#7834 COMPARISON OF SOIL TESTING AND SCANNING METHODS FOR IN-FIELD SPATIAL VARIABILITY ASSESSMENT OF SOIL FERTILITY: IMPLICATIONS FOR PRECISION AGRICULTURE

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ABSTRACT

Understanding spatial variability of soil fertility is a key to variable rate nutrient applications for precision fertilization. The objective of this study was to assess field spatial variability of soil fertility using two approaches, a gridded soil testing and a proximal sensing technique. Measurements were performed on a 12-ha field planned for corn. For the first approach, soil samples were taken from 161 geopositioned grid points and were analyzed for pH, electrical conductivity (EC_s), organic matter, phosphorus and potassium, while the second approach relied on a soil scanner (Veris U3) that uses sensors for measuring apparent electrical conductivity (EC_a), pH and organic matter. Three interpolation methods (IDW, Spline and Kriging) were used for comparative mapping of spatial variability of the selected soil parameters. The findings show that, in the case of the gridded soil testing, the three interpolation methods generated similar results based on map patterns and quadratic mean errors (QME), with universal kriging giving the least error. The EC_a obtained from Veris scanner data was relatively similar to soil EC_s obtained from gridded soil testing, with a significant correlation (R^2=0,67). High salinity levels were depicted by both methods. However, the maps obtained for organic matter and pH were different, with no significant correlation. This can be attributed to the fact that the pH and infrared readings might be biased by factors such as soil moisture and soil roughness. Although both approaches showed high contents of phosphorus and potassium in the soil, the trends depicted by their respective maps were different. These differences have important implications for the management of soil salinity, organic matter (and its contribution to soil N balance by mineralization), as well as for phosphorus and potassium that would require a drawdown strategy.

Keywords: precision fertilization, spatial variability, spatial interpolation, Veris U3, electrical conductivity, precision agriculture

INTRODUCTION

The heterogeneity of soil properties represents an important source of variability that can affect crop productivity (Mulla, 1993; Cambardella 1994; Mallarino et al. 2004). It is related to various inherent soil factors as well as to agricultural practices (Zwaenepoel and Le Bars, 1997). Conventional methods of soil testing can reflect soil fertility but overcome its in-field variability. In the context of precision farming, soil heterogeneity assessment and mapping require well distributed measurements and appropriate methods of interpolation. High density grid-sampling is considered most accurate for map representation but can be costly and time-constraining (Mallarino et al. 2004). Various sensing tools have been used for direct (ie. electrical conductivity) or indirect (ie. organic matter) measurement of some soil properties (Shibusawa, 2006). Their reliability depends on the type of sensor and the specific conditions of their use. Translating point-data to spatial variability maps is accomplished by spatial interpolation methods, such as IDW, Spline and Kriging. The latter informs better about spatial autocorrelation and spatial dependence (Tabor et al. 1985; Cambardella et al. 1994). The objectives of this study were (i) to assess soil spatial variability as a basis for precision fertilization using two methods, gridded laboratory soil testing and a sensing technique using a soil scanner with multiple sensors, and (ii) to compare three spatial interpolation methods for the case of the grid soil testing.

MATERIALS AND METHODS

The research was conducted on a 12-ha irrigated corn filed located in a farm adopting precision agriculture near the city of Fes, Morocco. The soil is a Vertic Calcixeroll. For the soil testing method, 161 regularly spaced composite soil samples were collected (0.2-m depth) on a regular grid in mid-February 2020 before sowing and analyzed for electrical conductivity (ECs) (1:5 soil extract), pH, organic matter (OM), available phosphorus (P) and potassium (K). In the case of the sensing method, a Veris U3 scanner (Veris Technologies®) contracted by the farm was passed throughout the field (with 15-m spacing) to collect data for apparent electrical conductivity (EC_a), pH and OM. Few samples were collected by the service provider for extrapolations for phosphorus and potassium based on own developed models.

In the case of the lab soil testing, spatial interpolation was performed using Inverse Distance Weight (IDW), Spline and Kriging using ArcGIS Geostatistical Analyst. Best optimization parameters and models were used each method and cross validations were based on QME and map patterns. In the case of kriging, the degree of spatial dependence was evaluated using the nugget/sill ratio (Cambardella et al.,1994). In the case of the scanner method, spatial interpolation was done by the kriging for EC_a, pH and OM. Phosphorus and potassium maps were derived by the Veris service provider and were made available to this study for comparisons. Mean values of scanner data situated within a 10 meters radius relative to the same positions of the grid sampling points were used for the purpose of correlations among the two methods.

