https://doi.org/10.56093/ijas.v90i6.1047795

Indian Journal of Agricultural Sciences **90** (6): 1170–5, June 2020/Article

Spatial variability assessment of soil available phosphorus using geostatistical approach

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Received: 28 August 2019; Accepted: 27 September 2019

ABSTRACT

Soil available phosphorus (P), a major plant nutrient, exhibits a high degree of spatial variability. Spatial variability assessment of P is necessary for its precise management using geostatistics. Therefore, the present study was conducted in an intensely cropped region of Ladian village of Ludhiana, Punjab during 2014-2016 to assess the spatial variability status of P under three prevalent land use systems, viz. berseem-based land use, rice-wheat system and poplar-wheat based agroforestry system. The classical statistics showed the variability of available-P in terms of percent coefficient of variation (%CV), but unable to distinguish variability between rice-wheat (CV=38.79%) and poplar-wheat system (CV=38.58%). Lower variability was observed in berseem-based land use (CV=15.21%), though the mean available-P content (46 kg/ha) was higher in this land use. However, the geostatistical techniques successfully demonstrated the spatial dependence of P within and in between land uses using nugget-sill (NS) ratio. Gaussian model was found suitable for describing the spatial structure of available-P under berseem-based land use; while, Exponential models were found suitable for rice-wheat and poplar-wheat systems. The value of NS ratio of available-P was 0.17 for poplar-wheat based land use, suggesting strong spatial dependence, whereas the rest other land uses exhibited moderate (NS=0.74) to weak (NS=0.82) spatial dependence of available P. The spatial variability maps of P were generated using ordinary kriging technique, demonstrated significantly the higher variability of P in poplar-wheat system than other systems. This variability should be considered before applying phosphatic fertilizers to this land use to get optimum response. The generated maps would assist the farmers for site-specific P management in the study area.

Key words: Available phosphorus, Geostatistics, Kriging, Semivariogram, Spatial variability

Soil available phosphorus (P) is a major nutrient, enhancing root growth, and crop productivity. But higher fixation of soil P reduces its availability and also induces variability in P status of soil (Singh and Giand 2019). Actually, various intrinsic and extrinsic factors cause spatial variability of available P. Intrinsic factors include pedologic and geologic soil forming factors such as parent material, climate, dominant flora and fauna etc.; whereas extrinsic factors include different agronomic interventions like tillage, fertilizer application, irrigation water management etc. (Liu *et al*. 2015). Blanket P fertilizer application without considering spatial variation leads to higher economic investment, soil quality deterioration and environmental pollution like eutrophication (Bhunia *et al*. 2018). Sustainable and site-specific P management can only mitigate such problems and thereby, improving P use efficiency. Thus, spatial variability assessment of P is essential prior to its application to crop field.

Both classical and geostatistical techniques are available for assessing spatial variability of available P. But the classical statistics cannot reveal the continuous variability in the presence of spatial autocorrelation between the sampling points. However, the geostatistical techniques can quantify such spatial autocorrelation using semivariograms, auto-correlograms etc. (Martin *et al.* 2016). Kriging is a statistical interpolation technique that can be used to map the continuous spatial variability of soil properties. Several researchers used various interpolation techniques to map soil organic carbon (SOC), soil available nitrogen (N), phosphorus (P), potassium (K) and other soil properties (Patil *et al*. 2011, Vasu *et al*. 2017).

The study region belongs to a highly productive region consisting of various land uses and it supports a high cropping intensity (205%) and induces variability. Generally, this record productivity is obtained by excessive application of NPK without considering their bad impacts on environment. Therefore, precise nutrient management

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with considering spatial variation is necessary for this region. However, till now no systematic study has been reported to characterize the effect of various land uses on the spatial variability of available-P employing geostatistics. Therefore, the objective of the study was to determine the spatial variability of available P using geostatistics in various land uses.

