

Performance Evaluation of Rainfall-Runoff Models for Predictions of Inflows to Bhumibol Reservoir in Thailand

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ABSTRACT

The Bhumibol reservoir in the Ping River basin is the largest reservoir in the Kingdom of Thailand. This reservoir has contributed to economic development of the country by supplying increased electricity and irrigation water demands as well as flood mitigation in riparian areas along the Ping and the Chao Phraya River. The prediction of inflows to the reservoir is crucial for the optimal management of water for irrigation, power generation and flood control. Properly customized rainfall-runoff models of the catchment could provide the basis for predicting the inflows to the reservoir. Hence, five lumped conceptual rainfall-runoff models were developed for the Ping River basin to simulate daily inflows to the Bhumibol reservoir. The rainfall-runoff models are Australian Water Balance Model (AWBM), Sacramento Soil Moisture Accounting Model, Simplified Hydrolog Model (SIMHYD), Soil Moisture Accounting and Routing Model (SMAR) and Tank Model. The evaluation of the performances of these models showed that all models are capable of predicting inflows. However, the SIMHYD, Sacramento, AWBM and Tank models perform better than SMAR model. Hence, these models could be employed for prediction of inflows to the reservoir with acceptable accuracy.

Keywords: Reservoir regulation, Rainfall-runoff model, Flood control, Inflow, Prediction.

1. Introduction

Reservoirs are the most important and effective storage structures to regulate the flow of water in space and time. They provide sustained flow of water for hydropower and irrigation and also smooth out extreme inflow to mitigate floods. To make the best use of water, optimal operation of reservoir is very important. Daily reservoir inflow predictions with lead-times of several days are essential to the operational planning and scheduling of hydroelectric power plants. Forecast information on reservoir inflow could be used to optimize short-term benefits by minimizing spills and maximizing the economic value of water for hydropower production and other water uses. Hence, forecast of future reservoir inflow can be very useful for efficient operation of reservoir. The added value by using inflow forecasting in combination with optimization can be significant (Madsen et al., 2009).

Reservoir operation is usually carried out on the basis of rule curves based on historical flows. Traditionally, reservoir rule curves are defined based on the driest envelope in the entire historical record and the same rule curve is used every year for reservoir operation. A common practice in Thailand is to lower the reservoir to a pre-specified level every year before the rainy season to accommodate the later

monsoon peak flows. This unconditional/static reservoir management strategy could be modified to evolve a dynamic reservoir management strategy if inflow forecasting models are developed which could then be used to predict inflows if the long range forecast of monsoon climate is available.

The inflow to the reservoir could be predicted using various methods. Chang and Chang (2006) have used Adaptive Neuro-Fuzzy Inference System (ANFIS) for prediction of water level in the Shihmen reservoir in Taiwan. Mohammadi et al. (2005) have compared the performance of artificial neural network (ANN), ARIMA time series and regression analysis models to predict the spring inflow in the Amir Kabir reservoir using snowmelt equivalent data and found that the ANN predicts better. Artificial neural networks have been widely used for reservoir inflow forecasting (see Sentu and Regulwar, 2011). Madsen et al. (2009) have employed NAM, MIKE11 and MIKE BASIN models for inflow forecasting and reservoir optimization for hydropower production from the Hoa Binh reservoir in Vietnam. Sankarasubramanian et al. (2009) used monthly updated precipitation forecasts from ECHAM4.5 forced with “persisted” sea surface temperatures for reservoir inflow forecasts to improve both seasonal and intraseasonal water allocation during the October–February season for the Angat reservoir in the Philippines. While there are many publications on the application of vari-

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ous models for reservoir inflow prediction, there are few studies on the comparisons of predictions. This study contributes to fulfill the gap by presenting the performance of five lumped conceptual models for the prediction of inflow to Bhumibol reservoir in Thailand. The models are Australian Water Balance Model (AWBM), Sacramento Soil Moisture Accounting Model, Simplified Hydrolog Model (SIMHYD), Soil Moisture Accounting and Routing Model (SMAR) and Tank Model. These models are chosen because they are easy to use and freely available in Rainfall-Runoff Library (RRL) software developed by eWater (<https://toolkit.ewater.org.au/Tools/RRL>).

