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Evaluation and comparison of ordinary kriging and inverse distance weighting methods for prediction of spatial variability of some chemical parameters of Dhalai district, Tripura

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Abstract : Interpretation and analysis of spatial variability of soil properties were carried out by ordinary kriging and inverse distance weighting (IDW) methods to generate continuous sample for site-specific management. A total of 535 soil samples (0-25 cm) were collected at an interval of 2 km grid in Dhalai district of Tripura, India. The data were interpolated by ordinary kriging and IDW with power 2. All the selected soil chemical parameters were strongly spatially dependent, but the range of spatial dependence was found to vary within soil parameters. Available potassium had the shortest range of spatial dependence (6.9 km) whereas pH had the longest range (23.7 km). The study shows that prediction of spatial variability for different soil parameters (except available nitrogen) may be better understood by ordinary kriging than by IDW method.

Additional key words : *Geostatistics, GIS, spatial interpolation, semivariogram, accuracy assessment*

Introduction

Soils are characterized by high degree of spatial variability due to the combined effect of physical, chemical and biological processes that operate with different intensities and at different scales (Goovaerts 1998). In recent years, considerable interest has been generated in assessment of the physical, chemical, and biological quality of agricultural soils (Carter *et al.* 1997; Haynes *et al.* 2003). Knowledge on spatial variation of soil properties is important in several disciplines, including agricultural field trial research and precision farming. Reports have shown that there is large variability in soil, crop, disease, weed and/or yield, not only in large-sized fields (Goovaerts 1998; McBratney and Pringle 1997; Corwin 2003; Godwin and Miller 2003; Vrindts *et al.* 2005), but also in small-sized fields (Mouazen *et al.* 2003). In precision farming, the concept of 'management zone' was evolved in response to this large variability with the main purpose of efficient utilization of agricultural inputs with respect to spatial variation of soils and its properties (Franzluebbers and Hons 1996; Atherton *et al.* 1999; Malhi *et al.* 2001). The most important way to gather knowledge in this aspect is to prepare soil maps through spatial interpolation of point-based measurements of soil properties (Santra *et al.* 2008).

Geostatistical methods can provide reliable estimates at unsampled locations provided that the sampling interval resolves the variation at the level of interest (Kerry and Oliver 2004). Spatial prediction techniques, also known as spatial interpolation techniques, differ from classical modeling approaches in that they incorporate information on the geographic position of the sample data points (Cressie 1993). The most common interpolation techniques calculate the estimate for a property at any given location by a weighted average of nearby data. A number of factors affect map quality including the nature of the soil variability (Salder *et al.* 1998), intensity of sampling and method of interpolation. Availability of a variety of interpolation methods has posed questions to the users as to which is the most appropriate method in different contexts and has stimulated several comparative studies of relative accuracy. Among statistical methods, geostatistical kriging-based techniques (Deutsch 2002) are widely applied and among deterministic interpolation methods, inverse distance weighting (IDW) method (Nalder and Wein 1998) is most often applied. Both models estimate values at unsampled locations based on the measurement at surrounding locations with certain assigned weights for each measurement. From a theoretical stand point, kriging is the optimal interpolation method (Isaake and Srivastava 1989); however, its correct application requires an accurate determination of the spatial structure *via* semivariogram construction and model-fitting.

Many researchers have compared IDW and kriging. In some cases, the performance of kriging was generally better than IDW (Hosseini *et al.* 1994; Dalthorp *et al.* 1999; Kravchenko and Bullock 1999; Kravchenko 2003; Reinstorf *et al.* 2005). Warrick (1998) also reported kriging to be better than IDW for mapping potato yield and soil properties. In other studies, IDW generally out-performed kriging (Nalder and Wein 1998). Gotway *et al.* (1996) observed the best results in mapping soil organic matter contents and soil NO_3^- levels when IDW was used as the interpolation technique. The results, however, have often been mixed (Schloeder *et al.* 2001; Mueller *et al.* 2001; Lapen and Hayhoe 2003). Kriging performance can be significantly offered by variability and spatial structure of the data (Leenaers *et. al.* 1990) and by the choice of variogram model, search radius and number of the closest neighboring points used for estimation. As might be expected, the performance of kriging improved relative to IDW when spatial structure was known. The objectives of this study were (i) to determine the spatial variability of selected soil nutrients, such as pH, organic carbon content, available nitrogen and available potassium with geostatistical analysis and (ii) to describe and predict the relative performance of ordinary kriging and IDW.

