PRELIMINARY RESULTS OF MULTISPECTRAL CAMERA MOUNTED ON UNMANNED AERIAL VEHICLE FOR SOIL PROPERTIES ESTIMATION AND MAPPING

Theodora Angelopoulou[1,2], Nikolaos Tziolas[2,3], Athanasios Balafoutis[1], Georgios Zalidis[2,3], Dionysis Bochtis[1]

[1]Centre for Research and Technology – Hellas (CERTH), Institute for Bio-economy and Agri-technology (iBO), 57001 Thermi, Thessaloniki, Greece

[2]Laboratory of Remote Sensing, Spectroscopy and GIS, Department of Agriculture, Aristotle University of Thessaloniki, Thessaloniki, 54124, Greece

[3]Interbalkan Environment Center (i-BEC), 18 Loutron Str., 57200 Lagadas, Greece

d.angelopoulou@certh.gr, ntziolas@auth.gr, a.balafoutis@certh.gr, zalidis@agro.auth.gr, d.bochtis@certh.gr

ABSTRACT

Soil quality continuously deteriorates due to extensive agricultural practices, risking food security. Thus, soil quality sustainability is vital to extend agricultural land productivity potential. However, soil properties estimation entails time consuming, laborious and expensive procedures. Smart agriculture schemes include novel and potentially low cost in situ observations such as unmanned aerial vehicles (UAVs) that are rapidly maturing and becoming viable alternatives to costlier traditional solutions for digital soil mapping. The objective of this research was to evaluate the capabilities of multispectral imagery (400-810 nm) predictive ability for soil properties estimation acquired in bare soil conditions in a 6-ha experimental field in Rizomilos, Thessaly, Greece. A comparative analysis was performed with laboratory spectral measurements of 18 soil samples (0–30 cm) collected from the same field covering the complete VNIR-SWIR range (400-2500 nm). The soil samples were also determined by wet chemistry methods to calibrate the developed prediction models. Considering the imagery data values, the laboratory spectral signatures and the produced spectral indices as input features, a support vector machine for regression algorithm (SVR) was used for model calibration. Laboratory soil spectroscopy resulted in R^2= 0.58 while UAV application R^2= 0.48.

Keywords*:* UAV, soil organic matter, multispectral, spectral indices**.**

1. INTRODUCTION

Soil as part of the natural environment, which is non-renewable to a great extent, is considered to be one of the most important natural resources that performs several ecological and non-ecological functions (Blum, 2005). Soil organic matted (SOM) is considered a significant soil parameter which affects soil fertility, sustainability of agricultural systems, and crop productivity. Therefore, there is an increasing concern about the SOM levels, specifically towards climate change adaptation and mitigation (Muñoz-Rojas *et al.*, 2017). The Greek soils in particular have shown low OM content ranging approximately form 1.0 to 1.5% (Tsadilas *et al.*, 2005). Consequently, there is a great interest in selecting the proper approach to achieve sustainable land use management to maintain or even increase SOM levels. However, conventional soil chemical analysis is time consuming and costly to provide the spatial variability information needed (Viscarra Rossel *et al.*, 2006). Therefore, other techniques are evaluated as alternative and cost-effective methods. Soil reflectance spectroscopy has been used in various domains from laboratory conditions to proximal and remote sensing applications. It has attracted much interest in soil science due to its advantages over conventional methods i.e. minimal to no sample preparation, simultaneous measurement of many constituents, large number of samples measured within a day and no chemicals requirement leading to a safer working environment (McBratney *et al.*, 2006).

The need to implement new technologies in agriculture for monitoring purposes that would allow site specific sustainable management practices, has led to the use of sensors mounted on UAVs for in situ observations to achieve inexpensive, rapid and high-resolution soil digital mapping. Their use has increased due to the high spatial resolution they provide, and the flexibility in the data acquisition timing (Angelopoulou *et al.*, 2019). Recent studies proposed the use of spectral indices, as derived by the data from different bands, in order to enhance the information instead of utilizing only the simple reflectance values (Gholizadeh *et al.*, 2018). To our knowledge there are limited studies for SOM estimation with the use of UAVs in real field conditions (Aldana-Jague *et al.*, 2016).

In this study we aim to compare the performance of laboratory soil spectroscopy to multispectral imagery acquired in bare soil conditions mounted on a UAV for SOM estimation. We also retrieved several spectral indices to assess their contribution in SOM estimation and to improve its prediction.

