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# Quantifying engineering parameters of expansive soils from their reflectance spectra

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ABSTRACT

Occurrence of expansive soils in construction sites has serious implications on planning, design, construction, maintenance, and overall performance especially of lightweight engineering infrastructures. Such soils are particularly susceptible to large volume changes in response to moisture content fluctuations following seasonal climatic variations. This can lead to deformation of structures built up on them. For this study, soil samples were collected from the eastern part of Addis Ababa. Specific expansive soil engineering parameters namely; Atterberg limits (LL, PL and PI), free swell and cation exchange capacity were measured in a soil mechanics laboratory. Reflectance spectra of each soil sample were acquired in a remote sensing laboratory using ASD fieldspec full range spectrometer. A multivariate calibration method, partial least squares regression (PLSR) analysis, through simple wavelength approach, was used to construct empirical prediction models for estimating engineering parameters of expansive soils from their respective reflectance spectra. Correlation coefficients of 0.90, 0.87, 0.71, 0.81 and 0.71 for CEC, LL, PL, PI and FS respectively were obtained. The correlation coefficients showed that large portion of variations in engineering parameters of expansive soils could be accounted for by spectral parameters. Apart from these high correlation coefficients, small root mean square errors of calibration (RMSEC) and prediction (RMSEP), standard error of calibration (SEC) and prediction (SEP) and minimum bias were obtained. The results indicate potential of spectroscopy in deriving engineering parameters of expansive soils from their respective reflectance spectra and hence, its potential applicability in supporting geotechnical investigations of such soils.



## 1. Introduction

Expansive soils are major geotechnical hazards that can pose severe limitations on performance and life time of lightweight engineering infrastructures. Major problems are: volume changes due to swelling and shrinking, which can lead to differential settlement and creep; decrease in bearing capacities and shearing strength when saturated; high erosion susceptibility when exposed in cuts or open excavations and difficult workability conditions. The problem is world wide (Chen, 1988; Nelson and Miller, 1992; Gourley et al., 1993; Ramana, 1993; Al-Rawas, 1999; Goetz et al., 2001; Shi et al., 2002; Kariuki et al., 2004) though particularly prone are places where there are significant climatic variations between dry and wet seasons.

Expansive soils, mainly black cotton soils cover nearly 40% surface area of Ethiopia. Foundations on expansive soils are subject to differential movements and heave. Subgrade conditions for roads on expansive soils are poor which often resulted in severe consequences to the construction economy (Netterberg, 2001; ERA, 2002; LEA, 2006). Broad range of difficulties and hazards that are experienced in pavement engineering have become challenging reminders of the requirement of careful consideration of expansive soils especially at feasibility and design stages of road projects.

Identifying expansive soils and quantifying their potential expansivity is a crucial concern in geotechnical site investigations. The purpose is to ensure proper site selection, environmentally compatible and economically feasible designing and construction. However, common geotechnical practices of characterizing expansive soils need dense sampling, thus are costly, labor intensive and time consuming. It is also impossible to obtain continuous representation of soil masses in space. These constraints can force engineers to take as few samples as possible and depend on interpreting the results as representative of the whole site. In the mean time, presence of expansive soils can be overlooked and their potential expansiveness can be underestimated. Therefore it is important to design a cost effective investigation technique that can support conventional geotechnical investigation and testing methods.

In this respect potential of remote sensing techniques, as tools, in assessing soil expansiveness have been reported (Van der Meer, 1999; Goetz et al., 2001; Chabrillat et al., 2002; Kariuki et al., 2003; Kariuki et al., 2004). Remote sensing employed spectroscopic techniques which rely on detecting and analyzing distinct spectral signatures of clay minerals in expansive soils. Spectroscopy is study of light as a function of wavelength reflected, absorbed, emitted or scattered from materials (Clark, 1999). The processes responsible for reflection, absorption, and emission are wavelength dependent and distinct for different materials. That is, spectral response of materials depend on particular crystal structure of materials and chemical structures of minerals within (Van der Meer, 1999). Thus, gives an opportunity to derive compositional

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information of materials from their spectra. Clay mineralogy is fundamental towards understanding geotechnical behavior (Perloff and Baron, 1976; Chen, 1988; Nelson and Miller, 1992; Mitchell, 1993; Gourley et al., 1993; Kariuki et al., 2004; Kariuki and Van der Meer, 2004) as well as spectral characteristics of expansive soils (Goetz et al., 2001; Chabrillat et al., 2002; Kariuki et al., 2004), thus provides a prospect to link the two. Van der Meer (1999) reported possibility of mapping clay soils from remotely sensed data based on the dependence of spectral signatures on soil constituent minerals. Goetz et al. (2001) established relationships between short wave infrared (SWIR) 1800–2400 nanometer spectral bands and soil swelling potential classes of Seed et al. (1962). Chabrillat et al. (2002) identified and mapped exposed clay minerals (the three most important clay minerals with respect of soil expansion; smectite, illite, kaolinite) from airborne remote sensing images based on diagnostic absorption bands in the SWIR spectral region. Kariuki et al. (2004) proposed models that made use of spectral parameters from selected single wavelength regions. They established a one-to-one link between engineering parameters and absorption feature parameters (position, depth, width, asymmetry and area of absorption band) at 1400 nm, 1900 nm and 2200 nm wavelengths. Fig. 1 shows what absorption feature parameters are schematically.

The purpose in this study is to develop empirical models for predicting specific engineering parameters of expansive soils from their respective reflectance spectra. A multivariate calibration method, partial least squares regression (PLSR) analysis, through simple wavelength approach, was used to link engineering and spectral parameters. The models provide numerical estimates of specific engineering parameters that can be directly used in practical engineering applications. Though atmospheric absorption bands in SWIR are reported to be significant in modeling engineering parameters (Goetz et al., 2001; Chabrillat et al., 2002; Kariuki et al., 2003) these bands were excluded in this study. The aim of doing so was identifying wavelength regions for providing an outlook in considering extension of the approach to optical remote sensing image data.