Materials and methods

Site description

The study was carried out in Dhalai district, Tripura extended between 23°25′ to 24°15′N latitudes and 91°45′ to 92°10′E longitudes covering an area of 255247 ha. (Fig. 1). The temperature during summer varies between 36°C and 16.9°C, and during winter it varies between 28°C and 5.3°C. Annual rainfall is 1850 mm, about 80 per cent is received from June to September and the rest during winter months. The geology of the district is represented by sedimentary rocks which ranged in age from Miocene (918 million years old) to loosely consolidated sediments of recent age (less than 1 million years old). The rocks are sandstone, siltstone and shale grading into clay. The district is divided into eight physiographic units *viz.* high relief, medium relief, low relief, flat topped denudational hills, residual hills, alluvial plain, flood plain and undulating plains. Majority of the area of the district is characterized by medium relief. The soils of the study area were classified as per USDA Soil Taxonomy into four orders *viz.* Entisols, Inceptisols, Alfisols and Ultisols as per USDA Soil Taxonomy. (Bhattacharya *et al.* 1996)

Soil sampling and analysis

A total of 535 soil samples were collected from the plough layer (0-25 cm) (each at an approximate interval of 2 km grid) were collected from the entire district with the help of hand-held global positioning system (GPS). Soil samples were air-dried and ground to pass through a 2-mm sieve. Available nitrogen (Subbiah and Asija 1956), available potassium (Richards 1954); organic carbon (Walkley and Black

