Swelling Clay Mapping For Characterizing Expansive Soils; Results From Laboratory Spectroscopy and Hysens Dais Analysis

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ABSTRACT

Data acquired from the hyperspectral airborne sensor DAIS-7915 over Antequera in southern Spain was processed to yield a quantitative soil swelling potential map based on three physicochemical soil properties currently used in engineering as measures of soil swelling namely cation exchange capacity (CEC), coefficient of linear extensibility (COLE), and Saturated moisture content (SP). The method adopted was the use of the statistical procedures of cluster analysis and factor analysis to obtain spectral parameters with a potential to classify the soils into classes based on existing classification thresholds of the three properties where laboratory, field and image extracted pixel spectral data analysis were used. Applying this on a pixel-by-pixel basis revealed images that described spatially and qualitatively the surface distribution of these properties and thus swell potential differences among the soils in the area. The results gave an indication of the possible use of airborne spectral data for swell potential estimation.

Keywords: Physicochemical properties, Absorption feature mapping, Derivative analysis, Factor analysis, Clay minerals

1.0 INTRODUCTION

Soils possess discrete spectral absorption bands resulting mainly from chemical activity of constituent minerals, organic matter and pore water [1]. Works based on laboratory field and airborne soil spectral reflectance has demonstrated their potential to provide information on soil properties among which are [2] quantitative estimation of moisture, organic matter and clay fraction [3], [4]. Airborne high spectral resolution sensors such as Airborne Visible Infrared Imaging Spectrometer (AVIRIS) and Digital Airborne Imaging Spectrometer (DAIS), have also been used to obtain soil surface compositional information [5] [6].

New remote sensing satellites such as HYPERION with 220 contiguous spectral bands in the 400-2500nm spectral range offer a new range of instruments that will in future make it possible to obtain such information from space allowing for easier establishment of soil properties by comparing pixel spectra and laboratory spectra with known quantitative information on these properties, providing faster and less expensive methods. This paper reports on the results where laboratory and field spectral data together with physicochemical soil properties namely; cation exchange capacity (CEC), saturated moisture content (SP) and coefficient of linear extensibility (COLE) are used to establish spectral parameters with a potential to derive information on soil swelling properties after which airborne DAIS hyperspectral data with a much lower number of spectral bands was used to try and obtain the same information.

1

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Study Area

The study area is to the south of Spain (figure 1) and lies between latitudes $4^0 31^/ 10^{//}$ E and $4\ ^0 51^/ 10^{//}$E and longitudes $37^0 00^/ 04^{//}$ N and $37\ ^0\ 10^/ 04^{//}$ N and is about 45km North of Malaga covering a strip of 3 by 21 km between the Municipalities of Antequera, and Campillos in a Northwest -Southeast direction. It falls within the continental Mediterranean type of climate and has a dry summer with an overall mean annual temperature of 17.6^{o}C and a rainfall concentrated between the months of October to April. The soils are rich in 2:1 type of clay minerals with interstratified illite/smectite and illites dominant. The soil formation has been greatly influenced by the geological and geomorphological processes thus the degree of development has a high correlation with the physiographic position. The main sources of parent material are multi-coloured marls, gypsum, dolomites and dolomitic limestone. Others include dolomitic breccias, limestone, white marls, bioclastic sandstone, conglomerates and calcareous sandstone.

The hilltops comprise of well-drained soils that are shallow and apparently well drained appearing as pockets spread out through the area. Texture ranges from sandy clay loam, to clay with colour generally dark. On the hillsides, old *Alfisols* occurs, and are subjected to erosion resulting in the exposure of the *Petrocalcic/Calcic* horizons and in some cases the bedrock, with the *Calcic* horizons playing an important role in shaping the landscape. The soils are well drained with textures ranging from loamy sand to clay loam on the surface and colour ranging from dark brown to reddish brown. On the foot slopes, remnants of the *Alfisols* are still predominant and are moderately deep to deep well-drained soils having a texture of sandy clay loam to clay and dark yellowish brown to yellowish brown colour. In the piedmont, young soils have developed over old *Alfisols* due to depositional and erosional processes which are shallow to moderately deep well drained soils with a sandy clay loam, to clay texture and a colour that varies from very dark brown to yellowish brown. The plain is composed of fluvial and lacustrine deposits. The soils developed from the lacustrine deposits are moderately deep and well drained, are strongly calcareous with sandy clay to clay texture and dark brown to brown in colour. Where occurring in depressions, the soils are imperfectly to moderately drained, shallow to deep with textures between sandy clay loams to clay loam. Along Guadalhorce river lies the alluvial plain where the soils are too recent to develop argillic horizons but on the higher terrace, the soils are deep with *Vertic* properties cracking at some time of the year. Textures are silty clay to clay and colour dark brown to brown.

