remote sensing

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Review

Remote Sensing Techniques for Soil Organic Carbon Estimation: A Review

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Abstract: Towards the need for sustainable development, remote sensing (RS) techniques in the Visible-Near Infrared–Shortwave Infrared (VNIR–SWIR, 400–2500 nm) region could assist in a more direct, cost-effective and rapid manner to estimate important indicators for soil monitoring purposes. Soil reflectance spectroscopy has been applied in various domains apart from laboratory conditions, e.g., sensors mounted on satellites, aircrafts and Unmanned Aerial Systems. The aim of this review is to illustrate the research made for soil organic carbon estimation, with the use of RS techniques, reporting the methodology and results of each study. It also aims to provide a comprehensive introduction in soil spectroscopy for those who are less conversant with the subject. In total, 28 journal articles were selected and further analysed. It was observed that prediction accuracy reduces from Unmanned Aerial Systems (UASs) to satellite platforms, though advances in machine learning techniques could further assist in the generation of better calibration models. There are some challenges concerning atmospheric, radiometric and geometric corrections, vegetation cover, soil moisture and roughness that still need to be addressed. The advantages and disadvantages of each approach are highlighted and future considerations are also discussed at the end.

Keywords: soil spectroscopy; soil organic carbon; VNIR–SWIR; machine learning; earth observation

1. Introduction

Soil organic carbon (SOC) holds a key part on the Carbon-cycle, as at a 1 m depth, soils store about 1500 Gt C, being the largest terrestrial carbon pool [1,2]. Therefore, carbon sequestration could potentially mitigate climate change [3]; as highlighted by the "4 per 1000 initiative" at the 21st conference of the parties to the United Nations Framework Convention on Climate Change (COP21), an increase of 0.4% per year would be considerably beneficial for reduction of GHG emissions [4]. Furthermore, SOC as a component of Organic Matter (OM) affects the physical, chemical and biological properties of a soil ecosystem and simultaneously enhances its structure and increases water and nutrient retention [5].

Soil is a complex mixture of organic and inorganic constituents with different physical and chemical properties, that shows large variability from site to site or even within the same field [6]. Therefore, the quantitative and qualitative estimation of soils components is a laborious procedure [7]. Hence, to optimize the monitoring and mapping capacity, there is a need for consistent datasets able to provide reliable information for SOC content estimation [8]. Despite the progress achieved in estimating

SOC dynamics by means of a number of research activities and projects, there is no internationally agreed definition of a standardized soil SOC information system [9]. This is partly because proper information integration at a scale to support complex strategies and monitoring approaches has until now been difficult and expensive to setup and be operational. Eswaran [10] reported a series of hindrances for accurate global carbon content estimations due to (i) very high spatial variability of SOC, (ii) soil types variability that constitute unreliable estimates, (iii) non-available reliable data, mainly of soil bulk density and (iv) vegetation and land use change considerations.

Since conventional methods for SOC monitoring are time consuming and costly [11], researchers investigated the implementation of alternative approaches that can be applied in different conditions and soil types [12]. Current trends are oriented towards the evaluation of Remote Sensing (RS) techniques as rapid, cost-effective and non-destructive, for the estimation of different soil properties [13], including SOC among others [14]. The functionality of the visible near infrared–shortwave infrared VNIR–SWIR sensors used for RS applications is based on the energy–matter interaction principles [15]. The electromagnetic radiation that is radiated on soil surface is reflected in distinct wavelengths and consequently, a spectrum is obtained by determining the fraction of the incident radiation that is reflected [16]. This spectrum encodes information able to provide information to derive qualitative and quantitative information of soil properties [17]. VNIR–SWIR spectroscopy is based on characteristic vibrations of chemical bonds in molecules [18]. Particularly, in the visible region (400–700 nm) the electronic transitions generate wide absorption bands related to chromophores that affect soil colour, while in the NIR–SWIR (700–2500 nm) weak overtones and combinations of these vibrations occur due to stretching and bending of the N-H, O-H, and C-H bonds [19,20].

One of the first studies that observed the influence of OM in soils' reflectance spectra showed different spectral signatures at different levels of OM oxidation [21]. Ben-Dor and Banin [22], evaluated laboratory NIR measurements and concluded that OH groups have strong absorption features at the regions of 1400–1900 nm, mainly due to soil water content, hydroxyls and clay content. It was also observed that soils' reflectance at specific wavelengths could be correlated with organic components (cellulose, lignin, starch) [23] and provide valuable qualitative and quantitative information [24–26]. The visible region of the electromagnetic spectrum could also provide valuable information for SOC estimation, considering that soil appears darker with increasing SOC content [27]. Figure 1 shows the spectral signature of a sandy loam soil with 5.43% OC content [28] and the important wavelength regions for SOC estimation according to several studies [29–31].