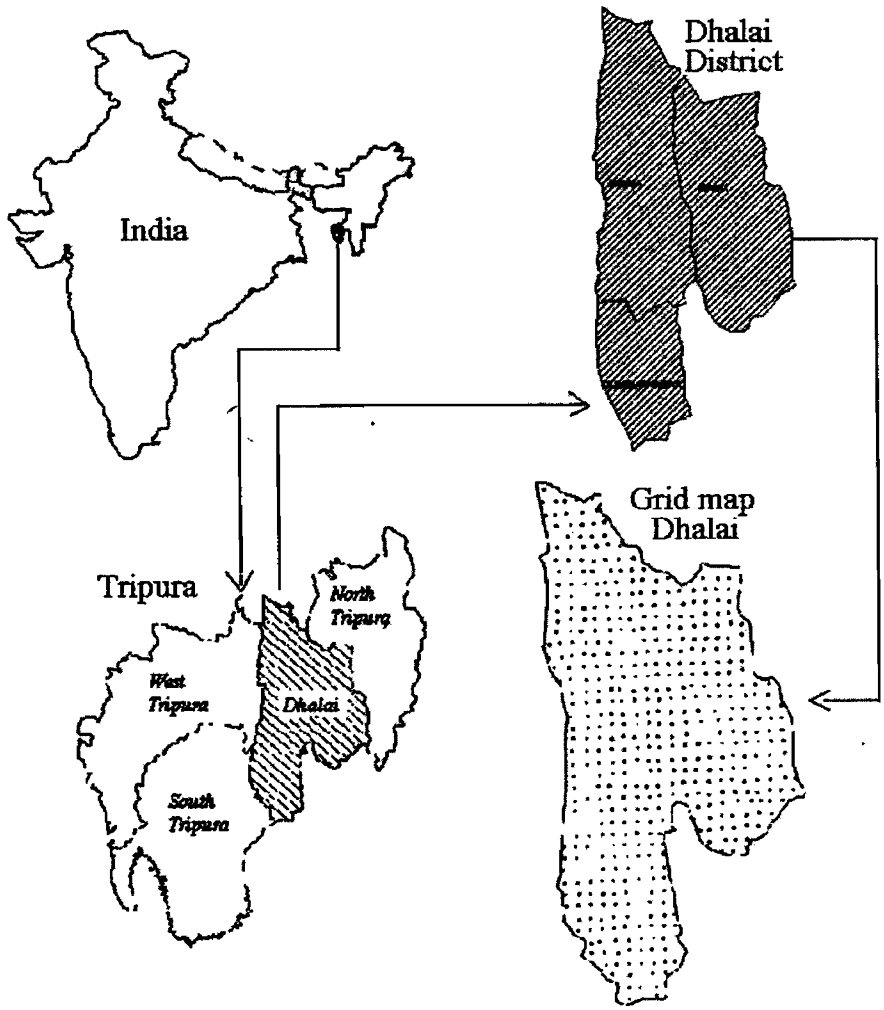

Fig. 1. Location and grid map of the study area

1934) and pH were determined.

Geostatistics

Geostatistics has been applied in soil science for more than 20 years (Burgess and Webster 1980; Webster 1994; Zhang *et al.* 2000). It uses the semivariogram to quantify the spatial variation of a regionalized variable. The fitted function to the experimental variogram provides the input parameters for spatial prediction by kriging (Krige 1951). The semivariogram is half the expected squared difference between paired data values z(x) and z(x + h) to the lag distance h, by which locations are separated (Webster and Oliver 2001).

$$\gamma(h) = \frac{1}{2} E[z(x) - z(x+h)]^2$$

The usual computing equation for the variogram is:

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

where $z(x_i)$ is the value of the variable Z at location of x_i, h is the lag distance and N(h) is the number of pairs of sample points separated by h. For irregular sampling, it is rare for the distance between the sample pairs to be exactly equal to h. Therefore, the lag distance h is often represented by a distance band.

Experimental semivariogram value for each soil property was computed and plotted with lag distance h. During pair calculation for computing the semivariogram, maximum lag distance was taken as half of the minimum extent of sampling area to minimize the border effect. Lag increment was fixed as 2.02 km as it measures by the distance between grid intervals in the registered map. In this study, omni-directional semivariogram was computed for each soil property because no significant directional trend was observed. Best-fit model with smallest nugget values with minimum root mean square error (RMSE) and root mean square standardized (prediction) errors (RMSSE) close to 1 were selected for each soil property. Finally, the cross-validation method was applied to validate the parameters of the model (Goovaerts 1997). Using the model semivariogram, basic spatial parameters such as nugget (C_0), partial sill ($C+C_0$) and range (a) were calculated. Nugget is the variance at zero distance, partial sill is the lag distance between measurements at which one value for a variable does not influence neighbouring values and range is the distance at which values of one variable become spatially independent of another (Lopez-Granados *et al.* 2002). Four commonly used semivariogram models were fitted for each soil property. These are the spherical, exponential, Gaussian and hole-effect model. In GIS domain, the point map was registered and then the point shape file was prepared. After that, all soil chemical data was entered against their grids. ArcGIS geostatistical analyst extension was used to carry out exploratory variogram analysis, and then this exploratory approach was extended to spatial interpolation by way of kriging. GIS model was built to compare the effectiveness of this geostatistical interpolation method to inverse distance weighting. Geostatistical analysis consisting of variogram calculation, kriging, IDW, cross-validation, and mapping was performed using the geostatistical analyst extension of ArcGIS 9.2 (ESRI 2008).

Accuracy assessment

Accuracy of the soil maps was evaluated through cross-validation approach (Davis 1987). Among three evaluation indices used in this study, mean absolute error (MAE), and mean squared error (MSE) measure the accuracy of prediction, whereas goodness-of-prediction (G) measures the effectiveness of prediction. MAE is a measure of the sum of the residuals (*e.g.* predicted minus observed) (Voltz and Webster 1990).

