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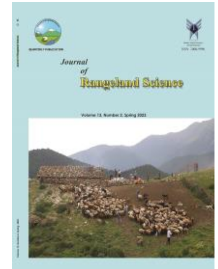

Research and Full Length Article:

Prediction of Soil Organic Carbon (SOC) in Semi-Arid Rangeland Using Multivariate Statistical Analysis based on Remotely Sensing Data (Case study: Neyshabur Rangeland, Khorasan-Razavi Province, Iran)

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Abstract. Prediction of Soil Organic Carbon (SOC) reservoirs is high priority in the rangelands managements in arid and semi-arid regions. This study was conducted to estimation carbon sequestration using Multivariate Linear Regression Analysis (MLR), Principal Component Analysis (PCA) and Euclidean Distance from the soil line (D) on remote sensing data in semi-arid rangelands of southwest of Neishabour, Khorasan Razavi province, Iran. The map of SOC was prepared using a total of 102 soil samples (depth 0-10 cm). Landsat 8 images of the study area were provided on 5 July 2018 and used to develop the models including (OLI, TIRS), visible, near-infrared, middle-infrared, and thermal infrared bands. Models were developed using SOC as dependent variable and spectral data of MLR, PC1 and Euclidean D soil line as independent variables. Then, the developed models were validated using additional samples (30 points). The results illustrated that the MLR, PCA, and Euclidean D soil line models explain 62, 45, and 53% of the total variability of SOC coupled with root Mean Square Error (RMSE) values 0.09, 0.21, and 0.05, respectively. Therefore, the MLR technique could provide superior predictive performance than that for PCA and Euclidean D soil line techniques. It was concluded that the SOC spatial information derived using the MLR technique had much greater spatial detail and higher quality than to that derived from the conventional soil map.

Key words: PCA, Multivariate regression, ETM^+, Rangeland soils

Introduction

Soil Organic Carbon (SOC) is the major terrestrial carbon pool (Stockmann, *et al.,* 2015). SOC is an important source of nutrients for plant growth and range production. There are some factors influencing SOC reservoirs, including land use type, soil type, climate, and vegetation (Gholami *et al*.,2021; Loveland and Webb, 2003). SOC plays a key role in soil quality and has plenty of positive effects on various biological, chemical, and physical characteristics of the soil. SOC is also one of the important factors affecting soil aggregate stability and plant production (Loveland and Webb, 2003). (Seybold *et al.,* 1997; Zeraatpisheh *et al.,* 2019) found that the SOC pool in croplands is a result of a long history of cultivation, and thus they argued that croplands have a large potential to restore SOC and sequester atmospheric CO_2 (Oldfield *et al*, 2019). This will also lead to a gradual restoration of soil fertility and, in many cases increase crop yield through nutrient use efficiency (Oldfield *et al*., 2019).

In addition, the role of SOC in improving soil properties, nutrient cycling and crop production to carbon sequestration in soil and the mitigation of global climate change effects is undeniable (Kumar and Lal, 2011).The importance of global warming in the future is related to SOC (Prentice, 2001). Furthermore, SOC is known as a sink or source of atmospheric CO_2 depending on the agricultural management (Smith, 1999; Kumar and Lal, 2011). It is notable that quantification of spatial variability of SOC helps to have a suitable implementation of management practices (Hummel, *et al.* 2001; Mendoza *et al.*, 2003; Matinfar *et al.*, 2021; Sainepo Bernice *et al.*, 2018). SOC is often highly spatially variable as affected by natural soil variability, climate, and topography.

In general, it can be said soil management affects the return and dynamics of soil organic matter by changing the quantity and quality of plant debris entering the soil, their seasonal and spatial distribution, the ratio between terrestrial and underground inputs, and by changing nutrient inputs (Rotich *et al.,* 2020; Kendler *et al.* 1999). However, the quality of prediction of the SOC content can be increased and spatial sampling intensities can be reduced by incorporating topographical attributes as an auxiliary variable source (Terra *et al.*, 2004; Mueller and Pierce, 2003; Guo *et al.*, 2019). Traditionally, information on the SOC is derived through standard procedures of soil sampling and laboratory analysis. Since conventional methods for SOC monitoring are time consuming and costly (Omran, 2017), researchers investigated the implementation of alternative approaches that can be applied in different conditions and soil types (Jandl *et al.*, 2014) Remote sensing is also known as a cost-effective and nondestructive analytical technique to evaluate SOC with acceptable accuracy (Frazier and Cheng, 1989; Mulder *et al.*, 2011). SOC has magnificent effects on the shape and nature of the soil reflectance spectrum. A wide spectral range found by different researchers to assess SOC content, suggesting that SOC is an important soil constituent across the entire spectrum (Ben-Dor, *et al.,* 1999).

Aı¨chi *et al*. (2009) developed a regional prediction model of SOC content based on laboratory measurements of reflectance within the visible and near-infrared spectral ranges. They showed good predictions of the SOC content are therefore still possible using a cheap spectrometer operating between 400 and 950 nm in a regional soil database which can be progressively enhanced. Muhaimeed and Taha (2017) in application of remote sensing and GIS based methods to predict the spatial distribution of SOC content in southern Iraq found that approach of using statistical correlation models derived from spectral indices processed from Landsat multispectral indices for a region of interest to predict spatial variations of SOC is successful.