2. Study Area

The Bhumibol reservoir lies in the Ping sub-basin of Chao Phraya river basin. Figure 1 shows the study area. The reservoir was constructed in the 1960s for the purpose of irrigation, flood control and hydroelectric power production. The dam is an arch-gravity type and is 154 m high, 486 m long and 8 m wide at its crest. It withholds a reservoir of 13,462 million m³ of which 9,762 million m³ is active or "useful" storage. The dam's catchment area is 26,400 km² while its surface area is 300 km². Its power plant contains eight different turbines for an installed capacity of 749 MW.

The Bhumibol reservoir provides water supply to both northern and central region of Thailand. The reservoir operation in Thailand is difficult because the country is susceptible to both drought and flood risks. The operation of the reservoir during a certain month could critically affect the flow during the subsequent months. Thailand gets rainfall from both southwest monsoon and northeast monsoon. The southwest monsoon usually starts in mid-May and ends in mid-October bringing a stream of moist air from the Indian Ocean towards Thailand causing abundant rain over the country. The northeast monsoon starts in mid-October and ends in mid-February causing abundant rain over the southern part while northern part remains relatively cold and dry.

Table 1 shows the seasonal rainfall for different regions of Thailand. The rainy season spanning from mid-May to mid-October provides about 75% of rainfall for the northern and central region. The northern region gets 8.5% rainfall in winter, 14.7% in summer and 76.8% in the rainy season. Similarly, the central region receives 10.2% rainfall in winter, 15.4% in summer and 74.4% in the rainy season. The deficit water supply during the winter and summer has to be supplemented by the water stored in the reservoir during the rainy season.

3. Data and Methodology

3.1. Data

The following data were used:

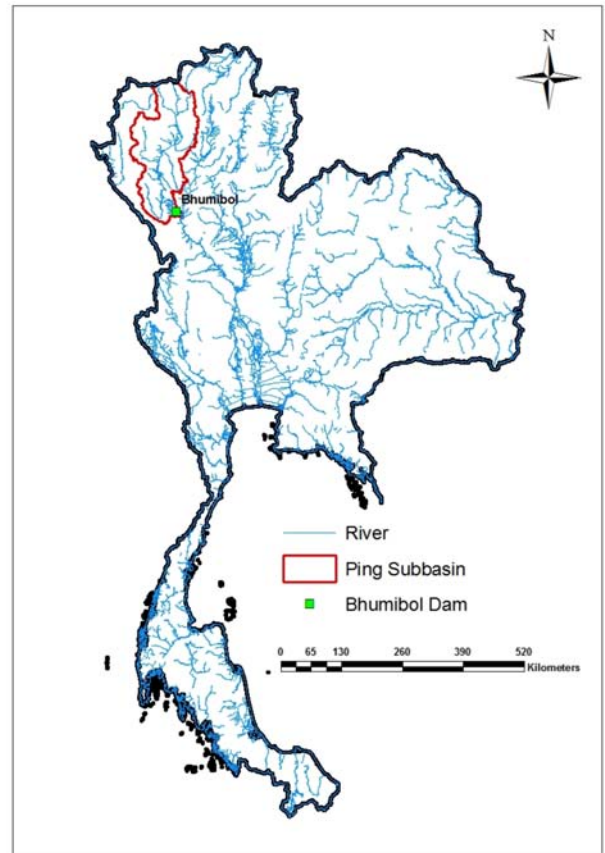


FIG. 1. Location of Bhumibol reservoir in Thailand.

TABLE 1. Seasonal rainfall (mm) in Thailand based on 1971-2000 period.

Region	Winter Season	Summer Season	Rainy Season	Total Rainfall (mm)
North	105.5	182.5	952.1	1240.1
Northeast	71.9	214.2	1085.8	1371.9
Central	124.4	187.1	903.3	1214.8
East	187.9	250.9	1417.6	1856.4
Southeast Coast	759.3	249.6	707.3	1716.2
Southwest Coast	445.9	383.7	1895.7	2725.3

1. A continuous series of mean catchment rainfall data computed from observed station rainfall data
2. A continuous series of catchment average potential/actual evapotranspiration data computed from observed pan evaporation data
3. Observed daily inflow values for the reservoir for model calibration and verification
4. Catchment area to convert flow into depth of runoff

