Pedotransfer functions: a tool for estimating hydraulic properties of two major soil types of India

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In recent years, georeferenced soil information system has gained significance in agricultural land-use planning and monitoring the changes in soil properties/soil quality induced by land-use changes. The spatio-temporal information on saturated hydraulic conductivity (sHC) and soil water retention–release behaviour is essential for proper crop and land-use planning. The sHC greatly influences the drainage process and soil water retention–release behaviour, ultimately affecting the crop growth and yield. However, sHC and water retention are not measured in a routine soil survey and are generally estimated from easily measurable soil parameters through pedotransfer functions (PTFs). In the present study, PTFs for sHC and water retention were developed separately for the soils of two food-growing zones of India (the Indo-Gangetic Plains (IGP) and the black soil region (BSR)). For the IGP soils, sHC is affected by the increased subsoil bulk density due to intensive cultivation. In BSR, presence of Na^+ and Mg^{++} ions affects the drainage and water retention of the soils. Therefore, these soil parameters were considered while developing the PTFs using stepwise regression technique in SPSS. The validation of PTFs was found to be satisfactory with low RMSE values and high model efficiency.

Keywords: Model efficiency, pedotransfer functions, regression analysis, saturated hydraulic conductivity, water retention.

Introduction

UNDER rainfed conditions, the yield of crops depends primarily on the amount of rainwater entering and stored in a soil profile, and the extent of soil water released during crop growth. The soil-moisture dynamics (including both retention and release) is greatly influenced by the saturated hydraulic conductivity (sHC), the nature and content of clay minerals, and also by the nature of the exchangeable cations. Among the soil parameters, $CaCO_3$ in the clay fraction, exchangeable Ca/Mg ratio, exchangeable sodium percentage (ESP) and sHC are the yield-influencing factors. The pedogenic relationships among the semi-arid climate, formation of pedogenic calcium carbonate (PC), exchangeable Ca/Mg, ESP and sHC helped establish the precise cause–effect relationship of natural chemical degradation in Vertisols of the country[1]. In soils of semi-arid and arid climates, the accelerated rate of formation and accumulation of PC leads to

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impairment of the percolative moisture regime in the subsoils. The poorer crop performance in soils of low mean annual rainfall (MAR, < 850 mm) has been attributed to the lack of soil water resulting from subsoil sodicity[2–4]. sHC decreased rapidly with depth in all the soils, but the decrease was maximum in sodic soils of semi-arid and arid climates with and without soil modifiers[1]. The decreased sHC restricts vertical and lateral movement of water in the subsoils. This causes severe land-use limitations to result in poor crop performance.

Information of soil hydraulic properties on both temporal and spatial scales therefore plays an important role, not only in natural resource management, but also in land-use planning, crop and environment modelling and for future monitoring of soil properties induced by dynamic land-use changes. This fact assumes added importance to agricultural land-use planning in view of the declining trends in factor productivity. However, direct measurement of some physical, chemical and hydrological properties of soils both in the field and laboratory are cumbersome, expensive, time-consuming and labour-intensive.

In recent years, several attempts have been made to estimate soil hydraulic properties indirectly from more easily measurable and more readily available soil properties such as particle size distribution on fine earth basis (size less than 2 mm; sand, silt and clay content), and organic matter or organic carbon content. Such relationships are referred to as pedotransfer functions (PTFs)[5–8]. PTFs can be categorized into three main groups, namely class PTFs, continuous PTFs and neural PTFs. Class PTFs calculate soil properties (e.g. soil hydraulic properties) for a textural class (e.g. sand) by assuming that similar soils have similar properties; continuous PTFs on the other hand, use measured percentages of clay, silt, sand and organic matter content to provide continuously varying soil properties across the textural triangle[9]. From a prediction point of view, PTFs can be distinguished into point and parametric PTFs. Point PTFs predict the water content at pre-defined soil water pressure heads, while parametric PTFs assume that the hydraulic properties can be described adequately with a hydraulic model containing a limited number of parameters.