Frazier and Cheng (1998) used Landsat Thematic Mapper (TM) band ratios to categorize various concentrations of organic matter and iron oxides. Chen *et al.* (2000) reported that the reflectance of aerial photography, illustrated a high correlation with SOC. The initial airborne experiments were carried out by Baumgardner *et al.,* (1970) and Al-Abbas *et al.,* (1972) to evaluate the relationship between organic matter and reflectance. Chen *et al.,* (2008) developed a relationship between the surface (0-15 cm) SOC concentration and the image intensity values from an aerial photograph using a logarithmic linear equation (R^2=0.93) on a Georgia coastal plain field. Sullivan *et al.,* (2005) reported a high correlation (r=-0.78) between spectral response remotely sensed by the IKONOS satellite and surface (0-15 cm) organic carbon of tilled soils in an Alabama coastal plain field. They also showed that SOC was negatively correlated with reflectance, the higher SOC concentration had a darkening effect which can lead to the reduction of reflected energy. In other studies, SOC was detected in the visible and NIR regions of the spectrum, where the relationship is linear or curvilinear (Henderson *et al.,* 1992). High-resolution secondary information such as remote sensing (RS) could be applied to obtain more detail in low extensive soil measurements like SOC (Vågen *et al.,* 2013). It is hypothesized that RS imagery may play a role in the detection of SOC variability in rangelands according to the relationship between SOC and forage growth conditions since the latter was highly correlated with RS data (Blackmer and Schepers, 1996; Yang and Everitt, 2002; Wang *et al.* 2018). Soil line is a linear relationship between reflectance and image intensity in the Red and NIR wavelengths (Campbell, 2006). Fox and Sabbagh, (2002) used an exponential function to measure the relationship between a pixel distance along the soil line with the OM of the soil. Fox and Metla (2005) developed relationships between remotely sensed bare soil images and surface organic matter content using principal component analysis (PCA). The PCA used to reduce the data dimensionality and to indicate the components and the schematic representation of the distribution responsible for the spectral variability in the dataset (Dwivedi, 2001; Ray *et al.,* 2002). Fox and Metla (2005) used the first principal component (PC1) to study the SOC content from remotely sensed data. In the present study, we attempted to estimate the SOC by MLR, PCA and Euclidean distance from the soil line D models using remote sensing data and also determine the most suitable model representing the variability of SOC in saline and calcareous soils of semi-arid of Iran.

Materials and Methods

Study area

This study was carried out in the South-West of Neyshabur, Iran (36°6.36′-36°10.38′N, 58°35.33′- 58°43.91′ E) (Fig. 1). The study site covers a surface area of about 5474 ha. In some parts of the area, accumulation of the soil particles delivered by surface runoff resulted in alluvial soil formation. On the basis of American soil classification Entisols and Inceptisols (USDA, 2014) are widely found in this region. Based on the long-term measured data from 1991 to 2018 acquired Meteorological service of Iran, the average monthly temperature varied from 1.72 to 27.81°C. The average lowest and highest temperatures occur on January and July, respectively, and the average annual rainfall was 237.9 m.

