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Mapping Surface Soil Characteristics of Barren Land by Using Geospatial Technology in NCT of Delhi

Sangita Singh# and Kiranmay Sarma*
[1]University School of Environment Management,
Guru Gobind Singh Indraprastha University, Sector 16C, Dwarka, New Delhi-110078, India
#Email: sangita.usem.007163@ipu.ac.in
*Email: kiranmay@ipu.ac.in

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Abstract

Mapping of barren land is considered to be of great concern as it is the most increasing land use type around the world. Mostly soil was assessed in terms of agricultural purposes but there is a need to assess the soil characteristics of barren lands as well. The present study aimed to determine and map the spatial variability in chemical properties of barren lands of NCT of Delhi. A total number of 22 sampling sites were selected and soil surface samples were collected during January 2018. The parametric analysis was done for soil pH, Electrical Conductivity (EC), Bulk Density (BD), Organic Matter (OM), Gypsum Requirement, Calcium Carbonate (%), Soil Calcium and Soil Magnesium. The results showed that the mean value ranges for pH (6-8.2), EC (70-6100 μs^{-1}), BD (1.46-2.79), OM (1.84-17.67), Gypsum Requirement (154.08-175.65 tons/ha), Calcium Carbonate % (41.85-132.52) were obtained. The study utilises the data for the thematic map generation for interpolation by using kriging tool. Interpolation maps were prepared for each of the parameter. From the analyzed description, a linear correlation existed between some of the parameters (soil pH and EC) followed by Gypsum requirement and calcium carbonate percentage. The study provides an idea for locals, administrators, policy makers as well as stakeholders to use the barren lands for developing green spaces in city or recreational sites. This study is an approach towards integration of field data with GIS integration using ArcGIS. Till date no study has been carried out in Delhi region regarding the mapping of barren fields.

Introduction

Soil is an ecologically essential component for maintaining and sustenance of several life processes (Minasny and McBratney 2010; 2016). It not only supports the biological components (biodiversity protection, food and water security) but also the atmospheric ones (carbon sequestration). It stores about three folds of organic carbon than plants biomass of terrestrial ecosystem and two fold of what present in atmosphere (Grunwald, 2010). Several studies considered soil as a top priority for global environmental policy agenda (Arrouays *et al*., 2017). Earlier, soil was tested only for the agricultural purposes (Scull *et al.,* 2003; Padarian *et al.,* 2019). Due to the latest advancements in terms of digital analysis and modelling of various data (Lagacherie *et al.,* 2006), a record for soil is also necessary not only in terms of agriculture but for environmental prospects (Ashtekar and Owens, 2013).

Soil mapping has evolved as a discipline linking field with laboratory and field observations with quantitative methods to infer on spatial patterns of soils (Shi *et al.,* 2009). The technological advances in the field of remote sensing, Global Positioning System (GPS) and Geographic Information System (GIS) have augmented the efficiency of soil survey (Zhang and Hartemink, 2019). The conventional methods used for soil mapping were slow, time consuming, expensive along with that there accuracy and precision were not reliable. It not only reduces the sampling field cost and laboratory analysis but also provide a general idea of the distribution statistically (Zhang *et al*., 2017). Mapping of soil characteristics have gained immense attention from last two decades (Zare *et al*., 2018). Although soil mapping is not a new concept, earlier soil maps were prepared for military purposes, food and fibre production (agriculture) based on land use (Zeraatpisheh *et al*., 2017). Now with advancement of technologies the purpose is changed to have a diverse approach of high resolution, pixel based soil products which can be associated later with error assessment (Boettinger *et al*., 2008; Yang *et al.,* 2011).

