SPECTRAL COLOR INDICES BASED GEOSPATIAL MODELING OF SOIL ORGANIC MATTER IN CHITWAN DISTRICT, NEPAL

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

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ABSTRACT

Space Technology provides a resourceful-cost effective means to assess soil nutrients essential for soil management plan. Soil organic matter (SOM) is one of valuable controlling productivity of crops by providing nutrient in farming systems. Geospatial modeling of soil organic matter is essential if there is unavailability of soil test laboratories and its strong spatial correlation. In the present analysis, soil organic matter is modeled from satellite image derived spectral color indices. Brightness Index (BI), Coloration Index (CI), Hue Index (HI), Redness Index (RI) and Saturation Index (SI) were calculated by converting DN value to radiance and radiance to reflectance from Thematic Mapper image. Geospatial model was developed by regressing SOM with color indices and producing multiple regression model using stepwise regression technique. The multiple regression equation between SOM and spectral indices was significant with R = 0. 56 at 95% confidence level. The resulting MLR equation was then used for the spatial prediction for the entire study area. Redness Index was found higher significance in estimating the SOM. It was used to predict SOM as auxiliary variables using cokringing spatial interpolation technique. It was tested in seven VDCs of Chitwan district of Nepal using Thematic Mapper remotely sensed data. SOM was found to be measured ranging from 0.15% to 4.75 %, with a mean of 2.24 %. Remotely sensed data derived spectral color indices have the potential as useful auxiliary variables for estimating SOM content to generate soil fertility management plans.

1. 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 CO2 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 al 1986 ,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 Thematic Mapper reflective data as an approach for estimation of soil organic matter content using cokringing spatial interpolation technique in seven VDCs namely Mangalpur,Sardanagar,Parwatipur,

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Sibnagar, Patihani ,Fulbari & Gitanagr VDC of Chitwan District of Nepal.

2. MATERIALS AND METHODS

2.1 Study Area

The study area is seven VDCs lying in North-western part of Chitwan district, Nepal (Fig.1), covering total area of 109.81 sq.km. The study area is ranging from 170 meter elevation from mean see level to 190 m with the average of 180 m and from less than 1° to 5° slope predominated by less than 1°. Geologically the study area is originated in tertiary and quaternary period consisting of sandstone, shale,conglomerate and active and recent alluvial plains and river terraces. Tributary of Raptari river is the major river draining lower part of the study area. The average maximum and minimum temperature of 10 years period (2000-2009) is found to be 30.95 °C and 18.18°C respectively with the average annual mean temperature of 24.57 °C. The average annual rainfall is 21931.64 mm out of which eighty three percent of annual total rainfall (1829.24 mm) is received during the months of rainy season.

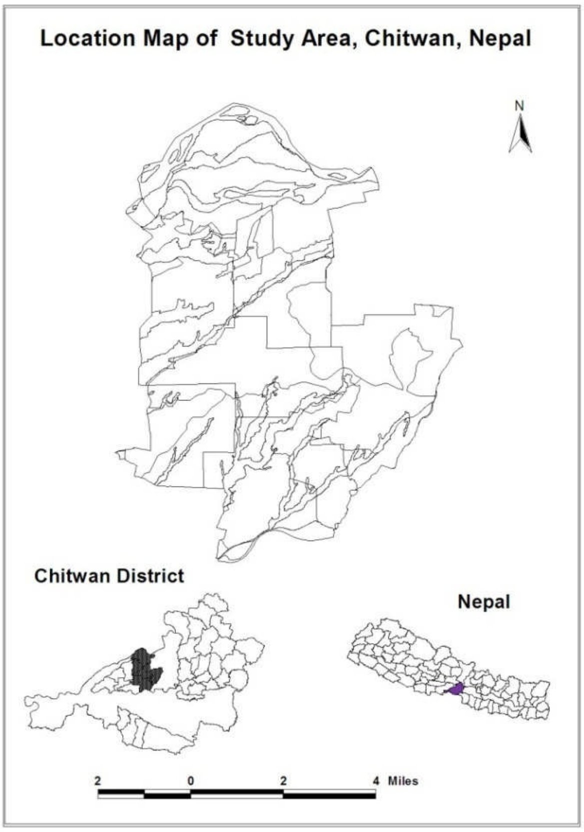

Fig 1: location map of study area

2.2 Image processing and generation of radiance and reflectance image and spectral color indices

In order to model/predict Soil organic matter content(SOM) in the study area using remotely sensed data as auxiliary variables, Landsat-5 image(row 41& path 142) was acquired on 7 April, 2010 .7-channel Landsat -5 of Thematic Mapper was downloaded at ftp://glcf.umiacs.umd.edu from Global Land Cover Facility of the University of Maryland, USA.DN value of each image was converted back to radiance image(L) using the equation 1:

$$L_\lambda = \textbf{"gain"} * \textbf{QCAL} + \textbf{"bias"} \quad \textbf{(1)}$$

Where L_λ = Spectral Radiance at the sensor's aperture in watts/(meter squared * ster * µm), **gain =** Rescaled gain (the data product "gain" contained in the Level 1 product header or ancillary data record) in watts/(meter squared * ster * µm), **QCAL =** the quantized calibrated pixel value in DN & **bias =** Rescaled bias (the data product "offset" contained in the Level 1 product header or ancillary data record) in watts/(meter squared * ster * µm). Then, to calculate at-sensor reflectance the equations are given in equation (2) &(3):

$$\text{Sun\_radiance} = [\text{Esun} * \sin(e)] / (\text{PI} * d^2) \quad (2)$$

$$\text{Reflectance} = \text{radiance} / \text{sun\_radiance} \quad (3)$$

where, d is the earth-sun distance in astronomical units, e is the solar elevation angle, and Esun is the mean solar exoatmospheric irradiance in W

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.