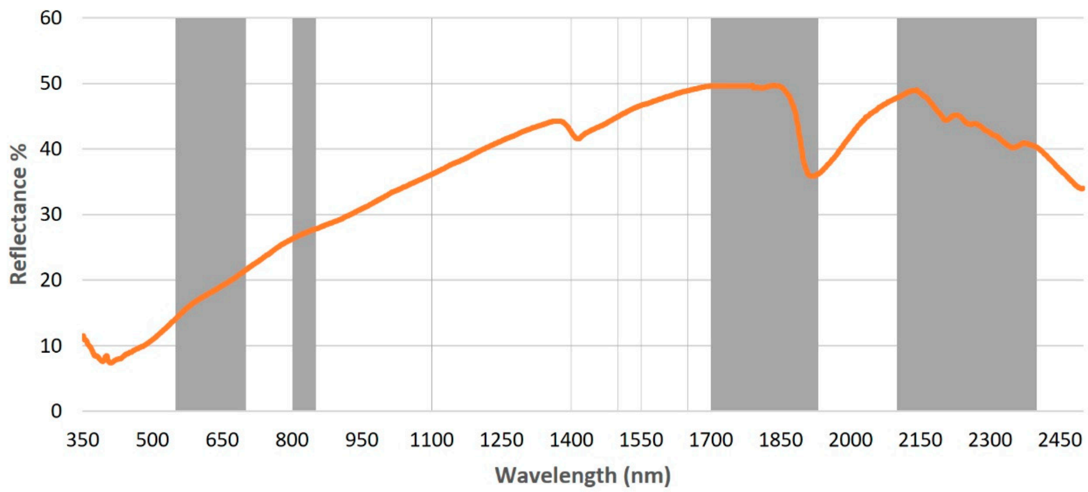

Figure 1. Spectral signature of a sandy loam soil with 5.43% organic carbon (OC) based on data from [28] and important wavelengths highlighted with grey color for soil OC (SOC) estimation according to bibliographic review.

The interactions between SOC and electromagnetic radiation in the VNIR–SWIR region have widely reported under laboratory conditions [30,32,33]. By leveraging the findings of the laboratory experiments a considerable amount of studies has been implemented under real field conditions based on manned and/or unmanned airborne systems, as well as satellite platforms [34]. However, there are limitations in much of the literature using these techniques for the direct quantification of SOC, regarding vegetation cover, soil moisture and roughness and instrument configurations that need to be addressed [33,35]. Moreover, correlating the spectral signatures with soil properties requires the use of multivariate statistical methods also known as chemometrics [36]. The most common approach is the use of partial least squares regression (PLSR) which describes linear relationships between the variables, though it has been observed that relationships are not always linear [37]. For that reason, machine learning algorithms are increasingly used for the correlation process [38,39]. The main focus of this review paper is to present current research (i.e., dedicated to last decade) of remote sensing techniques, illustrating state-of-the-art methods and tools for accurate and quantitative SOC estimation.

2. Sources of Remote Sensing Data

RS from diverse sources provide unprecedented data streams for the retrieval and hence monitoring of SOC across the VNIR–SWIR spectral range. In the context of imaging spectroscopy, the different sensor types can generally be mounted on either airborne [40] or spaceborne platforms. Concurrently, Unmanned Aerial Systems, (UASs) are rapidly maturing and becoming available to carry out the next generation of hand-sized hyperspectral imagers [41].

The aforementioned RS platforms are differentiated in terms of their spatial, spectral, and temporal resolution that consecutively specifies their accuracy and the field of application. A short description of the specifications of the remote sensors that have been used for the estimation of SOC is presented in the following sections.

2.1. Spaceborne

Spaceborne remotely sensed imagery has an immense potential as an enabling tool for the generation of spatial maps of the upper soil horizon, owing to the proven background in interlinkages among soil's specific chemical bonds and electromagnetic radiation. Optical satellite multispectral imagery started to be used extensively in quantitative SOC characterization with the launch of the first satellites in the 1980s [42]. Applications based on hyperspectral data became popular several years later when the Hyperion spaceborne system became operationally available [43].

Until now, their use was limited for soil observation due to (i) the required atmospheric, geometric and radiometric data corrections, (ii) simultaneous ground observations, (iii) the difficulty in finding large bare soil areas within a single image [44] and (iv) obstacles related to vegetation cover [45]. Consequently, there are few studies using satellite sensors for SOC estimation [46].

Currently, SOC estimation and mapping based on spaceborne data is undergoing a significant shift. The relevant USGS policy change, that enabled Landsat data to be distributed at no charge, can be considered a major milestone to that direction [47]. Furthermore, this is driven by the advent of the Big earth observation data era, spearheaded by Sentinel-2 free and open super spectral imagery, as well as by the emergence of large fleets of small satellites (e.g., Planet Cubesats, [48]). In addition, the forthcoming hyperspectral sensors, such as the Environmental Mapping and Analysis Program (EnMAP) [49], will soon provide unprecedented data streams (high spatial, spectral and temporal resolution) for the retrieval and hence monitoring of SOC, across the VNIR–SWIR spectral range.

2.2. Airborne

Airborne hyperspectral imaging has offered the ability for the spatial assessement of soil conditions providing more accurate mapping of the variabillity observed within the agricultural fields. The produced information can cover large areas even from a single flight mission, since aircrafts provide adequate flight duration [50]. It can also provide the data to segment a site according to its soil heterogeinity, while extending existing datasets of soil properties to support digital soil mapping [51]. Aircrafts have the capacity to carry great payloads that gives the ability for wide spectral range hyperspectral sensors to be mounted on them. In addition to that, airborne mounted sensors show more flexibility for a dedicated measurements time window, providing the ability to select the optimal flight conditions, while having the added advantage of operating under a high-cloud coverage [52].

2.3. Unmanned Aerial Systems

In the last few years, there has been scientific interest towards the use of UAS as novel and low cost observational platform for environmental monitoring [53]. UASs can make use of the latest advances in sensor science. In particular, advancements in sensors' specifications (size and spectral resolution) combined with the reduced cost, of both cameras and platforms, are the main reasons why UAS applications have exponentially increased. UAS combine characteristics of spaceborne (i.e short revisit time) and airborne platforms (i.e., high spatial resolution) and represent a unique opportunity to provide the resolution needed to cover the diversity of agri-environmental landscapes. In addition to that, the ever increasing analytical capabillities for data handling could provide the potential for less time consuming image interpretation [54]. Regardless of these advantages, there is limited research concerning soil properties estimation due to platform reliability i.e., stability, the mounted sensors spectral range, the limited payload, the limited flight duration and issues regarding image processing [55].

