

Spatial distribution of soil nutrients in a watershed of Himalayan landscape using terrain attributes and geostatistical methods

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Abstract Terrain attributes derived from digital terrain model (DTM) were used to study spatial variation of total soil C, N and available P in surface soils of a watershed of Himalayan landscape. Terrain attributes elevation, slope gradient and upslope catchment area (UCA) and terrain indices [terrain wetness index (TWI), water power index (WPI) and sediment transport index (STI)] were derived from DTM and evaluated for their potential in soil nutrients mapping. These nutrients showed positive correlation with UCA, TWI, SPI and STP terrain indices. Among these terrain indices, TWI showed highest correlation coefficient for TC ($r^2 = 0.71$), N ($r^2 = 0.67$) and P ($r^2 = 0.66$) followed by WPI and STI. Geostatistical analyses used to map these nutrients, co-kriging with TWI + NDVI, TWI and slope as co-variables, had improved the spatial prediction to 60.46, 55.81, 44.18 % for TC and 33.63, 21.78, 17.82 % for N, respectively, contrary to ordinary kriging. The prediction accuracy for P was improved with co-variables of TWI + NDVI and TWI by 30.03 and 4.50 %, respectively. The study clearly revealed that by integrating NDVI as co-variable has significantly improved the accuracy for TC followed by N and P. TWI alone as co-variable has improved the spatial prediction significantly.

Keywords Geostatistics · Terrain attributes · DEM · Soil nutrients mapping · Watershed

Introduction

Spatially explicit data of soil properties and nutrients are required for better assessment of soil potential for sustainable management of land resources and in precision agriculture. In recent years, availability of high-resolution satellite data and terrain data had provided large opportunities for predictive soil mapping to generate accurate spatially explicit soil maps (McBratney et al. 2003). The variability in soil properties in any landscape is an inherent natural phenomena conditioned by soil-forming factors. Its spatial distribution is also influenced by soil erosion and deposition processes occurring in the landscape. The effects of topography on spatial distribution of soil attributes and hydrologic processes have been intensively studied by several researchers (Moore et al. 1993; Bell et al. 1995; Herbst et al. 2006; Iqbal et al. 2005). Topography controls the flow of water and sediments; hence it mainly affects catenary soil development (Jenny 1941) and the formation of typical patterns of spatially distributed soil attributes and quality. C, N and P are major nutrients in soils governing soil quality and thus vegetation growth. At the regional scale, the distribution and quantity of SOC depend on several factors such as precipitation, temperature, soil texture, soil depth, land management, and vegetation type (Janzen et al. 1998) but at local scale, its spatial pattern is largely governed by topography.

Topography is one of the major factors affecting soil C and N contents at landscape level (Cambardella et al. 1994; Bourennane et al. 2000). Landscape attributes including slope, aspect and elevation, and land use may be the dominant factors impacting nutrients in the soil with homogeneous parent material and a single climate regime (Rezaei and Gilkes 2005). Terrain analysis intends to derive topographic parameters comprising a set of primary

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and secondary terrain attributes used in digital soil mapping applications (Behrens et al. 2010). Topographic gradients characterize the shape of the land surface thereby dictating the distribution of soil physical and chemical properties (Moore et al. 1991). Umali et al. (2012) investigated the effect of various management practices and topography on the variability of key soil properties. Several researchers (Moore et al. 1993; Zhang et al. 2012) established statistical relationships between topographic indices derived from digital elevation models, and spatially variable soil properties.

Geostatistics is primarily used as a tool to describe spatial patterns by semivariograms and to predict the values of soil attributes at unsampled locations. It recognizes the continuous nature of soils and can account for random variation through modeling the spatial correlation in soil properties often present in the landscape. It also facilitates integration of ancillary information such as terrain parameters available easily at higher resolution for spatial prediction of soil properties (McBratney et al. 2000). It has been extensively used for quantifying the spatial pattern of soil properties and environmental variables (Webster and Oliver 2001; Zhang and McGrath 2004). Geostatistical interpolation techniques such as kriging and co-kriging have been widely used to predict soil properties at unsampled locations and to understand their spatial variation in the landscape (Voltz and Webster 1990; Chien et al. 1997). Spatial dependency of soil properties was improved by incorporating secondary variables, known as co-kriging method (Goovaerts 2000; Triantafyllis et al. 2001; Mueller and Pierce 2003; Zhang and McGrath 2004).

The Himalayan landscape witnesses soil erosion by water where topography is a major factor in controlling the erosion and resulting in spatial variation of soil nutrients in the watershed. Thus, the present study aims to: (a) analyze the role of terrain attributes in controlling nutrients such as C, N and P in soil and (b) use terrain attributes and spectral vegetation index as co-variables in improving prediction of spatial distribution of soil nutrients using geostatistical methods.

Study area

The study area is located in the western part of Doon Valley in Dehradun District of Uttarakhand State of India (Fig. 1). The watershed covers an area of 8.05 km²; lies between 30°25′–30°30′N and 77°45′–78°00′E that falls within the Sitlarao watershed, belonging to Asan river system, a tributary of Yamuna River. The CartoDEM was used for terrain analysis. The combination of Cartosat-1 Image and Toposheet 53F/15 was used to delineate the

watershed boundary after proper knowledge of study area visit.

The climate of the study area is characterized by humid sub-tropical. The mean annual temperature ranges from 15 °C in winter to 35 °C in summer. The mean annual rainfall received is 2051 mm (1983–2008) and 70 % of rainfall is received during monsoon season (June–September). The soil texture is predominantly sandy loam to loam. The area comprised forest, agriculture and scrub as dominant land use/land cover.

Data used and methodology

Data used

IRS Cartosat-1 stereo digital data (24 December 2008) were used to generate digital elevation model (DEM) and Resourcesat-1 LISS IV digital data of 12 December, 2004 were used to prepare a land use/land cover map. Cartosat Stereo satellite data were processed using ERDAS to generate digital elevation model. 23 Nos. of GCPs were collected in the area using DGPS for geo-rectification. The DEM generated had the spatial resolution of 30 m and the vertical accuracy of RMSE 4.48 m. SOI Toposheet 53F/15 was used for georeferencing of satellite data and in the field survey.

