

Original Research Article

Assessment of Spatial variability of soil properties in Gopalapur microwatershed, Gundlupet Taluk, Chamaraajanagar District, Karnataka, India

ABSTRACT

Aim: Evaluation of geostatistical tools ~~were~~ used for assessing top soil variability to explore a scientific basis for predicting soil properties and to derive site specific nutrient management strategies.

Study Design: Grid soil survey for microwatershed level for soil nutrient study and an assessment of spatial variability of soils. Three interpolation methods such as ordinary kriging, inverse distance weighting (IDW), and spline were used to generate spatial distribution of different soil properties.

Place and Duration of Study: Gopalapur micro-watershed in Gundlupet tehsil 

Methodology: The Grid survey at 250 × 250 m interval was carried out and collected 97 georeferenced surface soil samples (0-15 cm) from five land use systems such as agriculture, scrubland, forest, grassland and fallow land. Three interpolation methods such as ordinary kriging, inverse distance weighting (IDW), and spline were used to generate spatial distribution of eleven soil variables viz., pH, EC, organic carbon, available K₂O, P₂O₅, sulphur / boron and DTPA extractable Cu, Fe, Mn, and Zn. Experimental variograms were fitted with the exponential, spherical, Gaussian and linear models using weighted least squares. The model with the smallest residual sum of squares (RSS) was further ~~interpolated~~  to find the number of neighbours that returned the best cross-validation result. The choice of the exponent value for IDW and splines as well as the number of the closest neighbours to include was decided from the root mean squared error (RMSE) statistic,

obtained from a cross-validation procedure.

Results: On this experimental field, ordinary kriging performed best for topsoil and exponential method of kriging gave the best results with smallest residual sum of squares (RSS). We conclude that ordinary kriging is superior method with the least RMSE and lowest RSS value for interpolation of topsoil spatial distribution.

Conclusion: The study shows that Ordinary kriging interpolation method is superior to geostatistical and deterministic methods. The performance of the exponential semi-variogram model is outstanding with ordinary kriging interpolation techniques. Inverse distance weighting (IDW) and spline methods.

Keywords: Cross-validation, Geostatistical interpolation, Kriging, Spatial prediction, Soil properties, Gopalapur, Watershed

1. INTRODUCTION

The utilization of mathematical and statistical functions for advanced surface modelling using deterministic geostatistical interpolation techniques have been regularly put into test in different fields of sciences. Studies have also proved that the performance of interpolation techniques heavily depends on the type of modelled phenomena, geometrical configuration of the samples, spatial resolution, world region and others ([1], [2], [3]).

Spatial variability of topsoil is an important indicator of soil quality, as well as distribution in the terrestrial ecosystem, for ecological modeling, environmental prediction, precision agriculture, and natural resources management ([4], [5], [6]). Different statistical and geostatistical approaches have been used in the past to estimate the spatial distribution of Soil ([7], [8]). Classical statistics could not make out the spatial allocation of soil properties at the unsampled locations. Geostatistics is an efficient method for the study of spatial allocation of soil characteristics and their inconsistency and reducing the variance of assessment error and execution costs ([9], [6], [10]). Earlier researchers have applied geospatial techniques to appraise spatial association in soils and to evaluate the

geographical characteristics [4]. Behera and Shukla, [11] reported that ordinary kriging (OK) and cokriging methods were better than inverse distance weighting (IDW) method for prediction of the spatial distribution of soil properties. Zare-mehrjardi et al. [12] used three different techniques including kriging, IDW and -radial basis function (RBF) for prediction of the levels of the soil salinity, acidity and organic matter, where as ordinary kriging is the most common type of kriging in practice and provides an estimate of surface maps of soil properties [13].

The accuracy of interpolation methods for spatially predicting soil properties has been analysed in several studies. There was a comparison between inverse distance weighting (IDW), ordinary kriging and lognormal ordinary kriging for soil properties phosphorous (P) and potassium (K) from 30 experimental fields by [14]. They found that if the underlying dataset is lognormally distributed and contains less than 200 points, lognormal ordinary kriging generally out performs both ordinary kriging and IDW; otherwise, ordinary kriging is more successful. Further Kravchenko and Bullock [15] also found ordinary (isotropic) kriging to be a better method than IDW for interpolating pH. In fact they judged splines to be a better than both IDW and kriging. In contrast, better results were reported for soil organic matter and nitrogen using IDW over kriging ([16], [17]). Therefore, the objective of this study was to compare based interpolation techniques for estimating the spatial distribution of soil properties and applied cross validation to evaluate the accuracy of interpolation method through the root mean square error (RMSE) measurement in Gopalapur microwatershed, Gundlupet taluk, Chamarajanagar district, Karnataka.