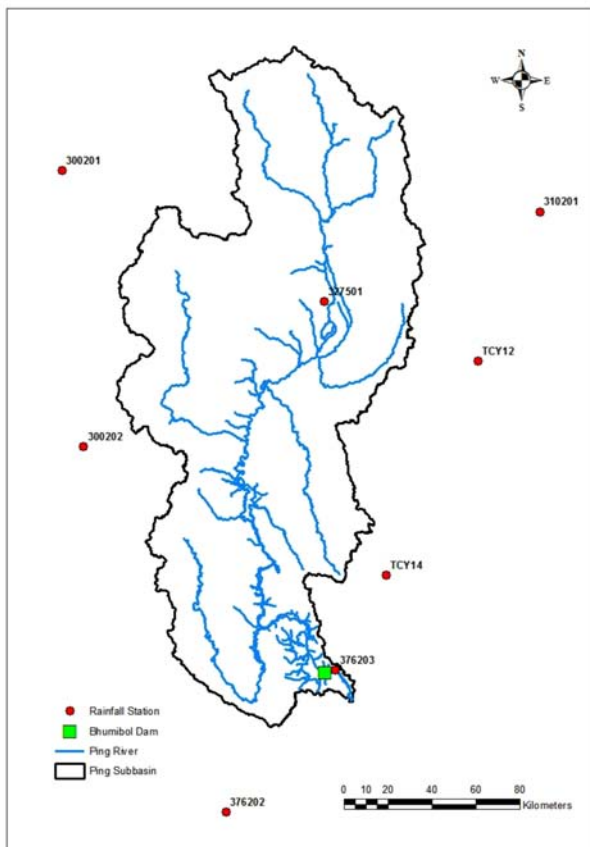


FIG. 2. The Ping basin and stations.

The reservoir inflow data for four years (01/01/2008-17/02/2012) have been obtained from Royal Irrigation Department of Thailand. Similarly, rainfall data for eight stations have been obtained from Thai Meteorological Department and Royal Irrigation Department for the same period. Pan evaporation data for six stations have also been collected from Thai Meteorological Department.

Figure 2 shows the location of the stations and Figure 3 presents the mean daily rainfall, mean pan evaporation and inflow data. Table 2 presents the list of stations.

3.2. Rainfall-Runoff Models

The Rainfall-Runoff Library (RRL) has been used in the study which was developed by eWater, a publicly owned not-for-profit organisation committed to ecologically sustainable water management in Australia and around the world. The software is freely available to download from the website (<https://toolkit.ewater.org.au/Tools/RRL>) by registering as a Toolkit member.

RRL currently contains five rainfall-runoff models, seven calibration optimizers, eleven objective functions and three types of data transformation methods. The

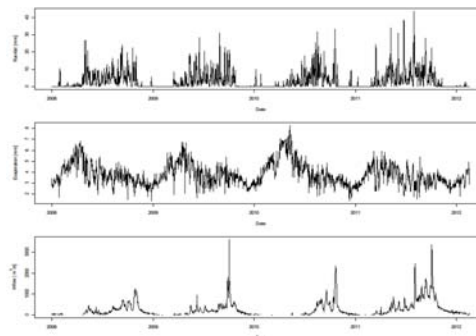


FIG. 3. Mean rainfall, mean pan evaporation and inflow.

TABLE 2. List of stations.

S. No.	Station No.	Station Name	Data Type
1	300201	Mae Hong Son	Rainfall, evaporation
2	300202	Mae Sariang	Rainfall, evaporation
3	310201	Phayao	Rainfall, evaporation
4	327501	Chiang Mai	Rainfall, evaporation
5	376202	Mae Sot	Rainfall, evaporation
6	376203	Bhumibol Dam	Rainfall, evaporation
7	TCY12	Lampang	Rainfall
8	TCY14	Ban Don Chai	Rainfall
9	963073	Bhumibol Reservoir, Khao Kaeo	Inflow, evaporation

graphical user interface comprises menus, dialogues and graph display tools. The rainfall-runoff models are Australian Water Balance Model (AWBM), Sacramento Soil Moisture Accounting Model, Simplified Hydrolog Model (SIMHYD), Soil Moisture Accounting and Routing Model (SMAR) and Tank Model. A detail description of these models could be found in Podger (2004). A brief description of the models is given below.