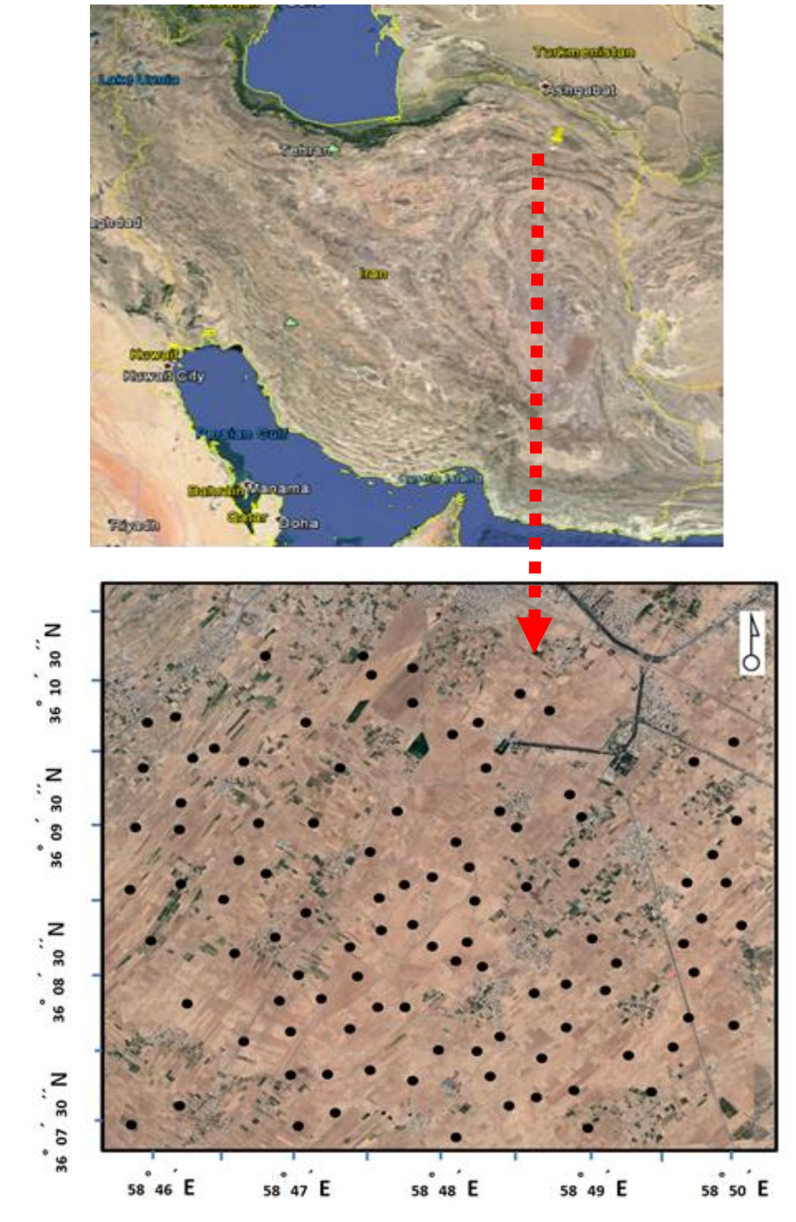

Fig. 1. Location of the study and distribution of studied points

A total of 102 soil samples were collected from 0-10 cm depth and sieved after drying by a 2 mm sieve. A Latin hypercube were used as a sampling method as shown in Fig. 1. Soil pH and Electrical conductivity (EC), soil particle size including sand, silt and clay content, calcium carbonate equivalent (CCE) contents were measured in the laboratory based on the standards of Iran Soil and Water Research Institute. The ESP parameter was determined by the ratio of sodium cation content to the sum of sodium and other cation in soil solution. The descriptive statistics for all soil properties are presented in Table 1.

Table 1. Descriptive statistics of study soil

Properties	Mean	Min	Max	Std. dev
Clay (%)	29.6	19.0	39.0	4.98
Silt (%)	47.5	35.0	63.0	4.8
Sand (%)	23.0	14.0	36.0	6.3
Organic carbon (OC%)	0.6	0.4	0.8	0.1
Calcium carbonate equivalent (CCE %)	12.5	9.0	15.5	1.9
pH	7.9	7.8	8.1	0.1
Electrical conductivity EC (dS m^{-1})	12.3	6.5	19.5	3.4
Exchangeable sodium (ESP %)	4.9	0.0	18.0	4.2

Multi spectral data and variables

Landsat7 ETM^{+} images of the study area were provided on 5 July 2018. Since the former date some data had been missed due to the technical problems of scan-line correctors, the data missing pixels were provided via geo-statistic method. In addition, these data were compared with Landsat 8 images and the comparison showed that the images of Landsat 7 present superior data. A single band data from the Landsat image were obtained with spatial resolution of 30 m. Also, Atmospheric correction was performed by the Black body method (French *et al.* 2003) to eliminate the possible effects of atmospheric factors in the ENVI software. The subset image covering the study area was introduced into the ENVI software and georeferenced using the landform map of Iran with a scale of 1:25000 with 0.1-pixel accuracy.

Soil Line concepts

The soil line approach is based on the Euclidean distance of a pixel to the soil line (Fox *et al.*, 2004). The latter links to the pixels with the smallest Red and NIR values, that is, the darkest soil in the field. This technique was developed to derive the relationship between a pixel’s Euclidean distance along the soil line and SOC. It uses values in the Red and NIR bands for pixels located specifically within the field of interest and soil measurements recorded at the same places to develop a model between soil Digital Number in the Red and NIR bands and SOC.

Principal component analysis (PCA)

PCA was applied to all pixels of images. That is a way to discover factors from a set of independent variables. Steps in PCA included calculating univariate statistics, covariance matrix, correlation matrix, the eigenvalues, and eigenvectors and the degree of correlation (Pallant, 2020). New images representing the PC1 values also were obtained. PC values were calculated by ENVI software.

Multiple Linear Regression (MLR),

MLR is a statistical technique that uses several explanatory variables to predict the outcome of a response variable (Kuhn, 2020). The goal of the MLR is to model the linear relationship between the explanatory (independent) variables and response (dependent) variable.

Validation

Statistical analysis was done to investigate the relationships of SOC and remote sensing data using SPSS software. Descriptive statistics such as means, minimum, maximum, coefficient of variation (CV) and skewness were also determined.

Samples were randomly separated into two groups. The first group which included 72 samples was used to develop the models and second group, including 30 samples was kept for model validations. The dependent variable was SOC and independent variables were digital numbers, Euclidean distance D and PC1 values. MLR equations were established to create models for SOC estimation from DN and univariate regression models were applied for estimating SOC by D and PC1 values. Root mean square error (RMSE) and R^2 were calculated to evaluate the performance of the three methods. The ability of each technique to predict SOC was investigated using correlation coefficients between the estimated and measured SOC.

The RMSE and Mean absolute error (MAE) were estimated based on Isaaks and Srivastava (1989):

$$RMSE = \left\{ \sum \left[Z^*(si) - Z(si) \right]^2 / n \right\}^{\frac{1}{2}}$$

$$MAE = \sum \left| \left[Z^*(si) - Z(si) \right] \right| / n$$

Where:

Z (si)= the measured value of z and

Z*(si) =the predicted value at the same location, and

n=the number of validated observations.

Results and Discussion

Descriptive statistics

The descriptive statistics and variations of SOC are illustrated in Table 2. The SOC content of 72 soil samples varied from 0.4 to 0.8%, with a mean of 0.6 and SD of 0.1.

The remote sensing data were normally distributed as confirmed by the Kolmogorov Smirnov test. According to the results the variability of SOC was low (CV=17). Norouzi *et al.* (2009) reported that the CV of SOC in hilly slope was high 40. Terra *et al* (2004) showed that the SOC was relatively low and only moderately variable (CV=21%). In the other study the CV of SOC in grassland and barren area were 33.5 and 35.2, respectively (Mishra *et al.* 2010).

The correlation between SOC with band 1, 2, 3, 5 and 7 was negative, and correlation between SOC and band 4 was positively significant ($p<0.01$). The Highest correlation was found between SOC and the DN of Band 2 (r =-0.47) (Table 3). According to Wu *et al.* (2009), positive correlation was observed between SOC and band 4 and a negative correlation was found between SOC and band 1, 2, 3, 5 which were in line with finding of our study.