Methodology

ArcGIS (Ver. 9.3) was used to carry out terrain analysis and integration of maps by spatial analysis. ERDAS Imagine (Ver. 9.0) was used to process the digital satellite data to prepare a land use/land cover map. The methodology in detail has been discussed as: (a) soil sampling to analyze total carbon and total nitrogen (TC and TN); (b) deriving primary and secondary terrain attributes from DEM; (c) statistical relationship of terrain attributes and soil nutrients; (d) variogram analysis to study spatial dependency of soil C and N using (1) kriging and (2) co-kriging methods of geostatistics; and (e) validating spatial prediction of soil nutrients in the landscape. Variogram analysis was done to understand the spatial pattern and trend of the data.

Soil sampling and analysis of total soil carbon (TC) and total nitrogen (TN)

Geostatistical analysis requires a closer sampling density to determine spatial dependency parameters for interpolation of data (Yemefack et al. 2005). Therefore, a regular grid sampling (Fig. 2) was carried out in the watershed. A total

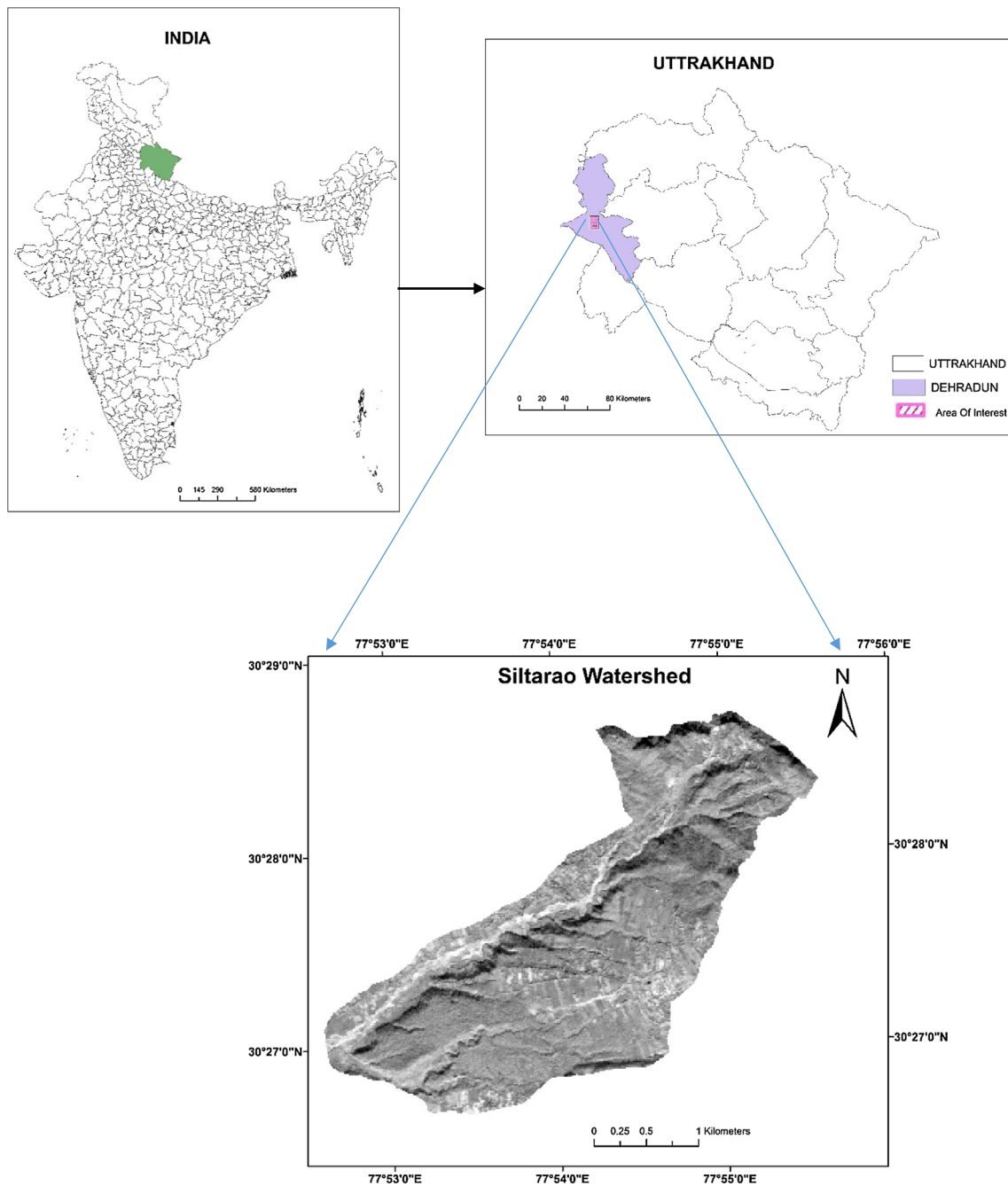


Fig. 1 Location of the study area

of 113 samples at spatial distance of 200 ± 25 m were collected and out of it 100 samples were used for prediction and remaining 13 samples for validation. The soil sampling was done in the month of April–May, 2010. Grid sampling positions were determined by marking grids on large-scale (1:10,000) satellite imagery of IRS Cartosat-1 data. Grids in the fields were located with the help of toposheet and ground features identified on the imagery.

