*Research article*

# Identifying the Minimum Number of Observed Rainfall Events Required for Optimal TOPMODEL Parameters in Mid-sized Equatorial Catchments

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Received 26 January 2019 Accepted 20 October 2019 (*Corresponding Author)

**Abstract** TOPMODEL, a topography-based, semi-distributed hydrological model was applied to the 84 $km^2$ Atari catchment in Eastern Uganda. The study sought to identify the minimum number of rainfall events needed to optimally calibrate 5 unknown parameters for yearly hydrological simulation. Model input data was daily averaged precipitation, river discharge and evapotranspiration for the year 2015 with the output being simulated discharge. A rainfall event was defined as consecutive days of effective rainfall - effective rainfall being a daily rainfall ≥ 5.0 mm. Parameterization was done for *Sequentially Accumulated Rainfall Events* (*SARE*), beginning with 1 event and sequentially progressing until all 54 observed rainfall events in the year were used. All SARE had similar starting dates with the end dates being variable. The 'true' parameters were those derived from inputting all observed rainfall events while the other instances of the parameters from partial SARE were classified as 'non-true'. Elimination criterion of 'non-true' parameters was set at an error of ±30%. Parameter values varied with the change in number of rainfall events, showing their dependence on rainfall characteristics. Downslope saturated transmissivity ($T_e$) and maximum root zone storage deficit ($SR_{max}$) were the most and least variable from their means respectively. Also, exponential decay parameter (*m)* and delay time constant ($t_d$) needed the least and the greatest number of rainfall events to stabilise within the ±30% error bounds respectively. Therefore, the minimum number of rainfall events required to calibrate TOPMODEL and to optimise $t_d$ in mid-sized equatorial catchments in Eastern Uganda are equivalent. Consequently, it required at least 49 rainfall events to calibrate TOPMODEL in 2015.

**Keywords** calibrate, modelling, rainfall event, SARE, TOPMODEL

## INTRODUCTION

Observed hydro-meteorological data are useful for irrigation and drainage planning. In areas that lack this data, hydrological models are used to predict stream discharge. One such model is TOPMODEL, a conceptual, semi-distributed hydrological model (Beven and Kirkby, 1979) that has been used worldwide. In Africa, TOPMODEL was applied in a humid tropical climate in

Nigeria (Campling et al., 2002) and in an Ethiopian catchment (Gumindoga et al., 2014). To date, the authors have not found published evidence of the application of TOPMODEL in Uganda.

Generally, Uganda has a scarcity of hydro-meteorological data, and worse still, even the available data is of poor quality, e.g., temporal gaps, unreliability, and inaccuracy of rating curves. Notably, most Ugandan rivers are ungauged, and bleaker still, only about 33% of installed water level gauging stations are currently operational (MWE, 2013).

Given the challenges above, hydrological models could come in handy. But hydrological models need calibration, a process that requires the input of observed hydro-meteorological data. For this reason, Atari catchment was chosen as a target site for the study. Unlike many catchments in Uganda, it is equipped with modern hydrological and meteorological monitoring facilities. The TOPMODEL concept was thus applied to the Atari catchment located in Eastern Uganda.

According to Coles et al. (1997); (1) Rainfall intensity influences rainfall-runoff response of a catchment, and (2) Calibrated parameters are only relevant to the rainfall event(s) that was used for their calibration. From these findings, it would be ideal to use all possible permutations of rainfall events to achieve representative parameters suitable for yearly hydrological simulations. However, given the previously mentioned observed data deficiencies in Uganda, it is necessary to have insight into the premise that limited observed data may be sufficient to calibrate model parameters which can be used for yearly hydrologic simulation. Therefore, the purpose of the study is to identify the minimum number of rainfall events required for optimal yearly TOPMODEL parameter calibration.

## METHODOLOGY

### Study Site

The study area is Atari, a headwater catchment of Mt. Elgon in Eastern Uganda, with a drainage area of 84 $km^2$ above the stream gauging station and a corresponding channel length of 33 km. Its topography is comprised of mountainous areas from where the main stream (Atari River) originates and flows to the relatively flat plains. From ASTER GDEM, the difference in height between the lowest and the highest point is 2,389 m. Of the 84 $km^2$, 35 $km^2$ (42%) is forest, 28 $km^2$ (33%) is agricultural area and 21 $km^2$ (25%) is rangeland.

