Development of pedo-transfer functions for estimating soil erodibility and soil aggregate stability from basic soil properties in submontane area using statistical methods and machine learning techniques for Northern India land

Abstract: Accelerated soil erosion in the lower *Shiwalik hills in Submontane area of Northern India land* results in deterioration of soil physical quality. Soil aggregation and soil erodibility are important parameters indicating soil physical quality but the quantification of these parameters is complex so efforts have been done to estimate these properties from easily measurable soil characteristics by using pedo-transfer functions (PTFs). Statistical PTFs are available for estimating of these properties but they don't explain the sufficient variability in data. Machine learning techniques may play an important role in this context. Therefore, the present study was planned to compare PTFs developed using statistical and machine learning techniques for *kandi* region of Punjab. The basic soil physico-chemical properties were measured across four locations with five land uses at each location at three depths and with three replications. Three data sets were prepared for these soil properties. When dataset 1, having six basic soil properties, was used for estimation of mean weight diameter (MWD) and erodibility (K), the prediction using artificial neural network (ANN) was slightly better than generalized linear model (GLM). When dataset 2, having those six basic soil properties which were having high correlation with soil structural parameters, was used for estimation of MWD and K, the prediction using GLM was slightly better than ANN. When dataset 3, having all 11 basic soil properties, was used for estimation of MWD and K, the prediction using ANN was significantly better than GLM. So, it may be concluded that ANN performs better for a large set of data and for a complex system having a greater number of variables whereas for small set of data and for simple system having less variables, the statistical methods perform better.

Keywords: erodibility; aggregate stability; PTFs; machine learning; artificial neural network; generalized linear model

1. Introduction

Land degradation is a major issue which affects capability of ecosystem services provided by the soil. The decline in soil quality caused by anthropogenic activities has been a global issue during the previous century and still it has remained high on the international agenda during the current century because of its impact on world food security and the environment quality. The lower Shiwalik hills in Submontane area of Northern India is suffering from severe soil erosion resulting in deterioration of soil physical quality in the region [1]. Stability of soil aggregates is considered as one of the most important indicators of soil physical quality. It is the measure of the resistance of soil aggregates against the structural decomposition because of raindrop impact, running water or wind [2-3]. Aggregate stability is a soil characteristic which is often linked to soil erodibility [4]. Soil cementing agents like clay, silt and organic matter which result in aggregate stability are usually correlated with soil aggregate stability [5]. The soil erodibility which is the measure of the resistance offered by the soil to both detachment and transport processes of soil erosion, is an inherent property of the soil. Itis influenced by soil physical characteristics including texture, structure, organic matter and chemical characteristics. Assessment of soil erodibility is important for erosion prediction and for planning suitable soil conservation measures. Mean Weight Diameter (MWD), Geometric Mean Weight Diameter (GMD) and percentage of Water Stable Aggregates (WSA) are the common parameters representing soil aggregate stability [6-7]. However, out of these indices, the MWD is the most widely used indicator for quantification of soil aggregate stability [8]. For the measurement of the aggregate stability, the most common method is wet sieving method [9]. For measurement of aggregate stability, Le bissonnais [7] proposed standard wet sieving method which consists of three treatments. These include fast wetting leading to slaking, slow wetting leading to microcracking and stirring of pre wetted aggregates for mechanical breakdown. However, evaluation of soil aggregate stability using these methods is time consuming and expensive. So, to overcome this difficulty, Pedo-transfer functions (PTFs) have been developed for predicting aggregate stability [10-12]. For example, easy to measure soil parameters like organic carbon, particle size distribution and bulk density are used in empirical multilinear regression-based models for estimation of complex soil properties like mean weight diameter [13]. Researchers have developed PTFs to estimate soil erodibility also from basic soil properties under various conditions. These PTFs have been used as an input for environmental simulation models. The pedo-transfer functions are used basically to translate the raw soil data into the more useful information. These PTFs include linear, logarithmic and other statistical models using various basic soil properties for estimation of soil aggregate stability and soil erodibility. There is normally poor performance of the regression based PTFs as they require prior information about input -output relationships. The statistical regression models require prior information about the relationship between independent and dependent soil properties and on other hand for the neural network model there is no need of this type of prior information. Recently artificial intelligence in the form of machine learning techniques is also being employed in predictive models. Machine learning is the combination of processes that gives machines an ability to learn without the use of specific software programmes. Machine learning methods like K Nearest Neighbor (KNN), Cubist, Artificial neural network (ANN) and Random Forest (RF) approaches have been deployed recently in development of PTFs. Out of these approaches, ANN is a simplified model representing the structure of the biological neural network in which interconnected processing units are organized in a specific topology. Multiple layers of information are arranged using a number of nodes. These nodes include an input layer for feeding the data into the system, one or more intermediate hidden layers in which the learning takes place and an output layer for providing the decision or prediction. No prior relationship between the input and output variables is required for machine learning techniques and it is one of their major advantage [14-15]. Although several statistical PTFs are available for estimating soil aggregate stability and soil erodibility from basic soil properties, still their standardization for identifying minimum data set is required for *kandi* region of Punjab. Machine learning techniques may play an important role in this context. Therefore, the present study has been planned to compare existing PTFs with developed PTFs using statistical and machine learning techniques with the objectives of Development of pedo-transfer functions for estimating soil erodibility and soil aggregate stability from basic soil properties using statistical methods and machine learning techniques. Comparison of estimated soil erodibility and soil aggregate stability using PTFs developed statistically, PTFs developed through machine learning techniques. Better estimation of soil erodibility and soil aggregate stability from easily measurable soil properties using PTFs may lead to better estimation of soil erosion which may help in management of soil erosion.

