Spatial Prediction of Soil Organic Matter Content Using Remote Sensing Based Spectral Color Indices, Nepal

Umesh K Mandal
Associate Professor
Central Department of Geography, Tribhuvan University, Kirtipur, Nepal
umesh_jee@hotmail.com

Key words: Color Indices, World View-2, coefficient of the estimator, Regression, SOM

Abstract

Remote Sensing Technology provides an efficient-cost effective means to assess soil properties essential for preparation of soil fertility management plan. Soil organic matter (SOM) is one of them affecting productivity of crops by controlling nutrient budgets in agricultural production systems. Spatial estimation of soil organic matter content (SOM) is essential when there is scanty of soil test laboratories, its strong spatial dependence and its measurement is a time and labor-consuming procedure and availability of remote sensing based spectral indices.

In the present attempt, soil organic matter content is estimated from remote sensing derived spectral color indices as Brightness Index (BI), Coloration Index(CI), Hue Index(HI), Redness Rndex(RI) and Saturation Index(SI) by generating multiple regression model using stepwise regression technique. The multiple regression equation between SOM and spectral indices was significant with R = 0.587 at 98% confidence level. The resulting MLR equation was then used for the spatial prediction for the entire study area.Coloration Index has shown higher significance in estimating the SOM(r= -0.432). Coloration Index was used to predict SOM as auxiliary variable using cokringing spatial interpolation technique. It was tested in Nayavelhani (62.31 sq.km) VDC of Nawalparasi district of Nepal using world view-2 remotely sensed data. SOM was found to be measured ranging from 0.14 % to 4.96 %, with a mean of 1.57 %. Remotely sensed data derived spectral color indices have the potential as useful auxiliary variables for estimating SOM content to generate soil fertility management plans.

Introduction

Soil is one of the most important natural resources providing life to all kinds of living beings as plants, animals and organism. Organic matter is vital soil properties for precision agriculture and essential macronutrient for increase soil fertility required for plant growth and development that is extremely associated with soil physical, chemical, and biological processes. Not only this, water and nutrient holding capacity are enhanced and soil structure is improved with increasing SOM but it is one of the most deficient soil nutrients in terrestrial ecosystems. Nepal's agriculture land consists of poor organic matter and nitrogen content with the dominance of acidic soil (Dawadi et al 2015) Proper and efficient management soil organic matter can enhance productivity and environmental quality along with reduction of the severity and costs of natural disasters, such as drought, flood, and disease (Chen and Aviad, 1990 and Stevenson and He, 1990). A part from this, increasing

SOM can reduce atmospheric CO_2 levels contributing to prevention of global warming (Yadav and Malanson, 2007).

Accurate measurement of soil organic matter content is essential since it is one of the key soil properties controlling nutrient budgets in agricultural production systems and it is done through soil test laboratories. Government of Nepal has limited soil test laboratories and recently proposed fifty new to be set up on PPP mode with a cost of NRs 2.5 million each along with strengthening of 16 existing soil test laboratories (7 under SMD and 9 under NARC) requiring a cost of NRs 5.0 million each to cater the demand of farmers and researchers(.Dawadi et al 2015). Estimation of this soil property at an acceptable level of accuracy is important; especially in the case when SOM exhibits strong spatial dependence and its measurement is a time,cost and labor-consuming procedure.

Remote sensing has been emerged to cater the wider interest of soil scientists with the application from soil survey to fertility mapping and nutrients estimation after the development of optical sensor in combination with field measurements (Ben-Dor, 2002 and. Dehaan and Taylor , 2003). Spectral reflectance data was used to study soil properties started as early in 1980s particularly using the near infrared reflectance (NIR) for the study of SOM (Krishnan et al. 1981, Pitts et al1986 ,Dalai and Henry 1986).

The presence of organic matter has a strong influence on soil reflectance significantly affecting the soil color that generally decreases over the entire short wave region as organic matter content increases (Stoner and Baumgardner, 1980, Coleman and Montgomery1987). The geostatistical method (ordinary kriging (OK), cokriging) , geometric method (inverse distance Weighting (IDW), local polynomial), and statistical methods such as the linear regression model (LR) have been the most commonly used interpolation technologies (Kravchenko A, Bullock DG1999).

