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Assessment of Spatial Variability of Soil Available Sulphur Using Geostatistical Techniques in a Part of Deccan Plateau of India

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Soil heterogeneity, soil formation factors and other human induced activities cause spatial variation of soil available nutrients. Knowledge on spatial variability of soil nutrients is essential for their successful management in crop field. Soil available sulphur (S) is an important secondary nutrient and it may vary spatially at any scale. Hence, the present study was conducted to assess the spatial variability of soil available S using geostatistical techniques. About 132 georeferenced surface soil samples were collected form a cultivated area of Katol block of Nagpur district, Maharashtra, India. Soil available S was determined chemically and the descriptive statistical analysis of S showed its good variability in terms of per cent coefficient of variation (CV= 81.74%). The results of geostatistical analysis showed its spatial variability in terms of nugget: sill ratio (NS ratio). The NS ratio *i.e.*, 0.37 indicated moderate spatial dependency of soil available S. The exponential model was found as a best suited semivariogram model for describing the spatial trend of soil S. Ordinary kriging (OK) technique was employed to generate spatial variability map of soil S to identify specific management zone of S. The present investigation suggested that the study area has moderate S content except north-east corner of the area, which is high in S content. Specific management of S is necessary to the central and north-west sides of the cropped areas of the study site. Thus, the study indicated a good potential of geostatistical technique especially with OK technique to generate S variability map for effective S management of the study area.

Key words: Available sulphur, geostatistics, ordinary kriging, semivariogram, spatial variability

Excessive application of inorganic fertilizers causes nutritional imbalances in the soil system of extensively cultivated area. Soil available sulphur (S) is an important secondary nutrient for crop plants particularly for oilseed crops like mustard, sesame, sunflower, groundnut *etc*. and its deficiency occurs widely in the agricultural crop fields throughout the world (Shukla *et al*. 2017). According to a recent report, about 39% of Indian soils are deficient in soil available S, although the extent of deficiency varies with various natural and anthropogenic factors (Shukla *et al*. 2014). Small field size and varied management practices also induce the spatial variability of soil S. Soil factors like pH and organic matter content influence the content and variability of soil S (Wang *et al*. 2016). A good understanding regarding the spatial variability of soil S is necessary for its effective management through delineating its various management zones. Such delineation will also assist in formulating the site-specific management strategies for soil available S.

Spatial variability assessment of soil S and other nutrients like phosphorus (P), potassium (K) *etc*. through classical statistical techniques is not sufficient due to its inability to reveal the continuous spatial variation in correlation with sampling locations (Shukla *et al*. 2017; Mondal and Sekhon 2019). Therefore, geostatistical techniques are lucrative alternative techniques, effectively discloses the spatial variability pattern or spatial autocorrelation of any nutrients through constructing semivariogram (Martin *et al*. 2016). Ordinary kriging (OK) is a good statistical interpolation technique, used to predict the value of a soil parameter at unsampled location and the uncertainty associated with the prediction. Spatial variability maps of various soil properties were generated through this OK technique by several

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researchers (Reza *et al.* 2012, 2018; Vasu *et al*. 2017; Mondal *et al*. 2020).

The study region (Katol block of Nagpur district) is a highly productive region showing a high degree of variability in terms of soil available nutrients status. Precise management of nutrients especially secondary or micronutrients are essential to keep up the production potential of this study region by emphasizing the spatial variability concerns. Till now, no systematic investigation has been reported on spatial variability of soil S for the study region using geostatistical techniques. Therefore, the present study was carried out to assess the spatial variability of soil available S using geostatistical technique and to delineate various S management zones through generating spatial variability map of S using OK technique.

Materials and Methods

Study area

The study area is situated at Katol block of Nagpur district, Maharashtra, India. The geographic coordinates of the study area are 21.27° N (latitude) and 78.58° E (longitude). Geomorphologically the study area is the part of the Deccan Plateau of India. The study area is characterized by semi-arid climatic conditions and the summer and winter temperature varies in between 5 °C to 45 °C. The average annual precipitation ranges from 800-1000 mm and thus, the study site supports a wide variety of agricultural crops like rice, wheat, maize *etc*. Mandarin orange is the most popular fruit crop of the study area.

