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RESERVOIR INFLOW SIMULATION USING MIKE NAM RAINFALL-RUNOFF MODEL: CASE STUDY OF CAMERON HIGHLANDS

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Abstract

Ringlet Reservoir in Cameron Highlands impounds water mainly from four main rivers namely Sg. Telom, Sg. Habu, Sg. Ringlet and Sg. Bertam. Due to the absence of gauge flow data, MIKE NAM rainfall runoff model was used to simulate inflow for short term and long term prediction. Peak flow is sensitive towards any changes in U_{max}, TG, $CQOF$, $CKBF$, $CKIF$ and $CK_{1,2}$. All parameters except $CK_{1,2}$ are sensitive in calculation of total volume. Model was calibrated for the period from 1999 to 2006 and validated for the period from 2010 to 2012 at two streamflow locations. The model is reliable to simulate flow satisfactorily especially during flood events. Model shows good agreement between the simulated and observed flow in terms of low flow, peak flow and total volume. Good calibration results were achieved for all scenarios, with NSE > 0.66, RSR < 0.6, R2 > 0.74 and PBIAS (%) < 15%.

Keywords: Calibration, MIKE NAM, NSE, Rainfall-runoff modelling, Reservoir, Statistical, Sensitivity analyses.

1. Introduction

As part of reservoir management, prediction of total inflow on daily, monthly, annual and on seasonal basis is important to prepare schedule of releases and usage of water resources. Most reservoirs are equipped with lake level gauge, however, not streamflow gauge at the main feeder rivers. Some gauges were located further upstream of the reservoir. In the absence of comprehensive gauging data at main rivers flowing into a reservoir, rainfall-runoff model is useful to simulate inflow time series based on rainfall and weather data. Simulation of inflow into reservoirs allows flood analyses, sediment inflow and design of hydraulic structures to be carried out. For instance, sediment inflow into a reservoir can be estimated using rating curves and flow duration curve; or using integrated runoff to sediment-discharge. This highlights the importance of inflow simulation into a reservoir.

To determine inflow into the reservoir, hydrological modelling can be used to simulate runoff generation from the sub-catchments. Hydrological modelling is used to describe the relationship between the various hydrological components in a hydrologic cycle. Rainfall-runoff modelling describes the process of generating streamflow hydrograph resulted from the excess rainfall onto the catchment, after taking into account various hydrological processes such as precipitation, evaporation, transpiration, groundwater, and interflow.

Gosain et al. [1] commented Rainfall-runoff modelling can be categorized into three categories namely; black-box (or stochastic), deterministic and conceptual model. Black box model describes the input and output data in mathematical terms without considering the physical processes involved, using mathematical equation and statistical concepts [2]. According to Abd and Sammen [3], the artificial neural network is considered as an efficient tool for modelling and prediction purposes, however, the quality of available data would greatly determine the accuracy of black box models.

Deterministic model or physically based model characterizes the physical processes in the catchment and requires large data including topography, soil, rainfall, vegetation, land use, geological and meteorological information such as humidity, temperature, wind speed and others, which often lacking and consume large computation time. SWAT is an example of the physically distributed hydrological model, which can simulate sediment and runoff in a catchment [4, 5]. SWAT was utilised for rainfall-runoff modelling in Langat River Basin [6], Upper Bernam [7] and also for sediment yield study such as in central Iran [8], Chesapeake Bay [9], northeast Ethiopia [10], Blue Nile [11], Bukit Merah, Malaysia [12].

Conceptual models are most commonly used due to its simplified computation and user-friendly approaches. It can be divided into semi-distributed and lumped model [13]. Lumped conceptual type of models simplifies the catchment to contain several storages and assigning the relevant parameters by ignoring the spatial variability of the catchment characteristics. Refsgaard and Knudsen [14] explained that most physically based models (deterministic) are distributed model while most conceptual are either semi-distributed or lumped model. Amir et al. [15] explained that despite the distributed model is physically based, there is no clear proof of its improved accuracy and efficiency, hence the conceptual lumped model is still preferred. MIKE NAM [16], HEC - HMS, Sacramento model and Tank model [17], Runoff Routing Model (RORB) [18] are the examples of the conceptual lumped model. HEC-HMS was used for hydrological modelling in oil palm catchment [19], flood estimation in Johor [20], in Kayu Ara river basin [21] and in many other areas worldwide. Tank Model was used for Kelantan flood study [22].

Although data-driven method especially Artificial Neutral Network (ANN) has gained interests in predicting inflow [23, 24], it requires extensive dataset covering all range of hydrological events to ensure the mathematical relationships derived among the factors are valid. This is usually unavailable for certain region. Distributed models are time-consuming and require complex datasets such as topography, weather, land use and soil type. Lumped model is usually the best choice for simulating inflow into the reservoir.

MIKE NAM has been used widely in Malaysia and other countries reservoir inflow simulation, flood forecasting, flood study, watershed management and decision support system. For example, MIKE NAM forms part of real-time streamflow forecasting and reservoir operation system in Maharashtra, India [25], Ho Ho Reservoir [26] and Upper Maule River Basin [27]. MIKE NAM were used in simulating flow into reservoir [28], prediction of daily runoff in Bina Basin, India [29], Lower Rideau River in Australia [30], Fitzroy basin [15], Vinayakpur [31], Layang-layang river [32] and forms part of simulation of sediment inflow in Cameron Highlands [33] and in various other studies.

Despite MIKE NAM being used in many areas, the calibration and sensitive parameters would vary from one study area to another, depending on the land use activities. Most studies illustrate limited information on the sensitivity analyses and none mentioned on how the land use variation affects the MIKE NAM parameters for calibration and simulation. This study investigates the impact of land use on the MIKE NAM parameters.

In this paper, MIKE NAM was used in to simulate inflow into Ringlet Reservoir. To ensure model's reliability for simulating continuous runoff or flood-based runoff, calibration was conducted multiple times at two locations to determine the best calibration parameters such that the model is robust to handle various scenarios. Model performance was assessed based on the overall pattern of hydrograph, the agreement to low and high flows and total volume. Additional statistical parameters were used to gauge model performance to guarantee the model is acceptable.