The conventional soil survey methods were relatively slow and expensive in contrast spatial soil databases were not precise enough to facilitate the soil information. The spatial variability in soil properties within a defined area can be mapped using an interpolation technique. In all the interpolation techniques, Kriging was considered to be more reliable in estimating the non sampling locations. It includes the prediction of unobserved locations from the observed variables by mapping the same in a GIS interface (Vaysse *et al*., 2015). The estimation of information provided by kriging of non sampled locations shows strong statistical linear unbiased data. However, the reliability of interpolation and spatial maps variability depends on the adequate sampling data. Various studies worldwide have included the methodology to introduce geostatistics to assess soil characteristics spatially. Among them some of them have used kriging to determine soil characteristics by parametric analysis. Pandey *et al*. (2018) worked on soil mapping of Bara district in Nepal by using kriging in which they carried out the study in 23 village development committees. They analysed soil parameters and correlated statistically with different type of models. In southern Spain, Lopez-Granados *et al*. (2005) estimated the spatial variability of organic matter (OM), pH, and potassium (K). Similarly, in Northeast China Zhang *et al*. mentioned seasonal spatial variability maps of nitrogen (N), phosphorus (P) and K. The main objective of this study was to determine and map the spatial distribution of variability in soil chemical properties of barren lands in the entire Delhi region. The study helps in certain way to have an idea of how the barren land is behaving in terms of its health. Once the lacking part is tracked it can be managed accordingly.

Materials and Methods

Study Area: Delhi, the National Capital Territory of India is a metropolitan city comprising a total area of 1,483 sq. km bordered by Haryana (West, South, and North) and Uttar Pradesh (East). Delhi lies between $28^0 24'17''$-$28^0 53'00''$ N latitudes and $76^0 50'24''$-$77^0 20'37''$ E longitudes. It is divided into eleven districts viz., New Delhi, North Delhi, North West Delhi, West Delhi, South West Delhi, South Delhi, South East Delhi, Central Delhi, North East Delhi, Shahdara, and East Delhi. Delhi, the metropolitan city is among the few cities undergoing rapid urbanization change in land use pattern in terms of soil health and quality. The dominant soil type mainly consists of alkaline and saline soils. Due to extensive urbanization the study area has experienced phenomenal change during last two decades in terms of farmland and barren land loss. In terms of weather, the main source of precipitation the monsoons are the dominating parameter. There are four seasons accordingly pre-monsoon, monsoon, post monsoon and winters. Average annual rainfall reported to be 790mm and temperature variation to be 47-48^{0}C in summers and 1-2^{0}C in winters.

