A MULTIVARIATE REGRESSION ANALYSIS FOR DERIVING ENGINEERING PARAMETERS OF EXPANSIVE SOILS FROM SPECTRAL REFLECTANCE

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Commission VII, WG VII/7

KEY WORDS: Expansive soils, PLSR, spectroscopy, engineering parameters, absorption feature parameters.

ABSTRACT:

Soil expansiveness is a major problem that need due attention in geotechnical investigations. It can detrimentally influence performance and life time of lightweight engineering infrastructures. For this study, soil samples were collected from eastern part of Addis Ababa city. Specific expansive soil engineering parameters; Consistency limits (liquid limits (LL), plastic limits (PL) and plasticity indices (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, was used to relate engineering parameters and absorption feature parameters calculated from the reflectance spectra of expansive soils at specific wavelengths (~1400 nm, ~1900 nm and ~2200 nm). Correlation coefficients obtained showed that a large portion of the variation in the engineering parameters (R=0.85, 0.86, 0.68, 0.83 and 0.64 for CEC, LL, PL, PI and FS respectively) could be accounted for by the spectral parameters. Results of the prediction models are high, indicating potential of spectroscopy in deriving engineering parameters of expansive soils from their respective reflectance spectra, and hence its potential applicability in geotechnical investigations of such soils.

1. INTRODUCTION

Expansive soils are major geotechnical hazards that can pose severe limitations on performance and life time of light weight 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 (Figure 1 shows problem on road infrastructure). The problem is world wide (Al-Rawas, 1999; Chen, 1988; Goetz et al., 2001; Gourley et al., 1993; Kariuki et al., 2004; Nelson and Miller, 1992; Ramana, 1993; Shi et al., 2002) though particularly prone are places where there are significant climatic variations between dry and wet seasons.



Figure 1. Failure of road pavement due to presence of exposed expansive soils beneath the side slope of road embankment (left), road side drain or ditch clogging due to slumping of expansive soil from bare back slope (right).

Identifying expansive soils and quantifying their potential expansiveness is crucial to ensure proper site selection, environmentally compatible and economically feasible designing and construction especially of lightly loaded structures. However, common geotechnical practices of characterizing expansive soils need dense sampling, thus are costly, labour intensive, time consuming and difficult to get a continuous representation of soil masses in space.

A great deal of effort has gone into investigating methods that can be supporting or alternate tools of estimating soil properties. Advances in remote sensing techniques have enabled discrimination of clay minerals that cause swelling and shrinkage in soils and mapping their abundances (Chabrillat et al., 2002; Goetz et al., 2001; Kariuki et al., 2003; Kariuki et al., 2004; Van der Meer, 1999). 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 nm spectral bands and soil swelling potential classes of Seed et al., (1962). Chabrillant 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-toone 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.

In this study we developed new empirical models for estimating specific engineering parameters of expansive soils from their respective reflectance spectra. A multivariate calibration method, partial least squares regression (PLSR) analysis, making use of all absorption feature parameters calculated from three wavelength regions (~ 1400 nm, ~1900 nm and ~2200 nm) was employed. Resulting models provide numerical estimates of engineering parameters that can be directly used in practical engineering applications.

2. MATERIALS AND METHODS

2.1 STUDY AREA

The study area is located in the eastern part of Addis Ababa city (Figure 2). Climate is cool to temperate with a mean annual temperature of 16 °C, and a mean annual rainfall of 1200 to 1600 millimetres (EMA, 1988). Elevation ranges from 2700 meters to 2300 meters above sea level.

2.2 SAMPLING AND LABORATORY ANALYSIS

Disturbed soil samples were collected through a stratified random sampling technique. Stratification was done through combining information on lithology and topography of the study area.

Engineering parameters that are commonly used for identification of and indirect estimation of soil expansiveness; consistency limits (liquid limits (LL), plastic limits (PL) and plasticity indices (PI)) following the standard test procedures of

AASHTO specifications (AASHTO, 2002) T89 and T90; cation exchange capacity (CEC) using methylene blue adsorption test 'spot' method (Verhoef, 1992) and free swell (FS) in accordance with the methods and procedures demonstrated by Head (Head, 1994) were measured in a soil mechanics laboratory.

Soil reflectance spectra were acquired using ASD fieldspec full range spectrometer (http://www.asdi.com) that covers the 350 to 2500 nm wavelength region of the electromagnetic spectrum.