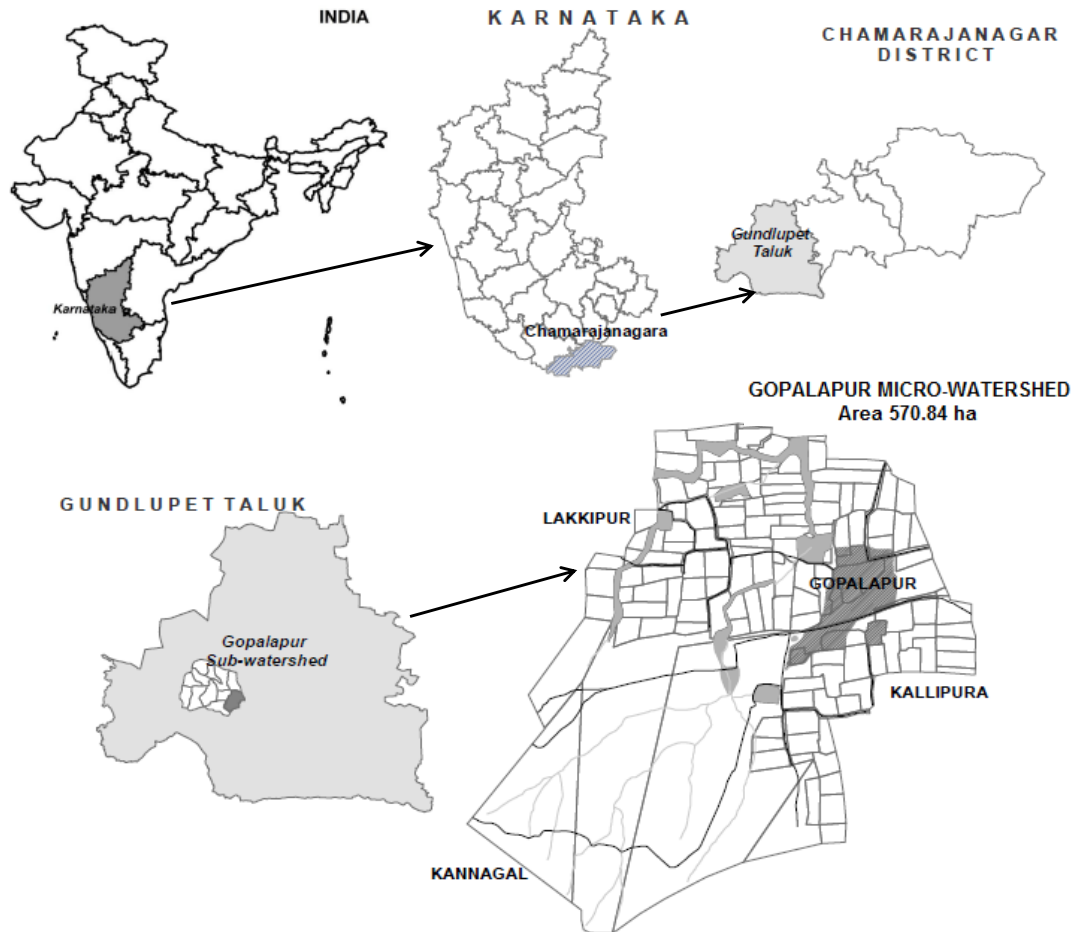
2. MATERIAL AND METHODS

2.1. Study area

The study was conducted in Gopalapur microwatershed, Gundlupet taluk, Chamarajanagar district, Karnataka, India. It is extended between $11^{\circ} 43' - 11^{\circ} 45' N$ latitudes and $76^{\circ} 34' - 76^{\circ} 36' E$ longitudes, covering an area of about 570.84 ha, bounded

61 by Kannagal, Lakkipur and Kallipura villages (Fig. 1). It has a total geographical area of 1.56
 62 M ha with 0.74 M ha under cultivation of which 0.22 M ha is irrigated. The mean elevation
 63 ranges from 450 to 900 m (S); most part of the zone is situated at 800-900 m.

64



65

66 **Fig. 1.** Location map of Gopalapur microwatershed

67

68 The major soils are Annurkeri (ARK) series (Rhodic PaleustalFs), Devarahalli (DRH)
 69 series (Typic RhodustalFs, Gopalapura (GPR) series (Typic RhodustalFs), Hindupur (HDR)
 70 series ((Paralithic Ustorthunts), honnegaudanahalli (HGH) series (Typic haplustepts),
 71 Kallugaudanahalli (KDH) series (Typic PaleustalFs), kallipura (KLP) series (Typic
 72 RhodustalFs) and Maddinahundi (MDH) series (Typic RhodustalFs). The average annual

73 rainfall ranges from 670 to 890 mm, of which about 55 to 75 per cent is received during the
74 kharif season. The climate is characterized as ustic soil moisture regime and
75 isohyperthermic soil temperature regime [18].

76

77 **2.2. Field survey**

78

79 Grid sampling technique was used for sampling in field with total 97 soil samples
80 were collected from different field including agriculture, scrubland, forest, grassland, and
81 fallow land of the area of Gopalapur microwatershed. A portable global positioning system
82 (GPS) was used to record each sample site. Coordinates of the grid points within the field
83 were recorded using GPS system (GARMIN etrex-30 x model). Surface soil samples at
84 depth of 0-15 cm were collected at a distance of 250 X 250 m grid from each site and mixed
85 well into a composite soil sample. Grid soil samples ~~should be~~ taken at a specific point,
86 either within the grid cell or at intersection points between grid cells, consisting of 8-10 cores
87 per sample were taken within a 10-foot radius (Fig. 2). Soil samples were air-dried and
88 passed through a 2 mm sieve for laboratory analysis.

