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Estimation of soil loss using artificial neural networks for Kalidevi watershed of Dhar, Madhya Pradesh, India

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ABSTRACT

Artificial neural network is a key tool for soil loss estimation and it is required for proper watershed management and other developmental work in situ. The study area, Kalidevi watershed where this study was carried out, comes under the Bagh block of the Kukshi tehsil of district Dhar of Madhya Pradesh and has been chosen for developing artificial neural network model for estimation of soil loss. Data on daily rainfall, API and days since 1st June and runoff were taken as input variables of period 2003-2005 during rainy seasons have been used for the analysis and development of ANN model for soil loss estimation. It is found that for soil loss modeling, an ANN model with four input variables with 60 neurons single hidden layer and one output and learned with Levenverg-Marquardt (LM) algorithm performed better for the estimation of soil loss.

1. INTRODUCTION

India supports around 16% of world human population on 2.4% of the global land area, the problem of soil deterioration is serious enough (Sebastian *et al.,* 1995). Hence there is a need to understand the rainfall-runoff process and soil erosion and quantify their magnitude in time and space (Lal, 2001). Estimation of the soil loss from the soil surface is important to understand the degree of soil degradation which restricts the land for potential agricultural use. Watershed development programme requires estimation of runoff and soil loss right from watershed prioritization to design of soil and water conservation structures.

Soil loss in ANN models is the key component of the watershed modeling in spatial and temporal basis. A number of parametric models have been developed to predict runoff and soil loss. These models are based on soil, land use, land cover and land forms, climatic and other topographic features of watershed. Furthermore, such models prove themselves highly costly as well as time effective to predict runoff and soil loss from a particular area in particular time period used in combination. Artificial Neural Networks (ANN) are highly adaptive to non-parametric data distribution and while other statistical methodologies require a set of assumptions to be fulfilled, the former make no prior hypotheses about the relationship between the variables. Neural networks are also less sensitive to error term, assumptions and they can tolerate noise, chaotic components and heavy tails better than most of the other methods. Sudheer *et al.* (2000) and Sarangi *et al.* (2005) pointed out that one of the most critical questions when applying ANN to modeling rainfall-runoff process is what architecture should be used to map the process effectively. Moreover, there are no fixed rules for developing an ANN. An attractive feature of ANNs is their ability to extract the relationship between input and output of a process without the physics being explicitly provided to them. These properties suggest that ANNs may be well suited for modeling for estimation of runoff as well as soil loss in any watershed.

Artificial neural network (ANN) models are developed to predict runoff and soil loss for a small agricultural watershed. Simulated runoff and soil loss were compared with observed values further evaluation and validation criterions were used for selecting the best performing models for further prediction. Cai (2004) used rainfall, soil texture, slope and geomorphologic parameters of watershed for estimation of sediment yield in multi-watershed studies. Cigizoglu and Kisi (2006) and Bhatt *et al.* (2011) also used the artificial neural network (ANN) approach, applied its domain and summarized for the estimation of suspended sediments (Soil loss) modeling through ANN of Turkish hydrological basins data sets which are measured independent from each other. Further this can be a time saving features since the input layers nodes are found by trial and error in general. Bhadra and Bandyopadhyay (2009); Sarkar *et al.* (2006); Jain and Srinivasulu (2004) also reported that Levenberg-Marquardt algorithm performs better for runoff and soil erosion modeling.

Study Area

The Kalidevi Watershed of district Dhar, Madhya Pradesh lies between 74^0 50' to 74^0 55'E longitudes and 22^{o}30' to 22^0 35' N latitudes and having total geographical area of 3135.12 ha. The watershed is located in agro-climatic zone-XII of Jhabua Hills (Mehta, 2004). The topography of the watershed is undulating with 1/6th of its total area as wasteland or forest and only 40% land is under cultivation and remaining part has very high altitude (190 to 800 m msl). Maximum part of the study area has shallow soil depth (Anonymous, 2006).The district is having a total geographical area of about 0.82 m ha with mean annual rainfall of 1085 mm. Location of the Kalidevi watershed is depicted in Fig.1.