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|z(x_i) - \hat{z}(x_i)\right|$$

Where $\hat{z}(x_i)$ is the predicted value at location i. Small MAE values indicate few errors. The MAE measure, however, does not reveal the magnitude of error that might occur at any point and hence MSE will be calculated,

$$MSE = \frac{1}{N}\sum_{i=1}^{N}[z(x_i) - \hat{z}(x_i)]^2$$

Squaring the difference at any point gives an indication of the magnitude, *e.g.* small MSE values indicate more accurate estimation, point-by-point. The G measure gives an indication of how effective a prediction might be relative to that which could have been derived from using the sample mean alone (Schloeder *et al.* 2001).

$$G = \left[1 - \frac{\sum_{i=1}^{N}[z(x_i) - \hat{z}(x_i)]^2}{\sum_{i=1}^{N}[z(x_i) - \bar{z}]^2}\right] \times 100$$

Where z is the sample mean. If G = 100, it indicates perfect prediction, whereas negative values indicate that the predictions are less reliable than using sample mean as the predictors. The comparison of performance between interpolations was achieved by using mean absolute error (MAE).

Results and Discussion

Descriptive statistics

Descriptive statistics for the analyzed 535 soil samples for different soil parameters are summarized in table 1. The minimum, maximum, mean, median, standard deviation (SD), skewness and kurtosis can describe variability of a soil property. The greatest and the smallest standard deviations were observed in case of available nitrogen (136.46) and organic carbon (0.39), respectively. 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 consequently, the variances are less reliable. A logarithmic transformation is considered where the coefficient of skewness is greater than one (Webster and Oliver 2001). Therefore, a logarithmic transformation was performed for pH and available potassium parameters because their skewness was greater than 1.

Table 1. Descriptive statistics of soil parameters (0-25 cm depth) of 535 soil samples

Parameters	Minimum	Maximum	Mean	Median	Std. dev	Skewness	Kurtosis
pH	4.1	7.3	5.13	5.1	0.47	1.14	6.32
Organic carbon (%)	0.14	2.55	1.04	1.0	0.39	0.68	3.68
Available N ($kgha^{-1}$)	56	1207	414.1	380	136.5	0.47	5.91
Available K ($kgha^{-1}$)	60.5	954	238.5	215	129.5	1.58	6.84

Semivariogram of soil properties

RMSE and RMSSE are presented in table 2 for different theoretical semivariogram models to fit the experimental semivariogram values for each soil property. Among different theoretical models tested, the Gaussian model was found as the best fit in most cases. In case of pH, spatial variation was the best described by the spherical model.

Table 2. Parameters for different theoretical semivariogram models

Soil properties	Semivariogram Model	RMSE[a]	RMSSE[b]
pH	Circular	0.429	0.954
	Spherical	**0.426**	**0.958**
	Exponential	0.430	0.951
	Gaussian	0.430	0.951
	Hole effect	0.430	0.948
Organic carbon	Circular	0.364	0.954
	Spherical	0.364	0.956
	Exponential	0.363	0.959
	Gaussian	**0.361**	**0.963**
	Hole effect	0.430	0.937
Available N	Circular	113.3	0.972
	Spherical	113.0	0.975
	Exponential	110.6	0.981
	Gaussian	**110.0**	**0.994**
	Hole effect	114.0	0.977
Available K	Circular	119.7	0.956
	Spherical	119.5	0.963
	Exponential	117.9	0.975
	Gaussian	**117.0**	**0.986**
	Hole effect	119.9	0.959

[a] ***Root mean square prediction error;*** [b] ***Root mean square standardized prediction error***

Table 3. Semivariogram parameters (ordinary kriging interpolation) of soil properties

Soil properties	Semivariogram model	Range (km)	Nugget (C_0)	Partial Sill (C)
pH	Spherical	23.7	0.185	0.0343
Organic carbon	Gaussian	10.6	0.1301	0.033
Available N	Gaussian	8.9	10927	4033.7
Available K	Gaussian	6.9	12183	3904.4