A recent approach to model PTFs is the use of artificial neural networks (ANNs)[10]. An ANN offers a fundamentally different approach for modelling soil behaviour. It is able to learn and generalize from experimental data, even if they are noisy and imperfect. This ability allows the computational system to learn constitutive relationships of materials directly from the results of experiments. Unlike traditional regression models, neural PTF needs no prior regression models to relate input and output data.

Many researchers have reported PTFs for water retention and sHC developed in different parts of the world. Despite significant progress made in PTF development across the world, there are limited studies on this aspect and its evaluation for the soils of developing countries, in general and for the soils of India, in particular[11–18]. Therefore, the present study was carried out to develop PTFs for estimation of soil hydraulic properties, viz. water retention and sHC using a few easily measurable parameters for soils of the Indo-Gangetic Plains (IGP) and the black soil region (BSR).

Materials and methods

Study area

The soils of two major food-growing regions of India, viz. IGP and BSR were selected for development of PTFs to estimate soil hydraulic properties, viz. water retention and sHC.

The Indo-Gangetic Plains

The IGP represents large alluvial plains dominated by three main rivers, the Indus, Ganges and Brahmaputra. They flow parallel to the Himalaya and drain into northern and eastern parts of India. The plains encompass an area of 73.0 m ha (ref. 19). The Indian part of the IGP, however, constitutes an area of 52.01 m ha (ref. 20). The major rivers in this region are the Ganges, Indus and Brahmaputra along with their main tributaries – Yamuna, Chambal, Gomti, Ghaghara, Kosi, Sutlej, Ravi, Beas, Chenab and Tista – as well as rivers of the Ganges Delta, such as the Meghna. The IGP ranks as one of the most extensive fluvial plains of the world. The nature and properties of the alluvium vary from sandy to clayey texture, calcareous to non-calcareous and acidic to alkaline. Though the overall topographic situation remains fairly uniform with elevations of 150 m amsl in the Bengal basin, and 300 m amsl in the Punjab plain, local geomorphic variations are significant[21].

The plains are one of the world's most intensely cultivated areas. The main crops grown are rice (*kharif*) and wheat (*rabi*). Other important crops grown in the region include maize, sugarcane, pulses, oilseeds and cotton.

Black soil region

Black soils are common in the semi-arid tropics (SAT) in India, although their presence was reported in the humid and arid bioclimates as well[22,23]. These soils are spatially associated with red soils to form a major soil group formed on various parent materials and climates. They have been reported in the various physiographic positions such as red soils on the hills and black soils in the valleys in Maharashtra and Madhya Pradesh[22,24,25]. The exactly opposite situation was found in Tamil Nadu (TN) where red soils are in the valleys and black soils on the hills[26]. Interestingly, these soils have also been reported in juxtaposition in TN, Maharashtra and Andhra Pradesh under similar topographic situation[27,28]. While black soils (Vertisols and their intergrades) are formed from basalts and other basic rocks[29], red soils are formed from various rock formations. Interestingly, spatially associated red and black soils can only be found in basalts. Some part of the amygdaloidal basalts contain zeolites[22,30–33] and in some other parts the basalts do not contain zeolites[25].

The BSR spreads in 76.4 m ha (ref. 20) and supports more than 60% of the rainfed agriculture in India. The main crops are rice, coarse cereals (sorghum, millets), pulses, oilseeds, maize, sugarcane and cotton, which are cultivated as largely *kharif* crops, but in some places as *rabi* crops as well.

During the last three to four decades, the IGP has been able to meet the food demand of the exponentially growing population by increasing the foodgrain production, mainly rice and wheat, using high input technologies. The foodgrain production was, however, not uniform across the region, because of the spatial variation in land resource characteristics and socio-economic conditions in the region[34]. Similarly, in the BSR the yield of crops remains stagnant or starts declining, which could be attributed to the constraint in soil moisture availability during the post-rainy season and impairment of drainage due to chemical degradation.