MATERIALS AND METHODS

The present investigation was carried out in an intensively cropped region of Ladian village of Ludhiana, Punjab (30.89^{o}N and 75.86^{o}E) during 2014-16. Geomorphologically the study site has a flat topography with gentle slope, receiving average annual rainfall of 600 mm. The study was conducted in three prevalent land use types of that region, i.e. berseem-based land use, rice-wheat cropping system and poplar-wheat based agroforestry system. A total number of 144 georeferenced surface soil samples (48 from each land use type) were collected by following a 7 m × 14 m grid pattern. The collected soil samples were properly air dried under shade, crushed in a wooden log to break the visible clods and passed through 2 mm sieve. Then the prepared soil samples were used for physico-chemical analysis. Soil available P was determined by following the Olsen method (Olsen *et al*. 1954). The 0.5 M $NaHCO_3$ buffered to *p*H 8.5 was used to extract the soil available P. Soil pH and electrical conductivity (EC) were measured in 1:2 soil: distilled water suspension following standard protocols (Jackson 1973). International pipetted method (G W Robinson 1922) was used to determine the soil texture.

The classical statistical analysis for the soil parameters was done with SAS 9.3 (SAS 2013, Institute Inc. Cary, NC, USA). The percent coefficient of variations (% CV), was calculated to characterize the variability of the studied properties. A classification criterion based on CV value was used here to classify the variable into low (CV <15%), medium (CV = 15-35 %) and high (CV > 35%) variable classes (Wilding 1985).The spatial variability analysis of soil available-P was conducted using geostatistical tools in ArcGIS 10.4.1 software. Variography analysis was done by constructing semivariograms. A semivariogram is a mathematical model and it can be expressed as (Schoning *et al.* 2006);

$$\gamma(\mathrm{h}) = \frac{1}{n(\mathrm{h})}\sum_{i=1}^{n(\mathrm{h})}[Z(xi+h) - \mathrm{Z(xi)}]^2$$

where, γ(h) indicates the extent of separation distance (sometimes referred to as lag distance, denoted as h), n(h) refers to the total number of observed pair at separation distance (h) and Z(xi+h) is the value of a regionalized or studied variable at a point (xi+h). The three basic parameters of a semivariogram model are nugget (C_0), sill (C_0+C) and range (a). The nugget value refers to the local variance that occurs due to sampling errors or measurement error. Sill value indicates the total variance associated with the measurement. The range is the separation distance of spatial dependence. The nugget: sill ratio (NS ratio) was used here to measure the spatial dependency of the studied soil parameter in those land uses. Camberdella *et al*. (1994) gave a criterion based on NS ratio to estimate the spatial dependence of soil properties. This criterion was used to classify the parameter into high (NS ratio<0.25), medium (NS ratio=0.25-0.75) and low (NS ratio >0.75) degree of spatial dependence. Experimental semivariogram models such as Gaussian, Exponential, Spherical models were selected to describe the spatial variability soil available-P and other soil properties based on the least root mean square error (RMSE) value. A RMSE value close to zero indicated the accuracy of prediction through semivariogram models. The semivariogram model should pass through the center of the cloud of binned values (red dots) and also pass through the averaged values (blue crosses) closely as much as possible to get best fit during the fitting of a particular model (Fig 1). Ordinary kriging (OK) technique was employed to produce the spatial variability maps of soil available-P for three different land uses. OK is the most widely used technique to estimate the value of a soil property at unsampled location using the structural property

