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DIGITAL MAPPING OF SOIL ORGANIC CARBON USING DRONE REMOTE SENSING

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ABSTRACT

Soil organic carbon (SOC) content is a key indicator of soil health informing about sustainable land management practices, but parcel-wide SOC mapping is challenging as it requires high-resolution data. Unoccupied Aerial Vehicles (UAVs) can collect data with cm-resolution but are not yet fully ready to be practically implemented. The aim of this study is to provide more insights in the explanatory capabilities of UAV-derived spectral and topographical variables. To this end, mixed models were employed to estimate the SOC content of three agricultural parcels with different crop types in Greece. Results showed variations in SOC content among parcels, with a vineyard and a kiwi orchard having higher values compared to a peach orchard. All models, containing topographical and/or spectral variables, explained 81% of SOC content variation of the training dataset. Besides crop type, other topographical and spectral variables were identified as significant predictors. The study emphasizes the feasibility of UAV data and specific modeling techniques for accurate SOC estimation at the parcel level, providing valuable insights for precision agriculture. The findings recommend further exploration, including machine-learning approaches in future studies.

Index Terms**—** soil organic carbon, digital soil mapping, unoccupied aerial vehicles, photogrammetry, multispectral

1. INTRODUCTION

Being one of the four major components of the soil, soil organic matter can be considered as a key indicator of soil health. As such, soil organic carbon (SOC) content and stocks are important indicators in ecosystem service assessments [1,2]. Carbon storage conditions soil properties for plant growth and soil activity, ensuring a.o. food security. Spatially explicit information about soil health indicators, and SOC in particular, at parcel level is becoming increasingly important for informing sustainable agricultural practices. Digital soil mapping (DSM) approaches, aiming to exploit the covariance of a soil variable with one or more of Jenny's soil forming factors [3] extended with geographic position, has often been presented as successful methods to generate region- and national-wide soil information. In order to be suited for soil mapping at parcel level, however, these methods require high-resolution input data [4], which cannot always be provided by satellite-based remote sensing platforms. To this end, Unoccupied Aerial Vehicles (UAVs) show great potential, as recent technical and jurisdictional advancements allow the collection of sub-meter spatial resolution imagery and directed them to the core of the increasingly data-driven agriculture [5]. However, more information about the spectral bands to be collected or topographical variables to be derived is still necessary to facilitate the implementation of UAV-data in DSM approaches. The aim of this study is to assess the performance of UAV-data as an input in digital soil mapping approaches to estimate the SOC content in three agricultural parcels.

2. MATERIAL AND METHODS

2.1. Study sites

The study was conducted in three distinct parcels covered by different crop types (kiwi, peach, grape), each located in different areas in Greece. Two of them are situated in the region of Imathia (the kiwi orchard of 2 ha in Agia Marina, the peach orchard of 0.8 ha in Stavros), and the 0.4 ha vineyard in Amynteo, Florina, as depicted in Figure 1. In the Imathia region, predominant crops include peaches and kiwis. Peaches thrive in well-drained loamy or sandy-loamy soils, particularly in the south-western area, while kiwis prefer loamy or silty loamy soils. Vinegrapes, grown for winemaking, adapt well to various soil types, with the region predominantly featuring sandy loam. The sandy loam composition ensures effective drainage, reducing the risk of waterlogged conditions that could contribute to disease development.

