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Stream Flow and Sediment Yield Modeling: A Case Study of Beles Watershed, Upper Blue Nile Basin

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Abstract

Modeling provides important planning tools that can be used in management of land and water resources which can be used in the understanding of dynamic processes and prediction of the existing processes. The evolution of a wide range of hydrologic catchment models employing the physical based and data driven approach introduces the need for objective test benchmark to assess the merits of different models in reconciling alternative approaches. The main objective of this study was to model stream flow and sediment yield by using ANN and SWAT models for the Upper Main Beles gauged catchment. The two models were calibrated and validated at Main Beles gauging station for both stream flow and sediment yield yielding reasonable results in monthly and daily time step. Two days antecedent values were considered during formulation of possible inputs for daily basis and no antecedent value were considered for monthly time step modeling for ANN model. Modeling by SWAT for stream flow yields a mean monthly stream flow of 65.28 m^3/s showing 2.48% deviation whereas the MLP neural model prediction was 67.37 m^3/s showing 5.76% deviation from the observed mean monthly flow. Total mean annual Sediment yield loading from Upper Main Beles simulated by SWAT and ANN model was 4.81 and 5.97 ton/ha/year underestimated by 12.9% and overestimated by 8.1% respectively excluding bed load contribution. The total mean annual sediment yield that was drawn from Upper Main Beles predicted by SWAT and ANN model was found 1,602,845.92 ton and 1,989,395.05 ton respectively. Sediment yield modeling by MLP neural model in both daily and monthly time step predicts better than SWAT including daily stream flow modeling. The calibrated parameter values of the two models can be considered for further hydrologic simulation of the watershed and their application in consideration of their simplicity in data requirement, purpose, prediction accuracy and change in land use dynamics of the watershed.

Keywords: Modeling; ANN; SWAT; Stream flow; Sediment yield; Beles catchment

Introduction

Knowledge of landscape morphology along with the hydrologic processes is required to conceptualize the generation of runoff and sediment loss from precipitation events. The consequences of soil erosion and sediment deposition occur both on and off-site. On-site effects are particularly important on agricultural land where the redistribution of soil within a field, the loss of soil from a field, the breakdown of soil structure and the decline in organic matter and nutrients result in a reduction of cultivable soil depth and a decline in soil fertility. Off-site problems result from sedimentation downstream, which reduces the capacity of rivers and retention ponds, enhances the risk of flooding and muddy floods and shortens the design life of reservoirs [1].

Ethiopia experiences persistent land, water and environmental degradation due to localized and global climatic anomalies. These leave the country to recurrent crop failures and severe food shortages. Low soil fertility coupled with temporal imbalance in the distribution of rainfall and the substantial non-availability of the required water at the required period are the principal contributing factors to the low and declining agricultural productivity [2].

Characterization and understanding of stream flow and sediment yield magnitude of a catchment is required for efficient design, planning, and management of river basin projects that deals with conservation and utilization of water for various purposes. To accurately determine the quantity of surface runoff and sediment yield that takes place in a river basin, understanding of the complex relationships between rainfall and runoff processes, which depend upon many geomorphological and climate factors, is necessary [3].

There was no any previous study in the study area specifically on examining the application of power full data driven "ANN" model and characterization of sediment yield which is very vital for future analysis to be made on the water resource of the study catchment regarding the proposed beles dam. The study catchment (Beles basin) is one of many basins in Ethiopia which are known having active stream networks and high potential water resources. Until the recent time the country has not properly utilized the existing water resource due to lack of research and sophisticated technology. The existing land and water resources system of Beles is adversely affected due the rapid growth of population, deforestation, surface erosion and sediment transport which needs provision of analytical/modeling expertise and tools to effectively manage the water resources of the basin. The basin has existing irrigation projects (upper and lower Beles) and there was a need for construction of dam [4]. Unless sedimentation for the existing projects as well as for the proposed dam was not properly managed, problems like difficulties in irrigation systems management leading to water shortage will exist.

Hence, proper utilization of the available soil and water resources of the watershed for development of irrigation and hydropower in Beles catchment will be characterized by the aid of hydrological models to know and take management measures for its water source potential.

Considering data availability, level of application, required accuracy, space and time scale objective, purpose and catchment size SWAT and

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ANN models have been used in order to characterize and estimate runoff and sediment loading. ANN is a vigorous technique to develop immense relationship between the input and output variables, and able to extract complex behavior between the water resources variables such as river sediment and discharge [5]. Artificial neural network (ANN) is the most well-known and powerful data-driven method and it has been prove to be useful in modeling complex hydrologic processes or non-linear systems such as sediment transport [6]. While SWAT watershed model is one of the most recent models developed by the USDA-ARS to predict the impacts of land management practices on water, sediment and agricultural chemicals yields in watersheds with varying soils, land use and management practices over long periods of time [7].

The main objective of this research is to model stream flow and sediment yield for Upper Main Beles gauged catchment by using ANN and SWAT models. More specifically, spatial distribution of sediment yield and identify sediment sensitive areas of the catchment by SWAT model, comparison of SWAT and ANN models for prediction of stream flow and sediment yield in daily and monthly time basis, identify better predicting model for further simulation in the catchment and quantification of the amount of sediment yield from Upper Main Beles watershed are addresses in this study.

The overall finding of this research revealed that both models give reasonable results of simulating stream flow and sediment yield in the watershed. The mean annual observed sediment yield obtained from sediment rating curve developed at Main Beles gauging station was 5.52 ton/ha/year which was underestimated by 12.9% by SWAT_CN model and overestimated by ANN(MLP) model by 8.1%.

Methodology

Before dealing out of any research, it is vital to make a strong search for the data and identifying clear and efficient methodology that describe the experimental design and so as to provide enough detail so that a competent worker can go through it.

Data is the crucial input in hydrological modeling. Data preparation, analysis and formatting to suit the required model input is important and has influences on the model output. The relevant time series data used for this study includes daily rainfall data, stream flows, suspended sediment yield, temperature (minimum and maximum), relative humidity, wind speed ,solar radiation and Spatial data (DEM, soil map, land use map). Data were collected from the Ministry of Water, Irrigation and Energy (MoWIE) and Ethiopian Meteorological Agency. The data type, source and it relevancy is described in the following Table 1.

