Accessing Spatial Variability of SOC Content Using GIS Based Interpolation Techniques

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ABSTRACT

Precision farming is a field which is gaining more importance every passing day. It involves finding out the accurate top soil constituents for farming application. The application of chemical and natural farming additives with a main purpose of increasing and preserving the yield, but it will be prone to spatial variability across the farm. To obtain accurate values sampling all across the field is not economic. Hence the need for interpolation to obtain accurate values. In this study we have used four interpolation techniques to study the variation of Soil organic carbon (SOC) in a 3 acre farm. They were namely Inverse Weighted Distance (IDW), Spline, Ordinary Krigging and Natural Neighbour. A total of 35 samples were taken across the farm, 30% of this data set was used for validation and 70% of the data set was used for calibration. The results obtained showed that IDW method had a deviation of less than 10% compared to the other methods. Hence out of the four techniques IDW is most suited for SOC variability for precision agriculture applications.

Keywords: ***Soil organic carbon, Precision farming, Inverse weighted distance, Spatial variation, Interpolation, farming, Ordinary krigging, Natural Neighbour, Spline.***

1. INTRODUCTION

Soil is the basic element of all living beings on earth. The top loose layer of the earth's surface, consisting of minerals and rock particles blended with decomposed organic matter (humus), and capable of holding water. Soils regulate ecosystem services [1] and assume a noteworthy role in the global system managing major biogeochemical cycles and energy.

Soil is a standout amongst the most important of agricultural production [2] and has dominant effect on crop yields and quality [3]. In-field soil data has been utilized for quite a long time by agriculturists to settle on choices concerning crop management practices.

Topsoil (0 to 20cm) has the highest concentrations of nutrients and microorganisms [4] and is the framework for most of the earth's soil biological activity. Soil properties are neither static nor homogenous with space and time. Topsoil has its major application in agriculture as plants obtain most of the nutrients from it. Information on soil properties at finer resolution are essential in many fields, more so in precision agriculture [5].

When it comes to precision agriculture accurate and precise values of the top soil constituents is a necessity. One such important constituent is soil organic carbon (SOC). In the past different geostatistical approaches have been used to estimate the spatial distribution of SOC [6]. Sampling all across the field is not economical and it a time intensive task. Geostatistics is an efficient method [7] for the study of spatial allocation of SOC content and its irregularities and reducing the variance of assessment error and execution costs.

In this paper an attempt has been made to assess the interpolation techniques to predict the variability of soil organic carbon across a farm plot. The farm had lateritic soil. The interpolation techniques used are Inverse Weighted Distance (IDW) [8], Spline [9], Ordinary Krigging [10] and Natural Neighbour [11]. The data set has been divided into calibration dataset (70%) and validation dataset (30%) and the accuracy of the results are compared.

2. AREA OF STUDY

The area chosen for this study is Saripalla situated in Mangalore, Karnataka, India. The site is 3 acres in area. It is an open flat surface that's consisting of lateritic soil. There used to be a rubber plantation before but now it is barren.

Sites for sampling were chosen in a gridded pattern of 25 m X 25 m for each cell.

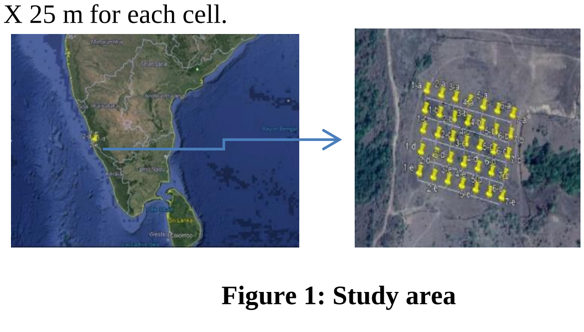

Figure 1: Study area

3. METHODOLOGY

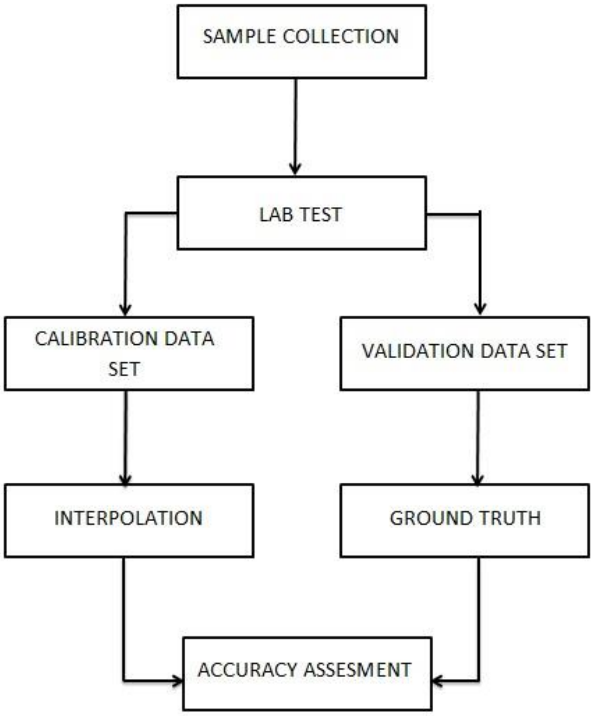

Figure 2: Methodology

The soil sample was collected from 35 sample sites. These sites were initially marked on Google earth and with the help of its coordinates were located. The sampling [12] was done by digging into the ground up to a depth of 15 cm using pickaxe and shovel. The sample was collected and stored in zip lock bags to avoid contamination.

