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Development of Pedo-transfer Functions for Estimating Soil Aggregation and Erodibility in *Kandi* Region of Punjab, India

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Quantification of soil aggregation and erodibility from easily measurable soil characteristics have been done by using pedo-transfer functions (PTFs) and PTFs developed were compared using statistical and machine learning techniques for the *kandi* region of Punjab. Dataset 1, having six basic soil properties, was used for the estimation of mean weight diameter (MWD) and erodibility (K), prediction using an artificial neural network (ANN) was slightly better than a generalized linear model (GLM). In dataset 2, six basic soil properties in dataset 1 having high correlation with soil parameters were used and prediction using GLM was slightly better than ANN. In dataset 3 including all 11 basic soil properties, prediction using ANN was significantly better than GLM. Thus, ANN performs better for a complex system having a greater number of variables whereas for a small set having fewer variables, the statistical methods perform better.

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

1. INTRODUCTION

Land degradation is a major issue that affects the 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 environmental quality. The lower Shiwalik hills in Submontane area of Northern India are suffering from severe soil erosion resulting in the deterioration of soil physical quality in the region [1]. The 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 structural decomposition because of raindrop impact, running water, or wind [2,3]. Aggregate stability is a soil characteristic that 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. It is influenced by soil's 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 aggregate stability, the most common method is the wet sieving method [9]. For the measurement of aggregate stability, Le bissonnais [7] proposed a standard wet sieving method that 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. Neural network models outperformed support vector machines and multiple regression models of low accuracy were produced by multiple linear regression. 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 the 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 input for environmental simulation models. The pedo-transfer functions are used basically to translate the raw soil data into more useful information. These PTFs include linear, logarithmic, and other statistical models using various basic soil properties for the 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 the other hand for the neural network model there is no need for 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 the ability to learn without the use of specific software programs. Machine learning methods like K Nearest Neighbor (KNN), Cubist, Artificial neural network (ANN), and Random Forest (RF) approaches have been deployed recently in the 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 several 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 the 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 the management of soil erosion.

2. MATERIALS AND METHODS

2.1 Soil Samples and Soil Properties

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* region's 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 were 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.

2.2 Soil Sample Analysis

Soil samples were air-dried, crushed, and sieved, using a 2mm sieve before being analysed for a variety of physicochemical 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 (Equation 1).

$$K = M^{1.14}(10^{-7})\ (12-\alpha) + 4.28(10^{-3})\ (\beta-2) + 3.29(10^{-3})\ (\gamma-3) \qquad (1)$$

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.

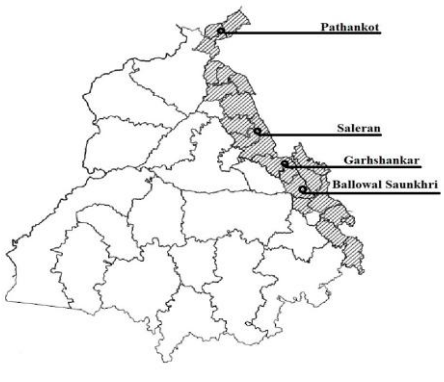


Fig. 1. Location of the study area

Fig. 2. Some photographs of selected land uses

2.3 Secondary Data Obtain from Literature for MWD and K

Table 1. Secondary data obtained from the 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 2. Secondary data obtained from the 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

2.4 Machine Learning Technique

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

A total of 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, and Organic carbon were used in Dataset 1. These are the available properties commonly in the literature also. This data set was prepared both from research data as well as from secondary literature.

Dataset 2: Properties which show a significant correlation in the 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).

2.5 Training and Testing of Data

For machine learning and Generalized linear model, training and testing of data was done. For training, 70% data was used and the remaining 30% data was used for testing.

2.6 Evaluation of PTFs

Different regression metrics were used to evaluate the model

2.7 Root Mean Square Error

The lower the RMSE value, the better the model performance. RMSE was used while calibration of the model to find the most sensitive parameters. This is a measure of the model's real inaccuracy and is calculated as given in Equation 2.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)}{n}} \quad (2)$$

2.8 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 was estimated using Equation 3.

$$R=\frac{\sum_{i=1}^{n}(oi^{-0}avg)\sum_{i=1}^{n}(s_i - s_{avg})}{\sqrt{\sum_{i=1}^{n}(O_i - O_{avg})^2 \sum_{i=1}^{n}(s_i - s_{avg})^2}} \quad (3)$$

2.9 Coefficient of Determination (R^2)

$$R^2 = 1-\frac{(\sum_{i=1}^{n}(P_i - O)^2)/(n-k)}{(\sum_{i=1}^{n}(O_i - O)^2)/(n-1)} \quad (4)$$

2.10 MAE (Mean Absolute Error)

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|P_{i-} O_i| \quad (5)$$

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 explanatory, and n is the number of values.

