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Using vNIR spectroscopy to assess changes in Ultisols of Pará State, Brazil

John Paul Schmidt[a,*], Daniel Markewitz[b], Francisco de Assis Oliveira[c], Andrew Sila[d], Aaron Hoyt Joslin[b]

[a] Odum School of Ecology, University of Georgia, Athens 30602, Georgia
[b] Warnell School of Forestry and Natural Resource, University of Georgia, Georgia
[c] Universidade Federal Rural da Amazonia, Brazil
[d] World Agroforestry Centre, Nairobi, Kenya

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ABSTRACT

To optimize sampling effort, knowledge of soil spatial variability is essential, but usually requires large and spatially detailed data sets. In this study, soils under secondary forests of four ages (1, 8, 15, 22 years) were compared within an agricultural landscape in the eastern Amazon (Igarapé Açu, eastern Pará state, Brazil). At three nested scales within each stand, topsoil samples were taken at two depths (0–10, 10–20 cm), scanned by VNIR, and analyzed chemometrically in the laboratory. Boosted regression trees (BRT) were then used to calibrate VNIR spectra to soil properties for a representative subsample. These models were moderately successful on cross-validated data ($R^2 \geq 0.75$) for total C, total N ($R^2 \geq 0.74$) and pH ($R^2 \geq 0.62$), as were linear mixed models regressing measured vs. predicted (via spectra) values on secondary forest age and soil depth. Differences in measured values were greatest between soil depths and 1-yr vs. older stands. Differences by stand age in pH, but not C and N were captured by regression models of predicted data. However, predicted values reflected with moderate accuracy the scale (samples within subplots, subplots within plots, plots within treatments) of measured variability in soil C, N, and pH. While there was little measured variability among samples within subplots, variability was highest at the plot scale for the 0–10 cm depth, and similar at the subplot and plot scale for the 10–20 cm depth. These results indicate that soil reflectance measures can be a useful tool for developing efficient soil sampling designs.

1. Introduction

In humid tropical regions, as forested lands are converted to agricultural uses, and marginal agricultural lands return to forest or agroforestry or cycle between successional forest and agriculture, understanding how soil properties change is fundamental to managing and sustaining the health and productivity of these ecosystems. Understanding soil organic matter (SOM) dynamics with changing land use is particularly important as SOM represents a key renewable resource critical to the maintenance of productivity in agroecosystems. SOM promotes the formation of soil aggregates, stores and exchanges ions, ameliorates soil physical conditions including infiltration, hydraulic conductivity, and soil moisture storage (Fernandes et al., 1997; Velasquez et al., 2005). Thus, identifying the factors that control the accumulation and loss of SOM is a critical need in developing sustainable agroecosystems in the humid tropics.

Within the Amazon basin, the clearing of native forest has resulted in areas dominated by pastures, traditional smallholder slash-and-burn cultivation with consequent fallow or secondary vegetation, perennial crop plantations such as black pepper, oil palm, cacao, and coffee, increasing areas of intensive annual crop agriculture of soybeans, maize, rice, and sugar cane, small-scale production of tropical fruits and subsistence crops within agroforestry systems, and managed landscapes for the extraction of Amazonian palm products. The agricultural frontier within the Amazon region continues to expand, affecting soil and natural resource integrity. As decreasing land availability leads to reduced fallow periods of secondary forest growth during which nutrient reaccumulation can occur, landscapes become dominated by degraded pasture and shrub vegetation. In recent years, pastures and secondary forests have, in turn, been increasingly converted to intensive, mechanized production of soybeans and grains. Here, loss of native fertility is overcome by the application of fertilizers and pesticides within these systems (Fearnside, 2001; Perrin et al., 2014).

The general patterns of reduced fallow leading to soil degradation, the dominant paradigm in our current understanding, are greatly complicated by the significant variability in soil types and climatic factors across Amazonia. Because most soil quality studies to date have

* Corresponding author.
E-mail address: jps@uga.edu (J.P. Schmidt).

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been restricted to a relatively small set of contrasts and a limited geographic scale, it has been difficult to make generalizations (for example on rates of nutrient depletion and recharge) across these sources of variability (Powers et al., 2011). Results have been further confounded by differences in land use history. Therefore, despite a growing body of research on nutrient dynamics in Amazonian primary forest and forest-derived land uses, the specific effects of widespread land-use change on nutrient contents and cycles in soil and vegetation are not well understood. This is made clear by the variability observed in soil responses to land use conversion in components such as soil organic matter, soil N, and base cations (Paul et al., 2010; Fujisaki et al., 2015).

Thus, despite the importance of soils, establishing robust generalizations of soil change across land use trajectories, particularly within the humid tropics, remains a challenge to ecologists and soil scientists: high spatial variability often means that large sample sizes are necessary to establish the power to detect differences between land use histories even within local areas of similar soil type (Powers et al., 2011; McGrath et al., 2001). Assembling large soil datasets is labor-intensive in the field as well as in the laboratory, where expensive laboratory analyses must be performed. Visible near-infrared (VNIR) spectroscopy, which has evolved over the last 20 years as a fast and non-destructive method for estimating soil properties offers a means for overcoming these barriers by providing the means for rapid and low-cost measurement of soil properties (Stenberg et al., 2010; Shepherd and Walsh, 2007; Ben-Dor and Banin, 1995).