Soil sampling and chemical analysis

A total of 132 georeferenced surface soil samples were collected from 0-15 cm soil depth using an auger. A handheld GPS device was used for georeferencing. After collecting the soil samples, they were subjected to air-drying. The samples were then grinded using a wooden pestle and mortar and passed through a 2-mm sieve before wet chemical analysis. Soil available S was determined using 0.15% $CaCl_2$ as an extractant (Williams and Steinberg 1969). The content of S was determined spectrophotometrically at a wavelength of 460 nm.

Descriptive statistical analysis

The descriptive statistical parameters like mean, median, minimum, maximum, standard deviation (SD), per cent coefficient of variation (% CV), skewness and kurtosis were calculated using SAS 9.2 software (SAS 2011) and excel spreadsheet to characterize the spatial distribution of soil available S in the study area. The variability of S was expressed in terms of % CV based on the criteria of Wilding *et al*. (1985). According to this criterion, a parameter is considered as highly, moderately and least variable when the CV value of that parameter is more than 35%, in between 15-35% and less than 15%, respectively.

Geostatistical analysis

The spatial variability analysis of soil available S using geostatistical tools and techniques were carried out in geostatistical analyst package of ArcGIS 10.4.1 software. A semivariogram was constructed using the semivariance of the studied soil property (S) to characterize the spatial pattern of soil available S. Semivariogram could be computed using the following expression:

$$\gamma(h) = \frac{1}{2n(h)}\sum_{i=1}^{n(h)}[z(xi+h) - z(xi)]^2 \quad \text{...(1)}$$

where, γ(h) = semivariance of the studied property, h = separation distance between two sampling points *i.e.*, one point if *xi* and another point is *xi+h*; z(xi) and z(xi+h) denotes the values of the studied parameter at those two above mentioned locations, respectively. Various important semivariogram models like exponential, spherical and Gaussian models were tested and the best model was selected based on least root mean square error (RMSE) values. The important parameters of semivariogram model like nugget, sill and their ratio (NS ratio) are also calculated from the semivariogram model to characterize the spatial distribution of soil available S. Nugget denotes the local sampling error, whereas sill denotes the total variance. Another important parameter is range, which denotes the separation distance between the sampling points. The NS ratio is generally used to characterize the continuous spatial variation of the studied parameter correlated with its sampling points. If the NS ratio is less than 0.25, in between 0.25-0.75 and more than 0.75, it indicates high, moderate and less degree of variability, respectively, for a particular parameter (Camberdella *et al*. 1994). The prediction accuracy of the best fitted model was tested through cross validation technique.

Interpolation maps of soil available S were generated using most widely used kriging technique called ordinary kriging (OK) technique.

Table 1. Descriptive statistical parameters of soil available sulphur in the study area

Statistical parameters of available S	Corresponding values
Minimum	1.10
Maximum	47.9
Mean	13.4
Median	9.14
Standard deviation (SD)	11.0
Coefficient of variation (%CV)	81.7
Skewness	1.16
Kurtosis	0.43

Results and Discussion

Descriptive statistics for soil available S

The summary of the descriptive statistical analysis was represented in table 1.

This descriptive statistical analysis for soil available S showed a high degree of variability in terms of per cent CV (CV=81.7%) which was much higher than 35% (Wilding *et al*. 1985). Such good variability was also obtained by Shukla *et al.* (2017), who reported CV= 79.5% for soil available S. The available S content varied from 1.1 to 47.9 mg kg^{-1} with a mean value of 13.4 mg kg^{-1}. The median value of the studied S was 9.14 mg kg^{-1}. Positive value of skewness indicated positively skewed distribution of S in the study area. The kurtosis (K) value was 0.43 denoted platykurtic distribution of S (K<3) in the study site.

Geostatistical analysis of soil available S

Geostatistical analysis was carried to characterize the spatial structure of soil available S through constructing the experimental semivariogram model. The important parameters of semivariogram model like nugget, sill, nugget: sill ratio etc. were provided in table 2.