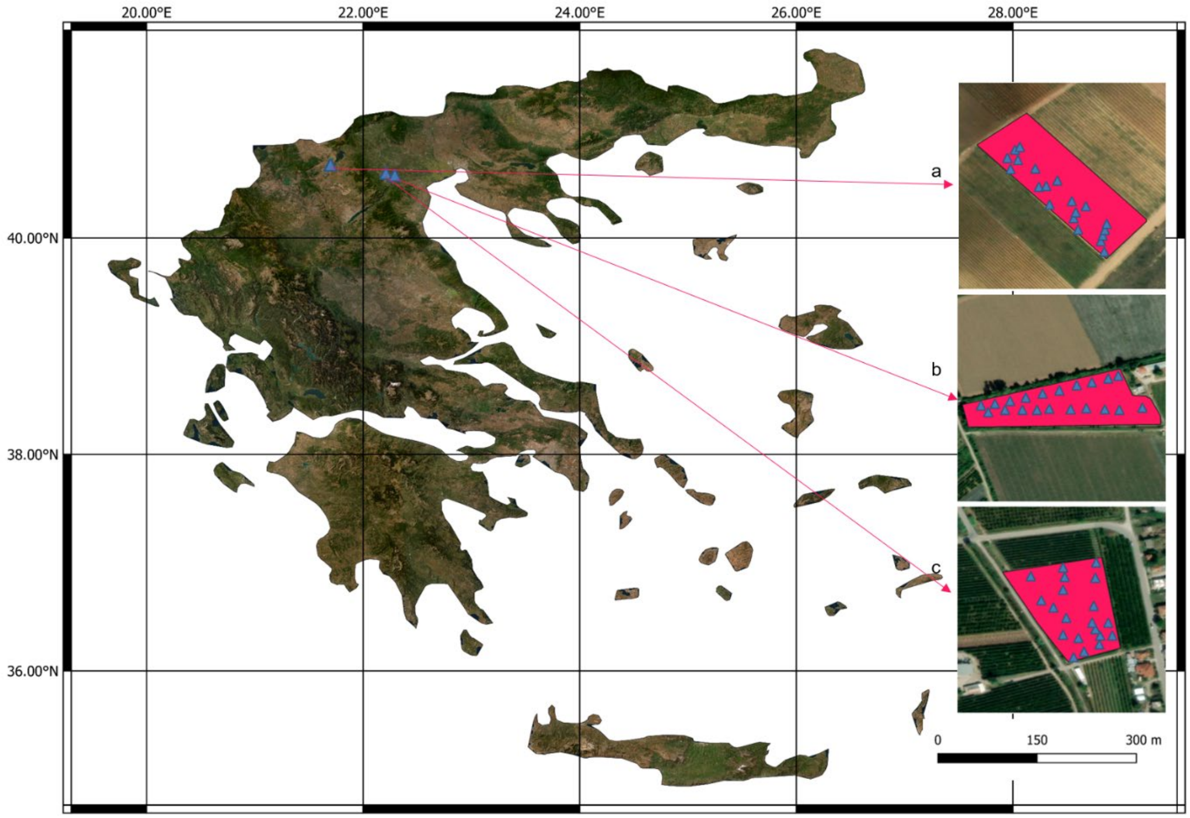

Figure 1: Geographical representation of the study sites: a) grape, b) peach, c) kiwi. The triangles represent the sampling locations.

2.2. Soil sampling

Soil samples were collected based on a randomized location selection strategy, with 20 sampling points distributed across the parcel in a zig-zag pathway [6] (Figure 1).This approach ensured a representative sampling of the entire parcel, capturing within parcel variability. Each sample is a mixture of 4 topsoil subsamples distributed at a cross shape next to the roots, aiming to avoid parcel areas that might be compacted due to the usage of machinery or heavy equipment. The mixed soil samples were transferred to the laboratory where they were air-dried and analyzed with the Walkley-Black method for soil organic carbon content determination [7].

2.3 UAV imagery collection and processing

For each of three study sites, two flight missions were executed. For the peach and kiwi orchards, this was done in April 2022, while the flights over the vineyard were carried out in June 2022. The first flight consisted of a double grid mission at 40 m AGL with a multirotor DJI Phantom 4 RTK with RGB (FC6310R_8.8_5472x3648) sensor and a horizontal and vertical image overlap of 80%, which were found to be the optimal flight parameters in earlier research [8]. All collected images were processed using Pix4Dmapper-software (Pix4D S.A., Lausanne, Switzerland). Following the principle of photogrammetry or structure-from-motion (SfM), processing involved image calibration, point cloud generation and densification and mosaicking of the resulting Digital Terrain Models (DTMs) and Digital Surface Models (DSMs). Next, these raster datasets were further processed in QGIS 3.22 software and used to compute the following variables: Slope, Topographic Position Index (TPI), Topographic Ruggedness Index (TRI) and Aspect. The second flight consisted of a single grid flight (40 m AGL, 80 % image overlap) with a multirotor DJI Matrice 210 V2 RTK platform equipped with a Micasense Altum sensor. This multispectral sensor collects information about the following bands: Blue (Center wavelength 475 nm), Green (560 nm), Red (668 nm), Red Edge (717 nm), Near infrared (NIR, 842 nm), Longwave Infrared (LWIR, 11 µm). The collected imagery was processed in Pix4Dmapper-software following the Ag Multispectral processing template. Apart from the individual bands, the following vegetation indices were computed: NDRE and NDVI. During the entire duration of the flights, an RTK connection was established with the DJI Base Station.

2.4. Digital soil mapping

To detect collinearity between the predictors, Pearson correlation coefficients (r) were calculated using R-software 4.1.3 (R Core Team, 2022). Of each pair of highly correlated predictor variables (|r| > 0.70), the variable with the weakest correlation with the SOC content was omitted from modelling.

Given the hierarchical nature of the dataset – 20 samples per crop type – a mixed model approach was selected as the most appropriate. In total, three different models were trained using the mgcv package in R [9]: (A) with only topographical variables resulting from SfM: Slope, Aspect, TPI and TRI (B) with only spectral variables: Blue, Green, Red, Red Edge, NIR, LWIR and indices NDVI and NDRE and (C) with a combination of topographical and spectral variables. In each model, crop type was added as a random intercept by representing it as a smooth term. Next, model selection was based on multimodel inference using the 'MuMIn'-package of R-software [10]. The global model contained all model variables mentioned for each model type (A, B, C), except those omitted after the collinearity analysis. With MuMIn's dredge function, a set of submodels nested in the global model was generated and ranked according to the Second-order Akaike Information Criterion (AICc). As recommended for small datasets [11], this criterion was used instead of AIC as the former takes into account an additional small-sample bias-correction term to prevent overfitting. Model averaged coefficients were calculated using the submodels with ΔAICc < 2, since these models are considered to substantially explain variation in the data [11]. The relative importance of each variable in the multimodel average (MMA) is reflected by the sum of the Akaike weights over all submodels.

