A Review on Soil Organic Carbon Estimation via Remote Sensing Approaches

HIGHLIGHTS:

- Soil reflectance spectroscopy used for estimation of soil organic carbon content.
- Visible near infrared-shortwave infrared sensors based on energy-matter interaction.
- Demand of multivariate statistical procedures to study soil characteristics.

ABSTRACT

Current review focuses on developments during past time on RS practices in VNIR-SWIR regions designed for estimation of soil organic carbon (SOC) content. Soil reflectance spectroscopy finds extensive applications such as sensors set-up on satellites, aircrafts as well as Unmanned Aerial System (UAS). This review briefly discusses research as well as studies on soil organic carbon analysis by employing RS practices. It is detected that prediction correctness lessens from Unmanned Aerial Systems (UASs) towards satellite platforms, although, machine learning help in superior production of calibration models. For coping with numerous challenges related to SOC observation of large region, hyperspectral sensors set-up on forthcoming satellite missions, airplanes as well as Unmanned Aerial System (UAS) provide special potential. Additionally, merits as well as demerits of individual approach are also briefly discussed here.

Keywords: Remote Sensing (RS), Soil Organic Carbon (SOC), Visible near infrared-shortwave infrared (VNIR-SWIR), Spaceborne, Airborne, Unmanned Aerial System (UAS).

1. Introduction

Soil is a mixture of organic as well as inorganic parts and their amount change from place to place or within the same place (Jandl, Rodeghiero et al. 2014). Owing to this, estimation of soil components (both quantitative as well as qualitative) is a burdensome process (Gehl and Rice 2007). Some logical as well as coherent datum intended to obtain information regarding soil organic carbon content (SOC) estimation must be required for the purpose to optimize monitoring as well as mapping capacity (Angelopoulou, Tziolas et al. 2019). SOC holds an integral part on carbon cycle and approximately 1500 Gt of carbon is stored in soils at 1 m depth (Jobbágy and Jackson 2000), (Scharlemann, Tanner et al. 2014). Additionally, SOC is a part of Organic Matter (OM) and has influence on physical, chemical, biological characteristics of soil ecosystem (Ontl and Schulte 2012). Eswaran et al., (Eswaran, Van Den Berg et al. 1993) stated some hurdles to estimate correct global carbon content. These are because of high spatial changeability of soil organic carbon, variableness of soil kinds which contains unpredictable estimates, inaccessibility of valid data as well as changes in plants and land usage.

Various traditional processes were used for SOC monitoring but they are laborious as well as expensive (Omran 2017). Studies were conducted to explore and apply other revolutionary procedures for all types of environments and all kinds of soil (Jandl, Rodeghiero et al. 2014) i.e., use of Remote Sensing (RS) practice is efficient, low cost in addition to environmentally sound aspect for analysis of various soil characteristics (Xu, Smith et al. 2017) such as SOC estimation etc. (Vaudour, Gilliot et al. 2016). Visible near infrared-shortwave infrared (VNIR-SWIR) sensors (find RS usages) work on principle of energy-matter interaction (Schwartz, Ben-Dor et al. 2012). Part of electromagnetic radiations (falling on soil exterior) that is reflected from soil surface is recorded as a spectrum which is enough to produce information (both qualitative as well as quantitative) regarding soil characteristics (Nocita, Stevens et al. 2015). In VNIR-SWIR, characteristic vibrations take place (Mohamed, Saleh et al. 2018) in visible region (400-700nm) i.e., electronic transitions occur which produce absorption bands linked to chromophore while on the other hand, in NIR-SWIR (700-2500 nm) weak overtones or such vibrations take place owing to extending as well as bending of some bonds such as N-H, O-H, as well as C-H bonds etc. (Rossel, Walvoort et al. 2006), (Stuart 2004). Association amongst SOC as well as electromagnetic radiations in VNIR, SWIR region has already been reported in laboratory conditions (Bartholomeus, Schaepman et al. 2008), (Stevens, Nocita et al. 2013), (Nocita, Stevens et al. 2013). In addition to laboratory trials, numerous studies have also been conducted in real field conditions founded on manned as well as unmanned airborne system, and satellite platforms (Gomez, Rossel et al. 2008). However, these practices have restrictions for direct SOC estimation including vegetation cover, soil wetness etc. (Nocita, Stevens et al. 2013), (Bartholomeus 2009). Furthermore, there is a demand of some multivariate statistical procedures called Chemometrics to associate spectral signatures with soil characteristics (Geladi 2003).

