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Modeling of sediment yield and nutrient loss after application of pre-determined dose of top soil amendments

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Abstract
Soil erosion and nutrient losses from hillslopes are the severe problems. North Western Himalayan Region (NWHR) of India always suffers from severe water erosion every year. This study was conducted in premises of Pantnagar, a town situated in Uttarakhand, NWHR. A field experiment was performed during monsoon season in 2018 under natural rainfall condition. Two soil amendments viz. biochar and anionic polyacrylamide (PAM) were used into the soil to reduce severe soil erosion and loss of major soil nutrients (N-P-K) from the plots. Twelve rainfall events were recorded which created runoff anyhow on the land surface and rainfall, runoff, sediment yield and major nutrient losses (N-P-K) were taken into account for the development of two models scenarios viz. sediment yield and nutrient loss. Two modeling techniques viz. multi-layer perceptron based artificial neural network (MLP-ANN) and multiple linear regression (MLR) were used. Every model was tested against quantitative performance evaluation criteria viz. Root mean square error (RMSE), Percent bias (PBIAS), Karl Pearson's coefficient of correlation (CC) and Nash-Sutcliffe efficiency (NSE) along with line diagram and scatter plots. Results demonstrated that MLR is better than MLP-ANN to simulate nutrient loss modeling with CC value ranging from 0.955 to 0.962 during testing period, whereas MLP-ANN was found better than MLR in simulating sediment yield with CC value as 0.938 during testing period. Results also revealed that MLP-ANN was found better performer for simulating non-linear and inconsistent data of sediment yield, whereas MLR was found better performer in case of linear data.

Keywords: biochar, anionic polyacrylamide, MLP-ANN, Multiple linear regression, natural conditions, Pantnagar

Introduction
Soil is the necessity to sustain the lives on earth. Soil maintains its quality by performing several functions under its capacity and land use boundaries. A healthy soil sustains agricultural productivity, maintains environmental air and its quality and subsequently enhances plant and animal growth. Its erosion and quality declination are most serious environmental problem worldwide. Surface runoff on upland areas such as hillslopes is often accompanied by soil erosion. Soil particles may be detached when the impact of raindrops exceeds the soil's ability to withstand the impulse at the soil surface. Detachment may also occur when shear stresses caused by flowing water exceed the soil's ability to resist these erosive forces. Vegetation as canopy and ground cover, and other surface cover such as gravel and rock fragments, protect the soil surface from direct raindrop impact, and also provide hydraulic resistance, reducing the shear stresses acting on the soil. Plant roots, incorporated plant residue, and minerals increasing cohesion tend to protect the soil by reducing the rate of soil panicle detachment by flowing water and raindrop impact.
Once detachment has occurred, sediment particles are transported by raindrop splash and by overland flow. Conditions which limit raindrop detachment limit the sediment supply available for transport by splash and flow mechanisms. Vegetative canopies intercept splashed sediment particles and limit sediment transport by splash. The rate of sediment transport by overland flow is influenced by the factors controlling the amount of sediment available for transport, the sediment supply, and by hydraulic processes occurring in overland flow such as raindrop impacts, depth of flow, velocity, and accelerations due to micro topographic flow patterns. Obviously, the steepness, shape, and length of slopes affect both flow patterns and the resulting sediment transport capacity of the flowing water.
Soil erosion has is an old phenomenon as mankind. It has worsened human civilization and the quest for better live by man.

It is either caused by natural agents or induced as a result socioeconomic development over the years. The eroded material from soil erosion cause both on-site and off-site effects which are detrimental to both flora and fauna. The effects could be exacerbated by inter and intra reactions within the ecosystem. Soil erosion processes usually result in the relocation of the top soil which is rich in organics, nutrients, and soil life elsewhere on-site where it builds up over time or is transported offsite where it accumulates in drainage channels. It is usually severe on unprotected sloppy areas [1]. Pollution of nearby water bodies and wetlands and the reduction in cropland productivity is linked to erosion process.

Among the major causes of soil erosion is rainwater, which breaks up soil, dislodges it from its surroundings, and washes it subsequently away as runoff. Land use type also has an effect on the soil erosion process [2, 3]. The soil erosion mechanisms have an effect on how much water the soil can hold, how rapidly water flows over the soil, and its movement below surface. Soil erosion adversely hinders the growth of plants, agricultural yields, quality of water, and recreation. It is a key cause of degradation of soils as it occurs naturally on all lands [4].

