

## Proximal Soil Sensing Platform for Effective Mapping of Soil Attributes in Brazil

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### Abstract

Sustainable management of agricultural lands requires detailed information on soil properties. Although the literature has shown the potential of PSS data integration to predict spatial variations of soil properties, most of these studies were done in temperate soils considering up to three sensors. Study cases here introduced to contribute in applying PSS to: (i) assess the spatial variation of tropical soil chemical and physical attributes; (ii) understand processes controlling spatial soil variations; and (iii) compare spatial dependence and patterns among proximally-sensed and laboratory-measured soil attributes. In three preliminary study cases PSS was applied for digital soil mapping, soil salinity mapping, and within-field crop variations. Hand held and “*on-the-go*” sensors, respectively, for point-based and continuous monitoring readings, include apparent electrical conductivity and magnetic susceptibility meters; gamma ray, X-ray fluorescence and near infrared spectrometers; and mechanical resistance meters among others. Variables were significantly correlated ( $p < 0.05$ ), and their spatial dependence structure (i.e.: variogram analysis) and the spatial distribution patterns (i.e.: kriging) were all-similar. In addition, combined PSS datasets have shown improved predictions of soil properties (i.e.:  $R^2_{adj}$  from 0.21 to 0.94). Results have indicated the potential of PSS to assess the spatial variation of soil attributes that are more difficult to collect and analyze, supporting detailed soil mapping for precision agriculture and related activities.

### Introduction

Proximal soil sensing (PSS) has proven over a decade its suitability to map soil variations with high spatial detail in support to land sustainable management and precision farming (Corwin and Lesch, 2005; Viscarra Rossel et al., 2011), where integrated multi-sensing platforms are now a trend approach. At field scale, the approach entails the use of geophysical sensors (Rhoades et al., 1999) from different types (e.g.: mechanic, electromagnetic, optical, etc.) to in-situ soil measurements, directly or indirectly predicting and mapping soil properties of interest. PSS has been applied to within-field attribute variations (Sanches et al., 2018), crop irrigation (Zhu et al., 2012), soil salinity and sodicity mapping (Rhoades et al., 1999) and digital soil mapping (Silva et al., 2016) include electrical conductivity meters, gamma ray, X-ray fluorescence and near infrared spectrometers, and mechanical resistance meters among others.

Strong correlations have been reported among soil sensor data and soil properties from laboratory analysis at different soil types around the world (Naderi-Boldaji et al., 2013; Piikki et al., 2016; Sharma et al., 2014, 2015). Strong correlations are mostly specific to certain soil property and sensor combinations. Therefore, selection of soil sensors to use depends on many factors, including target soil property, soil type, landscape characteristics, available technical assistance, sensor cost and portability. Aiming to better assist soil property predictions, the integration of data from different sensors has shown improved results (Piikki et al., 2016; Huang et al., 2014; Söderström et al., 2016), while data format and equipment connectivity and price are still a problem (Bitella et al., 2014).

In Brazil, most of the use of PSS technology for PA has been on apparent soil electrical conductivity (ECa), in particular by contact (VERIS Technologies, V3100), characterizing spatial variability of soil properties. Although Brazilian PA adopters mostly use for the delineation of management zones for soil fertility management, investments in PSS are still lacking (Bernadi & Inamasu, 2014). Where only recently the use of induced electromagnetic monitoring for ECa (Sanches et al., 2018) and sensor datasets fusion (Tavares et al., 2018) have been further addressed in precision farming applications. Although results in the literature has shown the potential of PSS data integration to predict soil properties, a review by Grunwald et al. (2015) showed in that most studies have been done in temperate soils and only considering up to two or three sensors in their predictions. Relationships among proximally-sensed and laboratory-measured soil properties datasets are still lacking when a larger number of sensors are used in combination. Only a few PSS data fusion reports have been done against tropical soil attribute datasets Piikki et al., 2016; Silva et

