Assessment of Geospatial analysis of soil properties using geostatistics models

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Research Article

Keywords: Soil chemical properties, Ordinary Kriging, Environmental Modeling, Geostatistical Analysis, Semivariogram, etc

Posted Date: August 5th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1914867/v1

Abstract

Accurate estimation of the spatial variability of soil properties is a critical component of agriculture ecosystem and environment modeling. The primary goal of this research is to determine soil characteristics and their spatial variability. The data was analysed for geographic variability using a combination of traditional analytical approaches and geostatistical methods. In October 2019, soil samples were taken from field through random sampling in Jagdalpur block of Bastar district, Chhattisgarh (India). Standard analytical procedures were used to assess pH, EC, Organic carbon, Iron, Nickel and Chromium in the soil. For direct envisaging of soil parameters, a conventional ordinary kriging (OK) interpolation was applied. Finally, by overlaying maps in a GIS context, the spatial distribution and correlation between OC and other soil parameters proclaimed.

Introduction

Soil is a living entity that forms as a result of pedogenic natural processes that occur during and after rock weathering. It is made up of mineral and organic elements that process certain chemical, physical, mineralogical, and biological qualities and provide a medium for plant growth at varying depths over the earth's surface [Biswas & Mukherjee, 1994]. Soil is a complex, diversified, and dynamic system, with qualities that alter across time and space [Rogerio, Ana, & de Quirijn, 2006]. Heterogeneity can exist on a large or small scale, even within the same soil type or community. Soil, as a natural resource, has inherent diversity due to the interaction of soil formation elements in the terrain. Variability can, however, be caused by farming, land use, and erosion. As a result of land degradation related to erosion, Salviano (1996) observed geographic heterogeneity in soil characteristics. The significance of spatial variability in soil properties has long been identified, and therefore must be considered every time field sampling is carried, as well as the research of its temporal and spatial changes.

Geographical information system (GIS) technologies have significant potential in the field of soil and have opened up additional opportunities for upgrading soil statistic systems since they provide a faster, more recurring, geographical, and temporal synoptic perspective. It also offers a cost-effective and precise method of determining landscape dynamics. For predicting rates of ecosystem processes, understanding how ecosystem functions work [Townsend et.al., 1995], and assessing the effects of future land use change on nutrients, assessing spatial variability distribution on nutrients in relation to site characteristics such as climate, land use, landscape position, and other variables is critical [Kosmas et.al., 2000].

Metals constitute around 80 of the 118 elements present in nature, the majority of which are only found in trace levels in the biosphere and biological components. There are at least twenty metal-like elements that cause well-organized hazardous effects in humans and their environments. Heavy metals are metals with a density greater than 6 mg/m3 and an atomic weight greater than iron. Zinc (Zn), copper (Cu), manganese (Mn), nickel (Ni), cobalt (Co), chromium (Cr), molybdenum (Mb), and iron (Fe) are some of the important metals and metalloids for living beings.

Metal pollution in soil ranges from less than 1 ppm to as high as 100,000 ppm due to human activities, and it accumulates on the soil surface, moves down to deep layers of soil, and eventually changes the soil physio-chemical properties directly or indirectly. In terms of heavy metal buildup, transport paths, and removal procedures, the roadside environment is a complicated system. As a result, understanding the level of heavy metal contamination on highway sites and its influx into plants is critical to the management of long-term urban environmental quality. Because of significant urban expansion and an exponential rise in the number of vehicles on highways with no effective pollution control measures, the study of heavy metals contamination on highway sights soil and its accumulation highway side plant is extremely important in India.

Two of the four study locations are close the National Mineral Development Corporation, while the other two are in separate directions. The study's major goal is to determine the impact of NMDC development on soil physicochemical parameters.

Materials And Method

Study area

The research was conducted in the Bastar area of Chattisgarh, India. Its headquarters are located in Jagdalpur. Jagdalpur has a hot, tropical monsoon climate. Summers are hot and last from March through May, with the average maximum temperature in May reaching 38.1 °C (100.6 °F). The weather cools down a bit during the monsoon season, which lasts from June through September and brings with it a lot of rain. The winters are pleasant and dry. It receives an average of 1324.3 mm of rain each year. It has an average temperature of 33.15°C in the summer and 20.73°C in the winter. In Jagdalpur, samples were taken from different locations covering an area of about 397 km^2. Soil samples (with three replications) at two soil depths, 0-20 cm and 20-40 cm, at 20m, 60m, and 500m (control site) distances from the side of the national highway. The study area is mainly under two main land use types which cover agricultural land and mining land.The soil samples were placed in airtight polythene bags and transported to the Deptt's PG laboratory, SHUATS, Prayagraj, Department of Soil Science and Agricultural Chemistry.

Soil Analysis

In mid October 2016, total 48 soil samples were air-dried, crushed, and sieved at a diameter of 2 mm. For the collection of soil sample a portable Global Positioning System was used to record the land coordination. Using a glass electrode pH metre, soil samples were tested for pH in both water and 0.01 M potassium chloride solution (1:1). [McLean, 1982]. The Digital Electrical Conductivity technique was used to determine EC. The Walkley and Black technique was used to calculate soil organic carbon. Wet digestion method was used to analyse soil iron, nickel, and chromium, using Aqua regia (1:3 HNO_3:HCl) for digestion and AAS to determine the results (Perkin Elmer A Analyst).

Statistical Analysis

The work's statistical analysis was completed in two parts. To recognise how data is distributed, conventional statistics such as mean, median, minimum, maximum, standard deviation (SD), skewness, and kurtosis were used to explain the distribution of data, and descriptive statistics were used to explore each soil property. Second, to assess the spatial dependency and spatial variability of soil parameters, geo-statistical analysis was performed using the kriging interpolation technique within the spatial analyst extension module of the ArcGis 10.2 software package. The kriging method is a statistical estimator that provides each observation statistical weight so that their linear structure is unbiased and has the lowest estimation variance [Kumke *et.al.,* 2005]. Because unbiased estimate minimises error variance, this estimator has a wide range of applications [Pohlmann,1993]. With data collected from the research area, the experimental variogram model was built using the Kriging approach. The spatial transformation was carried out in order to find the best model to employ with the parameters of the created maps.

The ordinary Kriging formula is as follows: [Isaaks and Srivastava, 1989; ESRİ, 2003].

$$Z(S_0) = \sum i = 1N\lambda_i Z(S_i)$$

where $Z(Si)$ is the measured value at the location (ith), λi is the unknown weight for the measured value at the location (ith) and $S0$ is the estimation location. The unknown weight (λp) depends on the distance to the location of the prediction and the spatial relationships among the measured values. The statistical model estimates the unmeasured values using known values. A small difference occurs between the true value $Z(S0)$ and the predicted value, $\Sigma\_iZ(Si)$. Therefore, the statistical prediction is minimized using the following formula:

$$Z(S_0) = \sum i = 1N\lambda_i Z(S_i)$$

Transferring data into a GIS system enables the Kriging interpolation technique. This allows for investigation in locations where there is no data. The model was evaluated using the following criteria: the average error (ME) must be near zero, and the square root of the estimated error of the mean standardised (RMSS) must be around one [Johnston *et.al.*, 2001]. The anisotropy effect was investigated when the models were being implemented.