In the current study, we investigated changes in soil properties across a chronosequence of successional forests, including an agroforestry system, in the eastern Amazon, while testing the utility of VNIR for expanding quantitative soil data. Space for time substitution through land-use chronosequences act as a surrogate for longitudinal studies of sites that repeatedly measure one location after it is cleared and passes through different types of management. Our study design includes a randomized landscape-level, nested, sampling design to quantify variability across scales. Although our motivation is ultimately to describe changes in soil C, N, P, pH and Ca, K, Mg, and Na stocks with stand age, the primary focus of this study was to determine whether variability in soil properties could be better assessed with VNIR, in the absence of chemometric analyses (Cobo et al., 2010), or as an extension of directly measured data (Kinoshita et al., 2016) as a means of optimizing field and analytical cost and effort. Therefore, of principal interest was the scale within stands ages at which variability was greatest. In initiating this work, our hypothesis was that for some soil constituents, variability at the smallest scales, e.g. within a ha, would be similar to that across different land use histories, in this case, the ages of successional stands.

2. Methods

2.1. Study site

The research site is at the experimental farm of the Universidade Federal Rural da Amazônia (UFRA) in the Municipality of Igarapé-Açu (0°55′–1°20′ S, 47°20′–47°50′ W) 110 km East of Belém, in northeastern Pará State, Brazil. This region, known as the Bragantina, is one of the oldest continually inhabited agricultural areas in the Amazon and the landscape is now completely dominated by human activities and secondary forests. Igarapé-Açu lies in the humid tropics and has an average annual temperature of 26 °C and annual rainfall of 2500 mm with a dry season from July to November (Diniz, 1991). Rainfall distribution during the rainy season is rather uniform and crop moisture requirements during this period are fully met. The landscape has a flat to slightly undulating relief and the soils around the study site are uniformly developed. The soils of the region correspond to Typic Kandiudults (Ultisols) in the USDA classification. These soils are loamy sands (80–90% sand) in the top 10 cm with clay content increases to around 30% at between 50 and 100 cm depth.

2.2. Land use contrasts

At the UFRA farm, we compared soils between four contrasting land use histories. The year-old successional field is an active research site in which a slash and mulch tractor mulches secondary vegetation after which a series of crops are planted. Typically, an N-fixing crop or cover crop species (e.g. clover, *Trifolium* ssp. or cowpea, *Vigna unguiculata*) is planted along with traditional crops like corn or manioc. Fallow periods are typically between 1 and 2 years with 1 to 2 years of cropping.

The 8 year-old, secondary forest stand was planted following mulch tractor treatment. Following mulching, manioc was planted in a mixed culture with either 3 or 5 species of native trees. The subplots sampled within this unfertilized successional forest did not include any planted N-fixers. Manioc was grown for 20 months prior to harvest, but planted trees were left to grow (Joslin et al., 2013).

We sampled within two additional successional stands of 15 and 22 years old that were never subjected to slash and mulch treatment. Deeper history of these stands, including frequency of fire or harvest, is not well established. Four 100 m^2 plots were randomly located within each secondary forest stand. Three 15 m^2 subplots were nested within each plot (Fig. 1). As a preliminary study to assess differences in surface soil, within each subplot three soil samples were collected at two depths, 0–10 cm and 10–20 cm. Total sample size was 288.

2.3. Soil analyses

Soils were dried at 45 °C overnight and ground in a SPEX 8000M Mixer/Mill (SPEXSamplePrep, Metuchen, New Jersey), and sieved to remove large particles with 2 mm mesh. The ground samples were then dried at 45 °C overnight again before a portion was weighed for analyses. Cations (K, Ca, Mg) were extracted using the Mehlich 1 double acid method (Helmke and Sparks, 1996; Suarez, 1996), total C and N were determined by elemental analysis (Micro-Dumas Combustion) (Nelson and Sommers, 1996; Bremner, 1996), total P was measured using an sulfuric acid and peroxide digest (Kuo, 1996), and pH was measured in aqueous solution (1:2.5 soil:solution ratio) (Thomas, 1996).

2.4. VNIR scanning

Visible near-infrared reflectance (VNIR) scanning followed the protocols of Vågen et al. (2006). Soil VNIR was measured using a FieldSpec FR spectroradiometer (Analytical Spectral Devices Inc.) at wavelengths from 350 to 2500 nm with a spectral sampling interval of 1 nm. Reflectance spectra were recorded at two positions by rotating the sample 90° to sample within dish variation. The average of ten spectra was recorded at each position to minimize instrument noise. Before reading each sample, reference spectra were recorded using calibrated Spectralon white (Labsphere R, Sutton, NH).

2.5. VNIR calibration

Owing to their flexibility, we chose boosted regression trees as the calibration algorithm (*gbm* package in R). The number of x-variables is limited to 400 by *gbm*. Therefore, to reduce the dimensionality of the reflectance data, we wavelet-transformed spectra (using R package soil.spec) after omitting bands 350 to 380 and 2460–2500 nm, which are in regions of low signal to noise. We used the resulting 128 wavelets as predictors of each constituent for a subset of the data that was composed of a single sample from each subplot ($n = 62$). Because of the small sample data set, model fits were assessed by comparing predicted values from internally cross-validated (Jafari et al., 2014) models to measured values for each constituent using root mean squared error of prediction (RMSEP). Models were tuned for best number of cross-validation folds and interaction depth as well as number of trees and shrinkage. Because calibration fits were low for all other constituents,

