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ABSTRACT: Cation exchange capacity (CEC) is an important soil property because it affects the assimilation of nutrients and buffers against soil acidification. Thus, knowledge of CEC is considered key to developing agricultural and environmental models for land management planning. However, in developing countries such as Sudan, there is a lack of soil CEC data due to the absence of research projects and funding to develop this information. Therefore, this research was conducted to predict CEC for large areas using specific soil physical characteristics, including soil texture and saturation percentage (SP), for which there is potentially available data. To achieve this goal, the properties of 430 soil samples (301 for training and 129 for validation) were obtained from the soil database of the Soil Survey Administration, Ministry of Agriculture, Sudan, which had different soil depth intervals (0–0.3 m, 0.3–0.6 m, 0.6–0.9 m, 0.9–1.5 m, and >1.5 m) from Entisols in the Northern State of Sudan. The data were stratified into homogeneous groups based on the textural classes of the main soil order. Then, regression models were performed and evaluated using the coefficient of determination (R^2), standard error of the estimate (SEE), and root mean square error (RMSE). The results indicated that in individual Entisols and textural classes, the combined soil covariates silt, clay, and SP were the best properties to predict CEC values (R^2 ranged from 0.86 to 0.99). The regression models did not provide statistically significant results for the silty clay loam textural class (R^2 ranged from 0.01 and 0.35). The findings of this modeling study could be applied to other Entisols worldwide with divergent textural classes, which could be used to verify the suggested CEC pedotransfer functions and/or improve them. This would help farmers correctly design soil management plans and prevent acidification issues if combined with other soil properties data.

KEYWORDS: soil quality, pedotransfer functions, land management, regression analysis, environmental modeling

TYPE: Article

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Introduction

Soil cation exchange capacity (CEC) is widely considered an important soil property and is used as an input variable in many agricultural and environmental models (da Silva et al., 2018; Keshavarzi et al., 2017; Liddicoat et al., 2018; Shiri et al., 2017; Sulieman et al., 2018). The CEC is commonly used as an indicator of soil quality (Golchin & Asgari, 2008; Swanepoel et al., 2015; Valle & Carrasco, 2018; Xu et al., 2006), nutrient retention (Mukhopadhyay et al., 2019), and the capacity to protect groundwater from contaminants, particularly cation contamination (Khaledian et al., 2017). It buffers fluctuations in soil pH and, therefore, nutrient availability (Hazelton & Murphy, 2016).

The determination of CEC in the laboratory is a painstaking and costly process because it involves saturation shaking and centrifugation of the soil suspension nine times before sodium can be accurately determined (Aladejana et al., 2018; Dohrmann, 2006). Thus, CEC modeling and prediction is a vital research topic, particularly in non-developed countries where nature-based solutions and agricultural management plans must be implemented due to rapid soil degradation, but information on CEC is lacking, and funds to obtain such information are extremely limited (Aladejana et al., 2018; Bajocco et al., 2018; Grinblat et al., 2015; Kouba et al., 2018; Tesfahunegn, 2019).

Several methods have been proposed to predict and quantify CEC from known soil properties. Many of these rely on statistical models, such as general linear models (Mishra et al., 2019; Sulieman et al., 2018), linear regression models (Seybold et al., 2005), a combination of principal components analysis with soil linear and regression models (Fox & Metla, 2005), fractal parameters using artificial neural networks (ANNs; Bayat et al., 2014), application of genetic expression programming (GEP) and multivariate adaptive regression splines (MARS) (Emamgolizadeh et al., 2015), a combination of adaptive neuro-fuzzy inference system (ANFIS) with data acquisition through remote sensing (Keshavarzi et al., 2017), and a mixture of ant colony organization algorithm and adaptive network-based fuzzy systems with multiple linear regression (Shekofteh et al., 2017). Soil data that have been used in these models include sand, silt, clay, organic carbon, pH, calcium carbonate equivalent (Khaledian et al., 2017), hyperspectral visible near-infrared (Vis–NIR) spectroscopy (Gogé et al., 2014; Gomez et al., 2012; Lu et al., 2013; Pirie et al., 2005; Rehman et al., 2019; Rossel & Webster, 2012; Ulusoy et al., 2016), apparent electrical conductivity as determined with the Veris-3100 (Koganti et al., 2017), and a combination of nuclear magnetic resonance (NMR), X-ray diffraction (XRD), and nitrogen adsorption–desorption isotherm analysis on clay minerals (Cheng & Heidari, 2018). Soil CEC has also been successfully quantified using Sentinel-2A (S2A) multispectral satellite images (Vaudour et al., 2019).

Among the various aforementioned statistical approaches, multiple regression (MR) methods have been widely applied to estimate soil CEC using different soil parameters, and their findings were highly accurate. For example, Kashi et al. (2014) employed MR to predict CEC using bulk density, soil texture, electrical conductivity, lime percentage, and sodium adsorption ratio (SAR) in soils of the Ghoshe Region in Semnan Province, Iran, and found that the performance of the model was very good ($R^2 = 0.77$; mean absolute error [MAE] = 1.85; root mean square error [RMSE] = 1.92 cmol + kg^{-1}). Likewise, Ghorbani et al. (2015) showed similar results when soil pH, soil organic carbon (SOC), and soil texture were used to predict CEC in soils of Golestan Province, Iran ($R^2 = 0.78$; MAE = 1.64; RMSE = 1.83 cmol + kg^{-1}). Seyedmohammadi et al. (2016) found that CEC was strongly correlated with clay and SOC contents ($R^2 = 0.77$) in the soils of Guilan province, northern Iran. Moreover, Olorunfemi et al. (2016) concluded that an MR model based on pH, clay content and SOC was the best one for predicting CEC in the forest soils of Nigeria ($R^2 = 0.71$; MAE = 1.16; RMSE = 1.39 cmol + kg^{-1}).

Several authors confirmed that soil texture can be a key property to model and predict CEC. Clay and decomposed organic matter (humus) are considered among the most important components that contribute to soil CEC variations, while silt has proven useful but to a lesser extent. Bayat et al. (2014), Khaledian et al. (2017), and Sulieman et al. (2018) mentioned that CEC was significantly positively influenced by clay content and negatively affected by sand content. Likewise, the saturation percentage (SP) is mainly determined by soil physical properties (Dane & Topp, 2002). Consequently, SP may also be used as a quantitative predictor of soil texture (Stiven & Khan, 1966), water-storage capacity, and CEC (Rodrigo-Comino et al., 2019). For instance, Aali et al. (2009) successfully used MR, ANNs, and ANFIS techniques with clay, silt, and organic carbon contents as independent variables to predict SP in the Boukan region in northwestern Iran.

