ENGINEER - Vol. LVI, No. 01, pp. [11-20], 2023

DOI: http://doi.org/10.4038/engineer.v56i1.7556

Temporal Transferability of Calibrated Hydrological Model Parameters: A Case Study of Gin Catchment, Sri Lanka

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Abstract: Lack of observed data for model calibration hinders the application of hydrological models in many poorly-gauged catchments, particularly in the humid tropical region. Despite much less attention given, it is vital to assess transferability of calibrated parameters in order to apply hydrological models in such catchments to assist their water resources planning and management activities. Thus, this study investigated temporal transferability of a lumped conceptual hydrological model's (MIKE 11 NAM) calibrated model parameters for rainfall-runoff simulations in two different time periods beyond its calibration period. Study area was selected as Gin catchment located in the humid tropical region. MIKE 11 NAM model was calibrated for the period 1995-1998 [Nash Sutcliffe coefficient (NSE) = 0.73, percent bias (PBIAS) = 3.9%, ratio of the root mean square error to the standard deviation of measured data (RSR) = 0.52] and validated for the period 1999-2002 (NSE=0.66, PBIAS = 8.7%, RSR = 0.59) for the Gin catchment. The temporal transferability of the calibrated model parameters was tested using two scenarios which formulated based on the temporal lag between the calibration period and the transfer period: scenario A having a 4-year time lag and scenario B having a 8-year time lag. Scenario A which evaluated the model performance using 2003-2006 streamflow data indicated only a marginal loss in the model performance in comparison to the calibration. It showed an overall 'good' performance (NSE=0.64, PBIAS = 8.6%, RSR = 0.59) including promising capability to reproduce the peak flows (<10th percentile) with Pearson's correlation coefficient of 0.6. However, scenario B which evaluated the model performance using 2007-2010 streamflow data indicated 'unsatisfactory' model performance (NSE=0.42, PBIAS = 13.6%, RSR = 0.76). Therefore, this study suggests that the calibrated parameters of MIKE 11 NAM model can be temporally transferred within a catchment with a 4-year time lag from the calibration period implying the applicability of this modelling framework for rainfall-runoff simulations especially in the catchments where streamflow data is sparse.

Keywords: Calibrated parameters, MIKE 11 NAM, Model performance, Rainfall-runoff, Temporal transferability

1. Introduction

Streamflow simulation is a widely used technology in the field of hydrology which assists water managers to plan, design, and manage water resource systems effectively. A wide range of mathematical models has been setup for rainfall-runoff simulation following the advent of the computer revolution in 1960s which elevated the field of hydrologic modelling to a new level [1]. Rainfall-runoff simulation models need a range of catchment specific parameters and hydro-meteorological input data including observed streamflow data. However, in most instances, the observed streamflow data are either unavailable or inadequate in quantity and quality in the context of spatial, temporal and spatio-temporal scales. Catchments with these types of unavailability or inadequacy of data can be considered as un-gauged catchments and according to Sivapalan et al. [2], most of the catchments around the world are either un-gauged or poorly-gauged.

Researchers showed interest to study runoff simulations in the un-gauged or poorly-gauged catchments by transferring the model parameters spatially, temporally or spatio-

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temporally; Blöschl and Sivapalan [3] identified the process of transferring model parameters to an un-gauged catchment from a hydrologically similar catchment using regionalization; as revealed by Merz et al. [4], in the concept of hydrological similarity based on the spatial proximity and catchment attributes, the catchment conditions varied smoothly across space and the catchments located close by behaved approximately similarly during a particular hydrologic event; Makungo et al. [5] showed reasonable results for runoff simulation in the un-gauged Nzhelele River catchment using MIKE 11 NAM and Australian Water Balance Model (AWBM) by transferring the parameters calibrated for the neighbouring Tshiluvhadi catchment in South Africa using the regionalization of parameters based on the spatial proximity and similarity of catchment attributes; Odiyo et al. [6] also followed a regionalization approach based on the spatial proximity using the lumped conceptual MIKE 11 NAM model to estimate the flow contributions to Luvuvhu River from Latonyanda River, downstream of Albasini Dam in South Africa; Apaydin et al. [7] used SLURP model to test the temporal transferability of model parameters for the Aksu basin in the Black Sea region in Turkey; Patil and Stieglitz [8] compared three parameter transfer schemes for two hundred and ninety four catchments in United States of America using EXP-HYDRO model which is a lumped model and identified the temporal transfer of parameters as the best scheme in comparison to the spatial and spatio-temporal schemes.

However, runoff simulation in un-gauged catchments is a relatively new area of study in Sri Lanka. In Sri Lanka, only a handful of studies has been conducted on runoff estimations in un-gauged or poorly-gauged catchments; Rajendran et al. [9] used watershed area ratio technique when simulating the un-gauged Hakwatuna Oya catchment in upper Deduru Oya basin by using HEC-HMS model and WEAP model calibrated and validated for Tittawella catchment. Jayasinghe and Rajapakse [10] used a spreadsheet based rainfall-runoff model to simulate the runoff in Erewwala catchment in Bolgoda River basin using the parameters which were calibrated for Kalu Ganga basin. Lakmali [11] compared three parameter transfer schemes, temporal, spatial and spatiotemporal, for Kalu River basin in Sri Lanka using a two-parameter monthly water balance model. Thus, research gaps of the existing studies for Sri Lanka demand application of a conceptual model to test the parameter transferability. Moreover, limited number of studies used the conceptual models to test the transferability of the model parameters in the temporal context in catchments located in humid tropical regions and MIKE 11 NAM lumped conceptual model has not been tested for the parameter transferability for Sri Lankan catchments. Therefore, this study focused on assessing the temporal parameter transferability of a lumped conceptual model, MIKE 11 NAM, by applying it to the Gin catchment, Sri Lanka. Gin River is the main source of drinking water supply to the Galle city, the capital city of Southern province of Sri Lanka. One of the major drinking water extraction points in the Gin River is located at Baddegama and daily streamflow data at Baddegama discharge gauging station was used for calibration of the model parameters in this study. Thus, the calibrated parameter values could be used for setting up of hydrological models to carry out future water resources assessment activities in the catchment.