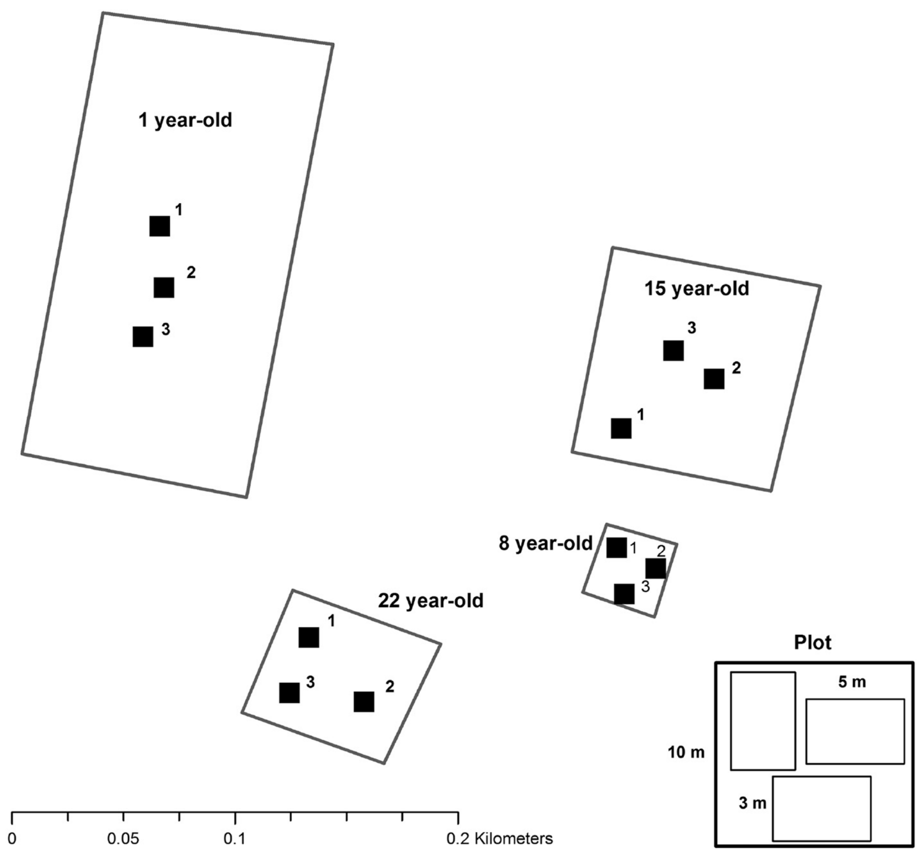

Fig. 1. Study site at Igarapé-Açu, Pará state, Brazil showing configuration of forests stands. Inset diagram shows placement of subplots within plots.

best models were used to predict only percent total C and N and pH values for the entire dataset (n = 288).

3. Statistical analyses

3.1. Comparing results of soil analyses

The experimental design for this study is pseudo-replicated. Although there are three subplots in each land use and three subsamples from each subplot, there are no true replicates of the land use. In other words, there is no other 1 or 22-year-old forest in another municipality. While this limits our ability to extrapolate broadly, the value of this study lies in the application of VNIR to issues of spatial variability.

We used a 3-level (plot, subplot, sample) linear mixed effects models – using *lme* in the nlme package – to test for differences in percent total C, total N, and pH by stand age and soil depth. We compared means using Tukey's test to compare means using *lsmeans* (least squares means) in the `lsmeans` package in R. Phosphorus, Ca, Mg, and K concentrations were log-transformed prior to regression analysis. To examine variation in space, we calculated the coefficient of variation by stand age, plot and subplot. Standard deviations for nested levels were generated using *lmer* (linear mixed effects model) in the `lme4` package in R.

3.2. Soil quality metric measured directly vs. predicted from VNIR calibration models

To simulate the use of VNIR spectra to measure soil quality directly, we compared results from the statistical analyses of measured values from the full dataset (n = 281) for percent total C and N and pH to analyses performed on values predicted from VNIR spectra for the entire data set from the subset of data containing a single sample for each subplot (n = 62) using the best calibration.

4. Results

4.1. Measured patterns in C, N, P, and cations

Percent total C and N, and cation concentrations were significantly lower from 10 to 20 cm than from 0 to 10 cm across all stand ages whereas percent total P and pH did not significantly differ with depth (Tables 1, 2, Figs. 2, 4). C and N also showed significant increases between 1-year-old and all older secondary forests stands with differences between older stands not detectable (Table 1). In contrast, pH was significantly lower across forest age from 1-year-old to 15-year-old, but 15 and 22 year-old stands did not significantly differ (Table 1). While significant decreases in pH with stand age were mostly captured in regressions on predicted data, increases in C and N were mostly not captured in regressions on predicted data or in some cases were significant in regression models of predicted, but not measured, data.

At both depth intervals, many contrasts in Ca and Mg between stand ages showed significant decreases with stand age, while significant decreases were found only for the 8–15 year and 1–22 year contrasts in P and the 8–15 year contrast in K. Within stand ages, P concentrations appear to decrease with depth but these differences were significant only for the 8-year-old stand (Table 2) (Fig. 3).

4.2. VNIR calibration

The best accuracy for VNIR calibration was achieved for % C (R^2 = 0.75 on training data), % N (R^2 = 0.74) (Fig. 4), and pH

Table 1
Contrasts by land use and soil depth for measured and predicted values of percent total C and N and pH from a 3-level mixed model (land use, plot, subplot). Contrasts are between stand ages in 0–10 cm soil depth (top panels), between stand ages in 10–20 cm soil depth (middle panels), and between soil depths within stand ages (bottom panels). Estimates reflect absolute change in mean value. Measured sample sizes were n_{0-10} = 26, 29, 30, 34, and n_{10-20} 21, 20, 27, 26 for 1, 8, 15, and 22 year-old secondary stands. Predicted values were estimated from spectral calibrations on sample sizes at both depths of n = 8, 8, 8, and 7.