89 **2.3 Laboratory methods**

90 Soil samples were air-dried at room temperature (30 °C) for some time, then grinded
91 and screened ~~before~~ starting the analyses. Soil reaction was determined in 1:2.5 soil/water
92 suspension using standard pH meter (Hanna instrument) and electrical conductivity using
93 conductivity meter (Toshniwal insts. Mfg.Pvt. Ltd, TC 17). Soil organic carbon (OC) was

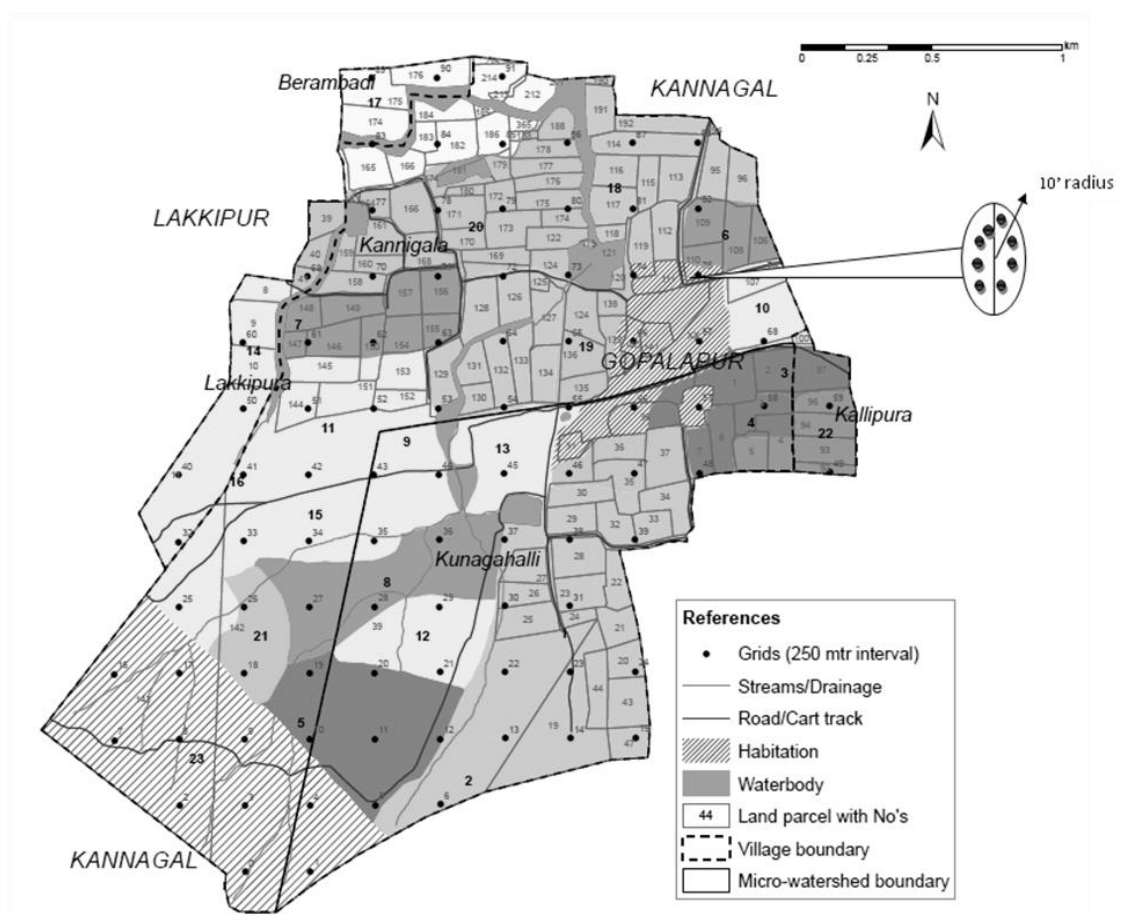


Fig. 2. Soil Map of Gopalapur microwatershed

estimated using the wet digestion method as described by [19] and expressed in percentage. 1N ammonium acetate (NH_4OAc) solution at pH 4.5 extractable potassium (K^+) was determined by Flame photometer [20]. DTPA-extractable micronutrients Fe, Mn, Zn and Cu were extracted by 0.005 M DTPA at pH 7.3 according to the method of [21] and the concentration of the micronutrients were estimated using atomic absorption spectrophotometer (Agilent Technologies, 200 series AA model). Available phosphorus determined by Olsen method [22] and available S by CaCl_2 extraction method [23]. The available Boron estimated by The Azomethine-H method by using Lab India (analytical) UV/VIS spectrophotometer [24].

108 2.4. Interpolation methods

109 2.4.1. Ordinary kriging

110 Ordinary kriging is the basic form of kriging. The prediction by ordinary kriging is a
 111 linear combination of the measured values. The spatial correlation between the data, as
 112 described by variogram, determines the weights. The presence of a spatial structure where
 113 observations close to each other are more alike than those that are far apart (spatial
 114 autocorrelation) is a prerequisite to the application of geostatistics [25]. The experimental
 115 variogram measures the average degree of dissimilarity between unsampled values and a
 116 nearby data value [26], and thus can depict autocorrelation at various distances. The value
 117 of the experimental variogram for a separation distance of h (referred to as the lag) is half
 118 the average squared difference between the value at $z(x_i)$ and the value at $z(x_i + h)$ [27]:

$$119 \quad \hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i) - z(x_i + h)]^2 \quad (1)$$

120 where $N(h)$ is the number of data pairs within a given class of distance and direction.
 121 If the values at $z(x_i)$ and $z(x_i + h)$ are autocorrelated the result of Eq. (1) will be small,
 122 relative to an uncorrelated pair of points. From analysis of the experimental variogram, a
 123 suitable model (e.g. spherical, exponential) is then fitted, usually by weighted least squares,
 124 and the parameters (e.g. range, nugget and sill) are then used in the kriging procedure.