al., 2016), two of which focusing on Amazonian Dark Earths specifically (Söderström et al., 2013, 2016). This work aims to introduce preliminary results from three case studies focused on tropical soils and in situ PSS multiplatform data fusion. It briefly describes field experiments from a research initiative aiming to diminish knowledge gaps in applying PSS to tropical Brazilian soils. Study cases are introduced to illustrate early learnings using and defining field-monitoring protocols with several PSS devices. The overall research aims to understand how proximal soil sensors could contribute to predict and map different chemical and physical soil processes. A general case studies objective was to identify which PSS technology would best suite specific soil properties, and how sensors could be combined among themselves, or with available legacy data, to improve soil properties prediction maps. Along to primary applications of PSS to delineate management zones and to optimize soil sampling in precision farming applications, the team motivation lies in the potential of proximal sensors to complement or substitute soil sampling and laboratory analyses of these properties, which are costly, time- and energy-consuming, and potentially polluting.

## Material and Methods

The three selected study cases are detailed below, where the selection of applied soil sensors were defined according to agricultural landscapes and production system demands, considering production-limiting factors, landscape characteristics, soil type, and target soil property. Sensor characteristics like portability ease of use, measurement support and the capacity to predict multiple soil properties were also taken into account, as well as external interfering factors and other accessibility limitations. For all study cases, soil spatial predictions followed classic methods for ordinary kriging (OK), regression-kriging (ROK) (Odeh et al., 1994) considering laboratory and PSS datasets, along to legacy data of landform attributes derived from digital elevation models and vegetation indices from remote sensing.

### Terraço Case Study

The use of in-situ PSS datasets as support for digital soil mapping has mostly been done in temperate soils. Therefore, this PSS data fusion study aimed to address the lack of reports on multisensor data modelling against tropical soil attribute datasets. Field experiment was conducted in a 3.4ha area in the municipality of Seropédica, RJ, southeastern Brazil, with central latitude -22.757356 and central longitude -43.663409 (Figure 1). The study area has 3.4 ha and has been under unimproved pasture (*Panicum maximum* Jacq.) for more than a decade. It is located in the Brazilian Atlantic Forest with tropical climate, dry winters and warm and humid summers. Soils are formed from granites, gneisses and migmatites, with intrusions of basaltic and alkaline rocks and sedimentary deposits. Analytical and digital mapping methods were applied to: (i) assess spatial variations of soil chemical and physical attributes; (ii) understand main factors of within-field spatial soil variations; and (iii) compare spatial dependence and patterns among PSS and laboratory-measured attributes. A set of hand held devices for point based PSS readings were used simultaneously to traditional soil survey procedures (Embrapa, 1999) and lab analysis (Donagemma et al., 2011). A 10 x 10-m sampling grid was set in the study area for in situ measurement of soil properties using two proximal soil sensors. The grid had 29 by 13 sites, totaling 377 sites. A 20 x 20-m sub-grid was derived by skipping every other site in both directions, totaling 105 sites. For independent validation of the maps, another 25 sites were allocated on the remaining sites on the 10 x 10-m grid using the conditioned Latin Hypercube sampling (Minasny & McBratney, 2006). PSS devices include: 1) a KT-10 (Terraplus Inc., Richmond Hill, Canada) for ECa and apparent magnetic susceptibility (MSa) readings by electromagnetic induction at 0-10, 0-20, and 0-40 cm soil depths; 2) an Embrapa prototype ECa sensor (Rabello et al., 2014); 3) a RS-230 BGO Super-SPEC gamma-ray spectrometer (Radiation Solutions Inc., Mississauga, Canada) counting equivalent uranium (eU), thorium (eTh), and potash (eK) emissions by a 103-cm<sup>3</sup> bismuth germanate oxide detector; 4) a CS650 water content reflectometer (WCR) (Campbell Scientific Inc., Logan, USA) to measure volumetric moisture contents ( $\theta$ ); 5) a PenetroLOG (Falker Automação Agrícola Ltda., Porto Alegre, Brazil) for cone penetration resistance (PR) readings, with a type 2 cone at 0-10 cm; and 6) a DP-6000 portable X-ray fluorescence (pXRF) spectrometer (Olympus Scientific Solutions Americas Inc., Waltham, USA) used in "Soil" mode to measure total element contents at soil surface. Measurements were taken at the soil surface cleaned off plant debris.

