International Journal of Plant & Soil Science

Volume 35, Issue 19, Page 302-309, 2023; Article no.IJPSS .105060
ISSN: 2320-7035

Quantitative Evaluation of the Spatial Variation of Surface Soil Properties in Continuous Paddy Growing Fields

Pepakayala Varalakshmi [a++*], S. Harish Kumar Sharma [a#], Kandrika Sreenivas [b†], T. L. Neelima [c‡], Y. Supriya [d^] and Y. N. Mohan Babu [e##]

[a] Department of Soil Science and Agricultural Chemistry, College of Agriculture, PJTSAU, Rajendranagar-500030, India.
[b] Soils and IRA Division, National Remote Sensing Center, Balanagar, Hyderabad-500037, India.
[c] Department of Agronomy, Remote Sensing Lab, WTC, PJTSAU, Rajendranagar-500030, India.
[d] Department of Statistics and Mathematics, College of Agriculture, PJTSAU, Rajendranagar-500030, India.
[e] Department of Agronomy, GPS Institute of Agricultural Management, Bengaluru-560058, India.

Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/IJPSS/2023/v35i193555

Open Peer Review History:
This journal follows the Advanced Open Peer Review policy. Identity of the Reviewers, Editor(s) and additional Reviewers, peer review comments, different versions of the manuscript, comments of the editors, etc are available here: https://www.sdiarticle5.com/review-history/105060

Original Research Article

Received: 13/06/2023
Accepted: 16/08/2023
Published: 19/08/2023

[++]Teaching Associate;
[#]Professor;
[†]Scientist-G & Head;
[‡]Senior Scientist;
[^]Professor and Head;
[##]Assistant Professor;
**Corresponding author: E-mail: varam6195@gmail.com;*

ABSTRACT

Soil degradation caused by poor land management practices is a major impediment to optimal land productivity. Soil spatial variability is required for agricultural productivity, food safety and environmental modeling. Rice is one of the important food resources for most of the world's population, especially in India and feeds more than 60 per cent population of the country. Telangana is on track to become India's rice bowl as rice production is expected to reach 1.3 crore tons in 2019–20.The present study was conducted in continuous paddy cultivated field of Machapur village of Siddipet district, Telangana, India to know the spatial variability of soil properties with a help of geostatistical model. For this, a total of 100 composite samples at 20*20 m grids in an area of 4 ha were collected. The pH of the soil, electrical conductivity (EC), organic carbon (OC), available nitrogen (N), phosphorus (P) and potassium (K) were all determined. The semivariogram model was used to create surface maps of soil properties using the ordinary kriging technique. The skewness values showed a normal distribution for all analyzed parameters except for Available K. Coefficient of variation ranged from 1.92% for pH to 34.08% for EC in topsoil indicating the heterogeneity of soil properties. Spherical model fits well with experimental semivariogram of pH, EC and AK. Exponential model better described the variation of soil OC and AN while the variation of AP was best described by Gaussian model. The soil pH, OC and available P were moderately spatially dependent whereas EC, available N and K were strongly spatially dependent. The cross validation results demonstrated the spatial prediction's smoothing effect. According to the findings of this study, a geostatistical model can directly reveal the spatial variability of lateritic soils and will assist farmers and decision makers in improving soil-water management.

Keywords: Geostatistics; kriging; semivariogram; spatial variability; continuous paddy growing fields .

1. INTRODUCTION

Soil is the soul of life. Soils have a high degree of spatial variability due to the combined effect of physical, chemical and biological processes that operate at various intensities and scales. Accurate estimation of quantitative information on spatial variability of soils is significant for intensive agriculture, sustainable development and natural resource management. Land use planning, agricultural field trial research and precision farming all benefit from understanding the spatial variation of soil properties. Both inherent and human-induced variability lead to non-uniform crop production at the field level. Thus, knowledge of the spatial variability of soil properties is critical for improving soil management and, as a result, crop productivity.