Figure 3: Sample collection

Soil organic carbon was tested using the standard muffle furnace test [13]. The parameters used were 500 degree Celsius for 30 minutes of heating. The carbon content for each sample was noted.

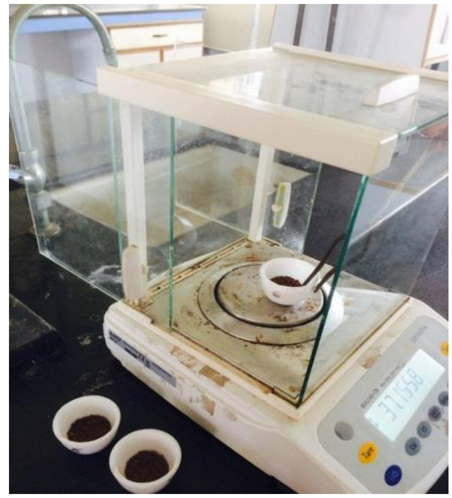

Figure 4: SOC determination

The samples were calibrated into two data sets namely calibration and validation data set. 30 samples were used for calibration and 5 samples were used for validation for the purpose of ground trothing.

The technique for estimation of unknown value between two known value and deducing missing values from a set of known values is called interpolation. Interpolation comes in use where the values around the missing values are known and its seasonality, repetition and long-term cycle is known.

On the calibration data set four types of interpolation techniques are used namely Inverse distance weighed, Spline, Natural neighbour and ordinary krigging.

Inverse distance weighted assumes that the values around a specific unknown value is more likely to be similar than that are further apart. That is the nearest values around unknown value have most influence on the unknown value.

Spline keeps low regards for the curvature of the surface and uses a mathematical equation [14] to assess the unknown value. Basically the surface is assumed to be a smooth one where the surface moves exactly over the input points.

The following equation (1) is used in for spline interpolation:

$$S(x,y) = T(x,y) + \sum_{j=1}^{N} \lambda_j R(r_j) \tag{1}$$

Where: j= 1, 2…..N.

N is the number of points.

λ_j are coefficient found by the solution of the system of a linear equations.

r_j is the distance from the point (x,y) to the jth point.

T(x,y) and R(r) are defined differently, depending on the selected option.

Ordinary Kriging is an advanced geostatistical method that produces an estimated surface from a scattered set of points with z-values [15]. It assumes that the distance or direction between data points show a spatial correlation that can be used to understand variation in the surface. The Kriging tool assigns a mathematical function to a known number of points, or all points within a known radius, to find the output value for each location.

Kriging is similar to IDW in a way that it weights the surrounding known values to predict values of unknown location. The following equation (2) is used in for krigings interpolation:

$$\hat{Z}(s_0) = \sum_{i=1}^{N} \lambda_i Z(s_i) \tag{2}$$

where:

$Z(s_i)$ = the measured value at the ith location

λ_i = an unknown weight for the measured value at the ith

location8

s_0 = the prediction location

N = the number of measured values

The technique used by Natural neighbour interpolation tool searches the nearest subset of input values to a query point and applies weights to them based on proportionate areas to interpolate a value[16]. This method is also known as Sibson or "area-stealing" interpolation. Its base identity is that its local, using only a subset of samples that surround a query point, and interpolated heights are guaranteed to be within the range of the values used. It does not regard trends and will not produce peaks, ridges, pits or valleys that are not already represented by the input values. The surface passes through the input values and is smooth throughout except at points of the input value.

4. RESULTS

The results obtained for the interpolation techniques are depicted in the figures below. In IDW method the power used was 2. In ordinary krigging spherical semivariogram was used.