Results And Discussion

Soil mapping and survey is significant because it aids in the evaluation of soil qualities and their application in agriculture, irrigation, and other land uses. The purpose of this study was to identify the geographic variability of several physical and chemical soil qualities in order to determine their current circumstances in the study region, hence the following are the results:

Table 1 shows a summary of the descriptive statistics of soil parameters, which indicate that they were all uniformly distributed. At depths of 0–20 cm, the coefficient of variance was 2.33 to 2.42, while at depths of 20–40 cm, it was 2.34 to 2.41. According to the guidelines set by Warrick, 1998 for the variability of soil qualities, all of the variables indicate minimal variation in terms of Coefficient of variance. The lowest coefficient of variation could be due to the area's homogeneous conditions, such as limited fluctuation in slope and direction, resulting in soil uniformity [Afshar et.al., 2009; Cambardella et al., 1994; Kamare, 2010]. At Raikot, Kesloor, and Chokawada, most soil parameters were substantially positively skew at both depths, such as pH and EC, although percent OC, Fe, Ni, and Cr were both symmetrical. The varied soil management strategies used in the research region, vehicle transportation, pollution, the parent material on which the soil is produced, the role of ground water depth, and irrigation water quality are all factors that influence chemical characteristics [Abel et.al., 2014; Al-Atab, 2008; Al-Juboory et.al., 1990].

Table 1
Descriptive statistics within the field grid for the variables at depth 0–20 cm

Raikot (Distance from NH at 20 m, 60 m and 500m)						
Statistics	pH	EC	%OC	Fe (mg/kg)	Ni (mg/kg)	Cr (mg/kg)
Mean	6.30	0.42	0.89	1585	6.13	6.33
Median	6.25	0.40	0.91	2088	7.50	5.00
SD	.162583	.043822	.080829	907.837541	3.647373	3.028751
Skewness	1.378	1.650	− .722	-1.728	-1.449	1.597
Kesloor (Distance from NH at 20 m, 60 m and 500m)						
Mean	6.62	0.48	0.88	2174	12.93	16.73
Median	6.60	0.46	0.88	2176	13.50	15.30
SD	.040415	.145662	.015275	37.040518	4.675824	2.569695
Skewness	1.732	.759	.935	− .242	− .537	1.729
Adawal (Distance from NH at 20 m, 60 m and 500m)						
Mean	7.06	0.56	1.08	2287	15.40	25.33
Median	7.07	0.56	1.06	2355	13.50	20.80
SD	.017321	.089007	.037859	135.795189	4.838388	10.279267
Skewness	-1.732	.067	1.597	-1.686	1.495	1.599
Chokawada (Distance from NH at 20 m, 60 m and 500m)						
Mean	6.88	0.46	0.92	2279	17.20	41.43
Median	6.96	0.47	0.92	2280	16.90	26.90
SD	.153080	.042395	.025166	.577350	2.662705	25.868385
Skewness	-1.724	− .690	.586	-1.732	.501	1.730

Table 2
Descriptive statistics within the field grid for the variables at depth 20–40 cm

Raikot (Distance from NH at 20 m, 60 m and 500m)						
Statistics	pH	EC	%OC	Fe (mg/kg)	Ni (mg/kg)	Cr (mg/kg)
Mean	6.23	0.44	0.74	1057	4.03	1.17
Median	6.21	0.43	0.75	1367	2.90	0.00
SD	.116762	.050342	.050332	621.027375	3.635015	2.020726
Skewness	.863	1.108	− .586	-1.687	1.267	1.732
Kesloor (Distance from NH at 20 m, 60 m and 500m)						
Mean	6.61	0.52	0.74	2081	11.83	11.77
Median	6.60	0.46	0.74	2091	11.10	10.10
SD	.023094	.161630	.020000	21.221059	4.247744	5.012318
Skewness	1.732	1.384	.000	-1.625	.754	1.331
Adawal (Distance from NH at 20 m, 60 m and 500m)						
Mean	7.00	0.64	0.91	2060	12.53	16.27
Median	7.06	0.64	0.92	2087	10.70	15.90
SD	.112694	.047522	.032146	151.767366	3.980368	1.582193
Skewness	-1.717	− .158	-1.545	− .766	1.633	.987
Chokawada (Distance from NH at 20 m, 60 m and 500m)						
Mean	6.77	0.49	0.73	2305	30.47	33.27
Median	6.71	0.50	0.72	2354	26.40	35.40
SD	.191398	.055103	.041633	84.293139	17.948909	7.433259
Skewness	1.216	− .980	1.293	-1.732	.967	-1.185

Table 3
Coefficient of variation within the field grid at depth 0–20 cm and 20–40 cm

Area	Coefficient of Variance (Depth 0–20 cm)	Coefficient of Variance (Depth 20-40cm)
Raikot 20 m	2.41	2.41
Raikot 60 m	2.42	2.43
Raikot 500 m	2.37	2.38
Kesloor 20 m	2.39	2.39
Kesloor 60 m	2.4	2.41
Kesloor 500 m	2.41	2.41
Adawal 20 m	2.36	2.39
Adawal 40 m	2.4	2.39
Adawal 500 m	2.4	2.4
Chokawada 20 m	2.33	2.36
Chokawada 60 m	2.38	2.39
Chokawada500 m	2.39	2.34

Geostatistical Analysis

Calculating semivariograms identified the possible spatial structure of the different soil parameters, and the best model that describes these spatial structures was identified. The results for the two depths are reported in Tables 4 and 5. The best fit model for each parameter was applied, and the Exponential and Gaussian models were the best match for all parameters. For each of the factors, the nugget effect (Co), the sill (Co + C), and the range of influence were documented. The degree of autocorrelation between the sampling points was discovered to be related to the spatial dependencies (Nugget/Sill ratio) and given in percentages. Table 4 illustrates the soil attributes based on the semivariogram model's variable features. The nugget variance is C0, the structural variance is C, and the degree of spatial variability is C0 + C, which is influenced by both structural and stochastic variables. The larger ratio suggests that stochastic influences like as fertilisation, agricultural measures, cropping patterns, and other human activities are the primary causes of spatial variability. The lower ratio indicates that temperature, parent material, terrain, soil qualities, and other natural variables play a substantial effect in spatial variability. The spatially dependent variables were classed as extremely spatially dependent if the ratio was less than 25, moderately spatially dependent if the ratio was between 25 and 75 percent, and weak spatially dependent if the ratio was greater than 75 percent. [Cambardella et al., 1994; Clark, 1979; Erşahin, 1999; Robertson, 1987].

Table 4
Geostatistical parameters of the fitted semivariogram models for soil properties and cross validation statistics at 0–20 cm depth and 20–40 cm depth respectivel

Variable	Nugget (C_0)	Sill (C_0 + C)	Range (A)	Nugget/Sill	Model	Spatial Class	RMS	ME
pH	0.0069	0.241	0.3534	0.29	Exponential	strong	0.152	0.038
EC	0	0.0109	0.1386	0	Exponential	strong	0.099	0.0389
OC	3.81	3.825	0.1701	0.98	Exponential	strong	0.058	0.255
Fe	0	230769.6	0.138	0	Exponential	strong	515.79	0.057
Ni	0	22.40	0.138	0	Exponential	strong	4.046	0.049
Cr	181.26	0	0.353	0	Exponential	Strong	15.22	0.044
Variable	**Nugget(C_0)**	**Sill (C_0 + C)**	**Range (A)**	**Nugget/Sill**	**Model**	**Spatial Class**	**RMS**	**ME**
pH	0.030	0.11	0.252	0.22	Exponential	Strong	0.207	0.016
EC	0	0.016	0.132	0	Exponential	Strong	0.121	0.060
OC	1.30	1.313	0.16	0.98	Gaussian	Strong	0.080	0.120
Fe	211036.30	444118.8	0.353	0.48	Exponential	Strong	535.15	0.027
Ni	0	194.33	0.132	0	Exponential	strong	12.69	0.057
Cr	34.64	286.12	0.353	0.12	Exponential	strong	7.85	0.016

For the 0–20 cm depth, Ph, EC,%OC, Fe, Ni and Cr had a strong spatial dependence with a ratio of 0.29%, 0.98% and 0% (Table 4).