"Traditional statistical methods can be used to define soil variability and it is assumed that soils have a random property. However, many reported that soil characteristics show spatial dependence" [1,2]. "In this regard, classical statistics is not capable of analyzing the spatial dependency of the variables since the data is assumed to be measured independently and it is thus possibly evaluated using a geostatistical approach" [3]. "For timely and accurate assessment and mapping of the spatial variability of soil fertility of un-sampled locations, geostatistical analysis methods are most helpful" [4], (Xu et al. 2013).

Owing to variation in topography, soil management and inherent soil properties; soil spatial variability is inevitable in Siddipet area of Telangana. Farming by the majority of farmers in the area also relies on small land holdings due to land fragmentation which is most common in the country. This compels farmers to intensively exploit their land as much as possible. Yet, soil management practices are far from adequate level. All these highlight the importance of having adequate information on the spatial variability of soil properties to support site-specific soil management decisions. Therefore, this study was carried out in continuous paddy cultivated field of Machapur village of Siddipet district, Telangana, India to estimate the soil variability for increasing productivity of soil.

2. MATERIALS AND METHODS

2.1 Study Area

A farmer field from Machapur village of Siddipet district having geographic coordinates from 18°11′1.43″ to 18°11′8.83″ N latitude and 78°53′10.54″ to 78°53′20.65″ E which belongs to the Central zone of Telangana which is most prominent for continuous rice growth was selected. Siddipet district receives 742.7 mm normal rainfall and experiences an average annual temperature range of 20.6° C to 33.5°C [5]. The texture of soil is red loamy in nature.

2.2 Soil Sampling Procedure and Laboratory Analysis

A farmer field of 4 hectares was selected in Machapur village of Siddipet district which is continuously under paddy cultivation. A total of 100 soil (point) samples were collected by making the grids of size 400 m^2 (20 m * 20 m) area. Grids were prepared to get the required number of samples by using QGIS 3.8 software. Three to four subsamples were collected at random locations inside a grid cell for making a composite sample. The collected soil samples were processed and analysed for pH, EC, OC, available N, P and K in laboratory. Soil pH was determined in 1:2.5 soil water suspensions by potentiometric method [6], electrical conductivity (EC) was determined in 1:2.5 soil-water extract using conductivity bridge [6]. "The organic carbon was determined by Walkley and Black's wet oxidation method" [7]. "Available N (Alkaline Permanganate method), available P (Olsen method); available K was extracted with 1 N NH_4OAc and then estimated by flame photometry" [8].

2.3 Statistical Analyses

The main statistical parameters, including mean, median, standard deviation, variance, coefficient of variance (CV) and maximum and minimum values, which are generally accepted as indicators of the central tendency and of the data spread, were analyzed. The normal distribution of the data was verified by the skewness (between -1 and +1) value.

2.4 Geostatistical Analysis

In order to interpolate the values of un-sampled locations and create maps of soil properties, standard kriging was used [9]. The scatter point set was used to create the semivariogram and the input point data set was used to quantify the spatial variation. Semivariograms that are represented as equations were calculated to determine the spatial variability's structure [1].

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

"In order to calculate the experimental semivariogram and select the best fitted model, popular theoretical models including circular, spherical, gaussian, and exponential were tested for each soil parameter data before mapping. The models offer details on the spatial organization in addition to the interpolation input parameters. Values of root-mean-square standardized error (RMSSE), mean standard error (MSE) and root-mean-square error (RMSE) were obtained to ascertain the fitted model. The best models of the fitted models were selected on the basis of error values computed from the entire data sets as suggested by Ewis, [10]; Gorai and Kumar [11]. Accordingly, the model showing lowest RMSE value was selected as a best fitted model" [12,13]. When the RMSE values for all models were equal, then RMSE values of models close to one were selected as best fitted model as suggested by Gorai and Kumar [11]. Next, the best models were used to analyse the spatial structure and provide the input parameters for interpolation.