2. Materials and Methods

2.1 Study Area and Data

This study focused on the upstream of the Gin River's catchment, lying approximately between 80°08" E to 80°40" E and 6°03" N to 6°26" N. The Gin catchment has a total drainage area of about 930 km^2 and the overall difference in the elevation is more than 1300 m. The Gin catchment is characterized by strong monsoonal rainy seasons, south west monsoon (between May and September) and north east monsoon (between November and February) followed by inter-monsoon rains during the remaining months of the year. Rainfall ranges from 2500 mm/year in the flood plains to over 3500 mm/year in the mountainous regions. Average temperature in the catchment varies between 24°C and 32°C with high humidity levels.

The catchment can be classified into three distinct landscape types, i.e., the lowlands, the midlands and the uplands. Soils in the catchment comprise Red Yellow Podzolic soil covering most of the uplands and midlands while alluvial, bog and half-bog soil types along streams and in the lowlands [12]. The catchment of the Gin River is rather a natural catchment in Sri Lanka having a natural rainforest and wildlife reserve covering considerable area in the uplands and the midlands. The lowlands and midlands are characterized by rain-fed paddy and other export-oriented crop cultivations, and settlements [13]. The present study addressed the catchment area which is upstream of the Baddegama discharge gauging station (6°11'23" N, 80°11'53" E) having an area of 780 km^2. Figure 1 illustrates the location of the Gin catchment, stream network and Baddegama discharge gauging station.

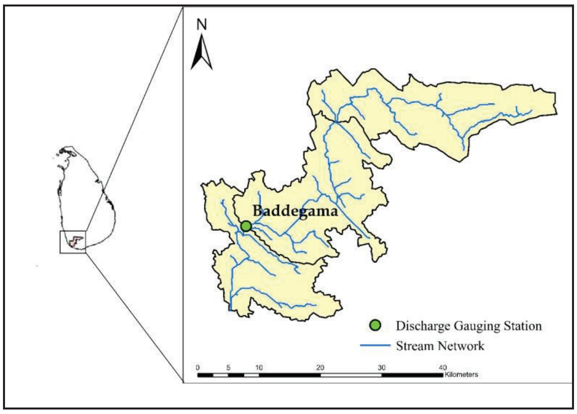

Figure 1 - Location of the Gin Catchment, Stream Network and Baddegama Discharge Gauging Station

Daily streamflow data at Baddegama discharge gauging station (1995-2010) were obtained from the Department of Irrigation, Sri Lanka. Daily evaporation data at Deniyaya and daily rainfall data at Anninkanda, Kudawa, Hiniduma, Baddegama and Labuduwa were obtained from the Department of Meteorology, Sri Lanka, covering the period 1995-2010. The Thiessen polygon method was used to calculate the mean areal rainfall. The Shuttle Radar Topographic Mission (SRTM) Digital Elevation Model (DEM) with 3 arc second resolution was used to delineate the Gin catchment [14]. Year 1999 land use map of the Gin catchment having 1:10,000 scale was collected from the Survey Department, Sri Lanka.

2.2 Hydrological Model

This study applied the Nedbør-Afstrømings-Model (NAM), a lumped conceptual module built in MIKE 11, to simulate rainfall-runoff in a continuous mode. The model has been successfully applied by previous researchers for hydrological investigations in many catchments including the catchments in Sri Lanka: rainfall-runoff simulations [15], [16], [17], model performance evaluation studies [18], land use change impact assessments on flood formations [19], and runoff simulations in un-gauged catchments [5], [6].

A lumped, conceptual rainfall-runoff model, MIKE 11 NAM, considers the catchment as a single entity. The model structure of the NAM is shown in Figure 2 [20]. The land phase of the hydrological cycle is imitated there. Different physical elements of the catchment that represent four mutually interrelated storages, namely, surface storage, snow storage, groundwater storage, and root zone storage, are used in the NAM rainfall-runoff process. Catchment runoff and the temporal variation of the soil moisture content, evapotranspiration, groundwater recharge, and groundwater levels are produced by the NAM and the catchment runoff is split conceptually into three components: overland flow, interflow and baseflow [21].