Contrast		C			C predicted			N			N predicted			pH			pH predicted		
		est.	S.E.	p	est.	S.E.	p	est.	S.E.	p	est.	S.E.	p	est.	S.E.	p	est.	S.E.	p
Stand age	1–8 yr	−0.367	0.062	< 0.0001	−0.028	0.042	0.998	−0.032	0.004	< 0.0001	−0.007	0.003	0.236	0.291	0.058	< 0.0001	0.179	0.045	0.002
within	1–15 yr	−0.279	0.061	0.0002	0.024	0.042	0.999	−0.025	0.004	< 0.0001	−0.003	0.003	0.987	0.586	0.058	< 0.0001	0.204	0.045	0.0002
0–10 cm	1–22 yr	−0.293	0.062	0.0001	0.018	0.042	1	−0.021	0.004	< 0.0001	0.000	0.003	1	0.705	0.058	< 0.0001	0.194	0.045	0.0005
depth	8–15 yr	0.087	0.062	0.848	0.052	0.042	0.921	0.007	0.004	0.631	0.004	0.003	0.781	0.294	0.058	< 0.0001	0.025	0.045	0.999
	8–22 yr	0.073	0.062	0.935	0.046	0.042	0.955	0.011	0.004	0.131	0.006	0.003	0.328	0.413	0.058	< 0.0001	0.014	0.045	1
	15–22 yr	−0.014	0.061	1	−0.005	0.042	1	0.004	0.004	0.984	0.002	0.003	0.997	0.119	0.058	0.445	−0.010	0.045	1
Stand age	1–8 yr	−0.068	0.064	0.963	−0.138	0.044	0.036	−0.009	0.004	0.407	−0.012	0.003	0.002	0.256	0.060	0.0008	0.208	0.047	0.0003
within	1–15 yr	−0.094	0.063	0.818	−0.128	0.043	0.062	−0.010	0.004	0.243	−0.011	0.003	0.004	0.677	0.060	< 0.0001	0.381	0.046	< 0.0001
10–20 cm	1–22 yr	−0.193	0.063	0.050	−0.143	0.043	0.022	−0.009	0.004	0.365	−0.010	0.003	0.025	0.691	0.060	< 0.0001	0.306	0.046	< 0.0001
depth	8–15 yr	−0.025	0.062	1.000	0.010	0.042	1	−0.001	0.004	1	0.001	0.003	1	0.420	0.059	< 0.0001	0.173	0.045	0.004
	8–22 yr	−0.124	0.062	0.487	−0.005	0.042	1	0.000	0.004	1	0.002	0.003	0.995	0.435	0.059	< 0.0001	0.097	0.045	0.383
	15–22 yr	−0.099	0.061	0.740	−0.015	0.042	1	0.001	0.004	1	0.002	0.003	0.999	0.014	0.058	1	−0.076	0.045	0.689
Depth	1 yr	0.355	0.063	< 0.0001	0.227	0.043	< 0.0001	0.023	0.004	< 0.0001	0.014	0.003	0.0001	−0.053	0.060	0.987	−0.067	0.046	0.831
within	8 yr	0.653	0.063	< 0.0001	0.117	0.043	0.116	0.046	0.004	< 0.0001	0.009	0.003	0.034	−0.088	0.059	0.813	−0.038	0.045	0.991
stand age	15 yr	0.541	0.061	< 0.0001	0.075	0.042	0.624	0.037	0.004	< 0.0001	0.005	0.003	0.543	0.038	0.058	0.998	0.111	0.044	0.205
	22 yr	0.455	0.061	< 0.0001	0.065	0.042	0.771	0.035	0.004	< 0.0001	0.005	0.003	0.652	−0.066	0.058	0.946	0.045	0.044	0.971

(R^2 = 0.62; Table 2). Calibration accuracy was < 40% for total P, K, Ca, and Mg. This may reflect characteristics of the soils scanned or various sources of error including machine error.

4.3. Direct measures vs. VNIR

Means and variances, by depth and forest age classes, of values predicted based on calibration models for C and N, closely track those of directly measured constituents (Fig. 2). Moreover, most of the significant contrasts in means by depth and stand age were captured in *lme* models using calibration models on the test data (Table 1). At 0–10 cm, estimates of variability at nested spatial scales are good approximations of the scale of variability for C and N at 0–10 cm (Fig. 4). Congruence between measured and predicted estimates of the scale of variability does not hold up for C and N at 10–20 cm where subplot scale variability is under-estimated probably due to small sample size (n = 23). Percent total C and N and pH show similar increases in variance in the 0–10 cm depth range as the scale increases in both measured and predicted values (Fig. 4), with little variance at the sample within subplot or subplot within plot scale. Variance increases with scale most closely match the actual variance of measured values in the case of pH. In 10–20 cm, variance of measured values is highest at the subplot scale in the case of C and similar at plot and subplot scales in the case of N. In either case, variance of predicted values approximated this pattern (Fig. 4). Variance of pH in the 10–20 cm depth is very similar to that of pH at 0–10 cm, while variance in predicted values shows a pattern more similar to C and N. Overall, these results demonstrate a divergence in the scale of variance between depths that is well-captured by values of C, N, and pH generated from prediction via spectral calibrations based on less than a quarter of the data.

5. Discussion

From direct measurements, we were able to detect a change in soil quality over a 22-year soil chronosequence in an Ultisol in the eastern Amazon. Percent C and N increased with forest stand age, although these increases were only marked between 1-year-old stands and all other age classes or between 1-year-old stands and 22-year-old stands, rather than exhibiting a clear signal of continuous accumulation. In contrast, pH appeared to decrease continuously with stand age, although 15 and 22 year-old stands did not significantly differ. Also, whereas decreases in C, N, K, Ca and Mg occurred with soil depth, this was not true for pH. Whether stand age can be assumed to be the only factor affecting soil change in these stands is not entirely clear as land use history, particularly in the use of fire, (Zarin et al., 2005) prior to the establishment of secondary forest may have differed enough to bear on current patterns. Yet, the relatively similar soil conditions in the 8, 15, and 22 year-old secondary forest stands may indicate a general similarity in history and relatively little time for soil properties to shift along a successional trajectory. The relationship between the trends we detected and general patterns of soil C accumulation and nutrient dynamics with forest regrowth in tropical forest regions remain ambiguous with relatively short-term (< 25 years) changes difficult to detect (McGrath et al., 2001; Feldpausch et al., 2004; Bernoux et al., 2009; Neumann-Cosel et al., 2011; Perrin et al., 2014) Table 3.