2. Study Area and Data Input

Cameron Highlands is located in the state of Pahang, West Malaysia as shown in Fig. 1. It is an active highland agriculture area and famous tourist spot. There are two major catchments namely Bertam and Telom. There have been a lot of issues related to Cameron Highlands, such as flood, water quality, water quantity, and sedimentation over the past decades. Cameron Highlands is also home to seven hydropower stations owned and operated by the national utility company Tenaga Nasional Berhad (TNB). Table 1 summarises the details of Cameron Highlands catchment.

Sg. Bertam, Sg. Ringlet and Sg. Habu drain directly into Ringlet Reservoir. The reservoir is a multipurpose reservoir and it is used for hydropower generation at Jor Power Station. In addition to that, water from Telom is diverted into Ringlet Reservoir via transfer tunnel. The reservoir has the original design storage of 6.7 million m^3, of which, 2 million m^3 is dead storage and 4.7 million m^3 is live storage.

The reservoir and its Sultan Abu Bakar Dam also serves as flood control in the densely populated Bertam Valley. The average elevation of the catchment is approximately 1180 m. Owing to its topography, 26% of the terrain is steeper than 25º and 60% of the land is steeper than 20° [33]. Average annual rainfall for Cameron Highlands and Batang Padang is 2,8000 m with average daily evaporation of 1.8 mm/day. Throughout the year, the catchment is subjected to two rainy seasons; from April to May and from September to November. Monthly rainfall ranges from the minimum of 100 mm in January and maximum of 300 mm in October to November. Mean annual temperature is 18 °C.

To ensure sufficient water for hydropower generation, TNB as the operator and owner of the power plants has installed and maintained a hydrological network for the area, consists of rain gauges and streamflow stations. In addition, rainfall and meteorological information such as evaporation were also obtained from Department of Irrigation and Drainage (DID) and Meteorological Department (MET). Availability of hydrological data for the catchment is shown in Table 2.

The catchment is also subjected to dynamic land use changes since 1960s whereby forest was converted to agricultural plots and urban area to support the increasing demand. Land use changes from 1947 to 2010 in the catchment according to category were plotted as in Fig. 2, summarized based on the information obtained from the Department of Agriculture. Land use differences within the sub-catchments shows that Lower Bertam has the highest percentage of agricultural activity while Ringlet has the most urban area, as summarised in Table 3.

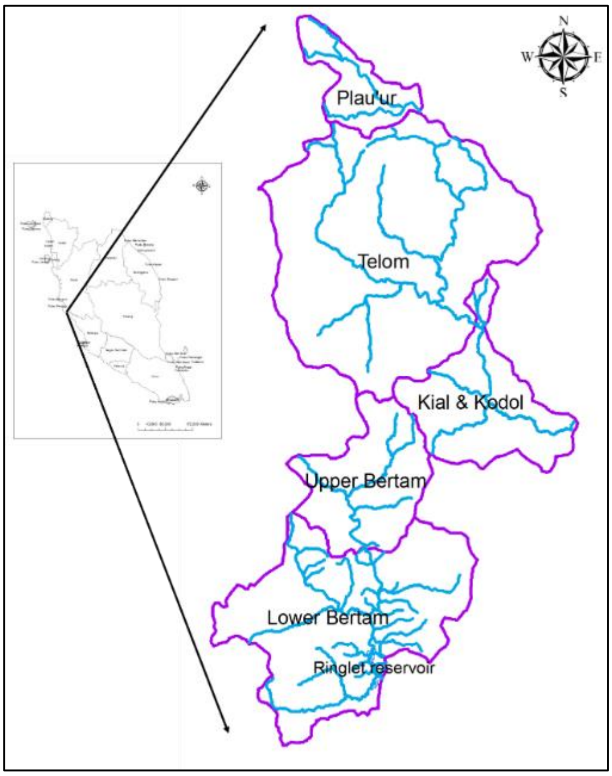


Fig. 1. Location of Cameron Highlands catchment and Ringlet Reservoir.

Table 1. Summary of Cameron Highlands Catchment.

Catchment	Sub-catchment	Area (km^2)	Cumulative area (km^2)
Bertam	Upper Bertam	21	
	Lower Bertam	50	71
Telom	Telom	78	
	Kial & Kodol	22	
	Plau'ur	9.8	110

Table 2. Data availability for Cameron Highlands.

No	Station no.	Name	GPS coordinate	Type of data
1	4513033	Gunung Brinchang	4.517, 101.383	Rainfall
2	9004	Sg. Palas Tea Estate	4.517, 101.417	Rainfall
3	9009	Kajiiklim Habu	4.418, 101.383	Rainfall
4	6003	Sg. Bertam	4.465, 101.387	Streamflow
5	1030	Kaji Iklim Tanah Rata	4.467, 101.383	Weather
6	9001	Blue Valley	4.586, 101.419	Rainfall
7	9002	Kg Raja	4.551, 101.417	Rainfall
8	9003	Telom Intake	4.542, 101.425	Rainfall
9	6002	Sg. Telom	4.543, 101.424	Streamflow

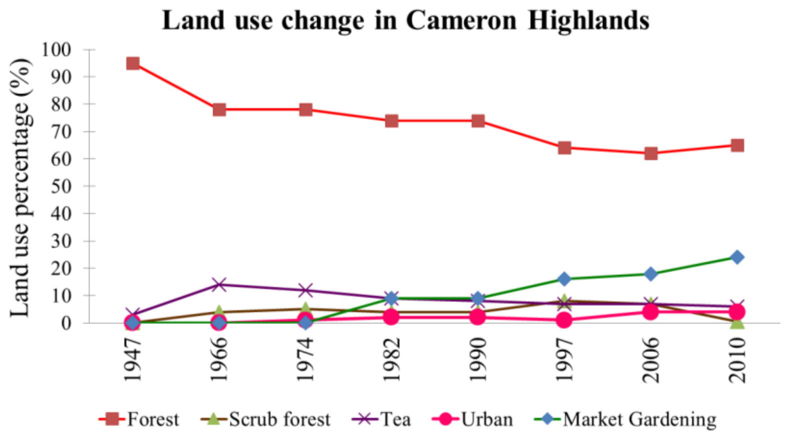


Fig. 2. Land use variation in Cameron Highlands.

Table 3. Land use differences (in %) within sub-catchment of Cameron Highlands.

