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Estimating Variograms of Soil Salinity Properties by Kriging, Remote Sensing and GIS Techniques in Indira Gandhi Nahar Pariyojana Irrigation Command of Rajasthan, India

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Abstract: Assessment of soil salinization in irrigated agriculture is important for evaluation of the long term sustainability of agricultural production. Development of salinity in the Indira Gandhi Nahar Pariyojana (IGNP) stage-I irrigation command of Rajasthan is emerging as a serious problem. Reliable estimates of spatial distribution of soil salinity is necessary from the crop management point of view. Soil pH and EC (Electrical Conductivity) were measured in 380 samples collected from various locations in the IGNP stage-I command. The data on pH and EC were interpolated with various semi-variogram models viz., linear, spherical, circular, exponential and Gaussian by ordinary kriging method. Among all the models evaluated, the exponential model showed the best result for the spatial variability in salinity. The semi-variogram maps prepared can be used for the identification of soil sampling locations precisely while mapping at the cadastral level/large scale. The study also demonstrated the possibility of mapping soil salinity using ordinary kriging methods.

Key words: Soil salinity, kriging, spatial variability and soil heterogeneity.

The assessment of soil salinization in irrigated agriculture is of critical importance for the evaluation of soil degradation and the sustainability of agricultural production (Soil and Plant Analysis Council, 1992). Conventionally, soil salinity is determined by laboratory analysis (Electrical conductivity of the saturated soil paste extract, ECe). The classical soil survey methods of field sampling, laboratory analysis and interpolation of these field data for mapping, especially in large areas are relatively expensive and time consuming. Remote sensing data can be used as a tool to overcome some of these problems (Fagbami, 1986). Dwivedi (1992) used LANDSAT MSS and TM data for detailed mapping and monitoring of salt affected soils in the frame of the reconnaissance soil map of India. Effects of image scale on the delineation of salt-affected soils were studied by visually interpreting the standard FCC prints of TM data at the 1:250000 scale and for the same area at the 1:50000 scale, and refinement of the boundaries of salt affected soils delineated at the 1:250000 scale, was achieved. De Dapper and Goossens (1996) used the GIS and remote sensing for monitoring and predicting soil salinity in the Nile delta fringes of Egypt. Studies related to spatial variability of soil properties are gaining momentum. Adhikari *et al.* (2011) highlight spatial variability of EC in desert soils. Spatial variability of exchangeable sodium, EC, soil pH and boron content was studied by Ardahanlioglua *et al.* (2003) and soil properties in general including soil pH, organic carbon and total nitrogen for Ethiopian soils by Tesfahunegna *et al.* (2011). These studies used various geostatistical interpolation techniques and found different regions of spatial variability from observed data.

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Creating maps typically involves sampling, measuring the variable of interest and estimating values at unsampled locations through some form of interpolation, plain regression, data aggregation, or other prediction techniques (McBratney *et al.*, 2003). Geostatistics offers a collection of deterministic and statistical tools aimed at understanding and modeling spatial variability. Kriging provides an unbiased optimal solution to the problem of estimating values at unknown locations.

IGNP is one of the most gigantic irrigation projects in the world aiming at transforming vast areas of desert in Rajasthan, primarily covered with aeolian sands and undulated terrain, into agriculturally productive area. Development of soil salinity has become the major problem in IGNP stage-I irrigation commands of Rajasthan. Multi band optical satellite data have potential to map part of these degraded areas rapidly. These degraded areas (manifested at surface) can be identified from IRS 1D LISS III images using digital image