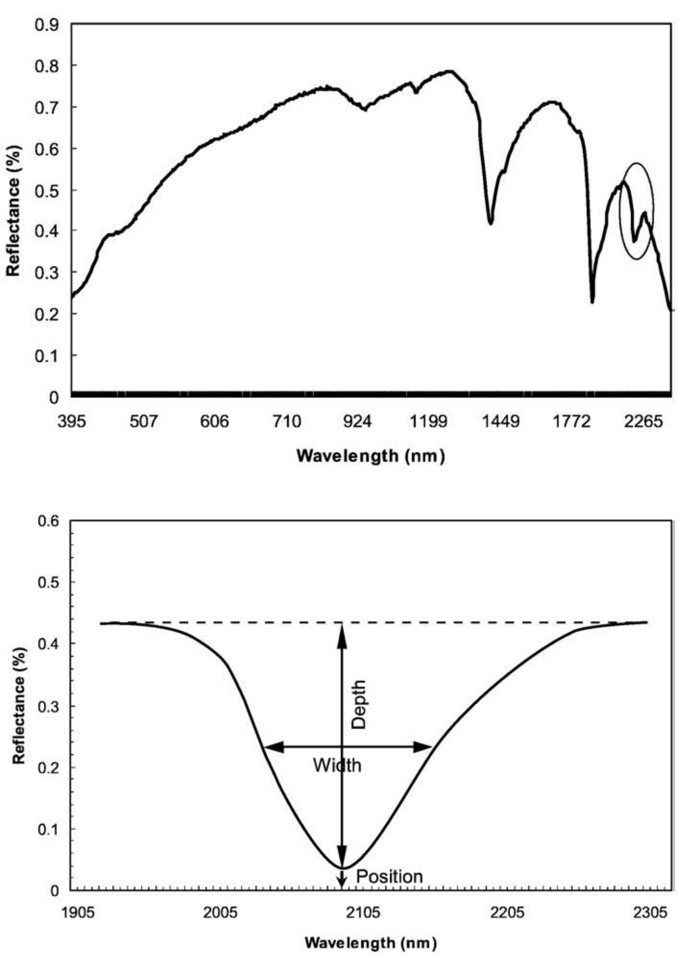


**Fig. 1.** Absorption feature parameters: a soil spectrum with absorption bands (top) and absorption feature parameters of an absorption band (bottom). Area of an absorption band is calculated as triangles left and right side of the position; dividing area at the left side of position by area at the right side of position gives asymmetry of the absorption feature.

## 2. Materials and methods

### 2.1. Study area

The study area is located in the eastern part of Addis Ababa (Fig. 2). Climate is cool to temperate with a mean annual temperature of 16 °C, and a mean annual rainfall of 1200 to 1600 millimeter (EMA, 1988). Addis Ababa is witnessing large population growth in the past decades and rapid expansion in all directions, engulfing much farmsteads and woodland into urbanized areas. Much construction activities are taking place in the study area (particularly CMC and Bole) and problems due to expansive soils are frequently reported.

Study area selection was based on combination of information on the topography, geology, soil types, previous studies and reports on damages to lightweight structures, and site observation. Topography ranges from rugged, hilly and mountainous at the northeastern (Kotebe) parts to flat towards the south and southwestern parts (Bole and CMC) of the study area. Elevation ranges from 2700 meters (northeastern parts) to 2300 meters (southern parts) above sea level. Soils in the former area are dominantly reddish in color while in the later area dark colored commonly known as black cotton soils and grey colored soils dominate. In between the two areas the soil is mainly reddish brown to dark brown in color. Soil map of the city, although gross (1:100,000) for the scale of this study, indicates three major soil types; luvisols, vertisols and nitosols (Fig. 2). According to the geological survey of Ethiopia, GSE (1990) the city is predominantly covered by alkaline basalts with inter-bedded pyroclastics, ignimbrites, trachytes and rhyolites.

### 2.2. Sampling and laboratory analysis

Disturbed soil samples were collected from open pits of depth of about 1 meter at which foundations of lightweight structures commonly constructed, through a stratified random sampling technique. Engineering parameters that are normally used for identification of expansive soils and indirect estimation of their expansivity namely; Atterberg limits (liquid limits (LL), plastic limits (PL) and plasticity indices (PI)), cation exchange capacity (CEC) and free swell (FS) were measured in a soil mechanics laboratory.

Atterberg limit tests were conducted following the standard test procedures of AASHTO specifications (AASHTO, 2000): AASHTO T89 for determining liquid limit of soils and AASHTO T90 for determining plastic limit and plasticity index of soils. Cation exchange capacity of the soil samples were measured using methylene blue adsorption test 'spot' method (Verhoef, 1992). Free swell tests were carried out in accordance with the methods and procedures demonstrated by Head (1994). Grain size analysis was conducted to determine particle size distribution of soil samples in accordance with ASTM standard test methods.

Mineralogical composition of soil samples were examined using X-ray diffractometer (XRD). The instrument used is Siemens D5000 diffractometer. Bulk as well as clay fractions of the soil samples were analyzed.

Soil reflectance spectra were acquired using ASD fieldspec full range spectrometer (http://www.asdi.com) that covers the 350 to 2500 nanometer wavelength region of the electromagnetic spectrum. Contact probe measurements were done on small portions of air-dried soil samples quartered from the whole sample to ensure representativeness. Time spent to acquire the reflectance spectra of soil samples was on the order of hours, which saved a great deal of