The present attempt was designed to evaluate the potential of spectral color index analysis of World View-2 Star trackers reflective data as an approach for estimation of soil organic matter content using cokringing spatial interpolation technique in Nayabhelhani VDC of Nawalparasi District of Nepal.

Materials and Methods

Study area

The study area is Nayabelhani VDC lying in central part of Nawalparasi district, Nepal (Fig.1), covering total area of 62.31 sq.km. The study area is ranging from 100 meter elevation from mean see level to 500 m with the average of 265 m and from less than 1° to greater than 30° slope predominated by 1-5°. Geologically the study area is originated in two different geological period as Pleistocene to middle Miocene and recent and Pleistocene. Arun Khola is the major river draining 1096 sq km of the total geographical area. The average

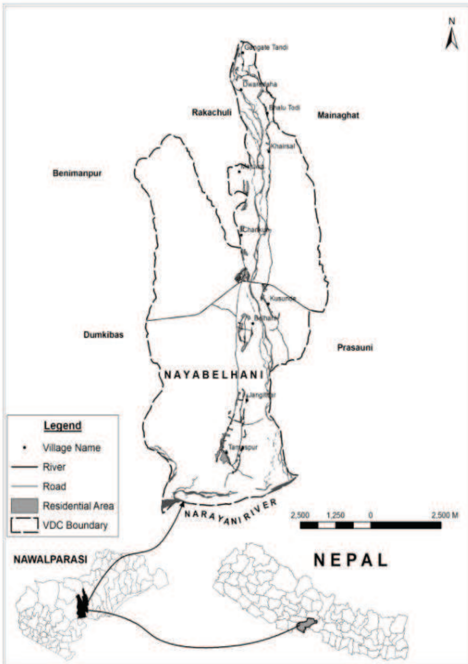

Fig 1: location map of study area.

maximum and minimum temperature of 5 years period (2006-2010) is found to be 30.78 °C and 18.99°C respectively with the average annual mean temperature of 24.89 °C. The average annual rainfall is 2851.44 mm out of which seventy percent of annual total rainfall (2015.70 mm) is received during the months of rainy season.

Image processing and generation of spectral color indices

In order to model/predict Soil organic matter content(SOM) in the study area using remotely sensed data as auxiliary variables, World View-2 image was acquired on 4 April, 2011 .8-channel World View-2 imagery of Star trackers was obtained over the study area from National Land Use Project(NLUP), Nepal(Table 1). Normalized difference vegetation index (NDVI), as widely used as vegetation spectral index in Remote Sensing was used for showing abundance of vegetation cover (Chen. and Brutsaert, 1998). Negative NDVI values were dominant indicating that the study area was comprised mostly of bare soil when the image was acquired.

Table 1: Technical specification of World View-2

Band No	Spectral range (nm)	Spatial Resolution mss (m)	Image Swath (km)
8	400-1040	1.85	16.4

Five spectral color indices as brightness index (BI), colouration index (CI), hue index (HI), redness index (RI) and saturation index (SI) were derived from World View-2 imagery of Star trackers. The method for generating these indices is presented in Table 2 using following formula(Mathieu and Pouget, 1998)

Table 2: Spectral color indices of World View-2 sensor

Index	Formula	Index Property
Brightness Index, BI	$(R^2+G^2+B^2)/3)^{0.5}$	Average reflectance magnitude
Saturation Index, SI	(R-B)/(R+B)	Spectra Slope
Hue Index, HI	(2*R-G-B)/(G-B)	Primary colours
Coloration Index, C	(R-G)/(R+G)	Soil Colour
Redness Index, RI	$R^2/(B*G^3)$	Hematite Content

