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Parameter Regionalization of Semi-Distributed Hydrologic Model for Peak Flow Predictions in Flood-Prone Monsoon-Climate Catchment in Sri Lanka

D.M.K.P. Dissanayake and T.N. Wickramaarachchi

Abstract: Most of the flood-prone rivers in developing countries are either partially gauged or completely ungauged and thus accurate runoff prediction in these catchments has become a challenging task. Wide range of parameter transferability techniques have already been assessed using various hydrological model applications to several catchments. However, there exists a knowledge gap urging to explore the transferability of semi-distributed hydrological model parameters within a monsoon-dominated catchment having a gauged upstream and an ungauged downstream to accurately predict peak flows in flood-prone downstream areas. Thus, this study aims to evaluate the spatial transferability of model parameters from upstream to downstream and vice versa, by applying semi-distributed Soil and Water Assessment Tool (SWAT) hydrological model to Nilwala catchment in Sri Lanka (1044 km^2) which is frequently susceptible to floods. The SWAT model was calibrated (2006-2010) and validated (2011-2015) with observed stream flow data at Urawa (6.24 N, 80.57 E) and Pitabeddara (6.21 N, 80.48 E) gauging stations in the Nilwala catchment. The calibrated and validated model parameters were then transferred from upstream to downstream (Urawa to Pitabeddara, Transfer scheme 1) and vice versa (Pitabeddara to Urawa, Transfer scheme 2) where both upstream and downstream catchments were having similar physiographic characteristics. As measured using the performance indices, the model performance efficiency was acceptable and the simulated hydrographs well represented the rising and falling limbs of the observed hydrographs for both transfer schemes. Results showed that Transfer scheme 1 performed best with high prediction performance as measured using the efficiency measures: coefficient of determination (R^2) of 0.72, Nash–Sutcliffe efficiency (NSE) of 0.63, Kling-Gupta efficiency (KGE) of 0.70 and, root mean standard deviation ratio (RSR) of 0.61 with the best simulation shown in the peak flow regime ($< Q_{10}$). Results revealed that transfer of the SWAT model parameters from upstream to downstream in flood-prone monsoon region catchments is viable, indicating the possibility of applying calibrated semi-distributed SWAT model to other partially gauged catchments in the monsoon region, particularly to the catchments with ungauged downstream to accurately predict the peak flow ($< Q_{10}$) in the downstream areas in supporting effective flood management.

Keywords: Partially gauged catchment, Peak flow, Spatial transferability, SWAT model

1. Introduction

An ungauged catchment is a catchment that is with inadequate quantitative and qualitative hydrological observations to enable the estimation of hydrological variables at the spatial and temporal scales [1]. In the context of developing countries, there are financial limitations in installing and managing the gauging stations incorporating the latest technologies [2]. As stated in a recent study by Wickramarachchi and Wijesekera [3], most of the rivers and tributaries in Sri Lanka are also ungauged or poorly gauged with limited availability of reliable data. Water resources management in ungauged catchment faces challenges, specially when designing hydraulic applications, forecasting applications and catchment management applications without sound knowledge on hydrological response of the ungauged catchments [4]. Hydrological modelling is an essential tool that can be used to accomplish a wide range of hydrological goals including conveying significant information on flow regimes and simulating runoff in the ungauged catchments [5]. Many studies have used rainfall-runoff models in order to simulate the runoff in ungauged catchments using water balance method and regionalization technique [6] because successful

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hydrological modelling often needs accurate inputs such as precipitation and runoff data [7]. However, most of the data needed for model calibration and validation is not available for the ungauged catchments.

Regionalization methods are identified as a reliable approach to simulate the runoff in ungauged catchments by transferring calibrated model parameter set from gauged donor catchment to target ungauged catchment based on the catchment similarity and proximity [8]. Regionalization is a challenge in hydrology since there is no universal methodology for regionalization [9]. The core idea of parameter regionalization is to lend the hydrological information from gauged to ungauged catchments using the three bases: similarity-based, regression-based, and hydrological signatures-based [2]. The similarity-based regionalization executes parameter regionalization through different catchment similarities [10] mainly based on spatial proximity and physical characteristics [2]. Proxy basin method is one of the widely used similarity-based regionalization methods for predicting continuous runoff in ungauged catchments [11]. Proxy basin method should be applied as a basic test when models are to be transferred from a gauged to an ungauged catchment and the model should be calibrated on a gauged catchment and validated on the other gauged catchment and vice versa. If the validation results of the two catchments are acceptable, the model might be used in the ungauged catchment [12].

Considering the global approaches related to the similarity-based regionalization methods, Karki et al. [11] successfully applied proxy basin method to two ungauged snow-fed catchments of Nepal but they did not study the predicted flow performance in different flow regimes. Swain and Patra [13] evaluated four regionalization methods for 32 catchments in India and the results from the spatial proximity were found to be better than the regression-based methods. Yang et al. [14] made a broad assessment of the regionalization methods in the high elevations of Norway and found that similarity approaches, including spatial proximity and physical similarity, performed superior to the regression-based approaches. Arsenault et al. [8] also assessed three regionalization methods in Mexico and exposed that the donor-based spatial-proximity regionalization method was preferred in the ungauged catchments in semi-arid and humid zones. Pugliese et al. [15] compared spatial proximity and regression-based methods for predicting flow duration curves (FDCs) in the Southeastern United States, and discovered that the two methods perform similarly throughout flow regimes. In the Sri Lankan context related to the runoff simulation in the ungauged catchments, Rajendran et al. [16] identified that HEC-HMS model calibrated with the parameters from hydrologically similar gauged catchment enabled runoff simulation on a daily basis with better prediction of peaks which facilitated the flood forecasting in Deduru Oya catchment. Siriwardana and Wijesekera [17] carried out a study in Attanagalu catchment and concluded that, amongst the three selected models, an empirical model they derived as the best model to compute design streamflow in an ungauged catchment based on the model parameters obtained from literature.

