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Digital Mapping of Soil pH and Electrical Conductivity Using Geostatistics and Machine Learning

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

This study investigates the spatial variability of soil pH and electrical conductivity (EC) in Suryapet district of Southern Telangana Zone through various digital soil mapping approaches. The 202 surface (0-15cm) soil samples were collected and analysed for pH and EC. The analysed data was further divided into calibration set and validation set in the ratio of 75:25. The geostatistical techniques like Ordinary Kriging, Inverse Distance Weighting (IDW) and Regression Kriging and data mining technique like random forest technique were used to predict the spatial distribution of pH and EC (dSm^{-1}) over the study area. The accuracy of these methods was assessed using validation data set by calculating RMSE, ME and R^2 values. The results showed that among all the

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approaches, random forest (RF) technique performed better with lower RMSE, ME and higher R^2 values for spatial prediction of soil pH (RMSE=0.014, ME=0.28 and R^2=0.81) and EC (RMSE=0.134, ME=0.022 and R^2=0.73). The RF predicted maps show that the pH of soils varied from neutral (6.5-7.5) to slightly alkaline (7.5-8.5) and the soils of Suryapet district were considered as non-saline (EC: 0-2 dSm^{-1}). The findings of the current study shows that among digital soil mapping techniques, random forest model can be an effective tool for assessing spatial variability of soil pH and EC for further studies.

Keywords: Ordinary kriging; inverse distance weighting; regression kriging; random forest technique; soil pH and EC.

1. INTRODUCTION

Soil pH is a measure of the acidity or alkalinity of the soil, profoundly influences nutrient availability and microbial activity, directly impacting plant growth and health. Different crops thrive in specific pH ranges, and maintaining an optimal pH level ensures that essential nutrients are readily accessible to plants. Similarly, electrical conductivity measures the soil's ability to conduct an electrical current, serving as an indicator of its salinity and nutrient content. Proper EC levels are crucial for preventing nutrient imbalances, ensuring efficient nutrient uptake by plants, and avoiding detrimental effects on soil structure. Monitoring and adjusting soil pH and EC are indispensable practices for sustainable agriculture, enabling farmers to make informed decisions regarding fertilization and soil management, ultimately fostering healthier and more productive crop yields. Hence it is necessary to evaluate the fertility status of the soil and promote the recommendations of soil test for balanced nutrition to maintain soil health.

The estimation of soil pH and EC over a large area using conventional method is time consuming and expensive. Geo-statistics provides an advanced methodology that facilitates quantification of the soil parameters and enables spatial interpolation over a larger area. The spatial variability of measured variables can be described and understood better using geostatistical approaches, in order to understand and characterise the spatial variability of soil chemical properties under various cropping patterns, semivariograms and kriging statistics have been widely used [1-5].

In some developed countries over the past ten years, the study of soil nutrient spatial variability with regard to site-specific soil nutrient management has greatly benefited from data from GPS (global positioning system), GIS (geographic information system) and geo-statistics [6] (Jin, 1998). The findings from these nations demonstrate that soil variability can occur at any size, from few millimetres to many hectares. With the aid of geostatistical software, geostatistical analysis, including the creation of sample variograms and kriging, were carried out. Semivariogram analysis and kriging were used in conjunction with geostatistical approaches to assess the degree of spatial dependency for each variable [7]. The Semivariogram measures the level of dissimilarity and describes how the data are correlated (connected) to distance.

Kriging is a spatial interpolation method that utilizes variogram models to generate the best linear unbiased estimates for unsampled locations, employing a weighted average of nearby data points within a predetermined range of influence. Variogram models are crucial for assessing prediction precision. In contrast, Inverse Distance Weighting (IDW) estimates values at specific points based on weighted distances from known data points. Regression kriging, on the other hand, blends ordinary least squares regression and kriging of the regression residuals, enhancing spatial predictions by incorporating additional variables like climate, topography, and vegetation data alongside sample information, making it particularly effective for predicting soil nutrient levels and other spatial datasets. Data mining techniques plays a vital role in the spatial prediction of soil nutrients effectively by considering other variables such as climate, land use, topography in addition to sampling data. It involves collecting soil samples, preprocessing the data, training the model, and evaluation of the model. Among such models, Random forest technique is one of the technique which gives the most appropriate outcome [8-10]. The model's accuracy is evaluated using validation data, and once validated, it can be applied to predict soil nutrient content across the study area.

2. MATERIALS AND METHODS

Study site: The study area covers parts of Suryapet district which is located in Southern Telangana state, India. It is located at 17.1500˚N and 79.6236˚E with an area of 3607 Sq.Km. The study area consists of crop land about 2202.47 Sq.Km *(http://www.ecostat.telangana.gov.in/).* The major crops cultivated includes Paddy, Cotton, Redgram and Maize. The Suryapet district experiences a tropical climate with mean annual Rainfall of about 821.0 mm. The mean annual temperature and Relative humidity of about 36˚ C and 62 % were observed respectively.

Soil sampling and laboratory analysis: A total of 202 surface (0-15cm depth) soil samples were collected from the parts of Suryapet district considering Land use, topography and soil type through stratified random sampling. The sampling points were drawn using the existing maps of LULC map (1:50000) and soil map (1:50000) (sources: NRSC, ISRO) The collected soil samples were air dried and the stones, visible root fragments and other debris were removed. Each sample is grinded and sieved through a 2 mm sieve for further analysis and potassium. Soil pH was measured by using Potentiometric method [11]. In this, the soil water suspension was prepared in the ratio of 1:2.5 and the readings were taken using pH meter after stirring the suspension about 30 minutes. Then soil water suspension was kept aside for 2 hours. After the settlement of soil particles, the supernatant solution was taken to determine EC using a digital conductivity meter [11].

Geostatistical analysis: Geostatistical analysis was accomplished using Arcgis 10.8 software. The 202 samples collected from the study area were divided into 75% for Calibration and 25% for validation data sets. The geostatistical methods used in the present study includes Ordinary kriging, Inverse Distance Weighting method and Regression kriging. All these three methods were employed using calibration data sets.