In African countries, intensive agricultural activities (e.g., excessive fertilization, improper pesticide usage, and heavy machinery usage) are being expanded with new soils and lands brought into production annually (Thomas, 2008). In addition, due to political and armed conflicts, this expanded agricultural sector is becoming more relevant (Enaruvbe & Atafo, 2019; Enaruvbe et al., 2019). These lands are usually quite large in size, which means large numbers of soil samples will have to be collected to carry out traditional soil surveys and land evaluation (Mekonnen et al., 2016, 2017). One example of this expanding agricultural dynamic is in Northern Sudan (NS), which is in a desert agro-ecological zone (about 30% of the total country) characterized by scarce precipitation and consequently a lack of natural vegetation. Irrigated agricultural practices are commonly concentrated along the Nile River, and the region depends on dates palm and field crops, such as sorghum, maize, millet, wheat, barley, and pulses (Food and Agriculture Organization [FAO] and World Food Programme [WFP], 2011). The main soil orders in NS are Aridisols (along sand dunes) and Entisols (along the Nile River terraces), according to soil taxonomy (Soil Survey Staff, 2014a).

The importance of CEC in assessing soil quality and its potential for various land management systems under different soil types and climate conditions is broadly accepted (Aparicio & Costa, 2007; Biswas et al., 2017; Chaves et al., 2017; Marinari et al., 2006; Masto et al., 2009; Mukhopadhyay et al., 2019; Pulido et al., 2017; Wan et al., 2018; Zuber et al., 2017). Knowledge of CEC is becoming increasingly important in dry areas because they suffer from many problems such as a lack of sufficient water to support plant growth and land degradation. Given the lack of funding to conduct traditional laboratory CEC analyses, it is necessary to develop models to predict CEC in the soils of regions such as NS. Therefore, this study's goal was to (1) investigate linear (LR) and nonlinear (NLR) statistical models to predict CEC using clay, silt, and SP as covariates, (2) verify the validity of the soil CEC model(s), and (3) identify the most suitable properties for CEC prediction among the selected covariates.

Materials and Methods

Study area and soil sampling

The study area is located at 27° 30' 17.28'' to 27° 37' 44.04'' E longitude and 19° 21' 43.2'' to 19° 53' 19.32'' N latitude, which covers about 1,500 km^2 in the Northern State (NS) of Sudan. According to *Soil Taxonomy* (Soil Survey Staff, 2014a), the study area has aridic and hyperthermic soil moisture and temperature regimes, respectively. Soils of NS are mostly Entisols and Aridisols (Soil Survey Staff, 2014a). These soils have been classified down to the subgroup level (Ministry of Agriculture, 1997). The soils of the area can be divided into two major groups based on their origin: (1) sedentary (residual) soils, which occupy partially elevated sites that seem to have been affected by chemical weathering during a former period was wetter than the present climate. They are medium-textured soils of grayish and dark grayish color and (2) transported soils which resulted from weathering products transported into the area either by wind (aeolian) or water (fluvial processes). Therefore, these involve two types of soils: (1) soils formed by wind deposits which are sandy and characterized by low fertility, low water holding capacity, and high infiltration rates. These soils are classified as Psamments at the suborder level. (2) Soils formed by water deposits from the Nile River during exceptionally high floods or by khors and wadies of a former wetter climate. These soils are classified as Fluvents. The geographical locations of the selected representative profiles are shown in Figure 1. Natural vegetation in the NS consists

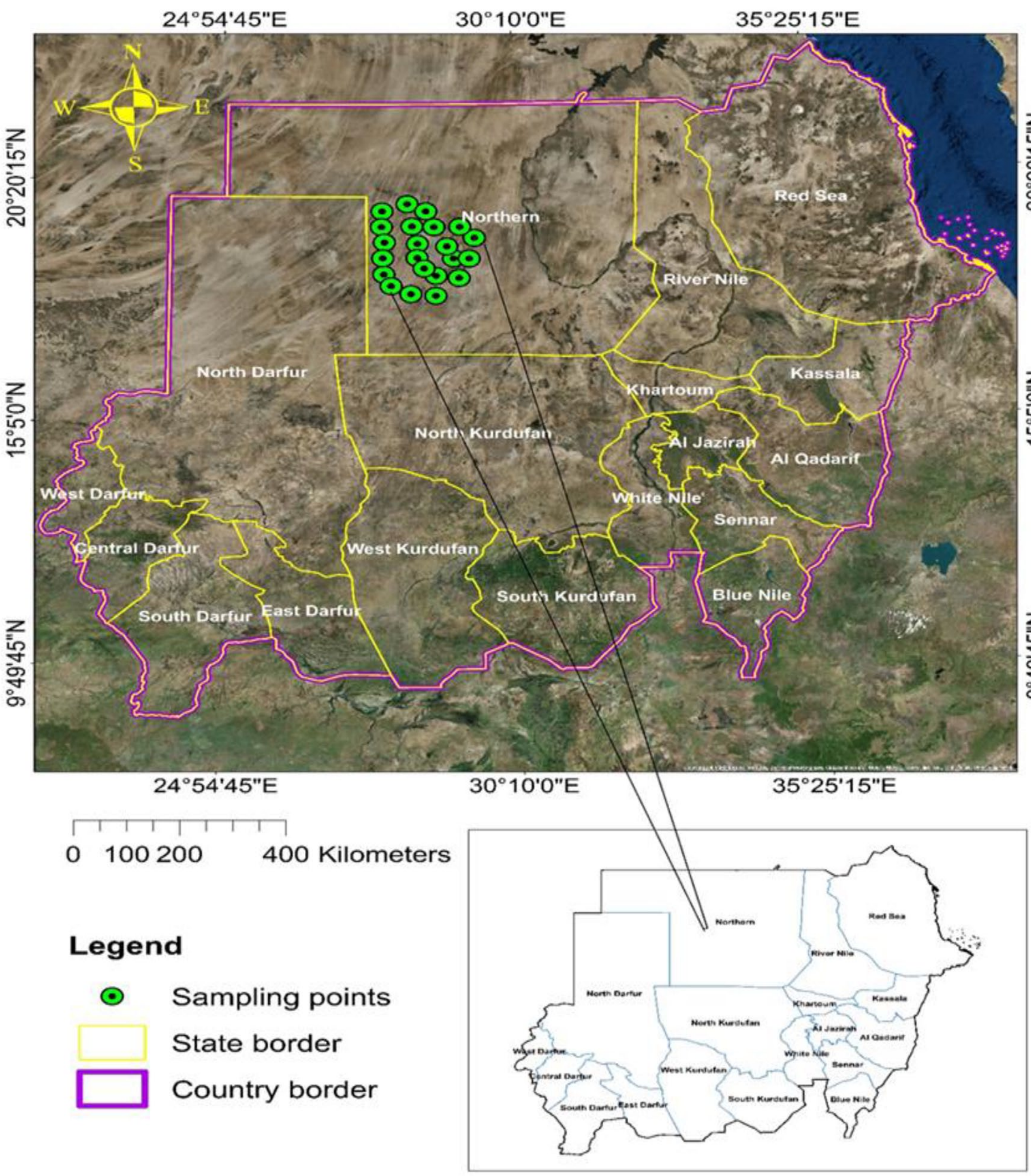

Figure 1. Study area and sampling points.