3. Review

3.1. Methodology

The bibliographic analysis in the domain of soil spectroscopy involved three steps: (a) collection, (b) filtering of relevant work and (c) detailed review and analysis of state-of-the-art related work. In the first step, a keyword-based search for peer reviewed journal articles was performed from the scientific database Scopus®. As main search keywords, we utilized the following query: "Remote sensing" OR "Airborne" OR "Satellite" OR "UAS" AND ["Soil Organic Carbon" OR "Soil Organic Matter"]. Results were limited by year, document type (article) and language (English). For the purpose of the review we have focused on articles from the last decade i.e., 2008–2018 while notable studies from 2019 were also added. The Scopus® analysis resulted in 382 articles. Restricting the search for articles to within those which have been cited at least three times, the initial number of articles was reduced to 340. An exception was applied in this rule for publications released within the last three years (2017–2019), and hence even zero citations were acceptable for the specific articles. It should be noted that a limitation of this work is the exclusion of papers and reports with less than three citations that may increase the risk of excluding important papers and findings. The research articles were limited to 37 after a pre-reading process, i.e., manual selection based on the title, abstract, graphical abstract (if presented), highlights, and key-words evaluation. In a second stage, based on the full-text evaluation, the most relevant articles were located and evaluated in depth for the review purposes. Certain articles were excluded due to inadequate results justification. Considering Scopus may fail to retrieve a significant percent of related works [56], previous reviews and surveys [7,9,19,27,38,46,54,57–65] were further examined for related work and references from the selected articles were also evaluated, resulting in 28 articles in total.

3.2. Applications of Remote Sensing Data in SOC Estimation

3.2.1. Spaceborne

In this section, we describe existing multispectral and superspectral, as well as (simulated) forthcoming hyperspectral satellite sensors used for SOC estimation in relation to the number of scientific publications across time.

It has been demonstrated that data from satellite sensors can be used as auxiliary variables for mapping soil properties. To that end, different geostatistical methods combined with various remote sensed variables were proven to be more accurate than using only ordinary kriging in predicting SOC spatial variability and development of high-quality maps [66,67]. Schillaci et al., [68] in order to assess SOC stocks modelled a set of topographical and environmental covariates with a Stochastic Gradient Treeboost. RS data were acquired from Landsat 7 ETM+ and it was found that the panchromatic Band 8 gave better predictions compared to NDVI. Mondal et al., [69] also showed that SOC distribution is highly correlated with other variables that could be derived from RS data, i.e., brightness, wetness and vegetation condition indices, as well as first and second derivative products of digital elevation models. However, this is out of the overarching objective of the current study, hence it will not be further discussed.

Previous studies have shown the way forward through the exploitation of the multiple features derived from spaceborne hyperspectral data, together with advanced regression analytics for estimating and mapping the spatial variability of SOC. Gomez et al. [34] used data from the Hyperion sensor on board the EO-1 satellite (400–2500 nm) and compared the predictions of SOC to in situ VNIR–SWIR measurements. To do so, the field spectra were resampled to cover the range of the Hyperion data. 'The Atmospheric Removal Program' algorithm was used to derive the soil surface reflectance from the radiance data. Consequently, the channels with a low Signal to Noise Ratio (SNR) and those located in the atmospheric absorption band were removed, resulting in 152 Hyperion bands from 242. Soils were categorized in four classes and it was observed that when concentration of SOC content dropped below 1%, it could not be determined irrespective of the spectral resolution or the number of soil samples. Results for the class with SOC concentration above 1%, had coefficient of determination R^2 = 0.66 for in-situ measurements and 0.51 for the Hyperion resampled spectra respectively. Estimations using the whole dataset resulted in R^2 equal to 0.73, probably due to the wider range of SOC content, concluding that the use of Hyperion hyperspectral data could be as useful as the use of in-field VNIR–SWIR data. Differences in accuracy could be attributed to the low SNR that hides spectral information and the 30 m spatial resolution of Hyperion. It should be mentioned that after the deactivation of Hyperion in 2017, there are no active hyperspectral satellite imagers across the VNIR–SWIR region. The advantages of utilizing spaceborne hyperspectral data imagery has been demonstrated by simulated data, as described by several studies.

Few simulation studies have been conducted to explore the potential to directly utilize the spectral signatures from hyperspectral imagery in order to predict soil properties. In this context, Castaldi et al. [70] evaluated the potential of three forthcoming satellite hyperspectral imagers (EnMAP, PRISMA [71] and HyspIRI [72]) compared to ALI and Hyperion (EO-1) for SOC estimation. To simulate the spectral data from the forthcoming satellite imagers, spectra acquired in laboratory conditions were resampled according to each sensors' spectral and radiometric specification. For that reason, a local soil spectral library with 166 samples and a representative dataset from the LUCAS soil database (713 samples) were utilized. The PLSR was used for model calibration and the Ratio of Performance to Interquartile Range (RPIQ) was selected to evaluate the results considering that the commonly used Residual Prediction Deviation (RPD) may not be sufficient for attributes that show skewed distribution [73]. Results from the resampled spectra with added noise and atmospheric effects were generally better for the local database ranging from R^2 = 0.36 for Sentinel-2 to R^2 = 0.51 for PRISMA. The results from the LUCAS database were significantly lower with R^2 ranging from 0.06 to 0.26 for Hyperion and PRISMA respectively. Nevertheless, it was suggested to wait for the launch of the forthcoming sensors and acquire real data for more representative and accurate estimations. Under the same scope, Steinberg et al. [74] evaluated the prediction accuracy from simulated data of the upcoming satellite sensor EnMAP, compared to the airborne AHS-160. Soil spectral reflectance from both sensors was quite similar with the satellite sensor showing differences in the detectors edges and at the locations of atmospheric bands. It was also highlighted that for the development of the simulated EnMAP data, the resolution of the sampling strategy is very important.

