MAPPING SURFACE SOIL PROPERTIES USING TERRAIN AND REMOTELY SENSED DATA IN ARSANJAN PLAIN, SOUTHERN IRAN

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ABSTRACT

Sustainable land management and land use planning require reliable information about the spatial distribution of the physical and chemical soil properties affecting both landscape processes and services. Spatial prediction with the presence of spatially dense ancillary variables has attracted research in pedometrics. The main objective of this research is to enhance prediction of soil properties such electrical conductivity (ECe), exchangeable sodium percentage (ESP), available phosphorus (P), organic matter (OM), total nitrogen (TN) and pH by making use of the ancillary variables as covariates. Methods that was used for this purpose may be divided into two groups: (i) those that use only a single variable in the prediction process (simple linear regression (SLR), ordinary kriging (OK)) and (ii) another that make use of additional variables as a part of prediction (simple kriging with a locally varying mean (SKLVM)). LISS-III data from Indian remoter sensing satellite (IRS-P6) were used as secondary data with SKLVM method. Mean square error (MSE) was used to evaluate the performance of the map prediction quality. It was concluded that SKLVM method provided the most accurate predictions based on the summary statistics of prediction errors from cross-validation for mapping OM, pH and ECe. Maps from these kriged estimates showed that a combination of geostatistical techniques and digital data from LISS-III receiver could improve the prediction quality of soil management zones, which is the first step for site-specific soil management.

Keywords: Geostatistics, Remote sensing, Kriging, Spatial prediction, IRS-P6

INTRODUCTION

Traditionally, farm managers consider fields as uniform pieces of land, and thus, fertilizers and other farm inputs are applied without taking into account spatial variations in field characteristics. This results in over-application and under-application in specific areas within a field. Efficient tools to measure within-field spatial variation in soil are important when establishing agricultural field trials and in precision farming. Spatial prediction of soil properties has become a common topic in soil science research. Variability in soil properties can present management challenges to producers (Goovaerts, 2000). This is enhanced by the advancement of technology that enabled collection of on-thego proximal sensors and also remotely-sensed imagery for use in precision agriculture and digital soil mapping (Lopez-Granados et al., 2005). Site-specific management or precision agriculture seeks to identify, analyze, and manage spatial and temporal variability within fields in order to optimize profitability, sustainability, and environmental protection (Robert et al., 1996; Duffera et al., 2007). Chaplot et al (2000) demonstrated that quality of soil hydromorphy prediction was highly improved by co-kriging of 10 and especially 60 pedological data points with a topographical regression model. Simbahan et al. (2006) reported that for reducing uncertainties, it was recommended that use independently measured, multivariate secondary information in regression kriging approaches for mapping of soil organic carbon. They indicated that geostatistical methods that utilized spatially correlated secondary information increased the quality of maps of soil organic carbon stock as compared to OK. Also, showed that regression kriging with ECe performed better than OK, kriging with an external drift or cokriging. Minasny and McBratney (2007) concluded that improvement in the prediction of soil properties does not rely on more sophisticated statistical methods, but rather on gathering more useful and higher quality data. Due to high cost and time-consuming nature of soil sampling and their analysis, research in developing methods for the creation of soil maps from sparse soil data is becoming increasingly important. In the past 20 years, the development of prediction methods that use cheap secondary information to spatially extend sparse and expensive soil measurements has been a sharpening focus of research (Odeh and McBeatney, 2000; Minasny and McBratney, 2007; McBratney et al., 2003; Lopez-Granados et al., 2005). Examples of secondary information include remote sensing imagery, elevation data and crop yield data. Furthermore, a number of proximal soil sensors are becoming more available; examples are the Soil Doctor Colburn, 1999 and the VERIS conductivity cart (Lund et al., 1999). Consequently, the potential for using the secondary information to aid soil mapping at the within-field extent is greater than ever before.

The introduction of ancillary, exhaustive spatial information linked to salinity might improve the mapping of this attribute. Many authors have shown that remote sensing, particularly within the visible spectral range, yields spatial information strongly correlated with salinity (Mougenot, 1993; Rahman et al., 1994; Khan et al., 2001; Metternicht and Zinck, 2003) or soil surface features with additional microwave remotely sensed data (Metternicht and Zinck, 1998; Sumfleth and Duttmann, 2007). Moreover, several authors have demonstrated the advantage of combining data from remote sensing with pinpoint information observed on the ground (Bishop and McBratney, 2001; Carré and Girard, 2002).