The methods and procedures used in this research work for modeling stream flow and sediment yield go through the following key steps to achieve the outlined objectives:

1 Collection of required data's according to the model requirement such as meteorological and hydrological data, DEM, soil map, land use/cover map and other related data's of the study area.

2 Preparation and Assessment of data sets (checking data quality).

3 Model setup and simulation, undertaking reasonable data set classification.

4 Result analysis bounded with the outlined objective.

The quality of time series data of rainfall and stream flow data were tested by quality assessment methods like test for absence of trend (by spear man correlation method), absolute homogeneity test (by rainbow software), relative homogeneity (by non-dimensional plot) and consistency test (by double mass curve method) resulting that all the data's are well qualified and are ready for further use. Sediment rating curve was developed in order to generate continuous daily sediment data from the available sediment concentration at main beles gauging station.

Rainfall and discharge are the common input variables used in ANN model study for predicting sediment yield [8]. In some researches, only discharge is taken into account. As one of the models used for the entitled purpose was Artificial Neural network (ANN) which have no any ground relationship with SWAT model rather than the data requirement provided that both models need the time series rainfall, stream flow and sediment data. As the model (ANN) is data driven model which highly depends on the user's capability to build the network by cross correlating the real world existing conditions during the input combination for obtaining well fitted desired output, the data requirement should have to be specified alone not with SWAT model. The general conceptual methodology (Figure 1).

Model setup

SWAT model: Before the model is set up and inputs are added, the computation of required water balance components for the simulation on the algorithm embedded in SWAT model should have to be identified. There are two types of model algorithms developed in SWAT model which vary in their process of computing surface runoff called SWAT CN and SWAT WB. The earlier developed algorithm (SWAT_CN) models occurrence of runoff from infiltration excess processes and the new version SWAT WB models runoff generated strictly from saturation-excess processes; no surface runoff will be generated with this algorithm until the soil becomes sufficiently saturated. A catchment might not have infiltration excess or saturation excess exclusively, but these may happen at the same place at different moments in time, or, at the same time, both processes might happen depending on the position of a place within the landscape, but the concern is better estimation and characterization of the spatial dynamics [9]. Infiltration excess method of runoff computation was used.

Station	RF	Max Temp.	Min Temp.	Relative Humidity	Wind Speed	Sun Shine hour	Record Length (years)	Accuracy	Source
Dangila	✓	✓	✓	✓	✓	✓	20	Relevant for use	ENMA
Pawe	✓	✓	✓	✓	✓	✓	20	Relevant for use	ENMA
Bahirdar	✓	✓	✓	✓	✓	✓	20	Relevant for use	ENMA
Sahurah	✓	✓	×	×	×	×	20	Relevant for use	ENMA
Chagni	✓	✓	✓	×	×	×	20	Relevant for use	ENMA
Enjibara	✓	✓	×	×	×	×	20	Relevant for use	ENMA

Where: ENMA: Ethiopian National meteorology Agency; ✓ stands for availability and × Not available.

Table 1: Data Type, Length and source of meteorological data.

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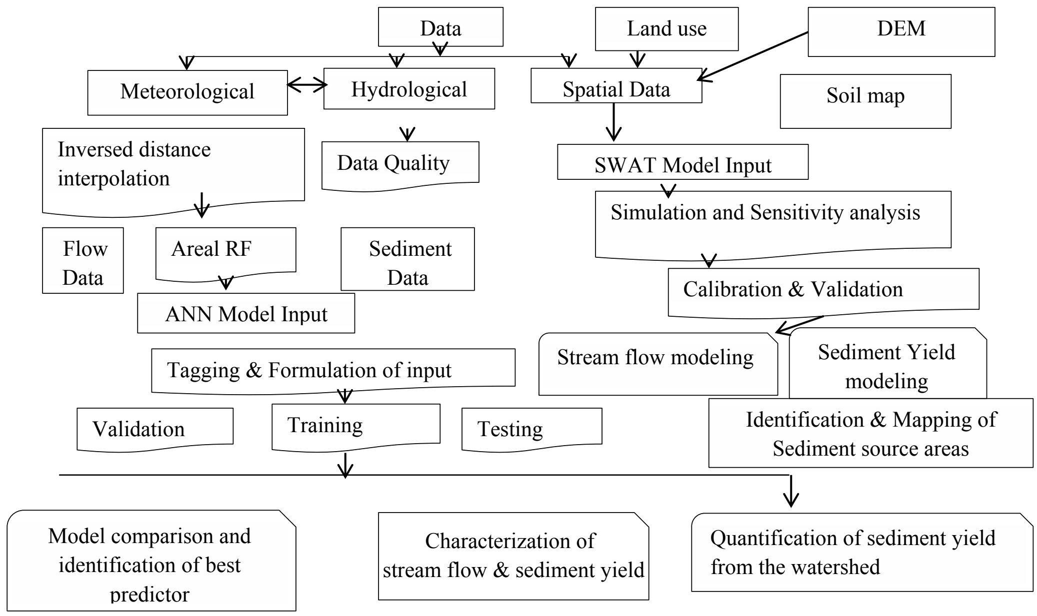

Figure 1: The general conceptual methodology.

Sensitivity analysis was conducted by setting the simulated scenario as a default simulation and the method of sensitivity analysis which was performed in this study was the built-in SWAT sensitivity analysis tool that uses the Latin Hypercube One-factor-AT-a-Time (LH-OAT) proposed by Morris [10], the analysis was performed by using the observed flow and sediment yield data at the Main Beles gauging station (considered outlet).

ANN model: The ANN is an information processing approach that resembles the structure and operation of the brain with considerable interest over their applications in hydrological modeling. The approach was developed in the 1940s by McCulloch and Pitts [11] and gradually progressed after that with advances in calibration methodologies [12].