Ordinary kriging: Ordinary Kriging is one of the most popular spatial interpolation techniques due to its ability to account for spatial autocorrelation and spatial variability, making it a robust tool for data prediction and mapping. The first step in Ordinary Kriging involves the estimation of a variogram from the given dataset. This involves calculating the semivariance for pairs of data points at varying distances and directions. The variogram graphically represents the spatial correlation range and nugget effect, allowing the selection of a suitable variogram model. The equation followed to compute the semivariogram is as follows:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \{Z(x_i) - Z(x_i + h)\}^2$$

Where γ(h) is semivariogram, N (h) is the couple number of sampling points, $Z(x_i)$ is the observed value of the variable x at location i and $Z(x_i + h)$ is the observed value of variable x at distance h.

The selection of an appropriate variogram model is the key to the spatial prediction of a measured soil property. Several statistical models, namely linear, exponential, Gaussian, circular, spherical, etc., can be chosen for modeling the empirical Semivariogram. A Semivariogram model has three major components, a sill, nugget, and partial sill (Fig. 2). Range represents the distance where the model first flattens. Sill represents the value at which the Semivariogram model attains the range (the value on the y-axis). A partial sill is a sill minus the nugget. The sill and range represent the magnitude of spatial variability and the spatial dependence of the variability respectively.

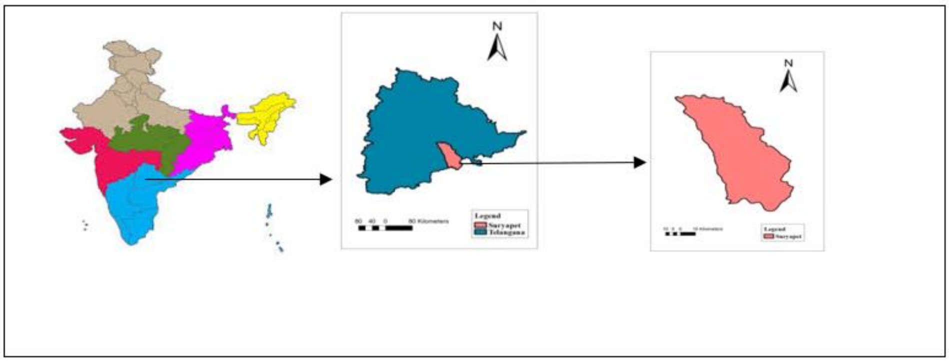


Fig. 1. Location of study site

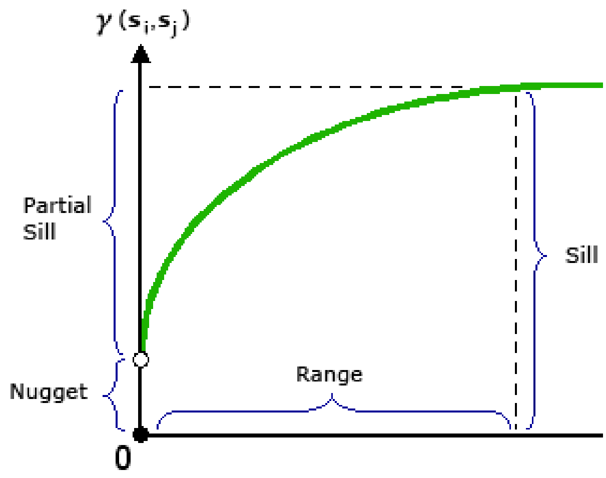


Fig. 2. Component of semivariogram model

IDW: Inverse Distance Weighting is a deterministic spatial interpolation method that assumes that the influence of a sample point on an unknown location is inversely proportional to its distance from that location. The IDW method assigns weights to nearby sample points based on their distances to the target location, giving higher weights to closer points and lower weights to more distant ones. These weights are then used to calculate a weighted average of the sample values, generating an estimated value for the unknown location. IDW estimates soil properties as

$$R(x) = \frac{\sum_{j=1}^{m} z\left(x_i\right) d_{ij}^{-r}}{\sum_{j=1}^{m} d_{ij}^{-r}}$$

where x is the estimation point, and xi are the data points. The weights (r) are connected to the distance by dij, which is the distance between the estimation point and the measured point.

Regression kriging: RK combines the strengths of both ordinary least squares regression (OLS) and kriging to predict values at unsampled locations in spatial datasets. The first step in the Regression kriging is generation of ordinary least square map of target variable which is dependent on independent variables such as soil forming factors. The second step involves generation of prediction map using the residual data produced from ordinary least square regression by ordinary kriging. The final output map of target variable is thus generated by the combination of above two maps. The regression equation used in regression kriging is:

$$Z(s) = \beta 0 + \beta 1X1(s) + \beta 2X2(s) +\ldots+ \beta nXn(s) + \varepsilon(s)$$

Where:
Z(s) is target variable at location s, β0, β1,…,βn are the regression coefficients, X1(s), X2(s),…, Xn(s) are the auxiliary variables and ε(s) denotes residual term (kriging error).

Data mining: Among the data mining techniques, random forest model was used in the prediction of soil pH and EC of the cultivated soils of Suryapet district.

Random Forest Technique: The software used for implementing random forest model was RStudio. The auxillary variables such as NDVI, LULC, DEM, maximum temperature, minimum temperature, mean temperature, rainfall and soil map were used in the prediction of soil parameters. For the calibration set, a Random Forest model was employed to identify influential variables, and their importance rankings were established. Subsequently, a refined Random Forest model was constructed, incorporating only the top-ranked variables to optimize predictive accuracy. This two-step approach aimed to enhance the model's performance by focusing on the most significant features identified in the variable importance analysis. The validation data set was used for assessing the prediction accuracy.