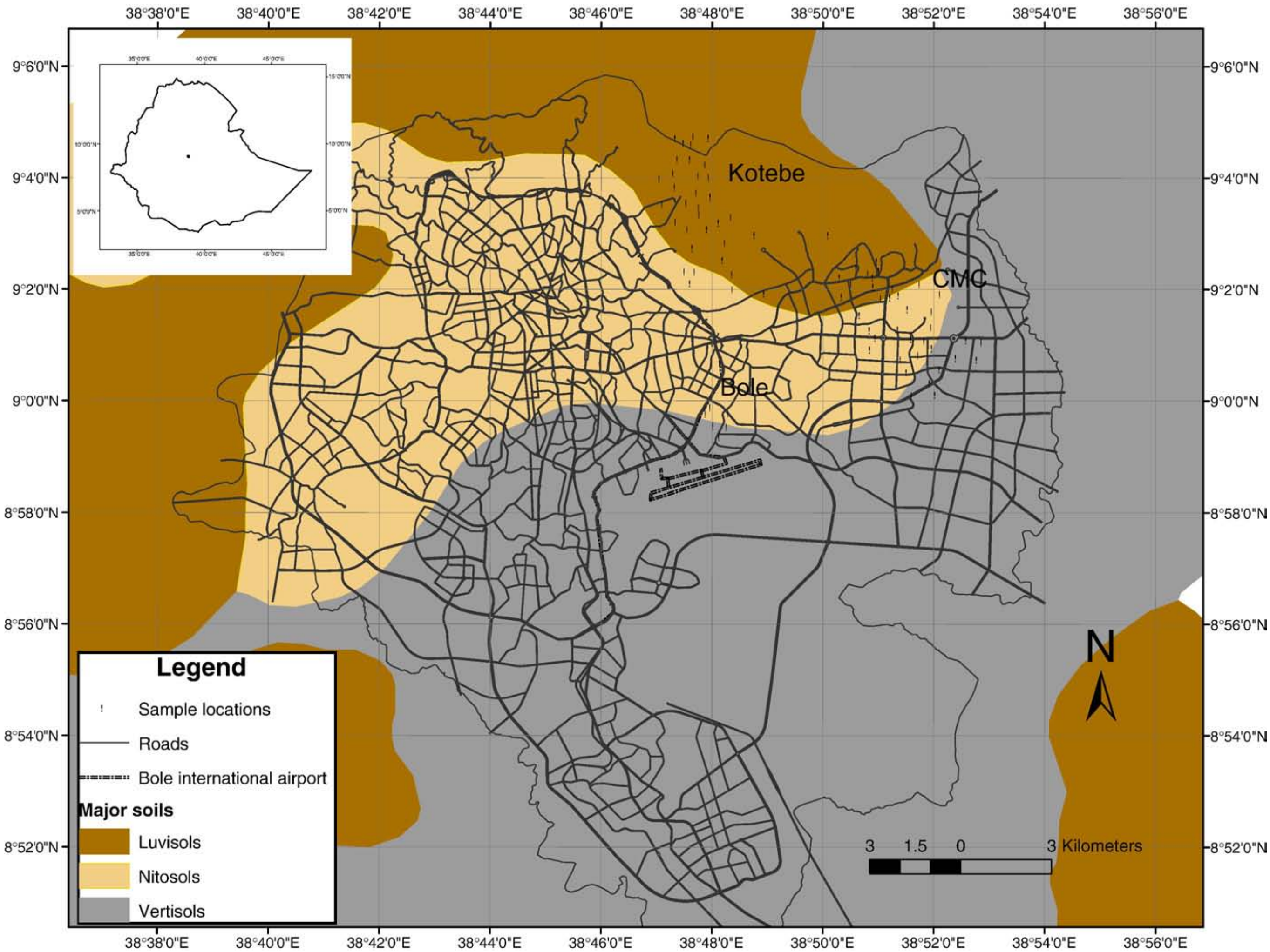


**Fig. 2.** Location map of the study area with names of places and distribution of sampling points overlaid on soil map of the city that shows spatial distribution of major soil types.

time in comparison with the conventional engineering tests that took several weeks time.

### 2.3. Multivariate (partial least squares) regression analysis

Partial least squares regression (PLSR) deals with prediction of set of dependent ($y$) variables from set of independent ($x$) variables. PLSR is particularly important when dealing with large number of variables that express common information (Brereton, 2000; Wold et al., 2001; Yeniay and Goktas, 2002). Though multiple linear regression (MLR) analysis can be employed to explore relationships between a number of predictors and response variables, with an increase in number of predictors it will not perform well due to multicollinearity problems. MLR assumes $x$ variables as linearly independent and require smaller number of $x$ variables than the number of observations. Significant predictors should also be well known in MLR (Brereton, 2000). In case of noisy data MLR tends to overfit. Another multivariate approach, principal component regression (PCR) analysis decomposes set of predictors into eigen vectors and scores to overcome collinearity. After achieving optimal projection of $x$ variables in few principal components, it regress them against the responses in a separate step. Unlike PCR, PLSR decomposes both predictors and responses simultaneously to capture their common variation, which will be projected into a small number of mutually independent factors. Decomposition and regression is a single step, through fewer principal components than that required by PCR. Hence PLSR reduces the impact of irrelevant $x$ variations in the calibration modeling by balancing the information in the $x$ and $y$ spaces (Martens and Naes, 1989; Wold et al., 2001). More information on the differences of the three multivariate calibration methods and their algorithms can be found in Brereton (2000), Martens and Naes (1989), Wold et al. (2001), Yeniay and Goktas (2002), http://www.camo.com.

Wold et al. (2001) demonstrated that with an appropriate scaling, one can focus a PLSR model on more important $y$-variables, and use experience to increase the weights of more informative $x$-variables. Variable selection is based on significance tests that show which variable contributes significantly to the model. Stability plots can be used to identify which variable causes perturbation to the models. Models performance can be evaluated by correlation coefficients, measures of the error terms (RMSEC, RMSEP, SEC and SEP), bias, residual and explained variance plots etc. Root mean square error of calibration (RMSEC) and prediction (RMSEP) are measures of average differences between predicted and measured response values at calibration and validation stages respectively. Standard error of calibration (SEC) and prediction (SEP) show the variation in precision of prediction over the whole samples at the calibration and prediction stages respectively, and are computed as standard deviation of residuals. Bias is interference error computed as the average values of the variation that is not taken into account by the model.

## 3. Results and discussions

### 3.1. Engineering parameters

Plotting results of liquid limits and plasticity indices of the soil samples on plasticity chart (Fig. 3) depicted that observed soil samples

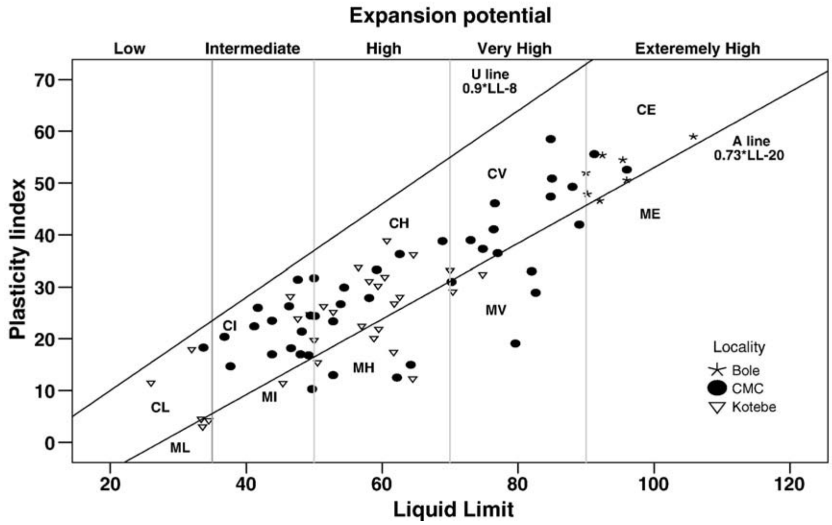


**Fig. 3.** Plasticity chart showing distribution of soil samples from the three localities with respect to different classes of expansion potential.

have a wide range of variability in their plasticity. Plasticity is directly proportional with soil expansivity (Perloff and Baron, 1976) and governed among other factors by the dominant type and amount of clay mineral present in soils (Chen, 1988; Nelson and Miller, 1992; Shi et al., 2002). Thus as for the spatial variability of the soil samples, we were also able to represent the required range of variability in their expansiveness.