One of the most widely employed practice is application of partial least squares regression (PLSR) for reporting direct association among variables (Peng, Shi et al. 2014). That's the basic reason of increased usage of machine learning algorithms for correlation procedures (Stenberg, Rossel et al. 2010), (Liakos, Busato et al. 2018).

This review article emphasizes on current research of remote sensing procedures, state-of- art procedures as well as instruments for current SOC estimation.

2. Remote sensing data sources

For renewal as well as monitoring of SOC crossways VNIR-SWIR spectral span, remote sensing (RS) via various sources gave statistics streams. Various kinds of sensors (in case of imaging spectroscopy) are set up on airborne (Castaldi, Chabrillat et al. 2018) or else spaceborne platforms. As a result, Unmanned Aerial Systems (UASs) are widely used to perform succeeding generation of hand-sized hyperspectral imagers (Aldana-Jague, Heckrath et al. 2016). Brief explanation of remote sensors requirements for SOC estimations are given below:

2.1. Spaceborne

Spaceborne remotely sensed imagery possess the power to generate spatial maps of higher soil horizon due to association of soil's definite chemical bonds as well as electromagnetic radiations. With inauguration of first satellite in 1980s, optical satellite multispectral imagery finds extensive applications in SOC estimation (quantitative) (Frazier and Cheng 1989). Additionally, owing to availability of Hyperion spaceborne system, usage of hyperspectral data also increased (Castaldi, Casa et al. 2014). However, their application for soil study was restricted owing to essential atmospheric, geometric, radiometric data amendment, obstacles in uncovering naked regions in one image (Demattê, Fongaro et al. 2018), as well as hurdles associated with vegetation cover (Barnes, Sudduth et al. 2003). Owing to these reasons studies on SOC estimation via satellite sensors are not many (Croft, Kuhn et al. 2012). Nowadays there is a remarkable change in SOC estimation as well as mapping founded on spaceborne data. One of the major achievements in this regard is relevant USGS policy variation (for dispersion of Landsat data freely) (Woodcock, Allen et al. 2008). Additionally, upcoming hyperspectral sensors i.e., Environmental Mapping and Analysis Program (EnMAP) shortly give unprecedental statistics for SOC estimation across VNIR-SWIR spectral span (Stuffler, Kaufmann et al. 2007).

2.2. Airborne

Spatial evaluation of soil environment gives correct mapping of changeability in agricultural field via Airborne hyperspectral imaging (Stevens, van Wesemael et al. 2008). It is also useful for data collection to divide a place in agreement with soil heterogeneity (Mulder, De Bruin et al. 2011). Airborne set-up sensors exhibit flexibleness for a specific measurement time window giving power to choose optimal flight condition and work under an extraordinary-cloud coverage (Usha and Singh 2013).

2.3. Unmanned Aerial System (UAS)

From past few years, UAS is an efficient as well as low price platform for environmental monitoring (Whitehead and Hugenholtz 2014). Owing to usage of innovative sensors, low cost, development in sensor's size as well as spectral resolution UASs have wide range of uses. Both spaceborne characteristics (i.e., brief revisit period) as well as airborne platforms (including an extraordinary resolution) are combined in UAS, and it is the distinctive characteristic of UAS to give resolution required on the way to protect diversity of agri-environmental landscapes (Pádua, Vanko et al. 2017). Inspite of these merits, research related to soil characteristics analysis is restricted owing to restricted payload, restricted flight duration as well as issues of image processing (Zhang and Kovacs 2012).

