AN APPROACH FOR OPTIMIZING HYDROLOGICAL PARAMETERS AT RIVER BASIN SCALE USING OPEN SENSOR NETWORKS

E.J. Warusavitharana[1], P.K.S. Mahanama[2], R. Ratnayake[3], B.H. Sudantha[4] and M. Cannata[5]
[1]Department of Town & Country Planning, University of Moratuwa, 10400 Moratuwa, Sri Lanka,
Email: emeshi@uom.lk
[2]Department of Town & Country Planning, University of Moratuwa, 10400 Moratuwa, Sri Lanka,
Email: mahanama@uom.lk
[3]Department of Town & Country Planning, University of Moratuwa, 10400 Moratuwa, Sri Lanka,
Email: rangajeewar@uom.lk
[4]Department of Information Technology, University of Moratuwa, 10400 Moratuwa, Sri Lanka,
Email: sudanthabh@uom.lk
[5]IST-DACD, University of Applied Sciences and Arts of Southern Switzerland (SUPSI), 6952 Canobbio, Switzerland,
Email: Massimiliano.cannata@supsi.ch

KEYWORDS: Parameter optimization, Warm-up period, Open sensor networks, 4ONSE, Deduru Oya basin

ABSTRACT: Manual and uneven distribution of hydro-meteorological stations, offline data, high cost of modeling software and state-owned stations' data, lack of trust in technology, and lack of expert knowledge, are the barriers that exist in most developing countries, which evade inclusion of hydrological modeling approaches for water resources management. As a solution for this, an open sensor network has been deployed in the Deduru Oya river basin of Sri Lanka to utilize open big data in the effective management of water resources. In absence of pre-determined parameter values for the river basin, the sub-catchment level parameter values for both wet and dry periods and daily and hourly time-steps have been estimated through inverse modeling approach, by way of fitting model simulations to observations. The model has been customized to utilize the estimated data of the weather generator to prevent the underutilization of open data in the stage of model stabilization.

1. INTRODUCTION

Hydrologic models represent parts of the hydrological cycle such as precipitation, evapotranspiration, infiltration, surface runoff, routing, and interflow/sub-surface flow, quantitatively. These quantitative measurements can be expressed in a water balance equation as variables. The equation expresses the balance between the water input and water output. Precipitation is the main source of water input that falls from the atmosphere as rain, snow, freezing rain, sleet, and hail. Evapotranspiration and surface runoff are the other processes associated with water output. The infiltration process represents the net loss of water which store as groundwater. In most hydrological models, the above hydrological processes are simulated by applying the input data such as rainfall, temperature, solar radiation, wind speed, relative humidity, and river discharge. Hydro-meteorological networks and satellite-based sensors are the key sources of providing these input data to run the hydrological model. However, most developing countries lack sufficient weather observing stations that provide continuous and near-real-time data for decision-making. As identified by Snow (2013), the commonly found challenges for a developing nation to maintain their weather network are inadequate funds, lack of locally available expertise knowledge, infrastructure and spare parts, and corrosion of electronic components.

Hence, during an emergency weather condition, getting a series of high temporal and spatial resolution dataset for modeling purposes becomes an issue. Thanks to the 4ONSE project (4 times Open and Non-Conventional technologies for Sensing the Environment), which was a joint research project between the University of Moratuwa, Sri Lanka, and the University of Applied Sciences and Arts of Southern Switzerland, an experimental sensor network has been deployed in Sri Lanka. This sensor network is comprised of 4 open-source components: hardware, software, standards, and data. The network was built on Arduino Mega 2560 open hardware platform. The communication part has been controlled by istSOS (Istituto Scienze Della Terra Sensor Observation Service) open-source software, which manages and dispatches observations of the stations as per the OGC-SOS (Open Geospatial Consortium-Sensor Observation Service) standard, in an interoperable way. The accuracy of the 4ONSE data has been checked with some reference stations' data in Sri Lanka and Switzerland before the application of those data in hydrological modeling (Sudantha, et.al, 2019; Strigaro, et.al, 2019). During the process of accuracy testing, the coefficient of determination was received as greater than 0.7 for all the main parameters at 10 minutes and daily time intervals.

All mathematical models in hydrology, which expresses as a function of time can be classified into several pairs as time-variant and time-invariant, stochastic and deterministic and, event-based and continuous. In time-invariant models, hydrological parameters are assumed as unchanging with time. Correspondingly, the deterministic models consider the same set of parameter values most of the time to simulate the outputs. However, in reality, hydrological parameters do not exist in constant form. Rather, they show temporal variation due to the changes in the climatic and geomorphological patterns. As any model parameter inherits stochasticity due to random changes in the environmental condition, the time-invariant and deterministic modeling approaches have now been considered obsolete. On contrary, stochastic models and time-variant models allow to incorporate parameter values as a range for different time scales. As stated by Abbaspour, et.al, (2018), "A stochastic model can be defined as a model that takes parameters in the form of a distribution and produces output variables in the form of a distribution". The third pair of event-based and continuous models can be distinguished based on the length of the simulation period. Event-based models usually consider single rainfall events with discrete rainfall pulses and require initial river discharge value to incorporate into the model. Conversely, continuous hydrological models necessitate a warm-up period to decide the initial condition of the catchment. A warm-up period is a mandatory option provided in some hydrological modeling tools such as SWAT (Soil and Water Assessment Tool), HYMOD (Hydrological MODel), IHACRES (Identification of unit Hydrographs And Component flows from Rainfall, Evaporation and Streamflow data), HBV-D (Hydrologiska Byråns Vattenbalansavdelning-D) and SWIM (Soil and Water Integrated Model). Berthet, et.al (2009) have identified warm-up period has a significant impact on the stability and convergence of the model. Depending on the saturation level of the soil, the warm-up period may range from one to several years. A lesser warm-up period is required in wetter periods, while a greater warm-up period is required in drier periods. However, the required time varies with land use, climatic condition, and the size of the basin.