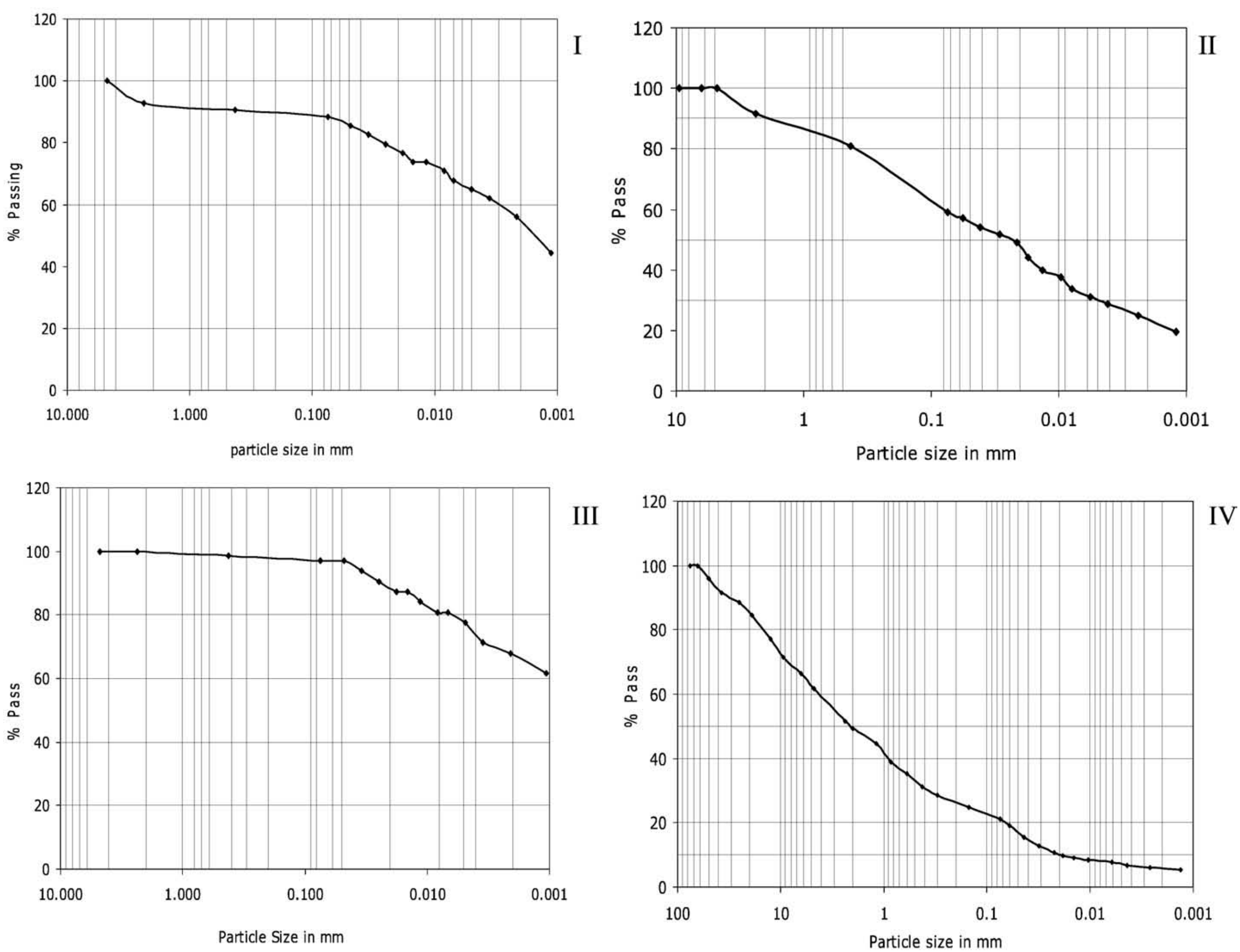


**Fig. 4.** Particle size distribution curves of some samples: I & II. Soil samples obtained from CMC; III Soil sample obtained from Bole; IV. Soil sample obtained from Kotebe areas.

