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Predictive model of phosphate availability in soil by using QGIS software

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Abstract
Site-specific fertilizer plans are effective to reduce waste and costs, considering that farm soils are not spatially uniform due to a considerable the amount of biochemical interactions that rule nutrients availability. In Salvadorian soils, phosphorus is a limiting macro-nutrient and farmers often use diammonium phosphate (DAP) as a palliative amendment, however, they disregard spatial variability and therefore causing fertilizer misuse. In this research, 55 soil samples were taken from a 30 hectare field and submitted to a lab to be treated with a dose of DAP in order to measure how much phosphate remained available through time in a root-free scenario. It was demonstrated that responses were not strictly proportional to the values of pH and Effective Cation-Exchange Capacity (ECEC), meaning that this variables were not sufficient to sustain traditional assumptions about phosphate availability across a field; the higher value of Pearson correlations for pH and ECEC data versus P availability measures was 0.4, and the maximum R^2 was 0.21, indicating that a statistical predictive model was not trustable. To contribute for a better agronomic analysis, a predictive model of phosphate availability is proposed in this paper. Data obtained from treated samples was processed to produce semivariogram graphs which fitted at least one of the standard models of linear, circular or spherical patterns. This also indicated that Kriging interpolation was convenient for representing data and establishing predictive models. Then, GIS software was used to create maps that modeled the stage of P availability trough time. The contribution of this work is the proposal of geostatistical software tools to improve soil nutrients requirement analysis based on soil samples, allowing the modeling of an entire farmland for a more precise fertilizer plans development.

Keywords: Soil fertility, plant nutrition, phosphate, fertilization, geostatistics.

Introduction

Phosphorus (P) is a vital nutrient for plants needed to carry out their biochemical reactions in a normal fashion. Its deficiency causes a remarkable loss of crop vigor, greatly reducing both yield quality and quantity (Sudara, Natarajan & Hari, 2002; Baker, Ceasar & Palmer, 2015) [67, 6]. Soils of El Salvador are generally poor in phosphorus (CENTA-FAO, 1998; Escobar, 2004) [10, 18]. so it is a very limiting nutrient that must be added to agricultural soils in the form of organic or inorganic fertilizer. In addition to the problem, farmland fertility is not very well managed and their pH has decreased in the last decades to values ranging between 4.0 and 5.5 (Muñoz, 2011) [51]. causing P immobilization (Füleky *et al.*, 2006; Lee, *et al.*, 2004; Memon *et al.*, 1991; Sakadevan *et al.*, 1998). [22, 37, 46].

Due to these reasons, it is common that Salvadorian entities recommend the use of phosphate fertilizers (Rodríguez, *et al.*, 2002*;* Basic Grain Program, 2013; Baker, Ceasar & Palmer, 2015) [60, 6].

However, the lack of knowledge about how this nutrient behaves at field conditions, usually leads farmers to fertilize at inappropriate timing and dose (Paliza, 1979; Margenot, Singh, Rao & Sommer, 2016) [52, 45]. Many factors can alter P availability across a field, often seeming to be random. For example, flooding areas can become more acid for the accumulation of minerals (Achudume, 2007; Kato *et al.*, 1996; Qureshi, Hussain, Ismail & Khan, 2016) [2, 34, 58]. lowering pH and releasin aluminum (Al) that causes redox reactions that adsorb phosphates (Pant *et al.*, 2002; Scanlan, Brennan, D'Antuono & Sarre, 2017) [54, 63]. In contrast, raising pH by liming can have a counter effect when soil is too humid because of forming highly adsorbing surfaces of aluminum, but instead favores

Phosphate desorption when humidity is moderated, due to the crystallization of Al compounds (Haynes, 1982; Scanlan, Brennan, D'Antuono & Sarre, 2017) [28, 63]. This indicates that even slight variances on clay composition can vary the soil response to P fertilizers over a field. Another important factor is that high levels of Effective Cation Exchange Capacity (ECEC) also facilitates the desorption of P and nutrients in general, however, ECEC value also tends to have considerable spatial variability for many reasons such as microbial activity, clay composition, flooding events and organic matter content (Grant, 2018; Liang *et al.*, 2006; Schalscha *et al.*, 1974; Hendershot *et al.*, 1993). As reported by Antello *et al.* (2007) [24, 39, 64, 31, 5].

enriched presence of decaying organic matter produces humic acids that compete against phosphate for adsorption in the exchange sites, increasing availability of this nutrient after fertilization.