Optimization of hydrological parameters which is also known as "parameterization", involves the identification of dominant parameters and their sensitive ranges of different spatial and temporal scales. Here, the temporal scale denotes the time-scale of the simulation – yearly, monthly, daily, hourly, sub-hourly, while the spatial scale denotes the spatial units of the model – catchments, sub-catchments, hydrological response units (HRU) with similar land uses, soil types and slopes. As the parameters which govern the hydrological processes differ with the geomorphological setup and the climatic condition of the watershed, their level of uncertainty is high. Hence, parameterization is the most cumbersome part of any hydrological modeling approach. Generally, the dominant parameters and their values are determined based on the previous field investigations and research conducted within and around the particular watershed area. Nevertheless, direct measurement of these parameters is cumbersome, time-consuming, labor-intensive, and expensive most of the time. Therefore, the most convenient way is to indirectly identify the dominant/sensitive parameters and estimating their values through model calibration, by way of fitting model simulations to observations (Zhang, et.al, 2014). This inverse modeling approach is more appropriate for hydrological models which operate as continuous models with long-term runs. As 4ONSE is a newly deployed network, it doesn't have adequate data for at least 2 years warm-up period. Hence, the objective of this research is to present an approach for optimizing the hydrological model parameters of a river basin where a new open sensor network exists, under the constraint of limited data available for the model warm-up period. The parameters were optimized at the sub-catchment scale for both daily and hourly intervals for both dry and wet periods. SWAT, SWAT weather generator, and SWAT-CUP (SWAT Calibration and Uncertainty Procedures) open-source tools have been used to develop the hydrological model, estimate the missing weather data of the warm-up period and optimize the model parameters respectively.

2. MATERIAL AND METHODS

2.1 The study area

The 4ONSE open sensor network has been deployed at Deduru Oya basin, which is the 4th largest river basin of Sri Lanka. The extent of the catchment is approximately 2687km^2 and there are 8 major reservoirs in the basin. Deduru Oya reservoir is the largest reservoir in the basin which is 75,000,000m^3 incapacity. It is located at the center of the basin and receives water from four streams (Deduru Oya, Kimbulwana Oya, Hakwatuna Oya, and Maguru Oya) which start from the central highlands. Accordingly, the upper watershed of the Deduru Oya basin can be further divided into four sub-catchments based on the four streams (Figure 1). Under the project, 27 weather stations and 6 river gauges have been deployed in the Deduru Oya river basin of Sri Lanka (Figure 2). As the hydrological parameters vary with rainfall pattern, the weather stations were deployed closer to the sub-basin's centroid at areas of high rainfall entropy values (Warusavitharana, et.al, 2018; Warusavitharana, 2020).