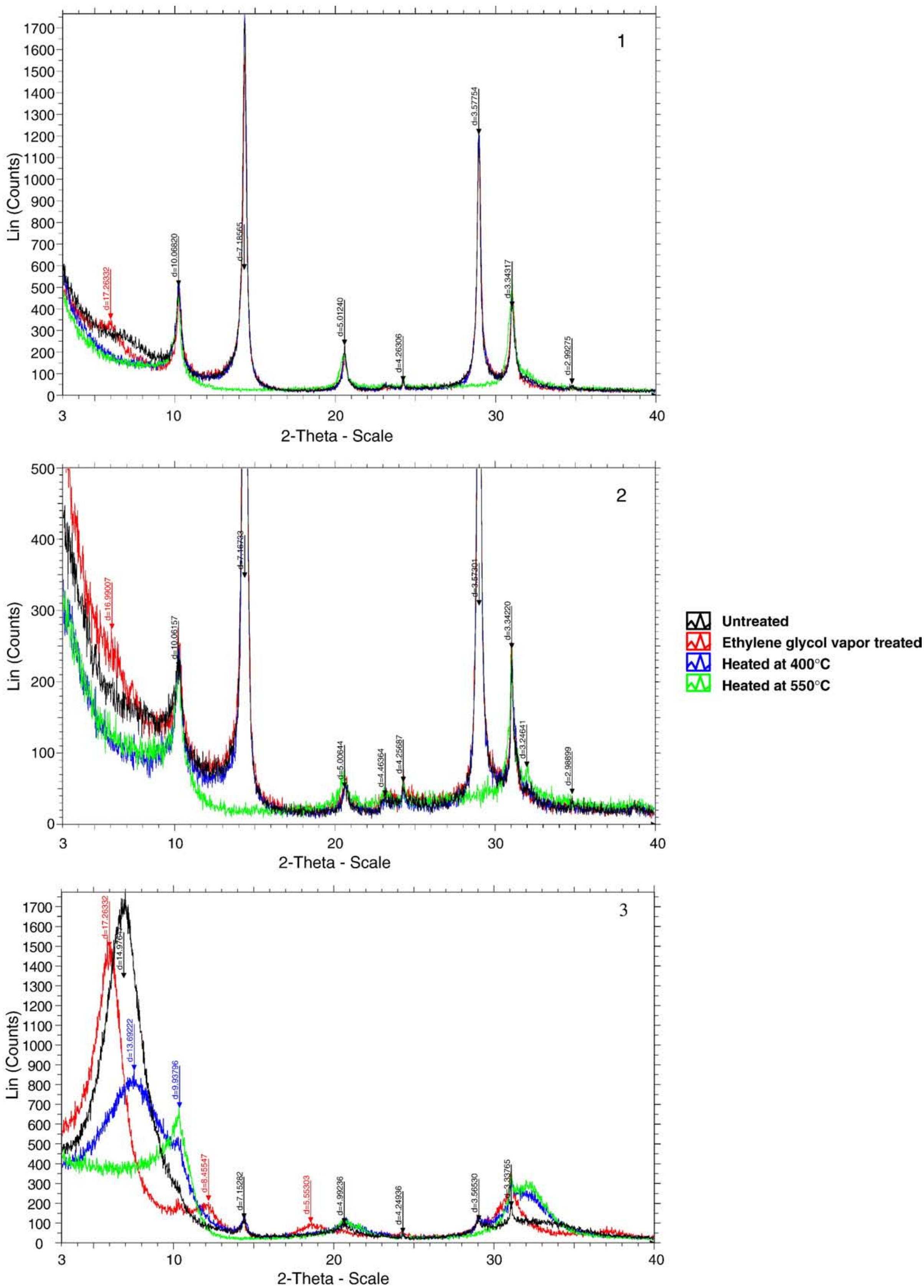


**Fig. 5.** X-ray diffraction patterns of the clay fractions of selected soil specimens from the three localities: (1) mixtures (soil sample from CMC); (2) kaolinites (soil sample from Kotebe) and (3) smectite (black cotton soil sample from Bole) categories of spectral analysis results.

**Table 1a**
Summary of Qualitative XRD results showing abundance of major (>30%), moderate (10–30%), minor (2–10%) and trace (<2%) mineral constituent of soil samples.

| | Sample | Major | Moderate | Minor | Trace |
|---|---|---|---|---|---|
| | Mineral assemblage (relative proportion based on peak heights) | | | | |
| 1 | Bulk | – | Montmorillonite, kaolinite, nontronite | Quartz, illite, potassium feldspar, goethite | Brookite |
| | Clay fraction | Kaolinite | Quartz, illite | Illite, montmorillonite | Potassium feldspar |
| 2 | Bulk | Montmorillonite | Quartz, nontronite | Kaolinite, potassium feldspar, plagioclase | Ilmenite, goethite, brookite |
| | Clay fraction | Montmorillonite | – | Illite, kaolinite, quartz | |
| 3 | Bulk | – | Quartz, kaolinite | Potassium feldspar, illite, plagioclase, montmorillonite, nontronite | Goethite, brookite, pyrite |
| | Clay fraction | Kaolinite | – | Quartz, illite | Potassium feldspar |

Grey and black cotton soils obtained from the flat low lying Bole area (located near to Bole international airport) and similar soil samples obtained from CMC area fall on extremely high plasticity portion of the chart. Whereas red soils found from the hilly areas of Kotebe mostly fall on low, intermediate and high plasticity portions of the chart. Reddish brown and dark brown soils obtained from the area in between Kotebe and CMC fall mainly on the Intermediate, high and very high plasticity portions of the chart. Some soil samples from Kotebe, and the area in between Kotebe and CMC exhibit high organic matter content as determined with loss on ignition (LOI) and their plasticity is high to very high. Kariuki and Van der Meer (2004) observed relationships between soil color and expansion potential which they attributed with degree of weathering and drainage. Though it is difficult to conclude that soil expansiveness is dictated by soil colors or vice versa, color seems to be of value as an indicator in our study area.

Grain size analysis showed that most of the soils are fine grained with more than 50% of particles passing number 200 sieve. Grey and black cotton soils from Bole and similar soils from CMC are finer gained (with 90–100% passing number 200 sieve) of which clay and colloid content of the soils is also high. On the contrary, some soil samples from Kotebe and the area in between Kotebe and CMC are found to be coarser grained. Typical particle size distribution of soil samples from the three localities are presented in Fig. 4.

XRD test results show that the soil samples contain clay minerals such as smectite (montmorillonite and nontronite), illite and kaolinite (Fig. 5) which significantly influence engineering behavior of expansive soil due to their high activity; and original minerals such as quartz, feldspar and mica are which are common constituents of expansive soils but do not contribute to the expansiveness of soils due to their low activity. Qualitative XRD analysis results are summarized in Table 1a and chemical analysis results are presented in Table 1b.

### 3.2. Spectral parameters

Differences in spectral characteristics among spectra of different soil samples were used in differentiating various clay mineral types that can be present in the soil samples. Position of absorption features, their shapes, types and number, depth intensity and asymmetry; shape of spectral curves, differences in slopes of spectral curves and variations in reflectance intensity of spectra were some of the important qualitative parameters that helped to identify spectrally dominant clay mineral from the soil reflectance spectra (Fig. 6). Some spectra show a sharp rise in slopes and variable reflectance intensity throughout the whole wavelength region of the electromagnetic spectrum. Others show lower reflectance intensity throughout the whole wavelength range and were on overall dark. The later also exhibited monotonously rising convex slopes in the visible near infrared (VNIR) wavelength region and less variable reflectance intensity in the SWIR. Some show moderate rise in slopes and also moderate increase in reflectance intensity from the VNIR to the SWIR wavelength regions.

Up on spectral interpretation, the spectra of the soil samples were grouped into three major classes of mineralogical composition (Table 2); smectites, mixtures and kaolinites. Among the smectites are montmorillonite and nontronite and of the kaolinite groups are halloysite and kaolinites. Those that are grouped under mixtures are a mixture of smectites, kaolinites and others.

Montmorillonite is a product of weathering of iron and magnesium rich parent materials and is one of the most common smectite minerals found in soils (Fitzpatrick, 1980; Pontual et al., 1997). Since the study area is located within the central plateau of Ethiopia, which is covered by rocks of volcanic origin where mafic rocks like basalt are abundant, occurrence of montmorillonite in the study area can be favored by the environmental conditions. Nontronite is also a common smectite mineral found in soils and weathered bedrock, whose formation is favored by alkaline to neutral pH environments, as well as by availability of iron and calcium minerals (Pontual et al., 1997).