To determine the spatial organization of the measured variables, three key parameters - nugget (C0), sill (C0 + partial sill (C)) and range (A0) values - were derived from the fitted models. According to Costa et al. [1], nugget variance (C0) refers to variance resulting from measurement error or short-range variability of the property that cannot be detected at the current scale of sampling. The sill is used to represent total variation, and the ratio of nugget to sill is used to classify spatial dependence [14]. The difference between correlated soil property values is indicated by the range. Also known as the separation distance, it is the distance past which the measured data are no longer spatially dependent [1].

3. RESULTS AND DISCUSSION

3.1 Descriptive Statistics for Soil Parameters

Table 1 shows a summary of descriptive statistics for measured soil properties. The variability in soil properties was interpreted using the coefficient of variation (CV). According to criteria given by Gualberto et al. [15] indicated that CV≤15% is accepted as the low variability, CV between 16-35% is considered as moderate variability and CV>35% is reported as high variability. According to CV values between 1.92% and 34.08%, soils in the study area showed diverse variation (Table 1).The least variable of the investigated parameters was soil pH, whereas AP variability was moderate. On the other hand, EC, OC, AN and AK showed a moderate variability. The heterogeneity of soil properties caused by uneven fertilization [16] and field micro relief [17].

Other researchers have also found that soil pH is more stable over time than other soil characteristics [18-20]. It is expected the occurrence of lower value of CV for pH, since their values vary within a narrow range. The CV of pH cannot be compared with those of other attributes because it is measured in logarithmic scale. EC varied with the differential concentration of dissolved salts due to natural drainage facility and land relief. Unequal duration of oxido-reduction processes, duration of water logging on these soils and proportion of decomposition of OM have implications on spatial pattern. Cropping practices are one of the key factors that influence soil fertility because they cause a variety of nutrient deficiencies to appear in the area, especially if the proper amount of additional fertilizer is not provided in the necessary ratios.

Referring the mean values (Table 1), the studied soil was neutral in soil pH (7.61); and non-saline in nature (0.37 dS m^{-1}); high in OC (0.77%) and AP (315.95 kg ha^{-1}); moderate in AK; and low in AN (171.86 kg ha^{-1}). Flooding conditions in paddy will neutralize the soil pH is the main reason for neutral reaction. Dissolution of salts in flooding water reduces the concentration of salts and also causes the leaching of salts are the reason for non-saline soils. Floodplain soils record higher OM content compared to soils located in other areas this may due to poor decomposition of organic material [21,22]. The possible reasons for low AN and moderate AK would be non-application of adequate dose of nitrogen fertilizer to the high yielding varieties which need large quantities of nutrients and losses due to leaching and gases emissions. High AP may be due to heavy fertilization with complex fertilizers as well as neutral soil reaction which increases phosphorous solubility [23].

According to Webster [24], skewness is the most serious departure from normality typically observed with soil data. Furthermore, all sampling intensities had asymmetry (skewness) coefficients that ranged from -1 to +1, indicating symmetric distributions. The data distribution of the all the analyzed soil parameters was normal with the exception of the available K which was long transformed in order to normalize data sets for geostatistical analyses.

3.2 Spatial Variability of Soil Properties

Table 2 and Fig. 1 present semivariogram analysis and defining parameters of soil characteristics. It is clear from the results that a uniform kriging model cannot be recommended for all the soil parameters. Different models were suitable for different parameters [25,19]. The best fit for pH and EC was provided by the spherical model. The exponential model best explained the semivariogram of soil OC and AN, while the gaussian model best explained the semivariogram of soil AP. For AK, the circular model worked best. According to papers on models, the soil pH was modeled as spherical [26,27]; the soil TN and OC were modeled as exponential [28,29] and Gaussian [4] respectively.

