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DISTRIBUTION OF QUANTITATIVE SOIL PARAMETERS IN PARTS OF KANNUR DISTRICT, KERALA, USING INVERSE DISTANCE WEIGHTED INTERPOLATION

K. Manjusha[1], Arun Kumar Gorati[2], S. Paulraj[3], S. Anbazhagi[4] and Muthukumar Muthuchamy[5]

ABSTRACT

The research focussed on the analysis of thirteen soil parameters, including pH, Soil Organic Matter (SOM), Organic Carbon (TOC), Total Nitrogen (N), Available Phosphorus (Av.P), Exchangeable Potassium (Ex.Potassium), Exchangeable Sodium (Ex.Sodium), Exchangeable Calcium (Ex.Calcium), Exchangeable Magnesium (Ex.Magnesium), Available Copper (Av.Cu), Available Zinc (Av.Zn), Available Manganese (Av.Mn), and Available Iron (Av.Fe) of Kannur district, Kerala. Thirty-four soil samples were taken during March 2022 from a depth of 15 cm using the random grid sampling method and were quantitatively analysed. Excel 2010 calculated the data's summary statistics. The investigation used Geostatistical wizard and Arctoolbox in ArcMap 10.6. Understanding the spatial autocorrelation of the data were made easier using the Global Moran's I tool (spatial statistics tools). Interpolation surfaces had created using the Inverse Distance Weighted method. For better results, the produced geostatistical layer was converted to a raster surface and displayed with map components. The Moran's I test showed no dataset clustering for any parameters, except Ex.Potassium, which had extremely low dispersion. The Root Mean Square Error (RMSE) values for the model were provided by IDW along with the prediction surface. The study reports the importance of the normality of the data for IDW, as skewed data exhibited high RMSE values. The prediction surface showed a best-fit model with low RMSE values for pH, SOM, TOC, N and Ex.Sodium. The rest of the parameters have deprived performance. Hence, for interpolation to works well the data must be normalized. The prediction layers can be used for improving agricultural practices in the district. The spatial distribution of soil properties for more areas will lighten the ideas for developing good agronomy practices.

(Key words: Interpolation, IDW, Moran's I, soil analysis, spatial autocorrelation)

INTRODUCTION

Soil forms a thin layer on earth's crust and forms a life supporting material for biotic components (More, 2022). The availability of nutrients and organic matter in the soil affects the plant growth (Yadav and Nisha, 2019). The soil has inherent and dynamic characteristics, including vertical and horizontal geographical fluctuation (Potdar *et al.*, 2020). It exhibits spatial variation owing to anthropogenic land use patterns and physical, chemical, and biological activity. Current management of soil resources depends on understanding the patterns and mechanisms underlying soil spatial variability. Researchers worldwide have investigated the spatial variability of soil chemical characteristics, including pH, organic matter content, accessible potassium, phosphorus, and nitrogen, and available and total micronutrients, in various soils and management practices. However, rare knowledge exists about the regional variability of chemical traits, including soil pH, electrical conductivity (EC), Soil Organic Carbon (SOC) concentration, and exchangeable cations (K^+, Ca^{2+}, and Mg^{2+}) in developing nations like India (Behera *et al.*, 2015). For efficient fertilizer applications and choosing suitable crops for an area, the soil resources database needs to be updated (Nayak *et al.*, 2022). Evaluating the soil resource variations and its mapping determines the soil behaviour fluctuations (Foroughifar *et al.*, 2013). Through spatial interpolation, the unknown values are estimated from the known points, subjected to the spatial autocorrelation, smoothness, and continuity of the known

1. Ph.D. Scholar, Dept. of Environmental Science, School of Earth Science Systems, Central University of Kerala, Kasaragod – 671321
2. P.G. Student, Dept. of Environmental Science, School of Earth Science Systems, Central University of Kerala, Kasaragod – 671321
3. Senior Scientist, CPCRI, Kasaragod, Kerala – 671124
4. Asstt.Professor, Dept. of Environmental Science, School of Earth Science Systems, Central University of Kerala, Kasaragod – 671321
5. Professor, Dept. of Environmental Science, School of Earth Science Systems, Central University of Kerala, Kasaragod – 671321

surfaces (Wu and Hung, 2016). Spatial autocorrelation explains the nearness and relatedness of the geographical entities grounded on Tobler's first law of geography of 1970 (Miller, 2004).