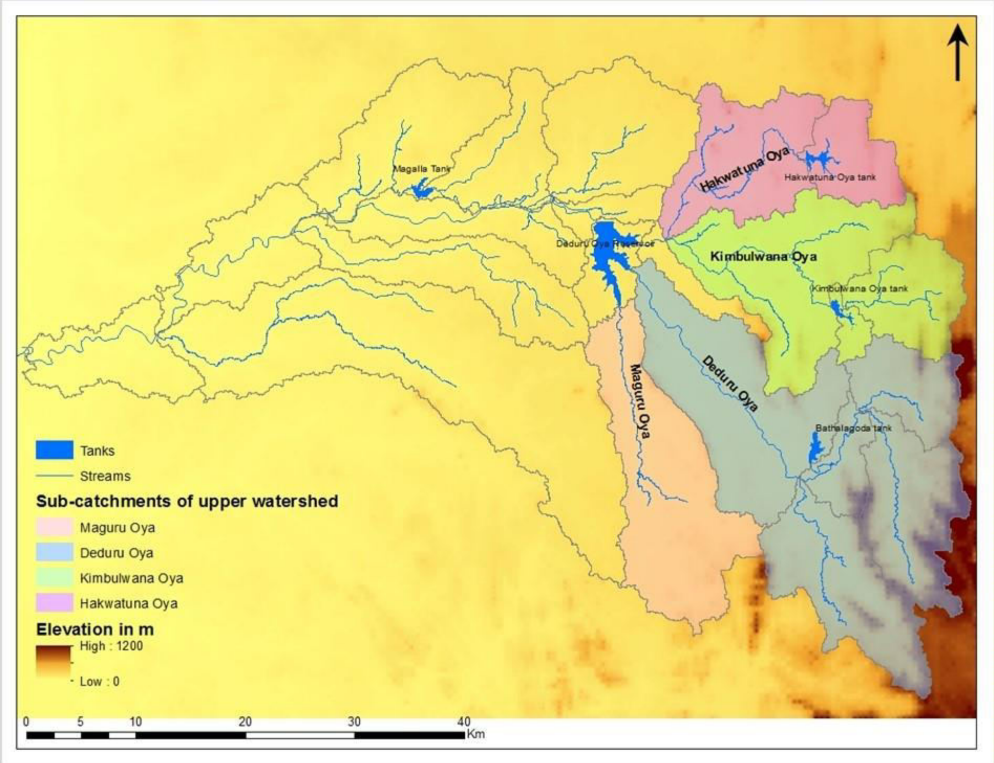


Figure 1: Upper sub-catchments of Deduru Oya watershed

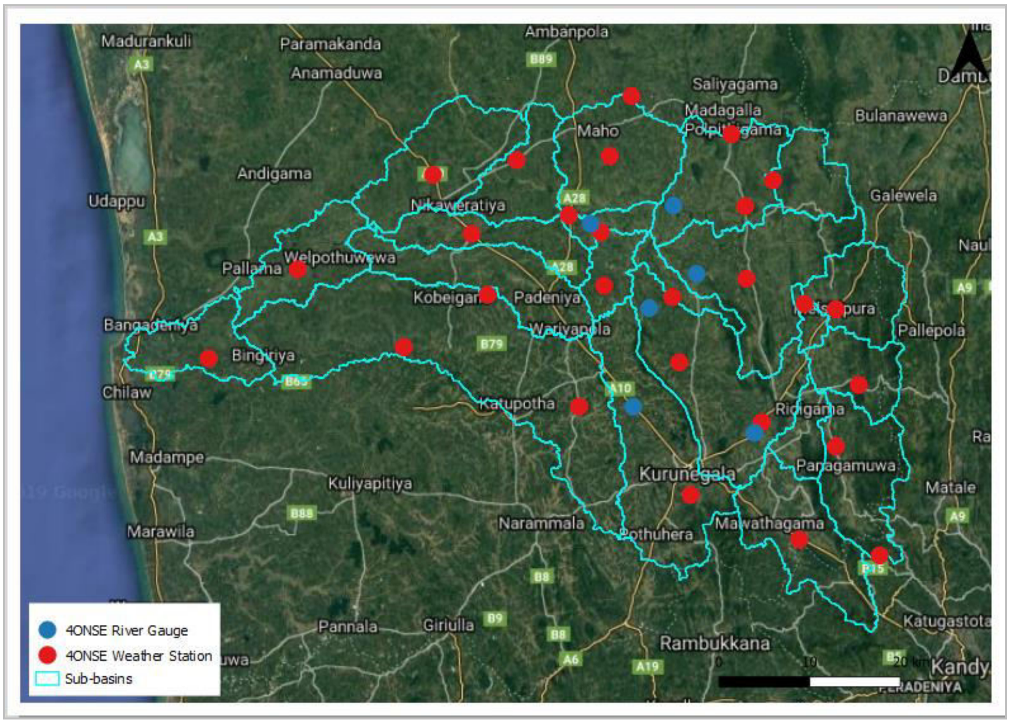


Figure 2: 4ONSE deployment at Deduru Oya basin

2.2 Application of open-source tools and data

The hydrological model required to optimize the model parameters has been developed in an open-source environment. The model development and parameterization have been primarily performed using the SWAT (Soil and Water Assessment Tool) hydrological modeling tool and its associated plugins and programs. Table 1 shows the different open-source tools used in this study and their applications. The details about the input data used in the model and their applications are given in Table 2.

Table 1: Open-source tools used in this study

Tool	**Application**
QGIS Brighton	• To process the vector and raster input data • The selected GIS interface to run the QSWAT plugin
QSWAT	• The plugin used in the QGIS software to run the SWAT model
SWAT Editor	• To read the project databases • To generate the missing weather data • To execute the SWAT run
SWAT-CUP	• To optimize the model parameters • To calibrate the model • To validate the model
istSOS	• To view and download the 4ONSE data

Table 2: Input data used in the SWAT model

No	**Input Data**	**Source & link**	**Resolution**	**Purpose**
01	Digital Elevation Model (DEM)	Shuttle Radar Topography Mission (SRTM) https://earthexplorer.usgs.gov/	1 arc second (approximately 30m)	To delineate the watershed and sub-basins boundaries
02	Stream Network	Produced by the Author	1:10,000	
03	Land use	Survey Department of Sri Lanka	1:50,000	To generate the Hydrological Response Units (HRUs)
04	Soil	FAO-UNESCO http://www.fao.org/geonetwork/srv/en/metadata.show?id=14116	1:5,000,000	
05	Historical weather data	Climate Forecast System Reanalysis (CFSR) https://globalweather.tamu.edu/	0.5 degree (approximately 55km) gridded dataset for the period of 1993 to 2013	To calculate the statistics to use in the SWAT's weather generator
06	Daily and hourly weather data	4ONSE weather stations https://geoservice.ist.supsi.ch/4onse/admin/	Sub-basin level	To run the model
07	Daily and hourly stream water levels	4ONSE river gauges https://geoservice.ist.supsi.ch/4onse/admin/ Irrigation Department	-	To calibrate the model