Geospatial locations of 113 soil sampling points were recorded using Garmin GPS receiver (GPS 12 CX) and soil samples of the surface layer (0–15 cm) were collected. Soil samples distribution in different land use/land cover are described in Table 1. The soils in the area are skeletal, having >35 % coarse fragments in the top layer. All soil samples were air dried to ensure the removal of soil moisture and stored in air tight containers for total carbon

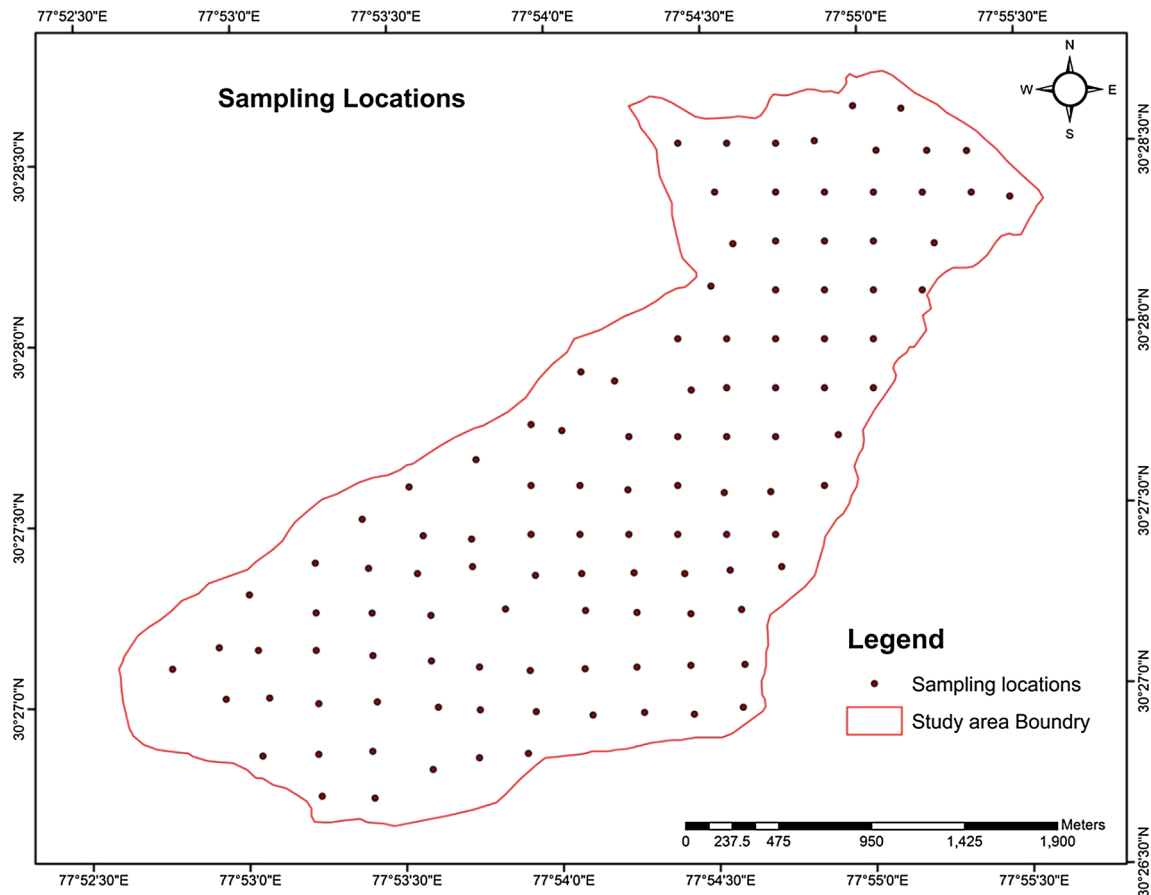


Fig. 2 Spatial distribution of soil sampling locations in the watershed

Table 1 Distribution of soil samples collected in various land use/land cover

Land use/land cover types	No. of samples
Dense forest	31
Moderate dense forest	15
Open forest	9
Agriculture	49
Orchard land	5
Total	113

(C) and nitrogen (N) analysis using CHNS analyzer (Nelson and Sommers 1982) and available phosphorus (P) by the Olsen and Sommers (1982) method.

Deriving primary and secondary terrain attributes from DTM

Cartosat DEM generated from stereo-cartosat-1 data was used to characterize primary and secondary terrain attributes using ArcGIS ver. 9.3. Primary terrain attributes such

as elevation, slope, plan curvature, profile curvature and flow accumulation and secondary attributes such as terrain wetness index (TWI), stream power index (SPI) and sediment transport index (STI) were generated. Terrain indices are used to characterize the water flow over the surface. These indices were used to analyze statistical relationship with soil nutrients. The terrain indices were calculated using Spatial Analyst in ArcGIS (Environmental Science Research Institute, Redlands, CA, USA, v 9.3). A brief description of various terrain indices derived using primary terrain attributes is discussed as below.

Terrain wetness index (TWI) It provides a relative index of whether a point in a landscape position is likely to receive runoff water by taking the natural log of the specific catchment area divided by the local slope (Beven and Kirkby 1993). It is a well-studied indicator of soil property and soil moisture distribution at different landscape positions. It is defined by:

$$TWI = \ln(A_s / \tan \beta) \quad (1)$$

where A_s is specific catchment area and β is slope in radians.

Higher TWI values indicate a point with high contributing area and/or lower slopes.

Stream power index It is indicative of erosive power of overland flow and could be used to identify suitable locations for soil conservation measures, to reduce the effect of concentrated surface runoff. High value areas show more prone to erosive power of runoff. It is expressed as:

$$SPI = A_s \times \tan \beta \tag{2}$$

Sediment transport index It is widely used to characterize the water flows in landscapes. It is suitable for identifying erosion processes. It accounts for the effect of topography on erosion.

$$STI = (A_s/22.13)^{0.6} \times (\sin \beta/0.0896)^{1.3} \tag{3}$$

Satellite data-derived spectral index

IRS Resourcesat-1 LISS IV (5.8 m) satellite data were used to generate normalized difference vegetation index (NDVI). The spectral index is most widely used for vegetation studies. It is often directly related to other ground parameters such as percent of ground cover, photosynthetic activity of the plant, amount of biomass and surface soil properties etc. NDVI can be used to better capture the spatial variability associated with soil (Rivero et al. 2009). NDVI value of natural vegetation cover (Forest/scrubland) was used as spectral index parameter in spatial prediction of soil properties in the study. NDVI using remote sensing IRS LISS IV was calculated as:

$$NDVI = (NIR - Red)/(NIR + Red) \tag{4}$$

where near infrared (NIR) and Red represent Band 3 and Band 2, respectively, in LISS IV data.

The value for NDVI lies between -1 and +1. Negative values correspond to water bodies, near to zero bare earth or barren lands and near to +1 correspond to highly vegetative lands.