2. MATERIALS AND METHODS

2.1 Study area

The study area was a 6-ha field located in Rizomilos, Volos in central Greece (Figure 1 Study area mapFigure 1). The field measurements were performed at bare soil, seed bed level conditions to minimize the effects of various surface conditions i.e. soil roughness and the existence of plants or plant residues.

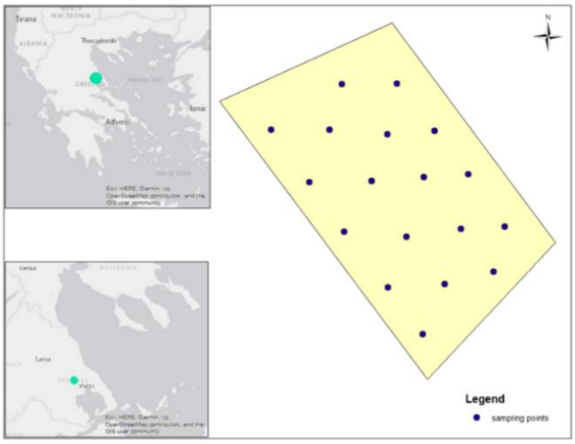


Figure 1 Study area map

2.2 Soil sampling and chemical soil analysis

In total 18 topsoil (0-30 cm) soil samples were collected (Figure 1) with a Dutch auger following the zigzag sampling pattern which is determined to obtain the best coverage on smaller areas. Soil samples were analyzed for soil texture, soil moisture and SOM content. To determine the percentage of sand, silt, and clay, the inorganic fraction of soil was measured by particle size analysis (Bouyoucos method analysis) and the total organic carbon was determined by the Walkley-Black method. The conversion to SOM was performed using the following equation:

Organic matter (%) = Total organic carbon (%) x 1.724 (Wiley, 1906)

2.3 Multispectral measurements

For this study the Parrot Sequoia+ multispectral camera (Parrot SA, Paris, France) was used. The camera has four separate sensors which cover the Green (530-570nm), Red (640-680nm), Red-edge (730-740nm) and NIR (770-810nm) regions. It was mounted on the eBee platform (https://www.sensefly.com/), and the flight altitude was 50 m. Photogrammetric processing was performed in the RAW imagery data. In this context, the PiX4D photogrammetric software (PiX4D SA, 2019) was fed with the aerial imagery data and their corresponding orientation metadata. We employed the structure from motion algorithm to find sparse point clouds, generate dense point clouds, build mesh and produce the high resolution orthomosaics of each band.

2.4 Laboratory spectral measurements

For the laboratory spectral measurements, the protocol developed by Ben Dor, Ong and Lau, (2015) was followed. The spectroradiometer used in the study was the PSR +3500 model of Spectral Evolution Company with a spectral range between 350-2500 nm. The procedure was as follows: (i) white reference measurement for instrument calibration, (ii) spectral measurement of the two internal standards for the standardization of soil spectral signatures, and (iii) soil sample measurement. The aforementioned calibration and standardization procedure was repeated for every five soil samples.

2.5 Spectral indices retrieval

Combining the spectral bands of the multispectral camera and the respective bands from the laboratory measurements, 14 spectral indices were calculated aiming at improving the prediction capability. The selected spectral indices were normalized difference vegetation index (NDVI), Green normalized difference vegetation index (GNDVI), transformed vegetation index (TVI), soil-adjusted vegetation index (SAVI), (1/green-1/red edge)*NIR (CRI), normalized difference red edge index (NDRE), NIR/red (SR), NIR/red edge (SR_E), red edge/NIR (CSM), (NIR/red edge)-1 (CI), optimized soil adjusted vegetation index (OSAVI), renormalized difference vegetation index (RDVI), weighted difference vegetation index (WDVI) and bright related index (BI2). The aforementioned indices were selected due to their sensitivity to changes in SOM content and bright related indices which are sensitive to soil texture as indicated in the literature (Levin et al., 2007; Gholizadeh *et al.*, 2018).

2.5 Regression and geostatistical analyses

An SVR algorithm with radial basis kernel was utilized for model calibration, due to its ability to generalize unseen data. Considering the low number of samples a leave one out cross validation was selected (Soriano-Disla *et al.*, 2014). Model evaluation was performed using the coefficient of determination (R^2), the root mean square error of prediction (RMSE) and the ratio of performance to interquartile distance (RPIQ). The same procedure was followed for both laboratory and UAV spectral measurements. The interpolation procedure followed for mapping SOM from laboratory spectral measurements was the inverse distance weighting (IDW).