To describe the surface variability, the Inverse Distance Weighted (IDW) method is a valid technique as no prior knowledge about the data is required (Liu *et al.*, 2013). It deterministically predicts the value at an unknown location by giving weights to the known points based on distance, and weights and power values have an inverse variation (Ikechukwu *et al.*, 2017; Wu and Hung, 2016). The IDW assigns weights to the available points concerning the distance. It results in the interpolation surface effectively in a simple manner and is advantageous over all other methods (Wu and Hung, 2016; Liu *et al.*, 2013). Schloeder *et al*. (2001) reported that IDW and Kriging work similarly and give more accurate prediction surface than the spline interpolation. Other studies also reported the efficiency of IDW over Kriging methods (Weber and Englund, 1992; Yanto *et al.*, 2022). Root mean squared error (RMSE) is an efficient way to determine the model's accuracy. It estimates the squared deviation of measured and predicted values (Chen and Liu, 2012). It calculates the best model fit in spatial modelling.

The present study aims at a) the estimation of the soil parameters in Kannur district, Kerala b) the spatial prediction of the parameters using IDW c) the effect of normality of the data on RMSE value of the interpolation model.

MATERIALS AND METHODS

Kannur district (Figure 1) extended with an area of 2970 Sq.km, which lies between 11°40' - 12°48'N latitude and 75°10' - 75° 57' E longitude. The altitude ranges from 10-1800 meters. The Kannur district favours Laterite soil, alluvium, coastal alluvium, hill soil, acid saline, and forest soil. According to the Department of Soil Survey and Soil Conservation, Kerala, the laterite soil is the most dominant soil type (Anonymous, 2023).

Using a gridded (10 rows x 10 columns) map, collected the soil samples during March 2022 in plastic covers from a depth of 15 cm. From each grid, samples had collected by mixing up the four subsamples of the same area. Air-dried the samples at room temperature for seven days and sieved using a 2 mm sieve. Analysis used the standard procedures for pH, Soil Organic Matter (SOM), Organic Carbon (TOC), Total nitrogen (N), Available Phosphorus (Av.P), Exchangeable Potassium (Ex.Potassium), Exchangeable Sodium (Ex.Sodium), Exchangeable Calcium (Ex.Calcium), Exchangeable Magnesium (Ex.Magnesium), Available Copper (Av.Cu), Available Zinc (Av.Zn), Available Manganese (Av.Mn), and Available Iron (Av.Fe) (Diehl *et al.*, 1950; Jackson, 1973; Lindsay and Norvell, 1978; Maiti, 2003; Piper, 1966).

Descriptive statistics of the soil dataset procured using Excel 2010 included mean, maximum, minimum, variance, standard deviation (SD), coefficient of variation (CV), skewness and kurtosis with a confidence interval of 95 %.

Global Moran's I test

In ArcMap 10.6, Generate Spatial Weights Matrix tool created an inverse distance weight matrix file (Euclidean Distance Method) by putting 10000 meters as a threshold distance and three as the number of neighbours. Moran's I tool of spatial statistics determined the spatial autocorrelation of the datasets using the generated spatial weights matrix file. Interpretation of the results used the p-value, z-score, and Index value in the spatial autocorrelation report provided after analysis (Anselin, 1995; Waldhor, 1996).