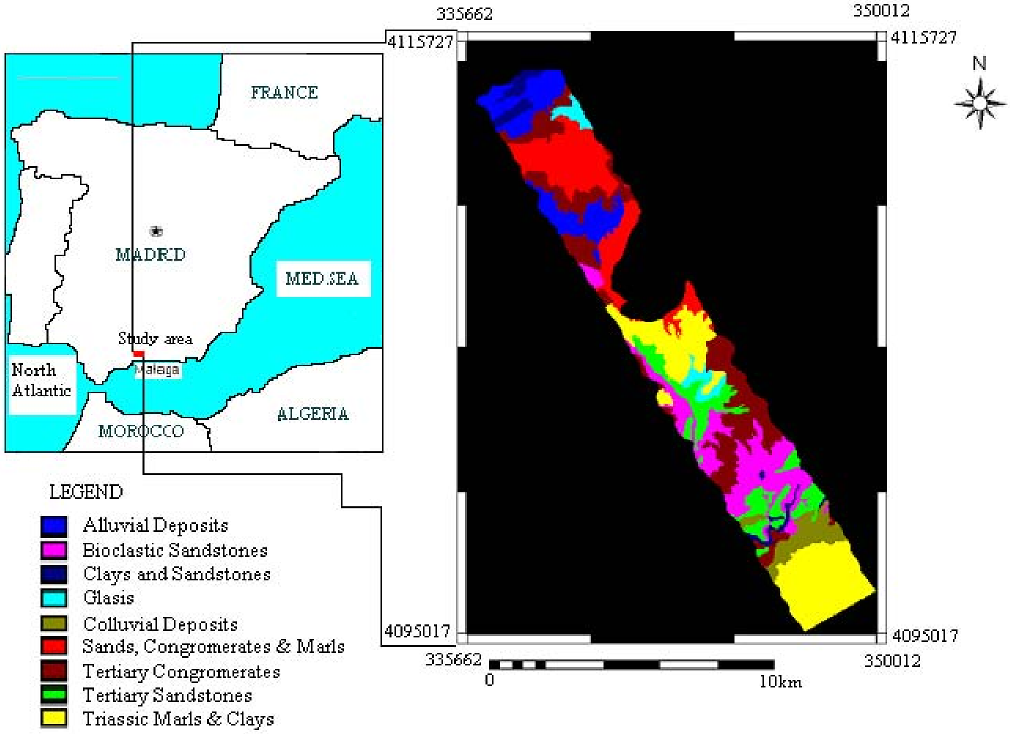

Figure 1. Location map showing soil parent material

2.0 MATERIALS AND METHODS

2.1 Data Acquisition

Four data sets were used in this analysis consisting of 1) soil physicochemical properties 2) laboratory spectral data, 3) field spectral data and 4) DAIS image data.

2.1.1 Field soil data sampling

Sampling sites were selected based on previously determined cation exchange capacity (CEC) values, in an existing soil database of the area, in the Soil Science Division of the International Institute for Geo-Information Science and Earth Observation (ITC), Enschede, in the Netherlands. The sample sites were selected to represent the range of soils within the area based on these CEC values. At each site three bulk and six clod samples were collected from the surface soils (0-20cm) within a five-meter radius at the same time in June 2001 when airborne hyperspectral data was acquired. Proper location of the selected sites was done using the global positioning system (GPS) in order to obtain samples as near to the existing data as possible**.** Other ancillary information, of each field spectra-measuring site, i.e. description of the soil, and percentage cover of both soils and vegetation was also recorded. Extra sites were randomly selected and added to the previously selected sites, resulting in a total of fifty sites.

2.1.2. Physicochemical data

This consisted of the estimation of the particle size distribution (PSD) cation exchange capacity (CEC), coefficient of linear extensibility (COLE) and saturated moisture (SP) content. Particle size analysis was by the pipette method while CEC was through the mechanical extractor method [7]. The Atterberg limits were by BS1377: Part 2:1990 method [8]. COLE was through the clod test method [9] while saturation moisture content was the difference in weight between saturation and oven dry states of the samples. The clay content was used to normalize the CEC to give cation exchange activity (CEAc) and the combination of the three properties used to group the soils within certain established thresholds within which they are assigned to a swelling potential class and a dominant clay mineral type.

2.1.3 Spectral data acquisition

In the laboratory spectra of split samples of those used for the physicochemical tests (passing the < 2 mm sieve and oven dried at 105^0C) were obtained using the PIMA (Portable Infrared Mineral Analyser) upgrade spectrometer and GER 3700. Both have an average spectral resolution of 10 nm with the PIMA covering the spectral range between 1300 nm and 2500 nm and GER 3700 the range between 400nm and 2500nm. Field measured spectra data at selected sites during the flight represented the field spectral data.