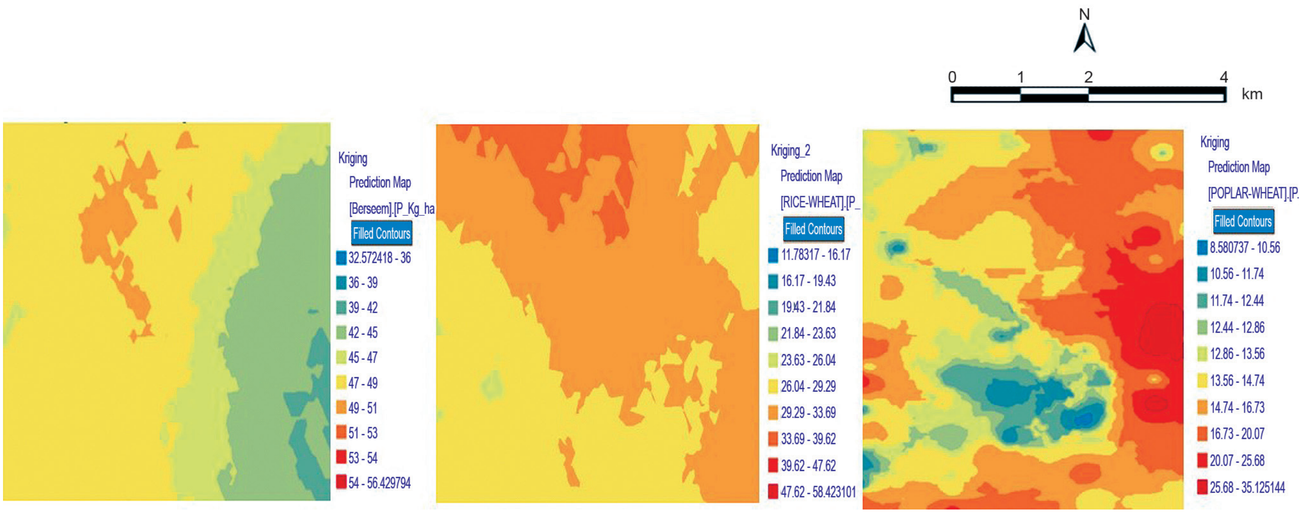

Fig 1 Spatial variability maps of available-P in (A) berseem-based, (B) rice-wheat, and (C) poplar-wheat land use systems.

of a semivariogram.

RESULTS AND DISCUSSION

Classical statistical analysis of soil available-P and other properties: The data obtained from classical statistical analysis revealed considerable amount of variability of soil P and other properties in terms of percent CV under various land use systems (Table 1). The analysis of particle size distribution confirmed the presence of clay to clay-loam texture in the studied land uses. All land use systems exhibited neutral to alkaline *p*H and the variability of *p*H was lower (CV<15%) as compared to other soil properties. Similar type of result was also found by Bhunia *et al.* (2018). The slightly alkaline *p*H might be attributed to the presence of sufficient number of exchangeable bases and calcium carbonate ($CaCO_3$) in the study area. Several other workers (Shukla *et al.* 2016, Reza *et al.* 2017) also reported lower variability of pH and it could be attributed to the existence of inherent soil buffering capacity that resisted the abrupt change.

In berseem-based land use, EC values varied from 0.38 to 0.71 dS/m with a mean value of 0.53 dS/m and 15.10 % CV. The EC values in rice-wheat cropping system ranged from 0.21 to 0.75 dS/m with a mean value of 0.47 dS/m and 27.66 % CV. The poplar-wheat system exhibited an average EC value of 0.42 dS/m and it varied from 0.21 to 0.58 dS/m. The mean EC value was higher for berseem-based land use indicating the presence of certain salinity hotspots that might have been arisen from depressions in the field. A moderately high variability of EC values was observed for rice-wheat field followed by poplar-wheat and berseem field in terms of percent CV values (CV > 15%) due to different level of agronomic management practices followed (Shukla *et al.* 2016, Bhunia *et al.* 2018). Soil available phosphorus (available-P) content followed the order of berseem>rice-wheat>poplar-wheat. Berseem field exhibited higher amount of available-P content that ranged from 33 to 56 kg/ha with a mean value of 46 kg/ha and a CV of 15.21%. In rice-wheat sequence, the available-P content varied from 12-58 kg/ha with a mean value of 30 kg/ha and with a moderate variability of 38.79%. Highest amount of mean available-P was recorded for berseem-based land use and it could be ascribed to dense population of berseem and the associated root biomass of this leguminous fodder crop. However, poplar-wheat agro-forestry system exhibited comparatively lower mean available-P content (16 kg/ha) than other land use types system due to the formation of Ca-P complex in the presence of calcium carbonate (Bhattacharyya *et al.* 2007). However, poplar-wheat system showed moderately higher P variability than rice-wheat and berseem-based land uses. Non-uniform management interventions of those land uses were also responsible for this variation. This finding was in the close conformity with the other studies done by several coworkers (Shukla *et al.* 2016, Reza *et al.* 2017, Bhunia *et al.* 2018).

Geostatistical analysis of soil available-P and other

Table 1 Descriptive statistics of selected soil properties for different land use systems