mainly of Acacia spp., mostly *Acacia ehrenbergiana*, along with others, such as *Leptadenia pyrotechnica*, *Balanites aegyptiaca* (L), and *Calotropis Procera*. A detailed soil survey was performed by the Soil Survey Administration (Ministry of Agriculture, 1997) to describe the morphological properties of the representative profiles including depth, color, structure, texture, gravels, consistence, the occurrence of nodules, and special features using the standard guidelines for soil profile description (Schoeneberger et al., 2012). The representative profiles were selected to cover all identified landform units in the area and the location of the soil profiles was recorded using a handheld global positioning system (GPS; Garmin Montana 680t). All profiles were excavated to the C horizon. At each profile site, soil samples were collected from five soil depth intervals with approximately 2–3 kg of soil material collected from each horizon.

Data source and extraction

Data from Part II (classification and correlation section) of the soil series of Sudan, provided by the Soil Survey Administration (Ministry of Agriculture, 1997), were used for this study. This database represents soil series from NS, River Nile State, and Khartoum State. The soil samples were collected from five standard depths: 0–0.3, 0.3–0.6, 0.6–0.9, 0.9–1.5, and >1.5 m. The data set contains complete soil properties including bulk density, SP, clay%, sand%, silt%, soil pH, ECe, exchangeable cations, $CaCO_3$, SAR, CEC, total organic carbon (TOC), total nitrogen, total phosphorus, and available macro- and micronutrients for 36 soil series of the Entisols, characterized by 430 soil samples (approximately 12 samples for each soil series).

Methods of analysis

The SP was calculated by the weight difference method, and particle size fractions were determined by the pipette method (Gee & Bauder, 2002). The CEC was determined with 1 M NH_4OAc at pH 7 (Soil Survey Staff, 2014b), Na^+ and K^+ concentrations were determined using a flame photometer (Jenway PFP7), and concentrations of Ca^{2+} and Mg^{2+} were determined by the titration method.

Statistical analysis

First, a bivariate linear correlation (Pearson) analysis was performed between CEC and the soil covariates at the order level (Entisols), and then split further into sub-orders based on the different textural classes of the main order. Based on the correlation results, only the variables that revealed significant differences at $p \leqslant 0.05$ were used in the regression equations to predict CEC. Following regression analysis, only the variables that yielded ⩾5% of the R^2 value in the regression models were used in the final regression models. Multiple linear and nonlinear regressions were used to establish the relationship between a dependent variable with the chosen independent variables.

$$y = a_0 + a_1x_1 + a_2x_2 + \cdots + a_nx_n \tag{1}$$

where y is the dependent variable; $a_1, a_2, \ldots, a_n$ are the regression coefficients; $x_1, x_2, \ldots, x_n$ are the independent variables.

All statistical analyses were performed using SPSS software, version 22 (IBM Corporation, 2012).

Testing the models' performance

The performance of all regression models was assessed using three common statistical standards: (1) coefficient of determination (R^2), (2) standard error of the estimate (SEE), and (3) RMSE. The SEE and RMSE were calculated from the differences between the predicted CEC values and measured values to determine the precision and bias of the prediction (Verfaillie et al., 2006). The three criteria above were calculated according to the following equations:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(pred_i - \overline{obs}\right)2}{\sum_{i=1}^{n}\left(obs_i - \overline{obs}\right)2} \tag{2}$$

$$\mathrm{SEE} = \frac{\sqrt{\sum\left(obs_i - pred_i\right)2}}{n} \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\sum^{n}\frac{\left(obs_i - pred_i\right)2}{n}} \tag{4}$$

where n is the number of points at ith site, obs is the determined CEC value, and $pred$ is the predicted CEC value from the regression models.

Results and Discussion

Regression of CEC for all soils in the Entisols

A summary of the descriptive statistics for the soil properties in the Entisols is shown in Table 1. There were high variations in CEC as indicated by the coefficient of variation (CV = 51.1%, Wilding, 1985). This was likely due to variation in the soil properties that control CEC (da Silva et al., 2018; Koganti et al., 2017), and clay had a similar CV (47.4%). Some of these soils were Fluvents formed along the river, and Fluvents often exhibit a wide textural range in their parent materials (Ahearn et al., 2005; Anderson, 1988; Cerdà, 1999; Challa et al., 2008; Martínez-Hernández et al., 2017). The correlation results for the Entisols (Table 2) showed highly positive CEC relationships with all different covariates (R^2 ranged from 0.71 to 0.98, significant at 0.01 level).

Table 3 shows the regression models, coefficient of determination (R^2), SEE, and RMSE for the CEC regressions using the covariates silt, clay, and SP; silt and clay; clay and SP; silt + clay; silt and SP; clay; and silt for the Entisols. All the equations were highly significant ($p > 0.001$). However, the R^2 value was highest and RMSE lowest for the regressions that used silt, clay, and SP to predict CEC. This indicates that CEC is affected by more than one factor. This result agrees with Asadu (1990), who reported that CEC could be predicted from soil organic matter (SOM) and clay content when grouped by taxonomic order (Inceptisols, Alfisols, Ultisols, and Oxisols), with this grouped order tending to reduce the variability in the soils. Drake and Motto (1982) noticed that the CEC prediction was improved when they grouped the soils based on their classification or district. This also agrees with Zeraatpisheh and Khormali (2012), who reported that about 96% of CEC variations were predicted by clay content, SOM content, and pH. Moreover, Khaledian et al. (2017) found that regression equations combining clay, silt, sand, pH, and organic carbon could explain 51%–93% of variations in CEC.

Using clay and silt to model CEC also gave high R^2 and low RMSE values, more or less equal to the regression that included all covariates (Table 3). This is different than the results of Krogh et al. (2000), who reported that approximately 90% of soil CEC variations could be explained by silt, clay, OC, and pH. The pH values of the soils in NS do not change much because of the high buffering capacity in these soils. Also, these soils are inherently low in SOM, rarely exceeding 0.5% (Sulieman et al., 2018). Khaledian et al. (2017) found that

Table 1. Summary for Descriptive Statistics of Measured Soil Properties for Entisols and Different Textural Classes.