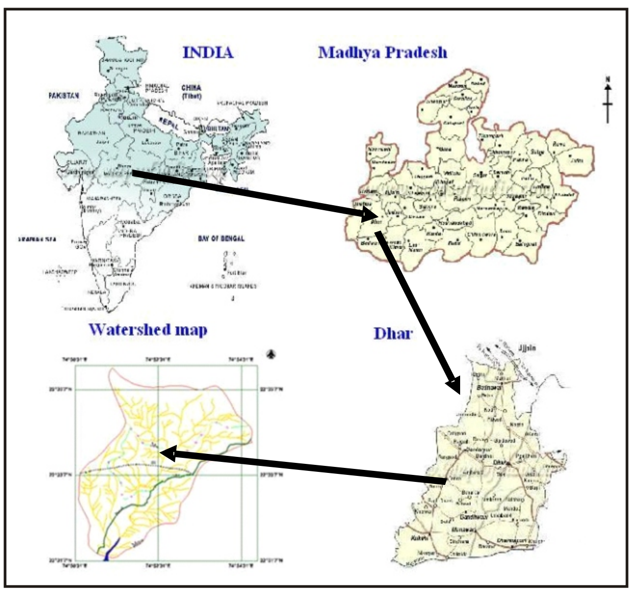

Fig. 1. Location of the Kalidevi watershed, Dhar, M.P., India

Climate

The climate plays an important role in soil developmentand watershed management. The intensity of weathering depends on climate. Dhar district has been classified as transitional ecosystem of moist semi-arid and dry sub-humid climate type with index (-) 41.9. The mean annual temperature varies from 18 to 22^{o}C with annual mean of 24.5^{o}C. The region experiences hot summer and mild winter with mean summer temperature of 29.5^{o}C and mean winter temperature of 18.7^{o}C.

2. MATERIALS AND METHODS

Topography and Slope

The study was associated with granite terrain plateau, hills and ridges, residual hills with narrow valleys, plain and flood plain. About 50% area of the watershed comes under moderately steep slope ranging from 8-15% and rest of the watershed area had gentle slope between 3-5%.

Soils

The knowledge about the type of soils and their extent is very essential for sustainable land use planning. In the study area mainly three type of soil taxonomy was found namely: Lithic Ustorthents - Lithic Ustorthent - Typic Haplustepts, Lithic Haplustepts - Vertic Haplustepts - Lithic Ustorthents and Vertic Haplustepts - Lithic Ustorthents these are locally named as Bhata Matasi, Matasi - Dorsa and Matasi Bhata, respectively (Verma *et al.,* 2006).

Soil Depth

The Soil depth is of vital importance for plant growth as it provides foothold to plant to draw the required water and nutrients from underground soil. Maximum part of the study area was having of shallow soil depth (25-50 cm), some area was under slightly deep soil category (50-75 cm) and also little part has deep soil (>100 cm).

Cropping Pattern

Various types of crop cover (land use) were reported about the watershed for the year 2003 to 2005. Report about the study area was dominated mainly by Soybean+Maize crop and larger area of the watershed was found under mixed cropping system. Open forest, dense forest, water body and wasteland were also reported during the years from 2003 to 2005.

Data Collection

Daily rainfall, temperature, runoff and soil loss data for the period 2003-2005 during rainy seasons recorded by the project Land Use Planning and Management of Natural Resources of Dhar District through Remote Sensing, College of Agriculture, Indore (M.P.) have been used for the analysis and development of model for soil loss.

Concept of Artificial Neural Network (ANN)

An ANN is a massively parallel-distributed information processing system that has certain performance characteristics resembling biological neural networks of the human brain (Haykin, 1994). The basic processing elements of the artificial neural networks are the artificial neurons, which is analogous to the biological neurons. The biological neuron is a specific type of cell of the human brain. The artificial neurons are analogous to the biological neuron in its structure as well as function. Artificial neurons are much simpler than the biological neuron. The structure of an artificial neuron is shown in Fig. 2.

