10% of the total data set (4/39 months). The mean annual discharge at Bumbuna, according to this short dataset, is 121 $m^3/s$ with a mean maximum of 434 $m^3/s$ in October and a mean minimum of 3 $m^3/s$ in March. The highest flows are reached between August and October and normally range between 150 and 400 $m^3/s$.

Further daily flow data for the Bumbuna gauge (1970–1976), since developing this framework, has come to light through the recent Ministry of Water Resources and DFID water security project (http://www.salonewatersecurity.com/). Rather than incorporate these extra data into the calibration, it was decided to use this as an opportunity to validate the approach presented here, so these extra years of data are only used in the validation.

### 4.3. Remotely sensed data (land-use data, SRTM DEM)

Land-use data was obtained from Landsat 30 m resolution multispectral image data, freely available from the USGS Global Visualisation Viewer (GloVis) website (http://glovis.usgs.gov/). Landsat satellite 5 and 7 images with spectral bands 4 (0.76–0.90 μm), 3 (0.63–0.69 μm) and 2 (0.52–0.60 μm) of the Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) instruments were obtained. Images were obtained for the years 1986, 1990, 2010, 2013 and 2014. These images were mostly from the months of December and January, as this is the middle of the dry season and is mostly cloud-free.

These images were then processed into Band 4,3,2 (false colour) composites that highlight vegetation and water while enhancing interpretation as the images produced are visually similar to those from colour infrared aerial photography. Various studies have used these bands to study land use change and monitor drainage patterns (see, for example, Kolios and Stylios, 2013).

There appeared to be very little change in the catchment upstream of the dam over the period from 1986 to 2013. The main noticeable changes are the narrow river gorge (Fig. 3b) that has been flooded by the dammed extent and downstream at the Addax site where the centre pivot irrigation circles can be clearly identified, confirming the location and scale of the agricultural demand area to be assessed.

The benefits of using remotely sensed data to better manage water resources, particularly in irrigated agriculture to determine land use and irrigated crop acres, have been illustrated by, for example, Kaplan and Myint (2012), and Yan and Roy (2016) both of whom used Landsat products to derive land use and irrigated crop areas. In this study, we assess a real-life example of a green field development whose spatial expanse, crop growth stage and water demands can in future be assessed using the timely, objective and accurate information provided by remote sensing (Ozelkan et al., 2016).

### 4.4. Numerical models

#### 4.4.1. Rainfall runoff model IHACRES

IHACRES is a lumped parameter, hybrid conceptual-metric model based on the Catchment Moisture Deficit model of Evans and Jakeman (1998). The main emphasis of the model is to represent rainfall-runoff behaviour occurring dominantly at catchment scale, rather than the very fine scale processes that lead to generation of stream flow from rainfall. It has been used around the world in many catchments to investigate catchment precipitation and stream flow generation (e.g. Kim and Han, 2016; Kim and Lee, 2014; Pollard and Han, 2012; Littlewood et al., 2010).

The model is composed of a non-linear module and a linear module as shown in Fig. 5. Details of this model are described in the Supplementary material. Calibration uses the two main modules; a non-linear loss module that converts rainfall ($r_k$), at a given time step $k$ (in this study, a monthly time step was used), into effective rainfall ($u_k$). Effective rainfall is converted into stream flow by the linear module, applying the Unit Hydrograph theory that takes the catchment as a series of stores arranged in linear or parallel fashion.

#### 4.4.2. Crop demand model—CROPWAT

CROPWAT, a model developed by the Land and Water Development Division of the United Nations Food and Agriculture Organisation, has been used by researchers (such as Tibebe et al., 2016; Nithya and Shivapur, 2016; Scarpare et al., 2016) to determine crop water requirements and irrigation water requirements in varied African climates. Crop water requirements, crop evapotranspiration ($ET_c$) and irrigation water requirements are derived from an algorithm that is based on reference (or potential) evapotranspiration ($ET_o$), using the Penman-Monteith Method (FAO, 1998). A detailed description of this model is given in the Supplementary material.

CROPWAT 8.0 (http://www.fao.org/nr/water/infores_databases_cropwat.html) was used to compute the gross irrigation water requirements for the project area of 10,100 ha. The quantity of water needed for crop growth is the Net Irrigation Water Requirement (NIWR), it is expressed in liters/second/ha (l/s/ha) for every month in this study. Information on irrigation efficiency is necessary to be able to transform NIWR into gross irrigation water requirement (GIWR), which is the quantity of water to be applied in reality, taking into account water losses. GIWR requirements were computed by dividing NIWR by the overall scheme irrigation efficiency (70%), which is the product of the conveyance efficiency and the field application efficiency. The subject of irrigation efficiencies is discussed at length in the FAO Irrigation Scheduling Manual (1989).