ANNs are basically based on the functioning of the biological processes of a human brain. As we learn the things in our day to day life and our actions are normally based on our past experiences. Similarly, ANNs are also trained with known input and output and then employed to predict the output with known input. For various complex nonlinear environmental problems, ANNs have an advantage over distributed parameter models due to the lesser data requirements and they are more suited for long-term forecasting [13]. The model was a vigorous technique to develop immense relationship between the input and output variables, and able to extract complex behavior between the water resources variables such as river sediment and discharge. It can produce robust prediction results for many of the water resources engineering problems by appropriate learning from a set of examples.

ANN predicts outputs using experiences learned from historical data. This method is widely used because it does not require detailed information of the physical process controlling the system and generally applicable using available hydrological data. The hydro-meteorological data's like areal rainfall, stream flow and sediment yield data's in daily and monthly basis were combined as input. Hence Multi-layer feed forward networks (MLP) are always trained in supervised manner with a highly popular algorithm known as the error back propagation algorithm; it was adopted for this study.

The procedure to go for modeling by artificial neural network is accompanied through the following procedural steps:-

1 Selection of neural network model (depending on literatures and trial & error was conducted after checking performance of the models).

2 Formulation of representative combination of inputs (Attempts were conducted with trial and error with least error propagation).

3 Classification of the data in training, testing and validation data's sets.

4 Transformation of data sets with in defined rescale range (Normalization) and selection of learning algorithm (rule) for the specified neural network.

5 Creating function approximating network (building the network)

6 Fixing the number of epochs, hidden layer, training algorithm, stopping criteria and Processing. Elements (PE's) until the error propagation and performance indicators fit well in all the selected neural network models.

7 Testing and cross validation of the data test in every sets of criteria's changed in step 6.

Result and Discussion

SWAT model

Stream flow modeling: The model was run for a period of eight years (from 01/01/1994 to 31/12/2002) excluding the validation period, is taken for sensitivity analysis. Sensitivity analysis was conducted to determine the influence of a set of parameters had on predicting total flow. Table 2 shows the most sensitive parameters for stream flow drawn by SWAT model.

The result denotes that ground water parameters like thresh fold depth of water in the shallow aquifer required for return flow to occur (Gwqmn), ground water evaporation coefficient (GW_Revap), base flow alpha factor (Alpha_Bf), and thresh hold depth of water in the shallow aquifer required for evaporation to occur (Revapmn) are found the influencing flow parameters (having relative mean sensitivity from small to high degree of sensitivity).

Stream flow calibration and validation: Adjustment was done till observed and simulated values were correlated well by changing the parameters in their allowable range. The SWAT default parameters values were adjusted as follows. First, the surface flow components of average annual water balance by adjusting the CN. An effort was also made to keep the curve numbers close to standard table values. Next, Gwqmn, Esco, SOL_AWC, Sol_Z, Blai, GW_REVAP & REVAPMN were adjusted till the deviation between simulated and observed values get minimized and the performance indicators lie in the acceptable range. Accordingly the final calibrated parameters (Table 3) were presented as shown table below for flow in Beles watershed.

After stream flow is calibrated the next step was validation with independent data sets which are not used in the calibration period without changing the fitted parameters. The validation was undertaken for a period of eight years (01/01/2003 to 12/31/2010).

Undulation of stream flow was observed during calibration and validation periods in both low and high flow seasons, this fluctuation might exist due to the models low capability to capture peak rainfall event, the data quality's occurred during filling missed data's and error during measurement records (Figures 2 and 3). During the calibration period the model slightly underestimates stream flow in the months August and July of years 1995, 1996, 1998, 2000 and 2001 and overestimates during low flow seasons.

The simulated and observed stream flow were compared and the performance of the model was checked (Table 4).

Sediment yield modeling: Sensitivity analysis for sediment yield is undertaken for a period of nine years including the model warm up period. The most sensitive parameters for sediment yield that insights for change in simulated values are taken in consideration for the matching with the observed sediment yield generated from sediment rating curve (Table 5).

Sediment calibration and validation: Like flow, sediment yield for a period of eight years (from 01/01/1995 to 31/12/2010) taking one year for model warm up period is taken as a calibration period and parameters are adjusted depending on the sensitive parameters identified during sensitivity analysis with in the allowable range. Accordingly attempts were made to get an optimum agreement between the observed and simulated flow and better result were found by the final calibrated parameter values as shown in the table below (Table 6).

Likewise, sediment yield validation was conducted for a period of eight years from 01/01/2003 to 31/12/2010 by keeping the calibrated parameters constant (Table 7).

The model underestimates the average annual sediment yield in both calibration and validation periods. The model underestimates by

Parameters	Rank	Mean sensitivity	Category of sensitivity
Alpha_Bf	11	0.0138	Small
Canmx	9	0.0394	Small
Sol_Awc	5	0.0601	Medium
Cn2	3	0.109	Medium
Revapmn	8	0.0418	Small
Gwqmn	1	0.261	High
Ch_K2	10	0.0145	Small
Esco	2	0.172	Medium
Epco	12	0.0134	Small
Sol_Z	4	0.0871	Medium
GW_Revap	6	0.0601	Medium
Blai	7	0.0447	Small

Table 2: Sensitivity analysis result for stream flow in Upper Beles Watershed.

Parameters	Default values	Allowable range to change	Adjusted parameter value
Gwqmn	0	0-5000	1200
Canmx	0	1-2	1.2
Alpha_Bf	0.048	0-1	0.05184
Sol_Awc	Default	± 25%	-20%
Cn2	Default	± 25%	-20 %
Revapmn	1	0-500	450
Esco	0	0-1	0.95
Sol_Z	Default	± 25%	15% (Added)
GW_Revap	0.02	0.02-0.2	0.05

Table 3: Result of final calibrated flow parameters for upper Beles Watershed.

Monthly time step	Over Year mean Monthly stream flow(m^3/s)		PBIAS	NSE	R^2
	Observed	Simulated			
Calibration(1995 - 2002)	54.034	58.56	-8.37	0.81	0.82
Validation(2003-2010)	73.36	72.006	1.84	0.79	0.8

Table 4: Calibration and validation statistics of observed and simulated stream flow.