The DAIS hyperspectral data was acquired on 28 June 2001 at an altitude of 10 000 feet (providing a pixel size of approximately 5 m×5 m) with a sensor that is sensitive to the visible (VIS), near infrared (NIR), short wave infrared (SWIR) and thermal infrared (TIR) spectral regions (0.4–14 nm) consisting of 79 channels with a bandwidth ranging from 0.9 nm in the VIS to 60 nm in the TIR. The image scene covered an area of 21km by 3 km in a northwest southeast direction. For this paper only the reflective portion of the electromagnetic radiation was used covering the VIS-SWIR (0.4–2.5 mm) spectral region with 72 spectral bands.

2.2 Data analysis

2.2.1 Spectral analyses

Analysis of the spectral data was by use of several currently applied techniques found to adequately represent information in the spectra i.e. absorption feature mapping [10] and the derivative analysis where finite approximation method was used [11].

2.2.2 Swelling potential categorization

The soils were classified into three swelling potential classes based on various classification thresholds (table 1) established over the years by different workers on the measured properties. These thresholds are a result of normalizing the measured properties with the clay content giving a relative measure of the clay influence on the various properties to that of sand and silt contents.

Table 1. Classification based on various schemes [12][13] [14][15]

Class	COLE	CEA_c	Saturation moisture	Estimated mineralogy
Low	<0.05	<0.2	<30	Kaolinite>50
Moderate	0.05-0.15	0.2-0.6	30-45	Illite>25
High	>0.15	>0.6	>45	Smectites>50

2.2.3 Statistical analysis

K-means cluster algorithm was used to first establish spectral parameters with a potential to give information on the measured soil properties suing the laboratory and field spectral data. The method is based on identifying homogeneous groups of cases within a heterogeneous data [16] establishing cluster centres to represent each class difference with the other clusters. The clusters were set at 3 and the initial centres as the three established thresholds in table 1. Resulting spectral parameter assignments were made based on their association with each of these categories and assumed to provide information on differences in the measured properties among the soils giving spectral thresholds and assumed to show variation in abundance of the various mineralogical assignments.

The second stage involved the use of factor analysis to establish quantitative assignments to the simultaneous variation in the spectral parameters and physicochemical properties by assigning the factor scores of the factor with strong assignments from the measured properties to a normalized scale. Factor analysis is based on common factors analysis, where elements on the principal diagonal are the communalities, which means that only the common variance of the variables are analyzed. Thus it has the advantage of removing the unique factors of each variable and optimizing the information content based on the common factors. The method is often used in data analysis to study correlations among large numbers of interrelated quantitative variables by grouping the variables into a few factors where variables in a factor are more highly correlated with one another than to those in another factor. This enables interpretation of factors in terms of their contributing variables. Here the factor with maximum contribution from the measured physicochemical properties was assigned to represent compositional differences and thus to varying swelling potential levels. Spectral parameters with strong loadings from this factor were assumed to show strong correlation to the compositional factors contributing to the differences in the measured physicochemical values.

2.2.4 Image data analysis

The atmospheric correction was performed with the Atmospheric/Topographic Correction (ATCOR4) model for wide FOV airborne imagery [17]. The visible (VIS) to near infrared (NIR) i.e. 0.49-1 µm, short wave infrared SWIR-1 (1.5-1.8 µm) were good, however problems existed with the spectrometers in the region 1.948-2.179 µm that made the data not useful. There was noise in 2.317 – 2.395 µm region that was minimized by use of the moving average smoothing technique prior to analysis. The procedures employed on the laboratory data were repeated on the image data where extracted pixels spectra at each of the soil sampling locations were used together with the resampled field and laboratory spectra for the statistical analysis. Resulting spectral assignments were then used on a pixel-by-pixel basis on the whole image.

3.0 RESULTS

Table 2 gives the summarised range and statistics of the measured physicochemical properties, showing a relatively wide variation in these properties. The mean for SP (50%) was relatively high as would be expected for clay soils, CEA_c (0.41) and COLE (0.053) were moderate thus classifying the soils as of moderate activity. The clay content was relatively high with an average of 46% and ranging between 27% and 71%.

Table 2. General information on engineering indices

Property	Minimum	Maximum	Average	Standard Deviation.
SP	28	76	50	0.33
CEA_c	0.12	0.7	0.41	0.12
COLE	0.01	0.108	0.053	0.39
Clay %	27	71	46.1	11.9

Table 3 provides the cluster centres based on the absorption feature parameters of the laboratory and field spectra and the physicochemical properties. Figure 2 shows the spread of samples in each cluster from their cluster centres based on the Euclidean distance where only a few samples seem to be significantly different from their means and in the 3rd cluster, thus showing each cluster to properly represent the assigned threshold. The 1st derivatives peak intensity at various wavelengths regions around the water and hydroxyl absorption features were found to give similar results. The results show that though other sources of variability between the soils are likely, the spectral variability seemed to give a good indication of the compositional differences and thus provide a good source of information on the swelling potential of the soils based on the three measured properties and the previously assigned minerals. Samples of high swell potential and assigned to abundant smectite in table 1 grouped in the second cluster whereas those of moderate and low potential grouped in the first and third clusters respectively proving the spectral parameters potential.