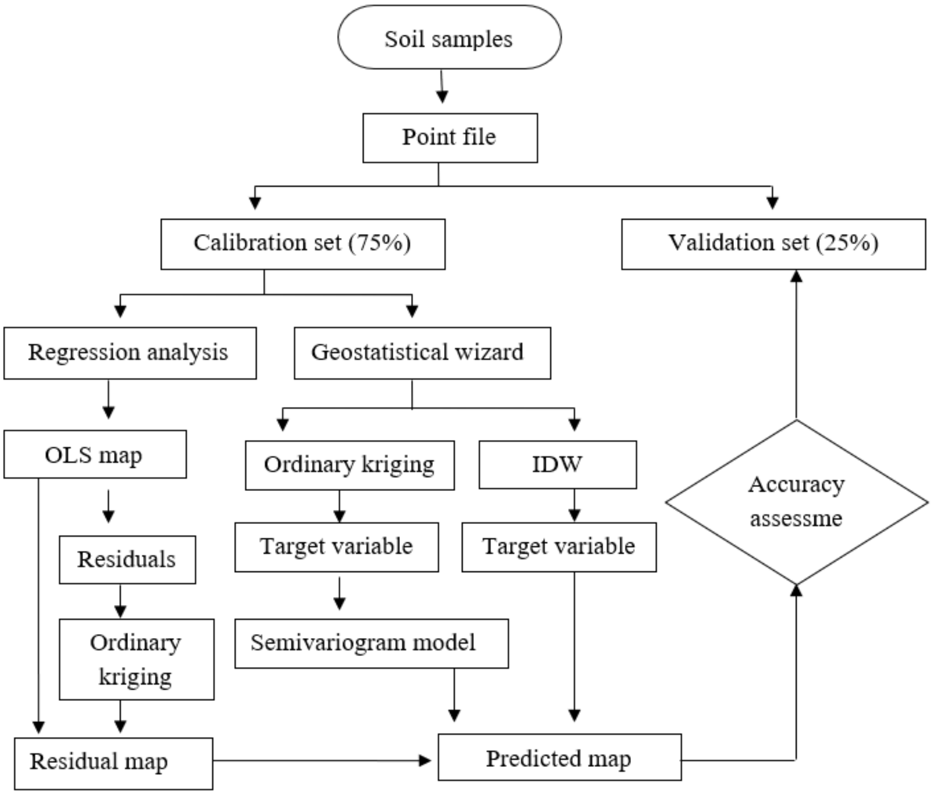


Fig. 3. Flow chart of Geostatistical analysis

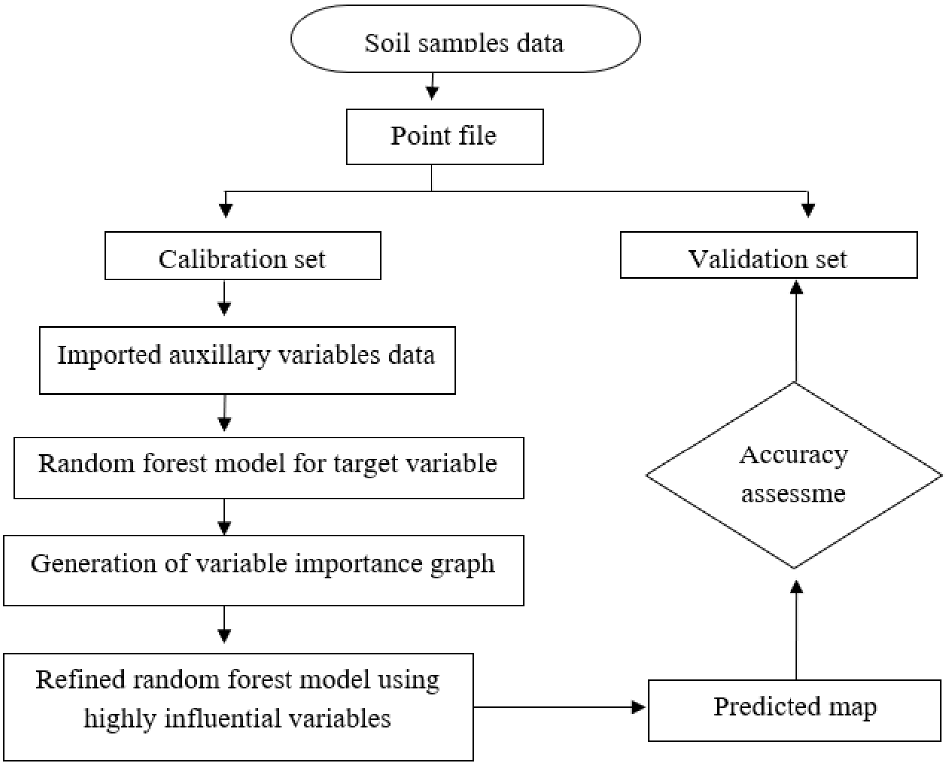


Fig. 4. Flow chart of Random forest model

Accuracy assessment: For assessing accuracy of predicted maps, validation data sets were used. The three validation indices used in the present study includes root mean square error (RMSE), coefficient of determination (R^2) and mean error (ME). The formulas for validation indices are as follows:

$$R^2 = RSS/ TSS$$

(Where RSS is Sum of Squares of Residuals, TSS is Total Sum of Squares.)

$RMSE = \sqrt{(\Sigma(\hat{y}_i - \bar{y}_i)^2 / N)}$

(y is the predicted values and y' is the observed values, N is the number of validation points)

$ME = (\Sigma| x - x_i |) / N$

(Where x is predicted value of data set, n= number of data values, x_i is observed values in the data set)

3. RESULTS AND DISCUSSION

Descriptive statistics: The concentration of soil pH at sampled locations ranged from 5.90 to 8.53 with a mean value of 7.42. Srinivasarao *et al.*, [12] also reported that the mean value of pH in the soils of Nalgonda district, Telangana was 7.4. pH is observed to have low variability across the study area with CV of 7.63%. The pH of calibration sites ranged from 5.90 to 8.53 with a mean value of 7.44 and CV value of 7.62% and the pH of validation sites ranged from 6.05 to 8.14 with a mean value of 7.37 and CV value of 7.69% (Table 1). Fig. 5 depicted the frequency distribution of soil pH, it showed that 46.5% of samples were characterized by pH range of 6.5 to 7.5 (neutral) and 46.5% of samples under 7.5 to 8.5 (slightly alkaline).