"The ratio of nugget and sill was used as a criterion to classify spatial dependence, with strong spatial dependence semivariograms having a nugget effect less than or equal to 25% of the sill, moderate spatial dependence semivariograms having a nugget effect between 25 and 75%, and low spatial dependence semivariograms having a nugget effect greater than 75%. The variation of intrinsic soil properties such as soil parent material, topography, texture, and mineralogy is associated with a strong spatial dependence" (Xu et al. 2013), [4,1]. However, a weak spatial dependence of soil characteristics suggested that extrinsic factors, such as soil fertilization and farming methods, were primarily responsible for the spatial variability [28,2]. Both intrinsic and extrinsic factors are probably responsible for controlling a moderate spatial dependence [4,1,28].

The nugget and sill ratio in the current study ranged from 6.32 to 73.16% (Table 2). A moderate degree of spatial dependence was seen in the soil pH, OC, AP and AK. Their ratio was within the range of 33.50 to 73.16%, indicating that both intrinsic and extrinsic factors were at play in the control of the properties. According to Laekemariam et al. [16,30], the study area's micro relief and intensive cultivation with poor soil management practices could have an impact on the soil's processes and nutrient contents. The nugget to sill ratio of EC and AK recorded nugget to sill ratios of 15.89 and 6.32%, respectively, indicating a strong spatial dependence that was controlled by intrinsic factors; this spatial dependence was likely attributed to change in the soil's micro relief.

Table 1. Descriptive statistics for soil properties

Variable	Unit	Minimum	Maximum	Mean	Median	Skewness	Kurtosis	SD	CV %
pH	-	7.26	7.94	7.61	7.60	-0.04	2.60	0.15	1.92
EC	dS m^{-1}	0.16	0.68	0.37	0.34	0.79	2.69	0.13	34.08
OC	g kg^{-1}	2.80	11.20	7.70	7.70	-0.34	2.71	0.19	24.32
N	kg ha^{-1}	100.00	230.00	171.86	169.00	-0.07	2.90	28.64	16.66
P_2O_5	kg ha^{-1}	247.00	360.00	315.95	314.00	-0.31	3.86	19.00	6.01
K_2O	kg ha^{-1}	121.00	384.00	206.33	198.50	1.28	5.23	47.44	22.99

Table 2. Model performance, semivariogram characteristics and Goodness of prediction values of soil properties

Variable	Transformation	Fitted semivariogram model	RMSE	MSE	RMSSE	G%	Nugget (C_0)	partial sill (C)	Sill (C_0+C)	range (m)	Spatial dependence $C_0/(C_0+C)$	Spatial dependence level
pH	No	Spherical	0.1292	0.1291	1.0043	21.21	0.0093	0.0106	0.0199	53.6	46.68	Moderate
EC	No	Spherical	0.0810	0.0839	0.9755	58.35	0.0015	0.0079	0.0094	43.3	15.89	Strong
OC	No	Exponential	0.1765	0.1812	0.9763	10.76	0.0245	0.0104	0.0349	84.3	70.24	Moderate
N	No	Exponential	20.000	20.610	0.9853	50.72	62.773	930.670	993.44	128.1	6.32	Strong
P_2O_5	No	Gaussian	17.555	17.638	0.9971	13.75	270.17	99.137	369.31	88.1	73.16	Moderate
K_2O	Log	Circular	42.726	40.046	1.0560	28.02	0.0163	0.0324	0.0487	46.0	33.50	Moderate