A proper understanding of the capabilities and limitations of hydrological models is required when selecting the most suitable model to accomplish the desired purpose [18]. The accurate estimates or predictions of catchment runoff mainly rely on the hydrological models that play important roles in a wide range of practical applications including flood predictions [7]. Nilwala catchment in Sri Lanka is recognized as one of the most vulnerable catchments for flooding. There were severe flood incidents recorded in 1940, 1969, 2003, and 2017 where these flood events caused people to lose not only their properties but also their lives [19]. For reliable flood risk assessment, development of effective flood protection measures, especially at the flood prone downstream areas, are required [20]. In the context of Nilwala catchment, most of the downstream flood affected areas are ungauged. Tank model, which is a lumped model, has been applied to the Nilwala catchment by Wickramarachchi and Wijesekera [3] to evaluate the performance of spatial transferability of the model parameters between the two gauging stations in the catchment. Study revealed that the lumped model successfully transferred the parameters spatially and simulated the runoff to an acceptable level. Moreover, using the mean ratio of absolute error as the objective function, the study showed its best performance in the intermediate flow region instead in the high flow region, though much requirement prevails in the flood-prone Nilwala catchment to accurately simulate the high flows. Furthermore, they suggested to conduct additional studies to further improve the model parameters to predict the high and low flows. Goodarzi et al. [21] also stated that the Tank model is weak in simulating the high flows. Lumped models consider the catchment as a single unit, averaging the variables over the catchment area while distributed models predict variables that are distributed in space, by discretising the catchment into a large number of elements solving the equations for the variables associated with every element. Semi-distributed models discretise a catchment into parts of similar characteristics, but are generally lumped in the representation of the processes at the Hydrologic Response Unit (HRU) scale [22]. Spatial heterogeneities of land use, soil and input variables are not considered in lumped conceptual models [23] and therefore, distributed models are more reliable than the lumped models [24] when accurate spatial data is available. The calibration and validation of lumped models depend on the accuracy of both inputs and outputs, and therefore, the uncertainty involved in estimating the input variables may cause significant changes in calibration and validation processes. Moreover, different set of parameter values may result in equal quality of good results in a lumped conceptual model [25]. In order to overcome these limitations related to the lumped conceptual models, the physically based distributed models have been applied [26]. Soil and Water Assessment Tool (SWAT) is a semi-distributed continuous-time based model [27] and can be recognized as one of the most reliable eco-hydrological models that has been used for a wide range of applications [28]. SWAT model has been applied in the studies related to the ungauged catchments all over the world. Warusavitharana [26] applied the SWAT model to Deduru Oya catchment in Sri Lanka to assess the uncertainty of parameterization in ungauged catchments and showed acceptable results. In the global context, Emam et al. [29], Meng et al. [30], Sisay et al. [31], and Wu et al. [32] applied the SWAT model to study ungauged catchments and they also achieved acceptable results. SWAT would be more suitable for ungauged catchments than lumped hydrological models since it is a semi-distributed model which uses detailed spatial data and parameters at sub-basin level and simulates processes at the sub-basin level. This allows SWAT to better account for spatial variability, unlike lumped models, which average parameters over the entire catchment. Therefore, SWAT can be identified as a reliable modelling tool to use for continuous-based streamflow simulation in the ungauged catchments.

The model performance in each flow regime has a noteworthy impact from the objective function during the model optimization [33]. Nash-Sutcliffe efficiency (NSE) is highly sensitive to high flows where minor deviations in the high flows may lead to a poor NSE value and therefore, NSE is more appropriate for estimating the high flows [34]. Therefore, in this study, the streamflow simulation was carried out using the SWAT model and NSE was selected as the primary objective function to evaluate the model performance.

Based on previous literature it is evident that there exists a knowledge gap in application of a semi-distributed hydrological model to flood-prone monsoon-climate catchment to evaluate the streamflow predictions in different flow regimes under the transfer of model parameters from upstream to downstream and vice versa within the same river basin. Particularly, peak flow prediction performance in downstream of a monsoon-climate catchment under semi-distributed model parameter transfer within the same catchment has rarely been investigated across the globe. Therefore, this study aims to apply a semi-distributed SWAT model to the flood-prone Nilwala catchment in Sri Lanka in order to evaluate the spatial transferability of the model parameters from upstream to downstream and vice versa using the proxy basin approach.

2. Materials & Methodology

2.1 Study Area

Study area is the flood-prone Nilwala catchment in southern province of Sri Lanka which locates between 80.37 E to 80.71 E and 5.94 N to 6.34 N. Nilwala River originates from Panilkanda in Deniyaya, travels about 70 km and flows to the sea at Thotamuna. The total catchment area is 1044 km^2 and receives significant rainfall from southwest monsoon and second inter-monsoon seasons, featuring typical humid tropical monsoon climate characteristics. Flooding is a major disaster in the Nilwala catchment mainly during the southwest monsoon, resulting in frequent floods causing deaths and severe damage to properties and infrastructure [35].