DEM and the digitized stream network were used to delineate the Deduru Oya catchment and sub-basin boundaries, based on 1% of the threshold. The threshold value denotes the percentage of cells in the DEM, need to form a stream. During the processes of watershed delineation, 22 sub-basins were received. However, considering the convenience of calibrating the model, the sub-basins of the upper catchment were grouped under four sub-catchments, based on the four streams of the upper catchment (Figure1). Land-use and soil layers were used to generate the HRUs. HRU is the smallest spatial unit in the model to compute the runoff. 4ONSE weather stations' data were applied to run the model. Rainfall, maximum and minimum temperature, solar radiation, relative humidity, and wind speed are the weather data need to run the model. SWAT's algorithms for infiltration, surface runoff, flow routing, impoundments, and lagging of surface runoff have been modified to allow flow simulations with a sub-daily time interval as small as one minute and, evapotranspiration, soil water contents, base flow, and lateral flow are estimated daily and distributed equally for each time step (Jeong, et.al, 2010). Therefore, when running the model at a sub-daily time interval, the precipitation data need to upload into the model at the sub-daily time step and all the other input data (maximum and minimum temperature, relative humidity, solar radiation, and wind speed) at a daily time step. The 4ONSE water level data were used to calibrate the model using SWAT-CUP standalone program. Before that, water level data were converted to discharge, based on Irrigation Department's stage-discharge relationship equations.

Since SWAT is a continuous model, the SUFI-2 (Sequential Uncertainties Fitting Version 2) inverse modeling approach has been applied to optimize the model parameters. Two years of the warm-up period have been assigned to stabilize the soil moisture condition. The 4ONSE is a newly deployed sensor network, in which the installation activities were completed in May 2019. Hence, the required data of the 2 years warm-up period were generated from SWAT's weather generator in SWAT editor. The model was customized to estimate the data during the warm-up period using the SWAT's weather generator. The relevant monthly weather statistics on rainfall, temperature, relative humidity, solar radiation, and wind speed, which are required to operate the weather generator have been calculated based on the historical gridded weather data of NCEP 's (National Centers for Environmental Prediction) CFSR (Climate Forecast System Reanalysis) database.

2.3 Simulation of hydrological processes in SWAT

In this study, hydrological processes were simulated at both daily and hourly time intervals. Penman-Monteith, Priestley-Taylor, and Hargreaves are the three options available in SWAT to compute the potential evapotranspiration (PET). Compared to the Priestly-Taylor method and Hargreaves method, in the Penman-Monteith method, four types of input weather data (air temperature, relative humidity, solar radiation, and wind speed) are used to estimate the PET. SWAT includes two methods to calculate the retention parameter in SCS (Soil Conservation Service) curve number method: soil moisture method and plant ET (evapotranspiration) method. A previous study conducted for the Deduru Oya basin has revealed that the soil moisture method is more capable of calculating the retention parameter of the Deduru Oya basin, as it is more dependent on soil storage (Warusavitharana, 2020).
SWAT provides two methods for estimating surface runoff: the SCS curve number (CN) method (SCS, 1972) and the Green and Ampt Mein Larson (GAML) excess rainfall method (Mein and Larson, 1973). CN method is an empirical model, which is based on the basic rainfall-runoff relationships of different land uses and soil types in a small rural watershed of the United States. GAML method is a physically-based model, which considers the direct relationship between infiltration and rainfall based on physical parameters allowing continuous surface runoff simulation (Jeong, et.al, 2010). Garen and Moore (2005) revealed, CN method is not suitable for simulating the continuous surface runoff at the sub-hourly interval, since it estimates the direct runoff using empirical relationships between the total rainfall and watershed properties. King et al. (1999) also suggest GAML is more appropriate for sub-hourly simulation than the CN method, due to its less bias over model prediction. Further, several studies (Wang & Yang, 2019; Yu, et.al, 2018; Bauwe, et.al, 2017; Boithias, 2017; Shannak, 2017; Yang, et.al, 2016) have revealed the better performance of GAML in simulating the peak flows during flashy storms. Hence, the GAML method has been chosen for sub-hourly surface runoff simulation. To simulate the runoff, the Muskingham method was applied as the stream network of the Deduru Oya basin follows a meandering pattern.