Semivariogram parameters (range, nugget and partial sill) for each soil property with the best-fitted model are presented in table 3. The range expressed as distance could be interpreted as the diameter of the zone of influence that represented the average maximum distance over which a soil property of two samples was related. At distances less than the range, measured properties of two samples became similar with decreasing distance between the two points. Thus, the range provided an estimate of areas of similarity. The zones of influence for pH was approximately 23.7 km; however, for organic carbon, available nitrogen, and available potassium they were much smaller, from 6.9 to 10.6 km only (Table 3). These distances stood for the minimum distances on an average, at which maximum variation occurred, and were larger than the distances among sampling locations. These studies proved that soil properties displayed spatial autocorrelation, and that structural factors, such as parent material, terrain, and water table, as well as random factors, such as fertilizer application, crop planting, soil management and codetermined soil properties (Goovaerts 1997). Nugget (C_0) defines the micro-scale variability and measurement error for the respective soil property, whereas partial sill (C) indicates the amount of variation, which can be defined by spatial correlation structure.

Ordinary kriging and cross-validation

Spatial maps prepared through ordinary kriging using the semivariogram parameters were cross-validated by leaving one sample out and predicting for that sample location based on rest of the samples. Evaluation indices resulting from cross-validation of spatial maps of soil properties are given in table 4. For all soil parameters, the G value was greater than zero. It indicates that spatial prediction using semivariogram parameters is better than assuming mean of observed value as the property value for any unsampled location. This also shows that semivariogram parameters obtained from fitting of experimental semivariogram values were fairly reasonable to describe the spatial variation.

Spatial maps of soil properties prepared through ordinary kriging are presented in fig. 2. pH, organic matter content, available nitrogen and available potassium had a large and similar spatial variability, eg. all soil nutrients decreased from north to south and from northeast to southwest.

IDW and cross-validation

Inverse distance weighting prediction was performed using power of 2. The results for different soil parameters, in terms of mean absolute error, mean square error and goodness of prediction obtained from cross-validation procedures are presented in table 5.

Table 4. Evaluation performance of ordinary kriging map of soil properties through cross-validation

Soil properties	Mean absolute error (MAE)	Mean square error (MSE)	Goodness of prediction (G)
pH	0.0021	0.184	18.66
Organic carbon	0.0004	0.132	14.56
Available N	0.1462	12331	33.65
Available K	0.6094	13924	16.85

For all soil parameters, the *G* value was greater than zero, which indicates that spatial prediction is better than assuming mean of observed value as the property value for any unsampled location. The interpolation maps of all soil properties using IDW with power 2 are presented in fig. 3.