Only two streamflow gauging stations are located in the Nilwala catchment. They are

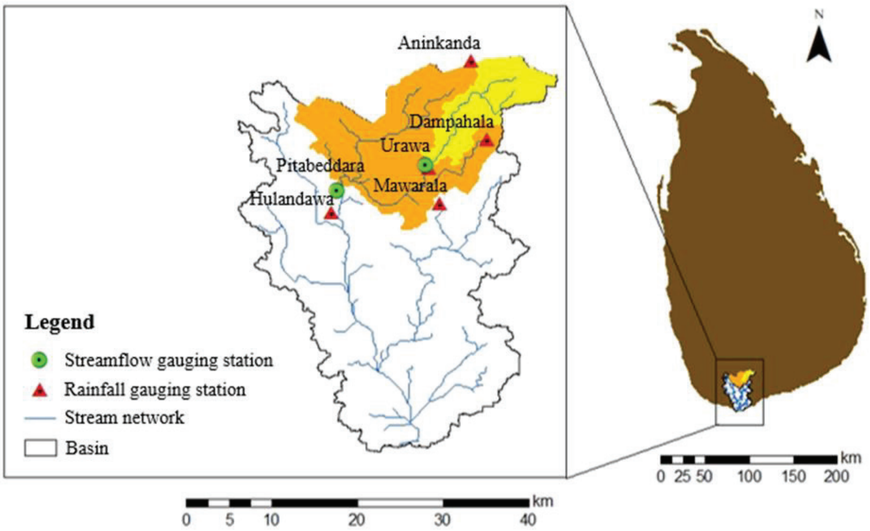

Figure 1 - Locations of the Study Area, Stream Network, Streamflow Gauging Stations and Rainfall Gauging Stations

Urawa and Pitabeddara which enclose drainage areas of 81 km^2 and 306 km^2, respectively. Both streamflow gauging stations cover only about 30% of the total catchment area, therefore, most of the downstream flood prone area of the catchment is ungauged. The locations of the study area, stream network, streamflow gauging stations and rainfall gauging stations are illustrated in Figure 1.

2.2 Data

Daily rainfall data at Aninkanda (6.35 N, 80.62 E), Dampahala (6.27 N, 80.63 E), Hulandawa (6.19 N, 80.47 E), Mawarala (6.20 N, 80.58 E) and Urawa (6.24 N, 80.57 E) rainfall gauging stations for 2002-2016 were collected from the Department of Meteorology, Sri Lanka and the Department of Irrigation, Sri Lanka. Consistency of the rainfall data was checked using both single-mass curves and double-mass curves. Missing data was estimated using the inverse distance method [36] because this method has been identified as the most suitable missing data estimation method for the three low-country zones in Sri Lanka: wet, intermediate, and dry [37].

Daily streamflow data at Urawa (6.24 N, 80.57 E) and Pitabeddara (6.21 N, 80.48 E) gauging stations for 2004-2016 was collected from the Department of Irrigation, Sri Lanka. Minimum and maximum temperature values from 2002 to 2016 at Galle meteorological station were collected from the Department of Meteorology, Sri Lanka. Land use data of year 2009 (1:10,000) was collected from the Survey Department, Sri Lanka. Soil map produced by Soil Science Society of Sri Lanka (1:250,000) was used for the study. Catchment delineation was done using the Digital Elevation Model (DEM) obtained from the Shuttle Radar Topography Mission (SRTM) data of 3 arc second resolution [38].

2.3 Hydrological Model

2.3.1 SWAT Model set-up

It has been verified that the SWAT model performs well for simulating hydrological processes, effects of land use change and climate change, and water and land management practices within various environmental circumstances [26]-[32]. SWAT is a continuous time, semi-distributed, process based model and water balance is the driving force behind the process of SWAT [27], [39]. SWAT requires rainfall data, minimum and maximum temperature data, wind speed data, solar radiation data, relative humidity data, elevation data, land use data, and soil data as the basic input data for the model. Solar radiation, wind speed, and relative humidity were estimated by SWAT weather generator based on the SWAT weather database file that included the same statistical properties as the observed data. Areal precipitation estimates for periods of a year or longer have relative uncertainty of 10% [39]. In SWAT, the catchment is divided into several sub-catchments, and these sub-catchments are further divided into Hydrologic Response Units (HRUs), which have a combination of similar topographical, soil, and land use features [27]. The hydrological cycle is calculated based on the water balance (Equation 1), which is controlled by climate inputs such as daily rainfall, and maximum and minimum temperature [39].

$SW_{t_i} = SW_0 + \sum_{i=1}^{t}(R_{day_i} - Q_{surf_i} - E_{a_i} - w_{seep_i} - Q_{gw_i})$ ...(1)

where, SW_{ti} and SW_0 are the final water content of soil on the i^{th} dayand early water content of soil respectively, t is time in days, R_{day_i} is daily precipitation on the i^{th} day, Q_{surf_i} is daily surface runoff on the i^{th} day, E_{a_i} is daily evapotranspiration (ET) on the i^{th} day, w_{seep} is daily percolation on the i^{th} day, and Q_{gw_i} is daily return flow on the i^{th} day. All units are given in mm.