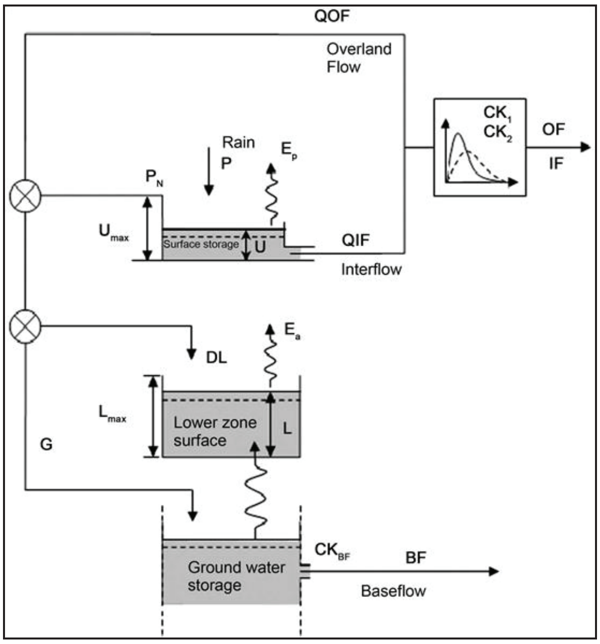

Figure 2 - Model Structure of the NAM [20]

In Figure 2, P is precipitation, E_p is potential evapotranspiration, E_a is actual evapotranspiration, U_{max} is maximum water content in surface storage, L_{max} is maximum water content in root zone storage, P_N is excess water, L is moisture content in the root zone storage, U is moisture content in surface storage, CK_1 and CK_2 are time constants for routing overland flow, G is infiltrating water, QIF is interflow, QOF is overland flow, BF is baseflow and CK_{BF} is time constant for routing the base flow.

2.3 Performance Criteria for the Hydrological Model

Graphical techniques [22] and statistical measures including Nash-Sutcliffe efficiency (NSE) [Eq.(1)] [23], percent bias (PBIAS) ([Eq.(2)] [24] and root mean square error (RMSE) - observations standard deviation ratio (RSR) [25] were selected according to Moriasi et al. [26] for evaluation of model performance during calibration, validation and scenario evaluation. RSR was calculated as the ratio of RMSE and standard deviation of measured data, as shown in Eq.(3). The NSE ranges from $-\infty$ to 1, determining the relative magnitude of the residual variance compared to the measured variance. According to Dobler et al. [27], it is particularly suitable for measuring the performance of high flows. A PBIAS of 0 represents a perfect fit. The PBIAS is a measure for the total volume differences between measured and observed data; a positive value indicates model underestimation, and negative values indicate model overestimation. RSR standardizes RMSE using the observations standard deviation, and it combines both an error index and the additional information recommended by Legates and McCabe [22]. RSR varies from the optimal value of zero which indicates perfect model simulation, to a large positive value. Lower RSR and lower RMSE indicate better model performance [26].

$$NSE = 1 - \left(\frac{\sum_{i=1}^{n} (Y_i^{obs} - Y_i^{sim})^2}{\sum_{i=1}^{n} (Y_i^{obs} - Y_i^{mean})^2} \right) \quad (1)$$

$$PBIAS = \left(\frac{\sum_{i=1}^{n} (Y_i^{obs} - Y_i^{sim}) \times 100}{\sum_{i=1}^{n} (Y_i^{obs})} \right) \quad (2)$$

$$RSR = \frac{RMSE}{STDEV_{obs}} = \frac{\left[\sqrt{\sum_{i=1}^{n} (Y_i^{obs} - Y_i^{sim})^2} \right]}{\left[\sqrt{\sum_{i=1}^{n} (Y_i^{obs} - Y_i^{mean})^2} \right]} \quad (3)$$

In the above equations, Y_i^{obs}, Y_i^{sim} and Y_i^{mean} are i^{th} observed streamflow, i^{th} simulated streamflow and mean of the observed streamflow, respectively, and n is the total number of streamflow observations.

2.4 Model Calibration, Validation and Evaluation Processes

In hydrologic modelling studies, proper model calibration is important to reduce uncertainty in model simulations. Ideal model calibration involves use of data that includes wet, average, and dry years [28] and use of multiple evaluation techniques [20], [22]. In this study, the parameters related to surface, root zone and groundwater storages were calibrated against time series of streamflow observations. The typical value range for each calibration parameter is shown in Table 1. The calibrated model parameters were obtained by two approaches: the automatic parameter estimation approach, Shuffled Complex Evolution (SCE) algorithm [29] and the manual approach, trial-and-error procedure. Auto calibration was set under the two objective functions: overall volume error [$F_1(\emptyset)$] [Eq.(4)] and overall root mean square error [$F_2(\emptyset)$] [18] [Eq.(5)].

The NAM model was calibrated and validated by continuous runoff simulations. Split sampling technique was used for the model calibration and validation. The periods 1995-1998 and 1999-2002 were used for the model calibration and validation, respectively, while the periods 2003-2006 and 2007-2010 were used for the model evaluation under scenario A and scenario B, respectively.

Table 1 - Parameter Range Used for Model Calibration

Parameter	Lower bound	Upper bound
Maximum water content in surface storage U_{max} (mm)	10	20
Maximum water content in root zone storage L_{max} (mm)	100	300
Overland flow runoff coefficient CQOF	0	1.0
Time constant for routing interflow CKIF (hour)	200	1000
Time constant for routing overland flow $CK_{1,2}$ (hour)	10	50
Rootzone threshold value for overland flow TOF	0	0.99
Rootzone threshold value for interflow TIF	0	0.99
Root zone threshold vale for Ground water recharge TG	0	0.99
Time constant for routing recharge CK_{BF} (hour)	1000	4000

$$F_1(\emptyset) = \left| \frac{1}{n} \sum_{i=1}^{n} \left[Y_i^{obs} - Y_i^{sim}(\emptyset) \right] \right| \quad (4)$$

$$F_2(\emptyset) = \left[\frac{1}{n} \sum_{i=1}^{n} \left[Y_i^{obs} - Y_i^{sim}(\emptyset) \right]^2 \right]^{\frac{1}{2}} \quad (5)$$

where, Y_i^{obs} is i^{th} observed streamflow, Y_i^{sim} is i^{th} simulated streamflow, $\emptyset$ is the set of model parameters to be calibrated, and n is the number of time steps in the calibration period.

