Geoderma Regional 28 (2022) e00475

Contents lists available at ScienceDirect

Geoderma Regional

journal homepage: www.elsevier.com/locate/geodrs

Prediction of soil hydraulic properties using VIS-NIR spectral data in semi-arid region of Northern Karnataka Plateau

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ARTICLE INFO

Keywords:
Hydraulic properties
Field capacity
Permanent wilting point
Vis–NIR spectroscopy
Random forest model
Alfisols
Vertisols

ABSTRACT

Field capacity (FC) and permanent wilting point (PWP) are the important soil hydraulic properties which determine the availability of water for plant growth. Conventional estimation of soil hydraulic properties is tedious and expensive which are normally derived from pedo-transfer functions. Visible and near-infrared (Vis-NIR) spectroscopy is a low-cost, non-destructive alternative method for the rapid estimation of soil properties. The present study was carried out to predict soil hydraulic properties using Vis-NIR spectral data in the semi-arid region of the Northern Karnataka plateau. Spectral data of 558 soil samples were acquired using Field Spec ASD Spectroradiometer and three models (support vector machine, random forest and partial least square regression) were evaluated for prediction of FC and PWP. The models were calibrated using 2/3rd of total observations and validated using 1/3rd of observations. The validation results showed that RF and SVM provided slightly higher performance compared to PLSR model. Permanent wilting point was predicted well (R^2 = 0.70–0.74, RMSE = 5.44–5.74%) compared to field capacity (R^2 = 0.66–0.69 and RMSE = 7.25–7.51%). Among the soil orders, FC and PWP of Vertisols were poorly predicted by Vis-NIR spectra (R^2 = 0.34&0.42) and moderately predicted for Alfisols (0.44&0.52) and Inceptisols (0.55&0.65) while excellent prediction was recorded for Entisols (0.83&0.76). The present results showed that Vis-NIR spectroscopy is helpful for fast estimation of hydraulic properties in semi-arid regions of the country with high accuracy.

1. Introduction

Soil hydraulic parameters such as field capacity and permanent wilting point play a major role in irrigation management (Tetegan et al., 2015), drought risk assessment (Poggio et al., 2010) and land use planning (Santra et al., 2018; Dharumarajan et al., 2019). Field capacity (FC) and permanent wilting point (PWP) are referred to the water retained in soil pores at a tension of −0.033 MPa and − 1.5 MPa, respectively. Estimating these hydraulic parameters which determine the available water holding capacity of the soil is crucial for the best management of water use efficiency especially in arid and semi-arid regions (Dharumarajan et al., 2021). These hydraulic properties are dynamic and varies with soil type, type of crop and growing season (Bouma, 2018). Many crop models also require these hydraulic properties for upscaling simulation models at the regional or national scale (e.g., STICS, Brisson et al., 1998; SWAT, Arnold and Fohrer, 2005; APSIM, O'Leary et al., 2016). Estimation of hydraulic properties using traditional methods at a large scale is time-consuming and expensive (Romano and Palladino, 2002; Patil and Singh, 2016). An alternative to traditional methods, pedo-transfer function (PTF) has been applied to estimate soil hydraulic properties using easily measured soil properties such as soil particle size fractions, organic carbon and bulk density. These predictive parameters are largely influenced by various intrinsic soil properties such as soil texture, structure, organic matter, bulk density and porosity.

Alternatively, visible and near-infrared (Vis-NIR) spectroscopy is used by researchers across the world for rapid estimation of soil properties (Lagacherie et al., 2008; Conforti et al., 2018; Hobley and Prater, 2019; Gomez et al., 2008a, 2008b; Justin et al., 2020; Sarathjith et al., 2015). Compared to traditional PTFs, spectroscopy has the advantage of estimating soil properties like FC and PWP rapidly from the spectral data rather than tedious laboratory measurements used in traditional PTFs. Though Vis-NIR spectroscopy is widely used in predicting soil properties, only limited works were carried out for the prediction of hydraulic

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https://doi.org/10.1016/j.geodrs.2021.e00475
Received 21 August 2021; Received in revised form 11 December 2021; Accepted 21 December 2021
Available online 25 December 2021
2352-0094/

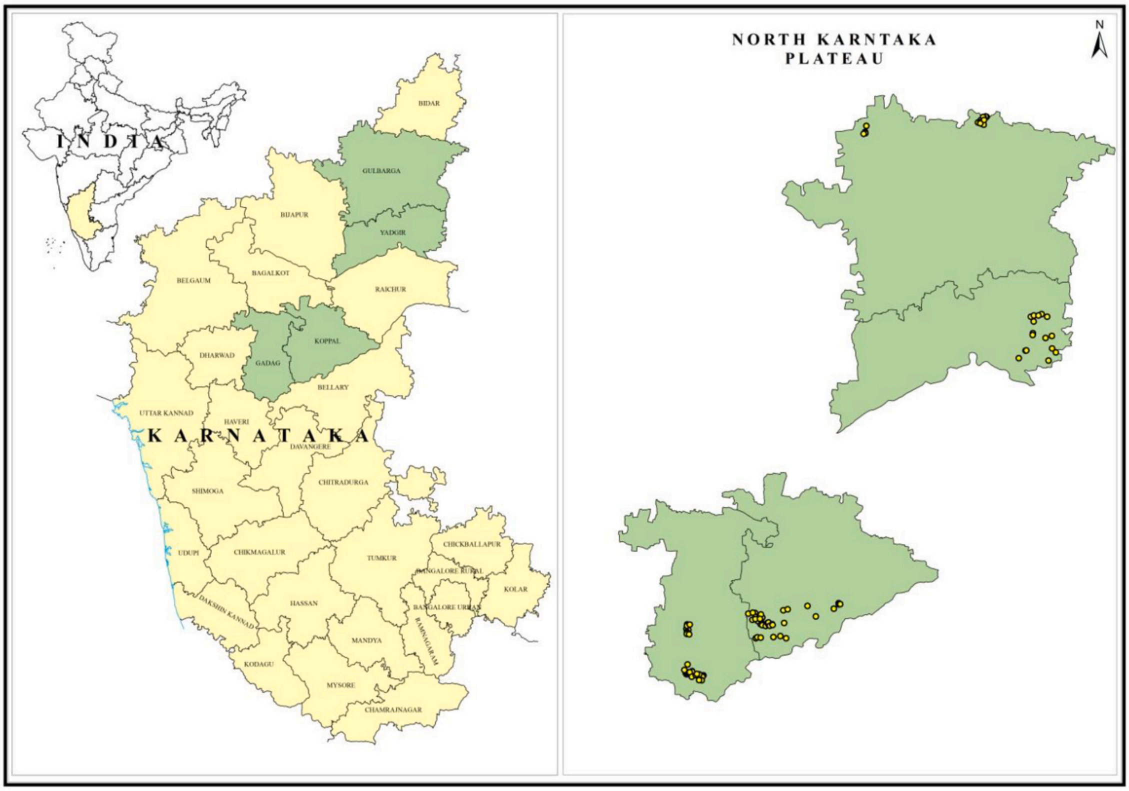

Fig. 1. Study area with profile points.