Catchments	Bareland	Forest	Grassland	Agriculture	Urban	Water body
Upper Bertam	9.30	57.93	19.11	5.79	7.87	0.11
Middle Bertam	4.72	62.63	20.38	9.14	3.05	0.08
Lower Bertam	8.72	18.32	42.82	21.25	8.62	0.00
Habu	4.92	43.75	28.99	19.24	3.08	0.03
Ringlet	18.58	26.88	31.02	10.98	12.29	0.24
Reservoir	3.56	49.02	13.46	18.29	3.03	12.84

3. MIKE NAM

Rainfall-runoff model (MIKE NAM) is part of MIKE 11 model used by many researchers worldwide. It is deterministic, lumped conceptual rainfall-runoff model, which is originally developed by the Technical University of Denmark [34]. The model uses the hydrological cycle to quantify water storage and flows in the watershed. The general structure of the model contains three interrelated storages, categorized as overland flow, interflow and base flow, as shown in Fig. 3. Traditional applications of the rainfall-runoff model include an extension of stream flow series for design purposes, flood modelling, water quantity simulation, flood forecasting, and prediction of reservoir inflow.

In general, there are nine (9) parameters in MIKE NAM, representing a surface zone, root zone, and groundwater storage. Snow storage is applicable to certain areas applicable to this. The upper and lower boundary is defined by default values in the manual and can be altered depending on the catchment characteristics itself [34]. Description of each parameter and its range of values is shown in Table 4.

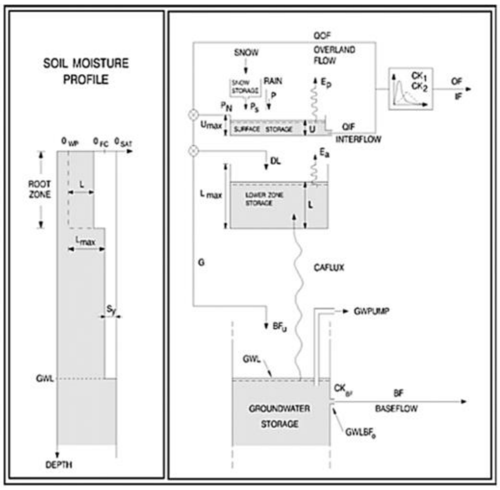


Fig. 3. MIKE NAM model structure [34].

Table 4. NAM parameters.

Parameters	Description	Lower bound	Upper bound
***U_{max}* (mm)**	Maximum water content in surface storage	10	**20**
***L_{max}* (mm)**	Maximum water content in the root zone storage	100	**300**
CQOF	Overland flow runoff coefficient	0.1	**1**
***CKIF* (hr)**	Time constant for interflow	200	**1000**
***$CK_{1,2}$* (hr)**	Time constant for routing interflow and overland flow	1	**50**
TOF	Root zone threshold value for overland flow	0	**0.99**
TIF	Root zone threshold value for interflow	0	**0.99**
TG	Root zone threshold for groundwater recharge	0	**0.99**
***CKBF* (hr)**	**BASEFLOW TIME CONSTANT**	**1000**	**5000**

4. Methodology

Rainfall-runoff model for Cameron Highlands was developed by delineating the catchment in Geographical Information System (GIS) software to obtain the catchment area. Thiessen polygon was utilized to generate the areal rainfall for the catchment. Rainfall, evaporation and observed flow on daily time series for a period of 1999 to 2012 were used.

Sensitivity analyses were first conducted to determine the most sensitive parameters of the factors affecting the model accuracy, such as peak flow, low flow and total volume. By varying one parameter within the upper and lower range and keeping the remaining eight (8) parameters constant, flow simulated from 1999 to 2006 was compared with the observed flow in terms of total volume and peak flow. From the sensitivity analyses, the most sensitive parameters were finalized and further adjusted during the calibration.

Calibration was conducted by adjusting the most sensitive parameters such that the simulated flow matches the recorded flow. MIKE NAM used multi-objective calibration aims to satisfy four objective functions; total volume, root mean square error (RMSE), RMSE for peak flows and RMSE for low flows. In MIKE NAM, calibration was first done automatically followed by manual fine-tuning of the value of parameters within a small range. Validation was conducted by using the calibrated parameters for different simulation period.

Separate calibration and validation period were chosen for Sg. Bertam and Sg. Telom, based on data availability and continuity. Sg. Telom has more missing streamflow data especially in 2008 and 2000. For long-term simulation, calibration of Sg. Bertam was conducted using data for period from 1999 to 2006, while the validation was conducted using data for period from 2010 to 2012. Daily data for period from 2004 to 2006 was used for calibration of Sg. Telom, while data for period from 2009 to 2010 was used for validation. For flood event at Sg. Bertam, peak flows in January 2009 and March to May 2011 were used for calibration, while peak flows in February 1999 were used validation. For Sg. Telom flood event, peak flows in January 2002, December 2006 and January 2011 were used for calibration and validation.

This study focuses on sensitivity analysis and adjustment of the calibration parameters based on land use difference within the sub-catchments. Typical flow simulation using lump model applies the calibrated parameters onto the other sub-catchments without taking into account the differences in land use. Since the study area is subjected to highly varied land use, the parameters were adjusted based on differences in the percentage of forest cover between sub-catchments.

Summary of the methodology used in this study is illustrated in Fig. 4. Model performance during calibration and validation period was assessed based on the overall agreement of the hydrographs, especially on the peak values and total volume.

Nash and Sutcliffe [35] commented, in addition, the model performance was also assessed based on seven (7) statistical parameters such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Relative Root Mean Square Error (RRMSE), Nash-Sutcliffe Efficiency Index (NSE), %Bias (PBIAS), Regression coefficient (R^2) and Ratio of RMSE (RSR). Most models are calibrated to achieve the smallest possible value of MAE, RMSE and RRMSE.

Models that achieve NSE > 0.75 is considered very well, good if NSE is between 0.65 and 0.75 and satisfactory is NSE is between 0.5 and 0.65. For the model with absolute PBIAS of less than 15%, the model is good and if absolute PBIAS is between 15% and 25%, the model performs satisfactorily. Another quantitative measure is RSR. If RSR is less than 0.6 the model is good and if RS is between 0.6 and 0.7, the model performs satisfactorily [36].