5.1. VNIR as a tool for increasing sample size in soil studies

A key finding of this study is that a coarse calibration for major soil constituents with a strong VNIR signal, i.e. those related directly to organic C content, percent total C and N and pH, offered the power to capture changes in the variance of these measures with scale. Thus, the goals of expanding sample sizes, better representing spatial variability, improving spatial prediction, and capturing the scale of variability (Kinoshita et al., 2016; Cobo et al., 2010) can be served by use of VNIR. Here, variability between 100 m^2 plots appears to be the scale at which

Table 2
Contrasts by land use and soil depth for predicted values of total P and K (log_{10} mg/kg), lower table, from a 3-level mixed model (land use, plot, subplot). Contrasts are between stand ages in 0–10 cm soil depth (top panels), between stand ages in 10–20 cm soil depth (middle panels), and between soil depths within stand ages (bottom panels). Estimates reflect absolute change in mean value.

Contrast		P			K			Ca			Mg		
		est.	S.E.	*p*	est.	S.E.	*p*	est.	S.E.	*p*	est.	S.E.	*p*
Stand age	1–8 yr	− 0.062	0.023	0.109	− 0.097	0.038	0.173	− 0.215	0.125	0.677	− 0.177	0.066	0.131
within	1–15 yr	0.031	0.022	0.867	0.021	0.038	0.999	0.307	0.124	0.212	0.073	0.066	0.953
0–10 cm	1–22 yr	0.061	0.022	0.119	0.033	0.038	0.988	0.451	0.125	0.008	0.051	0.066	0.994
depth	8–15 yr	0.093	0.023	0.0013	0.118	0.038	0.041	0.522	0.125	0.001	1.034	0.066	< 0.0001
	8–22 yr	0.124	0.023	< 0.0001	0.130	0.038	0.015	0.665	0.125	< 0.0001	0.793	0.066	< 0.0001
	15–22 yr	0.030	0.022	0.878	0.012	0.038	1	0.144	0.124	0.943	0.543	0.066	< 0.0001
Stand age	1–8 yr	0.033	0.023	0.854	0.012	0.039	1	0.151	0.130	0.942	0.123	0.069	0.623
within	1–15 yr	0.068	0.023	0.0703	− 0.026	0.039	0.998	0.704	0.128	< 0.0001	0.443	0.068	< 0.0001
10–20 cm	1–22 yr	0.089	0.023	0.0038	0.000	0.039	1	0.576	0.128	0.0003	0.202	0.068	0.061
depth	8–15 yr	0.035	0.023	0.789	− 0.038	0.038	0.974	0.553	0.126	0.0004	0.320	0.066	0.0001
	8–22 yr	0.056	0.023	0.220	− 0.012	0.038	1	0.425	0.126	0.019	0.079	0.067	0.934
	15–22 yr	0.021	0.022	0.982	0.026	0.038	0.997	− 0.128	0.124	0.969	− 0.241	0.066	0.007
Depth	1 yr	0.027	0.023	0.945	0.260	0.039	< 0.0001	0.707	0.128	< 0.0001	0.413	0.068	< 0.0001
within	8 yr	0.122	0.023	< 0.0001	0.369	0.038	< 0.0001	1.073	0.127	< 0.0001	0.714	0.067	< 0.0001
stand age	15 yr	0.064	0.022	0.091	0.213	0.037	< 0.0001	1.104	0.124	< 0.0001	0.784	0.065	< 0.0001
	22 yr	0.054	0.022	0.236	0.227	0.037	< 0.0001	0.832	0.124	< 0.0001	0.564	0.065	< 0.0001

variability is highest for C and N at 0–10 cm; at 10–20 cm variability appears to be higher at the subplot than plot scale. We did not measure soil texture, but this pattern may reflect very local shifts in sand or clay content (Desjardins et al., 2004). Thus, to increase the power of comparisons of soil quality by secondary stand age, increasing the number of plots within treatments will be most important at the 0–10 cm depth, while increasing the number of subplots within plots will be most important at 10–20 cm.

Our results demonstrate that VNIR spectroscopy can be a valuable tool for capturing spatial variability as a first step in developing spatial sampling designs – even when calibration accuracies are lower than those previously reported (O'Rourke and Holden, 2012). The causes of low calibration accuracies in our case are unclear, but point perhaps to insufficient sampling among distinct soil types, particularly those dominated by sand rather than clay. Moreover, our findings reflect the emerging value of spectral data capture as a tool to expand and speed sampling for soil quality (Soriano-Disla et al., 2014; Mirzaeitalarposhti et al., 2015) and directly detecting differences between agricultural systems, crops, and management types (e.g. Velasquez et al., 2005).

