FARM-SCALE MAPPING OF SOIL ORGANIC CARBON USING VISIBLE-NEAR INFRA-RED SPECTROSCOPY

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Abstract
Spatially enabled sensing technologies are now available for refining traditional methods of assessing soil carbon stocks and stock changes within the landscape, taking into account spatial variability. In this study visible near infra-red spectroscopy (VNIR) was trialled as a non-destructive and cost-efficient field method for estimating soil carbon stocks in a 68.5 hectare arable field. Soil carbon values (to 0.3 m) at one hundred positions have been spatialised using electromagnetic (EM) survey data to develop a total soil organic carbon (SOC) mapping method.

Soil carbon was estimated by (1) laboratory analysis and (2) chemometric processing of the VNIR soil spectra. To estimate the number of physical samples needed to provide an accurate calibration set for the chemometric processing of VNIR spectra, model performance was repetitively assessed using between 10 and 80% of soil analyses for the calibration set. Our results indicate that VNIR could accurately predict SOC using only 40% of the soil samples as a calibration set.

Mean estimations over 10 simulations of the total soil carbon present to 0.3 m depth in this paddock is 3476.2 T for Method 1 and 3555.73 T for Method 2. Method 2 used 60 % less soil carbon laboratory analyses, and only differs from the Method 1 result by 2.29 %.

Introduction
There is a need to quantify soil organic matter in New Zealand soils. This is partly because the potential for soils to regain or sequester additional carbon is a realistic mitigation strategy against increasing levels of atmospheric carbon dioxide, and partly because we need an improved method to verify any change in soil organic matter stocks. In addition, New Zealand, as a signatory to the Kyoto Protocol, is required to report on soil carbon stocks and stock changes with land-use change (Hedley et al., 2012).

The accurate assessment of soil organic carbon (SOC) stocks is an expensive process, involving extensive soil sampling, and costly laboratory analysis. Therefore, time and cost constraints have made the estimation of SOC at high spatial resolution impossible in practice, although this is necessary if we wish to account for the large acknowledged spatial variability of SOC within a landscape (Goidts et al., 2009). The emergence of affordable proximal and remote sensing technologies provide opportunity to develop refined methods for assessing SOC stocks, with the production of high-resolution carbon maps (Bellon-Maurel and McBratney, 2011; Minasny et al., 2006). These technologies are measuring physical light reflectance properties that can be used to estimate a wide set of chemical and physical soil properties. While in most cases they only provide an indirect measure of these properties, they allow us to cost and time effectively collect data at a much improved spatial and temporal resolution than existing conventional methods.

In this study, we estimate the SOC stocks at the paddock scale using a combination of two proximal sensing technologies, *i.e.* EM mapping (which collects electrical conductivity (EC) data) and field visible near-infrared spectroscopy (VNIR), along with the GPS positioning system. While EC and elevation data can be used as environmental predictors to map SOC, VNIR is a fast and cost-effective way to measure SOC content from a soil sample. Our research has tested whether VNIR spectroscopy can provide a new accurate field method to assess soil carbon stocks, reducing the need for costly laboratory analyses, allowing spatial variability of SOC stocks to be investigated, and reducing overall error of SOC stock estimation.

Material and methods

Study site

The field research site is a 68.5 ha irrigated maize *(Zea mays)* field in the Manawatu Sand Country, near Bulls. The topography is a sand plain, surrounded by low sand dunes, with a short range microrelief of small crescent-shaped dunes. Soils are Motuiti sands (Campbell, 1978) and are variably influenced by a high and fluctuating water table.