R^2 between 0.5 and 1 indicates acceptable model performance. These indicators were used in analysing the calibration results and the calibration parameters were adjusted until the model achieves results that satisfy the requirement of all statistical parameters.

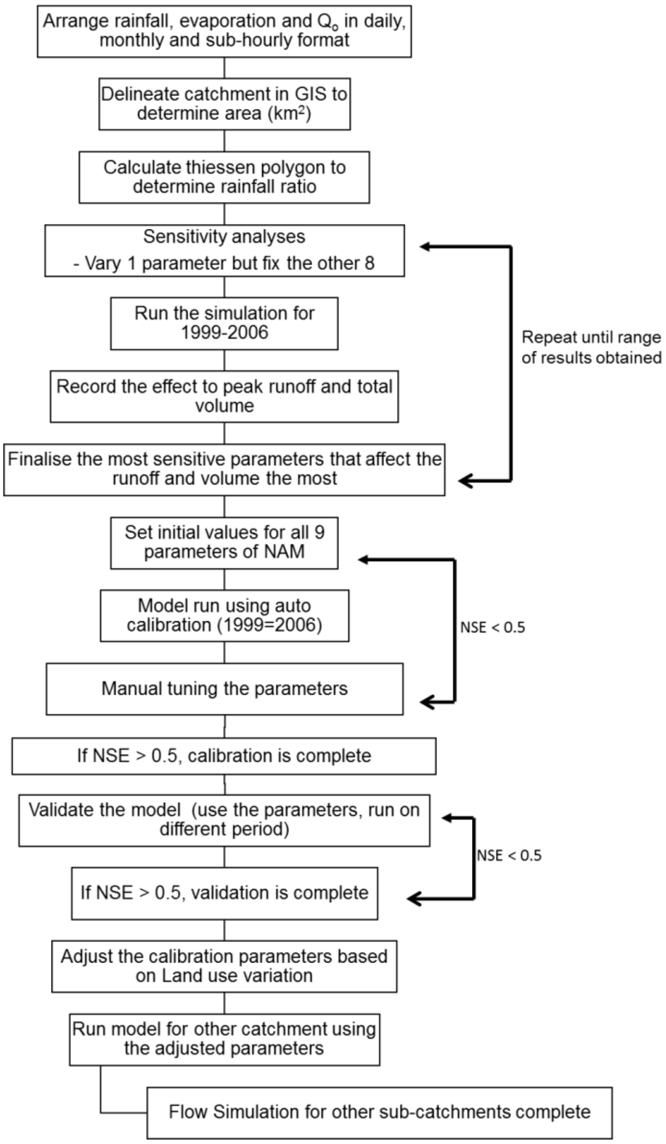


Fig. 4. Methodology used in the study.

5. Results and Discussion

5.1. Sensitivity analyses

From the sensitivity analyses, all parameters except $CK_{1,2}$ are sensitive in calculation of total volume. Peak flow is sensitive towards any changes in U_{max}, *TG*, *CQOF*, *CKBF*, *CKIF* and $CK_{1,2}$. Increase in *CQOF* and *CKIF* would increase the peak runoff, however, reduction of $CK_{1,2}$ increase the peak runoff. Results of the sensitivity analysis is summarised in Table 5. According to Shamsuddin and Hashim [32] and Loliyana and Patel [37], this result is slightly different to study in Johor and Chattisgarh. Study in Yerli highlighted three parameters namely *CQOF*, U_{max} and *TOF* that are sensitive to the total volume and R^2 value [38]. Another study in Purna River basin highlighted that L_{max} and U_{max} is sensitive towards total volume while *CQOF* influences the peak runoff. The significant influence of L_{max} on runoff volume and peak runoff is due to existence of major crop land affecting the root zone storage in the catchment. This indicates that sensitivity analysis depends on land use activities within the study and it is site specific [39]. Another reference also highlighted *CQOF* is sensitive towards the peak runoff values [29].

5.2. Calibration parameters

As presented by Madsen [40] and Abdul Razad et al. [41], MIKE NAM auto-calibration was implemented by giving all objectives equal weightage and by searching the solution by the shuffled complex evolution algorithm. Based on the results of auto-calibration, the parameters were further adjusted to achieve final calibration results. Table 6 summarises the final values of the calibration parameters**.**

Table 5. Summary of sensitivity analysis on MIKE NAM parameters.

Parameters	Range of change	Effect of total runoff volume if increase	Effect of peak flow if increase
U_{max}	10 - 19	Increased	Reduced
L_{max}	102 - 299	Decreased	No Effect
CQOF	0.05 - 0.8	Increase	Increase
CKIF	200 - 980	Decrease	Increase
$*CK_{1,2}$	5 - 50	No effect	Decrease
TOF	0.2 - 0.9	Reduced	No effect
TIF	0.09 - 0.9	Increased	No effect
TG	0.1 - 0.97	Decrease	Reduced
CKBF	1100 - 3998	Increase	Decrease

Table 6. Calibrated NAM parameters.

Parameters	Sg. Bertam		Sg. Telom	
	Continuous	Flood event	Continuous	Flood event
U_{max} (mm)	12.3	16.5	13.4	18
L_{max} (mm)	300	100	275	126
CQOF	0.227	0.49	0.147	0.165
***CKIF* (hr)**	963.8	208.2	743.1	228.2
$CK_{1,2}$ (hr)	19.6	4.19	10.7	5.56
TOF	0.00544	0.504	0.781	0.232
TIF	0.284	0.263	0.522	0.0681
TG	0.959	0.989	0.911	0.895
***CKBF* (hr)**	2521	4763	5952	3099

5.3. Model calibration and validation for Sg. Bertam

The calibration results for a continuous period of 1999 to 2006 using streamflow data at Sg. Bertam is illustrated in Fig. 5. It is clear from Fig. 5 that the hydrograph pattern matches well for most low and high flows, except during February 1999 and January 2000 where the observed peak flows were about 6 m3/s. This could be due to extremely high rainfall during that period, which does not occur on usual basis. Most peak flows occur in April, October and November each year. Figure 6 illustrates the cumulative volume for observed and simulated, with a total difference (or PBIAS) of -6.94%. For absolute PBIAS<15%, model is considered as good. Calibration was also conducted during flood event in January 2009 and May 2011. Both results achieved NSE of more 0.70, indicating a good simulation accuracy, as shown in Figs. 7(a) and (b).