Table 3. Final Cluster Centers

	Clusters		
	1	2	3
Asymmetry 1400	1.0796	.8989	1.0336
Depth 1900	0.0481	0.0865	0.0399
Wave position 2200	2207.30	2218.29	2206.37
Asymmetry 2200	0.96	0.62	1.15
CEA_C	0.41	0.6	0.23
SP	52.7	75.9	28.2
LE/% clay	0.05	0.09	0.02

However though there is a clear separation between low and high value classes based on both the measured physicochemical properties and spectral parameters, this cannot be said to be the case for the moderate value group as evident from the distance between the cluster centres (table 4) probably showing two clusters as more appropriate. The classification error of the individual samples was observed at below 16%. This resulted in the use of two clusters for the image data with much better results as will be discussed later.

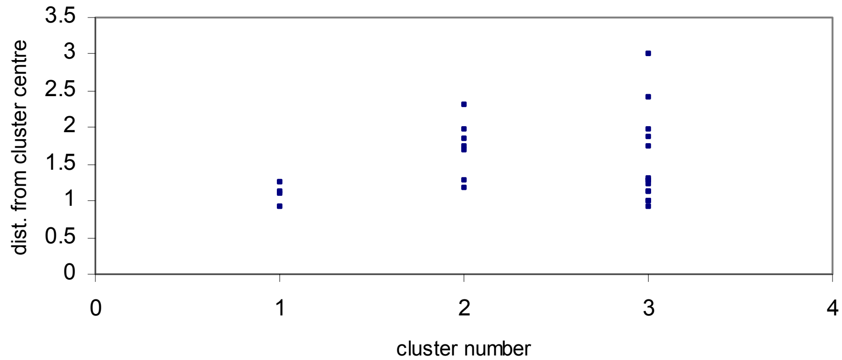

Figure 2. Variation in distance to cluster centers among used soil samples

Table 4 Distances between Final Cluster Centers

Cluster	1	2	3
1		25.392	14.298
2	25.392		38.724
3	14.298	38.724	

Table 5. Final Cluster Centers

	Cluster	
1st derivative peak	1	2
R_551	10.966	17.812
R_1606	3.047	-1.874
R_1698	2.745	1.414
R_2151	-2.518	1.220
R_2193	-6.867	-3.548
R_2252	-7.649	-5.872
R_2304	-10.441	-4.502
R_2342	-2.331	-8.026
COLE	.07	.02
SP	67.33	42.25
CEC	32.67	16.50

The laboratory results were applied on the DAIS image data with much lower spectral band pass where re-sampled field and laboratory data together with extracted pixel spectra of the various sampling sites were used and gave an indication of similar differences among the soils by giving clear separation between the samples into two clusters based on the 1st derivative analysis results where several wavelengths were established to give peak intensities with a potential to place the samples into the cluster memberships ($p < 0.01$). They included; 1606nm, 1698nm, 2151nm, 2252nm 2193nm, 2304nm and 2342nm whose peak positions are all in spectral regions, which have been assigned to spectral anomalies in clay minerals reflectance and to the presence of Al-OH and Mg-OH in dioctahedral and trioctahedral clays [18]. Table 5 provides the final cluster centres after 25 iterations of both the spectral parameters and the measured properties among the soil samples whereas figure 3 gives an illustration of the samples distribution in terms of distance from their respective cluster centres where only a few samples are seen to be at great distances from their centres thus appearing as offshoots in what is generally a distribution well within short Euclidean distances.

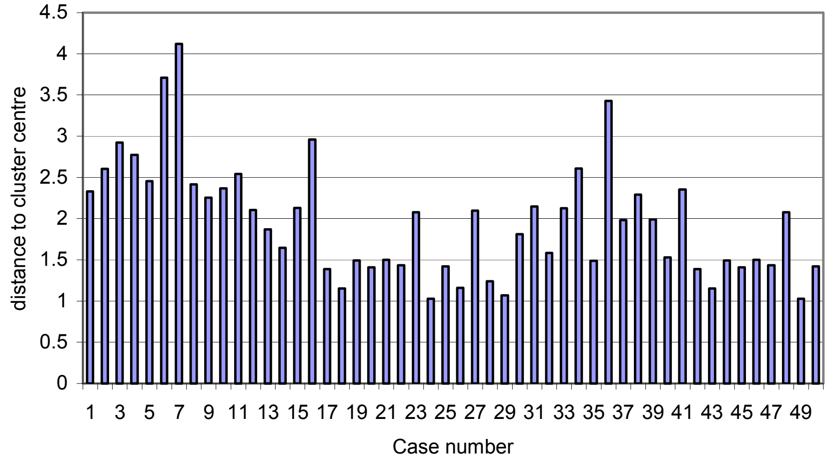

Figure 3. Variation in distance to cluster centers in used soil samples with DAIS extracted pixel data

Figure 4 gives an illustration of the resampled average spectra of soils in each of the two clusters where it is significantly evident that the spectrum of cluster 1, comprising of the higher value soils shows a generally lower albedo at all wavelengths relative to that of cluster 2. This is as would be expected for soils with significant contents of the high swelling smectites whose possession of structural water and formation of complexes with organic matter due to their generally lower positions in the landscape, could explain the lower reflection relative to those in the second cluster presumed to consist of the much lower swelling potential minerals soils whose albedo is generally higher based on their better drainage and probably less presence of organic matter complexes. It is important to point out here that of the samples used in this classification only less than 10% were misclassified thus showing the selected spectral assignments as good in the characterization of the soils on the basis of the three swell indicator properties.