GROUPS	SOIL PROPERTIES	MEAN	SD	SE	CV%	MINIMUM	MAXIMUM
Entisols (*n* = 301)	Silt (%)	14.76	10.74	2.80	72.75	0.00	59.00
	Clay (%)	21.85	10.36	2.22	47.40	1.00	50.00
	Silt + clay (%)	36.62	18.10	2.43	49.44	2.00	90.00
	SP	33.89	14.14	2.99	41.72	8.00	98.00
	CEC (cmol + kg^{-1})	20.90	10.68	2.34	51.11	3.00	54.00
Sandy clay loam (*n* = 126)	Silt (%)	13.65	2.32	0.31	17.00	10.00	20.00
	Clay (%)	25.65	3.43	0.46	13.37	20.00	33.00
	Silt + clay (%)	39.36	3.93	0.53	9.98	32.00	48.00
	SP	32.93	4.42	0.59	13.42	26.00	42.00
	CEC (cmol + kg^{-1})	23.33	3.17	0.43	13.59	18.00	30.00
Sandy loam (*n* = 101)	Silt (%)	11.84	4.89	0.80	41.30	6.00	29.00
	Clay (%)	15.57	2.35	0.39	14.45	12.0	25.00
	Silt + clay (%)	27.35	5.83	0.96	21.32	19.0	45.00
	SP	25.19	6.19	1.02	24.57	8.00	43.00
	CEC (cmol + kg^{-1})	14.46	3.09	0.51	21.44	11.0	25.00
Loamy sand (*n* = 53)	Silt (%)	7.55	2.59	0.77	33.64	4.00	10.00
	Clay (%)	7.91	2.47	.074	31.23	4.00	12.00
	Silt + clay (%)	15.55	2.07	0.62	13.31	12.0	18.00
	SP	26.73	6.18	1.86	23.12	19.0	37.00
	CEC (cmol + kg^{-1})	6.73	1.62	0.49	24.07	4.00	9.00
Clay (*n* = 7)	Silt (%)	19.00	5.10	1.93	26.79	15.00	30.00
	Clay (%)	45.00	3.13	1.84	7.43	41.00	50.00
	Silt + clay (%)	64.14	5.11	1.93	7.97	58.00	71.00
	SP	61.43	9.52	3.59	15.5	55.00	82.00
	CEC (cmol + kg^{-1})	44.71	4.86	1.84	10.85	40.00	54.00
Sandy (*n* = 7)	Silt (%)	2.86	1.57	0.59	55.08	0.00	4.00
	Clay (%)	3.57	1.72	0.65	48.11	1.00	6.00
	Silt + clay (%)	6.43	2.37	0.90	36.87	2.00	9.00
	SP	22.71	1.25	0.47	5.52	21.0	24.00
	CEC (cmol + kg^{-1})	5.00	1.91	0.72	38.30	3.00	8.00
Silty clay loam (*n* = 7)	Silt (%)	51.86	4.63	1.75	8.93	46.00	59.00
	Clay (%)	29.43	5.91	2.23	20.08	18.00	35.00
	Silt + clay (%)	81.29	8.26	3.12	10.16	64.00	90.00
	SP	60.14	6.91	2.61	10.99	49.00	72.00
	CEC (cmol + kg^{-1})	38.71	3.99	1.51	10.31	31.00	43.00

SD: standard deviation; SE: standard error; CV: coefficient of variation.

Table 2. Correlations (Pearson) for CEC with Studied Soil Covariates for All Entisols and the Different Textural Classes.

GROUPS	VARIABLES	SI, CL, AND SP	CL AND SP	CL	SI AND CL	SI	SI + CL	SI AND SP
Entisols		0.98**	0.96**	0.93**	0.98**	0.71**	0.94**	0.89**
Sandy clay loam		0.98**	0.98**	0.97**	0.98**	0.13ns	0.76**	0.98**
Sandy loam		0.92**	0.92**	0.39*	0.85**	0.84*	0.85**	0.87**
Loamy sand		0.97**	0.94**	0.88**	0.92**	0.70*	0.48ns	0.77**

Silt: Si; clay: Cl; SP: saturation percentage; ns: non-significant.
*Correlation is significant at the 0.05 level.
**Correlation is significant at the 0.01 level.

Table 3. Regression Equations for CEC with Different Soil Properties in the Entisols and Different Textural Classes.

SOIL ORDER	VARIABLES	PTF MODEL	R^2	SEE	RMSE (CMOL + KG^{-1})
Entisols (*n* = 301)	Silt, clay, SP	CEC = –2.29 + 0.22 silt + 0.77 clay + 0.09 SP***	0.96	2.18	2.21
	Silt, clay	CEC = –1.53 + 0.28 silt + 0.84 clay***	0.95	2.23	2.26
	Clay, SP	CEC = –3.08 + 0.73 clay + 0.24 SP***	0.94	2.66	2.72
	Silt + clay	CEC = 0.68 + 0.55 (silt + clay)***	0.88	3.54	3.74
	Silt, SP	CEC = –0.58 + 0.0.9 silt + 0.6 SP***	0.73	4.75	5.50
	Clay	CEC = –0.04 + 0.98 clay***	0.89	3.32	3.46
	Silt	CEC = 11.12 + 0.66 silt***	0.44	5.40	7.96
Sandy clay loam (*n* = 126)	Silt, clay, SP	CEC = –1.13 + (–0.06) silt + 0.09 clay + 0.63 SP***	0.96	0.61	0.62
	Silt, clay	CEC = 0.78 + (–0.03) silt + 0.89 clay***	0.94	0.66	0.66
	Clay, SP	CEC = 0.19 + 0.16 clay + 0.58 SP***	0.95	0.60	0.62
	Silt + clay	CEC = –1.36 + 0.63 (silt + clay)***	0.60	1.62	2.06
	Silt, SP	CEC = 1.21 + (–0.07) silt + 0.7 SP***	0.96	0.69	0.70
	Clay	CEC = 0.30 + 0.9 clay***	0.94	0.80	0.81
	Silt	CEC = 25.34 + (–0.15) silt	0.01	0.52	3.12
Sandy loam (*n* = 101)	Silt, clay, SP	CEC = –3.31 + 0.17 silt + 0.5 clay + 0.31 SP***	0.86	1.17	1.21
	Silt, clay	CEC = 4.6 + 0.51 silt + 0.24 clay***	0.75	1.46	1.63
	Clay, SP	CEC = –5.96 + 0.62 clay + 0.43 SP***	0.84	1.17	1.21
	Silt + Clay	CEC = 2.11 + 0.45 (silt + clay)***	0.72	1.38	1.64
	Silt, SP	CEC = 5.92 + 0.37 silt + 0.16 SP***	0.76	1.32	1.52
	Clay	CEC = 7.16 + 0.47 clay	0.13	1.04	2.82
	Silt	CEC = 8.11 + 0.54 silt***	0.72	1.51	1.67
Loamy sand (*n* = 53)	Silt, clay, SP	CEC = 2.05 + (–0.10) silt + 0.52 clay + 0.05 SP***	0.94	0.47	0.43
	Silt, clay	CEC = 3.13 + (–0.10) silt + 0.0.55 clay***	0.91	0.65	0.60
	Clay, SP	CEC = 0.74 + 0.59 clay + 0.05 SP***	0.93	0.56	0.52