Berseem-based land use							
Parameter	Mean	Minimum	Maximum	Median	%CV	Skewness	Kurtosis
Sand (%)	45.00	40.00	48.00	45.00	4.90	-0.41	-0.84
Silt (%)	26.00	14.00	37.00	26.00	24.00	0.03	-0.81
Clay (%)	40.00	30.00	48.00	40.00	13.00	-0.43	-0.56
*p*H	7.81	7.48	7.99	7.83	1.66	-1.18	1.02
EC (dS/m)	0.53	0.38	0.71	0.54	15.10	0.13	-0.62
Available P (kg/ha)	46.00	33.00	56.00	47.00	15.21	-0.28	-1.21
Rice-wheat system							
Sand (%)	34.00	28.00	39.00	33.00	7.35	0.64	0.30
Silt (%)	25.00	13.00	35.00	24.00	19.40	-0.21	0.09
Clay (%)	43.00	30.00	49.00	44.00	11.24	-0.88	-0.08
*p*H	8.19	7.73	8.63	8.21	1.95	-0.43	2.37
EC (dS/m)	0.47	0.21	0.75	0.47	27.66	0.21	0.09
Available P(kg/ha)	30.00	12.00	58.00	27.00	38.79	0.69	-0.27
Poplar-wheat system							
Sand (%)	37.00	31.00	48.00	37.00	9.89	1.09	1.08
Silt (%)	19.00	9.00	30.00	19.00	22.63	-0.02	0.72
Clay (%)	42.00	35.00	49.00	43.00	9.23	-0.18	-1.03
*p*H	7.99	7.65	8.47	7.98	1.88	0.39	1.33
EC (dS/m)	0.42	0.21	0.58	0.43	19.05	-0.47	0.99
Available P(kg/ha)	16.00	9.00	35.00	14.00	38.58	1.58	2.36

properties: The spatial variability of soil available P and other properties were analyzed through geostatistical techniques. The structural properties of the semivariogram models such as nugget, sill and their ratio, were calculated for each soil parameter to describe their spatial variability (Table 2). Gaussian, Exponential and Spherical models were found suitable for various soil properties. The best semivariogram models were selected based on lower RMSE values. Among the physical properties, percent clay content was better described by the Exponential model for all three land uses. Gaussian model was found as suitable for pH in maximum land uses. Reza *et al.* (2017) also showed the suitability of Gaussian model for characterizing the variability of *p*H. Whereas, the Spherical model was found appropriate for revealing the spatial variability of EC. Exponential model successfully described the spatial trend of soil available-P in rice-wheat and poplar-wheat systems. However, in berseem-based land use, Gaussian model performed well in disclosing the spatial variability trend of soil available-P. Several other researchers also reported these semivariogram models like Spherical model (Fu *et al.* 2010, Reza *et al.* 2017), Gaussian, Spherical and Circular (Vasu *et al.* 2017) and Exponential model (Bhunia *et al.* 2018), for portraying the spatial variability of soil available P under different soil conditions. Thus, the outcome of our study maintained a good conformity with their findings. The nugget value was used to indicate the field level micro variability. The highest nugget (C_0=112.204) value was observed for P under rice-wheat land use and lowest (C_0=7.242) for poplar-wheat based land use. A higher sill value of soil P for all land uses indicated high total variability of P. The nugget-sill ratio (NS ratio) was utilized for determining the spatial dependence of each soil parameter. The studied physicochemical parameters showed variety of spatial dependence ranging from weak to strong spatial dependence according to the classification criteria based on NS ratio, provided by Camberdella *et al*. (1994). However, P exhibited different degrees of spatial variability and spatial dependence for all three land uses. The NS ratios were 0.82, 0.74 and 0.17 indicated weak (>0.75), moderate (NS= 0.25-0.75) and strong (<0.25) spatial dependence for available-P in berseem, rice-wheat and poplar-wheat systems respectively. Strong spatial dependence of available-P in poplar-wheat system could be ascribed to the intrinsic variations of native soil P, related to pedologic and geologic soil forming factors and higher microbial activity. On the other hand, berseem-based land use and rice-wheat system exhibited weak spatial dependence of soil available-P probably due to non-uniform management interventions (Bhunia *et al.* 2018).

The spatial variability maps of available-P for various land uses were generated through OK in Fig 1 (A= berseem-based land use, B= rice-wheat system, and C= poplar-wheat systems).

