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A novel spectro-temporal approach for predicting soil physical properties

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ABSTRACT: This study evaluated quantitative relationships between soil surface reflectance and inherent soil properties to produce digital soil maps supporting precision soil conservation and sustainable water management. Relationships were studied at the laboratory, field and watershed scales. Successive radiometric measurements were taken in the laboratory on 119 undisturbed soil cores following a drying process. Multi-temporal spectral indices were developed from reflectance values quantifying soil moisture, organic matter content and texture. These indices were subsequently validated under uncontrolled moisture conditions on 47 field sites. At the catchment scale (43 km^2), the indices were systematically derived from multiple Landsat images acquired under wet and dry conditions. The indices were significantly related to soil moisture (R^2 = 0.80) and organic matter content (R^2 = 0.89). Prediction models derived from satellite imagery confirmed the potential of spectral indices for mapping soil texture, organic matter content and drainage.

1 INTRODUCTION

Currently available soil maps do not portray the spatial resolution of soil biophysical properties needed to support site-specific management. Updating and upgrading these soil maps using conventional soil survey methods is slow and resource-consuming. Therefore, alternative methods need to be developed using the relationship between soil properties and ancillary data acquired by satellite, airborne and terrestrial sensors (McBratney et al., 2000). As soil reflectance depends on soil moisture, organic matter (OM) content, soil color and texture, it is hypothesized that 1) permanent (OM, color and texture) and non permanent (moisture) soil properties can be derived using multitemporal soil reflectance datasets and 2) reflectance measurements taken under dry soil conditions can be used to normalize soil effect and give a more robust estimate of soil moisture (Liu et al., 2002, Lobell & Asner 2002). The goal of this study was to determine the relationship between soil properties and reflectance over a range of moisture conditions. More specifically, spectral indices revealing soil texture, OM, color and moisture were developed under controlled environment and validated under field conditions. Finally, the relevance of these spectral indices for digital soil mapping was assessed at watershed scale from a series of Landsat images and morphological soils datasets.

2 SITE DESCRIPTION

The Ewing Creek watershed (42.5 km^2) is located in the southern part of the Province of Quebec (45°09′21″N 73°04′36″W). It is a tributary of the Pike River, which flows into the Missisquoi Bay of Champlain Lake (Fig. 1). Corn and soybeans are the dominant crops in the watershed, which ranges in elevation from 29 to 60 m. Mean annual precipitation and temperature are 1150 mm and 6°C, respectively. Land drainage is the main limiting factor of crop productivity and most fields benefit from systematic tile drainage. The spatial distribution of the soil sediments follows a topographic