In setting up the SWAT model, slope map of the catchment was derived from the DEM and the slopes were aggregated into five classes. Land use types were re-classified into eight classes according to the SWAT land cover database as shown in Table 1. For the six soil types, soil properties were interpreted as per the FAO/UNESCO Soil Map of the World [40]. The catchment was delineated into 22 sub-catchments with 363 HRUs which defined with land use (10%), soil (10%) and slope (10%) threshold. Soil Conservation Service (SCS) curve number method [41] was used to estimate the surface runoff and the Penman-Monteith equation [42] was applied to calculate the potential evapotranspiration. The streamflow was routed and calculated according to the variable storage routing method [39].

Table 1 - Land Use Types

Landuse type	SWAT Code	Category
Agricultural Land-Generic	AGRL	Agricultural area
Forest-Mixed	FRST	Forest area
Residential-Low Density	URLD	Homesteads
Residential-High Density	URHD	
Institutional	UINS	
Barren	BARR	Rock and bare area
Water	WATR	Water area
Wetlands-Non-Forested	WETN	

2.3.2 Model uncertainty analysis, sensitivity analysis, calibration, and validation

To estimate optimal values for the model parameters, Sequential Uncertainty Fitting version 2 (SUFI-2) interface of SWATCUP was used in the calibration. SUFI-2 accounts for the uncertainty of parameters along with all the uncertainties from other driving variables such as rainfall. Uncertainty of the parameters was quantified using 95% prediction uncertainty (95PPU) which was calculated based on 2.5% and 97.5% levels of the cumulative distribution of the output variable [43].

Sensitivity analysis paves the way to understand the effect of the parameters on the overall model performance. The most sensitive parameters were identified by proceeding a sensitivity analysis; the process of identifying the rate of change in model output with respect to the changes in model input parameters [27]. Based on the "P-Value" and "t-Stat", seven parameters were identified as the most sensitive parameters for the model calibration and validation. All the parameters were calibrated considering the parameter qualifier as "r__" (relative method), where the existing parameter value multiplied by "1 + given value".

A two-year time period was used as the warm-up period (2004-2005) to initialize the SWAT model input and stabilize the model. The periods 2006-2010 and 2011-2015 were used for the calibration and validation of the SWAT model, respectively, for each of the two streamflow gauging stations, namely, Urawa and Pitabeddara.

2.3.3 Model performance valuation criteria

The model performance was evaluated based on four statistical indicators (three performance indexes and one error measure) and one hydrological signature. To assess the performance of the model statistically, Nash-Sutcliffe efficiency (NSE) [Equation 2] [44], coefficient of determination (R^2) [Equation 3], root mean standard deviation ratio (RSR) [Equation 4] [45], and Kling-Gupta efficiency (KGE) [Equation 5] [46] were used. NSE, R^2, and KGE were categorized under the performance indices and RSR was categorized under the error measures. Performance of the model was assessed graphically, based on the flow duration curves (FDCs) which categorized under the hydrological signatures [47]. NSE is highly sensitive to high flows and it indicates the model performance in estimating the timing and magnitude of the high flows [34]. NSE ranges from -∞ to 1 where the optimum value is 1. R^2 describes the proportion of collective variance between the observed and the simulated values. It ranges from 0 to 1, with higher R^2 values indicating less error variance.

RSR standardizes root mean square error (RMSE) using the standard deviation of the observations and it was calculated as the ratio of RMSE and standard deviation of observed data. RSR ranges within 0 to positive infinity and the optimum value is 0.

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}\left(Q_{s,i} - Q_{o,i}\right)^2}{\sum_{i=1}^{n}\left(Q_{s,i} - \overline{Q_o}\right)^2} \qquad \text{...(2)}$$

$$R^2 = \frac{\left[\sum_{i=1}^{n}(Q_{s,i} - \overline{Q_s})(Q_{o,i} - \overline{Q_o})\right]^2}{\sum_{i=1}^{n}(Q_{s,i} - \overline{Q_s})^2 \sum_{i=1}^{n}(Q_{o,i} - \overline{Q_o})^2} \qquad \text{...(3)}$$

$$\mathrm{RSR} = \frac{RMSE}{STDEV_{obs}} = \frac{\sqrt{\sum_{i=1}^{n}\left(Q_{s,i} - Q_{o,i}\right)^2}}{\sqrt{\sum_{i=1}^{n}\left(Q_{s,i} - \overline{Q_o}\right)^2}} \qquad \text{...(4)}$$

where, Q_o is the observed data series, Q_s is the simulated results series, the overbar represents the mean value of the data series, and n is the sample number.

$$\mathrm{KGE} = 1 - \sqrt{(r-1)^2 + (\alpha-1)^2 + (\beta-1)^2} \qquad \text{...(5)}$$

where, $\alpha = \frac{\sigma_s}{\sigma_o}$, $\beta = \frac{\mu_s}{\mu_o}$ and r is the linear regression coefficient between the simulated and the observed streamflow, μ is the average, σ is the standard deviation, and the subscripts o and s represent observations and simulations, respectively. KGE includes a correlation term, a bias term, and a variability term and has its optimum value at unity.

2.4 Spatial Transferability of the Model Parameters

Proxy basin method, which is one of the oldest and widely applied regionalization methods, was used in this study to transfer the hydrological model parameter values [10], [13], [14]. Since this method assumes that the calibrated model parameters can be transferred to a nearby similar catchment, spatial proximity and hydrological similarity of the Urawa and Pitabeddara sub-catchments were checked first [11].