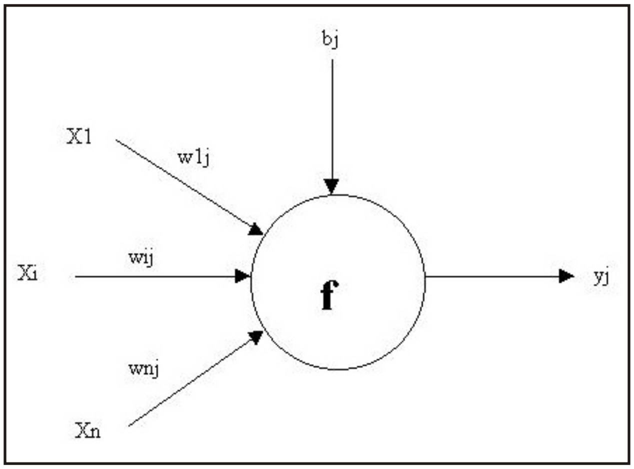

Fig. 2. Structure of an artificial neuron

Development of ANN Based Soil Loss Model

To develop ANN based model for soil loss estimation; one input layer, one hidden layer and one output layer has been considered to design an ANN network. The input variables are rainfall, average temperature, Antecedent Precipitation Index (API, last five days rainfall amount), days since 1st June and runoff depth. All parameters that affect the runoff are supposed to affect the soil erosion process. Hence, to develop model for soil erosion estimation all input parameters used in developing runoff model along with runoff depth has been considered as input variables. Initially the ANN architecture consisted of all five input variables, 45 numbers of neurons and training algorithm as Levenberg-Marquardt. Sixty percent of total length of data was used for training of the model and rest 40% for validation. The "tansig" and "purelin" activation function were used as the transfer function at hidden and output layers, respectively. Model was improved with various training algorithms, numbers of input variables, numbers of neurons and length of record. The normalization method found suitable for ANN based runoff model *i.e.,* mapminmax has been used for scaling the input and target data.

Training Algorithms

Training algorithms, which are comparable with the best training algorithm for ANN based runoff model, have been considered for evaluation of performance of soil loss model. These algorithms are-trainlm, traingda, traincgp, trainscg and trainbfg. The algorithm that performed better during training and validation was selected for further improvement.

Input Variables

Five input variables namely; rainfall, average temperature, API, days since 1st June, runoff depth and one output variable- soil loss in 24 hours have been used in the model development. It was assumed that all five variables have significant effect on performance of ANN model. An attempt was made to evaluate the model performance with lesser input variables along with various combinations. Various models developed with combinations of input variables are listed in table 1 below. The model that performed best was considered for further refinement.

Number of Neurons

ANN models have been developed and evaluated for their performance with 45 neurons. Model with more number of neurons takes more time for training. Also very

Table: 1
ANN models for soil loss with combinations of input variables

Model	Output	Input				
	Y	X1	X2	X3	X4	X5
	Soil loss (tons)	Rainfall (mm)	Av. Temp. (^{o}C)	API	Days since 1st June	Runoff depth (mm)
M1	√	√				
M2	√		√			
M3	√			√		
M4	√				√	
M5	√					√
M12	√	√	√			
M13	√	√		√		
M14	√	√			√	
M15	√	√				√
M25	√		√			√
M123	√	√	√	√		
M124	√	√	√		√	
M125	√	√	√			√
M135	√	√		√		√
M145	√	√			√	√
M1234	√	√	√	√	√	
M2345	√		√	√	√	√
M1345	√	√		√	√	√
M1235	√	√	√	√		√
M12345	√	√	√	√	√	√

high numbers of neurons do not help in generalization of the model. Hence by trial and error, optimum number of neurons was selected by evaluating the model performance with varying number of neurons *i.e.*, 10, 20, 30, 40, 45, 50, 55, 60, 65, and 70. Number of neurons that performed better was considered for further improvement of ANN model.

Length of Record for Training and Validation

The datasets included the daily record of four input variables for the total duration of 276 days during monsoon periods of year 2003, 2004 and 2005. In order to ensure good approximation of ANN model for soil loss number of data pair used in the study as described in Materials and Methods and elsewhere, are used which are more than total weights of ANN model.

3. RESULTS AND DISCUSSION

Development of ANN Based Model for Estimation of Soil Loss

An attempt has been made to develop ANN based model for estimation of runoff from Kalidevi watershed. One input layer one hidden layer and one output layer has been considered for ANN model. As “minmax” method of normalization of input and target vectors have proved better over the “std” method for ANN based model for runoff development, the same has been adopted fro soil loss modeling. Initially 45 neurons have been taken into hidden layer and 60% of total data set is used for training of the data. There are five input variables used for developing ANN based soil loss model. These variables are - daily rainfall, average temperature, API, days since 1st June, and daily runoff. All the five input variables have been used for evaluating the training algorithm. For developing ANN based soil loss models, performance of 12 training algorithms were evaluated (Table 2). Some of the algorithms performed well whereas some performed very poor.