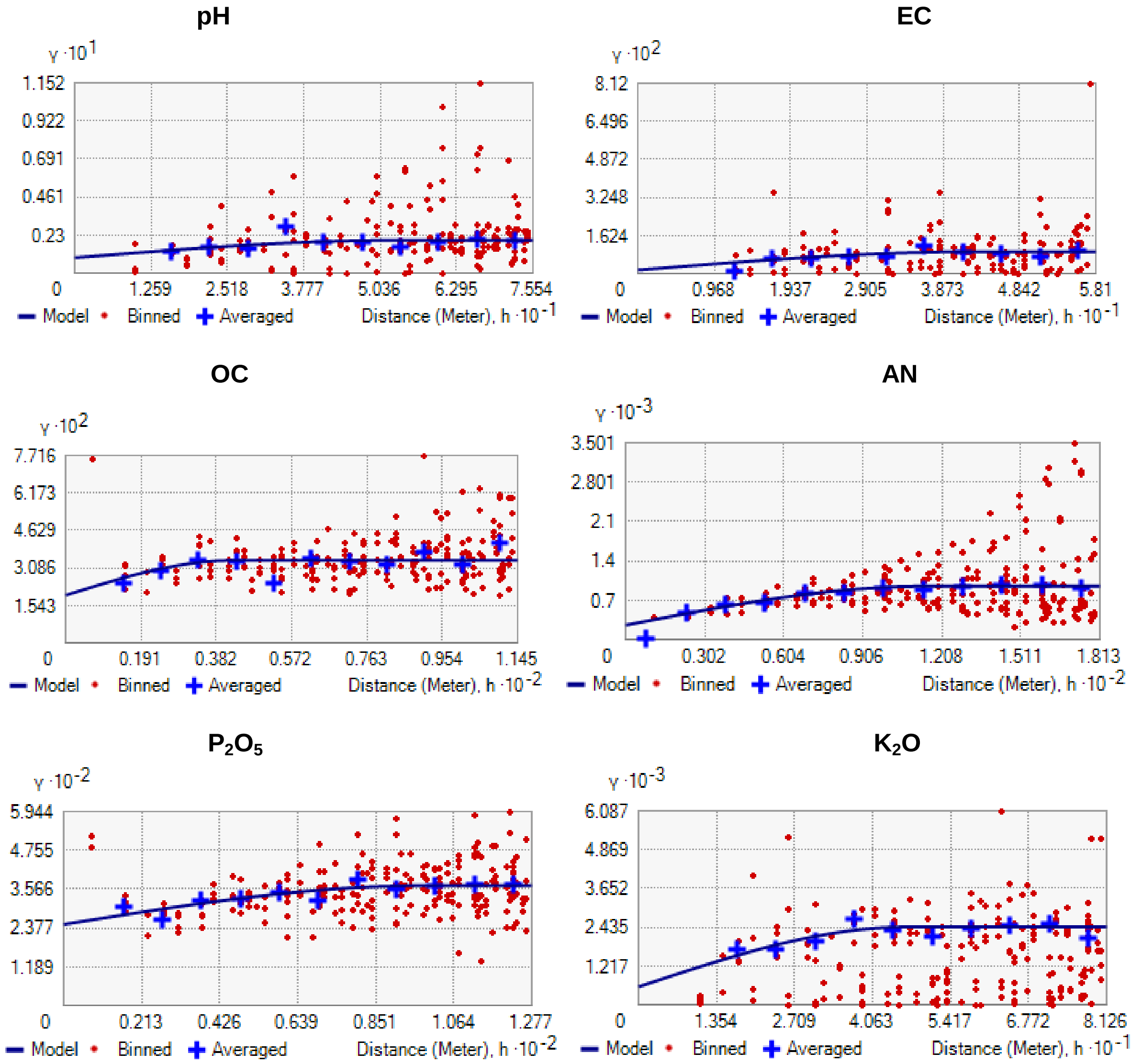

Fig. 1. Semivariograms of soil properties with the lines indicating selected best fit model

According to the data, the reported range values for pH, EC, OC, AN, AP, and AK were 53.6, 43.3, 84.3, 128.1, 88.1, and 46.0 m, respectively. It is possible that the sampling strategy used in this study was adequate for examining the spatial pattern of the soil properties because the spatial range of all studied soil properties was greater than the sampling intervals (20 m) in the field under study [29]. Overall, the higher the range suggests the more soil homogeneity within its own scale.

