published by

EQA - International Journal of Environmental Quality
ISSN 2281-4485 - Vol. 44 (2021): 1-8
Journal homepage: https://eqa.unibo.it/

Low-cost digital mapping of soil organic carbon using optical spectrophotometer and Sentinel-2 image

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Article info
Received 23/12/2020; received in revised form 9/2/2021; accepted 15/3/2021.
DOI: 10.6092/issn.2281-4485/12071

Abstract
Nowadays, scientific research is involved to identifying methods for measuring and mapping soil properties allowing the cost reduction for sampling and laboratory analyses. In precision agriculture, it is of interest to obtain accurate spatial distribution maps of soil organic carbon to drive fertilization and variable rate seeding. The aim of this work is to test the Nix™ Pro spectrophotometer using both dry and wet topsoil color for the estimation of the total organic carbon (TOC) in a geographically limited area with relatively low soil variability. The relationships obtained using multiple linear regression were not very accurate (R^2 0.54, p-value < 0.001) due to a high variance between the measured and predicted vaues. However, starting from a soil geo-resistivity survey and free remote sensing images, this method has proved effective in increasing the number of measured points thus making an important contribution to the creation of an interpolated precision maps of soil organic carbon, calibrated for the study area.

Keywords
organic carbon, soil color, remote sensing, spectrophotometer

Introduction

In soil survey, Munsell soil color is consider an important indicator to depict soil horizon and diagnostic criterion throughout Soil Taxonomy and World reference base classification systems. According to Ibáñez (2013), soil color has become one of the most innovative indicators used to adjust modification and fertilizer rates in precision farming. Soil organic carbon (SOC) plays a major role in many chemical and physical processes in the soil environment, and it is a dynamic soil quality strongly dependent to agricultural management (Tugel et al., 2005). The soil color reflects the content in organic matter but the quantitative relationships are disturbed mainly due to the differences in moisture, iron oxides and calcium carbonate content (Vodyanitskii Y., & Savichev A. 2017). It is clear that the soil colour becomes an important parameter to be determined, but obtains the maximum validity if acquired in standard moisture and lighting conditions.

A quantitative contribution can be introduced through the application of algorithms for the analysis of the soil profile image. There are several commercial applications that scan soil images to derive soil properties from the visible spectrum (380-700 nm). Socit is a smartphone apps that was developed by the James Hutton Institute of Aberdeen and provides an estimate of the organic matter content in the soil and free of charge for users in the United Kingdom (Aitkenhead M. et. Al., 2013). Another interesting application, from University of Moscow, is SoColEx 1.0, Soil Color Extractor software it can be used in association with Nix Pro to estimate

DOI: 10.6092/issn.2281-4485/12071

the variation of organic carbon in soil horizons. A measurement protocol ensures complete consistency between the images obtained by the digital camera, the color measured using Nix Pro, and the soil samples taken for chemical analysis. (Kirillova & Artemyeva, 2015). All those methods are about Digital soil morphometrics which is defined as the application of instruments and techniques for measuring and mapping soil profile properties and deriving continuous depth functions (Hartemink A. & Minasny B. 2016).

Although VIS-NIR conventional spectrometers (like Fieldspec and many others) is more accurate for rapid assessment of soil quality, all of these currently do appear to be rather expensive. Another type like MEMS-based (Micro Electro-Mechanical Systems) are less precise and therefore cheaper (nowadays around 7000 euros), they are still a rather expensive investment for soil surveyors and also is less efficient in estimating physical characteristics than electromagnetic induction sensors. The electrical conductivity of the soil allows to investigate the soil at different depths simultaneously and well correlated with: texture, stoniness, water retention capacity, internal drainage, degree of compaction and salinity (Sudduth K. et. al., 2005). The proximal sensing recent literature recommends the integration of geophysical soil monitoring data with information acquired through multispectral (VIS-NIR) spectrometry to obtain a complete characterization of soil properties (Ortuani B. et.al., 2019). In this work we use georesistivity survey, free sentinel2 multispectral (VIS-NIR) imagery and soil color spectrophotometer to obtain a low-cost characterization of TOC and potentially TN and TC.

Materials and methods

The study area is located in landscape of the "low fluvio-glacial plain" with low runoff and depressions around the town of Roncoferraro (Mantua, Italy). The composition of sediments is mainly clayey and silty, the quality is calcareous and they were deposited by alluvial flow during the last "Wurmian" glaciation (Bini et.al., 2004). The mapped area comprises 60 Ha, divided into 6 parcels of about 10 Ha each in which 7/9 auger holes soil investigation was made. From parcels a total of n. 51 topsoil samples were collected.

