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# Using Remote Sensing and GIS techniques for predicting soil Organic Carbon in Southern Iraq

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**Introduction**

Soil organic matter is a major source of Nitrogen used by crops and at any given time, 95 to 99 percent of the potentially available nitrogen in the soil is in organic forms, either in plant and animal residues, in the relatively stable soil organic matter, or in living soil organisms, mainly microbes such as bacteria. Data on field soil total organic carbon and Nitrogen content is important for determining existing C : N ratios to guide optimal rates of nitrogen fertilizer application. Because laboratory measurement of C is expensive and time-consuming, the total number of samples that can be analysed is limited and therefore hinders the characterization of soils and their spatial variation at broader scales (Bouma, 2001; Mermut and Eswaren, 2001; Salehi, et al., 2003) . Hence, there is a need for reasonable landscape and regional-scale estimations of C based on limited numbers of samples distributed across an area of interest which can be done by using remote sensing and GIS techniques( Zhu, 2000). The present study aimed to develop remote sensing and GIS based methods to predict the spatial distribution content of soil organic carbon for soils Of the study area in Sothern Iraq.

**Methodology :**

The study area was selected in the region of Al-Kufa city, Al-Najaf province of southern Iraq. The study area characterized by a hot desert climate (Koppen-Geiger BWh) dominated by Fluvents and Salids. 35 sites across the 27,664 ha study area, representing key variations in topography, crop types and soil types were selected for field sampling of surface horizons (0 - 25 cm depth)( Figure 1 ), and laboratory analysis for the target soil properties including soil organic carbon, and other physical and chemical soil properties using common laboratory analysis methods following USDA (2004) and Klute (1986).Year 2015 March 23,for LANDSAT OLI images of the study area, obtained from the USGS EROS Centre, were used to calculate a range of indices from the distributed spectral values for evaluation; including SAVI, EVI, MNLI and GDVI (Table 1 ). Statistical correlations were applied between soil organic carbon , measured soil properties and indices to determine the best-performing models for prediction. The prediction accuracy of SOC was verified by comparing the predicted and measured values using 35 randomly selected field observations. Then the best fitting models developed using the statistical correlation (Equations 1- 4) were used to study the correlation between the predicted and the laboratory determined values of SOC . The best fitting models are represented by the following equation :

$$SOC = 32.588 + 8.495\ln(SAVI) - 57.965(SAVI) \ldots\ldots\ldots\ldots \ldots \qquad \ldots R^2 = 0.924^{**(1)}$$