3. Results and Discussion

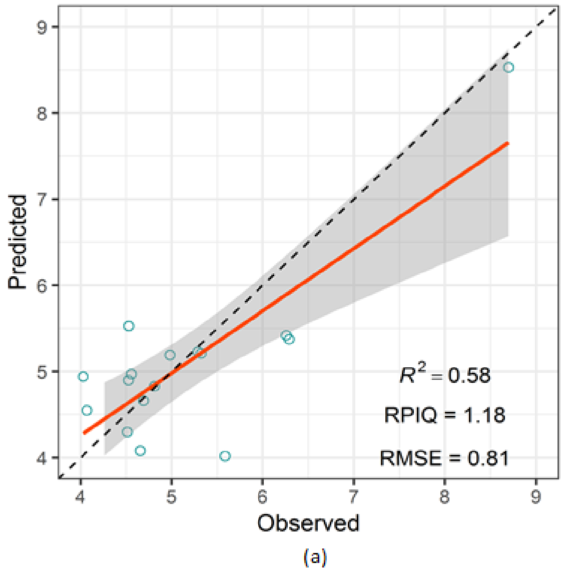
3.1 Physicochemical analysis of soil samples

Soil texture was mainly characterized as clay loam to sandy clay loam since clay content ranged from 20.1 % to 38.1 % and sand content from 22.3 % to 45.6 %. The SOM content was found to range between 3.74 – 8.81 % which is considered adequate for most cultivations.

3.2 Soil organic matter prediction and mapping using spectroscopic data

The estimation of SOM using data from laboratory spectral measurements with the combined use of the spectral indices provided relatively good results with the SVR algorithm (C=32, sigma=0.1218). The statistical accuracy regarding R^2= 0.58, RMSE = 0.81 % and RPIQ = 1.18 indicated potential distinction between high and low values (Figure 2a). Compared to other studies (Nawar *et al.*, 2016), the results show lower accuracy which could be attributed to the small dataset and the small range and low variability of the SOM values.

The use of the SVR (C=16, sigma=0.084) algorithm to predict SOM from the multispectral data showed lower coefficient of determination (R^2 = 0.48) and ratio of performance to interquartile distance (RPIQ = 1.58) compared to the laboratory measurements. However, the RMSE was lower (RMSE = 0.74 %). This could lead to the inference of relatively similar results between the two approaches (Figure 2b). A related study from Aldana-Jague *et al.*, (2016) showed better accuracy, but that was a long term experiment conducted in Rothamsted, UK using data of high variability in soil organic carbon content. In addition, the study area was significantly larger. Overall, the most predominant spectral range was at red band. This band appears to be associated with SOM (Tsakiridis *et al.*, 2019). Among all spectral indices, SAVI provided the strongest correlations with SOM. This is consistent with previous studies (Gholizadeh *et al.*, 2018).



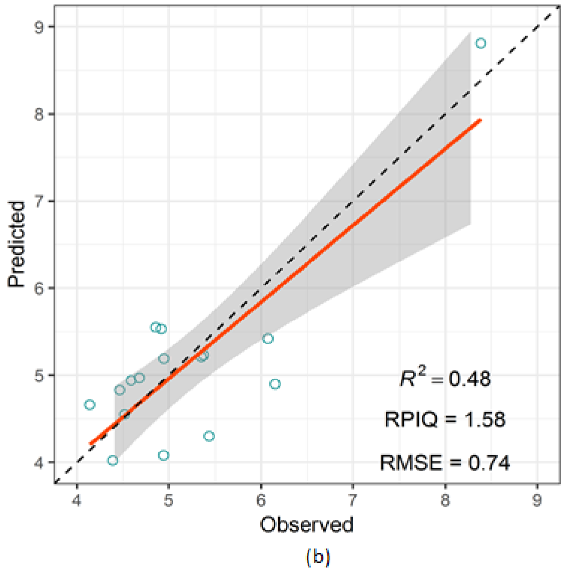


Figure 2. Scatter plots of chemically measured SOM vs. predicted values of SOM from laboratory (a) and UAS measurements (b) based on SVM regression coefficients

Figure 3 shows the generated SOM maps from laboratory (a) and UAV spectral measurements (b). The spatial distribution of SOM derived by the IDW method has slightly underestimated higher values of SOM. The UAV method overestimated the predicted values when SOM was high and underestimated when SOM content was low. This can also be seen in the scatter plot (Figure 2b). Comparing the two images both approaches gave similar results as it is shown in the upper part of the field, presenting the potential of using UAS for SOM estimation.