Climate and cropping patterns determine the total water needs of a scheme. Climatic variables used in calculations were assumed to be representative of current conditions on the ground, and a mono-cropping regime of sugarcane was used (since the project grows only sugarcane for ethanol production).

### *4.5. Application of the assessment framework*

Application of the assessment framework in the Rokel-Seli catchment of Sierra Leone involved the collation of monthly river flow data over the available number of years from the GRDC (in this study, only 3 years of continuous historical flow data, January 1976–March 1979, were available), derivation of hydroclimatological data (rainfall, temperature) from the CRU TS 2.1 and GPCC datasets and use of the SRTM DEMs from the USGS Global Visualisation Viewer (Glovis) for location based extraction of the catchment watershed from the downloaded full global dataset.

The further local rainfall data from Makeni (Fig. 4) that has recently come to light through the recent Ministry of Water Resources and DFID water security project (http://www.salonewatersecurity.com/) was used as another framework input dataset for comparison with the global climate data. In addition, the further flow data that became available was used for validation of the hydrological modelling within the assessment framework.

The climate data used as inputs to the IHACRES rainfall runoff model were also used as inputs to the FAO's CROPWAT model which was run for the period between 1961 and 1994. Full flow and low flow calibrations of the hydrological model were carried out using three different rainfall datasets (GPPC, CRU and Observed data), resulting in six different model calibrations, three calibrations for the full flow period and three calibrations constrained to low flows.

Results were then analysed against two objective functions, the Nash Sutcliffe Efficiency (NSE, defined by Nash and Sutcliffe, 1970) and the coefficient of determination ($R^2$) for both untransformed and natural logarithm transformed stream flows so as to assess the performance of model calibration and validation whilst ensuring that both high and low flow simulations are adequately evaluated. NSE ranges between $-\infty$ and 1.0, with NSE = 1 being the optimal value. Values of greater than 0.5 are generally considered acceptable (Moriasi et al., 2007). For the correlation coefficient ($R^2$), which ranges from $-1$ to 1, typically values greater than 0.5 are considered acceptable in watershed simulation studies (Santhi et al., 2001; Van Liew et al., 2007 in Moriasi et al., 2007).

Synthetic river flow simulations were then compared to demands simulated by FAO's CROPWAT model. Crop water needs within the catchment are met mostly by rainfall; however, seasonal variations show irrigation during the dry season will be necessary for optimum yields. The high variability of stream flows compared to crop water requirements warranted the assessment of the highest dry season demands against modelled low river flows, therefore emphasising the importance of carrying out model runs with calibration fits emphasised for low flows.

## 5. Results

### *5.1. IHACRES modelling results*

For the calibration of the IHACRES model, three years of GRDC data (January 1976–December 1978) were used, while for the validation, the five years (May 1970–December 1975) of newly rediscovered data from the Sierra Leone Water Security Project were used. A total of six calibration runs were carried out to evaluate model performance for 3 different input datasets and both high and low flow calibration parameters. We defined here these model runs as follows; full flow calibration using the CRU rainfall dataset (CRU-FF), the GPCC rainfall dataset (GPCC-FF), the Observed rainfall dataset (OBS-FF); and low flow calibration runs using the CRU (CRU-LF), GPCC, (GPCC-LF) and the Observed datasets (OBS-LF) were used to establish the variability inherent in global datasets and the effect, if any, on estimation of available river flows.

The model parameters that showed greatest sensitivity to model performance during model runs were the drying rate at reference temperature ($\tau_w$) and the reference temperature ($f$). These parameters were adjusted during the grid search process within IHACRES in order to improve the fit statistics for the objective function ($R^2$). Grid searching for IHACRES entails a search through parameter space to find a good parameter set in the non-linear module and the user specifies a start, end and step value for the grid search. The final adjusted parameter values for the parameters for all model runs are summarised in the supplementary text, Table S3.