A noticeable change occurred when advanced data mining techniques applied in order to maximize the bare soil areas by leveraging the short revisit time of existing multispectral satellite sensors. Demattê et al. [44] introduced a powerful data mining procedure to retrieve soil spectral reflectance from satellite images able to provide the best representative reflectance of soils for each band during a selected timeframe. In this rationale, Gallo et al. [75] applied a PLSR algorithm over a dataset derived from a bare soil composite image in order to predict soil properties (including soil organic matter) with a moderate accuracy.

More recently, Gholizadeh et al. [76] proved the advantages of Sentinel-2 to derive high-quality information on variations in SOC comparing to airborne sensors, especially where SOC levels were relatively high. In that regard, they applied a simple SVM model to train prediction models over the spectral signature of Sentinel-2 and a set of spectral indices. The best SOC and Sentinel-2 spectral bands correlations were obtained from B4 and B5 followed by B11 and B12. Similarly, several spectral indices such as BI, BI2, GNDVI and SATVI seems to provide strong correlations with SOC. In this context, Castaldi et al. [77] illustrated that the spatial resolution and spectral characteristics are adequate to describe SOC variability both within field and at regional scale. They developed partial least square regression (PLSR) and random forest (RF) models using Sentinel-2 resulting RPD values ranging from 1.0 to 2.6 for various pilot areas. Similar findings were provided by Vaudour et.al. [78]. The above studies and their respective results are summarized in Table 1.

Table 1. Studies for SOC estimation with the use of space borne platforms.

Sensor	Spectral Range (nm)	Algorithm/ Multivariate Method	R^2	RMSE ($g \cdot kg^{-1}$)	RPD	Reference
Hyperion	400–2500	PLSR	0.51	0.73	1.43	[34]
Landsat ETM+	450–2350	ANNSK	0.63	0.27	-	[66]
EnMAP	420–2500	PLSR	0.25–0.67	0.20–0.48	1.17–1.80	[70]
PRISMA	400–2500	PLSR	0.26–0.65	0.21–0.48	1.17–1.45	[70]
HyspIRI	380–2510	PLSR	0.23–0.60	0.22–0.48	1.15–1.65	[70]
EnMAP	420–2500	autoPLSR	0.67	2.8	1.7	[74]
Sentinel-2	440–2200	PLSR/RF	-	1.9–25.2/2.0–18.6	1.1–2.6/1.0–2.2	[77]
Sentinel-2	440–2200	PLSR	0.56	1.23	1.51	[78]
Sentinel-2	440–2200	SVM	-	0.08–0.24	1.60–1.92	[76]

3.2.2. Airborne

Stevens et al. [79] evaluated the potential of the Airborne Hyperspectral Sensor 160 (AHS, Caravan International Corporation, USA) with spectral range from 430 nm to 2540 nm to estimate SOC content over large bare areas of various soil types. The acquired spectra were correlated with 325 soil samples with SOC content ranging from 7 to 61 g C kg^{-1}. The reflectance decreased from sandy to colluvial-alluvial soils, not only due to variations in SOC content, but possibly to heterogeneity in mineralogy and soil moisture content. To improve the model's accuracy, the dataset was split into groups according to soil type, region and image number. Comparing the results of the PLSR, penalized spline regression (PSR) and SVM modelling for global calibrations, SVM was considered to be the most appropriate technique (R^2 = 0.74), probably due to the large dataset. It was also noted that local calibrations were affected by the heterogeneity of soil types i.e., from sandy to clayey soils.

Nevertheless, airborne data still need atmospheric correction and favorable weather conditions, while difficulties arise from large pixel size and varying quality of the sensor's stability and sensitivity [80]. Stevens et al. [50] also noted the local character of the predictions when comparing the airborne AHS 160 sensor, laboratory and in-situ spectral measurements. Spectral signatures acquired in laboratory and in situ conditions with a portable instrument were approximately the same, while the RS spectrum showed great differentiation in the region between 1900–2500 nm, indicating complications with the atmospheric correction and radiometric calibration. Results showed a decreasing accuracy from laboratory to airborne sensing techniques with RPD values ranging from 2.11 to 1.47 respectively on account of different sensor characteristics, environmental variation, and different measurement conditions. Regardless the poor predictions of airborne hyperspectral imaging, its potential was promising and controlling external parameters could increase the accuracy of a model. Hbirkou et al. [81] evaluated the performance of the airborne hyperspectral sensor HyMap (Integrated Spectronics, Sydney, Australia) and assessed the effect of soil roughness and vegetation cover to the SOC prediction models in field scale. The study was conducted after a period of dry weather to reduce the effects of moisture content. The PLSR models from the complete dataset (n = 204) showed considerable accuracy with $R^2 = 0.83$, while in specific sites ranged from 0.34–0.73, in contrast with the findings of Stevens et al. [79] who reported that local models generated better results. Soil roughness had a significant impact on the models' accuracy since the most unfavorable conditions (i.e., grubbing and 30% straw cover) resulted in $R^2 = 0.34$, similar observations were made by Lagacherie et al. [82]. It was also reported that vegetation cover is more feasible to distinguish from soil rather than straw residues due to the fact that soil and straws had similar spectral signatures. Even if results were promising, the authors suggested that flight campaigns are more suitable to be conducted under the same surface conditions.