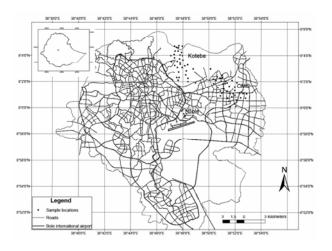


Figure 2. Location map of the study area with names of places and distribution of sampling points.

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). 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 Brereten (2000), Martens and Naes (1989), Wold et al., (2001), Yeniay and Goktas (2002), http://www.camo.com.

3. RESULTS AND DISCUSSIONS

3.1 ENGINEERING AND SPECTRAL PARAMETERS

Values of engineering parameters indicate that the soil samples have a wide range of variability in their expansion potential (e.g. Figure 2 plasticity chart). Distribution of samples on plasticity chart is useful in getting indication of soil expansion potential (Dakshanamurty and Raman, 1973). Consistency or Atterberg limits are ranges of consistency (the ease with which a soil can be deformed) of cohesive soils as a function of changes in moisture content (Perloff and Baron, 1976). They represent empirical boundaries which divide various states that cohesive soils exhibit with varying amount of moisture content; solid, semisolid, plastic and semi-liquid states. Since water has a significant effect on engineering behaviour of clayey soils in such a way that clayey soils with higher moisture content are weaker and easily deformable than their same varieties with lower moisture content (Lambe and Whitman, 1979; Mitchell, 1993; Perloff and Baron, 1976), determination of consistency limit values of such soils has proved to be useful in engineering applications.

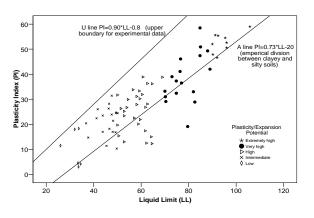


Figure 3. Distribution of soil samples on plasticity chart.

Differences in spectral characteristics among spectra of different soil samples were used in differentiating various clay mineral types 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. Up on spectral interpretation, spectra of soil samples were grouped into three major classes of mineralogical composition; smectites, mixtures and kaolinites (Figure 3). Among smectite classes are montmorillonite and nontronite and of kaolnite groups are halloysite and kaolinites. Those that are grouped under mixtures are a mixture of smectites, kaolinites and others.

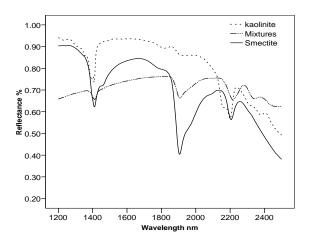
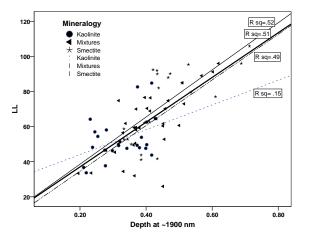
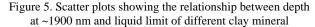


Figure 4. Variability in spectral characteristics of different soil samples (no offset). Note the differences in shapes of spectral curves; overall reflectance intensity, shape, position and number of absorption bands among the spectra.

Relationships between measured engineering parameters and mineralogical classes obtained upon spectral interpretation with respect to the magnitude of relationship each mineralogical classes show with absorption feature parameters were examined (Figure 4).





categories; showing the magnitude of the linear relationship per mineralogical groups (kaolinites, mixtures & smectites).

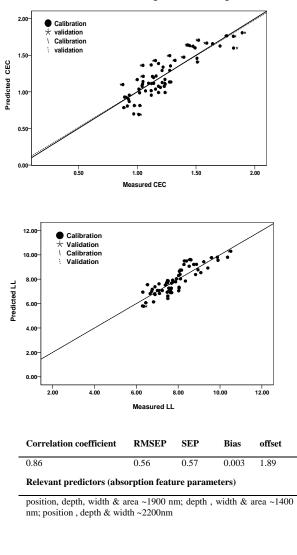
The magnitude of relationship between absorption feature depth at ~ 1900 nm and liquid limit of samples is highest for smectites that exhibit strong absorption band at ~ 1900 nm due to adsorbed water in their structure, followed by mixtures. Kaolinites that show no (kaolin) or less resolved (halloysite) absorption at ~ 1900 nm show the lowest correlation between liquid limit and depth of absorption feature at ~ 1900 nm.

3.2 PARTIAL LEAST SQUARES (PLSR) PREDICTION MODELS

Absorption feature parameters (position, depth, area, width of absorption feature) calculated from absorption bands at ~1400

nm, ~1900 nm and ~2200 nm were used for predicting engineering parameters.