Soil erosion causes are basically water and wind, with each of these contributing to a significant level of yearly soil loss. The erosion phenomenon is sometimes slow, where it usually occurs immediately unnoticed, it can also occur at a rapid rate resulting in a great loss of the upper part of the soil. Among the greatest adverse worldwide environmental concerns is soil erosion. This is because it causes not only soil nutrient deprivation and degradation of land, but it also leads to many notable off-site environmental problems such as flooding, water siltation, and pollution [5]. The erosion process is becoming a major setback to the sustainable development of natural resources and the environment, which ultimately calls for suitable monitoring and evaluation.

Himalayas of India always suffered from heavy soil erosion because of their slopped land surfaces, which causes severe reduction in soil properties. Eroded soil carries useful field nutrients and reduces soil productively in such regions [6]. If such problem was not considered on high priority then adverse effect may occur within few decades [7]. Soil erosion and nutrients loss from such places are always the interest of soil conservationist.

Because of inconsistent behaviour of sediment yield with rainfall and runoff parameters modeling sediment yield and nutrients loss using appropriate modeling technique is always the challenge for the researchers. Apart from this very few studies was reported on event based modeling of such parameters. This study involved two modeling techniques viz. multi-layer perceptron based artificial neural network and multiple linear regression (MLR) for modeling event based data in Mollisols soils of Pantnagar. Artificial intelligence based models were reported as well suitable for such non-linear modeling [8, 9, 10, 11, 12, 13, 14]. MLR was also applied successfully in many fields to get desired results [15, 16, 17].

Materials and Methods

Description of experimental site and amendments used

This study was conducted in premises of Pantnagar, a town situated in Uttarakhand, India. It lies at a longitude of 79° 29' 31.5" E and latitude of 29° 01' 12" N. The soil of this region is silty clay loam in texture. Two soil amendments viz. biochar and anionic polyacrylamide (PAM) were used into the soil to reduce severe soil erosion and loss of major soil nutrients (N-P-K) from the plots of size 3m × 3m prepared over the uniform slope of 12%. Experiment was repeated on two more similar plots located nearby to first plot for reducing experimental error, if any.

Experiment was performed during monsoon season in 2018 under natural rainfall condition. Ground rice husk based biochar was applied at 800 g/m^2 [18] and liquid anionic PAM (0.50% solution) was applied at 2 g/m^2 [19, 20].

Variables used for modeling and model development

Twelve rainfall events were recorded using tipping bucket recording rainguage (Table 1). These rainfall events were those which created runoff anyhow on the land surface. In this study, rainfall, runoff, sediment yield and major nutrient losses (N-P-K) were taken into account for the development of models.

Table 1: Rainstorms selected for study

S. No.	Date	Rainfall depth (mm)	Rainfall duration (h)
1.	22-Jun-2018	10.668	6.25
2.	23-Jul-2018	28.956	3.96
3.	24/25-Jul-2018	30.734 and 0.254	23.01 and 9.97
4.	28-Aug-2018	9.144	1.68
5.	29-Aug-2018	3.810	6.88
6.	31-Aug-2018	18.796, 11.176 and 0.254	1.29, 4.69 and 7.59
7.	02-Sep-2018	3.048	0.14
8.	03-Sep-2018	26.67 and 1.778	6.84 and 1.10
9.	04-Sep-2018	0.254 and 22.352	5.98 and 1.77
10.	11-Sep-2018	9.906 and 0.254	2.38 and 4.85
11.	13-Sep-2018	3.302	1.78
12.	22-Sep-2018	2.032	1.41

Table 2: List of scenario of models

Model	Output-input scenario
Sediment yield model	$S_Y = f(R, Q)$
Nutrient loss model	$Nut._L = f(R, Q, S_Y)$

Note: S_Y is sediment yield, $Nut._L$ is nutrient (i.e. N, P and K) loss, R is rainfall depth and Q is runoff depth.

