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# Soil classification using visible/near-infrared diffuse reflectance spectra from multiple depths

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ABSTRACT

Visible/near-infrared diffuse reflectance spectroscopy (VNIRDRS) offers an alternative to conventional analytical methods to estimate various soil attributes. However, the use of VNIRDRS in soil survey and taxonomic classification is still underexplored. We investigated the potential use of VNIRDRS to classify soils in a region with variable soils, geology, and topography in southeastern Brazil. Soils were classified in the field according to the Brazilian Soil Classification System, and visible/near-infrared (400–2500 nm) spectra were collected from three depth intervals (0–20, 40–60 and 80–100 cm) and combined in sequence to compose a pseudo multi-depth spectral curve, which was used to derive the classification models. Principal component (PC) analysis and multinomial logistic regression were used to classify 291 soils (202 in calibration and 89 in validation mode) at the levels of order (highest), suborder (second highest) and suborder plus textural classification (STC). Based on the validation results, best classification was obtained at the order level (67% agreement rate), followed by suborder (48% agreement) and STC (24% agreement). The inherent complexity and variability within soil taxonomic groups and in contrast the strong similarity among different groups in terms of soil spectra and other attributes cause confusion in the classification model. This novel approach combining spectral data from different depths in multivariate classification can improve soil classification and survey in a cost-efficient manner, supporting sustainable use and management of tropical soils.



## 1. Introduction

Soil survey has been traditionally done by combining the surveyor's interpretation of soil–landscape relationships and field expertise with supporting maps, aerial and/or satellite images, and soil data. Albeit this strategy has been widely used to map soils at a range of geographic scales, currently it still does not fully incorporate newly available forms of data collection and interpretation. This is the case, for example, of proximally sensed data, including soil electrical conductivity and visible/near-infrared (VNIR) diffuse reflectance.

Visible/near-infrared diffuse reflectance spectroscopy (VNIRDRS) has been applied to estimate many soil attributes used in soil survey, including organic matter, carbon, pH, macro- and micronutrients, water content, and others (Chang et al., 2001; Du and Zhou, 2009; Stenberg et al., 2010; Vasques et al., 2008; Viscarra Rossel et al., 2006). Because VNIRDRS uses little sample preparation and rarely chemicals, and can be used to simultaneously estimate various soil attributes, it can reduce time and cost of analyses. In this case, gain obtained from VNIRDRS applies to data collection and analysis, but only indirectly to final soil classification and survey.

One of the difficulties of classifying soils based on the spectral reflectance is to combine spectral data from multiple depths. Usually, researchers evaluate the spectral response of soils depth by depth, or only at one depth, which can lead to incomplete interpretations, since most soil taxonomic systems evaluate multiple horizons together in the classification keys. Thus, it is necessary to derive a soil classification method that integrates the spectral response of soils from multiple depths. Viscarra Rossel & Webster (2011) were able to discriminate soil horizons and soil classes from the Australian soil classification using vis-NIR spectra and suggest that vis–NIR spectroscopy could make an important contribution to the definition and identification of classes in an effective system of soil classification. To our knowledge, there is no other work published on the topic so far.

Therefore, to improve efficiency of soil classification, we propose a direct application of VNIRDRS to derive soil classes according to the Brazilian Soil Classification System (SiBCS; EMBRAPA, 2006). We hypothesized that the diffuse reflectance spectra of soils from three depth

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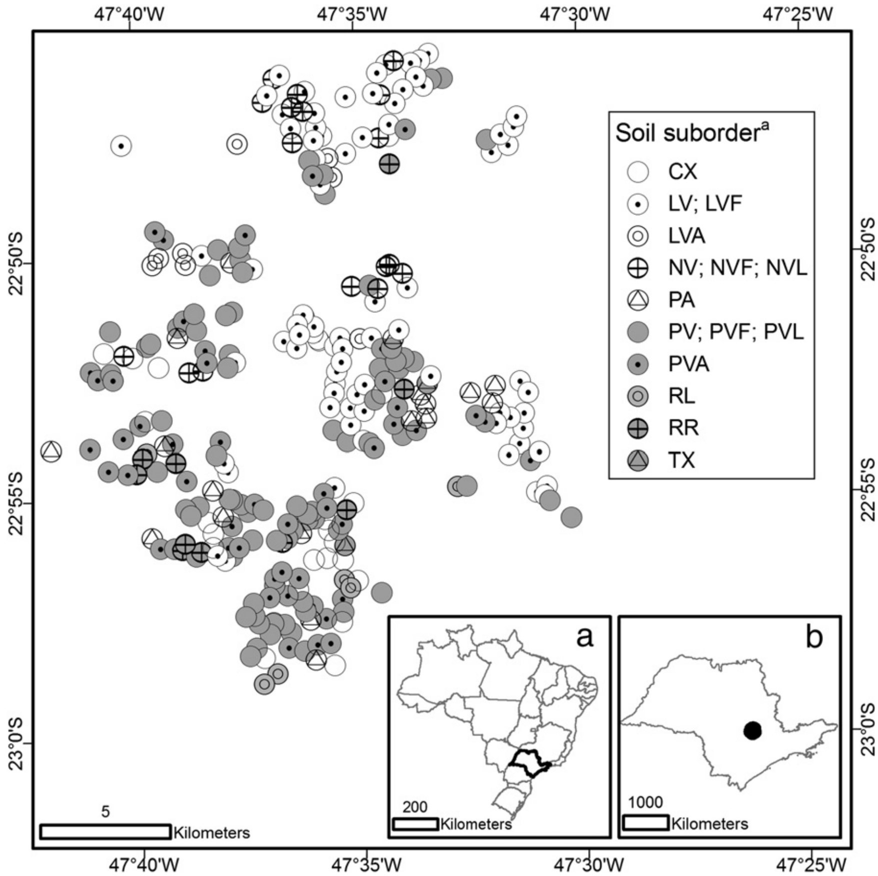