The EC at sampled locations in the study area ranged from 0.001 to 1.79 dSm^{-1} with a mean value of 0.43 dSm^{-1} and it exhibited medium variability (61.3%) across the study area. Similar findings were reported by Srinivasarao *et al.* [12], they reported the mean EC value of 0.29 dS m^{-1} in the soils of Nalgonda district, Telangana. It was observed that the EC of calibration sites ranged from 0.001 to 1.52 dSm^{-1} with a mean value of 0.44 dSm^{-1} and CV value of 57.2%. EC of validation sites ranged from 0.06 to 1.79 dSm^{-1} with a mean value of 0.38 dSm^{-1} and CV value of 74.7% (Table 1). The frequency distribution of EC was depicted in Fig. 6, which showed that 100% of samples were categorized under non saline (0 to 2 dSm^{-1}).

Table 1. Descriptive statistics of soil pH and EC at calibration and validation sites

Parameters	Minimum	Maximum	Mean	SD	Skewness	Kurtosis	CV
Calibration site (n=152)							
pH	5.90	8.53	7.44	0.57	-0.35	-0.49	7.62
EC (dSm^{-1})	0.001	1.52	0.44	0.25	1.05	2.00	57.2
Validation site (n=50)							
pH	6.05	8.14	7.37	0.57	-0.45	-0.77	7.69
EC (dSm^{-1})	0.06	1.79	0.38	0.29	2.56	10.58	74.7

Frequency distribution of pH and EC (dSm^{-1}) at sampled locations:

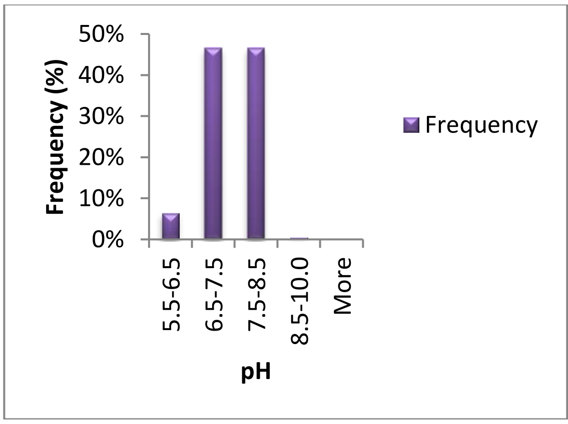


Fig. 5. Soil pH

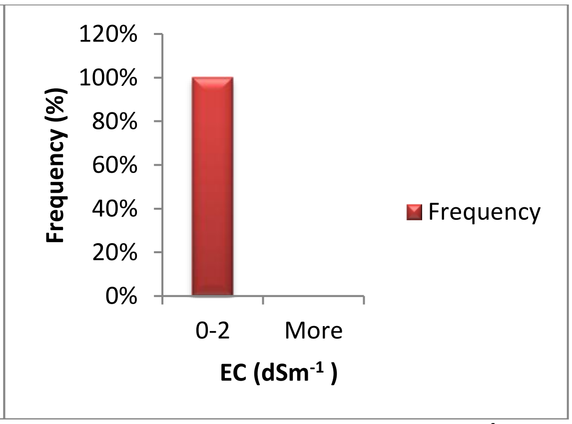


Fig. 6. EC (dSm^{-1})

Spatial prediction of soil pH:

Ordinary kriging: The spatial variability of soil pH was analyzed by calculating the structural properties of its semivariogram models including range, nugget, sill and nugget-sill ratio. Here the exponential model was considered as the best fitted model for revealing the spatial variability of soil pH (Fig. 7). Dey *et al.* [13] and Reza *et al.* [14] also reported the exponential model was the best fit model for revealing the spatial variability of pH. The nugget-sill ratio of soil pH was 0.55 which exhibited moderate spatial dependence (Table 2). Moharana *et al.* [15] and Amer *et al.*, [16] also reported the moderate spatial dependence for soil pH. Fig. 13 depicted that the pH of study area ranged from 6.57 to 8.32. In general, pH is considered to be stable soil parameter [17]. However, the variability in pH may be due to pedogenic processes influenced by the microtopographical variations, nature of parent material and type of fertilizer used [18,19]. Out of 3529 Sq km of study area, 1807 Sq km of area was categorized under pH range of 6.5-7.5 (neutral) and 1722 Sq km of area was categorized under pH range of 7.5-8.5 (slightly alkaline).

IDW: Fig. 14 depicted that the pH of study area ranged from 6.09 to 8.51. Alaie *et al*. [20] also reported that the soil pH ranged from slightly acidic to slightly alkaline. Out of 3529 Sq km of study area, 13 Sq km of area was categorized under pH range of 5.5-6.5 (slightly acidic), 1892 Sq km of area was categorized under pH range of 6.5-7.5 (neutral) and 1623 Sq km of area was categorized under pH range of 7.5-8.5 (slightly alkaline).

RK: For accurate prediction of soil pH, the independent variables like, mean temperature, DEM, LULC and NDVI were taken based on highest R^2 value. The exponential model was considered as the best fitted model for residual analysis using ordinary kriging. The nugget-sill ratio of residual soil pH was 0.16 which exhibited strong spatial dependence (Table 3). Gia Pham *et al*., [21] also reported strong spatial dependence for residual soil pH. Fig. 15 depicted that the pH of study area ranged from 6.04 to 8.46. Out of 3529 Sq km of study area, 1.43 Sq km of area was categorized under pH range of 5.5-6.5 (slightly acidic), 1777 Sq km of area was categorized under pH range of 6.5-7.5 (neutral) and 1751 Sq km of area was categorized under pH range of 7.5-8.5 (slightly alkaline).