2.5 Temporal Transfer of Model Parameters

The MIKE 11 NAM model was tested for the temporal transferability of calibrated model parameters for two different time periods using two scenarios: scenario A having a 4-year time lag and scenario B having a 8-year time lag from the calibration period, respectively. Model parameters from the calibration period (1995-1998) were transferred to scenario A which evaluated the model performance using 2003-2006 flow data and scenario B which evaluated the model performance using 2007-2010 flow data. In both scenarios, it was assumed that no significant changes occur among environmental variables between the calibration period and the transfer periods.

3. Results and Discussion

3.1 Model Calibration and Validation Results

The optimum values of the model parameters obtained during the calibration procedure are outlined in Table 2. The parameter values fall within the ranges recommended by DHI [30]. Overall, the MIKE 11 NAM model simulated the timing and the magnitude of streamflow reasonably well. Visual inspection indicates that the simulated streamflow values match the observations reasonably well during the calibration [Figure 3(a)], despite a slight underestimation of some peaks during the validation [Figure 3(b)]. According to Figure 4(a), slight underestimation of the simulated cumulative daily streamflow values can be observed for the calibration period. This underestimation is comparatively larger for the simulated cumulative daily streamflow values for the validation period [Figure 4(b)]. Differences between the observed and simulated streamflow are possible due to the limited number of rainfall gauging stations used in the study which formed comparatively bigger Thiessen polygons particularly in the middle area of the catchment.

As reflected by the statistical measures used to evaluate the model performance (Table 3), MIKE 11 NAM shows a good agreement between the observed and simulated streamflow values for both calibration and validation. The NSE for both calibration and validation runs are 0.73 and 0.66, respectively (Table 3). The NSE values fall within the acceptable range (NSE > 0.50) as recommended by Moriasi et al. [26]. The computed PBIAS for both calibration and verification runs are 3.9% and 8.7%, respectively. As recommended by Moriasi et al. [26], the PBIAS values obtained in the calibration and verification runs fall within the acceptable range of ±25%. The RSR values for both the runs fall within the acceptable range

Table 2 - Calibrated Model Parameters

Parameter	Optimum value
Maximum water content in surface storage U_{max} (mm)	11
Maximum water content in root zone storage L_{max} (mm)	105
Overland flow runoff coefficient CQOF	0.73
Time constant for routing interflow CKIF (hour)	215
Time constant for routing overland flow $CK_{1,2}$ (hour)	49.5
Rootzone threshold value for overland flow TOF	0.15
Rootzone threshold value for interflow TIF	0.0156
Root zone threshold vale for Ground water recharge TG	0.07
Time constant for routing recharge CK_{BF} (hour)	1010

given in Moriasi et al. [26] (RSR < 0.70). The overall performance of the MIKE 11 NAM in this study compared to earlier studies carried out in different regions indicates that the findings are reasonable [5], [6], [18], [31]. Since the optimized parameter values and performance measures fall within the acceptable ranges, MIKE 11 NAM model was able to reasonably simulate the rainfall-runoff generation process in the Gin catchment.

3.2 Model Performance based on Temporal Transfer Scenarios

In this study, the calibrated model was applied for runoff simulations at two other time periods with an implicit assumption that the calibrated model parameters were temporally stable. The performance of the MIKE 11 NAM model across the two parameter transfer schemes, scenario A (4-year time lag from the calibration period) and scenario B (8-year time lag from the calibration period), were compared. As shown in Table 3, the overall model performance is better for scenario A (NSE = 0.64; decline of 12.3% compared to calibration, PBIAS = 8.6%; increase of 115% compared to calibration, RSR =0.59; increase of 15.4% compared to calibration) in comparison to scenario B (NSE = 0.42; decline of 42.5% compared to calibration, PBIAS = 13.6%; increase of 241% compared to calibration, RSR =0.76; increase of 46.1% compared to calibration). The observed and simulated hydrographs for scenario A and scenario B are given in Figure 5 and Figure 6, respectively.

Statistical indices which evaluated the model performance (Table 3) and the observed and simulated hydrographs (Figure 5) suggest that the model performance has only very slight decrease for scenario ‘A’ in comparison to the model calibration. The model has underestimated some of the peak flows, however, it has reasonably simulated most of the peak flows and low flows.

The model performance has significantly decreased for scenario B which had 8-year time lag from the calibration period. Most of the peak flows and low flows have been underestimated (Figure 6). All the model performance indices (Table 3) show a significant decline in comparison to the model calibration.

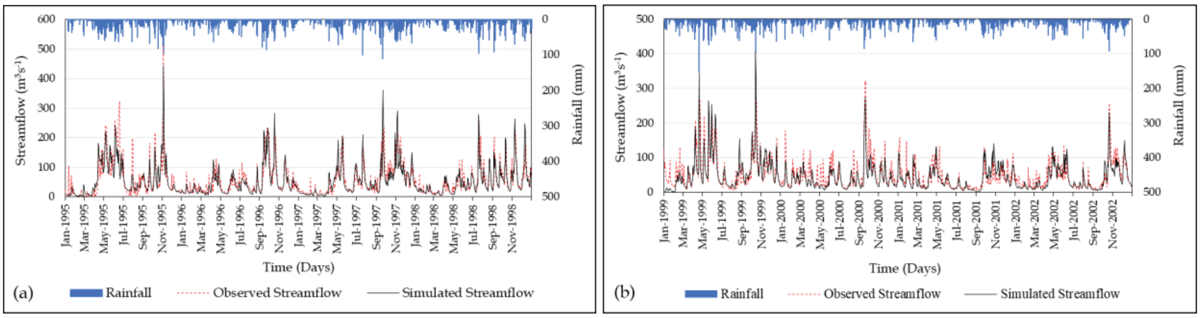

Figure 3 – Observed and Simulated Hydrographs: (a) Calibration (1995-1998); (b) Validation (1999-2002)

