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Surrogate prediction of saturated hydraulic conductivity of seasonally impounded soils

N.G. Patil* and A. Chaturvedi

National Bureau of Soil Survey and Land Use Planning, Nagpur - 440 010, Maharashtra, India
**Email: nitpat03@yahoo.co.uk*

ABSTRACT

Large tracts of Jabalpur district in Madhya Pradesh get inundated by rainwater during monsoon, due to slow-permeable nature of the soils. Information on hydraulic characteristics of such soils is necessary for any plan aimed at management for sustainable agricultural production. Hierarchical pedotransfer functions (PTFs) to predict saturated hydraulic conductivity (K_s) using texture, bulk density, organic carbon, field capacity and permanent wilting point as input variables were calibrated using statistical and neural regression tools. Statistical indices were used for evaluation of calibrated PTFs in describing fitted data (accuracy) as well as predictive ability (reliability). Performance of PTF using textural data as an input was better than the other PTFs requiring greater input/number of variables. Mean RMSE varied from 0.35 to 4.43 cm d^{-1} in statistical regression PTFs tested for accuracy. Reliability of the statistical PTFs as indicated by mean RMSE also varied greatly with a range of 4.56 to 55.26 cm d^{-1}. In general, neural PTFs exhibited better performance with relatively lower mean RMSE (1.58 to 17.42 cm d^{-1}) in evaluation for accuracy as well as reliability (1.48 to 36.37 cm d^{-1}). The results implied that more soil properties need to be considered as candidate variables influencing saturated hydraulic conductivity. As a PTF calibration tool artificial neural networks proved superior to statistical regression as evidenced by evaluation indices.

Key words: pedotransfer function, artificial neural network, soil-water retention, saturated hydraulic conductivity, waterlogged soils

Introduction

Simulation of water flow through the *vadose* zone requires information on hydraulic properties of soils. Soil-water retention characteristics (SWRC) and saturated hydraulic conductivity (K_s) are the two soil properties, which are vital to such simulations. Measurement of soil hydraulic properties in laboratory is complex, time-consuming and arduous task. Therefore, over the last two decades, use of pedotransfer functions (PTFs) to estimate the hydraulic properties from basic soil data is increasing (Jain *et al.,* 2004; Leij *et al.*, 2002; van Genuchten *et al.,* 1992; Veerecken *et al.*, 1990). PTFs relate hydraulic properties to easily measurable or available soil properties. PTFs could be developed using different techniques (Wosten *et al.*, 2001) like regression (Rawls and Brakensiek, 1985; Wosten *et al.,* 1995), artificial neural network (ANN) (Jain *et al.,* 2004; Minasny *et al.,* 1999; Minasny and McBratny, 2002; Pachepsky *et al.,* 1996; Schaap *et al.,* 1998). Recently genetic programming was employed (Parsuraman *et al.,* 2007) to estimate saturated hydraulic conductivity (K_s) from basic soil data, but most of the reported studies make use of neural networks. For instance, Schaap *et al.* (1998) developed an ANN based PTF, which reportedly performed better than four published PTFs in estimating water retention data and six published PTFs in estimating K_s. They used dataset of 4515 samples in the USA. Later Schaap *et al.* (2001) developed ANN based public domain computer code, '*Rosetta'*, which implements five hierarchical PTFs for the estimation of water retention and the saturated and unsaturated hydraulic conductivity. The dataset used for calibrating *Rosetta* was derived from soils in temperate to sub-tropical climates of North America and Europe. These studies have shown effectiveness of ANN in predicting hydraulic properties. However, it must be noted that the PTFs were based on large dataset.

Unfortunately, in India, no large data on soils are available. We hypothesized that location-specific database from India should be used for calibrating PTFs and evaluated for accuracy so that they acquire spatial capabilities. Routinely collected information in India generally includes soil textural data, bulk density (dry) and intermittent data on water held at 33 kPa (field capacity) and 1500 kPa (permanent wilting point). Hence we used data collected by Patil *et al.* (2009) for the investigation.