3.2.1 AUSTRALIAN WATER BALANCE MODEL

The Australian Water Balance Model (AWBM) is a catchment water balance model that computes runoff at the outlet of the catchment using rainfall and evapotranspiration data as input with daily or hourly time scales. Figure 4 shows the schematic diagram of the AWBM model. The model consists of eight parameters and it uses three surface storage elements to simulate partial areas of runoff. The

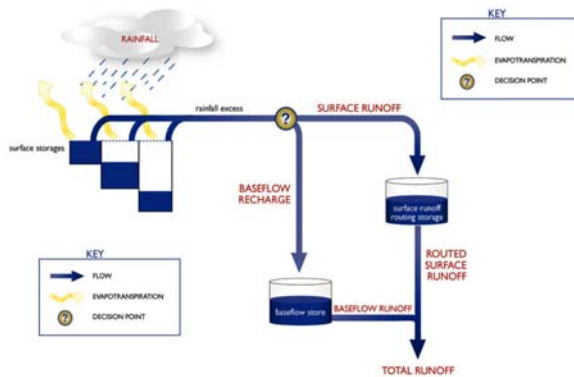


FIG. 4. Schematic diagram of AWBM model.

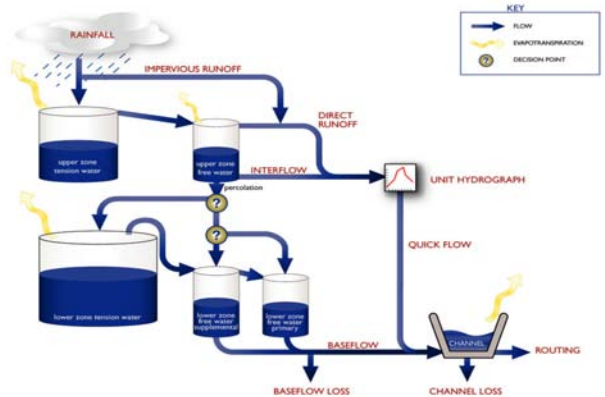


FIG. 5. Schematic diagram of Sacramento model.

water balance of each surface storage element is calculated independently of the others.

The water balance equation can be described as follows:

$$store(n,t) = store(n,t-1) + rain(t) - evp(t) \quad (1)$$

where, $n = 1$ to 3.

The three parameters A1, A2 and A3 (which represent the proportions of the areas of the catchment) are constrained with the following relationship.

$$A1 + A2 + A3 = 1 \quad (2)$$

Hence, only A1 and A2 are set and A3 is calculated from equation (2).

When runoff occurs from any storage element, part of the runoff recharges the base flow storage. The fraction of the runoff used to recharge the base flow storage is $BFI \cdot \text{runoff}$, where BFI is the base flow index i.e. the ratio of base flow to total flow in the stream. The remainder of the runoff, i.e. $(1 - BFI) \cdot \text{runoff}$, is surface runoff. The base flow storage is depleted at the rate of $(1 - K) \cdot BS$ where BS is the current moisture in the base flow storage and K is the base flow recession constant.

The surface runoff is routed through storage to simulate the delay of runoff reaching the outlet of a catchment. The surface storage acts in the same way as the base flow storage, and is depleted at the rate of $(1 - KS) \cdot SS$, where SS is the current moisture in the surface runoff storage and KS is the surface runoff recession constant of the time step being used.

3.2.2 SACRAMENTO SOIL MOISTURE ACCOUNTING MODEL

The Sacramento soil moisture accounting model is a conceptual model with spatially lumped parameters which attempts to parameterize soil moisture characteristics in a manner that logically distributes applied moisture in various depths and energy states in the soil and that has rational

percolation characteristics (Burnash et al., 1995; Burnash and Ferral, 1973). The model represents the distribution of soil moisture by an upper and lower zone. Within each zone the moisture is separated into tension water (water held tightly by soil particles) and free water (water which can move within the soil mantle). Figure 5 shows the schematic diagram of the Sacramento model.

The movement of water between the two zones is controlled by a physically based percolation equation which is controlled by the contents of the upper zone free water and the soil moisture deficiency in the lower zone. The model also includes a representation of the impervious portion of a catchment. The model contains five states and sixteen parameters defining the capacities of the soil zones, the drainage rates of the zones, the shape of the percolation curve, and the size of the impervious areas. The model has a basic approach for simulating the effects of frozen ground. A time series of temperature is required for analysis of frozen ground effects. The model uses precipitation (rain plus melt) and evapotranspiration as input to simulate the runoff from the outlet of the catchment. Observed runoff data are required for model calibration and verification. The model is suitable for large river basins.

3.2.3 SIMPLIFIED HYDROLOG MODEL

Simplified Hydrolog Model (SIMHYD) is a simplified version of the daily conceptual rainfall-runoff model, HYDROLOG, that was developed in 1972 (Porter and McMahon, 1971) and the more recent MODHYDROLOG (Chiew and McMahon, 1994). It estimates daily stream flow from daily rainfall and potential evapotranspiration data. It has seven parameters. The structure of SIMHYD is shown in Figure 6.