The best fitted semivariogram model was found exponential model for characterizing the spatial variability of soil available S, which was similar to the findings of Shukla *et al*. (2017). The nugget: sill was used to describe the spatial dependence of soil S in the study area. The ratio (NS = 0.37) showed moderate spatial dependence of soil S. However, Shukla *et al*. (2017) reported strong variability of S (NS = 0.25). Strong variability can be attributed to the intrinsic factors of soil formation, whereas extrinsic factors are mainly responsible for weak variability (Liu *et al*. 2006). In the present study both intrinsic and extrinsic factors including anthropogenic factors like fertilization, irrigation water management *etc*. were equally accountable for such moderate variability of S. Spatial variability of a certain soil parameter can be decided on the basis of the criteria given by Camberdella *et al*. (1994).

The cross-validation parameters for best suited semivariogram model (here exponential model) were computed for OK technique to evaluate the accuracy of the model. The best fitted model was selected based on least RMSE value. The cross-validation parameters like coefficient of determination (R^2), root mean square error (RMSE), mean standardized error (MSE), root mean square standardized error (RMSSE) and average standardized error (ASE) were tabulated in table 3.

The negative value of MSE indicated underestimation of soil available S. moderately good R^2 value (R^2 = 0.45) denoted good prediction of S by the prediction model used in OK technique. Lower RMSSE value pointed out good prediction by the semivariogram model. A scatter plot was constructed using measure vs predicted values of available S for graphical representation of few cross-validation parameters and the accuracy of the prediction (Fig. 1).

After constructing the semivariogram model, the spatial interpolation map or spatial variability map of soil available S was generated through ordinary kriging technique to delineate the S management zones (MZs) in the study area. The spatial interpolation map of soil S was portrayed in Fig. 2.

Table 2. Semivariogram parameters of soil available sulphur of the study area

Semivariogram parameters	Corresponding values
Nugget (C_0)	0.749
Partial sill (C)	1.241
Sill (C_0+C)	1.99
Nugget: Sill ratio (NS ratio)	0.37
Spatial dependence	Moderate
Range (m)	415

Table 3. Cross validation parameters of soil available sulphur obtained from exponential model

Cross validation parameters	Corresponding values
Coefficient of determination (R^2)	0.45
Root mean square error (RMSE)	11.44
Mean standardized error (MSE)	-0.024
Root mean square standardized error (RMSSE)	0.758
Average standard error (ASE)	16.19

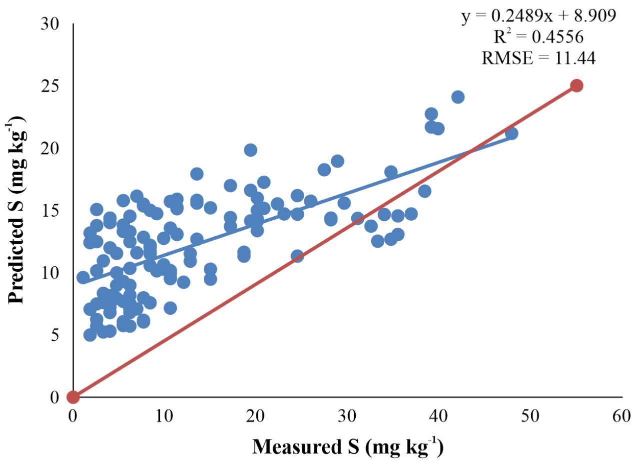

Fig. 1. Scatter plot of measured vs model predicted values of soil available sulphur (blue line = trend line, orange line = reference line or 1:1 line)

Our study categorized the available S content into 10 distinct classes along with its zonation. The spatial variability map exhibited variable amount of S at various quadrants of the study area. Higher amount of available S content was noticed at the north-east corner of the study area almost more than 24 mg kg^{-1} which might be due to the presence of organic matter dump at that corner of the area. Major portion of the whole study area exhibited the presence of moderate amount of S (9.32-12.46 mg kg^{-1}), whereas some other portion especially north-west, western and central portion of the study area exhibited very less amount of S (1.10 to 7.18 mg kg^{-1} of S). Similar types of results were also reported by several researchers, who identified four important management zones (MZs) of S like MZ-1, MZ-2, MZ-3 and MZ-4 (Tripathi *et al*. 2015; Shukla *et al*. 2017). Among the four identified MZs, MZ-3 contributed highest area (47.7%) followed by MZ-2 (31.5%). The MZ-1 and MZ-4 comprised of very less area *i.e.* 21% of the study area. Shukla *et al*. (2017) mentioned that soil and climatic factors along with various crops and nutrient management practices could cause prominent zonation of S and induce variation in S content. As the present study area belongs to the Deccan Plateau, the heterogeneous parent materials, lithological and geological factors might be responsible for such variations in S contents.