The study reported here was conducted to i) calibrate PTFs for predicting K_s from readily available soil properties *viz.* texture (sand, silt and clay percentages), bulk density, organic carbon content, soil-water retained at -33 kPa and -1500 kPa suctions ii) to evaluate the developed PTFs against measured subset, and iii) compare relative merits of statistical and neural regression as a tool of PTF development

Material and methods

Study area is located in Jabalpur district of Madhya Pradesh state in Central India. The district lies between 22^0 49' and 24^0 80' N latitude and 78^0 21' and 80^0 58' E longitude. It receives on an average 1300–1500 mm rainfall, mostly during rainy season. The soils of the area are mainly clayey and classified as *Vertisols* and associated soils (Tomar *et al.,* 1996). Low infiltration rate (poor vertical drainage) of the soils combined with plain topography (poor horizontal drainage) and high amount of rainfall received in relatively short period of time make nearly 5 million ha (50 % area of the district) agricultural lands inundated. The crops are grown in dry season using residual soil moisture.

The soil database reported by Patil *et al.* (2009) was used for the study. Main features of the data are presented in Fig.1 and Table 1. Two techniques namely statistical regression and neural regression were used to build PTFs. For developing ANN based PTFs, software 'Neurointelligence' and 'Neuropath' were used. 'Neurointeligence' provides multiple choice functions (*e.g.* radial basis function, hyperbolic function etc.) to relate property of choice (saturated hydraulic conductivity) to other properties (texture, bulk density etc.). The architecture of neural network can be selected by the user; input-output functions can also be selected. 'Neuropath' does not provide such flexibility. Based on the earlier experience, feed forward neural network model with three hidden nodes was preferred (Patil *et al.*, 2009, 2010).

Calibrating PTFs

Statistical and neural-regression PTFs were calibrated. Five levels of input information were identified for establishing dependencies between basic soil properties and K_s.

- Input level 1: Textural data (data on sand, silt, and clay fraction-SSC)
- Input level 2: Level 1 + bulk density data (SSCBD)
- Input level 3: Level 2 + organic carbon content (SSCBDOC)
- Input level 4: Level 3 + -33kPa data (SSCBDOCFC)
- Input level 5: Level 4 + -1500 kPa data (SSCBDOCFCPWP)

The data sets were partitioned into 'training' (75 % observations) and 'test' (25 % observations) sets. Upon finding an appropriate network model, the PTF was calibrated. For network training, Levenberg-Marquardt (L-M) algorithm was chosen due to the fact that the data are small. Mayr and Jarvis (1999), van Genuchten *et al.* (1992) and other researchers used the same algorithm to develop PTFs. Further, for fair comparison between regression and ANN PTFs, it was desirable to seek minimization of sum of squares error. In the present study evaluation of developed model was done through statistical indices for testing its 'accuracy' to describe fitted