Inverse Distance Weighting Method (IDW)

The complete analysis used the Geostatistical wizard in ArcMap 10.6. The inverse distance weighted tool interpolated a surface from the data points for all parameters with no spatial autocorrelation. The geostatistical wizard selected parameters and optimised the model's power function. Settings of Search Neighbourhood allowed choosing the type, shape, maximum and minimum neighbours, and sector type to run the model. Chen and Liu (2012) defined IDW as follows;

$$\mathbf{P} = \sum_{i=1}^{n} \qquad \textbf{...(E.1)}$$

Where, P = unknown parameter value; w = weighting for the known points; p = known data points. The neighbourhood type selected the standard option and chose the model with the most minor Root Mean Square Error (RMSE) by changing the number of neighbours and sector type. RMSE provided in the prediction error window is copied to Excel for validation. The geostatistical layer created is exported to a raster surface, changed the symbology, and exhibited as a map. The value of CV, skewness and kurtosis had used to interpret the IDW models by comparing them with RMSE values.

RESULTS AND DISCUSSION

Soil Analysis

The descriptive statistics of the parameters showed in Table 1. The pH exhibited an acidic range of 5.2 - 6.4, with moderate skewness in the data (0.69). Generally, a pH value of 5-7.5 is expected (Robinson and Metternich, 2006). The presence of acidic soil tends to the availability of high rainfall in the area. As pH known to affect the plant growth, nutrient contents, toxicity and microbial flora, its determination talks about the overall chemistry of the soil. SOM and TOC exhibited a normal distribution and mean values of 5.84±0.84 and 3.42±0.49 %, respectively, obeyed the presence of 58 % of the SOM as TOC in soils (Griffin *et al.*, 2013). N exhibited a mean value of ~5 % (0.24) of the mean of soil organic matter. The data showed highly positive skewness in the case of Av.P and had a mean value of 0.29±0.45 mg kg^{-1}. Exchangeable cations that are readily available for plant roots, such as Ex.Potassium, Ex.Calcium, Ex.Magnesium and Ex.Sodium represented with mean values of 19.04±8.10, 528.24±272.06, 171.18±47.20 and 13.08±2.62 mg kg^{-1}, respectively. Data showed a positive skewness for Ex.Potassium and Ex.Calcium. The analysis of available micronutrients for plant uptake, such as Av.Cu, Av.Zn, Av.Mn and Av.Fe revealed mean values of 1.78±1.72, 2.13±2, 38.99±25.70, and 25.16±14.05 mg kg^{-1}, respectively. The skewness in most of the dataset might connect to the sampling bias or estimation errors. Hence, outliers were not removed before interpolation, as it was challenging to identify whether measurement error or sampling effects.

Spatial Autocorrelation

Spatial autocorrelation revealed the relationship of the variables with their spatial structure, which means a systematic variation exists spatially. Index value ranges from -1 to 1; high positive values represent the clustering of the data points; lower negative values tend to an interspersed or mixed data points, and values near zero mark the absence of spatial autocorrelation in the data. The analysis report from the ArcMap 10.6 gave the z-score and p-value for the interpretation. The p-value showed the significance for the spatial autocorrelation below 0.1, and the z-score above 1.65 and below -1.65. The Ex.Potassium showed a tendency towards dispersed distribution in the data (z-score = -1.70), and all other parameters had random distribution in the data. Hence, IDW had chosen for interpolation as it is a simple and effective method that gives exact surface variability without considering spatial autocorrelation. The results of the Global Moran's I test showed in Table 2.

IDW

The power value for each parameter optimisation occurred in the Geostatistical wizard of ArcMap 10.6. Hence, changes had made only in the number of maximum and minimum neighbours (15:10, 10:3, and 5:3) and sector type and chose the best model with a low RMSE value (Table 3). The distribution is not skewed for N but had a kurtosis value of 4.59, which was greater than 3 points to the leptokurtic distribution. Hence, for N optimised power value of 2.84 created the interpolation surface.

Likewise, the Ex.Sodium with no skewness and a kurtosis value of 3.43 created an interpolation surface with a distance power of 1. That showed the effect of high kurtosis value in optimising power value in the case of N. Like Ex.Sodium, the Ex. Magnesium, which was not skewed, with mesokurtic distribution (<3), predicted the surface with the same power value of 1. For all other datasets, the optimised power value was 1. The number of maximum and minimum neighbours used for all the parameters except Ex.Magnesium was 15 and 10, respectively, with eight sectors. The Ex.Magnesium used 10 and 3 as maximum and minimum neighbours, respectively, with eight sectors. Table 3 describes the RMSE for all the parameters, and the prediction surface had chosen the one with a low RMSE value for each parameter.