It is generally considered that the critical limit of $CaCl_2$ extractable S is 10 mg kg^{-1} (Williams and Steinberg 1969). As various portions of the study site contain less than 10 mg kg^{-1} of S, thus management of S is crucial for those zones especially the central, north-west and western sides of the area. Excessive chemical fertilizer application to the study area to obtain higher level of crop productivity may be another reason for such type of S deficiency in that area. Higher S content of the area might be attributed to the lower pH and acidification of the area by leaf litter, coming from the nearby citrus plantation crops.

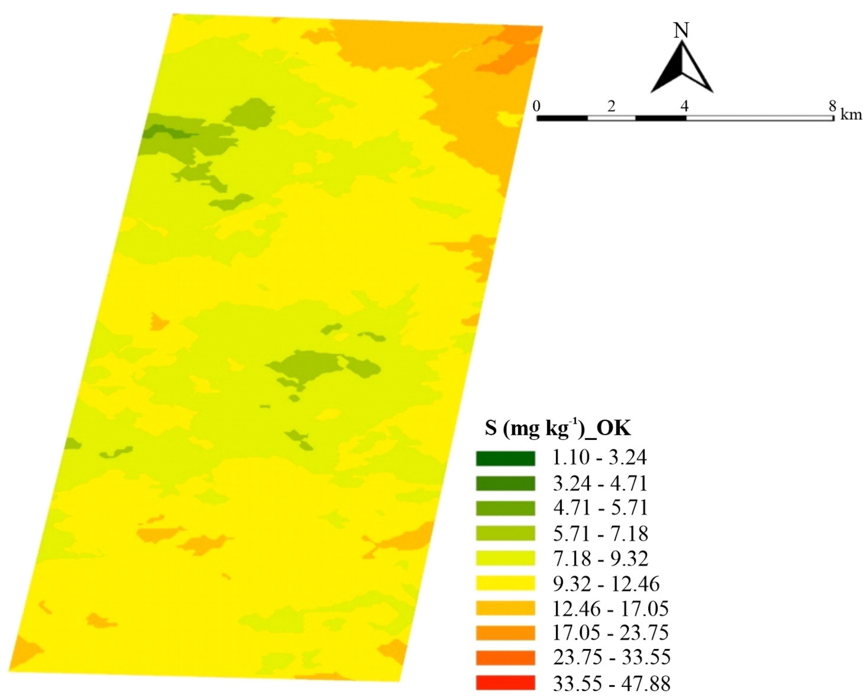

Fig. 2. Spatial distribution map of soil available sulphur using ordinary kriging technique

Similar results were also reported by other researchers (Benison and Bowen 2013; Shukla *et al*. 2017). Weathering of S containing minerals like pyrites, marcasites, *etc*. also increases S content (Cieslik *et al*. 2017). However, the present study demonstrated the lower to moderate S content in the study area which could be ascribed to less addition of S containing fertilizers and more crop uptake in this highly productive area. The deficiency of S was much more prominent in north-west and central portion of the site. Therefore, the study recommended to apply adequate amount of S containing elements or fertilizers for those two quadrants of the study area and apply less or no S containing fertilizers to the north-east corner of the study site to optimise the economic investment.

Conclusions

The present study provided a better insight regarding the spatial variation of soil available S concentration in the study area. Classical statistical analysis also revealed higher amount of variability of soil available S. Geostatistical analysis revealed that the exponential model was the best fitted semivariogram model for characterizing the spatial structure of soil available S. Available S content showed moderate spatial dependence in the study site as the site was much influenced by both natural and anthropogenic activities. The OK technique could be successfully employed for generating spatial interpolation map of available S. The study emphasized the application of S containing fertilizers to north-west, western and central portions of the study area for successful crop production of the area. Thus, the generated spatial variability map of soil available S could be used as a primary guide of farmers for region-specific management of S in the study area.

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