(Continued)

Table 3. (Continued)

SOIL ORDER	VARIABLES	PTF MODEL	R^2	SEE	RMSE (CMOL + KG^{-1})
	Silt + clay	CEC = 3.22 + 0.22 (silt + clay)	0.08	0.47	1.38
	Silt, SP	CEC = 7.78 + (−0.42) silt + 0.08 SP*	0.60	0.90	1.00
	Clay	CEC = 1.83 + 0.62 clay***	0.89	0.75	0.74
	Silt	CEC = 10.15 + (−0.45) silt**	0.51	0.68	1.13
Clay (n = 7)	Silt, clay, SP	CEC = 41.77 + (0.76) silt + 0.51 clay + (−0.56) SP	1.00	4.34	3.63
	Silt, clay	CEC = 25.26 + (−0.24) silt + 0.53 clay**	0.99	4.70	3.92
	Clay, SP	CEC = 33.92 + (0.48) clay + (−0.18) SP**	0.96	4.56	3.79
	Silt + clay	CEC = 49.5 + (−0.07) (silt + clay)	0.12	5.35	4.49
	Silt, SP	CEC = 67.47 + (0.69) silt + (−0.58) SP	0.82	4.65	3.89
	Clay	CEC = 14.58 + (0.67) clay**	0.94	4.85	4.06
	Silt	CEC = 51.41 + (−0.35) silt	0.68	5.02	4.18
Sandy (n = 7)	Silt, clay, and SP	CEC = −24.64 + 0.38 silt + 0.45 clay + 1.19 SP	0.85	0.80	0.68
	Silt, clay	CEC = 2.35 + 0.53 silt + 0.32 clay	0.28	1.78	1.51
	Clay, SP	CEC = −25.29 + 0.47 clay + 1.26 SP	0.76	1.03	0.87
	Silt + clay	CEC = 2.33 + 0.42 (silt + clay)	0.26	1.80	1.52
	Silt, SP	CEC = −20.98 + (0.41) silt + 1.09 SP	0.70	1.16	0.98
	Clay	CEC = 3.79 + (0.34) clay	0.09	2.00	1.69
	Silt	CEC = 3.46 + (0.54) silt	0.20	1.88	1.59
Silty clay loam (n = 7)	Silt, clay, SP	CEC = −2.43 + 0.55 silt + 0.38 clay + 0.02 SP	0.35	1.27	1.10
	Silt, clay	CEC = −1.41 + 0.55 silt + 0.4 clay	0.24	1.27	1.09
	Clay, SP	CEC = 26.74 + 0.55 clay + (−0.07) SP	0.29	2.98	2.52
	Silt + clay	CEC = −1.47 + 0.45 (silt + clay)	0.01	1.38	3.79
	Silt, SP	CEC = −10.06 + 0.64 Silt + 0.26 SP	0.25	2.03	1.72
	Clay	CEC = 24.28 + 0.49 clay	0.18	3.00	2.53
	Silt	CEC = 4.62 + 0.66 silt	0.14	2.82	2.39

PTF: pedotransfer function; SEE: standard error of the estimate; RMSE: root mean square error; SP: saturation percentage; CEC: cation exchange capacity.
*Significant at 0.05 level.
**Significant at 0.01 level.
***Significant at 0.001 level.

SOM was not a significant factor determining CEC in soils with low SOM contents.

The regression model using just silt to determine CEC was also significant (R^2 = 0.44), which agreed with Morrás (1995), who reported that the silt fraction of two loess soils in the southern region of the Chaco Basin, Argentina, was responsible for between 1/6 and 1/3 of the total soil CEC. This also agreed with Turpault et al. (1996), who reported that clay could have coated the coarser particles and therefore transformed silt and sand into negatively charged particles. This could have been the reason that these fractions influenced CEC. The combination silt + clay also gave a significant regression with high R^2 and relatively low RMSE (Table 3).

Regression of CEC on the different textural classes in individual Entisols

Results of the general statistics for CEC and other soil variables of the different textural classes for Entisols are presented in Table 1. Medium and low variations in CEC values were indicated by the medium and low CV in all textured classes (CV = 10.31%–24.07%) except for sandy textured soils which showed high CEC variation (CV = 38.30%). Medium and low variation in CEC is likely due to medium and low variations in the soil properties used to predict CEC. Furthermore, CEC in sandy, loamy sand, and sandy loam was more variable (CV = 38.30%, 24.07%, and 21.44%, respectively) than in the sandy clay loam, clay, and silty clay loam (CV = 13.59%, 10.85%, and 10.31%, respectively) soils. The correlation results for the sandy clay loam, sandy loam, and loamy sand textural classes (Table 2) mostly revealed highly positive CEC relationships for all covariates with R^2 values that ranged from 0.77 to 0.98 (significant at 0.01 level). However, the CEC was not correlated with silt ($R^2 = 0.13$) or silt plus clay ($R^2 = 0.48$) in the sandy clay loam and loamy sand textural classes, respectively.

The coefficients of determination (R^2) of CEC regression on (silt, clay, and SP), (silt and clay), (clay and SP), (silt + clay), (silt and SP), (clay), and (silt) for the six different soil textural classes are given in Table 3. In general, for all soil textures, R^2 values were highest for the MRs for sandy clay loam, sandy loam, loamy sand, clay, and sand, respectively. This agreed with Ersahin et al. (2006), who reported that particle size distribution could estimate CEC and grouped textures from sandy loam to clay. The lowest R^2 value was obtained for silt clay loam ($R^2 = 0.35$) and was not significant ($p > 0.05$). The regression equations were highly significant ($p \leqslant 0.001$) to significant ($p \leqslant 0.01$) in all divisions except the regression using silt and SP for loamy sand, which was significant at ($p \leqslant 0.05$), and sandy and silty clay loam textural classes, which were not significant ($p \geqslant 0.05$).

Values for R^2 using clay content for all regressions of the clay and loamy sand textures were higher than for silty clay loam, sandy loam, and sand. However, sandy texture, as expected, had the lowest R^2 values. This could be associated with the influence of clay on CEC as compared to sand.