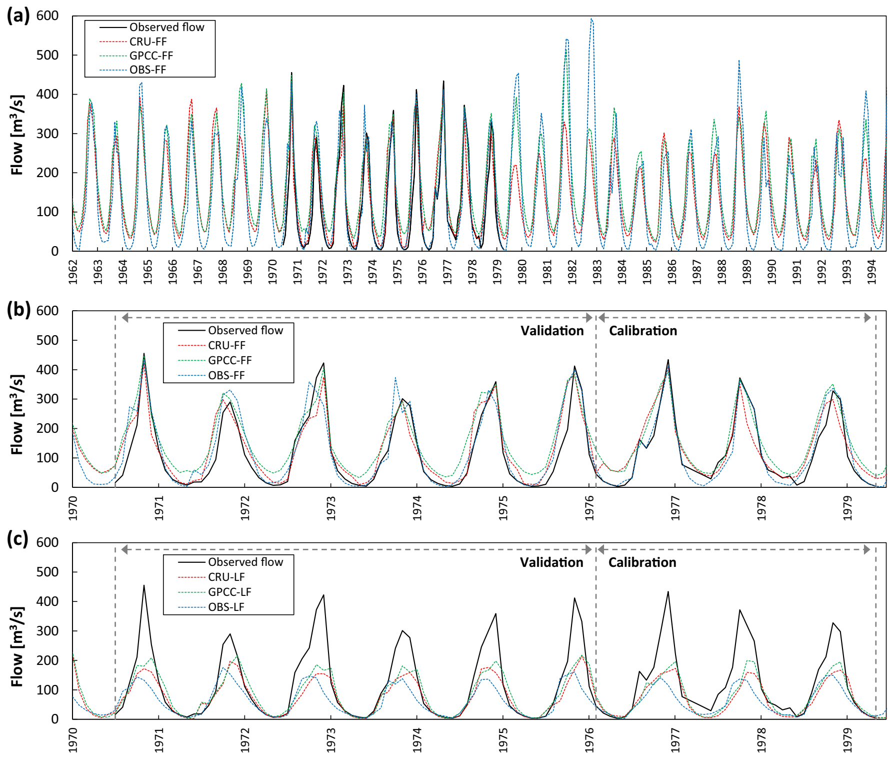


**Fig. 6.** (a) Calibrated IHACRES model run for the full period 1961–1994 using three different input datasets, CRU, GPCC and OBS, (b) Full flow calibration (January 1976–December 1979) and validation (December 1970–December 1975) of IHACRES, showing comparison of model performance with CRU, GPCC and OBS, (c) Low flow calibration and validation of IHACRES with CRU, GPCC and OBS as inputs.

### *5.2. Stream flow simulation, calibration and validation*

The sub catchment outlet for the Rokel-Seli River catchment (Fig. 2b) was located at the present Bumbuna dam site (and historical river gauge site), covering a catchment area of 3803 $km^2$. Flow simulations using two global (CRU and GPCC) and one observed dataset (OBS) resulted in naturalised river flows, excluding the influence of the current dam. The current influence of the dam reservoir releases for maintaining steady flows during the dry season was absent (nor was the dam constructed during the simulation period).

Full flow calibration for all three datasets produced good values for both the objective functions used ($R^2$ and NSE respectively), with OBS-FF (0.94, 0.93) marginally outperforming both the global datasets CRU-FF (0.82, 0.80) and GPCC-FF (0.89, 0.80). Realistic reproduction of high flows was observed for all datasets, (Fig. 6b), with a closer reproduction of maximum flows compared to minimum flows (see Table S4 in supplementary text for full results).

Low flow simulations were calibrated using a subset of the observed flows between January 1, 1976 to December 31, 1978 in an effort to constrain model performance toward better simulation of low flows. This subset was selected using a threshold for low flow based on the mean of the observed flow data (120.6 $m^3/s$), only flows below this threshold were used during the low flow calibration (CRU-LF, GPCC-LF and OBS-LF). The calibrated model was then run for the full simulation period 1961–1994 (Fig. 6c). Low flow calibration for all three runs produced accurate performances, with model results for CRU-LF (0.73, 0.42) GPCC-LF (0.76, 0.52) and OBS-LF (0.80, 0.28) showing a worse fit overall compared to the full flow calibrations, but with a better estimation of low flows (see Table S4).

Model validation using data for 1970–1975 for full flow calibrations (Fig. 6b) resulted in $R^2$ and NSE values of CRU-FF (0.84, 0.82), GPCC-FF (0.88, 0.74) and OBS-FF (0.86, 0.83), while using low-flow values (Fig. 6c) gave $R^2$ and NSE values of CRU-LF (0.89, 0.80), GPCC-LF (0.88,0.44) and OBS-LF (0.68, 0.66) respectively (see Table S4). Although the models underestimate most of the seasonal peaks (hence the lower NSE), this is not a problem for our analysis as we are interested in a good prediction of low flows, which are more critical in the assessment of water requirements within the catchment (Fig. 7).