RF: Fig. 16 shows that the soil pH in the study area varied from 6.5 (neutral) to 8.0 (slightly alkaline). Suleymanov *et al*. [22] also reported neutral and slightly alkaline soils with mean value of 7.2. It was observed that the best m_{try} value was 3, which was taken based on low OOB error value indicates that only three variables were considered as the optimum number of variables used for the prediction of soil pH (Fig. 9). It was observed that the independent variables that played significant role in the spatial prediction of soil pH were precipitation, DEM, maximum temperature, NDVI and minimum temperature (Fig. 11). Out of 3529 Sq km of study area, 2140 Sq km of area was categorized under pH range of 6.5-7.5 (neutral) and 1369 Sq km of area was categorized under pH range of 7.5-8.5 (slightly alkaline).

Spatial prediction of soil EC:

Ordinary kriging: Among all the semivariogram models, the tetraspherical semivariogram model was the best fit model to assess the spatial variability of EC across the study region. It was observed that nugget-sill ratio of EC was 0.73 which exhibited moderate spatial dependence (Table 2). Similar findings were reported by Dey *et al.* [13] and Tagore *et al.* [23]. Fig. 17 depicted that the EC of soils of Suryapet district ranged from 0.17 - 0.82 dSm^{-1} and the soils of total study area were non-saline (0-2 dSm^{-1}). This might be due to leaching of salts to lower horizons [24].

IDW: The EC of soils of Suryapet district ranged from 0.08 – 1.77 dSm^{-1} as shown in Fig. 18 and it was observed that the soils of total study area were non-saline (0-2 dSm^{-1}). Similar findings were reported by Desavathu *et al.* [25].

RK: The independent variables like rainfall and DEM were used in the prediction of EC and the stable semivariogram model was the best model for residual analysis. It was observed that nugget-sill ratio of residual EC was 0.92 which exhibited weak spatial dependence (Table 3). Fig. 19 depicted that the EC of soils of Suryapet district ranged from 0.2 – 0.72 dSm^{-1} and the soils of total study area were non-saline (0-2 dSm^{-1}).

RF: The EC of the soils of Suryapet district ranged from 0.23 to 0.98 dSm^{-1} (Fig. 20) and considered as non-saline (0-2 dSm^{-1}). Dharumarajan *et al*., [26] also reported non-saline soils in Bukkarayasamudrum mandal of

Anantapur district with the range of 0.11–0.97 dsm⁻¹. Fig. 10 depicted that two variables were considered as the optimum number of variables used for the prediction of EC, which was selected based on low OOB error values. In Fig. 12, it was depicted that mean temperature, DEM, sub order, minimum temperature and maximum temperature were considered as important variables for spatial prediction of electrical conductivity.

Table 2. Semivariogram parameters of soil pH and EC of study area

Parameter	Model	Nugget	Partial sill	Sill	Nugget /Sill	Range	Spatial dependence
pH	Exponential	0.16	0.14	0.3	0.55	9.23	moderate
EC (dSm^{-1})	Tetraspherical	0.05	0.02	0.1	0.73	10.9	moderate

Semivariogram models of soil pH and EC of study area:

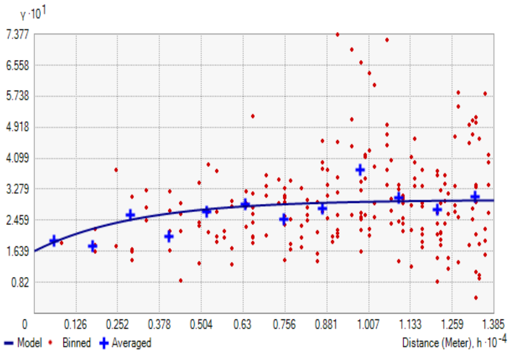


Fig. 7. Exponential model of soil pH

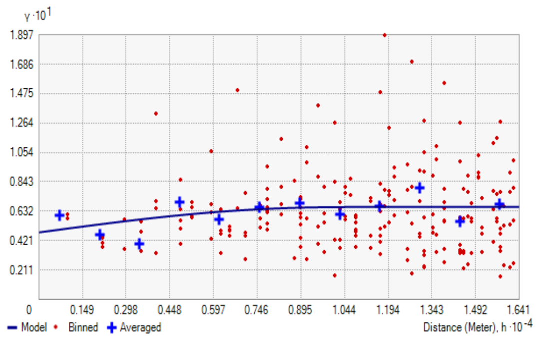


Fig. 8. Tetraspherical model of EC

Table 3. Semivariogram parameters of residuals of soil pH and EC

Parameter	Model	Nugget	partial sill	sill	Nugget /sill	Range	Spatial dependence
pH	Exponential	0.042	0.227	0.269	0.16	8191.2	Strong
EC(dSm^{-1})	Stable	0.069	0.0058	0.075	0.92	9438.9	Weak

Best m_{try} value for prediction of soil pH and EC:

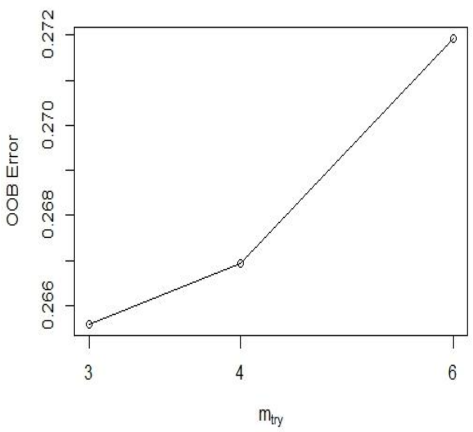


Fig. 9. Soil pH

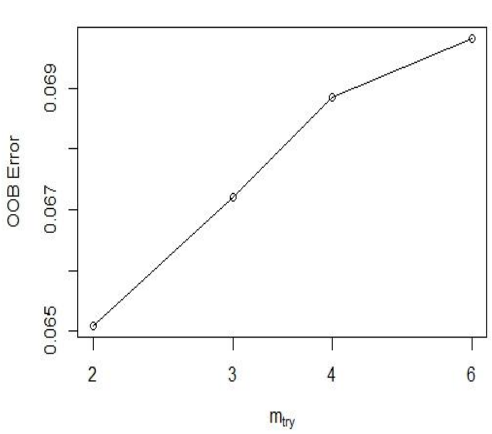


Fig. 10. EC

Variable importance ranking for prediction of soil pH and EC:

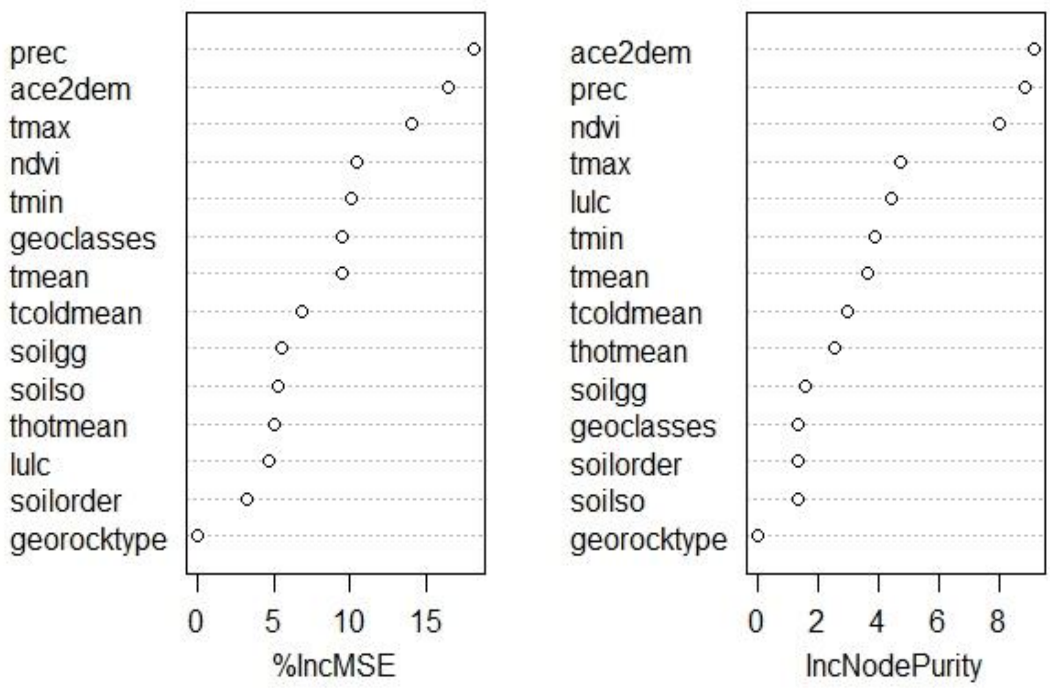


Fig. 11. Soil pH

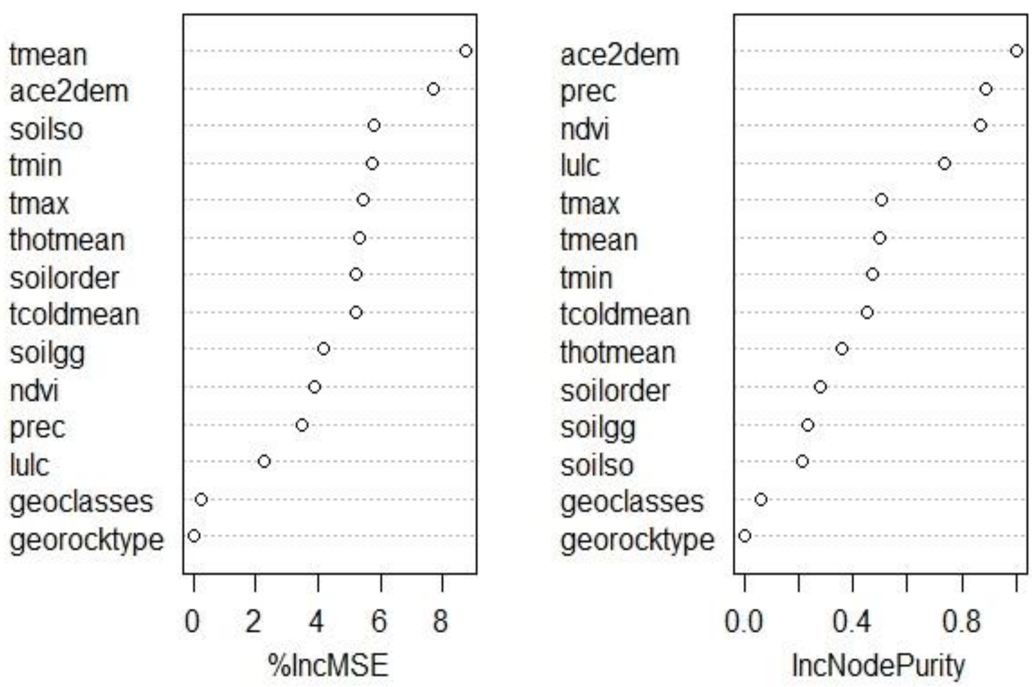
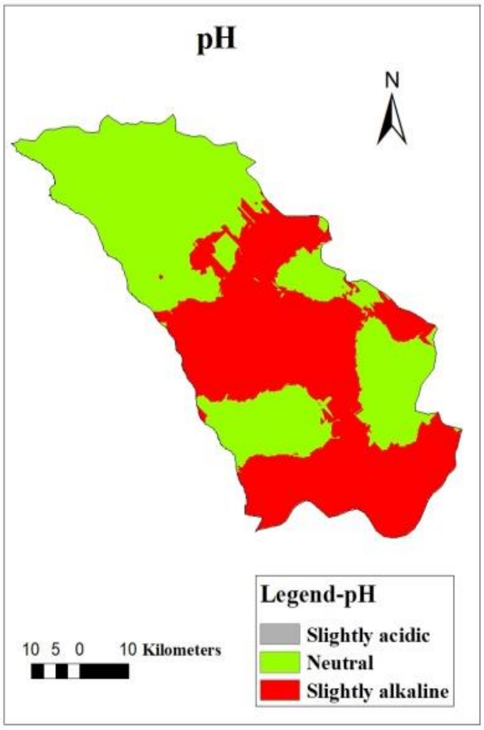