### Diba Case Study

Soil salinization as result of natural or human-induced processes is a major environmental issue for agricultural sustainability, particularly in arid and semi-arid regions. The study was conducted in a family farm at Baixo Açú irrigated perimeter, Alto do Rodrigues, RN, northeast Brazil. The 3.6ha Pacovan banana

(*Musa paradisiaca* L.) field, with central latitude  $-5^{\circ}22'33,32''$  and central longitude  $-36^{\circ}43'56,80''$ , was chosen to evaluate the responsiveness of an “*on-the-go*” ECa sensor to map soil salinity by electromagnetic induction. Soils in the region are mostly argissolos, cambissolos, and planossolos (Embrapa, 1999), from Jandaraíra calcaric rocks. Due to its semi-arid conditions (Koppen: BSh), the area is subject to natural soil salinization processes that have been increased by irrigated crop production. The EM38-MK2 (Geonics Limited, Mississauga, Canada) was used for continuous ECa and MSa readings (N=15,200 points) on a zig-zag footstep tracks in “1m” mode, on both vertical and horizontal orientations. For soil salinity from laboratory analysis, soil core samples were collected in a 35 points uniform grid, at 0-10cm depth. PSS dataset fusion was considered in model predictions with legacy data covariates derived from remote sensing. In addition to evaluate model improvements of PSS fusion with different remote sensing datasets, the study further aimed to understand how different spatial resolution sources would influence this evaluation. The digital elevation model (DEM) and its derived topographic landform indices was obtained from SRTM datasets with 30m spatial resolution. Soil-adjusted Vegetation Index (SAVI) and Normalized Difference Vegetation Index (NDVI) were derived from spectral responses from Sentinel 2 satellite imagery, with 20m spatial resolution.

### Broek Case Study

Soil compaction, erosion and structure quality are major issues in no-till crop production systems at Campos de Holambra, SP, southeast Brazil (Fig. 3). A 71ha central pivot area, with central latitude  $-23^{\circ}34'29.84''$  and central longitude  $-48^{\circ}55'44.67''$ , with intensive crop production of soya, corn and edible beans. Aiming to predict within-field spatial crop yield variations as a function of soil physical properties, PSS dataset fusion considered landform and soil samples for a fast quantitative soil structure diagnostic (DRES). A soil structure quality index (IQEs) was calculated for 15 points in soil topsequence lines as proposed in Ralisch et al. (2017). DEM and its derived topographic landform indices was obtained from SRTM datasets as well. A crop yield map was available for edible beans productivity from the immediately previous season. Two “*on-the-go*” sensors were simultaneously mounted in a pickup truck driving at speeds from 15 to 20 km.h<sup>-1</sup>. The EM38-MK2 was used for continuous ECa and MSa readings (N=4,720 points) in “1m” mode with vertical orientation. The Medusa 1200 gamma-ray spectrometer (Medusa Radiometrics, Groningen, The Netherlands) was used to count eU and eTh emissions by a 205-cm<sup>3</sup> CsI detector.