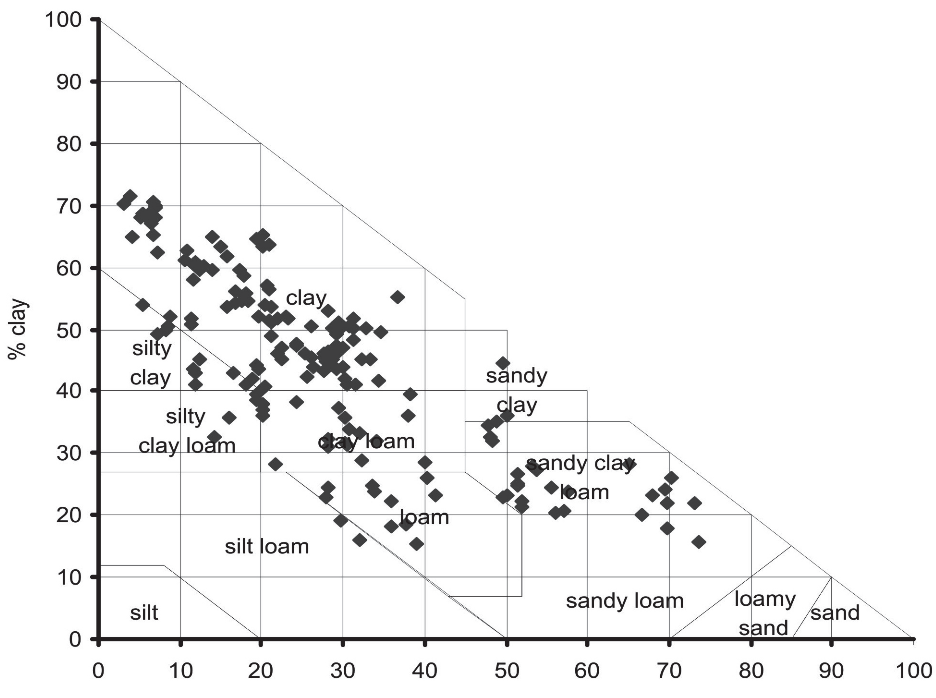

Fig. 1. Textural classification of study soil samples

Table 1. Statistical summary of basic properties of 175 soil samples

Statistic	Sand (%)	Silt (%)	Clay (%)	Bulk density (Mg m^{-3})	Organic carbon (%)	Field capacity (m^3 m^{-3})	Wilting point (m^3 m^{-3})
Mean	27.62	27.82	44.01	1.43	0.39	0.30	0.15
Standard error of measurement	1.214	0.763	1.091	0.009	0.032	0.005	0.000
Coefficient of Variation	0.58	0.36	0.33	0.09	1.09	0.21	0.29
Minimum	3.12	3.82	15.21	1.20	0.10	0.12	0.04
Maximum	73.49	53.25	71.50	1.73	3.60	0.40	0.24

data, while the predictions by PTFs were evaluated for 'reliability' by comparing with testing dataset.

Analysis of the soil samples indicated that 103 out of 175 horizons had clay texture (USDA classification). Clay loam, sandy clay loam and sandy clay texture was recognized in 18, 22 and 10 horizons, respectively. Remaining 22 horizons belonged to five different textural classes. This study pertains to three major classes namely clay, clay loam and sandy clay loam.

Performance Evaluation

Performance of the PTFs was evaluated based on one-to-one correspondence between measured and predicted values of Ks. Statistical indices *viz.* root mean square error (RMSE), mean absolute error (MAE), degree of agreement (d), and maximum absolute error (ME) were based on squared difference between measured (M_i) and estimated (E_i) value, where 'i' indicates ith value of dataset containing 'n' values.

Root Mean Square Error

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Ei - Mi)^2}{n}} \tag{1}$$

Index of Agreement

$$d = 1 - \frac{\sum_{i=1}^{n}(Ei - Mi)^2}{\sum_{i=1}^{n}\left(\left|Ei - \overline{M}\right| + \left|Mi - \overline{M}\right|\right)^2} \tag{2}$$

Maximum Absolute Error

$$ME = Max\left|Ei - Mi\right| \tag{3}$$

Mean Absolute Error

$$MAE = \sum_{i=1}^{n}\frac{\left|Ei - Mi\right|}{n} \tag{4}$$

Table 2. Regression of PTFs to estimate saturated hydraulic conductivity.

PTF
Clay soils
HC=-9.50369+0.225644*SAND+0.177611*SILT+0.123012*CLAY
HC=8.232089+0.167218*SAND+0.122096*SILT+0.128874*CLAY-10.7378*BD
HC=8.802201+0.163785*SAND+0.119829*SILT+0.125287*CLAY-10.8404*BD-0.28099*OC
HC=9.375558+0.158644*SAND+0.118295*SILT+0.122676*CLAY-10.8216*BD-0.2624*OC-1.00354*FC
HC=21.93144+0.052977*SAND+0.00767*SILT+0.012036*CLAY-12.1265*BD-0.91467*OC-6.5644*FC+13.77544*PWP
Clay loam soils
HC=141.5684-1.2318*A2-1.451*B2-1.28743*C2
HC=133.2795*A2-1.064*A2-1.18391*B2-0.92469*C2-13.4949*D2
HC=129.9656-1.01947*A2-1.1353*B2-0.89395*C2-13.3886*D2-3.51472*E2
HC=235.6504-1.843598*A2-1.95678*B2-1.63472*C2-20.8992*D2-7.73723*E2-50.9435*F2
HC=305.5908-2.335328A2-2.43819*B2-2.22281*C2-26.4966*D2-12.738*E2-105.299*F2+50.0665*G2
Sandy clay loam soils
HC=-53.8808+0.577689*SAND+0.494765*SILT+0.601673*CLAY
HC=-83.2948+0.801333*SAND+0.712936*SILT+0.853216*CLAY+4.539317*BD
HC=-38.903+0.403375*SAND+0.276604*SILT+0.392439*CLAY+2.564544*BD+0.068825*OC
HC=-28.5963+0.380911*SAND+0.307287*SILT+0.421496*CLAY-1.53973*BD+0.005255*5*OC-18.9586*FC
HC=-33.3571+0.409268*SAND+0.353803*SILT+0.489289*CLAY-0.95418*BD-0.006959*OC-12.6871*FC-14.736*PWP