Several studies have explored the potential benefits of using secondary information to map different variables. For example, Goovaerts (2000) compared Thiessen polygons, inverse distance weighting (IDW), SKLVM, kriging with an external drift and collocated cokriging for mapping precipitation. With the latter three approaches elevation was used as the secondary variable and these techniques resulted in smaller prediction errors than the univariate ones.

Remotely sensed data can be useful for improving existing coarse-scale soil survey information at a regional scale. Thus, Odeh and McBratney (2000), Bishop and McBratney (2001), and Kerry and Oliver (2003) demonstrated that AVHRR (Advanced Very High Resolution Radiometer) data from the NOAA (National Oceanic and Atmospheric Administration) series of satellites, bare soil LANDSAT TM (Thematic Mapper) imagery and bare soil aerial colour photograph have been useful for the field-extent creation of different soil property maps using different prediction models (statistical and geostatistical techniques). They used the soil spectral variation for spatial prediction of soil attributes at a regional scale. The major objectives of our study was to compare different prediction methods such as simple linear regression (SLR), ordinary kriging (OK) and method that make use of secondary or ancillary variables (LISS-III receiver data from IRS-P6) as a part of prediction such as simple kriging with a locally varying mean (SKLVM) in order to determine the most appropriate approach to spatially transfer data from a limited number of sampling points to unsampled locations.

MATERIALS AND METHODS

STUDY SITE

The study area is found in Badjgah plain that located in Fars province, southern Iran at geographical coordinates of 29˚42′ to 29˚46′ N latitude and 53˚10′ to 53˚17′ E longitude. Soils were developed over the parent material of limestone. The mean annual precipitation, evaporation and temperature are 333.4 mm, 919.1 mm and 15.2 ºC, respectively. Soil moisture and temperature regime are xeric and thermic, respectively. The prominent soils of Badjgah plain are somewhat affected with salinity and/or sodicity because of high evaporation. Extensive areas of the Badjgah plain have become and continue to be degraded by salinization due to the use of low-quality irrigation water with inappropriate irrigation methods. As a result, agricultural production of the Badjgah plain has declined significantly in the last two decades.

SOIL SAMPLING, LABORATORY ANALYSIS AND REMOTE SENSED DADA

Eighty-five soil samples, on 08 September 2006, from the top soil (depth of 0-30 cm) were collected and geo-referenced using GPS receiver (accuracy of ± 5 m), analyzed for ECe, P, OM, pH, TN and ESP. ESP was determined using the ammonium acetate (NH_4OAc) method (Thomas, 1982); soil pH was measured with a glass electrode pH meter (McLean, 1982). Soluble salts were calculated by measurement of ECe in the soil extraction by the use of a conductivity meter (Rhoades, 1982). OM was determined dichromate oxidation procedure (Allison, 1965). Total nitrogen (TN) was determined with the Kjeldahl method (McGill and Figueiredo, 1993), available phosphorus (P) was measured by the Olsen method (Olsen et al., 1954).

Remote sensed data is now considered as an appropriate tool for deriving information in spatial and temporal domains by providing multi-spectral reflectance data at regular intervals in a synoptic mode. The satellite data used in this research is IRS-P6 scene, dated 08 September 2006. Both geometric the correction and conversion of original digital number measures to the surface reflectance values was carried out in conjunction with the atmospheric correction. The imaging sensors on IRS-P6 that was used is a multispectral Linear Imaging Self-Scanner (LISS-III) in visible (0.52-0.59 µm, band 1; 0.62-0.68 µm, band 2), near-IR spectral bands (0.77-0.86 µm, band 3) with spatial resolution of around 23 meters and a Short Wave IR (SWIR) band (1.55-1.75 µm, band 4) with a resolution of around 70 meters.

PREDICTION METHODS

A brief description of the prediction methods used is given below.

SIMPLE LINEAR REGRESSION (SLR)

Every sampled soil point was located in the satellite image and its corresponding digital value in four bands (band 1, 2, 3 and 4) was extracted. It was verified that all variables (i.e., soil properties and spectral values in visual range) were normally distributed. Pearson linear correlations were determined between soil variables and spectral values in four bands, accepting a confidence level of 95%. Regression equations were calculated for those soil variables that showed higher significant correlations with digital data. It should be imply that band combinations and principal component analysis obtained from four bands had not any more accuracy that these four main bands; therefore, we have presented results of the four main bands in Table 1.