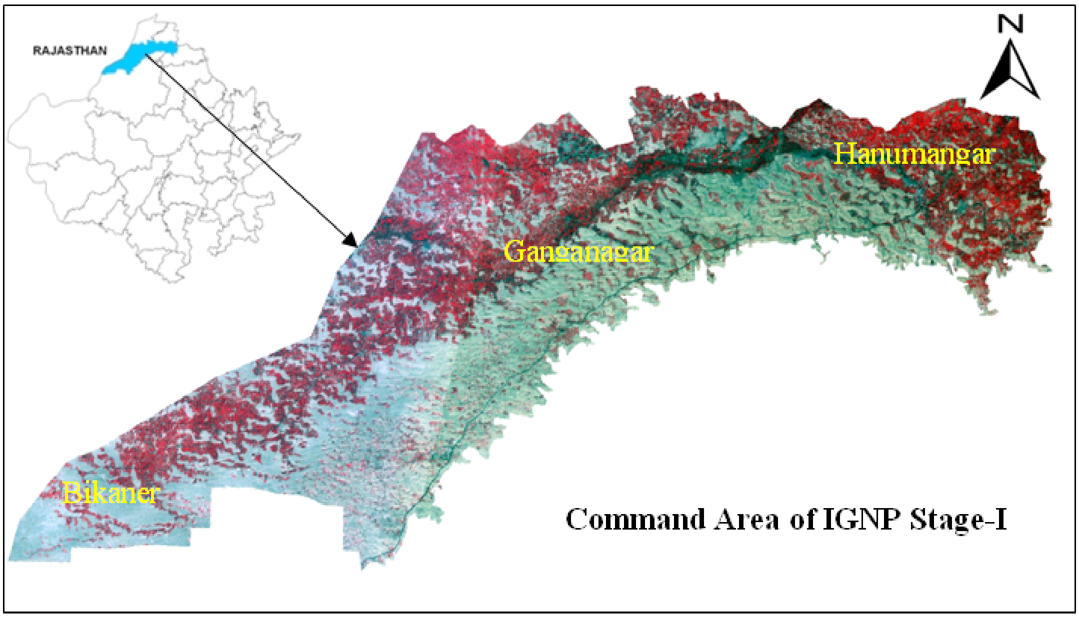

Fig. 1. FCC of study area (LISS III data).

processing. These saline soils appear dull white/ bluish white to white on satellite imagery (False Colour Composite). These are secondary salinized lands caused due to excessive irrigation, rise of water table, presence of inherent salts in alluvium, in pockets having thick zone of lime/gypsiferous material in sub strata and lack of adequate drainage. As such the EC values of such soils are >4 dS m^{-1} and pH values less than 8.5. Salt affected lands are sometimes occurring around waterlogged areas. Spatial estimation and prediction of salinity is necessary for land evaluation in order to develop and determine leaching factor and the precise management for maximum production.

This study has been undertaken with the objective of mapping spatial variability in soil salinity in IGNP stage-I using kriging, GIS and remote sensing techniques. Various semi-variogram models are also evaluated.

Materials and Methods

The study area, IGNP stage-I, lies between 25°1′38.85″ N to 29°29′52.31″ N latitudes and 72°16′22.78″ E to 75°24′5.51″ E longitudes, covering a total area of approximately 843988 ha (Fig. 1). The area falls under hot arid climate. The mean annual rainfall is 281 mm with a coefficient of variation of 50%. The mean maximum and minimum temperatures are 43.03°C and 5.05°C, respectively. Soils of this region are deep to very deep with fine to coarse texture mostly belonging to Entisols. Northern irrigated Ghaggar plain is dominated by fine and moderately fine textured soils. In southern rainfed zone the major soil groups are sandy to loamy sand at places underlained by lime concretion and gypsiferous substrata. The soils are low in nitrogen, organic carbon and phosphorus contents.

IRS 1D LISS III data of 2003-04 (Zaid and Kharif seasons) were used for the study. Sites for soil sample collection were selected judiciously based upon spectral characteristics of the area over satellite image mainly during summer season and other ancillary information like soil survey report published by National Bureau of Soil Survey & Land Use Planning (Shyampura and Sehgal, 1995).

Soil samples were collected randomly from surface soils (0-15 cm depth) from 380 locations across the study area. The exact location of the soil samples were precisely defined in the field by using GPS and plotted on the map (Fig. 2). Simple random sampling method is more precise and less subject to the bias of the sampler than the judgment sampling method. Sampling units were selected randomly and independently and were irrespective of any judgment regarding spots previously taken (Pleysier, 1995; Petersen and Calvin, 1965).

Soil pH and EC were measured in the laboratory in 1:2 soil water suspensions (Jackson, 1973; Rhoades and Schilfgaarde, 1976). The coordinates of sampling points were transferred onto base map and spatial variability analysis was