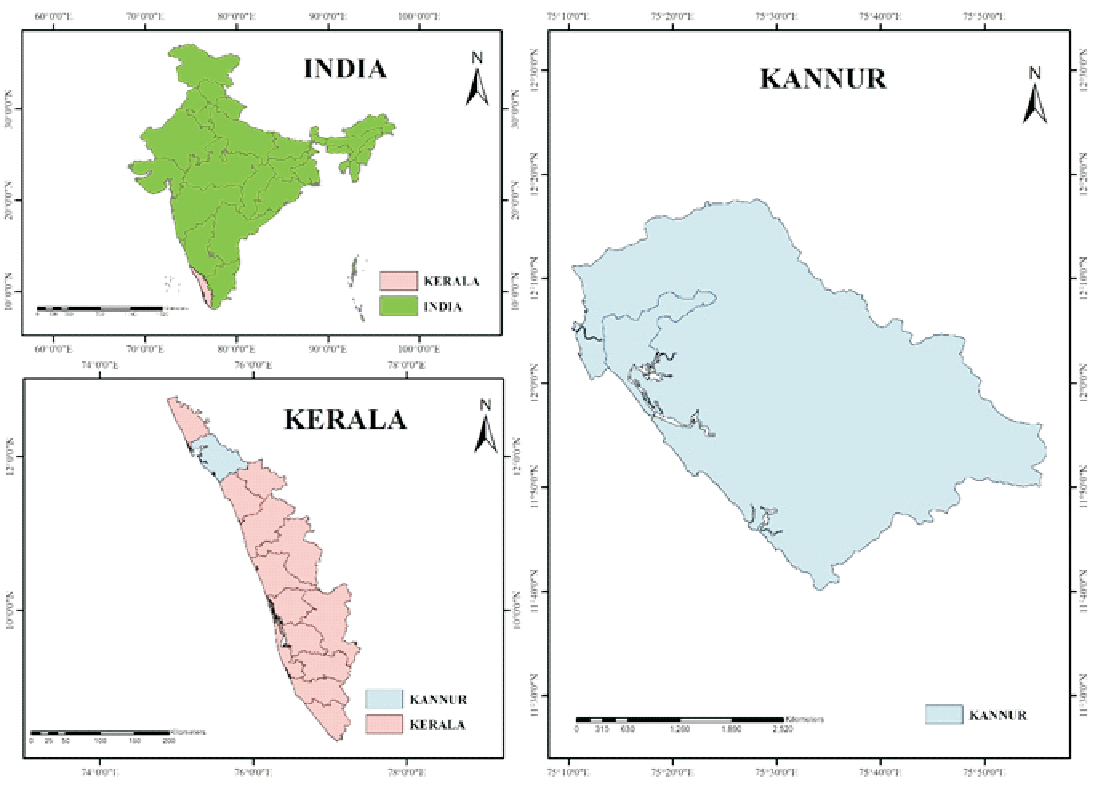

Figure 1. Study area

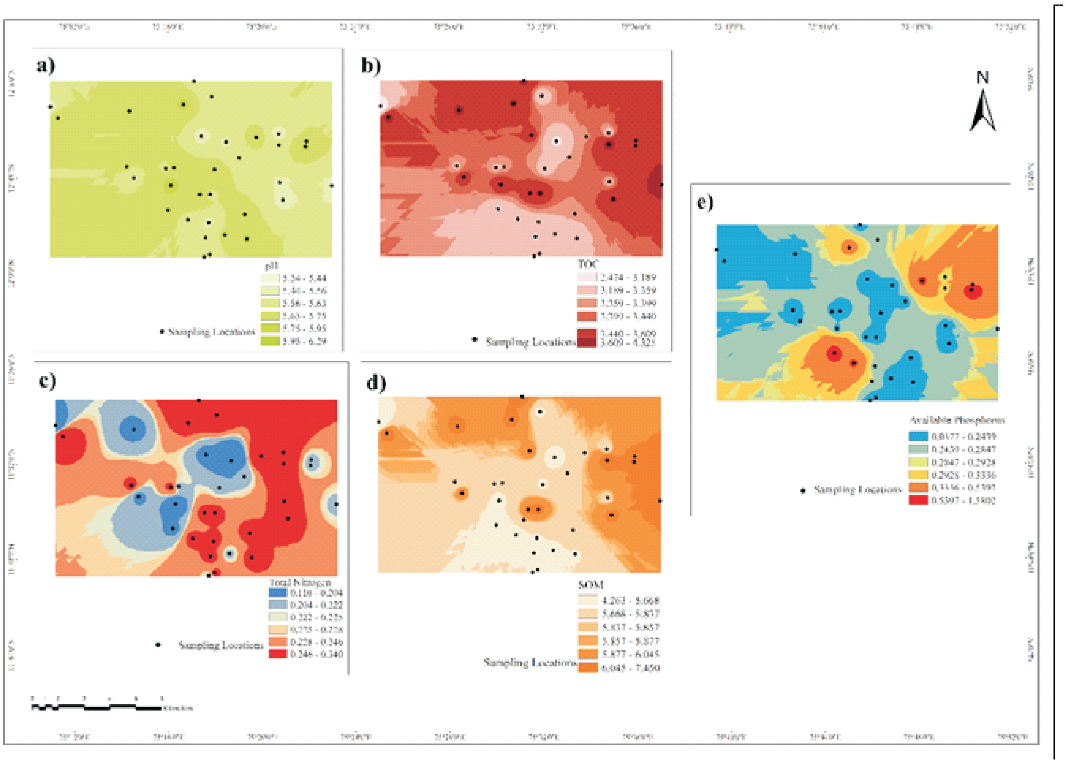

Figure 2. Prediction surface of IDW a) pH, b) TOC, c) N, d) SOM, e) Av.P

Table 2. Index value, z-score and p-value from Global Moran's I test for all parameters

Soil Parameters	Moran's I Value	z-score	p-value
pH	-0.13	-0.78	0.43
SOM	-0.09	-0.42	0.67
TOC	-0.12	-0.69	0.49
N	0.15	1.39	0.17
Av.P	-0.013	0.15	0.88
Exchangeable Cations			
Ex.Potassium	-0.24	-1.70*	0.09
Ex.Sodium	0.07	0.77	0.44
Ex.Calcium	-0.07	-0.35	0.73
Ex.Magnesium	-0.002	0.22	0.83
Micronutrients			
Av.Cu	-0.09	-0.57	0.57
Av.Zn	-0.2	-1.39	0.17
Av.Mn	0.05	0.66	0.51
Av.Fe	-0.06	-0.24	0.81

*indicates a z- score value which tends to disperse pattern

When linked to the mean value of the parameters, the RMSE value for pH, SOM, TOC, N and Ex.Sodium was low. These parameters had non-skewed data, and the interpolation model formed the best fit (Figure 2 and Figure 3).However, the Ex.Magnesium's high value of RMSE (45.79) suggested the model was poor in predicting the unknown surface (Figure 3). Though it was not skewed, the high CV (27.58%) in the data made the prediction less precise. The models exhibited satisfactory results for the pH with moderate skewness and the least CV (RMSE = 0.3). The model was unfit for Av.Fe (Figure 4) with moderate positive skewness (RMSE = 14.96) and high CV (55.86%). For the rest of the parameters (Figure 3 and Figure 4), skewness and CV were high, and the model were unfit with high RMSE values (Table 1).

