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Basin Scale Performance of a Distributed Rainfall-Runoff Model Using Uncertainty Modelling Approach in Data Scarce Region

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Abstract

Lack of hydrological information of the most basins in Tanzania increase uncertainties in understanding hydrological processes in the basin, and consequently leads to risks decision making related to significant water resources development plans and climate change adaptation. The lack of hydrological information also is coupled with uncertainty related to the predictions of future climate and land use change. Some of the gaps can be filled using rainfall-runoff modeling, which results can be used to generate reliable information to enable decision making and planning for water resources management. This paper discusses the results of applying a semi-distributed rainfall-runoff model which was established for the Little Ruaha Sub-Basin, using the available historical data, with a goal of understanding processes of runoff generation and the inherent uncertainty related to data. Issues of water resources assessment in the basin and approaches used to address them, and some directions for future research are discussed. There are challenges associated with the quality of data for model set-up and understanding of the model structure. Despite these challenges, there remain many opportunities to improve the methods used for water resources assessment and management within the basin.

Keywords: hydrological modeling, uncertainty, rainfall-runoff modeling

1. Introduction

The Soil and Water Assessment Tool (SWAT) is a hydrological simulation tool that is widely used by researchers and postgraduate students in Tanzania. This could be attributed to the free online spatial dataset (elevation, soil, land cover) necessary for setting up SWAT. However,

the ease of setting up SWAT using the available information does not mean that the model will give behavioral results. The calibration of hydrological models for water resources assessments is often difficult due to the large numbers of model parameters, and the difficulty increases with the model complexity. Similarly, calibration and uncertainty analysis are a pre-requisite of any hydrological modeling study. Despite, the claimed wide use of SWAT in Tanzania, the whole issue of uncertainty has been ignored, where the uncertainty framework within SWAT is used for the optimization of objective functions only [1]. In this study, SWAT2009 was used to explore the implementation of the uncertainty analysis framework for the meaningful application of the results.

SUFI 2 framework is used for the implementation of uncertainty analysis in this study. The framework was selected because it takes fewer runs in comparison to other calibration procedures tailored for SWAT. According to [2–5] SUFI-2 parameter uncertainty accounts for all sources of uncertainties such as uncertainty in input data, model structure, and parameters. All uncertainties are quantified by a measure referred to as the P-factor, which is the percentage of measured data bracketed by the 95% prediction uncertainty (95PPU) and R-factor which is the measure of the width of the uncertainty band.

The concept behind the uncertainty analysis of the SUFI-2 algorithm is illustrated graphically in **Figure 1**. The diagram illustrates that a single parameter value (black dot) leads to a single model response (**Figure 1a**), while the propagation of the uncertainty in a parameter (shown

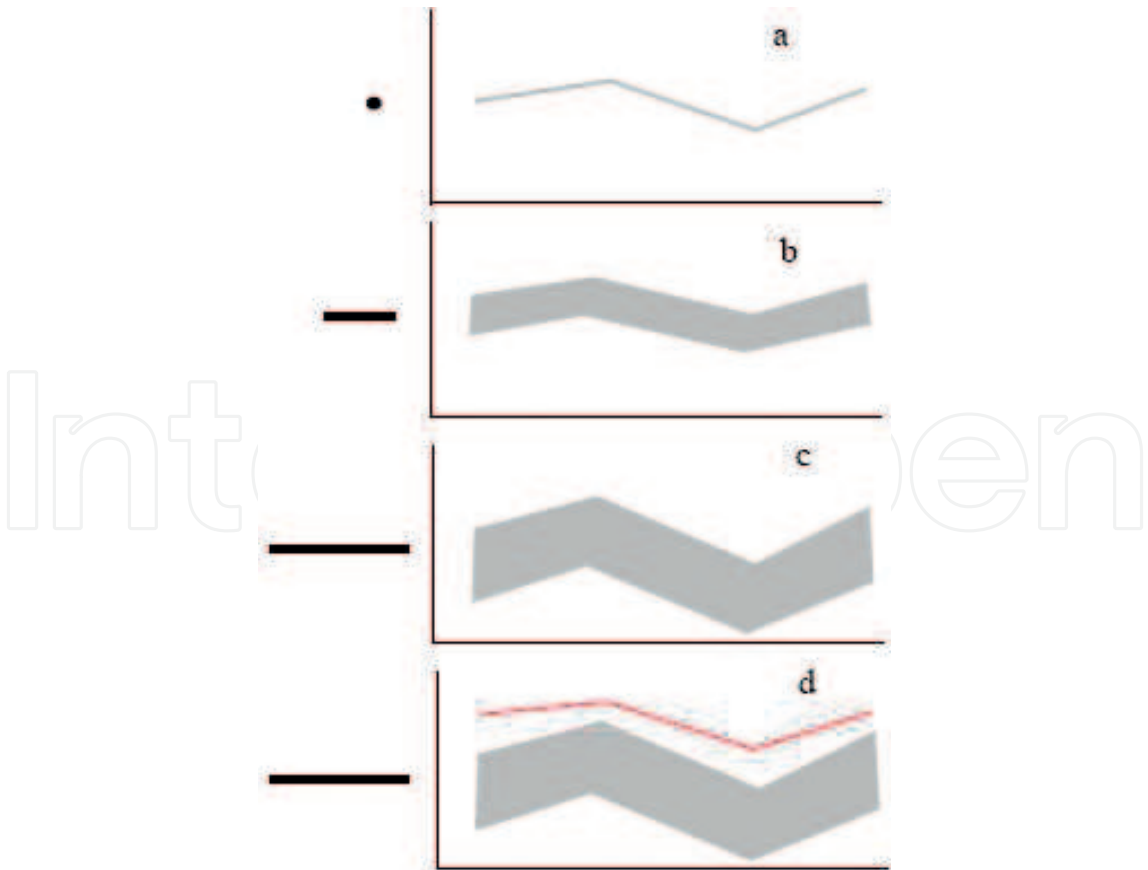


Figure 1. A conceptual illustration of the relationship between parameter uncertainty and prediction uncertainty.

by a line) leads to the 95PPU illustrated by the shaded region in **Figure 1b**. As parameter uncertainty increases, the output uncertainty also increases (**Figure 1c**). SUFI-2 normally begin with a large parameter uncertainty (within a physically meaningful range) to make sure that the observed data falls within the 95PPU, then decreases this uncertainty in steps while monitoring the P-factor and the R-factor. If the initial parameter ranges are equal to the maximum physically meaningful ranges and still cannot find a 95PPU that brackets any or most of the data (**Figure 1d**), then the conceptual model needs to be re-examined [4]. In each step, initial parameter ranges are updated by calculating the sensitivity matrix, an equivalent of a Hessian matrix, followed by the calculation of the covariance matrix, 95% confidence intervals of the parameters, and correlation matrix. Parameters are then updated in such a way that the new ranges are smaller than the previous ranges and are centered on the best simulation. More details on SUFI-2 and its algorithm can be found in Abbaspour et al. [3, 4]. The uncertainty analysis in this study was implemented in the two stages;

1. Assigning initial parameter ranges: the complete physical range of each parameter was used to explore the surface response using Latin Hypercube sampling and to select the initial range for each parameter.
2. Derivation of a reduced parameter range and predictive uncertainty: the procedure identifies a range for each parameter in such a way that upon propagation:
 - The 95% prediction uncertainty (95PPU) between the 2.5th and 97.5th percentiles contain (brackets) a predefined percentage of the measured data, and
 - The average distance between the 2.5th and 97.5th prediction percentiles is less than the standard deviation of the measured data [3, 4].