To study correlation of terrain attributes and soil nutrients

Pearson coefficient of correlation (*r*) and corresponding coefficient of determination (*r*²) were computed for all pairs of terrain attributes (predictor variables) and topsoil attributes (predicted variables) to evaluate its predictive capacity. Linear relationships of soil nutrients and terrain attributes such as slope, elevation, *A_s*, TWI, STI and SPI were studied using statistical software. Terrain attributes with highest correlation coefficient were selected as co-variable for co-kriging interpolation.

Variogram analysis to study spatial dependency of soil nutrients using geostatistics

The geostatistical analyses were carried out using ArcGIS software (version 9.3) and its extension module of Spatial Analyst (version 2.0). Before applying inferential statistics to study spatial dependency of soil properties, some statistical parameters such as minimum, maximum, mean and SD of the soil properties were calculated to get an impression of how the sample data are distributed (Snedecor and Cochran 1980). Data were visualized by histogram and box plot using geostatistical software R and Geostatistical wizard of ArcGIS.

Variogram analysis Computation of variogram also known as semivariogram is a common way of visualizing spatial dependence. An experimental variogram estimates the average semi-variance of all the point pairs in a bin separated by certain vector by the equation:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} (Z(i) - Z(i+h))^2 \tag{5}$$

Variogram parameters such as sill, nugget and range provide quantitative expression of spatial structure for the measured property. *Sill* is the maximum semi-variance that reflects the variability in the absence of spatial dependence. *Nugget* is the semi-variance as the separation approaches to zero and reflects the unexplained variability of the spatial structure. Range defined as separation distance at which the sill is reached and reflects the distance at which there is no evidence of spatial dependence (Rossiter 2007).

Experimental variograms were computed with geostatistical wizard of ArcGIS for the given dataset and fitted with some theoretical model to explain the local spatial dependence of the soil properties. The computed variogram was then compared on the basis of sum of squared differences to obtain best fitted model.

$$SSD = \sum_{i=0}^n (Z_i - Z_i^*) \tag{6}$$

Corresponding partial sill, nugget and range of the fitted variogram were computed.

The ratio of the nugget to the total sill was assumed to be criterion to classify spatial dependence of soil properties. Ratio lesser than 25 % and higher than 75 % corresponds to strong and weak spatial dependence, respectively (Chang et al. 1998), while ratio between 25 and 50 % indicates moderately high and from 50 to 75 % falls in moderate spatial dependence.

$$NSR = \frac{C_o}{C_o + C_s} \times 100 \tag{7}$$

where C_0 is the nugget and C_s is the partial sill.

Kriging and co-kriging are typical geostatistical prediction methods used in the study. Ordinary kriging and co-kriging do not require stationarity of the mean over the entire domain. Ordinary kriging uses the local mean in the estimation, whereas simple kriging uses the global mean; thus, simple kriging would be biased if the local mean is different from the global mean. Therefore, the ordinary kriging and co-kriging were selected in this study.

Kriging It provides a theoretical weighted moving average of the input parameter over the distance between sampling sites (lag distance). It is the prediction procedure using known values and semivariogram to determine the unknown values. Ordinary Kriging, a standard version of kriging is computed as:

$$Z_o = \lambda_1 Z_1 + \lambda_2 Z_2 + \dots + \lambda_n Z_n \quad (8)$$

where λ_i are the associated weights (Isaaks and Srivistava 1989).

Ordinary Co-kriging It is a geostatistical technique developed to improve the estimation of a variable using the information on other spatially correlated variables which are generally more densely sampled. The variables are called co-regionalized and are spatially dependent.

$$Z_o = \sum a_i Z_i + \sum b_j V_j \quad (9)$$

where the a_i ($i = 1, 2, \dots, n$) are the weights applied to the z samples and the b_j ($j = 1, 2, \dots, m$) are the weights applied to the V samples.

Validation of spatial prediction of soil nutrients in the landscape

Prediction accuracy is usually tested by comparing predicted values with measured values and applying some measures of goodness of fit. In the study, 13 random sample points excluded from the total data set were used for validation. The predicted values at each validation point were extracted using point extraction tool of ArcGIS. Residuals were calculated and plotted in EXCEL spreadsheet. To test the goodness of fit, root mean square error (RMSE) was calculated.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=0}^n (Z_i - Z_i^*)^2} \quad (10)$$

To estimate the improvement of spatial prediction of one method relative to the other method, a relative improvement (RI) (Pang et al. 2009) was used to measure. The prediction accuracy of the x -geostatistical method over the reference method was calculated as

$$RI_x = (RMSE_x - RMSE_{ref}/RMSE_{ref}) \times 100 \quad (11)$$

where $RMSE_x$ and $RMSE_{ref}$ are RMSE value of the geostatistical predicted and reference methods, respectively. The reference method taken in the study was ordinary kriging (OK) method.

Results and discussion

The spatial distribution of soil nutrients in the landscape is discussed as below.

Statistical relationship between terrain attributes and soil nutrients

Topography is one of the most important soil-forming factors in the hilly landscape and causes variability of soil properties. It also affects infiltration and runoff potentials of the landscape and plays a significant role in the redistribution of soil nutrients through water across the landscape (Ovalles and Collins 1986; Kravchenko et al. 2002; Creed et al. 2002). Soil C and N had shown a higher degree of spatial correlation caused by intrinsic factors of the topography that controls the movement and storage of water, sediment and solutes (Sahrawat 2004).

The Pearson correlation analysis was performed to identify the relationships between terrain attributes and total soil carbon (TC), nitrogen (N) and phosphorus (P) (Table 2). The elevation and slope terrain parameters were observed with negative correlation whereas positive correlation with UCA, TWI, SPI and STP terrain attributes. Higher elevation and steeper slope area had lowest TC and N and vice versa. Slope had significant negative correlation with TC ($r^2 = -0.64$) and N ($r^2 = -0.61$). Similarly, Guo et al. (2009) showed negative correlation of soil organic matter with slope and elevation in a hilly area in South-Western China. The upslope contributing area (UCA) terrain attribute has been observed to have a positive

Table 2 Pearson correlations coefficient between terrain attributes and soil nutrients

Terrain attributes	TC	TN	P
Elevation	-0.2	-0.17	-
Slope	-0.64	-0.61	-0.40
UCA	0.38	0.39	0.29
TWI	0.71	0.67	0.66
SPI	0.41	0.43	0.28
STI	0.28	0.25	0.35

UCA Upslope contributing area, TWI terrain wetness index, SPI stream power index, STI sediment transport index, TC total carbon, TN total nitrogen, P available phosphorus

correlation with TC ($r^2 = 0.38$), N ($r^2 = 0.39$) and P ($r^2 = 0.29$).