With the use of a GIS software, it is possible to create geographical models to identify site-specific requirements of fertilizers, helping the decision making process which otherwise would be very imprecise (Denton, Aduramigba-Modupe, Ojo, Adeoyolanu, Are, Adelana & Oke, 2017; Rogowski, 1996) [15, 61].

The creation of a predictive model of nutrient availability is possible by taking georeferenced soil samples to experiment different fertilizer doses in a laboratory, then measure their responses to create a representative model of an actual farmland. This technique can provide important information for a better estimation of fertilizer needs, the period of time during which nutrients will be available for plants, especially if it is planned to be incorporate major treatments such as aglime. This paper describes the use of software tools for variogram creation, Kriging interpolation and statistical analysis to discuss the results.

Materials and Methodology

Soil Sampling

The amount of 55 samples were taken from a 34 hectare farm land located in Santa Ana, El Salvador. Prior soil analysis revealed that actual nutrient availability was relatively uniform across the majority of the area. Sampling method corresponded to a predesigned grid pattern of four parallel transects (Fig. 1.A) according to the slope curvature as indicated by Gregorich & Carter (2007) [25]. Similar to the methodologies used by Walvoort *et al.* (2010), Ching *et al.* (2009), Cockx *et al*. (2007) and Fox & Protz (1981) [71, 11, 13, 21]. each sample was composed by 10 subsamples that were taken in a circular pattern of 20 meters diameter.

For extracting the soil at field capacity, a metallic tube of 10 cm diamater was used, deepening it until collecting 1 Kg of soil as done by López-Granados *et al.* (2002) [42,43]. then mixing those sub samples to obtain a final homogeneous portion of 2 Kg, labeled as a sample and recording its correlative number, GPS coordinates and altitude.

The whole set of samples was named as "S" series and then each of them was divided by half to create 2 new sub series, "P0" and "P", equal in all properties.

Inorganic Phosphorus test with DAP

Values of pH, ECEC and available phosphate were measured for each P0 sample, to determine natural conditions.

Each sample of the "P" sub series was divided in three sub samples "P-10", "P-20" and "P-30", and then applied with 257 mg of diammonium phosphate previously diluted in 10 ml of distilled water.

This treatment was based in the traditional fertilization dose used in El Salvador of 257 Kg per hectare, which amounts to 25.7 grams distributed over the area of one square meter, which corresponds to 257 mg per each 100 cm^2 of sampling area.

Testing traditional doses of fertilizer has been reported as convenient for nutrient efficiency analysis (Szulc *et al.,* 2016; Amarasinghe *et al.,* 2014; Weijabhandara *et al.,* 2011; Magomedov *et al.,* 2010; Kumar *et al.,* 2009 and Abdoulaye & Sanders, 2005) [68, 4, 72, 44, 35, 1].

To determine how much of the phosphate reremained available through time, laboratory measures were performed over P-10, P-20 and P-30, ten days, 20 days and 30 days respectively after treatment.

Data analysis

Statistical software Statgraphics® 18 and GNU/PSPP 1.2 were used to compare relationships of pH and ECEC of "P0" versus phosphorus availability of the "P" sub series. Data of each sample was tabulated according to its correlative of the "S" series, in other words, unifying data of "P0" and "P", using the following variables: sample id, latitude, longitude, terrain altitude, pH, ECEC, phosphate concentration at initial conditions, phosphate concentration at 10 days (P-10), 20 days (P-20) and 30 days (P-30) after treatment.

Relationships were analyzed performing regressions between variables, obtaining the Coefficients of Determination and Pearson Correlations. Then geostatistical analysis with semi-variograms using VESPER Software (Bernardi *et al*. 2016; Molin & Faulin, 2013; Whelan *et al.*, 2002) [7, 49, 73]. was performed to validate the possibility of a GIS predictive model. Finally, the software QGIS 3.4 and SAGA GIS 7, were used to interpolate variability maps with the Kriging algorithm that represent a predictive soil response to phosphate treatment, in accordance with the GIS models discussed by Pandey *et al.* (2009), Hlaing *et al.* (2008), Erdogan *et al.* (2007), Scull *et al.* (2003) and Zhu *et al.* (2001) [53, 32, 17, 65, 78].

Results and Discussion

Prior soil analysis revealed the fertility conditions of the farmland, indicating that pH, Cu, Zn and Na were low, while ECEC, P, K, Mn, Fe and Al were medium, and B, Ca, Mg, S and M.O. content were high (Table 1).