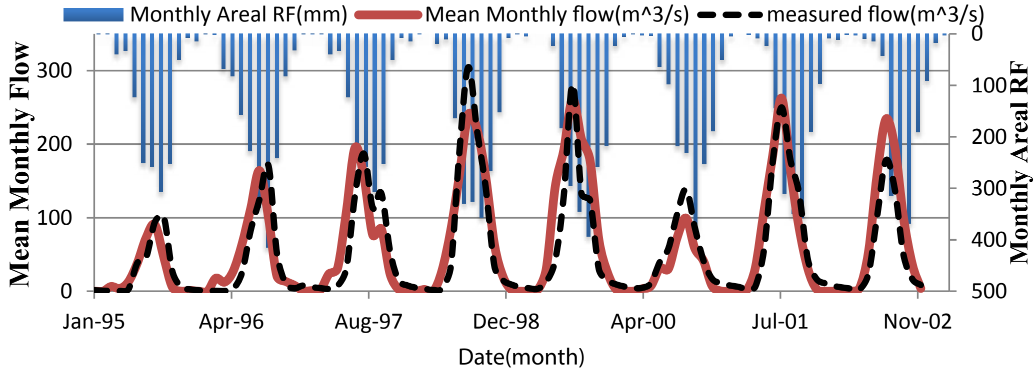

Figure 2: Observed and simulated stream flow hydrograph on mean Monthly time step during the calibration period.

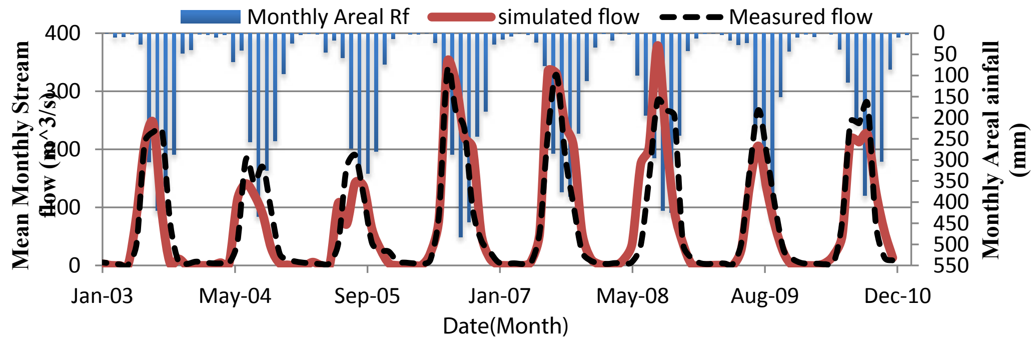

Figure 3: Observed and simulated stream flow hydrograph on mean Monthly time step during the validation period.

Parameter description	Parameter code	Rank	Mean sensitivity	Category of sensitivity
Channel Cover factor	Ch_Cov	7	0	Negligible
Channel Erodiblity factor	Ch_Erod	7	0	Negligible
Channel sediment routing	Spcon	1	2.78	Very High
Sediment re entrained in channel routing	Spexp	3	0.016	Medium
USLE-Cover and management factor	Usle_C	4	0.0879	Medium
USLE-Support practice factor	Usle_P	2	2.5	Very High

Table 5: Result of sensitivity analysis for sediment parameters.

Parameters	Default values	Allowable range	Adjusted parameter value
Spcon	0.0001	0.0001-0.01	0.000309
Usle_C Dominantly Cultivated	0.2		0.1
Moderately Cultivated	0.2	0.001-0.5	0.002
Wood Land dense	0.001		0.001(Not Changed)
Wood land open	0.001		0.003
Bush land	0.001		0.002
Rock land	0.003		0.002
Grass land	0.003		0.002
Spexp	1	1 to 2	1.5
Usle_P	1	0-1	0.704

Table 6: Final calibrated sediment parameters for Upper Main Beles watershed.

10.4% from the observed annual average sediment yield loading during the calibration period and by 18.23% during the validation period.

Spatial pattern of sediment source areas : The 17 year measured annual sediment yield generated from rating curve at main Beles gauging station was found 5.52 ton/ha/year and the simulated sediment yield by SWAT model is 4.81 ton/ha/year.

Monthly Time step	Annual average Sediment Yield (t/ha/yr.)		PBIAS	NSE	R^2
	Observed	Simulated			
Calibration (1995-2002)	4.42	3.96	5.54	0.8	0.81
Validation (2003-2010)	6.91	5.65	4.98	0.75	0.79

Table 7: Calibration and validation statistics of observed and simulated sediment yield.

The mean annual sediment yield from Beles watershed is around 4 ton/year /ha and the basin contributes 6% from the whole Blue Nile basin [14]. The study shows that the Beles basin is the 7th higher sediment yield potential area from the 16 sub basins of Abbay Basin following Guder, North Goajjam, Jemma, South Goajjam, Weleka and Finchaa sub basins. The result obtained from this research has made reasonable agreement with this study. Land use /land cover was found the influential parameters for sediment yield rather than the existing surface runoff and precipitation.

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As the study conducted by Hurin [15] soil formation rates for erosion in different agro ecological zone of Ethiopia have range of 2 to 18 ton/ha/year tolerable soil loss levels.

Out of the 29 sub basin created by the model, nine of the sub basins have sediment yield above 10 ton/ha/year but all the area are in tolerable range. Some of the sub basins having high areal coverage have contributed low runoff and sediment yield and vice versa, this may arise due to the existing HRU in each sub basins has revealed different surface runoff contribution in respective with the soil properties and land use effect that have on surface runoff generation.

The highest sediment yield sub basin areas are those which are covered with cultivated (dominantly and moderately cultivated) and Haplic luvisols with small coverage of chromic luvisols. The yellow and red highlighted areas of the watershed are potential areas which are sucepible for erosion and sediment yield. The HRU distribution for the selected sub basins clearly indicates the land cover (cultivated area) is the major controlling factor for sedimnet potential areas. Sub basins having sediment yield above 6 ton/ha/year were selected as high to medium range sediment source areas of the watershed as shown in Figure 4.