At the lower depth i.e. 20–40 cm pH, EC, %OC, Fe, Ni and Cr had a strong spatial dependence (0.22%, 0%, 0.98%, 0.48% and 0.12%) (Table 4).

The nugget effect values for EC, Fe, and Ni were the lowest at both depths, implying that the research area's random variance of variables is low, implying that close and far samples had comparable and distinct values, respectively. As a result, tiny and close to zero nugget effects suggest spatial continuity between surrounding sites, as evidenced by the findings of [Vieira and Paz Gonzalez, 2003] and [Mohammad *et.al.*, 2007]. The presence of a sill on the variogram denotes second-order stationarity, indicating that the variance and covariance are present [Bohling, 2005].

Conclusion

Assessing geographic variability and mapping soil attributes is a necessary pre-requisite for soil and crop management, as well as for identifying areas of land degradation. Because these maps will quantify regional variability and offer the foundation for regulating it, the creation of soil nutrient maps is the first stage in precision agriculture. It would also aid in minimising the quantity of inputs provided to the soil in the form of supplements in order to avoid overburdening the soil, which could result in pollution and land degradation. The findings reveal that soil attributes' regional distribution and spatial dependence might differ even within the same local government jurisdiction. It also highlights the efficiency with which GIS tools may be used to interpret data. These findings can be utilised to provide recommendations for best management practises in the area, and perhaps to improve smallholder farmers' livelihoods.

Declarations

Author Declarations

Author's Contribution: P. Smriti Rao and Ashish David carried out the experiment. Tarence Thomas helped supervise the project. All authors contributed to writing the manuscript.

Conflicts of interest/Competing interests: The author's declare they have no competing interest

Funding: No funding was received for this study

Ethics Declaration statement: Not applicable

Consent to Participate: Not applicable

Consent for publication: Not applicable

Availability of data and material/ Data availability: No link available

References

1. Abel, C., Kutywayo, D., Chagwesha, T. M., & Chidoko, P. (2014). Assessment of irrigation water quality and selected soil parameters at Mutema irrigation scheme, Zimbabwe. *Journal of Water Resources and Protection*, *6*, 132–140.
2. Afshar, H., Salehi, M. H., Mohammadi, J., & Mehnatkesh, A. (2009). Spatial variability of soil properties and irrigated wheat yield in quantitative suitability map, a case study: Share e Kian Area, Chaharmahaleva Bakhtiari province. *Journal of Water and Soil*, *23*, 161–172.
3. Al-Atab, S. M. S. (2008). *Variations of soil properties and classification in some area of Basrah Governorate* (PhD Thesis). College of Agriculture, University of Basrah, Basrah.
4. Al-Juboory, S. R., Alaqid, W. K. Alaqidi, & Al-Issawi, S. M. (1990). Effect of soil management practices on Chemical and physical properties of a soil from great Mussayb Project. *Iraqi journal of Agriculture Sciences*, *21*, 107–116.
5. Biswas, T. D., & Mukherjee, S. K. (1994). *Textbook of soil science*. New Delhi: Tata McGraw-Hill Publishing Company Limited.
6. Black, C. A. (1965). *Methods of soil analysis. Agronomy No. 9, Part 2*. Madison, WI: American Society of Agronomy.

7. Bohling, G. (2005) Introduction to Geostatistics and Variogram Analysis. Kansas Geological Survey, 1, 1–20.
8. Brown, G., Newman, A. C. D., Rayner, J. H., Weir, A. H. (1978). The structure and chemistry of soil clay minerals In D. J. Greenland & M. H. B. Hayes (Eds.), *The chemistry of soil constituents*(pp. 29178). New York, NY: Wiley.
9. Buol, S. W., Hole, F. D., McCracken, R. J., & Southard, R. J. (1997). *Soil genesis and classification* (4th ed., p. 527). Ames: Iowa State University Press.
10. Cambardella, C. A., & Karlen, D. L. (1999). Spatial analysis of soil fertility parameters. *Precision Agriculture*, *1*, 5–14.
11. Cambardella, C. A., Moorman, T. B., Parkin, T. B., Karlen, D. L., Novak, J. M., Turco, R. F., & Konopka, A. E. (1994). Field-scale variability of soil properties in central Iowa soils. *Soil Science Society of America Journal*, *58*, 1501–1511. http://dx.doi.org/10.2136/sssaj1994.03615995005800050033x
12. Clark, I. (1979). *Practical geostatistics* (p. 129). London: Applied Science Publishers. Du Feng, L. Z., XuXuexuan, Z. X., & Shan, L. (2008). Spatial heterogeneity of soil nutrients and aboveground biomass in abandoned old-fields of Loess Hilly region in Northern Shaanxi, China. *Acta Ecologica Sinica, 28*, 13–22.
13. Erşahin, S. (1999). Alluvial soil in a field, some physical and chemical properties of the spatial variability of the determination. *SU Journal of the Faculty of Agriculture*, *13*, 34–41.
14. ESRİ. (2003). *The principles of geostatistical analysis* (p. 54). Federal Fertilizer Department. Federal Ministry of Agriculture and Rural development. (2012). *Fertilizer use and management practices for crops in Nigeria* (4th ed., pp. 40–41).
15. Isaaks, E. H., & Srivastava, R. M. (1989). *An introduction to applied geostatistics*. New York, NY: Oxford University Press.
16. Jackson M. L. (1958). *Soil chemical analysis* (p. 125). Engle wood cliffs, NJ: Prentice Hall.
17. Johnston, K., Hoef, M., Krivoruchko, K., & Lucas, N. (2001). Using ArcGIS geostatistical analyst. New York, NY: ESRI.
18. Kamare, R. (2010). *Spatial variability of production, density and canopy cover percentage of Nitrariaschoberi L. in Meyghan Playa of Arak by using geostatistical methods* (M.Sc Thesis, 76pp). Tarbiat Modares University, Tehran.
19. Kosmas, C., Gerontidis, St., & Marathianou, M. (2000). The effect of land use change on soils and vegetation over various lithological formations on Lesvos (Greece). *Cantena*, *40*, 51–68.
20. Kumke, T., Schoonderwaldt, A., & Kienel, U. (2005). Spatial variability of sedimentological properties in a large Siberian lake. *Aquatic Sciences*, *67*, 86–96. http://dx.doi.org/10.1007/s00027-004-0734-5
21. López-Granados, F., Jurado-Expósito, M., Atenciano, S., García- Ferrer, A., Sánchez de la Orden, M. S., & García-Torres, L. (2002). Spatial variability of agricultural soil parameters in southern Spain. *Plant and Soil*, *246*, 97–105. http://dx.doi.org/10.1023/A:1021568415380
22. Mclean, E.O. (1982) Soil pH and Lime Requirement. In: Page, A.L., Ed., Methods of Soil Analysis. Part 2. Chemical and Microbiological Properties, American Society of Agronomy, Soil Science Society of America, Madison, 199–224.