Collection of soil data

Soil information on 38 physical and chemical parameters was collected from 209 soil layer observations of 30 soil profiles representing the IGP of India with rice–wheat-based cropping system. For BSR, soil information on physical and chemical properties was collected from 275 soil layer observations of 62 soil profiles having 26 soil physical and chemical properties and representing the shrink–swell soils of BSR of India with cotton-based cropping system.

Development of PTFs

Stepwise multiple regression technique was used for developing PTFs in a statistical software SPSS (version 18.0). These PTFs were developed separately for soils of the BSR and IGP and will be used for estimating sHC, water retention at –33 and –100 kPa (for BSR soils only) and –1500 kPa, and bulk density (BD).

First, the soil datasets were subjected to analysis of data consistency and adequacy. Scatter plot diagram was used to identify the variables and form a working hypothesis about their relationship. Furthermore, a scatter plot helps identify outliers – values that lie abnormally far from the cluster of data points. Thereafter, the variables used for PTFs, were selected considering the cause–effect relationship and correlation coefficients amongst them.

The statistical analyses for mean, standard deviation, maximum and minimum values, indicating the central tendency and spread of the dataset, were carried out for the selected variables. Stepwise regression technique was used in SPSS to develop multiple regression models as PTFs. A criterion of 5% and 10% significance levels was used for acceptance and rejection respectively, of an independent variable.

Selection of best fit regression model as PTF

Based on the F values, coefficient of determination (R^2) and adjusted R^2, an effective and efficient regression model was selected as the best-fit regression model as PTF. The adjusted R^2 was calculated from the following expression

$$R^2_{\text{adj}} = 1 - \frac{(1-R^2) \times (N-1)}{(N-n-1)}, \quad (1)$$

where N is the number of observations and n the number of regressors. The effectiveness of a regression model is measured by the values of R^2 and adjusted R^2 (Table 1). A more effective regression model will have highest R^2 value with more number of predictor variables. However, the model may not be efficient. The efficiency of a regression model is assessed by the F value. An efficient model will have the most significant or highest F ratio with less number of predictor variables. However, the model may not be effective. Hence a compromise is made to select a best-fit regression model looking at the largest increase in the value of adjusted R^2 while introducing a new predictor variable into the model[35].

Multi-collinearity amongst the independent variables is also considered while selecting the best-fit regression model. Multi-collinearity analysis is carried out for identifying highly correlated independent variables in a single regression model, which usually produces large standard errors and beta coefficients, often more than 1.0. If the correlation coefficients of independent variables are more than 0.8, then the variables are highly correlated and can produce regression models with unstable estimates of regression coefficients and large standard errors[36]. Tolerance and variance inflation factor (VIF) can be used as diagnostic statistics for multi-collinearity analysis. Small tolerances imply multi-collinearity problems. VIF is

Table 1. Criteria for effectiveness (R^2 or R^2_{adj}) of a regression model

Value of R^2/adjusted R^2	Performance
0.00–0.25	Very poor and unacceptable
0.25–0.50	Poor, may be acceptable
0.50–0.75	Good
0.75–0.90	Very good
> 0.90	Multi-collinearity problem in the regression model

calculated as the reciprocal of tolerance. The tolerance is estimated from the coefficient of determination (R^2) as below

$$\text{Tolerance} = 1 - R^2, \tag{2}$$

$$\text{VIF} = \frac{1}{\text{Tolerance}}. \tag{3}$$

Low inter-correlation among independent variables indicates that VIF is closer to unity. However, if VIF is more than 10, then there could be multi-collinearity problems in the regression models.