Secondary terrain attributes showed cumulative effect of slope gradient and shape that affect the spatial distribution of soil nutrients. It showed that nutrient distribution was largely influenced by erosion and water distribution in the hilly landscape. Among the terrain indices, TWI showed highest correlation coefficient for TC ($r^2 = 0.71$), N ($r^2 = 0.67$) and P ($r^2 = 0.66$) followed by WPI and STI. A highly significant positive correlation between TWI and TC, N and available P was observed whereas negative correlation with slope parameter. Empirically, under natural conditions, Manning et al. (2001) showed a negative correlation of soil moisture with elevation and high soil carbon accumulation in low lying areas. Mueller and Pierce (2003) showed that topographical wetness index (TWI) reflects the redistribution of water over landscape and is the most appropriate secondary variable in determining SOC distribution. Several researchers reported a strong relationship between terrain attributes and soil C at a field scale (Moore et al. 1993; Yoo et al. 2006).

Spatial prediction of soil nutrients

Descriptive statistics of total samples (113 Nos.) revealed that the total carbon in surface soil varies in the range of 0.22–2.66 % with a mean value of 1.23 % and SD of 0.61. The total nitrogen (N) was found to vary in the range of 0.03–0.37 % with a mean value of 0.17 % and SD of 0.09. P in the soil ranged from 3.21 to 79.48 ppm with mean value of 32.21 and SD of 17.17. The data showed skewness of 0.31 for TC, 0.14 for TN and 1.12 for P. Skewness indicates departure of data from normality, and a value of <1 denotes normal distribution of the data. A logarithmic transformation was considered where the coefficient of skewness is greater than one (Webster and Oliver 2001). Therefore, a logarithmic transformation was performed for P to make the data Gaussian in nature.

Ordinary kriging: semivariogram of soil nutrients

In the study, isotropic variogram was computed for soil TC, N and P as no significant differences in spatial dependency were observed by anisotropic semivariogram. A spherical theoretical covariance model suitable for spatial fields was fitted to experimentally derived covariance values for minimum RMSE value. The semivariogram model with the smallest residual sum of squares was selected as the best fitting model. The semivariogram model parameters for TC, N and P were computed with the fitted model (Table 3). The range of the semivariogram for TC was larger than N and P. The range describes the distance at which values of one variable become spatially

Table 3 Model parameters of isotropic spherical semivariograms calculated for selected soil properties

Parameter	TC	TN	P
Variogram model	Spherical	Spherical	Spherical
Nugget variance (C_0)	0.59 (%)	0.63 (%)	0.95 ppm
Structural variance (C_s)	0.32 (%)	0.28 (%)	0.41 ppm
Total sill ($C_0 + C_s$)	0.91 (%)	0.91 (%)	1.36 ppm
Range (m)	301.1	289.6	278.1
Nugget–sill ratio (NSR) (%)	64.8 (%)	69.2 (%)	69.8 ppm
Spatial dependence class	Moderate	Moderate	Moderate

TC Total carbon, TN total nitrogen, P available phosphorus

independent of another (Kerry and Oliver 2007). It is used to know the soil sampling interval for future survey. Sill indicates the lag distance between measurements at which one value for a variable does not influence neighboring values.

The variogram for TC, N and P showed lowest nugget variance for TC followed by N and P. The large nugget value for P compared to TN and TC showed more variations of its value over small distances. The small nugget value exhibits adequate sampling density to reveal the spatial structure. The range for all three nutrients varies from 278 to 301 m. It supported appropriate soil sampling distance of 200 m for establishing spatial autocorrelation for these soil nutrients in the watershed. It validates a good spatial structure of interpolated soil nutrients maps in the study (Goovaerts 1997).

The nugget to sill ratio (NSR) was assumed to be the criterion to classify spatial dependence of soil properties. Ratio lesser than 25 % and higher than 75 % corresponds to strong and weak spatial dependence, respectively (Chang et al. 1998), while ratio between 25 and 50 % indicates moderately high and from 50 to 75 % falls in moderate spatial dependence. The NSR (%) values for kriging semivariogram were 65, 69 and 70 % for TC, TN and available P, respectively, revealing its moderate spatial dependence. Zhang et al. (2012) reported moderate spatial correlation for soil organic matter based on C0/sill ratio.

Co-kriging method for spatial prediction of soil nutrients

The incorporation of terrain variables into a regression kriging model is a suitable method for increasing the accuracy of prediction of these soil properties (Sumfleth and Duttmann 2008). Terrain indices i.e. terrain wetness index (TWI) and slope were found to be most correlated with soil nutrients (TC and TN) and TWI with available P. The terrain indices can be used as secondary variable to characterize the spatial trend of primary variables (soil nutrients) to generate interpolated map using ordinary kriging. Co-kriging was applied to soil variables having

significant correlations with terrain attributes. The semi-variogram model parameters using terrain parameters as co-variables for TC, N and P were computed with the fitted model (Table 4). Use of terrain parameters as co-variables in fitting semivariogram model has lowered the model parameters values significantly for all the nutrients showing significant improvement of spatial predictability of soil TC, N and P in the landscape. The nugget effect (variance) has reduced to very small (0.19–0.21) and the values for all the nutrients were very close. NSR has reduced to 44.28, 49.41 and 30.72 % for TC, N and available P and has been categorized as moderately high spatial dependency. The NDVI value of the forest area was taken as co-variable along with TWI for co-kriging and that had improved the correlation coefficient for TC ($r^2 = 0.62$) but was not observed in case of N and P. Reduction of the RMSE values to large extent for all three nutrients was also noticed.