Continuous runoff estimation is vital in hydrology, specially, for ungauged catchments [9]. Thus, the calibrated model at each streamflow gauging station was used to simulate the streamflow for continuous 15 years, 2002-2016, with two years warm-up period at the beginning. The model parameters were then transferred from upstream to downstream (Urawa to Pitabeddara, Transfer scheme 1) and vice versa (Pitabeddara to Urawa, Transfer scheme 2). Following that, the transferability of the model parameters was examined based on the model performance efficiency criteria. This study utilized the land use data of year 2009 which is in the middle of the simulation period (2002-2016) and assumed stationarity in the land change pattern throughout the simulation period.

3. Results & Discussion

3.1 Comparison of the Catchment Characteristics

As shown by Nepal et al. [5], since both Urawa and Pitabeddara sub-catchments of the Nilwala basin are located in a similar climatic zone, there exists a good potential to transfer the parameters spatially. Moreover, both sub-catchments are located in close proximity, and therefore it is reasonable to investigate other attributes including land use, soil types, and slopes since these three attributes are the three main input data types required to define the HRUs in the SWAT model [48]. Figure 2, Figure 3, and Figure 4 illustrate the land use, slope distribution and soil types across the study area, respectively.

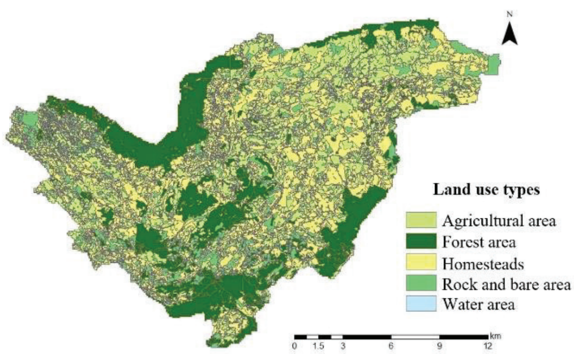

Figure 2 - Land Use Distribution (year 2009)

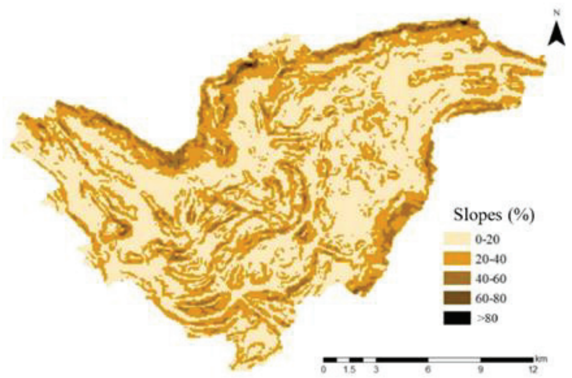

Figure 3 – Slope Distribution

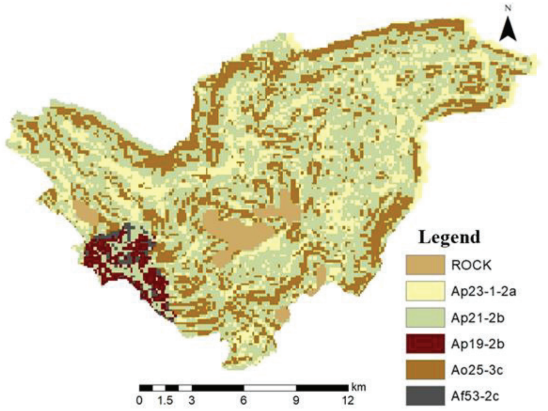

Figure 4 – Soil Types

The major soil type present in the catchment is identified as Acrisols which is associated with humid tropical climates [49]. Table 2 illustrates the quantitative comparison of Urawa and Pitabeddara sub-catchments based on the three main attributes: land use, soil types, and slopes.

Land use distribution presented in Table 2 shows certain similarity to the land use pattern in upper Nilwala catchment stated by Wickramarachchi and Wijesekera [3]. Area covered by homesteads, agricultural use and forest accounts for about 85% of the total area of each sub-catchment. Additionally, both sub-catchments have almost similar distribution of rock and bare areas. Sandy textured soil is the dominant soil in both sub-catchments covering about 55% of the area in each sub-catchment. Other soil categories also distributed in similar percentages in both sub-catchments (Table 2). Soil texture is a significant factor which affects the hydrological cycle. For example, infiltration rate is directly affected by the soil texture due to its geological characteristics such as permeability, compaction, bulk density, porosity and so on [50]. Slope has a great impact on soil erosion and surface runoff because steep slopes cause the increment of surface runoff and soil loss [51]. According to the slope distribution shown in Table 2, it is notable that there are no any significant deviations between the two sub-catchments. Thus, it was assumed that both sub-catchments represent almost similar hydrological behavior related to the soil properties and slope distribution. Therefore, due to approximately similar physical characteristics, Urawa and Pitabeddara sub-catchments were assumed to have similar hydrological behavior.

Table 2 - Comparison of Urawa and Pitabeddara Sub-catchments based on Land Use, Soil Types, and Slopes

Attribute	Urawa sub-catchment	Pitabeddara sub-catchment
Land use %		
Homesteads	40.93	25.80
Forest area	11.48	35.87
Agricultural area	31.22	25.22
Rock and Bare area	8.01	7.93
Water area	8.36	5.18
Soil category %		
Sandy	55.70	54.60
Silty	16.32	16.48
Clayey	27.18	27.16
Rocky	0.80	1.76
Slope %		
0 - 20%	63.31	55.76
20% - 40%	33.04	39.23
40% - 60%	2.55	4.90
60% - 80%	0.33	0.10

3.2 Hydrological Modelling and Model Performance Evaluation

The most sensitive parameters obtained in the SWAT simulations are presented in Table 3. The most sensitive parameters of the SWAT model were determined using the global sensitivity analysis technique. In this technique, the sensitivities are determined by calculating a regression system, which regresses the Latin hypercube generated parameters against the objective function values [52].