Fig. 12. EC

Spatial variability maps of soil pH:



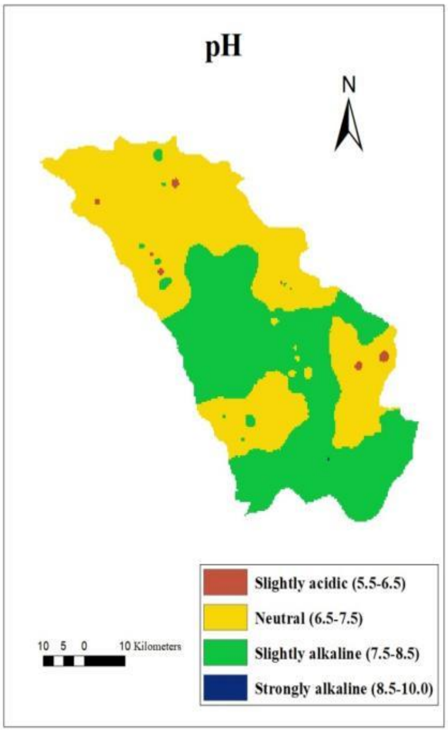
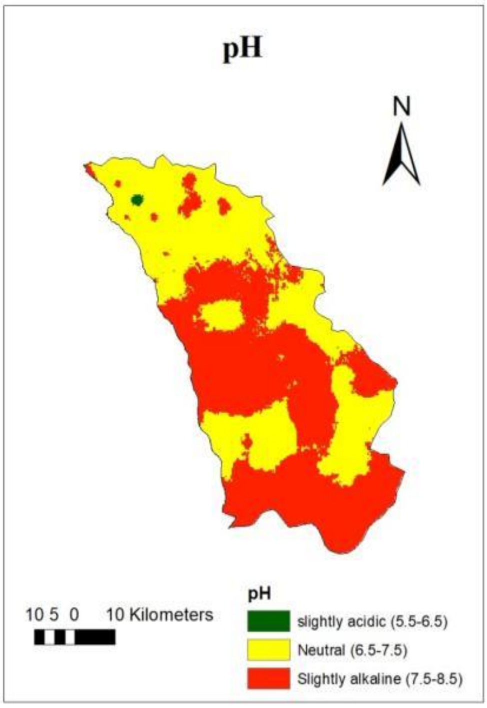


Fig. 13. Ordinary kriging **Fig. 14. IDW**



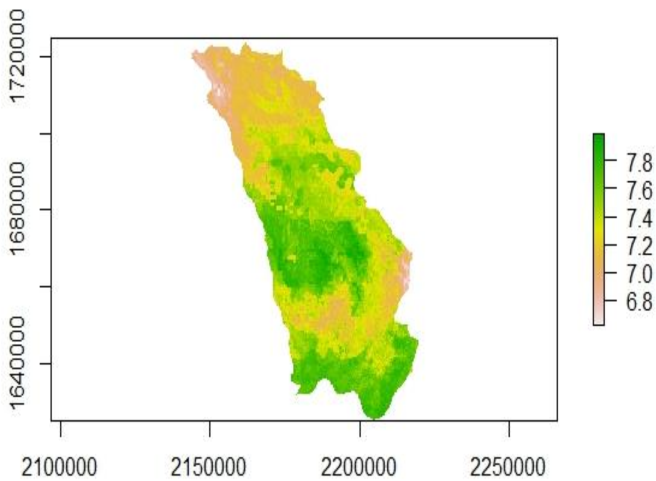


Fig. 15. RK **Fig. 16. RF**

Spatial variability maps of EC:

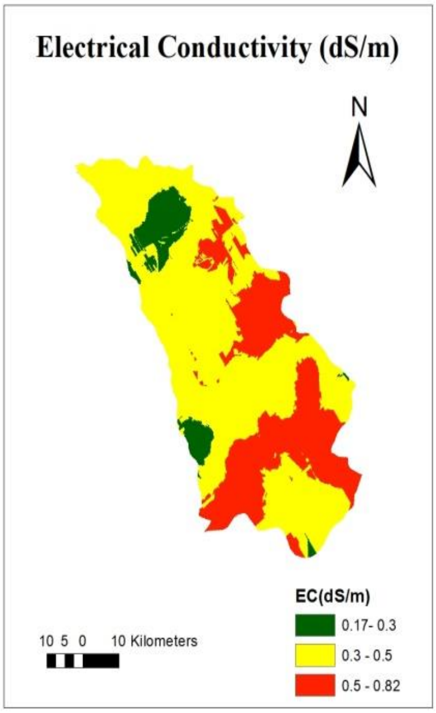


Fig. 17. Ordinary kriging

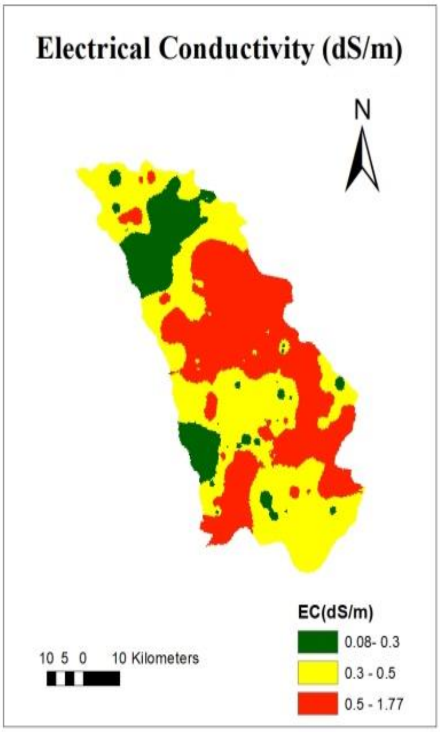


Fig. 18. IDW

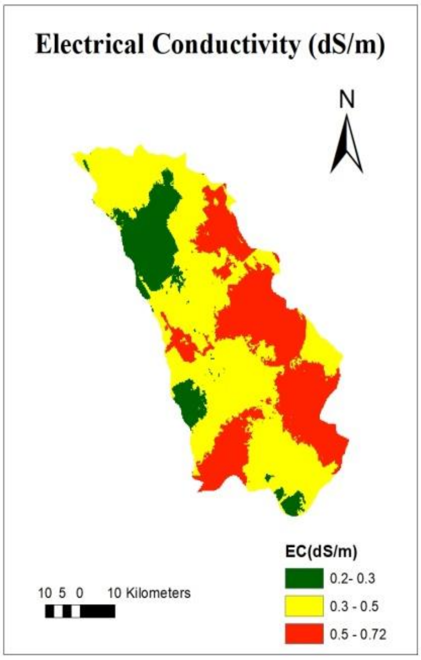


Fig. 19. RK

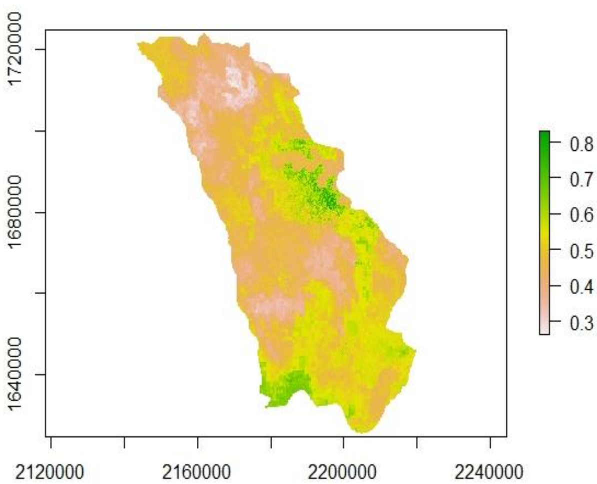


Fig. 20. RF

Accuracy assessment and comparison among the DSM approaches: The accuracy assessment of ordinary kriging, IDW, regression kriging and random forest technique was done using validation data set by calculating RMSE, ME and R^2 values.

Soil pH: Among all the techniques used, random forest technique was considered as the best technique for predicting soil pH with high R^2, low RMSE and ME values. The R^2, RMSE and ME values of 0.81, 0.28 and 0.014 were observed respectively (Table 4). Similar R^2 value of 0.78 was reported by Tziachris *et al*.,[27].

Electrical Conductivity (EC): Table 4 showed that the random forest technique of data mining approach was the best model in predicting EC of soils of Suryapet district with high R^2, low RMSE and ME values of 0.7256, 0.134 and 0.022, respectively. Similar R^2 value for EC was reported by Dharumarajan *et al*., [26].

Table 4. Accuracy assessment of ordinary kriging, IDW, regression kriging and random forest technique in the prediction of soil pH and EC

Interpolation method	R^2	RMSE	ME
Ordinary kriging			
pH	0.37	0.45	-0.037
Electrical conductivity	0.16	0.27	0.055
IDW			
pH	0.20	0.56	-0.10
Electrical conductivity	0.07	0.27	0.067
Regression kriging			
pH	0.33	0.55	0.181
Electrical conductivity	0.07	0.212	0.026
Random forest model			
pH	0.81	0.28	0.014
Electrical conductivity	0.73	0.134	0.022

Validation of soil properties predicted through random forest model:

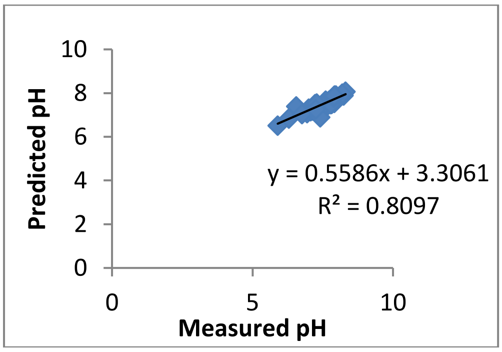


Fig. 21. Soil pH

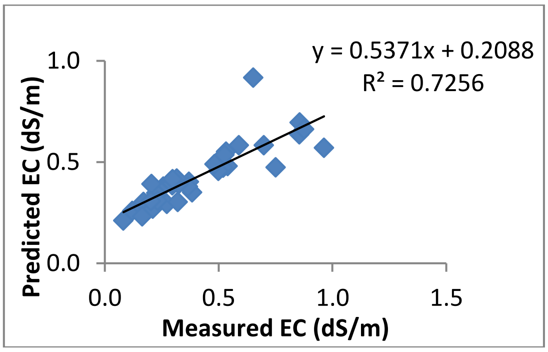


Fig. 22. EC (dS/m)

4. CONCLUSION

The performance of geostatical methods like ordinary kriging, inverse distance weighting method (IDW), regression kriging and data mining technique i.e., random forest technique used in the present study was evaluated by calculating RMSE, ME and R^2 values. The model with high R^2 value and low RMSE and ME values was considered as the best model. In the current study, random forest technique showed high R^2 values and low RMSE and ME values for soil pH and EC in comparison with geostatistical methods. Thus, random forest technique was considered as the best model for spatial prediction of soil pH and electrical conductivity of soils of Suryapet district.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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