125 2.4.2. Inverse distance weighting (IDW) method

126 Similar to kriging, inverse distance weighting (IDW) directly implements the
 127 assumption that a value of an attribute at an unsampled location is a weighted average of
 128 known data points within a local neighborhood surrounding the unsampled location. The
 129 formula of this exact interpolator [28], [29]):

$$130 \quad x(x_0) = \frac{\sum_{i=1}^n z(x_i) d_{ij}^{-r}}{\sum_{i=1}^n d_{ij}^{-r}} \quad (2)$$

Where x_0 is the estimation point and x_i are the data points within a chosen neighborhood. The weights (w) are related to distance by d_{ij} , which is the distance between the estimation point and the data points. The IDW formula has the effect of giving data points close to the interpolation point relatively large weights whilst those far away exert little influence. The higher the weight used the more influence points close to x_0 are given.

136 **2.4. 3. Splines method**

The Spline method can be thought of as fitting a rubber-sheeted surface through the known points using a mathematical function. In Arc GIS, the spline interpolation is a radial basis function (RBF). These functions allow analysts to decide between smooth curves or tight straight edges between measured points. Splines consist of polynomials, which describe pieces of a line or surface, and they are fitted together so that they join smoothly [30]. Splines produce good results with gently  surfaces, and thus are often not appropriate when there are large changes in the surface values within a short horizontal distance.

145 **2.5. Data transformation and interpolation**

Geostatistical analysis is best performed on gaussian distribution  When non-normality is apparent, transformations of the data can assist to make it approximately normal. Skewness is the most common form of departure from normality. If a variable has positive skewness, the confidence limits on the variogram are wider than they would otherwise be and as a result, the variances are less reliable. A logarithmic transformation is considered where the coefficient of skewness is greater than 1 and a square-root transformation if it is between 0.5 and 1 [30]. Applying ordinary kriging to logarithmic transformed data is the essence of lognormal kriging. It is important to note that for logarithmic transformations, the back transformation through exponentiation tends to

155 exaggerate any error associated with interpolation, with extreme values the worst affected.
 156 To mitigate this effect, we use an unbiased back-transform as shown in Eq. (3) [26].

$$157 \quad \hat{y}(x_i) = \exp\left[\hat{y}(x_i) + \frac{\sigma^2(x_i)}{2}\right] \quad (3)$$

158

159 where $\sigma^2(x_i)$ is the corresponding lognormal kriging variance, $\hat{y}(x_i)$ the lognormal
 160 kriging estimate and $\hat{z}(x_i)$ is the corresponding back-transformed result in the original data
 161 domain.

162 2.6. Criteria for comparison through cross validation

163 It is common practice to use cross-validation to validate the accuracy of an
 164 interpolation [31]. Cross-validation is achieved by eliminating information, generally one
 165 observation at a time, estimating the value at that location with the remaining data and then
 166 computing the difference between the actual and estimated value for each data location [1].
 167 Cross-validation is an excellent scheme for solving the inconvenience of redundant data
 168 collection [33], [30]), and hence all of the collected data can be used for estimation. The
 169 cross-validation technique is used to choose the best variogram model among candidate
 170 models and to select the search radius and lag distance that minimises the kriging variance
 171 ([32], [33]). It is also used to assist in finding the best parameters from those tested for IDW
 172 [34] and splines. To compare different interpolation techniques, we examined the difference
 173 between the known data and the predicted data using the mean error (Eq. (4)), the root
 174 mean squared error (Eq. (5)), the average kriging standard error (Eq. (6)), the root mean
 175 square standardized prediction error (Eq. (7)) and the mean standardized prediction error
 176 (Eq. (8)). Eqs. (6)-(8) are only applicable to kriging as they require the kriging variance. Eqs.
 177 (4) and (5) are applicable to all of the interpolation techniques applied in this research.

$$178 \quad ME = \frac{1}{N} \sum_{i=1}^N \{Z(x_i) - \hat{z}(x_i)\} \quad (4)$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N \{z(x_i) - \hat{z}(x_i)\}^2} \quad (5)$$

$$\text{AKSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N \sigma^2(x_i)} \quad (6)$$

$$\text{RMSP} = \sqrt{\frac{1}{N} \sum_{i=1}^N \left(\frac{\text{ME}}{\sigma^2(x_i)} \right)^2} \quad (7)$$

$$\text{MSPE} = \sqrt{\frac{1}{N} \sum_{i=1}^N \frac{\text{ME}}{\sigma^2(x_i)}} \quad (8)$$

where $\hat{z}(x_i)$ is the predicted value, $z(x_i)$ the observed (known) value, N the number of values in the dataset and σ^2 is the kriging variance for location x_i ([35], [30], [14], [31]).

The mean error should ideally be zero, if the interpolation method is unbiased. The calculated ME, however, is a weak diagnostic for kriging because it is insensitive to inaccuracies in the variogram. The value of ME also depends on the scale of the data, and is standardized by dividing by the kriging variance to form the MSPE. An accurate model would have a MSPE close to zero. If the model for the variogram is accurate, then the RMSE should equal the kriging variance, so the RMSP should equal 1. If the RMSP is greater than 1, then the variability in the predictions is being underestimated, and vice versa. Likewise if the average kriging standard errors (AKSE) are greater than the root mean square prediction errors (RMSP), then the variability is overestimated, and vice versa ([35], [30]).