Remote sensing, in combination with multivariate geostatistical methods, has the potential to improve the prediction of soil properties at landscape scale. The normalized difference vegetation index (NDVI) had been widely used for evaluating the spatial pattern of vegetation type and its productivity (Gamon et al. 1993). Yan-li et al. (2013) examined directly the soil parameters with the NDVI. Fabiyi et al. (2013) investigated the correlation between soil fertility and NDVI using geospatial techniques in the south-western Nigeria. Rivero et al. (2009)

predicted soil total phosphorus (TP) using remotely sensed data and ancillary landscape properties as supporting variables. Sahrawat (2004) also observed spatial distribution of total C, N contents in relation to the NDVI. Therefore, NDVI has been used as secondary variable along with terrain parameters in analyzing spatial distribution of soil nutrients in the natural vegetation cover (forest land) area of the watershed.

Validation and improvement of different geostatistical prediction methods

Coefficient of determination (r^2) and root mean square error (RMSE) for geostatistical prediction methods (Table 5) showed that the ordinary kriging had the lowest coefficient of determination and highest RMSE values as compared to co-kriging with slope, TWI and TWI + NDVI. As ordinary kriging considers only primary soil variable whereas co-kriging takes into account the secondary variables that helped in improving spatial prediction (López-Granados et al. 2005; McBratney et al. 2000; Odeh and McBratney 2000). Among the primary and secondary terrain attributes, TWI showed highest correlation with soil nutrients (Table 2). Thus, TWI along with NDVI was used as co-variables in co-kriging that has improved the correlation coefficient for TC ($r^2 = 0.62$), N ($r^2 = 0.58$) and available P ($r^2 = 0.53$). RMSE computed was lowest with co-variables of TWI + NDVI for TC (0.17), N (0.067) and available P (7.15) followed by TWI and slope parameter. Higher RMSE for available P was observed in comparison to TC and N using all the methods due to large variation of available P in the soil. The minimum RMSE indicated to the high correlation of soil nutrients with TWI + NDVI parameter. Ordinary kriging had high RMSE for P showed low correlation, whereas the correlation was improved by integrating TWI and TWI + NDVI as co-variables. Spatial map for total carbon, nitrogen and available phosphorus generated using co-kriging with TWI and TWI + NDVI is shown in Fig. 3a–c. However, ordinary kriging had higher RMSE than co-kriging which showed improved prediction highlighting the benefit of residual kriging. The co-kriging with

Table 4 Model parameters of isotropic spherical semivariograms calculated for selected soil properties using co-variables

Parameter	TC	TN	P
Variogram model	Spherical	Spherical	Spherical
Nugget variance (C_0)	0.19 (%)	0.21 (%)	0.20 ppm
Structural variance (C_s)	0.239 (%)	0.284 (%)	0.451 ppm
Total sill ($C_0 + C_s$)	0.429 (%)	0.599 (%)	0.651 ppm
Range (m)	229.1	256.6	238.1
Nugget–sill ratio	44.28 (%)	49.41 (%)	30.72 ppm
Spatial dependence class	Mod. high	Mod. high	Mod. high

TC Total carbon, TN total nitrogen, P available phosphorus

Table 5 Prediction results of selected method using RMSE and coefficient of determination as comparison criterion

Geostatistical methods	TC		TN		P	
	R^2	RMSE	R^2	RMSE	R^2	RMSE
Ordinary Kriging	0.45	0.43	0.40	0.101	0.44	10.22
Co-kriging (Slope)	0.51	0.24	0.52	0.083	–	–
Co-kriging (TWI)	0.57	0.19	0.58	0.079	0.52	9.76
Co-kriging (TWI + NDVI)	0.62	0.17	0.58	0.067	0.53	7.15