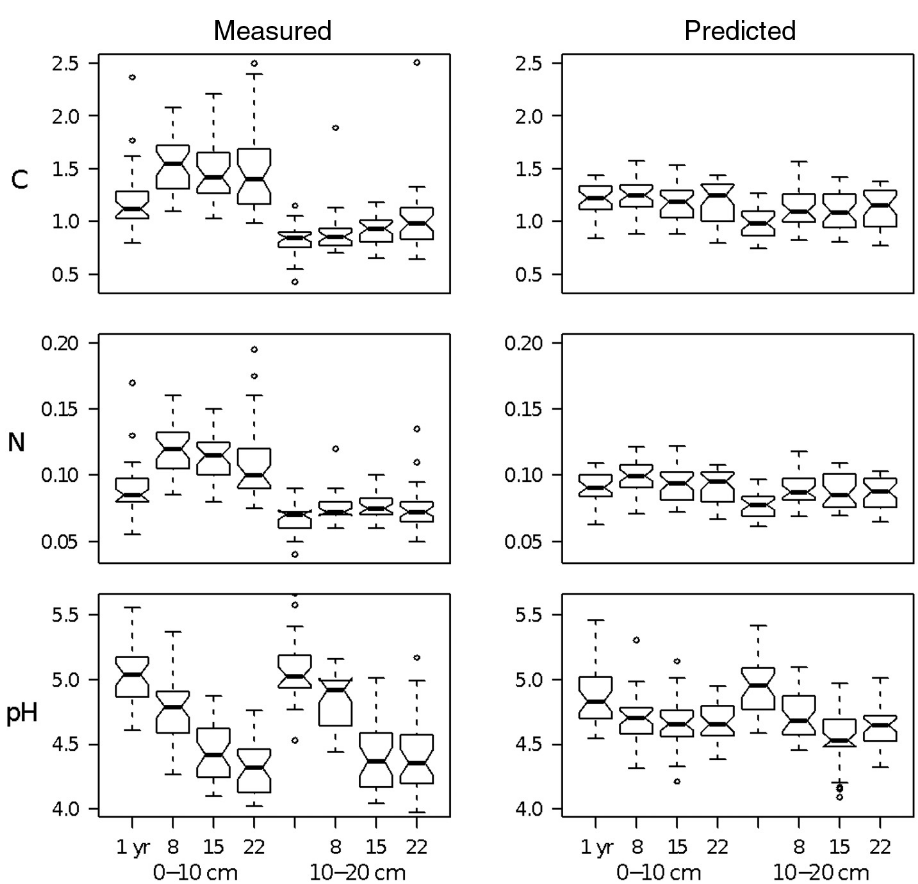

Fig. 2. Box-and-whisker subplots by land use (1, 8, 15, and 22 year-old secondary forest) and soil depth (0–10 and 10–20 cm), (n_{0-10} = 26, 29, 30, 34, n_{10-20} 21, 20, 27, 26) of percent total C, N, and for pH (water) – measured values, left, values predicted from spectra based on calibrations, right. Boxes define the upper (0.75) and lower (0.25) quartiles, heavy lines medians, and open circles outliers.

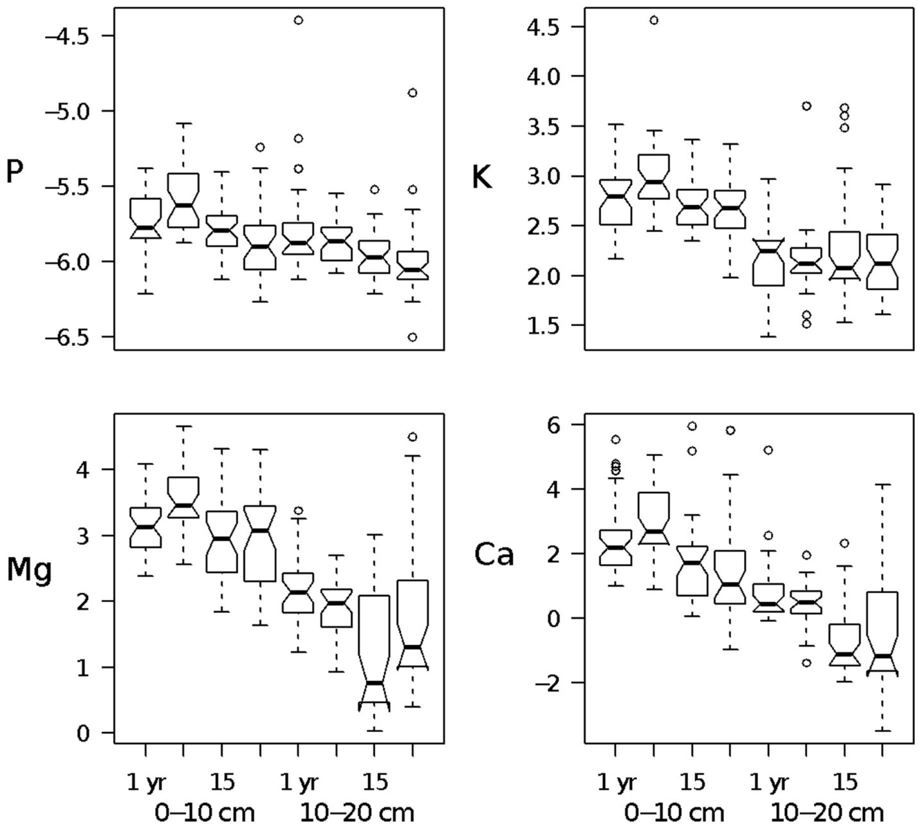

Fig. 3. Box-and-whisker subplots by land use (1, 8, 15, and 22 year-old secondary forest) and soil depth (0–10 and 10–20 cm), (n = 26, 29, 30, 34, 21, 20, 27, 26) of total P, and mg kg^{-1} of cations (Ca, Mg, K, and Na). Values of P and cations were $\log_{10}$-transformed. Boxes define the upper (0.75) and lower (0.25) quartiles, heavy lines medians, and open circles outliers.