The model performance was assessed based on the two conditions being fulfilled and a good agreement between the simulated and the observed data for a calibration and validation period. In theory, the P factor values range between 0 and 100%, while the R-factor ranges between 0 and infinity [4]. A P-factor of 1 and R-factor of zero is a simulation that exactly corresponds to measured data. The degree of departure from these numbers is used to judge the strength of calibration. It is possible to achieve a good P-factor at the expense of a larger R-factor; therefore, there should be a balance between the two factors [4]. Other performance measures used are the R^2 and Nash-Sutcliffe (CE) coefficient.

2. Study area

The Little Ruaha basin (**Figure 2**) falls within the African land surface where the infiltration of the topsoil is good, and interflow is an important component of the River discharge. The soils in the upper part are deeply weathered and have a good soil structure. The total area for this sub-catchment is approximately 5200 km². The headwaters of the Little Ruaha River (gauging station 1 ka31) originate from a permanent swamp covering an area of approximately 30–50 km². The seasonal variation of the runoff is less apparent for the Little Ruaha

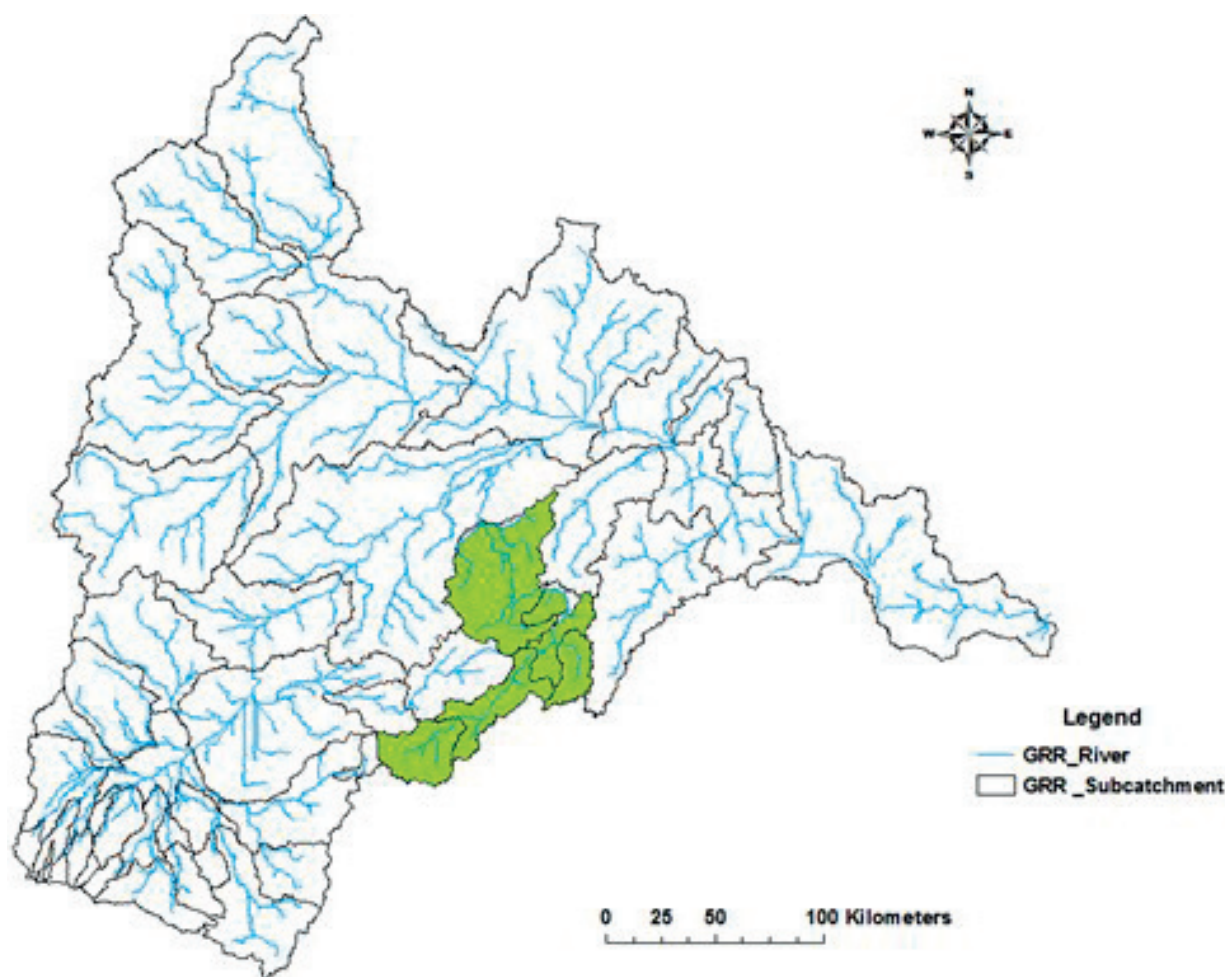


Figure 2. The Great Ruaha River Basin with Little Ruaha River sub-basin (presented in green).

River, due to a considerable infiltration and ground water recharge during the wet season which is favored by relatively high and often less intensive rainfall [6]. The maximum and minimum recorded flows of the River are 775.0 and $2.8 \text{ m}^3 \text{ s}^{-1}$ during March and October, respectively. Estimates of groundwater recharge are discussed in the Water Master Plan for Iringa, Ruvuma, and Mbeya regions [7]. Based on the CCKK report, the base flow component constituted about 80% of the total annual stream flow, which is consistent with the fact that the catchment is characterized by swamps in the headwaters but also, has highly permeable soils. This implies that there is high recharge.