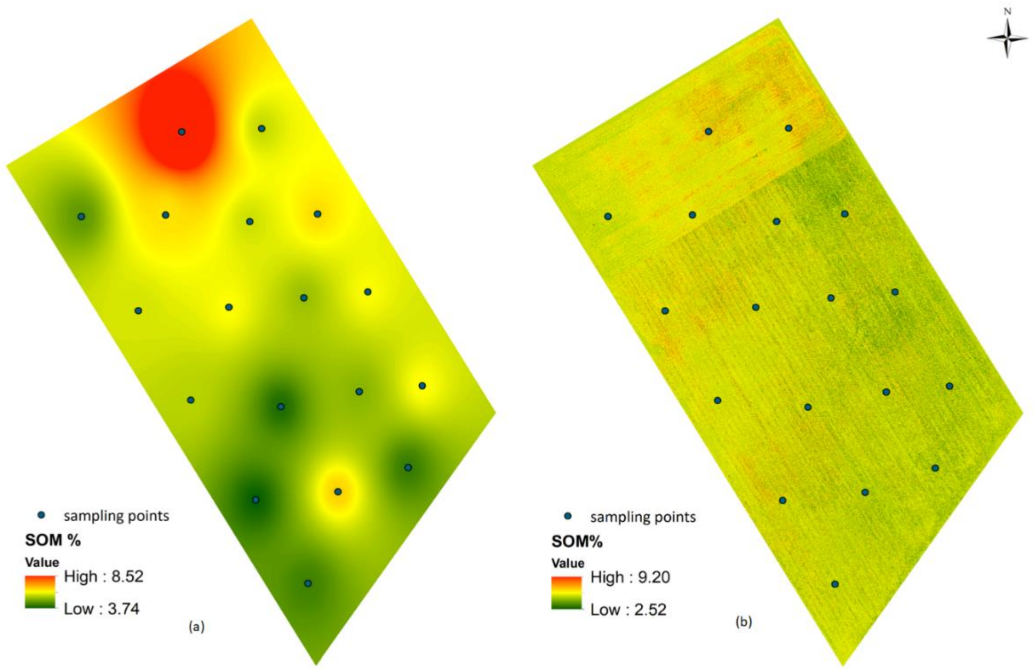


Figure 3. Maps of SOM generated from laboratory (a) and UAS measurements (b)

4. Conclusions

According to the preliminary results both laboratory and UAV spectral measurements showed adequate and similar performance for SOM estimation. Considering the spatial distribution derived from both instruments and modelling approaches the data trend was similar. The data acquisition procedure plays a very important role in the accuracy of soil property's estimation under real field conditions, and its practicality depends on appropriate radiometric calibration and other corrective tasks that are necessary in the pre-flight and post-flight steps (i.e. radiometric and geometric corrections to maintain the scientific rigor of the results). Although multispectral imaging lacks in spectral information compared to laboratory soil spectroscopy, it could provide data with higher spatial resolution and less effort. In this context, we can conclude that UAVs enable the provision of vast spatial coverage for soil parameters estimation paving the way for constant mapping and monitoring soil campaigns. To achieve better results it is imperative to perform experiments in regions with various agricultural management tehniques and different levels of OM showing. The alignment of multispectral aerial data with laboratory and proximal sensing data is the field to which science has turned its attention in order to exploit the large soil spectral libraries that have been created around the world.

Acknowledgement

The work was supported by the project "Research Synergy to address major challenges in the nexus: energy-environment-agricultural production (Food, Water, Materials)"—NEXUS, funded by the Greek Secretariat for Research and Technology (GSRT)—Pr. No. MIS 5002496.

References

Aldana-Jague, E., Heckrath, G., Macdonald, A., van Wesemael, B., Van Oost, K . (2016) 'UAS-based soil carbon mapping using VIS-NIR (480-1000 nm) multi-spectral imaging: Potential and limitations', Geoderma, 275, pp. 55–66. doi: 10.1016/j.geoderma.2016.04.012.