ORDINARY KRIGING (OK)

OK with a global variogram was used as a basis of comparison with other methods, as predictions may only be derived from ground measurements:

$$z_{OK}{}^{*}(s_0) = \sum_{i=1}^{m} w_i(s_i) \times z(s_i)$$

where m is the number of neighbours considered and wi (si) are the weights derived from variogram fitting (Goovaerts, 1997).

SIMPLE KRIGING WITH LOCALLY VARYING MEAN (SKLVM)

Simple kriging (SK) is the most basic form of kriging. With SK, the mean is assumed to be constant and known. If we can estimate the mean at locations in the domain of interest then this locally varying mean can be used to inform prediction. SKLVM prediction is defined as:

$$\hat{z}\,SKLVM(\mathbf{u}_0) - \hat{m}_{SK}(\mathbf{u}_0) = \sum_{\alpha=1}^{n} \lambda_{\alpha}^{SK}(u0)\left[z(\mathbf{u}_{\alpha}) - \hat{m}_{SK}(\mathbf{u}_{\alpha}) \right],$$

where $\hat{m}$ simple kriging is a known locally varying mean. The locally varying mean can be estimated in various different ways. One approach is to use regression (presented in SLR approach) to predict at all observation locations and all locations where SKLVM predictions will be made. Then, the semivariogram of the residuals was computed, modelled, cross-validated and simple kriging on the residuals was carried out. The final estimate of every soil property was obtained by adding the trend estimate to the simple kriged estimate of the residuals (Goovaerts, 1997; Vanderlinden, 2001). This method was applied to the soil variables showing significant correlations with digital values in four bands at P≤0.01, i.e., OM, pH and ECe with band 1 (Table 1).

COMPARISON BETWEEN THE DIFFERENT METHODS

For the purpose of comparison, several comparison indices can be used as a measurement of the prediction quality, however, the most common of which is the mean square error (MSE) which measures the average square difference between the actual soil variable $z(xi)$ and its estimate $z^*(xi)$:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left[z(x_i) - z^*(x_i)\right]^2$$

where n = soil variable data set (Goovaerts, 2000). The comparative performance of the prediction models was measured by using MSE of OK as the standard, which did not take into account the digital numbers (Bishop and McBratney, 2001). The MSE of OK was calculated as reported in Lopez-Granados et al. (2005).

RESULTS AND DISCUSSION

SIMPLE LINEAR REGRESSION (SLR)

Pearson linear correlations between soil parameters and spectral values (Table 1) revealed that OM, pH and ECe showed highest correlations by using the spectral data in the band 1, although these correlations were relatively moderate (0.5-0.6). Negative correlations meant that small digital numbers for the band 1 corresponded to high values of pH. P, TN and ESP were the soil properties having the lowest correlation coefficients (being non significant). Regression equations for the highest correlation coefficients between soil properties and spectral data are presented in Table 2. In all cases, the band 1 from LISS-III receiver data was used for fitting the regression equations because its correlation coefficients were

Table 1. Pearson linear correlations between soil parameters and spectral values for blue, green and red wavebands

Bands	pH	ECe	P	ESP	OM	TN
Band 1	-0.61**	0.57**	0.21 ns	0.4 ns	0.69**	0.38 ns
Band 2	-0.29*	0.23*	0.31 ns	0.22 ns	0.31 *	0.11 ns
Band 3	-0.22ns	0.27 ns	0.15 ns	0.15 ns	0.42 ns	0.14 ns
Band 4	0.23 ns	0.22 ns	0.2 ns	0.1 ns	0.25 ns	0.09 ns

* Significant at 0.05 level.

** Significant at 0.01 level.

Table 2. Regression equations between soil parameters and spectral values for the blue waveband

Regression equations	Determination coefficient (R^2)
Organic matter (%) = 0.567 + 0.0044 * band 1	**0.476**
pH = 8.623− 0.0025 * band 1	**0.372**
ECe= 4.4213+ 0.00764 * band 1	**0.325**

higher and significant. Maps of OM, pH and ECe could be easily illustrated in remote sensing software such as ILWIS using presented equations in Table 2.