According to the soil map of the Lombardy Region at a scale of 1: 50.000, the study area is characterized by two Soil Typological Units (STU) SSA (Spinosa) and STR (Strale). The SSA and STR soils are distributed in consociation in the landscape throughout the lower Mantuan-Veronese plain and partly in the central Mantuan plain between Villimpenta and Castelbelforte town (Fig.1). SSA1/STR1 delineation is described as a well-suitable agricultural soil Map Unit (MU) at regional scale with total extension about 10.100 Ha (source: Losan soil database; https://losan.ersaflombardia.it/). The land use of this soil is the silage corn yield in rotation with the soy and, historically, with paddy. SSA soils are more clayey than STR and are classified respectively as Vertic Hypercalcic Calcisols and Gleyic Hypercalcic Calcisols according to WRB 2014.

During farm scale soil survey, the fields were acquired through the electromagnetic method with the acquisition system developed by SOING S.r.l. called "EMAS Electromagnetic Agri Scanner". This device is composed of a 4x4 motorcycle that pulls a sled (without any metal element) equipped with a high precision electromagnetic instrument, GPS and guide system. This equipment made it possible to measure the electrical resistivity of the soils rapidly and continuously at three different depths from the ground base level: 0-50 cm, 0-100 cm, 0-180 cm. The complete coverage of 60 ha and soil survey is achieved in about 2 days. The sampling scheme is based on the variations in electrical resistivity and the sampling depth was always 0-30 cm in order to make the map of the physical and chemical parameters of soil more coherent, net of the real depth of the ploughed horizon (Ap).

Classical physico-chemical analysis were performed for n. 31 collected soil samples in particular texture (sand, silt, clay), coarse fragments, pH, total organic carbon content (TOC), total (TC) and active calcium carbonate content (AC), total nitrogen (TN), cation exchange capacity (CEC), see Tab.1. Those 31 samples are then used as a validation set and another 20 samples were taken for increasing the number of interpolations points.

The range of soil colors detected with Munsell color chart at the moist state varies from 2.5Y 4/2, 2.5Y 4/3 and 2.5Y 4/4 corresponding respectively to the range of dark greyish brown, greyish brown and olive brown. The color of total 51 soil samples was subsequently recorded with the Nix™ Pro sensor (Nix Sensor Ltd., Hamilton, ON, Canada).

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Table 1. *Descriptive statistics of some physical and chemical parameters of 31 investigated soils.*

Means								
TOC dag/g	**pH**	**TN g/kg**	**TC dag/g**	**AC dag/g**	**Clay dag/g**	**Sand dag/g**	**C. frag dag/g**	**CEC cmol(+)/kg**
1.00	8.1	1.27	18.0	6.6	35	15	0.3	23.3
Standard deviations								
0.13	0.3	0.24	6.5	3.9	8	10	0.1	3.5

It is a wireless portable spectrophotometer that operates exclusively on the visible bands. It's a black diamond-shaped device with two light sources and a color sensor on the tip, allows you to always record in standard lighting condition (fig2). It stores in the CIELAB 3-dimensional color space with the possibility of converting it into the corresponding Munsell code. It is managed via mobile phone app and charged via a micro-USB port; the cost just over 300 €. It can be used both in-field or in laboratory and also to calibrate photos of soil samples and not requires soil expertize. (Stiglitz R. Y. et al., 2017) has already been tested with good results on the predictivity of organic carbon and iron content, based just on color in the dry condition by depth of soil profiles

The CIELAB color space is widely used in many fields because it facilitates mathematical comparisons. It is one of the standard color spaces defined in 1976 by the CIE (Commission Internationale de l'Eclairage or International Commission for Illumination). In this three-coordinate system, L indicates the Luminance, while the chromaticity is defined with the parameters A and B. The ability to plot these three colors variables in a three-dimensional color space facilitates mathematical modeling and steps in multiple regression models (Liles G. C. et. al., 2013). Using aqp toolkit and starts from the CIELAB system it is possible to generate a color signature for each soil calculating the proportions or quantities of the white, red, green, yellow and blue pigments (Tab.2)

The Algorithms for Quantitative Pedology (aqp) (Beaudette D. et. al., 2013) is a useful package for R software, widely used for digital soil morphometric processing.