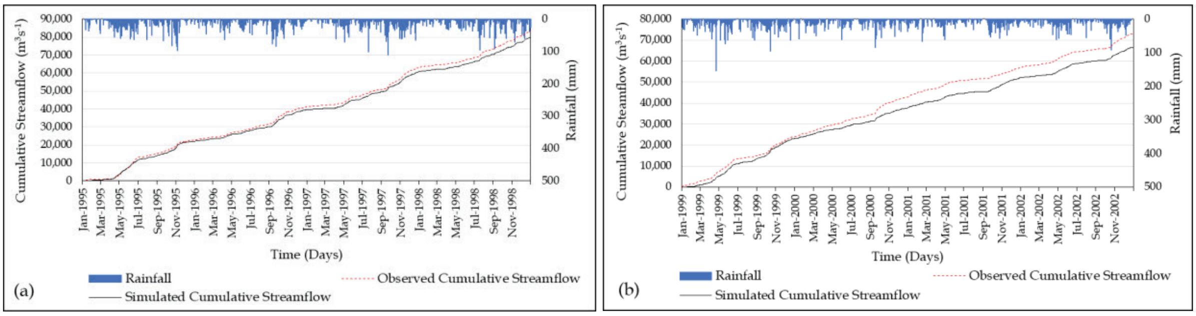

Figure 4 - Observed and Simulated Cumulative Daily Streamflow Values: (a) Calibration (1995-1998); (b) Validation (1999-2002)

Scatter plots of the observed versus simulated streamflow values with the 1:1 line for scenario A and scenario B are shown in Figure 7(a) and Figure 7(b), respectively. For scenario A, the data points shown in Figure 7(a) are closely scattered along both sides of the 1:1 line showing less systematic bias while the observed and simulated values in scenario B show somewhat weak relationship with data points sparsely scattered along the 1:1 line with significant positive bias [Figure 7(b)]. Considering all the criteria, the model performance can be considered as 'good' for scenario A while scenario B falls into 'unsatisfactory' category according to Moriasi et al. [26].

In line with the findings of this study, Patil and Stieglitz [8] demonstrated the overall superior performance of the temporal parameter transfer schemes over the spatial transfer scheme and observed a depletion of lumped hydrological model's performance (EXP-HYDRO model) when the temporal gap between calibration periods was increased to 8 years. Rainfall-runoff simulation conducted by Apaydin et al. [7] using a semi-distributed model (SLURP model) in Aksu basin in Turkey also showed a significant decrease in the model performance when the parameters were transferred with a time lag of ten years. Moreover, as concluded by Van der Linden and Woo [32], hydrological model parameters must be recalibrated at regular intervals, i.e., 5-10 years, since the use of calibrated parameters for extended periods without modification produced misleading evaluations. As revealed in the present study, the decrease in the model performance with higher temporal lag from the calibration period might be attributed to the divergent physical characteristics of the catchment which agreed with the findings by Van der Linden and Woo [32]. Some of the MIKE 11 NAM calibrated parameter values were related to physiographic characteristics of the catchment [21], particularly to the catchment land use, which might have changed across the two periods.

Table 3 - Model Performance Evaluation

	NSE	PBIAS (%)	RSR
Calibration (1995-1998)	0.73	3.9	0.52
Validation (1999-2002)	0.66	8.7	0.59
Scenario A (4-year time lag from the calibration period)	0.64	8.6	0.59
Scenario B (8-year time lag from the calibration period)	0.42	13.6	0.76