Validation of PTFs

Validation is commonly used to indicate a procedure aimed at analysing performance of simulation models and/or mathematical models such as PTF models. It follows some standard validation/efficiency criteria to verify whether the performance of any developed simulation model or PTF is acceptable or not. Generally, it is performed with an independent dataset that is not used for the development of the model or PTF. The size of the dataset used for this purpose is one-third or one-fourth of the full size dataset. During validation process, various error indices and efficiency criteria are used for testing the reliability, accuracy and performance of a developed simulation model or PTF. The error indices such as mean absolute error (MAE), mean square error (MSE) and root mean square error (RMSE) are useful as they indicate error (difference in the estimated and measured values) in the units (or squared units) of the parameter under consideration. RMSE, MAE and MSE values of 0 indicate a perfect fit. RMSE and MAE values less than half the standard deviation of the measured data may be considered low[37] and that is appropriate either for validation of simulation model or PTF.

The efficiency criteria functions are coefficient of determination (R^2), Nash–Sutcliffe efficiency (NSE), also known as model efficiency (EF); NSE with logarithmic values, and index of agreement (*d*), which are generally used in the validation of simulation model or PTFs.

The coefficient of determination (R^2) is defined as the squared ratio between the covariance and multiplied standard deviations of the observed and predicted values (eq. 5)[38]. It can also be expressed as the squared value of the coefficient of correlation. Therefore, it estimates the combined dispersion against the single dispersion of the observed and predicted series. The range of R^2 lies between 0 and 1, which describes how much of the observed dispersion is explained by the prediction. The fact that only the dispersion is quantified is one of the major drawbacks of R^2 if it is considered alone. A model which systematically over- or under-predicts all the time will still result in good R^2 values close to 1.0, even if all predictions were wrong.

The NSE or EF is defined as one minus the sum of the absolute squared differences between the predicted and observed values normalized by the variance of the observed values during the period under investigation[39]. EF indicates how well the plot of observed versus simulated data fits the 1 : 1 line. It ranges between $-\infty$ and 1.0 (1 inclusive), with EF = 1 being the optimal value. Values between 0.0 and 1.0 are generally viewed as acceptable levels of performance, whereas those < 0.0 indicate that the mean observed value is a better predictor than the simulated value, suggesting unacceptable performance. The largest disadvantage of the EF is that the differences between the observed and predicted values are calculated as squared values. As a result larger values in a time series are strongly overestimated, whereas lower values are neglected[40]. Similar to R^2, the EF is not sensitive to systematic model over- or under-prediction.

In the present study, RMSE, coefficient of determination (R^2) and EF were used as validation criteria for the developed PTFs using the following expressions

$$\text{RMSE} = \sqrt{\frac{\sum(\text{Observed} - \text{Predicted})^2}{\text{Number of observations}}}, \tag{4}$$

$$R^2 = \left[\frac{\sum(\text{Observed} - \text{Mean}_{\text{observed}})(\text{Predicted} - \text{Mean}_{\text{predicted}})}{\sqrt{\sum(\text{Observed} - \text{Mean}_{\text{observed}})^2} \times \sqrt{\sum(\text{Predicted} - \text{Mean}_{\text{predicted}})^2}}\right]^2, \tag{5}$$

$$\text{ME} = \left[1 - \frac{\sum(\text{Observed} - \text{Predicted})^2}{\sum(\text{Observed} - \text{Mean}_{\text{observed}})^2}\right]. \tag{6}$$

Results and discussion

PTF for estimating water retention of BSR soils

Point PTFs to estimate water retention at –33, –100 and –1500 kPa for the BSR soils were developed using 75 soil layer observations of 14 soil profiles. Based on cause–effect relation and expert opinion soil parameters, viz. clay, fine clay, organic carbon, cation exchange capacity (CEC), $CaCO_3$, ESP, exchangeable magnesium percentage (EMP) and exchangeable calcium percentage (ECP) were selected as independent variables. Statistical analysis for measures of central tendancy was carried out for the selected variables (Table 2). The water retention at –33 kPa varied from 21.4% to 49.3% with a mean value of 35.5% and standard deviation (SD) of 6.74%, whereas water retention at –100 kPa varied from 15.7% to 43.1%