As shown in Table 3, the correlation between SOC with band 1, 2, 5 and 7 was significantly negative ($p<0.01$). Broge *et al.* (2005) reported that the spectral reflectance data within the visible and near infrared range were correlated with the SOC content using multi-spectral aerial imagery and topographic data. The results of Broge *et al.* (2005) observed a significant negative correlation ($p<0.05$) between SOC and band 1, 2, 3, 4 which was in line with our observations (Broge *et al.*, 2005).

Table 2. The descriptive statistics of study area soil organic carbon

Variable	Unit	Min	Max	Mean	CV%	Std	No Obs.
SOC	%	0.4	0.8	0.6	17	0.1	72

Table 3. Descriptive statistics of Landsat Enhance Thematic Mapper Digital number and Pearson correlation coefficients (r) between SOC and auxiliary data

Bands	Min	Max	Mean	StDev	Range	Skew	Correlation SOC Vs. auxiliary data
Band1	98	120	108.75	5.08	22	0.11	-0.47 **
Band2	101	131	116.5	6.75	30	-0.02	-0.48 **
Band3	134	177	156.74	10.36	43	0.00	-0.27 **
Band4	110	187	131.81	13.08	77	0.65	0.29 **
Band5	132	211	168.93	17.43	79	0.01	-0.27 **
Band7	107	173	142.4	15	66	-0.05	-0.44 **

**= Significant at 1% probability level.

Models implementation

A MLR model was developed between SOC and the soil Digital Number (DN) in different bands as:

$$SOC(\%) = 0.01\,(band2) - 0.013\,(band3) + 0.069\,(band\ 5)$$

With R^2, MAE and RMSE values of 0.61, 0.09 and 0.02, respectively. Univariate nonlinear models were used to develop the relationship between SOC, the first principal component (PC1) and Euclidean distance (D) values. PC1 accounted for 97% of the variance in the dataset. Therefore, among PC values, only the relationship between PC1 and SOC was evaluated.

Exponential functions were determined to show the most appropriate relationships (Fig. 2). Digital number (DN) of red and NIR bands were extracted and plotted opposite of each other and soil line was obtained for each image (Fig. 2).

It is required to identify the minimum point along the soil line, to calculate the Euclidean distance (D) of each pixel intensity value from the soil line's minimum point:

Where NIR and R are the NIR and red DNs at the sampling location, and are the NIR and red DNs for the minimum point on the soil line (Fox *et al.*, 2004; Richards, 2013).

D indicates the position of pixels along with the soil line in the dimension of DN. The lower value of D shows that the desired pixel is close to the soil line. The equation was applied to the original images, and then the images representing the distribution of D were obtained.