Five spectral color indices as brightness index (BI), colouration index (CI), hue index (HI), redness index (RI) and saturation index (SI) were derived from Thematic Mapper of Landsat.

Table 1: Technical specification of Thematic Mapper

Band No	Spectral range (nm)	Spatial Resolution (m)	ImageSwath(km)
7	400-1250	30	185

The method for generating these indices is presented in Table 2 using following formula (Mathieu and Pouget, 1998). Three channels having the center wavelength of Blue (B = 480 nm), Green(G = 545 nm) and Red(R= 660 nm) of Landsat-5 image data were used to generate indices and corresponding image values associated to SOM samples were extracted to perform the relations.

Table 2: Spectral color indices of Thematic Mapper sensor

Index	Formula	Index Property
Brightness Index, BI	$(R^2+G^2+B^2)/3)^{0.5}$	Average soil reflectance magnitude
Saturation Index, SI	(R-B)/(R+B)	Spectral Slope
Hue Index, HI	(2*R-G-B)/(G-B)	Dominant wavelength, Primary colors
Coloration Index, C	(R-G)/(R+G)	Hematite/hematite+geothite ratio,Soil Colour
Redness Index, RI	$R^2/(B*G^3)$	Hematite Content

2.3 Soil Survey and Analysis

A total of 391 soil samples from epipedon were collected from different land use mainly from agriculture fields in May 6, 2011(Fig 2). 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).

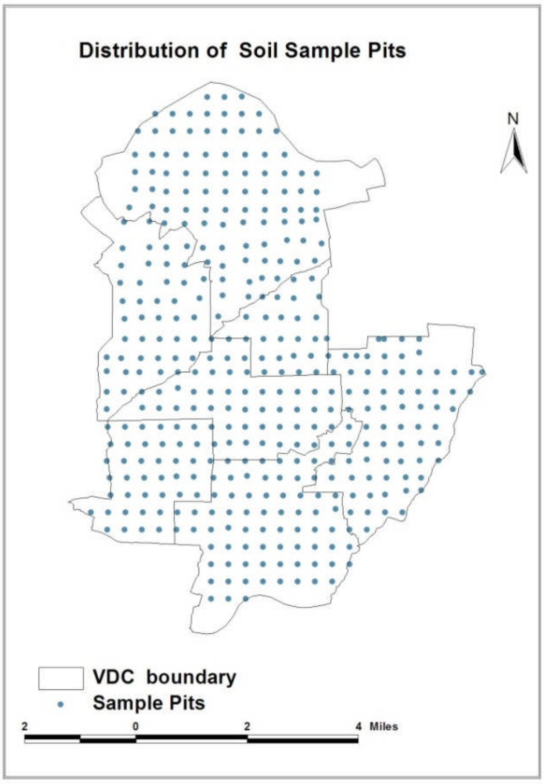

Fig 2: Distribution of soil samples.

2.4 Kriging and Cokriging

Kriging utilizes the spatial dependence of a particular soil characteristic. Some attributes such as SOM and Redness Index(RI) are dependent. This dependence can be used in estimation as well as the spatial dependence. When one or more variables are estimated by a linear combination using both the spatial and inter-variable dependence, the technique is known as *co-kriging or co-regionalization.*

The matrix formulation of cokriging has been described by the scientists (Journeland Huijbregths ,1978 and Myers,1982,1983). The cokriging estimate is a linear combination of both primary and secondary data values and is given by the equation (4).

$$\hat{u} = a \cdot u + b \,.\, v \qquad (4)$$

where $\hat{u}_o$ is the estimate of U at location o; $u_1,\ldots,u_n$ are the primary data at n nearby locations; $v_1,\ldots,v_m$ are the secondary data at m nearby locations; $a_1,\ldots,a_n$ and $b_1,\ldots,b_m$ are the cokriging weights that must be determined.

The development of the cokriging system is identical to the development of the ordinary kriging system. The definition of estimation error is given in equation (5)

$$R = \hat{u} - u = a \cdot u + b \cdot v - U \qquad (5)$$

Kriging calculates the values of weight, a_i by estimating the spatial structure of the variable’s distribution represented by a semivariogram model as spherical in this case as equation(6):

$$\gamma(h) = \begin{cases} C + C \;\; ----- \;\; \text{for } 0 \leq h \leq a \\ C + C \;\; \text{for } h \geq a \end{cases} \qquad (6)$$

Similarly cokriging calculates the values of weight, a_i by estimating the spatial structure of the co-variable’s distribution represented by a cross semivariogram model using a Gaussian model as equation (7):

$$\gamma(h) = C + C \quad 1 - \exp \; -\frac{h}{a} \qquad (7)$$

where $\gamma(h)$ is semivariogram value, C_0 is the nugget value , C_1 or θ_s is the sill value , a or θ_a is the range value , and h is the lagged distance or distance between two places.