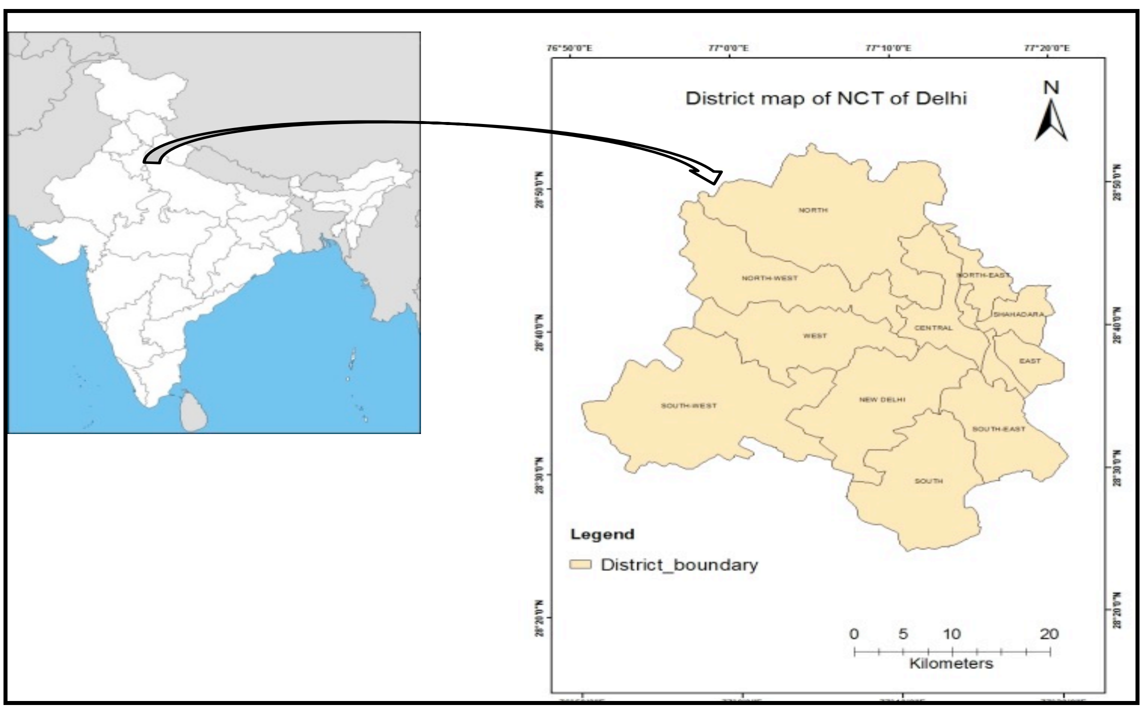

Figure 1: District map of NCT of Delhi

Soil sampling and analysis

Soil surface samples (0 to 10cm) were collected during January 2018 using a soil auger in the study area. From the total land area those locations were selected which are having no or sparse vegetation. The sites were barren lands which are not used for any purpose. The study was carried out in all the 11 districts of Delhi. A total of 2 sites were selected from each of the district contributed to 22 samples (Table 1) which were analysed for pH, Electrical conductivity (EC), Bulk Density, Organic Matter (OM), Gypsum Requirement, Calcium Carbonate (%), Soil Calcium and Soil Magnesium (Table 2). Collected soil samples were air dried at normal temperature and sieved through a 2 mm sieve for chemical analysis conducted at the Earth science lab, Guru Gobind Singh Indraprastha University.

Table 1: Selected study sites with latitude and longitude

Sites	**District**	**Site name**	**longitude**	**latitude**
S1	West Delhi	Bakkarwala	77.01881	28.65901
S2	North west Delhi	Kanjhawala	77.00424	28.72355
S3	North Delhi	Bawana	77.04455	28.77973
S4	North Delhi	Bakoli	77.14638	28.80960
S5	Central Delhi	Badarpur majra	77.20874	28.76359
S6	Shahdara	Usmanpur	77.25515	28.70233
S7	North east Delhi	Khazoori khas	77.25722	28.72345
S8	North east Delhi	Sonia vihar	77.25390	28.73745
S9	Shahdara	shahdara	77.28613	28.67482
S10	East Delhi	Gazipur	77.32720	28.63235
S11	East Delhi	Mayur vihar	77.28673	28.60835
S12	West Delhi	Punjabi bagh	77.12420	28.66200
S13	North West Delhi	Wazirpur	77.16380	28.70020
S14	Central Delhi	Kamla nagar	77.18937	28.67549
S15	South East Delhi	Jangpura	77.18937	28.67544
S16	South East Delhi	Aali village	77.29921	28.51572
S17	South Delhi	Asola	77.20853	28.44255
S18	South Delhi	Santmat ashram	77.19411	28.49457
S19	New Delhi	Vasant kunj	77.15758	28.52152
S20	New Delhi	Dhaula kuan	77.15450	28.59457
S21	South West Delhi	Dwarka	77.02686	28.58687
S22	South West Delhi	Ujwa village	76.91886	28.60088

Kriging: It is a type of spatial interpolation technique where non sampling locations were predicted according to the sampling ones. Several studies have reported this method good in terms of prediction studies. It is beneficial over the other methods as IDW and other forms as in this the error percentage can also be minimised.

Ordinary kriging is based on the assumption that the mean of the process is constant and invariant within the spatial domain. Expressed as:

$$\mathbf{z(x) = \mu + e(x)}$$

where, $\boldsymbol{\mu}$ is an unknown constant and generally considered the mean value of the regionalized variable; $\boldsymbol{z(x)}$ is the value of regionalized variable at any location x with stochastic residual $\boldsymbol{\varepsilon(x)}$ with zero mean and unit variance (Gupta and Sarma, 2014; Pandey *et al.,* 2018; Mondal *et al.,* 2017).