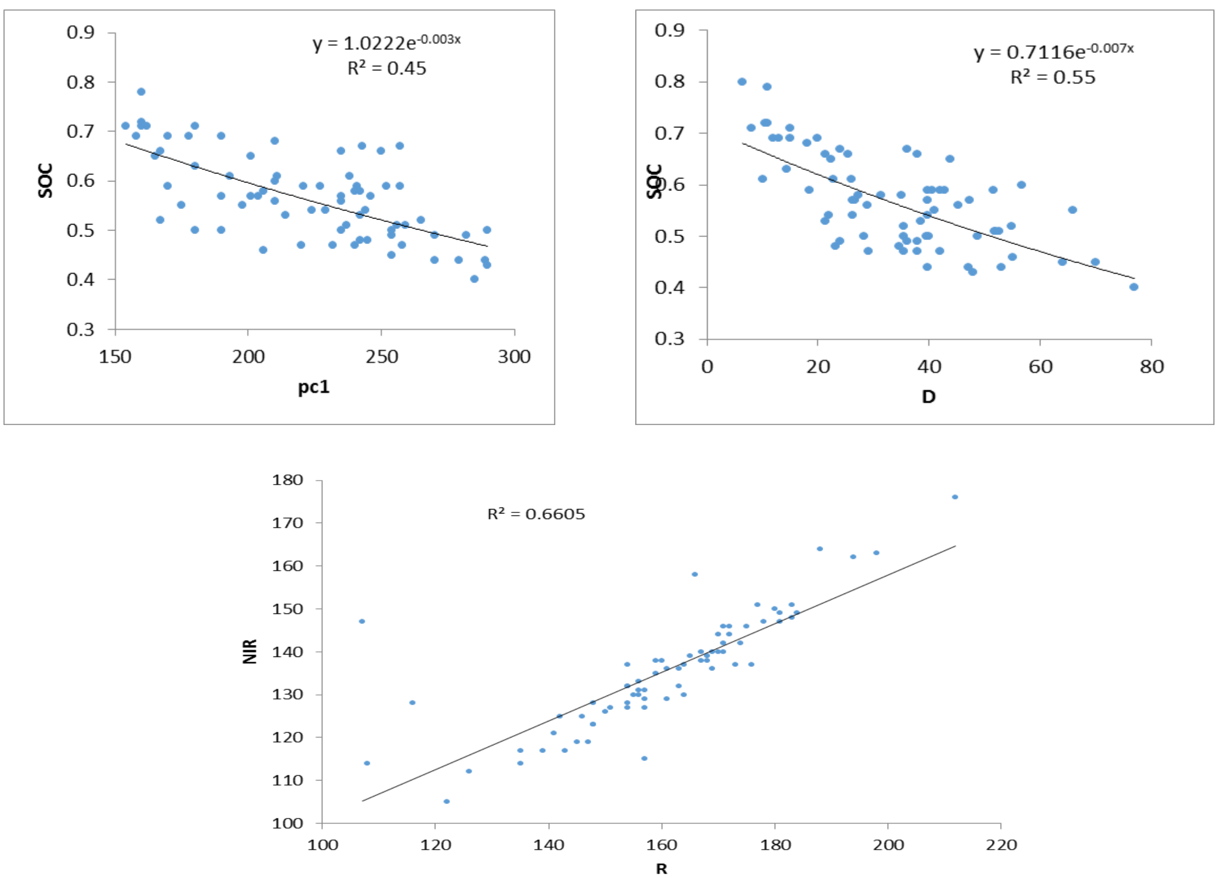

Fig. 2. The regression modes of SOC vs. PC1 (Soil organic carbon prediction vs. first principal component) and SOC vs. D (Euclidean distance from soil line) and between (DN values of R vs. NIR bands)

The models were utilized to predict SOC values based on D soil line, PC1, and DN of bands. In addition, linear regressions were developed between predicted values and actual SOC (measured in the laboratory) to evaluate the accuracy of each technique (Fig. 3).

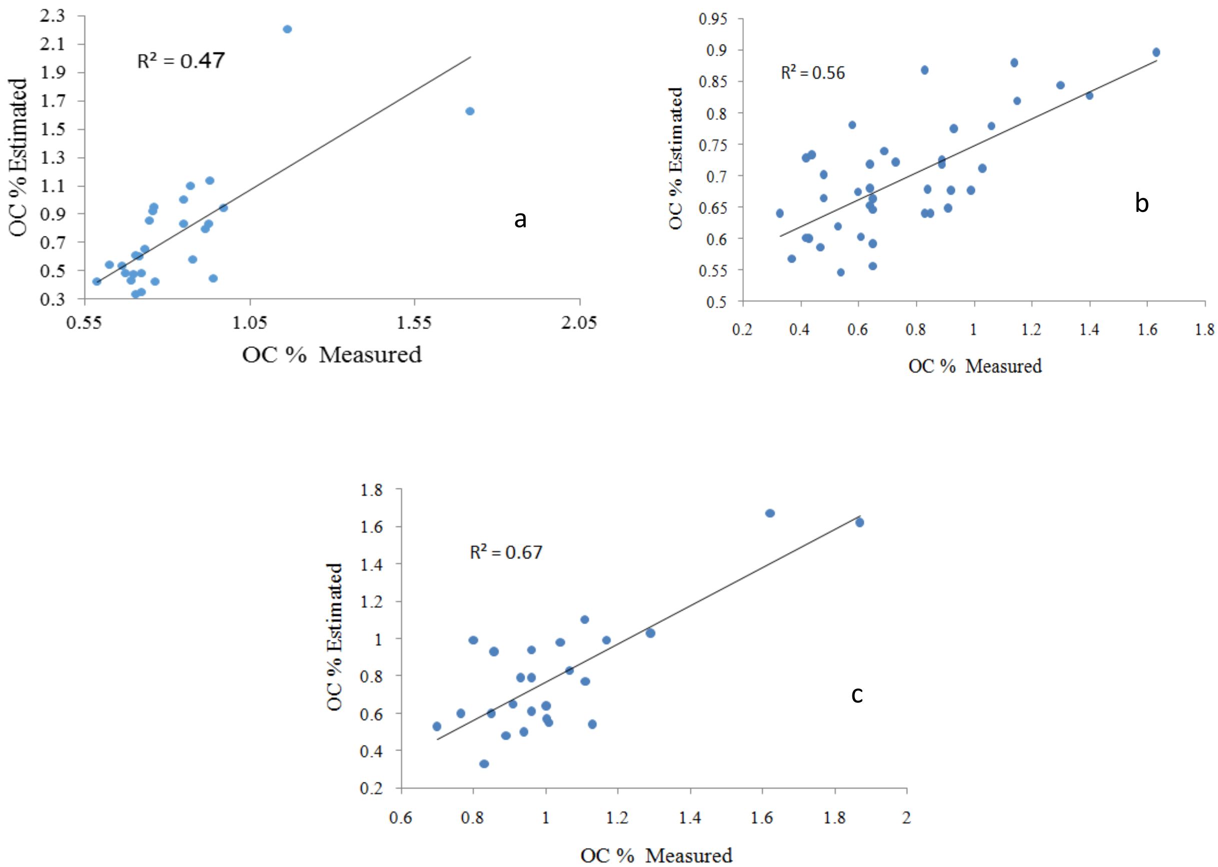

Fig. 3. The relationships between SOC Measured vs. SOC predicted in three conditions a) PC1, b) D from soil line and c) MLR techniques

The statistical parameters of three models used to estimate SOC are presented in Table 4. In this regard, MAE and RMSE also were calculated. Estimation of the three models in the study area resulted in root mean square error (RMSE) values of 0.03, 0.13 and 0.09, mean absolute error (MAE) values of 0.06, 0.11 and 0.08 using MLR, PCA and D from soil line models, respectively.

