Soil mapping at regional scale using ASTER and VNIR spectroscopy

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Abstract

The use of satellite data as a measure of spatial and spectral variability for soil mapping constitutes the link between proximal and remote sensing. This paper proposes a sparse sampling approach which makes use of constrained Latin Hypercube to determine the spatial and spectral variability in soil properties at a regional scale. The sampling approach was successful in representing major variability. In addition, the spectral similarity between field and laboratory spectra was high and therefore the field spectra are suitable for soil property analysis. Of course, vegetation influences the field spectra and therefore it is recommended to select spectra based on low NDVI-values.

Keywords: Soil mapping, VNIR spectroscopy; Remote sensing; Regional scale

Introduction

Soil and terrain information is needed for policy-making, land resource management, and for monitoring the environmental impact of development. Global and regional models that address climate change, land degradation and hydrological processes need soil input parameters with complete area coverage. Especially in development countries information about solids is sparse while at the same time resources for data acquisition are limited (Mulder et al., 2011). Therefore, we propose a sparse sampling approach which utilizes remote sensing data to determine the spatial variability in soil properties on a regional scale. This approach would reduce the financial constraints on soil property mapping. This paper examines whether the sampled locations do represent the spectral variability found within remote sensing data. Also, field spectra and laboratory spectra are compared to find out if the former can substitute the latter in an attempt to further reduce data acquisition costs. The spectral similarity of the spectra was determined by the comparing spectral angles.

Materials and Methods

<u>Sampling scheme</u>

The research area is located in Northern Morocco, centred at 34,0 N, -4,5W and covers an area of 15000 km^2 with the Rif Mountains being the northern border and the Anti-Atlas Mountains being the southern border. An optimal sampling scheme was developed with use of constrained Latin Hypercube sampling (LHS) which is a stratified random procedure for sampling variables from their multivariate distributions, for more details we refer to McKay et al. (1979) and Minasny & McBratney (2006). The Latin Hypercube consisted of the first three principal components from ASTER imagery and the ASTER GDEM, representing variation in topography. Hence, the ASTER imagery was not used to provide the spectral resolution for soil analysis, but rather as a data source for spectral variability.

To increase efficiency of the fieldwork, the Latin Hypercube sampling was constrained by the distance to the roads and steepness of slopes. Using simulated annealing, 100 sites were optimised to optimally sample the Latin Hypercube (Fox and Metla, 2005).

<u>On-site sampling</u>

On-site spectral measurements were taken with an ASD Fieldspec Pro FR spectroradiometer, covering the 350-2500 nm wavelength region. For these measurements, Valeri plot sampling (Rossello and Baret, 2007) on a 15*15 meter plot was used to estimate the full spectral variability. On the corners and the centre of the plot a mixed soil sample was taken of the top 5 cm. The soil samples were dried at 70° C, sieved at 2mm and spectral measurements were taken under laboratory conditions with the same spectroradiometer and the contact probe.

<u>Spectral Angle Mapper (SAM)</u>

In order to determine the spectral similarity of the spectra the spectral angle was calculated between the field spectra and the laboratory spectra. This is achieved by treating them as vectors in a space with dimensionality equal to the number of spectral bands of the field spectra, this algorithm is called the Spectral Angle Mapper (SAM). A spectral angle smaller than 0.1 radians was considered as the threshold indicating similarity. SAM is an feature-based analysis, which means that the presence of the absorption feature is taken into account but the depth of the absorption feature does not matter, only the angular difference (Kruse et al., 1993). This is ideal for comparing the different sets of spectra collected in the field and under laboratory conditions. However, vegetation might influence the absorption features, therefore two different analyses were performed. In the first analysis, the average of the field spectra taken with valeri-plot sampling was used to calculate the spectral angle, including the measurements taken on more vegetated sites. This analysis is referred to as ‘Averaged field spectra’. The second analysis included the sample measured on-site with the lowest Normalized Difference Vegetation Index (NDVI, Tucker 1979) and is referred to as ‘Lowest NDVI spectra’.

Results

<u>Constrained Latin Hypercube Sampling</u>

Owing to difficult field circumstances related to accessibility and topography, 73 sites could be sampled during the fieldwork campaign. Main limitations in the field were related to accessibility and topography. In the variable space from the DEM it can be seen that the largest gaps occur for higher altitude (Fig. 1). In order to solve this problem in the field, similar soil characterises were selected at lower altitudes when possible. Therefore, the variable space for the principal components is better sampled. However, the samples do cover the extend of the multivariate distribution which would indicate that the planned special and spectral information needed for soil mapping is collected during the field campaign.

<u>Similarity of the field and laboratory spectra</u>

In Figure 2 an example is presented with field and laboratory spectra and similarity is apparent since the overall shape of the spectrum and locations of absorption features are alike. The spectral signatures from the field were pre-processed; The atmospheric and bad bands were removed, resulting in a spectral range from 350 nm to 2460 nm; The spectra were smoothed over the remaining spectral range. The spectral angle was calculated between the pre-processed spectra and the laboratory spectra.

Figure 3 shows a medium strong relation (R^2 = 0.5089) between the spectral angle and the NDV calculated from the field spectra. This suggests that the absorption features are influenced by vegetation. n Table 1, the summarizing statistics are presented for the two analyses on spectral similarity between field and laboratory spectra. This table shows that for both the ‘Averaged field spectra’ and the ‘Lowest NDVI spectra’ the average spectral angle was were smaller than 0.1 radians. The maximum angles are larger than 0.1 radians which indicates that for some samples the similarity is too low, what would result in misclassification. The large angles might be contributed to the high coverage of non-photosynthetic vegetation and soil moisture conditions in-situ. Both the standard deviation and the number of samples with an angle larger than 0.1 radians is lower for the ‘Lowest NDVI spectra’.