RESULTS AND DISCUSSION

Spatial Variability Using the Gridded Soil Testing Data

The soil parameters measured presented different degrees of variability, with pH and OM showing low CVs (2,6% and 13,2% respectively) and EC_s, phosphorus and potassium showing high CVs (61.7%, 59,7 % and 39.2, respectively). Values ranged from 0,1 to 1,14 ds/m for ECs, from 7,7 to 8,3 for pH, from 2,04 to 4,35% for OM, from 21,3 to 512 ppm (P_2O_5) for phosphorus, and from 226 to 982 ppm (K_2O) for potassium. High skewness of ECs, pH P and K were noticed indicating that these properties have particular high local distribution.

The spatial variability maps obtained with the 3 interpolation methods showed similar trends and patterns for all the measured parameters. For the purpose of this short article, only maps with kriging method are presented (Figure 1). Kriging (Universal) showed the smallest MQE. Overall, the maps revelled the existence of a general NE-SW gradient for all measured parameters.

The EC_s map revealed a high salinity area in the SW part of the field (0,5 to 1,14 ds/m), exceeding corn salt tolerance. The low range (92m) and nugget/sill ratio (0.09) of EC_s obtained from the kriging semi-variogram indicates a strong spatial dependence (<0,25) inferring that variability is affected more by structural extrinsic factors (topography and drainage) than by farming practices (Tabor et al. 1985; Cambardella et al., 1994; Goovaerts, P., 1998).

Soil pH variations across the field (map not shown) were relatively small (0.6 pH unit). The alkaline conditions are attributed to the presence of active $CaCO_3$ (2,5 to 7,3%) that tends to buffet soil pH around 8.2. The high alkaline conditions, in the eastern part of the field, can affect soil conditions, mainly micronutrient availability, with risks of iron chlorosis.

In general, the soil OM map did not show great variability, with the 2.5-3.5% class being the dominant. OM accumulation in the western part of the field can be related to residue management. Although the overall amplitude differences are not too high across the field, short-terms management of residues and organic amendments are needed to level up OM contents. Kriging variogram gave a range of 594m and nugget/sill ratio of 0,69 indicating a weak spatial dependence compared to EC_S. Similar results were reported by other studies (Miao and Mulla, 2006).

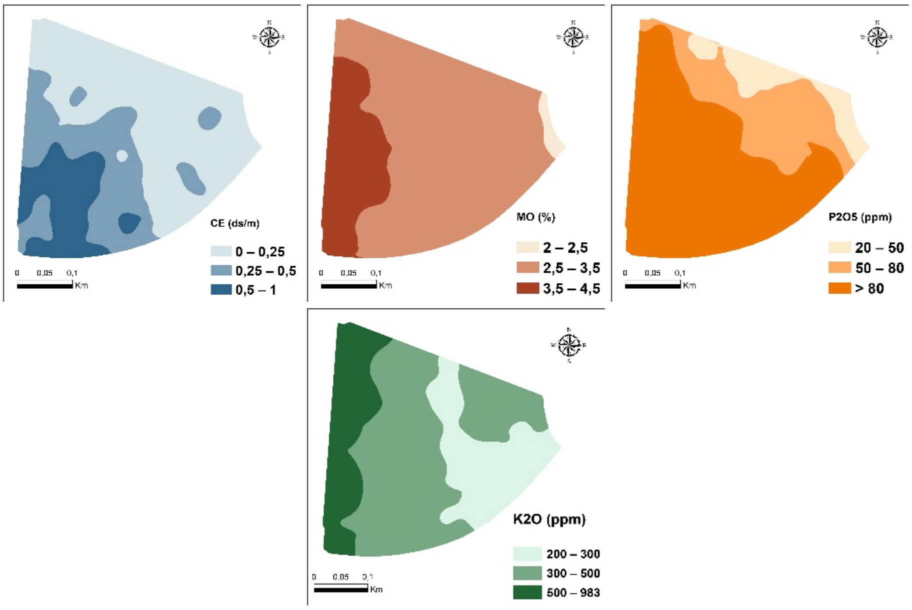

Figure 1. Spatial variability maps of ECs, organic matter, phosphorus and potassium based on grid laboratory soil testing data

The maps of soil available phosphorus were also quite similar among the three interpolators, with kriging yielding a smoother map. The P level was in general very high (>50 ppm) indicating that the phosphorus fertilization practice leads to a build-up of this nutrient and needs to be drawdown to a reasonable level. The kriging semi-variogram gave a range of 594 meters and a nugget/sill ratio of 0,13 that indicate large autocorrelation distances and high spatial dependence, inferring a stronger influence of management practices (Cambardella et al., 1994).

The exchangeable K maps revealed also a general E-W decreasing trend with high levels (>300 ppm K_2O) on more than two thirds of the field. These high K levels are most probably related to the mineralogy of the soil clays which are illite rich (Bouabid et al., 1996). In fact, K fertilizers were not applied on this field for several years. Kriging semivariogram gave a range of 393m, while the nugget/sill ratio was very low (1,6), suggesting a high spatial dependence which corroborates that variation of K are more related to inherent soil conditions than to fertilizer practice.

