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Daily Streamflow Forecasting of the Gauged Molawin Watershed Using Model Combinations and the Ungauged Eastern Dampalit Watershed by Spatial Proximity Regionalization

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Abstract

Five-, four-, and three-model combinations using Australian Water Balance Method (AWBM), Sacramento, SimHyd, Soil Moisture Accounting and Routing (SMAR), and Tank were implemented to produce streamflow simulations for the gauged Molawin watershed of the Makiling Forest Reserve. Remarkable improvements in the Nash-Sutcliffe Efficiency (NSE) were achieved. The best model – the four-model combination WAM(4) – registered calibration and validation NSE values of 0.929 and 0.830, respectively; a volumetric fit index of 90.84%; and relative peak flow errors generally within 50%. By spatial proximity regionalization, WAM(4) was used to generate a 20-year streamflow data for the ungauged Eastern Dampalit watershed. The study demonstrates an effective strategy in improving rainfall-runoff simulations, and provides a scientifically sound approach to streamflow data generation for watersheds that are ungauged.

Keywords: Catchment hydrology, Makiling Forest Reserve, Nash-Sutcliffe Efficiency, rainfall-runoff modeling, spatial proximity regionalization, streamflow simulation, watershed

Introduction

The Philippines has abundant water resources as a consequence of its geographical set-up. Moreover, it thrives with a relatively high annual average rainfall of about 2,500 millimeters. However, water resource management remains a huge problem in the country. Water supply during rainy seasons cause destructive flooding especially in riversides and urban areas, and has often resulted to major economic losses. Addressing these problems require adequate flood monitoring and effective water resource management. For these to be done properly, important data such as rainfall and streamflow relations in the country's watersheds have to be available and reliable. Only with adequate and reasonably acceptable data can water managers make intelligent decisions or appropriate interventions on the country's water problem. However, many watersheds for which streamflow information is needed are usually ungauged, as most of these catchments are found in headwaters in mountainous areas which are difficult to monitor due to the remoteness of the location (Goswami et al., 2006). This lack of streamflow data for water management and planning has posed a constant challenge to the government.

The problem caused by the limited availability of streamflow records for many watersheds in the country is further compounded by the difficulty of finding a single model that satisfactorily predicts streamflow under various catchment conditions. In rainfall-runoff modeling, there is often no single model that is reliable enough to simulate rainfall-runoff relations. As such, some hydrologists suggest simultaneously generating runoff simulations using different models and combining results from these models to come up with better streamflow predictions (Shamseldin et al., 1997). This method of forecast combination was pioneered by Bates & Granger (1969) and was well reviewed by Clemen (1989). It is based on the principle that each model reflects different characteristics of the process and integrating these may be a way of exploiting all related information (Goswami et al., 2006; Shamseldin et al., 1997). Each model has its immanent advantages and disadvantages, hence it is quite reasonable to combine the models so that the strengths of each model are accentuated while the weaknesses are undermined.

With the foregoing premise, we endeavored to produce better rainfall-runoff simulations for the gauged Molawin watershed of the Makiling Forest Reserve (MFR) using a model combinations approach, and generate a reasonably reliable streamflow data. The combination methods used are simple averaging method (SAM) and weighted averaging method (WAM). Moreover, using spatial proximity regionalization procedures, we also attempted to generate a 20-year streamflow data for the ungauged Eastern Dampalit watershed of the same forest reserve. Regionalization is the transfer of model parameters from one watershed to another through regression, spatial proximity or physical similarity methods (Zhang and Chiew, 2009). Of the three, Merz and Blöschl (2003) found spatial proximity to be the best method and was therefore employed in this study. The individually optimized lumped conceptual models (Australian Water Balance Method [AWBM], Sacramento, SimHyd, Soil Moisture Accounting and Routing [SMAR], and Tank) for the Molawin watershed used by Clanor et al. (2015) served as our data source in generating the rainfall-runoff simulations of model combinations.

The 20-year daily streamflow simulation data for the watersheds will allow for the derivation of other important hydrologic data such as peak flow for flood forecasting, low flows for irrigation capability assessment, and monthly or annual runoff volume for water yield studies. Since streamflow information is an important requirement in hydrologic studies, having the data readily available simplifies and encourages future studies in the catchments. Moreover, the entire procedure for conducting streamflow predictions in an ungauged catchment demonstrated in this paper can be duplicated for other watersheds in the country, making this paper a valuable reference for local hydrologic studies.

Methodology

Study area

The study area is in the Makiling Forest Reserve (MFR), which is situated within 14°6’ to 14°11’ north latitude and 121°09’ to 121°15’ east longitude. The whole of the MFR is currently under the exclusive jurisdiction and control of the University of the Philippines Los Baños as a laboratory for research, protection, and development of the forest according to Republic Act No. 6967 of the 1987 Philippine Constitution. It has four watersheds namely Molawin-Dampalit, Cambantoc, Greater Sipit and Tigbi (Lapitan et al., 2011) of which the Molawin-Dampalit watershed zone is the largest (Figure 1). The Molawin-Dampalit watershed has the most complex drainage system among the four and the Molawin and the Dampalit creeks are the most prominent creeks in the area. The headwater of the major creeks originates from Mount Makiling’s Peak II. The Molawin-Dampalit watershed is one of MFR’s major drainage systems in terms of size and importance to lowland communities. It also has the highest density of creeks and rivers due to its many perennial streams as well as many smaller and intermittent streams.