3. Review

3.1. Uses of remote sensing statistics in SOC estimation

For mapping soil characteristics, statistics via satellite sensors find its uses as auxiliary variables. On behalf of this purpose, forecasting of SOC spatial changeability as well as progress of high-quality maps via combination of geostatistical methods with variety of remote sensed variables is more correct as compared to simple Kriging (Mirzaee, Ghorbani-Dashtaki et al. 2016), (Wang, Waters et al. 2018). Schillaci et al., (Schillaci, Lombardo et al. 2017) customized set of topographical as well as environmental covariates with a Stochastic Gradient Treeboost for assessment of SOC stocks-Landsat 7ETM+ was used to get RS data and results showed that panchromatic Band 8 resulted in superior forecasting as compared to NDVI. Modal et al., (Mondal, Khare et al. 2017) founded from RS data that variables such as radiance, moisture, as well as plant vegetation condition indication affect SOC dispersal to a great extent. Castaldi et al., (Castaldi, Palombo et al. 2016) studied power of 3 upcoming satellite hyperspectral imagers (EnMAP, PRISMA (Labate, Ceccherini et al. 2009) as well as HyspIRI (Roberts, Quattrochi et al. 2012)) in comparison with ALI besides Hyperion (EO-1) for SOC estimation. For stimulation of spectral statistics via upcoming satellite imagers, spectra in laboratory set-up were resampled in accordance with sensor's spectral as well as radiometric requirements. Owing to this a regional soil spectral library having 160 samples and datum from LUCAS soil database were used. On behalf of result analysis, PLSR was employed intended for model standardization Ratio of Performance to Interquartile Range (RPIQ) (Bellon-Maurel, Fernandez-Ahumada et al. 2010). For local database results from resampled data are superior varied as of $R^2 = 0.36$ for Sentinel-2 and $R^2 = 0.51$ for PRISMA. Outcomes obtained from LUCAS database have lesser R^2 i.e., varied from 0.06 to 0.26 for Hyperion as well as PRISMA correspondingly (Angelopoulou, Tziolas et al. 2019).

Steinberg et al., (Steinberg, Chabrillat et al. 2016) worked on estimation and study of prediction correctness via simulated statistics of forthcoming satellite sensor EnMAP in comparison with airborne AHS-160. Results confirmed similarity among soil spectral reflectivity obtained via sensors beside satellite sensor. To make progress in simulated EnMAP statistics, resolution of sampling strategy is crucial. For forecasting soil as well as soil organic matter characteristics, Gallo et al., (Gallo, Demattê et al. 2018) employed PLSR algorithm on datum obtained from naked soil composite image. Gholizadeh et al., (Gholizadeh, Žižala et al. 2018) stated that for obtaining an extraordinary-quality information on fluctuations in SOC, Sentinel-2 is more reliable as compared to airborne sensors. For that reason, they used modest SVM model to direct prediction models over spectral signature of Sentinel-2 as well as a set of spectral marks. B4 as well as B5 after B11 and B12 gave superior SOC as well as Sentinel-2 spectral band association. Additionally, some other spectral marks i.e., BI, BI2, GNDVI as well as SATVI also resulted in strong association with SOC. Castaldi et al., (Castaldi, Hueni et al. 2019) observed that to express SOC changeability at both inside area as well as at geographical level spectral resolution as well as spectral properties are sufficient. For variety of pilot sites, they established Partial Least Square Regression (PLSR) as well as Random Forest (RF) models by making use of Sentinel-2 RPD values obtained by this way varied from 1.0-2.6. Vaudour et al., (Vaudour, Gomez et al. 2019) also reported identical results. Table 1 summarizes SOC analysis by employing spaceborne platforms.

3.2. Airborne

Power of airborne hyperspectral sensor 160 (AHS, Caravan International Corporation, USA) for SOC content estimation for naked place of soil kinds was assessed by Stevens et al., (Stevens, Udelhoven et al. 2010). Spectral span changes from 430 nm to 2540 nm. Received spectra were linked through 325 soil samples having SOC content varied from 7-61 gC/ kg. Owing to heterogeneousness in mineralogy as well as soil humid content, there was decline in reflectance from sandy to colluvial-alluvial soils. When findings of PLSR, Penalized Spline Regression (PSR) as well as SVM for worldwide calibration were matched, it became clear that SVM was the most efficient as well as suitable approach ($R^2 = 0.74$) owing to large datum.

There is a demand of atmospheric amendments as well as suitable weather circumstances in case of airborne data since large pixel size as well as changing standard of sensor's strength in addition to sensitivity may cause numerous problems (Brook and Dor 2011). Hbirkou et al., (Hbirkou, Pätzold et al. 2012) worked on assessing power of airborne hyperspectral sensor HyMap (Integrated Spectronics, Sydney, Australia) in addition to studied consequences of soil raggedness as well as vegetation cover towards SOC projection models at field level. Complete experiment is carried out in dry weather. PLSR models from thorough datum (n = 204) produced results with $R^2 = 0.83$ which in specific places varied from 0.34-0.73. Soil raggedness greatly affect model's correctness as most negative conditions giving $R^2 = 0.34$. Comparable findings were reported by Lagacherie et al., (Lagacherie, Baret et al. 2008).