Table 2. Descriptive statistics of the selected variables used in PTFs for water retention ($N = 75$)

Soil property	Minimum	Maximum	Mean	Standard deviation
Water retention (kPa)				
– 33	21.4	49.3	35.5	6.74
–100	15.7	43.1	31.0	6.94
– 1500	8.1	27.1	17.9	3.91
Clay (%)	30.5	72.1	54.9	10.94
Fine clay (%)	12.6	60.0	35.0	11.66
CEC	27.5	71.7	48.9	11.99
OC (%)	0.23	1.08	0.5	0.18
$CaCO_3$ (%)	0.9	26.3	10.9	6.47
ECP (%)	20.0	90.0	65.7	14.92
EMP (%)	11.0	71.0	28.7	11.52
ESP (%)	0.5	28.0	4.6	5.3

Table 3. Multiple regression models with statistical parameters

Suction (kPa)	Model with predictor variables		r	R^2	Adjusted R^2	Std. error of the estimate	F value	VIF	AIC
33	1	(Constant)	0.79	0.63	0.62	4.16	121.70		217.97
		CEC						1.000	
	2	(Constant)	0.87	0.75	0.74	3.41	108.88		189.35
		CEC						1.145	
		ESP						1.145	
	3	(Constant)	0.90	0.82	0.81	2.95	104.7		169.25
		CEC						2.645	
		ESP						1.146	
		Clay						2.541	
100	1	(Constant)	0.84	0.71	0.71	3.75	180.30		202.53
		CEC						1.000	
	2	(Constant)	0.88	0.77	0.77	3.34	123.60		186.39
		CEC						1.145	
		ESP						1.145	
	3	(Constant)	0.91	0.83	0.82	2.96	111.72		169.57
		CEC						2.645	
		ESP						1.146	
		Clay						2.541	
1500	1	(Constant)	0.80	0.64	0.64	2.36	129.99		133.10
		CEC						1.000	
	2	(Constant)	0.83	0.70	0.69	2.19	82.37		122.77
		CEC						1.145	
		ESP						1.145	
	3	(Constant)	0.85	0.72	0.71	2.12	60.16		119.49
		CEC						1.264	
		ESP						1.267	
		EMP						1.327	

VIF, Variance inflation factor; AIC, Akaike information criteria.

(SD = 6.94%) and at –1500 kPa, it varied from 8.1% to 27.1% (SD = 3.91%). Amongst other soil physical and chemical properties, maximum standard deviation of 14.92% was observed in ECP followed by the CEC (SD = 11.99%) and fine clay (SD = 11.66%). The multiple regression models generated in different steps with soil parameters as predictor variables and statistical parameters are shown in Table 3.

Considering the F values, R^2 and adjusted R^2, the best-fit regression models were selected for estimating the water retention at –33, –100 and –1500 kPa suctions, as given as below

$$MC_{33} = 2.583 + 0.346 \times (\text{CEC}) + 0.249 \times (\text{clay}) + 0.494 \times (\text{ESP}), \quad (7)$$

Table 4. Descriptive statistics of the selected variables used in PTF for sHC (N = 200)

Soil property	Minimum	Maximum	Mean	Std. deviation
sHC (mm h^{-1})	0.1	39.0	9.460	7.5223
Silt (%)	14.2	49.0	30.710	7.3783
Clay (%)	35.1	84.6	63.525	9.7810
pH (%)	6.3	9.1	8.215	0.4323
OC (%)	0.0	1.4	0.544	0.2467
$CaCO_3$ (%)	0.9	46.7	9.408	6.7084
ECP (%)	20.0	90.0	60.370	12.9502
ESP (%)	0.3	44.1	4.866	6.7150
Exchangeable Ca/Mg	0.3	11.1	2.507	1.3249

Table 5. Multiple regression models with statistical parameters for PTF to estimate sHC