2.1. Geology

The geology of the Little Ruaha basin is mainly covered by the Usagarans System. The system covers the Great Ruaha and Kilombero catchments, in Great Ruaha, the system mostly covers Iringa region where Little Ruaha flows. These are rocks extending N-NE and S-SW of the Archean Tanzania Craton. The rocks formed between (2.1–1.8) Ga striking W-E to SW. Geologists have used different abbreviations for ages (time before present) and duration (amount of time elapsing between two different events). Ages are abbreviated from Latin:

Ga (giga-annum) is a billion years, Ma (mega-annum) is a million years, ka (kilo-annum) is a thousand years. Major rock types in the system are crystalline limestone, graphite schists, and gneiss metamorphosed under amphibolites facies condition due to granitization and migmatization which took place during Pan African tectonothermal event 0.5 Ga which affected the Mozambique mobile belt. The system also contains granulites and granitic intrusions (1.8–1.85) in some parts of Iringa region, volcanic rhyolite lavas, granite gneiss, eclogite, and agglomerates are found in some areas of Kilombero in the Udzungwa Mountains and the Kilombero basins. The volcanic behavior in lower Kilombero is witnessed with high-temperature ground water recorded at monitoring borehole located at Ikule primary school in Ifakara and the volcanic soil. The rock types in the Usagaran system are dominant in Iringa, Mufindi, Njombe, Kilolo, Kilosa and Kilombero districts, which are in Great Ruaha and Kilombero catchments. The rocks are found in a part of Makete district though other parts are affected and dominated by Rungwe volcanic (anorthosites, basalts, peridotites, pyroxenites).

2.2. Soils

The soils in the upper parts are deeply weathered and have good soil structure, but the relatively high rainfall has resulted in heavily leached soils with low fertility. The soils in the lower part Agro-ecological zone 8 are moderately fertile red clays and loams although sandy soils with low fertility are quite common.

2.3. Topography

The basin is characterized by flat to undulating topography and inselbergs are common. While humid forest remnant covers the upper part of the zone, Acacia scrubland is more typical in the lower drier areas. The characteristic features of the basin, apart from the Rift Valley system, are the surrounding uplifted and warped plateaus. Covering nearly 90% of the total Iringa and Mbeya regions, the plateaus represent by far the most common land form. Fault-lines and erosion scarps separate them and are the result of steady erosion that has taken place since the Late Jurassic period.

2.4. Climate

Rainfall is highest in the south-eastern part of the basin about 1200–1400 mm in the steep upper catchments areas, decreasing with altitude to 800–1000 mm in the middle part of the catchment which has undulating topography, whereas the lower parts of the catchments south-west of Iringa only receive about 700 mm. The rainfall is unimodal. Rain normally starts in November/December and ends in April/May. In the upper catchment areas rainy season often continues into the beginning of June for example in 1994 the rainy season finished in Iringa by mid-April whereas it was still raining in the upper part of the basin until the beginning of June.

2.5. Land use and farms

Most of the population in this catchment depends on agricultural production, and the farming systems which evolved in this zone are predominantly smallholder with the average cultivated

area varying from 1 to 2 ha per household. Large-scale farming is limited a few numbers of individuals and companies (often parastatals). Maize is the dominant crop in most of the smallholder farming systems. Maize is grown in mixtures most often beans but intercropping with sunflower and cowpeas are also common. Peas are very important crop and are often grown at the beginning of the dry season and are most often grown on broad ridges. Sorghum and millet are also grown, but the production is very minor compared to maize even in the drier areas where, the more drought resistant sorghum would be more appropriate than maize which is much more water demanding. In the area potatoes are an important crop where transport facilities are good they are often grown as a cash crop. The area under cultivation varies considerably within the zone approximately 25–75% with the highest land use pressure in the area around Iringa, where there has been severe overutilization of the land resources which has led to severe erosion.

3. Methodology

The gauging station 1 ka31 (Little Ruaha at Mawande) was used for SWAT2009 model calibration for the period 1971–1979. Daily stream flow data from this station were checked for quality, and this involved the identification of errors from suspicious extreme values. **Figure 3** illustrates the percentage of available data points, missing data points, and removed data points. Six percent (6%) of the data was deleted from the time series, and 2% of the data was missing. Therefore only 92% of the record was used for the calibration method. Both manual and automatic calibration approaches were used for this study. The pre-calibration parameter sensitivity analysis was performed to identify parameters that are expected to have a strong influence on the model simulation results.

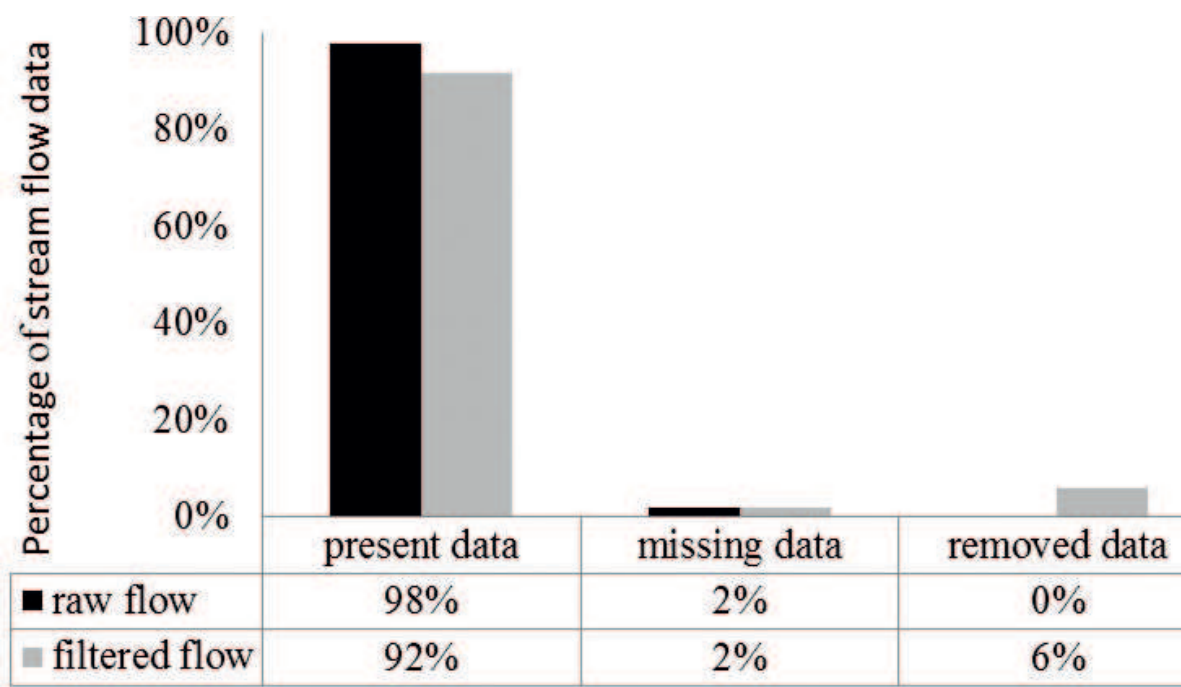


Figure 3. Summary of the screened daily stream flow data used in this study.

In this study, the Sequential uncertainty fitting (SUFI-2) approach was combined with SWAT to quantify parameter uncertainty of the stream flow simulations for the Little Ruaha River (5195 km²). The SWAT2009 model was setup for the whole GRR basin but the analysis presented here is based on one major tributary only. The hydrological response units (HRU) were characterized using the dominant land use, soil, and slope to keep the complexity of the analysis to a practical limit for the uncertainty propagation. Daily stream flow data from this station were checked for quality, and this involved the identification of errors from unexplained extreme value.