Applications of RS techniques have numerous restrictions (Ben-Dor, Chabrillat et al. 2009) however, research on naked soil is recommend for data achieved via airborne mounted sensors (Denis, Stevens et al. 2014). Franceschini et al., (Franceschini, Demattê et al. 2015) worked on spectral combination of naked soil having photosynthetic as well as non-photosynthetic vegetation. Statistics was achieved via ProSpecTIR V-S sensor (SpecTIR LLC, Reno, N). Guerschman et al., (Guerschman, Hill et al. 2009) suggested linear unmixing methodology for naked soil fractional cover analysis. There were 89 collected samples which were split into four categories in accordance with naked soil fractional cover quartile. PLSR models were employed for individual category. From results it became obvious that soil spectral albedo reduces by upsurging in organic matter (OM) as well as clay content. However, forecasting of OM content in laboratory environment having $R^2 = 0.70$ was more correct in contrast to airborne hyperspectral sensors having $R^2 = 0.33$. Residual Spectral Unmixing (RSU), a spectral unmixing practice was established by Bartholomeus et al., (Bartholomeus, Kooistra et al. 2011) for elimination of vegetation effect of mixed pixels as well as enhancing SOC changeability analysis in enclosed maize fields.

Diek et al., (Diek, Schaepman et al. 2016) produced multi-temporal composites via Airborne Prism Experiment (APEX) in addition to making use of crop rotation to escalate naked soil regions. For hiding of green vegetation as well as for non-agricultural places, various spectral evidence in addition to renovated agricultural field block map was employed consecutively. Nevertheless, for XOM analysis, R^2 value was 0.39 ± 0.04 which showed that besides vegetation cover, some other elements need to be considered such as soil wetness as well as raggedness. Bayer et al., (Bayer, Bachmann et al. 2016) suggested a feature-founded forecasting model for SOC estimation founded on naked soil field spectra in HyMap's spectra resolution. Iterative Spectral Mixture Approach was employed for resolving problem of mixed pixels giving 45.4 % upsurge in model range. Little predictions were due to various kinds of vegetation, low spatial resolution as well as decreased correctness of geo-correction applications. Castaldi et al., (Castaldi, Chabrillat et al. 2018) suggested bottom practice for SOC estimation purposes by making use of existing advanced great soil spectral collections. Owing to this LUCAS topsoil datum (Toth, Jones et al. 2013) was merged along with APEX sensor statistics. Correctness of model was examined via entirely independent verified datum producing comparable RMSE of 4.3 gC/ kg to conventional procedures (RMSE = 3.6 gC/ kg).

Vohland et al., (Vohland, Ludwig et al. 2017) examined various spectral variable selection procedures such as Competitive Adaptive Reweighted Sampling (CARS) (an approach that "iteratively retains informative variables") as well as genetic algorithm (GA) to enhance predictions. Results showed that PLSR models based on fuel spectrum produced inferior findings when compared with spectral variable selection i.e., GA provided $R^2 = 0.85$ for airborne dimensions in case of SOC estimation. Peón et al., (Peón, Recondo et al. 2017) correlated predictions obtained via Hyperion as well as AHS consecutively. They concluded that both sensors have comparable spectral associations in red region chiefly at 610 as well as 679-681 nm. Main findings regarding SOC estimation employing usage of airborne platforms are summarized in table 2.

3.3. Unmanned Aerial Systems (UASs)

For variety of environmental as well as climate variable estimation founded on UAS applications development was made (McGwire, Weltz et al. 2012), (Li, Niu et al. 2016), (Capolupo, Kooistra et al. 2015) but these platforms are not employed for soil environment observing. As far as there is just 1 finding for SOC estimation (Aldana-Jague, Heckrath et al. 2016) by employing multispectral Mini-MCA6 from Tetracam Inc. (450-1050 nm) (Chatsworth, CA, USA) onboard a UAS platform on the way to assess its effectiveness for SOC predictions. Optimum conditions for flight compaign were cloudless sky, little vegetation shelter, as well as dehydrated soil. Suggested procedure has excellent power for SOC monitoring employing an algorithm producing mean SVM coefficient of determination of 0.95 as well as a RMSE of 0.21 % in cross authentication in comparison with dry combustion laboratory procedures. Table 3 showed SOC estimation study via UAS.