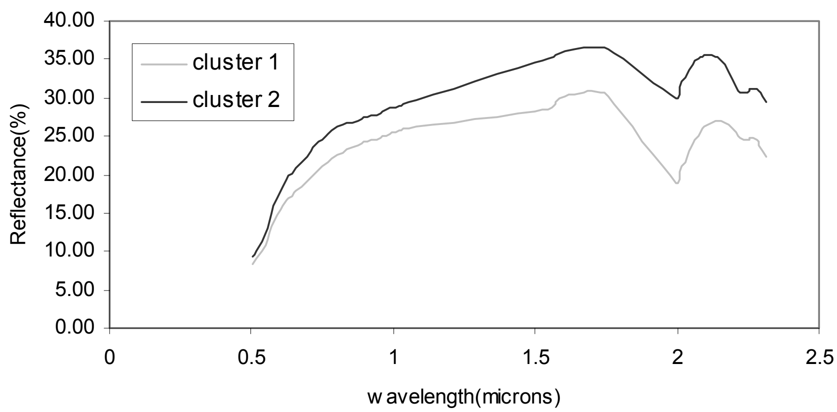

Figure 4. Average spectra of low and high properties value soils

The second stage involved quantization of these relationships based on the factor analysis statistical procedure where the factor extraction was done with criteria that the minimum acceptable eigenvalue must be greater than 1 [19]. The first two factors explained more than 87% of the variance where factor 1 grouped the measured physicochemical properties with some of the spectral parameters both of which had high factor loadings. The second factor only had high loadings from mainly spectral parameters not found in the cluster analysis to closely relate to the measured properties and thus was interpreted to consist of insignificant information as to their variability (figure 5).

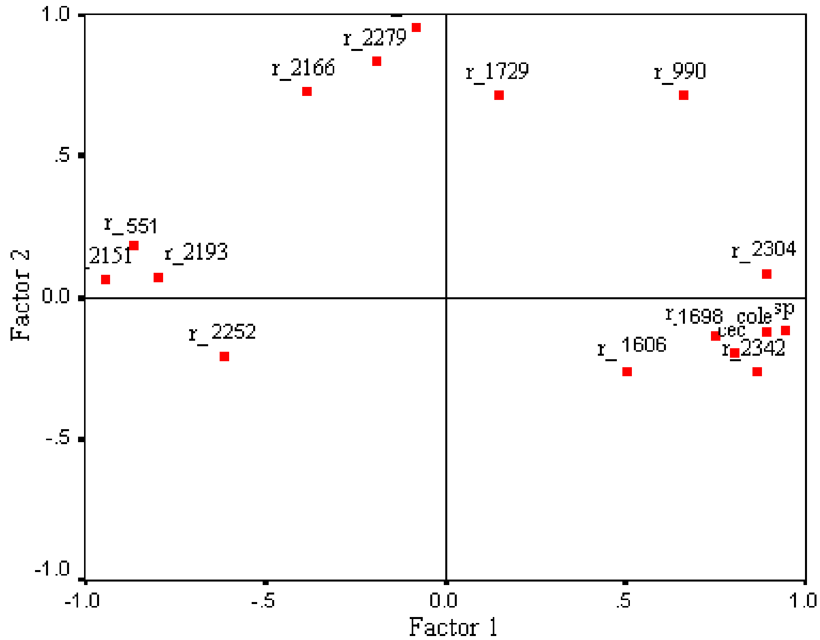

Figure 5. DAIS data reduction to obtain spectral calibration wavelengths

Spectral parameters with high factor loadings in factor 1 were interpreted to represent the reflectance spectral information on the measured properties among the samples. The factor loadings were; COLE (0.86), CEC (0.76), SP (0.92) and for the spectral parameters 551nm(-0.82), 1606nm(0.52), 1698nm(0.75), 2151nm (-0.88), 2252nm(-0.55) 2193nm(-0.7), 2304nm(0.94) and 2342nm(0.77). This confirmed the cluster membership assignments and led to the conclusion that the factor could be used to explain variation in the soil swelling properties among the used soil population, by assigning the soil samples to their factor scores.