Table: 2
Description of Training Algorithms with their Acronyms used in ANN modeling

S. No.	Acronyms	Training Algorithms
1	LM-Trainlm	Levenverg Marquardt algorithm
2	GD-Traingd	Batch Gradient Decent
3	GDM-Traingdm	Batch Gradient Decent with momentum
4	GDA-Traingda	Variable learning rate
5	GDX-traingdx	Variable learning rate
6	RP-Trainrp	Resilient Backpropagation
7	CGF-traincgf	Fletcher-Reeves Update (Conjugate gradient)
8	CGP-traincgp	Polak-Ribiere Update (Conjugate gradient)
9	CGB-traincgb	Powell/Beale Restarts (Conjugate gradient)
10	SCG-trainscg	Scaled Conjugate gradient
11	BFGS-trainbfg	Quasi-Newton algorithm

Trainlm

The Levenberg-Marquardt algorithm has syntax 'trainlm' and has been designed to approach second-order training speed without having to compute the Hessian matrix. The performance of trainlm algorithm is shown in Fig. 3.

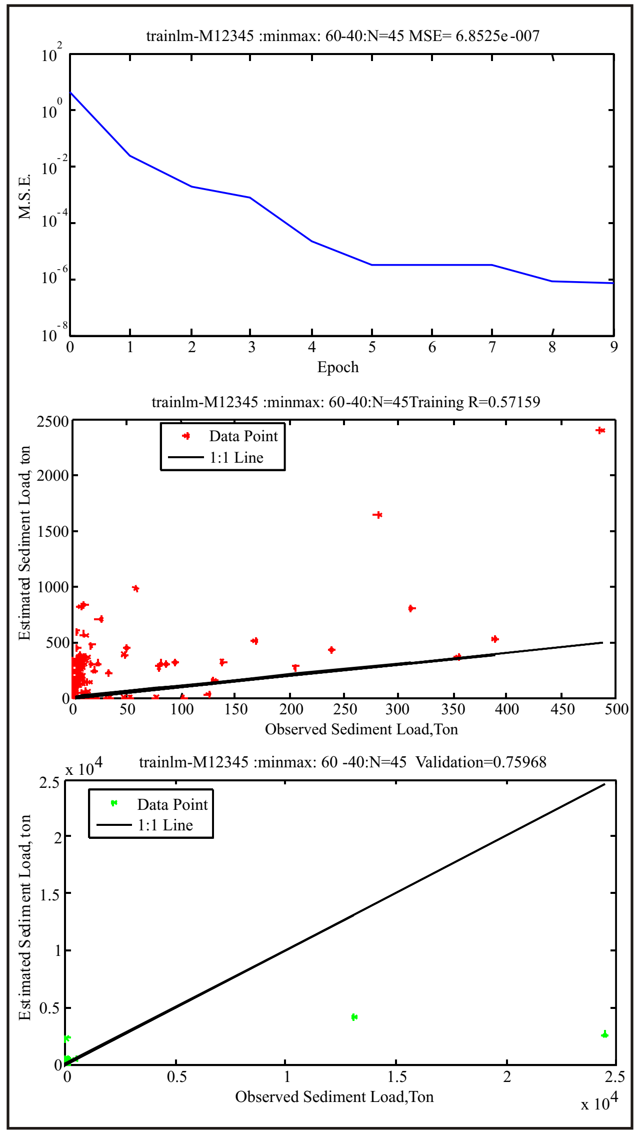

Fig. 3. Performance of ANN model for soil loss estimation with trainlm training algorithm

It can be seen that MSE during training is 6.85x10^{-7} at 9 epochs. ANN architecture have finalized during training with very low number of iterations/epochs as the MSE was targeted to be 10^{-10}; however, it could not be achieved. As depicted in Fig. 4 and Fig. 5, there is no reduction in MSE with further iterations and in case of Fig. 5, the MSE reduced to 10^{-08} with 150 iterations. The algorithm trainlm resulted into correlation coefficient (R) between model output and target (runoff) as 0.572 during training of the model and R during validation of model is 0.760. RMSE is 334 and 2299 and MAE is 256 and 502, during training and validation, respectively (Table 3). The trainlm algorithm performed better during validation than during training of the model.