Figure 5 and Figure 6 show the simulated and observed hydrographs for the calibration and validation at Pitabeddara and Urawa, respectively. Overall, the SWAT model worked well for both Pitabeddara and Urawa; simulated streamflow captured timing and shape of rising and recession curves of the observed hydrograph, but failed to capture some of the extreme high flows at Pitabeddara. Moreover, some of the low flows (>Q_{90}) at Pitabeddara have been overestimated. Low flow overestimation by the SWAT model in a mountainous catchment in Pakistan has already been reported by Khan et al. [53]. Golmohammadi et al. [54], Moreira et al. [55] and Nyeko [56] also demonstrated the overestimation of flows by the SWAT model. According to Nyeko [56], some processes related to losses, such as evapotranspiration underestimation by the model, may have caused overestimation of the surface runoff. Comparatively low overall model performance is shown for Urawa in comparison to Pitabeddara. That might be due to the non-uniformly distributed rainfall gauge representation for Urawa with high altitudinal gradient compared to Pitabeddara since location and density of meteorological monitoring stations play a vital role in the general accuracy of model results as stated by Stehr et al. [57] and Wickramaarachchi et al. [58].

One of the limitations in the SWAT modelling has been identified as its simplicity in modelling the groundwater component which creates a single layered shallow aquifer which affects infiltration, groundwater flow, storage, and runoff estimations especially when impermeable surfaces are presented [59].

Table 4 presents the values of different statistical indicators obtained during the model calibration and validation processes. According to the criteria stated by Moriasi et al. [45], NSE, R^2, and RSR for both calibration and validation at Pitabeddara, and calibration at Urawa showed a "good level" of rating. Also, KGE values for both calibration and validation at Pitabeddara tended to be close to 1 (≥ 0.72), which is optimum. For the validation performance at Urawa, R^2 showed a "good level" of rating while NSE and RSR showed a "satisfactory level" which can be accepted. Moreover, KGE values for both calibration and validation at Urawa were ≥ 0.64. Therefore, the performance of the SWAT model at both Pitabeddara and Urawa is acceptable based on the statistical criteria.

Moreover, hydrological performance of the SWAT model was evaluated based on the signature indices derived from the FDCs. FDC is a cumulative frequency curve that shows the percentage of time during which specified streamflows were equalled or exceeded in a given period. FDC indicates a quantitative idea of flow simulations at different flow regimes: low, intermediate, and peak. It is essential to have an idea of the model performance in different flow regimes in a catchment, such as low flows and peak flows, because they are important in managing water resources and controlling floods [5]. SWAT model's performance in the different flow regimes was evaluated using the FDCs, peak flows (Q_{10}) and low flows (Q_{90}) representing the flow values that exceeded 10% and 90% of the time, respectively [18]. Figure 7 and Figure 8 depict the FDCs during 2006-2015 at Pitabeddara and Urawa, respectively. Compared to the low flows, peak flows and intermediate flows have been simulated well in matching with the observed flows (Figure 7 and Figure 8). Moreover, results showed lower error percentages in the peak flow region (31.3% at Pitabeddara; 33.5% at Urawa) compared to the low flow region (83.4% at Pitabeddara; 78.2% at Urawa). In line with the findings of the present study, the success of the SWAT model in simulating the peak flows has previously been noted in limited number of studies [60], [61].

Table 4 - Statistical Indicators of Model Performance during Calibration and Validation

		NSE	R^2	KGE	RSR
Pitabed-dara	Calibration	0.72	0.72	0.81	0.53
	Validation	0.67	0.67	0.72	0.58
Urawa	Calibration	0.65	0.65	0.78	0.60
	Validation	0.51	0.52	0.64	0.70

Table 3 - SWAT Calibrated Parameters

Parameter	Pitabeddara			Urawa		
	Minimum	Maximum	Fitted value	Minimum	Maximum	Fitted value
SOL_AWC.sol	2.16	2.18	2.18	2.34	3.35	2.35
SOL_K.sol	-0.16	-0.07	-0.08	-0.89	-0.77	-0.78
CN2.mgt	-3.09	2.95	2.03	-1.07	0.24	-0.84
ALPHA_BF.gw	-1.87	-1.66	-1.75	-3.78	-3.31	-3.61
GWQMN.gw	-0.97	-0.93	-0.96	3.49	3.94	3.73
HRU_SLP.hru	1.47	1.61	1.50	-1.61	-1.35	-1.30
ESCO.bsn	2.66	3.49	3.35	-0.80	-0.62	-0.67