## Results and Discussion

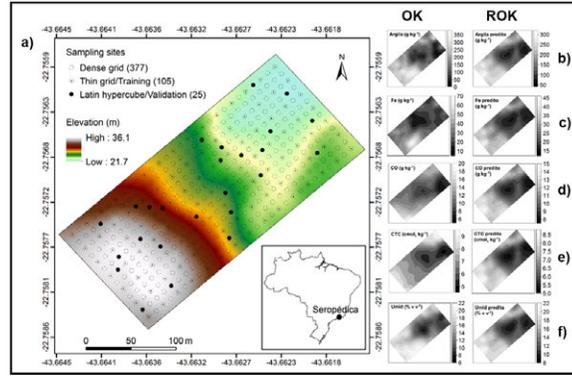
### Terraço Case Study

Most laboratory- and sensor-measured soil properties were significantly correlated. The highest correlations among laboratory-measured properties were found between BS and CEC (0.87), clay and moisture (0.85), and OC and CEC (0.76). The sensor variables with highest correlations with laboratory-measured properties were eTh with clay (0.78), and CS650 WCR  $\theta$  with laboratory-measured  $\theta$  (0.76). The CS650 WCR  $\theta$ , and both the RS-230 BGO dose rate and eTh had moderate to high correlations ( $> 0.50$ ), indicating potential variables for PSS fusion. Prediction models had moderate to good fits with  $R^2_{adj} > 0.50$  for all soil properties but bulk density. The highest adjusted  $R^2$  were found for clay, and moisture, both as a function of combined sensors plus CS650 WCR, stressing the importance of including a soil moisture sensor in proximal sensor combinations. For best correlation soil properties, the quality of predictions was reasonably similar among interpolation approaches (Table 1), meaning modest improvements in map accuracy achieved by using sensor covariates. Sensor-aided derived maps were more detailed (Fig. 1), since predictions had more dense datasets and to interpolate from. Derived maps show similar spatial trends among OC, CEC, Clay, and soil moisture.

**Table 1. Model validation results for laboratory soil properties predicted as a function of PSS data fusion from individual, and combined proximal soil sensors in a 3.4-ha field in Terraço Case Study.**

Soil Attribute	RMSE <sup>*1</sup>			
	Mean Error		OK	ROK
	OK	ROK	OK	ROK
Clay (g kg <sup>-1</sup> )	21	21	60	62
Fe (g kg <sup>-1</sup> )	7,5	8,6	14,4	16,0
OC (g kg <sup>-1</sup> )	1,2	1,5	2,9	3,1
CEC (cmol <sub>c</sub> kg <sup>-1</sup> )	0,9	0,9	1,5	1,5
$\theta$ (% m v <sup>-1</sup> )	4,1	3,9	5,8	5,9

\*1 Root Mean Square Error - A measure of precision of prediction and it should be as small as possible for unbiased and precise predictions.



**Figure 1.** This illustrates the Terraço case study location map with elevation model and sampling design (a) with correlations between soil attribute maps estimated by Ordinary Kriging (OK), from laboratory results, and Regression-Kriging (ROK), from PSS datasets, for: Clay (b); Fe (c); OC (d); CEC (e); and  $\theta$  (f).

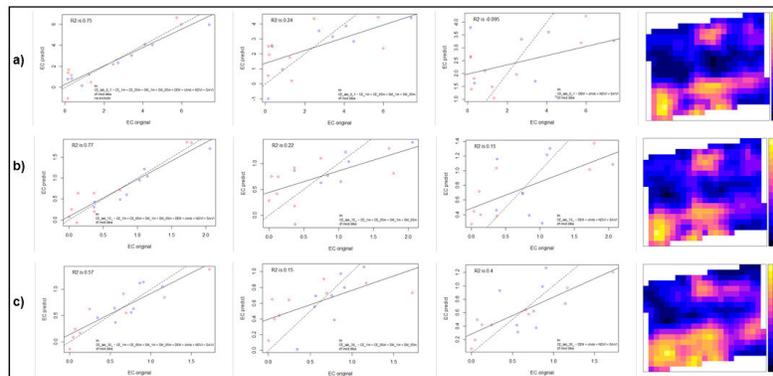
### Diba Case Study

In all soil depths considered, soil salinity predictions were best fitted for PSS dataset fusion with derivative indices from digital terrain analysis and remote sensing imagery. From DEM terrain derivatives, only the Channel Network Base Level (CHNB) was selected during model training (Table 2). Individually, PSS data has performed better over combinations of terrain and imagery derivative indices on shallower readings. The better fitting of legacy data combination over PSS dataset alone in deeper readings (30-50 cm) was understood as a result from inconsistent field operation issues, as taking along the EM38 in shoulder strap mode, around 70 cm distant from ground surface. Predicted maps at different depths have shown consistent results as for the expected process of higher salt concentrations in deeper soil horizons of a sand soil area (Fig. 2). Figure 2 also shows the relevance of PSS data fusion for improved model fit dispersion graphics.