Validation was carried out on daily basis from 2010 to 2012. The model is able to match the observed flow satisfactorily, with NSE value of 0.569 and PBIAS of 4.85%, as shown in Figs. 8 and 9. Model validation during flood event in February 1999 also indicated good performance with NSE value of 0.768.

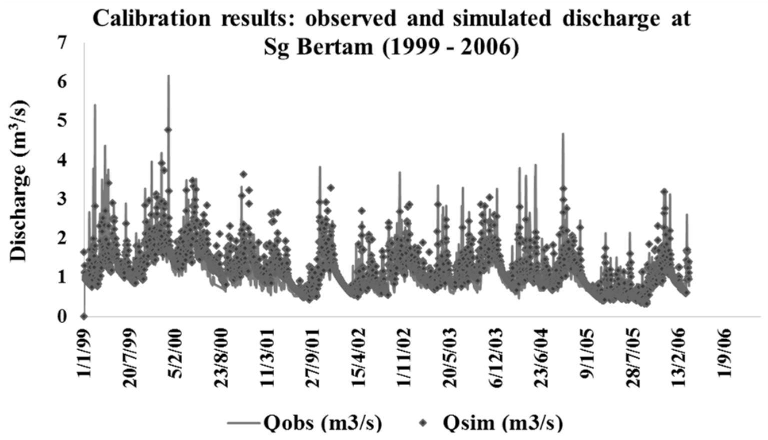


Fig. 5. Comparison between observed and simulated flow for Sg. Bertam.

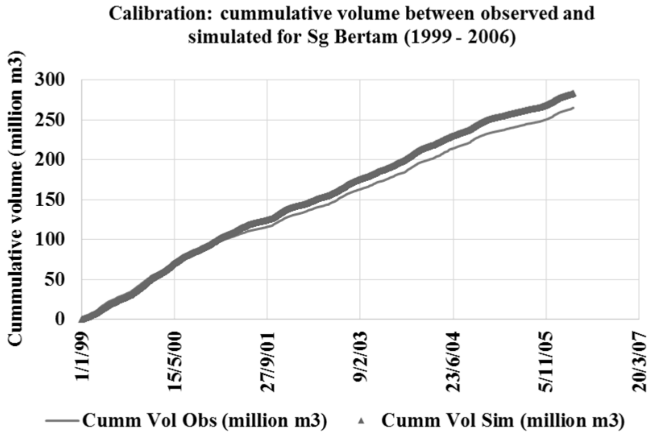
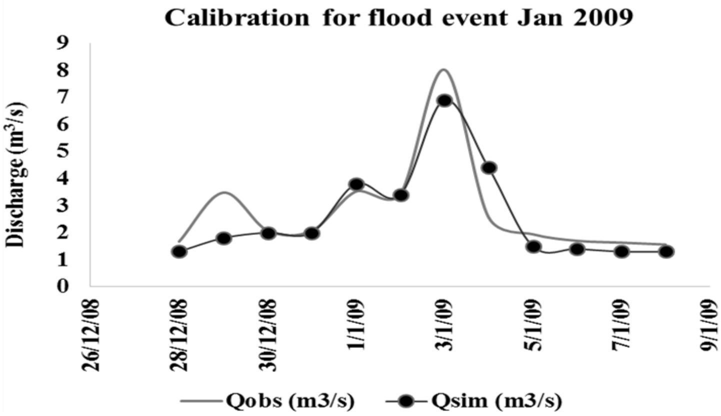
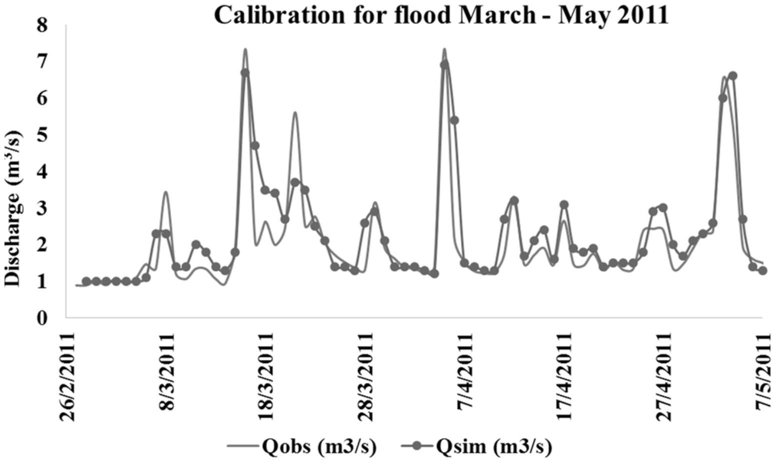


Fig. 6. Cumulative volume of observed and simulated flow.



(a) January 2009.



(b) March to May 2011.

Fig. 7. Daily flow during flood event.

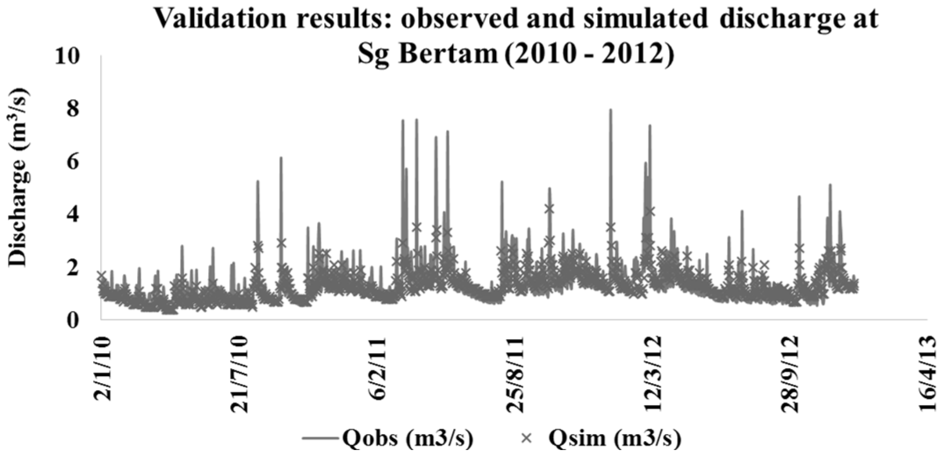


Fig. 8. Observed and simulated flow during validation period (2010-2012).