The performance/effectiveness/of interpolation was evaluated based on Goodness-of-Prediction. This technique compares the observed values with the predicted ones. Ideally, the predicted values should be the same as the measured ones, but in reality, data points would scatter due to natural variations and uncertainties. The current study's Goodness of Prediction (G) coefficients ranged from 13.17 to 45.22% (Table 2). Data regarding the predictive performances in the present study gave an indication of good predictions. The positive coefficients signified that interpolation technique and predictions are more reliable than using the sample means [31]. Thus, it was determined that the kriging interpolation method was a useful tool for the area's intervention programs addressing the spatial variability of soil properties.

4. CONCLUSIONS

The soil properties in the current findings have shown significant variability even though the same management practices and cropping pattern were used. Therefore, managing variability is necessary to raise field productivity. Through the study, it was established that the geostatistical kriging interpolation method facilitates precise estimation of spatial variability of soil parameters.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Costa C, Papatheodorou EM, Monokrousos, N, Stamou GP. Spatial variability of soil organic C, inorganic N and extractable P in a Mediterranean grazed area. Land Degradation & Development. 2015;26(2):103-109.
2. Ozgoz E, Gunal H, Acir N, Gokmen F, Birol M, Budak M. Soil quality and spatial variability assessment of land use effects in a typichaplustoll. Land Degradation & Development. 2013;24(3):277-286.
3. Patil SS, Patil VC, Al-Gaadi KA. Spatial variability in fertility status of surface soils.World Applied Sciences Journal. 2011;14(7):1020-1024.
4. Behera SK, Shukla AK. Spatial distribution of surface soil acidity, electrical conductivity, soil organic carbon content and exchangeable potassium, calcium and magnesium in some cropped acid soils of India. Land Degradation & Development. 2015;26(1):71-79.
5. Weather and Climatology of Telangana. Telangana State Development Planning Society (TSDPS) & Directorate of Economics and Statistics (DE&S), Planning Department, Government of Telangana; 2021.
6. Jackson ML. Soil Chemical Analysis. Prentice Hall of India Private Limited, New Delhi. India; 1973.
7. Walkley A, Black CA. Estimation of organic carbon by chromic acid titration method.Soil Science. 1934;37:29-38.
8. Chapman HD, Pratt PF. Methods of Analysis for Soils, Plants, and Waters. Riverside, CA: University of California; 1961.
9. Singh KN, Rathore A, Tripathi AK, SubbaRao A, Khan S. Soil fertility manning and its validation using spatial prediction techniques. Journal of the Indian Society of Agricultural Statistics. 2010;64:359-365.
10. Ewis E. Omran improving the prediction accuracy of soil mapping through geostatistics. International Journal of Geosciences. 2012;3:574–90.
11. Gorai AK, Kumar S. Spatial distribution analysis of groundwater quality index using GIS: A case study of ranchi municipal corporation (RMC) area. GeoinforGeostat: An Overview. 2013;1:2.
12. Dey P, Karwariya S, Bhogal NS. Spatial variability analysis of soil properties using geospatial technique in katni district of Madhya Pradesh, India. International Journal of Plant & Soil Science. 2017; 17(3):1-13.
13. Bogunovic I, Kisic I, Mesic M, Percin A, Zgorelec Z, Bilandzija D, Jonjic A, Pereira P. Reducing sampling intensity in order to investigate spatial variability of soil pH, organic matter and available phosphorus using co-kriging techniques. A case study of acid soils in Eastern Croatia. Archives of Agronomy and Soil Science. 2017a;63(13): 1852-1863.
14. Martin JR, Alvaro-Fuentes J, Gonzalo J, Gil, C, Ramos-Miras, JJ, Corbi JG, Boluda R. Assessment of the soil organic carbon stock in Spain. Geoderma. 2016;264:117-125.
15. Gualberto SAA, Nanni MR, da Silva distribution Junior CA, Cezar E, Crusiol LGT, Silva GFC, de Carvalho Gasparotto A. Spatial of soil chemicals attributes in sugar cane crop area. African Journal of Agricultural Research. 2016;11(48): 4886-4893.
16. Laekemariam F, Kibret K, Mamo T, Gebrekidan H. Soil–plant nutrient status and their relations in maize-growing fields of Wolaita Zone, southern Ethiopia. Communications in Soil Science and Plant Analysis. 2016a;47(11):1343-1356.
17. Vasu D, Singh SK, Tiwary P, Chandran P, Ray SK, Duraisami VP. Pedogenic processes and soil–landform relationships for identification of yield-limiting soil properties. Soil Research. 2016;55(3):273-284.
18. Reza SK, Baruah U,Sarkar D. Mapping risk of soil phosphorus deficiency using geostatistical approach: Acase study of Brahmaputra plains, Assam, India; 2012b.
19. Reza SK, Baruah U, Sarkar D, Singh SK. Spatial variability of soil properties using geostatistical method: A case study of lower Brahmaptra plains, India. Arabian Journal of Geosciences. 2016a;9(6):1-8.