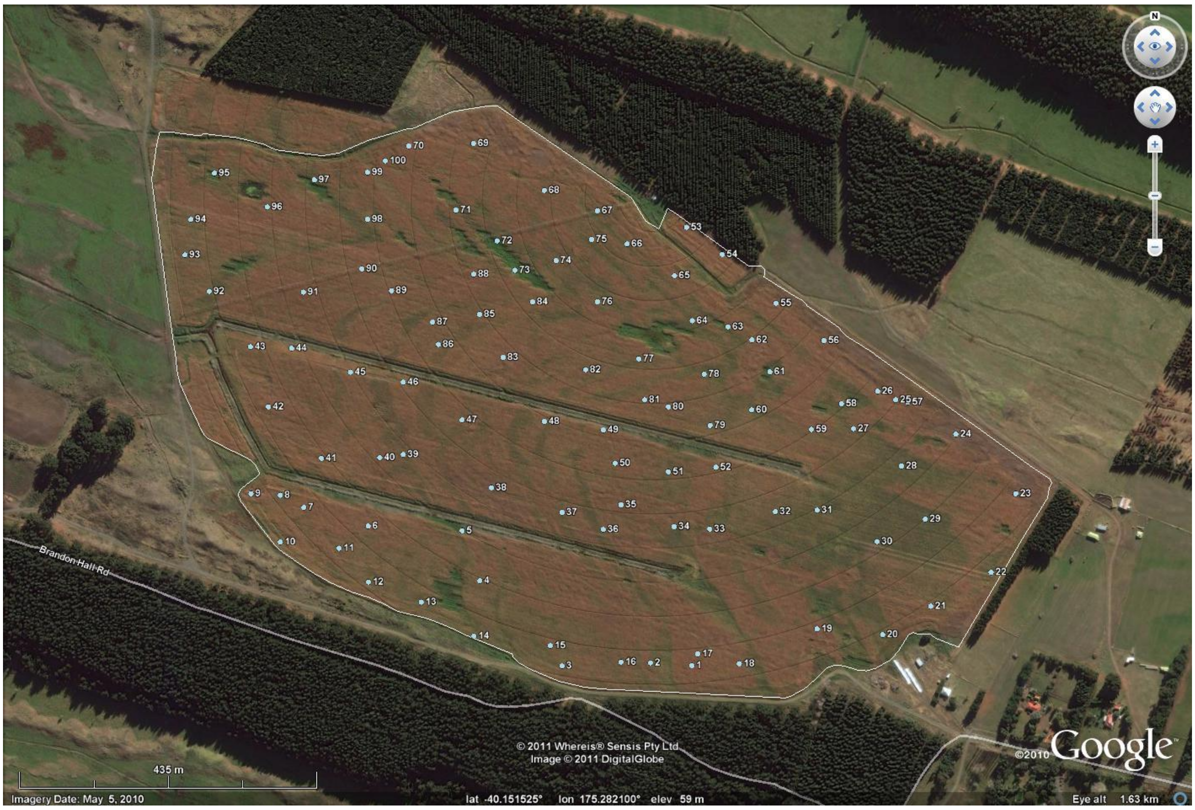

Figure 1. Study site near Bulls, Manawatu, showing the 100 sampling positions.

Assessment of soil variability

An on-the-go electromagnetic mapping system with RTK-DGPS was used to quantify soil variability (Hedley et al., 2004) at high resolution (5 m) based on measured electrical conductivity (EC). The system maps EC at two depths: the EM31 maps EC to 5 m, and the EM38 sensor maps EC to 1.5 m. Raw data have been interpolated onto a 5 m x 5 m grid (Figure 2).

