II Pedometrics
Nov, 24th to 27th, 2021
Brazil

An optimized sample for assessing soil property variations across the field and within management zones efficiently

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Thematic Session: Advances in soil sensing

Abstract

An optimized sampling design to assess soil property variation across the field and within management zones is proposed and validated in a 72-ha crop field in southeastern Brazil. An optimized sample (18 sites) was derived by spatial simulated annealing from proximal sensor covariates. Soil properties were measured at 0-10 cm and validated against those measured at 72 sites on a regular grid. The optimized and regular grid samples had equal global spatial trend models and means for soil clay, pH and exchangeable Ca, Mg and K, and different ones for organic C and available P. Within zones, equal means between sampling designs were found for all soil properties in the “North” zone, and for most properties in the other two zones. Soil property correlations against proximal sensor variables were honored by the optimized samples in most cases, both globally and within zones. The optimized soil sample reduces costs while keeping most soil information for guiding management decisions.

Keywords: Proximal soil sensing; Spatial simulated annealing; Spatial trends; Precision agriculture

Introduction

Site-specific soil management requires knowing the spatial distribution of soil properties that guide management recommendations. Producing this information using uniform soil sampling on a regular grid across the field may be expensive due to soil sampling and analysis costs. Alternatively, on-the-go field sensors measure soil properties at many sites covering the field efficiently (ADAMCHUK et al., 2004) and can provide data to delineate management zones (VASQUES et al., 2021) and optimize soil sampling (DOMENECH et al., 2017).

For optimizing soil sampling, it is desirable that the number of sites is reduced while keeping enough soil information to support management decisions. For that, an optimized sampling design can be proposed, considering management zones and soil variation measured by proximal sensors, and validated to confirm that it represents soil property variation across the field and within zones.

Thus, the objectives are to: (a) produce an optimized sampling design to assess soil property variation; (b) compare global spatial trend models from optimized *versus* regular grid samples; and (c) compare soil property means and correlations against proximal sensor variables from optimized *versus* regular grid samples, globally and within management zones.

Methodology

Three management zones were delineated on a 72-ha no-till irrigated crop field in Itaí, São Paulo, southeastern Brazil, by k-means clustering based on kriged maps of proximal sensor variables, including apparent electrical conductivity (aEC) and magnetic susceptibility (aMS) measured by a EM38-MK2 sensor (Geonics, Mississauga, Canada), and equivalent thorium (eTh) and uranium (eU) contents measured by a MS1200 gamma radiometer (Medusa, Groningen, Netherlands) (VASQUES et al., 2021). Soils in the field are *Latossolos* (Oxisols, Ferralsos).

To assess soil property variation across the field, a regular grid sampling design comprising 72 sites was derived (Figure 1a, black dots). An optimized sampling design comprising 18 sites (Figure 1a, red dots) was derived by selecting six sites in each zone by spatial simulated annealing (SAMUEL-ROSA, 2019) reproducing the marginal distributions and correlations among aEC, aMS, eTh and eU. Soil samples were taken at 0-10 cm at the 90 sites (72+18) and analyzed for clay, organic C (OC), pH, available P, and exchangeable bases, according to Teixeira et al. (2017) (Figure 1b-h). Sensor variable values from their kriged maps were extracted to the 90 sites.

To check whether the optimized samples capture the global spatial trends of soil properties, analyses of variance and F tests (p=0.05) were used comparing first-degree spatial trend models – soil property=f(x*y) – against full models including the sampling design and interaction terms – soil property=f(x*y*sampling design). In addition, spatial trend models were derived from optimized and regular grid samples, respectively, and compared by Chow's test (p=0.05).

Welch's analysis of variance was used to compare soil property means from the optimized *versus* regular grid samples globally, using all observations from both sets, and locally at each zone, respectively. Soil property correlations against proximal sensor variables from the optimized *versus* regular grid samples were compared at p=0.05 using Fisher r-to-z transformation of correlation coefficients, both globally and at each zone, respectively.

Results and discussion

The global spatial trend models did not differ significantly between optimized and regular samples for all soil properties except OC and available P, according to both F and Chow's tests. Soil OC and available P models differed significantly between sampling designs in the regression intercepts, but not in the slopes of either the x or y variable, that is, the geographic coordinates. This shows that all soil property trends described by the regular grid samples in both the E-W and N-S directions were captured by the optimized samples.