23. Mohammad Zamani, S., Auubi, S., & Khormali, F. (2007). Investigation of spatial variability soil properties and wheat production in some of farmland of sorkhkalateh of Golestan province. *Journal of Science and Technical Agriculture and Natural Recourses*, *11*, 79–91.
24. Pohlmann, H. (1993). Geostatistical modelling of environmental data. *CATENA*, *20*, 191–198. http://dx.doi.org/10.1016/0341-8162(93)90038-Q
25. Robertson, G. P. (1987). Geostatistics in ecology: Interpolating with known variance. *Ecology*, *68*, 744–748. http://dx.doi.org/10.2307/1938482
26. Rogerio, C., Ana, L. B. H., & de Quirijn, J. L. (2006). Spatiotemporal variability of soil water tension in a tropical soil in Brazil. *Geoderma*, *133*, 231–243.
27. Salviano, A. A. C. (1996). *Variabilidade de atributos de solo e crotalária júncea em solo degradado do município de Piracicaba – SP* (p. 91). Piracicaba: Tese (Doutorado), Escola Superior de Agricultura Luiz de Queiroz, Universidade de São Paulo.
28. Townsend, A. R., Vitousek, P. M. & Trumbare, S. E. (1995). Soil organic matter dynamics along gradients intemperature and land use on the Island of Hawaii. Ecology, 76, 721–733
29. Vieira, S.R., and A. Paz-González. 2003. Analysis of the spatial variability of crop yield and soil properties in small agricultural plots. *Bragantia* 62:127–138.

Figures

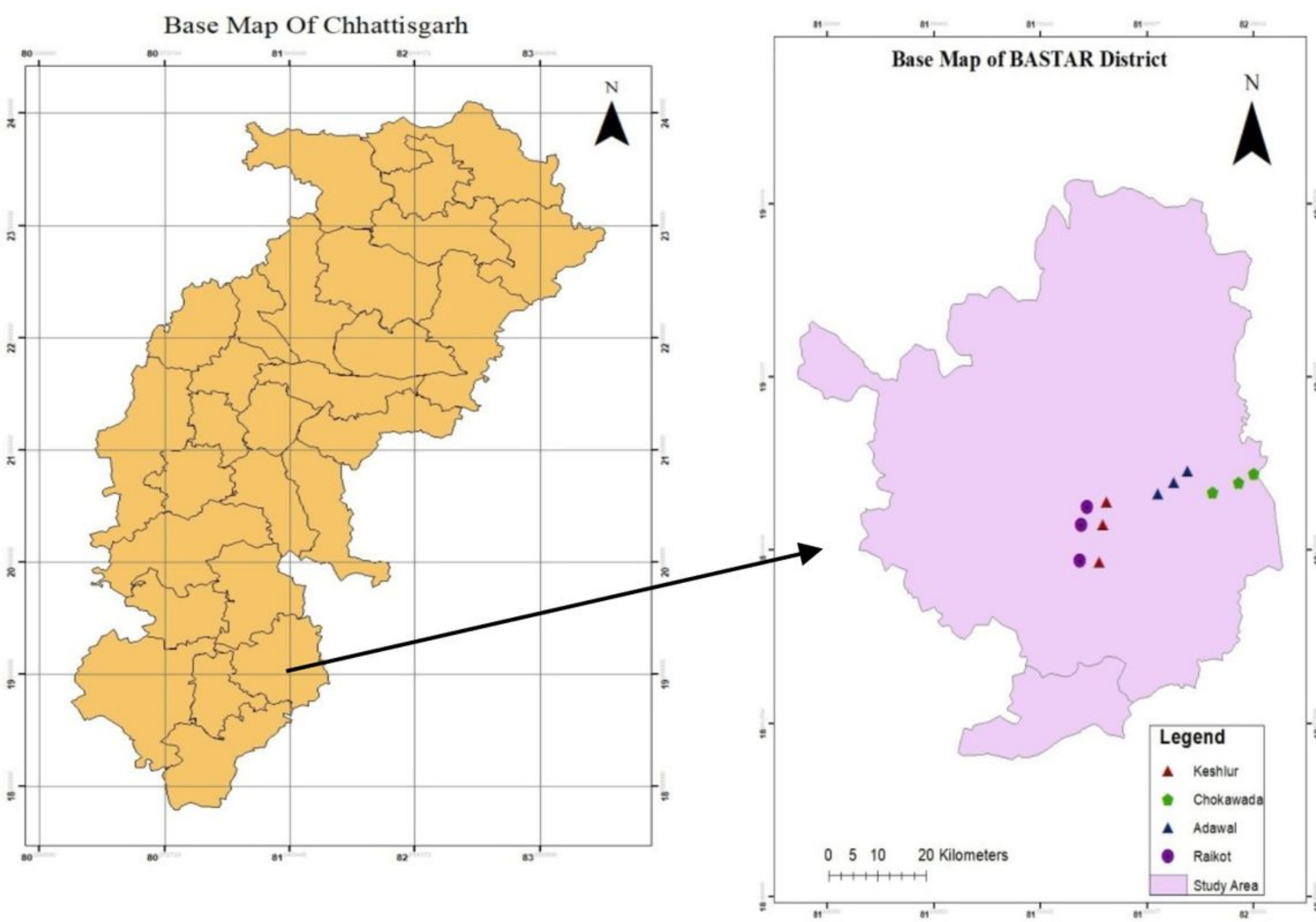


Figure 1

Map of the study area of Bastar district, Chhattisgarh, India showing the sample locations