Table 3. RMSE value, power, number of neighbours and sector type used for IDW

Sl. No.	Soil Parameters	RMSE	Power	Maximum Neighbours	Minimum Neighbours	Sector Type
1	pH	0.3	1	15	10	8 sectors
2	SOM	0.91	1	15	10	8 sectors
3	TOC	0.53	1	15	10	8 sectors
4	N	0.04	2.84	15	10	8 sectors
5	Av.P	0.47	1	15	10	8 sectors
			Exchangeable Cations			
1	Ex.Potassium	9.09	1	15	10	8 sectors
2	Ex.Sodium	2.61	1	15	10	8 sectors
3	Ex.Calcium	291.36	1	15	10	8 sectors
4	Ex.Magnesium	45.79	1	10	3	8 sectors
			Micronutrients			
1	Av.Cu	1.76	1	15	10	8 sectors
2	Av.Zn	2.18	1	15	10	8 sectors
3	Av.Mn	26.43	1	15	10	8 sectors
4	Av.Fe	14.96	1	15	10	8 sectors

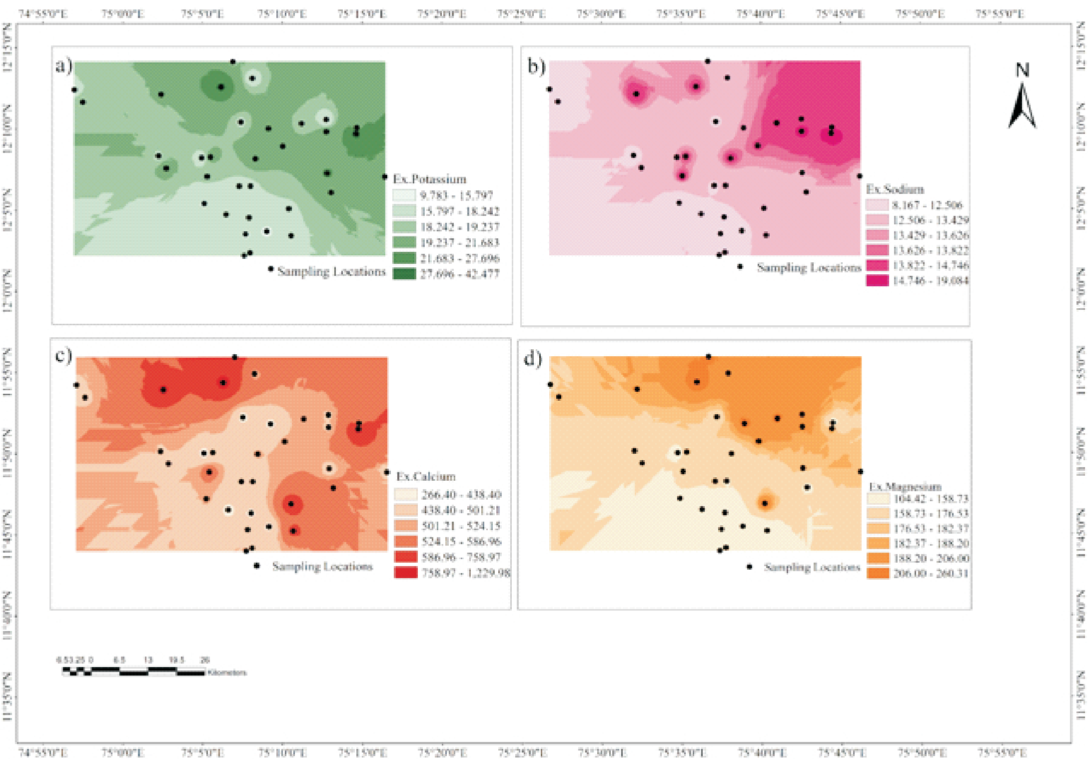

Figure 3. Prediction surface of IDW a) Ex.Potassium, b) Ex.Sodium, c) Ex.Calcium, d) Ex.Magnesium

Table 1. Descriptive statistics and RMSE value (IDW) of soil parameters used in the study