### *5.3. CROPWAT model results (irrigation water requirements)*

Crop water requirements ($ET_c$), which were used to estimate gross irrigation water needs during the three month dry season (with its attendant water requirement peak), were computed using CROPWAT, with three sets of climatic data (GPCC, CRU and Observed data) used as input to assess the implications of using differing climatic datasets (precipitation

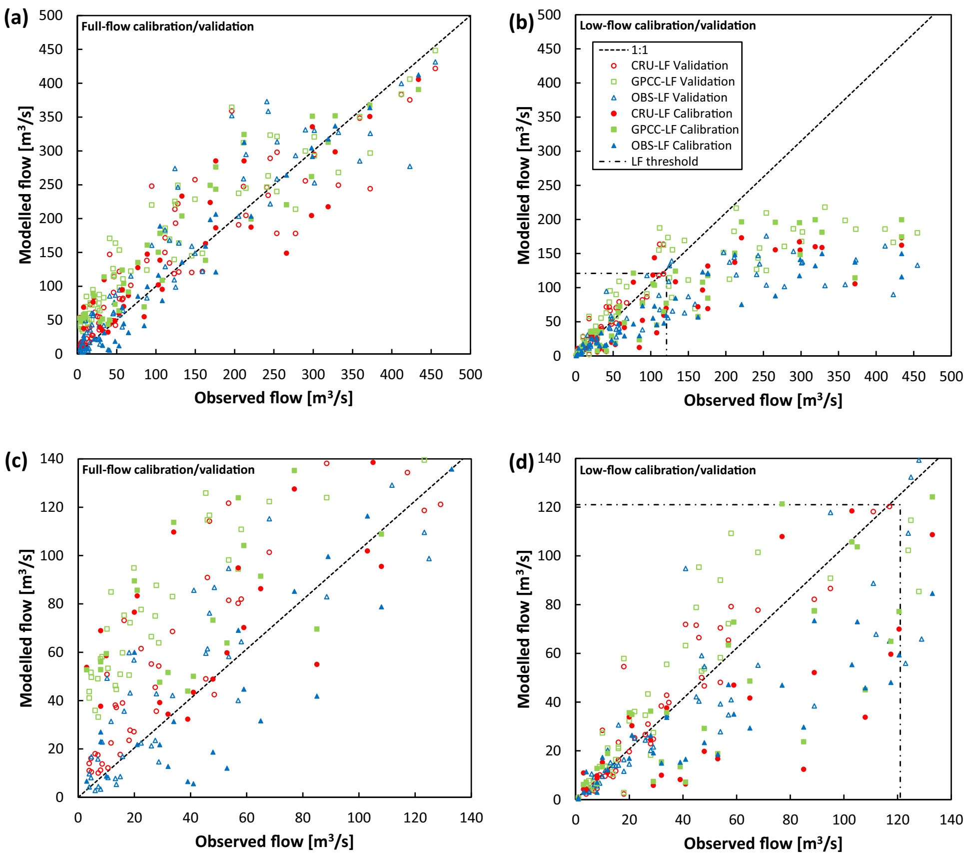


**Fig. 7.** Scatter plots of modelled vs observed stream flow for calibration and validation runs using CRU, GPCC and OBS datasets in (a) full flow calibration/validation (b) low flow calibration/validation model runs, (c) and (d) show the same data but zoomed in to the low-medium flow range.

and temperature) from the period January 1961 to December 1994. The year 1961 is used as a spin-up boundary condition year for the model as the dry season starts in January and the CROPWAT model relies on rainfall input from the previous month (i.e. December 1960).

Peak periods of irrigation water needs occur consistently between January (CRU 6.2 $m^3$/s, GPCC 5.8 $m^3$/s, OBS 5.8 $m^3$/s), February (CRU 7.4 $m^3$/s, GPCC 7.6 $m^3$/s, OBS 7.3 $m^3$/s) to March (CRU 7.2 $m^3$/s, GPCC 7.3 $m^3$/s, OBS 7.1 $m^3$/s), with a mean monthly irrigation water demand of 6.9 $m^3$/s for all three datasets.