Results and Discussion

Parametric analysis: Recently with the confinement of data the techniques to estimate and predict soil attributes have also gained precision. Statistical analysis of soil properties were done including calculating minimum, maximum, mean, standard deviation (SD), skewness, kurtosis and coefficient of variation (CV%). The study includes the presentation of final data in terms of interpolation maps. The main purpose to use this interpolation was to minimize the error percentage including estimating the non sampled locations (Srivastava and Ramanathan, 2008; Santra *et al.,* 2017; Nussbaum *et al.,* 2018). Interpolation is used as a predictive technique as practically it is not possible to estimate large no of samples. The same was mentioned in other studies as well. Interpolation technique estimates the weighted sums of the adjacent sampled values. For each of the parameter the rating charts followed were, based on recommendations given by the Department of Agriculture and Cooperation Ministry of Agriculture (GoI) the analysed parameter were categorised accordingly (Table 3). In order to further understand the spatial variability distribution regression and correlation analysis were also done.

Table 2: chemical parameters and their methods

Parameters	**Methods**	**unit**
Soil pH	Electrometric method	-
Electrical conductivity (EC)	Conductometric method	$dS.m^{-1}$
Bulk density	Weighing bottle method	-
Organic Matter (OM)	Walkley and black wet oxidation method	%
Gypsum Requirement	Complexometric titration	-
Calcium Carbonate%	Complexometric titration	%
Soil Calcium and Magnesium	Versenate titration method	-

Table 3: Rating and class values by DIRD, Pune (2009)

Parameter	Unit	Rating	Class
Soil pH	-	<4.5	Strongly acidic
		5.3-6.0	Moderately acidic
		6.6-7.0	Neutral
		7.6-8.3	Moderately alkaline
		>9	Extremely alkaline
EC	$dS.m^{-1}$	0 to 1	Good soil
		1 to 2	Poor seed emergence
		2 to 4	Harmful to sensitive crops
		Above 4	Harmful to most of the crops
Bulk density	-	1.6	Sandy soil
		1.4	loam
		1.3	Silt loam
		1.1	clay
% organic carbon	%	Less than 0.20	Very low
		.021 to 0.40	Low
		0.41 to 0.60	Moderate
		0.61 to 0.80	Moderately high
		0.81 to 1.0	High
		More than 1.0	Very high
Calcium carbonate %	%	Less than 1	Low
		1-5	Medium
		5-10	High
		10-15	Very high

Description of chemical properties includes the statistical part related with the present estimated values. The statistical summary used in the study is represented in table 4. The heterogeneity and variability was interpreted using the coefficient of variation (CV%). The mean ranges were from 0.06 (soil pH) to 1.38 (soil EC) along with the standard deviation from 0.33(BD) to a high of 1367.12(EC). Among the parameters with a mean of 7.60, the range of pH was from 6 to 8.2, 70 to 6100 with a mean of 989.95 for EC. Apart from the chemical properties of parameters two of the macronutrients were also analysed. Namely calcium and magnesium with a range of 10-130 (mean=49.73) and 0.5-14 (mean=6.82) respectively. The spatial distribution of each soil property was mapped by characterizing of the similar group of values by interpolation technique.

High variability was observed, maximum deviation was observed in EC values. Whereas from the above table 4 it can also be concluded that, a linear correlation existed between some of the parameters (soil pH) followed by Gypsum requirement and calcium carbonate percentage.

Generation of soil maps: Maps depicting soil chemical properties were produced using kriging in ArcGIS software. For each of the parameters thematic maps were prepared depicting the values at sampling locations (Brevik *et al.,* 2016; Boettinger *et al.,* 2008).

Based on the data estimated the results were represented according to the range and validation of data (Biswas and Zhang, 2018; Behrens *et al.,* 2006; 2010).