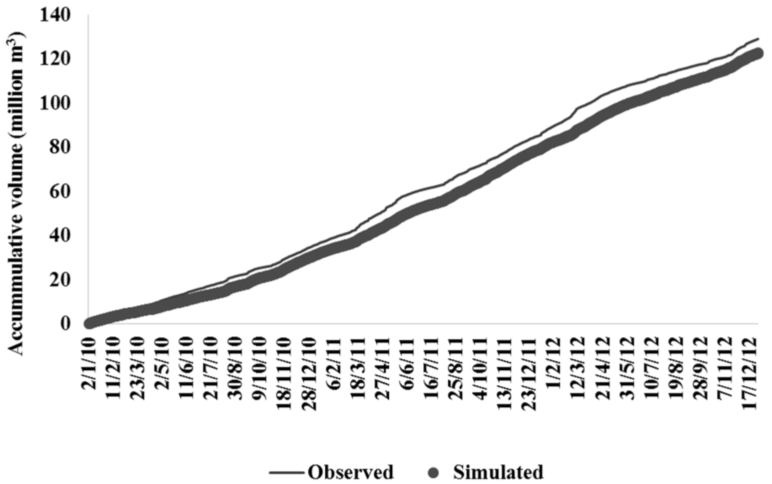


Fig. 9. Cumulative volume of observed and simulated flow during validation period (2010-2012).

5.4. Model calibration and validation for Sg. Telom

The calibration results for continuous period of 2004 to 2006 using stream flow data at Sg. Telom is illustrated in Fig. 10, showing good agreement between the recorded and simulated flow for both low and high flow. Observed peak flows in 2005 are much lower compared to 2004 and 2006 due to less rainfall amount in Telom catchment in 2005. Figure 11 illustrates the cumulative observed and simulated volume, with total difference (or PBIAS) of 0.052%. Good calibration for flood events as shown in Figs. 12(a) and (b) at Sg. Telom in January 2002 and December 2006 were achieved, with NSE values of more than 0.79. Calibration results for both continuous simulation and during flood events at Sg. Telom are good whereby the simulated flow matches with observed flow in terms of timing, rate and volume.

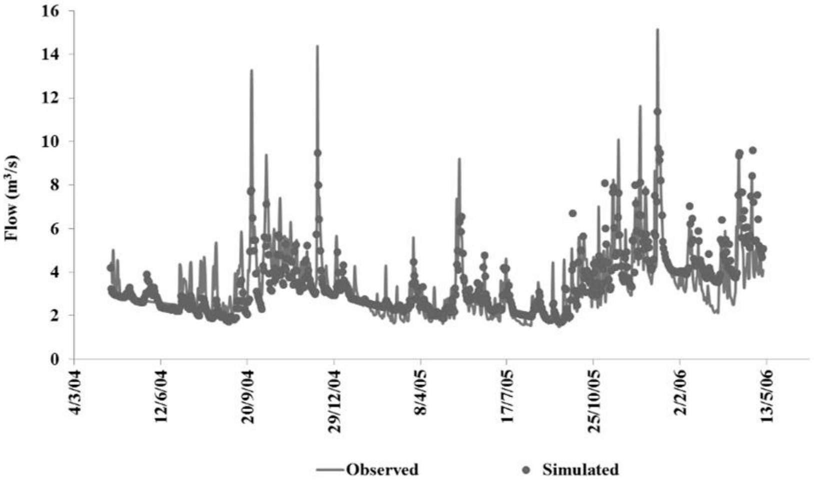


Fig. 10. Comparison between observed and simulated flow for Sg. Telom (2004-2006).

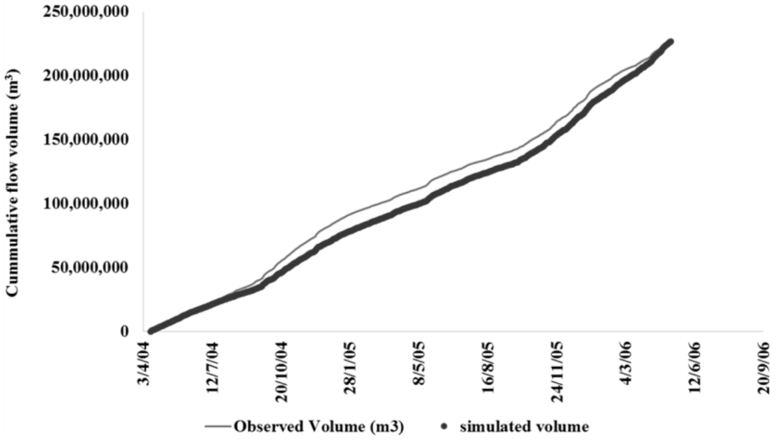
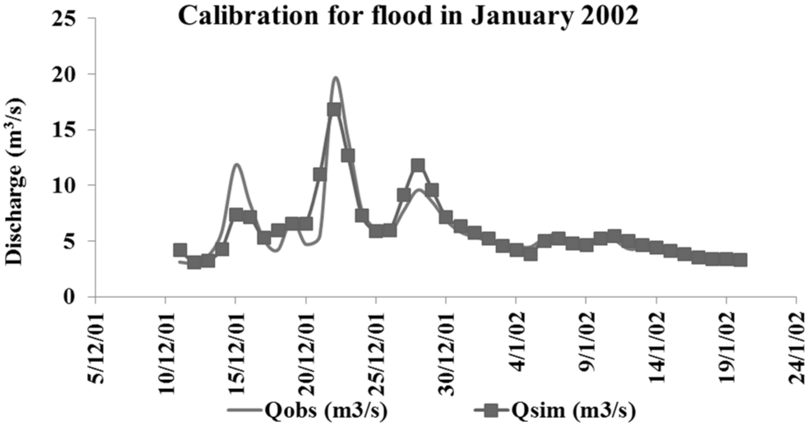
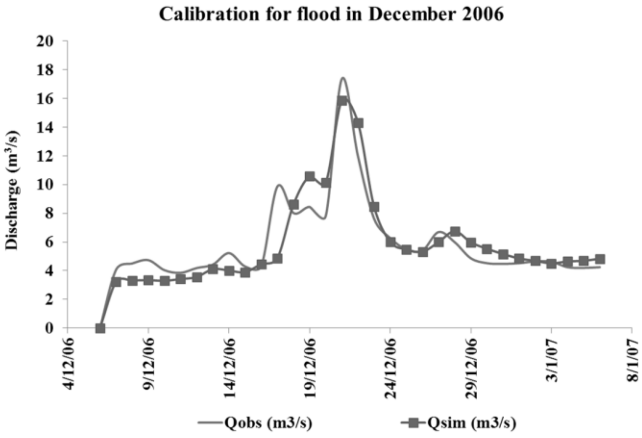


Fig. 11. Comparison between observed and simulated accumulative volume of flow for Sg. Telom (2004 - 2006).



a) January 2002.



b) December 2006.