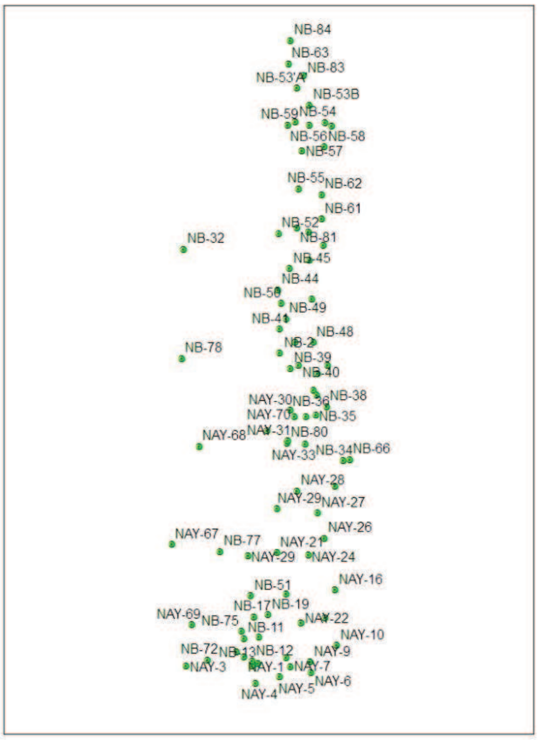

Fig 2: Distribution of soil samples.

Three channels having the center wavelength of Blue (B = 480 nm), Green(G = 545 nm) and Red(R= 660 nm) of World View-2 image data were used to generate indices and corresponding image values associated to SOM samples were extracted to perform the relations.

Soil Survey and Analysis

A total of 65 soil samples from epipedon were collected from different land use mainly from agriculture fields in January 6, 2013. Walkley-Black is one of three methods used for organic matter content determination. The calculation of organic matter assumes that 77% of the organic carbon is oxidized by the method and that soil organic matter contains 58% C. Since both of these factors are averages from a range of values, it would be preferable to omit them and simply report the results as "easily oxidizable organic C." (Schulte and Bruce , 2009).

RESULTS AND DISCUSSIONS

Statistical Modeling

In the present investigation, Statistical modeling has been initiated with the performing correlation, and regression Multivariate correlation and regression analysis was performed to examine the nature, direction and strength of association between soil organic matter content and World View-2 image derived spectral color indices as variables respectively. Relationship between spectral color indices as independent or predictor variables and SOM as a dependent or criterion variable was characterized.

Multiple regression analysis was performed to test the spatial dependency of soil organic matter content on spectral based color indices of World View-2 sensor. A t-test showed that only regression coefficient of Brightness Index(BI) among five indices was found significant at 1 percent significant level along with ANOVA reported that the model is significant at the 2 percent level indicating that using the model is better than guessing the mean. As a whole, the regression does a good job of modeling soil organic matter content (SOM). Nearly thirty-five percent variation in SOM is explained by the model (R^2. = 0.35). Although multiple correlation coefficient was found moderate(R=0.59), individual indices as predictors are suffering from multi-collinearties problem indicated by low value of percentage of Tolerance and high value of Variance Inflation Factor (VIF) in the regression analysis (Norusis, 1993). Multicolinearity is used to describe a situation where the predictor variables are highly correlated with each other affecting to inflate the coefficient of estimators with their wrong direction, making unreliable inference and wider confidence interval (Greene, 2008). Geometric technique, stepwise multiple regression, orthogonalization process and principle component analysis (PCA) are various ways of tackling the problem of multicollinearity (Frisch, 1934). Among them, stepwise multiple regression is used for eliminating all redundant indices and producing an underlying substantial one for estimating SOM.

Relationship between spectral color indices and soil organic matter content

Karl Pearson's correlation coefficient analysis was performed between five RS based spectral color indices and the soil organic matter content (SOM) as dependent variable. The correlation coefficient was revealed negative moderate correlation except for the Brightness Index(BI) and Hue Index(HI) , which may have been influenced by the presence of vegetation cover in some regions of the study area (Table 3). Soil organic matter (SOM) content was found significantly negative correlated only with Coloration Index (r = -0.478), Saturation Index(r = -0.435) at 0.01 significant level and Redness Index(r = -0.414) at 0.05 significant level and (Table 3). Such significant correlation coefficient was investigated after removal of outliers found in three observations and data transformation did not enhance the correlation coefficient rather decrease . Thus it is not required because of already having symmetric distribution of variate as usually being done in skewed distribution.