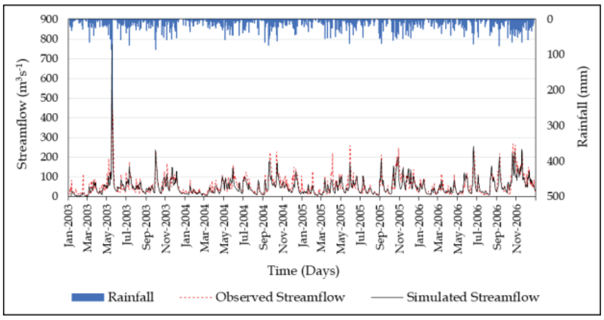

Figure 5 - Observed and Simulated Hydrographs for Scenario A

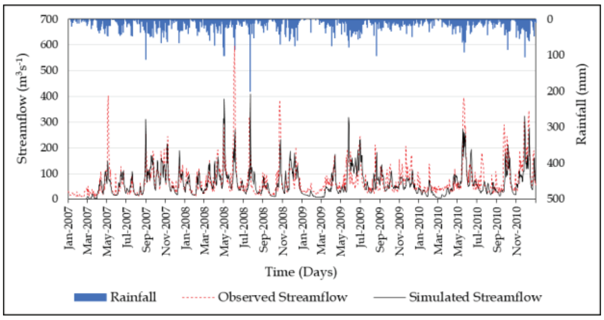

Figure 6 - Observed and Simulated Hydrographs for Scenario B

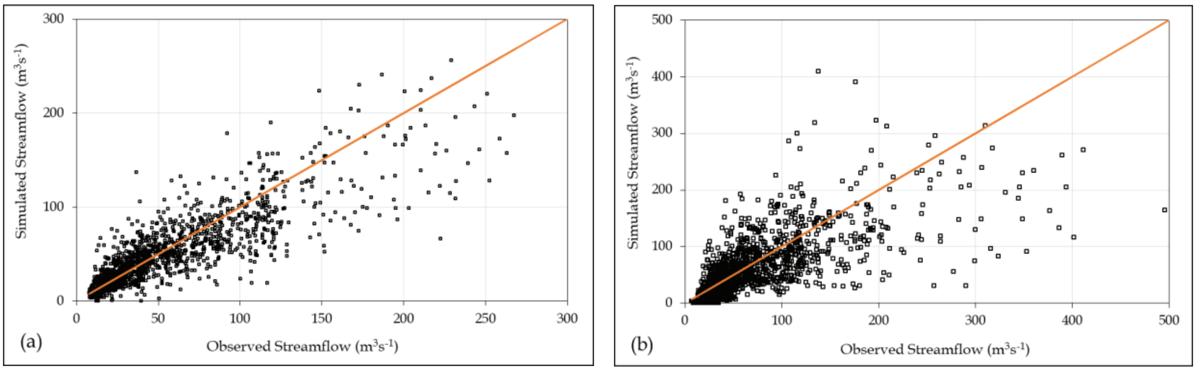

Figure 7 - Scatter Plot of Observed versus Simulated Streamflow: (a) Scenario A; (b) Scenario B

3.3 Model Suitability Analysis in Peak and Low Flow Regimes for Scenario A

In order to assess the model performance for scenario A in peak flow and low flow regimes, flow duration curves were developed. According to EPA [33], peak flow was defined as the values falling below the 10th percentile in the distribution of streamflow values while low flow was defined as the streamflow values falling above the 90th percentile. Flow duration curves of the observed and simulated streamflow for scenario A reveal some inconsistency in curve matching in the peak flow regime and in the low flow regime (Figure 8). Simulations reasonably captured the peak flow in comparison to the low flow. According to Smakhtin [34], it is a challenging task in hydrology to simulate the low flows which take place in dry seasons as a seasonal phenomenon due to the complexity of groundwater processes.

In assessing the goodness-of-fit between the observed and the simulated flows in scenario A, Pearson's correlation coefficient (r) which describes the degree of collinearity between the simulated and the observed data was used [26]. The correlation coefficient, r, which ranges from -1 to 1, is shown in Eq.(6).

$$r = \frac{\sum_{i=1}^{n}(X_i - X_i^{mean})(Y_i - Y_i^{mean})}{\left[\sqrt{\sum_{i=1}^{n}(X_i - X_i^{mean})^2}\sqrt{\sum_{i=1}^{n}(Y_i - Y_i^{mean})^2}\right]} \qquad (6)$$

where, X_i, Y_i, X_i^{mean} and Y_i^{mean} are i^{th} observed streamflow, i^{th} simulated streamflow, mean of the observed streamflow and mean of the simulated streamflow, respectively, and n is the total number of streamflow observations.

In scenario A, simulated flow correlated well with the observed flow in the peak flow region ($r > 0.6$) in comparison to the low flow region ($r < 0.3$). Thus, the model performance in the peak flow region can be judged as 'satisfactory' [35]. Therefore, it is evident that the MIKE 11 NAM model can adequately reproduce the peak flow components of runoff hydrograph using the transferred model parameters with 4-year temporal lag.

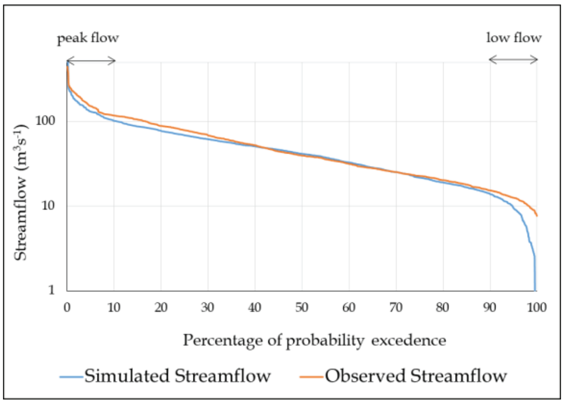

Figure 8 - Flow Duration Curves of Observed and Simulated Streamflow for Scenario A

4. Conclusions

This study demonstrated that the performance of a hydrological model can vary in the same catchment when the calibrated model is applied for rainfall-runoff simulations beyond the calibration period without modification to the calibrated parameters. The extent of variation of the model performance, however, differed with the temporal gap between the calibration period and the transfer period. With a temporal gap of 4 years, performance of the MIKE 11 NAM model decreased slightly but the model was able to adequately simulate the rainfall-runoff generation process in the Gin catchment by reliably reproducing the timing and shape of rising and recession curves of the hydrographs. With the same temporal gap, the model performed well in the peak flow region (<10th percentile) in comparison to the low flow region (>90th percentile) highlighting the successful peak runoff simulations by the MIKE 11 NAM using the transferred model parameters. When the temporal gap was increased to 8 years, the model performance drastically reduced. Therefore, it is recommended to update the calibrated model parameters whenever they are used for runoff simulations in extended periods in the catchments where physiographic catchment characteristics are supposed to change. The findings of the present study have vital implication for rainfall-runoff simulations in catchments where data availability is a critical issue. The modelling framework presented in this study will pave the way for future researchers to carry out hydrological modelling based investigations in the catchments where streamflow data is sparse.