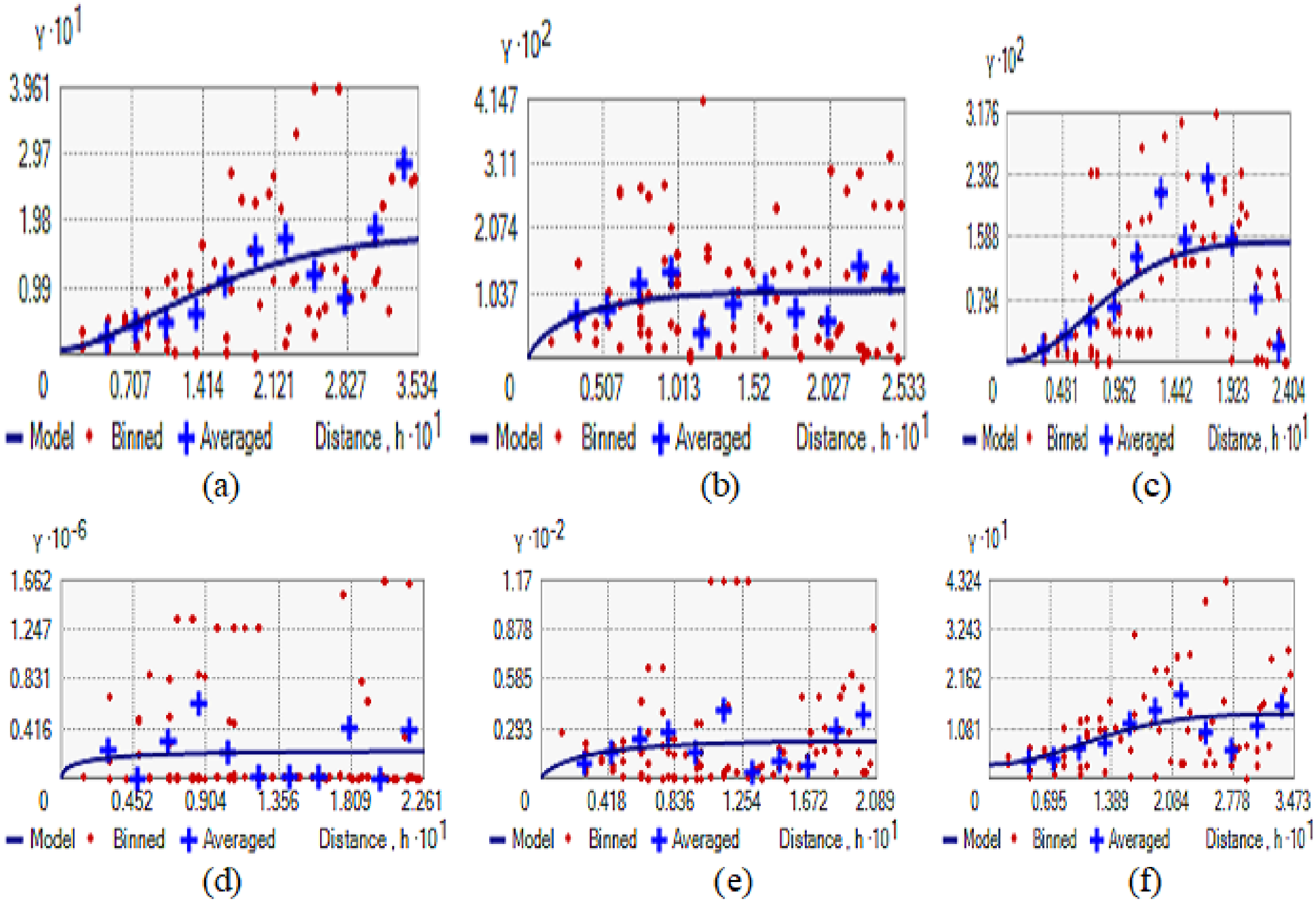


Figure 2

Semivariogram parameters of best fitted theoretical model to predict soil properties at 0-20 cm depth, **a.** pH **b.** EC **c.** %OC **d.** Fe **e.** Ni and **f.** Cr

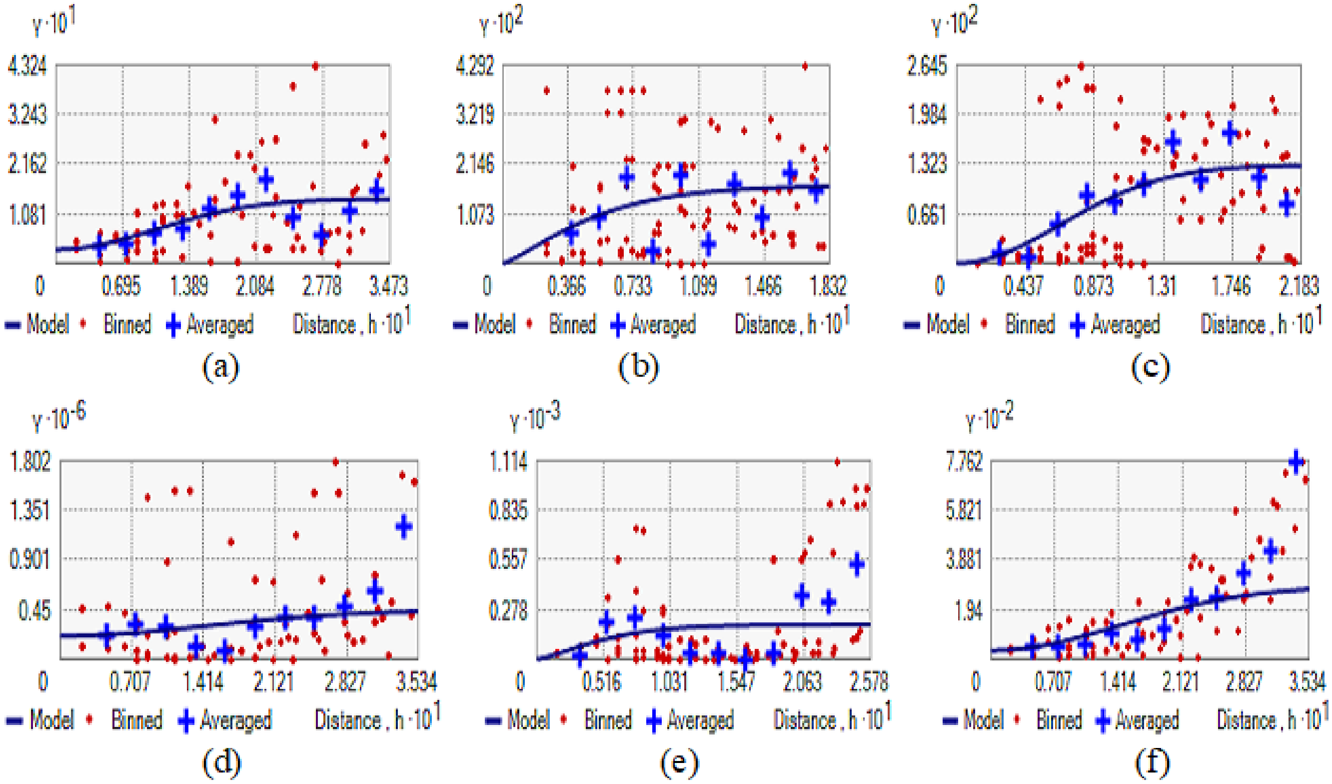
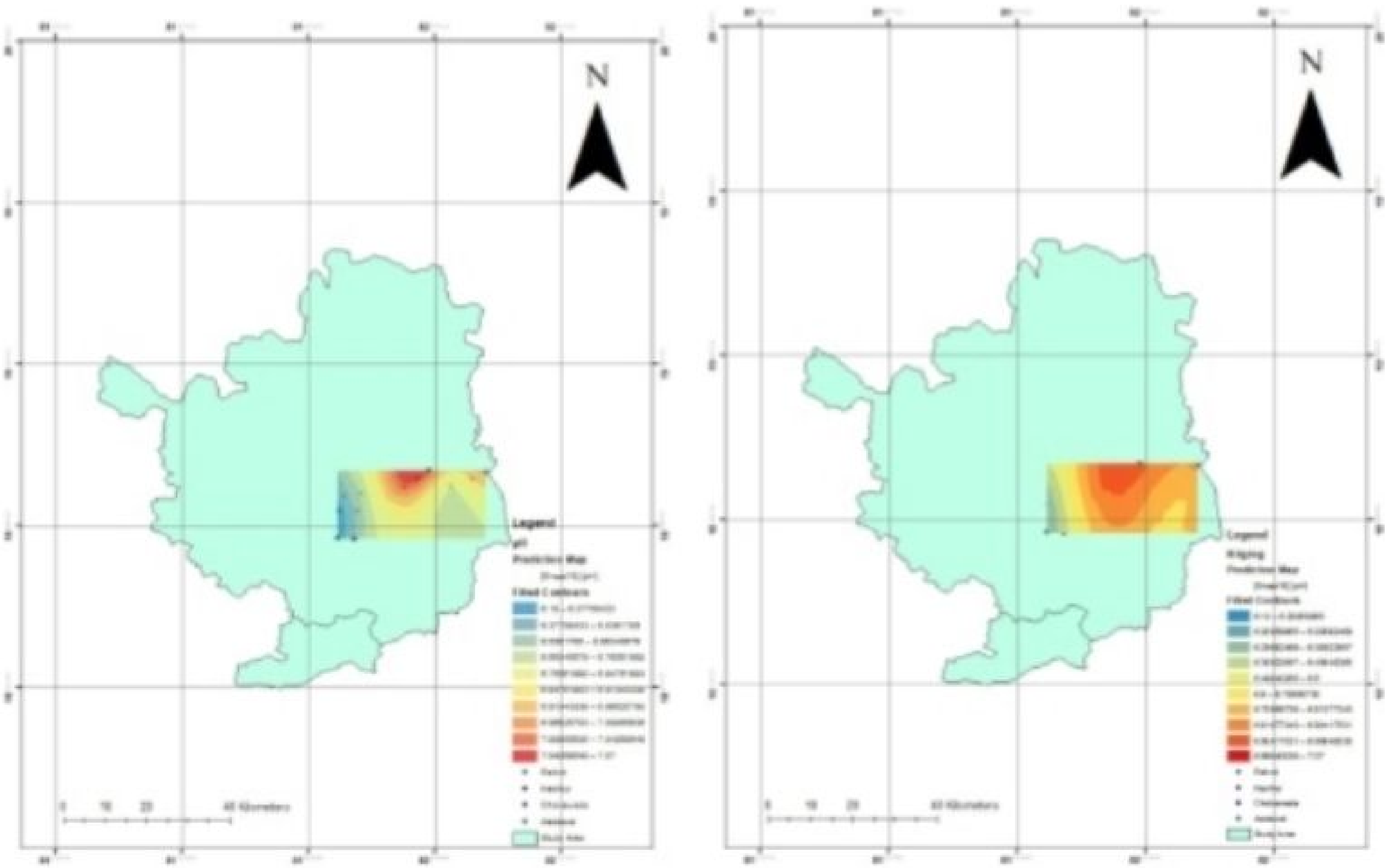