Table 4: Statistical variation in parameters

Parameter	Min	Max	Mean	SD	Skewness	Kurtosis	CV%
Soil pH	6	8.2	7.60	0.47	-1.83	5.39	0.06
EC	70	6100	989.95	1367.12	2.79	9.15	1.38
Bulk density	1.46	2.79	2.21	0.33	-0.57	0.55	0.14
% organic matter	1.84	17.67	12.15	3.93	-0.92	0.77	0.32
Gypsum requirement (tons/ha)	154.08	175.65	166.75	6.14	-0.43	-0.30	0.03
Calcium carbonate %	41.85	132.52	77.04	23.66	0.35	-0.14	0.30
Soil calcium	10	130	49.73	30.70	1.02	0.84	0.61
Soil magnesium	0.5	14	6.82	3.36	0.21	-0.46	0.49

Soil pH: Done by electrometric method, based on measuring the e.m.f. (millivolts) of reference buffer with the test solution. Generally defined as the negative logarithm of the active hydrogen ion(H^+) in the soil solution. It is a measure of soil sodicity, acidity or neutrality. It is an important factor as it facilitates the nutrient conditions in soil. Generally low values of pH indicates acidic nature and alkaline when higher. In the study it was observed that most of the sites reported to be showing alkaline nature of soil (Tyagi and Sarma, 2018). The values ranged from 6 to a high of 8.2 with 7.60 as overall mean value (Table 4). It was also reported that the loss of basic Cation and other nutrients through erosion and leaching leaves the hydrogen and aluminium ions that contributes to soil acidity (Gupta and Sarma 2013; 2014). Most of the microbial activities and soil processes are favoured by a specific pH range. Highest values reported to be at S-3 (Bawana), S-5 (Badarpur Majra), S-11(Mayur Vihar) and S-16 (Aali village) lowest to be at S-12 (Punjabi bagh).

Electrical conductivity: It is measured for the ionic composition present in soil sample. Normally reported in $dS.m^{-1}$, the value gives information on the total amount of the soluble salts. Salted soils are generally classified for two criteria, one on the basis of total soluble salts and another for sodium absorption ratio. The salts having higher sodium content or organic matter content shows significantly high values that can be estimated by analysis. Similar studies were also reported by various researchers (Manchanda *et al.,* 2002; Hu *et al.,* 2005; Gupta and Sarma 2013; 2014). In the study area the range for EC was found to be 70-6100 with a mean of 989.95, from the above values because of the high heterogeneity of soil samples the maximum variation was observed. The highest range of value was reported at S-1 (Bakkarwala) close to agricultural areas and lowest was observed at various locations throughout.

Bulk density: It is a measure of porosity of soil. It is of great importance than particle density in understanding the physical condition of soil. It is generally defined as the ratio of the mass of the oven dry soil to its bulk volume (Kumar et al., 2016). The pore space (%) for sandy soil (40), loam (47), silt loam (50) and clay (58) are predefined. The range estimated were from 1.46-2.79 with 2.21as the mean value. Highest value was observed at site 10 (Gajipur) and lowest at site 12 (Punjabi bagh).

Organic matter%: It is defined as the total % of carbon multiplied by a factor of 1.724. It is generally used to define the organic content in soil. Lower values of OM leads to several deficiencies in nutrients of soil whereas higher values indicate a healthy soil (Sreenivas *et al.,* 2016; Mishra and Mapa, 2019; Minasny *et al.,* 2006). This single parameter can change the whole dynamics of soil. The values ranges from 1.84 to 17.67 where 12.15 as the mean value observed. The highest value was reported to be at site 4 and 7. As suggested in other studies, some of the factors directly depict the content of OM in soil (Zhang *et al.,* 2010; Zhao *et al.,* 2016; Dembele *et al.,* 2016). It can be low because of high OM decomposition rate or it can be due to high air temperature which decreases the total organic carbon (SOC) of soil. Higher value OM results in lower values of bulk density which indicates good pore space and a healthy soil (Kumar *et al.,* 2016).

Gypsum requirement: For the saline and sodic soil, it is an attempt to measure the quantity of gypsum (calcium sulphate) required to replace the sodium from the exchange complex (Martin *et al.,* 2016; Kempen *et al.,* 2019; Guo *et al.,* 2019). The sodium so replaced is removed through leaching of soil. The soil treated with gypsum becomes dominated with calcium in the exchange complex. The range varies from 154.08 to 175.65 with a mean of 166.75, highest value was reported to be at S-4 (Bakoli) and S-22 (Ujwa village) lowest at S-7 (Khazoori khas) and S-8(Sonia vihar).