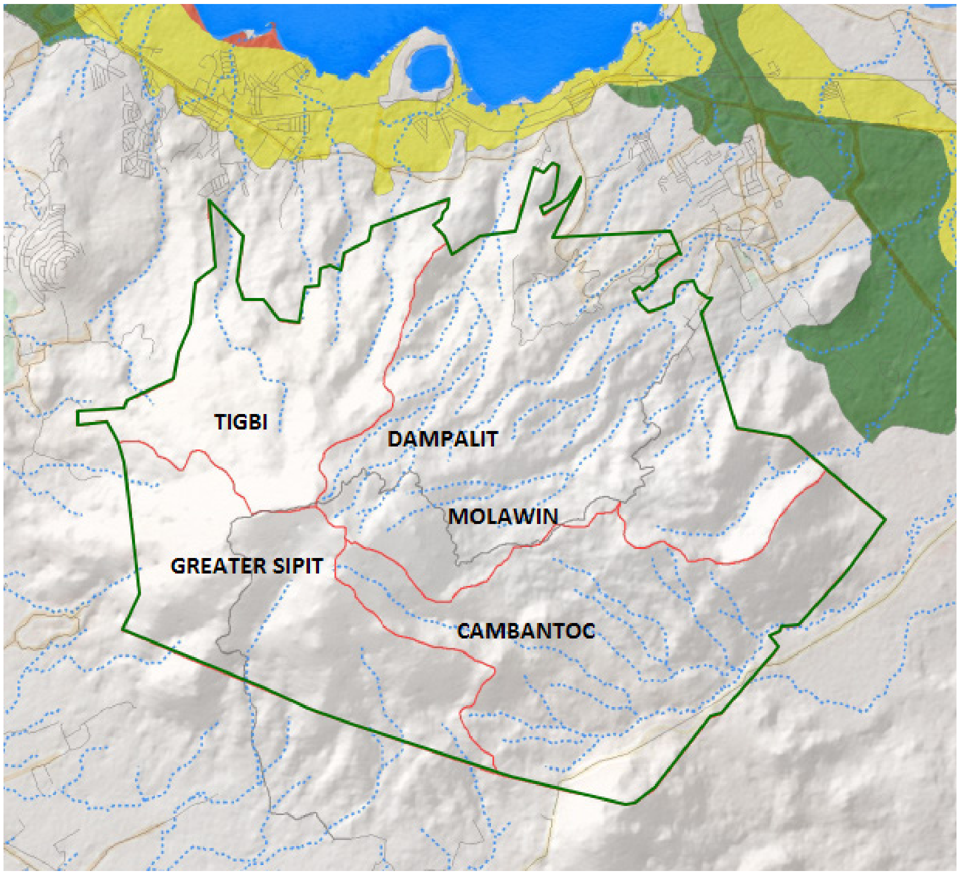

Figure 1. Location map of the Molawin-Dampalit watershed zone (MCME, 2015).

The terrain of the MFR was described by Saplaco et al. (2001) to be varying from gentle slopes to bumpy hills with 20 meters above sea level (masl) and 1143 masl as the lowest point and peak, respectively. The dominant slope in the MFR, occupying almost 40% of the reserve, ranges from 18% - 30% which is characterized by rolling to moderately steep slope. The majority of the reserve area is found within the elevation of 200 masl to 500 masl based on Table 1. For visualization, the elevation map of the MFR is shown in Figure 2. Based on the map, the Molawin and Dampalit watersheds share very similar topography.

Table 1. Area and percent distribution of the elevation categories at MFR (Saplaco et al., 2001).

ELEVATION RANGE (m)	AREA (ha)	PERCENT (%)
< 100	113.96	2.62
100 – 200	548.32	12.61
200 – 300	777.82	17.89
300 – 400	810.01	18.63
400 – 500	716.29	16.48
500 – 600	455.28	10.47
600 – 700	341.88	7.86
700 – 800	242,87	5.59
800 – 900	199.90	4.60
900 – 1000	103.97	2.39
> 1000	36.57	0.85
Total	4346.87	100.00