TC Total carbon, TN total nitrogen, P available phosphorus

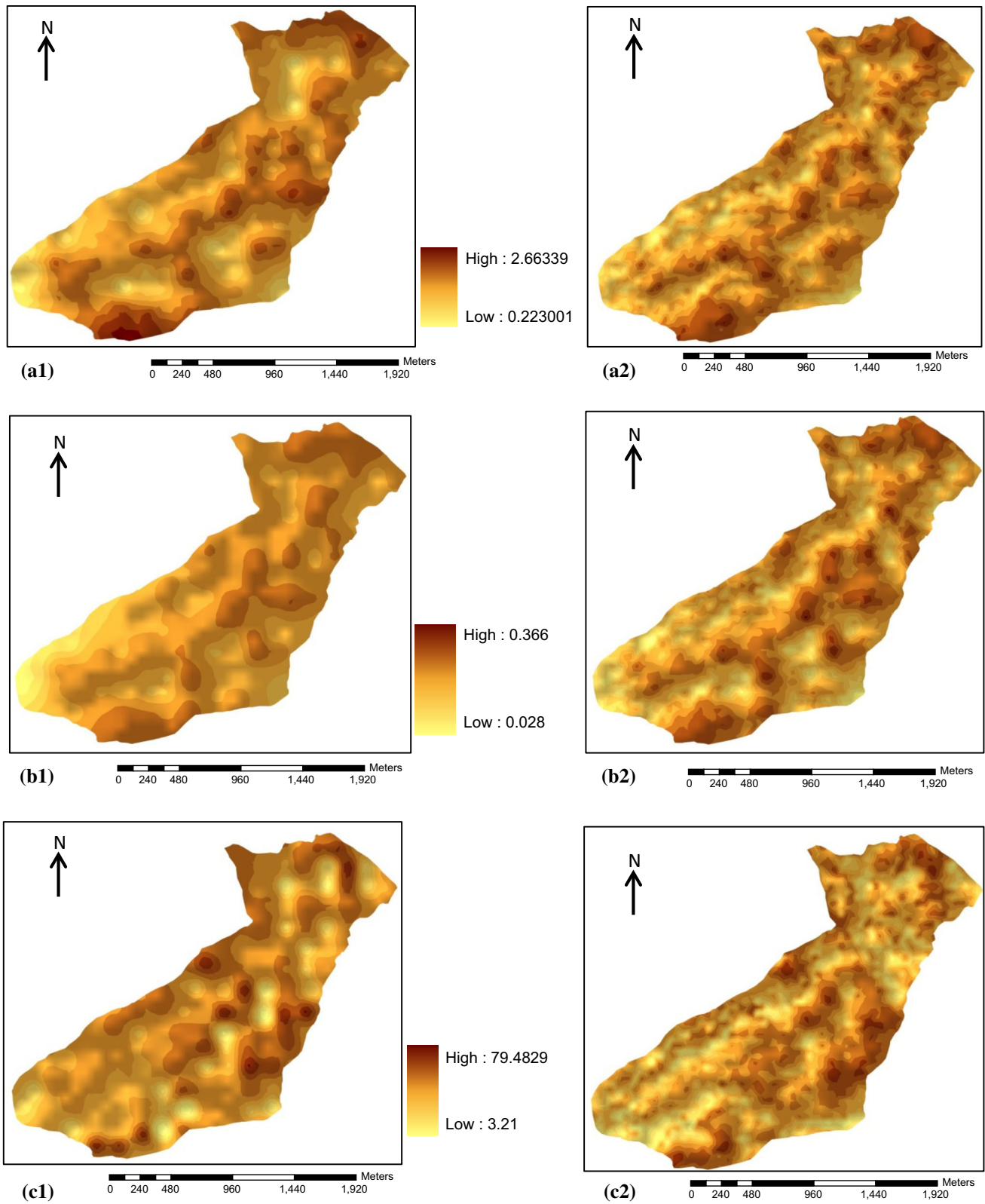


Fig. 3 Spatial prediction of soil nutrients by ordinary and co-kriging with TWI + NDVI, respectively, for total carbon (a1, a2), total nitrogen (b1, b2) and available phosphorus (c1, c2)

TWI + NDVI, TWI and slope as co-variables had improved the performance with respect to the ordinary kriging by 60.46, 55.81, 44.18 % for TC and 33.63, 21.78, 17.82 % for N, respectively. The prediction accuracy for P was improved with co-variable of TWI + NDVI and TWI by 30.03 and 4.50 %, respectively. It clearly showed that integrating NDVI as co-variables has significantly improved the accuracy for TC followed by N and P. TWI alone as co-variable has improved the performance by 55.81, 21.78 and 4.50 % for TC, N and P, respectively, relative to the ordinary kriging.

Conclusions

Topography significantly influences the distribution of soil nutrients in the watershed characterized by hilly topography in the Himalayan landscape. Terrain attributes (primary and secondary) and geostatistical methods were attempted to improve spatial prediction of soil nutrients. Ordinary kriging with primary variable had shown poor correlation resulting in high RMSE. Terrain parameters such as terrain wetness index (TWI) and slope were found most correlated with soil nutrients (TC and TN) and TWI with available P. Among the terrain indices, TWI showed highest correlation coefficient for TC ($r^2 = 0.71$), N ($r^2 = 0.67$) and P ($r^2 = 0.66$) followed by WPI and STI. Secondary terrain parameters had shown high correlation with soil nutrients. Therefore, they were used as co-variable in kriging which had markedly improved the spatial prediction of soil nutrients in the watershed. Co-kriging with the use of TWI and spectral Indices (NDVI) as secondary variables showed the lowest RMSE and highest coefficient of determination. The Co-kriging with TWI + NDVI, TWI and slope as co-variables has improved the performance with respect to the ordinary kriging by 60.46, 55.81, 44.18 % for TC and 33.63, 21.78, 17.82 % for N, respectively. Hence, it can be used as the best prediction method for mapping TC, TN and available P in the watershed of hilly topography. The results showed that the incorporation of ancillary terrain variables can distinctly improve the prediction of soil properties. The spatial prediction of soil nutrients has necessitated the need to identify critical area for sustainable management in the watershed. Spatially explicit data of soil nutrients are required for improved assessment of soil nutrient loss modeling at landscape and watershed scale.

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References

- Behrens T, Zhu A, Schmidt K, Scholten T (2010) Multi-scale digital terrain analysis and feature selection for digital soil mapping. *Geoderma* 155(3–4):175–185
- Bell JC, Butler CA, Thompson JA (1995) Soil terrain modelling for site-specific agricultural management. In: Robert PC, Rust RH, Larson WE (eds) Site-specific management for agricultural systems. American Society of Agronomy, Madison, pp 209–228
- Beven KJ, Kirkby MJ (1993) A physically-based, variable contributed area model of basin hydrology. *Hydrol Sci Bull* 24:43–69
- Bourennane H, King D, Couturier A (2000) Comparison of kriging with external drift and simple linear regression for predicting soil horizon thickness with different sample densities. In: Collins M et al (eds) Developments in quantitative soil resource assessment (PEDOMETRICS '98). *Geoderma Special Issue*, vol 97, No. 3–4, pp 255–272
- Cambardella CA, Moorman TB, Novak JM, Parkin TB, Karlen DL, Turco RF, Konopka AE (1994) Field-scale variability of soil properties in central Iowa soils. *Soil Sci Soc Am J* 58:1501–1511
- Chang YH, Scrimshaw MD, Emmerson RHC, Lester JN (1998) Geostatistical analysis of sampling uncertainty at the Tollesbury managed retreat site in Blackwater Estuary, Essex, UK: kriging and cokriging approach to minimize sampling density. *Sci Total Environ* 221:43–57
- Chien YJ, Lee DY, Guo HY, Houngh KH (1997) Geostatistical analysis of soil properties of mid-west Taiwan soils. *Soil Sci* 162:291–298
- Creed F, Trick CG, Band LE, Morrison IK (2002) Characterizing the spatial pattern of soil carbon and nitrogen pools in the Turkey Lakes Watershed: a comparison of regression techniques. *Water Air Soil Pollut Focus* 2:81–102
- Fabiyo OO, Ige-Olumide O, Fabiyo AO (2013) Spatial analysis of soil fertility estimates and NDVI in south-western Nigeria: a new paradigm for routine soil fertility mapping. *Res J Agric Environ Manag* 2(12):403–411
- Gamon JA, Field CB, Roberts DA, Ustin SL, Valentine R (1993) Functional patterns in annual grassland during an AVIRIS overflight. *Remote Sens Environ* 44:239–253
- Goovaerts P (1997) *Geostatistics for natural resources evaluation*. Oxford University Press, New York
- Goovaerts P (2000) Geostatistical approaches for incorporating elevation into the spatial interpolation of rainfall. *J Hydrol* 228:113–129
- Guo PT, Liu HB, Wei W (2009) Spatial prediction of soil organic matter using terrain attributes in a hilly area. In: International conference on environmental science and information application technology, ESIAT, Wuhan, pp 759–762
- Herbst M, Diekkruger B, Vereecken H (2006) Geostatistical co-regionalization of soil hydraulic properties in a micro-scale catchment using terrain attributes. *Geoderma* 132:206–221
- Iqbal J, Read JJ, Thomasson AJ, Jenkins JN (2005) Relationships between soil-landscape and dryland cotton lint yield. *Soil Sci Soc Am J* 69:872–882
- Isaaks EH, Srivastava RM (1989) *An Introduction to applied geostatistics*. Oxford University Press, Inc., New York
- Janzen HH, Campbell CA, Izaurralde RC, Ellert BH, Juma N, McGill WB, Zentner RP (1998) Management effects on soil C storage on the Canadian prairies. *Soil Till Res* 47:181–195
- Jenny H (1941) *Factors of soil formation—a system of quantitative pedology*. McGraw-Hill, New York
- Kerry R, Oliver MA (2007) The analysis of ranked observations of soil structure using indicator geostatistics. *Geoderma* 140:397–416
- Kravchenko AN, Bullock DG, Boast CW (2002) Joint multifractal analysis of crop yield and terrain slope. *Agron J* 92:1279–1290