In SIMHYD, daily rainfall first fills the interception store, which is emptied each day by evaporation. The excess rainfall is then subjected to an infiltration function

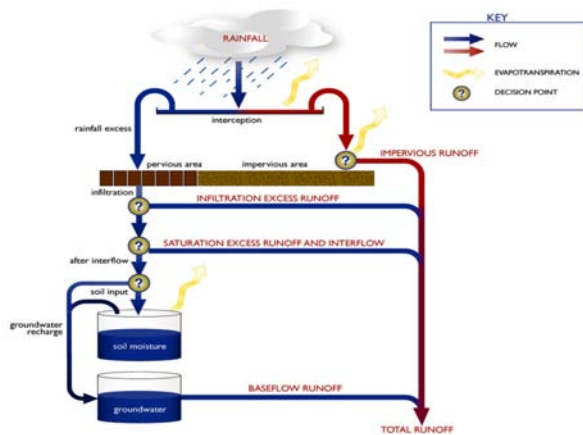


FIG. 6. Schematic diagram of SIMHYD model.

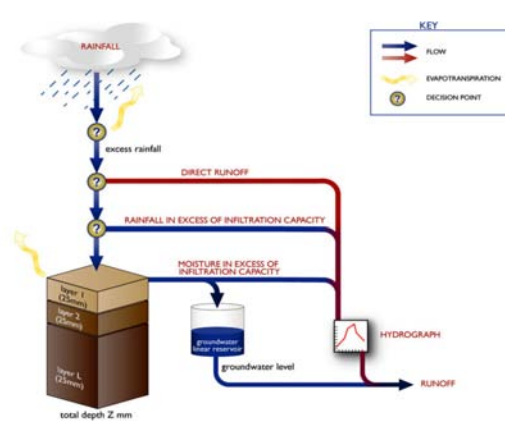


FIG. 7. Schematic diagram of SMAR model.

that determines the infiltration capacity. The excess rainfall that exceeds the infiltration capacity becomes infiltration excess runoff.

Moisture that infiltrates is subjected to a soil moisture function that diverts the water to the stream (interflow), groundwater store (recharge) and soil moisture store. Interflow is first estimated as a linear function of the soil wetness (soil moisture level divided by soil moisture capacity). The equation used to simulate interflow therefore attempts to mimic both the interflow and saturation excess runoff processes (with the soil wetness used to reflect parts of the catchment that are saturated from which saturation excess runoff can occur). Groundwater recharge is then estimated, also as a linear function of the soil wetness. The remaining moisture flows into the soil moisture store.

Evapotranspiration from the soil moisture store is estimated as a linear function of the soil wetness, but cannot exceed the atmospherically controlled rate of areal potential evapotranspiration. The soil moisture store has a finite capacity and overflows into the groundwater store. Base flow from the groundwater store is simulated as a linear recession from the store. The model therefore estimates runoff generation from three sources –infiltration excess runoff, interflow (and saturation excess runoff) and base flow.

3.2.4 SOIL MOISTURE ACCOUNTING AND ROUTING MODEL

The Soil Moisture Accounting and Routing (SMAR) model is a lumped conceptual rainfall-runoff model comprising two components in sequence, a water balance component and a routing component (O’connell et al., 1970; Kachroo, 1992; Tuteja and Cunnane, 1999). A schematic diagram of the SMAR model is shown in Figure 7.

The water balance component divides the soil column into horizontal layers, which contain a prescribed amount of water at their field capacities. Evaporation from soil

layers is treated in a way that reduces the soil moisture storage in an exponential manner from a given potential evapotranspiration demand. The routing component transforms the surface run-off generated from the water balance component to the catchment outlet by a gamma function model form (Nash and HRS, 1960), a parametric solution of the differential routing equation in a single input single output system. The generated groundwater run-off is routed through a single linear reservoir and provides the groundwater contribution to the stream at the catchment outlet. The SMAR model contains nine parameters; five of which are water balance parameters and four are routing parameters.

3.2.5 TANK MODEL

The tank model is a simple model, composed of four tanks laid vertically in series as shown in Figure 8. It consists of fifteen parameters. Precipitation is put into the top tank, and evaporation is subtracted sequentially from the top tank downwards. As each tank is emptied the evaporation shortfall is taken from the next tank down until all tanks are empty. The outputs from the side outlets are the calculated runoffs. The output from the top tank is considered as surface runoff, output from the second tank as intermediate runoff, from the third tank as sub-base runoff and output from the fourth tank as base flow (Sugawara, 1995).