**Table 2. Model training results for the laboratory soil electrical conductivity map predicted as a function of data from an individual ECa sensor, and combined legacy data derivatives (DEM and Vegetation Indices) in a 3.6ha field from Diba case study. For each soil depth the best model fit are shown in bold and italic.**

Soil Depth Interval (cm)	Model training Selected Covariates	R	R <sup>2</sup> <sub>adj.</sub>
0 - 10	<b><i>ECa + MSa + DEM + CHNB*1 + NDVI + SAVI</i></b>	<b><i>0.88</i></b>	<b><i>0.75</i></b>
	ECa + MSa	0.43	0.24
	DEM + CHNB*1 + NDVI + SAVI	0.17	-0.09
10 - 30	<b><i>ECa + MSa + DEM + CHNB*1 + NDVI + SAVI</i></b>	<b><i>0.88</i></b>	<b><i>0.77</i></b>
	ECa + MSa	0.42	0.22
	DEM + CHNB*1 + NDVI + SAVI	0.36	0.15
30 - 50	<b><i>ECa + MSa + DEM + CHNB*1</i></b>	<b><i>0.78</i></b>	<b><i>0.57</i></b>
	ECa + MSa	0.36	0.15
	DEM + CHNB*1 + NDVI + SAVI	0.55	0.39

\*1 Channel Network Base Level (m) – Is a morphometric measure giving the altitude above the channel network in the same units as the elevation data



**Figure 2.** Model training dispersion graphics for soil salinity predictions in Diba case study are shown from left to right for best PSS fusion fit, PSS data only, and derivatives indices from DEM and Sentinel 2 imagery. Final salinity prediction maps are also shown for different soil depths, as for: a) 0-10 cm, b) 10-30 cm, and c) 30-50 cm.

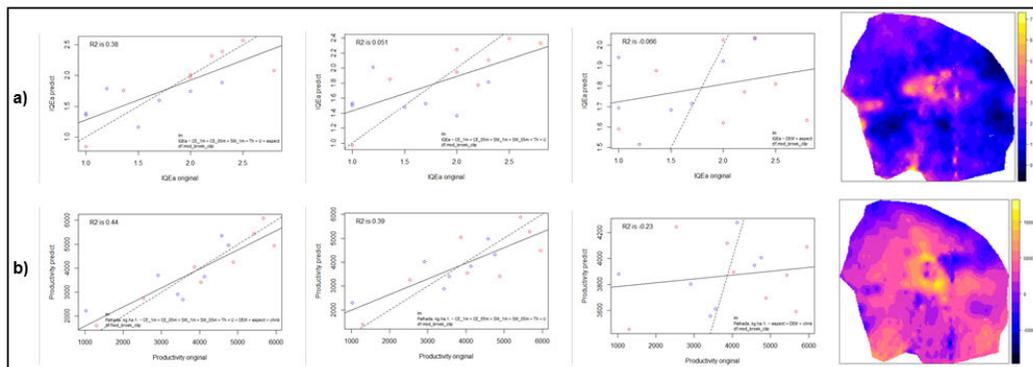
## Broek Case Study

Model fitting for soil physical properties were not significantly improved with additional PSS data fusion from the EM38 MK2 and Medusa 1200 sensors, as in relation to pure terrain derivative indices. Although the overall model fit considering PSS fusion with legacy data was moderately higher (Table 3), the limited PSS contribution was understood for the insufficient number of soil structure samples (N=15) in great contrast to spatially well distributed and dense PSS readings (N= 4,720). In contrast, the PSS data fusion only from the two sensors could stand by itself, having a significant gain over single terrain index combinations. From DEM derivatives, the Channel Network Base Level (CHNB) was only select during model training for the IQEs predictions, while aspect could contribute to both production parameters; soil structure and crop yield (Table 3). Predicted maps for soil structure quality and crop yield have shown consistent spatial trends as could be expected for soil compaction processes (Fig. 3). Figure 3 also shows the relevance of quantity and spatial distribution of soil core samples as a limiting factor to improve model fit dispersion graphics.