The results show the loadings to portray the information as coming mainly from wavelength positions associated with strong presence of clays rich in Al-OH (2151nm, 2193nm) and Mg-OH (2304nm) cited in many writing as a reflection of the strength of the combination of fundamental OH stretching (ν) and bending (δ) modes of OH-metal-OH bonds in the octahedral and trioctahedral positions respectively. High albedo in clays has been assigned to one of the other significant positions (1698nm) also described by [20] as best for mapping clay content in surface soils and in several studies has been established to show strong correlation with CEC (one of the three measured physicochemical properties). The strong correlation with CEC has been attributed to CEC being closely related to soil constituents that do exhibit spectral behaviour namely clay type and content [21]. The position attached to Fe-OH (2252nm) was relatively weaker in the results that probably reflect the presence of ferric iron association with well-drained and weathered soils. [22] attributed the reflection intensity at the 551nm region to iron hydroxides containing water and products of significant weathering, which could also probably explain its significance in the results.

At a vegetation cover as high as 15% surfaces have been described to appear as soil [23] whereas vegetation cover in excess of 40% makes the spectral behaviour that of vegetation. Based on these assumptions and prior to application of the above results on the whole DAIS scene, the image was classified into vegetated and scarcely vegetated/bare soil regions using the Normalised Difference Vegetation Index (NDVI) (figure 6) where masking of highly vegetated area assumed to consist of greater than 40% vegetation cover was set at NDVI > 0.5 that has been reported as appropriate [24] when establishing soil surface properties. All the other areas were used for the classification based on the previous assumptions.

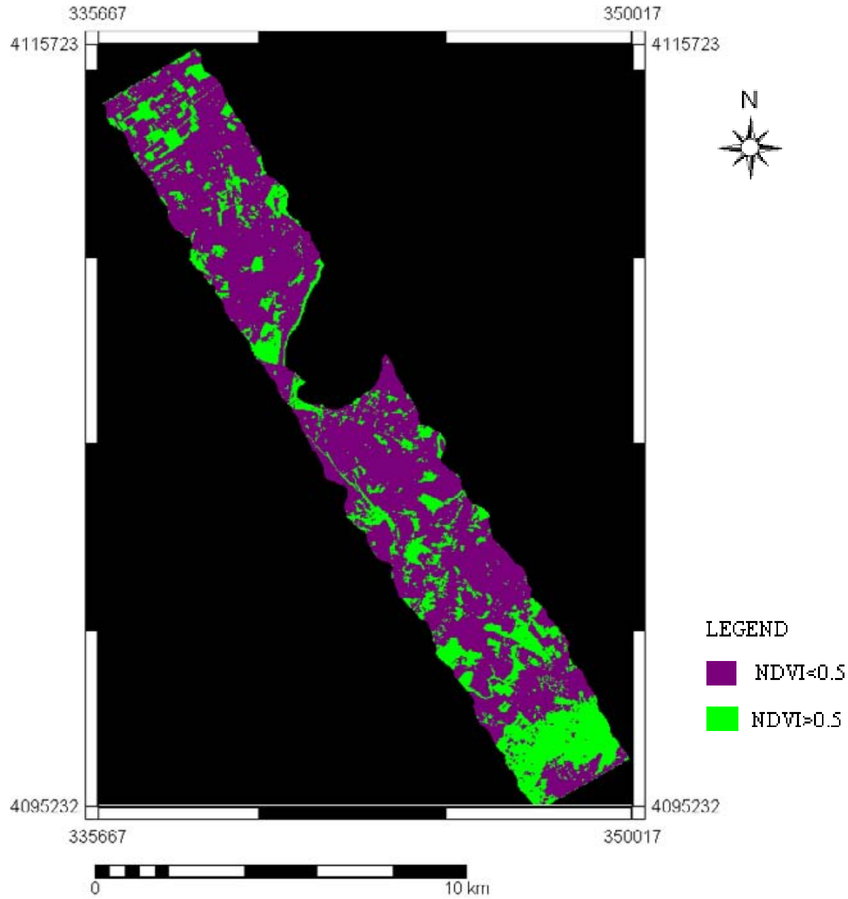

Figure 6. Criteia for masking Areas with heavy vegetation (NDVI >0.5)

Figure 7 shows the resulting classification of the image based on the obtained results where the factor scores established in the common factor based on the spectral and the measured properties were used to classify the entire image by assigning the selected spectral parameters weights based on their contribution to this factor and scaling the range between 0 and 1 thus areas with a value of 0-4 being mainly those of low measured property values, 0.4-0.7 moderate and greater than 0.7 as of high values. The results to a great extent gave a relatively good indication of the measured property differences based on field knowledge where it was found to mainly classify the soils into low to moderate property values that are characteristic of the soils in the area.

Misclassifications however did occur as would be expected probably due to variations resulting from other sources. The results however seem to indicate that despite these other sources of variability, the composition differences influencing the soil physicochemical properties play a significant role in their spectral characteristics that can be used to obtain information on their differences probably confirming observation by [25] that soil patterns remain visible even in the presence of some vegetation and the fact that, drainage and moisture holding capacity differences among soils tend to influence their overall reflectance.