The strongest correlation observed in MLR that its (R^2=0.56) values was higher than those for PCA and soil line techniques. Fox and Metla (2005) observed similar regression coefficients in PCA, soil line, and the MLR techniques. Our results showed that PCA and soil line techniques were less accurate than MLR which was in contrast with findings of by these authors. The relatively poor accuracies of the D soil line and PCA techniques indicated that these methods are not suitable to evaluate some significant relationships between spectral reflectance and SOC. The soil line technique used red and NIR, failing to use the green and short wave infrared, which were significantly correlated with SOC (Fig. 2). PCA reduced the variance in the data and also in a pure bare soil image; the PC1 theoretically corresponds to the D from the soil line, which may cause a reduction in accuracy. Fox and Sabbagh (2002) and Fox and Metla (2005) reported that Dvaurom soil line and PCA can be used to select in situ soil samples in order to detect of SOC heterogeneity in the field. As a result, PCA and soil line techniques present less accuracy when compared with MLR which uses all data bands. Finally, with the data extracted from the MLR model, a digital carbon map of the region was generated by interpolation method (Fig. 4).

Table 4. Statistical parameters of three models used to estimate SOC

Techniques	R^2	RMSE	MAE
MLR	0.67	0.03	0.06
PCA	0.47	0.13	0.11
Euclidean D Soil line	0.54	0.09	0.08

RMSE=root mean square error
MAE=mean absolute error
MLR= multivariate linear regression
PCA=principal component analysis

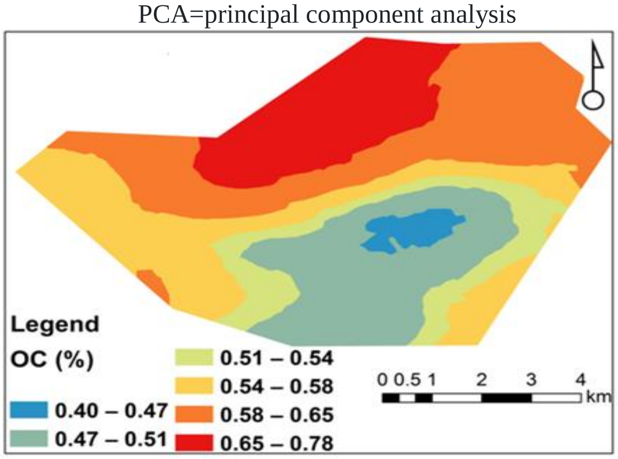

Fig. 4. Predicted SOC map using Data from model MLR estimation

Conclusion

The study area was in arid and semi-arid climates therefore it is necessary to identify spatial variability of SOC content in this climatic situation. On the other hand, conventional methods of SOC measuring as important indicators of nutrient quality and carbon sequestration in soil stabilization are very time-consuming and costly. This study was conducted to estimate the SOC by remote sensing data as cheap and available data and using MLR, PCA, and D from soil line techniques and also to determine the best technique which explains the variability of SOC in a hilly region of central Iran.

The strength of PCA and D from soil line techniques in the estimation of SOC was approximately similar. The Euclidean distance from soil line and PC1 were correlated with SOC; however, their accuracy was not strong enough to predict SOC. In general, the multivariate linear regression (MLR) technique provided the most accurate approach for the prediction of SOC from remotely sensed data. MLR was accurate enough for use in SOC mapping. It was concluded that the variables extracted from Landsat 7 data with the help of statistical model can be a fast, cheap and acceptable tool for estimating SOC in arid and semi-arid regions.

References

Al-Abbas, A. H., Swain P. H. and, Baumgardner M. F., 1972. Relating organic matter and clay content to the multispectral radiance of soils, Soil Sci. 114,pp. 477–485.

Aı¨chi H., Fouad Y., Walter C., Viscarra Rossel R.A., Zohra Lili Chabaane, Mustapha Sanaa. 2009. Regional predictions of soil organic carbon content from spectral reflectance measurements. Biosystems Engineering, doi:10.1016/j.biosystemseng.2009.08.002.

Baumgardner, M. F., Kristof S. J., Johansen C. J. and Zachary A. L., 1970. Effect of organic matter in the multispectral properties of soils, Proceedings of the Indiana Academy of Science. 79,pp.413–422.

Ben-Dor, E., Irons, J.R. and Epema, G.F., 1999. Soil Reflectance. In: Rencz, N., Ed., Remote Sensing for the Earth Sciences: Manual of Remote Sensing, John Wiley and Sons, New York,pp. 111-188.

Blackmer T.M., and Schepers J.S., 1996. Aerial photography to detect nitrogen stress in corn, Journal of Plant Physiology, 148 (3-4),pp. 440-444.

Broge, N. H., Greve M. H. and Larsen R., 2005. Estimating topsoil organic matter content in two experimental fields in Denmark using multi-spectral aerial imagery and topographic data, Geografisk Tidsskrift, Danish Journal of Geography. 105(2)pp. 1-14.

Campbell, J. B., 2006. Introduction to remote sensing (4th Ed.). New York, USA: Guilford Press.

Chen, F., Kissel D. E., West L. T. and Adkins W. 2000. Field-scale mapping of surface soil organic carbon using remotely sensed imagery, Soil Sci. Soc. Am. J. 64,pp. 746–753.

Chen, F., West L. T., Kissel D. E., Clark R. and Adkins W., 2008. Field-scale mapping of soil organic carbon in soil-landscape modelling, Proceedings of the 8th International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Sciences, Shanghai, P. R. China, pp.294-301.

Dwivedi, M. R. 2001. Soil resource mapping: A remote sensing perspective. Remote Sensing Reviews 20(2),pp. 89-122.

Fox, G. A. and Sabbagh G. J., 2002. Estimation of soil organic matter from red and near-infrared remotely sensed data using a soil line Euclidean distance technique, Soil Sci. Soc. Am. J. 66,pp. 1922-1929.

