remote sensing

Editorial

Remote Sensing for Soil Organic Carbon Mapping and Monitoring

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Remote sensing soil properties in a coherent manner is now feasible from regional to global scales. As the change in soil organic carbon (SOC) over time is an important indicator of soil health and for CO_2 sequestration, the determination and mapping of SOC content from optical Earth observation sensors is currently an area of rigorous research. An example of this increased interest is the pre-operational Soil Monitoring System developed in the WorldSoils project, financed by the European Space Agency (ESA contract no. 400131273/20/I-NB), that aims at providing yearly estimations of SOC at a European scale. Within this framework, our Special Issue aims to highlight the latest developments in remote sensing of SOC and contains 15 contributions ranging from reviews to the applications of SOC prediction using satellite imagery, proximal or laboratory spectroscopy, and the use of SOC maps as an indicator of soil degradation.

Three reviews highlight the historic and recent trends in this rapidly evolving topic. Tziolas et al. [1] focus on such achievements over the 2019–2021 period. They provide insight into the latest trends concerning the use of artificial intelligence techniques, the efforts undertaken to share harmonised datasets, the need for data fusion, and the continuous efforts undertaken to increase the resolution of and the inherent processing requirements for the wealth of Earth observation data. Vaudour et al. [2] focus on satellite-based spectral approaches for SOC assessment used during the last decade. They review the pre-processing and modelling approaches, highlight the need for bare soil conditions and recommend focusing on temporal mosaicking, testing the influence of possible disturbing factors and mitigating their effects by incorporating non-spectral ancillary information. Sharma et al. [3] focus on tidal wetlands as an important reservoir of so-called blue carbon. In contrast to the two previous reviews mainly focusing on bare soils in croplands, this review reveals that the direct detection of SOC is, in wetlands, hindered by vegetation. Hence, their review focuses on combining remote sensing with other data sources and co-variates and investigating the vertical profile of SOC content rather than only the surface layer.

The free and open availability of satellite imagery, facilitated by the Copernicus programme, has provided support to the mapping of surface soil properties and in particular SOC. At the same time, constraints on the selection of optimal soil conditions for large areas have arisen. The next five papers address these constraints, i.e., selecting bare soil pixels, dealing with disturbance of soil moisture content and creating temporal composites of images. The latter are a great asset for optimising the coverage of bare dry soil pixels in a region for which the pixels are not all in optimal conditions at a single moment of acquisition. Urbina-Salazar et al. [4] investigated the effects of the acquisition time of Sentinel 2 imagery, sampling period and Sentinel 1 soil moisture products on the SOC prediction

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of a cropland region in southwestern France. Moreover, they investigate the benefits of integrating terrain-derived attributes in the SOC prediction model. They show that Sentinel 1 soil moisture products were helpful in extracting pixels under the driest conditions and hence in improving the performance of the SOC prediction model. Zepp et al. [5] used compositing techniques of multitemporal satellite images as an alternative to retrieve exposed soils. They applied the soil composite mapping processor (SCMaP) to the Landsat archive containing images covering Bavaria, Germanyfor the period 1984–2014, and show that a 30-year SCMaP soil reflectance composite (SRC) averages exposed soil areas over several years and produces spectra for pixels with a relatively constant soil moisture content, resulting in an accurate SOC prediction model (R^2 = 0.67). Dvorakova et al. [6] had a different approach for selecting bare soil pixels from a soil reflectance composite. Instead of averaging long time series, they selected the 'greening-up' period based on a time series of normalised difference vegetation index (NDVI) values and conclude that the best SOC prediction models (R^2 = 0.54) could be obtained in the greening-up period using a strict normalised burn ratio 2 (NBR2) threshold. Möller et al. [7] provided a new method for increasing the spatial resolution of SOC prediction maps. They used multi-temporal soil reflectance composites (SRC) as an explanatory variable in order to generate aggregation levels on which to apply a random forest SOC prediction model. Compared to the use of terrain attributes, the use of SRC parameters leads to significant model improvement at scales corresponding to the average field size. Heiden et al. [8] used temporal composites instead of single-date multispectral images to account for the frequent vegetation cover of soils and, thus, to obtain broader spatial coverage of bare soil pixels. Most soil compositing techniques require thresholds derived from spectral indices such as the NDVI and NBR2 to separate bare soils from all other land cover types. They present a novel histogram separation threshold (HISET) methodology deriving spectral index thresholds. Angelopoulou et al. [9] evaluated airborne HySpex and spaceborne PRISMA hyperspectral data for SOC and carbonate estimation in a cropland area of northern Greece. The results indicate that the accuracy of the spaceborne PRISMA sensor is only slightly lower compared to that of the airborne hyperspectral sensor (R^2 = 0.78 vs. 0.76), even if the PRISMA was only in its commissioning phase.

Research in the laboratory and in proximal sensing continues and contributes to the better spectral modelling of SOC once the spectral resolution of the satellites matches that of laboratory instruments, as is already the case for the PRISMA and EnMAP spaceborne hyperspectral sensors. It is expected that highly accurate spectral models can be developed in the laboratory and transferred to the signal of hyperspectral satellites. Obviously, protocols for the acquisition of such large spectral libraries need to be strictly controlled. Xu et al. [10] showed that soil–probe contact measurements resulted in the optimum spectral quality and estimation accuracy; that sieving the soil sample into particle sizes below 1 mm and drying before spectral measurement effectively enhanced spectral quality and estimation accuracy; and that the variation in soil temperature did not have a distinct influence on spectral quality. Moreover, laboratory spectroscopy contributes to the improved modelling of SOC with different compositions. Francos et al. [11] examined the extent to which a generic approach can assess SOC contents of different origins using spectral-based models. They created an artificial big dataset composed of pure dune sand as a SOC-free background, which was mixed with increasing amounts of different organic matter (OM) sources obtained from commercial compost of different origins. Some environments such as forests and grassland are unlikely to yield satisfactory SOC prediction models from remote sensing. Forests are particularly difficult environments as they show a strong vertical gradient in SOC content from organic to mineral horizons. Thomas et al. [12] developed a large spectral library for forests and demonstrated that vis-NIR spectroscopy is suitable for assessing humus conditions in Saxon forests (Germany), not only for mineral horizons but also for organic Oh horizons in particular.

The last three contributions focus on SOC as an indicator of soil degradation. Qi et al. [13] developed a spectrally based soil erosion mapping approach for a catchment in the black soil region of northeast China. They built a classification scheme for Sentinel-2 bare soil composites for pixel-wise soil erosion mapping based on spectral features related to SOC mobilisation. Baiamonte et al. [14] addressed SOC sequestration in conservation agriculture at a regional scale. For Mediterranean countries, they noticed an over estimation of 0.11 Mg ha^{-1} yr^{-1} when the aridity index and soil erosion were considered. Ding et al. [15] investigated the SOC content in thermo-erosion gullies, i.e., typical thermokarst features in upland permafrost. They explained 53% (R^2) of the SOC content variation using a machine learning approach on co-variates from UAV images.

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