Although the average phosphorus availability among P-10, P-20 and P-30 samples showed little variability trough time (Table 2), normality tests suggest otherwise. Kurtosis levels indicated awide dispersion among the data in P-10 and P-20, both of which could be represented by a platykurtic curve. Also, the P-10 values had a distribution with a slightly negative skewness (-0.30), while the P-20 values have a moderate negative skewness (-0.72). On the other hand, P-30 has a very slightly positive skewness distribution (0.18). This tests indicated very little normality on collected data. Likewise, pH and ECEC had also very little normality. This coincides with the findings of Lobell & Burke (2010) and Minasny & McBratney (2007), [41, 48]. who determined that conventional statistical calculations are not sufficient to model the values of spatial variability in soils.

Table 1: Results of initial soil test

Mo	pH	ECEC	P	K	Ca	Mg	S	Cu	Mn	B	Fe	Zn	Na	Al
%		*(meq/c)*	*(ppm)*											
4.8	4.6	10.5	22	91	1665	265	180	2	13	0.7	50	2.5	121	81

Source: Own elaboration with field data.

Table 2: Descriptive statistics for soil variables

	pH	ECEC	P0	P-10	P-20	P-30
Mean	4.28	10.25	24.93	54.8	54.98	56.28
CV (%)	14.04	8.15	5.93	22.09	30.78	23.99
Kurtosis	-1.33	0.3	0.19	-0.27	0.92	-0.12
Skewness	-0.22	0.95	0.32	-0.3	-0.72	0.18
Range	1.99	3.1	5.7	46.34	73.99	52.99
Minimum	3.17	9	22.4	29.96	9.31	33.11
Maximum	5.16	12.1	28.1	76.3	83.3	86.1

Source: Own elaboration.

The Pearson correlation coefficients (Table 3) among the variables showed no significance, having maximum positive correlations for pH and "P" series in ranges from -0.15 to 0.40, and between ECEC and "P" series, all being negative in ranges from -0.45 to -0.26, indicating a non existent relationship. Likewise, the analysis of the coefficients of determination, R^2 and adjusted R^2 (Table 4), showed that the changes in pH and ECEC are not good response predictors, invalidating the reliability of regression models. In the same way, Petrone, Price and Carey (2004) [56]. demonstrated that the lack of understanding about spatial variability of soils makes difficult to create a predictive model, due to the fact that soil reactions are not only determined by the interaction of just one or two variables. To determine the existing correlations in this case, geostatistical analysis was needed (Miller, Singer & Nielsen, 1988; Bocca, Morbidelli, Melone & Moramarco, 2007), [47, 9]. prefearably using semivariance analysis and kriging interpolation to model the soil responses.

Table 3: Pearson Correlation of variables

	pH	ECEC	P-10	P-20	P-30	P0
pH	-	-0.44	-0.15	-0.28	-0.21	0.40
ECEC	-0.44	-	-0.41	-0.26	-0.45	-0.35
P-10	-0.15	-0.41	-	0.78	0.54	-0.28
P-20	-0.28	-0.26	0.78	-	0.52	-0.11
P-30	-0.21	-0.45	0.54	0.52	-	0.04
P0	0.40	-0.35	-0.28	-0.11	0.04	-

Source: Own elaboration

Table 4: Regression data of ECEC vs available P

	ECEC vs P available		pH vs P available	
Tests	R^2	R^2 adjusted	R^2	R^2 adjusted
P0	0.04	0.00	0.06	0.02
P-10	0.20	0.16	0.01	-0.03
P-20	0.02	-0.02	0.20	0.16
P-30	0.08	0.04	0.21	0.18

Source: Own elaboration.