2. Materials and Methods

Soil samples and Soil properties

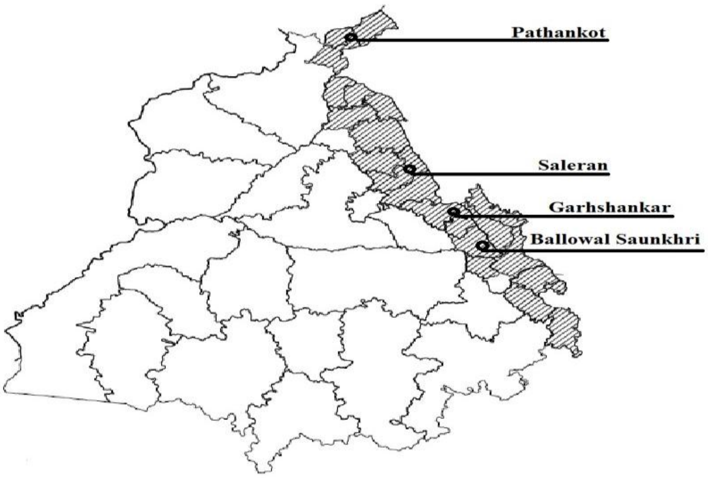


Figure 1. Location of study area

The study was conducted at four locations in submontanous kandi region of Punjab in the districts of Pathankot ($32^0$33`N, $75^0$69`E), Saleran ($31^0$59`N, $75^0$97`E), Garhshankar ($31^0$28`N, $76^0$21`E) and Ballowal Saunkhri ($31^0$09`N, $76^0$38`E). The *Kandi* regions climate varied from semi-arid to sub humid. The yearly rainfall in the area is around 1090 ± 340 mm. The rainfall distribution is bimodal, with 75–80% of total rainfall falling between June and September and 20–25% falling between the winter months (October to March). Soil samples were taken from Agroforestry, Grassland, Horticulture, Forestry and Agriculture in each of the four locations. Soils were sampled at three depths within each land use: 0-7.5, 7.5-15 and 15-30 cm. A total of 180 data points was there by taking 4 locations, 3 replications, 5 land uses and three depths from each location. Soil samples were analysed for basic soil properties like pH, EC, OC, CEC, calcium carbonate, bulk density, Fe and soil particle size analysis and applied soil properties like soil aggregation and soil erodibility.