PLS1 analysis (predicting a single engineering parameter at a time) method implemented in The Unscrambler software was used for the multivariate calibration and validation. Outlier detection was performed through analyzing residuals, leverages, normal probability plots of residuals both in the X and Y spaces, stability plots etc. Sufficient number of PLS factors were determined based on significance tests and through examining RMSE of residual variances of each PLS factor. Regression coefficients that significantly contribute to the models were selected based on uncertainty limit tests. Full cross validation method was used for calibrating and validating models.



Correlation coefficient	RMSEP	SEP	Bias	offset				
0.85	0.15	0.15	0.000	0.31	-			
Relevant predictors (absorption feature parameters)								

position, depth, width & area ~1900 nm; depth & area ~1400 nm; position & width ~2200nm

Figure 6. Results of PLSR modeling for liquid limit and cation exchange capacity showing the regression overview (measured versus predicted values) in the calibration and validation stages. As indicated by the correlation coefficients (Figure 5) a large portion of the variation in the engineering parameters could be accounted for by the spectral parameters. Estimation errors, both RMSEP and SEP are small indicates that expected error will be within acceptable limits if prediction is done on new samples using these models. Bias, which is average value of the difference between predicted and measured values, is also small for the given number of PLS factors indicating that effect of bias in the modelling is negligible (Martens and Naes, 1989).

	Correlation coefficient	RMSEP	SEP	Bias	offse t		
PL	0.68	0.60	0.60	0.000	1.65		
PI	0.83	0.47	0.48	0.000	0.65		
FS	0.64	0.22	0.22	0.001	0.97		
	Relevant predictors (absorption feature parameters)						

PL Position, depth & area ~1900 nm; depth & area ~1400 nm; position, depth & width ~ 2200 nm.

PI Position, depth & area ~1900 nm; depth & area ~1400 nm; position, depth, width & area ~ 2200 nm.

FS Position & depth ~1900 nm; depth ~1400 nm; position & width ~ 2200 nm.

Table 1. Summary of model results for engineering parameters (PL, PI and FS)

Position and depth ~1900 nm; depth ~ 1400 nm; position and width ~ 2200 nm are found to be significant predictors for all the five engineering parameters: LL, PL, PI, CEC and FS (Figure 6 and Table 1). Water bearing clay mineral groups, smectites produce absorption features due to the OH stretching at ~1400 nm; and due to combination of H-O-H bending and OH-stretching near ~1900 nm. Combination of fundamental OH stretching and bending with Al, Mg, or Fe ions are known to produce absorption features at ~2200 - 2300 nm , and these are diagnostic of clay minerals (Clark, 1999). According to Clark, (1999) absorption features ~ 1400 nm is due to OH and H_2O which can be caused by kaolinite/ smectite/ illite clay minerals; absorption features ~ 1900 nm is associated with H_2O which can be caused by smectite/ illite clay mineral species; and absorption features ~ 2200 nm is related with Al-OH, Mg-OH, or Fe-OH bending which can be caused by kaolinite/ smectite/ illite clay minerals.

4. CONCLUSIONS

In this paper, relationships between expansive soil engineering parameters and absorption feature parameters calculated from their respective reflectance spectra were examined. We were able to quantify engineering parameters from soil reflectance spectra employing a multivariate regression analysis, PLSR. The results confirm spectroscopy's potential in assessing engineering characteristics of expansive soils both in identification of expansive soils and subsequent quantification of their engineering parameters (Figure 3 and 5). Apart from supplying a great deal of information within a short period of time and of being cheaper, accuracy of spectroscopic estimates seem also reliable.

Laboratory spectroscopy can be utilized for measuring soil samples from any depth. It require small volume of samples for

the measurement with no or little sample preparation, making dense sampling easy as compared with the requirement of large volume of samples to perform engineering tests, and the tedious and time consuming testing procedures using conventional techniques. Hence, it can be of great benefit in avoiding undersampling of sites. The approach can be useful in getting an estimate of engineering parameters of expansive soils, in early stages of construction projects where site information on geotechnical behaviour of soils is limited. Therefore, spectroscopy can play an important role particularly in identifying sites that might need due attention and further detailed geotechnical assessment with respect to the presence of potentially expansive soils.

ACKNOWLEDGEMENT

The authors are greatly indebted to Mr. Bekele Negussie of the Ethiopian Roads Authority (ERA) for facilitating field work data collection in Addis Ababa. We would also like to acknowledge and Mr. Hailu Chekun and all the staff members of the Alemgena Soil Testing Centre of ERA for provision of laboratory facility and help in determining engineering parameters of soils.

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