Two model scenarios viz. sediment yield and nutrient loss were developed (Table 2). Data were divided into two datasets; training and testing. First half data were used for training and remaining half were used for testing of the model. Every model was tested against quantitative performance evaluation criteria (Table 3) along with line diagram and scatter plots. The following modeling techniques were used in this study;

Table 3: Quantitative performance evaluation indices

Parameter	Relationship	Range
Root mean square error (RMSE)	RMSE = $\sqrt{\frac{\sum_{i=i}^{N}(y_{ci}-y_{oi})^2}{N}}$	0 to ∞
Percent bias (PBIAS)	PBIAS = $\frac{\sum_{i=1}^{N}(y_{ci}-y_{oi})}{\sum_{i=1}^{N}(y_{oi})} \times 100$	-∞ to + ∞
Karl Pearson's coefficient of correlation (CC)	CC = $\frac{\sum_{i=1}^{N}(y_{oi}-y_{om})(y_{ci}-y_{cm})}{\sqrt{\sum_{i=1}^{N}(y_{oi}-y_{om})^2}\sqrt{\sum_{i=1}^{N}(y_{ci}-y_{cm})^2}}$	-1 to +1
Nash-Sutcliffe efficiency (NSE)	NSE = 1- $\frac{\sum_{i=1}^{N}(y_{oi}-y_{ci})^2}{\sum_{i=1}^{N}(y_{oi}-y_{om})^2}$	-∞ to +1

Note: y_{ci} and y_{oi} are the computed and observed value for i^{th} observation and N is total number of observations in data set and y_{om} and y_{cm} are the mean of computed and observed values.

Multi-layer perceptron (MLP)

MLP based artificial neural network (MLP-ANN) is network architecture, having at least one hidden layer in between input and output layer. One neuron cannot solve a complex problem; therefore, many neurons are used for addressing complex problems. MLP was used in many studies of various disciplines such as mathematics, statistics, computer science, time series analysis, pattern identification and classification. Feed-forward neural network with back-propagation (BP) algorithm is the most commonly used MLP method for solving various engineering problems. The objective of the BP algorithm is to find the optimal weights [21], which would create an output vector y = (y_1, y_2,……., y_p) as closely as possible to the observed value of the output vector t = (t_1,t_2,....., t_k) with a selected accuracy. The input data are multiplied by initial weights, then the weighted inputs are added by simple summation to yield to each neuron. Let x_i (i = 1,2,...,m) are inputs and w_i (i = 1,2, …,m) are respective weights. The net input to the node is given as;

$$net = \sum_{i=1}^{n} x_i w_i \quad \ldots (1)$$

The net input then goes through activation function f and then the output y of the node is computed as;

$$y = f\,(net) \quad \ldots (2)$$

The calculated error at the output layer is returned back to the hidden layers and then passed on to the input layer, so that updates for the connection weights are determined using the sum of square error E, which can be written as;

$$E = \frac{1}{2}\sum_{k=1}^{no}(y_k - t_k)^2 \quad \ldots (3)$$

Where, t_k is the observed output or output desired at the k^{th} neuron and y_k is the calculated output at the same neuron. Weights are updated and changed from their old values to minimize the error. The learning process starts with a random set of weights. Weights are updated through error back-propagation during the training process at each iteration in order to reach better efficient weights. The transfer function is also used at each of the processing neurons to find out the output of a processing element [22, 23, 11, 12]. In this study, linear sigmoid activation function and Delta-bar-delta learning algorithm were used to train the network. Training parameters used to train the MLP-ANN are given in Table 4.

Table 4: Training parameters for MLP-ANN

Parameter	Value
Number of hidden layers	1
No. of neurons	varied from 1 to 20
Activation Function	Linear sigmoid
Learning algorithm	Delta-bar-delta
Threshold value of Mean Square Error (MSE)	0.001

Multiple linear regression (MLR)

MLR analysis is commonly used to describe quantitative relationships between a dependent variable and two or more independent variables.

$$y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots .. + \beta_k x_k \quad \ldots(4)$$

where, y is a dependent variable, x_1, x_2,...., x_k are the independent variables, k is total inputs, β_1, β_2,...., β_k are partial regression coefficients and α is an intercept.

Results and Discussion

General performance rating for NSE and PBIAS was adapted in this study [24]. General performance rating of RMSE was not reported in literature review for such modeling because it varies with the range of the variables. However, the value of RMSE close to zero was preferred. Correlation coefficient (CC) ≥ 0.75 and coefficient of determination (R^2) ≥ 0.6 was also considered acceptable in this study [25, 24]. Testing results were preferred to training results for model selection.