It is evident from the above table, that performance of ANN model trained with trainlm *i.e.* Levenberg-Marquardt algorithm performed better than other algorithms. The

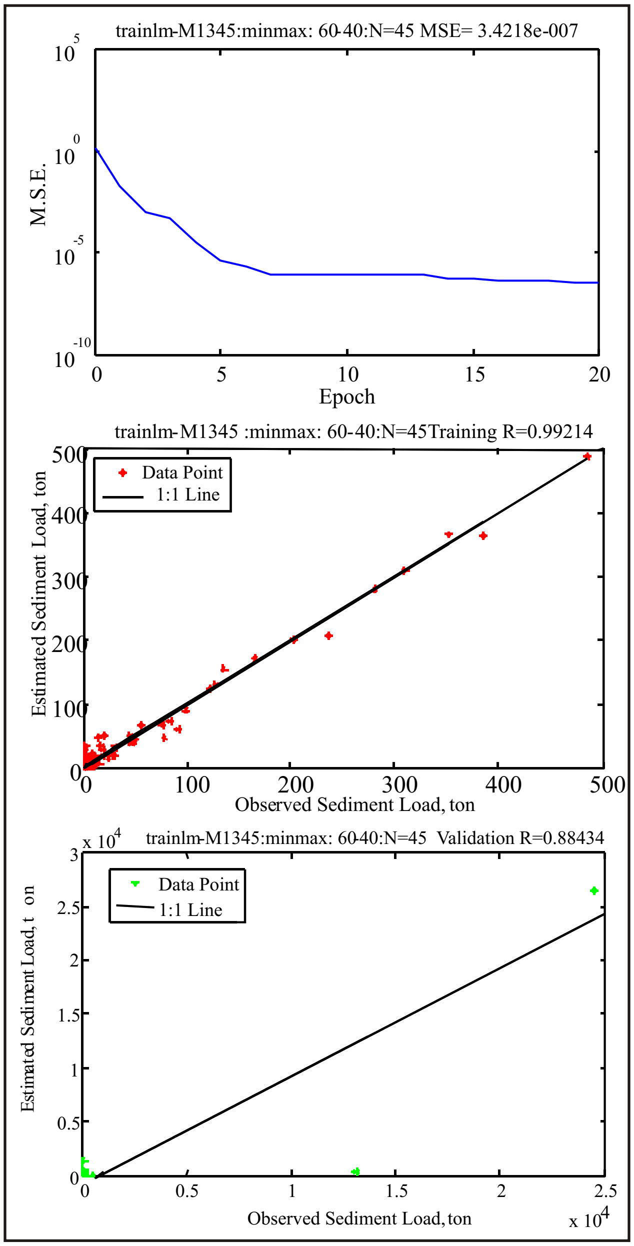

Fig. 4. Performance of ANN model for soil loss estimation with trainlm training algorithm