For the purposes of this study Sentinel-2 level L2A remote sensing image was acquired under bare soil conditions (after harvest) and soil radiometric index including the Brightness Index (BI, BI2), Coloration Index (CI) and Redness Index (RI) were derived in the SNAP application environment from the bands listed in Tab.3. In this way, only the visible and NIR (near infrared) bands were considered, which in sentinels have a geometric resolution of 10 m avoiding loss of detail in farm scale map.

Scanned colors have been measured for wet and air dry 31 soil samples, which have been sieved at 0.5 mm. Topsoil conductivity, soil radiometric indices and CIELAB coordinates in both dry and wet states and their difference were used as initial predictors (Tab.4). The difference of light indicators (ΔL, ΔA and ΔB) will give the value of the corresponding changes in soil color, due to the influence of organic matter.

First cross-correlation analysis carried out (Tab.5) and then a step-wise multiple regression analysis was conducted to develop an organic carbon model (Tab.6). The resulting residuals, mean square errors (RMSE), coefficients of determination (R^2) and regression coefficients were used to evaluate the models and finally to predict the response variable. Model predictions performance were evaluated using the same data used in their construction by regress observed Vs. predicted. The result n.6 parcel maps are obtained by regression kriging on Saga-Gis software. It is a spatial interpolation technique that combines a regression of the dependent variable on auxiliary variables.

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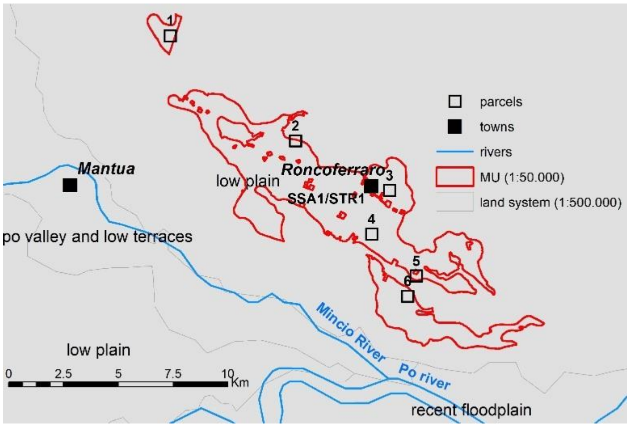

Figure 1. *Locations of study areas and soil map unit SSA/STRof Lombardy Region at 1:50.000 scale.*

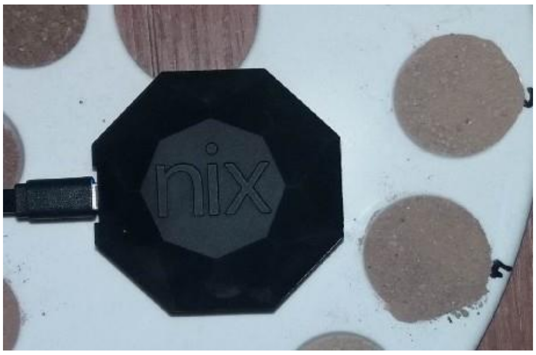

Figure 3. *The Nix Pro™ sensor connected to asmartphone and soil samples sieved at 0.5 mm.*

Table 2. *CIELAB coordinates descriptions*

Pigment	Proportion of color signature	CIELAB color coordinates definition
white	proportion or quantity of CIELAB L-values	brightness or lightness to darkness
red	proportion or quantity of CIELAB positive A-values	chrominance from red to green
green	proportion or quantity of CIELAB negative A-values	
yellow	proportion or quantity of CIELAB positive B-values	chrominance from yellow to blue
blue	proportion or quantity of CIELAB negative B-values	

Table 3. *Spectral color indices of Thematic Mapper sensor*

Index		Name	Formula	Index Property
RI	Pouget et al. (1990)	Redness index	$(R * R)/(G * G * G)$	soil colour variations
CI	Pouget et al. (1990)	Coloration index	$(R - G)/(R + G)$	high concentration of carbonates and salts
BI	(Escadafal, 1989)	Brightness index	$\sqrt{((R * R) + (G * G))/2}$	average of the brightness of a satellite image
BI2	(Escadafal, 1989)	Brightness index2	$\sqrt{((R * R) + (G * G) + (NIR * NIR))/3}$	average of the brightness of a satellite image