Modeling sediment yield

Quantitative performance evaluation indices of both models for sediment yield are presented in Tables 5 and 6. During training period, performance of MLP-ANN and MLR models was found to be very good with NSE as 0.992 and 0.961, respectively; correlation coefficient (r) as 0.997 and 0.980, respectively; RMSE as 22.772 kg/ha and 49.475 kg/ha, respectively; and PBIAS as -2.601 and 0.000, respectively. During testing period, performance of MLP-ANN and MLR models was found unsatisfactory with NSE as 0.340 and 0.214, respectively; RMSE as 160.367 kg/ha and 175.043

kg/ha, respectively; and PBIAS as 59.956 (unsatisfactory) and 18.581 (good), respectively. However, both techniques showed acceptable values of correlation coefficient (CC) as 0.938 and 0.882, respectively, during testing period. Testing results were preferred to the training results and best model was selected on the basis of testing results. In this manner, no model was selected for sediment yield modeling. However, performance of MLP-ANN model during testing was found better than the MLR. For MLP-ANN, model structure was obtained as 2-19-1 which includes two inputs and nineteen neurons in single hidden layer for a single output.

Table 5: Quantitative performance evaluation indices for sediment yield modeling during training period

Technique	Structure/Parameter	Performance indicators			
		NSE	CC	RMSE (kg/ha)	PBIAS
MLP-ANN	2-19-1	0.992	0.997	22.772	-2.601
MLR	S_Y = -185.92 + 7.38*R* + 204.25*Q*	0.961	0.980	49.475	0.000

Table 6: Quantitative performance evaluation indices for sediment yield modeling during testing period

Technique	Structure/Parameter	Performance indicators			
		NSE	CC	RMSE (kg/ha)	PBIAS
MLP-ANN	2-19-1	0.340	0.938	160.367	59.956
MLR	S_Y = -185.92 + 7.38*R* + 204.25*Q*	0.214	0.882	175.043	18.581

Fig. 1 shows the observed and computed sediment yield using both models during testing period. Line plots indicate that MLP-ANN model over-estimates the peak value of sediment yield (E9-18), whereas MLR model estimate the peak value of sediment yield (E9-18) very close to the observed value. Scatter diagrams reveal that sediment yield is over-estimated for larger values and under-estimated for smaller values using MLR model. Sediment yield was found to be over-estimated for all values using MLP-ANN model. Instead of this, MLP-ANN model also nicely demonstrated that most of the data points are close to the 1:1 line in comparison to other models. Coefficient of determination (R^2) is quite acceptable and on the basis of R^2during testing period, the performance of both models was ordered as MLP-ANN (0.880) > MLR (0.778).

Modeling nitrogen loss

Quantitative performance evaluation indices of both models for nitrogen loss modeling are presented in Tables 7 and 8. During training period, performance of MLP-ANN and MLR models was found to be very good with NSE as 0.995 and 0.960, respectively; correlation coefficient (CC) as 1.000 and 0.992, respectively; RMSE as 0.096 kg/ha and 0.275 kg/ha, respectively; and PBIAS as 1.767 and -8.906, respectively.