Since the application of RS techniques can have many constraints [83], studies on bare soil provide more controllable conditions and are preferable for data acquired by airborne mounted sensors [84]. Although, it is difficult to find large non-vegetated areas with bare soils. For that reason, Franceschini et al. [85] studied the spectral mixture of bare soil with photosynthetic and non-photosynthetic vegetation. The data acquisition was made with the ProSpecTIR V-S sensor (SpecTIR LLC, Reno, NV). For bare soil fractional cover estimation, the linear unmixing methodology proposed by Guerschman et al. [86] was used. A maximum bare soil cover was estimated and then the pixels were categorized until they reach 30% less from that value. The 89 collected samples were divided in four classes according to the bare soil fractional cover quartile and then PLSR models were generated for each class. It was observed that soil spectral albedo decreases when OM and clay content increases. Still, predictions for organic matter content in laboratory conditions ($R^2 = 0.70$) were found substantially more accurate compared to the airborne hyperspectral sensors ($R^2 = 0.33$). Nonetheless, excluding the areas with high vegetation cover led to the loss of information concerning soil properties in the specific area. Bartholomeus et al. [87] introduced Residual Spectral Unmixing (RSU) a spectral unmixing approach, to remove the vegetation influence of mixed pixels and improve SOC variability estimation in partially covered maize fields. For that purpose, the AHS-160 sensor was used in the field campaign along with laboratory spectral measurements. The RSU was applied to all spectra to produce a new spectrum of the bare soil and resulted in a bare soil reflectance image. The RSU spectrum was used for PLSR model calibration and it was found that SOC estimations are very sensitive to the effect of the vegetation cover, leading in over or underestimation according to the spectral pre-processing technique used. Overall, the RSU gave predictions similar to studies with bare soils, identifying the in situ SOC variation.

Finding large areas with bare soils is more difficult in temperate climates. Diek et al. [88] aimed to increase bare soil areas, by creating multi-temporal composites using the Airborne Prism Experiment (APEX) and exploiting crop rotation. To mask green vegetation, different spectral indices were used, while for non-agricultural areas an updated agricultural field block map was used. It was observed that the time of the flight campaign significantly influenced the number of overlapping pixels. However, for SOM estimations the R^2 was 0.39 ± 0.04 suggesting that there are factors to be addressed, such as soil moisture and roughness in addition to the vegetation cover. Bayer et al. [89] proposed a feature-based prediction model for SOC estimation that was developed based on bare soil field spectra in HyMap's spectra resolution. For solving the issue of mixed pixels, the Iterative Spectral Mixture Approach was used and resulted in a 45.4% increase of the sample area. Low predictions were attributed to the high spectral mixtures of the non-agricultural environment, i.e., different types of vegetation, the low spatial resolution and the reduced accuracy of the geo-correction applications that influences the validation with ground data. In a different approach, Homolová et al. [90] compared a plant trait-based model to a RS approach to compensate for the lack of available data. The study showed that data acquired by the AISA Dual system (400–2450 nm) (Specim, Finland) provided better results for SOC estimation (R^2 = 0.73) compared to the plant trait-based model (R^2 = 0.31).

The selected strategy for spectral acquisition, was found to affect the performance of calibration models, hence Vaudour et al. [14] suggested that combining airborne hyperspectral data with synchronous field spectra measurements needs to be performed on close dates for reliable results. While airborne estimations are time-effective there is still the need for field data collection for model calibration and alignment between remote and laboratory spectra. To address this drawback, Castaldi et al. [40] proposed a bottom-up approach for SOC estimation exploiting the already developed large soil spectral libraries. For this reason, the LUCAS topsoil database [91] was combined with data from the APEX sensor. The concept of the approach is that no analytical laboratory measurements are required; instead the most appropriate laboratory spectral data are selected from the whole dataset as independent variables. The models' accuracy was tested with a completely independent validation dataset giving similar Root Mean Square Error, RMSE of 4.3 g C kg^{-1} to the traditional approaches (RMSE = 3.6 g C kg^{-1}).

Most studies use the full spectral range for model calibration to create SOC prediction models. Vohland et al. [92] evaluated different spectral variable selection methods i.e., competitive adaptive reweighted sampling (CARS), a method that "iteratively retains informative variables" and genetic algorithm (GA) to improve predictions. It was observed that PLSR models depending on the full spectrum gave poorer results in comparison to those with the spectral variable selection. Particularly, for SOC estimations the application of the GA gave R^2 = 0.85 for airborne measurements. Peón et al. [93] compared the predictions made from Hyperion and AHS respectively and observed that both sensors had similar spectral correlations in the red region mainly at 610 and 679–681 nm. The above studies and their respective results are summarized in Table 2.

Table 2. Studies for SOC estimation with the use of airborne platforms.

Sensor	Spectral Range (nm)	Algorithm/Multivariate Method	R^2	RMSE ($g \cdot kg^{-1}$)	RPD	Reference
AHS-160	430–2540	PLSR, PSR, SVMR	0.53–0.89	3.13–6.22	1.47–3.15	[79]
AHS-160	430–2540	PLSR	-	1.7	1.47	[50]
HyMap	450–2500	PLSR	0.34–0.83	0.76–1.10	1.14–2.32	[81]
ProSpec TIR V-S	400–2500	PLSR	0.33	3.82	1.25	[85]
AHS-160	430–2540	PLSR	0.62	1.34	1.8	[87]
AISA-Eagle	400–1000	PLSR	0.44	4.05	1.4	[14]
AHS-160	430–2540	SLR, SMLR, PLSR	0.27–0.60	6.44–8.70	1.18–1.60	[93]
AISA Dual system	400–2450	SML	0.73	8.4	-	[90]
APEX	400–2500	PLSR	-	4.3	2.5	[40]
HyMap	450–2500	PLSR	0.73–0.85	0.19–0.25	1.94–2.62	[92]