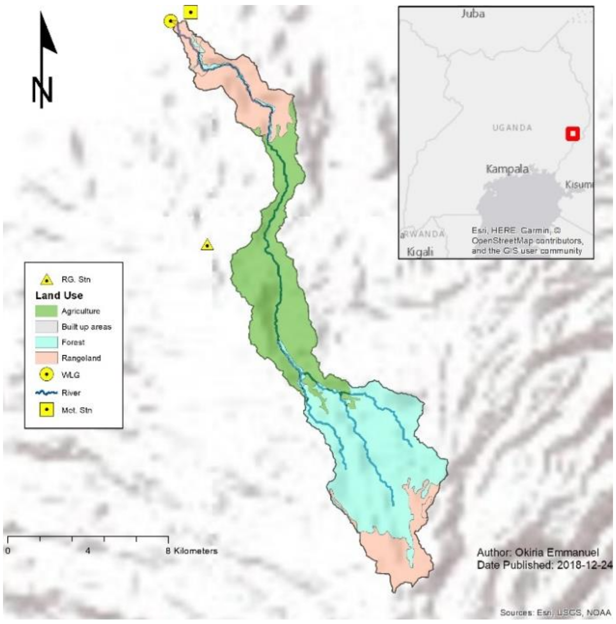


**Fig. 3 Instrumentation and land use in Atari catchment**

*RG. Stn is rain gauge, WLG is water level gauge, Met. Stn is meteorological station*

Under the Project on Irrigation Scheme Development in Central and Eastern Uganda (PISD) (JICA, 2017), hydro-meteorological monitoring equipment were set up in Atari catchment in 2015, viz., a mid-stream rain-gauge to detect catchment rainfall, a downstream meteorological station to measure evapotranspiration parameters and a water level sensor at a control section of Atari River.

## TOPMODEL

### 1) Description of TOPMODEL

TOPMODEL is a conceptual, semi-distributed model suggested by Beven and Kirkby (1979). It divides the soil layer into root zone, unsaturated zone and saturated zone. The upper soil layers (root zone and unsaturated zone) are analysed at grid-scale as distributed models while the lower layer (saturated zone) is computed as a catchment scale lumped model. TOPMODEL evaluates the state of wetness of the surface layer of a basin from the Topographical Index (*TI*).

$$\boldsymbol{TI = ln\frac{a_i}{\tan\beta_i}} \tag{1}$$

Where $a_i$ is upstream contributing area per unit contour length, $\tan\beta_i$ is local slope and $i$ is grid number.

*TI* is derived from a Digital Elevation Model (DEM) and it spatially evaluates the amount of surface flow. Details of TOPMODEL are in Mukae, et al. (2017) and Beven and Kirkby (1979).

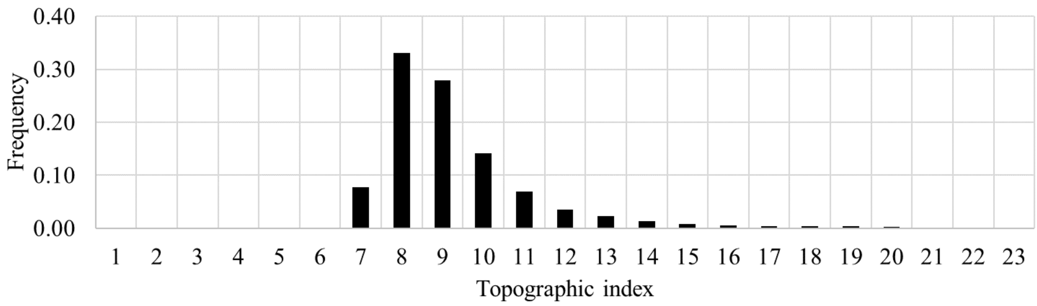


**Fig. 4 Histogram of *TI* distribution for Atari catchment**

### 2) Computational Procedure of TOPMODEL

Input data is observed daily precipitation, observed river discharge, actual evapotranspiration ($ET_a$) and a *TI* that is derived from 30 m grid DEM. Rainfall was measured for each event and other hydro-meteorological parameters were recorded at 10-minute logging intervals, but the daily averages were used for computation.