Coefficient of variation

$$Cv = \frac{\sigma}{\mu}$$

where, n represents the number of data used for modelling and E_i and M_i represent measured and computed values, respectively. $\bar{E}$ and $\bar{M}$ represent mean estimated and measured values while S_M and S_E represent standard deviation of measured and estimated values. The units of errors were the same as that of Ks (cm d^{-1}). The RMSE statistic indicates the model's ability to predict away from the mean. It imparts more weight to high values because it involves square of the difference between observed and predicted values. Ideally the model should have smallest overall dispersion (RMSE). The degree/index of agreement was both a relative and bounded measure (0<d<1). The soil data were subjected to basic statistical analysis to find mean (ì), standard deviation (ó), standard error (S.E.), and coefficient of variation (Cv). We considered RMSE as a primary indicator in evaluation as it is the most commonly reported indicator in the literature (Wosten *et al.,* 2001).

Results and discussion

PTFs calibrated using statistical regressions are presented in Tables 3, 4, 5, 6 and 7. The statistical indices for clay soils are presented in Table 3, while those for clay loam and sandy clay loam are presented in Table 4 and 5. The PTFs were also evaluated for across the texture

Table 3. Evaluation indices denoting 'accuracy' and 'reliability' of the point PTFs in predicting saturated hydraulic conductivity (clay soils)

Index	Method	Input levels 1		2		3		4		5	
		ACCU	REL	ACCU	REL	ACCU	REL	ACCU	REL	ACCU	REL
RMSE	MLR	2.249	12.88	1.883	64.09	1.883	66.06	1.883	65.63	1.863	67.67
	A1	2.259	2.118	**1.469**	**1.68**	1.804	1.746	**1.291**	**1.582**	2.206	1.715
	A2	1.765	6.611	1.405	6.538	2.831	6.831	0.875	6.73	1.033	6.575
MAE	MLR	1.811	12.48	1.528	61.55	1.527	63.41	1.527	63	1.515	64.42
	A1	1.862	1.822	**1.169**	**1.361**	1.469	1.467	**0.984**	**1.156**	1.567	1.287
	A2	1.465	6.222	0.957	6.166	1.499	6.393	0.654	6.303	0.687	6.157
ME	MLR	5.229	16.71	4.451	88.17	4.408	90.91	4.388	90.39	4.321	96.53
	A1	5.101	3.36	**3.908**	**3.197**	5.412	3.784	**5.15**	**3.565**	7.936	3.584
	A2	4.307	9.959	6.538	10.04	10.77	9.984	3.402	10.02	4.699	10.09
d	MLR	0.498	0.207	0.745	0.052	0.745	0.051	0.745	0.051	0.752	0.05
	A1	0.415	0.504	**0.868**	**0.811**	0.762	0.756	**0.912**	**0.84**	0.764	0.813
	A2	0.772	0.354	0.906	0.361	0.697	0.337	0.962	0.342	0.954	0.352

A1-PTFs developed using 'Neurointelligence', A2- PTFs developed using 'Neuropath'

Table 4. Evaluation indices denoting 'accuracy' and 'reliability' of the point PTFs in predicting saturated hydraulic conductivity(clay loam soils)

Index	Method	Input levels 1		2		3		4		5	
		ACCU	REL	ACCU	REL	ACCU	REL	ACCU	REL	ACCU	REL
RMSE	MLR	2.465	0.224	2.204	0.413	2.197	0.296	1.898	8.26	1.55	14.43
	A1	3.122	1.923	**2.505**	**1.229**	3.133	1.809	**2.962**	**1.497**	4.158	0.947
	A2	3.399	10.12	3.3104	10.11	3.4013	10.12	3.2672	10.08	3.2161	10.08
MAE	MLR	1.842	-0.05	1.635	0.06	1.644	0.051	1.561	0.244	1.268	0.311
	A1	2.497	1.775	**2.142**	**0.875**	2.519	1.718	**2.267**	**1.448**	3.067	0.9
	A2	2.68	9.964	2.588	9.952	2.69	9.962	2.451	9.929	2.415	9.928
ME	MLR	6.214	0.046	4.296	-0.06	4.494	-0.05	3.623	-0.28	3.261	-0.37
	A1	5.699	2.523	**5.344**	**2.302**	6.088	2.362	**5.457**	**2.002**	11.02	1.328
	A2	8.44	11.64	8.255	11.63	8.43	11.64	8.282	11.6	8.075	11.62
d	MLR	0.697	0.24	0.772	0.1	0.775	0.124	0.855	-3.53	0.916	-11.5
	A1	0.294	0.086	**0.734**	**0.859**	0.279	0.075	0.373	0.46	**0.374**	**0.941**
	A2	0.379	0.246	0.378	0.246	0.378	0.246	0.314	0.247	0.315	0.246