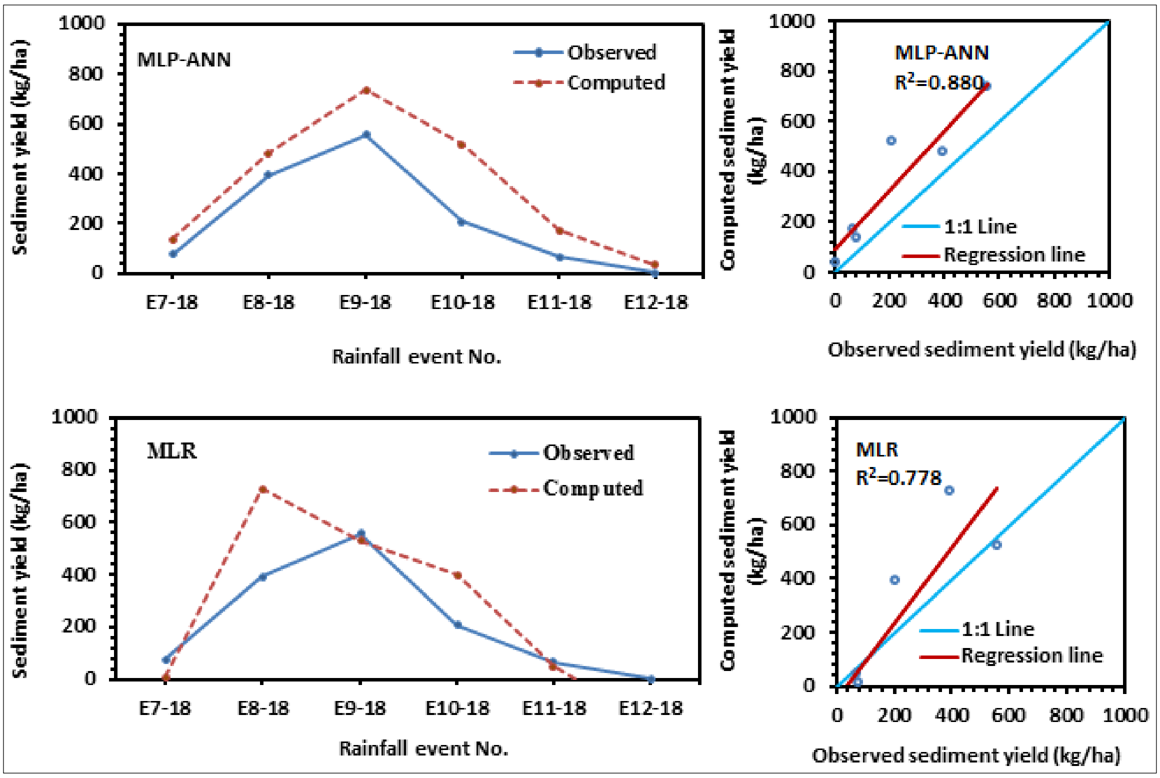

Fig 1: Line plot (left) and scatter diagram (right) of observed and computed sediment yield using MLP-ANN and MLR models during testing period

Table 7: Quantitative performance evaluation indices for nitrogen loss modeling during training period

Technique	Structure/Parameter	Performance indicators			
		NSE	CC	RMSE (kg/h)	PBIAS
MLP-ANN	3-20-1	0.995	1.000	0.096	1.767
MLR	$N = 0.168+0.015R-0.527Q+0.006S_Y$	0.960	0.992	0.275	-8.906

Table 8: Quantitative performance evaluation indices for nitrogen loss modeling during testing period

Technique	Structure/Parameter	Performance indicators			
		NSE	CC	RMSE (kg/ha)	PBIAS
MLP-ANN	3-20-1	0.537	0.945	0.706	66.480
MLR	$N = 0.168+0.015R-0.527Q+0.006S_Y$	0.828	0.962	0.430	-20.493

During testing period, performance of MLP-ANN and MLR models was found to be satisfactory to very good with NSE as 0.537 (satisfactory) and 0.828 (very good), respectively; RMSE as 0.706 kg/ha and 0.430 kg/ha, respectively; and PBIAS as 66.480 (satisfactory) and -20.493 (very good), respectively. However, all models showed acceptable values of correlation coefficient (CC) as 0.945 and 0.962, respectively, during testing period. On the basis of testing results, the MLR model performed better than the MLP-ANN model.

Fig. 2 shows the observed and computed values of nitrogen loss from both models during testing period. Line plots show that MLP-ANN model over-estimates the peak value of nitrogen loss, whereas MLR model under-estimate the peak for E9-18. Scatter diagrams show that nitrogen loss was over-estimated for MLP-ANN model, whereas for MLR model, nitrogen loss was over-estimated for smaller values and under-estimated for larger values. Instead of this, MLR model showed that most of the data points were quite close to the 1:1 line in comparison to other models. Coefficient of determination (R^2) was found to be very good and quite acceptable for both models. On the basis of R^2valuesduring testing period, order of performance of the models was obtained as MLR (0.926) > MLP-ANN (0.893).