References

1. Singh, V. P., "Hydrologic Modeling: Progress and Future Directions", *Geosci. Lett.*, Vol. 5, No. 15, 2018. https://doi.org/10.1186/s40562-018-0113-z.

2. Sivapalan, M., Takeuchi, K., Franks, S.W., Gupta, V.K., Karambiri, H., Lakshmi, V., Liang, X., McDonnell, J. J., Mendiondo, E. M., O'Connell, P. E., Oki, T., Pomeroy, J. W., Schertzer, D., Uhlenbrook, S., & Zehe, E., "IAHS Decade on Predictions in Ungauged Basins (PUB), 2003-2012: Shaping an Exciting Future for the Hydrological Sciences", *Hydrol. Sci. J.*, Vol. 48, No. 6, 2003, pp. 857-880. https://doi.org/10.1623/hysj.48.6.857.51421.

3. Blöschl, G., & Sivapalan, M., "Scale Issues in Hydrological Modelling: A Review", *Hydrol. Process.*, Vol. 9, No. 3-4, 1995, pp. 251-290. https://doi.org/10.1002/hyp.3360090305.

4. Merz, R., Blöschl, G., & Parajka, J., *Regionalization Methods in Rainfall-runoff Modelling using Large Catchment Samples*, IAHS-AISH Publication, 307, 2006, pp.117–125.

5. Makungo, R., Odiyo, J. O., Ndiritu, J. G., & Mwaka, B., "Rainfall-Runoff Modeling Approach for Ungauged Catchments: A Case Study of Nzhelele River Subquaternary Catchment", *Phys. Chem. Earth*, Vol. 35, No. 13-14, 2010, pp. 596-607. https://doi.org/10.1016/j.pce.2010.08.001.

6. Odiyo, J. O., Phangisa, J. I., & Makungo, R., "Rainfall-Runoff Modelling for Estimating Latonyanda River Flow Contributions to Luvuvhu River Downstream of Albasini Dam", *Phys. Chem. Earth.*, Vol. 50-52, 2012, pp. 5-13. https://doi.org/10.1016/j.pce.2012.09.007.

7. Apaydin, H., Anli, A. S., & Ozturk, A., "The Temporal Transferability of Calibrated Parameters of a Hydrological Model", *Ecol. Modell.*, Vol. 195, No. 3–4, 2006, pp. 307–317. https://doi.org/10.1016/j.ecolmodel.2005.11.032

8. Patil, S. D., & Stieglitz, M., "Comparing Spatial and Temporal Transferability of Hydrological Model Parameters", *J. Hydrol.*, Vol. 525, 2015, pp. 409–417. https://doi.org/10.1016/j.jhydrol.2015.04.003.

9. Rajendran, M., Gunawardena, E. R. N., & Dayawansa, N. D. K., "Runoff Prediction in an Ungauged Catchment of Upper Deduru Oya Basin, Sri Lanka: A Comparison of HEC-HMS and WEAP Models", *International Journal of Progressive Sciences and Technologies*, Vol. 18, No. 2, 2020, pp. 121–129.

10. Jayasinghe, S. N., & Rajapakse, R. L. H. L., "Hydrological Modelling Approach for Flood and Water Pollution Control in an Ungauged Catchment - A Case Study in Erewwala Catchment in Bolgoda River Basin, Sri Lanka", *Proceeding of the UMCSAWM Water Conference on Demonstrating the Strength of Water Engineering and Management Capability through Case Study Applications*, University of Moratuwa, Sri Lanka, 2017.

11. Lakmali, E. N., Transferability of Model Parameters for Monthly Streamflow Estimation in Ungauged Watersheds in Kalu River Basin, MSc Thesis, University of Moratuwa, Sri Lanka, 2020.

12. Wickramaarachchi, T. N., Ishidaira, H., & Wijayaratna, T. M. N., "An Application of Distributed Hydrological Model, YHyM/BTOPMC to Gin Ganga Watershed, Sri Lanka", *Engineer: Journal of the Institution of Engineers, Sri Lanka*, Vol.45, No. 2, 2012, pp. 31-40. http://doi.org/10.4038/engineer.v45i2.6939

13. Wickramaarachchi, T. N., Ishidaira, H., & Wijayaratna, T. M. N., "Projecting Land Use Transitions in the Gin Catchment, Sri Lanka", *Research Journal of Environmental and Earth Sciences*, Vol. 5, No. 8, 2013, pp. 473–480. http://dx.doi.org/10.19026/rjees.5.5677.

14. Reuter, H. I., Nelson, A., & Jarvis, A., "An Evaluation of Void Filling Interpolation Methods for SRTM Data", *Int. J. Geogr. Inf. Sci.*, Vol. 21, No. 9, 2007, pp. 983-1008. https://doi.org/10.1080/13658810601169899.

15. Doulgeris, C., Georgiou, P., Papadimos, D., & Papamichail, D., Evaluating Three Different Model Setups in the MIKE 11 NAM Model. In Lambrakis, N., Stournaras, G., & Katsanou, K., (Eds.), *Advances in the Research of Aquatic Environment. Environmental Earth Sciences*,

Springer, 2011, pp. 241-249. https://doi.org/10.1007/978-3-642-19902-8_28.

16. Jayapadma, J. M. M. U., Wickramaarachchi, T. N., Silva, G. H. A. C., Ishidaira, H., & Magome, J., "Rainfall-Runoff Modelling Using MIKE 11 (NAM Model): A Case Study of GIN River Basin", *Proceedings of the International Symposium on Advances in Civil and Environmental Engineering Practices for Sustainable Development (ACEPS-2018)*, Galle, Sri Lanka, March, 2018, pp. 231-238.