**a. The water balance equation of the root zone:**
The amount of water that is stored in the root zone is calculated from the water balance of rainfall [L], $ET_a$ [L], maximum storage deficit in the root zone ($SR_{max}$) [L] and storage deficit in the root zone ($SRZ$) [L]. When $SRZ < 0$, the excess water ($EX_i$) flows to the unsaturated zone ($SUZ_i$) [L]. Potential evapotranspiration ($ET_0$) is calculated by the Penman-Monteith method (Allen et al., 1998). $ET_a$ is treated as a function of $ET_0$, $SR_{max}$ and $SRZ$.

$$\boldsymbol{ET_a = ET_0\left(\frac{SRZ_i}{SR_{max}}\right)} \tag{2}$$

**b. The water balance equation of the saturated zone:**
Base flow discharge, ($Q_{sub}$) [LT$^{-1}$] is calculated using the parameters $m$, and $T_e$ [L$^2$T$^{-1}$], catchment mean *TI*, ($\lambda$) [-] and the mean storage deficit in the watershed $\overline{S}_i$ [L]:

$$\boldsymbol{Q_{sub} = T_e e^{\lambda \overline{S}_i/m}} \tag{3}$$

**c. The water balance equation of the unsaturated zone**

The unsaturated zone is a temporary water storage zone that links the root zone to the saturated zone. The mean storage deficit in the watershed at the start of the calculation (initial time step), $\overline{S}_i$ is obtained from Eq. (3), assuming that the initial discharge is $Q_0$ [$LT^{-1}$].

$$\boldsymbol{\overline{S}_i = -m \ln \frac{Q_0}{T_e e^{-\lambda}}} \tag{4}$$

Like in Fig. 3, $S_i$ [L] expresses the storage deficit of each grid and $UZ_i$ [$LT^{-1}$] is the amount of water supplied from the unsaturated zone to saturated zone, with *i* being the grid number. Since, cells with the same value of *TI* are considered to be hydrologically similar, computation is done for each *TI* class (Fig. 2) and not for every individual grid. If $S_i$ is $\leq 0$, then the *TI* class is considered to be saturated, and excess water inflow from the root zone ($EX_i$) becomes surface flow, as shown in Fig. 3. If $S_i > 0$, the excess water inflow is temporarily added to $SUZ_i$.

$$\boldsymbol{UZ_i = \frac{SUZ_i}{S_i t_d}} \tag{5}$$

where $t_d$ [$TL^{-1}$] is the delay time constant, a parameter that expresses the period of retention.

TOPMODEL requires the calibration of 5 unknown parameters, namely; exponential decay parameter (*m*), mean value of downslope transmissivity when the soil is just saturated ($T_e$), delay time constant ($t_d$), maximum root zone storage deficit ($SR_{max}$) and initial root zone storage deficit ($SRZ_{initial}$) using the Monte-Carlo method. Nush-Sutcliffe efficiency (*NS*) and Root Mean Square Error (*RMSE*) are the evaluation functions adopted to compare agreement between observed and simulated discharge. Having evaluated the parameters, it is then possible to simulate river discharge following a rainfall-runoff event.

$$\mathbf{NS} = \mathbf{1} - \left(\frac{\sum_1^n EV}{\sum_1^n MV}\right) \tag{6}$$

$$\mathbf{RMSE} = \sqrt{\frac{\sum_1^n EV}{n}} \tag{7}$$

Where *EV* is error variance ((observed value - simulated value)$^2$), *MV* is mean variance ((observed value – mean observed value)$^2$) and *n* is number of observation days.