Table 3: Pearson's correlation coefficient between soil organic matter (SOM) and image color index

	Brightness Index (BI)	Coloration Index(CI)	Hue Index(HI)	Redness Index(RI)	Saturation Index(SI
SOM	0.291	**-0.478**	0.155	**-0.414**	**-0.3435**

Stepwise multiple regression was performed among five remote sensing based spectral color indices after removing outliers and multi-colinearity problem by using following equation(1).

$$\mathrm{SOM_i} = \mathrm{aV^b} \qquad (1)$$

Where $\mathrm{SOM_i}$ is the mean content of Soil Organic Matter (SOM) . V is the Coloration index(CI) ; and a, and b are numerical constant of the regression equation. In this equation, soil organic matter (SOM) content is said to be a function of Coloration Index (CI). The resulting least square fit has the form:

$$\mathrm{SOM_i} = 0.384 - 9.06 * \mathrm{CI} \qquad (2)$$

The result of stepwise multiple regression analysis as indicated by t-test shows that only Coloration Index(CI) remained as a statistically significant predictor variable ($P < 0.009$).The coefficient of determination, R^2 of the model was investigated of 0.19 , implying that nineteen percent of the variation in the mean soil organic matter content of Nayabelhani village development committee of Nawalparasi district, Nepal can be accounted for by the Coloration Index(CI) only.

Spatial modeling and prediction of soil organic matter content

The resulting multiple regression equation was used for spatial modeling of soil organic matter content. The sample data of SOM was characterized by the range from 0.147% to 2.383 % with the mean of 1.441 % and median of 1.457% . The mean and median value of SOM is almost similar that meets the requirement of normal distribution for kringing and cokrining after removal of extreme value from distribution. After that, second problem in the spatial distribution of SOM is the existence of global trend or directional effects(non-random that is depicted by trend analysis and can be addressed by using mathematical formula like second order polynomial equation.

Th semivariogram of SOM provided a clear description of its spatial structure with some insight into possible processes affecting its spatial distribution whether there is spatial autocorrelation. The semivariograms of both SOM and Coloration Index of World View-2 were well fitted with a spherical model. Spherical model of semivariogram is characterized by nugget of 0.082,partial sill of 0.289 and 946.91 for kriging and nugget of 0.0144, Partial sill of 0.225 and range of 1027.62 for and cokriging. Range is the distance where fitted semivariogram(yellow line) levels off indicating that there is little autocorrelation beyond the range . Sill is the value of semivariogram model attaining at the range. Partial sill is the sill minus the nugget.The nugget/sill ratios of the fitted semivariogram models for SOM and CI of World View-2 were as low as 0.22 and 0.06, respectively.