A1-PTFs developed using 'Neurointelligence', A2- PTFs developed using 'Neuropath'

Table 5. Evaluation indices denoting 'accuracy' and 'reliability' of the point PTFs in predicting saturated hydraulic conductivity (sandy clay loam soils)

Index	Method	Input levels									
		1		2		3		4		5	
		ACCU	REL	ACCU	REL	ACCU	REL	ACCU	REL	ACCU	REL
RMSE	MLR	0.065	33.88	0.057	33.78	0.047	33.42	0.825	33.42	0.774	33.24
	A1	6.465	**25.26**	8.983	**25.99**	11.39	**13.46**	8.452	**13.46**	4.581	**8.255**
	A2	17.19	36.38	17.53	36.39	16.68	36.37	16.44	36.37	19.29	36.36
MAE	MLR	0.058	29.36	0.049	29.28	0.035	29.01	0.604	29.01	0.642	29.19
	A1	5.407	**19.87**	7.893	**22.5**	10.24	**11.53**	6.601	**11.53**	3.97	**6.33**
	A2	13.59	31.9	13.74	31.91	13.27	31.88	13.1	31.88	14.12	31.88
ME	MLR	0.102	48.81	0.113	48.77	0.141	48.6	2.659	48.6	2.242	48.26
	A1	13.31	**37.93**	14.58	**44.64**	18.64	**22.16**	20.21	**22.16**	7.993	**13.09**
	A2	37.83	52.02	40.1	52.02	36.29	52.01	35.75	52.01	41.01	52
d	MLR	0.175	0.458	0.596	0.46	0.812	0.467	0.923	0.467	0.933	0.479
	A1	0.945	**0.338**	0.883	**0.255**	0.745	**0.667**	0.913	**0.667**	0.974	**0.932**
	A2	0.406	0.439	0.412	0.439	0.389	0.439	0.391	0.439	0.464	0.439

A1-PTFs developed using 'Neurointelligence', A2- PTFs developed using 'Neuropath'

Table 6. Evaluation indices denoting 'accuracy' and ''reliability' of the point PTFs (HC all data)

Index	Method	Input levels									
		1		2		3		4		5	
		ACCU	REL	ACCU	REL	ACCU	REL	ACCU	REL	ACCU	REL
RMSE	MLR	4.4889	4.9772	4.4541	4.2706	4.4267	4.2717	4.4241	4.2685	4.4005	5.0413
	A1	4.7105	4.7476	**2.7522**	**4.7464**	3.4055	5.3069	**3.1742**	**3.7655**	3.3672	4.8648
	A2	2.9817	11.8788	2.3251	12.2166	2.1173	12.0297	2.2474	12.0325	2.3611	11.8477
MAE	MLR	2.9502	4.4174	2.8810	2.9224	2.8404	2.9295	2.8321	2.9444	2.8706	4.1130
	A1	3.4447	3.0251	**1.7340**	**2.8853**	2.3559	3.0164	**2.1242**	**2.3092**	2.2323	2.8021
	A2	1.9371	9.0950	1.5315	9.3364	1.5225	9.1821	1.3836	9.1780	1.3093	9.1014
ME	MLR	25.1760	11.8700	26.2270	15.8953	26.2780	15.9204	26.0460	15.6071	25.3360	14.6416
	A1	19.2620	19.5730	**23.5450**	**21.1620**	15.9770	23.7180	**24.7530**	**15.0760**	25.9120	19.4649
	A2	17.9640	37.9150	14.6270	37.9170	8.7030	37.9170	13.4370	37.9810	16.6080	37.1201
D	MLR	0.7674	0.6942	0.7721	0.7132	0.7763	0.7149	0.7767	0.7161	0.7804	0.6509
	A1	0.7797	0.8284	**0.9384**	**0.8768**	0.9100	0.8238	**0.9129**	**0.9233**	0.8907	0.8311
	A2	0.9164	0.3825	0.9558	0.3698	0.9637	0.3769	0.9667	0.3765	0.9578	0.3844

A1-PTFs developed using 'Neurointelligence', A2- PTFs developed using 'Neuropath'