The best fit for pH semivariogram was the exponential model (Fig. 1.B), meaning that the soil acidity values gradually reached the sill and the relationship among sampling points existed in distances of no more than 100 meters. ECEC exhibited the pattern of a semivariance linear mod model (Fig. 1.C), meaning that the spatial variability increased linearly across distance but having no plateau and therefore there is no exact point of distance from which the data can be calculated to be properly correlated. That is the same case of P-10 (Fig. 1.D), in which the semivariance showed very high amplitude at any distance, also indicating that soil responses to fertilization are not correlated even in distances of less than 100 meters. The P-20 measures showed a circular model tendency (Fig. 1.E), indicating a very high variance at the asymptotic level after range of 252.2 meters, however, the semivariance algorithm was capable to determine correlation between the points situated before that range value. There is a similar case for P-30 because the graph exhibited a spherical model tendency with a flattening of spatial dependence after the range of 165.1 meters (Fig. 1.F), also finding a correlation despite of the relative dispersion of the data. All of these computer tests, demonstrated the high spatial variability of the soil, but also showing evidence of the possibility for a predictive model for fertilizer treatments using semivariance analysis as a prior step for Kriging interpolation. As previously suggested, phosphate availability could not only be altered by low pH and poor ECEC as general indicators of soil fertility as sometimes suggested (Ahmad *et al.*, 2011; Fageria & Barbosa, 2008; Haefele *et al.*, 2014) [3, 19 27]. but instead by a large number of different factors among which the most probable were the interaction among oxide types of Al and Fe (Haynes & Mokolobate, 2001; Devau *et al.*, 2009) [29, 16]. the amount and type of Ca molecule present, principally in the form of $CaCO_3$ (Hopkins & Ellsworth, 2005; Coelho *et al.* 2004; Smyth & Sanchez, 1980) [33, 14, 66]. as in the case of the soil used for this study in which pH was low despite of the high availability of Ca. Other important factors are: the amount of C and the biological activity (Liptzin & Silver, 2009; Parvage *et al*. 2013; Giardina *et al.*, 1995) [40, 55, 23]. the role of P on CH_4 and NH_4 oxidation (Zhang *et al.* 2011; Veraart *et al.*, 2015; Phillips, 1998), the soil-water interaction (Boomer & Bedford, 2008; He *et al.*, 2006; Gutiérrez-Boem & Thomas, 1998) [76, 70, 57, 8, 26]. the CO_2 proceeding from atmosphere and organic matter decomposition (Wieder *et al.* 2008; Cleveland *et al.*, 2006; *Zang et al.*, 2014) and sulphur oxidation (Miransari, 2010; Rajan, 1983) [74, 12, 77, 59, 62, 59]. Due to all of these complexities, maps modeling based on ordinary Kriging interpolation is a rapid and feasible way to establish predictive analysis of soil-fertilizer responses on a short distance grid scale (Tripathi *et al.*, 2015; Li, 2010; Yasrebi *et al.*, 2009; Mueller *et al.*, 2004; Lark & Ferguson, 2004). [69, 38, 75, 50, 36].

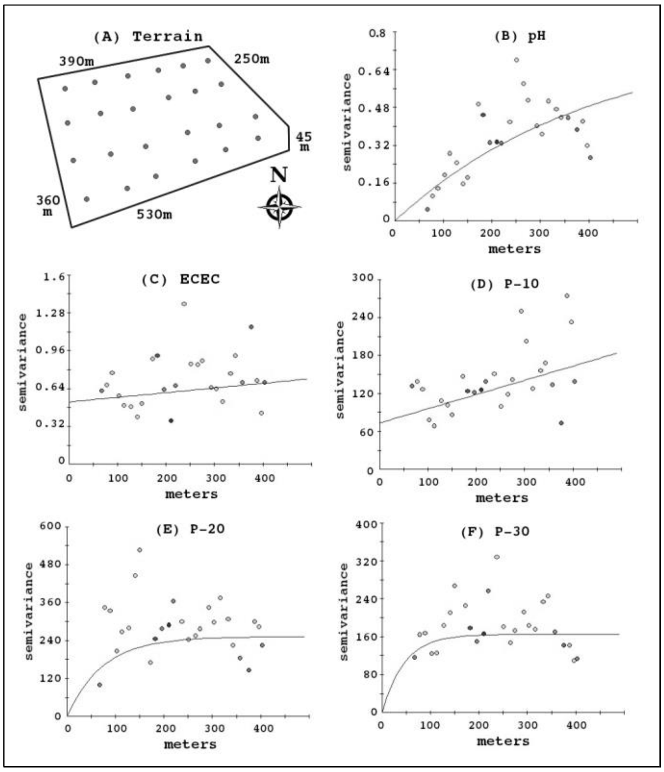

Fig 1: Sampling points of terrain and semivariograms of soil pH, ECEC, phosphate available 10 days after treatment (P-10), after 20 days (P-20) and after 30 days (P-30).