Halloysite can occur in soils and uppermost weathered part of bedrock as a result of weathering of aluminium rich minerals (Pontual et al., 1997) that are also abundant in the study area and its surroundings. Kaolinite on the other hand, can be derived from almost all silicate minerals (Pontual et al., 1997) hence is a commonly occurring clay mineral in soils (Fitzpatrick, 1980).

Fig. 7 presents relationship between some of measured engineering parameters and mineralogical classes obtained upon spectral interpretation. Though large sample variability is evidenced, centers of samples in each mineralogical category suggested positive relationship between engineering parameters and sample mineralogy. As the mineralogy changes towards the highly expansive clay minerals (from kaolinites to smectites), values of engineering parameters also get higher. The observed large variability of samples in each mineralogical class can be attributed to the inhomogeneous nature of the soil samples. That is presence of other clay minerals apart from the dominant ones and interference from non clay soil constituents on both engineering and spectral parameters.

### 3.3. Partial least squares regression (PLSR) prediction models

All wavelengths of the ASD fieldspec acquired soil spectra that also fall within the nine ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) band sets in the VNIR and SWIR were used. Hence atmospheric absorption bands are excluded which resulted in a total of six hundred and twelve variables. That is, during PLSR modeling the laboratory spectra were limited into wavelengths

**Table 1b**
Chemical analysis results.

| Sample | $SiO_2$ % | $Al_2O_3$ % | $Fe_2O_3$ % | MgO % | CaO % | $Na_2O$ % | $K_2O$ % | $TiO_2$ % | $P_2O_5$ % | MnO % | $Cr_2O_3$ % | $V_2O_5$ % | LOI % | Sum % |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 53.4 | 19.6 | 6.28 | 0.69 | 1.11 | 0.52 | 1.17 | 0.77 | 0.07 | 0.03 | <0.01 | 0.02 | 15.1 | 98.8 |
| 2 | 51.1 | 14.4 | 8.47 | 1.73 | 2.84 | 0.54 | 1.24 | 1.37 | 0.07 | 0.27 | 0.02 | 0.03 | 17.8 | 99.9 |
| 3 | 53.9 | 19.0 | 7.95 | 0.63 | 0.30 | 0.77 | 1.86 | 1.22 | 0.15 | 0.17 | 0.01 | 0.02 | 13.2 | 99.2 |

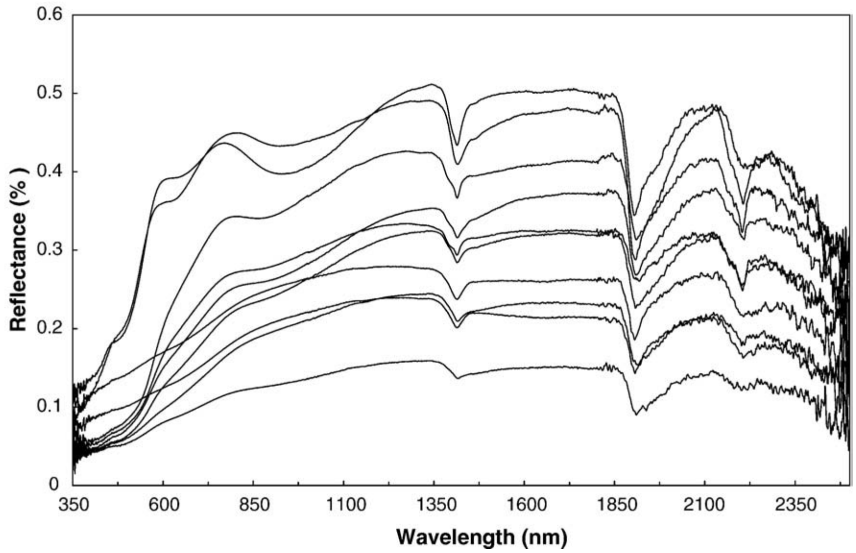


**Fig. 6.** Variability in spectral characteristics of different soil samples (no offset). Note the differences in shapes of spectral curves; slopes; overall reflectance intensity; shape, position and number of absorption bands among the spectra.

of ASTER bands aiming to identify wavelength regions for extension of the approach to optical remote sensing image data. However, the current study deals with estimation of engineering parameters from laboratory soil spectra. Distributions of spectral variables were examined. Appropriate transformations (logarithmic) were carried out on variables that showed skewed distributions to make their distribution fairly symmetrical (Wold et al., 2001). Different spectral data preprocessing techniques (Martens and Naes, 1989; Selige et al., 2006) were applied on the soil spectra prior to performing PLSR analysis. Spectral data normalization was done through dividing each variable by the maximum value for better account of spectral range. Martens and Naes (1989) mentioned the need to normalize spectral input data in order to remove uncontrollable scale variations. Multiplicative scatter correction, MSC (in this case common amplification) was done to avoid scatter effects from the soils texture, grain size and porosity. The aim of MSC is to prevent effects of scattering from being imposed on the phenomena of interest that one need to model. Full cross validation, leave one out at a time method was used to validate the models.

**Table 2**
Spectral characteristics of dominating minerals in the soil samples.

| | Dominating Clay Mineral | Spectral characteristics |
|---|---|---|
| Smectites | Montmorillonite $(Ca, Na)_{0.67}Al_4(Si,Al)_8O_{20}(OH)_4 \cdot nH_2O$ | Show strong absorption features at ~1400 nm, ~1900 nm and ~2200 nm; depth of the features being intense at ~1900 nm and ~1400 nm coupled with sharp minima and asymmetric shape. |
| | Nontronite $(Ca,Na)_{0.66}Fe_3^{+4}(Si,Al)_8O_{20}(OH)_4 \cdot nH_2O$ | Show diagnostic absorption feature at ~2270 nm to ~2296 nm and strong water absorption features at ~1410 nm and ~1910 nm which show similar depth intensity and asymmetric shape as montmorillonite. |
| Kaolinites | Halloysite $Al_2Si_2O_5(OH)_4 \cdot 4H_2O$ | Show diagnostic doublet features at ~1390 nm and ~1412 nm, and ~2175 nm and ~2210 nm respectively coupled with water absorption feature at ~1910 nm. |
| | Kaolinite $Al_2Si_2O_5(OH)_4$ | Show diagnostic doublet features at ~1400 nm and ~1450 nm, and ~2166 nm and ~2206 nm respectively; no or less well resolved absorption feature at ~1900 nm. |

The models show high prediction performance evidenced by high correlation coefficients and low errors in terms of RMSEC and RMSEP, SEC and SEP and Bias (Table 3). Significant predictors show slight differences, but fall within similar spectral regions. Fig. 8 presents results of the regression analysis for CEC. It can be noted that less than 5% of the samples fall outside the 95% confidence ellipse (Fig. 8A); the remaining unexplained variance in CEC by the spectral parameters is small after fitting three PLS components (Fig. 8C); CEC values during calibration and validation showed negligible deviations (Fig. 8D) suggesting the model fitted to the calibration data set described the prediction data set as good as possible for the validation method that is used is this analysis i.e. full cross validation, leave one out at a time method. Hence, it is clear that there exists a powerful relationship between engineering and spectral parameters.