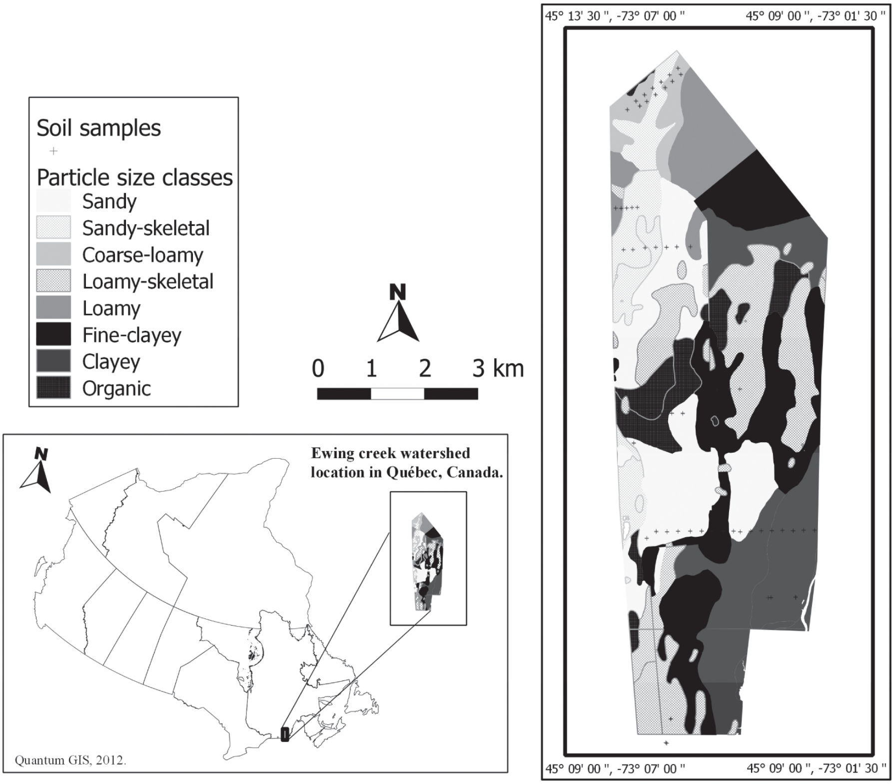

Figure 1. Location of the Ewing Creek watershed in southern Quebec, Canada; soil map showing the spatial distribution of family particle size classes of major soil surface materials (1948).

gradient, from marine (Champlain Sea) to lacustrine (Lampsilis Lake) deposits overlying glacial till dating from the Quaternary period. This distribution largely explains the spatial variability in soil properties in the study area. Soils are ranging from poorly to imperfectly drained Gleysols, Podzols or Brunisols and are generally rich in carbonates. Thin organic deposits (bogs or marshes) are present in old abandoned fluvial channels or pits. In upper areas, the Proto St. Lawrence River has exposed glacial deposits, carrying clays and leaving behind coarse-loamy to loamy-skeletal materials. The most recent soil survey information available in this area has been published at a scale of 1:63,360 in 1948.

3 METHODS

Relationships between soil properties and radiometric signal were studied with a three-step/scale approach. The first step investigated relationships between soil properties and reflectance values measured in the laboratory, under controlled moisture conditions, to derive three normalized spectral indices. The adequacy of these indices in explaining soil properties was then investigated under uncontrolled moisture conditions during two field campaigns (validation). Finally, the spectral indices derived from calibration were applied on Landsat images to evaluate their relevance for creating soil property maps. All statistical procedures were realized with the R statistical software. SAGA GIS was used for spatial data treatment and ATCOR 2/3 was used for computing radiometric and atmospheric corrections.

3.1 *Laboratory experiment*

Undisturbed soil samples (n = 119) of the surface layer (0–10 cm) were located by GPS and collected along eight transects using 800 cm^3 copper cores. Soil morphological data acquired by Michaud et al. (2009) were used to guide the soil sampling strategy to assure soil diversity in terms of soil texture, OM and drainage. The soil cores were immersed in water for 48 hours to reach saturation. During the drying process, 12 reflectance measurements

(350–2500 nm) were collected using the ASD pro FR portable spectroradiometer and soil samples weighed for soil moisture determination. The final reflectance measurement was taken on dried samples (103°C for 48 hours). Spectral signatures were treated to simulate Landsat 7 bands and used to develop spectral indices expressing soil moisture, OM, soil color and soil texture. Following the lab experiment, laboratory analyses were used to determine the sand (%), silt (%), clay (%) and OM (%) for each soil core. Soil color was determined under wet and dry conditions using the Munsell Color System (hue, value and chroma).

3.2 *Field scale experiment*

Spectral indices were developed and validated from field data collected during two field campaigns in May and June 2009. Radiometric measurements simulating the sensors of Landsat TM7 were collected with a ASD FR Pro portable spectroradiometer on 47 sites selected from the population of 119 core sampling sites used for the lab experiment. The volumetric soil moisture content was estimated on site from four electrical conductivity measurements using a portable probe (ThetaProbe ML2x) in the first 6 cm. Laboratory analysis were used to determine the soil texture and OM.

3.3 *Watershed scale experiment*

Landsat images, a digital elevation model and soil morphological data were combined to produce maps of textural properties for the A and B horizons, as well as drainage classes. Radiometric and atmospheric corrections were applied to a series of 9 (1990–2001) Landsat spring images (TM5-TM7) representative of contrasting soil moisture conditions. Each image had its land use classified to isolate bare soil. Moisture conditions were documented from historic climatic data and reflectance values. A single image was selected to represent the driest condition, while the others were associated with wet conditions. Spectral indices were calculated for every Landsat image following the method developed in the lab experiment. Landscape units and elevation classes were derived from the digital elevation model. Five landscape units were retained from the LandmapR toolkit (MacMillan, 2000). Conceptually, both landforms and elevation classes were expected to correlate with the domain of superficial deposit as well as soil moisture conditions.