3. RESULTS AND DISCUSSIONS

3.1 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 Thematic Mapper 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 Thematic Mapper sensor. A t-test showed that regression coefficient of Redness Index(RI) among five indices were found significant at 5 percent significant level along with ANOVA reported that the model is significant at the 5 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-two percent variation in SOM is explained by the model (R^2. = 0.32). Although multiple correlation coefficient was found moderate (R=0.56), individual indices as predictors are suffering from multi-collinearities 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.

3.2 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 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 with Brightness Index ($r = -0.408$) and Redness Index ($r = -0.342$) at 0.05 significant level (Table 3). Such significant correlation coefficient was investigated after removal of outliers found in five 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	-0.408	-0.344	0.312	-0.432	-0.344

Stepwise multiple regression was performed among five remote sensing based spectral color indices after removing outliers and multi-colinearity problem by using following equation(8).

$$\mathrm{SOM} = f(\mathrm{a}) \qquad (\ )$$

Where SOM_i is the mean content of Soil Organic Matter (SOM) . a is the Redness Index(RI). In this equation, soil organic matter (SOM) content is said to be a function of Redness Index (RI). The resulting least square fit has the form:

$$\mathrm{SOM} = 0.385 - 2.736 * \mathrm{RI} \qquad (9)$$

The result of stepwise multiple regression analysis as indicated by t-test shows that only Redness Index(RI) remained as a statistically significant predictor variable ($P < 0.05$).The coefficient of determination, R^2 of the model was investigated of 0.25 , implying that twenty-five percent of the variation in the mean soil organic matter content of seven Village Development Committees of Chitwan district, Nepal can be accounted for by only Redness Index(RI).

3.3 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 0.150 % to 4.750 % with the mean of 2.241 % and median of 2.260% . 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 Redness Index of Thematic Mapper was well fitted with a spherical model. Spherical model of semivariogram is characterized by nugget of 0.538,partial sill of 0.077 and range of 12778.3 for kriging and nugget of 0.555, partial sill of 0.066 and range of 12778.3 for 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 RI of Thematic Mapper were as low as 0.89 and 0.88, respectively.

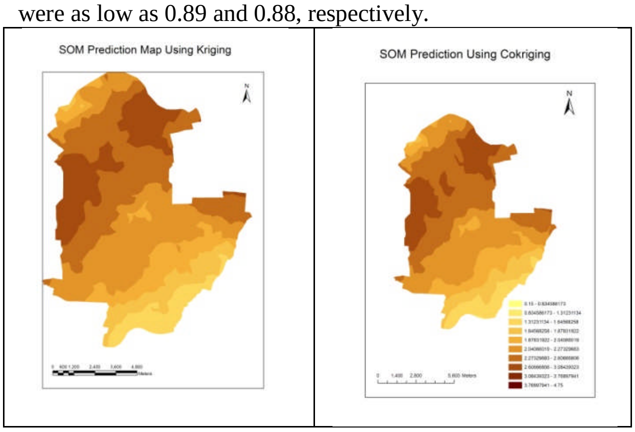

Fig 3: Predicted soil organic matter (SOM) content (%)by kriging and cokriging.

Strong spatial variability was investigated from the maps of predicted SOM content generated by both kriging and cokriging spatial interpolation technique with spectral derived Redness index (RI) from Thematic Mapper image data (Fig. 3) and the SOM content in the north western part of the study area area was found to be higher as compared to outer portion. Some 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 north-western part of the study area (Fig. 3).

The minimum and maximum values of SOM prediction by kriging were found as 1.27 % and 2.81 % respectively and the same values of SOM prediction by cokriging with spectral Redness index were investigated as .99 and 2.92 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 4.75 %, respectively. The mean and standard deviation of SOM prediction by the two methods were 2.14% and 0.60 for kriging 2.24% and 0.28 for cokriging, respectively and the mean and standard deviation of SOM content from the soil samples were 2.24%and 0.37 respectively. The measured value of mean SOM (2.23 %) was found to be closer to the SOM prediction (2.24%) by cokriging than kriging(2.14%). 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 0.032 and 0.765 for kriging and 0.030 and 0.705 for cokriging. It is found that the predicted SOM content by cokriging was less than that by 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.

4. CONCLUSIONS

Soil organic matter (SOM) content in the study area was found significantly negative correlated with remote sensing derived spectral color indices as the Bright Index , and Redness Index having moderate correlation coefficient where as it was found positive low correlation with the hue index . The correlation coefficient between the SOM and redness index was found highest among all indices the largest in absolute value. The stepwise multiple regression model showed that redness Index(CI) was found as a statistically significant predictor variable explaining low coefficient of determination, R^2 of 0.25 . 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 Thematic Mapper 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.

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