3. RESULTS AND DISCUSSION

3.1. Summary statistics and description of soil properties

The soil analysis of Gopalapur microwatershed showed that about 584 ha area varies in soil reaction  H ranges from strongly acidic to strongly alkaline (4.76 to 8.93). Mostly the soils are non-saline ranging from 0.007 to 0.56 dS m⁻¹ (Table 1) with high variation of 66.14%. In general, soils with a pH of between 5 and 7.5 present no problems. A pH above 9 indicates that salinity and sodicity are likely, although not all sodic and saline

soils are alkaline [36]. Soil organic carbon ranges from 0.22 to 1.5%. High co-efficient of variation 154.72 was observed in P_2O_5 with mean of $43.58 \pm 67.42 \text{ kg ha}^{-1}$ and 65.40% CV in K_2O with $373.38 \pm 244.18 \text{ kg ha}^{-1}$. The average value of sulphur and Boron is 8.21 ± 5.93 and $0.50 \pm 0.28 \text{ mg kg}^{-1}$. Co-efficient of variation (CV%) was observed high in all micronutrients with mean $\pm$ SD value of Cu 1.69 ± 0.67 , Fe 19.88 ± 17.11 , Zn 0.37 ± 0.36 and $19.03 \pm 11.45 \text{ mg kg}^{-1}$ of Mn respectively.

3.2. Interpolation and interpretation

Omnidirectional experimental variograms for all properties were calculated using Eq. (1). The exponential, spherical, gaussian and linear models were fitted to the experimental variogram and the model with the lowest residual sum of squares (RSS) was chosen as optimal. Table 2 summarises the RSS for each fitted model for all soil properties. The variogram of topsoils OC, K_2O , S, B, Cu and Mn appears to exhibit a pure nugget effect, which may be because of too sparse a sampling to adequately capture autocorrelation.

There is no clear range and sill, nor is the nugget variation small compared to the spatially dependent random variation. It is perhaps inappropriate to fit any model to this experimental variogram. Nonetheless, the exponential model was implemented as it returned the best fit. The fitted variogram for subsoil EC, depicting the range to be around 503.28 m (0.01 sill). The exponential variogram model provided the best fit to the experimental variogram. The experimental variogram for electrical conductivity appears erratic and without a distinct structure. It provided moderate to weak spatial dependence. The experimental variogram for organic matter appears to have quite good structure and a gradual approach to the range, with the exponential and linear model providing the best fit.

The number of closest samples chosen varied from 13 to 20, with a five-sample interval. The best-found kriging parameters were selected from the cross-validation results (Table 3). For topsoil EC the lowest root mean square error (RMSE) 0.1166 was found with a neighborhood of 13 points. The mean error (ME) and mean standardized prediction error (MSPE) suggests that the predictions are relatively unbiased. Since the average kriging

standard error (AKSE) is greater than the RMSE, the kriging variance is larger than the true estimation variance and indicates that the variogram model is overestimating the variability of the predictions, except two variables S and Zn. The root mean square standardized error (RMSP) also suggests the same since it is less than 1. It is likely that the RMSP is less than 1 because the fitted exponential model exceeds the observed variances (shown by the squares) at short lags, particularly the first lag (and also the third, fifth and seventh), and it is these lags that dominate the kriging systems [30]. 

Table 1. Summary statistics for soil properties

Soil property	N	Min	Max	Range	Mean ± SD	Median	Variance	CV (%)	Skew- ness	Kurto- sis
pH	97	4.76	8.53	3.77	6.80 ± 1.00	6.65	1.00	14.72	0.12	- 1.03
EC (dS m ⁻¹)	97	0.007	0.56	0.56	0.18 ± 0.12	0.17	0.01	66.14	1.00	0.73
OC (%)	97	0.22	1.50	1.28	0.65 ± 0.27	0.60	0.07	42.40	0.48	- 0.31
P ₂ O ₅ (kg ha ⁻¹)	97	2.29	316.02	313.73	43.58 ± 67.42	18.32	4546.57	154.7 2	2.44	5.66
K ₂ O (kg ha ⁻¹)	97	130.86	1275.37	1144.50	373.38 ± 244.18	311.73	59626.06	65.40	1.60	2.41
S (mg kg ⁻¹)	97	0.72	26.10	25.38	8.21 ± 5.93	7.24	35.21	72.25	1.01	1.05
B (mg kg ⁻¹)	97	0.01	1.08	1.07	0.50 ± 0.28	0.48	0.08	56.87	0.14	- 0.67
Cu (mg kg ⁻¹)	97	0.66	3.56	2.89	1.69 ± 0.67	1.54	0.46	40.04	0.66	- 0.19
Fe (mg kg ⁻¹)	97	2.53	68.80	66.27	19.88 ± 17.11	14.20	292.95	86.06	1.30	0.71
Zn (mg kg ⁻¹)	97	0.08	1.86	1.77	0.37 ± 0.36	0.24	0.13	96.54	2.55	7.02
Mn (mg kg ⁻¹)	97	3.37	42.50	39.13	19.03 ± 11.45	13.90	131.17	60.18	0.53	- 1.03

N = Number of samples, Min = Minimum, Max = Maximum, SD = Standard Deviation, CV= Coefficient of Variation.