3.1. Sensitivity analysis

Sensitivity analysis allows for the identification of model parameters that exert a strong influence on the model output, thus largely controlling the behavior of the simulation process. In this study, a sensitivity analysis was carried out using the Latin Hypercube One-factor At a Time (LH-OAT) algorithm [8, 14]. The Sensitivity analysis minimizes the number of parameters to be used in the calibration step. The Latin Hypercube simulation is based on a Monte Carlo approach with stratified sampling. The results of the sensitivity analysis are parameters arranged in ranks, where the parameter with a maximum effect obtains rank 1, and parameter with a minimum effect obtains the rank which corresponds to the number of all analyzed parameters. The parameter that has a global rank 1 is categorized as “very important,” rank 2–7 as “important,” rank 8–27 “slightly important” and rank 28 as “not important” [14].

The sensitivity analysis in this study was done using (i) automatic global sensitivity analysis in SUFI-2, (ii) manual analysis of the sensitive parameters based on the output of the global sensitivity analysis. The global sensitivity analysis in SUFI-2 is not able to analyze all the parameters in SWAT; it analyses the sensitivity of the pre-defined 27 parameters (**Table 1**). In this approach, parameter sensitivity is determined using the multiple regression equations, which regresses the Latin Hypercube generated parameters against objective function values. The *t*-stat and *p*-value are statistical measures used to evaluate sensitivity in SWAT-CUP. A *t*-stat is used to identify the relative significance of each parameter by providing a measure of sensitivity (larger absolute values are more sensitive). *p*-Values determined the significance of the sensitivity where a value close to zero has more significance. Both manual and automatic calibration followed the sensitivity analysis. The manual calibration was performed based on the understanding of the sub-basin characteristics. The results of the global sensitivity analysis indicated the sensitive parameters and helped to guide the initial parameter ranges. The calibration procedure involved the following steps:

1. Sensitivity analysis
2. Manual calibration
3. SUFI-2 set up (automatic calibration)
4. Assigning initial parameter ranges
5. Latin Hypercube sampling is used to sample the parameter distributions
6. Model simulations are performed, and objective functions are calculated for each of the *n* (*n* = 2000 for this study) simulations.

Parameter	Description	<i>t</i> -Stat	<i>p</i> -Stat	Rank	Process
ALPHA_BF	Base flow alpha factor for recession constant (days)	-34.23	0.00	1	Ground water
CN2	SCS runoff curve number for moisture condition II	-12.90	0.00	2	Runoff
SURLAG	Surface runoff lag time (days)	-1.54	0.12	3	Runoff
REVAPMN	Threshold water depth in the shallow aquifer for revap (mm)	-1.51	0.13	4	Groundwater
SOL_K(2)	Saturated hydraulic conductivity soil layer 2 (mm h ⁻¹)	-1.39	0.16	5	Soil
GWQMN	Threshold water depth in the shallow aquifer for flow (mm)	-1.28	0.19	6	Groundwater
SLSUBBSN	Average slope length (mm ⁻¹)	1.17	0.19	7	Topography
BLAI	Leaf area index for crop	1.05	0.29	8	Crop
CANMX	Maximum canopy storage (mm)	0.60	0.54	9	Runoff
CH_N2	Manning's "n" value for the main channel	0.58	0.55	10	Channel
HRU_SLP	Average slope steepness of the HRU	-0.56	0.57	11	Topography
GW_REVAP	Groundwater "revap" coefficient	-0.46	0.63	12	Groundwater
BIOMIX	Biological mixing efficiency	-0.39	0.69	13	Soil
EPCO	Plant evaporation compensation factor	0.24	0.80	14	Evaporation
SOL_AWC	Available soil water capacity (mm H ₂ O/mm soil)	0.21	0.82	15	Soil
RCHRG_DP	Deep aquifer percolation fraction	-0.21	0.83	16	Groundwater
ESCO	Soil evaporation compensation factor	-0.10	0.91	17	Evapotranspiration
GW_DELAY	Movement of water from shallow aquifer to the root zone	0.09	0.92	18	Groundwater
CH_K2	Channel effective hydraulic conductivity (mm h ⁻¹)	0.07	0.94	19	Channel

Table 1. Parameter sensitivity ranking and category of the most sensitive parameters.

3.2. Assigning initial parameter ranges

The results of the sensitivity analysis indicated the sensitive parameters and helped in guiding the setup of the initial parameter ranges. It was important to consider the physical meaning of each parameter and its effects on the sub-basin behavior. Therefore, the initial parameter sets were guided by the understanding of the physical basin characteristics and the default upper and lower limits established in SWAT. In SWAT default parameters can be modified for the whole sub-basin (lumped), or in a distributed way for individual sub-basins or hydrological

response units. **Table 2** shows the initial parameter ranges of the sensitive 20 parameters, where the most sensitive parameters are presented in row 2–10.

3.3. Parameter distributions

The identifiability of parameters was examined visually using scatter plots of model parameter values versus CE. **Figure 4** shows scatter plots with the values of each parameter defined versus their corresponding Nash-Sutcliffe efficiency (CE), where the parameter values were obtained from Latin Hypercube sampling of the initial range defined using 2000 simulations. Scatter plots of the parameter values versus objective function were used to examine the identifiability of individual parameters. Based on the scatter plots the identifiable parameters are expected to show a distinct maximum, and lack of a distinct maximum indicates the difficulty in getting the optimal values that give a good model performance, therefore, the parameter becomes poorly identifiable. It is evident that none of the parameters are identifiable.

Parameter	Lower limit	Upper limit	Change option
v__ALPHA_BF.gw	0.00	1.00	Replacement
r__CN2.mgt	–50	50	Relative
v__SURLAG.bsn	0.00	24.00	Replacement
v__REVAPMN.gw	0.11	0.80	Replacement
r__SOL_K (2).sol	0.39	4.28	Relative
a__GWQMN.gw	1983	2889	Absolute
r__SLSUBBSN.hru	0.13	0.33	Relative
v__BLAI{120}.CROP.DAT	3.63	6.95	Replacement
v__CANMX.hru	2.87	8.51	Replacement
v__CH_N2.rte	0	0.3	Replacement
r__HRU_SLP.hru	0	10	Relative
a__GW_REVAP.gw	0.02	0.12	Absolute
r__BIOMIX.mgt	0.11	0.69	Relative
v__EPCO.hru	0	0.4	Replacement
r__SOL_AWC (2).sol	0	0.9	Relative
v__RCHRG_DP.gw	0	1	Replacement
v__ESCO.hru	0	1	Replacement
a__GW_DELAY.gw	0	129	Absolute
v__CH_K2.rte	24.27	94.18	Replacement
r__SOL_K (1).sol	0.66	5.55	Relative

Table 2. Defined upper and lower limits of initial parameter ranges, the extension of the files in which they are located, and the option used for carrying out changes.