- López-Granados F, Jurado-Exposito M, Pena-Barragan JM, Garcia-Torres L (2005) Using geostatistical and remote sensing approaches for mapping soil properties. *Eur J Agron* 23:279–289
- Manning G, Fuller LG, Eilers RG, Florinsky I (2001) Topographic influence on the variability of soil properties within an undulating Manitoba landscape. *Can J Soil Sci* 81(4):439–447
- McBratney A, Odeh I, Bishop T, Dunbar M, Shatar T (2000) An overview of pedometric techniques for use in soil survey. *Geoderma* 97:293–327
- McBratney AB, Mendonca ML, Minasny B (2003) On digital soil mapping. *Geoderma* 117:3–52
- Moore ID, Gryson RB, Landson AR (1991) Digital terrain modelling: review of hydrological, geomorphological, and biological applications. *Hydrol Process* 5:3–30
- Moore ID, Gessler PE, Nielsen GA, Peterson GA (1993) Soil attribute prediction using terrain analysis. *Soil Sci Soc Am J* 57:443–452
- Mueller T, Pierce F (2003) Soil carbon maps: enhancing spatial estimates with simple terrain attributes at multiple scales. *Soil Sci Soc Am J* 67:258–267
- Nelson DW, Sommers LE (1982) Total carbon, organic carbon, and organic matter. *Methods of soil analysis*. American Society of Agronomy, Madison, pp 539–579
- Odeh IO, McBratney AB (2000) Using AVHRR images for spatial prediction of clay content in the lower Naomi Valley of eastern Australia. *Geoderma* 97:237–254
- Olsen SR, Sommers LE (1982) Phosphorus. *Methods of soil analysis*. American Society of Agronomy, Madison, pp 403–430
- Ovalles FA, Collins MD (1986) Soil–landscape relationships and soil variability in north central Florida. *Soil Sci Soc Am J* 50:401–408
- Pang S, Li TX, Wang YD, Yu HY, Li X (2009) Spatial interpolation and sample size optimization for soil copper (Cu) investigation in cropland soil at county scale using cokriging. *Agric Sci China* 8(11):1369–1377
- Rezaei SA, Gilkes RJ (2005) The effects of landscape attributes and plant community on soil chemical properties in rangelands. *Geoderma* 125:167–176
- Rivero RG, Grunwald S, Binford MW, Osborne TZ (2009) Integrating spectral indices into prediction models of soil phosphorus in a subtropical wetland. *Remote Sens Environ* 113:2389–2402
- Rossiter DG (2007) Notes on applied geostatistics. ITC, Enschede
- Sahrawat KL (2004) Organic matter accumulation in submerged soils. *Adv Agron* 81:169–201
- Snedecor GW, Cochran WG (1980) *Statistical methods*, 7th edn. Iowa State University Press, Iowa
- Sumfleth K, Duttman R (2008) Prediction of soil property distribution in paddy soil landscapes using terrain data and satellite information as indicators. *Ecol Ind* 8:485–501
- Triantafyllis J, Odeh I, McBratney A (2001) Five geostatistical models to predict soil salinity from electromagnetic induction data across irrigated cotton. *Soil Sci Soc Am J* 65:869–879
- Umali BP, Oliver DP, Forrester S, Chittleborough DJ, Hutson JL, Rai SK, Ostendorf B (2012) The effect of terrain and management on the spatial variability of soil properties in an apple orchard. *Catena* 93:38–48
- Voltz M, Webster R (1990) A comparison of kriging, cubic splines and classification for predicting soil properties from sample information. *Soil Sci* 41:473–490
- Webster R, Oliver M (2001) *Geostatistics for environmental scientists*. Wiley, New York
- Yan-li Li, Xian-zhang P, Zhou R, Wang CK, Liu Y, Shi R, Chen D, Zhao Q (2013) Long-term changes of soil fertility factors and their relationships with NDVI. *CJE* 32(3):536–541
- Yemefack M, Rossiter DG, Njomgang R (2005) Multiscale characterization of soil variability within an agricultural landscape mosaic system in southern Cameroon. *Geoderma* 125:117–143
- Yoo K, Amundson R, Heimsath AM, Dietrich E (2006) Spatial patterns of soil organic carbon on hillslopes: integrating geomorphic processes and the biological C cycle. *Geoderma* 130:47–65
- Zhang CS, McGrath D (2004) Geostatistical and GIS analyses on soil organic carbon concentrations in grassland of southeastern Ireland from two different periods. *Geoderma* 119:261–275
- Zhang S, Huang Y, Chongyang S, Ye H, Du Y (2012) Spatial prediction of soil organic matter using terrain indices and categorical variables as auxiliary information. *Geoderma* 171–172:35–43