properties (Santra et al., 2009; Arslan et al., 2014; Babaeian et al., 2016). Arslan et al. (2014) evaluated the ability of spectral data to predict hydraulic properties such as FC and PWP using 305 soil samples and obtained very good results. Pittaki-Chrysodonta et al. (2018) established soil water retention function using spectral data and predicted the soil water retention with very good approximation than classical PTFs. Using Vis-NIR spectral database of New Zealand soils, Blaschek et al. (2019) predicted FC and PWP and achieved good accuracy with root mean squared errors less than 7% and 5% for FC and PWP, respectively. Very limited studies are available for mapping hydraulic properties in Indian soil types using spectral data (Santra et al., 2009; Gulfo et al., 2012). Santra et al. (2009) evaluated the performance of pedotransfer and spectrotransfer functions in the estimation of soil hydraulic properties for Chilika lake catchment of Odisha and found that spectrotransfer functions established from proximal spectral reflectance in 350–2500 nm had comparable accuracy with PTFs in terms of RMSE. Gulfo et al. (2012) manifested that usage of hyperspectral reflectance (350–2500 nm) for soil moisture content estimation using the reflectance of 240 soil samples collected from the Indian Agricultural Research Institute farm, New Delhi.

A key limitation in deploying Vis-NIR spectroscopy is that the reference data associated with the spectra are not consistent with geographical locations. Hence, local calibrations have to be developed for each geographic region of the state. In this context, the present study is carried out to examine the usefulness of laboratory Vis-NIR spectral data in the estimation of hydraulic parameters by different statistical techniques in semi-arid region of northern Karnataka plateau. Successful spectral prediction models would enable produce accurate available water content maps of the area for better soil management practices.

2. Materials and methods

2.1. Study area

The present study of estimating soil hydraulic properties was carried out in part of the northern Karnataka plateau region (Fig. 1). The topographic variations of the northern Karnataka plateau ranged between 300 and 600 m with sporadic hills. The substantial area is underlined by basalts with a continuation of Deccan trap of Maharashtra. This region experiencing hot semi-arid climate with average an annual rainfall of 712 mm. The major soils are represented by shallow to deep black soils, red loam soils, red clay soils, alluvio-colluvial soils and laterite gravelly soil. Based on agroecological sub-regions of India, the study area has a length of growing period of 90–120 days. Rainfed crops like sorghum, pigeon pea and pearl millet are the predominant crops in this region.

2.2. Datasets used for the study

Soil samples collected under SUJALA III project (Hegde et al., 2018) (www.http://watershed.kar.nic.in/SujalaIII_Doc.htm) were used for this study. Soil profiles were located based on the soil-landform and land use relationship and dug up to 2 m or depth limited by rock. From each profile, horizon-wise soil samples were collected for analysis. Totally 558 soil samples were collected and the samples were analysed at ICAR-National Bureau of Soil Survey and Land Use Planning as per standard protocol. FC and PWP were measured in the laboratory using pressure plate apparatus. The saturated soil samples were placed in the pressure plate extractor and the pressure was applied at 0.03 and 1.5 MPa suction until water ceased to drain out for estimation of FC and PWP, respectively. Soil water content of each sample was determined gravimetrically based on wet and dry weight, which was obtained by placing samples in an oven heated to 105 °C.

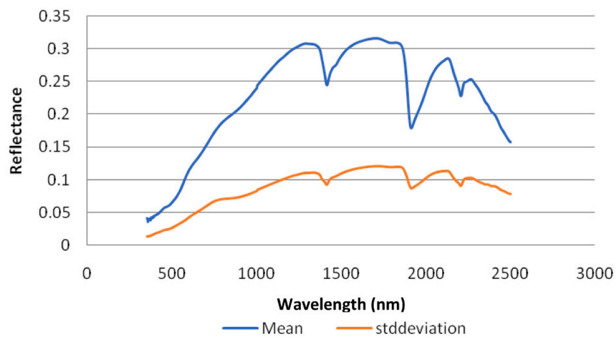

Fig. 2. Distribution of spectral reflectance (mean and standard deviation) of soils of Northern Karnataka Plateau ($N = 558$).

Table 1
Statistics of field capacity and permanent wilting point in Northern Karnataka Plateau ($N = 558$).

Statistics	FC (%)	PWP (%)
Mean	29.83	18.88
Max	67.57	43.73
Min	0.92	3.15
SD	13.05	10.52
Kurtosis	−0.68	−0.79
Skewness	0.18	0.35
CV(%)	43.74	55.72

2.3. Spectral data acquisition

Soil spectral data was developed using an ASD Field Spec spectroradiometer. The ASD FieldSpec used a flexible fibre optic cable fed through a Pistol grip for easy pointing and recording. Processed soil samples were illuminated using four tungsten quartz halogen lamps set at 36° angles within the laboratory environment. The soil spectral reflectance was recorded for the wavelength range of Visible and NIR bands from 350 to 2500 nm. A white reference measurement was made for every 5 samples using a piece of Spectralon. For each sample, the reflectance spectra were recorded for three times and the middle one was used for the prediction of soil hydraulic properties. Mean spectral reflectance of Northern Karnataka Plateau soils are presented in Fig. 2.