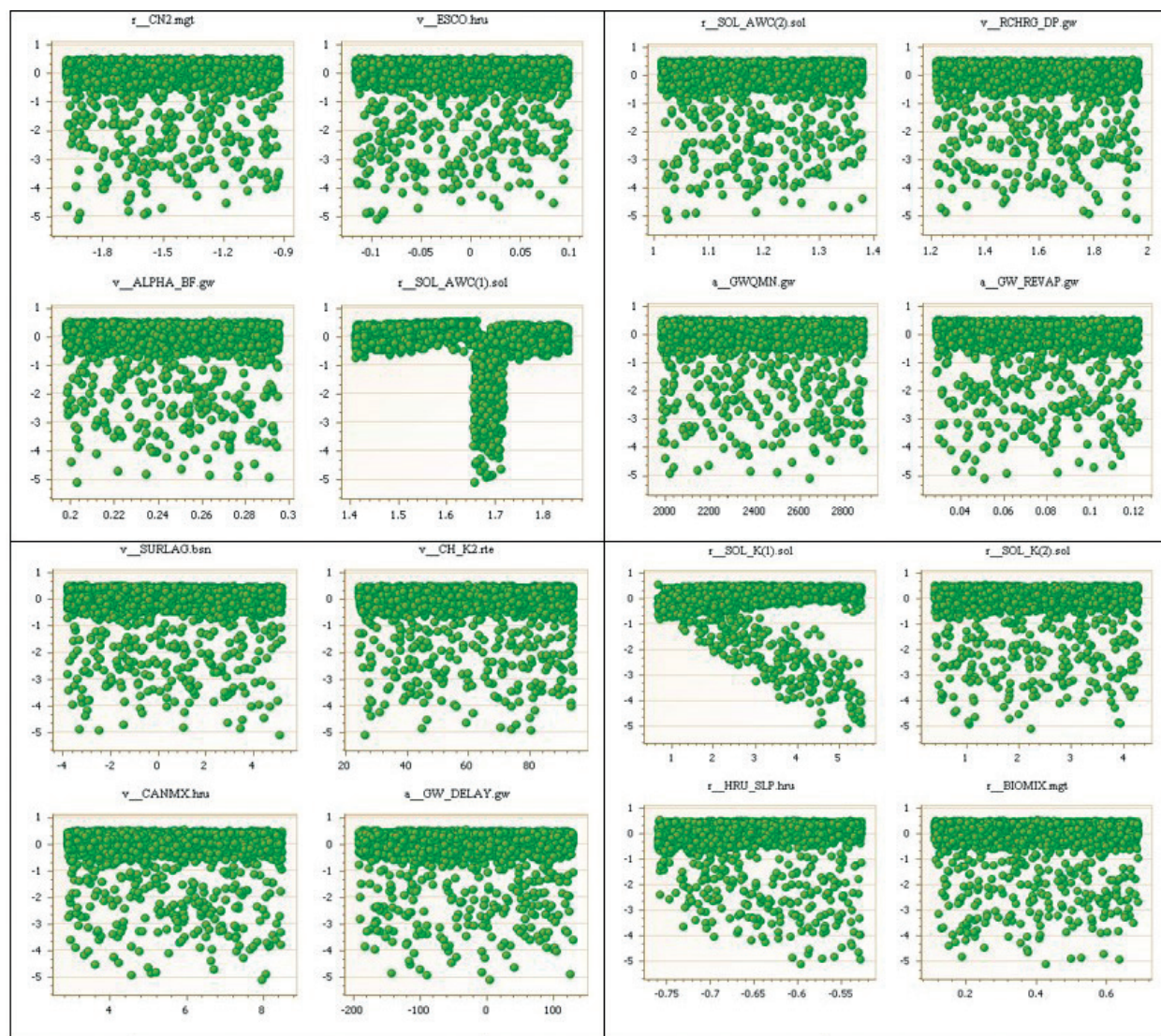


Figure 4. Scatter plots of the calibrated parameters of Little Ruaha River basin (Gauging station 1 ka31) versus Nash-Sutcliffe efficiency, obtained from Latin Hypercube sampling of the large initial range using 2000 simulations.

However, it should be noted that in-identifiability of a parameter does not indicate that the model was not sensitive to these parameters. The sensitivity analysis results identify the most sensitive parameters to be considered for calibration but do not consider the interactions between parameters, therefore having the most sensitive parameters does not mean that the parameter will be identifiable. Estimation of an-identifiable parameters is difficult because there may be many combinations of these parameters that would result in similar model performance (equifinality). Many factors might have led to the non-identifiability of parameters in this study. The interactions between parameters may have contributed to the equifinality which might be associated with the simplified representation of the sub-basin (dominant HRU). Interactions between soil parameters (soil depth and available water capacity) and ground water parameters (Groundwater delay) is expected in SWAT. It is hard to explain these interactions since SWAT considers two soil layers (root zone and unsaturated zone) and ground water (conceptual shallow and deep aquifer stores) and there is not enough information regarding sub-surface water processes to will enable a better explanation of the parameter interactions.

3.4. Final calibrated parameter ranges

Latin Hypercube sampling was used to sample parameters within the initial ranges using 2000 ensembles and a uniform distribution. The CE was used to get optimum parameter values and to separate behavioral from non-behavioral parameter sets, where a cutoff limit of CE = 0.45 was used. **Table 3** shows the parameter range and optimal value for the best simulation. ALFA_BF is the most sensitive parameter followed by CN. **ALPHA_BF** parameter is a direct index of ground water flow response to changes in recharge. The ALPHA_BF value between 0.1 and 0.3 reflects an area with the slow response to changes in flow, a value of 0.9–1 reflects an area with a rapid response to changes in flow. For the Little Ruaha sub-basin, a value of 0.25 was obtained. The CN is the parameter that determines the amount of runoff to be generated from a sub-basin, so it was expected to be sensitive for the Little Ruaha sub-basin with an optimal value of –1.69. **SURLAG** was the third most sensitive parameter and is the fraction of runoff that reaches a sub-basin outlet on any given day. SURLAG was sensitive for this sub-basin because of the low time of concentration, and an optimum value of 3.5 days was obtained. **REVAPMN** presents the threshold depth of water in the shallow aquifer for return flow to the root zone to occur. This parameter is most important in areas where the water table is high or areas with deep-rooted crops. An optimum

Parameter name	Lower limit	Upper limit	Optimal SUFI-2
v__ALPHA_BF.gw	0.00	1.00	0.25
r__CN2.mgt	–50	50	–1.69
v__SURLAG.bsn	0.00	24.00	3.5
v__REVAPMN.gw	0.11	0.80	0.57
r__SOL_K (2).sol	0.39	4.28	1.36
a__GWQMN.gw	1983	2887.18	2071.38
r__SLSUBBSN.hru	0.13	0.33	0.32
v__BLAI{120}.CROP.DAT	3.63	6.95	4.82
v__CANMX.hru	2.87	8.51	5.95
v__CH_N2.rte	0	0.3	0.06
r__HRU_SLP.hru	0	10	0.75
a__GW_REVAP.gw	0.02	0.12	0.10
r__BIOMIX.mgt	0.11	0.69	0.40
v__EPCO.hru	0	0.4	0.004
r__SOL_AWC (2).sol	0	0.9	1.10
v__RCHRG_DP.gw	0	1	1.94
v__ESCO.hru	0	1	0.02
a__GW_DELAY.gw	0	129	–31.05
v__CH_K2.rte	24.27	94.18	59.94
r__SOL_K (1).sol	0.66	5.55	0.66

Table 3. Final parameter ranges calibrated using SUFI-2.