20. Shukla AK, Behera SK, Lenka NK, Tiwari PK, Prakash C, Malik RS, et al. Spatial variability of soil micronutrients in the intensively cultivated Trans-Gangetic Plains of India. Soil and Tillage Research. 2015;163:282-289.
21. Ceddia MB, Villela ALO, Pinheiro EFM, Wendroth O. Spatial variability of soil carbon stock in the Urucu river basin, Central Amazon-Brazil. Science of the Total Environment. 2015;526:58-69.
22. Bogunovic I, Pereira, P, Brevik EC. Spatial distribution of soil chemical properties in an organic farm in Croatia. Science of the total environment. 2017b;584:535-545.
23. Bogunovic I, Kisic I, Jurisic A. Influence of wildfire and fire suppression by seawater on soil properties. Applied Ecology Environment Research. 2015;13(4):1157-1169.
24. Webster R. Statistics to support soil research and their presentation. European Journal of Soil Science. 2001;52(2):331-340.
25. Mousavifard SM, Momtaz H, Sepehr E, Davatgar N,Sadaghiani MHR. Determining and mapping some soil physico-chemical properties using geostatistical and GIS techniques in the Naqade region, Iran. Archives of Agronomy and Soil Science. 2013;59(11):1573-1589.
26. Nourzadeh M, Mahdian MH, Malakouti MJ, Khavazi K. Investigation and prediction spatial variability in chemical properties of agricultural soil using geostatistics. Archives of agronomy and soil science. 2012;58(5):461-475.
27. Tesfahunegn GB, Tamene L, Vlek PL. Catchment-scale spatial variability of soil properties and implications on site-specific soil managemet in northern Ethiopia. Soil and Tillage Research. 2011;117:124-139.
28. Guan F, Xia M, Tang X, Fan S. Spatial variability of soil nitrogen, phosphorus and potassium contents in Moso bamboo forests in Yong'an City, China. Catena. 2017;150:161-172.
29. Laekemariam F, Kibret K, Mamo T, Shiferaw H. Accounting spatial variability of soil properties and mapping fertilizer types using geostatistics in southern Ethiopia. Communications in Soil Science and Plant Analysis. 2018;49(1):124-137.
30. Laekemariam F,Kibret K, Mamo T, Karltun E,Gebrekidan H. Physiographic characteristics of agricultural lands and farmers' soil fertility management practices in Wolaita zone, Southern Ethiopia. Environmental Systems Research. 2016b; 5(1):1-15.
31. Karydas CG, Gitas IZ, Koutsogiannaki EN, Lydakis-Simantiris, Silleos GN. Evaluation of spatial interpolation techniques for mapping agricultural topsoil properties in Crete. EARSe Le Proceedings. 2009;8(1): 26–39.

Peer-review history:
The peer review history for this paper can be accessed here:
https://www.sdiarticle5.com/review-history/105060