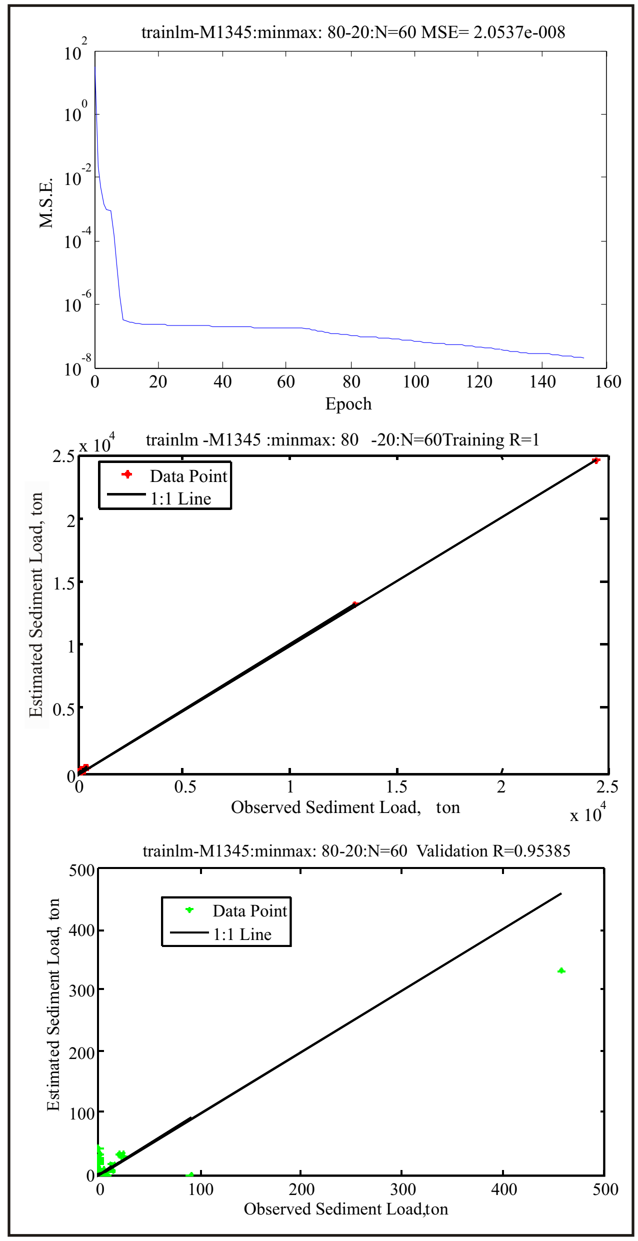

Fig. 5. Performance of ANN model for soil loss estimation trained with 80% of data set

Table: 3
Performance of ANN model for soil loss estimation with different Algorithm (M12345, N=45, minmax, 60-40)

Algorithm	R (trg)	R (Val)	MSE (trg)	MSE (Val)	RMSE (trg)	RMSE (Val)	MAE (trg)	MAE (Val)
Trainlm	0.572	0.760	$6.85xe^{-7}$	0.0348	334	2299	256	502
Traingda	0.353	0.743	0.3479	0.7137	6490	6379	3153	3869
Traincgp	0.105	0.565	0.0326	0.0975	1882	3594	881	1756
Trainscg	0.379	-0.060	0.0130	0.1639	1345	3537	526	1238
Trainbfg	0.285	0.502	0.0035	0.0612	606	2343	323	891

Levenberg-Marquardt (LM) algorithm has been considered for further improvement of the ANN based soil loss model.

Input Variables for ANN Based Soil Loss Model

ANN model with minmax normalization function and five input variables performed better with Levenberg-Marquardt training algorithm. Now the ANN model for soil loss estimation shall be evaluated with varying input variables to optimize the model performance. Number of neurons shall be 45 in the hidden layer and 60% of total data shall be used for training the model and 40% for model validation. The response variable is daily soil loss.

It can be seen that including all five input variables in the model, performance of model not necessarily improves. An ANN model can perform better with lesser input variables. Comparing the model performance parameters given in the above Table, it can be observed that model M-15, M-123 M135 and M-1345 performed better than all others. It is quite difficult to say, which model performed best as some models performed better during training than others, while other models performed better during validation as indicated by R, RMSE and MAE. Hence average of the performance indicator value during training and validation has been computed. It is found the average value of R is 0.9380, 0.9215, 0.8870 and 0.8540 for model M-1345, M-15, M-135 and M-123, respectively. RMSE is 628.5, 675.5, 1120, 1114 and, MAE is 79.0, 91.0, 152.5, and 190.0 for model M-1345, M-15, M-135 and M-123, respectively. Hence it can be stated that Model M-1345 performed best. If two input variables are to be taken model M-15 can be selected. With three input variables, model M-135 performed better than model M-123.

Model with 60 neurons (R= 0.933, RMSE=1110, MAE=145) performed better than model with 55 neurons (R=0.872, RMSE=1550 and MAE=254) during validation with independent data set (Table 5). Hence, it can be stated that performance of the model M-1345 with 60 neurons trained with Levenberg-Marquardt algorithm with 60% data set is best among models with other number of neurons evaluated. This model architecture has been further refined with different length of data set used for training of the model and its validation.

Effect of Length of Record on Performance of ANN Model for Soil Loss Estimation

Performance of the model M-1345 with "trainlm" training algorithm and 60 neurons, when trained with When model is trained with 80% of data set, its performance has been improved (Table 6). The correlation coefficient between estimated soil loss and observed soil loss is 1.000 during training of the model and 0.95385 during its validation with 20% length of data set.