2.4. Spectroscopic modelling

To predict field capacity and permanent wilting point, three data mining algorithms (support vector machine, random forest and partial least square regression model) were evaluated. The support vector machine (SVM) is a technique based on statistical learning theory which generates optimal separating hyperplane to segregate the overlapping classes which are not possible in a linear analysis. In regression analysis, SVM finds the best fit in the feature space and uses a loss function to find the regression line which minimizes model errors. The best separating hyperplane can be found by solving a nonlinear convex problem that depends on a cost parameter C. The SVM model available in the R package “e1071” was used for prediction (Meyer et al., 2017) and “tune ()” function was used for optimization of hyperparameters. Linear kernel was set and ten values ranging between 0 and 5 were tested for C, and the optimal value was defined for the best overall accuracy obtained when performing a 10-fold cross-validation on the training dataset. Random forest model (RFM) works based on the assemblage of regression and classification trees by means of two levels of randomization for each tree in the forest (Breiman, 2001). Three important parameters used to determine the size and fitting of Random forests are number of tree (ntree), minimum no of samples at terminal node (nmin) and number of predictors. RandomForest 4.6 package was used for prediction. Using trial-and-error method RF parameters were optimized and ntree of 1000 and mtry of 7 were used for the final model. Partial least square regression (PLSR) model is one of the model, widely used to establish the relationship between spectral data and soil properties. PLSR was implemented using pls package in R environment and PLSR factors were constructed using leave-one-out cross-validation (Gomez et al., 2008a, 2008b).

The datasets were segregated randomly into 2/3rd of datasets for calibration (368 samples) and 1/3rd of datasets for validation (190 samples). The performance of models was evaluated for validation datasets (50 iterations) using classical indicators such as coefficient of determination (R^2), root mean square error (RMSE), mean error (ME), concordance correlation coefficient (CCC) and Ratio of performance to deviation.

Table 2
Statistics of field capacity and permanent wilting point in different soil order of Northern Karnataka Plateau.

Statistics	Alfisols (129)		Vertisols (144)		Inceptisols (153)		Entisols (31)	
	FC (%)	PWP (%)	FC (%)	PWP (%)	FC (%)	PWP (%)	FC (%)	PWP (%)
Mean	22.5	13.7	42.7	30.3	32.0	19.3	19.3	11.5
Max	44.7	24.4	61.5	42.8	67.6	43.7	41.7	32.5
Min	3.9	1.0	27.2	16.5	6.3	2.4	3.1	0.9
SD	8.1	6.0	7.5	6.6	12.8	9.8	11.0	8.5
CV(%)	35.7	44.3	17.5	21.8	39.8	51.0	57.0	74.0

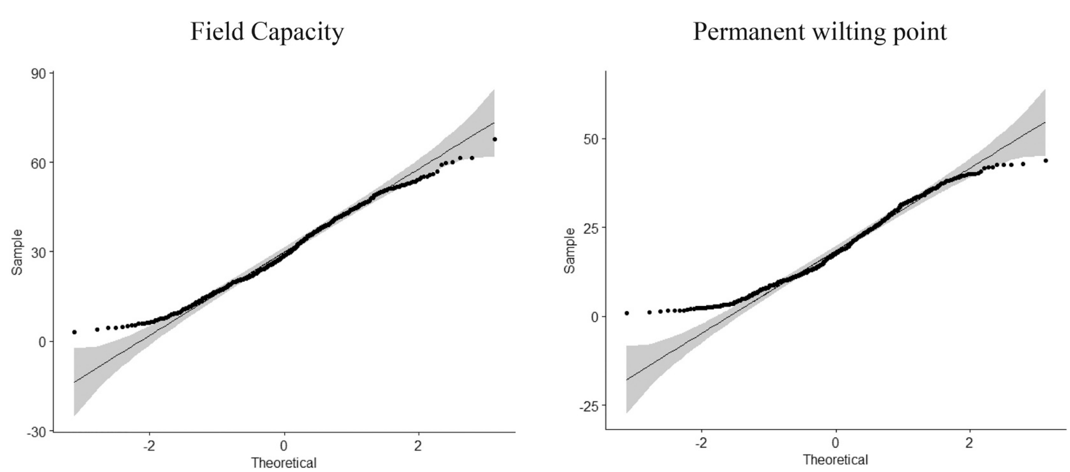

Fig. 3. Q-Q plots of field capacity and permanent wilting point.

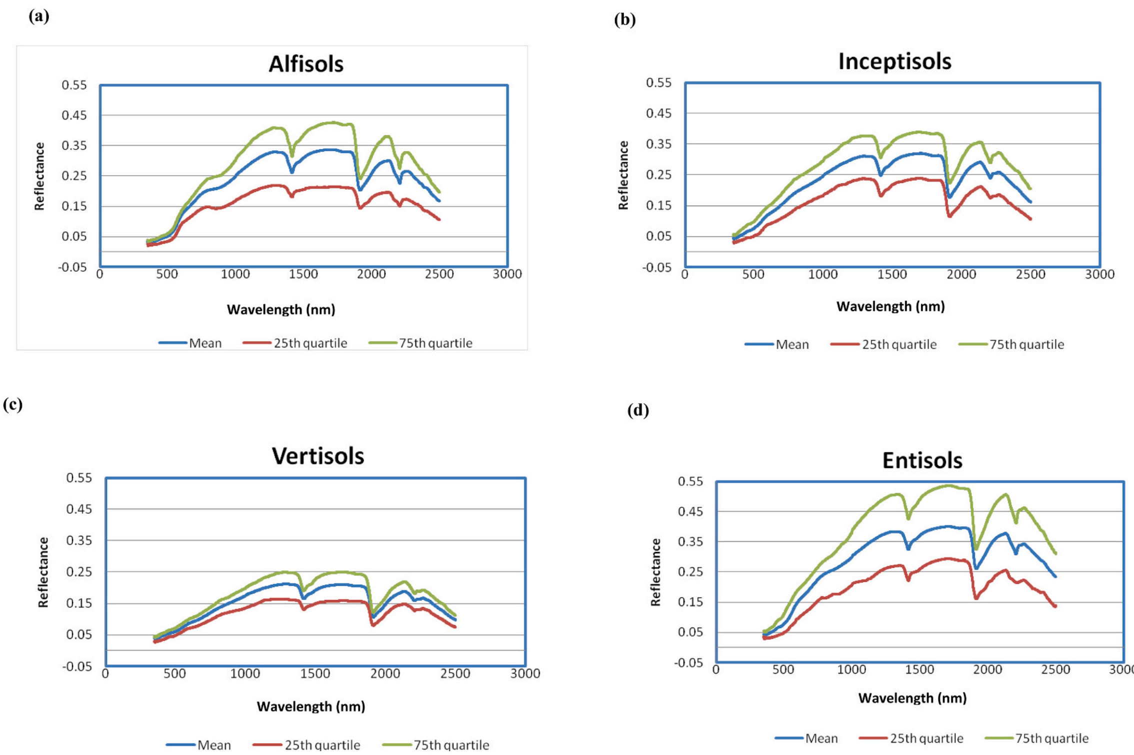

Fig. 4. Distribution of spectral reflectance in different orders of study area (a) Alfisols, (b) Inceptisols, (c), Vertisols, (d), Entisols.