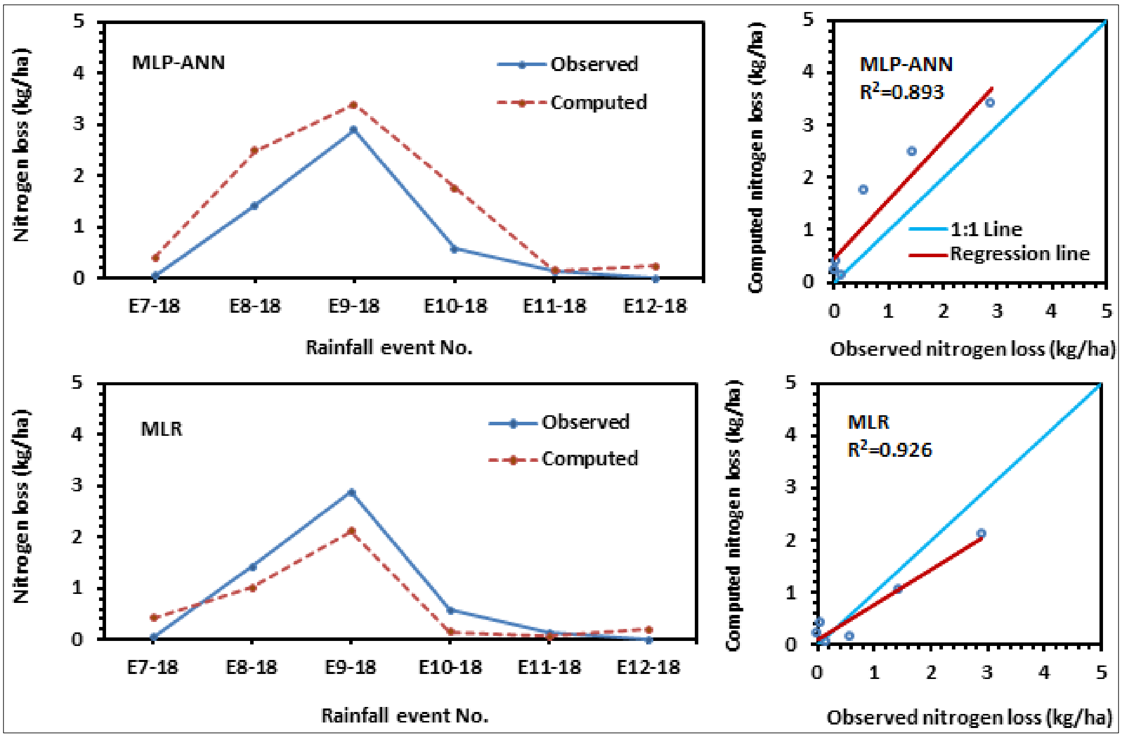

Fig 2: Line plot (left) and scatter diagram (right) of observed and computed nitrogen loss using MLP-ANN and MLR models during testing period

Modeling phosphorus loss

Quantitative performance evaluation indices of both models for phosphorus loss are presented in Tables 9 and 10. During training period, performance of MLP-ANN and MLR models was found to be very good with NSE as 0.985 and 0.990, respectively; correlation coefficient (CC) as 0.999 and 0.995, respectively; RMSE as 0.013 kg/ha and 0.011 kg/ha, respectively; and PBIAS as -6.680 and 0.000, respectively. During testing period, performance of MLP-ANN and MLR models was found to be unsatisfactory to very good with NSE as 0.327 (unsatisfactory) and 0.879 (very good), respectively; RMSE as 0.067 kg/ha and 0.028 kg/ha, respectively; and PBIAS as 64.583 (satisfactory) and 2.468 (very good), respectively. However, both models showed acceptable values of correlation coefficient (CC) as 0.965 and 0.956, respectively, during testing period. On the basis of testing results, the order of performance of models was obtained as MLR (very good) > MLP-ANN (unsatisfactory).

Table 9: Quantitative performance evaluation indices for phosphorus loss modeling during training period

Technique	Structure/Parameter	Performance indicators			
		NSE	CC	RMSE (kg/ha)	PBIAS
MLP-ANN	3-8-1	0.985	0.999	0.013	-6.680
MLR	$P = (0.82\text{-}0.54R\text{-}22.87Q+0.53S_Y)\times10^{-3}$	0.990	0.995	0.011	0.000

Table 10: Quantitative performance evaluation indices for phosphorus loss modeling during testing period

Technique	Structure/Parameter	Performance indicators			
		NSE	CC	RMSE (kg/ha)	PBIAS
MLP-ANN	3-8-1	0.327	0.965	0.067	64.583
MLR	$P = (0.82\text{-}0.54R\text{-}22.87Q+0.53S_Y)\times10^{-3}$	0.879	0.956	0.028	2.468

Fig. 3 shows the observed and computed phosphorus loss from both models during testing period. Line plots show that MLP-ANN model over-estimated the peak value of phosphorus loss, whereas MLR model under-estimated the peak for E9-18. Scatter diagrams show that phosphorus loss is over-estimated for MLP-ANN model, whereas for MLR model, phosphorus loss was found to over-estimate for smaller values and under-estimate for larger values. Instead of this, MLR model showed that most of the data points were quite close to the 1:1 line in comparison to other models. Coefficient of determination (R^2) was found to be very good and quite acceptable for both models. On the basis of R^2values during testing period, the order of performance of both models was obtained as MLP-ANN (0.932) > MLR (0.914).