This agreed with Liddicoat et al. (2018), who established a pedotransfer function (PTF) to predict CEC in alluvial soils across multiple geochronological settings using clay content and SOM as soil covariates. Their results showed there was a direct relationship between these variables and soil CEC. Martel et al. (1978) also reported that fine clay and total clay content in lowland soils in Quebec were more highly related to CEC than to surface area and/or SOM content.

R^2 for the regression on silt were higher for sandy loam, clay and loamy sand compared to the R^2 values for clay, sand, and silty clay loam soil textures (Table 3). This could have been due to the high silt content, which gave it a high contribution to CEC compared to the other textural classes, which had lower values of R^2 due to a large amount of sand. This agreed with Curtin and Smillie (1981), who reported that silt significantly contributes to total CEC when its content is large relative to clay and sand content. This also coincides with McAleese and McConaghy (1957), Martini (1970), and Alxiades et al. (1973), who stated that silt and even sand could make a significant contribution to soil CEC. Lower values of R^2 were obtained for the regression equations of all multiple- and single-factor regressions (Table 3). However, this disagreed with Ersahin et al. (2006), who reported that particle size distribution could estimate CEC when grouped by textural class from sandy loam to clay. This finding also disagreed with Rashidi and Seilsepour (2008), who suggested using silt and clay to predict CEC. The equations may have failed to predict CEC due to the small sample size for silty clay loam.

Clay and silt gave high R^2 values that were more or less equal to the MRs for sandy clay loam, sandy loam, loamy sand, and clay textural classes in all Entisols. This coincided with Rashidi and Seilsepour (2008), who reported that silt and clay contents could significantly contribute to CEC prediction. Soil pH values in Sudan do not vary much because of the high buffering capacity in these soils (Sulieman et al., 2016, 2018; Sulieman & Ibrahim, 2013). In some textural classes (loamy sand, clay, sandy, and silty clay loam), the R^2 values using the silt plus clay regression were very low. The analysis of variance (ANOVA) test indicated that there was no significant difference between mean values of measured and predicted CEC. However, for the clay, sandy, and silty clay loam regressions, the equations were not suitable due to a low number of observations ($N = 7$). The PTF models that gave the best prediction of CEC for the studied soils are given in Table 4.

Performance of the models

Results of the prediction error indices (R^2, Adjusted R^2, and SEE) obtained from the validation of PTF-CEC models are shown using 129 samples for Entisols without textural classes partitions samples for sandy clay loam samples for sandy loam (Figure 2(a) to (g)), and 11 samples for loamy sand (Figure 3(a) to (g)) from the validation data set. For the Entisols (Figure 4), the best values were obtained when using a combination of silt, clay, and SP as covariates, Figure 4(a); $R^2 = 0.96$, R^2 adj. = 0.96, SEE = 2.18, and RMSE = 2.21 cmol + kg^{-1}, while silt alone (Figure 4(e)) gave the worst indices ($R^2 = 0.44$, R^2 adj. = 0.44, SEE = 5.4, and RMSE = 7.96 cmol + kg^{-1}). For the different textural classes (Figures 2, 3, and 5), the sandy clay loam using

Table 4. Multiple Regression Equations Suggested for Use to Predict CEC in the Entisols of Northern Sudan.

GROUP	BASES OF DIVISION	PTF MODEL	R^2	SEE	RMSE (CMOL + KG^{-1})
Soil order	Entisols	CEC = −2.29 + 0.22 silt + 0.77 clay + 0.09 SP ***	0.96	2.18	2.21
Textural classes	Sandy clay loam	CEC = −1.13 + (−0.06) silt + 0.09 clay + 0.63 SP ***	0.96	0.61	0.62
	Sandy loam	CEC = −3.31 + 0.17 silt + 0.5 clay + 0.31 SP ***	0.86	1.17	1.21
	Loamy sand	CEC = 2.05 + (−0.10) silt + 0.52 clay + 0.05 SP ***	0.94	0.47	0.43

PTF: pedotransfer function; SEE: standard error of the estimate; RMSE: root mean square error; SP: saturation percentage; CEC: cation exchange capacity.
*Significant at 0.05 level.
**Significant at 0.01 level.
***Significant at 0.001 level.

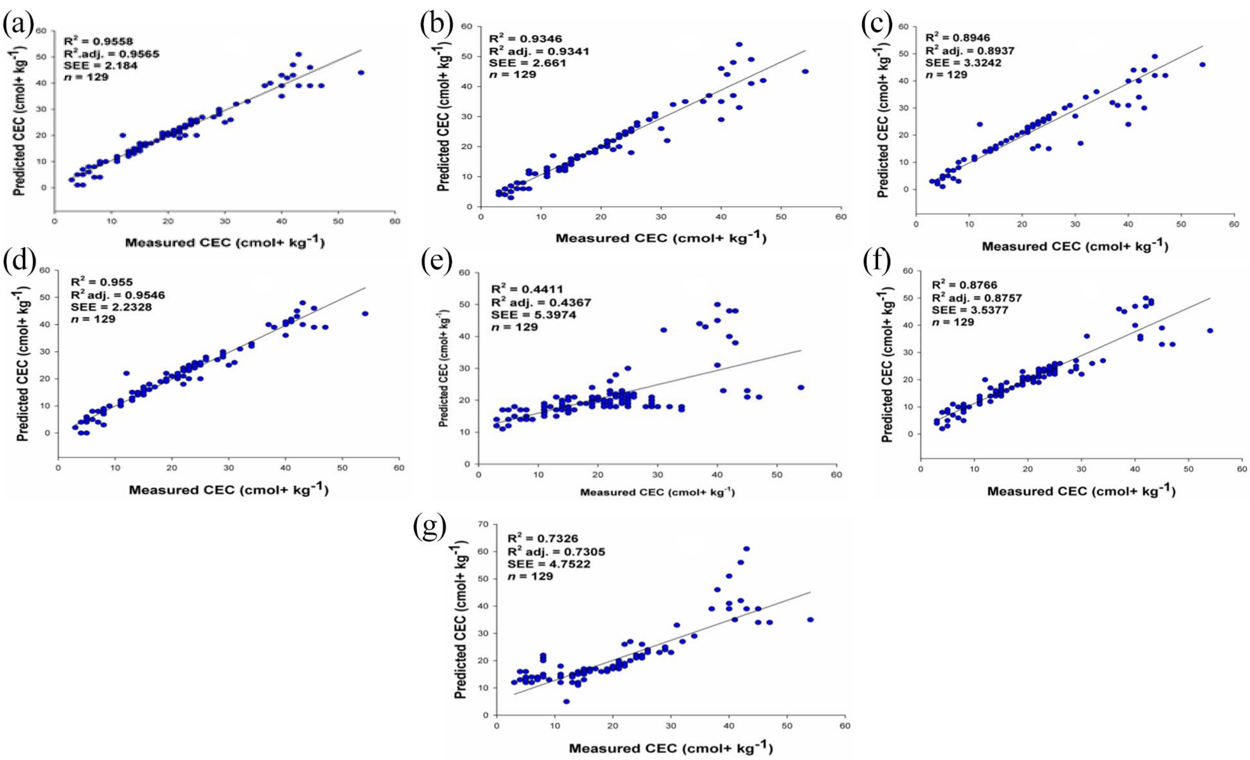

Figure 2. Predicted versus measured CEC for the sandy loam textural class of Entisols using (a) silt, clay, and SP, (b) clay and SP, (c) clay, (d) silt and clay, (e) silt, (f) silt + clay, and (g) silt and SP as covariates.