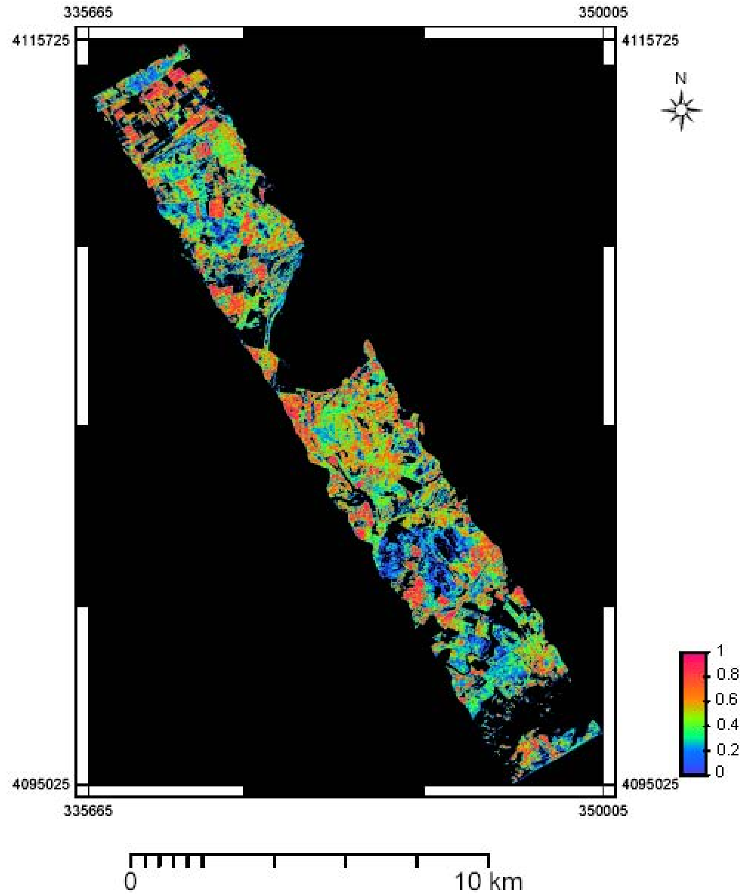

Figure 7. Classification based on spectral parameters and measured properties.

The results show that in addition to absorption features, changes of the spectral slope can play a significant role in the estimation of soil properties from hyperspectral data with much lower spectral band numbers relative to those regularly used in the laboratory and field measurements, despite the atmospheric interference. This has found use in other soil property estimations [5] making the obtained results significant. Thus though the hyperspectral data might not give as precise measurements as the laboratory procedures it could be a good tool for quick assessment on the surface properties and thus a start to more detailed assessment in the field or at a laboratory scale. It should be pointed out though, that caution should be taken when using such information since spectral noise could be introduced into the results based on the amplification of noise by derivative procedures, which could lead to irrelevant band assignments to compositional differences.

Comparing this with the parent material map (figure 8) show some correlation where the moderate to relatively high property values soils fall mainly into parent materials consisting of marls, clays and alluvial deposits. Sandstones and conglomerates seem to give low value soils. This probably confirms [21] conclusions that parent material is a key component in the resulting soil spectral characteristics and the results of [26] who found parent material to affect the spectral reflectance in all wavelengths when working with deltaic, alluvial and marine outwash soils.