Both spectral and topographical datasets were related to morphological soil data through discriminant analysis. Significant discriminant functions were subsequently inverted and applied to remote sensing datasets to produce soil property maps. Since the method is applicable solely to bare soil conditions, several classifications were produced by combining variables from different images in a stepwise approach. Optimal classifications were selected according to three statistical parameters: the global success of the classification (%) and the intra-class classification success (%). Finally, independent analytical and morphological soil datasets were used to evaluate the efficiency (analysis of variance) and the accuracy (confusion matrix) of the soil property maps.

3.4 *Spectral indices and statistical analyses*

Spectral indices for all three study scales were developed under three assumptions: 1) soil moisture, OM, soil color saturation and heavier soil texture tend to be negatively correlated with soil reflectance (ρ), 2) spectral data representative of the driest soil condition best reflect permanent properties effect and 3) the combination of wet (ρ_{wet}) and dry reflectance (ρ_{dry}) would yield a normalized brightness index (NBI) which represents soil moisture. Under these assumptions, spectral measurements were used to derive three new spectral indices which are related to soil OM content (OMI, Eq. 1), texture and color (COI, Eq. 2) and volumetric moisture content (NBI, Eq. 3).

$$OMI = \frac{1}{TM2_{dry}{}^{2}} \tag{1}$$

$$COI = \frac{TM7_{dry}{}^{2}}{TM2_{dry}} \tag{2}$$

$$NBI = \log\left(\frac{TM7_{dry}TM2_{dry}{}^{-1}}{TM7_{wet}}\right)^{3} \tag{3}$$

where TM_i is the reflectance value measured in the ith Landsat bands in dry or in wet condition. Linear regression analyses were used to evaluate relationships between soil properties and the spectral indices. Two criteria were used to test the quality of prediction: the root mean square error (RMSE) and the coefficient of determination (R^2). The effect of the experimental design (lab vs field) on spectral X soil properties relationships was also investigated through an analysis of covariance (ANCOVA), using soil moisture as the covariate.

4 RESULTS AND DISCUSSION

The training dataset for the lab experiment (n = 119) showed a wide range of soil types. Overall, 114 soil samples were classified as mineral soils, while five were considered as organic. Textural classes varied from silty clay to loamy sand, with silty clay loam dominating. Overall OM levels were relatively low (median: 3.4%, mean: 6.4%), ranging from 1.5 to 73.2%. The validation dataset (field experiment, n = 57) exhibited similar statistics.

4.1 *Reflectance measurements*

Figure 1 shows the reflectance of four representative soil textural groups (sandy, loamy, clayey and organic soils) under wet and dry conditions. As expected, wet soils have a lower reflectance value than dry soils. Reflectance values also show a decreasing trend with heavier soil texture (sandy and loamy > clayey > organic), under both soil moisture conditions, but they increase with wavelength. The B5 and B7 bands were more sensitive to soil moisture and soil texture variation. These observations support the assumption that reflectance values can be used to monitor permanent and non permanent soil properties. However, the dynamics of the spectral shape vary amongst soil types and soil moisture contents. These variations suggest an interaction between soil moisture, soil texture and OM on reflectance. The analysis of reflectance data showed that the inverse squares of the B1 (blue) and B2 (green) bands were correlated with OM. This spectral region corresponds with the results of Bartholomeus et al. (2008). The B2 band was selected since the reflectance value of the B1 band is influenced by the atmosphere.