Modeling potassium loss

Quantitative performance evaluation indices of both models for potassium loss modeling are presented in Tables 11 and 12. During training period, performance of MLP-ANN and MLR models was found to be very good with NSE as 0.985 and 0.988, respectively; correlation coefficient (CC) as 0.996 and 0.994, respectively; RMSE as 0.029 kg/ha and 0.026 kg/ha, respectively; and PBIAS as 1.859 and 0.000, respectively.

During testing period, performance of MLP-ANN and MLR models was found to be unsatisfactory to very good with NSE as 0.331 (unsatisfactory) and 0.909 (very good), respectively; RMSE as 0.139 kg/ha and 0.051 kg/ha, respectively; and PBIAS as 71.188 (unsatisfactory) and 6.396 (very good), respectively. However, both models showed acceptable values of correlation coefficient (CC) as 0.886 and 0.955, respectively, during testing period. On the basis of testing results, the order of performance of different models was obtained as MLR (very good) > MLP-ANN (unsatisfactory).

Table 11: Quantitative performance evaluation indices for potassium loss modeling during training period

Technique	Structure/Parameter	Performance indicators			
		NSE	CC	RMSE (kg/ha)	PBIAS
MLP-ANN	3-13-1	0.985	0.996	0.029	1.859
MLR	$K = (37.61+1.27R\text{-}91.07Q+1.16S_Y)\times10^{-3}$	0.988	0.994	0.026	0.000

Table 12: Quantitative performance evaluation indices for potassium loss modeling during testing period

Technique	Structure/Parameter	Performance indicators			
		NSE	CC	RMSE (kg/ha)	PBIAS
MLP-ANN	3-13-1	0.331	0.886	0.139	71.188
MLR	$K = (37.61+1.27R\text{-}91.07Q+1.16S_Y)\times10^{-3}$	0.909	0.955	0.051	6.396

Fig. 4 shows the observed and computed potassium loss of both models during testing period. Line plots show that MLP-ANN and MLR model over-estimated the peak value of potassium loss for E9-18. Scatter diagrams show that potassium loss is over-estimated for MLP-ANN model, whereas for MLR model, phosphorus loss was found to over-estimate only for smaller values. Besides this, MLR model also showed the exact fit and under-estimation for larger values of potassium loss, respectively. Instead of this, MLR model showed that most of the data points are quite close to the 1:1 line in comparison to MLP-ANN model. Coefficient of determination (R^2) was found to be very good and quite acceptable for both model. On the basis of R^2valuesduring testing period, the order of performance of both models could be obtained as MLR (0.913) > MLP-ANN (0.785).

Above modeling results showed that MLR model was superior to MLP-ANN models in simulating major nutrient losses (N, P, K) and MLP-ANN model was found better than the MLR in simulating only sediment yield. On the basis of modeling results, this was revealed that MLR model performed well in three model scenarios and MLP-ANN model performed well only in sediment yield scenario. These finding also revealed that by and large MLR model was effective and efficient model in comparison to MLP-ANN model and MLR model could be successfully applied in modeling the field based data conducted under natural rainfall conditions.

Conclusions

This study was conducted in premises of Pantnagar, a town situated in Uttarakhand, North Western Himalayan Region (NWHR), India. Entire research was focused on the Modeling of sediment yield and nutrient using two modeling techniques viz. MLP-ANN and MLR. Results demonstrated that multiple linear regression based modeling technique is better than MLP-ANN to simulate nutrient loss modeling, whereas MLP-ANN was found better than MLR in simulating sediment yield. MLP-ANN was found better performer for simulating non-linear and inconsistent data of sediment yield, whereas MLR was found better performer in case of linear data.