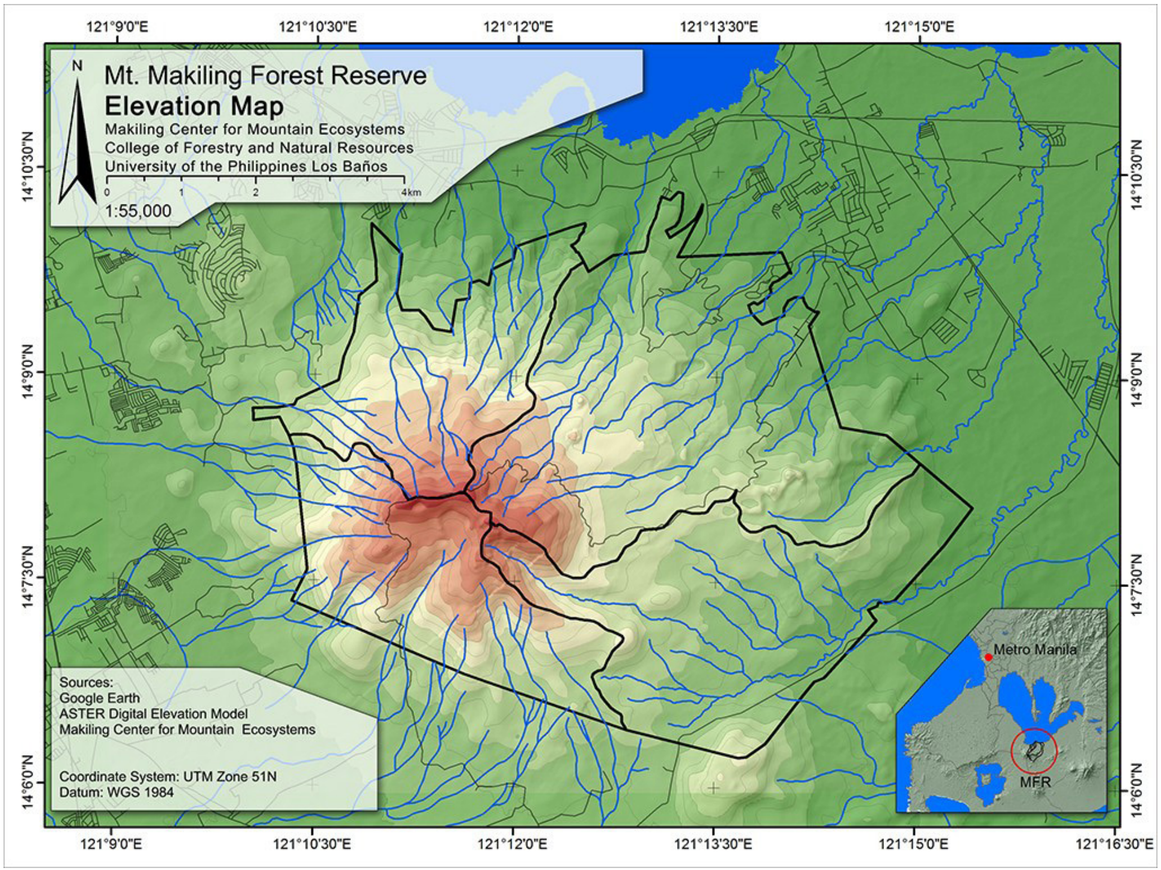

Figure 2. Elevation map of the Makiling Forest Reserve (MCME, 2015).

The land cover map of the MFR shows that much of the Tigbi and Greater Sipit watersheds comprises broadleaved closed forests (Figure 3). The Cambantoc watershed has a more varied land cover which include wide grassland and agroforest areas, aside from the mossy forest peak. On the other hand, the Molawin-Dampalit watersheds are mostly open forests and, according to Lapitan et. al 2011, are dominated by dipterocarp species, indigenous non-dipterocarp species, and agroforest zones for various crops.

In terms of soil type, the MFR is predominantly composed of the Macolod series (Figure 4). The low-lying areas of the Molawin-Dampalit, Tigbi, and Cambantoc watersheds, however, are composed of the Lipa soil series.

Based on the modified Corona classification of the Philippine Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA), the climate type that prevails in the MFR is Type I. This is supported by the 2011 year-length plot of rainfall in the area which shows pronounced wet and dry seasons and the maximum rainfall occurring within June to September (Figure 5).

The 377-hectare Molawin watershed was chosen as the gauged catchment, as it is the only watershed in the MFR that has enough streamflow record for modeling. For the ungauged catchment, the Eastern Dampalit watershed with an area of about 435 hectares was considered due to its proximity to the gauged catchment, its similarity with the latter in terms of physical features (e.g. topography, land cover, soil series) and climatic conditions, and also for its relatively large stream network configuration that drain to a single major stream.