3.2.3. Unmanned Aerial Systems

Despite the progress made for the estimation of several environmental and climate variables based on UAS applications [94–96], the adoption of these platforms is still not optimal for soil ecosystem monitoring. To our knowledge there is only one study for SOC estimation [41]. They used a multispectral Mini-MCA6 from Tetracam Inc. (450–1050 nm) (Chatsworth, CA, USA) on-board a UAS platform to evaluate its efficiency for SOC predictions. It should be mentioned that a detailed work plan has been deployed in order to obtain optimal conditions, able to minimize the various effects of soil moisture and roughness. The conditions for the flight campaign were considered optimal with a cloudless sky, low vegetation cover and dry soil to minimize the soil moisture effects. The proposed methodology showed great potential for SOC monitoring using an SVM algorithm and resulted in a mean coefficient of determination of 0.95 and a RMSE of 0.21% in cross validation (in 161 soil samples), comparable to dry combustion laboratory methods (Table 3). Nonetheless, an overestimation for low SOC concentrations and an underestimation of the high SOC values was observed.

Table 3. Study for SOC estimation with the use of UAS.

Sensor	Spectral Range	Algorithm/Multivariate Method	R^2	RMSE ($g{\cdot}kg^{-1}$)	RPD	Reference
Mini-MCA6	450–1050 nm	SVM	0.95	0.21	-	[41]

4. Discussion

4.1. Overview of the Remote Sensing Techniques

RS techniques vary depending on their spatial, spectral, temporal and radiometric resolution and the platforms that are mounted on as illustrated in Figure 2. Selecting the proper technique depends on the field of application, the measured property and the expected accuracy. These technologies have shown their great use for monitoring environmental parameters towards management of natural resources and their rapidly increasing use is due to the significant advancements in terms of sensors specifications. Sensors mounted on satellite platforms have improved from panchromatic to multispectral and the forthcoming hyperspectral, such as EnMAP, HyspIRI, and PRISMA. Hence the availability of these sophisticated hyperspectral sensors, could expedite RS applications in the field of agriculture, while contribute to an advancement of operational applications for environmental purposes. Subsequently, they could provide valuable information on soils' condition and SOC estimation either directly or by providing auxiliary data. Consequently, they could supply the necessary data for accurate and up-to-date soil maps to meet the current and future needs for soil monitoring. Figure 3 shows the trend of scientific publication across the various RS techniques.

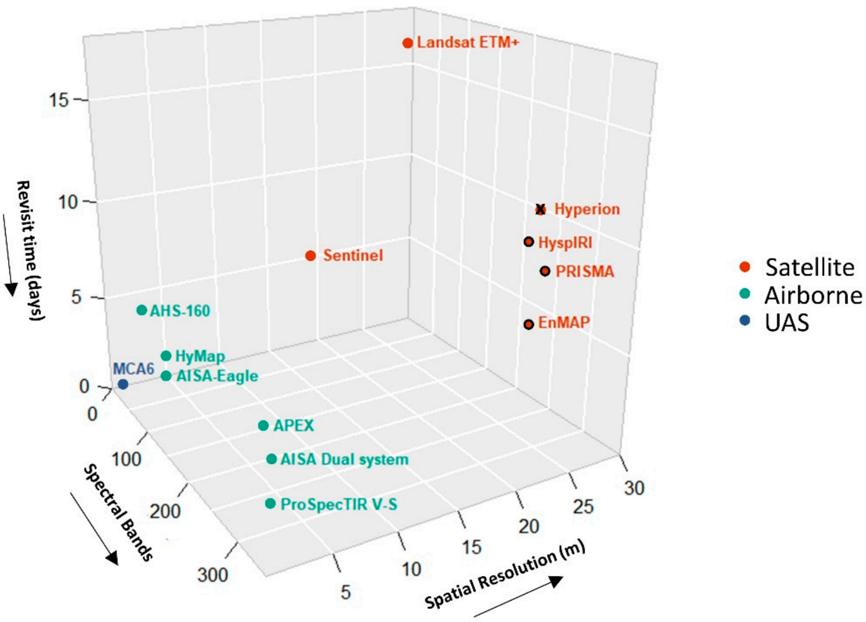

Figure 2. An overview of spatial spectral and temporal resolution of different RS systems that have been applied in SOC estimation. The black outlined symbols indicate the forthcoming remote sensing systems, while the x mark indicate that Hyperion is not in operational status.

The main advantages of RS applications can be summarized as follows: (i) they are a non-destructive way to gather information about soil properties, (ii) the provided data cover large geographical areas, (iii) they can provide information about inaccessible areas, (iv) they provide data that hold information for several attributes, (v) they have the ability to provide concise data and (vi) provide the means to reduce traditional and laborious soil sampling campaigns.