Calcium carbonate: Also known as lime content in soil. Lime aids in preserving soil structure and may serve as a source of calcium in the reclamation of alkali soil (Grinand *et al.,* 2017; Grimm *et al.,* 2008). The maximum value was reported to be at site 10(Gazipur) and lowest at site 2(Kanjhawala) and 4(Bakoli).

Calcium and magnesium: Apart from the chemical properties, two of the macronutrients were also determined namely calcium and magnesium. Although the distribution of the two varies, their ionic component serve as a nutrient in the Cation exchange capacity of soil constitutes to 60-80% of total exchangeable cations (Meena *et al.,* 2006; Antwi *et al.,* 2016). Calcium and magnesium clay increases the physical condition of soil. It develops a good crump structure by virtue of the flocculation and aggregation of primary particles allow free movement of water without stagnation and contains suffient air for the proper aeration in soil. Such soils are considered to be healthy soils. For calcium highest value reported at site 10 (Gazipur) and lowest at site 2(Kanjhawala) and 3(Bawana), for magnesium highest at site 13 (Wazirpur) and lowest at site 19 (Vasant kunj).

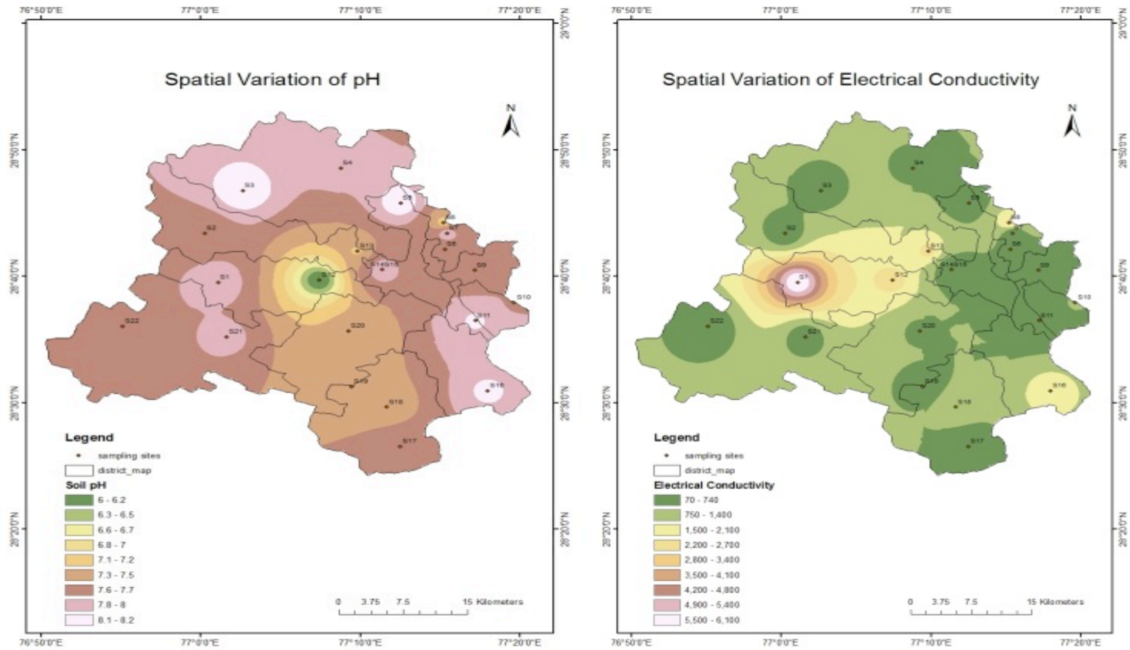

Figure 2: Spatial variation of soil pH and EC

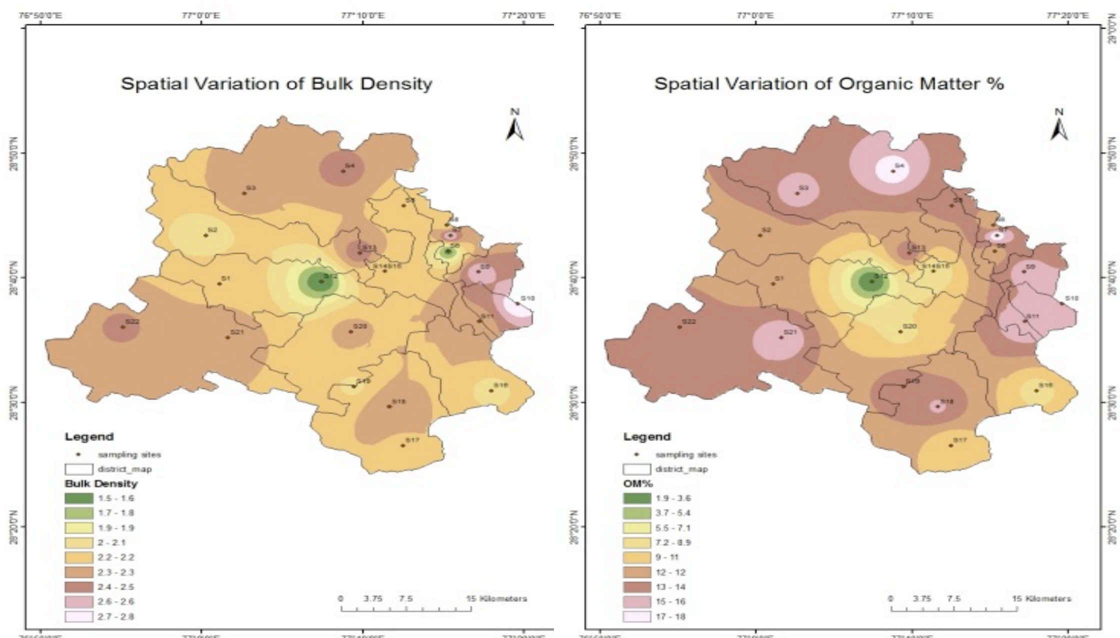

Figure 3: Spatial variation in bulk density and OM (%)