Figure 2. Some photographs of selected land uses

Soil sample analysis

Soil samples were air dried, crushed and sieved, using a 2mm sieve before being analysed for a variety of physico-chemical properties. Undisturbed soil samples were also taken in the form of huge clods of roughly 40-50 cm diameter using a spade from 0-15 and 15-30 cm depths at four locations in each land use. The clods were carefully transported to the laboratory and dropped from a height of 90-100 cm on grassy ground, breaking at natural weak spots. Wet sieving was done with the resultant aggregates. Using cores, separate samples were taken for bulk density assessments. Soil texture was analyzed by International pipette method [16], Organic carbon by Rapid titration method [17], Calcium Carbonate by Puri's method [18], Cation exchange capacity by Ammonium acetate extraction method [19], pH by 1:2 soil water suspension [20], Electrical conductivity [21], Aggregate stability by Wet sieving method using Yoder apparatus [22], Bulk density by Core method [23], Iron by Atomic absorption spectroscopy [24].The nomographic expression proposed by [25] can be used to estimate K from easily observable soil parameters such as texture, organic content, structure and permeability. Singh and Khera [1] provided a modified technique for estimating K.

$$K = M^{1.14}(10^{-7})\ (12-\alpha) + 4.28(10^{-3})\ (\beta-2) + 3.29(10^{-3})\ (\gamma-3)$$

Where, M =M was calculated as 100 X (percentage of aggregates and primary particles<2.0 mm). α =Organic matter (%) β = structure code γ = permeability rating.

Machine learning technique

An open-source **Big ML** software was used to estimate the soil aggregate stability and soil erodibility for machine learning technique and Multi linear regression equation (GLM). For machine learning and Generalized linear model, training and testing of data was done. For training 70% data was used and remaining 30% data was used for testing.

Total 180 data points (Four locations X five land uses X three depths X three replications) were generated for 11 basic soil characteristics and three applied soil properties. Three data sets were prepared for these soil properties as described below:

Dataset 1 Properties like Sand, silt, clay, bulk density, EC, Organic carbon were used in data set 1. These are the properties which are available commonly in literature also. This data set was prepared both from research data as well as from secondary literature.

Dataset 2 Properties which show significant correlation in correlation matrix for (MWD and K) were used in dataset 2. These are clay, Fe, calcium carbonate, pH, EC, OC and BD.

Dataset 3 (K, MWD) All 11 properties from research data were used in dataset 3. These are coarse sand, fine sand, silt, clay, Fe, calcium carbonate, pH, EC, OC, BD and Cation exchange capacity).

Secondary Data Obtain from Literature for MWD and K

Table Ⅰ. Secondary data obtained from literature for MWD

References	PTFs (Basic properties)	Applied property
[26]	Clay, EC, Sand, OC, Silt, Bulk density	MWD
[27]	Clay, EC, Sand, OC, Silt, Bulk density	MWD
[28]	Clay, EC, Sand, OC, Silt, Bulk density	MWD

[29]	Clay, EC, Sand, OC, Silt, Bulk density	MWD
[30]	Clay, EC, Sand, OC, Silt, Bulk density	MWD
[31]	Clay, EC, Sand, OC, Silt, Bulk density	MWD
[32]	Clay, EC, Sand, OC, Silt, Bulk density	MWD
[33]	Clay, EC, Sand, OC, Silt, Bulk density	MWD
[34]	Clay, EC, Sand, OC, Silt, Bulk density	MWD
[35]	Clay, EC, Sand, OC, Silt, Bulk density	MWD
[36]	Clay, EC, Sand, OC, Silt, Bulk density	MWD
[37]	Clay, EC, Sand, OC, Silt, Bulk density	MWD
[38]	Clay, EC, Sand, OC, Silt, Bulk density	MWD
[39]	Clay, EC, Sand, OC, Silt, Bulk density	MWD
[40]	Clay, EC, Sand, OC, Silt, Bulk density	MWD
[41]	Clay, EC, Sand, OC, Silt, Bulk density	MWD