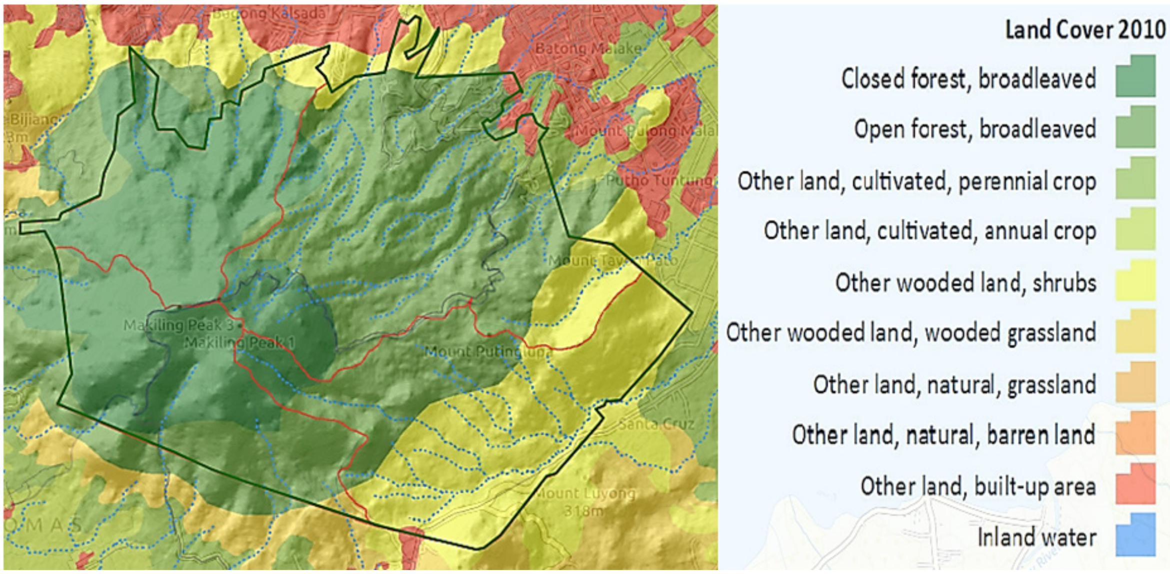

Figure 3. Land cover map of the Makiling Forest Reserve (MCME, 2015).

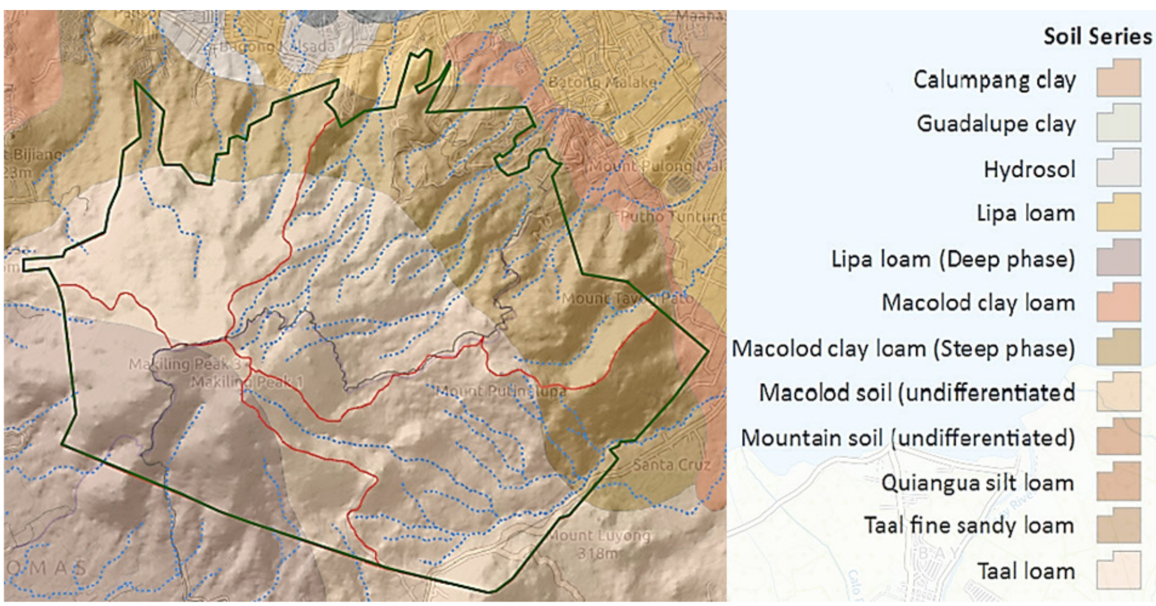

Figure 4. Soil series map of the Makiling Forest Reserve (MCME, 2015).

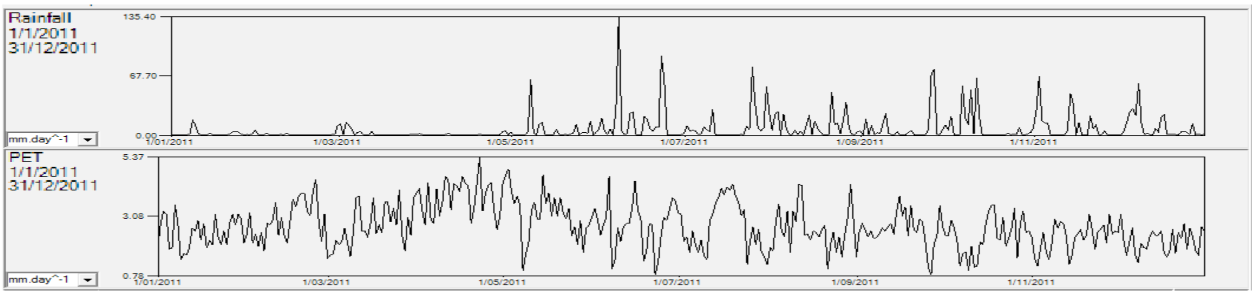

Figure 5. Rainfall time series in the MFR for 2011 generated using the software Rainfall Runoff Library.

Model source and model combinations

The individual models considered in this study are AWBM, Sacramento, SimHyd, SMAR, and Tank, whose parameters have been previously optimized for the Molawin watershed by Clanor et al. (2015) using the software Rainfall Runoff Library (Version 1.0.5) developed by the Cooperative Research Center for Catchment Hydrology (CRCCH). The resulting calibration and validation Nash-Sutcliffe efficiencies (NSE) from this previous work are summarized in Table 2. Based on the validation NSE, the arrangement of the models from best to poorest is Tank, SimHyd, Sacramento, SMAR, and then AWBM.