Model	r	R^2	Adjusted R^2	Std. error of the estimate	F value	VIF	AIC
(Constant)	0.787	0.620	0.618	4.6485	323.102		618.61
pH						1.000	
(Constant)							600.99
pH	0.810	0.656	0.652	4.4350	187.740	1.047	
Exchangeable Ca/Mg						1.047	
(Constant)							592.65
pH						1.049	
Exchangeable Ca/Mg	0.821	0.673	0.668	4.3317	134.707	1.052	
Clay						1.008	

$$MC_{100} = -1.918 + 0.383 \times (\text{CEC}) + 0.228 \times (\text{clay}) + 0.361 \times (\text{ESP}), \quad (8)$$

$$MC_{1500} = 0.541 + 0.306 \times (\text{CEC}) + 0.146 \times (\text{ESP}) + 0.058 \times (\text{EMP}), \quad (9)$$

where MC_{33} is the soil water retention at –33 kPa; MC_{100} the soil water retention at –100 kPa and MC_{1500} is the soil water retention at –1500 kPa.

The values of VIF for the selected regression models are less than 10 and the F values are highly significant for the selected regression models (Table 3). CEC is one of the predictor variables in all four regression models selected as PTFs to estimate water retention at –33, –100 and –1500 kPa. Clay content and ESP and/or EMP are other predictor variables. Clay with its very large adsorption surface and CEC which reflects the negative charge of clays greatly influence the soil water content due to adsorption of di-polar water molecules. Moreover, in the lesser suctions (moisture tensions), i.e. from –33 to –100 kPa, soil water has more contribution from capillary water that is affected by the amount and type of clay, and also CEC. However, in higher suctions, i.e. –1500 kPa, the adsorbed soil water contributes more to the soil water content which is influenced by the amount of exchangeable cations present in the soil exchange complex. Thus, selection of clay, CEC and ESP and/or EMP as predictor variables is justified for estimating water retention for BSR soils.

PTF for estimating sHC of BSR soils

A PTF was developed for estimating sHC of the BSR soils using 200 soil layer observations of 46 soil profiles. Based on cause–effect relationship supplemented by expert opinion, soil parameters, viz. silt, clay, pH, organic carbon (OC), $CaCO_3$, ESP, ECP and exchangeable Ca/Mg were selected as independent variables used in SPSS for developing PTFs. Statistical analyses were carried out for the selected soil parameters (Table 4). The multiple regression models generated in different steps with soil parameters as predictor variables and statistical parameters are shown in Table 5.

Based on the F values, R^2 and adjusted R^2, the best-fit regression model (3), i.e. last regression model in Table 5, was selected to estimate sHC for the BSR soils. The soil parameters, viz. clay, pH and exchangeable Ca/Mg are used as predictor variables in the PTF which is expressed as

$$\text{sHC} = 120.637 - 13.094 \times (\text{pH}) - 0.102 \times (\text{clay}) + 1.151 \times (\text{exchangeable Ca/Mg}). \quad (10)$$

PTF for estimating sHC of the IGP soils

For the IGP soils, a PTF was developed for estimating sHC using 100 soil layer observations of 20 soil profiles. Based on expert opinion, soil parameters, viz. sand, silt, clay, fine clay, water dispersible clay (WDC), pH, OC, BD and ESP were selected as independent variables. The

Table 6. Descriptive statistics of the selected variables used in PTF to estimate sHC (N = 100)

Soil property	Minimum	Maximum	Mean	Standard deviation
sHC (mm h^{-1})	0.0	5.9	1.720	1.5964
Sand (%)	1.2	80.6	37.266	22.9597
Silt (%)	10.4	71.8	41.837	17.6086
Clay (%)	5.8	58.5	20.908	10.2317
Fine clay (%)	3.5	32.8	13.811	7.8342
WDC (%)	0.6	6.4	3.806	1.0237
pH (1 : 2)	5.9	9.4	8.403	0.6857
OC (%)	0.1	1.7	0.322	0.2439
ESP (%)	1.0	29.0	6.955	6.0933
BD (Mg m^{-3})	1.3	2.0	1.674	0.1268

WDC, Water dispersible clay.