3.2 Parameter optimization

Parameter optimization or parameterization is a process of adjusting the model parameters to minimize the difference between simulated results and observation. As per the parameterization scheme in SWAT-CUP, three changes can be applied to the model parameters:

1) Type V - replacing the existing parameter value
2) Type A - given value is added to the existing parameter value
3) Type R - existing parameter value multiplied by (1+ given value)

SWAT_CUP usually recommends applying the type R for spatial parameters (parameters related to land use and soil properties). In addition, considering the convenience of examining more parameter space (value range), type R has been applied to parameters with a large range. For all the other parameters, type V has been applied.
SWAT model has more than 50 parameters and not all of them are useful in developing the hydrological model. Therefore, identification of dominant/sensitive parameters and their values are important to identify, before calibrating the model. SWAT-CUP program has two methods to identify the dominant/sensitive parameters: (1) One-at-a-time (OAT) local sensitivity analysis (2) All-at-a-time (AAT) global sensitivity analysis. OAT shows the sensitivity of a selected parameter if all the other parameters are kept constant at some value, while AAT shows the sensitivity of each parameter while allowing all other parameters to change. AAT produces sensitive parameters at the end of the analysis after performing a large number of runs with a statistically acceptable result. However, this study

intends to identify the sensitive parameters, before running the model. Hence, OAT analysis has been performed to identify the sensitive parameters. However, the limitation of OAT is that the sensitivity of one parameter is more often dependent on the values of other parameters and the parameter values which need to fix at the beginning are unknown (Abbaspour, et.al, 2018). The other limitation is, OAT requires considerable time to decide whether a parameter is sensitive or not, by specifying different parameter ranges. For example, suppose the range of a parameter is 0 – 20. The parameter might be sensitive for the 0 – 1 range, although it is insensitive for the entire 0 - 20 range. Therefore, considerable time was taken in this study to identify the sensitive parameters and their suitable parameter ranges through OAT analysis.

SWAT-CUP contains several methods to calibrate and uncertainty analysis of SWAT models. They are:

1) SUFI-2 (Abbaspour et.al, 2015)
2) GLUE (Beven and Binley, 1992)
3) ParaSol (Van Griensven and Meixner, 2006)
4) MCMC (Kuczera and Parent, 1998)
5) PSO (Kennedy and Eberhart, 1995)

In this study, the SUFI-2 (Sequential Uncertainties Fitting Version 2) algorithm was used to calibrate the model. SUFI-2 algorithm operates as an Inverse Modelling approach, in which the suitable parameter values are decided based on the observed streamflow/discharge. As it follows a stochastic modeling approach, a range of values is applied to parameters instead of single values. This algorithm suggests new parameter ranges at the end of each iteration. The suggested new parameter ranges are used to perform another iteration if the performance of the previous iteration is unsatisfactory. Accordingly, the selected sub-catchments have produced acceptable results (both visually and statistically) during the 4th iteration. Thus, the most suitable parameter ranges have been obtained at the 4th iteration. In this study, 500 runs were performed at each iteration. When performing more iterations, the parameter ranges become smaller and enlarge a better region of the parameter space (Abbaspour C., 2008).

SWAT-CUP contains several objective functions to determine the fitness of the model statistically. In this study, the fitness of the model has been tested through the Nash-Sutcliffe Efficiency method (NSE) given in Equation 1.

$$\textit{Maximize}: \qquad NSE = \frac{\sum_{i=1}^{n}(O_i - \bar{O})^2 - \sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2}$$ Equation 1

In addition, SWAT-CUP also measures the goodness of fit (R2), which ranges between 0 and 1 (Equation 2). This indicates the proportion of the variance in the measured data. The higher value indicates less error variance. Usually, $R^2 > 0.5$ is considered as acceptable (Van Liew, et.al., 2003; Santhi, et.al., 2001).

$$R^2 = \frac{\sum_{i=1}^{n}(O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}\sqrt{\sum_{i=1}^{n}(P_i - \bar{P})^2}}$$ Equation 2

Where n is the number of observations in the period under consideration, O_i is the ith observed value, $\bar{O}$ is the mean observed value, P_i is the ith model-predicted value, and $\bar{P}$ is the mean model-predicted value.

Further, in the SUFI-2 algorithm, the fitness between the simulated result and the observed values are expressed as 95PPU – 95% prediction uncertainty. Each simulation produces two statistics: P-factor and R-factor. P-factor is the percentage of observed data simulated in the model. Hence, (1 – P factor) is the percentage of observed data not simulated well in the model, in other words “model error”. R-factor is the thickness of the 95PPU envelope. It is calculated as per Equation 3:

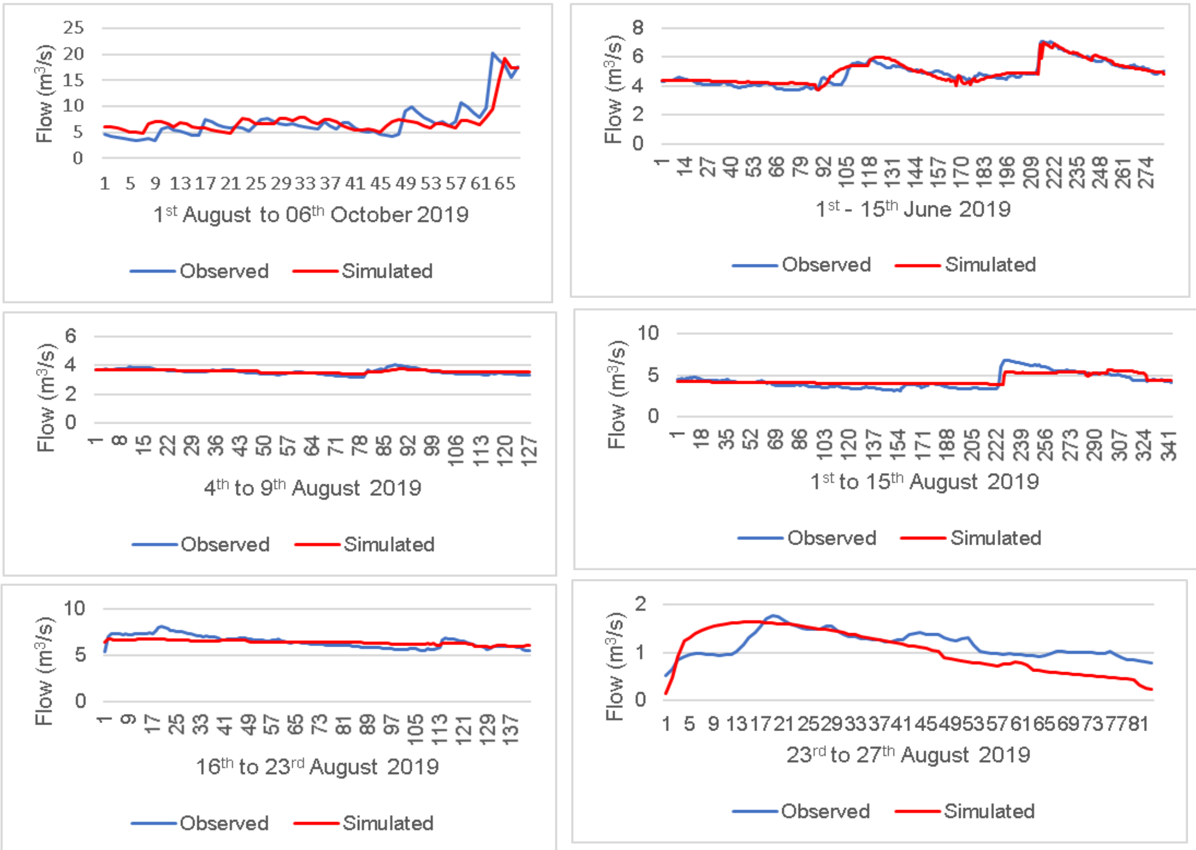
$$R - factor = \frac{\frac{1}{n_j}\sum_{t_{i=1}}^{n_j}\left(x_s^{t_i,97.5\%} - x_s^{t_i,2.5\%}\right)}{\sigma_{oj}}$$ Equation 3

Where $x_s^{t_i,97.5\%}$ and $x_s^{t_i,2.5\%}$ are the upper and lower boundary of the 95PPU at time step t and simulation t.

For model outputs related to discharge, SWAT-CUP recommends P-factor greater than 70%, while having an R-factor of around 1. It gives the P-factor and R-factor the best simulation. The subsequent section shows the results of the parameter optimization done for the largest sub-catchment of the basin, which is the Deduru Oya sub-catchment. Compared to the other three sub-catchments, the Deduru Oya reservoir receives the largest inflow from the Deduru Oya sub-catchment.

4. RESULTS AND FINDINGS

Initially, the performance of the hydrological model was tested at daily time step. The default parameter values in the SWAT model and the daily 4ONSE data were used for this initial run. However, due to the significance difference in the simulated flow and the observed flow, the model was regionalized first by examining the stream flow signatures. Then the parameters were optimized for the hourly time step. The stream flow simulated by the SWAT at daily and hourly time step by applying the optimized parameters relevant to particular time step are illustrated in Figure 3. The



statistical results related to simulated results are given in Table 3. The model could not be further validated for daily time-step due to the unavailability of continuous dataset after the month of October. As per the statistical results given in Table 3, the performance of the model in simulating the hydrological processes at daily and hourly time steps is satisfactory. The Davis rain gauge used in the 4ONSE weather stations usually have an error percentage of ±4% for rain rates up to 50mm/hour and ±5% for rain rates within the range of 50mm/hr to 100mm/hr. This is the main causative factor for why some of the peaks was unable to reach to its level.

Figure 3: Simulated results of the hydrological model, after application of 4ONSE data

Table 3: Statistical results related to daily and hourly simulation

Period	Daily / Hourly	P factor	R factor	R^2	NSE
1st August to 6th October 2019	Daily	0.87	0.98	0.69	0.69
1st to 15th June 2019	Hourly	0.96	0.76	0.76	0.75
15th to 30th June 2019	Hourly	0.96	0.89	0.89	0.88
4th to 9th August 2019	Hourly	1.0	0.53	0.77	0.55
1st to 15th August 2019	Hourly	0.74	0.54	0.67	0.63
16th to 23rd August 2019	Hourly	0.83	0.00	0.67	0.43

The sensitive parameters at both daily and hourly time-steps have been showed in Table 4 and 5 respectively.