Five, four and three-model combinations were performed using simple averaging method (SAM) and weighted averaging method (WAM) using the individual models. The five-model combinations, SAM (5) and WAM (5), included all the models. The four-model combinations, SAM (4) and WAM (4), do not include the model that appeared to be the poorest based on the validation NSE. Finally, the second worst model was also dropped for SAM (3) and WAM (3). As such, AWBM was omitted in the four-model combinations; and AWBM and SMAR were dropped in the three-model combinations.

The streamflow estimates from the model combinations were performed using a spreadsheet application. For WAM, the weights of each model were determined and optimized using the generalized reduced gradient algorithm through the Solver function in Microsoft Excel 2010. A minimum weight for each of the models for every combination in WAM was set. This was determined in an iterative manner by first setting the minimum weights as 0.01 and increasing in 0.01 steps until a maximum NSE was achieved.

The resulting five-, four-, and three- model combinations were then treated as individual models whose calibration and validation NSEs were computed using spreadsheet.

Table 2. NSE values of the individual models for the Molawin watershed (Clanor et al., 2015).

MODELS	NSE*	
	Calibration	Validation
AWBM	0.706	0.599
Sacramento	0.914	0.800
SimHyd	0.878	0.802
SMAR	0.822	0.709
Tank	0.928	0.809

*NSE < 0.8, unsatisfactory; 0.8 < NSE < 0.9, fairly good fit; NSE > 0.9, very good model fit

Averaging methods for the model combinations

Simple averaging method (**SAM**)

SAM is considered as the most straightforward combination method as it is simply the arithmetic mean of the model results. Using equal weight distribution among the outputs, it emphasizes equal importance of the models (Shamseldin et al., 1997) even if the objective function suggests that one has more significant results than the others. The equation used in SAM is presented below:

$$Q_{SAM-N} = \frac{1}{N}\sum_{1}^{N} Q_i$$

where Q_{SAM-N} is the combined streamflow using SAM with N models, N is the number of models combined, and Q_i is the streamflow output of the ith model.

Weighted averaging method (**WAM**)

WAM is very similar to SAM except that varying weight distributions for each model is assigned. This method may be used alternatively instead of SAM as the latter may appear to be insufficient (Armstrong, 1989) for the case when some models in the combination constantly perform worse than the others (Shamseldin et al., 1997). The equation used in WAM is presented below:

$$Q_{WAM-N} = \frac{1}{N}\sum_{1}^{N} a_i \; x \; Q_i$$

where Q_{WAM-N} is the combined streamflow using WAM with N models, and a_i is the weight assigned to the ith model.

Model efficiency criteria

Three model criteria were considered in this study, namely, NSE, relative error of peak flow, and index of volumetric fit. Among these, NSE was used as the objective function or the criterion to be optimized. NSE was also the only objective function considered in choosing the best model; the other two model efficiency criteria were used to further describe the suitability of the chosen model for some applications.

Nash-Sutcliffe efficiency (**NSE**)

NSE measures how a certain model simulation is able to predict better the actual streamflow compared to simply using the average stream flow as the simulation (Goswami et al., 2002b). An NSE value of 1.0 means perfect model simulation while a value of zero suggests that the simulation is only as good as using the average runoff as the daily streamflow (Goswami et al., 2010). The NSE is computed using the equation

$$NSE = 1 - \frac{\sum[(Q_o)_i - (Q_s)_i]^2}{\sum[(Q_o)_i - Q_{ave}]^2}$$

where $(Q_o)_i$ is the observed streamflow at the ith day, $(Q_s)_i$ is the simulated streamflow at the ith day, and Q_{ave} is the average of the observed streamflow data at the time period.

Index of volumetric fit (**IVF**)

The index of volumetric fit (IVF) is expressed as the ratio of the total volumes of the simulated and observed streamflows (Goswami et al., 2002a). This measure is specifically important if the model will be used in water yield studies as it can check if the model maintains water balance (Goswami et al., 2010). Also, this can detect model bias in underestimating or overestimating streamflows. An IVF value close to one means a good water balance on the model simulation. The IVF is expressed mathematically as

$$IVF = \frac{\sum(Q_s)_i}{\sum(Q_o)_i}$$

where $(Q_o)_i$ is the observed streamflow at the ith day, and $(Q_s)_i$ is the simulated streamflow at the ith day.

Relative error of peak flow (**RE$_p$**)

This criterion was included in this study as an accurate peak flow simulation is particularly necessary in flood forecasting (Shamseldin et al., 1997). The value of this objective function ranges from zero to positive infinity; as this is a measure of error, a lower value indicates more accurate simulation. The relative error of peak flow is computed using the equation below:

$$RE_p = \frac{|(Q_p)_s - (Q_p)_o|}{(Q_p)_o}$$

where RE_p is the relative error of the peak flow, $(Q_p)_s$ is the peak flow in the simulation, and $(Q_p)_o$ is the observed peak flow.