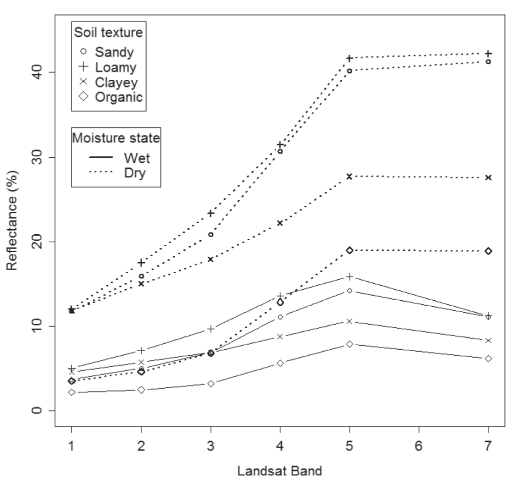

Figure 2. Reflectance spectra of simulated Landsat 7 bands associated with four representative soil samples under wet and dry conditions.

4.2 *Organic Matter Index (OMI)*

The OMI calculated from eq. (2) was linearly correlated with OM. OMI explained 87 and 81% of the total variance under laboratory and field conditions, respectively, with a relatively low RMSE (3.7%) and without any bias related to soil texture. Distribution of error, with respect to the OM content, remains relatively low. For example, 60% of the sample population, which has a residual value lower than 1%, has a median value of 3% (Fig. 3a). The difference in the ANCOVA models slope values between the lab and the field experiments suggests that the field method tends to underestimate OM (Table 1). This discrepancy can be explained by the relatively higher soil moisture for the dry image of the field experiment (23.6% ± 5) in comparison to the laboratory measurements (0.5% ± 0.69). By lowering the reflectance value, moisture decreases the sensitivity of the index and the threshold detection of organic matter.

4.3 *Normalised Brightness Index (NBI)*

The normalization of wet reflectance by that of the corresponding dry soil led to the development of a novel soil moisture index (NBI) exhibiting a significant linear relationship with soil moisture. This index explains 79 and 57% of the total variance observed in laboratory and field conditions, respectively, without any bias for soil texture or OM, and with a relatively low error (5.6 and 3.6%, respectively). The far-infrared band (TM7) yielded the best results but satisfactory regressions could also be modelled using the mid-infrared (TM5) and the near-infrared (TM4). Significantly differences in ANCOVA regression parameters for lab and field experiment were observed (Table 1) and attributed to measurement error (Thetaprobe sensor on gravelly sites) of soil moisture and also to the lower range of observed soil moisture conditions in the field experiment. To ensure that soil moisture contents in dry measurement had a consistent effect on error, 11 new series of the normalized soil moisture indices were calculated by permuting "dry reflectance" (ρ_{dry}) measurements with reflectance taken at time 1 to 11. Soil moisture of ρ_{dry} content had no effect on the strength of the regression equations as shown by the R^2 and RMSE obtained for each of the 11 regression equations (Fig. 3b).

4.4 *Spectral indices and prediction of soil properties at watershed scale*

The success of classification obtained by prediction models derived from discriminant analysis confirms the relevance of spectral indices

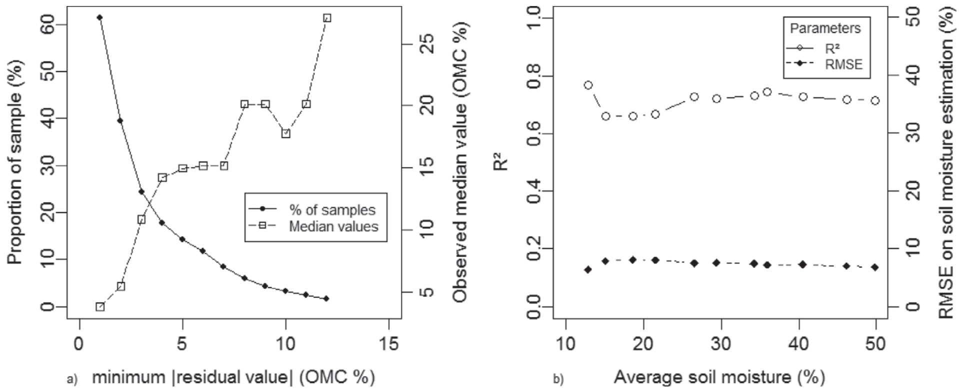

Figure 3. Proportion of training samples and associated observed median values of OM as a function of minimum absolute residual values of OM (a). Coefficient of determination and root mean square error for normalized soil moisture indices as a function of average soil moisture derived under eleven distinct permutations of "dry" measurement (b).