ORDINARY KRIGING (OK)

Table 3 indicates mean, coefficients of variations (CV), standard deviation and skewness of the soil parameters. 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 1 and a square-root transformation applied if it is between 0.5 and 1 (Webster and Oliver, 2001). Therefore, a logarithmic transformation performed for ECe, pH and ESP parameters because, their skewness was greater than 1. The CV of soil properties except pH and TN were fairly high, indicating that soil properties were generally heterogeneous (Table 3). The highest CV value was for ESP, while the CV value for pH was the lowest. Anisotropic semivariograms did not show any differences in spatial dependence based on direction and therefore isotropic semivariograms were chosen. The geostatistical analysis indicated two spatial distribution models and spatial dependence levels for the soil parameters. Exponential and spherical models were used to define soil properties (Table 4). Nugget effect was higher for

ESP, TN and P compared to pH, OM and ECe. This indicated that these soil properties had

When the distribution of soil properties is strongly or moderately spatially correlated, the mean extent of these patches is given by the range of the semivariogram. A larger range indicates that observed values of the soil variable are influenced by other values of this variable over greater distances than soil variables which have smaller ranges (Lopez-Granados et al., 2005). Range value varied from 1811 m (for pH) to 4924 m (for OM).

Generally, range values of ECe and pH were smaller than that of the other soil properties. The low nugget variance/total variance ratio and small range values for some soil properties exhibited patchy distribution pattern. The patchy distribution can be related to the near level of groundwater to soil surface and predominated topography in Badjgah plain (Cemek et al., 2007).

Table 3. Descriptive statistics for studied soil properties

Parameters	Mean	S.Da	C.Vb	Min	Max	Skewness
pH	7.83	0.27	3.4	7.5	8.4	1.46
ECe (dSm-1)	6.52	4.25	65.2	2.8	21.2	2.11
ESP (%)	10.8	11.19	103.6	3.21	70.17	3.81
OM (%)	1.84	0.73	39.7	0.11	3.21	-0.17
P (mg kg-1)	18.2	8.2	45.1	7.2	30.1	0.4
TN (%)	0.032	0.02	62.5	0.016	0.069	0.12

aStandard deviation; bCoefficient of variations

Table 4
Semivariogram models and models parameters for studied soil properties

Parameters	(+)Spatial distribution and model	Nugget (C0)	Sill (C0+C)	Range (m)	Nugget /Sill (%)	r2	RSS*
pH	S. Spherical	0.11	1.2148	1811	9	0.81	0.00021
ECe (dSm-1)	M. Spherical	0.51	1.1806	2121	43.2	0.81	0.00024
ESP (%)	M. Spherical	7.80	12.704	2942	61.4	0.61	0.0008
OM (%)	S. Exponential	0.475	2.247	4924	21.13	0.95	0.0001
P (mg kg-1)	W. Exponential	10.24	14.581	3054	70.23	0.75	0.00132
TN (%)	M. Spherical	6.421	10.25	2648	62.63	0.68	0.0001

(+) Spatial distribution (S-strong spatial dependence (≤25%); M-Moderate spatial dependence (26-75%); W-weak spatial dependence (>75%); Pure Nugget- no spatial correlation (100%) and their spatial distribution model.

*Residual sum of squares (often the model with the lowest RSS chooses as optimal).

SIMPLE KRIGING WITH LOCALLY VARYING MEAN (SKLVM)

This method was applied to the soil variables showing significant correlations with digital values in four main bands at $P \leq 0.01$, i.e., OM, pH and ECe with band 1 (Table 1). This kriging method is an interpolation that incorporates secondary information into the kriging system. It uses the ancillary (or secondary) information to characterize the spatial trend of the primary (target) variable and performs simple kriging on the residuals (Goovaerts, 1997). Table 5 shows the semivariogram of residuals for OM, pH and ECe with the fitted model. Fig. 1 shows the maps of OM, pH and ECe estimates obtained by SKLVM. The Nugget effect, sill, semivariogram model and range of the residuals semivariograms were approximately similar of raw semivariogram.

Sill semivariance of OM was 2.247 and 2.127, for ECe it was 1.1806 and 1.1906, for pH it was 1.2148 and 1.2811 for the raw soil parameter semivariogram and the residual semivariogram, respectively, indicating the lag distance between measurements at which one value for a variable does not influence neighboring values (Tables 4 and 5). Goovaerts (1999) found a similar trend when he incorporated a digital elevation model into the mapping of annual erosivity values using the same kind of kriging. The residual semivariogram model of pH was pure nugget, which was similar to that of the raw semivariogram and means that pH and ECe were considered strong-spatially correlated.