The lowest RMSE was found using 20 and 13 nearest neighbours for subsoil S and Zn. The ME and MSPE suggests that the predictions are relatively unbiased. Given that the AKSE is smaller than the RMSE, the variability is being under predicted. Since the RMSP is

243 **Table 2. Descriptive statistics and geostatistical analysis of soil parameters in the**
 244 **topsoil (0-15 cm depth) at Gopalapur microwatershed.**

Soil properties	Spatial dependence	Nugget t	Partial sill	Sill	Range	Nugget / Sill	RMSP	RSS
<i>pH</i>								
Spherical	Moderate	0.4204	0.8000	1.22	2,549	0.34	0.91	8.2E -28
Exponential	Strong	0.1862	1.0297	1.22	2,549	0.15	1.01	7.0E -28
linear	Moderate	0.3561	0.8644	1.22	2,549	0.29	0.96	4.1E -29
Gussian	Moderate	0.5635	0.6705	1.23	2,549	0.46	0.89	1.6E -28
<i>EC (dS m⁻¹)</i>								
Spherical	Moderate	0.0095	0.0039	0.01	503.28	0.71	0.99	1.4E -30
Exponential	Moderate	0.0082	0.0053	0.01	503.28	0.61	0.99	2.5E -30
linear	Weak	0.0101	0.0034	0.01	503.28	0.75	0.99	7.2E -31
Gussian	Weak	0.0111	0.0024	0.01	503.28	0.82	0.99	3.4E -31
<i>OC (%)</i>								
Spherical	Moderate	0.0196	0.0335	0.05	1,108	0.37	1.00	5.1E -31
Exponential	Pure nugget	0.0	0.0545	0.05	1,108	0.0	0.99	2.1E -29
linear	Pure nugget	0.0	0.0545	0.05	1,108	0.0	0.98	3.4E -30
Gussian	Moderate	0.0275	0.0265	0.05	1,108	0.51	1.00	4.5E -30
<i>P₂O₅ (kg ha⁻¹)</i>								
Spherical	Moderate	2,735	2,116	4,851	1,100	0.56	0.99	1.4E -26
Exponential	Strong	27.70	4,784	4,812	739.60	0.01	0.93	3.7E -26
linear	Moderate	3,189	1,722	4,912	1,100	0.65	0.99	3.2E -26
Gussian	Moderate	3,189	1,722	4,912	1,100	0.65	0.99	3.2E -26
<i>K₂O (kg ha⁻¹)</i>								
Spherical	Moderate	29,438	34,589	64,027	2,475	0.46	0.92	7.2E -25
Exponential	Strong	16,375	49,305	65,681	2,475	0.25	0.91	1.3E -24
linear	Pure nugget	0.0	66,090	66,090	2,475	0.0	0.92	1.4E -24
Gussian	Moderate	36,876	27,815	64,692	2,475	0.57	0.95	9.2E -26
<i>S (mg kg⁻¹)</i>								
Spherical	Moderate	13.40	28.40	41.80	1,167	0.32	1.03	2.0E -27
Exponential	Pure nugget	0	42.45	42.45	1,167	0.0	1.09	5.6E -27
linear	Moderate	19.16	23.16	42.32	1,167	0.45	1.02	7.2E -28
Gussian	Moderate	19.16	23.16	42.32	1,167	0.45	1.02	7.2E -28
<i>B (mg kg⁻¹)</i>								
Spherical	Moderate	0.04	0.05	0.08	1,022	0.44	0.97	1.3E -30
Exponential	Strong	0.01	0.0714	0.09	1,022	0.17	0.97	3.5E -30
linear	Pure nugget	0.0	0.0863	0.09	1,022	0.0	0.97	8.7E -30
Gussian	Moderate	0.05	0.0346	0.08	1,022	0.59	0.96	1.0E -30
<i>Cu (mg kg⁻¹)</i>								
Spherical	Moderate	0.2780	0.2048	0.48	939.40	0.58	0.97	1.9E -29
Exponential	Moderate	0.1830	0.3095	0.49	949.47	0.37	0.97	1.4E -29
linear	Pure nugget	0.0	0.5007	0.50	949.47	0.0	0.97	3.9E -30
Gussian	Moderate	0.33	0.1529	0.49	904.99	0.69	0.97	2.0E -29
<i>Fe (mg kg⁻¹)</i>								
Spherical	Moderate	181.00	124.72	305.72	837.66	0.59	0.97	1.1E -26
Exponential	Moderate	114.81	198.40	313.22	837.66	0.37	0.96	5.8E -27
linear	Strong	57.63	258.25	315.88	837.66	0.18	0.96	2.7E -27
Gussian	Moderate	837.66	216.16	93.40	309.56	0.70	0.97	1.7E -27
<i>Zn (mg kg⁻¹)</i>								
Spherical	Moderate	250.76	145.77	396.53	823.90	0.63	0.88	4.9E -27
Exponential	Moderate	0.0843	0.0934	0.18	755.43	0.47	1.05	1.3E -30
linear	Moderate	0.0541	0.0920	0.15	843.85	0.37	0.96	7.2E -31
Gussian	Moderate	0.1000	0.0442	0.14	843.85	0.69	0.95	1.3E -30
<i>Mn (mg kg⁻¹)</i>								
Spherical	Moderate	42.64	123.21	165.85	1,280	0.26	0.94	2.9E -28
Exponential	Pure nugget	0.0	169.37	169.37	1,280	0.0	0.92	8.8E -27
linear	Moderate	61.37	91.36	152.73	1,506	0.40	0.95	5.1E -27
Gussian	Moderate	69.59	82.60	152.19	1,426	0.46	0.95	5.7E -27

245 Spatial distribution (S – Strong spatial dependence; M – Moderate spatial dependence; W – Weak spatial
 246 dependence; Pure Nugget – no spatial correlation), and spatial distribution model. RMSP, root mean square
 247 standardized prediction error.
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greater than 1, the kriging variance is smaller than the true estimation variance, possibly a result of the twelve lag being underestimated by the Spherical and exponential model. IDW was estimated with powers of one, two, three and four. The precision of IDW is also affected by the choice of the number of the closest samples used for estimation; hence, this was fifty nine neighbours for the two powers used. Cross-validation was used to find the best agreement between the measured data and the IDW estimates. In all cases, the best weighting parameter was found to be one. This suggests that the weights diminish slowly from the sample point over the chosen radius. Linear, quadratic and cubic splines were implemented using the same neighborhood variation as used for kriging and IDW. In all cases, the best exponent value was found to be three (cubic splines) suggesting that lower order polynomials were insufficient at representing the variation on the soils. The best cross-validation parameters for IDW and splines are shown in Table 4.