3. RESULTS & DISCUSSION

3.1. Soil indicators

The SOC content varied across and within the different parcels (Figure 2), with higher values found in the vineyard (1.50 ± 0.22 %) and kiwi orchard (1.33 ± 0.05 %), and the lowest in the peach orchard (0.84 ± 0.05 %).

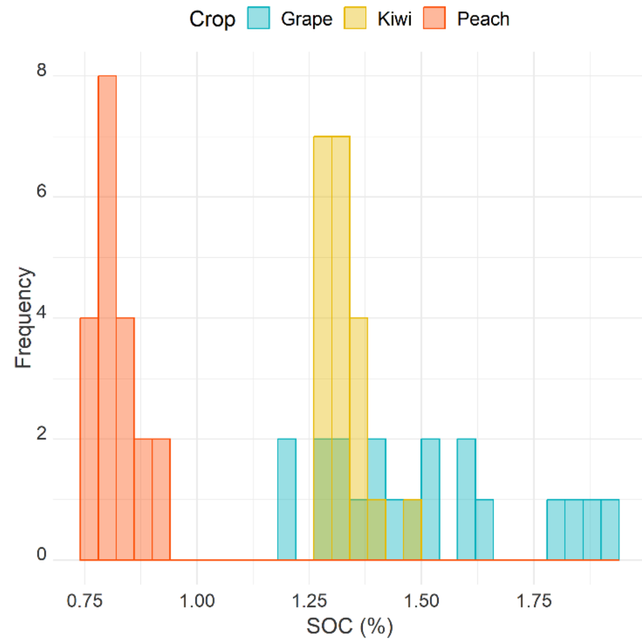

Figure 2: Histogram of the observed soil organic carbon (SOC) content for the three parcels.

3.2. Digital soil mapping

Based on the collinearity analysis, the following variables were dropped: Blue, Green, Red, Red Edge and NDRE. In general, the goodness-of-fit indicators did not vary considerably between the three model types (Table 1). These models were capable to explain 81 % of the variation in the SOC content based on the training dataset, which is in line with similar research [12]. In each model, the most important variable was the smooth term describing the crop type (Table 2). Since the parcels were located in different regions with different soil characteristics, this was to be expected. In both models taking topographical variables into account, TPI was found to be the second most important variable. The variable coefficient was in both cases negative, which can be explained by the geomorphological interpretation of this index. As observed by [13], low TPI values generally correspond to concave landscape positions found in valley bottoms and at the foothill, which typically have higher carbon contents.

Table 1: Goodness-of-fit indicators of each trained model.

Goodness-of-fit indicator	Model A: SfM-variables	Model B: MS variables	Model C: combination of SfM and MS
$R^2{}_{train}$	0.83	0.83	0.84
$R^2{}_{adj,train}$	0.81	0.81	0.81
$RMSE_{train}$ (%)	0.13	0.13	0.13
$rRMSE_{train}$ (%)	10.60	10.59	10.50

Table 2: Importance and coefficients of the variables contained in each multimodel average.

Model type	Variable	Relative Importance	Variable coefficient
A	Intercept		1.21
	Grape / Kiwi / Peach	1.00	0.27 / 0.11 / -0.39
	TPI	0.26	-2.47
	Slope	0.19	0.002
	TRI	0.17	0.35
B	Intercept		1.31
	Grape / Kiwi / Peach	1.00	0.28 / 0.11 / -0.39
	Blue	0.26	0.31
	NIR	0.22	0.05
	LWIR	0.15	$-3.87\ 10^{-6}$
C	Intercept		1.25
	Grape / Kiwi / Peach	1	0.27 / 0.11 / -0.38
	TPI	0.30	-2.93
	Blue	0.23	0.28
	NIR	0.19	0.04
	Slope	0.09	0.0008
	TRI	0.08	0.18
	LWIR	0.08	$-2.02\ 10^{-6}$

4. CONCLUSION

Recent studies have investigated the potential of utilizing UAV data from bare soil, combined with terrain attributes, to estimate and map SOC, yielding comparable results. Despite employing limited spectral bands, we assessed performance across diverse fields, delving into the concept of mapping UAV data in multiple fields with different crops by following specific protocols in data acquisition. Furthermore, relying on a minimal set of indices allowed us to explore edge processing techniques for real-time estimation in the future, as extensive calculations are not necessary and can be executed on the edge. Therefore, the study recommends the inclusion of these approaches in studies using UAV-based solutions and other explanatory variables to improve the estimate of SOC, though further studies are still required, amongst others taking into account the inclusion of AI-based or machine-learning approaches such as random forest models or extreme gradient boosting methods.

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