Parameters	Mean	Maximum	Minimum	Variance	SD	CV (%)	Kurtosis	Skewness	RMSE
pH	5.6	6.4	5.2	0.08	0.28	4.90	3.23	0.69 (MS)	0.3
SOM (%)	5.84	7.58	4.24	0.70	0.84	14.37	2.31	0.25 (NS)	0.91
TOC (%)	3.42	4.40	2.46	0.24	0.49	14.39	2.22	0.13 (NS)	0.53
N (%)	0.24	0.34	0.11	0.002	0.04	18.53	4.59	-0.14 (NS)	0.04
Av.P (mg kg^{-1})	0.29	1.84	0.008	0.20	0.45	155.31	7.90	2.44 (HS)	0.47
Exchangeable Cations									
Ex.Potassium (mg kg^{-1})	19.04	47.50	8	65.63	8.10	**42.54**	7.12	1.84 (HS)	9.09
Ex.Sodium (mg kg^{-1})	13.08	20.20	7.20	6.86	2.62	20.02	3.43	0.46 (NS)	2.61
Ex.Calcium (mg kg^{-1})	528.24	1300	220	74015	272.06	**51.50**	4.64	1.51 (HS)	291.36
Ex.Magnesium (mg kg^{-1})	171.18	276	96	2228	47.20	**27.58**	2.52	0.24 (NS)	45.79
Micronutrients									
Av.Cu (mg kg^{-1})	1.78	9.06	0.19	2.94	1.72	96.6	9.37	2.73 (HS)	1.76
Av.Zn (mg kg^{-1})	2.13	9.51	0.47	4.01	2.00	94	5.22	2.27 (HS)	2.18
Av.Mn (mg kg^{-1})	38.99	133.90	11.13	660.24	25.70	**65.90**	4.75	1.96 (HS)	26.43
Av.Fe (mg kg^{-1})	25.16	65.43	2.30	197.55	14.05	**55.86**	0.52	0.72 (MS)	14.96

SD : Standard Deviation, CV : Coefficient of Variation, NS : Not Skewed, MS : Moderately Skewed, HS : Highly Skewed

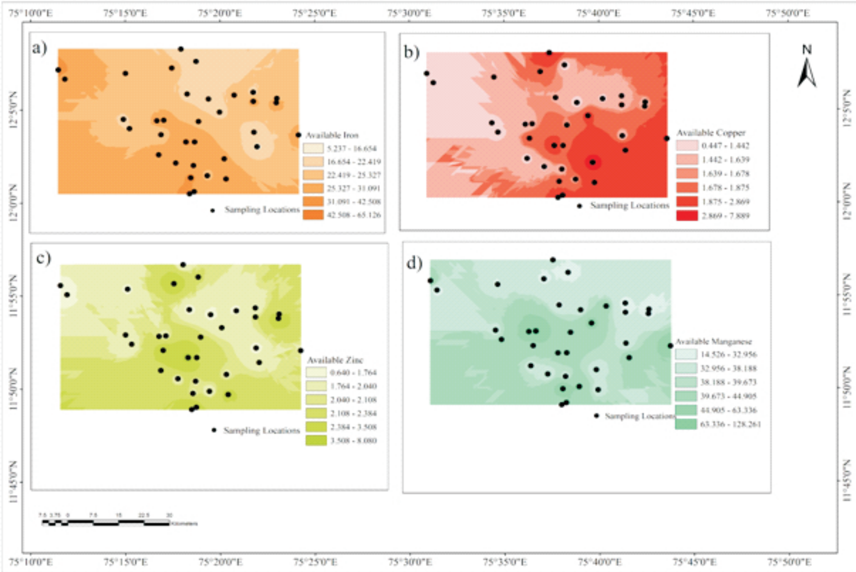

Figure 4. Prediction surface of IDW a) Av.Fe, b) Av.Cu, c) Av.Zn, d) Av.Mn

The results suggest that the IDW interpolation could be affected by the normality and the data spreading.The interpolation works well with an optimised exponential value of 1 for skewed and not skewed data. However, data with low skewness but high kurtosis value optimise the power above 2. RMSE forms a reasonable estimation of model fit for the IDW interpolation. Interpolation gave the best surface prediction for pH, SOM, TOC, N and Ex.Sodium with the least RMSE values. The dataset's normality affected the interpolation, depicting that the skewed data exhibits high RMSE values. The best parameter model from this study will pave the way to achieve good agricultural and horticultural practices in the parts of the Kannur district. Future research can be focused on the interpolation for the whole district with complete sampling and by including more soil parameters. Soil fertility index also can be concentrated further to improve agronomic practices.

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