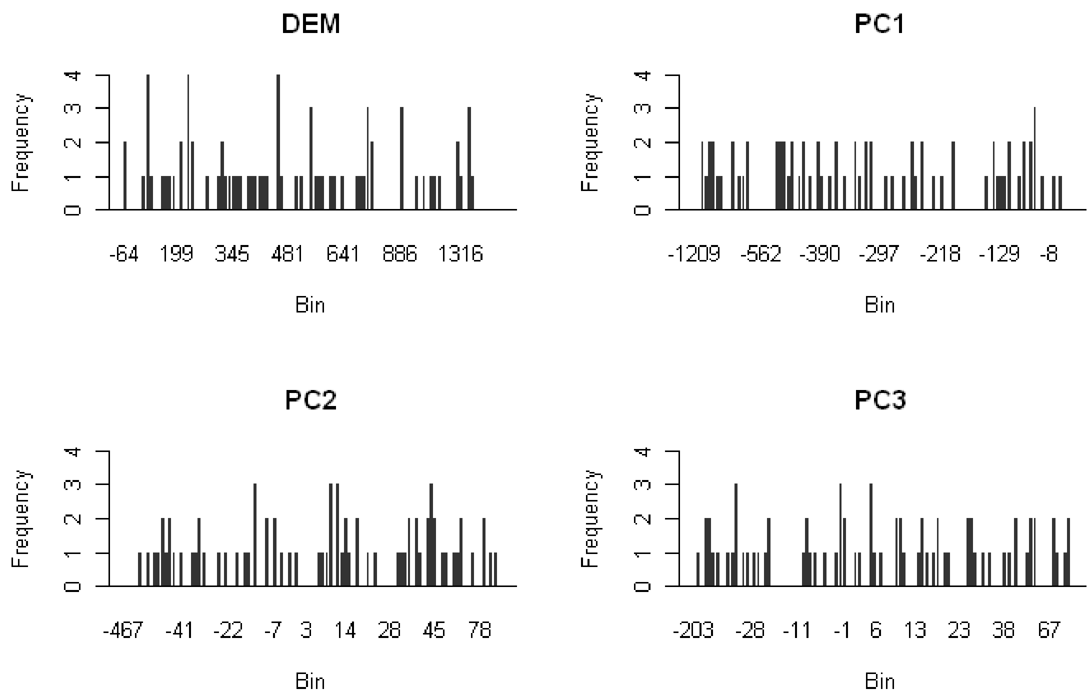
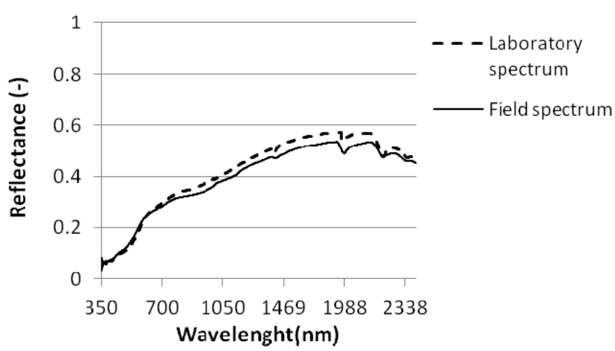


Figure 1: Distribution of the field samples over the defined intervals for the Latin Hypercube, which consists of Principal Component 1, 2 and 3 and the Digital Elevation Model (DEM).



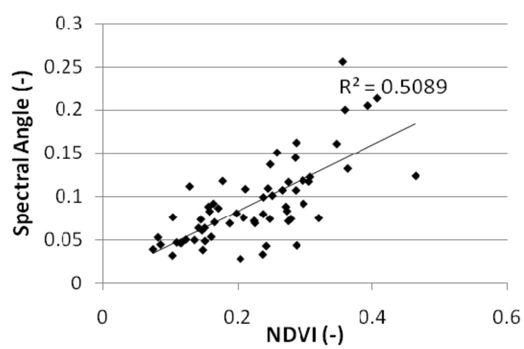


Figure 2: Example spectral signature measured under field and laboratory conditions

Figure 3: Relation between NDVI and Spectral angle.

Table 1: Summarizing statistics for the calculated spectral angles for the two datasets.

	Averaged field spectra	Lowest NDVI spectra
Average angle	0.089	0.077
Minimum	0.012	0.020
Maximum	0.396	0.333
Standard deviation	0.063	0.053
Average NDVI	0.220	0.160
No. samples < 0.1^{rad}	21	13

These results show that the spectral similarity between field and laboratory spectra decreases with increasing vegetation coverage.

Conclusion and discussion

In this paper we proposed a sparse sampling method, which made use of remote sensing data to determine the spatial variability in soil properties on a regional scale. Firstly, we have shown that using constrained Latin hypercube sampling a relatively small sample can represent the spatial and spectral variability within ASTER satellite images and a Digital Elevation Model (DEM). Secondly, we found large spectral similarity between field spectra and laboratory data and therefore the field spectra can be utilized for soil property analysis. Of course, green vegetation influences the field spectra and therefore it is recommended to select spectra based on low NDVI-values. The use of satellite data as a variability measure for a sparse sampling approach seems to be promising. The approach outlined in this paper could be used on finer scales as well. However, ASTER does not have the spatial and spectral resolution to detect the spatial and spectral variability at these scales. Therefore, higher resolution data would be required for the constrained Latin Hypercube approach. In our opinion, the use of satellite data as a measure of spatial and spectral variability for soil property mapping on a regional scale constitutes a useful link between proximal and remote sensing.

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