Table Ⅱ. Secondary data obtained from literature for K

References	PTFs (Basic properties)	Applied property
[42]	Clay, EC, Sand, OC, Silt, Bulk density	K
[43]	Clay, EC, Sand, OC, Silt, Bulk density	K
[44]	Clay, EC, Sand, OC, Silt, Bulk density	K
[45]	Clay, EC, Sand, OC, Silt, Bulk density	K
[46]	Clay, EC, Sand, OC, Silt, Bulk density	K
[47]	Clay, EC, Sand, OC, Silt, Bulk density	K
[29]	Clay, EC, Sand, OC, Silt, Bulk density	K
[48]	Clay, EC, Sand, OC, Silt, Bulk density	K

Evaluation of PTFs

Different regression metrics were used to evaluate the model

Root mean square error

Lower the RMSE value, better the model performance. RMSE was used while calibration of the model for the purpose of finding the most sensitive parameters. This is a measure of the model’s real inaccuracy and its calculated as

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)}{n}}$$

Coefficient of correlation

The correlation Coefficient indicates how close the observed and projected regression lines are to an ideal match. This coefficient is normally between -1 to +1 and is estimated it as follows:

$$R = \frac{\sum_{i=1}^{n}(o_i - {}^{0}avg)\sum_{i=1}^{n}(s_i - s_{avg})}{\sqrt{\sum_{i=1}^{n}(O_i - O_{avg})^2 \Sigma_{i=1}^{n}(s_i - s_{avg})^2}}$$

Coefficient of determination (R^2)

$$R^2 = 1 - \frac{(\Sigma_{i=1}^{n}(P_i - O)^2)/(n-k)}{(\Sigma_{i=1}^{n}(O_i - O)^2)/(n-1)}$$

MAE (Mean Absolute Error)

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|P_i - O_i|$$

Where O_i is the observed aggregate stability and P_i is the anticipated aggregate stability, respectively, O is the mean of the observed values, k is the total number of explanatories, and n is the number of values.

3. Results

Basic Soil properties

The Basic soil properties were analysed and results were concluded, the pH varies from 6.6-7.7, EC Varies from 0.10-0.23dS m^{-1}, Organic Carbon 0.59-0.92%, Cation Exchange Capacity: 8.41-13.71 C mol kg^{-1}, Calcium Carbonate 0.06-0.09%, Bulk density: 1.27-1.48 Mg m^{-3}, Fe content varies from 11.9-21.9 mg kg^{-1}, Mean weight diameter 0.46-2.59 mm, K erodibility factor varies from 0.16-0.33.Textural class at Pathankot and Saleran was loamy sand, at Ballowal Saunkhri it was sandy loam and at Garhshankar it was sandy clay loam.

Development of PTFs statistically for aggregate stability and soil erodibility

Estimating MWD

Using Dataset 1 soil properties

MWD= 4.21+0.07*Sand + 0.02*Silt + 0.01*Clay + 0.87***OC – 2.36*BD – 11.23 *EC**

R^2=0.61, MAE =0.46, MSE =0.35, RMSE =0.59

Using Dataset 2 soil properties

MWD = 5.23-0.009*pH-**11.43*EC**+ **1.10*OC** + **0.53*$CaCO_3$- 2.10*BD** + 0.005*Clay+0.009*Fe

R^2=0.56, MAE =0.38, MSE =0.56, RMSE=0.74

Using Dataset 3 soil properties

MWD = 4.71+0.03*pH-**9.15*EC** + **0.87*OC**+ 0.001*CEC + **0.37*$CaCO_3$- 2.61*BD** + 0.01*Coarse sand-0.02*Fine sand + 0.03*Silt -0.01*Clay + **0.02*Fe**