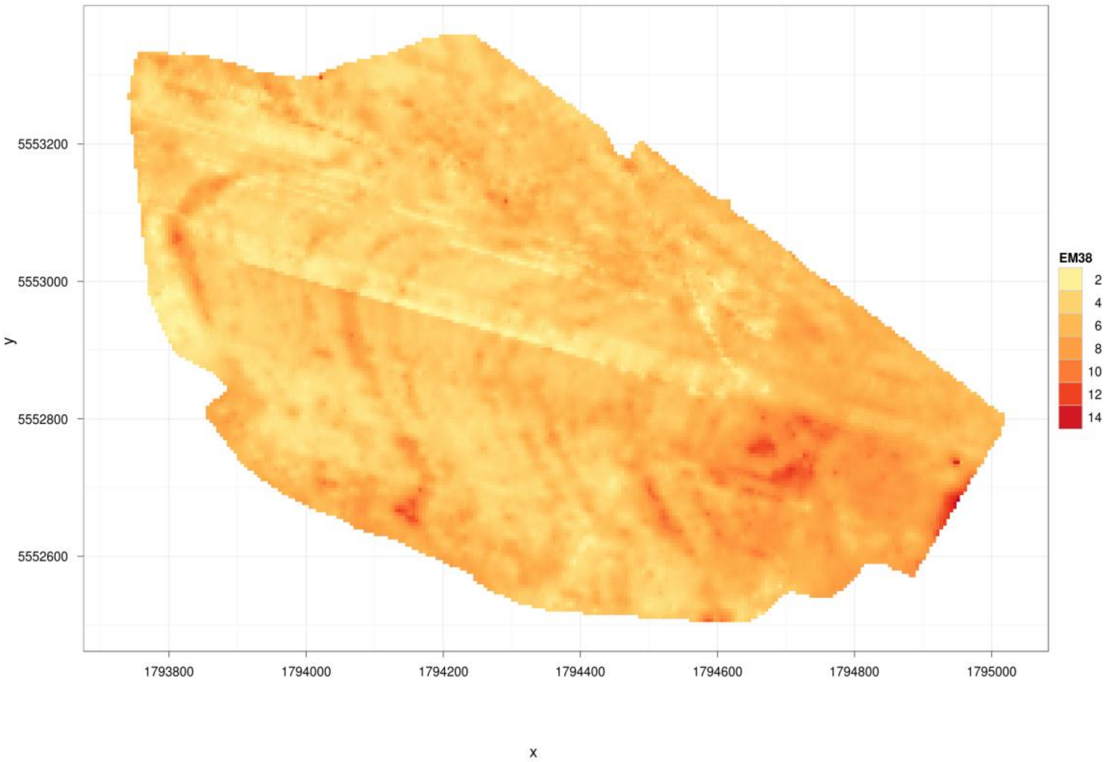

Figure 2. EM38 map of the study site (legend shows EC in mS/m).

In addition to the EC data, the electromagnetic mapping system collects elevation data through its RTK-DGPS unit. This elevation data has been used to create a high-resolution digital elevation model (DEM). The elevation values have been interpolated onto the same 5 m grid as the EC data. Geostatistical analysis and modelling have been undertaken using the R programming language (R Development Core Team, 2012).

A suite of terrain attributes has then been derived from this DEM to be used as environmental covariates for SOC modeling. The SAGA wetness index (SWI) was extracted from the DEM in SAGA GIS (Olaya and Conrad, 2009), while the slope, maximal curvature, profile curvature, total curvature, flow accumulation, topographic convergence index (TCI) and topographic wetness index (TWI) were extracted in GRASS GIS (Neteler and Mitasova, 2008). The EC and terrain layers form the stack of covariates used to model SOC.

Soil sampling

100 positions were selected for soil sampling (Figure 1) and scanning from the EC data (Figure 2) by systematic sampling of the ordered EC dataset, to proportionally represent the full range of EC values encountered in the EM survey. Soil cores were then collected at each selected position, using a Giddings hydraulic coring truck, and these cores were extruded onto a liner (Figure 3) for scanning at 1-cm intervals using an ASD FieldSpec 3 VNIR spectrometer. Sampled wavelengths ranged from 350 to 2500 nm with a 1-nm resolution. The soil cores were then divided into 0–0.1 m, 0.1–0.2 m and 0.2–0.3 m subsamples for laboratory analysis of bulk density and total organic carbon at these three depths.

Figure 3. Scanning a core in the field, with some examples of the produced spectra.

Prediction of soil organic carbon across the paddock

This study compares two SOC estimation strategies (Figure 4). Method 1 uses conventional soil sampling and laboratory analysis, while Method 2 uses VNIR spectroscopy to reduce the number of required laboratory analyses, hence improving the cost of SOC accounting.