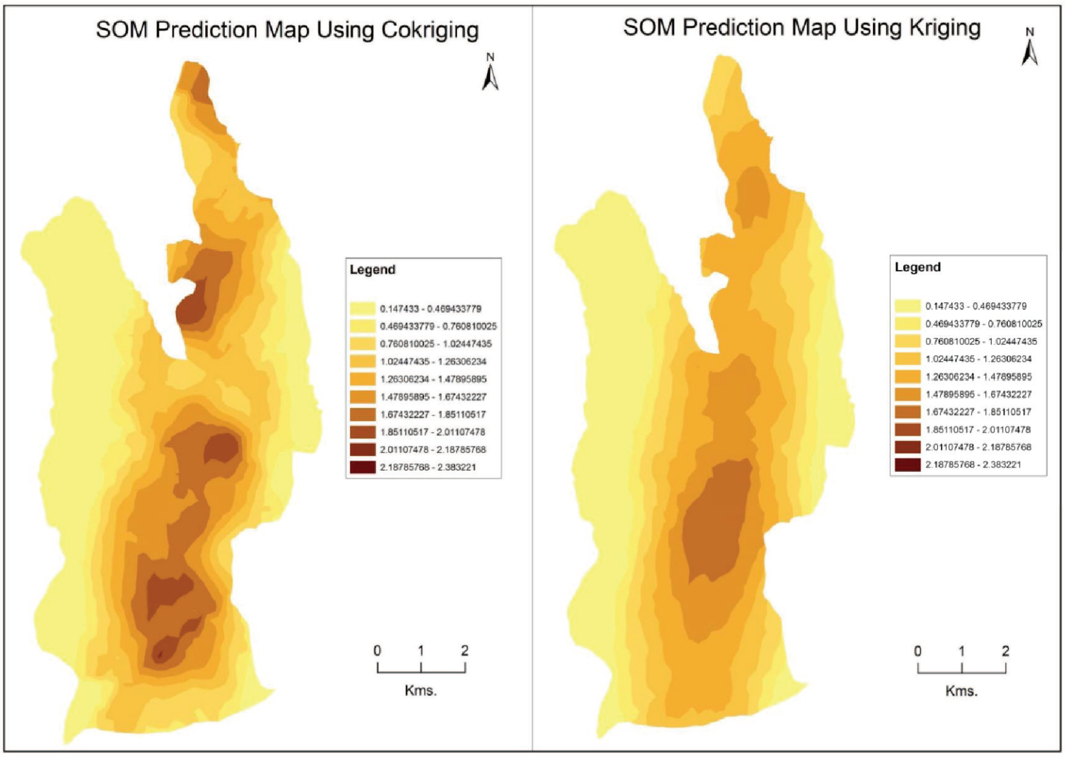

Fig 3: Predicted soil organic matter (SOM) content (%)by kriging and cokriging.

Strong spatial variability was investigated from the maps of predicted SOM content generated by both kriging and cokriging spatial interpolation technique with spectral derived coloration index (CI) from World View -2 image data (Fig. 3) and the SOM content in the central part of the Nayabelhani VDC area was found to be higher as compared to outer portion. A large difference was found in the local variability in the spatial distribution of predicted SOM content in the two prediction maps. It was interested to state that predicted SOM map by kriging showed less spatial detailed as compared to cokriging in certain localities in the central and northern part of the study area (Fig. 3).

The minimum and maximum values of SOM prediction by kriging were found as 0.95 % and 1.71 % respectively and the same values of SOM prediction by cokriging with spectral coloration index were investigated as 0.67 and 1.92 respectively. SOM predicted values of minimum and maximum by cokriging seemed to nearer to the measured values of minimum and maximum as 0.15% and 2.38 %, respectively. The mean and standard deviation of SOM prediction by the two methods were 1.43% and 0.27 for kriging 1.41% and 0.24 for cokriging, respectively and the mean and standard deviation of SOM content from the soil samples were 1.40%and 0.60 respectively. The measured value of mean SOM (1.40 %) was found to be closer to the SOM prediction (1.41%) by cokriging than kriging(1.43%). Similarly, it was found that the standard deviation of predicted SOM by both kriging and cokriging were less than that of the soil organic matter measured from laboratory and the standard deviation of predicted SOM by cokriging was found less in comparison to kriging.

The mean of predictions and average standard error of prediction from cross-validation by the two methods were 0.03 and 0.62 for kriging and 0.01 and 0.61 for cokriging. It is found that the predicted SOM content by cokriging was less than that by kriging.

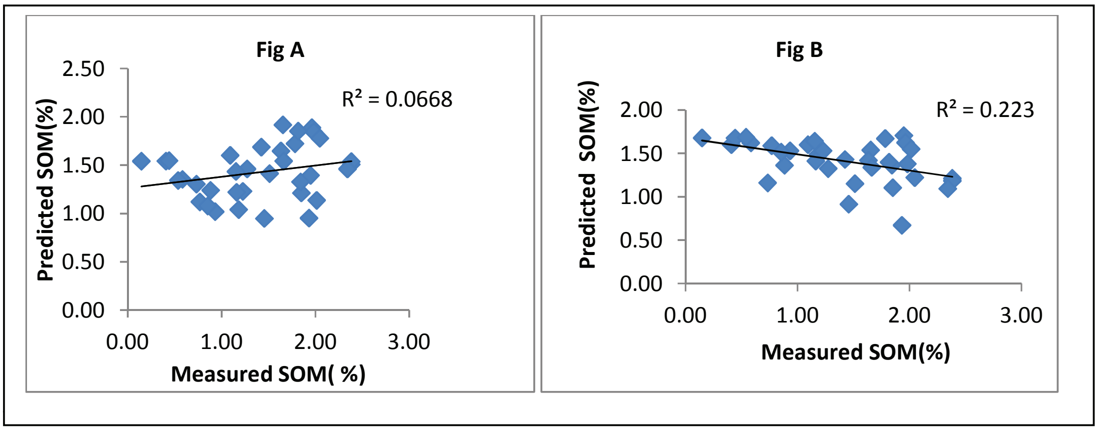

Fig 4: Measured soil organic matter (SOM) content (%) vs. the predicted SOM content (%) from cross-validation by (a) kriging and (b) cokriging