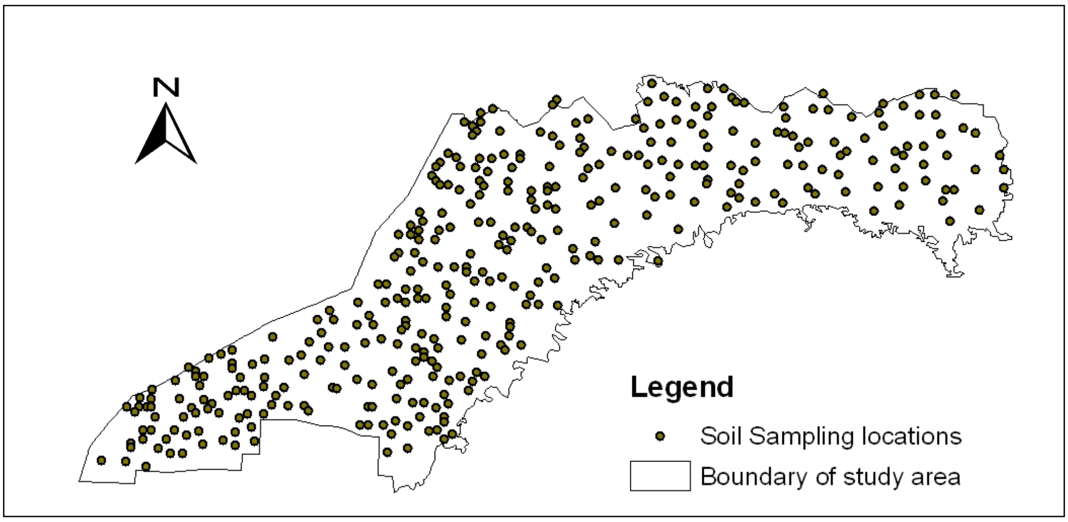

Fig. 2. Soil sample location map of study area.

performed to visualize the continuous surface of pH and EC variation.

Kriging technique weights the surrounding measured values to derive a prediction for an unmeasured location. The general formula for this interpolators is formed as a weighted sum of the data (Pierre, 1997; Goovaerts, 1997; Oliver, 2010):

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

where, $Z(s_i)$ = the measured value at the i^{th} location; λ_i = an unknown weight for the measured value at the i^{th} location; S_0 = the prediction location; and N = the number of measured values.

However, with the kriging method, the weights are based not only on the distance between the measured points and the prediction locations, but also on the overall spatial arrangement of the measured points. To use the spatial arrangement in the weights, the spatial autocorrelation must be quantified. Thus, in ordinary kriging, the weight, λ_i, depends on a fitted model to the measured points, the distance to the location to be predicted, and the spatial relationships among the measured values around the predicted location.

Semi-variogram modeling is a key step between spatial description and spatial prediction. The empirical semi-variogram provides information on the spatial autocorrelation of datasets. However, it does not provide information for all possible directions and distances. For this reason, and to ensure that kriging predictions have positive kriging variances, it is necessary to fit a model which is a continuous function or curve and to the empirical semi-variogram. Abstractly, this is similar to regression analysis, in which a continuous line or curve is fitted to the data points. Various semi-variogram models like linear, spherical, circular, exponential and Gaussian were attempted. The Arc info and ArcGIS 9.2 softwares were used for analysis.

In this study different semi-variogram models were evaluated based on statistical performance parameters of coefficient of determination (R^2) and mean square error (MSE). Coefficient of determination is the proportion of variability in a data set that is accounted for by a model. The MSE is a frequently used measure of the differences between values predicted by a model or an estimator and the values actually observed. These models of spatial correlation are then used along with kriging to develop large scale maps showing the spatial pattern of soil pH and soil EC status in the selected study area.

Results and Discussion

pH and EC variations have been mapped through ordinary kriging interpolation technique using several empirical models. However, variability was highlighted better through exponential model (Fig. 3 and 4). From these maps we grouped soil pH and EC variability and subsequently identified areas prone to salinity. The exchangeable sodium percentage (ESP) values were also examined and found below 15. Hence, sodicity problem is not present in this area.

EC varied from 0.05 to 19.44 dS m^{-1} with an average and standard deviation of 0.51 and 1.6443, respectively, across all the samples collected. The variation in pH was from 6.96 to 10.96, mean and standard deviation values were found to be 8.31