Figure 3

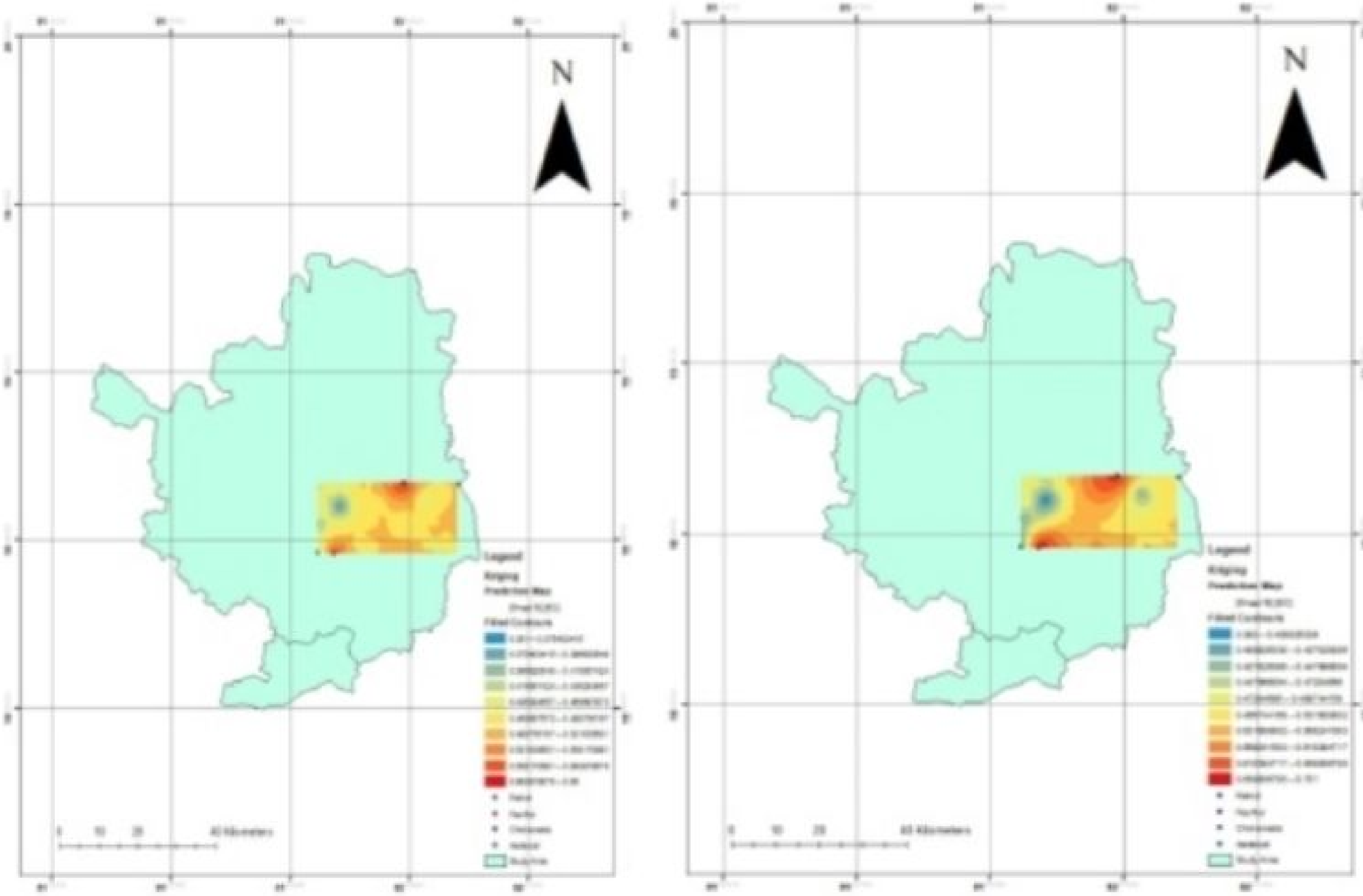
Semivariogram parameters of best fitted theoretical model to predict soil properties at 20-40 cm depth, **a.** pH **b.** EC **c.** %OC **d.** Fe **e.**Ni and **f.** Cr



(a) (b)