17. Shamsudin, S., & Hashim, N., "Rainfall-Runoff Simulation using Mike 11 NAM", *J. Civil Eng.*, Vol. 15, No. 2, 2002, pp. 1-13.

18. Wickramaarachchi, T. N., & Rathnayake, R. M. K., "Performance Evaluation of Single and Multi-objective Calibration in Rainfall-Runoff Modelling", *Engineer: Journal of the Institution of Engineers, Sri Lanka*, Vol. 54, No. 2, 2021, pp. 77–90. http://doi.org/10.4038/engineer.v54i2.7444.

19. Jayapadma, J., Souma, K., Ishidaira, H., Magome, J., & Wickramaarachchi, T.N., "The Effect of Incorporation of Embankment Information for Flood Simulation of the Gin River, Sri Lanka", *J. Disaster Res.*, Vol.17, No.3, 2022, pp. 475-486. http://doi.org/10.20965/jdr.2022.p0475.

20. Willmott, C. J., "On the Validation of Models", *Phys. Geogr.*, Vol. 2, No. 2, 1981, pp. 184-194. https://doi.org/10.1080/02723646.1981.10642213.

21. DHI, *MIKE 1D - DHI Simulation Engine for 1D River and Urban Modelling - Reference Manual*, Danish Hydraulic Institute (DHI), Hørsholm, Denmark, 2017, 334 p.

22. Legates, D. R., & McCabe, G. J., "Evaluating the Use of Goodness-of-fit Measures in Hydrologic and Hydro-Climatic Model Validation", *Water Resour. Res.*, Vol. 35, No. 1, 1999, pp. 233-241. https://doi.org/10.1029/1998WR900018.

23. Nash, J., & Sutcliffe, J., "River Flow Forecasting through Conceptual Models Part I - A Discussion of Principles", *J. Hydrol.*, Vol. 10, No. 3, 1970, pp. 282-290. https://doi.org/10.1016/0022-1694(70)90255-6.

24. Gupta, H. V., Sorooshian, S., & Yapo, P. O., "Status of Automatic Calibration for Hydrologic Models: Comparison with Multilevel Expert Calibration", *J. Hydrol. Eng.*, Vol. 4, No. 2, 1999, pp. 135-143. http://doi.org/10.1061/(ASCE)1084-0699(1999)4:2(135).

25. Singh, J., Knapp, H. V., Arnold, J.G., & Demissie, M., "Hydrologic Modeling of the Iroquois River Watershed using HSPF and SWAT", *J. Am. Water Resour. Assoc.*, Vol. 41, No. 2, 2005, pp. 343-360. https://doi.org/10.1111/j.1752-1688.2005.tb03740.x.

26. Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D., & Veith, T., "Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulation", *Trans. Am. Soc. Agric. Biol. Eng.*, Vol. 50, No. 3, 2007, pp. 885-900. http://doi.org/10.13031/2013.23153.

27. Dobler, C., Bürger, G., & Stötter, J., "Assessment of Climate Change Impacts on Flood Hazard Potential in the Alpine Lech Watershed", *J. Hydrol.*, Vol. 460-461, 2012, pp. 29–39. http://doi.org/10.1016/j.jhydrol. 2012.06.027.

28. Gan, T. Y., Dlamini, E. M., & Biftu, G. F., "Effects of Model Complexity and Structure, Data Quality, and Objective Functions on Hydrologic Modeling", *J. Hydrol.*, Vol. 192, No. 1-4, 1997, pp. 81-103. https://doi.org/10.1016/S0022-1694(96)03114-9.

29. Duan, Q., Sorooshian, S., & Gupta, V. K., "Effective and Efficient Global Optimization for Conceptual Rainfall-Runoff Models", *Water Resour. Res.*, Vol. 28, No. 4, 1992, pp.1015-1031. https://doi.org/10.1029/91WR02985.

30. DHI, *MIKE 11 - A Modelling System for Rivers and Channels – User Guide*, Danish Hydraulic Institute (DHI), Hørsholm, Denmark, 2016, 512p.

31. Hafezparast, M., Araghinejad, S., Fatemi, S.E., & Bressers, "A Conceptual Rainfall-Runoff Model Using the Auto Calibrated NAM Models in the Sarisoo River", *Hydrol. Curr. Res.*, Vol. 4, No. 1, 2013, pp. 1-6. http://doi.org/10.4172/2157-7587.1000148.

32. Van der Linden, S., & Woo, M., "Transferability of Hydrological Model Parameters between Basins in Data-sparse Areas, Subarctic Canada", *J. Hydrol.*, Vol. 270, No. 3-4, 2003, pp. 182–194. https://doi.org/10.1016/S0022-1694(02)00295-0.

33. EPA, 2007. *An Approach for Using Load Duration Curves in the Development of TMDLs*, U.S. Environmental Protection Agency, Washington, 68 p.

34. Smakhtin, V., "Low Flow Hydrology: A Review", *J. Hydrol.*, Vol. 240, No. 3-4, 2001, pp. 147–186. https://doi.org/10.1016/S0022-1694(00).

35. Kachholz, F., & Tränckner, J., "Long-Term Modelling of an Agricultural and Urban River Catchment with SWMM Upgraded by the Evapotranspiration Model UrbanEVA", *Water*, Vol. 12, No. 11, 2020, 3089. https://doi.org/10.3390/w12113089.