### 5.4. Water availability assessment

Seasonal irrigation water demands were determined for the key withdrawal period (January–March), with gross maximum irrigation water needs over the three month dry season being 7.92 $m^3$/s for CRU, 7.73 $m^3$/s for GPCC and 7.92 $m^3$/s for OBS (the mean of all three 7.86 $m^3$/s), demonstrating minimal variance in water demand even with the different input rainfall datasets. Inter-annual variability of water demand during this period (Fig. 8a) is also minimal, as stable temperatures and lack of rainfall are consistent factors for this period from year to year. Since variability in irrigation water demand for all three datasets and throughout the modelled period was minimal, for our water availability assessment, we considered a mean maximum demand of 7.86 $m^3$/s, representing a worst case scenario during the drier years which are typified by low stream flow.

A direct comparison of irrigation water needs against available flow (Fig. 8b) was conducted, firstly for the lowest flow year, then for three different lesser flow extremes, that is 1 in 10 years, 1 in 5 years and 1 in two years lowest flow years (see Table S6). Low flow statistics (exceedance probability) were calculated according to standard methods (Searcy, 1959). The mean monthly flow for the three month dry season is calculated for each of the 32 years and these annual values are ranked from low to high, from where the exceedance probability can be calculated. This was undertaken only for the low flow calibrated models flow outputs (CRU-LF, GPCC-LF and OBS-LF), as these were felt to represent better actual low flows during the 3 month dry season period of assessment.

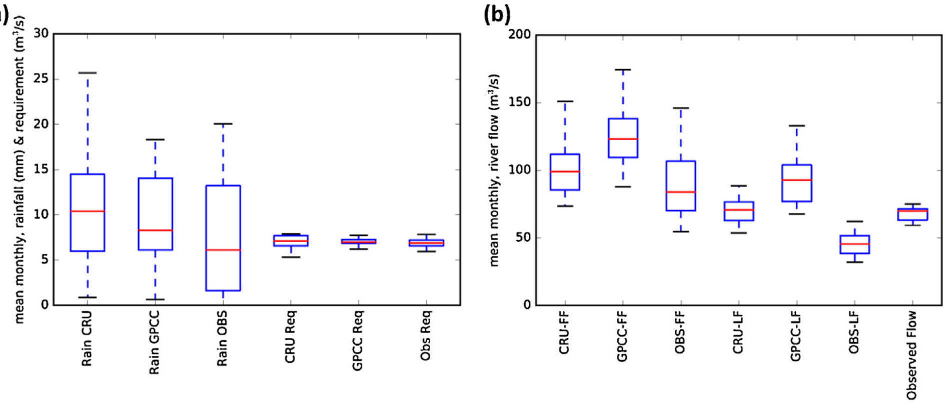


**Fig. 8.** (a) Comparison of mean monthly irrigation water demands against mean monthly rainfall during the three month dry season, (b) Modelled mean monthly flows for both full and low flow scenarios.

Using the mean of the maximum crop water requirements during the three month dry season ($7.86 m^3/s$), percentages of demand relative to available river flow were then computed. This resulted in mean maximum demand of 17.6% (CRU-LF 18.4%, GPCC-LF, 17.1% and OBS-LF 17.4%) of low river flows during the lowest flow year in the catchment.

### 5.5. Discussion

Low and full flow scenarios of water availability in the River Rokel-Seli are generated using a lumped hydrological model forced with different global datasets to evaluate their suitability in estimating naturalised stream flows. For all model runs, it has been demonstrated that flow variability in the river is higher than that in the crop water requirements. Therefore, it is critical to establish the reliability of flow during the low-flow periods, when catchment demands are highest (January–March), so as to ensure equitable abstraction from the river.

The rainfall runoff model successfully generated a time series of flow data with overall model fits of $R^2$ 0.88 and NSE 0.85 for the three full flow model runs (CRU-FF, GPCC-FF and OBS-FF), and $R^2$ 0.48 and NSE 0.32 for the low flow model runs (CRU-LF, GPCC-LF and OBS-LF) showing that the model works reasonably well for the Rokel-Seli catchment, implying that most of the characteristics of the observed hydrologic response were satisfactorily reproduced. Good model validations were achieved for both the full and low flows, and whilst the model over predicted low flows when run for the full flows, it performed better when constrained to a sub-set of low flows during calibrations with global datasets (CRU-LF and GPCC-LF). Given the results of this application exercise, we would recommend preferential calibration of models to low flows is a crucial part of a reliable assessment where abstractions are likely to be highest during the low flow period, as is usually the case for irrigation abstractions.