**significant at the 0.01 probability level

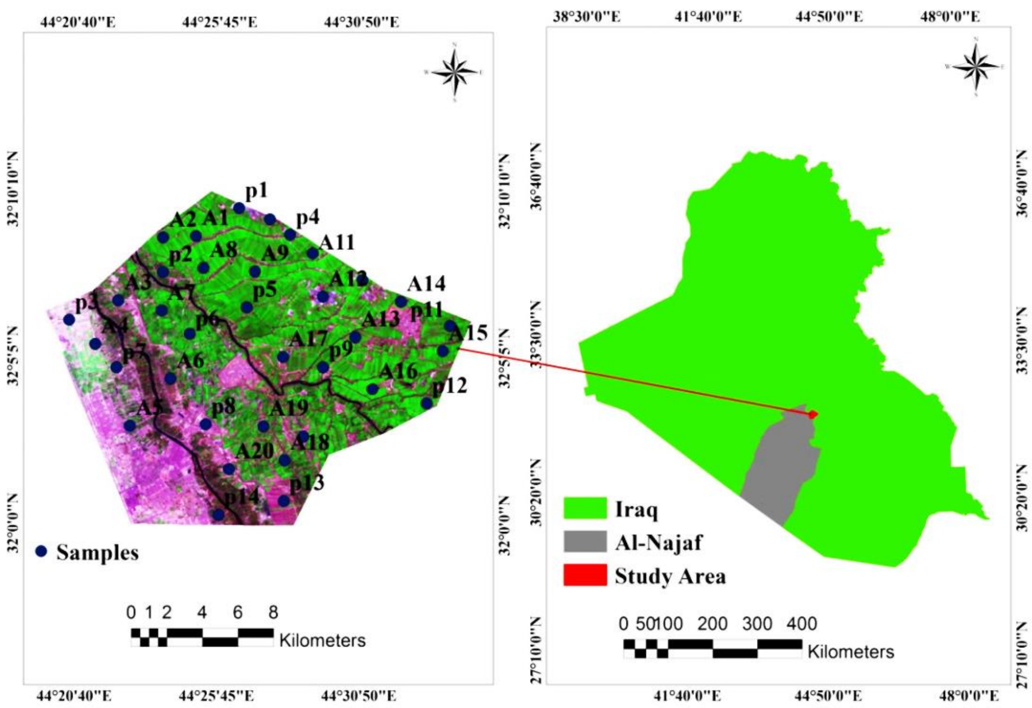


**Figure 1: Location of the study area and the selected study sites.**

**Table 1: Formulae of the vegetation indices**

| Index | Full Name | Formula | References |
|---|---|---|---|
| SAVI | Soil-Adjusted Vegetation Index | $\frac{(1+L)(\rho_{NIR}-\rho_R)}{(\rho_{NIR}+\rho_R+L)}$ Low vegetation, L = 1, intermediate, 0.5, and high 0.25 | Huete (1988) |
| EVI | Enhanced Vegetation Index | $G * \frac{(\rho_{NIR}-\rho_R)}{(\rho_{NIR}+C1*\rho_R-C2*\rho_B+L)}$ $\rho_B$ = reflectance of blue band, G = 2.5, C1 = 6, C2 =7.5 and L = 1 | Huete et al. (1997) |
| GDVI | Generalized Difference Vegetation Index | $\frac{\rho_{NIR}^n-\rho_R^n}{\rho_{NIR}^n+\rho_R^n}$ n is power number, an integer of the values of 1, 2, 3, 4... n. | Wu (2012) |

Note: $\rho_{NIR}$ and $\rho_R$ are respectively reflectance of the near infrared (NIR) and red (R) bands; $\rho_B$ = and $\rho_{MIR}$ are respectively that of blue band and of the middle infrared band (like TM band 5)

**Results and Discussions :**

**Prediction of SOC:**

The results of laboratory measurement of some soil properties indicate that the content of OC in the study soils are very low, ranging from 0.69 to 7.55 gm/kg with mean value of 5.79 gm/kg and standard deviation of 2.05 gm/km .The best developed statistical model (Equation 1) was used to predict the content of SOC in the study area. The relationships between measured versus predicted content for SOC are shown in Figure 5 .The results show very strong correlation between the measured content of SOC and the predicted with $R^2 = 0.9531$ ($p < 0.01$). The regional map for spatial distribution of SOC in the surface soils horizon of the study area was developed by using the best fitting model (Equation 1), as shown in Figure 2. The result found three classes for SOC. Class 3 (> 7.5 gm/kg SOC) was the most dominant and occupied 38.68 % of the total study area. These areas were the most productive agriculturally and also had low salinity levels. Class 1 (< 5 gm/kg SOC) covered 24.22 % of the study area and were associated with high salinity levels, and were in topographic lows in proximity to the Tigris river, with poor drainage.

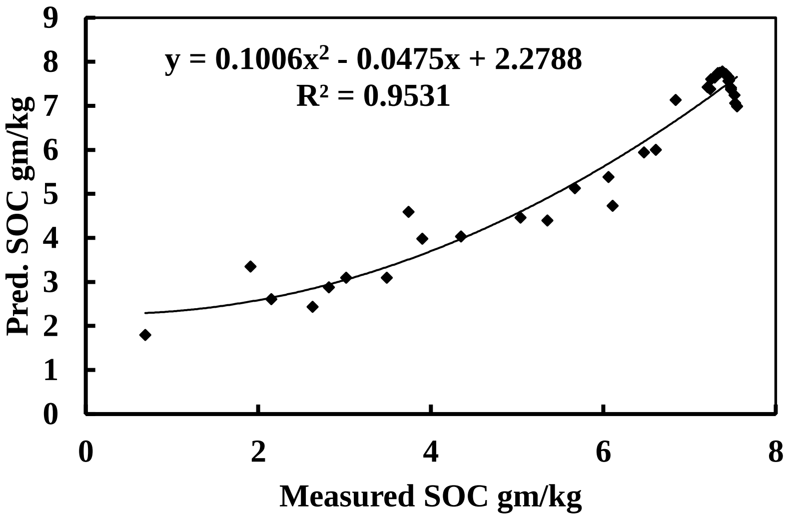


**Figure 2: Relationship between measured and predicted content for SOC (gm /kg ) in the Surface horizon of the study area**