ANN model

Stream flow modeling

Monthly basis stream flow modeling: In this stage the combination of inputs doesn't consider the antecedent values since the previous month flow contribution to the current month flow was not logical and the lag time is less than a few days. The only input at this time was mean monthly areal rainfall.

$Q_t=f(RF_t)$

The network topology was fixed by trial and error through variation of the governing parameters (Table 8) of the neural network. The current flow (Q_t) at this time step modeling considers only the current rainfall (RF_t). The learning algorithm, transfer function, number of hidden layer and its PE was determined by trial and error until the desired output (simulated stream flow) was fitted to the desired input (measured stream flow).

From the entire trials luvenbegMulti quadrant learning (LM) algorithm with hyperbolic tangent transfer function (Tanh) linked with one processing elements and iteration of 1000 epochs has shown better result (trial 5) as seen from Table 9 below. The performance of these network yields R^2, NSE and PBIAS of 0.762, 0.76 and -1.38% in the training data set and 0.608, 0.60 and 13.14% in the testing data set. Summary of best performing network was presented in Table 10 below which reveals the representative parameters for monthly based stream flow modeling. The following combination were taken for this study (Table 8)

Daily basis stream flow modeling: At this time antecedent time step values of rainfall and flow was considered for predicting current flow, logical assumption of inputs were combined by trial and error and efforts were made to select better combination by formulating correlation between inputs. Inputs having high correlation (R) have given priority for the desired output. The two days lag time was taken in computing the current value of required output considering the lag time movement between peak rainfall and runoff time. Inputs have the correlation with Qt as:

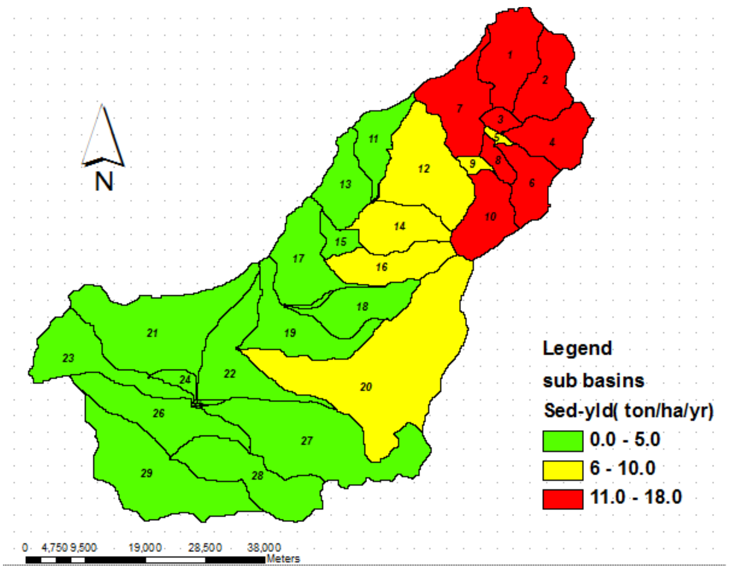

Figure 4: Spatial distribution annual average sediment yield contibution from sub basins of Upper Main Beles watershed.

Trails	Training Algorithm and transfer function		Calibrated parameters		
			Number of Hidden layer	Number of Epoch	Number PE
Trail 1	Conjugate Gradient	Tanh	1	1700	6
Trail 2	LM	Tanh	1	1700	6
Trial 3	Conjugate Gradient	Sigmoid	2	300	16-10
Trial 4	LM	Sigmoid	2	300	16-10
Trial 5	LM	Tanh	1	1000	13
Trial 6	Conjugate Gradient	Sigmoid	2	1400	18-16

Table 8: Combination of neural parameters yielding better results.

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Trials	Period	R^2	NSE	PBIAS	Mean Monthly stream flow(m/s)	
					Observed	Simulated
Trial 1	Training	0.71	-0.27	0.71	63.01	63.18
	Testing	0.50	0.45	29.11	97.39	69.04
Trial 2	Training	0.73	0.73	-0.01	63.01	63.01
	Testing	0.47	0.43	26.99	97.39	71.10
Trial 3	Training	0.69	0.69	-0.05	63.01	63.04
	Testing	0.52	0.45	31.18	97.39	67.02
Trial 4	Training	0.75	0.75	-3.27	63.01	65.07
	Testing	0.47	0.45	16.24	97.39	81.58
Trial 5	Training	0.763	0.76	-1.38	63.01	63.88
	Testing	0.61	0. 602	13.14	89.58	77.81
Trial 6	Training	0.69	0.69	-0.03	63.01	63.03
	Testing	0.65	0.60	25.26	89.58	66.95

Table 9: Result of Multilayer perceptron network model performance for each trail (Monthly based stream flow modeling).

Performance	Flow	
	Training	Testing
MSE	1812.298434	5943.116023
NMSE	0.239575215	0.437935395
MAE	25.61679399	47.85085505
Min Abs Error	0.22947798	0.393445254
Max Abs Error	185.1868266	245.8595947
R	0.873170153	0.765935661

(Where: MSE: Mean Square Error; NMSE: Normalized Mean Square Error; MAE: Mean Absolute Error; r: Linear Correlation coeffiecnt)

Table 10: Summary of best performing network (monthly based stream flow modeling).

Assuming the desired output at time "t", is Q_t, the rainfall to be considered at two lag, one lag and current day values are RF_{t-2}, RF_{t-1} & RF respectively and the antecedent values of flow Q_{t-2} and Q_{t-1}, though the current flow at those time steps will have the probability of the following combinations

$$Q_t=F(R_t) \quad (1)$$

$$Q_t=F(Q_{t-1},RF_t) \quad (2)$$

$$Q_t=F(R_t,RF_{t-1},Q_{t-1}) \quad (3)$$

$$Q_t=F(Q_{t-2},Q_{t-1}) \quad (4)$$

$$Q_t=F(RF_t,Q_{t-2},Q_{t-1},RF_{t-1},RF_{t-2}) \quad (5)$$

$$Q_t=F(RF_t,Q_{t-2},Q_{t-1},RF_{t-1}) \quad (6)$$

$$Q_t=F(RF_t,Q_{t-2},Q_{t-1}) \quad (7)$$

All the listed inputs in the Table above have reasonable correlation for daily basis. So those has been independently by varying the learning algorithm (starting from conjugate gradient to more complex LM learning algorithm), transfer function (sigmoid & hyperbolic tangent functions), number of epoch, processing elements and number of hidden layer. The variation of epoch, processing elements and number of hidden layer were varied many times and at each variation the model performance was checked. Hyperbolic tangent is recommended transfer function in case of the input variables have noisy data. The final calibrated network parameters were as shown in Table 11.