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Results

The detailed pedological survey has ascertained the presence of the same STU at broader scale, confirming a quite low pedodiversity rate. Descriptive statistics are given in Tab.1, where a low standard deviation indicates that the values tend to be close to the mean. Statistical modeling has been initiated with the correlation matrix, was performed to examine the nature, direction and strength of association between soil organic carbon content and other variables. It is important to note how electrical conductivity RESt is related to image derived spectral color indices CI, BI and BI2 but not to RI which instead is dependent by TOC and TN. The dependence between TOC and RI can be used in estimation as well as the spatial dependence. The result of stepwise multiple regression analysis as indicated by t-test shows that only Redness Index (RI) remained as statistically significant predictor continuous variable. Regression kriging is a way of integrating secondary information (auxiliary variable), spatially exhaustively known an consist in two steps. First use the fitted function to provide an initial estimate for each grid value of the map with the ancillary variable and then interpolate the residuals by simple kriging using the fitted variogram and add them to the map with initial estimates from regression equation (Fig.5).

The coefficient of determination, R^2 of the model was investigated of 0.18, implying that eighteen percent of the variation in the mean soil organic matter content of six parcels in SSA1/STR1 delineation can be accounted for by only RI.

Table 4. *Pearson Correlation matrix and significance levels for the considered data set. As (A dry value), Bs (B dry value), Ls (L dry value), ΔA (A difference dry-wet), ΔB (B difference dry-wet), ΔL (L difference dry-wet), CI (Coloration index), BI (brightness index), BI2 (Brightness index 2), RESt (topsoil resistivity ohm 0-50 cm), TN (total nitrogen), TC (total carbonates), TOC (Total organic carbon). Significance level symbol: pale grey <0.05; medium grey <0.01; dark grey <0.001.*

	As	Bs	Ls	ΔA	ΔB	ΔL	CI	BI	BI2	RI	RESt	TC	TN
Bs	0.64												
Ls	0.23	0.48											
ΔA	0.17	0.01	-0.27										
ΔB	0.16	0.34	-0.23	0.75									
ΔL	0.08	0.54	0.25	0.39	0.75								
CI	0.15	0.1	0.44	-0.04	0.01	0.31							
BI	0.04	0.05	0.22	-0.03	0.18	0.42	0.83						
BI2	-0.18	-0.08	-0.3	0.23	0.31	0.07	-0.56	-0.12					
RI	0.2	0.01	0.42	-0.02	-0.3	-0.1	0.59	0.06	-0.80				
RESt	0.04	0.22	0.18	0.07	0.3	0.45	0.44	0.50	-0.06	-0.05			
TC	0.11	0.21	0.54	-0.53	-0.48	-0.1	0.14	0.2	0.12	-0.06	0.23		
TN	-0.22	-0.03	-0.52	0.16	0.51	0.31	-0.2	0.13	0.29	0.57	0.03	-0.37	
TOC	-0.33	-0.29	-0.65	0.31	0.43	0.19	-0.3	-0.04	0.35	-0.45	-0.16	-0.49	0.80

Since the values of CIELAB coefficients A and B are always positive, we can fix that the color space of the dataset can be represented only as proportion between 0 to 1 of the white, red, and yellow pigments (Tab.5).

DOI: 10.6092/issn.2281-4485/12071

Table 5. *Statistical summary of pigments proportion determined for 51 soil sample*

mean				
whitepigment	yellowpigment	redpigment	greenpigment	bluepigment
0.49	0.35	0.16	0.00	0.00
Standard deviations				
0.03	0.02	0.02	0.00	0.00

This method of data standardization could be useful for modeling active carbonate content (AC) which consist in finely divided fraction of calcareous particles (smaller than 50 µm in size). This carbonate fraction is susceptible to rapid mobilization and is chemically active and it proved potential modelable only with the proportion of white pigment, explaining ~ 30% of the variance.

Table 6. *Coefficients of the multiple regression model for g/dag soil organic carbon content predictivity*

Variabile	Estimate	Std. Error	t value	P value	Significance
Intercept	-13.7872	9.4690	-1.456	0.1569	
Ls	0.8177	0.1801	4.541	0.0001	***
ΔB	-2.0320	0.5488	-3.703	0.0009	***
RI	-0.9506	0.2860	-3.324	0.0025	**

Residual standard error: 4.4, F-statistic: 13.02 on 3 and 27 degrees of freedom

Multiple R-squared: 0.5912, Adjusted R-squared: 0.5458, P value:1.9e-05

Significance label: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

The R^2 of 0.54 indicates how much of the linear variation of observed values is explained by the variation of predicted values.
Using the coefficient of determination (R^2), root mean squared error (RMSE), and residual plots, model fit was assessed. Predictors that were determined insignificant were removed and the model was run again. This process was repeated until only significant predictors Ls, ΔB and RI remained in the TOC prediction model (Tab.6). Finally the measured TOC content was then plotted against the predicted TOC content for comparison (Fig. 4).