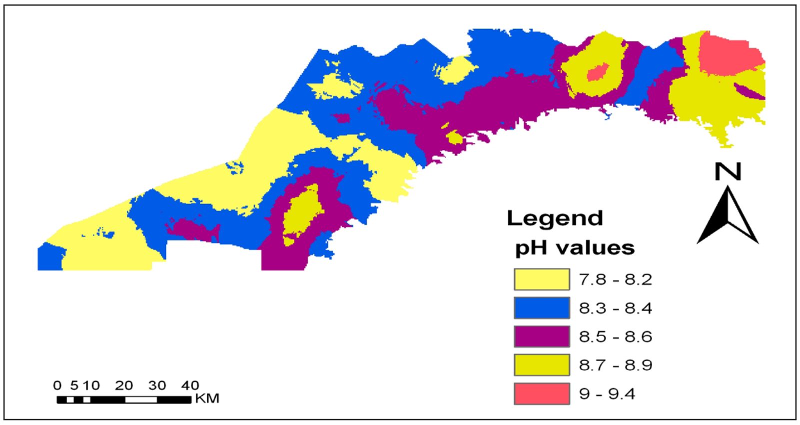

Fig. 3. pH variation mapped through ordinary kriging interpolation method using exponential model.

and 0.4414, respectively. All the models showed a strong spatial variability in respect of pH and EC. All the models were evaluated based on statistical performance parameters of coefficient of determination and mean square error. Results of evaluation of various semi-variogram models are shown in Table 1.

Table 1. Coefficient of determination (R^2) and mean square error (MSE) for different semi-variogram models

Model	pH		EC	
	R^2	MSE	R^2	MSE
Linear	0.404	0.1193	0.227	2.1957
Spherical	0.428	0.1154	0.268	2.1226
Exponential	0.468	0.1089	0.326	2.0252
Gaussian	0.288	0.1395	0.062	2.5682
Circular	0.433	0.1146	0.246	2.1680

Results from Table 1 reveal that exponential model was among the best for this analysis because it explained maximum variability in the data set. For both pH and EC, coefficient of determination was found highest for the exponential model and it was lowest for Gaussian model. Mean square error was lowest with value of 0.1089 and 2.0252, respectively, for pH and EC in case of exponential model. Performance of Gaussian model was found worst with highest values of MSE. The prior knowledge of this salinity distribution in the area played a vital role in fitting the exponential model.

From the spatial variability maps generated areas under various pH and EC categories were calculated (Table 2). Similar study of variability in pH and soil salinity representing horizontal distribution in continuous model was mapped earlier using appropriate interpolation techniques (Darwish, 1998).

Ordinary kriging method has been used in this study for data generated from small scale mapping. But for large scale or cadastral level mapping the spatial variability has been taken from above semi-variogram maps. Based on above maps a particular area was delineated with spatial variability and analyzed for detailed soil

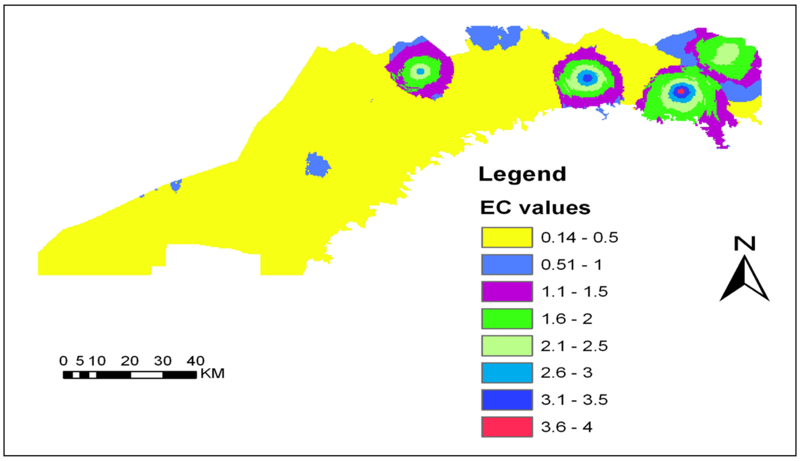

Fig. 4. EC variation mapped through ordinary kriging interpolation method using exponential model.

Table 2. Area under different pH and EC values

pH range	Area (ha)	EC range	Area (ha)
7.8-8.2	196326	0.1-0.5	649477
8.3-8.4	302629	0.5-1.0	40875
8.5-8.6	208446	1.0-1.5	63256
8.7-8.9	109418	1.5-2.0	60097
9.0-9.4	27169	2.1-2.5	21609
		2.6-3.0	6102
		3.1-3.5	2229
		3.6-4.0	343
Total	843988	Total	843988

properties. This variogram can also be used in small study areas to identify the locations very accurately by spatial and geo statistical methods. The semi-variograms showed the zones of higher variability which indirectly helped in identification of soil sample locations precisely. Therefore, the kriging outputs (semi-variogram maps) are very much useful for mapping spatial variability in large scale/cadastral level.

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