The total runoff is calculated as the sum of the runoffs from each of the tanks. The runoff from each tank is calculated as

$$q = \sum_{x=1}^4 \sum_{y=1}^{nx} (C_x - H_{xy}) a_{xy} \quad (3)$$

where, q = runoff in mm, C_x = water level of tank x , H_{xy} = outlet height, a_{xy} = runoff coefficient for the respective

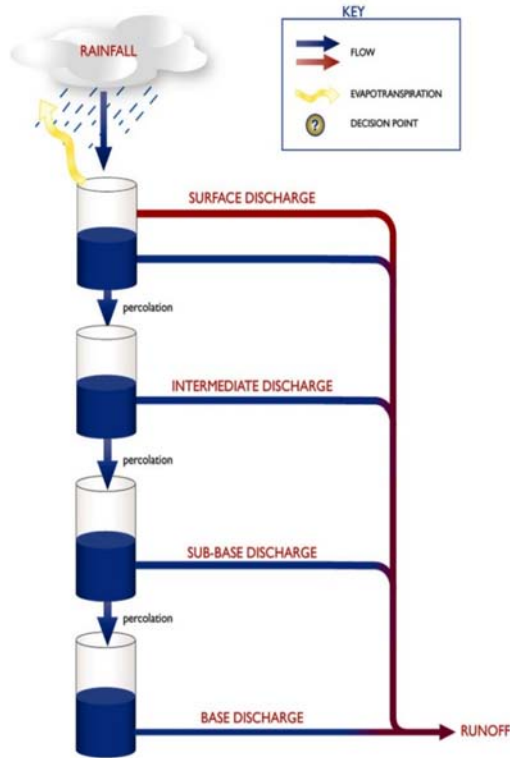


FIG. 8. Schematic diagram of Tank model.

tank outlet. If water level is below the outlet, no discharge occurs. The evapotranspiration is calculated using Beken's equation.

$$ETA = \sum_{x=1}^4 1 - \exp(-\alpha C_x) \quad (4)$$

where, ETA = evapotranspiration in mm, α = evapotranspiration coefficient and C_x = water level of tank. The infiltration in each tank is calculated using:

$$I_x = C_x B_x \quad (5)$$

where, I_x = infiltration in mm, C_x = water level of tank x and B_x = infiltration coefficient of tank x .

The amount of water in each tank affects the amount of rainfall, infiltration, evaporation and runoff. The storages are calculated from the top to the bottom tank. The evaporation is initially deducted from the first storage up to a maximum of the potential rate. The remaining potential evapotranspiration is taken from each of the lower tanks until the potential rate is reached or all of the tanks have been evaporated. After evaporation has been taken from the tanks rainfall is added to the top tank and based on the

revised level runoff, infiltration is estimated. This is subsequently deducted from the storage level. The next tank subsequently receives the infiltration from the tank above. The process continues down through the other tanks.

3.3. Model Calibration Method

Calibration could be done manually, automatically or combination of both. The RRL provides many different types of optimizers for calibrating models. However manual calibration is also an important aspect of model calibration. Manual calibration can be used to investigate how the different parameters change the shape of the simulated hydrograph and also to refine an optimized calibration. The RRL provides a manual calibration tab in the calibration dialogue which contains a dynamic update checkbox, a list of calibration parameters and an update graph button.

There are seven generic optimization algorithms available in RRL. These are

1. Uniform random sampling
2. Pattern search
3. Pattern search multi start
4. Rosenbrock
5. Rosenbrock multi start
6. Genetic algorithm
7. SCE-UA

A custom calibration method is also available for AWBM model. There are 8 primary objective functions available as follows.

1. Nash-Sutcliffe criterion
2. Sum of square errors
3. Root mean square error (RMSE)
4. Root mean square difference about bias
5. Absolute value of bias
6. Sum of square roots
7. Sum of square of the difference of square root
8. Sum of absolute difference of the log

There are three secondary objective functions as given below:

1. Runoff difference in
2. Flow duration curve
3. Base flow method 2

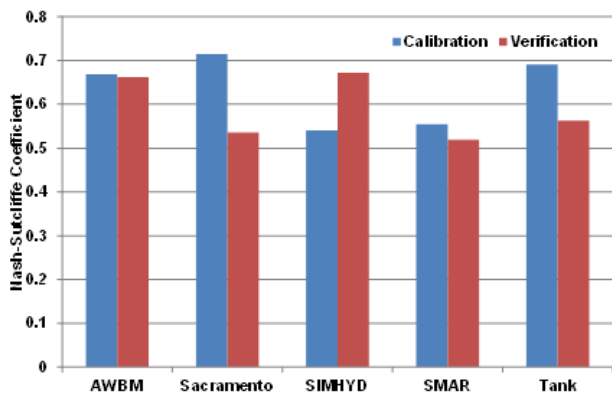


Fig. 9. Nash-Sutcliffe coefficients for calibration and verification period.