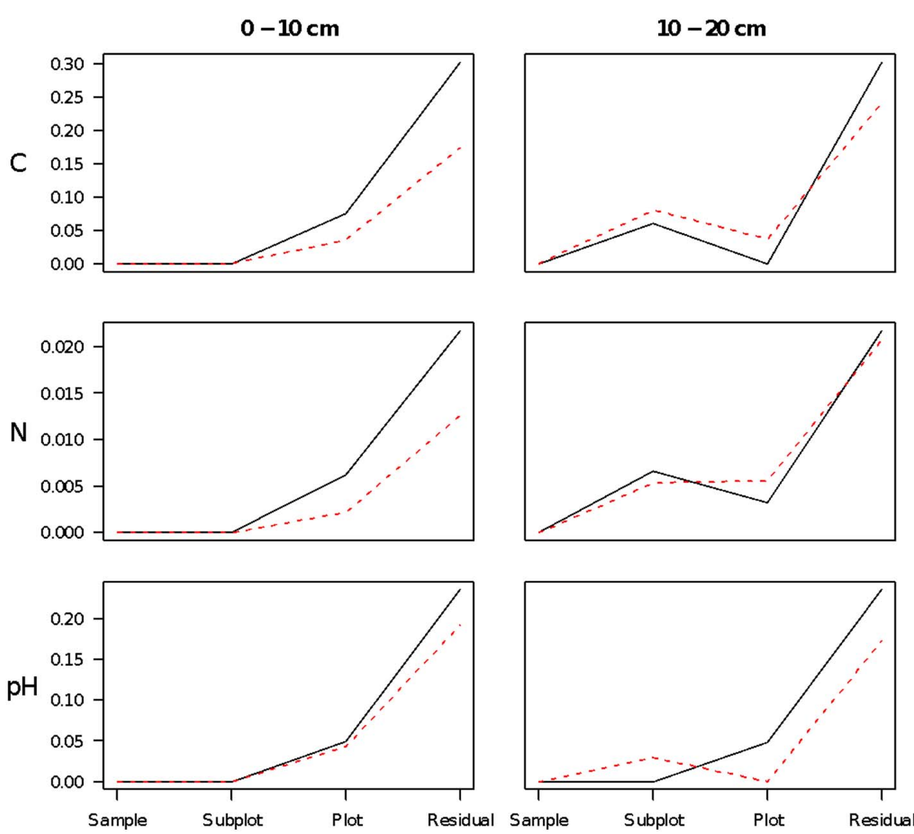

Fig. 4. Components of variability (plot and subplot) by depth, 0–10 cm on the left, 10–20 cm on the right, from linear mixed effects models of percent total C and N, and pH as a function of stand age (1, 8, 15, and 22 year-old). Dashed lines indicate standard deviations by scale for constituent values predicted from calibrations based on spectra.

Table 3
Root mean squared error of prediction (*RMSEP*) and coefficient of determination (R^2) on holdout test data of calibrations of eight soil constituents to soil spectra, and mean value for each $\log_{10}$-transformed constituent and pH.

Constituent	Test RMSEP	Test R2	Mean	SD
C	0.177	0.75	1.18	0.40
N	0.013	0.74	0.09	0.03
pH	0.227	0.62	4.63	0.37

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Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version, at doi: https://doi.org/10.1016/j.geodrs.2017.09.003. These data include the Google map of the most important areas described in this article.