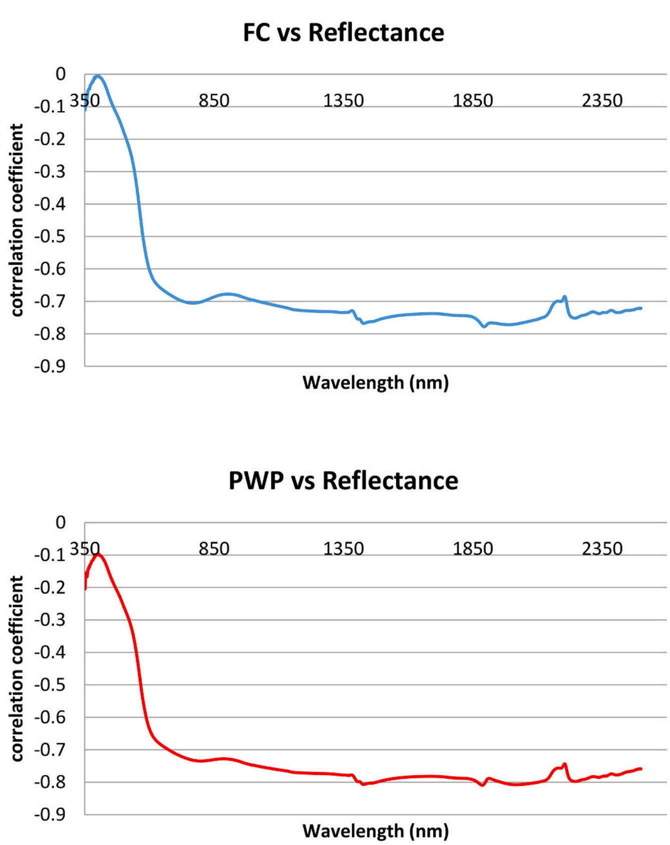

Fig. 5. Correlation coefficients between FC, PWP and spectral reflectance at different wavelengths.

$$R2 = 1 - \frac{\sum_{i=1}^{n}(pi - oi)^2}{\sum_{i=1}^{n}(oi - \overline{oi})^2}$$

$$ME = \frac{1}{n}\sum_{i=1}^{n}(oi - pi)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(oi - pi)^2}$$

Where, pi and oi are predicted and observed values, $\overline{pi}$ and $\overline{oi}$are means of predicted and observed values.

$$CCC = \frac{2\rho\sigma_0\sigma_p}{\sigma_{0+}^2\sigma_p^2 + (\mu_0 - \mu_p)^{2.}}$$

μ_0 and $\mu_p$are the means of observed and predicted values and $\sigma_0{}^2$*and* $\sigma_p{}^2$are corresponding variance ρ is pearson correlation coefficient between observed and predicted values.

$$\text{Ratio of performance to deviation (RPD)} = \frac{SD}{RMSE}$$

where SD is the standard deviation of observed values. Dunn et al. (2002) suggested the following limits for RPD for estimating soil properties using Vis-NIR spectroscopy viz. RPD < 1.6 poor, 1.6–2.0 acceptable, RPD > 2.0 excellent.

3. Results and discussion

3.1. Statistics of soil properties

The summary statistics of FC and PWP are presented in Table 1. FC varied from 0.92 to 67.57%, with a mean of 29.83% and PWP varied from 3.15 to 43.73% with a mean 18.88%. PWP has registered high coefficient of variation compared to FC. Both FC and PWP have positive

Table 3
Performance of models for prediction of FC and PWP in Northern Karnataka Plateau (50 iterations).

Properties	FC					PWP				
	R^2	CCC	RMSE	Bias	RPD	R^2	CCC	RMSE	Bias	RPD
RF	0.69 (0.03)	0.81 (0.02)	7.29 (0.47)	0.01 (0.63)	1.8 (0.12)	0.74 (0.03)	0.84 (0.02)	5.47 (0.31)	−0.03 (0.39)	1.93 (0.11)
SVM	0.68 (0.03)	0.80 (0.01)	7.34 (0.44)	−0.35 (0.49)	1.78 (0.11)	0.73 (0.04)	0.84 (0.02)	5.49 (0.28)	−0.18 (0.47)	1.92 (0.09)
PLSR	0.66 (0.04)	0.79 (0.02)	7.57 (0.42)	−0.01 (0.65)	1.72 (0.10)	0.70 (0.03)	0.82 (0.02)	5.80 (0.32)	−0.01 (0.45)	1.81 (0.10)