Table 7. Multiple regression models with statistical parameters for PTF to estimate sHC

Model	r	R^2	Adjusted R^2	Std error of the estimate	F value	VIF	AIC
(Constant)	0.747	0.559	0.554	1.0658	124.095		16.98
Sand						1.000	
(Constant)							8.98
Sand	0.776	0.601	0.593	1.0182	73.179	1.031	
ESP						1.031	
(Constant)							3.21
Sand						1.062	
ESP	0.795	0.632	0.621	0.9834	54.962	1.032	
BD						1.033	

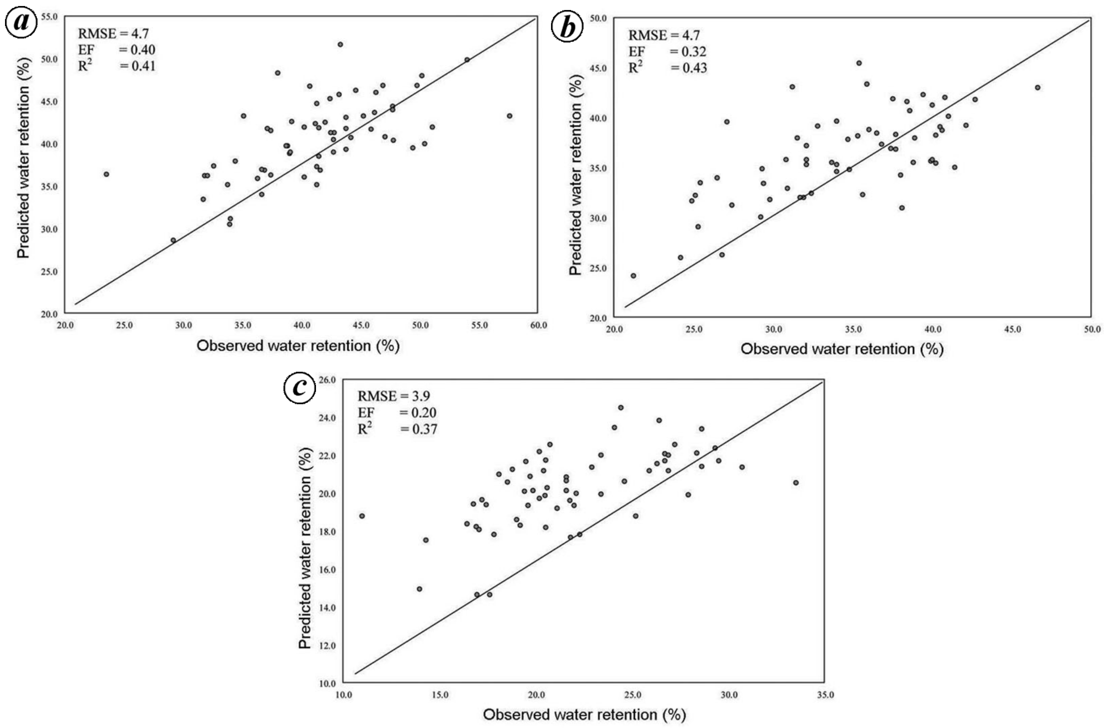

Figure 1. Distribution of observed and predicted water retention at (***a***) –33 kPa; (***b***) –100 kPa; (***c***) –1500 kPa.

statistical analyses were carried out for some important parameters (Table 6). Stepwise regression technique was used in SPSS to develop multiple regression models as PTF (Table 7).