References

Ben-Dor, E., Banin, A., 1995. Near-infrared analysis as a rapid method to simultaneously evaluate several soil properties. Soil Sci Soc Am J 59, 364–372.
Bernoux, M., Cerri, C.C., Cerri, C.E.P., Neto, M.S., Metay, A., Perrin, A.S., Scopel, E., Tantely, R., Blavet, D., de Piccolo, M.C., Pavei, M., 2009. Cropping systems, carbon sequestration and erosion in Brazil: a review. In: In Sustainable Agriculture. Springer, Netherlands, pp. 75–85.
Bremner, J.M., 1996. Phosphorus. In: Sparks, D.L. (Ed.), Methods of Soil Analysis: Chemical Methods, Part 3. Soil Science Society of America, Madison,WI, pp. 1085–1121 SSSA No. 5. 5.3.
Cobo, J.G., Dercon, G., Yekeye, T., Chapungu, L., Kadzere, C., Murwira, A., Delve, R., Cadisch, G., 2010. Integration of mid-infrared spectroscopy and geostatistics in the assessment of soil spatial variability at landscape level. Geoderma 158, 398–411.
Desjardins, T., Barros, E., Sarrazin, M., Girardin, C., Mariotti, A., 2004. Effects of forest conversion to pasture on soil carbon content and dynamics in Brazilian Amazonia. Agr Ecosyst Environ 103, 365–373.
Diniz, T.D. de A.S., 1991. Climatic characteristics of the Eastern Amazon region. In: Studies on the Ttilization and Conservation of Soil in the Eastern Amazon Region, (Final Report of the Agreement between EMBRAPA-CPATU-GTZ, Eschborn).
Fearnside, P.M., 2001. Soybean cultivation as a threat to the environment in Brazil. Environ Conserv 28, 23–38.
Feldpausch, T.R., Rondon, M.A., Fernandes, E., Riha, S.J., Wandelli, E., 2004. Carbon and nutrient accumulation in secondary forests regenerating on pastures in central Amazonia. Ecol Appl 14, 164–176.
Fernandes, E.C., Motavalli, P.P., Castilla, C., Mukurumbira, L., 1997. Management control of soil organic matter dynamics in tropical land-use systems. Geoderma 79, 49–67.
Fujisaki, K., Perrin, A.S., Desjardins, T., Bernoux, M., Balbino, L.C., Brossard, M., 2015. From forest to cropland and pasture systems: a critical review of soil organic carbon stocks changes in Amazonia. Glob Chang Biol 21, 2773–2786.
Helmke, P.A., Sparks, D.L., 1996. Phosphorus. In: Sparks, D.L. (Ed.), Methods of Soil Analysis: Chemical Methods, Part 3. Soil Science Society of America, Madison,WI, pp. 551–574 SSSA No. 5. 5.3.
Jafari, A., Khademi, H., Finke, P.A., Van de Wauw, J., Ayoubi, S., 2014. Spatial prediction of soil great groups by boosted regression trees using a limited point dataset in an arid region, southeastern Iran. Geoderma 232, 148–163.
Joslin, A.H., Markewitz, D., Morris, L.A., Oliveira, F., Figuereido, R.O., Kato, O.R., 2013. Soil and plant N-budget 1 year after planting of a slash-and-mulch agroforestry system in the eastern Amazon of Brazil. Agroforest. Syst. 87, 1339–1349.
Kinoshita, R., Roupsard, O., Chevallier, T., Albrecht, A., Taugourdeau, S., Ahmed, Z., Van Es, H.M., 2016. Large topsoil organic carbon variability is controlled by Andisol properties and effectively assessed by VNIR spectroscopy in a coffee agroforestry system of Costa Rica. Geoderma 262, 254–265.
Kuo, S., 1996. Phosphorus. In: Sparks, D.L. (Ed.), Methods of Soil Analysis: Chemical Methods, Part 3. Soil Science Society of America, Madison,WI, pp. 869–919 SSSA No. 5. 5.3.
McGrath, D.A., Smith, C.K., Gholz, H.L., Oliveira, F.A., 2001. Effects of land-use change on soil nutrient dynamics in Amazônia. Ecosystems 4, 625–645.
Mirzaeitalarposhti, R., Demyan, M.S., Rasche, F., Poltoradnev, M., Cadisch, G., Müller, T., 2015. MidDRIFTS-PLSR-based quantification of physico-chemical soil properties across two agroecological zones in Southwest Germany: generic independent validation surpasses region specific cross-validation. Nutr. Cycl. Agroecosys. 102, 265–283.
Nelson, D.W., Sommers, L.E., 1996. Total carbon, organic carbon, and organic matter. In: Sparks, D.L. (Ed.), Methods of Soil Analysis: Chemical Methods, Part 3. Soil Science Society of America, Madison,WI, pp. 961–1010 SSSA No. 5. 5.3.
Neumann-Cosel, L., Zimmermann, B., Hall, J.S., Breugel, M., Elsenbeer, H., 2011. Soil carbon dynamics under young tropical secondary forests on former pastures—a case study from Panama. Forest Ecol. Manag. 261, 1625–1633.
O'Rourke, S.M., Holden, N.M., 2012. Determination of soil organic matter and carbon fractions in forest topsoils using spectral data acquired from visible-near infrared hyperspectral images. Soil Sci Soc Am J 76, 586–596.
Paul, M., Catterall, C.P., Pollard, P.C., Kanowski, J., 2010. Recovery of soil properties and functions in different rainforest restoration pathways. Forest Ecol. Manag. 259, 2083–2092.
Perrin, A.S., Fujisaki, K., Petitjean, C., Sarrazin, M., Godet, M., Garric, B., Horth, J.C., Balbino, L.C., Silveira Filho, A., de Almeida Machado, P.L.O., Brossard, M., 2014. Conversion of forest to agriculture in Amazonia with the chop-and-mulch method: does it improve the soil carbon stock? Agr Ecosyst Environ 184, 101–114.
Powers, J.S., Corre, M.D., Twine, T.E., Veldkamp, E., 2011. Geographic bias of field observations of soil carbon stocks with tropical land-use changes precludes spatial extrapolation. Proc. Natl. Acad. Sci. U. S. A. 108, 6318–6322.
Shepherd, K.D., Walsh, M.G., 2007. Infrared spectroscopy—enabling an evidence-based diagnostic surveillance approach to agricultural and environmental management in developing countries. J. Near Infrared Spec. 15, 1–19.
Soriano-Disla, J.M., Janik, L.J., Viscarra Rossel, R.A., Macdonald, L.M., McLaughlin, M.J., 2014. The performance of visible, near-, and mid-infrared reflectance spectroscopy for prediction of soil physical, chemical, and biological properties. Appl. Spectrosc. Rev. 49, 139–186.
Stenberg, B., Rossel, R.A.V., Mouazen, A.M., Wetterlind, J., 2010. Chapter 5 - Visible and near infrared spectroscopy in soil science. In: Sparks, Donald L. (Ed.), Advances in Agronomy. vol. 107. Academic Press, pp. 163–215.
Suarez, D.L., 1996. Phosphorus. In: Sparks, D.L. (Ed.), Methods of Soil Analysis: Chemical Methods, Part 3. Soil Science Society of America, Madison,WI, pp. 575–601 SSSA No. 5. 5.3.
Thomas, G.W., 1996. Phosphorus. In: Sparks, D.L. (Ed.), Methods of Soil Analysis: Chemical Methods, Part 3. Soil Science Society of America, Madison,WI, pp. 475–490 SSSA No. 5. 5.3.
Vågen, Tor-G., Shepherd, K.D., Walsh, M.G., 2006. Sensing landscape level change in soil fertility following deforestation and conversion in the highlands of Madagascar using vis-NIR spectroscopy. Geoderma 133, 281–294.
Velasquez, E., Lavelle, P., Barrios, E., Joffre, R., Reversat, F., 2005. Evaluating soil quality in tropical agroecosystems of Colombia using NIRS. Soil Biol Biochem 37, 889–898.
Zarin, D.J., Davidson, E.A., Brondizio, E., Vieira, I.C.G., Sá, T., Feldpausch, T., Schuur, E.A.G., et al., 2005. Legacy of fire slows carbon accumulation in Amazonian forest regrowth. Front Ecol Environ 3, 365–369.