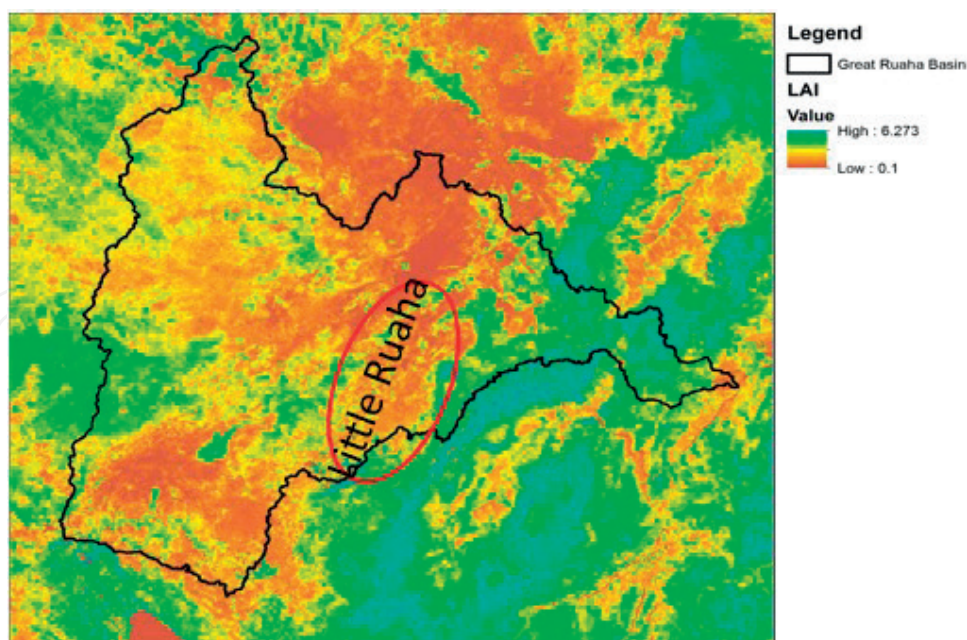


Figure 5. Spatial variations in leaf area index within the Little Ruaha basin.

value of 0.57 was obtained. SOL_K (2) is the saturated soil hydraulic conductivity (mm h^{-1}). In this study, a SOL_K value of 1.66 mm h^{-1} was used. This parameter relates to water flow rate to the hydraulic gradient and is a measure of the rate of water movement through the soil.

The GWQMN is the threshold water level in the shallow aquifer for return flow to occur (mm). The ground water flow to the main channel is allowed only when the depth of water in the shallow aquifer is equal to or greater than the threshold depth of water in the shallow aquifer required for the return flow to occur. An optimum value of 2071.38 (mm) was obtained. The obtained value for the mean slope steepness of the basin (SLSUBBSN) is 0.32, indicating that the sub-basin is influenced by low to moderate slopes and has implications for the runoff generation process. The optimum value for the maximum potential LAI is 4.82. The value corresponds to the MODIS data which indicates LAI for the Little Ruaha catchment ranges from low to moderate values (Figure 5). CANMIX represents the maximum canopy area, and an optimum value of 5.95 mm was obtained. This value corresponds to the leaf area index indicated in (Figure 5). The Manning roughness coefficient “n” for channel flow (CH_N (2)) is the parameter that influences channel roughness, an optimum value of 0.06 was obtained.

4. Model simulation results and uncertainty analysis

SWAT was calibrated against observed data for gauging station 1 ka31 for the period 1970–1971. Calibration results yielded satisfactory results given the data scarcity. CE and R^2 values of 0.54 and 0.62 were achieved for the calibrated period. The P-factor (% of measured data bracketed by 95% prediction uncertainty) was 0.58 and 0.21 for the full range and behavioral simulations, respectively. The R factors for the full range and behavioral parameters were

1.91 and 0.36, respectively. These results confirm quite large uncertainty of the simulated discharge due to the large equifinality in parameters and reliability of input data (precipitation and daily evaporation data). **Table 4** shows a summary of model performance for the calibrations and a comparison between all parameter sets (full range) and behavioral parameter sets. In presenting results, the following performance measures were used;

- The relative distance between the observed data and the 95PPU (R-factor)
- The percentage of observations covered by the 95PPU (P-factor)
- Nash-Sutcliffe efficiency (CE)
- Coefficient of correlation (R^2)

Station	Simulations	P-factor	R-factor	CE	R2
1ka31	Full range	0.58	1.91	54%	62%
	Behavioral	0.21	0.36	54%	62%

Table 4. Summary of performance statistics for the best simulation.