In all the possible combinations the governing parameters are changed different times until the network gives good result, the main challenge during the networking was avoiding the negative values. The result shown in Table 12 are best results obtained from each combination after a number of network simulation.

From the results combination six yields better results and it is concluded that hidden layer and learning algorithms are the main contributing parameters that automatically change the generated values (Table 12). The daily average stream flowing from upper Beles gauged watershed is predicted as 60.54, 70.32 and 83.46 m³/s during the training, validation and testing period showing good correlation with the observed values.

Sediment yield modeling

Monthly basis sediment yield modeling: The current month sediment yield value is taken to have nonlinear relationship with the current values of areal rainfall and stream flow. The modeling was started by tagging the mean areal rainfall and mean monthly stream flow as an input and monthly sediment yield as a desired output ,dividing the datasets only into training and testing (80% and 20% respectively) in similar way with the monthly time step modeling of stream flow. Conjugate gradient and LM learning algorithm by varying transfer function and other parameters were iteratively changed to fix the network. The only combination of input at this time was:

$$S_t=f(Q_t,RF_t)$$

The modeling attempt in some trials has shown negative values in the output and over fitting occurs when the number of hidden layer was varied to 1-3 with variation in learning algorithm and transfer function; this is due to high regularization of the weight decay at each level of iteration. During those low performances, the network was set to stop training with the maximum epoch number. The calibrated parameters for all combination were presented in Table 13 and results for the respective combination in Table 14 below.

All the trials have shown good performance and it was found difficult to select the best performing network, but around five of the trials have shown negative values in the training period except trail 5. Even if alteration of network parameters were conducted to avoid the derivation of negative values, the negative values were minimized but not avoided totally

Combinations	Number of PE's	Number of Epoch	Transfer function	No of hidden layer	Learning algorithm
Combination 1	5	1000	Tanh	1	LM
Combination 2	8	1200	Tanh	1	LM
Combination 3	6	1400	Tanh	1	LM
Combination 4	1	1600	Sigmoid	1	Conjugate gradient
Combination 5	1	1500	Tanh	1	LM
Combination 6	4	1500	Tanh	1	Conjugate gradient
Combination 7	1	1300	Tanh	1	LM

Table 11: Final MLP Calibrated parameters for all combination yielding better results.

Combination	Period	R^2	NSE	PBIAS	Daily Avg stream flow (m^3/s)	
					Observed	Simulated
Combination 1	Training	0.25	0.26	-7.07	60.62	65.64
	Validation	0.31	0.30	1.80	69.60	69.01
	Testing	0.26	0.22	32.32	94.26	65.51
Combination 2	Training	0.66	0.66	0.36	60.63	60.66
	Validation	0.58	0.58	3.30	69.61	67.96
	Testing	0.62	0.57	16.23	94.26	81.09
Combination 3	Training	0.68	0.68	-0.12	60.63	60.70
	Validation	0.60	0.60	1.83	69.61	68.99
	Testing	0.62	0.59	14.96	94.26	82.32
Combination 4	Training	0.66	0.66	-1.89	60.63	61.77
	Validation	0.60	0.60	0.60	69.61	69.86
	Testing	0.66	0.63	9.69	94.26	87.42
Combination 5	Training	0.69	0.68	-15.31	60.63	69.91
	Validation	0.58	0.56	-14.99	69.61	80.04
	Testing	0.63	0.63	1.79	94.26	92.56
Combination 6	Training	0.69	0.69	0.15	60.63	60.54
	Validation	0.61	0.60	-1.03	69.61	70.32
	Testing	0.68	0.67	11.45	94.26	83.46
Combination 7	Training	0.68	0.68	-2.43	60.63	70.57
	Validation	0.62	0.61	-1.39	69.61	70.57
	Testing	0.70	0.69	6.16	94.26	88.45

Table 12: Results of multilayer perceptron network model performance for each combination (daily based stream flow modeling).

Trails	Training Algorithm	Transfer function	Iterated parameters		
			Number of Hidden layer	No. of Epoch	Number PEs
Trail 1	Conjugate Gradient	Sigmoid	1	2000	15
Trial 2	LM	Tanh	1	600	8
Trial 3	Conjugate Gradient	Sigmoid	2	1100	4_4
Trial 4	LM	Sigmoid	2	900	5_4
Trial 5	Conjugate Gradient	Sigmoid	3	1400	4-4-4
Trial 6	LM	Tanh	3	1000	4-4-4

Table 13: Final MLP Calibrated parameters for all combination yielding better results (monthly based sediment yield modeling).

Trails		R^2	PBIAS	NSE	Mean monthly sediment yield loading(t/month)	
					Observed	Simulated
Trial 1	Training	0.9590	0.0663	0.9090	147110.2	147012.6
	Testing	0.9542	2.6193	0.9480	248234.1	241732.2
Trial 2	Training	0.9296	-0.0257	0.9100	147110.2	147148.0
	Testing	0.8887	1.7510	0.8873	248234.1	243887.6
Trial 3	Training	0.9600	0.0184	0.9360	147110.2	147083.1
	Testing	0.9542	3.7929	0.9470	248234.1	238818.9
Trial 4	Training	0.9450	-0.2697	0.9300	147110.2	147507.0
	Testing	0.9364	-0.2558	0.9360	248234.1	248869.1
Trial 5	Training	0.9889	-0.2971	0.9887	147110.2	147547.2
	Testing	0.9629	4.9278	0.9623	248234.1	236001.7
Trial 6	Training	0.9399	-0.0558	0.9199	147110.2	147192.3
	Testing	0.8988	0.5440	0.8987	248234.1	246883.7

Table 14: Results of Multilayer perceptron network model performance for each combination (monthly based sediment yield modeling).