For evaluating the performance of the model, scatter plot was constructed among the measured SOM value versus predicted SOM by both methods: kriging and cokriging. It was outstanding to mention that remote sensing based spectral color index by cokriging model of SOM prediction had a relatively higher coefficient of determination (R^2 = 0.223). This illustrates that spatial prediction by cokriging with remotely sensed data was an improvement over spatial prediction by ordinary kriging.

Spatial dependency reflecting variability of soil properties was investigated by the appropriate semivariogram model and its parameters as nugget and sill. The ratio of nugget/sill was considered to be a basis for the classification of level of the spatial dependence as values lower than 25% for strong , higher than 75% for weak and between 25% and 75% for moderate spatial dependence (Chang et al., 1998; Chien et al., 1997). In the present analysis, spherical model of semivariogram was used and the nugget/sill ratios for both kriging and cokriging were found lower than 25%, that demonstrated strong spatial dependence of SOM and it indicated the importance of quantifying spatial variability for spatially predicting SOM in the study area. This demonstrates that remote sensing derived spectral color indices as auxiliary variables can improve the precision of SOM prediction in similar landscapes as investigated in this study.

CONCLUSIONS

Soil organic matter (SOM) content in the study area was found significantly negative correlated with remote sensing derived spectral color indices as the Coloration Index , Saturation Index and Redness Index having moderate correlation coefficient where as it was found positive low correlation with the brightness index and hue index . The correlation coefficient between the SOM and coloration index was found highest among all indices the largest in absolute value. The stepwise multiple regression model showed that coloration Index(CI) was found as a statistically significant predictor variable explaining low coefficient of determination, R^2 of 0.19 . Thus, it can be inferred that it was unable to obtain a satisfactory SOM prediction using a remote sensing derived spectral color indices.

In the same time it can be suggested that the predicted SOM map by cokriging with remote sensing covariates was an improvement over that by ordinary kriging and that by the remote sensing-based color indices in terms of describing spatial variability and reliability of the spatial estimation of SOM. The cokriging as a spatial interpolation technique showed that remotely sensed data such as World View-2 imagery have the potential as healthy auxiliary variables for improving the accuracy and reliability of SOM prediction.

The SOM content in the study area had a strong spatial dependency and its spatial concentration was found more (> 2.0 %) in the central part where as it was low (<1.0 %) in the marginal portion. In order to improve fertility status of soil and agricultural productivity, land management options should be developed to enhance SOM content in this area. A valuable and useful information for improving soil quality and managing nutrient budgets for agricultural production in the area can be provided by the methods of prediction used in this study.

References

Ben-Dor, E. (2002). Quantitative remote sensing of soil properties. *Advances in Agronomy. Israel.*

Chen, Y., and T. Aviad. (1990). Eff ect of humic substances on plant growth P 161–186. In P. Maccarthy et al. (ed.) Humic substances in soil and cropsciences: Selected readings. ASA, Madison, WI.

Chen, D., and W. Brutsaert. (1998). Satellite-sensed distribution and spatialpatterns of vegetation parameters over a tallgrass prairie. *J. Atmos. Sci.* , 55:1225–1238.

Coleman T., Montgomery O. (1987) - *Soil moisture, organic matter and iron content effect on spectral characteristics of selected Vertisols and Alfisols in Alabama*. Photogrammetric Engineering and Remote Sensing, 53: 1659-1663.

Chang, Y.H., M.D. Scrimshaw, R.H.C. Emmerson, and J.N. Lester. 1998. Geostatistical analysis of sampling uncertainty at the Tollesbury managed retreat site in Blackwater Estuary, Essex, UK: Kriging and cokriging approach to minimise sampling density. Sci. Total Environ. 221:43–57.

Chien, Y.L., D.Y. Lee, H.Y. Guo, and K.H. Houng. 1997. Geostatistical analysis of soil properties of mid-west Taiwan soils. Soil Sci. 162:291–297.