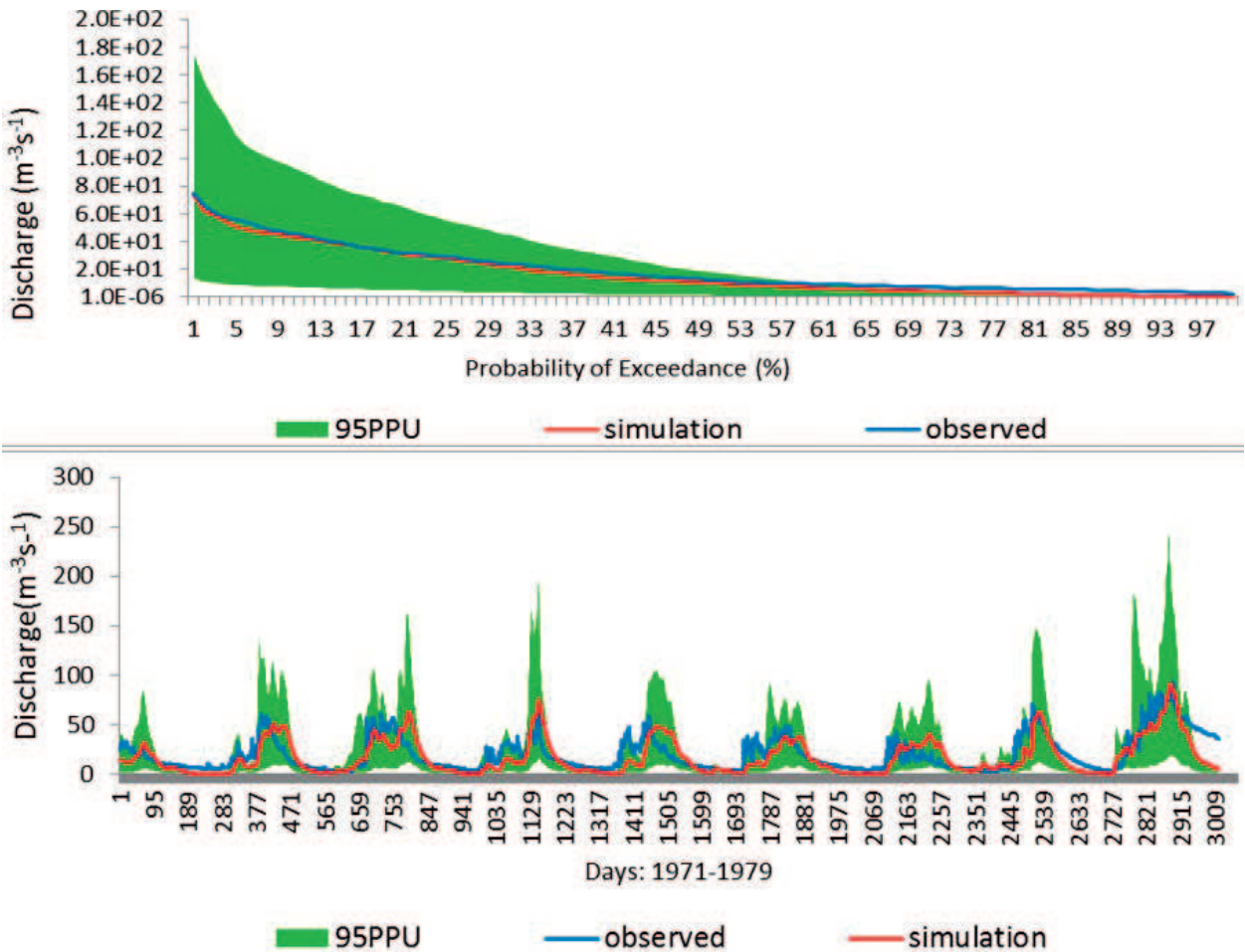


Figure 6. Calibration at 1 ka31-Mawande (95PPU for full range simulations).

Uncertainty analysis was implemented using the SUFI-2 algorithm. **Figures 6 and 7** show the results of the daily flow uncertainty analysis carried out in the sub-basin for the full range and behavioral parameter sets respectively. The shaded area represents the 95% predictive uncertainty (95PPU), whereas the blue lines correspond to the observed discharges and the red lines correspond to the simulated flow at the sub-basin outlet. For the full range simulations (**Figure 6**) it was found that the observations fall within the lower and upper 95% prediction uncertainty in high and moderate flow but with large uncertainty. **Figure 6** shows that the 95% prediction uncertainty of behavioral simulations ($CE \geq 45\%$) does not bracket the observed flow, only 15% of the data were bracketed, indicating that some processes are not well represented in the model. The prediction limits obtained with SUFI-2 are highly dependent on the threshold selected to separate behavioral from non-behavioral parameter sets. It is also important to note that in SUFI-2 parameter uncertainty is presented as a uniform distribution in the final parameter range, while parameter interactions are ignored and contribute to the large equifinality observed in these results.

Final calibration parameters for the Little Ruaha Drainage System with a Coefficient of Evaluation (CE) of 0.54 and R^2 of 0.62 for the best simulation regardless of the parameter set. The results

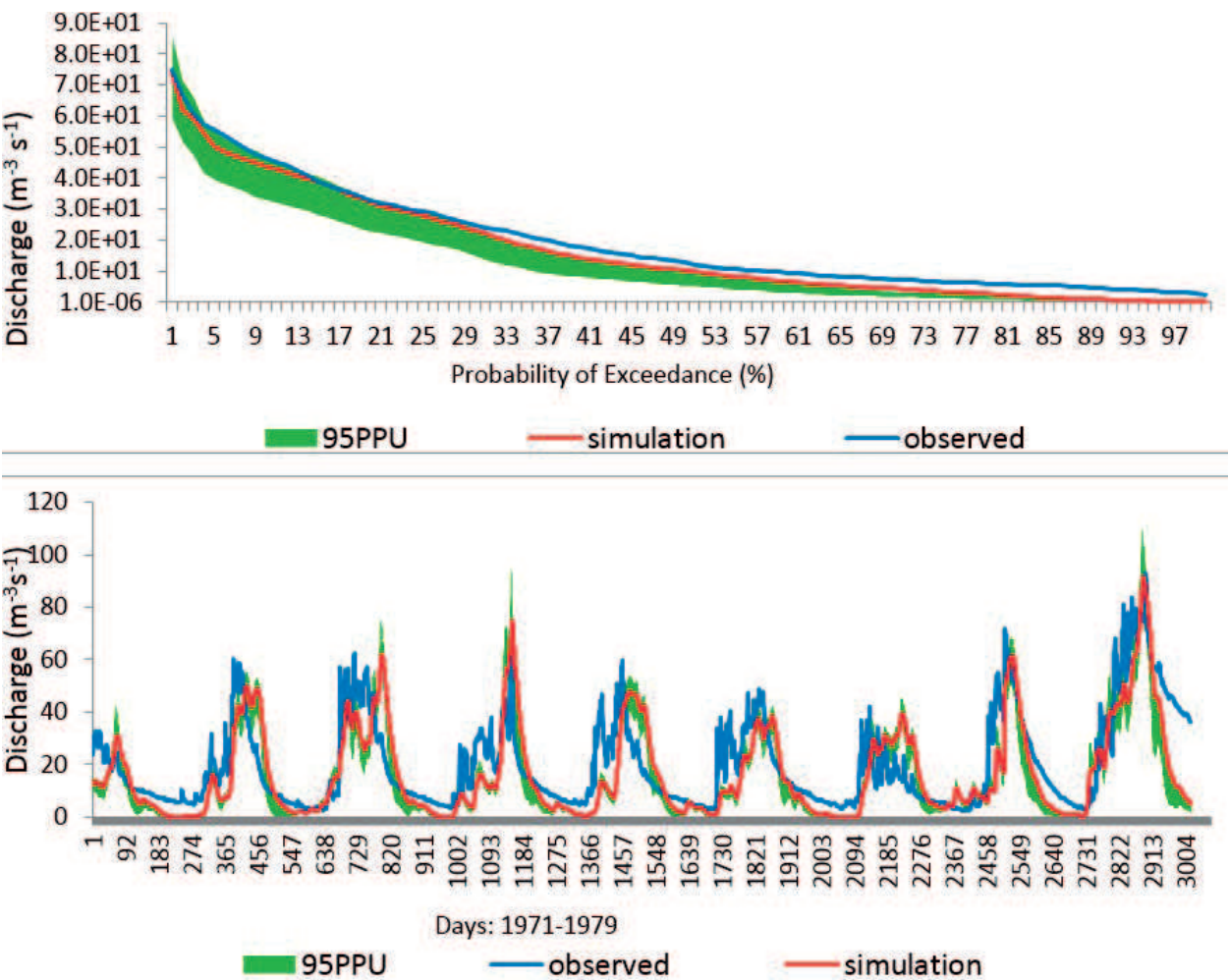


Figure 7. Calibration at 1 ka31-Mawande (95PPU for behavioral simulations).