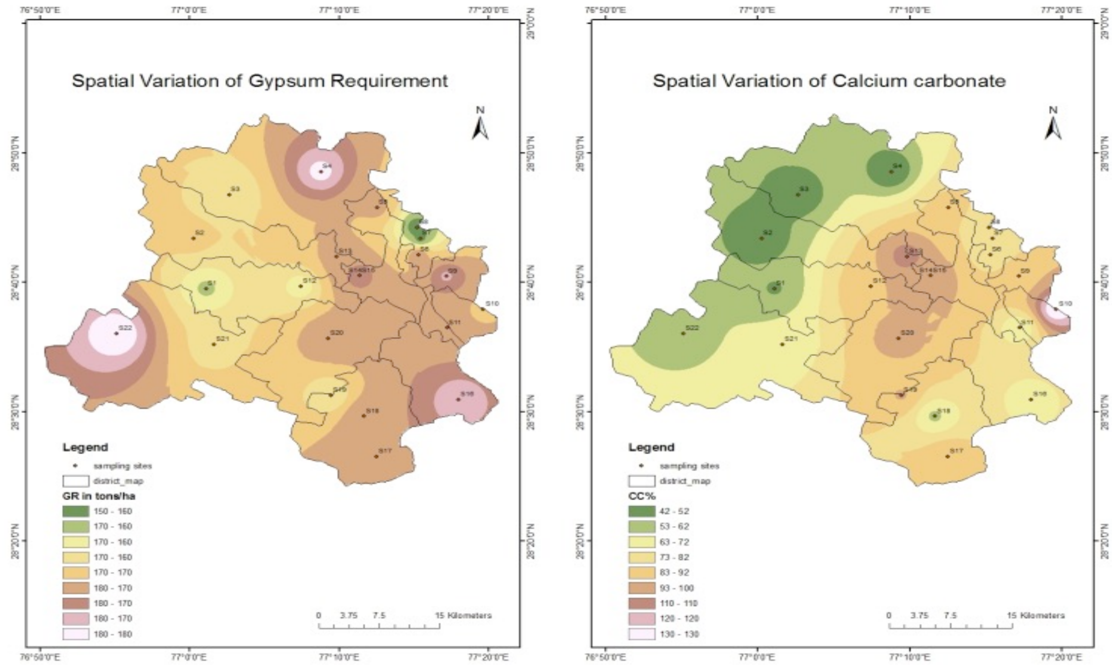

Figure 4: Spatial variation of gypsum requirement and calcium carbonate (%)

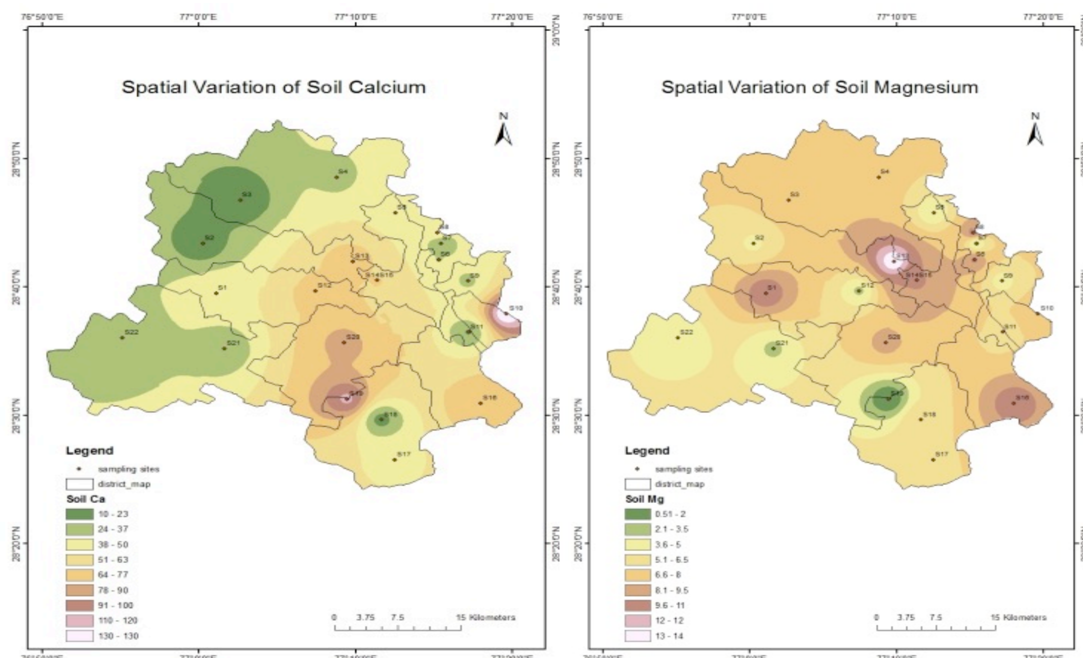

Figure 5: Spatial variation in soil calcium and magnesium

Conclusions

From the above observations it can be concluded that the application of the geostatistical approach, improves the description of spatial variability for soil chemical properties on a field scale. The descriptive statistics depicted that few of the parameters were inter-related and linearly correlated as well. Interpolation techniques serves as a good measure for predicting the non sampled locations as practically it is impossible to map each and every kilometre or to have a large sample size. The maps were found to have good description without additional explanation. The present study shall be helpful in predicting the role of soil mapping in terms of various parameters of soil. The study provides an idea for policy makers to use the barren lands for developing green spaces in city or recreational sites, along with this seasonal variation can also be done for providing better idea or for understanding the conditions efficiently.

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Authors Contribution: *Sangita Singh (Ph.D. Scholar) performed the research work, data collection and writing of the manuscript and also the corresponding author; Kiranmay Sarma (Associate Professor) has contributed in GIS part and its interpretation including the editing of manuscript.*

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