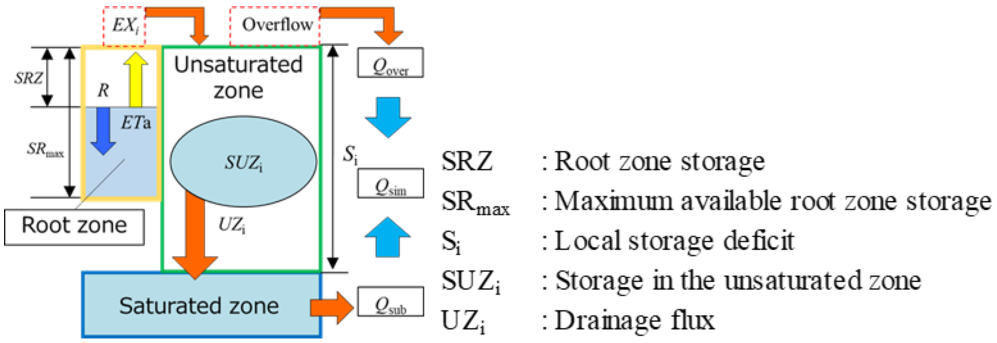


**Fig. 5 Schematic of TOPMODEL (Source: Mukae, et al., 2017)**

## Data Requirement

The input data for TOPMODEL is precipitation, river discharge and meteorological data used to estimate $ET_0$. Averaged daily data for 2015 was used. A rainfall event was defined as consecutive days of effective rainfall, and effective rainfall as that daily rainfall ≥ 5.0 mm (Ali and Mubarak, 2017).

From 2015-March-24 to 2015-December-14, 54 rainfall events were observed. Correspondingly, the total amount of precipitation, evapotranspiration and river discharge was

1,646 mm, 1,149 mm and 499 mm from where it was inferred that 30% of the precipitation is discharged to the downstream via the river.

### Description of Study-defined Terminologies and Methods

Table 1 is a representation of the *Sequentially Accumulated Rainfall Events* (*SARE*) concept. All the SARE had the same starting date but the end dates were variable.

The 'true' parameters were those derived from inputting *all SARE* in 2015 while 'non-true' parameters were those got by using *partial SARE* during model calibration. The 'true' parameters were considered to be optimal for full year hydrological simulation because they were assumed to represent an *average characteristic* of all observed events in 2015, which is not the case with 'non-true' parameters.

The percentage error of 'non-true' parameters was determined by comparison with the 'true' parameter value – The 'non-true' parameters with maximum error of ± 30% were classified as good and therefore close enough to 'true' value. Equation (8) shows computation of error of 'non-true' parameter,.

$$\boldsymbol{Error} = \left(\frac{\boldsymbol{ntp}-\boldsymbol{tp}}{\boldsymbol{tp}}\right) \times \mathbf{100\%} \tag{8}$$

where *ntp* is 'non-true' parameter value and *tp* is 'true' parameter value.

Parameterisation was done for SARE beginning with the $1^{st}$ event and sequentially progressing until all 54 rainfall events in 2015 were used. In total, model calibration was done 54 times. However, it was impossible to evaluate the $1^{st}$ event alone since its *NS* value was infinity. Results from 1 SARE were thus omitted from further analysis.

**Table 1 The SARE Concept**

| Rainfall event count | Sequentially Accumulated Rainfall Events (SARE) | | | | | | | Calculate unknown parameters ($m$, $T_e$, $t_d$, $SRZ_{initial}$ and $SR_{max}$) |
|---|---|---|---|---|---|---|---|---|
| 1 | 1st event | | | | | | → | non-true parameter value of 1 SARE |
| 2 | 1st event | 2nd event | | | | | → | non-true parameter value of 2 SARE |
| 3 | 1st event | 2nd event | 3rd event | | | | → | non-true parameter value of 3 SARE |
| . | . | . | . | | | | | . |
| . | . | . | . | | | | | . |
| . | . | . | . | | | | | . |
| 53 | 1st event | 2nd event | 3rd event | · · · | 53rd event | | → | non-true parameter value of 53 SARE |
| 54 | 1st event | 2nd event | 3rd event | · · · | 53rd event | 54th event | → | true parameter value |

*Yellow indicates the partial target rainfall event(s), which is used to calculate the unknown parameters for each SARE occurrence. Orange indicates all SARE.*