Globally, the Welch's tests showed that only OC and available P differed significantly between optimized and regular grid samples, though OC means were similar (Table 1). Locally, all soil properties had equal means between sampling designs in the "North" zone, while significant differences were found for pH, available P and exchangeable Mg in the "Southeast" zone, and for clay, OC and available P in the "Southwest", though their means were similar between designs, except P. Mean soil exchangeable K varies between designs, but their high within-group variances hinder statistically significant differences.

Globally, correlations among soil properties and proximal sensor variables from the regular grid samples were honored by the optimized samples for all paired variables except pH x aEC, and P x eU. The same behavior was observed within the management zones, where most soil property-proximal sensor correlations were respected by the optimized samples. Significant differences in correlations between sampling designs were observed for: pH x aEC, Ca x aEC, Mg x aEC, and Mg x aMS in the “North”; Ca x eTh in the “Southeast”; and Mg x eTh in the “Southwest”.

Overall, the optimized samples captured the global spatial trends of most properties and honored their mean values both globally and locally within management zones, as mean property values were very close between designs (except for available P and exchangeable K) despite significant differences in some cases (Table 1). They also captured the correlations among soil properties and proximal sensor variables both globally and within zones. This represents a reduction of 75% (from 72 to 18 sites) in soil sampling and analysis costs, while keeping most soil information.

Conclusions

Soil sampling and analytical costs can be reduced considerably by reducing the sample size while keeping most soil information across the field and within management zones. For that, a combination of proximal sensor surveys that catch soil variations efficiently across the field and a sample optimization algorithm like spatial simulated annealing can be used with positive results, as shown in this paper.

In principle, management decisions based on soil data obtained at the optimized sampling sites would be mostly correct. Along these lines, whether investing in more samples, say one sample per hectare, provides more accurate management decisions that are worth the extra cost is open for debate and further research.

Acknowledgements

Funding was provided by Embrapa grant number 32.12.12.004.00.01 and Itaipu Binacional grant number 45.000.32.537. The Associação do Sudoeste Paulista de Irrigantes e Plantio na Palha (ASPIPP) and Agro Mario A.J. Van Den Broek Ltda are acknowledged.

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Table 1. Soil property means from regular grid and optimized samples. Equal letters indicate equal means between sampling designs globally, and within management zones, respectively, according to Welch's tests at p=0.05.

Property	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean
	Global				North				Southeast				Southwest			
	Grid		Optimized		Grid		Optimized		Grid		Optimized		Grid		Optimized	
Clay (g kg^{-1})	72	413[a]	18	424[a]	33	392[a]	6	367[a]	27	430[a]	6	463[a]	12	433[b]	6	443[a]
OC (g kg^{-1})	72	15[a]	18	14[b]	33	14[a]	6	13[a]	27	16[a]	6	15[a]	12	15[a]	6	13[b]
pH	72	6.6[a]	18	6.5[a]	33	6.6[a]	6	6.6[a]	27	6.6[b]	6	6.7[a]	12	6.4[a]	6	6.2[a]
P (mg dm^{-3})	72	143[a]	18	99[b]	33	141[a]	6	137[a]	27	151[a]	6	79[b]	12	127[a]	6	81[b]
Ca ($cmol_c$ dm^{-3})	72	6.3[a]	18	5.9[a]	33	6.0[a]	6	5.7[a]	27	6.7[a]	6	6.2[a]	12	6.4[a]	6	5.9[a]
Mg ($cmol_c$ dm^{-3})	72	1.9[a]	18	2.0[a]	33	1.8[a]	6	1.9[a]	27	2.1[b]	6	2.2[a]	12	1.9[a]	6	1.9[a]
K ($cmol_c$ dm^{-3})	72	458[a]	18	501[a]	33	451[a]	6	173[a]	27	583[a]	6	1110[a]	12	197[a]	6	220[a]

N, number of observations; Stdev, standard deviation.