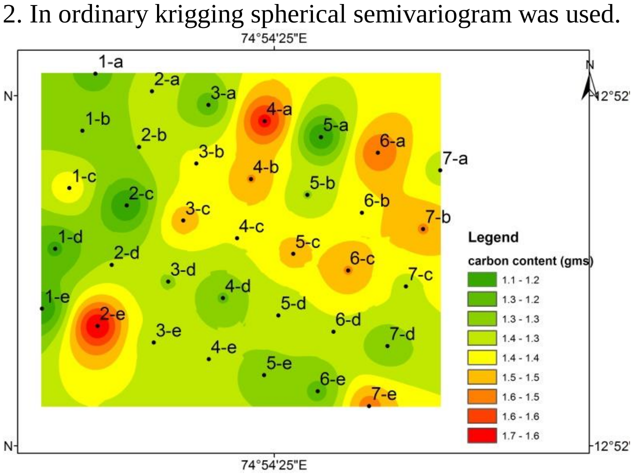

Figure 5: IDW output

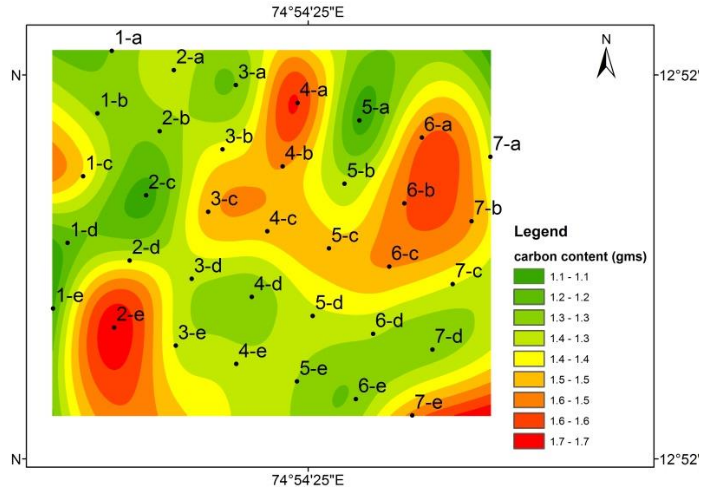

Figure 6: Spline output

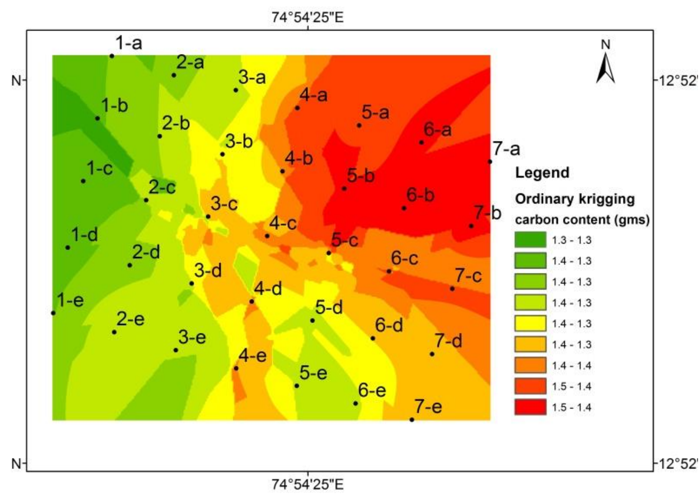

Figure 7: Krigging output

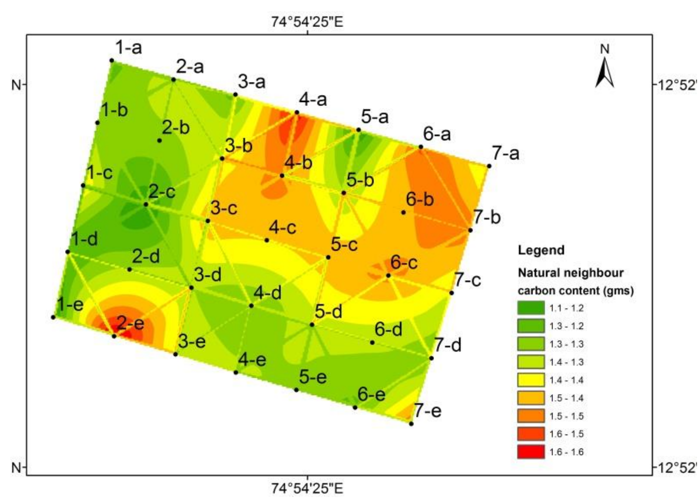

Figure 8: Natural neighbor

The results were tabulated using the validation data set which was not used for calibrating the results. The average error was found using the difference between the original and interpolated SOC content. Root mean square deviation (RMSD) represents the sample standard deviation of the differences between predicted values and observed values. The RMSD serves to aggregate the magnitudes of the errors in predictions for various times into a single measure of predictive power. RMSD is a measure of accuracy, to compare forecasting errors of different models for a particular data and not between datasets, as it is scale-dependent [17].

$$\mathrm{RMSD} = \sqrt{\frac{\sum_{t=1}^{n} (\hat{y}_t - y_t)^2}{n}}. \quad (3)$$

The Error and RMSD is tabulated in the table below along with the percentage change with the actual value.

Interpolation method	Error (gms)	RMSD (gms)	Percentage change (%)
IDW	0.028	0.1392	9.87
Spline	0.028	0.1392	11.22
Krigging	0.036	0.1392	10.87
Natural neighbour	0.028	0.1443	11.18

5. CONCLUSION

From the results, we can infer that there is very little change in interpolation techniques used. IDW method gives the best results in terms of RSMD and percentage change. Other than IDW all the other methods give a percentage error greater than 10%. For a change of distance of 25 meters the interpolation deviation of greater than 10% may not be acceptable for precision farming applications.

This is an indication of interpolation taking only SOC content into consideration. More studies have to be conducted to assess the accuracy of interpolation for different top soil constituents.

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