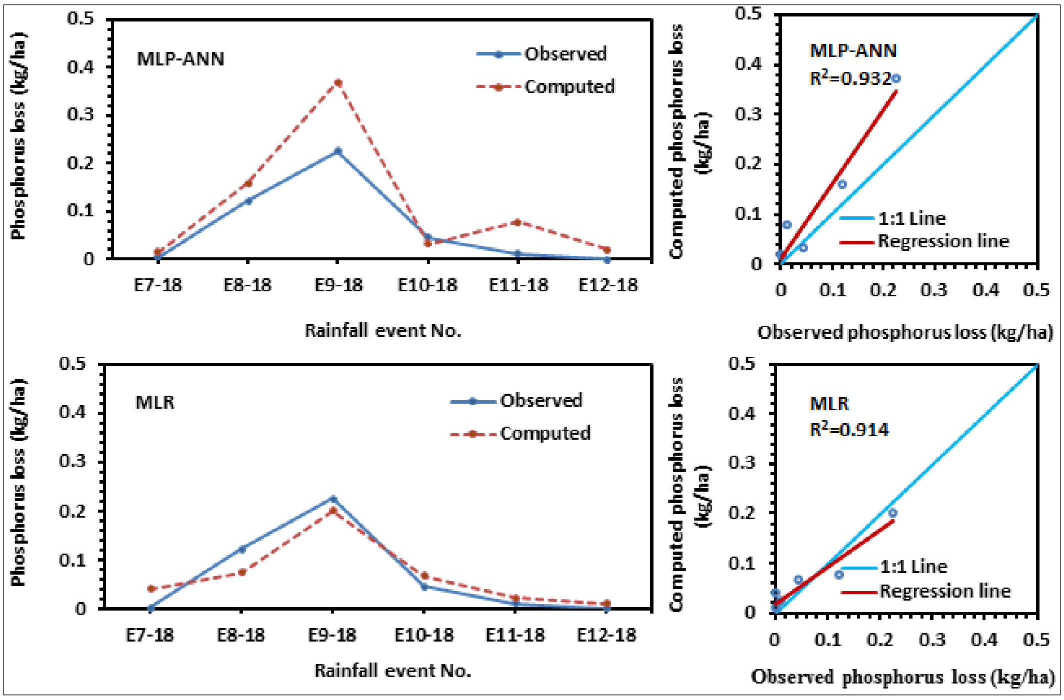

Fig 3: Line plot (left) and scatter diagram (right) of observed and computed phosphorus loss using MLP-ANN and MLR models during testing period

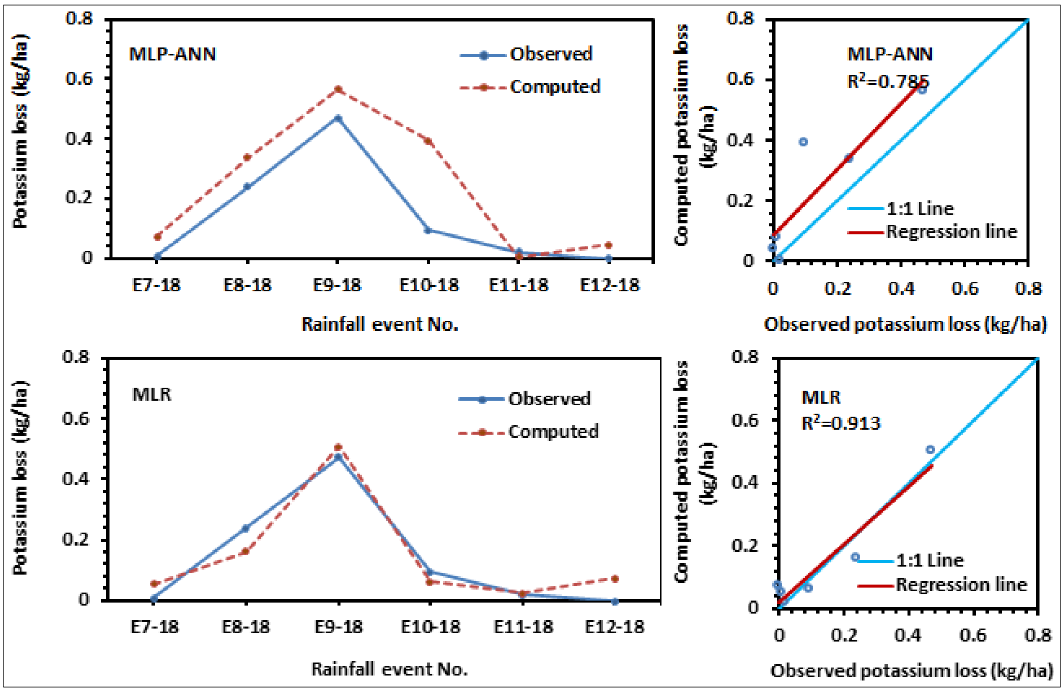

Fig 4: Line plot (left) and scatter diagram (right) of observed and computed potassium loss using MLP-ANN and MLR models during testing period

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