The ordinary kriging gave the lowest error (RMSE value) and lowest RSS value in the spatial interpolation of three soil depths among all geostatistical methods. and spline methods gave the best results among the deterministic methods. Overall the performance of the geostatistical methods was thoroughly compared with that of the deterministic methods. Ordinary kriging and related geostatistical techniques incorporate spatial autocorrelation and statistically optimize the weights. Ordinary kriging methods often give better interpolation for estimating values at unmeasured locations ([37], [38], [39], [40], [41], [42], [43], [44]). Among the three interpolation methods, the performance of ordinary kriging was best in comparison with IDW and spline interpolation models.

The interpolated maps of all soil properties using the method with the lowest RMSE from the cross-validation process were developed. Exponential method as in ordinary kriging revealed the best-fit semivariogram models for studied soil properties. The nugget/sill ratio values indicate moderate spatial dependence for EC, Cu, Fe and Zn, pure nugget for OC, S,

and Mn, whereas strong spatial dependence for pH, P_2O_5 , K_2O and B. The kriged surface map of soil pH exhibited different distribution pattern using ordinary kriging with exponential methods (Fig. 3 (a) and (b)). Analysis of the isotropic variograms indicated that, soil pH was well described by exponential model with strong spatial dependence of 2549 m (Table 2). This is attributed to inherent soil properties as well as management factors including fertilization and cropping sequences as practiced in the study area. The spatial distribution maps developed for soil properties could be the primary guide for site-specific nutrient management plans and designing future soil sampling strategies in microwatershed.

Table 3. Parameters found when the kriging model returned the lowest cross-validation RMSE for all soil properties under study in Gopalapur microwatershed

Soil property	Neigh-bours	Model type	ME	RMSE	AKSE	RMSP	MSPE	Regression function
pH	20	Exponential	-0.0010	0.7323	0.7341	1.0164	0.0020	$y = 0.6208 * x + 2.5712$
EC (dS m ⁻¹)	13	Exponential	-0.0014	0.1166	0.1180	0.9893	-0.0108	$y = 0.1762 * x + 0.1457$
OC (%)	20	Exponential	-0.0008	0.1871	0.1932	0.9889	-0.0038	$y = 0.5923 * x + 0.2483$
P_2O_5 (kg ha ⁻¹)	16	Exponential	-0.8591	56.6060	61.5555	0.9288	-0.0104	$y = 0.3032 * x + 24.1605$
K_2O (kg ha ⁻¹)	20	Exponential	-1.3120	175.5571	193.0649	0.9167	-0.0041	$y = 0.6104 * x + 144.7849$
S (mg kg ⁻¹)	20	Exponential	0.0108	5.7801	5.3994	1.0895	0.0054	$y = 0.1588 * x + 6.7567$
B (mg kg ⁻¹)	20	Exponential	0.0012	0.2495	0.2602	0.9716	0.0029	$y = 0.2222 * x + 0.3803$
Cu (mg kg ⁻¹)	20	Exponential	-0.0042	0.6386	0.6609	0.9757	0.6386	$y = 0.1312 * x + 1.4800$
Fe (mg kg ⁻¹)	19	Exponential	0.0636	16.0765	16.7582	0.9665	0.0025	$y = 0.1727 * x + 16.0120$
Zn (mg kg ⁻¹)	13	Exponential	-0.0135	0.4513	0.4258	1.0534	-0.0264	$y = -0.0216 * x + 0.3738$
Mn (mg kg ⁻¹)	14	Exponential	0.4751	10.2340	11.3973	0.9277	0.0288	$y = 0.3867 * x + 12.8815$

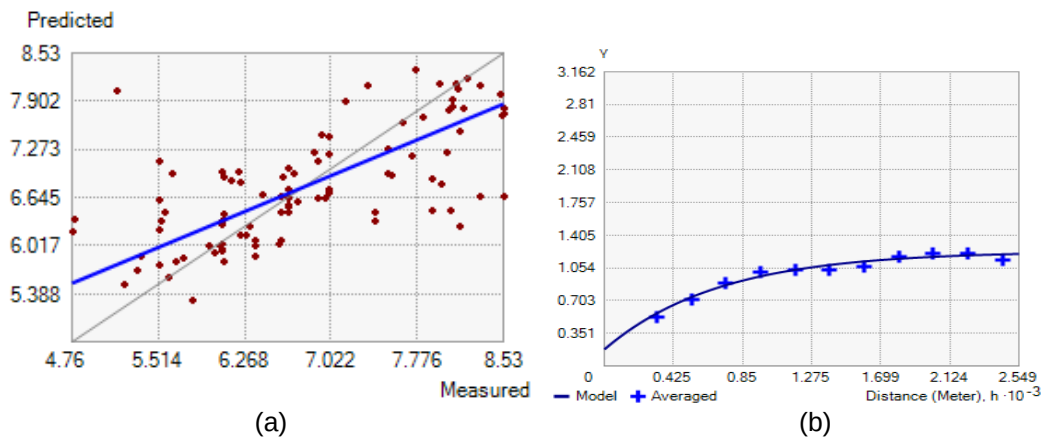
ME, mean error; RMSE, root mean squared error; AKSE, average kriging standard error; RMSP, root mean square standardized prediction error; MSPE, mean standardized prediction error.