Regionalization

Regionalization is the transfer of model parameters from one watershed to another (Blöschl & Sivapalan, 1995). Common methods of regionalization include regression, spatial proximity, and physical similarity. The regression method relates physical and climatic characteristics of the catchment with the model parameters. The physical similarity method, on the other hand, uses the model parameters of a similar catchment in terms of physical properties. The third method, spatial proximity, involves adopting the model parameters from the geographically nearest gauged catchment under the assumption that the catchments have similar climatic and physical attributes due to proximity. In practice, this means that after a best model combination has been determined for predicting streamflow in the gauged Molawin watershed, the model parameters and combinations composing the model may be utilized for predicting streamflow in adjacent or nearby catchments such as the ungauged Eastern Dampalit watershed. Because the location of the Molawin and Eastern Dampalit watersheds warrants the assumption of similarity in climate, and because available data (e.g. topography, land cover, soil type) confirm similarity in their physical attributes, the spatial proximity method was employed in this study.

Results and Discussion

The model combinations were performed by first extracting the streamflow simulation results from calibration and validation of the individual models as applied on the gauged Molawin watershed. The simulations were imported to Microsoft Excel to handle the combination process and the NSE values were computed manually in the spreadsheet after they have been subjected to either SAM or WAM.

In WAM, a minimum weight was set to maintain the significant contribution of each model in the simulation. Without this consideration, some models would have been set with negative or almost zero weights in the weight optimization process. This value was determined iteratively by optimizing the average NSE value for calibration and validation. The minimum weight for each model was first set to 0.01 and was raised by an increment of 0.01 until a maximum NSE was obtained. The optimized weight distribution and minimum weights for the corresponding model combinations are shown below in Table 3.

As might be expected, the biggest weight contributions were from the Tank model, which had previously been determined as the best individual rainfall-runoff model for the Molawin watershed. However, there appears to be no obvious trend on the weight contribution of the best individual model in relation to the number of models embedded in a model combination so that

Table 3. Optimized and minimum weights for WAM.

MODEL COMBINATION	MINIMUM WEIGHT	MODELS				
		AWBM	Sacramento	SimHyd	SMAR	Tank
WAM (5)	0.07	0.07	0.0700	0.07	0.07	0.7200
WAM (4)	0.13	-	0.1449	0.13	0.13	0.5951
WAM (3)	0.16	-	0.1781	0.16	-	0.6619

a maximum NSE is achieved, which is probably a consequence of the inherent complexity of each model and the models having individual strengths and weaknesses. Nevertheless, the NSE results of the model combinations were summarized in Table 4 and compared.

From Table 4, it is clear that the model combinations generally have greater NSE values than the individual models highlighting the significance of extending rainfall-runoff modeling tasks to using model combinations. In fact, a comparison of the validation NSE of the group of individual models and that of the model combinations by Duncan Multiple Range Test at 0.05 and 0.01 significance levels reveal that there is significant difference between the NSE values of the two modeling approaches. However, the same test reveals that there is no significant difference between NSE results obtained by SAM and WAM.

Table 4. Summary of NSE values for the individual models and model combinations.

MODELS	NSE*	
	Calibration	Validation
AWBM	0.706	0.599
Sacramento	0.914	0.800
SimHyd	0.878	0.802
SMAR	0.822	0.709
Tank	0.928	0.809
SAM (5)	0.896	0.814
SAM (4)	0.915	0.832
SAM (3)	0.920	0.824
WAM (5)	0.929	0.823
WAM (4)	0.929	0.830
WAM (3)	0.929	0.821

*NSE < 0.8, unsatisfactory; 0.8 < NSE < 0.9, fairly good fit; NSE > 0.9, very good model fit