Wavelength regions in the VNIR spectral region are influenced by and associated with spectral features of organic matter and properties related to iron-bearing minerals (Ben-Dor and Banin, 1994). The overall dark spectra and strongly convex shapes exhibited by some soil spectra (Fig. 6) are due to the influence of organic matter (Ben-Dor and Banin, 1994) that present within the soil samples (Table 1b loss on ignition, LOI). Some soil spectra showed presence of iron-oxides in the soil samples (Fig. 6) which is also reflected in the XRD result (Table 1a). According to Wan et al. (2002), presence of amorphous clay size particles including iron-oxides in soils has an intensifying effect on soil expansivity. Viscarra et al. (2006) reported association of spectral features ~650 nm wavelength regions with sand content. Note the negative relation between CEC and wavelengths ~650 nm (Fig. 8B) and the presence of this wavelength region as a significant predictor for the other engineering parameters in Table 3. Hence, the significance of the VNIR wavelengths in modeling engineering parameters can be attributed to spectral signatures of organic matter, sand and iron-oxide minerals that constituent the soil samples.

In the SWIR spectral region, identified wavelengths (Table 3 and Fig. 8B) as significant predictors of engineering parameters of interest mainly fall between ~2100 nm and 2420 nm. Clark, 1999; Goetz et al., 2001 and Kariuki et al., 2004 associated spectral features in these wavelength regions with combination of fundamental OH stretching and bending with Al, Mg, or Fe ions; and reported that those are diagnostic of clay minerals. This is supported by the chemical analysis results presented in Table 1b, XRD patterns shown in Fig. 5 and mineral assemblage in Table 1a.

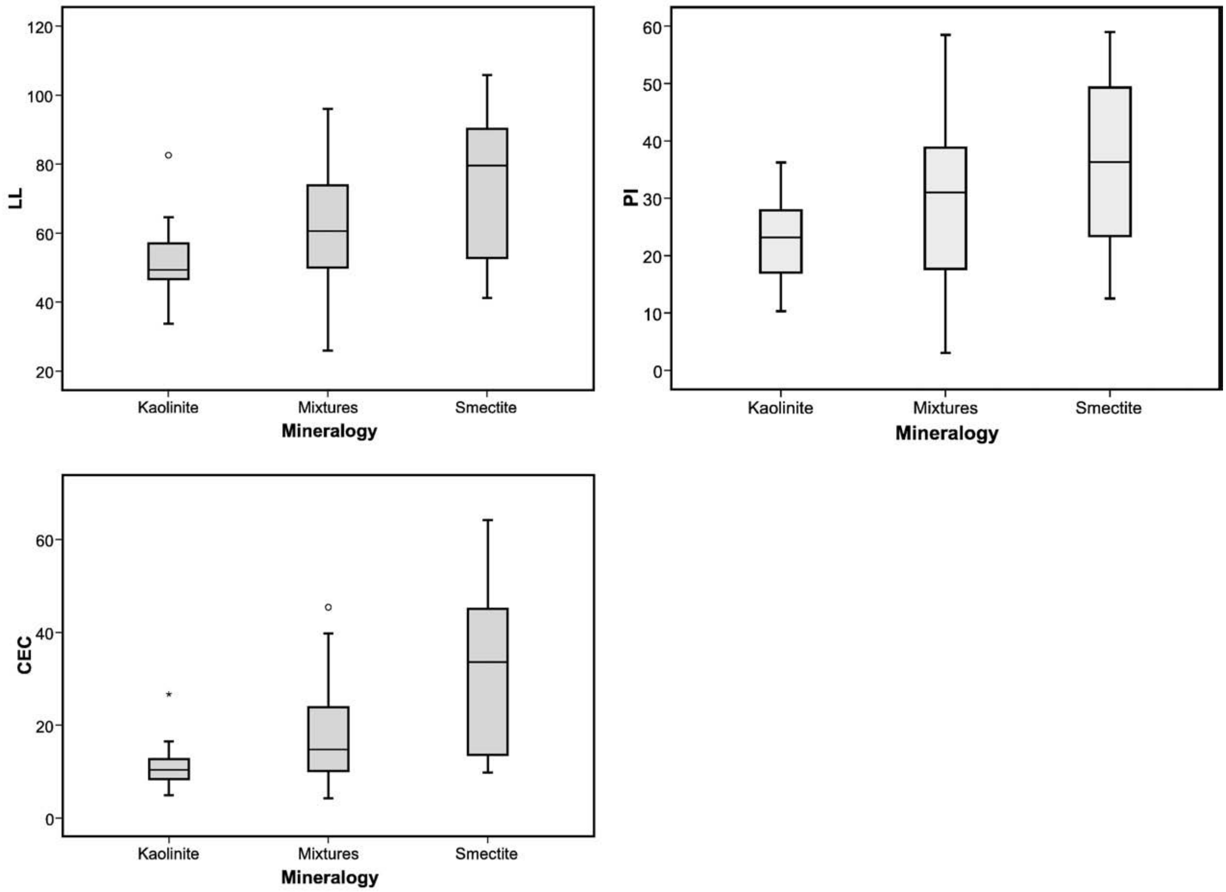


**Fig. 7.** Relationship between Measured LL, PI and CEC with mineralogical composition of soil samples interpreted from their reflectance spectra suggesting positive relationships between engineering and spectral parameters.

Resulting spectrally active wavelength regions in modeling engineering parameters of expansive soils gave indications of relevant wave bands to look into in attempting to extrapolate laboratory spectroscopic experiments to image data. This on the other hand, is of benefit for large scale (covering a wide area) mapping of expansive soil engineering parameters.