Figure 4

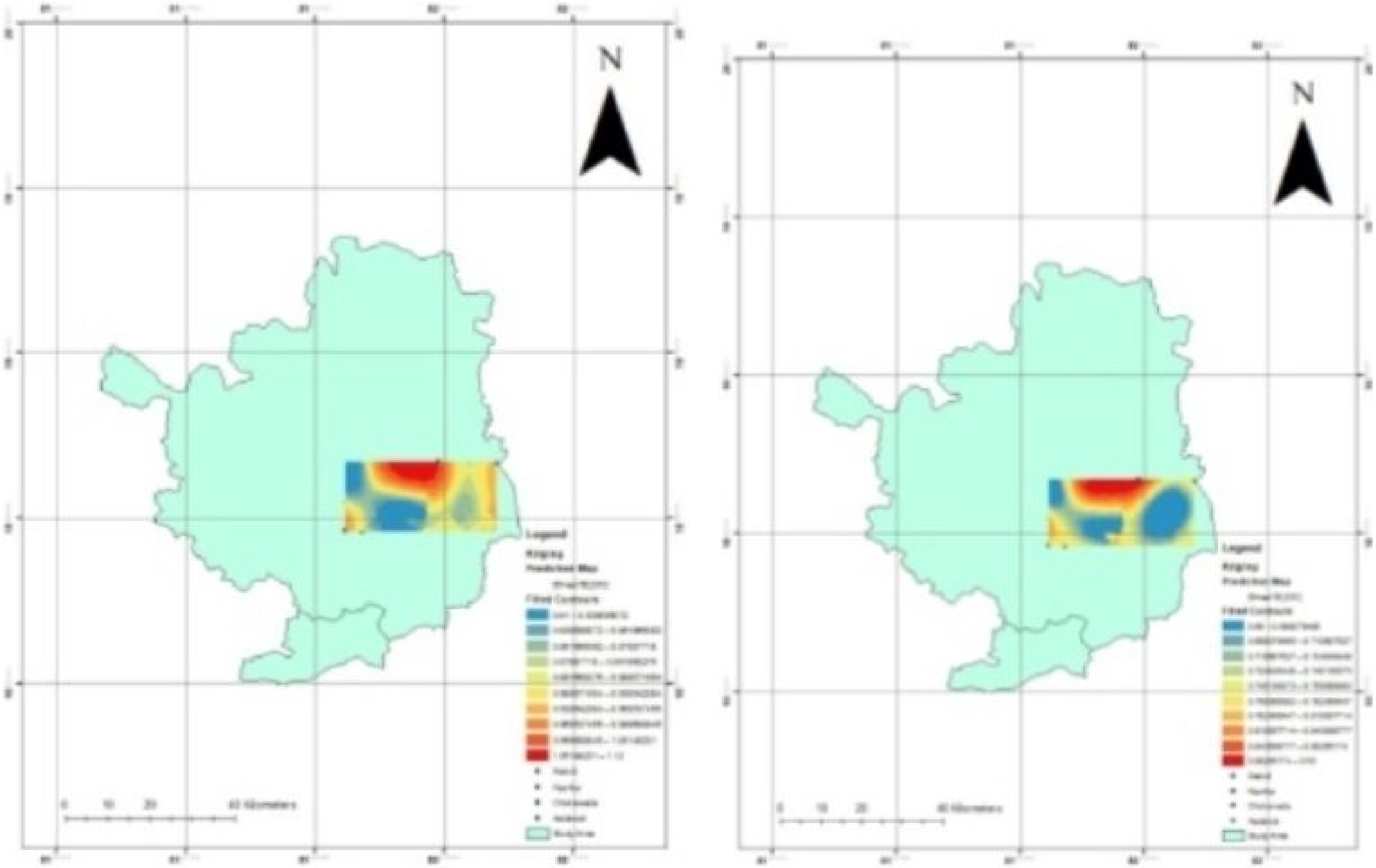
(a) pH at 0-20cm and (b) pH at 20-40cm



(a) (b)

Figure 5

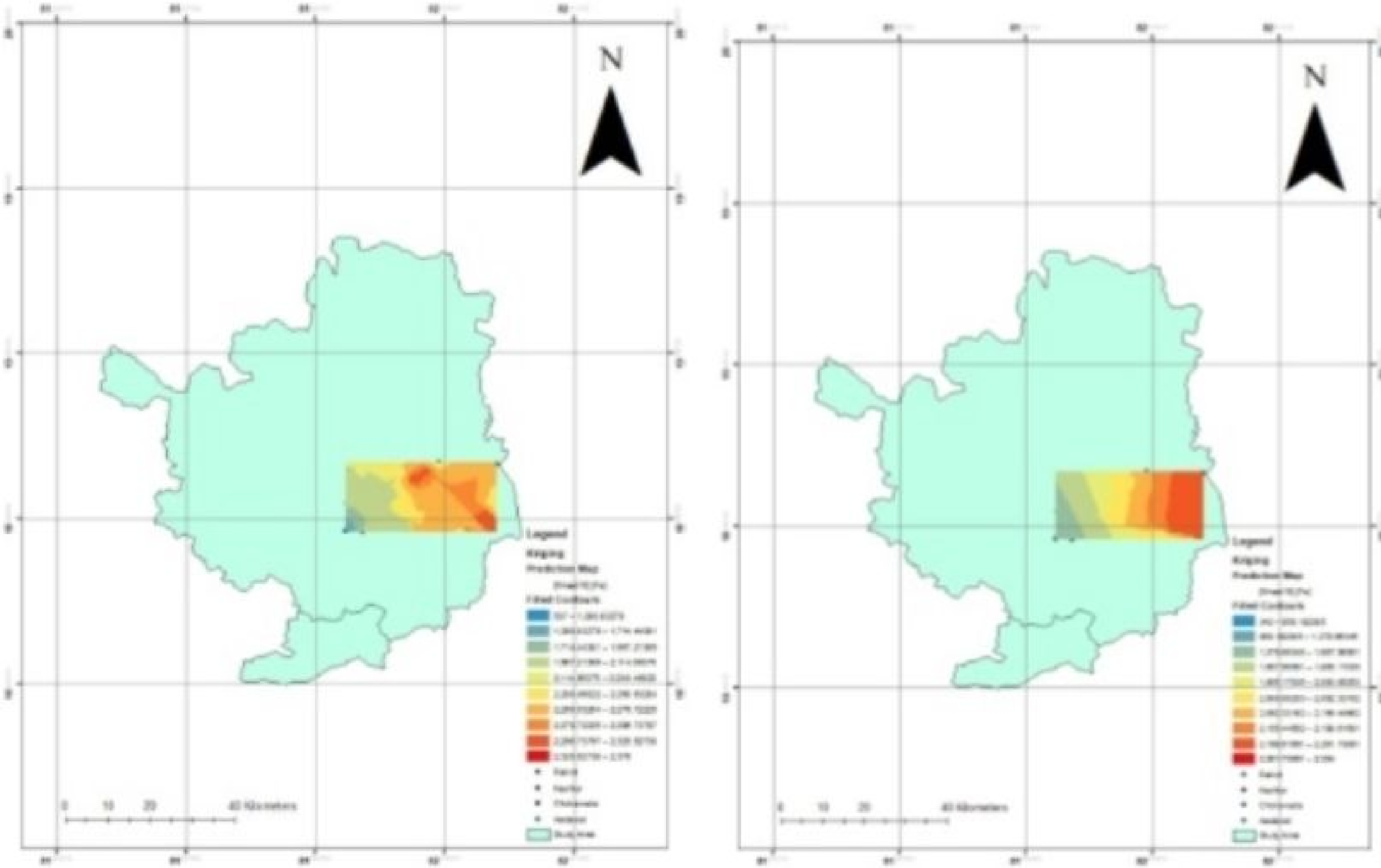
(a) EC at 0-20cm and (b) EC at 20-40cm



(a) (b)