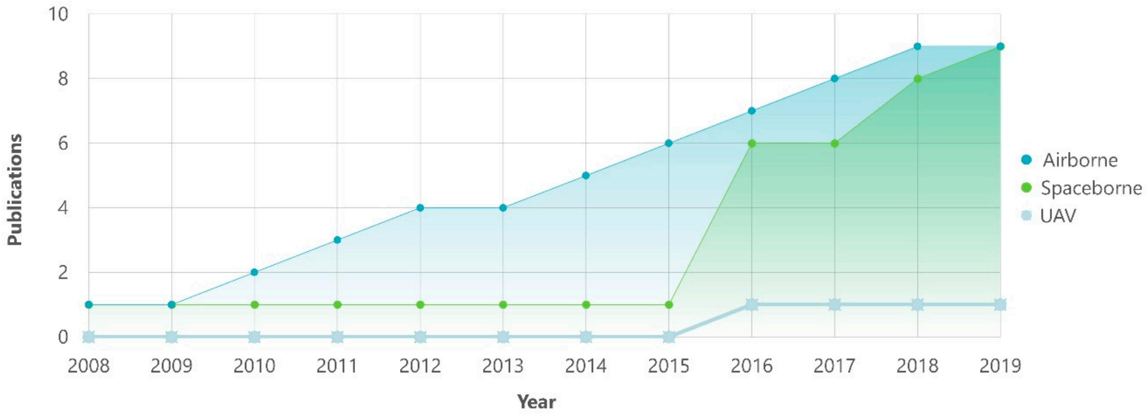

Figure 3. Cumulative illustration of published articles in the last decade (2008–2018) according to the domain of application.

However, RS techniques have low signal to noise ratio [97], low spectral resolution [34] and are subjected to geometric and atmospheric distortions [98]. Another issue that concerns the RS community, is scale effects, i.e., transferring information across scales. Assuming that the retrieval models and algorithms are derived at small scales, when the same models are utilized at large scales, uncertainties may occur [99]. In addition to that, the analysis of hyperspectral data is a challenge on its own concerning (i) the increase of data volume with the increase of the spectral bands, (ii) the effects of atmospheric absorptions requires advanced pre-processing techniques in order to be addressed, (iii) the hyperspectral data need correction for bidirectional reflectance distribution function effects and (iv) the reduction of the spectral dimensionality of the data.

Comparing the platforms of RS applications, it is obvious that the main differences are related to data acquisition, automation, resolution (temporal, spatial, spectral and radiometric) and cost of operation. Satellite platforms have a pre-fixed temporal resolution which in cases could be beneficial to create time series data, though their course could not be altered leading to distorted images affected by weather conditions, with no information about the investigated site. On the other hand, airborne and UASs flights could provide a more scheduled flight plan according to the needs of the end user, with the latter showing greater flexibility in the time of the flight [100]. Airborne applications have higher operational cost and complexity while UASs could be more easily operated with affordable cost for farmer scale. Due to their distance from the ground airborne applications provide higher spatial resolution that addresses the agricultural monitoring scale, ranging from few meters to centimeters for UAS applications.

The main disadvantage RS techniques share is that estimations are limited for the few first centimeters of the topsoil, though subsoil information is also critical to be evaluated. UAS's effectiveness is limited by its flight duration and payload capacity. Consequently, the spectral range of the mounted sensors is limited, since VNIR–SWIR sensors are quite heavy. Specifying the most important wavelengths for SOC estimations could lead to the use of small size hyperspectral sensors that could be utilized for specific applications. To generate quality products from aerial platforms reliable protocols for data acquisition and processing still needs to be determined (Table 4).

Moreover, RS techniques are highly affected by external factors, such as soil moisture, structure, roughness, vegetation, changes in atmospheric conditions that need to be addressed for accurate quantitative estimations [101]. Vegetation cover and soil moisture content may lead to SOC overestimation and inaccurate predictions in general, though the development of various spectral unmixing techniques have been promising for segregating bare soils from vegetation cover [86].

Table 4. Summary of RS platforms for SOC monitoring in terms of their benefits and drawbacks.

Platform	Benefits	Drawbacks
Satellites	• Obtain topsoil information from large areas • Provide information for inaccessible areas • Provide auxiliary data • Consistent temporal resolution for creation of time series • Short revisit time • Provide free data	• Atmospheric absorptions interfering with the spectral measurements • Low signal-to-noise ratio due to a short integration time over the target area • Mixed pixels contain more than bare soil surface (e.g., vegetation) • Need for geometric, atmospheric corrections
Airborne	• Provide information for inaccessible areas • Few imagery instruments but becoming more available in the range of (1000–2500 nm) • High spatial resolution	• Need for certain meteorological conditions for remote sensing applications • Limitation of measurements only in a thin layer of topsoil • Legal constrains for the flights • High operational complexity • High cost
UASs	• Flight plan can be scheduled according to weather condition • High spatial resolution	• Limited flight duration • Limited payload • Need for atmospheric, geometric corrections • Legal constrains for the flights

Similar to laboratory soil spectroscopy, selecting the proper calibration technique remains challenging as in most cases the specific procedures depict local character of the predictions and hence less model transferability [102]. Multivariate statistical methods are used for model calibration, with PLSR being the most frequently used, and the pre-processing techniques vary to such extend in each study that there is not an agreed upon method that for SOC estimation. Nevertheless, there is a growing interest towards machine learning techniques that in several cases have proven their ability to outperform PLSR in generating prediction models for soil properties estimation (Figure 4). In that respect, Carmon et al. [103] based on machine learning techniques developed automated data handling solutions for modelling SOC, allowing the processing of the massive volumes of information arising out of pre-processed data, towards the extraction of information related to spectral assignment explanation. On the other hand, Tsakiridis et.al. [104] proposed a form of ensemble learning whereby a novel genetic algorithm-based stacking model made synergetic use of multiple models developed from different pre-processed spectral sources to enhance the predictions of SOC in diverse Soil Spectral Libraries (SSLs).