(Table 6) performance (without classification as per USDA). It could be observed from the tables that mean RMSE indices varied from 0.35 to 4.43 cm d^{-1} in statistical regression (Table 7) PTFs tested for accuracy. Reliability of the statistical PTFs as indicated by mean RMSE also varied greatly with a range of 4.56 to 55.26 cm d^{-1}. In general, neural PTFs exhibited better performance with relatively lower mean RMSE (1.58 to 17.42 cm d^{-1}) in evaluation for accuracy as well as reliability (1.48 to 36.37 cm d^{-1}). Other indices also confirmed these findings. Thus accuracy and reliability of the developed models/PTFs varied greatly. Except for sandy clay loam soils, where statistical PTFs have an advantage of lower RMSE (0.35 cm d^{-1}), all other RMSE values suggest poor performance of statistical PTFs. An evaluation in terms of reliability for sandy clay loam soils showed that the PTFs were not robust as indicated by high RMSE 3354 cm d^{-1}. Thus, it was clear that as a tool neural regression has a distinct edge over statistical regression for PTF calibration. Of the two neural algorithms 'Neurointelligence' performed relatively better. This could be attributed to the in-built capabilities of this algorithm to use multi-layered feed forward network as against single layer feed forward layer used in 'Neuropath'.

Large number of input parameters used in PTF development failed to improve the performance. It could

Table 7. Mean RMSE in evaluation for accuracy and reliability of PTFs

Accuracy				Reliability			
Clay	Clay loam	Sandy clay loam	Combined data	Clay	Clay loam	Sandy clay loam	Combined data
1.95	2.06	0.35	4.44	55.27	4.72	33.55	4.57
1.81	3.18	7.97	3.48	1.77	1.48	17.29	4.69
1.58	3.32	17.43	2.41	6.66	10.10	36.37	12.00
1.58	1.59	0.28	2.87	52.97	0.12	29.17	3.47
1.41	2.50	6.82	2.38	1.42	1.34	14.35	2.81
1.05	2.56	13.56	1.54	6.25	9.95	31.89	9.18
4.56	4.38	1.05	25.81	76.54	-0.14	48.61	14.79
5.50	6.72	14.95	21.89	3.50	2.10	28.00	19.80
5.94	8.30	38.20	14.27	10.02	11.63	52.01	37.77
0.70	0.80	0.69	0.77	0.08	-2.91	0.47	0.70
0.74	0.41	0.89	0.89	0.74	0.48	0.57	0.86
0.86	0.35	0.41	0.95	0.35	0.25	0.44	0.38

be seen from the tables that use of textural information (level 1) in calibration and validation provided better PTFs than the other hierarchical PTFs using large variables as an input. Neural PTFs are expected to improve with use of more number of variables. However, no such pattern was observed in the present investigation. In fact, the performance of PTFs declined. Soil aggregation is assumed to improve with increased organic matter, which is confirmed by several reports finding positive correlation between K_s and OM/OC (Auerswald, 1995; Lado *et al.,* 2004; Mbagwu and Auerswald, 1999). The impounded soils of the tract were however very poor in organic carbon (<1 %). The data indicate no significant change in predictive ability of PTF after including OC as a predictor variable. Inclusion of soil-water retention parameters did not lead to any improvement. It could be argued that the PTFs with less input requirement (textural data) are a better option than the PTFs with large inputs. However, the PTFs must be robust (reliable), which was not observed here. Nevertheless, in absence of any information on Ks, the proposed PTFs could be used for estimation. Thus, atleast a prediction closer to the measured value could be obtained. These results indicate that the waterlogged soils of the study area may have unique characteristics that developed over years of impounding and hence chemical or other properties need to be investigated for their influence on Ks. Another possible reason for lack of robustness could be the number of data points used for calibrating PTFs. With additional data particularly for clay loam and sandy clay loam soils, the PTFs could be improved. The PTFs reported here need to be strengthened with additional data. The relatively better ability of PTFs based on textural information could also be due to the higher percentage of clay in these soils in general. Higher clay content could have masked the effect of other variables to an extent that the neural modeling capabilities were unable to detect the underlying relationship between Ks and other factors influencing it.

Conclusions

Pedotransfer functions (PTFs) to estimate saturated hydraulic conductivity of impounded soils of Jabalpur district were developed. PTFs using textural composition as an input showed relatively better performance than the PTFs using more variables as an input and hence recommended for use. Other PTFs using more input variables lacked accuracy as well as reliability. Neural regression was concluded to be a better technique of calibrating PTFs.

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