Standard deviation in parenthesis

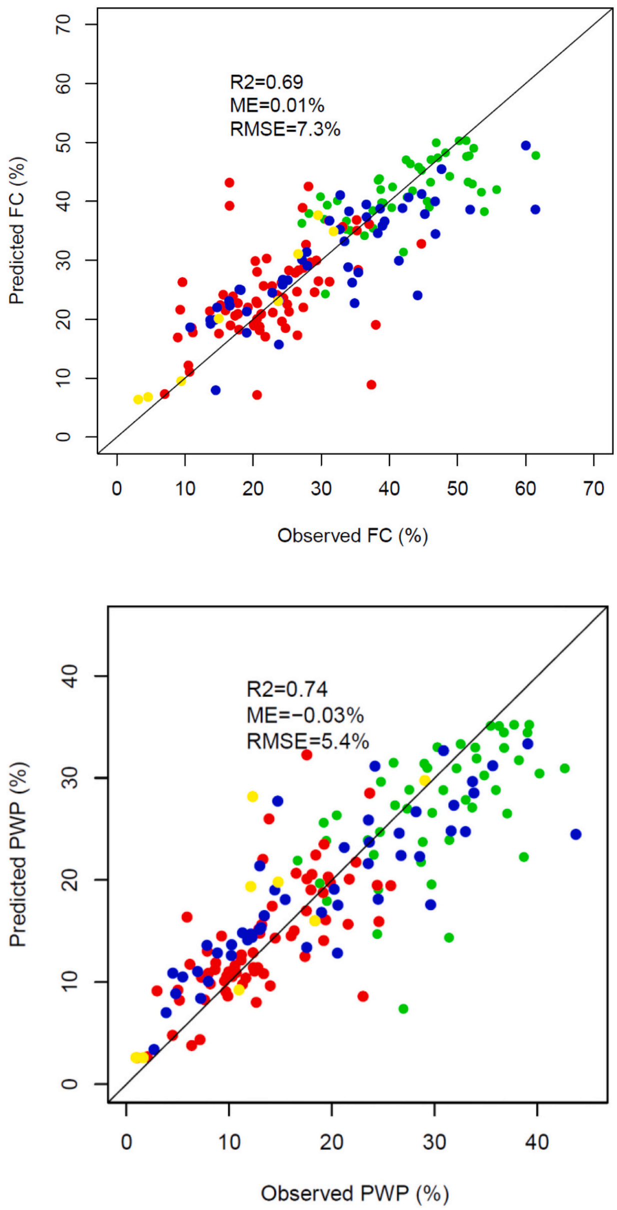

Fig. 6. Scatter plots of predicted versus observed FC and PWP for validation datasets using RF method (Vertisols- green points, Alfisols-red points, Inceptisols-blue points, Entisols-yellow points).

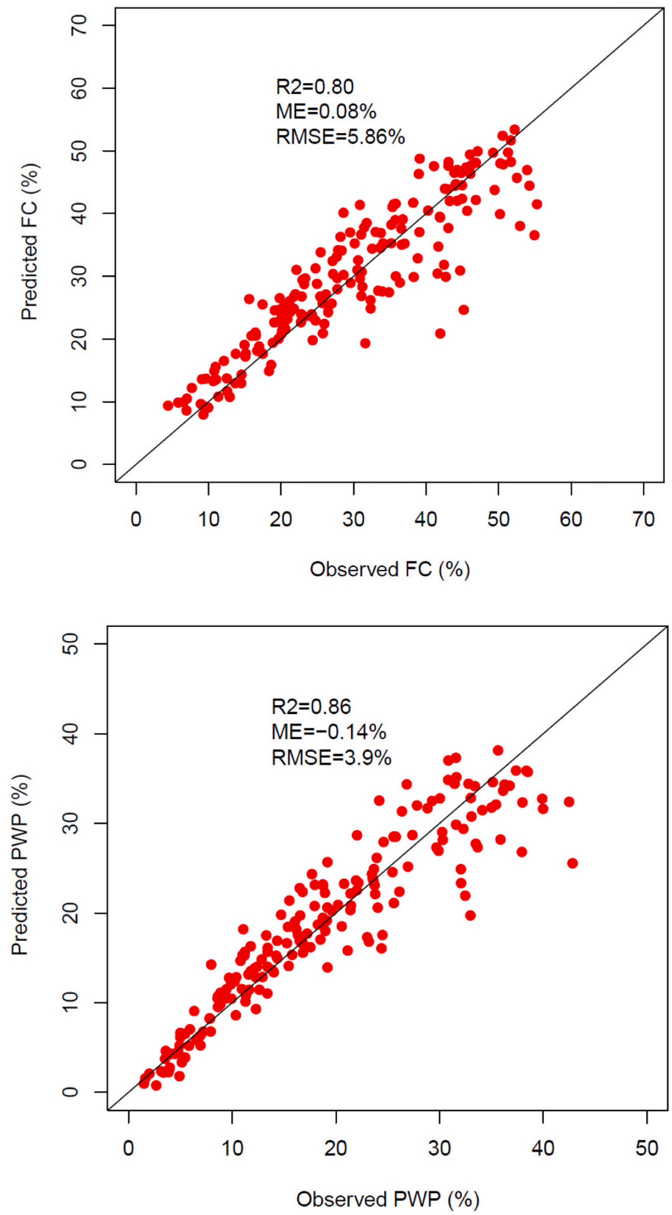

Fig. 7. Performance of conventional PTFs in predicting water content at Field capacity and Permanent wilting point for validation datasets.

skewness and negative kurtosis. Normality of FC and PWP were also checked using quantile-quantile plot (Q-Q plots) and the results showed that both FC and PWP were approximately normally distributed (Fig. 3). Among the dominant soil orders in the study area, Vertisols have higher mean FC (42.7%) and PWP (30.3%) and Entisols have lower mean FC (19.3%) and PWP (11.5%). Entisols have high variability of both FC and PWP followed by Inceptisols and Alfisols (Table 2). Fig. 2 explains the strong absorption features of OH functional group of free water near 1400, 1900 nm and directly related to the soil water content (Stenberg et al., 2010). Distribution of spectral reflectance in different orders of the study area is presented in Fig. 4. Spectral curves indicated that soils with higher FC and PWP have lower reflectance values and those with lower FC and PWP have higher reflectance values throughout the spectral region (350–2500 nm). Reduced reflectance intensity of soils might be attributed to increase in matric potential which is in agreement with

Table 4
Performance of RF model for prediction of FC and PWP in different soil orders of Northern Karnataka Plateau (50 iterations).

Soil order	FC					PWP				
	R^2	CCC	RMSE	Bias	RPD	R^2	CCC	RMSE	bias	RPD
Alfisols (129)	0.44 (0.09)	0.60 (0.06)	5.85 (0.56)	−0.08 (0.77)	1.40 (0.14)	0.52 (0.05)	0.67 (0.03)	4.09 (0.47)	−0.03 (0.43)	1.49 (0.17)
Vertisols (144)	0.34 (0.08)	0.48 (0.06)	6.13 (0.42)	0.04 (0.68)	1.23 (0.09)	0.42 (0.10)	0.55 (0.06)	5.10 (0.38)	−0.02 (0.66)	1.30 (0.10)
Inceptisols (153)	0.55 (0.09)	0.68 (0.06)	8.73 (0.94)	0.02 (1.12)	1.48 (0.16)	0.65 (0.09)	0.77 (0.06)	5.80 (0.71)	−0.01 (0.90)	1.71 (0.21)
Entisols (31)	0.83 (0.09)	0.77 (0.05)	4.81 (1.37)	0.53 (1.86)	2.28 (0.85)	0.76 (0.13)	0.72 (0.08)	4.28 (1.51)	−0.35 (1.25)	2.29 (0.95)

Standard deviation in parenthesis

previous studies (Zhu et al., 2010; Knadel et al., 2014). The inverse relationship of soil moisture (hydraulic properties) and spectral reflectance was reconfirmed with the negative correlation coefficient (FC: −0.005 to −0.79 and PWP: −0.09 to −0.81) (Fig. 5).