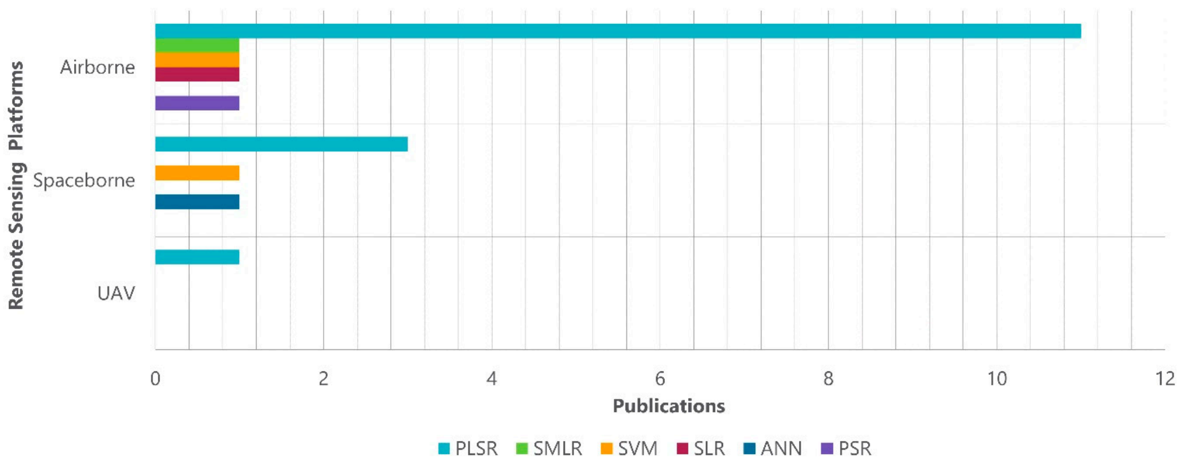

Figure 4. Number of articles which used specific multivariate calibration technique (PLSR: Partial Least Squares Regression; SMLR: Stepwise Multiple Linear Regression; SVM: Support Vector Machines; SLR: Simple Linear Regression; ANN: Artificial Neural Networks; PSR: Penalized-spline Signal Regression; MLR: Multiple Linear Regression) in each EO domain.

4.2. Future of Soil Spectroscopy in SOC Estimation

Within the broader context of climate change, the emerging threats at global, regional, and local scales can be mitigated by improving the adaptive capacity of all stakeholders in the agricultural sector upon which rationalization of agricultural production will balance out negative environmental pressures [105].

There is a need to integrate in situ data as acquired by portable spectrometers with RS data imagery to develop a holistic approach able to overcome the hindrances aforementioned. Moving from point measurements to spatially explicit indicators consists the transition from micro- to macroscales, but also involves a whole new set of challenges. Several scientific groups are leaning towards the development of SSLs. Creation of SSLs require less effort and cost compared to analytical wet chemistry methods that also have a great environmental impact due to the chemical reagents used [106]. However, it was observed that their use was limited for local estimations. Recently, local regression approaches that make use of combined spectral sources and geographical proximity were developed to select the most representative samples from the SSL database and enhance the SOC estimation [102,107]. Another challenge is the lack in comparability between different studies since the model evaluation and accuracy is not measured with the same methods and studies are deprived of certain information that is necessary for the comparison between them. In addition, different protocols for soil sampling and measurements together with different instrumentation are factors that also hinder the reliability of the results, while predictions are affected by the reference method the soil properties were measured [28,108].

The recent efforts in integrating data from different sensors, such as satellite and airborne platforms [40] with data from ground-based measurements (e.g., SSLs) [109] consist a reasonable approach to make fairly accurate predictions of SOC, motivating interested parties to transform and reorient agricultural systems onto climate smart agriculture pathways for mitigating components of the greenhouse gases balance and eliminate the degradation of land resources. Furthermore, the recent advances in sensor science support the innovation potential by exploiting the multiple research and operational assets in soil spectroscopy domain to effectively monitor SOC stocks for accounting purposes [110]. By that means, the generally low SOC content could ultimately increase via the adoption of appropriate management practices [111].

The importance of RS platforms, as an accurate source of data, cannot be over-stated, in order to develop new observational modalities and improve measurements, monitoring, and reporting activities at various scales within the context of the sustainable development goals set by the United Nations [112]. In this line, the role of RS data could be highlighted as a proxy for estimating SOC and produce large scale maps within the framework of soil related indicators (e.g., SDG Indicator 15.3.1, Proportion of land that is degraded over total land area and also might be useful to establish relevant policies [113,114]

Potentially, SSLs could be a strong base for the forthcoming hyperspectral remote sensing of soils from space [115] as they might then be used for enhanced applications in support of the Copernicus program, and for synergistic use with mobile proximal soil [116] and airborne [40] sensors as well as for the new evolving technology of drones sensing.

5. Conclusions

The present review aimed at highlight the progress done within the last decade on using RS techniques in the VNIR–SWIR region for SOC estimations. Several types of regression analysis methodologies were discussed. Through this review, we concluded that hyperspectral sensors mounted on the upcoming satellite missions, airplanes, and UAS provide unique capabilities for addressing the enormous challenges inherent to the SOC regular monitoring and reporting of large areas. Moreover, we concluded that recent advances in machine learning could facilitate for increasing the overall accuracy and robustness of the models. In that context, a wide range of studies has been carried out and highlighted the use of soil spectroscopy as a key enabler for soil properties applications due to their low cost and spatial coverage. However, the systematic exploitation of satellite imagery lags greatly due to factors (roughness, soil moisture, vegetation cover) that act as deterrents for robust estimations. In addition to that, the use of UASs for SOC estimations is still at its infancy, although their application seems promising considering the advancements in sensors specifications, i.e., small size hyperspectral sensors. In the light of the above, it could be suggested that an integration of remote and proximal sensing technologies should be considered imperative to develop cost-effective and accurate monitoring solutions at a high spatial resolution for decision making in land-use issues.

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