**Table 3. Model training results for soil structure quality and edible beans productivity predicted as a function of data from combined proximal soil sensors alone and legacy data derivatives from DEM in a 71ha field from Broek case study. For each predicted map the best model fit are shown in bold and italic.**

Predicted Map	Model Selected Covariates	R	R <sup>2</sup> <sub>adj.</sub>
Soil Structure Quality Index (IQEs)	<i><b>ECa + MSa + eTh + eU + DEM + Aspect</b></i>	<b>0.62</b>	<b>0.38</b>
	ECa + MSa + eTh + eU	0.07	0.05
	DEM + Aspect	0.01	-0.06
Edible Beans Yield (ton.ha <sup>-1</sup> )	<i><b>ECa + MSa + eTh + eU + DEM + CHNB<sup>*1</sup> + Aspect</b></i>	<b>0.80</b>	<b>0.44</b>
	ECa + MSa + eTh + eU	0.65	0.39
	DEM + CHNB <sup>*1</sup> + Aspect	0.03	-0.23

\*1 Channel Network Base Level (m) – Is a morphometric measure giving the altitude above the channel network in the same units as the elevation data.



**Figure 3. Model training dispersion graphics for soil structure quality (a) and edible beans yield (b) predictions in Broek case study are shown from left to right for best PSS fusion fit, PSS data fusion only, and derivatives indices from DEM. Final best fit predicted maps are also shown for: a) IQEs and b) crop yield.**

The hypothesis that proximally-sensed soil properties have similar spatial dependence and spatial distribution patterns to those of the soil attributes measured in the laboratory for different soil chemical and physical process simulations has been somehow confirmed. Further analysis including existing soil fertility data is still under computational phases, which could strength the overall research discussions. Finally, preliminary results have indicated that PSS data fusion has great potential to predict spatial variations of soil attributes whose measurement by conventional methods are more demanding. A potential for better efficiency in assessments of key soil processes is suitable to support of precision farming related activities.

## Conclusion

For three case studies considered PSS data fusion has proven to improve regression models from a combination of soil sensors and/or legacy data derivative indices over those predictions from individual sensors. Portable point-based soil sensors have shown great potential to support digital soil mapping approaches, in which the pXRF sensor has produced the best predictions for chemical and physical soil properties among individual proximal soil sensors.

Proximal soil sensors allow the production of better soil property maps by ordinary kriging of sensor-based predictions with better spatial coverage. Proximal soil sensors can be used in place of laboratory soil analysis for soil property mapping, especially when used in combination.