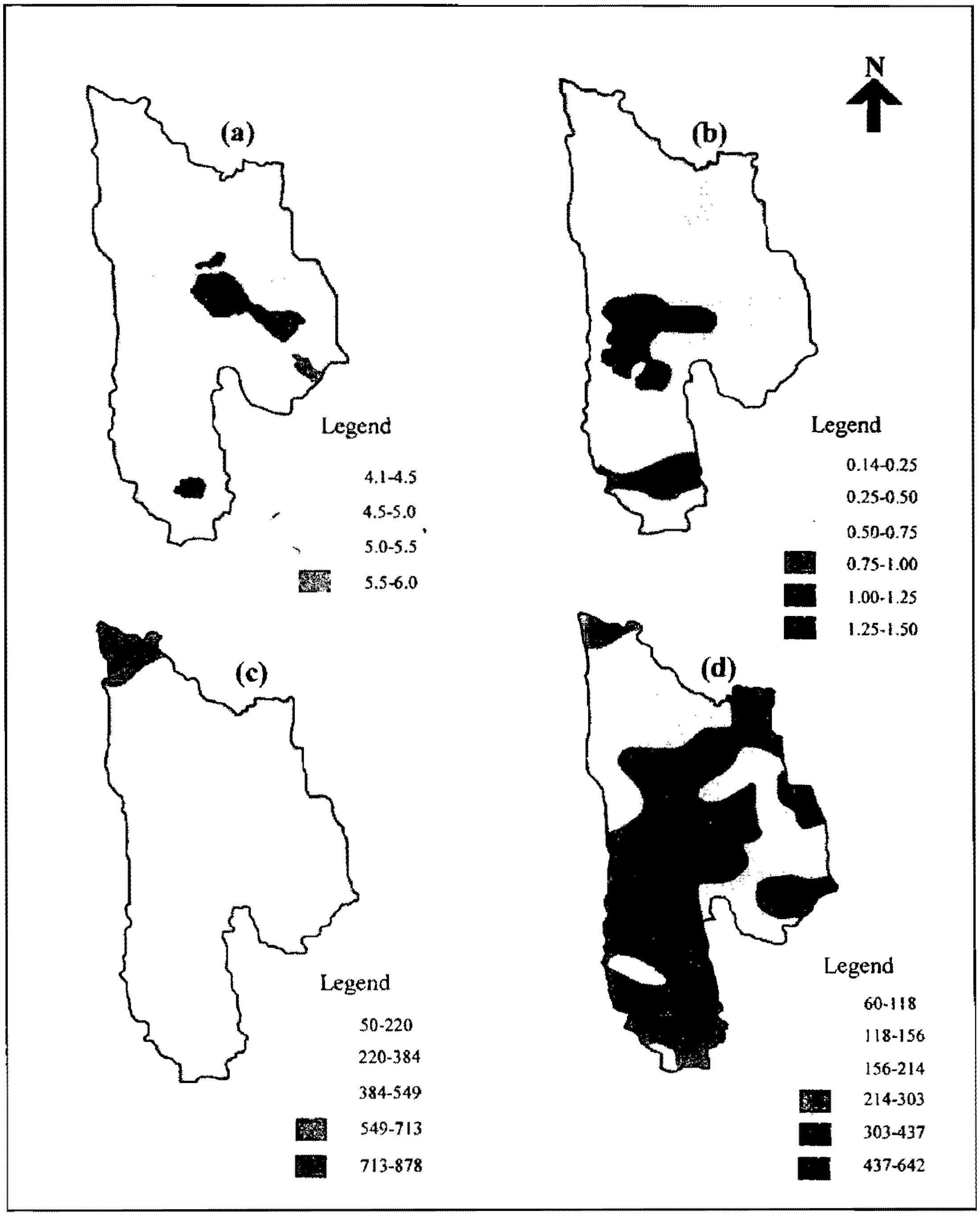

Fig.2. Ordinary krigged map of soil properties (a) pH, (b) organic carbon (%), (c) available nitrogen (kg ha^{-1}) and (d) available potassium (kg ha^{-1})