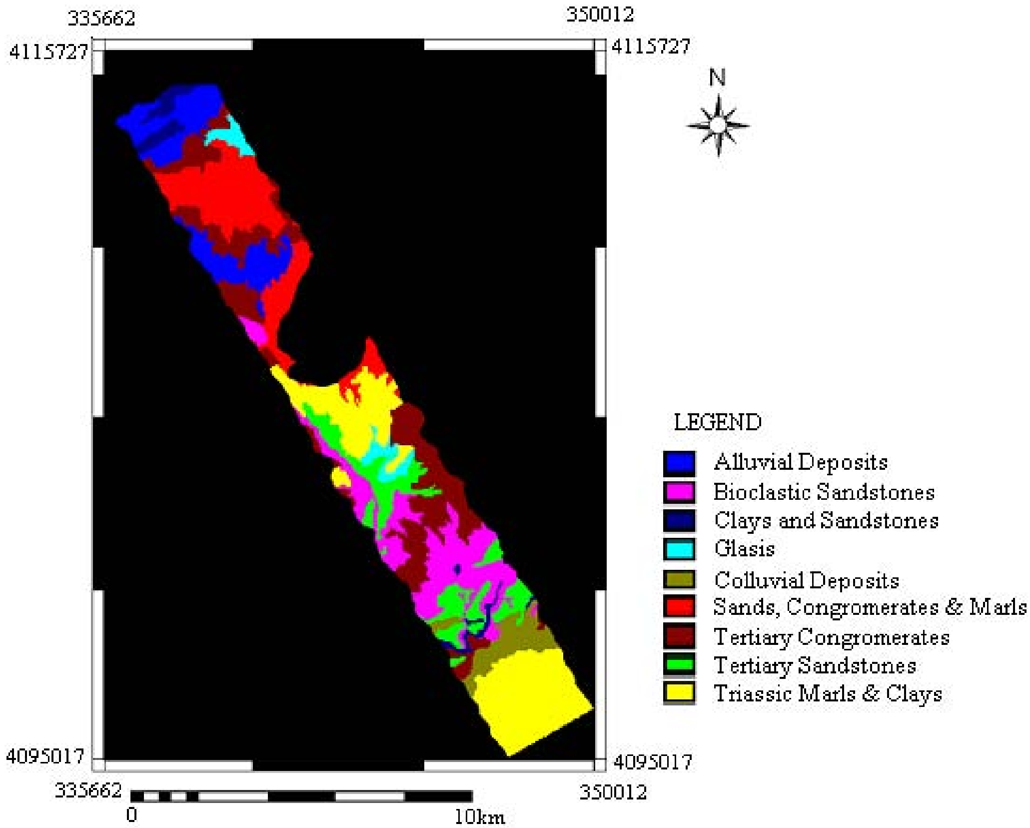

Figure 8. Parent material distribution map

4.0 DISCUSSION

The laboratory results show that soil compositional differences has great influence on their resulting spectral parameters which can be used to classify them on the basis of their associated property differences. The differences in the absorption feature parameters in terms of strength of the hydroxyl (OH) and molecular water features relative to the presence of clay minerals with a potential to influence the measured swelling potential indicator properties were seen in the variations in depths, asymmetries and position shifts which as previously described is a function of the soil clay mineralogy and their structural differences which as seen in the established classification tables result in surface area differences a key to the variation in the soil physicochemical properties. The clusters give an estimation of the discrete boundaries within which spectral parameters can be used to classify soils in terms of their swelling potential based on these classes and reflect the covariance between the soil physicochemical properties and their spectral response. Several reports have cited the potential of using spectral data to establish soil properties resulting from soil constituents with obvious spectral character and has been described as pronounced for CEC, one of the used properties, relative to others such as the particle size classes and bulk density [27].

This seems to be evident even in the lower spectral band number of the airborne image data where the spectral derivatives gave significant information s to the compositional differences a fact that could be attributed to the manipulation enhancement of weak absorption [28] and suppression of physical influences [29], thus providing clearer information on the absorption mechanism by minimizing interfering properties such as the soil surface roughness and grain size distributions. The results are also in line with [30] observations of spectral data providing information on underlying processes bringing about the soil composition differences such as the soil internal drainage that has been described to influence reflectance. Thus the generally high reflectance at all wavelengths by the well-drained soils and lower reflection by the poorly drained soils could be attributed to this and has previously been documented by [25]. A clear evidence of this is in the two averaged spectra for the resulting clusters providing the discriminating spectral parameters for the image classification of which established significant wavelengths have all been described to provide important information on soil water and mineralogy [31] [32][33][34] further confirming the approach as viable in soil property studies.

The results could therefore be taken to provide a strong case for the potential application of remote sensing to soil properties estimation more so those related to presence of clay minerals and their interaction with moisture that can be assigned to indicate differences in affinity for water. They give an indication of the potential role of reflectance spectroscopy as a primary or complementary tool in such determinations, though they also show the limitations of hyperspectral data relative to laboratory data in terms of information content.

5.0 CONCLUSIONS

The results show that both absorption feature parameters and other data manipulations that enhance potential differences in the reflectance among soils consist of information, which with proper calibration can be used to differentiate soils on the basis of their physicochemical properties. This could easily be attributed to the covariance between the soil properties without a primary response in the soil spectra (used indices) with those possessing such a response (the clay mineralogy and soil water) making it possible to use the spectral diagnostics of the primary response factors to obtain information on their co-varying properties. The resolving capacity of the airborne data was however insufficient to resolve some of the most diagnostic spectral parameters established in laboratory data to provide details as to the molecular structural differences among the compositional elements. This probably calls for the applications of higher bandwidths in the airborne data acquisition that would resolve some of these unique feature parameters and probably help in minimising on the possibility of including spectral noise in the analysis which as previously discussed is enhanced when using the derivatives.

It was clear though that surface spectral reflectance holds information representative of the soil compositional differences and with proper data manipulations could be used to derive related properties even though other sources of variability could have been in play. The results confirm reflectance spectroscopy as a tool that adds value to the existing soil properties classifications schemes by filling the information gap as to causative compositional factors by adding a physical basis of diagnostic differences of the clay mineral types in the reflected soil spectra. The results lay the foundation of establishing a faster method of characterizing soil in terms of their swelling potential and other related properties.

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