## RESULTS AND DISCUSSION

### Parameter Descriptive Statistics

**Table 2 'True' and 'non-true' parameters**

| | | $m$ | $T_e$ ($\times 10^6$) | $t_d$ | $SRZ_{initial}$ | $SR_{max}$ | $NS$ | $RMSE$ |
|---|---|---|---|---|---|---|---|---|
| 'true' value | | 24 | 762 | 0.013 | 0.006 | 0.008 | 0.57 | 0.73 |
| 'non-true' value | Min | 18 | 40 | 0.011 | 0.002 | 0.004 | 0.48 | 0.00 |
| | Max | 53 | 987 | 0.020 | 0.009 | 0.009 | 0.92 | 0.73 |
| | Mean | 21 | 587 | 0.017 | 0.006 | 0.007 | 0.68 | 0.53 |
| | s.d* | 5 | 257 | 0.003 | 0.001 | 0.001 | 0.10 | 0.19 |
| | CoV** | 0.25 | 0.44 | 0.16 | 0.24 | 0.16 | 0.15 | 0.36 |

* *Standard deviation,* ** *Coefficient of variance = Standard deviation / Mean*

Table 2 shows the descriptive statistics of the calibrated parameters. 'Non-true' parameter values vary from 18 to 53, 40 to 987, 0.011 to 0.020, 0.002 to 0.009 and 0.004 to 0.009 for parameters $m$, $T_e$, $t_d$, $SRZ_{initial}$ and $SR_{max}$ respectively. In addition, *NS* and *RMSE* varies from 0.48 to 0.92 and from

0.00 to 0.73 correspondingly. Based on the classification criterion of *NS* values by Foglia et al. (2009), the goodness of fit varies from 'good' to 'excellent'. The coefficients of variance (CoV) for 'non-true' parameters are 0.25, 0.44, 0.16, 0.24 and 0.16 for $m$, $T_e$, $t_d$, $SRZ_{initial}$ and $SR_{max}$ in that order. It follows that, $T_e$ and $SR_{max}$ are the most and least variable respectively. It is then clear that the 5 parameters are changeable depending on the number of rainfall events.

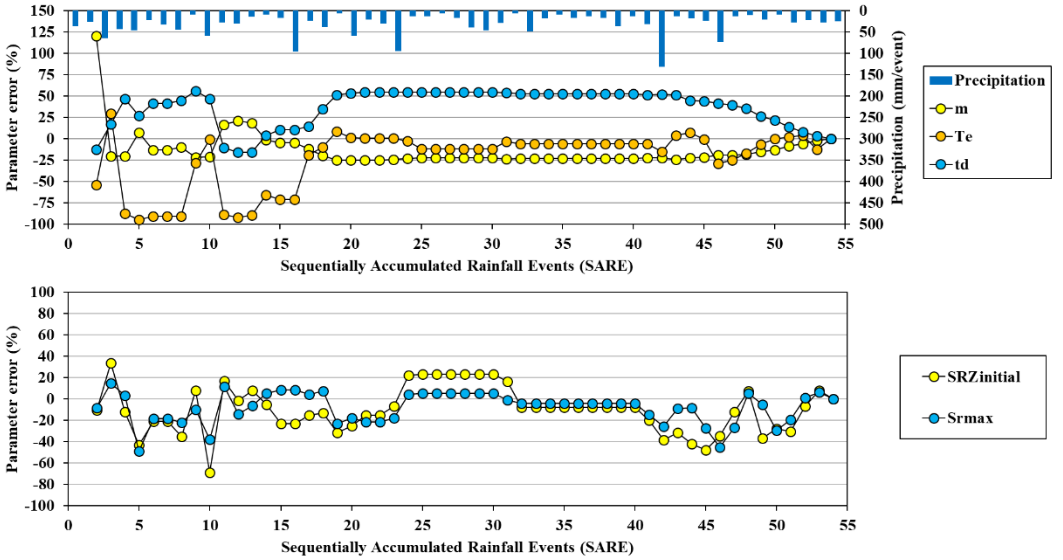


**Fig. 6 Error plots of calibrated parameters**

## Parameter Trends

Fig. 6 is a graph of the parameter error under different numbers of SARE conditions and Fig. 5 shows the trend of evaluation functions with the number of SARE.