Table: 4
Performance of ANN model for soil loss estimation with different input variables

Model	R		MSE		RMSE		MAE	
	trg	Val	trg	Val	Trg	Val	trg	Val
M1	0.673	0.774	$1.4127*10^{-5}$	0.0359	145	1728	45	200
M2	0.592	0.032	$2.1087*10^{-5}$	0.0467	56	2653	25	358
M3	-0.146	0.099	$2.1264*10^{-5}$	0.0463	525	2665	294	645
M4	0.005	-0.033	$1.6342*10^{-5}$	0.0582	571	2788	79	555
M5	0.587	0.550	$5.256*10^{-6}$	0.0433	363	2556	76	373
M12	0.589	0.975	$1.2644*10^{-5}$	0.0163	97	1542	39	196
M13	0.380	0.956	$9.3333*10^{-6}$	0.0314	242	2001	69	278
M14	0.712	0.885	$1.1147*10^{-5}$	0.0217	49	1768	24	256
M15	0.954	0.889	$2.9780*10^{-6}$	0.0118	21	1330	8	174
M123	0.899	0.809	$6.3409*10^{-6}$	0.0392	31	2197	10	370
M124	0.441	0.851	$9.3725*10^{-6}$	0.0178	805	1612	601	846
M125	0.984	0.462	$9.7379*10^{-7}$	0.0466	12	2434	5	300
M25	0.728	0.968	$4.7978*10^{-6}$	0.0079	68	1076	55	163
M135	0.979	0.762	$1.4558*10^{-6}$	0.0329	14	2226	5	300
M145	0.991	0.464	$6.1218*10^{-7}$	0.0399	10	2353	4	267
M1234	0.549	0.990	$4.3044*10^{-6}$	0.0363	208	2316	68	332
M2345	0.221	0.584	$2.5323*10^{-6}$	0.0323	369	2211	292	595
M1345	0.992	0.884	$3.4218*10^{-7}$	0.0105	10	1247	4	154
M1235	0.293	0.433	$1.1518*10^{-6}$	0.0557	184	2488	129	409

Table: 5
Performance of ANN model for soil loss estimation with different number of neurons in the hidden layer

No. of Neuron	R (trg)	R (Val)	MSE (trg)	MSE (Val)	RMSE (trg)	RMSE (Val)	MAE (trg)	MAE (Val)
10	0.019	0.928	$8.6173*10^{-6}$	0.0127	495	1452	361	455
20	0.816	0.736	$2.8772*10^{-6}$	0.0450	52	2601	41	379
30	0.361	0.880	$3.0344*10^{-6}$	0.0191	152	1694	107	299
40	0.954	0.877	$2.5020*10^{-6}$	0.0422	36	2358	20	330
45	0.992	0.884	$3.4218*10^{-7}$	0.0105	10	1247	4	174
50	0.467	0.274	$3.4439*10^{-7}$	0.0566	150	2591	83	474
55	0.999	0.872	$1.1957*10^{-8}$	0.0165	1.1	1550	0.5	254
60	0.999	0.933	$6.0164*10^{-8}$	0.0083	3	1110	1	145
65	0.553	0.401	$3.8800*10^{-8}$	0.0418	144	2512	117	424
70	0.993	0.800	$3.1912*10^{-7}$	0.0751	7	2532	4	360
80	0.807	0.864	$8.4865*10^{-8}$	0.0788	47	2163	19	320
90	0.672	0.987	$2.1682*10^{-8}$	0.0051	116	827	74	225

Table: 6
Performance of ANN model for soil loss estimation, trained with different lengths of data set

Training with % of data set	R (trg)	R (Val)	MSE (trg)	MSE (Val)	RMSE (trg)	RMSE (Val)	MAE (trg)	MAE (Val)
50	0.258	0.969	$3.0483*10^{-7}$	0.0071	290	706	141	355
60	0.999	0.933	$6.0164*10^{-8}$	0.0083	3	1110	1	145
70	0.999	0.124	$6.7373*10^{-7}$	0.0154	136	1459	86	230
80	1.000	0.954	$2.0537*10^{-8}$	$5.846*10^{-6}$	1.5	23.59	0.78	9.15

As far as using a very high value of neurons 45 to 60 in hidden layer is concerned, the fact is that number of neurons should be excessively on higher side. As the number of neurons increases the ANN models training and processing time increases and models became more specific but lack in generalization. Also with availability of computing machine with high RAM and more storage facility, the computing time is not a constraint. So the ANN model developed in the study reported is very site specific, as land use and land cover of the watershed have not been used as input parameter. Therefore taking the higher neurons improved the performance of ANN Model.

Results revealed that ANN model for soil loss estimation with four input variables (daily rainfall, API, days since 1st June and daily runoff) with 60 neurons in the hidden layer when trained with 80% of the data set by Levenberg-Marquardt training algorithm and input and target vector scaled with Minmax normalization method performed best with R=1 during training and R= 0.953 during validation of the model. RMSE and MAE during training of the model are 1.5 and 0.78, respectively. RMSE and MAE during validation of the model have been found as 23.59 and 9.15, respectively. These values of error between estimated soil loss and observed soil loss are lowest among all combinations tested for optimization of model performance.