show reasonable performance in the hydrologic simulations but with large uncertainties. The model performance statistics achieved in this study are like the ones achieved in other studies in Tanzania [10], but one point that should be noted is that, after calibration, parameters should have physical meaning. With the large equifinality in the parameter sets, it was not possible to get identifiable parameter sets, and it is hard to say that behavioral parameters sets are representatives of the basin's behavior. This observation highlights the challenges associated with implementing SWAT for water resources use in Tanzania and other developing countries.

5. Discussions and conclusions

The SWAT2009 was applied to the Little Ruaha sub-basin. The model was set up using a coarse spatial dataset, interpolated rainfall data, and a single dominant HRU. Sensitivity analysis results showed that ALPHA_BF, CN2, SURLAG, REVAPMN, CH_K2, GWQMN, SLSUBBSN, BLAI, and CANMX are the most sensitive parameters in the basin. The Little Ruaha drainage system falls within the African land surface where the infiltration of the topsoil is good, and interflow is an important part of the total River discharge. The soils in the upper part are deeply weathered and have a good soil structure. This explains the sensitivity of the surface and subsurface parameters. The drainage is dominated by steep topography, and this explains the sensitivity of the mean slope length of the basin. Sensitivity analyses enabled the most sensitive model parameters to be identified for further calibration, but this does not mean that sensitive parameters will also be identifiable. Out of the 27 parameters, 20 were identified as sensitive, but the interactions between these parameters were not considered during the sensitivity analysis.

Final calibration parameters for the Little Ruaha Drainage System are presented in **Table 4**, with a CE of 0.54 and R^2 of 0.62 for the best simulation regardless of the parameter set. This is since the behavioral parameter sets are within the non-behavioral parameter sets. The results show reasonable performance in the hydrologic simulations but with large uncertainties. The model performance statistics achieved in this study are like the ones achieved in other studies in Tanzania [10], but one point that should be noted is that, after calibration, parameters should have physical meaning. With the large equifinality in the parameter sets, it was not possible to get identifiable parameter sets, and it is hard to say that behavioral parameters sets are representatives of the basin's behavior. Ref. [13] reviewed the use of the SWAT model in the Nile Basin countries, including Tanzania, and found that the model produced satisfactory or good results, but almost all the case studies reviewed gave results based on the wrong process representation. These results were problematic because when different studies in the same or similar sub-basins are compared, they give different results. In peer-reviewed papers [9, 10] some documented parameter values were not realistic, but this information was not reported in those papers [11]. This observation highlights the challenges associated with implementing SWAT for water resources use in Tanzania and other developing countries.

Even though the model gave satisfactory results based on the performance measures, a critical analysis of **Figures 6** and **7** suggests a different picture. **Figure 6** showed that there is good agreement between observed and simulated flow but associated with very large uncertainty in high to moderate flows, and the uncertainty band does not bracket the low flows. Running

the model with the behavioral parameter sets shows a reduction in P-factor and R-factor values (Table 4). Figure 7 shows that while the uncertainty band has been reduced, the model is under-simulating both high and low flows, and does not bracket the moderate to low flows. This could be associated with input data uncertainties, or some processes are not well represented in the model. ALPHA_BF was the most sensitive parameter identified through the sensitivity analysis, and apart from a lack of observed ground water information, difficulties of SWAT in simulating ground water flow [12] might have contributed to the negative aspects of these results.

This study assessed model uncertainty using a combined uncertainty approach that assumes all sources of uncertainty have been considered within the model. In such an approach it is hard to separate the sources of uncertainty, and therefore a follow-up analysis of uncertainty should be undertaken by determining how erroneous input data influence model results. Although not assessed within the research questions of this study, the results highlight potential uncertainties in the input rainfall and evaporation data. The use of these data was justified and used in the simulations but could potentially have influenced the overall model performance and uncertainties that cannot be explained.

The uncertainty analysis was carried out using 20 sensitive parameters, which is a large number considering the interactions between them. Therefore, some less sensitive parameters should be fixed and allow only the most sensitive parameters to vary. This will reduce the effect of parameter interactions and hence the none-uniqueness problem. Although this model has been shown to generate reasonable results, it is worthwhile to consider the challenges associated with setting up a distributed model. In this research, large-scale spatial datasets have been used, and a homogenous model was assumed because the spatial data resolution was insufficient to represent large numbers of hydrological response units. However, even when the resolution was sufficient, attribute values for most of the parameters are lacking. Because of difficulties associated with parameter representation across spatial scales, it is better to use a homogenous set up because biases and uncertainty can be added by the modeler when trying to parameterize values within the hydrological response unit at a size larger than its coverage. The overall conclusions from this assessment include;

- The SUFI-2 approach has capabilities of identifying behavioral parameter. However, the results are influenced by large equifinality.
- The scatter plots of the parameter values against objective functions obtained after simulation provided an initial qualitative overview of the uncertainties involved in the representation of basin's behavior.
- The 95% of the predictive uncertainty (95 PPU) for stream flow computed using SUFI-2 using the Latin Hypercube sampling with 2000 runs, did not bracket all simulations, indicating that some processes are not represented in the model. Hence additional information is needed to improve the results.
- It is also important to emphasize that the prediction limits obtained with SUFI-2 are highly dependent on the threshold selected to separate behavioral from non-behavioral parameter sets and that the subjective choice of the threshold value and objective function can lead to additional uncertainty in the simulation results.

Developing an understanding of the hydrological processes that occur in a system is critical for the effective assessment and management of water resources. However, the lack of observational data represents a serious challenge to understanding that is difficult to resolve, especially when there are so many factors that contribute to hydrological variation and change. Scientists and practitioners within the southern African region are attempting to develop the most effective methods for water resources assessment that will contribute to effective water resources management. This study has employed the uncertainty approach for setting up the rainfall-runoff model for the Little Ruaha River basin and the assessment of uncertainties associated with simulations of naturally hydrological responses. The aim was to explore uncertainties in modeling hydrological responses and to establish a behavioral model that can be used for water resources management and future decision making. This approach has addressed a range of key issues in hydrological modeling; these include the uncertainties associated with input data, parameter equifinality and the importance of realistic uncertainty representation using constraints.

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