3.2. Prediction of hydraulic properties from spectral data

Field capacity and permanent wilting point were predicted using Vis-NIR spectral data and the results were presented in Table 3. A higher explained variance (R^2) indicates a better fit between the measured value and predicted value, while lower RMSE indicates better prediction accuracy. The validation results showed that the present models explained 66–69% of the variation for prediction of FC with the RMSE of 7.29–7.57% and 70–74% of the variation for prediction of PWP with the RMSE of 5.47–5.80%. RF recorded the highest RPD for both FC (1.8) and PWP (1.93). Similar accuracy was obtained in several studies using various models. Arslan et al. (2014) used PLSR model using 305 soil spectra and recorded better results for prediction of FC (R^2 = 0.77; RMSE = 5.24%, RPD = 1.81) and PWP (R^2 = 0.78; RMSE = 3.87%, RPD = 2.0). Leone et al. (2019) used Vis-NIR for the prediction of FC and PWP using PLSR model and estimated the FC and PWP with R^2 of 0.8 and 0.81 and RPD of 2.05 and 2.18, respectively. Viscarra Rossel and Webster (2012) employed Cubist model to predict FC (RPD = 1.68) and PWP (RPD = 1.95) based on spectral data from the Australian soil spectral library. Recently Blaschek et al. (2019) used PLS-SVM prediction model for prediction of PWP and FC and recorded RMSE = 4.41 and 6.68%, R^2 = 0.78 and 0.70, RPD = 2.12 and 1.81, respectively. Similarly, Mashalaba et al. (2020) used random forest algorithm to predict soil-water retention characteristics in rainfed vineyards of central Chile and captured variability of 40–54% for FC and 48–57% for PWP at different depth ranges.

3.3. Comparison with conventional pedotransfer function

Pedotransfer function (PTF) was developed using multiple linear regression model for prediction of FC and PWP. The model was calibrated using 2/3 of samples and validated using 1/3 of samples. PTFs were developed using clay, CEC, silt and organic carbon and obtained an accuracy of 80% (RMSE = 5.86%) and 86% (RMSE = 3.99%) for the prediction of FC and PWP, respectively (Fig. 7). Though the present results from spectral data are slightly lesser than PTFs, by considering the time and cost involved in laboratory measurements of particle size distribution and CEC to develop PTFs, prediction based on VIS-NIR spectroscopy is highly useful for rapid estimation of soil hydraulic properties.

3.4. Performance of different models

Among the models, RF and SVM slightly performed well for the prediction of FC and PWP compared to PLSR. RF recorded the highest explained variance (R^2 = 0.69) with RMSE of 7.29% and CCC of 0.81 for the prediction of FC (Fig. 6). RF and SVM performed better for prediction of PWP (R^2 = 0.74 and 0.73) compared to PLSR model (R^2 = 0.70). Unlike machine learning algorithms, PLSR modelling is not accounting nonlinear relationship between spectral data and dependent variables (Chauchard et al., 2004; Araújo et al., 2014). In addition, machine learning techniques such as RF and SVM are capable to make very efficient spectral variable selection (Morellos et al., 2016) compared to PLSR. Viscarra Rossel and Behrens (2010) reported that compared to PLSR, SVM produced the smallest RMSE values for predictions of the soil organic carbon, clay content and pH using all Vis–NIR wavelengths. Ghasemi and Tavakoli (2013) studied the performance of the RF algorithm on the spectroscopic data with PLSR and nonlinear SVM and concluded that RF performed well and has potential for modelling linear and nonlinear multivariate calibration.

3.5. Performance of the RF model across soil orders

Random forest model was employed to predict FC and PWP for the most abundant soil order of the study area namely Alfisols, Vertisols, Inceptisols and Entisols. The results showed (Table 4) that both FC and PWP were poorly predicted in Vertisols (R^2 = 0.34 and 0.42 for FC and PWP) when compared to Alfisols (R^2 = 0.44 and 0.52 for FC and PWP) and Inceptisols (0.55 and 0.65 for FC and PWP). Intensity of spectral reflectance influences the prediction accuracy. The poor prediction of hydraulic properties in Vertisols might be due to decreased reflectance of increased finer particles which can retain more water (Santra et al., 2009). Entisols were better predicted with R^2 = 0.83 and R^2 = 0.76 for FC and PWP, respectively with excellent RPD (>2.0). Compared to other soil orders, Entisols have large amount variability for FC (CV of 57%) and PWP (CV of 74%). The spectral reflectance of Entisols recorded was more than Vertisols due to its brightness and comparatively lesser available water content than Vertisols. The model poorly predicted the soils with the highest FC and PWP values. Vertisols have high capacity of water retention due to increased specific surface areas of clay particles. The dominance of 2:1 clay minerals in Vertisols could increase the attraction of water molecules and absorption near 1400 and 1900 nm with increasing clay content. Similar observation was found by Knadel et al. (2018) in air-dried Lerbjerg soil. Further, Vertisols also more likely to have conventional lab analysis errors due to their specific characteristics. Therefore, the measured values for Vertisols are likely to have a larger uncertainty compared to other soil orders.

4. Conclusions

In the present study, we evaluated three models (support vector machine, random forest and partial least square regression) for the prediction of FC and PWP using Vis-NIR spectral data. Random forest model performed well for prediction of both FC (0.69) and PWP (0.74). Hydraulic properties in Vertisols were poorly predicted by Vis-NIR spectra (R^2 = 0.34–0.42) compared to other soils. Overall, the results are comparable to conventional PTFs developed by easily measurable soil properties. The outputs can be used for running various simulation models for assessing crop growth and also provide the opportunity to develop high-resolution maps of hydraulic properties for sustainable soil management and irrigation planning.

Declaration of Competing Interest

None.