Daily basis sediment yield modeling: Similarly with daily stream flow modeling, the daily basis sediment yield modeling considers daily areal rainfall, daily stream flow with two days antecedent values, two days lag sediment yield and one day lay sediment yield as an input, current sediment yield as desired output. The transfer function and learning algorithm with other network parameters are iteratively changed until the network performance gets optimum. The possible combinations were attained through logical mapping by trial and error and considerations of correlation between inputs with the desired sediment yield were used as an initial criterion. Inputs have the correlation with St as: The following possible combination of inputs was tested:

$$S_t=F(RF_t,Q_t) \quad (8)$$

$$S_t=F(Q_t,Q_{t-1}) \quad (9)$$

$$S_t=F(Q_t,Q_{t-1},RF_t) \quad (10)$$

$$S_t=F(RF_t,Q_{t-2},Q_{t-1},RF_{t-1}) \quad (11)$$

$$S_t=F(RF_t,RF_{t-1},Q_{t-1},S_{t-1}) \quad (12)$$

$$S_t=F(Q_t,Q_{t-2},Q_{t-1},S_{t-1},S_{t-2}) \quad (13)$$

$$S_t=F(RF_t,Q_t,Q_{t-2},Q_{t-1},RF_{t-1},RF_{t-2},S_{t-1},S_{t-2}) \quad (14)$$

The statistical performance of all the combination after a number of trail yield the following results (Tables 15 and 16).

From all the results combination 7 having inputs rainfall at t-2, t-1 and t, flow at time t-2, t-1 and t and also antecedent sediment yield at time t-1 and t-2 have resulted best from the other combination of input. Conjugate gradient training algorithm with hyperbolic tangent transfer function combined with two hidden layers (5-6 arrangement) and 1600 epochs were the calibrated parameters for this combination. The statistical performance of this combination results the R^2, NSE and PBIAS of 0.964, 0.96 and -1.37% in the training period, in the cross validation period 0.995, 0.992 and -2.97% in the cross validation period, and 0.983, 0.98 and 0.94% in the testing period respectively.

SWAT and ANN model comparisons

Both models slightly underestimate and overestimate the peak time stream flow and sediment yield of the watershed. The overall mean monthly stream flow estimation by the SWAT was more close-fitting to the observed stream flow than the ANN model, but the overall monthly average sediment yield estimation by the ANN was more fitted to the observed sediment than the SWAT model showing stream flow was better predicted by SWAT model and sediment yield was better predicted by ANN model (Figures 5 and 6). The hydrograph of validation period were as presented in Figures 5 and 6.

The over year mean monthly observed stream flow gauged at Main Beles gauging station was 63.7 m^3/s which was overestimated by 2.48% by SWAT_CN model and 5.76% by ANN _MLP model (Table 17).

Combinations	Number of PE's	Number of Epoch	Transfer function	Number of hidden layer	Learning algorithm
Combination 1	3	2500	tanh	1	LM
Combination 2	10 – 10	600	tanh	2	Conjugate gradient
Combination 3	12	200	tanh	1	LM
Combination 4	8 – 8	800	sigmoid	2	Conjugate gradient
Combination 5	6 – 6	1800	tanh	2	Conjugate gradient
Combination 6	5 – 5	1500	tanh	2	Conjugate gradient
Combination 7	5 – 6	1600	tanh	2	Conjugate gradient

Table 15: Calibrated parameters (daily based sediment yield modeling).

Combination	Period	R^2	NSE	PBIAS	Daily Average sediment yield loading(t/day)	
					Observed	Simulated
Combination 1	Training	0.951	-1.281	0.95626	4603.172	4662.163
	Validation	0.946	-1.83	0.99	5390.025	5489.039
	Testing	0.995	0.391	0.99294	8093.45	8061.765
Combination 2	Training	0.92	-3.95	0.92	4603.17	4784.81
	Validation	0.96	-5.26	0.96	5390.03	5673.31
	Testing	0.96	-7.34	0.94	8093.45	8687.33
Combination 3	Training	0.95	0.95	0.534	4603.172	4578.57
	Validation	0.99	0.99	-0.98	5390.025	5443.301
	Testing	0.96	0.98	-0.37	8093.45	8123.47
Combination 4	Training	0.56	0.56	-6.42	4603.17	4898.5
	Validation	0.46	0.45	-7	5390.03	5767.11
	Testing	0.39	0.38	17.76	8093.45	6655.75
Combination 5	Training	0.53	0.53	0.55	4603.17	4577.7
	Validation	0.48	0.47	-0.36	5390.03	5409.31
	Testing	0.42	0.39	21.59	8093.45	6346.16
Combination 6	Training	0.93	0.93	-0.41	4603.17	4621.89
	Validation	0.98	0.98	0.74	5390.03	5350.13
	Testing	0.98	0.98	3.33	8093.45	7823.58
Combination 7	Training	0.964	0.96	-1.37	4603.17	4666.23
	Validation	0.995	0.992	-2.97	5390.03	5549.98
	Testing	0.983	0.98	0.94	8093.45	8017.01

Table 16: Training, validation and testing statistics (daily based sediment yield modeling).

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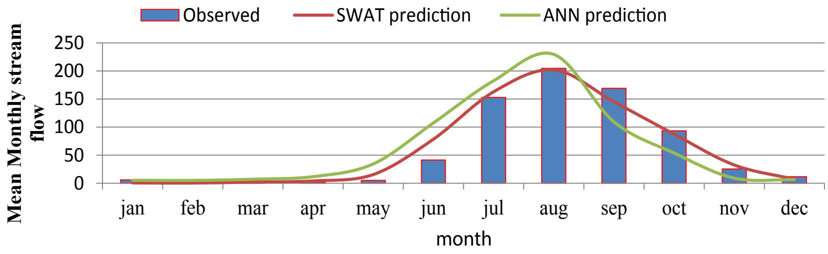

Figure 5: Over year mean monthly Stream flow prediction by ANN and SWAT.