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## References

- Bitella, G., Rossi, R., Bochicchio, R., Perniola, M., & Amato, M. (2014). A Novel Low-Cost Open-Hardware Platform for Monitoring Soil Water Content and Multiple Soil-Air-Vegetation Parameters. *Sensors*, doi:10.3390/s141019639
- Bernardi, A.C.C., & Inamasu, R.Y. (2014). Adoção da agricultura de precisão no Brasil In: Bernardi, A.C.C.; Naime, J.M.; de Resende, A.V.; Bassoi L.H.; Inamasu, R.Y. (Ed.). *Agricultura de precisão: resultados de um novo olhar*. (pp.559-577). Brasília: Embrapa, 2014.
- Corwin, D.L., & Lesch, S.M., 2005. Apparent soil electrical conductivity measurements in agriculture. *Computers and Electronics in Agriculture* 46, 11–43.
- Donagema, G. K.; Campos, D. V. B.; Calderano, S. B.; Teixeira, W. G.; & Viana, J. H. M. (2011) *Manual de métodos de análise de solo*. 2. ed. rev. Rio de Janeiro: Embrapa Solos (Documentos, v. 132)
- EMBRAPA. (1999). *Sistema brasileiro de classificação de solos*. EMBRAPA Produção de Informação, Brasília.
- Grunwald, S., Vasques, G.M., Rivero, R.G., 2015. Fusion of soil and remote sensing data to model soil properties. *Advances in Agronomy* 131, 1–109.
- Holland, J.E., Biswas, A., Huang, J., & Triantafyllis, J., 2017. Scoping for scale-dependent relationships between proximal gamma radiometrics and soil properties. *Catena* 154, 40–49.
- MINASNY, B.; MCBRATNEY, A. B. A conditioned Latin hypercube method for sampling in the presence of ancillary information. *Computers and Geosciences*, v. 32, p. 1378-1388, 2006.
- Naderi-Boldaji, M., Sharifi, A., Alimardani, R., Hemmat, A., Keyhani, A., Loonstra, E.H., Weisskopf, P., Stettler, M., & Keller, T., 2013. Use of a triple-sensor fusion system for on-the-go measurement of soil compaction. *Soil and Tillage Research* 128, 44–53.
- Odeh, I.O.A., McBratney, A.B., & Chittleborough, D.J., 1994. Spatial prediction of soil properties from landform attributes derived from a digital elevation model. *Geoderma* 63, 197–214.
- Piikki, K., Söderström, M., Eriksson, J., John, J.M., Muthee, P.I., Wetterlind, J., & Lund, E., 2016. Performance evaluation of proximal sensors for soil assessment in smallholder farms in Embu County, Kenya. *Sensors* 16, 1950.
- Ralisch, R.; Debias, H.; Franchini, J.C.; Tomazi, M.; Hernani, L.C.; Melo, A.S.; Santi, A.; & Martins, A.L.S. (2017). DRES, Diagnóstico rápido da estrutura do solo. <http://www.infoteca.cnptia.embrapa.br/infoteca/handle/doc/1071114>.
- Rhoades, J.D., Corwin, D.L., Lesch, S.M. Geospatial measurements of soil electrical conductivity to assess soil salinity and diffuse salt loading from irrigation. 1999. In: CORWIN, D.L., LOAGUE, K., ELLSWORTH, T.R. (Eds.), *Assessment of Non-point Source Pollution in the Vadose Zone*. Geophysical Monograph 108 American Geophysical Union, Washington, DC, pp. 197–215.
- Sanches, G.M., Magalhães, P.S.G., Remacre, A.Z., Franco, H.C.J. 2018. Potential of apparent soil electrical conductivity to describe the soil pH and improve lime application in a clayey soil. *Soil & Tillage Research* 175, 217-225, 2018.
- Sanches, G.M., & Magalhães, P.S.G. (2018). Sensor de indução eletromagnética (IEM) para mapeamento da variabilidade espacial do solo em lavouras de cana-de-açúcar. In *Proceedings of the Congresso Brasileiro de Agricultura de Precisão - ConBAP 2018* (pp. 198-204) Curitiba, Paraná, AsBraAP.
- Sharma, A., Weindorf, D.C., Wang, D., Chakraborty, S., 2015. Characterizing soils via portable X-ray fluorescence spectrometer: 4. Cation exchange capacity (CEC). *Geoderma* 239–240, 130–134.
- Silva, S.H.G., Poggere, G.C., Menezes, M.D., Carvalho, G.S., Guilherme, L.R.G., & Curi, N., 2016. Proximal sensing and digital terrain models applied to digital soil mapping and modeling of Brazilian Latosols (Oxisols). *Remote Sensing* 8, 614.
- Söderström, M., Isendahl, C., Eriksson, J., Araújo, S.R., Rebellato, L., Schaun, D.P., Stenborg, P., 2013. Using proximal soil sensors and fuzzy classification for mapping Amazonian Dark Earths. *Agricultural & Food Science* 22, 380–389.
- Tavares, T.R., Eitelwein, M.T., Martelo, M., Trevisan, R.G., & Molin, J.P. (2018). Fusão de dados de condutividade elétrica e imagens Sentinel 2A para caracterização da textura do solo. In *Proceedings of the Congresso Brasileiro de Agricultura de Precisão - ConBAP 2018* (pp. 96-104) Curitiba, Paraná, AsBraAP.
- Viscarra Rossel, R.A., Adamchuk, V.I., Sudduth, K.A., McKenzie, N.J., Lobsey, C., 2011. Proximal soil sensing: an effective approach for soil measurements in space and time. *Advances in Agronomy* 113, 237–282.
- Zhu, Q., Liao, K., Xu, Y., Yang, G., Wu, S., Zhou, S. (2012) Monitoring and prediction of soil moisture spatial-temporal variations from a hydrogeological perspective: A review. *Soil Research*, doi:10.1071/sr12228.

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