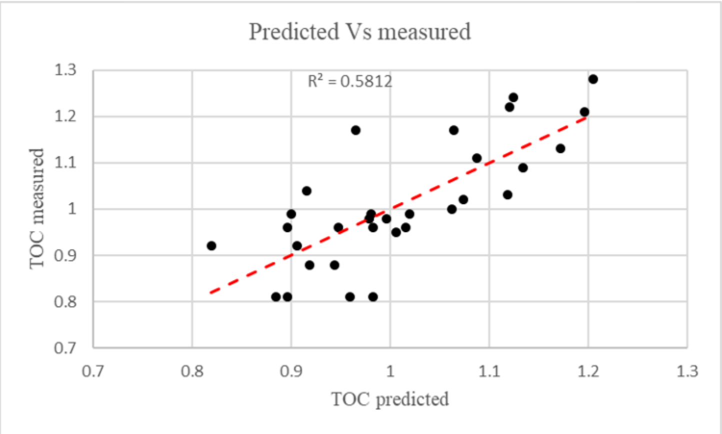

Figure 4. *Measured values versus predicted data regression scatterplot.*

DOI: 10.6092/issn.2281-4485/12071

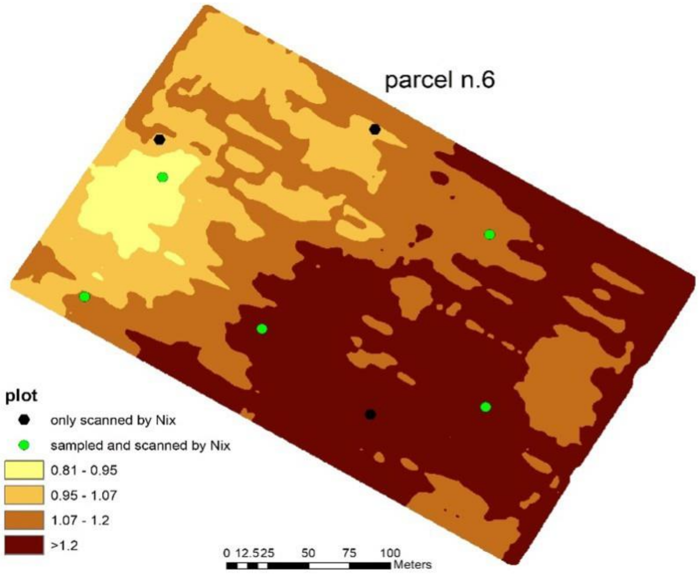

Figure 5. *Parcel Map of TOC g/dag interpolated by regression kriging.*

Conclusions

This research demonstrates georesistivity survey alone is not predictive towards chemical variables such as TOC and needs to be integrated with other measures. As it was reasonable to expect it mainly related to the darkness of the of fine earth sample. In second instance the difference of soil's color ranges from yellow to blue (ΔB) may be important indicator for TOC and for TN, which was in agreement with results obtained by (Stiglitz, R.Y et. al 2018). Last was found significance relationship between Redness Index and TOC, which was in agreement with results reported by (Umesh K. Mandal, 2016).
The colorimetric approach with spectrophotometer in connection with free remote sensing, albeit simply, and moderately accurate, has proved useful to improve the prediction model on TOC. This approach has proved valid, although the soils properties are rather similar to each other. From this analisys, it is clear that also the TC is directly proportional to brightness component and AC so much better with the white pigment proportion of the soil sample; while TN content could be modeled as well as TOC.
This method also allows us to save on the number of samples to be analyzed in a geoelectric and/or georesistivity field survey. Soil sample roughness can have a very large impact on the measured color and variations between repeat measurements. For this reason, <0.5 mm sieved soil is the best suitable for determining TOC. Finally, it can be considered a valid field tools available to the soil scientists as a tool for digital soil morphometrics approach for simple determination of standard lightness Munsell color.

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