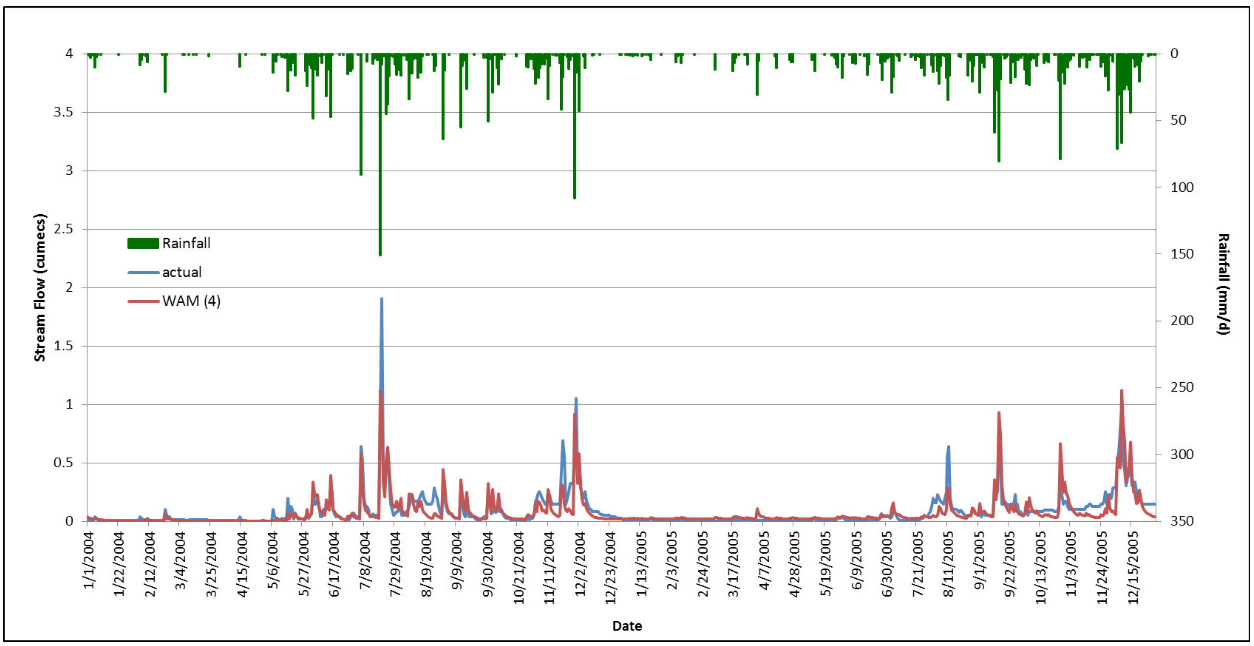

Figure 6. Two-year plot of actual and WAM (4) - simulated streamflows of the Molawin watershed.

Table 5. RE_p values for observed streamflows greater than 0.6 m³/s using WAM (4).

Date	Streamflow		RE_p* (%)
	Actual	Simulated	
July 6, 2004	0.6414	0.5756	-10.26
July 19, 2004	0.8886	1.1123	25.17
July 20, 2004	1.9082	0.9033	-52.66
November 21, 2004	0.6880	0.2979	-56.70
November 29, 2004	0.6880	0.9186	33.52
November 30, 2004	1.0537	0.5855	-44.43
August 12, 2005	0.6414	0.2677	-58.27
September 15, 2005	0.7360	0.9292	26.24
December 7, 2005	0.7855	0.4563	-41.91
December 8, 2005	0.9423	1.1190	18.76
June 21, 2006	0.9423	0.6773	-28.12
July 13, 2006	1.1115	0.4677	-57.92
September 27, 2006	2.1364	1.9402	-9.18
September 28, 2006	13.9602	12.6282	-9.54
December 11, 2006	0.6880	1.1946	73.63
August 8, 2007	0.8637	0.6365	-26.31
August 17, 2007	0.8958	0.8631	-3.66
August 30, 2007	1.0432	0.9580	-8.17
October 23, 2007	1.1115	0.5949	-46.47
October 28, 2007	0.8107	0.4651	-42.63
November 19, 2007	1.2007	0.7251	-39.61
November 20, 2007	2.7560	2.0661	-25.03
November 21, 2007	3.7880	4.4317	16.99
December 5, 2007	1.0253	0.5191	-46.45
December 26, 2007	0.8623	0.5026	-41.72
January 12, 2008	3.0687	0.4284	-86.04
June 21, 2008	7.3778	2.2535	-69.46
June 22, 2008	1.5874	1.8206	14.69
July 1, 2008	0.6414	0.5027	-21.63
December 11, 2008	1.3560	0.5090	-62.47
April 21, 2009	1.5534	0.6409	-58.74
May 7, 2009	1.0824	0.6466	-40.26
June 6, 2009	0.7606	0.4299	-43.48
June 24, 2009	0.6880	0.4373	-36.44
July 17, 2009	1.3881	0.5329	-61.61
July 18, 2009	0.6645	0.2783	-58.11
July 27, 2009	0.8363	0.2590	-69.03
July 31, 2009	0.8363	0.8222	-1.69
September 25, 2009	0.9973	0.9844	-1.29
September 26, 2009	7.3779	5.4319	-26.38

* Negative values represent underestimation of actual peak flow.

The summary of results in Table 4 also shows that the WAM models are best in terms of calibration NSE. Among them, WAM (4) appears to be the best model with a validation NSE of 0.830 which is markedly higher than that of the previously determined best individual model, Tank, which registered a validation NSE of 0.809 (Clanor et al., 2015). Although SAM (4) registered the highest validation NSE of 0.832, the NSE results from SAM and WAM were found to be not significantly different from each other. Because WAM is conceptually superior to SAM we opted to use WAM (4) in the gauged and ungauged catchment simulations.

The simulation using WAM (4) was done by first running the individual models included in the combination using their calibrated parameters and then combining the results using the optimized weights. For illustration, Figure 6 presents a portion of the streamflow simulation plotted against the actual streamflow.

Other statistical measures were also computed to check the reliability of the simulation in approximating the actual streamflow. These are the index of volumetric fit (IVF) and the relative error of peak flow (RE_p). The IVF reveals that the simulation was able to produce a total runoff volume which is about 90.84% of the actual.

The peak actual streamflow of 13.96 m^3/s which was recorded on 28 September 2006 was simulated in WAM (4) as about 12.63 m^3/s, giving a RE_p value of 9.54%. For a better assessment of the ability of the model to simulate peak flows, the RE_p for observed streamflows greater than 0.6 m^3/s are presented in Table 5. Results show that the model often underestimates peak flows and generally provides RE_p values within 50%. There are, however, no established value range descriptions for IVF and RE_p; hence, these values have to be carefully considered when the result of the simulation is planned to be used.