**Table 3**
Summary of the results of the PLSR modeling for the five engineering parameters (CEC, LL, PL, PI and FS) showing models performance indices.

| Engineering parameters | Correlation coefficients | RMSEC | SEC | Bias | Offset |
|---|---|---|---|---|---|
| *Calibration* | | | | | |
| CEC | 0.92 | 0.12 | 0.12 | 0.00 | 0.19 |
| LL | 0.89 | 0.52 | 0.52 | 0.00 | 1.70 |
| PL | 0.74 | 0.54 | 0.55 | 0.00 | 1.44 |
| PI | 0.84 | 0.46 | 0.47 | 0.00 | 0.62 |
| FS | 0.74 | 0.19 | 0.19 | 0.00 | 0.74 |
| *Validation* | | | | | |
| CEC | 0.90 | 0.12 | 0.12 | 0.00 | 0.21 |
| LL | 0.87 | 0.54 | 0.55 | 0.00 | 0.84 |
| PL | 0.71 | 0.57 | 0.57 | 0.00 | 0.71 |
| PI | 0.81 | 0.50 | 0.50 | 0.00 | 0.68 |
| FS | 0.71 | 0.20 | 0.20 | 0.00 | 0.80 |

| Engineering parameters | Spectrally active wavelength regions (nm) |
|---|---|
| CEC | 520–560, 630–777, 834–860, 2145–2164, 2217–2247, 2405–2412 |
| LL | 520–560, 637–778, 837–860, 2149–2163, 2223–2242, 2247–2264, 2335–2425 |
| PL | 520–545, 653–674, 2149–2153, 2160–2162, 2223–2250, 2335–2425 |
| PI | 520–583, 630–797, 838–1655, 2150, 2165–2181, 2219–2282, 2332–2394, 2407–2412 |
| FS | 532–537, 630–690, 854–860, 2149–2155, 2160, 2218–2296 |

## 4. Conclusions

In the current study we demonstrated that;

- There exists a strong correlation between engineering parameters and reflectance spectra of expansive soils.
- It is possible to identify clay mineralogy (as is also vividly confirmed by XRD results) and quantitatively characterize expansive soils from their reflectance spectra.
- Excluding atmospheric absorption bands seem to have little effect on the wealth of information content of the soil spectra with respect to estimating engineering parameters of interest.
- Wavelength regions to look into for extension of the approach into optical airborne or satellite remote sensing data are indicated.

Overall the presented results confirm spectroscopy's potential in contributing to geotechnical investigation of expansive soils. This is both in identification of expansive soils and subsequent quantification of their engineering parameters. Apart from supplying a great deal of information within a short period of time and of being cheaper, the accuracy of spectroscopic measurements seem also reliable (Table 3, Fig. 8). Besides dense sampling of sites is possible which can be of great benefit in avoiding under-sampling. The approach can be useful in getting estimates of engineering parameters of expansive soils, in early stages of construction projects where site information on geotechnical behavior of soils is limited. Therefore, spectroscopy can

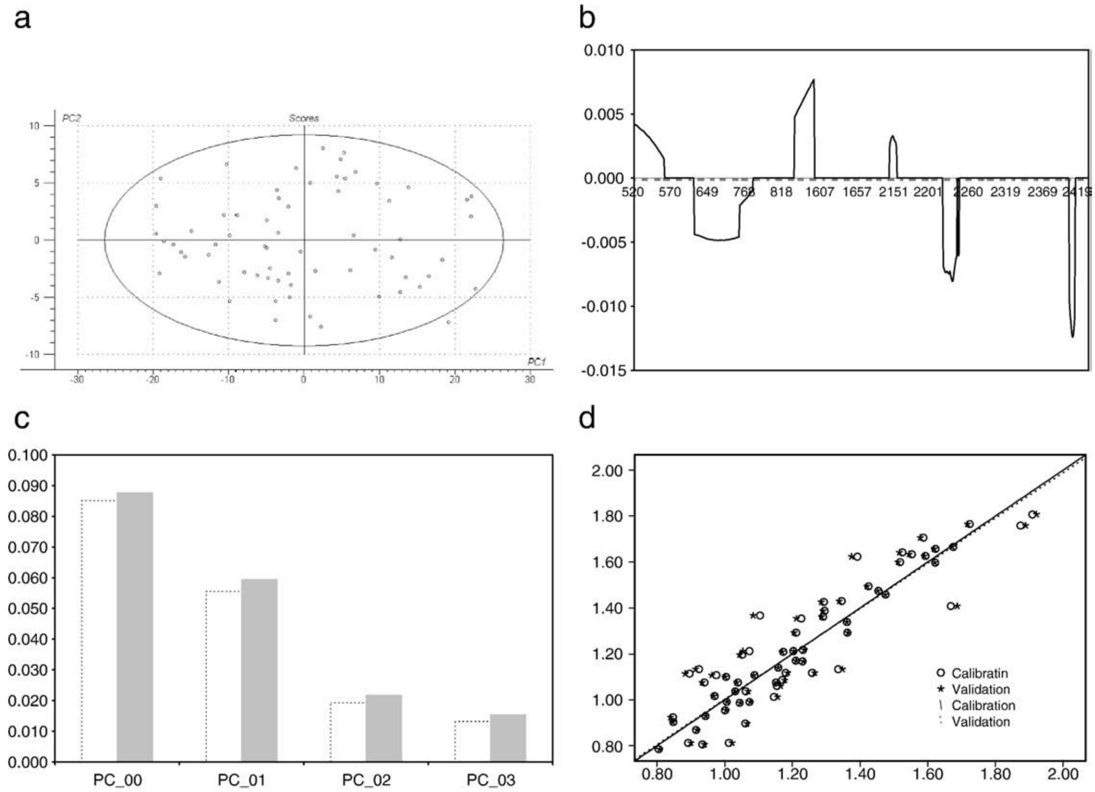


**Fig. 8.** Results of PLSR modeling for CEC showing: A) Scores principal components 1 versus 2 with samples in the 95% confidence ellipse showing that there is no particular grouping of samples, but rather a random pattern (one population) suggesting a single model can fit the data. Note that there are no outlying samples lying outside the rest of the cloud. Only one sample lies outside the 95% confidence ellipse; under normal situation it is expected that about 5% of the samples to lie outside the ellipse. B) Regression coefficients or statistically significant wavelength regions in predicting CEC from the laboratory soil reflectance spectra. These wavelength regions can be used in attempting to extrapolate or use airborne or satellite images for mapping spatial variability in soil expansiveness. C) Residual variance (white during calibration and grey during prediction stages) showing the remaining variation that is not taken in to account by the model is minimum after fitting three PLS components. Suggesting much of the variability in CEC is explained by the model. D) Regression overview showing the relation between predicted and measured CEC. Calibration and prediction points lie very close to each other, suggesting the model fitted to the calibration data set described the prediction data set as good as possible. NB. Full cross validation, leave one out at a time method was used.

play an important role particularly in identifying sites that might need due attention and further detailed geotechnical assessment with respect to presence of potentially expansive soils.

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