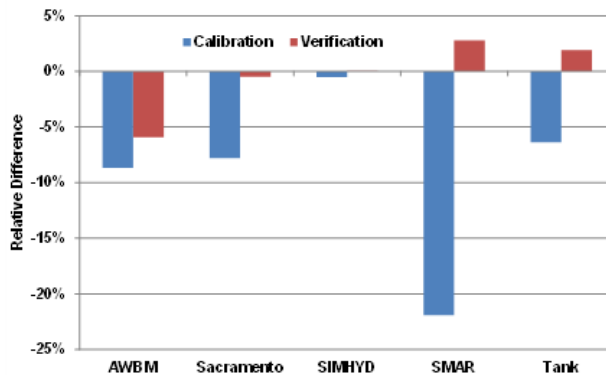


Fig. 10. Relative differences for calibration and verification period.

4. Results

The observed data were available for four years only. Hence, two years data were taken for calibration and the remaining data were taken for verification set. The first five months data of calibration set (01/01/2008 - 31/05/2008) and verification set (01/01/2010 - 31/05/2010) have been selected for the warm up of the model. The warm up period provides the estimate of the initial soil moisture storage. Calibration and verification periods have been specified from 01/06/2008 to 31/12/2009 and 01/06/2010 to 17/02/2012 respectively.

Table 3 presents the summary of the data set. Mean areal rainfall and mean pan evaporation were calculated by arithmetic average method. Since SMAR model uses pan evaporation as input, the Pan factor for this model is 1. Other models use either potential evapotranspiration or actual evapotranspiration as input. Hence, the Pan factor of 0.75 was used for other four models. Among seven optimization methods, genetic algorithm has been found to be the most effective to find the optimal values of parameters. Nash-Sutcliffe criterion has been selected as objective function. The set of optimal parameter values for each model are presented in Table 4.

Figures 9 and 10 present the comparative values of Nash-Sutcliffe coefficient and relative difference for calibration and verification period for different models.

Figures 11 and 12 present the observed and simulated inflows obtained by different models for calibration and verification period.

The results show that all models are good in conserving runoff volume with SIMHYD, AWBM, Sacramento and Tank models performing relatively better than SMAR model. In terms of Nash-Sutcliffe coefficient, Sacramento model performed better for calibration set with Nash-Sutcliffe coefficient of 0.715 whereas SIMHYD performed better for verification set with Nash-Sutcliffe coefficient of

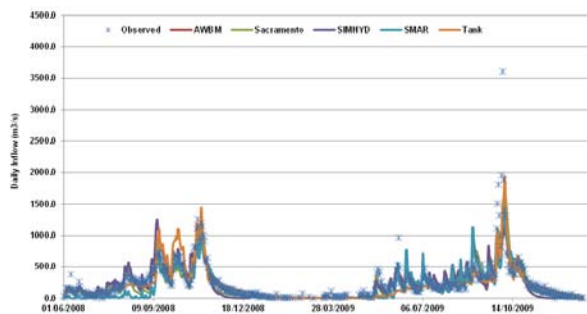


Fig. 11. Observed and simulated inflows for calibration period.

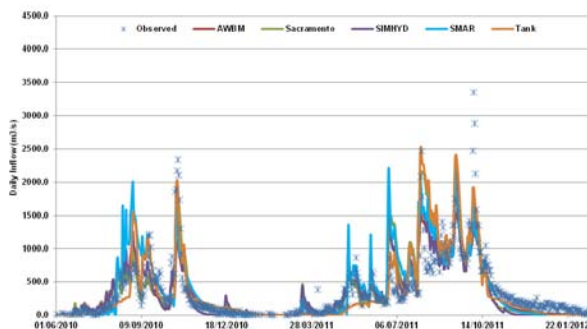


Fig. 12. Observed and simulated inflows for verification period.