R^2=0.59, MAE =0.50, MSE =0.44, RMSE=0.66

Estimating soil erodibility

Using Dataset 1 soil properties

K **=** -0.76+ 0.005*Sand + **0.01*Silt- 0.01*Clay- 0.02*OC+ 0.20*BD+ 0.93*EC**

R^2=0.65, MAE =0.04, MSE= 0, RMSE=0

Using Dataset 2 soil properties

K = 0.03 +0.06*pH +**0.82*EC – 0.005*OC +** 0.07*$CaCO_3$ **+ 0.10***BD - **0.05*Clay-0.04*Fe**

R^2=0.85, MAE =0.03, MSE=0, RMSE=0

Using Dataset 3 soil properties

K = -0.40+0.04*pH +**0.63*EC – 0.001*OC** + 0.008*CEC + 0.076*$CaCO_3$+ **0.16*BD** + 0.03* Coarse sand + 0.003* Fine sand + 0.006* Silt **-0.003*** **Clay -0.007*Fe**

R^2=0.73, MAE =0.04, MSE =0, RMSE=0

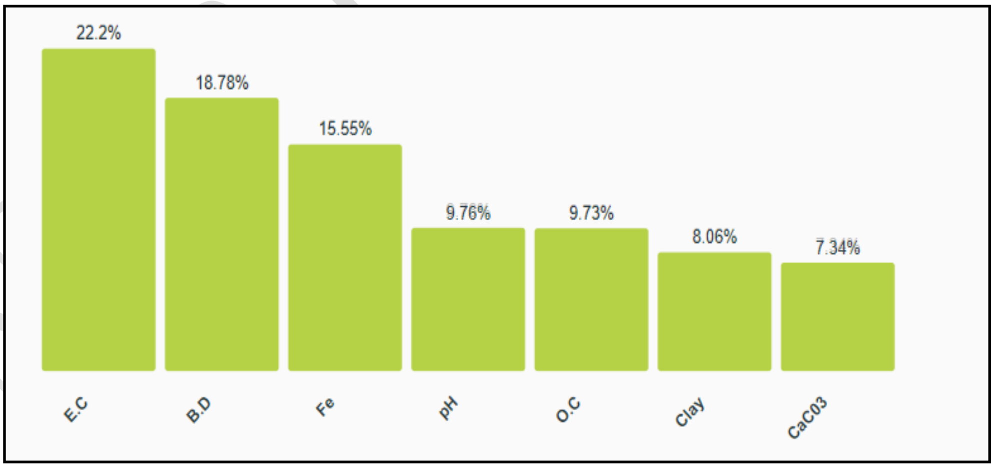
Development of PTFs by machine learning for soil erodibility and aggregate stability

Estimating MWD

Using Dataset 1 soil properties

Figure 3. Properties of field importance and Different Regression metrics for MWD using dataset 1