Dawadi Durga P , Chandra P Risal, Kiran H Maskey, Balaram Rijal Tuk B Thapa., 2015. Mobile Soil Test Laboratory: Experience of Soil Management Directorate to aware Farmers about Soil Health Proceedings of the Second National Soil Fertility Research Workshop "Celebrating International Year of Soils ,2015" Healthy Soils for Healthy Life " 24-25 March, 2015, Organized by: , CIMMYTE, IRRI, Soil Science Division Nepal Agricultural Research Council(NARC), Khumaltar Lalitpur,Nepal

Dehaan, R. L. and Taylor, G. R., 2002, Field-derived spectra of salinized soils and vegetation as indicators of irrigation-induced soil salinization. Remote Sensing of Environment, 80, p 406-417. (2002).

Greene W.H. (2008) - Econometric Analysis. Fourth edition, New Delhi: Dorling Kindersley, India, pp. 56-61.

Krishnan P., Butler B.J., Hummel J.W. (1981) Close-range sensing of soil organic matter. Transactions of the American Society of Agricultural Engineers (ASAE), 24 (2): 306-311. doi: http://dx.doi.org/10.13031/2013.34246.

Kravchenko A, Bullock DG (1999) A comparative study of interpolation methods for mapping soil properties. Agronomy Journal 91: 393,400.

Schulte E. E. and Bruce Hoskins. (2009). *Recommended Soil Testing Procedures for the Northeastern United States:Cooperative Bulletin No. 493.*

Frisch, R. (1934). *Statistical Confluence Analysis by means of Complete Regression Systems.* Oslo University, Institute of Economics, Publication No-5.

Gerritse and Robert G. (1988). Role of soil organic matter in the Geochemical cycling of chloride and bromide. *Journal of Hydrology, CSIRO, Wembley, Australia* , p 83-95.

Norusis/spss, Marija J., 1993: SPSS for WindowsTM : Professional StatisticsTM, Release 6+.SPSS Inc. 444 N Michigan Avenue. Chicago, Illinois 60611.

Pitts M.J., Hummel J.W., Butler B.J. (1986) - *Sensors utilizing light reflection to measure soil organic matter.* Transactions of the American Society of Agricultural Engineers (ASAE), 29 (2): 422-428. doi: http://dx.doi.org/10.13031/2013.30166.

R. Mathieu and M. Pouget, 1998, Relationships between satellite-based radiometric indices simulated using laboratory reflectance data and typic soil colour of an arid environment. Remote Sensing of Environment, 66, p 17-28.

R.C. Dalai and R.J. Henry. (1986). Simultaneous determination of moisture, organic carbon and total nitrogen by near infrared reflectance spectroscopy. . *Soil Sci Soc Am J, 50,* , 120-123.

R. L. Dehaan and G. R. Taylor . (2003). Image-derived spectral endmembers as indicators of salinization . *International Journal of Remote Sensing 24(4, 20)* , p 775-794. .

Stevenson, F.J., and X. He. 1990. Nitrogen in humic substances as related to soil fertility. p. 91–109. In P. Maccarthy et al. (ed.) Humic substances in soil and crop sciences: Selected readings. ASA, Madison, WI

Stoner. E. R., and M. F. Baumgardner. (1980). Physicochemical, Site, alld Bidirectiollal Reflectance Factor,Characteristics of Uniformly Moist Soils. *LARS Tech. Rep. 111679. Purdue University, West Lafayette,* .

Stoner, E. R., and M. F. Baumgardner. (1981). Characteristic variations in reflectance of surface soils. *Soil Sci. Soc. Am. J. 4S* , :1161_1165.

Wu, Chunfa, Jiaping Wu,Yongming Luo,Limin Zhang &Stephen D. DeGloria. (2009). Spatial Prediction of Soil Organic Matter ContentUsing Cokriging with Remotely Sensed Data. *Soil Sci. Soc. Am. J(SSSAJ): Volume 73: Number 4 July–August* , p 1206.

Yadav, V., and G. Malanson,. (2007). Progress in soil organic matter research: Litter decomposition, modeling, monitoring and sequestration. Prog. Phys.Geogr. 31:131–154. *Prog. Phys.Geogr* , 31:131–154.