Depending on the F values, R^2 and adjusted R^2, the best-fit regression model (3), i.e. last regression model in Table 7, was selected to estimate BD of the IGP soils. The soil parameters, viz. clay, OC and ESP are used as predictor variables in the PTF which is expressed as below

$$\text{sHC} = 4.079 + 0.047 \times (\text{sand}) - 0.054 \times (\text{ESP}) - 2.238 \times (\text{BD}). \quad (11)$$

Validation of PTFs

PTFs developed to estimate water retention in BSR soils were validated with 63 soil layer observations of 14 soil profiles. The statistical parameters like RMSE and EF were considered to quantify the errors of estimation. The 1 : 1 lines for observed and predicted values were also plotted to illustrate the distribution of values along a straight line of slope (Figure 1). It also gives an idea about over- or under-predictions by the developed PTF. The estimated values of RMSE, EF and R^2 for the PTFs to estimate the water retention at –33, –100 and –1500 kPa are given in Table 8. The study shows that the performance of the developed PTFs is quite satisfactory with low RMSE values and high EF (Figure 1).

The validation of PTF for estimating sHC of BSR soils was carried out using 26 soil layer observations of 7 soil profiles. RMSE and EF were 6.40 mm h^{-1} and 0.09 respectively. The performance of this PTF was not satisfactory. However, this may be acceptable since the EF is more than zero. Besides, the number of observations used for validation was less. Hence, the PTF needs to be validated with more number of observations, since it overestimates the prediction of sHC for BSR soils (Figure 2).

Table 8. RMSE and EF values estimated for validating PTFs of water retention

PTF	RMSE (%)	EF	R^2
Water retention at (kPa)			
–33	4.7	0.40	0.41
–100	4.7	0.32	0.43
–1500	3.9	0.20	0.37

RMSE, Root mean square error; EF, model efficiency.

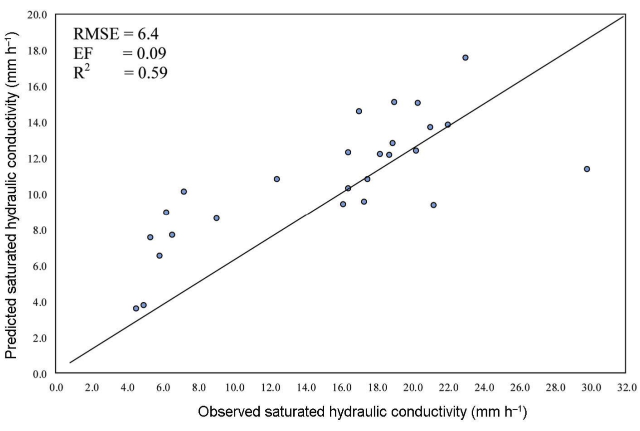

Figure 2. Distribution of observed and predicted sHC.

Conclusion

The dynamics of water in soil is related to the drainage process and its retention–release behaviour, which ultimately leads to crop and land-use planning. The sHC greatly influences the drainage process and soil water retention–release behaviour. However, sHC and water retention are not measured in a routine soil survey and are generally estimated from easily measurable soil parameters through PTFs. The PTFs for sHC and water retention are developed separately for the soils of two food-growing zones of India (the IGP and BSR). For the IGP soils, sHC is affected by the subsoil BD, which is increased due to intensive cultivation. In the BSR, the presence of Na^+ and Mg^{++} ions affects the drainage and water retention of the soils. Therefore, these soil parameters were separately considered while developing the PTFs using stepwise regression technique in SPSS in these two different types of regions represented by different types of soil and their associated problems. The validation of PTFs was satisfactory with low RMSE values and high EF. However, since the validation is a continuing process, the developed PTFs need to be tested with different soil datasets having more number of observations.

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ACKNOWLEDGEMENTS. The present study was carried out by the National Agricultural Innovative Project (NAIP) (Component 4), sponsored research on ‘Georeferenced soil information system for land use planning and monitoring soil and land quality for agriculture’ through Indian Council of Agricultural Research, New Delhi. The financial assistance is gratefully acknowledged.