Using Dataset 2 soil properties



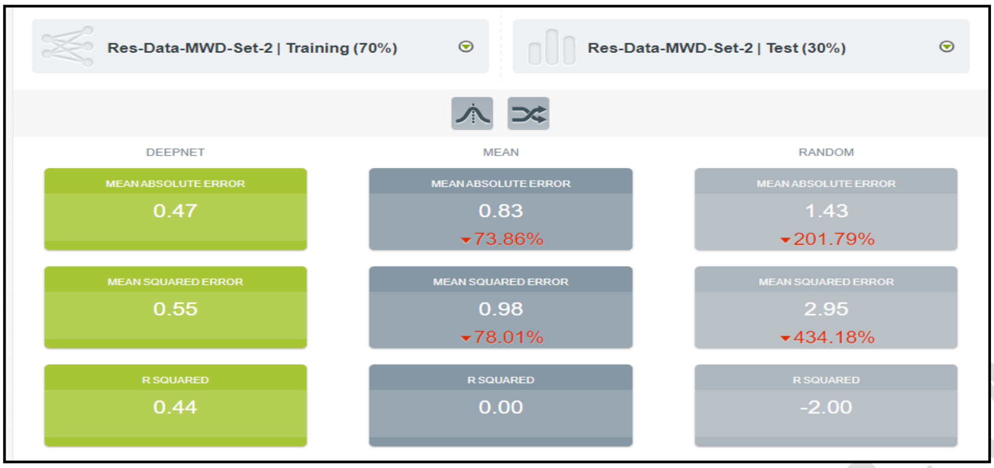
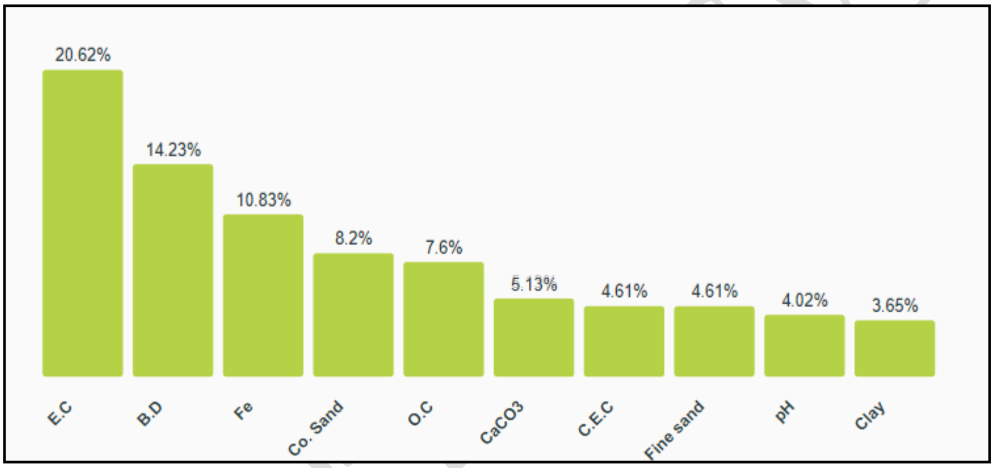


Figure 4. Properties of field importance and Different Regression metrics for MWD using dataset 2

Using Dataset 3 soil properties



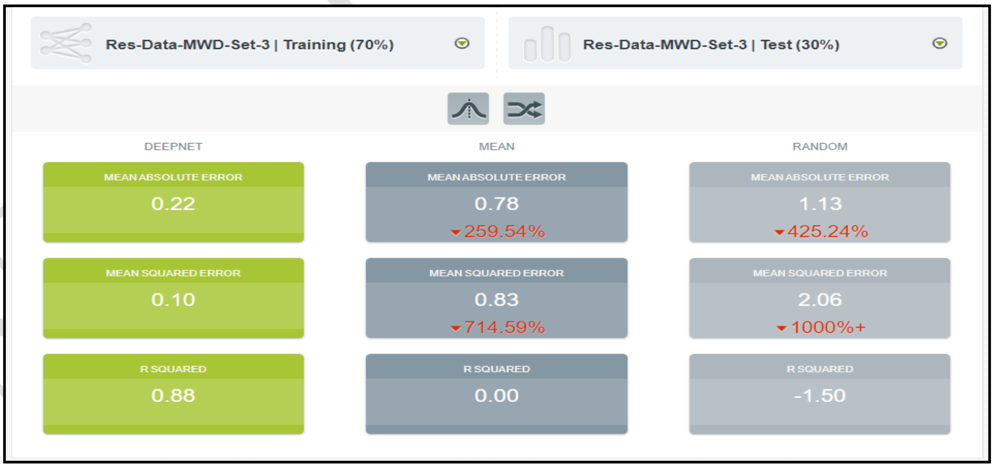


Figure 5. Properties of field importance and Different Regression metrics for MWD using dataset 3

Estimating soil erodibility

Using Dataset 1 soil properties

Figure 6. Properties of field importance and Different Regression metrics for K using dataset 1