OK is a statistically optimal and unbiased estimator

Table 2 Semivariogram parameters of soil attributes in different land use systems

Parameter	Model	Nugget (C_0)	Partial sill (C)	Sill (C_0+C)	Nugget/sill (NS ratio)	Spatial dependence	RMSE
Berseem-based land use							
Sand	Gaussian	5.943	0.932	6.875	0.86	Weak	1.043
Silt	Exponential	17.495	3.252	20.747	0.84	Weak	0.967
Clay	Exponential	3.135	13.412	16.547	0.19	Strong	0.965
*p*H	Spherical	0.004	0.007	0.011	0.36	Moderate	0.990
EC	Spherical	0.014	0.005	0.019	0.74	Moderate	0.941
P	Gaussian	44.55	9.33	53.88	0.82	Weak	0.987
Rice-wheat system							
Sand	Spherical	2.848	1.431	4.279	0.66	Moderate	0.947
Silt	Gaussian	9.031	6.181	15.212	0.59	Moderate	1.037
Clay	Exponential	10.585	1.611	12.196	0.87	Weak	1.024
*p*H	Gaussian	0.014	0.006	0.020	0.70	Moderate	0.127
EC	Spherical	0.012	0.002	0.014	0.86	Weak	1.014
P	Exponential	112.204	39.556	151.771	0.74	Moderate	1.092
Poplar-wheat system							
Sand	Gaussian	2.593	3.861	6.454	0.40	Moderate	0.979
Silt	Exponential	6.827	11.739	18.566	0.37	Moderate	0.969
Clay	Exponential	5.391	1.483	6.874	0.78	Weak	0.954
*p*H	Gaussian	0.012	0.010	0.022	0.54	Moderate	0.866
EC	Spherical	0.015	0.714	0.729	0.02	Strong	0.942
P	Exponential	7.242	35.048	42.289	0.17	Strong	1.023

that can predict the value of a soil property at unsampled locations and it also ascertains the extent of uncertainty associated with this prediction (González *et al.* 2014). The spatial distribution maps showed the variable concentration of available P throughout the field of various land uses. In berseem-based land use, the available-P content was comparatively lower throughout the eastern side of this land use (36 kg/ha) as compared to other portions such as central and northern portions (50 kg/ha) of this land use. In rice-wheat system, higher amount of available-P (45 kg/ha) were observed in the northern and central part of this land use. The available-P varied from low range, i.e. 8-9 kg/ha at slightly above the south west position of the land use to high range, i.e. 35 kg/ha at eastern, south east and also the north east side of the agroforestry-based land use system. The spatial distribution maps of berseem and rice-wheat exhibited less variation of available P as compared to poplar-wheat system. Higher P variability and also strong spatial dependence in poplar-wheat system indicated the potential of agroforestry system for enhancing the growth of beneficial microbial population especially P solubilizing microorganisms and their activity through adding leaf-litters (organic input). Because higher microbial activity can promote a good spatial pattern of soil properties and increase the availability of nutrients like NPK, thus uptake of nutrients (Donoghue *et al.* 2019). The similar scattered distribution pattern of soil available-P was also portrayed by Reza *et al.* (2017). Although, in our study, available P content was less in poplar-wheat system due to relying only on native P and organic leaf litter input as nutrient sources. It is a well-known fact that the organic matter contains almost all nutrients but in little amount. Therefore, our study suggested applying adequate amount of phosphatic fertilizers particularly to those quadrants of the poplar-wheat field, lower at P content with due considering the P variability. On the other hand, excessive P fertilization has increased the P concentration in rest two land uses. Therefore, it is recommended to apply less or no phosphatic fertilizers to those land uses. Otherwise, economic investment will be more.

Thus, the present study provides a better insight about the spatial variability of soil available P within the field scale of different land uses for its better management. Geostatistics proved its superiority to classical statistics in accurate quantification of spatial variability of soil P in various land uses because geostatistics traced out significantly higher variability of available-P in poplar-wheat system as compared to other two systems; whereas, the classical statistics could not. Strong spatial variability of available P in poplar-wheat system hinted the careful examination of spatial variation before phosphatic fertilizer application. The study recommends point based application of adequate P fertilizer to poplar-wheat system and less or no P fertilizer application to berseem and rice-wheat fields, based on the respective spatial variability maps of P. Therefore, these spatial variability maps could be used for site-specific available-P management and to optimize the cost of cultivation. However, this study could be extended to other important nutrients for precise nutrient management of the study area.

ACKNOWLEDGEMENTS

The first author would like to thank the Indian Council of Agricultural Research (ICAR) for providing financial support in the form of Junior Research Fellowship (JRF) for conducting this research work. The authors are grateful to the Department of Soil Science, Punjab Agricultural University (PAU) for giving necessary facilities of this study. The authors would like to acknowledge respected editors and reviewers for their spontaneous support.

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