3. RESULTS AND DISCUSSION

3.1 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 is 0.59-0.92%, Cation Exchange Capacity: is 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.

3.2 Development of PTFs Statistically for Aggregate Stability and Soil Erodibility

3.2.1 Estimating MWD

Using Dataset 1 soil properties, equation 6 has been obtained:

MWD**=** 4.21+0.07*Sand + 0.02*Silt + 0.01*Clay + 0.87*OC – 2.36*BD – 11.23 *EC (6)

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

A multilinear regression equation was developed for dataset 1. It was observed that Sand, Silt, clay, OC, BD and EC explained the 61% variability for MWD. OC, BD and EC played a significant role in the estimation of MWD.

Using Dataset 2 soil properties, equation 7 has been obtained:

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 (7)

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

A multilinear regression equation was developed for data set 2. It was observed that pH, EC, OC, Calcium carbonate, Clay, Fe, BD explained the 56% variability for MWD.EC, OC, calcium carbonate and bulk density played a significant role in the estimation of MWD.

Using Dataset 3 soil properties, equation 8 has been obtained:

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 (8)

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

A multilinear equation was developed for data set 3. It was observed that pH, EC, OC, CEC Calcium carbonate, Coarse sand, fine sand, Clay, Fe, BD explained the 59 % variability for MWD.EC, OC, calcium carbonate, Fe, and bulk density played a significant role in it.

3.2.2 Estimating soil erodibility

Using Dataset 1 soil properties, equation 9 has been obtained:

K = -0.76+ 0.005*Sand + 0.01*Silt- 0.01*Clay- 0.02*OC+ 0.20*BD+ 0.93*EC (9)

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

A multilinear regression equation was developed for the data set 1. It was observed that Sand, Silt, clay, OC, BD and EC explained the 65% variability for K. Silt, Clay, OC, BD, EC played a significant role in the estimation of K.

Using Dataset 2 soil properties, equation 10 has been obtained:

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 (10)

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

A multilinear regression equation was developed for dataset 2. It was observed that pH, EC, OC, Clay, Fe, BD explained the 85% variability for K and properties like EC, OC, Clay, Fe, BD played a significant role in the estimation of K.

Using Dataset 3 soil properties, equation 11 has been obtained:

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 (11)

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

A multilinear regression equation was developed for dataset 3. It was observed that pH, EC, OC, CEC Calcium carbonate, Coarse sand, fine sand, Clay, Fe, BD explained the 73% variability for K. EC, OC, BD, Clay and Fe played a significant role in the estimation of K.

3.3 Development of PTFs by Machine Learning for Soil Erodibility and Aggregate Stability

3.3.1 Estimating MWD

Using Dataset 1 soil properties:

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

When ANN was used for the estimation of MWD for data set 1, the model predicted the role of various properties and it was observed that EC played the most important role. Different weightages were given to other soil properties also (Fig. 3). Fig. 3 is the snapshot of the prediction of the MWD by the model. The regression metrics are also given and it showed that soil properties used in dataset 1 explained 64 % of the variability.

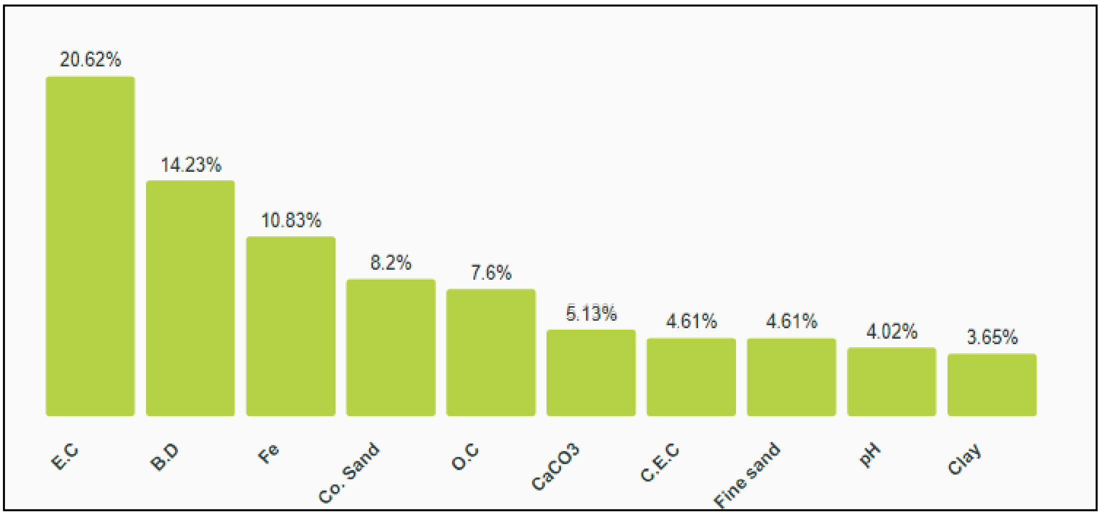
Using Dataset 2 soil properties:

When ANN was used for the estimation of MWD for data set 2, the model predicted the role of various properties and it was observed that EC played the most important role. Different weightages were given to other soil properties also (Fig 4.). Fig 4 is the snapshot of the prediction of the MWD by the model. The regression metrics are given in Fig. 4 and it showed that soil properties used in dataset 2 explained 44% of the variability.

Using Dataset 3 soil properties:

When ANN was used for the estimation of MWD for data set 3, the model predicted the role of various properties and it was observed that EC played the most important role. Different weightages were given to other soil properties also Fig. 5. Fig. 5 is the snapshot of the prediction of the MWD by the model. The regression metrics are given in and it showed that soil properties used in dataset 3 explained 88 % of the variability.

Fig. 4. Properties of field importance and different Regression metrics for MWD using dataset 2



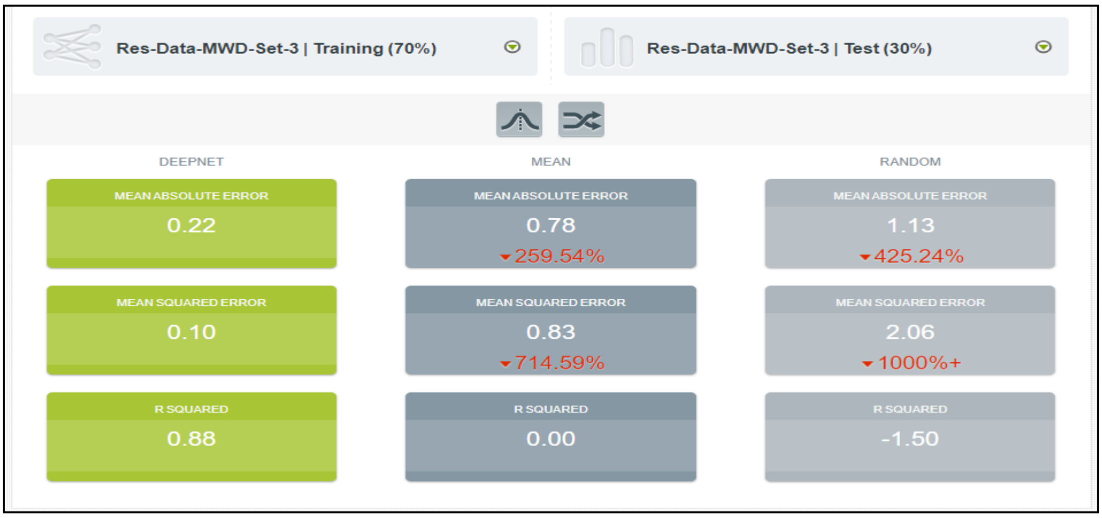


Fig. 5. Properties of field importance and different regression metrics for MWD using dataset 3

3.3.2 Estimating soil erodibility

Using Dataset 1 soil properties:

Fig. 6. Properties of field importance and different regression metrics for K using dataset 1

When ANN was used for the estimation of K for data set 1, the model predicted the role of various properties and it was observed that Clay played the most important role. Different weightages were given to other soil properties also (Fig. 6). Fig. 6 is the snapshot of the prediction of the K by the model. The regression metrics are given in Fig. 6 and it showed that soil properties used in dataset 1 explained 79 % of the variability.