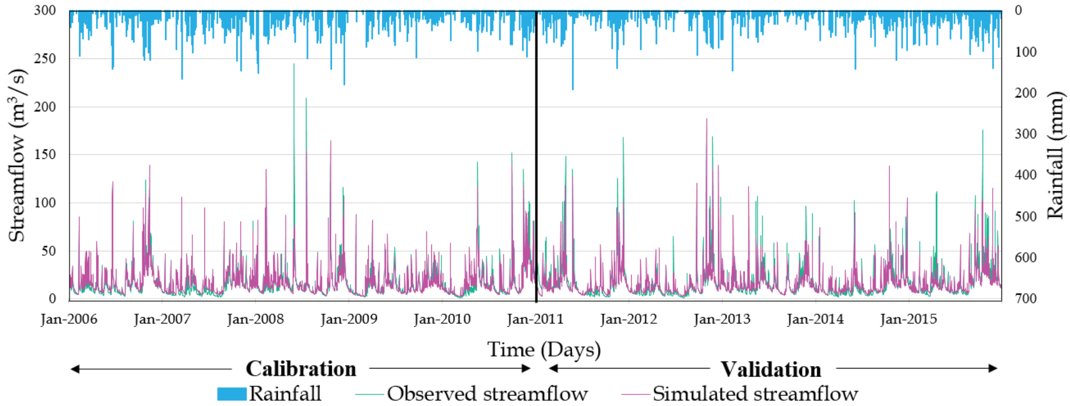

Figure 5 - Calibration and Validation Hydrographs at Pitabeddara

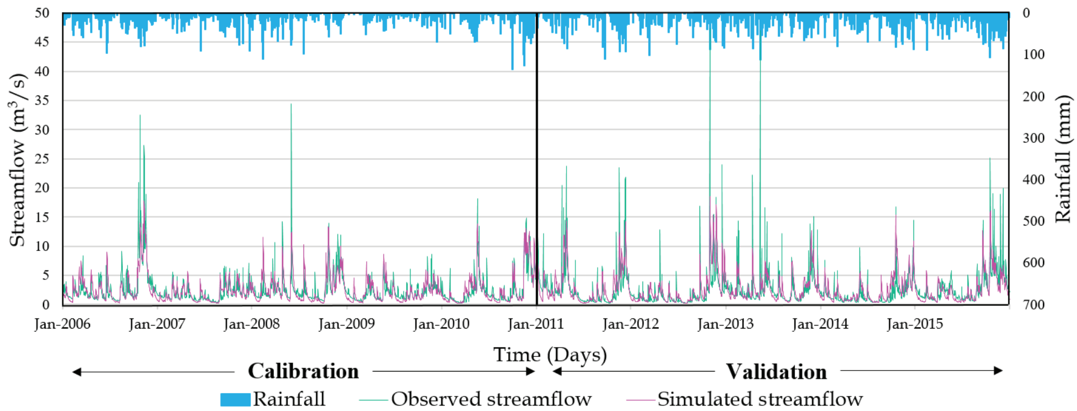

Figure 6 - Calibration and Validation Hydrographs at Urawa

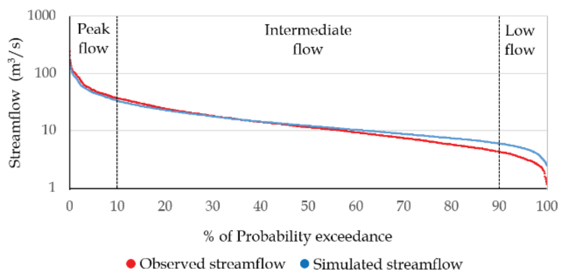

Figure 7 - Flow Duration Curve of Observed versus Simulated Streamflow at Pitabeddara

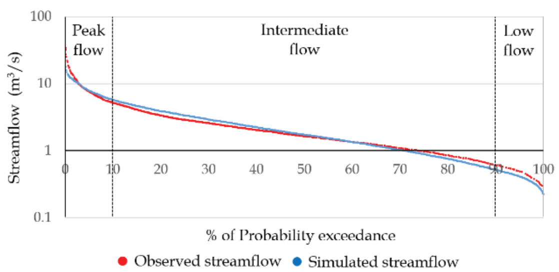

Figure 8 - Flow Duration Curve of Observed versus Simulated Streamflow at Urawa

3.3 Spatial Transferability of the Model Parameters between Upstream and Downstream

Model evaluation statistics for the SWAT model's parameter transfer schemes are shown in Table 5. Statistical performance for the transfer schemes quantified by both NSE and RSR values were in the "satisfactory level" while R^2 values were in the "good level" [45]. KGE values for both transfer schemes were greater than 0.5, however, KGE value for the Transfer scheme 1 was closer to the optimum value of 1 than for the Transfer scheme 2 [46]. Based on the statistical criteria, both upstream to downstream (Transfer scheme 1) and downstream to upstream (Transfer scheme 2) transfer of the SWAT model parameters were at an acceptable level. Statistically, Transfer scheme 1 performed well compared to the Transfer scheme 2.

Table 5 - Statistical Indicators of Model Performance for the Transfer Schemes

	NSE	R^2	KGE	RSR
Transfer scheme 1	0.63	0.72	0.70	0.61
Transfer scheme 2	0.57	0.73	0.54	0.66

Error percentages in simulating the peak flows, intermediate flows, and low flows were 31.8%, 59.1% and 69.1%, respectively, for the Transfer scheme 1, and 28.6%, 89.8% and 236.5%, respectively, for the Transfer scheme 2. Even though both the transfer schemes met acceptable results, Transfer scheme 1 showed more capability than Transfer scheme 2 since it simulated all the flow regions: peak flows, intermediate flows and low flows, reasonably well. Particularly, it is evident that the SWAT model with the transferred model parameters simulated the peak flows ($< Q_{10}$) with minimum error compared to the intermediate flow and low flow regions. Jajarmizadeh et al. [62] also revealed successful simulation of the peak flows in comparison to the low flows using the SWAT model which confirmed the findings of the present study.