From the study using geostatistical-variogram analysis and spatial interpolation (kriging) methods, the categorization of each nutrient under study was developed showing areas of low, medium and high status of available organic carbon (OC), sulphur, boron and zinc in Gopalapur microwatershed (Fig. 4). The results showed that low available organic

291 **Table 4. Parameters returning the lowest RMSE from cross-validation for IDW and**
 292 **splines for all soil properties in Gopalapur microwatershed**

Soil property	Power	Neighbours	ME	RMSE	Regression function
<i>pH</i>					
IDW	2	59	0.01757	0.73602	$Y = 0.46449 * X + 3.66663$
Splines	2	59	-0.00152	0.72682	$Y = 0.58338 * X + 2.83686$
<i>EC (dS m⁻¹)</i>					
IDW	2	59	0.00060	0.11263	$Y = 0.10634 * X + 0.16104$
Splines	2	59	-0.00030	0.11531	$Y = 0.22084 * X + 0.13858$
<i>OC (%)</i>					
IDW	2	59	-0.00125	0.18869	$Y = 0.53212 * X + 0.29835$
Splines	2	59	-0.00143	0.18848	$Y = 0.54756 * X + 0.28473$
<i>P₂O₅ (kg ha⁻¹)</i>					
IDW	2	59	-0.07402	60.00457	$Y = 0.19860 * X + 32.06700$
Splines	2	59	-0.45752	60.95836	$Y = 0.24696 * X + 27.61652$
<i>K₂O ((kg ha⁻¹))</i>					
IDW	2	59	1.89161	189.38637	$Y = 0.42880 * X + 209.55707$
Splines	2	59	0.14801	185.62964	$Y = 0.47196 * X + 180.76546$
<i>S (mg kg⁻¹)</i>					
IDW	2	59	0.02579	5.54145	$Y = 0.11028 * X + 7.59641$
Splines	2	59	-0.03734	5.54782	$Y = 0.08694 * X + 7.04385$
<i>B (mg kg⁻¹)</i>					
IDW	2	59	-0.00047	0.25686	$Y = 0.10227 * X + 0.44605$
Splines	2	59	0.00071	0.25686	$Y = 0.21032 * X + 0.39096$
<i>Cu (mg kg⁻¹)</i>					
IDW	2	59	-0.00283	0.64750	$Y = 0.02943 * X + 1.63646$
Splines	2	59	-0.00118	0.64528	$Y = 0.09479 * X + 1.52360$
<i>Fe (mg kg⁻¹)</i>					
IDW	2	59	0.34636	16.33791	$Y = 0.10351 * X + 17.96223$
Splines	2	59	0.18602	16.51950	$Y = 0.22248 * X + 14.73876$
<i>Zn (mg kg⁻¹)</i>					
IDW	2	59	0.00306	0.36158	$Y = 0.02198 * X + 0.36705$
Splines	2	59	-0.00142	0.35862	$Y = 0.20746 * X + 0.28035$
<i>Mn (mg kg⁻¹)</i>					
IDW	2	59	-0.11574	9.46321	$Y = 0.26845 * X + 13.56133$
Splines	2	59	0.03046	9.34184	$Y = 0.41293 * X + 11.09632$

293 ME, mean error; RMSE, root mean squared error
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 297 (a)
 298 (b)
 299 **Fig. 3. Ordinary kriging showing pH as (a) predicted and measured value and (b) model and**
 300 **averaged value with distance both exponentially.**
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Fig. 4. (a) Soil organic carbon, (b) Available sulphur, (c) boron and (d) zinc area in ha (%) under Gopalapur microwatershed.

carbon is in 180 ha area (31.49%) and concentrated mostly in northern and northeastern parts of the watershed, 58.52% of area under sulphur (334 ha) in northern, northeast, northwest and southern part, whereas available boron under 251 ha area (43.92%) concentrated in central, northeast, northwest and small patch in southern part and Zinc under 412 ha (72.09%) as deficient covering all parts of watershed. In practice, identifying these zones are useful for effective nutrient management of farm lands by calibrating soil test values with crop response curves.

4. CONCLUSION

The clear understanding of topsoil properties distribution is the key issue for agricultural and environment management. Due to relative ~~provision~~ of a variety of methods, many algorithms are presently applied, and research continues, aiming at ~~the definition of~~ the “best” method for delineation of spatial distribution of soils. The methods are evaluated using efficiency and error estimates of interpolation techniques. The accuracy is assessed by residual sum of squares (RSS), and errors are represented by the root mean square error (RMSE), mean error (ME) and root mean square standardized prediction error (RMSP). The study shows that Ordinary kriging interpolation method is superior ~~than~~ geostatistical and deterministic methods. The performance of the exponential semi-variogram model is outstanding with ordinary kriging interpolation techniques ~~than~~ IDW and spline methods. Finally, the results guide to the amplification of trustworthy soil available nutrients maps which can significantly contribute to proper application of microwatershed and agricultural study.

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