Spatial Variability Maps Using Veris U3 Scanner

The EC_a map obtained by the Veris U3 using universal kriging (Figure 2) shows a very patchy pattern, but still displays a NE-SW gradient similar to that depicted in the map obtained by the grid laboratory soil testing. The map revels also that the SW part of the field has a high EC_a. Correlation among EC_a and EC_s was highly significant (R^2 of 0.67). Compared to the 1:1

curve, it appears that for low salt levels (<0.020 ds/m), the scanner seems to underestimate measurements, and for higher salt levels (>0.020 ds/m), it tends to overestimate EC measurements.

The OM map shows contents within close range compared to the laboratory grid soil testing map, but with different trends. The <2.5% class being the dominant, and the class >3.5% being negligeable. Some agreement for the intermediate class (2,5-3,5%) were observed in the middle part of the field. No significant correlation was obtained with MO obtained with soil the grid laboratory testing method. This lack of correlation can be attributed to various factors, such as the state of organic residues decomposition, soil moisture, aggregate heterogeneity and soil surface roughness (Shonk et al., 1991; Sudduth and Hummel, 1993; Christy, 2008; Bricklemyer and Brown, 2009; Morgan et al., 2009;).

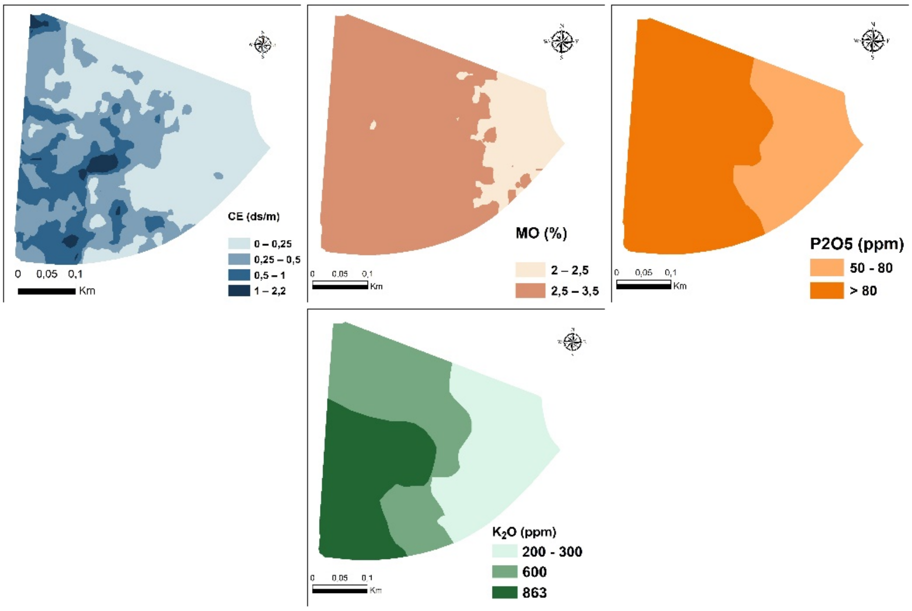

Figure 2. Spatial variability maps of EC_a, organic matter, phosphorus and potassium based on Veris U3 scanner data

The maps of phosphorus and potassium provided by the Veris service provider (using own models) and made available to this study by the farm showed also different class extents and trends compared to those obtained by the gridded soil test method. In the case of P, both methods show that the class '>80 ppm' was the dominant, but the extents these classes were different. While the gradient of P was relatively E-W in the case of the scanner method, it was rather NE-SW in the case of the laboratory grid soil testing method (Figure 1 & 2). In the case of potassium, both methods revelled high soil K contents, but the trends were also different, especially for classes higher than 300 ppm. Recommendations in both cases would be toward no, or minimum, P and K applications in a small part of the field only. The observed differences for both P and K could be attributed to the models used by the service provider for extrapolations for these two elements across the field, which rely on a small number of tested soil samples (4 samples for 13 ha). A greater number of P and K testing could provide a better portrayal of the spatial variability of P and K using the various Veris U3 sensed parameters.

CONCLUSIONS

Spatial interpolation using IDW, Spline and Kriging generated similar map trend with close MQEs. Kriging gave smoother limits among the classes adopted. Soil EC_s showed small variations and low spatial dependence compared to the other parameters. Apparent EC_a map obtained using the Veris scanner showed similarity with laboratory grid soil test EC_s, with a significant correlation. However, differences among the two methods were shown for organic matter, pH, phosphorus and potassium. Differences for OM can be attributed to artefacts in sensing by the scanner due to factors such as soil moisture and surface roughness, while those observed for P and K can be attributed to the small number of soil-tested samples used for extrapolations. The spatial variability revealed on this field has important implications for site-specific management of salinity, organic matter and nutrients.

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