FDCs during 2004-2016 for Transfer scheme 1 is illustrated in Figure 9 with peak flows ($< Q_{10} \approx 35.4$ m³/s) and low flows ($>Q_{90} \approx 3.9$ m³/s) and it shows the performance of the SWAT model in simulating the streamflow in different flow regimes. Peak flows were simulated quite well showing a close agreement with the observed when the model parameters were transferred from the upstream sub-catchment to the downstream sub-catchment (Transfer scheme 1).

95PPU (95% prediction uncertainty) is included in the SWAT model output in stochastic calibration approach which provides envelope of good alternatives expressed by the 95PPU generated by certain parameter ranges. For clarity, a representative segment of the observed hydrograph for one hydrological year (from October 2005 to September 2006) for the Transfer scheme 1 was plotted with the 95PPU band (Figure 10). It shows that more observations fall into the 95PPU bands of the simulated outputs. SWAT simulations with the transferred model parameters performed satisfactorily with a narrow relative thickness of the 95PPU band (0.8 out of a perfect value of zero) with acceptable model output uncertainty [43]. Thus, the results indicated that the SWAT model performed well in simulating the peak flows in the Nilwala catchment with the transferred model parameters from the upstream sub-catchment to the downstream sub-catchment.

The results imply that the peak flows in flood-prone downstream locations could be accurately predicted by the semi-distributed hydrological model SWAT using the calibrated parameters in upstream locations. This depicts the capability of the SWAT model to be used as an effective flood management tool in monsoon-dominated catchment having a gauged upstream and an ungauged downstream.

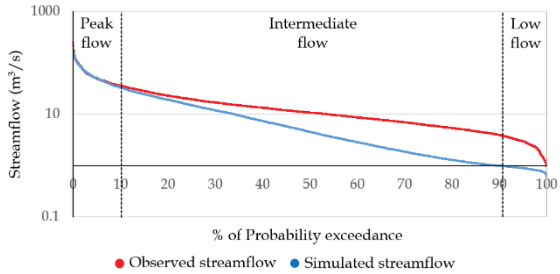

Figure 9 - Flow Duration Curves of Observed versus Simulated Streamflow for the Transfer Scheme 1

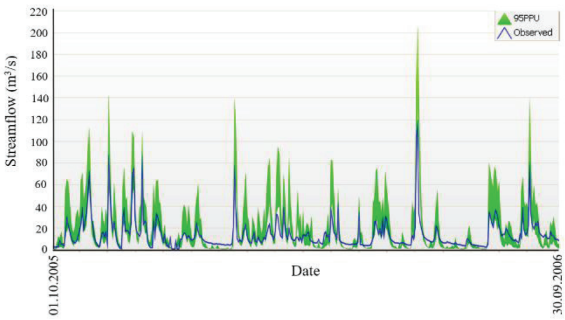

Figure 10 - Simulation Results of Transfer Scheme 1 showing the 95PPU Envelop along with the Observed Streamflow (October 2005 to September 2006)

4. Conclusion & Recommendations

This study explored the applicability of the semi-distributed SWAT model to simulate the peak flow ($< Q_{10}$) in the Nilwala catchment, a flood-prone monsoon-climate catchment with spatial transferability of the model parameters within the same catchment. Such an investigation is vital for predicting the hydrological implications especially within the context of partially gauged tropical monsoon-climate catchments located in many developing countries. The study revealed that transfer of the SWAT model parameters using the proxy basin approach between two sub-catchments within the Nilwala basin having reasonably similar physical characteristics is viable.

As shown by the model performance statistical measures, spatial transfer of calibrated model parameters from upstream sub-catchment to downstream sub-catchment and vice-versa produced acceptable results, however, the model parameter transferability from the upstream to downstream performed well (NSE = 0.63, R^2 = 0.72, KGE = 0.70 and RSR = 0.61) compared to the model parameter transferability from the downstream to upstream (NSE = 0.57, R^2 = 0.73, KGE = 0.54 and RSR = 0.66). Error percentages associated with the flow simulations in different flow regimes showed overall minimum error in the peak flow region (< Q_{10}) in comparison to the intermediate flow and low flow regions. In addition, in the peak flow region, an excellent match between the observed and simulated percent exceedance probability curves was evident demonstrating an accurate parameter transferability potential from the upstream to downstream.

The present study which used two gauged streamflow datasets of the Nilwala catchment concluded that the SWAT model has a very good overall capability to predict the peak flows in a flood-prone downstream area of a monsoon-climate catchment using the model parameters calibrated for its upstream. This demonstrated that the SWAT model and a single well-operating streamflow gauging station at the upstream can optimally use the available resources to reasonably predict the peak flows in the downstream area.

The results of this study provide insight into the possible capability of the SWAT model to predict the peak flows under spatial transferability of model parameter, and therefore provide an important contribution to the peak streamflow estimation in partially gauged monsoon-climate catchments, a vital aspect in managing the floods in ungauged downstream areas. Furthermore, the findings of this study could help local authorities managing the water resources in the Nilwala catchment to further improve their flood resilience design and planning strategies and will provide them with a calibrated tool to assess potential hydrological impacts of further downstream ungauged area of the Nilwala catchment. However, further research is still needed to better understand the low flow and intermediate flow prediction potential using semi-distributed models in flood-prone catchments under the parameter transferability.

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