After interpolating values of each study variable, contour lines with colored areas were generated (Fig. 2 and 3) for a more understandable representation of the spatial variability. The values of pH presented on Fig. 2.B, tended to slightly increase in the same direction of the slope drainage on Fig 2.A, while the ECEC on Fig. 2.C decreases. The actual value of phosphate availability or average “P0” (Fig. 2.D) was higher in areas with less acidity and more ECEC. The results of the experiment indicated that the predictive distribution of phosphate availability 10 days after fertilization or “P-10” (Fig. 3.A) is superior en areas with greater ECEC than pH. Low adsorption and the root-free scenario on “P-20” caused phosphate concentration to stay high for 20 days (Fig. 3.B), even experiencing a slight increase in the areas with the lowest pH. The values obtained 30 days after fertilization or “P-30” (Fig. 3.C), were similar in proportion with the ones obtained at natural conditions “P0”, but with magnitudes about twice as big. While there were no roots removing nutrients from the samples, the available phosphate remained increased during a month.

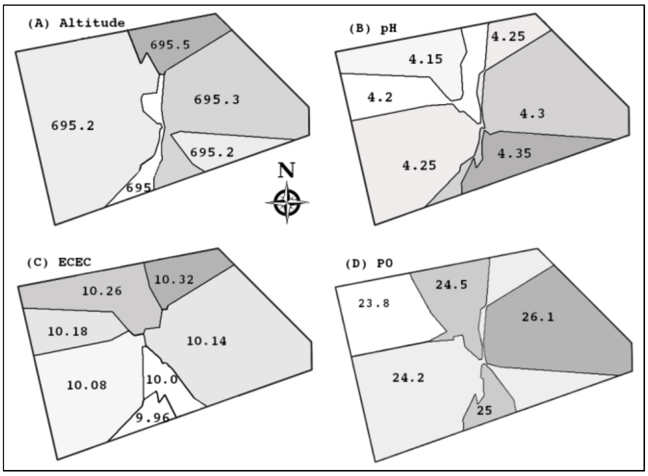

Fig 2: Spatial variability maps of natural conditions of altitude (A), pH (B), ECEC (C) and current phosphate availability (P0) expressed in ppm.

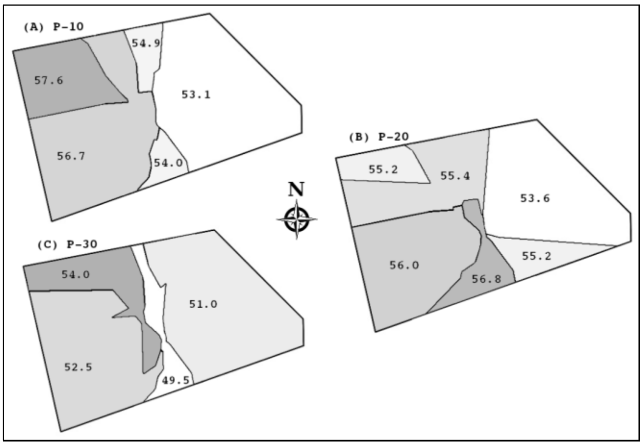

Fig 3: Predictive maps elaborated with data from the experiment, measuring phosphate availability in ppm in three different moments after fertilization: 10 days lapse (A), 20 days lapse (B) and 30 days lapse(C).

Conclusion

The integration of GIS tools has allowed us to develop soil surveys in a much more efficient way, reducing the time consumption and increasing the detail of phosphate behavior in soil which is not only in proportional funcion of pH and CEC, indicating that these two variables are not enough to predict the response of a farm soil to fertilizers. Despite of the high concentrations of Ca and Mg, the studied soil was very acid but with a good ECEC that allows good phosphate availability even a month after fertilization.

Treating georeferenced samples of a soil in order to obtain data from their responses and then processing the data using Kriging algorithm in a GIS software, is not only proper for adequating more site-specific agronomy management plants but also a constitute a practical and reliable tool for cases in which traditional statistics fail and deepening in the complexity of chemical soil reactions is not feasible.

This constitutes a very convenient, productive and trustable use of technology for academia and farmland owners, to take advantage of geostatistical and laboratory produced data. With the use of GIS, we managed to interpret the results from series of soil samples in order to build a bidimensional model that can be understandable by all audiences, allowing agriculture processionals or practitioners to improve fertilization plans in terms of nutrients requirements and their availability trough time, therefore increase their effectiveness while also reducing costs and waste of agrochemicals while also diminishing environmental impact.

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