Figure 6

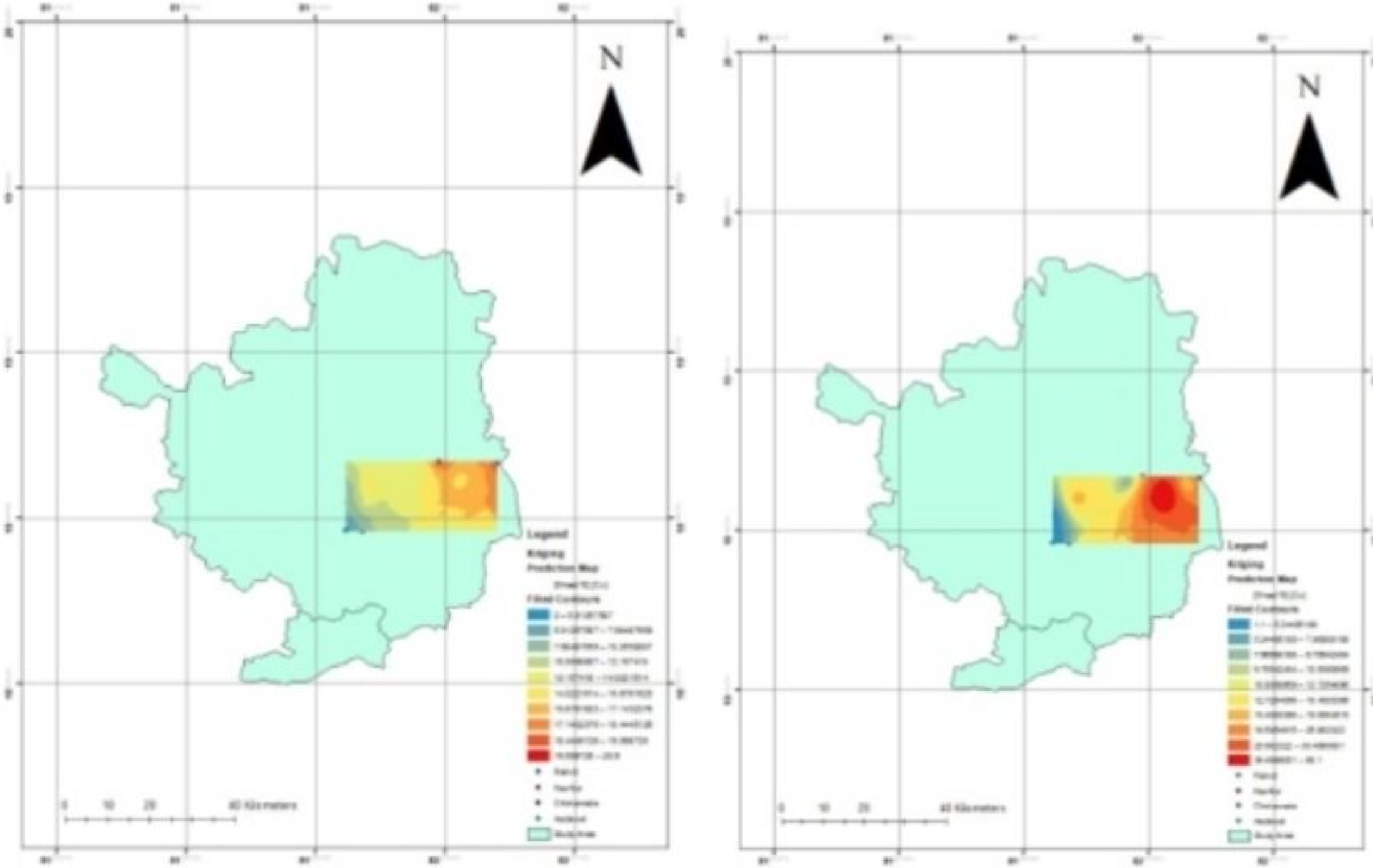
(a) OC at 0-20cm and (b) OC at 20-40cm



(a) (b)

Figure 7

(a) Fe at 0-20cm and (b) Fe at 20-40cm



(a) (b)

Figure 8

(a) Ni at 0-20cm and (b) Ni at 20-40cm

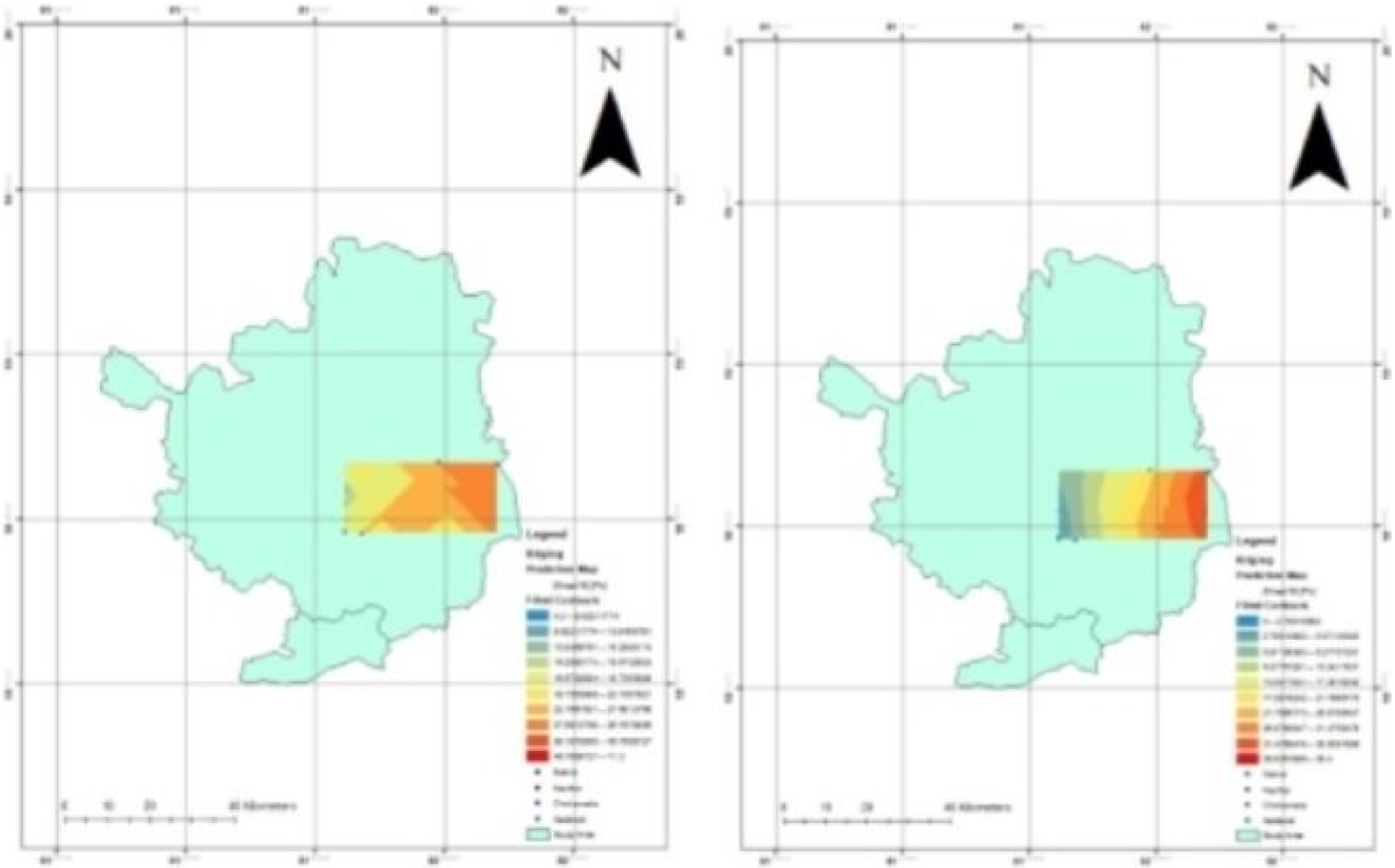


Figure 9

(a) Cr at 0-20cm and (b) Cr at 20-40cm