Angelopoulou, T., Tziolas, N., Balafoutis, A., Zalidis, G., Bochtis, D. (2019) 'Remote Sensing Techniques for Soil Organic Carbon Estimation: A Review', Remote Sensing, 11(6), p. 676. doi: 10.3390/rs11060676.

Blum, W. E. H. (2005) 'Functions of Soil for Society and the Environment', Reviews in Environmental Science and Bio/Technology. Kluwer Academic Publishers, 4(3), pp. 75–79. doi: 10.1007/s11157-005-2236-x.

Ben Dor, E., Ong, C. and Lau, I. C. (2015) 'Reflectance measurements of soils in the laboratory: Standards and protocols', Geoderma, 245–246. doi: 10.1016/j.geoderma.2015.01.002.

Gholizadeh, A., Žižala, D., Saberioon, M., Borůvka, L. (2018) 'Soil organic carbon and texture retrieving and mapping using proximal, airborne and Sentinel-2 spectral imaging', Remote Sensing of Environment, 218(September), pp. 89–103. doi: 10.1016/j.rse.2018.09.015.

Levin, N., Kidron, G. J. and Ben-Dor, E. (2007) 'Surface properties of stabilizing coastal dunes: combining spectral and field analyses', Sedimentology. John Wiley & Sons, Ltd (10.1111), 54(4), pp. 771–788. doi: 10.1111/j.1365-3091.2007.00859.x.

McBratney, A. B., Minasny, B. and Viscarra Rossel, R. (2006) 'Spectral soil analysis and inference systems: A powerful combination for solving the soil data crisis', Geoderma, 136(1), pp. 272–278. doi: 10.1016/j.geoderma.2006.03.051.

Muñoz-Rojas, M., Abd-Elmabod, S.K., Zavala, L.M., De la Rosa, D., Jordán, A. (2017) 'Climate change impacts on soil organic carbon stocks of Mediterranean agricultural areas: A case study in Northern Egypt', Agriculture, Ecosystems & Environment. Elsevier, 238, pp. 142–152. doi: 10.1016/J.AGEE.2016.09.001.

Nawar, S., Buddenbaum, H., Hill, J., Kozak, J., Mouazen, A.M. (2016) 'Estimating the soil clay content and organic matter by means of different calibration methods of vis-NIR diffuse reflectance spectroscopy', Soil and Tillage Research. Elsevier, 155, pp. 510–522. doi: 10.1016/J.STILL.2015.07.021.

Soriano-Disla, J.M., Janik, L.J., Viscarra Rossel, R.A., Macdonald, L.M., McLaughlin, M.J. (2014) 'The Performance of Visible, Near-, and Mid-Infrared Reflectance Spectroscopy for Prediction of Soil Physical, Chemical, and Biological Properties', Applied Spectroscopy Reviews. Taylor & Francis, 49(2), pp. 139–186. doi: 10.1080/05704928.2013.811081.

Tsadilas, C. D., Mitsios, I. K. and Golia, E. (2005) 'Influence of Biosolids Application on Some Soil Physical Properties', Communications in Soil Science and Plant Analysis. Taylor & Francis Group , 36(4–6), pp. 709–716. doi: 10.1081/CSS-200043350.

Tsakiridis, N.L., Theocharis, J.B., Ben-Dor, E., Zalidis, G.C. (2019) 'Using interpretable fuzzy rule-based models for the estimation of soil organic carbon from VNIR/SWIR spectra and soil texture', Chemometrics and Intelligent Laboratory Systems. Elsevier, 189, pp. 39–55. doi: 10.1016/J.CHEMOLAB.2019.03.011.

Viscarra Rossel, R.A., Walvoort, D.J.J., McBratney, A.B., Janik, L.J., Skjemstad, J.O. (2006) 'Visible, near infrared, mid infrared or combined diffuse reflectance spectroscopy for simultaneous assessment of various soil properties', Geoderma, 131(1), pp. 59–75. doi: 10.1016/j.geoderma.2005.03.007.

Wiley, H. W. (1906) Principles and practice of agricultural analysis; a manual for the study of soils, fertilizers, and agricultural products; for the use of analysists, teachers, and students of agricultural chemistry. 2d ed., re. Easton, Pa. : The Chemical publishing co. Available at: https://www.biodiversitylibrary.org/item/75931.