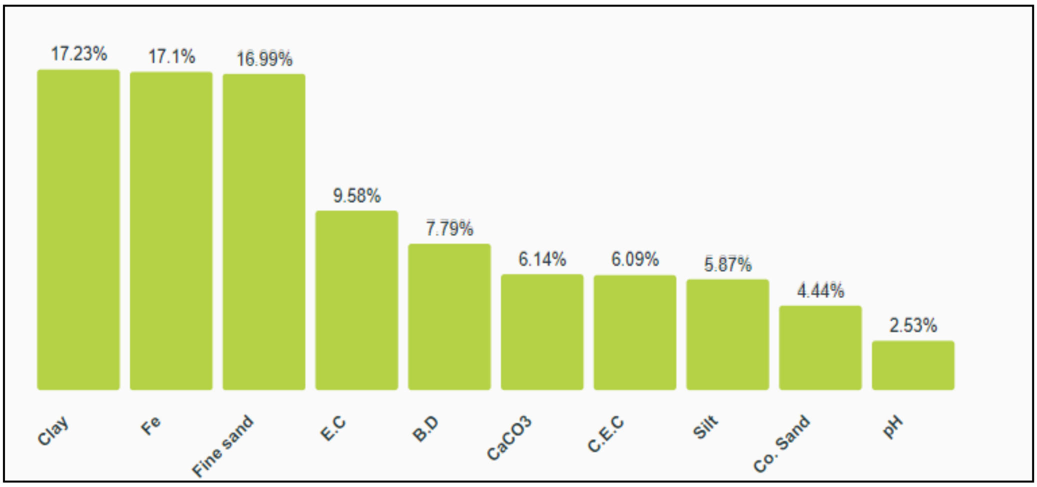
Using Dataset 2 soil properties:

When ANN was used for the estimation of K for data set 1, the model predicted the role of various properties and it was observed that Clay played the most important role. Different weightages were given to other soil properties also (Fig. 7). Fig. 7 is the snapshot of the prediction of the K by the model. The regression metrics are given in Fig. 7 and it showed that soil properties used in dataset 2 explained 73 % of the variability.

Using Dataset 3 soil properties:

When ANN was used for the estimation of K for data set 1, the model predicted the role of various properties and it was observed that Clay played the most important role. Different weightages were given to other soil properties also (Fig. 8). Fig. 8 is the snapshot of the prediction of the K by the model. The regression metrics are given in Fig. 8 and it showed that soil properties used in dataset 2 explained 73 % of the variability.

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



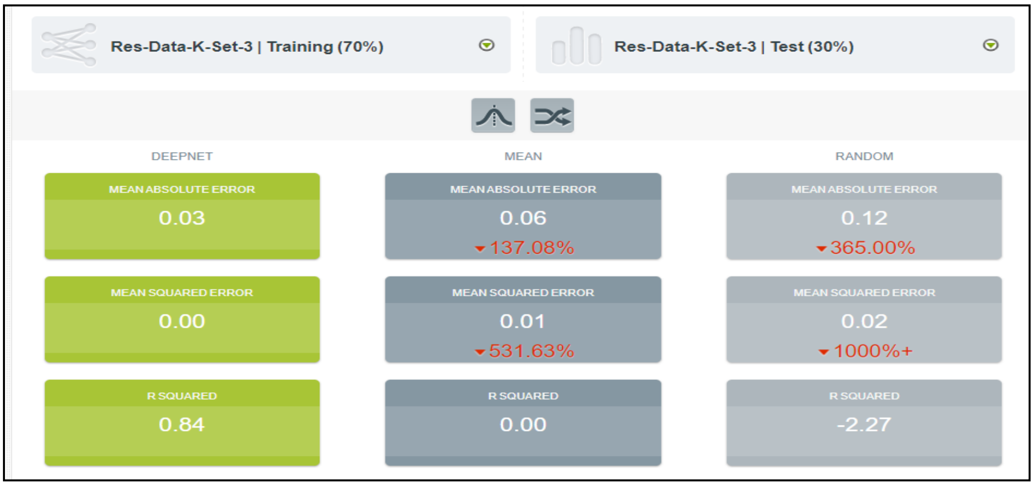


Fig. 8. Properties of field importance and Different Regression metrics for K using dataset 3

3.4 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 the 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 a complex system having a greater number of variables whereas for a small set of data and for a simple system having fewer variables the statistical methods perform better.

Table 3. Comparing 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

4. 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 the GLM model, the R^2 values between actual and predicted MWD and K were 0.61 and 0.65, respectively. Whereas for the same dataset 1, using the ANN model, the R^2 values between actual and predicted MWD and K were 0.64 and 0.79, respectively. For dataset 2, using the GLM model, the R^2 values between actual and predicted MWD and K were 0.56 and 0.85, respectively. Whereas for the same dataset 2, using the ANN model, the R^2 values between actual and predicted MWD and K were 0.44 and 0.73, respectively. For dataset 3, using the GLM model, the R^2 values between actual and predicted MWD and K were 0.73 and 0.59, respectively. Whereas for the same dataset 3, using the 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 a complex system having a greater number of variables whereas for a small set of data and for a simple system having fewer variables, the statistical methods perform better.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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