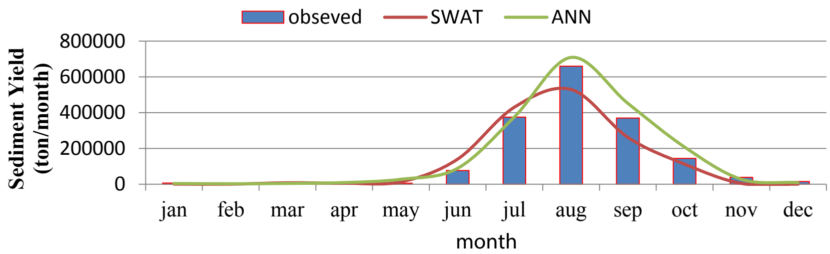

Figure 6: Over year Monthly sediment yield loading prediction by ANN and SWAT model.

	Over year annual average sediment loading (ton/ha/yr.)	Deviation (%)	Remark
Observed	5.52		
ANN(MLP)	5.97	8.1	Over estimation
SWAT_CN	4.81	12.9	Under estimation

Table 17: Over year mean annual sediment yield loading results by ANN and SWAT (1994-2010).

As seen from the Tables 4-17 the mean annual observed sediment yield obtained from rating curve developed at Main Beles gauging station was 5.52 ton/ha/year which was underestimated by 12.9% by SWAT_CN model and overestimated by ANN(MLP) model by 8.1%.

Conclusions

SWAT model was calibrated and validated for stream flow and sediment yield to check the model prediction capability for further characterization of the watershed, the sensitive parameters were adjusted. The model performance indicator was in the acceptable range and gives reliable estimates. Co-efficient of determination and Nash Sutcliff was 0.83 and 0.82 in the calibration and 0.8 and 0.79 in the validation period respectively for stream flow modeling. Similarly the performances during sediment yield modeling gives values of R^2 and NSE of 0.81 and 0.79 in the calibration period and 0.8 and 0.75 in the validation periods respectively. The results was accomplished in both daily and monthly time step but the monthly time step modeling was by SWAT model has better estimate. The modeling by SWAT model in daily time step has shown poor performance in both stream flow and sediment yield. The model simulates mean monthly flow of 65.28 m^3/s and sediment loading of 4.81 ton/ha /year from Upper Main Beles in considered time step (1994-2010). Land use was found a major contributing factor that affects sediment yield in the study area.

The modeling conducted by artificial neural network was also conducted for stream flow and sediment yield in Upper Main Beles catchment in daily and monthly basis. Multi-layer perceptron neural network model by varying learning algorithm, transfer function, processing elements, epoch and number of hidden layer was iterated to obtain better results. The input combination for monthly time step doesn't consider antecedent values of defined inputs since the lag time is not more than a few days and is not logical. The daily time step input combination takes two days antecedent lag time and possible input combination were tried till the network topology is fixed to yield better results.

The monthly time step modeling of stream flow has shown better performance with Levenberg multi quadrant learning algorithm, hyperbolic tangent transfer function, one hidden layer, 13 processing elements and 1000 epoch giving R^2 of 0.762 and 0.59 and NSE of 0.61 and 0.6 in the training and testing period respectively which was in acceptable ranges. Whereas the daily time step modeling gives better result with combination of four PEs, conjugate gradient learning algorithm, hyperbolic tangent transfer function, 1500 epochs and one hidden layer which yields R^2 of 0.691,0.61 and 0.68 and NSE of 0.69,0.6 and 0.67 in training , cross validation and testing period respectively. Current daily areal rainfall (RF_t), one day lag time rainfall (RF_{t-1}), stream flow at one day lag time (Q_{t-1}) and at two days lag time (Q_{t-2}) were found the best combination for determining current value of stream flow in daily time step analysis. The results in both time step modeling were acceptable range. The simulated mean monthly stream flow is 67.4m^3/s in the baseline 1994 to 2010.

Similarly modeling sediment yield by multilayer perceptron was done in monthly and daily time step. The monthly time step modeling considers mean monthly areal rainfall and mean monthly stream flow as an input and monthly sediment yield as desired output. From all the trail during this time step modeling conjugate gradient learning algorithm with sigmoid transfer function, three hidden layer having 4-4-4 processing elements in the input, hidden & output layers and 1400 epoch yields better result. The network topology gives R^2 of 0.9889 and 0.9629 and NSE of 0.9887 and 0.9623 in the training and testing period respectively. The results were very attractive and considerable agreement was obtained with some overestimation.

The daily time step sediment yield modeling with combination of inputs daily rainfall considering current (RF_t), one day lag (RF_{t-1}), two day lag (RF_{t-2}) and stream flow of current (Q_t), one day lag (Q_{t-1}) and sediment yield of one lag (S_{t-1}) and two days lag (St-2) gives a better result among all the formulated possible combinations. Conjugate gradient learning algorithm and hyperbolic tangent transfer function in combination with two hidden layer of 5-6 arrangement of processing elements and 1600 epochs gives better result for the specified combinations. The combination yield R^2 of 0.962, 0.995 and 0.98 and NSE of 0.96, 0.992 and 0.98 in the training, cross validation and testing periods respectively. The overall annual average sediment yield prediction in upper main Beles catchment by multilayer perceptron neural network in time step 1994 to 2010 was 5.97 ton /ha/yr.

The effort in describing hydrological phenomenon in physical terms form the pixel to catchment scale (bottom up approach) , is not fully acknowledged by the proponents of data driven models (top down approach) who don't require the derivation of rigid model structure from the physical balance equations. Similarly the proponents of physical based models do not acknowledge the merits of data driven models. So the two models should have to be used interchangeably but according to purpose and prediction accuracy.

The data driven model (ANN) can be used for Beles catchment in characterizing stream flow and sediment yield when the watershed has not shown significant change in catchment characteristics (land use and slope). The model was powerful and has capability of approximating stream flow as well as sediment yield. When the watershed has shown significant change in land use dynamics, SWAT model will take the priority for characterizing stream flow and sediment yield in Beles watershed.

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