Acknowledgements

Authors thank Karnataka Watershed Development Department and World Bank for funding the Sujala III project. The authors thank ATCHA, ANR-16-CE03-0006 project for providing spectroradiometer for recording spectral data. The authors also acknowledge Dr. Laurent Ruiz, Indo-French Cell for Water Sciences, Bangalore and Philippe Lagacherie, INRAE, UMR LISAH, Montpellier, France for their guidance in developing spectral library of Karnataka. The authors also thank Sebastien Troiano, from INRAE, UMR LISAH, for his help in setting up the lab-spectral Laboratory. The authors also thanks Dr. Arti Koyal, CTO, NBSS&LUP for helping in recording of spectral data.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.geodrs.2021.e00475.

References

Araújo, S.R., Wetterlind, J., Demattê, J.A.M., Stenberg, B., 2014. Improving the prediction performance of a large tropical Vis-NIR spectroscopic soil library from Brazil by clustering into smaller subsets or use of data mining calibration techniques. Eur. J. Soil Sci. 65, 718–729. https://doi.org/10.1111/ejss.12165.

Arnold, J.G., Fohrer, N., 2005. SWAT. 2000. Current capabilities and research opportunities in applied watershed modelling. Hydrol. Process. 19 (3), 563–572.

Arslan, H., Tasan, M., Yildirim, D., Koksal, E.S., Cemek, B., 2014. Predicting field capacity, wilting point, and the other physical properties of soils using hyper spectral reflectance spectroscopy: two different statistical approaches. Environ. Monit. Assess. 186, 5077–5088. https://doi.org/10.1007/s10661-014-3761-2.

Babaeian, E., Homaee, M., Montzka, C., Vereecken, H., Norouzi, A.A., van Genuchten, M. Th., 2016. Soil moisture prediction of bare soil profiles using diffuse spectral reflectance information and vadose zone flow modelling. Remote Sens. Environ. 187, 218–229. https://doi.org/10.1016/j.rse.2016.10.029.

Blaschek, M., Roudier, P., Poggio, M., Hedley, C.B., 2019. Prediction of soil available water-holding capacity from visible near-infrared reflectance spectra. Sci. Rep. 12833 https://doi.org/10.1038/s41598-019-49226-6.

Bouma, J., 2018. Comment on Minasny and Mc Bratney, 2017. Limited effect of organic matter on soil available water capacity. Eur. J. Soil Sci. 69, 154. https://doi.org/10.1111/ejss.12509.

Breiman, L., 2001. Random forests. Mach. Learn. https://doi.org/10.1023/A:1010933404324.

Brisson, N., Mary, B., Ripoche, D., H'el'ene, M., Ruget, F., Nicoullaud, B., Gate, P., Devienne-barret, F., Recous, S., Plenet, D., Cellier, P., Machet, J., Marc, J., Del'ecolle, R., 1998. STICS: a generic model for the simulation of crops and their water and nitrogen balances. 1. Theory and parameterization applied to wheat and corn. Agronomie 18 (5–6), 311–346.

Chauchard, F., Cogdill, R., Roussel, S., Roger, J.M., Bellon-Maurel, V., 2004. Application of LS-SVM to non-linear phenomena in NIR spectroscopy: development of a robust and portable sensor for acidity prediction in grapes. Chemom. Intell. Lab. Syst. 71, 141–150. https://doi.org/10.1016/j.chemolab.2004.01.003.

Conforti, M., Matteucci, G., Buttafuoco, G., 2018. Using laboratory Vis-NIR spectroscopy for monitoring some forest soil properties. J. Soils Sediments 18, 1009–1019. https://doi.org/10.1007/s11368-017-1766-5.

Dharumarajan, S., Hegde, R., Lalitha, M., Kalaiselvi, B., Singh, S.K., 2019. Pedotransfer functions for predicting soil hydraulic properties in semi-arid regions of Karnataka Plateau, India. Curr. Sci. 116 (7), 1237–1246. https://doi.org/10.18520/cs/v118/i5/771-777.

Dharumarajan, S., Hegde, R., Lalitha, M., Vasundhara, R., 2021. Predicting and mapping of soil hydraulic properties in Karnataka. J. Indian Soc. Remote Sens. https://doi.org/10.1007/s12524-021-01336-3.

Dunn, B.W., Beecher, H.G., Batten, G.D., Ciavarella, S., 2002. The potential of near-infrared reflectance spectroscopy for soil analysis—a case study from the Riverine Plain of south- eastern Australia. Aust. J. Exp. Agric. 42, 607–614. https://doi.org/10.1071/EA01172.

Ghasemi, J.B., Tavakoli, H., 2013. Application of random forest regression to spectral multivariate calibration. Anal. Methods 5, 1863–1871. https://doi.org/10.1039/c3ay26338j.

Gomez, C., Lagacherie, P., Coulouma, G., 2008a. Continuum removal versus PLSR method for clay and calcium carbonate content estimation from laboratory and airborne hyperspectral measurements. Geoderma 148, 141–148. https://doi.org/10.1016/j.geoderma.2008.09.016.

Gomez, C., Viscarra Rossel, R.A., Mcbratney, A.B., 2008b. Soil organic carbon prediction by hyperspectral remote sensing and field vis-NIR spectroscopy: an Australian case study. Geoderma 146 (3–4), 403–411. https://doi.org/10.1016/j.geoderma.2008.06.011.

Gulfo, E., Sahoo, R.N., Sharma, R.K., Khanna, M., 2012. Soil moisture assessment using hyperspectral remote sensing. In: Proceedings of the Second National Workshop on Challenges and Opportunities of Water Resources Management in Tana Basin, Upper Blue Nile Basin, Ethiopia. Blue Nile Water Institute, BahirDar University, Ethiopia, pp. 69–77.

Hegde, R., Niranjana, K.V., Srinivas, S., Danorkar, B.A., Singh, S.K., 2018. Site-specific land resource inventory for scientific planning of Sujala watersheds in Karnataka. Curr. Sci. 115 (4), 645–652. https://doi.org/10.18520/cs/v115/i4/644-652.

Hobley, E.U., Prater, I., 2019. Estimating soil texture from vis–NIR spectra. Eur. J. Soil Sci. 70, 83–95. https://doi.org/10.1111/ejss.12733.

Justin, G.K., Kumar, S., Arya Raj, A., 2020. Soil organic carbon prediction using visible–near infrared reflectance spectroscopy employing artificial neural network modeling. Curr. Sci. 119 (2), 377–381. https://doi.org/10.18520/cs/v119/i2/374-377.