**Fig. 1.** Soil sampling site locations. (a) Brazil. (b) State of São Paulo. [a]Brazilian soil suborders and corresponding soil classes in Soil Taxonomy (da Costa and Nanni, 2006; Soil Survey Staff, 2010): CX, Haplic Cambisol — Inceptisols; LV, Red Latosol, LVA, Red–Yellow Latosol, LVF, Ferric Red Latosol — Oxisols; NV, Red Nitosol, NVF, Ferric Red Nitosol, NVL, Latosolic Red Nitosol, PA, Yellow Argisol, PV, Red Argisol, PVA, Red–Yellow Argisol, PVF, Ferric Red Argisol, PVL, Latosolic Red Argisol — Alfisols, Ultisols; RL, Lithic Neosol, RR, Regolithic Neosol — Entisols, Inceptisols; TX, Haplic Luvisol — Alfisols.

intervals could be used to classify soils with good accuracy (agreement rate higher than 75%) at the order and suborder levels, according to the SiBCS (which uses soil color to classify soils at the suborder level).

## 2. Material and methods

### 2.1. Soil sampling and field classification

The study was conducted near the city of Piracicaba, in the central-eastern part of the state of São Paulo, Brazil (Fig. 1), in a region that has been primarily used for sugarcane production in the last 30 years. Mean annual precipitation and temperature in the region are 1328 mm and 21.6 °C, respectively (1961 to 1990; CEPAGRI, 2011), while elevations vary from about 489 to 709 m, and slopes from 0 to 32%. Soils in the region are in most part derived from sandstone, siltstone and shale, and less prominently from limestone, basalt and colluvial deposits (Mezzalira, 1966).

A total of 291 soil profiles were visited and classified in the field at the suborder level according to the SiBCS (Table 1). Soil samples were taken at three depth intervals (0–20, 40–60 and 80–100 cm) and analyzed chemically and granulometrically according to Camargo et al. (1986). Textural classification was added to refine the suborder classes into *suborder plus textural classification* (STC) groups. Five textural groups were created (Table 2), based on the clay content, adapted from EMBRAPA (2006).

The complete dataset was separated into a calibration set containing 202 samples and a validation set with 89 samples. The separation involved the stratification of the dataset into suborders followed by random selection of the samples (approximately 2/3 for calibration and 1/3 for validation) within each suborder. The calibration set was used to derive the classification models, whereas the independent validation was set apart to exclusively validate the derived models.

In some cases the letter F (as in *Ferric*) was included to indicate high iron content (18 to 36%) in the diagnostic horizon of Latosols (Oxisols), Argisols (Alfisols, Ultisols) and Nitosols (Alfisols, Ultisols). At the STC level, the *Ferric* designation was kept; at the suborder level, *Ferric* soils were grouped with non-*Ferric* soils of the same suborder for modeling.

**Table 1**
Soil suborders as classified in the field according to the Brazilian Soil Classification System (SiBCS; EMBRAPA, 2006), and corresponding classes in Soil Taxonomy (Soil Survey Staff, 2010).

| Abbreviation | SiBCS suborder[a] | Soil Taxonomy class[b] | Observations |
|---|---|---|---|
| CX | Haplic Cambisol | Inceptisols | 21 |
| LV | Red Latosol | Oxisols | 66 |
| LVA | Red–Yellow Latosol | Oxisols | 8 |
| LVF | Ferric Red Latosol | Oxisols | 16 |
| NV | Red Nitosol | Alfisols, Ultisols | 9 |
| NVF | Ferric Red Nitosol | Alfisols, Ultisols | 6 |
| NVL | Latosolic Red Nitosol | Alfisols, Ultisols | 3 |
| PA | Yellow Argisol | Alfisols, Ultisols | 18 |
| PV | Red Argisol | Alfisols, Ultisols | 52 |
| PVA | Red–Yellow Argisol | Alfisols, Ultisols | 59 |
| PVF | Ferric Red Argisol | Alfisols, Ultisols | 2 |
| PVL | Latosolic Red Argisol | Alfisols, Ultisols | 14 |
| RL | Lithic Neosol | Entisols, Inceptisols | 6 |
| RR | Regolithic Neosol | Entisols, Inceptisols | 9 |
| TX | Haplic Luvisol | Alfisols | 2 |
| Total | | | 291 |

[a] The last word indicates the soil order (highest hierarchical level).
[b] Correspondence based on da Costa and Nanni (2006).