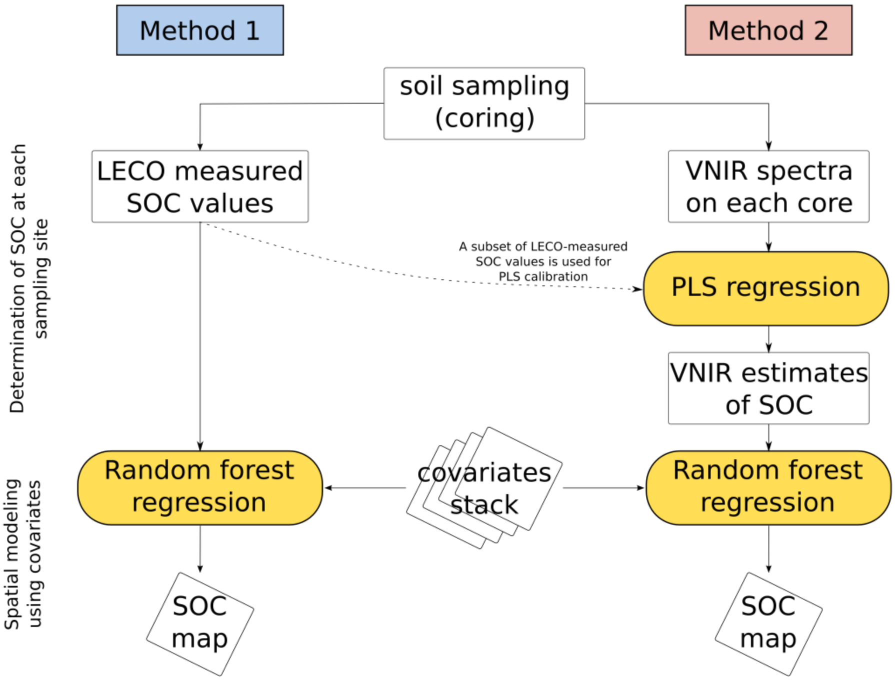

Figure 4. Methodology for the lab-based method (Method 1) and the VNIR-based method (Method 2).

Method 1: Conventional soil sampling with laboratory analysis

Method 1 uses a set of covariate layers (EM38, EM31 and terrain attributes derived from the DEM) to infer SOC values spatially across the paddock, for the three depth intervals at which soil data has been collected. In this method, the model is using SOC values that have been obtained using Leco Induction furnace (Leco, 2003) analysis.

Method 2: VNIR based method

The VNIR method aims at reducing the number of laboratory analyses required to provide a good estimate of SOC over the paddock. The first step is to estimate the SOC values for the collected soil cores using chemometric spectral processing of the collected VNIR spectra. The second step involves the same spatial modelling approach as for Method 1.

To estimate the SOC values from the VNIR spectra that have been collected along the soil core at each sampling site, the partial least square regression (PLSR) modelling method is used. This method uses a calibration set, *i.e.* actual SOC values against which SOC estimates can be regressed. VNIR spectra are averaged on the three depths intervals at which soil has been sampled (0 – 0.1 m, 0.1 – 0.2 m, 0.2 – 0.3 m).

Then, a PLSR model is built using a calibration set, which is a subset of the 300 lab-analysed soil samples. To estimate the number of physical samples needed to provide an accurate model for total soil carbon estimation, the Ratio of Performance Deviation (RPD) has been assessed for different calibration set sizes containing between 10 and 80% of the total sample number. These tests have been repeated 30 times. RPD is the ratio of the standard deviation of the reference data in the validation set to the standard error of prediction (Bellon-Maurel and McBratney, 2011).

Spatial modelling

Covariates EM38, EM31 and DEM-derived terrain attributes have been extracted for each soil carbon sampling location based on their GPS location. SOC has then been modelled at each depth interval between 0 and 0.3 m. The lab-based approach has 3 depth intervals (0 – 0.3 m, with 0.1-m steps), while using the VNIR method, soil carbon can be estimated every 0.01 m, resulting in 30 depth intervals between 0 and 0.3 m.

For both methods, modelling of the actual soil carbon measurements (for the lab-based approach) and VNIR-based soil carbon estimates (for the VNIR-based approach) using the EM31, EM38 and DEM-derived covariates has been done for each depth interval using random forest regression (Breiman, 2001), a powerful data mining regression method.

The resulting models have been applied to the covariates to estimate the soil carbon content on each cell of a 5-m-resolution grid. For both approaches, the modelling step is repeated 10 times. At the end of this process, 3 layers of SOC estimates, corresponding to the three depth intervals of investigation, are obtained for the lab-based method, while 30 layers of SOC estimates, corresponding to the depths at which VNIR data was available, are obtained for the VNIR-based method.

Results

Size of the calibration set

Based on the RPD results (Figure 5), we chose a minimum relative size of the calibration set of 40%, based on thresholds proposed by Chang *et al.* (2001).