the covariates silt, clay, and SP (Figure 5(a)) had the best PTF fit with R^2 = 0.9617, R^2 adj. = 0.96, SEE = 0.61, and RMSE = 0.62 cmol + kg^{-1}. However, the sandy loam textural class with variable clay (Figure 2(c)) showed the worst indices (R^2 = 0.15, R^2 adj. = 0.12, SEE = 1.04, and RMSE = 3.79 cmol + kg^{-1}).

Conclusion

In this study, PTF models were established to predict soil CEC in the Entisols of NS, including their different common textural classes, to support future land management planning for cultivated and grazing areas in NS. The findings revealed that there are no significant differences between CEC measured and predicted using most of the studied equations. MRs gave the highest values of R^2 for all the Entisol textural variations; therefore, these equations are recommended for CEC prediction in the study area (Table 4). The results showed that silt and clay are very important factors for predicting CEC in these soils. Prediction of CEC using soil properties should be attempted for other soils in NS, particularly for the Vertisols of the central clay plain, mainly because these soils are the most extensive soils of agricultural significance in the country. Establishing practical PTF for predicting CEC would be efficient when time and cost are limiting. Consequently, the findings of this study will provide baseline for policymakers and farmers to estimate CEC accurately and adequately in time and helps to prescribe fertilizers. However, developing applicable PTF for a wide range of environmental and geographical regions, PTFs need to be verified in several similar and diverse regions.

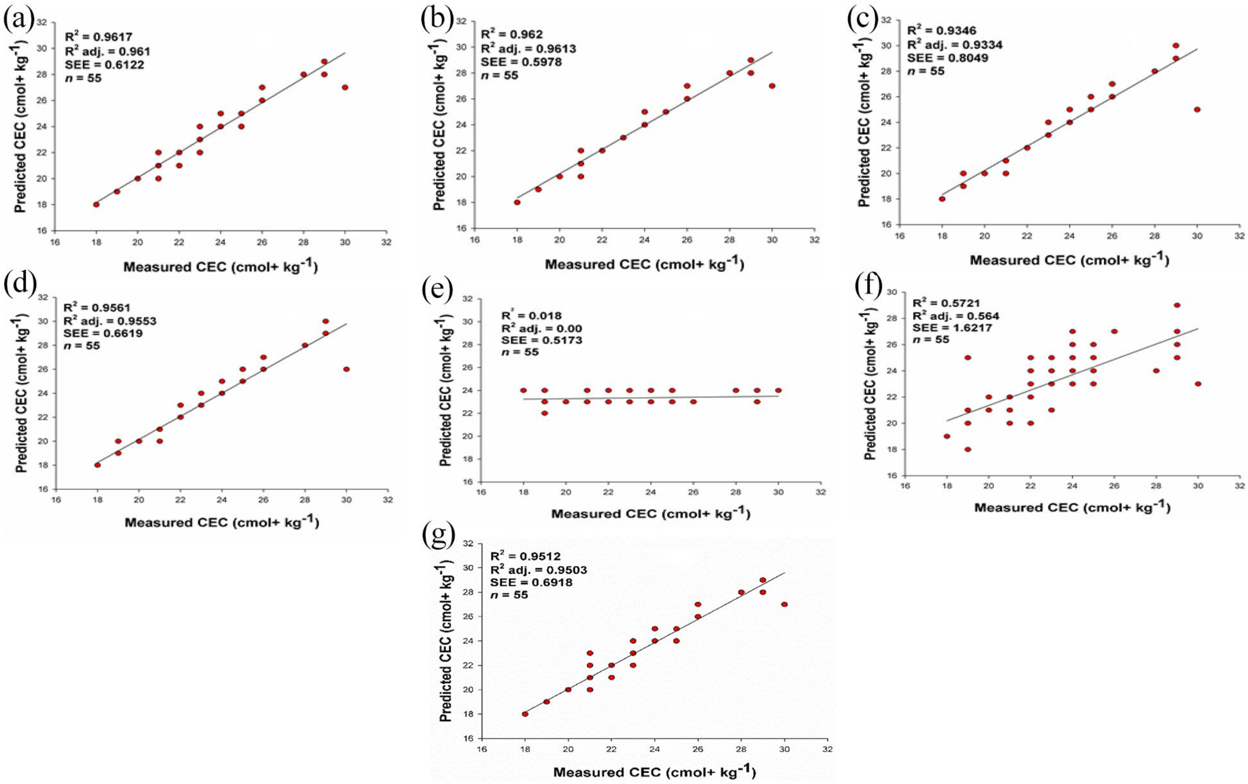

Figure 3. Predicted versus measured CEC for the loamy sand textural class of Entisols using (a) silt, clay, and SP, (b) clay and SP, (c) clay, (d) silt and clay, (e) silt, (f) silt + clay, and (g) silt and SP as covariates.