Fox G. A., Sabbagh G. J. Searcy, S. W., and Yang C. 2004. An Automated Soil Line Identification Routine for Remotely Sensed Images, Soil Sci. Soc. Am. J. 68,pp.1326–1331.

Fox G. and Metla R., 2005. Soil Property Analysis using Principal Components Analysis, Soil Line, and Regression Models. Soil Science Society of America Journal.69(6),pp. 1782-1788.

Frazier B. and Cheng Y.,1989. Remote sensing of soils in the eastern Palouse region with Landsat Thematic Mapper. Remote Sensing of Environment. 28,pp.317-325.

French A.N., Norman J.M. and Anderson M.C., 2003. A simple and fast atmospheric correction for spaceborne remote sensing of surface temperature, Remote Sensing of Environment 87,pp. 326–333.

Gholami A., Yongqiang Y., Sadoddin A. and Zhang W.2021, Soil Organic Carbon Stock Changes in Response to Land-use Changes in Iran, Journal of Rangeland Science, 2021, 11(3),pp. 247-268.

Guo Z., Adhikari K., Chellasamy M., GreveM. B. Owens P. R. and GreveM. H., 2019. Selection of terrain attributes and its scale dependency on soil organic carbon prediction: Geoderma, 340, pp.303-312.

Henderson, T. L., Baumgardner M. F., Franzmeier D. P., Stott D. E. and Coster D. C.,1992. High dimensional reflectance analysis of soil organic matter, Soil Sci. Soc. Am. J. 56,pp. 865-872.

Hummel J. W., Sudduth K. A. and Hollinger S. E., 2001. Soil moisture and organic matter prediction of surface and subsurface soils using an NIR soil sensor, Comput. Electron. Agric. 32,pp. 149–165.

Jandl, R., Rodeghiero, M., Martinez, C., Cotrufo, M.F., Bampa, F., van Wesemael, B., Harrison, R.B., Guerrini, I.A., deB Richter, D., Jr. and Rustad, L., 2014. Current status, uncertainty and future needs in soil organic carbon monitoring. Sci. Total Environ. 468–469,pp. 376–383.

Kuhn, M., 2020. Caret: Classification and Regression Training. R package version 6.0-85. https://CRAN.R-project.org/package,caret.

Kumar, S, Lal R., 2011. Mapping the organic carbon stocks of surface soils using local spatial interpolator: Journal of Environmental Monitoring, 13(11),pp. 3128-3135.

Isaaks E.H. and Srivastava R.M., 1989. Spatial continuity measures for probabilistic and deterministic geostatistics. Math Geol 20, 313–341, https://doi.org/10.1007/BF00892982.

Loveland P. and Webb J., 2003. Is There Critical Level of Organic Matter in the Agricultural Soils of Temperate Regions: Review. Soil Tillage Research, 70,pp.1-18.

Matinfar H. R., Maghsodi Z., Mosavi S.R. and Rahmani A., 2021. Evaluation and Prediction of Topsoil organic carbon using Machine learning and hybrid models at a Field-scale, Catena, 202. 105258.

Mendoza Vega J., Karltun E., and Olsson M.. 2003. Estimations of amounts of soil organic carbon and fine root carbon in land use and land cover classes, and soil types of Chiapas highlands, Mexico و Forest Ecology and Management, 177,pp. 191-206.

Mishra U., Lal R., Liu D. and Meirvenne M. V., 2010. Predicting the Spatial Variation of the Soil Organic Carbon Pool at a Regional Scale, Soil Sci. Soc. Am. J. 74,pp. 906-914.

Mueller T. G. and Pierce F. J., 2003. Soil carbon maps: Enhancing spatial estimates with simple terrain attributes at multiple scales, Soil Sci. Soc. Am. J. 67,pp.258–267.

Muhaimeed Ahmad S. and Taha Auras M. 2017. Using Remote Sensing and GIS techniques for predicting soil Organic Carbon in Southern Iraq. Global symposium on soil organic carbon, Rome, Italy, pp. 21-23.

Mulder V., De Bruin, S., Schaepman, M., and Mayr, T. 2011. The use of remote sensing in soil and terrain mapping, A review: Geoderma, 162(1-2),pp. 1-19.

Norouzi M., Ayoubi S., Jalalian A., Khademi H. and Dehghani A. A., 2009. Predicting rainfed wheat quality and quantity by artificial neural network using terrain and soil characteristics, Acta Agriculturae Scandinavica Section B- Soil and Plant Science,1(12),pp. 341-352.

Oldfield, E.E., Bradford, M.A. and Wood, S.A. 2019. Global meta-analysis of the relationship between soil organic matter and crop yields. Soil 5,pp. 15–32.

Omran, E.S.E. 2017. Rapid prediction of soil mineralogy using imaging spectroscopy. Eurasian Soil Sci. 50,pp. 597–612.

Pallant, J. 2020. SPSS survival manual: A step by step guide to data analysis using IBM SPSS. Routledge.

Prentice I. C., 2001. The carbon cycle and atmospheric carbon dioxide. In: Climate Change 2001: The Scientific Basis (IPCC). Cambridge: Cambridge University Press,pp. 184–237.

Ray S. S., Singh J. P., Dutta S., and Panigrahy S., 2002. analysis of within field variability of crop and soil using field and spectral information as a precursor to precision crop management. international archives of the photogrammetry, Remote Sensing, 34, pp.302-307.

Richards J. A., 2013. Remote Sensing Digital Image Analysis, Springer Heidelberg New York Dordrecht London.