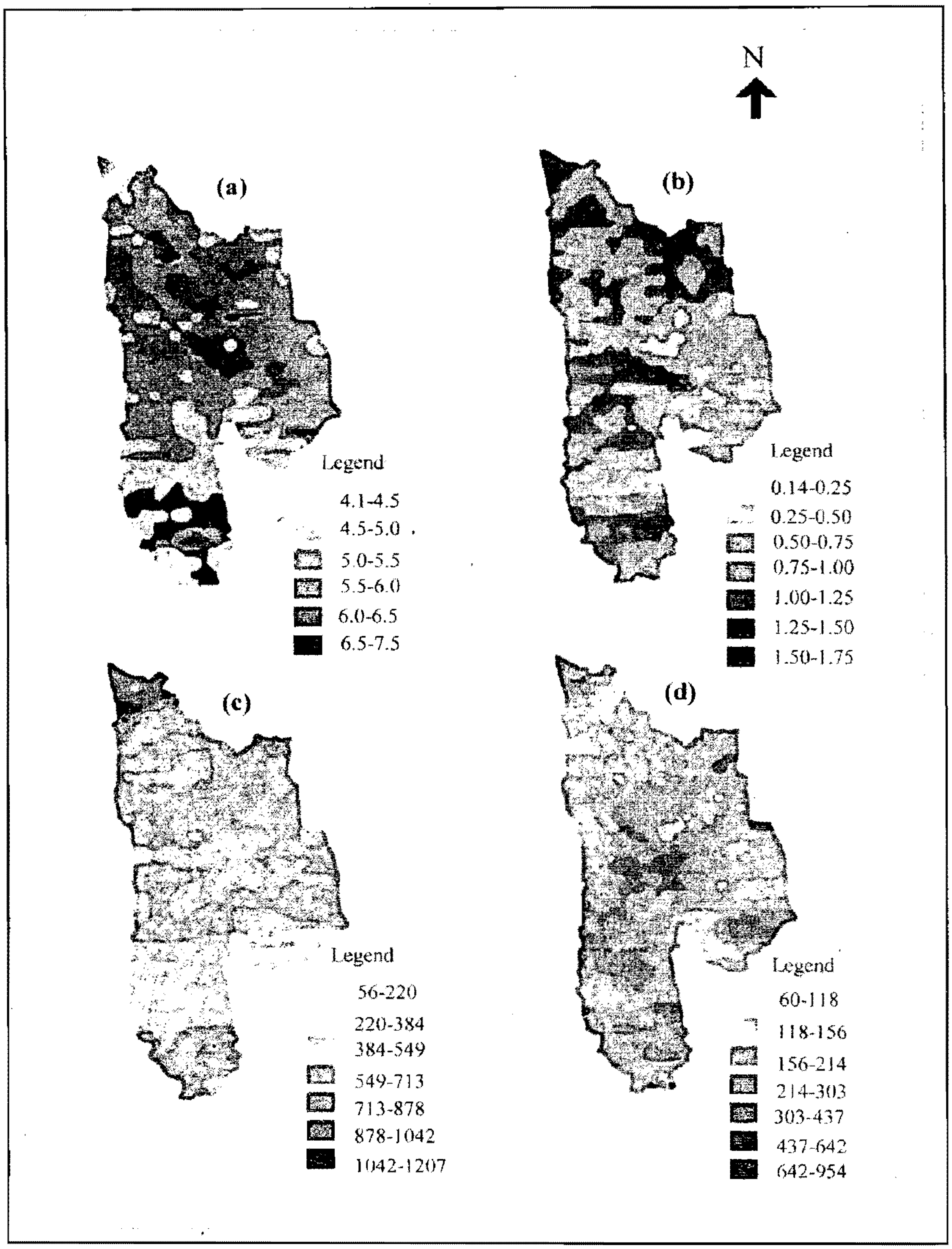

Fig.3. Inverse distance weighting map of soil properties (a) pH, (b) organic carbon (%), (c) available nitrogen (kg ha^{-1}) and (d) available potassium (kg ha^{-1})

Table 5. Evaluation performance of IDW map of soil properties through cross-validation

Soil properties	Mean absolute error (MAE)	Mean square error (MSE)	Goodness of prediction (G)
pH	0.0048	0.171	22.28
Organic Carbon	0.0011	0.135	13.52
Available N	0.0088	11989	35.19
Available K	0.8850	13833	17.39

Comparison between ordinary kriging and IDW

Based on MAE (Table 6) obtained form ordinary kriging and IDW, results show that ordinary kriging for all soil paramenters in this study except available nitrogen was better than IDW. To select the best accurate method using table 6 represents the gist of results in this research for both prediction methods. Results indicate that ordinary kriging gives the best performance among all applied methods. .

Table 6. Comparison between two geostatistical interpolations based on Mean Absolute Error (MAE)

Type of interpolation	pH	Organic Carbon	Nitrogen	Potassium
Ordinary Kriging	0.0021	0.0004	0.1462	0.6094
Inverse distance weighting	0.0048	0.0011	0.0088	0.8850

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