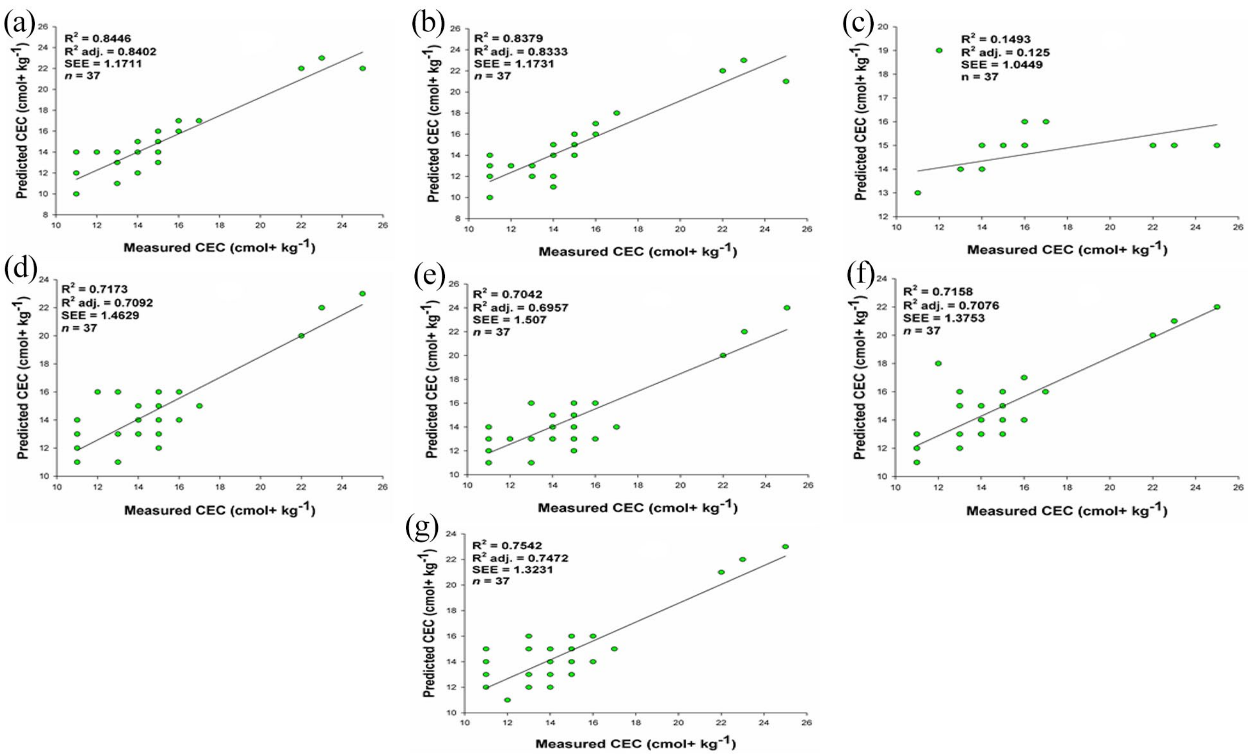

Figure 4. Predicted versus measured CEC for Entisols using (a) silt, clay, and SP, (b) clay and SP, (c) clay, (d) silt and clay, (e) silt (f) silt + clay, and (g) silt and SP as covariates.

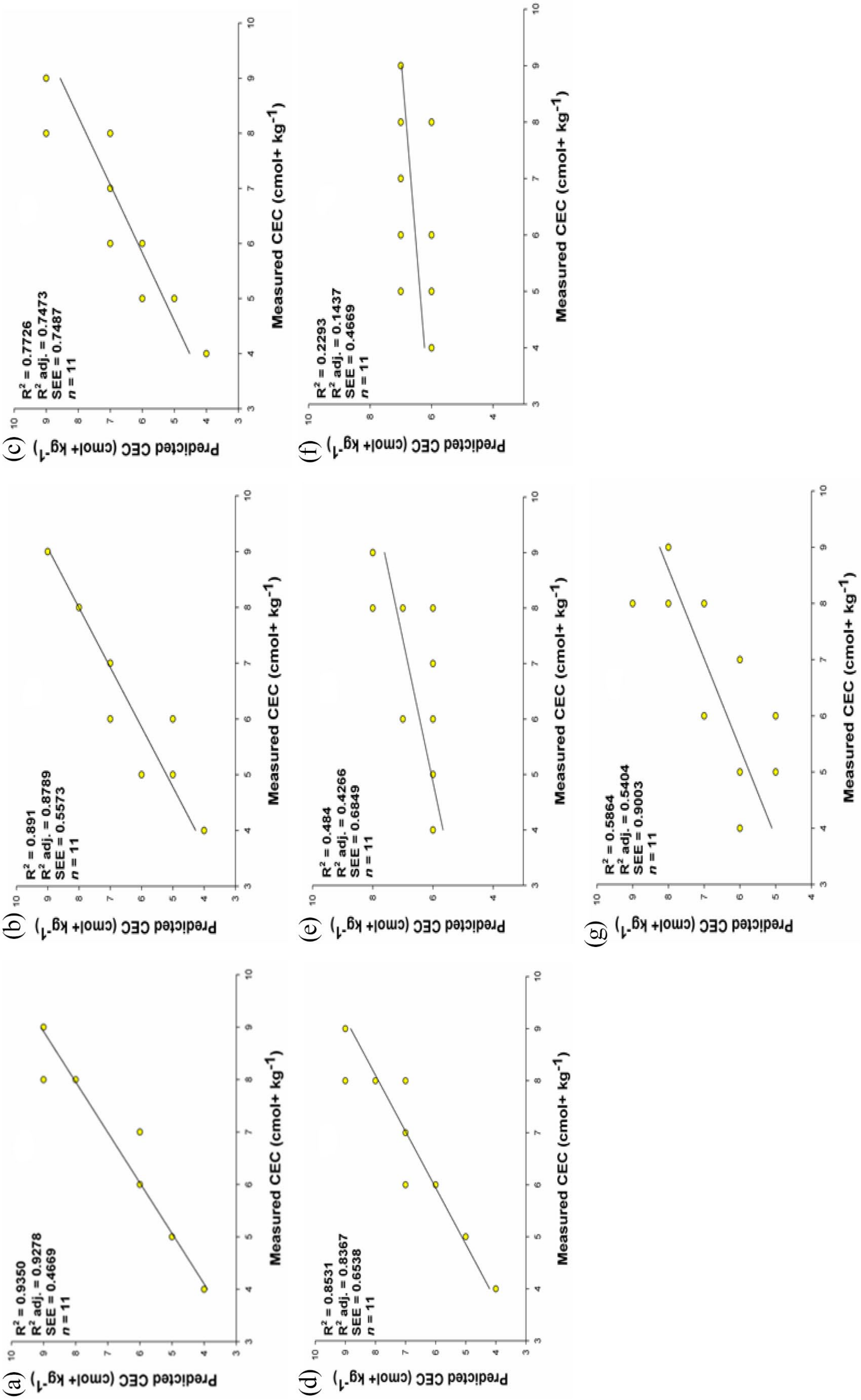

Figure 5. Predicted versus measured CEC for the sandy clay loam textural class of Entisols using (a) silt, clay, and SP, (b) clay and SP, (c) clay, (d) silt and clay, (e) silt (f) silt + clay, and (g) silt and SP as covariates.

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Author Contributions

Conceptualization: M.S., I.I., M.Z., G.M., M.A., and E.C.B.; validation models test: M.S., M.Z., and G.M.; formal analysis: M.A.; investigation: I.I.; resources: M.A.; data curation: M.A. and I.I.; writing—original draft preparation: M.S., I.I., M.Z., G.M., and E.C.B., writing—review and editing: M.S., M.Z., G.M., and E.C.B., visualization: M.A., and M.S.; supervision: I.I.; project administration: I.I. All authors have read and agreed to the published version of the manuscript.

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