Assessment of Total, Stable and Labile Soil Carbon Using Visible/Near-Infrared Diffuse Reflectance Spectroscopy

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Introduction

Models to predict soil properties have become more accurate and less costly. Advances in information technology and the development of new sensors and instruments have facilitated the collection and analysis of data. Carbon is of great importance to soils. Its strong relationship with soil organic matter influences the soil physical, chemical and biological processes. Hence, the analysis of the distribution and dynamics of soil carbon is an essential requirement for sustainable land management. Visible/near-infrared diffuse reflectance spectroscopy (VNIRS) is gradually becoming recognized as a fast, cheap and accurate alternative for the investigation of soil properties.

Objectives

To develop VNIRS models of soil organic carbon (SOC) and fractions by testing 6 pre-processing transformations of soil VNIR reflectance spectra and 5 calibration methods.

Methods

Lab analysis: Total organic carbon (TOC) and hydrolysable carbon (after digestion with 6N HCl) (HC) were measured with a Thermo Electron FlashEA Elemental Analyzer; Recalcitrant carbon (RC) was calculated as the difference between TOC and HC; Dissolved organic carbon was measured on a Shimadzu TOC Analyzer after hot water extraction, then filtered into 2 classes: <0.7 µm (DOC07) and <0.2 µm (DOC02).

Spectroscopy: VNIR spectra were derived with an ASD QualitySpec Pro spectroradiometer (350-2500 nm) on oven-dried samples.

Sampling design: Composite soil sampling at 0-30-cm depth at 141 sites in a stratified random design, with 102 randomly selected for calibration, and 39 were set aside for validation.

Pre-treatment of SOC fractions: Log-10 normalization.

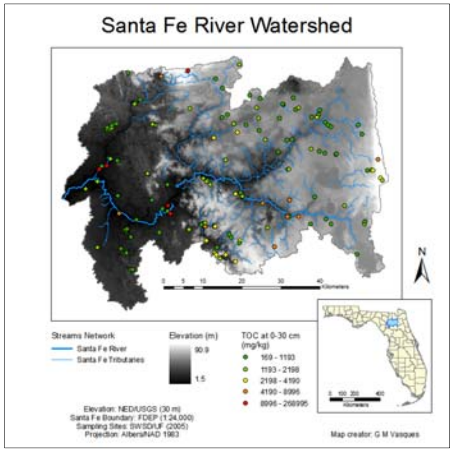
Calibration methods: Stepwise Multiple Linear Regression (SMLR) with a stepping probability of 0.05 in SPSS 11; Principal Components Regression (PCR), and Partial Least-Squares Regression (PLSR) in Unscrambler 9.5; Regression Tree (RT), and Committee Trees (CT) in CART 5.0.

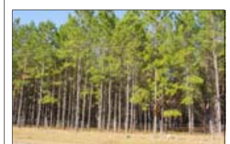
Best model selection: The best methods and pre-processing techniques were selected based on the coefficient of determination of validation (R_v^2). Root mean squared errors (RMSEC for calibration; and RMSEV for validation) were also calculated.

Pre-processing techniques: Savitzky-Golay smoothing and averaging (SAV); Normalization by the range (NRA); Log(1/reflectance) (LOG); Norris gap derivative with search window of size 7 (NGD-7); Savitzky-Golay first derivative with first-order polynomial and search window of size 9 (SGF-1-9); and standard normal variate transformation (SNV).

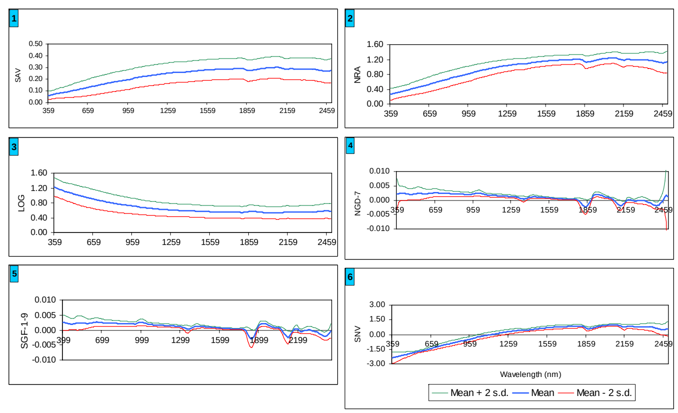
Methods

Study area: Santa Fe River watershed (3,585 km²) in north-central Florida; Major soil orders: Ultisols (47%), Spodosols (27%), and Entisols (17%); Major land uses/land covers: pine plantations (30%), rangeland and crops (29%), upland forest (11%) and wetlands (14%).





Soil Spectra



Results

Statistics	(mg/kg)				
	TOC	HC	RC	DOC07	DOC02
Observations	141	141	141	141	141
Minimum	2,670	37	1,150	214	221
Maximum	201,988	29,399	181,738	9,000	8,995
Median	10,529	2,892	7,382	644	664
Mean	14,828	3,707	11,122	799	809
Std. Deviation	21,993	3,292	19,194	827	818
Skewness	6.35	4.58	6.64	7.37	7.57

Results

SOC and fractions	Best model	Number of factors	Calibration		Validation	
			R_c^2	RMSEC	R_v^2	RMSEV
TOC	LOG-PLSR	12	0.93	0.082	0.86	0.078
HC	SAV-PLSR	5	0.49	0.218	0.40	0.285
RC	SAV-PLSR	11	0.90	0.109	0.82	0.108
DOC07	SAV-PLSR	8	0.89	0.100	0.84	0.086
DOC02	SNV-PLSR	6	0.81	0.110	0.69	0.100

All the methods were sensitive to the regions of absorption features of C-H, O-H, N-H and H_2O. The best VNIRS models for all SOC fractions were obtained using PLSR. Some advantages of PLSR are: rapidness, ease of use, and flexibility to deal with correlated and missing data. Linearity is assumed in SMLR, and to some extent in PCR and PLSR. Alternatively, non-parametric methods are more flexible to deal with non-linear relationships. Regression trees were not well suited for the estimation of SOC fractions using VNIRS, as they predicted discontinuous values and produced the worst results. Hydrolysable carbon was poorly correlated with VNIR soil spectra, with the best model explaining only 40% of the total variance of the validation sample.

VNIRS vs. Conventional Lab Analysis

Characteristics	VNIRS	Conventional
Ease of sample preparation	Good	Fair
Ease of analysis	Fair	Fair
Speed	Good	Poor
Labor	Good	Fair
Equipments cost	Fair	Fair
Use of supplies	Good	Poor
Cost per sample	Good	Fair
Accuracy	Good	Good

Conclusions

(1) Except for HC, VNIRS provided accurate models to predict TOC and SOC fractions, with PLSR being the best method.

(2) The comparative performance of the models for the TOC and SOC fractions was:

TOC > DOC07 > RC > DOC02 > HC

(3) Future research will test the accuracy of VNIRS models of SOC fractions at the landscape scale by producing maps of SOC fractions across the Santa Fe River watershed and comparing them with maps derived from laboratory data.

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