4. Discussion

4.1. Summary of remote sensing technique

There are various kinds of RS practices founded on their three-dimensional, spectral, chronological as well as radiometric resolution and platforms on where they are set-up (shown in Fig. 1). Based on type of use, property to be quantified, as well as correctness of results, suitable approach is selected.

Rapid as well as extensive uses of these applications are due to developments in sensors requirements. Sensors set-up on satellite platforms have upgraded from panchromatic towards multispectral as well as upcoming hyperspectral i.e., EnMAP, HyspIRI as well as PRISMA. Owning to availability of such hyperspectral sensors, essential information regarding soil's condition, SOC estimation can be obtained via RS applications. Additionally, to meet present as well as upcoming demands for soil monitoring essential datum for correct up-to-date soil maps can also be obtained via RS practice. RS practices have merits that these are environmentally sound practices to obtain data related to soil properties, provide data of those sites/ places that are inaccessible, provide concise information and lower the chances of laborious soil sampling work (Angelopoulou, Tziolas et al. 2019).

RS practices have issues that they possess little signal to noise proportion (Minu, Shetty et al. 2016), little spectral resolution (Gomez, Rossel et al. 2008), as well as undergo geometric and atmospheric manipulations (Jakob, Zimmermann et al. 2017). There exists another problem i.e., scale effects, for example, variations take place when retrieval models as well as algorithms are derived at small and large levels (Wu and Li 2009). Additionally, external parameters like soil wetness, structure, raggedness, vegetation greatly affect correct quantitative estimation via RS practices (Wu and Li 2009). Table 4 summarized some merits as well as demerits of RS platforms for SOC monitoring (Angelopoulou, Tziolas et al. 2019).

Multivariate statistical practices find applications for model calibration employing PLSR, and pre-processing practices changes in each study. However, for generating prediction models for soil characteristics, there is significant interest in connection with machine learning approaches having power to outperform PLSR as shown in Fig. 2 (Angelopoulou, Tziolas et al. 2019).

4.2. Future of soil spectroscopy in SOC estimation

To reduce global as well as local level threats, capability of all stakeholders in agricultural sections must be enhanced resulting in elimination of negative environmental pressures (Lipper, Thornton et al. 2014). Research is continued for establishing SSLs. Production of SSLs take place at low price and with little effort in comparison to analytical wet chemical procedures (accountable for environmental issues owning to chemicals used in them) (Demattê, Dotto et al. 2019), however, usage of SSLs was restricted on behalf of confined estimations. Nowadays confined regression procedures involving application of spectral sources as well as geographical proximity were established for improving SOC estimation (Lobsey, Viscarra Rossel et al. 2017), (Tziolas, Tsakiridis et al. 2019). Additionally, lack in comparability among various studies is another challenge. This is because of reason that similar procedures are not employed for model assessment as well as correctness and particular data required for making comparison between them is also missing in studies (Romero, Ben-Dor et al. 2018).

Importance of RS platforms cannot be exaggerated for establishing new observational modalities and enhancing computing, observation, and description practices at different levels in context of manageable progress objectives set by United Nations (Anderson, Ryan et al. 2017). Hence, purpose of RS data is as a proxy designed for SOC estimation resulting in large level maps within frame of soil related indicators such as SDG indicator 15.3 (Tóth, Hermann et al. 2018), (Keesstra, Bouma et al. 2016). Possibly, SSLs proved to be excellent foundation for upcoming hyperspectral remote sensing of soils from space (Guanter, Kaufmann et al. 2015) because they could find uses in support of Copernicus program as well as for collaborative usage with mobile proximal soil (Kühnel and Bogner 2017) besides airborne sensors (Castaldi, Chabrillat et al. 2018).