There is some similarity in the map pattern of OM, pH and ECe as produced by OK and SKLVM methods (Fig. 1). However, OK over-smoothed the spatial variability of OM, pH and ECe. Comparatively, it seems that SKLVM reflects local variation more than OK, but it is necessary to compare the MSE to evaluate this.

Table 5. Semivariogram models of the residuals

Soil parameters	Semivariogram model	Nugget	Range (m)	r^2	Sill
Organic matter (%)	Exponential	0.485	4901	0.97	2.127
pH	Spherical	0.10	1881	0.89	1.2811
ECe	Spherical	0.41	2131	0.96	1.1906

COMPARISON BETWEEN DIFFERENT PREDICTION METHODS

MSE for different methods for pH, ECe and OM (Table 6) shows that the generic geostatistical technique, such as OK, exhibited the highest MSE because it does not take into account the secondary information and only uses the primary soil variable. spatial variability in small distances.The large nugget semivariance suggest that an additional sampling of these variables at smaller lag distances and in larger numbers is needed to detect spatial dependence.

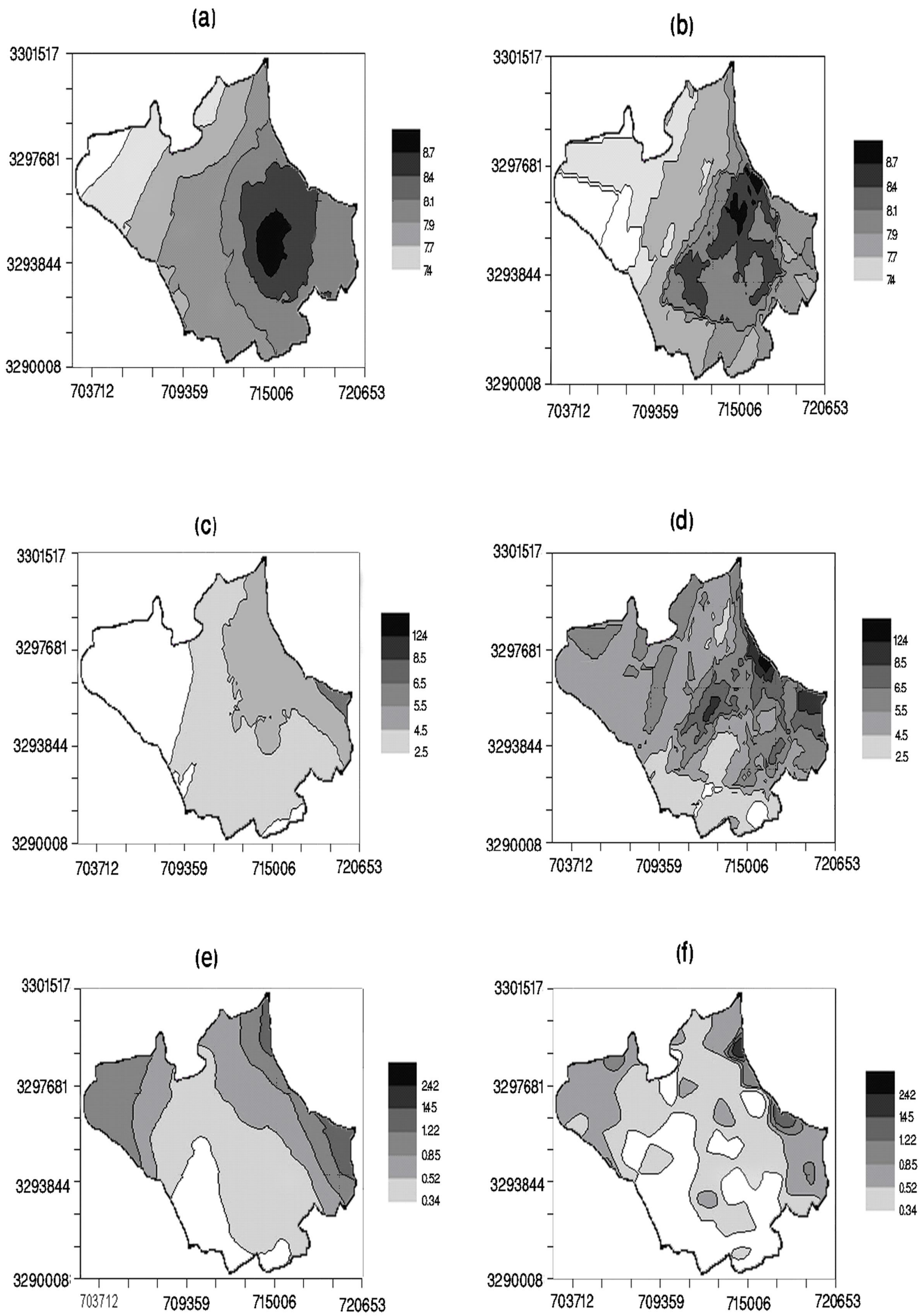

Fig. 1. Soil maps obtained using OK method: (a) pH, (c) ECe (dSm^{-1}), and (e) OM (%); and soil maps obtained using SKLVM: (b) pH, (d) ECe (dSm^{-1}), and (f) OM (%)

Comparing the other prediction methods, higher predictions errors were obtained when only SLM was considered for ESP, P and TN. SKLVM was clearly the best method for the prediction of OM, pH and K showing the lowest MSE values. Also, the best prediction method for mapping ESP, P and TN was obtained from SLM.

Bourennanen et al. (2000) compared linear regression with kriging with an external drift (This method also uses secondary variable) for mapping soil horizon thickness, using slope gradient as the secondary variable. They found that kriging with an external drift provided more accurate predictions than linear regression. Pardo-Igu´zquiza and Dowd (2002) compared OK, SKLVM, kriging with an external drift, cokriging and Bayesian integration for prediction using wireline-logs of acoustic-impedance recorded at nine boreholes, with acoustic-impedance values from a 3D seismic survey as secondary data. On the basis of the mean absolute relative error (MARE) cokriging provided the most accurate predictions, followed by SKLVM. However, on the basis of the mean squared error (MSE) and other statistics the authors considered SKLVM the preferred method in their application.

In general, estimation method using spectral data had more favorable MSE results than prediction methods using only soil variables, indicating that the correlation of soil variables with spectral data is more important for mapping soil variables than the spatial correlation of available soil measurements. Thus, the least accurate estimation for OM, pH and ECe, with highest MSE values, was OK because the spectral data were ignored and only the spatial component of soil variables was considered.