Ideally, if we had more observed data to calibrate the hydrological model, more reliable flow series statistics would be derived. However, given the aim here is to demonstrate that a reliable assessment can still be made in a data scarce context, the 3 years of observed data used to model the catchment flows are still instructive in generating correlations between requirements versus observed flow, especially during low flow periods. This is confirmed by good model validation with independent data.

Stream flow variation is demonstrably higher than crop water requirements for all model scenarios. During the low flow periods, the model scenarios CRU-LF, GPCC-LF and OBS-LF all had near similar demand estimates for the driest year at 18.4%, 17.1% and 17.4% of available river flows. Demand estimates when using the GPCC dataset closely matched the results of the observed dataset as compared to the CRU data. However this may not translate to other catchments and in fact use of either global dataset results in a similar assessment of water availability regardless of their differences.

The operation plans for the now completed (2009) phase I Bumbuna Dam include release of water year-round for electricity generation purposes (Independent Evaluation Group—World Bank, 2016). This discharge (and that of the planned phase II) may help sustain low flows during future dry seasons and should become an essential component of a future catchment management plan, particularly if downstream dry season water use increases. However, during the initial years of operation, various problems have prevented a constant, reliable flow discharge, so it is difficult at this stage to assess how the dam operation will actually affect flows in the future.

Future research on the application of this framework will need to further explore the uncertainties in the data and models used. We have explored the sensitivity of the assessment framework results to different input datasets and calibrations, and demonstrated that the assessment conclusions relating to relative abstraction quantities to river flow availability remain robust even when considering these differences. Substituting different hydrological models in the framework and testing full model parameter uncertainties of each model could also be useful, providing a better sense of the range of uncertainty inherent in the modelling process. However, while it is acknowledged here that uncertainty quantification is scientifically important (Trigg et al., 2014), for the practitioner interested in making fundamentally basic decisions regarding water availability, it is more important to use provably robust methods than to provide a potentially confusing assessment of all uncertainties possible. As the science of uncertainty assessment matures to the point where it can be applied easily and understandably for the practitioner, then this framework can be expanded to incorporate these methods. In the mean-time, we have demonstrated that as a minimum and where possible, sensitivity testing should be included to ensure assessment conclusions are robust.

### *5.6. Conclusions*

Water resource allocation practices in Africa are largely hampered by unreliable and inadequate data on water resources availability. In developing countries, such as Sierra Leone, hydrometeorological data required to quantify water availability are usually missing, although some historical records of short duration exist which can be utilised to reconstruct water resource scenarios. In this study, we proposed and applied a framework that relies on both local and global datasets to establish long term water availability scenarios in a catchment facing mounting water needs against a poorly quantified resource, underlining the risk of over allocation due to data scarcity.

Six rainfall runoff model runs split into full and low flow scenarios were carried out to unearth the variability of different global datasets against observed gauge data. In the full flow scenario, the global datasets CRU-FF and GPCC-FF, performed acceptably against the chosen objective functions $R^2$ and NSE for both untransformed (CRU-FF; 0.82, 0.80, GPCC-FF; 0.89, 0.80) and natural logarithm transformed values (CRU-FF; 0.69, 0.49, GPCC-FF; 0.77, 0.42). For the low flow scenarios CRU-LF and GPCC-LF, model calibration was constrained to low flows, thus performing better against natural log transformed values for both $R^2$ and NSE (CRU-LF; 0.71, 0.58, GPCC-LF; 0.77, 0.71) as compared to the full flow runs.

To evaluate the impact of water withdrawals from the Rokel-Seli during the three month dry season irrigation requirement peak, the modelled scenarios of water availability were analysed against irrigation water demands. The variability of irrigation water demands when using two global datasets compared to the observed dataset within the crop water model was minimal, with results ranging for mean seasonal demands ranging from CRU (7.09 $m^3$/s), GPCC (6.97 $m^3$/s) and OBS (6.68 $m^3$/s). Results showed the global datasets slightly overestimating the requirements, however this can be attributed to the averaging effect of spatial interpolation of rainfall within these datasets as compared to point measurements for the observed data.

In general, drier years require more water and using the framework, it was demonstrated that flow variability has a much higher variability than crop demand. Therefore it is most critical to determine water needs during periods of lowest river flow. Ranking the years using probability of exceedance for low flows, we found that the lowest flow year crop requirement varies between 17.1–18.4%, for all input datasets used (Table S6).

The framework presented thus proved to be robust and capable of providing long term missing data to reconstruct water availability scenarios, whilst being relatively easy to apply. Furthermore, this framework could be extended to include other global datasets/models and address further water resource allocation questions.

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## Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ejrh.2016.10.001.

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