Fig. 12. Daily flow during flood event.

For Sg. Telom, model validation using the daily flow from 2009 to 2010 performed satisfactorily with NSE > 0.5, as shown in Fig. 13. Validation for flood event in January 2011 performed better, with NSE value of 0.843. The peak flow matches well with the recorded flow on 30th January 2011, as shown in Fig. 14.

Based on calibration and validation results for both Sg. Bertam and Sg. Telom, MIKE NAM is reliable to model the rainfall - runoff process under long-term period and during flood event in Cameron Highlands catchment. NSE values during calibration and validation for continuous simulation are NSE > 0.65 and NSE > 0.52 respectively. In modelling the flood event, NSE values for both calibration and validation are well above 0.7, indicating good model performance.

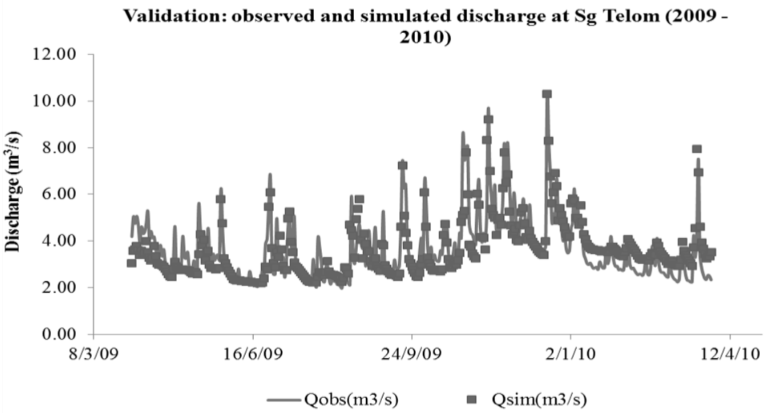


Fig. 13. Comparison between observed and simulated flow for Sg. Telom during validation period (2009-2010).

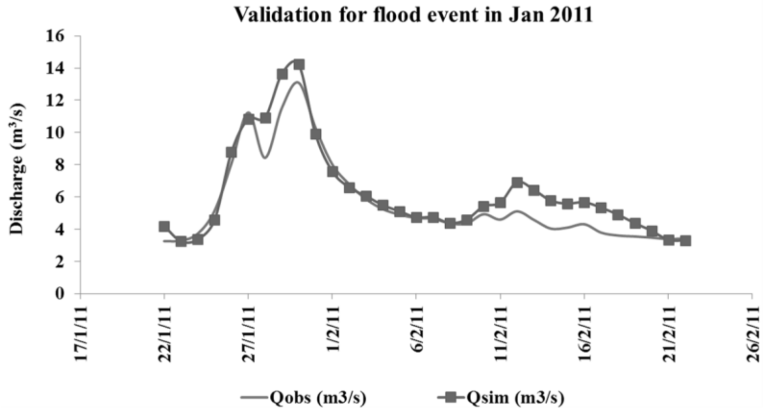


Fig. 14. Daily flow during flood event in January 2011.

5.5. Statistical evaluation of model performance

Although the NSE and graphical plots are usually good to visualise the overall model results, models were further assessed using statistical parameters. Table 7 shows the calibration and validation results for Sg. Bertam, for both continuous and flood event simulation, while Table 8 summarised model performance at Sg.

Telom. In general, both models achieve low values of RMSE, MSE, MAE and RRMSE, which indicate good model performance. NSE results are all above 0.66, R2 > 0.74, RSR<0.66 and average PBIAS is < 15%. The results clearly show that the model is well calibrated and satisfy all statistical parameters requirement.

Based on the NSE, R^2, PBIAS and RSR, model performance during flood events at both locations is better than for continuous simulation. This is because calibration during flood event is normally easier than for continuous simulation since smaller and shorter range of data input is involved. Based on almost similar values of NSE, R^2, PBIAS and RSR at Sg. Bertam and Sg. Telom, model performance for continuous simulation are almost similar. However, model performance during flood event at Sg. Telom is better compared to that of Sg. Bertam.

Table 7. Summary of statistical parameters assessed for calibration and validation at Sg. Bertam.

Parameters	Sg. Bertam				
	Daily		Flood		
	Calibration 1999-2006	Validation 2010-2012	Calibration in January 2009	Calibration May 2011	Validation in February 1999
RMSE (m^3/s)	0.359	0.571	0.997	0.729	0.556
MSE	0.129	0.326	0.994	0.531	0.309
MAE (m^3/s)	0.243	0.339	0.612	0.456	0.358
RRMSE (m^3/s)	0.309	0.419	0.450	0.369	0.330
PBIAS (%)	-6.904	4.852	16.561	-10.386	-4.279
NSE	0.663	0.569	0.712	0.696	0.768
R^2	0.826	0.776	0.877	0.863	0.892
RSR	0.580	0.656	0.537	0.551	0.482

Table 8. Summary of statistical parameters assessed for calibration and validation at Sg. Telom.