Table 1. Regression parameters of linear regression models explaining organic matter content and soil moisture from spectral indices derived under laboratory and field experiments.

Soil properties	Organic matter (%)					Soil moisture (%)				
Regression parameters	R^2	RMSE	Slope	Intercept	n	R^2	RMSE	Slope	Intercept	n
Laboratory	0.87	3.66	1479***	–1.15*	119	0.79	5.58	7.27***	106***	1353
Field	0.81	3.97	1051***	–0.81	46	0.58	3.57	2.65***	54.3***	46

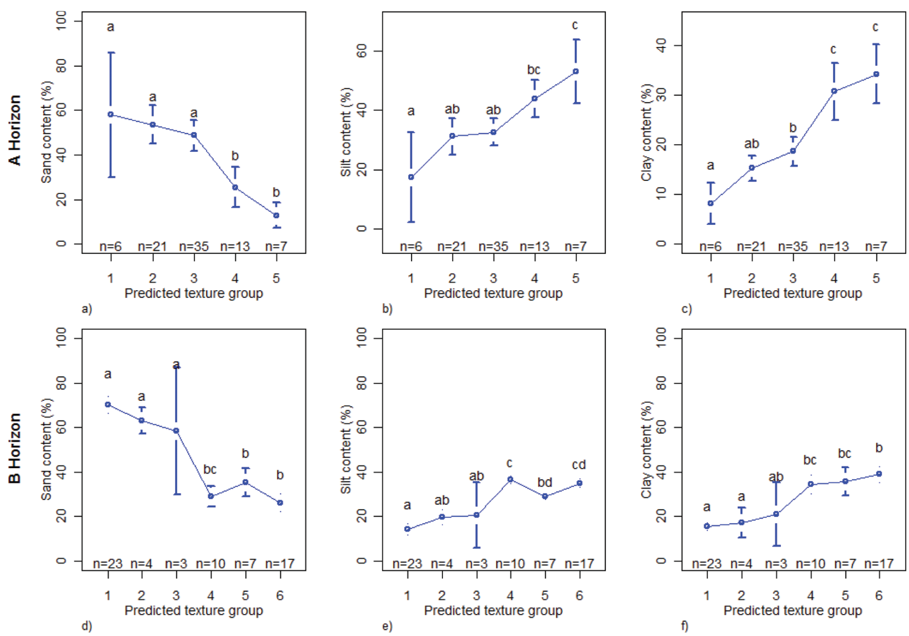

Figure 4. Mean values of the sand, silt and clay content in the A and B horizons of independent samples according to the predicted texture groups (1: Sandy, 2: Coarse loamy, 3: Loamy, 4: Fine loamy, 5: Fine clayey, 6: Very-fine clayey). Texture groups with different letters in the same plot have significantly different mean values ($P_{Tukey} < 0.001$).

to recognize three soil properties: A horizon texture, B horizon texture and drainage conditions. The overall successes of the classification were respectively 55, 46 and 74%. The successes reached 91, 77 and 90% respectively when including predicted values deviating from one class, suggesting that classifications were relatively consistent. Soil variables were best explained by COI (eq. 2, representing texture and OM) and NBI (drainage). Elevation class and landscape entities also contributed significantly to the prediction of soil texture in the B horizon and drainage conditions. Both variables can be related to water dynamics and pedogenetic processes. Sand, silt and clay contents of independent samples from A and B horizons were shown significantly different among predicted texture groups through ANOVA (Fig. 4). This indicates that spectral indices combined in a spectro-temporal approach can be used to delineate soil properties. Larger standard deviation is related to groups having fewer samples.

5 CONCLUSION

This study evaluated the potential of multi-temporal reflectance measurements to reveal permanent and non permanent soil properties. Spectral indices were linearly related to soil moisture and OM, without any bias related to other soil properties. The relevance of these spectral indices for digital soil mapping was further demonstrated using a series of Landsat images applied to bare soils of a watershed in southern Quebec. Digital soil maps generated with this approach provided spatial guidelines to implement soil zone management within field units, with potential benefits to crop profitability, soil quality and preservation of water quality.

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