Table 4: Sensitive parameters and their ranges at daily time step

Parameter	**Description**	**Optimum range**
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur	0.96 – 1.38
CN2	Initial SCS runoff curve number for moisture condition II)	(-0.14) – (-0.03)
CH_N2	Manning's "n" value for main channel	0.07 – 0.11
CH_N1	Manning's "n" value for the tributary channels	0.49 – 0.74
ALPHA_BNK	Baseflow alpha factor for bank strorage (days)	(-0.02) – 0.31
CH_K2	Effective hydraulic conductivity in main channel alluvium	25.57 – 39.70
ESCO	Soil evapotranspiration compensation factor	0.41 – 0.64

Table 5: Sensitive parameters and their ranges at hourly time step

Parameter	**Description**	**Optimum range**
CN2	Initial SCS runoff curve number for moisture condition II)	(-0.3) – 0.1
SOL_BD	Moist bulk density	(-0.08) – 1.77
MSK_X	Weighting factor for wedge storage	0 – 0.1
MSK_CO2	Muskingum coefficient for low flow	0 – 8.1
MSK_CO1	Muskingum coefficient for normal flow	1.0 – 5.2
ALPHA_BF	Baseflow alpha factor	0 – 0.2
SOL_K	Saturated hydraulic conductivity	(-0.47) – (-0.04)
SURLAG	Surface runoff lag coefficient	(-0.5) – 1.0
CH_K2	Effective hydraulic conductivity in main channel alluvium	1.1 – 27.3
CH_N1	Manning's "n" value for the tributary channels	(-0.3) – 0.7
CH_N2	Manning's "n" value for main channel	0 – 0.7
GW_REVAP	Groundwater "revap" coefficient	0.1 – 0.2
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur	0.8 – 2.0

Several parameters such as SOL_AWC (available water capacity of the soil layer), ESCO (soil evapotranspiration compensation factor), GW_DELAY (ground water delay time) and SURLAG (surface runoff lag coefficient) parameters have shown sensitivity only for hourly simulation. As the time narrows down to hours, the contribution of SOL_AWC, ESCO and GW_DELAY parameters have become insignificant and the SURLAG parameter, which characterizes the time of concentration at HRU level, has become significant in simulating the hourly flows. In SWAT database, the default value of SURLAG parameter is 4.0. The model recommends that the actual range of SURLAG varies within 0 – 1, which denotes more water is held in storage. SOL_AWC is a soil parameter which expresses the available water capacity of the soil layer for plants. This parameter has shown more sensitivity during daily time step due to the reasons of low clay content, greater depth of wetting and high rate of evapotranspiration in the basin area. ESCO parameter represents the soil evaporation compensation factor. As the SWAT's algorithms for evapotranspiration is estimated on daily basis and distributed equally for sub-daily time step, the sensitivity of ESCO parameter can be seen only during daily time step. The default value of ESCO in SWAT database is about 0.95. However, the optimization results suggest the value of ESCO could be lower than 0.95, which implies the possibilities of extracting more of the evaporative demand from lower levels. GW_DELAY is the next parameter which shows sensitivity only at daily time step. It represents the groundwater delay time which is the time taken to travel from bottom of the soil profile to shallow aquifer through vadose zone after the rainfall. Usually GW_DELAY expresses in days due to the slow movement of water. Accordingly, during the parameter optimization, SUFI2 algorithm in the SWAT-CUP program produced a range of parameter values, instead of single values. Owing to heterogeneity of parameters, the same set of parameters cannot be used continuously to produce the simulations. Hydrological parameters often cause for changes as a result of changes in the climatic and geographic processes.

5. CONCLUSION

The main objective of this study is to demonstrate the potential of the fully open-source framework in optimizing the parameters at river basin scale. Five types of open-source tools (QGIS Brighton version, QSWAT, SWAT Editor, SWAT-CUP, istSOS) have been used to develop the hydrological model. The input data of the model has been obtained from 4ONSE open-source network, which has been built from three open-source technologies (Open hardware – Arduino, Open software – istSOS, Open standards – OGS-SOS). The hydrological model presented in this research follows the stochastic modelling approach during the model parameterization. Therefore, the same set of parameters cannot be applied for the model for every occasion. Estimation of variation of parameter values with reference to different time periods (i.e. rainfall seasons, months) is tiresome, time consuming and labor and capital intensive. However, the approach presented in this research avoids the necessity of pre-determined parameter values and allows users to determine them at any time. As the deterministic modelling approach has now been considered as outdated, the stochastic hydrological modelling approach presented in this research can be used to estimate the parameter values suitable for different time periods or different rainfall intensities. Over the last few decades, different researchers, practitioners and hobbyists have developed open hardware and software-based stations for environmental monitoring. However, application of combined open-source platforms to collect, store, sort, process and analyze data to support hydrological modelling at river basin scale have not been found in the literature as yet. Therefore, this is the initial study which was utilized combined open-source technologies, for parameter optimization at river basin scale.

5. REFERENCES

Abbaspour, C., 2008. SWAT calibrating and uncertainty programs. SWAT-CUP user manual. Switzerland: Eawag Zurich.

Abbaspour, K., Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H., & Klove, B., 2015. A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high resolution large-scale SWAT model. Journal of Hydrology, 524, 733-752.