WAM (4) was also used for the streamflow simulation in the ungauged Eastern Dampalit watershed. As there is no streamflow records for the catchment, calibration and validation were not possible. Instead of calibrating parameters, the spatial proximity regionalization procedure was considered and the calibrated parameters obtained when modeling rainfall-runoff relations

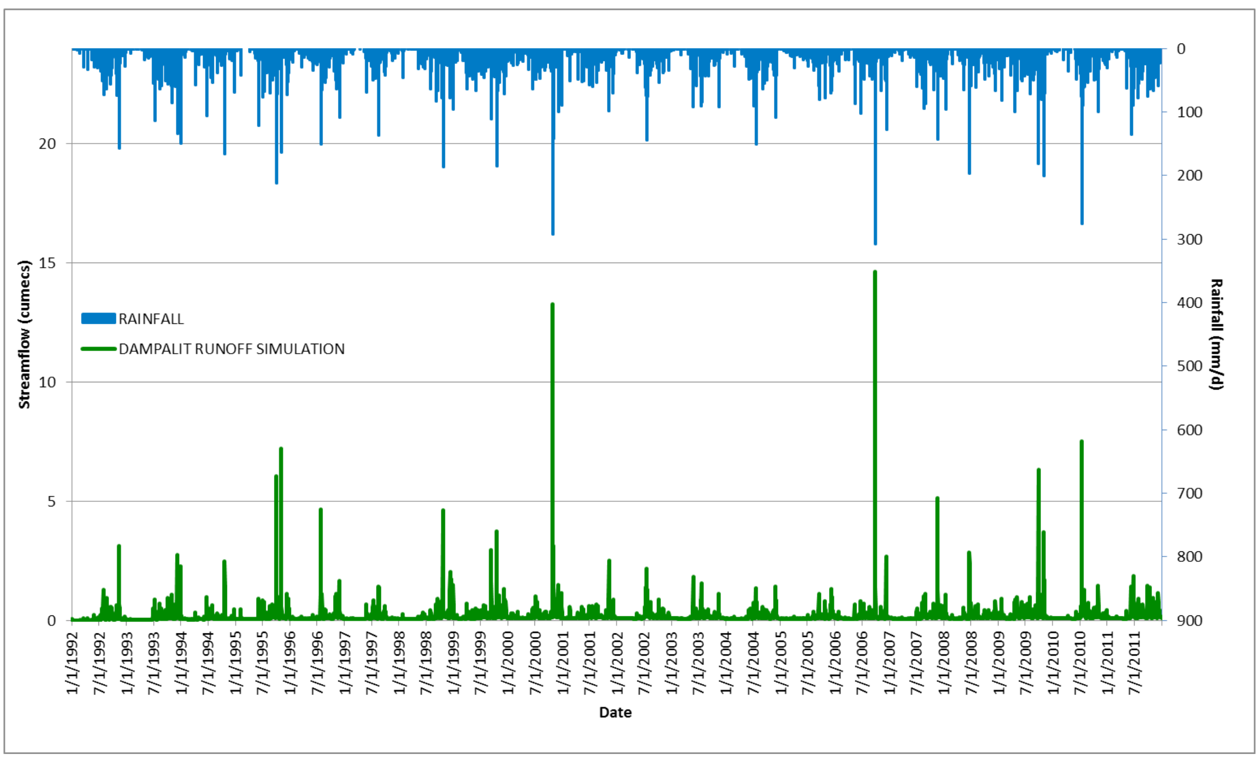

Figure 7. Streamflow simulation for the Eastern Dampalit watershed from 1992 to 2011.

in the Molawin watershed were directly adopted, that is, the individual models comprising WAM (4) were again run in RRL to generate streamflow simulations for the Eastern Dampalit watershed. The final simulated streamflow for the ungauged catchment was then calculated by applying the optimized weights for each individual model in the combination.

There was, however, no substitute for the validation process which is considered an inherent limitation in ungauged rainfall-runoff modeling. The daily streamflow simulation from 1992 to 2011 of the ungauged Eastern Dampalit watershed is presented in Figure 7.

Applications and Limitations of the Model

The model combination WAM (4) may be used for any future streamflow modeling of the Molawin watershed for as long as the data requirements (e.g. rainfall, evapotranspiration) of the individual models in the combination are available. However, having been derived from lumped conceptual models, WAM (4) cannot be expected to represent the physical attributes of the watershed.

When doing ungauged streamflow simulation, the requirements for regionalization must be met whatever the regionalization approach might be. Moreover, when using lumped conceptual models such as the individual models employed in this study, it is important to consider the area and location of the catchment as this approach works best for specific catchment types with area of less than 10 square-kilometers and are located upstream (Moore et al., 2007).

Conclusions

Remarkable improvements in streamflow simulation can be achieved when using rainfall-runoff model combinations. Through this approach, higher NSE values are obtained compared to when using individual models. Moreover, streamflow simulations from model combinations help provide other hydrologic information such as estimated total runoff volume and peak streamflow that are in close agreement with observed values. With these outcomes, reliable streamflow data can be conveniently and confidently generated.

Streamflow data may be generated for ungauged catchments provided that appropriate regionalization techniques are employed. Although there is no direct way of verifying outcomes due to absence of actual streamflow, working with generated streamflow data remains the better alternative for water management and planning purposes where ungauged catchments are involved.

To further establish the applicability of spatial proximity regionalization in simulating streamflow in the ungauged Eastern Dampalit watershed, it is recommended that a geomorphologic comparison with the donor watershed be performed.

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