4. CONCLUSIONS

An ANN based model for soil loss has been developed for the Kalidevi watershed, Dhar of Madhya Pradesh,India. The developed soil loss model for the area has 60 neurons in a single hidden layer, four input variables, and Levenverg-Marquardt training algorithm. The ANN model for soil loss has correlation coefficient of 0.953. The ANN based soil loss models developed based on recorded runoff and other input variables performed well during model training as well as validation with independent data set. For ANN based modeling, 'MinMax' method of normalization is found better than 'Std' method. Levenverg-Marquardt training algorithm of back propagation performed better than other twelve algorithms evaluated. With 45 neurons in the hidden layer, four input variables (rainfall, API, days since 1st June and runoff), ANN model for soil loss resulted in to R as 0.992 and 0.884 during training and validation. Model with all five input variables resulted R as 0.571 and 0.759 during training and validation, respectively. With 60 neurons in the hidden layer, four input variables (rainfall, API, days since 1st June and runoff) ANN model for soil loss resulted in to R as 0.999 and 0.933 during training and validation respectively. While with 45 neurons in the hidden the model resulted R as 0.992 and 0.884 during training and validation, respectively. With 80-20% length of records used, during training and validation, ANN model with four input variables (rainfall, API, days since 1st June and runoff) for soil loss resulted into R as 1.000 and 0.953 during training and validation, respectively. While with 60-40% length of records the model resulted R as 0.999 and 0.932 during training and validation, respectively.

REFERENCES

Anonymous. 2006. Land Use Planning and Management of Natural Resources of Dhar District through Remote Sensing. An annual report of AICRP project College of Agriculture Indore MP-submitted to ISRO Bangalore.

Bhadra, A. and Bandyopadhyay, A. 2009. Development of an ANN model for runoff prediction. *Water Resour. Res*., 29(4): 46-53.

Bhatt, V.K., Shrmishta Pal and Tiwari, A.K. 2011. Prediction of runoff and sediment yield for Damodar and Mayurkashi basin using artificial neural network and regression analysis. *Ind. J. Soil Cons.,* 39(2): 100-107.

Cai, A. 2004. Artificaial neural network method for soil erosion forecasting. Chinese Academy of Sciences, Shanghai.

Cigizoglu, H.K., Kisi, O. 2006. Method to improve the neural network performance in the suspended sediment estimation. *J. Hydrol.,* 317 (3-4): 221-238.

Haykin, S. 1994. Neural networks a comprehensive foundation. *IEEE* press.

Jain, A. and Srinivasulu, S. 2004. Development of effective and efficient rainfall and runoff models using integration of deterministic, real-coded genetic algorithms and Artificial neural network techniques, *Water Resour. Res.*, 40, W04302.

Lal, R. 2001. Soil degradation by erosion*, Land degrad. Dev.*, 12: 519-539.

Mehta, P.K. 2004. Agroclimatic Zones in the interest of Farmers. A popular article published in *Khet Aaur Bazaar*, October-November, 2004.

Sarangi, A., Madramootoo, C., Enright, A.P., Prasher, S.O. and Patel, R.M. 2005. Performance evaluation of ANN and geomorphology-based models for runoff and sediment yield prediction for a canadian watershed. *Curr. Sci.,* 89: 2022-2033.

Sarkar A., Agarwal, A. and Singh, R.D. 2006. Artificial neural network models for rainfall-runoff forecasting in hilly catchment. *J. Ind. Water Resour. Soc*., 26(3-4): 5-12.

Sebestian, M., Jayaraman, V. and Chandrashekhar, M.G. 1995. Space technology applications for sustainable development of watersheds. A Technical report, *ISRO, Bangalore* pp.1-41.

Sudheer, K.P., Gosain, A.K. and Ramasastri, K.S. 2000. A data-driven algorithm for constructing artificial neural network rainfall-runoff models. *Hydrol. Process.*, 16(6): 1325-1330.

Verma, S.K., Singh, J., Tiwari, S.C. and Ranade, D.H. 2006. Runoff estimation by using remote sensing and GIS from watershed. *J. Soil Water Conserv*., 5(3):49-53.