Knadel, M., Deng, F., Alinejadian, A., Wollesen de Jonge, L., Moldrup, P., Greve, M.H., 2014. The effects of moisture conditions from wet to hyper dry on visible near-infrared spectra of Danish reference soils. Soil Sci. Soc. Am. J. 78, 422–433. https://doi.org/10.2136/sssaj2012.0401.

Knadel, M., Moldrup, P., Wollesen de Jonge, L., 2018. Visible-near-infrared spectroscopy prediction of soil characteristics as affected by soil-water content. Soil Sci. Soc. Am. J. https://doi.org/10.2136/sssaj2018.01.0052.

Lagacherie, P., Baret, F., Feret, J.B., Madeira Netto, J., Robbez-Masson, J.M., 2008. Estimation of soil clay and calcium carbonate using laboratory, field, and airborne hyperspectral measurements. Remote Sens. Environ. 112 (3), 825–835. https://doi.org/10.1016/j.rse.2007.06.014.

Leone, A.P., Leone, G., Leone, N., Galeone, C., Grilli, E., Orefice, N., Ancona, V., 2019. Capability of diffuse reflectance spectroscopy to predict soil water retention and related soil properties in an irrigated lowland district of southern Italy. Water 11, 1712. https://doi.org/10.3390/w11081712.

Mashalaba, L., Galleguillos, M., Seguel, O., Olivares, J.P., 2020. Predicting spatial variability of selected soil properties using digital soil mapping in a rainfed vineyard of Central Chile. Geoderma Reg. 22 https://doi.org/10.1016/j.egodrs.2020.e00289.

Meyer, D., Dimitriadou, E., Hornik, K., Andreas, W., Friedrich, L., 2017. E1071: Misc Functions of the Department of Statistics, Probability Theory Group (Formerly: E1071), tuwien, R package version 1.6–8. available at: https://CRAN.Rproject.org/package=e1071.

Morellos, A., Pantazi, X.-E., Moshou, D., Alexandridis, T., Whetton, R., Tziotzios, G., Wiebensohn, J., Bill, R., Mouazen, A.M., 2016. Machine learning based prediction of soil total nitrogen, organic carbon and moisture content by using VIS-NIR spectroscopy. Biosyst. Eng. 152, 104–116.

O'Leary, G.J., Li Liu, D., Ma, Y., Li, F.Y., McCaskill, M., Conyers, M., et al., 2016. Modelling soil organic carbon 1. Performance of APSIM crop and pasture modules against long-term experimental data. Geoderma 264, 227–237. https://doi.org/10.1016/j.geoderma.2015.11.004.

Patil, N.G., Singh, S.K., 2016. Pedotransfer functions for estimating soil hydraulic properties: a review. Pedosphere 26 (4), 417–430. https://doi.org/10.1016/S1002-0160(15)60054-6.

Pittaki-Chrysodonta, Z., Moldrup, P., Knadel, M., Iversen, B.V., Hermansen, C., Greve, M. H., de Jonge, L.W., 2018. Predicting the campbell soil water retention function: comparing visible–near infrared spectroscopy with classical pedotransfer function. Vadose Zone J. 17, 1–12. https://doi.org/10.2136/vzj2017.09.0169.

Poggio, L., Gimona, A., Brown, I., Castellazzi, M., 2010. Soil available water capacity interpolation and spatial uncertainty modelling at multiple geographical extents. Geoderma 160 (2), 175–188. https://doi.org/10.1016/j.geoderma.2010.09.015.

Romano, N., Palladino, M., 2002. Prediction of soil water retention using soil physical data and terrain attributes. J. Hydrol. 265, 56–75. https://doi.org/10.1016/S0022-1694(02)00094-X.

Santra, P., Sahoo, R.N., Das, B.S., Samal, R.N., Pattanaik, A.K., Gupta, V.K., 2009. Estimation of soil hydraulic properties using proximal spectral reflectance in visible, near-infrared, and shortwave-infrared (VIS–NIR–SWIR) region. Geoderma 152, 338–349. https://doi.org/10.1016/j.geoderma.2009.07.001.

Santra, P., Kumar, M., Kumawat, R.N., Painuli, D.K., Hati, K.M., Heuvelink, G.B.M., Batjes, N.H., 2018. Pedotransfer functions to estimate soil water content at field capacity and permanent wilting point in hot Arid Western India. J. Earth Syst. Sci. 127 https://doi.org/10.1007/s12040-018-0937-0.

Sarathjith, M.C., Das, B.S., Wani, S.P., Sahrawat, K.L., Gupta, A., 2015. Comparison of data mining approaches for estimating soil nutrient contents using diffuse reflectance spectroscopy. Curr. Sci. 110, 25. https://doi.org/10.18520/cs/v110/i6/1031-1037.

Stenberg, B., Viscarra Rossel, R.A., Mouazen, A.M., Wetterlind, J., 2010. Visible and near infrared spectroscopy in soil science. In: Sparks, D.L. (Ed.), Advances in Agronomy, Vol. 107. Academic Press, Burlington, VT, USA, pp. 163–215.

Tetegan, M., Richer de Forges, A.C., Verbeque, B., Nicoullaud, B., Desbourdes, C., Bouthier, A., Arrouays, D., Cousin, I., 2015. The effect of soil stoniness on the estimation of water retention properties of soils: a case study from Central France. Catena 129, 95–102. https://doi.org/10.1016/j.catena.2015.03.008.

Viscarra Rossel, R.A., Behrens, T., 2010. Using data mining to model and interpret soil diffuse reflectance spectra. Geoderma 158, 46–54. https://doi.org/10.1016/j.geoderma.2009.12.025.

Viscarra Rossel, R.A., Webster, R., 2012. Predicting soil properties from the Australian soil visible–near infrared spectroscopic database. Eur. J. Soil Sci. 63, 848–860. https://doi.org/10.1111/j.1365-2389.2012.01495.x.

Zhu, Y., Weindorf, D.C., Chakraborty, S., Haggard, B., Johnson, S., Bakr, N., 2010. Characterizing surface soil water with field portable diffuse reflectance spectroscopy. J. Hydrol. 391, 133–140. https://doi.org/10.1016/j.jhydrol.2010.07.014.