Parameters	Daily		Flood		
	Calibration 1999-2006	Validation 2010-2012	Calibration in January 2009	Calibration May 2011	Validation in February 1999
RMSE (m^3/s)	0.986	0.969	1.416	1.315	1.041
MSE	0.973	0.939	2.006	1.730	1.084
MAE (m^3/s)	0.683	0.664	0.833	0.894	0.778
RRMSE (m^3/s)	0.279	0.256	0.238	0.228	0.185
PBIAS (%)	0.052	5.041	-1.638	0.523	-10.96
NSE	0.650	0.523	0.794	0.803	0.843
R^2	0.813	0.744	0.892	0.910	0.954
RSR	0.591	0.690	0.454	0.444	0.396

5.6. Reservoir inflow simulation

Land use variations within the sub-catchments are considered before applying the calibrated parameters in Sg. Bertam and Sg. Telom basin. Each calibrated parameters are adjusted based on the ratio of forest cover of the sub-catchment to that of Sg. Bertam sub-catchment. For instance, Lower Bertam is assigned with lowest U_{max} and

L_{max} as it is most developed sub-catchment with the least forest cover. Ringlet is assigned with highest *CQOF* as it has the highest percentage of urban area. Summary of the parameters used for each sub-catchment is shown in Table 9.

Using the parameters as in Table 9, runoff is simulated from each sub-catchment to derive daily inflow at Sg. Ringlet, Sg. Habu and Sg. Bertam. Simulated total inflow into Ringlet Reservoir as illustrated in Fig. 15. From the simulation, average daily inflow into Ringlet reservoir is 6.55 m^3/s, with maximum of 21 m^3/s.

Table 9. Adjusted MIKE NAM parameters for other sub-catchment.

Sub catchment	Area (km^2)	U_{max}	L_{max}	*CQOF*	*CKIF*	$CK_{1,2}$
Upper Bertam	20.98	12.3	300	0.227	963.8	19.60
Habu	19.12	12.0	296.5	0.210	930.4	18.9
Middle Bertam	13.44	12.3	297.7	0.161	813.7	16.5
Ringlet	9.72	11.4	294.5	0.383	719.4	14.6
Lower Bertam	4.34	11.3	294.1	0.316	529.6	10.8
Reservoir	2.82	12.0	294.9	0.165	449.6	9.1

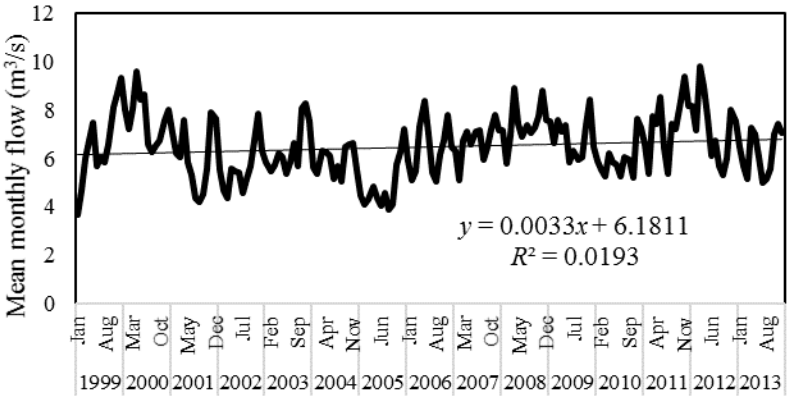


Fig. 15. Simulated mean monthly flow into Ringlet Reservoir using MIKE NAM.

6. Conclusions

Cameron Highlands is located in a highland area at elevation of more than 1000 m above sea level, surrounded by active agricultural and tourism activities. The catchment experiences average annual rainfall of 2800 mm with bi-annual heavy rainfall season. There are two main catchments, namely Telom and Bertam of which, major rivers of Sg. Telom and Sg. Bertam drain into Ringlet Reservoir. Hydrological modelling using MIKE NAM was conducted to simulate runoff in the catchment. Model was calibrated for continuous and flood event simulation. Performance of MIKE NAM was assessed based on overall pattern of the hydrograph, agreement to peak and low flows and using seven (7) statistical parameters such Root Mean Square Error (RMSE), Mean Square Error (MSE), Mean Absolute Error (MAE), Percentage of Bias (PBIAS), Nash-Sutcliffe Efficiency Index (NSE), Relative Root Mean Square Error (RRMSE), Regression (R^2) and Ratio of RMSE (RSR).

The results indicate that MIKE NAM rainfall runoff model was good to simulate the rainfall runoff process in Cameron Highlands on continuous period and during flood event. The model is reliable to simulate flow satisfactorily especially during flood events. Model shows good agreement between the simulated and observed flow in terms of low flow, peak flow and total volume. Good calibration results were achieved for all scenarios, with NSE > 0.66, RSR <0.6, $R^2 > 0.74$ and PBIAS (%) <15%. From the sensitivity analyses, all parameters except $CK_{1,2}$ are sensitive in calculation of total volume. Peak flow is sensitive towards any changes in U_{max}, *TG*, *CQOF*, *CKBF*, *CKIF* and $CK_{1,2}$. Increase in *CQOF* and *CKIF* would increase the peak runoff, however, reduction of $CK_{1,2}$ increase the peak runoff. To reflect the land use difference between the sub-catchments, each calibrated parameters are adjusted based on the ratio of forest cover of the sub-catchment to that of Sg. Bertam sub-catchment.

Runoff is simulated from each sub-catchment to derive daily inflow at Sg. Ringlet, Sg. Habu and Sg. Bertam. From the simulation, average daily inflow into Ringlet reservoir is 6.55 m^3/s, with maximum of 21 m^3/s.

To further improve reliability of this model for flash flood and sediment transport application, simulation of shorter runoff is recommended, in terms of hourly or sub-hourly runoff simulation. MIKE NAM model can be used for event-based and flood forecasting, sediment transport and continuous simulation for water resources management purpose.

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Nomenclatures

$CK_{1,2}$	Time constant for routing interflow and overland flow, hour
CKBF	Baseflow time constant, hour
CKIF	Time constant for interflow, hour
CQOF	Overland flow runoff coefficient
L_{max}	Maximum water content in the root zone storage, mm
TG	Root zone threshold for groundwater recharge
TIF	Root zone threshold value for interflow
TOF	Root zone threshold value for overland flow
U_{max}	Maximum water content in surface storage, mm

Abbreviations

GIS	Geographical Information System
MAE	Mean Absolute Error
NSE	Nash-Sutcliffe Efficiency Index
PBIAS	Percent Bias
R^2	Regression coefficient
RMSE	Root Mean Square Error

RORB	Runoff routing model
RRMSE	Relative Root Mean Square Error
RSR	Ratio of RMSE

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