Rotich H.K., Richard N., Onwonga, Mbau J. S. and Koech O. K. 2020. Projected Changes in Soil Organic Carbon Stocks over a 50-Year Period under Different Grazing Management Systems in SemiArid Grasslands of Kenya, Journal of Rangeland Science, 10(4),p.357-369.

Sainepo Bernice M., Gachene Charles K. and Karuma Anne. 2018. Effects of Land Use and Land Cover changes on Soil Organic Carbon and Total Nitrogen Stocks in the Olesharo Catchment,Narok County, Kenya. Journal of Rangeland Science, 8(3),pp.296-308.

Seybold C., Mausbach M., Karlen D. and Rogers H., 1997. Quantification of soil quality. National Soil Survey Center, Captter7.

Smith, K. A., 1999. After the Kyoto Protocol: can soil scientists make a useful contribution. Soil use and Management 15,pp. 71-75.

Stockmann, U., Padarian, J., McBratney, A., Minasny, B., de Brogniez, D., Montanarella, L., Hong, S.Y., Rawlins, B.G. and Field, D.J. 2015. Global soil organic carbon assessment. Glob. Food Secur. 6,pp. 9–16.

Sullivan D. G., Shaw J. N. and Rickman D., 2005. IKONOS Imagery to estimate surface soil property variability in two alabama physiographies, Soil, Water Manage. Conserv. 69,pp.1789-1798.

Terra J. A., Shaw J. N., Reeves D.W., Raper R.L., van Santen E. and Mask P.L., 2004. Soil carbon relationships with terrain attributes, electrical conductivity, and a soil survey in a coastal plain landscape, Soil Sci. 169,pp. 819-831.

Vågen T. G., Winowiecki L. A., Abegaz,A., and Hadgu K. M., 2013. Landsat-based approaches for mapping of land degradation prevalence and soil functional properties in Ethiopia: Remote Sensing of Environment, 134,pp. 266-27.

Wang B., Waters C., Orgill S., Cowie A., Clark A., Li Liu D., Simpson M., McGowen I., and Sides T., 2018. Estimating soil organic carbon stocks using different modelling techniques in the semi-arid rangelands of eastern Australia: Ecological indicators, 88,pp. 425-438.

Wu C., Wu J., Luo Y., Zhang L. and DeGloria S. D., 2009. Spatial prediction of soil organic matter content using cokriging with remotely sensed data, Soil Sci. Soc. Am. J. 73,pp. 1202-1208.

Yang C. and Everitt J.H., 2002. Relationships Between Yield Monitor Data and Airborne Multidate Multispectral Digital Imagery for Grain Sorghum. Precision Agriculture 3,pp. 373–388.

Zeraatpisheh, M, Ayoubi S., Jafari A., Tajik S. and Finke, P., 2019. Digital mapping of soil properties using multiple machine learning in a semi-arid region, central Iran: Geoderma, 338, pp. 445-452.

برآورد کربن آلی خاک در مراتع نیمه خشک با استفاده از روش‌های آماری چند متغیره بر اساس داده‌های سنجش از دور (مطالعه موردی: مراتع نیشابور، استان خراسان رضوی، ایران)

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چکیده. برآورد کربن آلی خاک (SOC) یک عامل مهم برای مدیریت منابع طبیعی است. به منظور برآورد کربن آلی خاک در مراتع نیمه خشک از روش های تجزیه رگرسیون خطی چند متغیره، تجزیه و تحلیل مولفه های اصلی (PCA) و فاصله اقلیدسی از خط خاک (D) بر روی داده‌های سنجش از دور استفاده شد. به منظور تهیه نقشه SOC در مجموع ۱۰۲ نمونه خاک (عمق ۰-۱۰ سانتی متر) از منطقه مورد مطالعه واقع در جنوب غربی نیشابور، استان خراسان رضوی، ایران جمع آوری شد. تصاویر Landsat 8 (OLI, TIRS) از منطقه مورد مطالعه در ۲۵ خرداد ۱۳۹۷ تهیه گردید و برای توسعه مدل‌ها از باندهای طیفی محدوده مرئی، مادون قرمز نزدیک و مادون قرمز حرارتی استفاده شد. مدل‌های بین متغیر وابسته SOC و متغیرهای مستقل داده‌های طیفی با استفاده از تجزیه رگرسیون، مولفه اصلی اول و فاصله اقلیدسی از خط خاک برازش داده شدند. سپس مدل‌های توسعه یافته توسط نمونه‌های دیگری اعتبار سنجی (۳۰ درصد نمونه‌ها) شدند. نتایج نشان داد که مدل‌های MLR، PCA و فاصله اقلیدسی از خط خاک D به ترتیب ۶۲ ، ۴۵ و ۵۳ درصد از تنوع کل مقادیر SOC توجیه کردند و عدد خطای RMSE به ترتیب ۰/۰۹، ۰/۲۱ و ۰/۰۵ بود. بنابراین، تکنیک رگرسیون خطی چند متغیره MLR بعنوان پیش‌بینی کننده برتر را در مقایسه با تکنیک های PCA و فاصله اقلیدسی از خط خاک برای تهیه نقشه SOC در منطقه مورد مطالعه بود. نتایج نشان داد که اطلاعات فضایی کربن آلی خاک که با استفاده از تکنیک MLR به دست آمده است دارای جزئیات فضایی بیشتر و کیفیت بالاتری در مقایسه با اطلاعات مشتق شده از نقشه خاک معمولی است.

کلمات کلیدی: تجزیه به مولفه‌های اصلی، رگرسیون چند متغیره، ETM^+، خاک‌های مرتعی