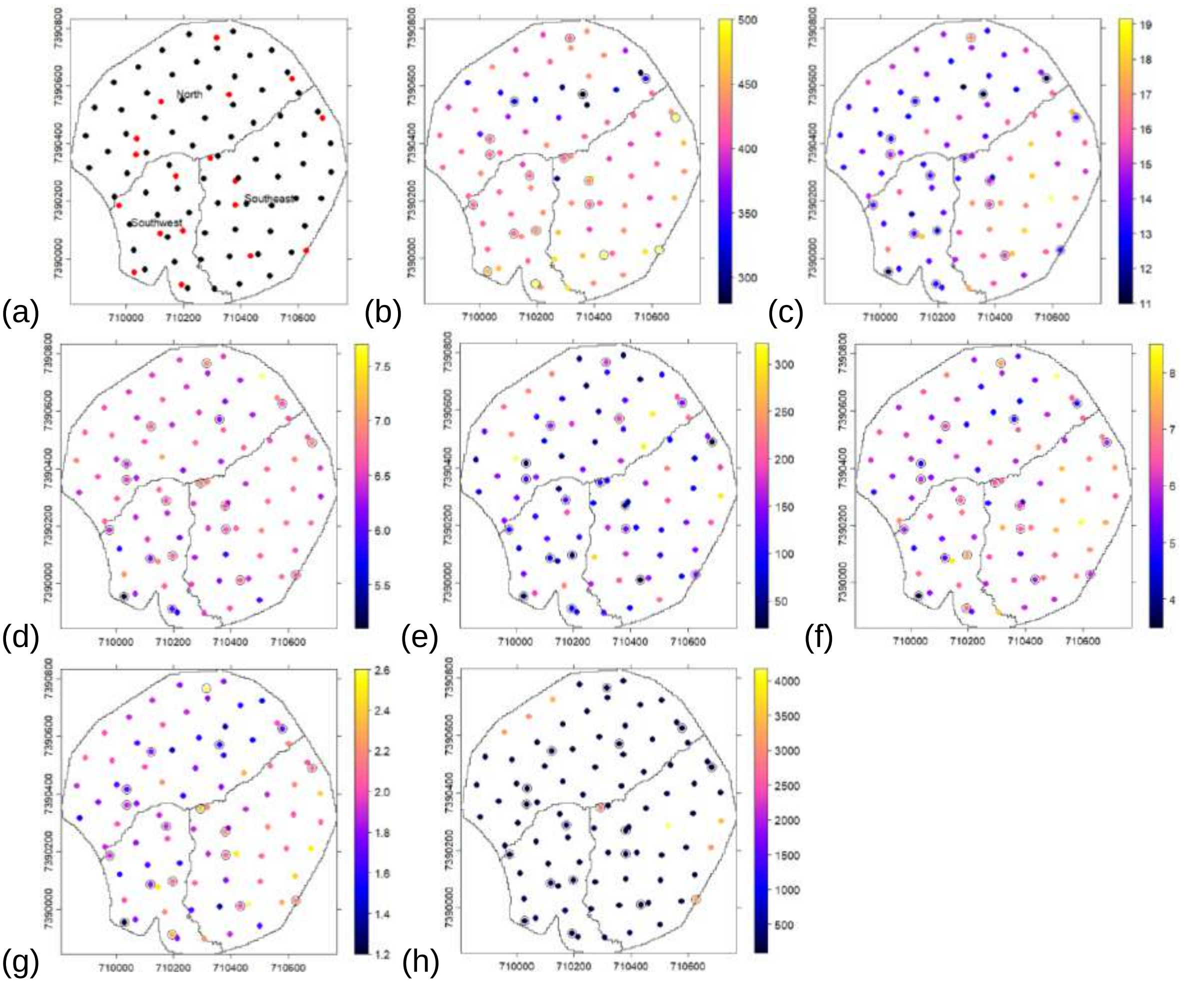

Figure 1. (a) Soil management zones, regular grid samples (black dots) and optimized samples (red dots); (b-h) Soil clay (g kg^{-1}), organic C (g kg^{-1}), pH, available P (mg dm^{-3}), and exchangeable Ca, Mg and K ($cmol_c$ dm^{-3}), respectively. Optimized samples are circled in the soil property maps. Coordinates are in UTM zone 22S.