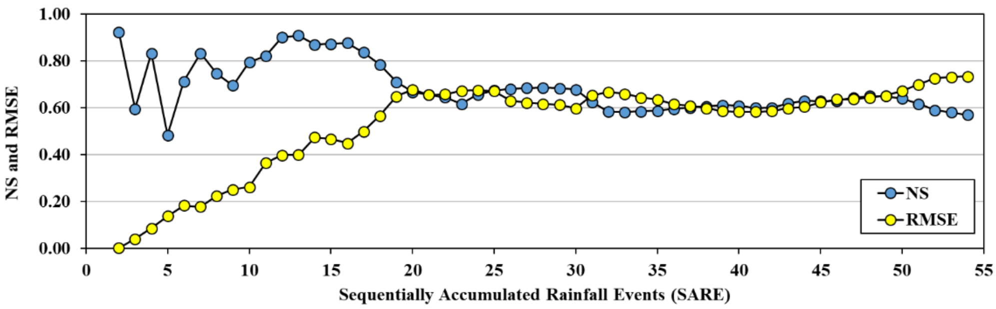


**Fig. 7 Evaluation function under different SARE**

The mean errors for $SR_{max}$, $SRZ_{initial}$, $m$, $T_e$ and $t_d$ are -8%, -10%, -13%, -23% and 37% correspondingly. It takes 3 SARE for parameter $m$ to stabilise within an error rage of ±30%. From 1 up to 16 SARE, $T_e$ is highly changeable, with error ranging from -95% to -54%. It requires at least 17 SARE to stabilise parameter $T_e$ within ±30% error range. The first instance of low observed event precipitation (9.4 mm at 10$^{th}$ event) seemed to cause $T_e$ value to increase sharply. From 1 up to 18 SARE, $t_d$ shows no observable trend, with error ranging from 4% to 56%. However, from 19 to 43 SARE, parameter $t_d$ stabilises within a narrow error range of 52% to 55%. The parameter value then begins to steadily decrease at 44 SARE, eventually falling within acceptable error range at 49 SARE. Although $SR_{max}$ and $SRZ_{initial}$ are the least variable parameters with respect to their means, there is no discernible trend of their behaviour with the number of SARE. This might be because of the gross uncertainties in calibrating soil storage deficits, as observed by Coles et al. (1997) and Campling et al. (2002). But, different from $T_e$, it is seen that there is a large reduction in both $SR_{max}$ (-38%) and $SRZ_{initial}$ (-69%) at 10 SARE.

*NS* and *RMSE* decrease and increase respectively with increasing SARE. It seems that as the number of SARE increases, the parameters become an average representation of many more varied rainfall characteristics, but not the best representation for each individual rainfall event.

Parameter $m$ is the least affected by the rainfall events inputted while parameter $t_d$ is the most affected, requiring at least 3 and 49 SARE respectively to stabilise within ±30% error bounds. Therefore, the minimum number of rainfall events required to calibrate TOPMODEL and to optimise $t_d$ in mid-sized equatorial catchments in Eastern Uganda are equivalent. Consequently, it requires at least 49 rainfall events to calibrate TOPMODEL in 2015.

Summarily, it is seen that rainfall characteristics influence the parameterization of TOPMODEL in mid-sized equatorial catchments.

## CONCLUSION

A hydrological model, TOPMODEL, was applied to a different number of *Successively Accumulated Rainfall Events* (*SARE*) to examine parameter sensitivity to rainfall characteristics. In this study we deduce the following: (1) Dependence of calibration parameters on rainfall characteristics was evident, with exponential decay parameter ($m$) being the least affected and delay time ($t_d$) being the most affected by rainfall event characteristics; Further, (2) in mid-sized equatorial catchments, $t_d$ was the determining parameter for the minimum number of SARE needed for calibrating TOPMODEL for yearly hydrological simulation. To confirm the observations presented here, more yearly observed hydro-meteorological data and studies on other catchments is needed. Furthermore, future studies should consider hydrological conditions like base flow, rainfall intensity and effective discharge in order to better understand the effect of rainfall events.

## ACKNOWLEDGEMENTS

The study was done during graduate studies at Tokyo University of Agriculture, Tokyo, Japan, courtesy of scholarship from Japan International Cooperation Agency (JICA), Japan.

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