Using Dataset 2 soil properties

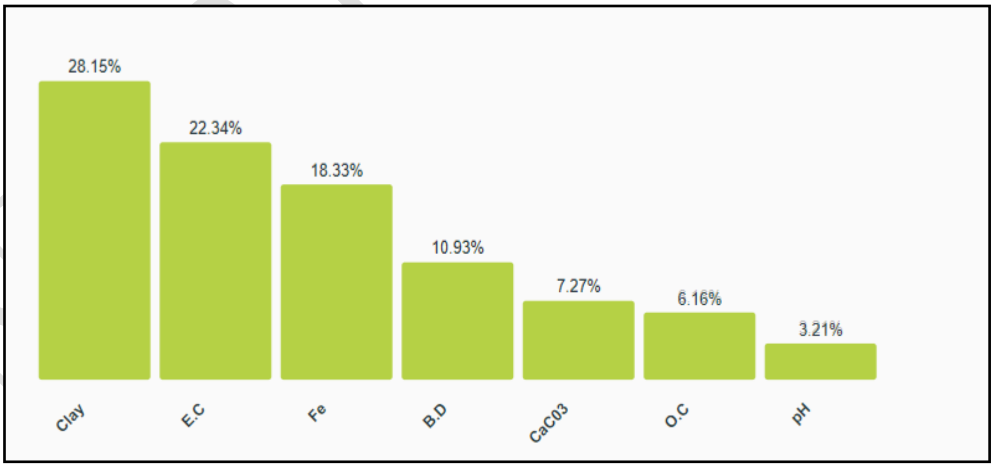


Figure 7. Properties of field importance and Different Regression metrics for K using dataset 2

Using Dataset 3 soil properties

Figure 8. Properties of field importance and Different Regression metrics for K using dataset 3

Comparison between different PTFs developed through machine learning and statistically

The value of comparing the ANN and GLM models, the results showed that ANN explained the variability much better than the GLM for dataset 3, in which eleven soil properties were used, for prediction of all three complex soil properties i.e. K, MWD. This is also evident from the values of MAE, MSE and RMSE obtained using GLM and ANN. Whereas, for data set 1 and data set 2, where the number of basic soil properties used was less, the results were not consistent. Comparing the ANN and GLM it was concluded that ANN performs better for a large set of data and for a complex system having a greater number of variables whereas for small set of data and for simple system having less variables the statistical methods perform better.

Table 3: Comparing of ANN and GLM

Different Data set	MAE		MSE		RMSE		R^2	
	GLM	ANN	GLM	ANN	GLM	ANN	GLM	ANN
Data set 1 (MWD)	0.46	0.46	0.35	0.37	0.59	0.6	0.61	0.64
Data set 1 (K)	0.03	0.03	0.00	0.00	0.00	0.00	0.65	0.79
Data set 2 (MWD)	0.38	0.47	0.56	0.55	0.74	0.74	0.56	0.44
Data set 2 (K)	0.03	0.03	0.00	0.00	0.00	0.00	0.85	0.73
Data set 3 (MWD)	0.50	0.22	0.44	0.10	0.66	0.31	0.59	0.88
Data set 3 (K)	0.03	0.03	0.00	0.00	0.00	0.00	0.73	0.84

5. Conclusions

Machine learning (ANN) and Statistical model (multi-linear regression / GLM) was used for developing PTFs for aggregate stability and soil erodibility. Three types of datasets were made for basic soil properties and were used for prediction of MWD and K. 70% of the total available, research and literature data was utilized to train the model, while 30% was used to test the model. For dataset 1, using GLM model, the R^2 values between actual and predicted MWD and K were 0.61 and 0.65, respectively. Whereas for same dataset 1, using ANN model, the R^2 values between actual and predicted MWD and K were 0.64 and 0.79, respectively. For dataset 2, using GLM model, the R^2 values between actual and predicted MWD and K were 0.56 and 0.85, respectively. Whereas for same dataset 2, using ANN model, the R^2 values between actual and predicted MWD and K were 0.44 and 0.73, respectively. For dataset 3, using GLM model, the R^2 values between actual and predicted MWD and K were 0.73 and 0.59, respectively. Whereas for same dataset 3, using ANN model, the R^2 values between actual and predicted MWD and K were 0.88 and 0.84, respectively. So, it may be concluded that ANN performs better for a large set of data and for a complex system having a greater number of variables whereas for small set of data and for simple system having less variables, the statistical methods perform better.

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