0.672. In terms of relative difference of runoff volume, SIMHYD model performed better for both calibration and verification set. The relative difference of SIMHYD model was within 5% for both calibration and verification period. Generally, Nash-Sutcliffe coefficient greater than 0.5 and relative difference less than 10% is considered acceptable. All models achieved Nash-Sutcliffe coefficient greater than 0.5. However, the relative difference of SMAR model was -21.94% for calibration set.

The observed and simulated hydrograph plots show that all models underestimate the peak flows of 2009 and 2011

TABLE 3. Summary of data set.

Data set	Start date	End date	Length	Missing	Total (mm)	Mean (mm)	Std. dev. (mm)	Skew (mm)
Evaporation	01-01-08	17-02-12	1509	0	5710.07	3.784	1.052	0.815
Rainfall	01-01-08	17-02-12	1509	0	5042.725	3.342	5.439	2.652
Obs. Runoff	01-01-08	17-02-12	1509	330	1172.786	0.995	1.259	3.122
Calib. Obs. Runoff	01-06-08	31-12-09	579	73	440.28	0.87	1.015	4.19
Verif. Obs. Runoff	01-06-10	17-02-12	627	67	702.071	1.254	1.484	2.423

TABLE 4. Model parameters.

AWBM		Sacramento		SIMHYD		SMAR		Tank	
Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value
A1	0.31	Adimp	0.0235	Baseflow Coefficient	0.14	C	0.26	H11	400
A2	0.3	Lzfpn	32.55	Impervious Threshold	10	G	0.95	a11	0.2
BFI	0.71	Lzfsn	36.27	Infiltration Coefficient	200	H	0.05	a12	0.1
C1	23.5	Lzpk	0.286	Infiltration Shape	1.3	Kg	0.06	a21	0.54
C2	482	Lzsk	0.027	Interflow Coefficient	0.032	N	1	a31	1
C3	1490	Lztwm	371.76	Pervious Fraction	0.989	NK	1	a41	0
KBase	0.9	Pctim	0.0039	Rainfall Interception Store Capacity	3.43	T	0.7	alpha	3
KSurf	0.97	Pfree	0.27	Recharge Coefficient	0.714	Y	3000	b1	0.008
		Rexp	2.62	Soil Moisture Store Capacity	572	Z	150	b2	0.52
		Rserv	0.68					b3	0.08
		Sarva	0.0078					C1	90
		Side	0.447					C2	90
		Ssout	0.0627					C3	77
		Uzfwm	77.8					C4	17
		Uzk	0.051					H12	262
		Uztwm	9.41					H21	0.39
		Zperc	14.43					H31	18
								H41	90

during calibration and verification period. This shows the limitation of these models for peak flow forecasting. Nevertheless, SIMHYD, Sacramento, AWBM and Tank models could be employed for prediction of inflows to the reservoir with reasonable accuracy.

5. Conclusion

The Ping basin in the Northern Thailand gets about 75% of annual rainfall during monsoon season spanning from mid-May to mid-October. During this period, the flood in the Ping River causes loss of life, damage to infrastructures and the environment downstream up to the Bangkok. Rest of the time, there is a deficit of water availability for hydropower and irrigation. Hence, the Bhumibol reservoir has been constructed to provide the regulated water supply for hydropower and irrigation throughout the year and for the purpose of flood control.

The reservoir is operated based on rule curve derived from historical flow records and the same rule curve is used each year. A common practice in Thailand is to lower the reservoir to a pre-specified level every year before the rainy season to accommodate the later monsoon peak flows. This unconditional/static reservoir management strategy could be modified to evolve a dynamic reservoir management strategy if inflow forecasting models are available. The inflow to the reservoir could be predicted using various methods. This study utilized five lumped conceptual models available in Rainfall-Runoff Library (RRL) developed by eWater, Australia. The skills of the models in terms of Nash-Sutcliffe coefficient and relative difference have been computed. Comparison has also been done by visualizing hydrograph plots of the observed and simulated series. It is found that all models are good in conserving runoff volume but underestimate the peak flows. In terms of Nash-Sutcliffe coefficient, all models achieved the value greater than 0.5. In terms of relative difference

of runoff volume, SMAR model showed poor performance with -21.94% for calibration set. However, the relative difference for other four models was below 10%. Hence, Sacramento, AWBM, SIMHYD and Tank models could be employed for prediction of inflows to the reservoir with acceptable accuracy. However, care should be taken while employing these models in peak flow forecasting.

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