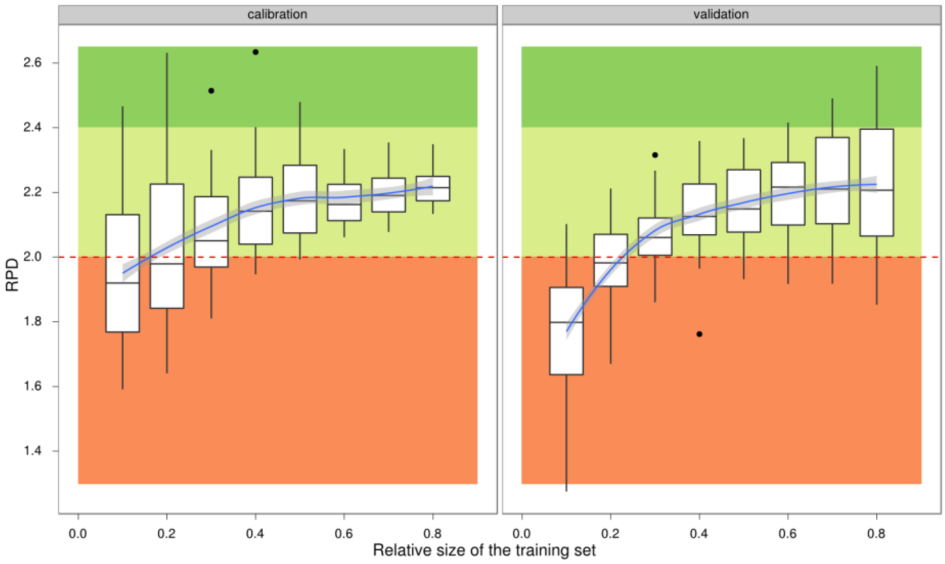

Figure 5. Choice of the size of the calibration set using the RPD. Colour bands show the model quality thresholds proposed by Chang *et al.* (2001).

Spatial modelling

The integration of those estimations over the depth domain gives the map in Figure 6, showing the amount of total soil carbon for each cell of the 5-m grid. While the VNIR-based method gives some extreme values in different points of the paddock, the general pattern is similar to that given by the lab-based method.

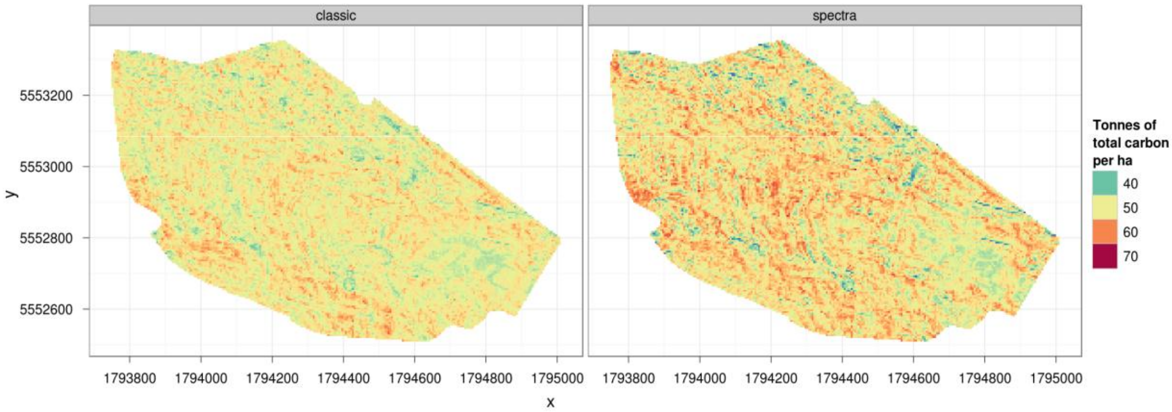

Figure 6: Maps of the total amount of soil carbon using lab-based measurements (left) and VNIR estimates (right).

The mean estimation over the 10 simulations of the total soil carbon present between 0 and 0.3 m on this paddock is 3476.2 T (50.75 T/ha) for Method 1 and 3555.73 T (51.91 T/ha) for Method 2, this method uses 60 % less soil carbon laboratory analyses, and only differs in its predicted total carbon value by 2.29% compared with Method 1.

Future research will develop the presented approach to estimate and map the uncertainty of the SOC predictions. This is a requirement to reduce the error term related to soil carbon stock estimation.

Conclusion

Preliminary results illustrate the potential use of VNIR technology in the field to support traditional soil sampling for soil carbon accounting. Our project has shown that VNIR, as a support to lab-based soil carbon measurements, improves economic efficiency of soil carbon accounting projects and the spatial representation of the soil carbon point estimates, using spatial data analysis with covariates EM38, EM31 and DEM-derived terrain attribute data layers. Our VNIR scanning method of field soil cores also provides better depth resolution, with one measure every centimetre, at a marginal cost.

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