On the other hand, SLR method resulted in the poorest prediction because low correlations between soil attributes and spectral values were obtained, probably due to the spatial component being ignored.

Despite this, when secondary information is available it should be incorporated into map soil attributes because the MSE for simple linear regression is lower than the MSE for OK. Bishop and McBratney (2001) found that when kriging of the residuals was incorporated to different prediction models studied, the RMSE (root mean square error) was lower. They indicated that kriging with an external drift, an interpolation method very similar SKLVM which also performs kriging on the residuals, was the best prediction method for mapping soil properties using bare soil aerial photograph.

They also concluded that when secondary information is available, it should be used because generic geostatistical techniques that only use the primary variable, such as OK, do not obtain the prediction performance of the methods that incorporate that secondary information.

Table 6. Mean square errors for the compared prediction methods when estimating soil properties

Prediction method	pH	ECe	OM	ESP	P	TN
Simple linear regression	1.731	2.951	1.822	4.254	8.580	9.51
Ordinary kriging	1.813	3.232	2.254	2.245	3.254	4.14
SKLVM	0.766	1.337	0.913	-	-	-

CONCLUSIONS

The results here indicate that when secondary information especially remote sensed data is available, it should be used to model the deterministic trend in the variation of a soil surface attribute. Also, this study has demonstrated that sparse and expensive soil measurements combined with secondary information, such as remotely sensed (spectral) data from IRS-P6, and geostatistical techniques were adequate to map soil properties accurately. The relationship between spectral (digital) data in the band 1 from LISS-III receiver data and OM, pH and ECe developed in this research might be applied to other fields in southern Iran, especially in all Badjgah plain soil that have the same qualities. For variables presenting a high or moderate correlation with spectral data, as secondary information, kriging with varying local means results accurate estimates because it uses spectral data to derive the local mean or trend of any soil property. Therefore, precision farming could be benefited by such enhanced technique where the data of remote sensing or other cheap valuable secondary variable of soil parameter are available.

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