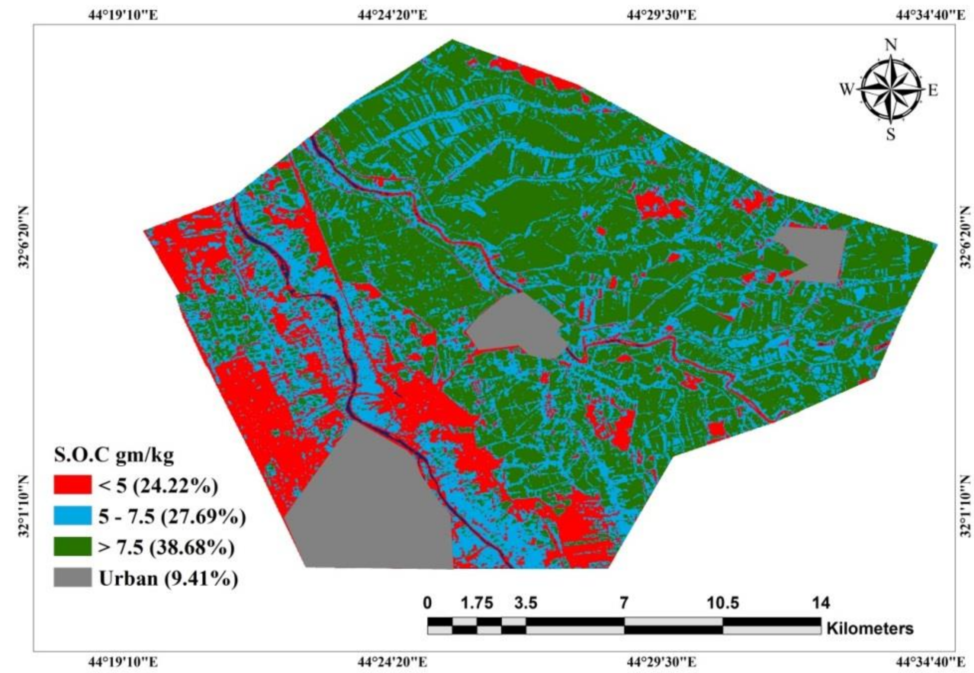


Figure 3 :Spatial distribution pattern of the predicted soil organic carbon content ( gm/km) in the surface horizon of study area.

Soil organic carbon in the study area varied closely with salinity levels and crop types ( figure 4 ) . The results demonstrate the successful 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, while maintaining 'ground-truth' accuracy by laboratory analysis of samples collected from the field.

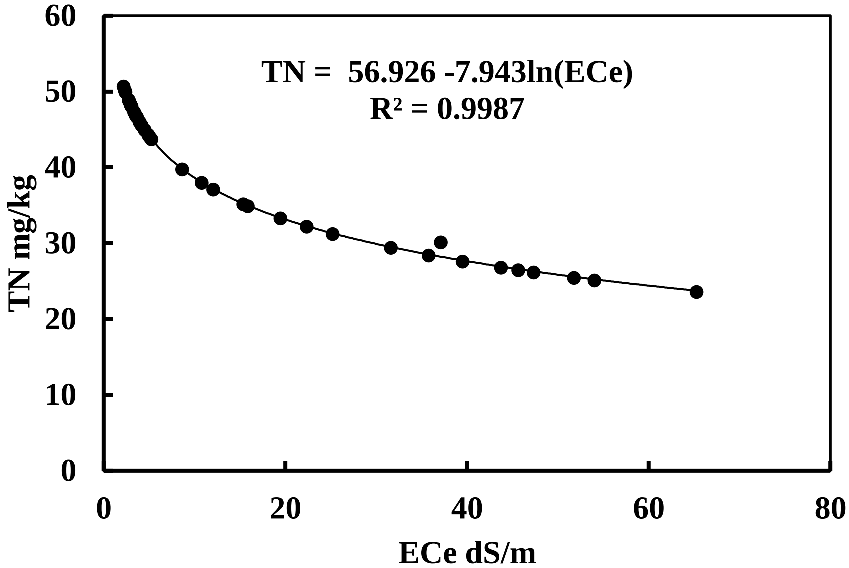


Figure 4: Relationship between TN content and ECe in the surface horizon of the study area

**Conclusion :**

The modelled variations corresponded well with the expected factors affecting C n soils which were land cover, parent material and soil salinity. Total SOC showed strong negative correlation with salinity ($R^2 > 0.9$, $p < 0.01$). We demonstrate the successful 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, while maintaining 'ground-truth' accuracy by laboratory analysis of samples collected from the field. The results of this study can be used to develop statistical model which best fitting to developed the general map for spatial distribution of SOC in Iraqi soils .

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