Abbaspour, K., Vaghefi, S., & Srinivasan, R., 2018. A guideline for successful calibration and uncertainty analysis for soil and water assessment: A review of papers from the 2016 International SWAT conference. Water, 10(6), 1-18. doi:10.3390/w10010006

Bauwe, A., Tiedemann, S., Kahle, P., & Lennartz, B., 2017. Does the temportal resolution of precipitation input influence the simulated hydrological components employing the SWAT model? Journal of the American Water Resources Association, 53(5), 997-1007.

Berthet, L., Andreassian, V., Perrin, C., & Javelle, P., 2009. How crucial is it to account for the antecedent moisture conditions in flood forecasting? Comparison of event-based and continuous approaches on 178 catchments. Hydrology and Earth System Sciences Discussions, 13, 819-831.

Beven, K., & Binley, A., 1992. The future of distributed models: model calibration and uncertainty prediction. Hydrological processes, 6(3), 279-298.

Boithias, L., Sauvage, S., Lenica, A., Roux, H., Abbaspour, K., Larnier, K., Sanchez-Perez, J., 2017. Simulating flash floods at hourly time-step using the SWAT model. Water, 9(12), 929.

Garen, D., & Moore, D., 2005. Curve number hydrology in water quality modelling: Uses, abuses, and and future directions 1. Journal of the American Water Resources Association, 41(2), 377 - 388.

Jeong, J., Kannan, N., Arnold, J., Glick, R., Gosselink, L., & Srinivasan, R., 2010. Development and integration of sub-hourly rainfall-runoff modeling capability within a watershed model. Water Resources Management, 24(15), 4505-4527.

Kennedy, J., & Eberhart, R., 1995. Particle swarm optimization. In Proceedings of ICNN'95 - International Conference on Neural Networks, 4, pp. 1942 -1948.

King, K., Arnold, J., & Bingner, R., 1999. Comparison of Green-Ampt and curve number methods on Goodwin Creek watershed using SWAT. Transactions of the ASAE, 42(4), 919.
Kuczera, G., & Parent, E., 1998. Monte Carlo assessment of parameter uncertainty in conceptual catchment models: The Metropolis algorithm. Journal of Hydrology, 34(4), 1681-1619. doi:10.1214/009053606000000515
Mein, R., & Larson, C., 1973. Modelling infiltration during a steady rain. Water resources research, 9(2), 384 - 394.
Santhi, C., Arnold, J., Williams, J., Dugas, W., Srinivasan, R., & Hauck, L., 2001. Validation of the swat model on a large river basin with point and nonpoint sources. Journal of the American Water Resources Association, 37(5), 1169-1188.
SCS, US., 1972. National engineering handbook. In Hydrology Section 4.
Shannak, S., 2017. Calibration and Validation of SWAT for sub-hourly time steps using SWAT-CUP. International Journal of Sustainable Water and Environmental Systems, 9(1), 21-27.
Snow, J. T., 2013. Non-Traditional Approaches to Weather Observations in Developing Countries.
Strigaro, D., Cannata, M., & Antonovic, M., 2019. Boosting a weather monitoring system in lowincome economies using open and non-conventional systems: Data quality analysis. Sensors, 19(5)
Sudantha, B.H., Warusavitharana, E.J., Ratnayake, R., Mahanama, P.K.S., Warusavitharana, R.J., Tasheema, R.P., Cannata, M. and Strigaro, D., 2019. 4ONSE as a complementary to conventional weather observation network. 4th International Conference on Information Technology Research (ICITR), University of Moratuwa, Sri Lanka.
van Griensven, A., & Meixner, T., 2006. Methods to quantify and identifu the sources of uncertainty for river basin water quality models. Water Science and Technology, 53(1), 51-59.
Van Liew, M., & Garbrecht, J., 2003. Hydrologic simulation of the Little Washita River experimental watershed using SWAT. Journal of American Water Resources Association, 39, 413-426.
Wang, K., & Yang, X., 2019. The Comparison of Two Empirical Runoff Yield Models and Three Physical Models. . DEStech Transactions on Computer Science and Engineering
Warusavitharana, E. J., 2020. Semi-distributed parameter optimization and uncertainty assessment for an ungauged catchment of Deduru Oya Basin in Sri Lanka. International Journal of River Basin Management, 18(1), 95-105.
Warusavitharana, E., Ratnayake, R., Mahanama, S. and Cannata, M., 2018. An approach to determine the optimum spatial distribution of hydrometeorological stations for hydrological modelling: 4ONSE deployment. 39th Asian Conference on Remote Sensing (ACRS 2018). 15 – 19 October 2018, Kuala Lumpur, Malaysia
Yang, X., Liu, Q., He, Y., Luo, X., & Zhang, X., 2016. Comparison of daily and sub-daily SWAT models for daily streamflow simulation in the Upper Huai River Basin of China. Stochastic environmental research and risk assessment, 30(3), 959-972.
Yu, D., Xie, P., Dong, X., Hu, X., Liu, J., Li, Y., & Xu, S., 2018. Improvement of the SWAT model for event-based flood simulation on a sub-daily timescale. Hydrology and Earth System Sciences, 22(9), 5001-5019.