5. Conclusions

Current review focuses on development during past time on RS practices in VNIR-SWIR regions designed for estimation of soil organic carbon (SOC) content. From this review paper, we summarized that for coping with numerous challenges related to SOC observation of large region, hyperspectral sensors set-up on forthcoming satellite missions, airplanes as well as Unmanned Aerial System (UAS) provide special potential. Numerous studies have been conducted regarding development in machine learning as well as exploring effectiveness of soil spectroscopy application for studying soil characteristics. However, some parameters like roughness, soil wetness, vegetation cover etc. affect satellite imagery to a great extent. For this reason, a combination of both remote as well as proximal sensing technologies should be taken into consideration for establishing low price as well as effective monitoring solutions having high spatial resolution.

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Author's contribution

All authors contributed equally to manuscript.

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Authors will ensure transparency of data.

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The data that support this study are available in the article and accompanying online supplementary material.

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Table 1

Summary of SOC analysis by employing spaceborne platforms.

Reference	Sensor	Spectral series (nm)	Algorithm/ multiv
(Gomez, Rossel et al. 2008)	Hyperion	400-2500	PLSR
(Mirzaee, Ghorbani-Dashtaki et al. 2016)	Landsat ETM+	450-2350	ANNSK
(Castaldi, Palombo et al. 2016)	EnMAP	420-2500	PLSR
(Castaldi, Palombo et al. 2016)	PRISMA	400-2500	PLSR
(Castaldi, Palombo et al. 2016)	HyspIRI	380-2510	PLSR
(Steinberg, Chabrillat et al. 2016)	EnMAP	420-2500	AutoPLSR
(Castaldi, Hueni et al. 2019)	Sentinel-2	440-2200	PLSR/ RF
(Vaudour, Gomez et al. 2019)	Sentinel-2	440-2200	PLSR
(Gholizadeh, Žižala et al. 2018)	Sentinel-2	440-2200	SVM

Table 2

Summary of main findings regarding SOC estimation employing usage of airborne platforms.

@ >p(- 12) * >p(- 12) * >p(- 12) * >p(- 12) * >p(- 12) * >p(- 12) * >p(- 12) * @ **Reference** & **Sensor** & **Spectral series (nm)** & **Algorithm/ multivariate approach** & **R^2** & **RMSE (g/ kg)** & **RPD**
(Stevens, Udelhoven et al. 2010) & AHS-160 & 430–2540 & PLSR, PSR, SVMR & 0.53–0.89 & 3.13–6.22 & 1.47-3.15
(Stevens, van Wesemael et al. 2008) & AHS-160 & 430–2540 & PLSR &

-

& 1.7 & 1.47
(Hbirkou, Pätzold et al. 2012) & HyMap & 450–2500 & PLSR & 0.34–0.83 & 0.76–1.10 & 1.14-2.32
(Franceschini, Demattê et al. 2015) & ProSpec TIR V-S & 400–2500 & PLSR & 0.33 & 3.82 & 1.25
(Bartholomeus, Kooistra et al. 2011) & AHS-160 & 430–2540 & PLSR & 0.62 & 1.34 & 1.8
(Vaudour, Gilliot et al. 2016) & AISA-Eagle & 400–1000 & PLSR & 0. 44 & 4.05 & 1.4
(Peón, Recondo et al. 2017) & AHS-160 & 430–2540 & PLSR & 0.27–0.60 & 6.44–8.70 & 1.18-1.60
(Homolová, Schaepman et al. 2014) & AISA Dual system & 400–2450 & SLR, SMLR, PLSR & 0.73 & 8.4 &

-

(Castaldi, Chabrillat et al. 2018) & APEX & 400–2500 & PLSR &

-

& 4.3 & 2.5
(Vohland, Ludwig et al. 2017) & HyMap & 450–2500 & PLSR & 0.73–0.85 & 0.19–0.25 & 1.94-2.62

Table 3

SOC estimation study via UAS.

Reference	Sensor	Spectral series (nm)	Algorithm/ multivariate
(Aldana-Jague, Heckrath et al. 2016)	Mini-MCA6	450–1050	SVM

Table 4

Summary of merits as well as demerits of RS platforms for SOC monitoring (Angelopoulou, Tziolas et al. 2019).

Platform	Merits
Satellites	Short revisit time, produced auxiliary records, gave free of cost informat
Airborne	Extraordinary spatial resolution, gave data of unreachable places, tools a
Unmanned Aerial Systems (UASs)	Extraordinary spatial resolution, designing of flight strategy by taking w

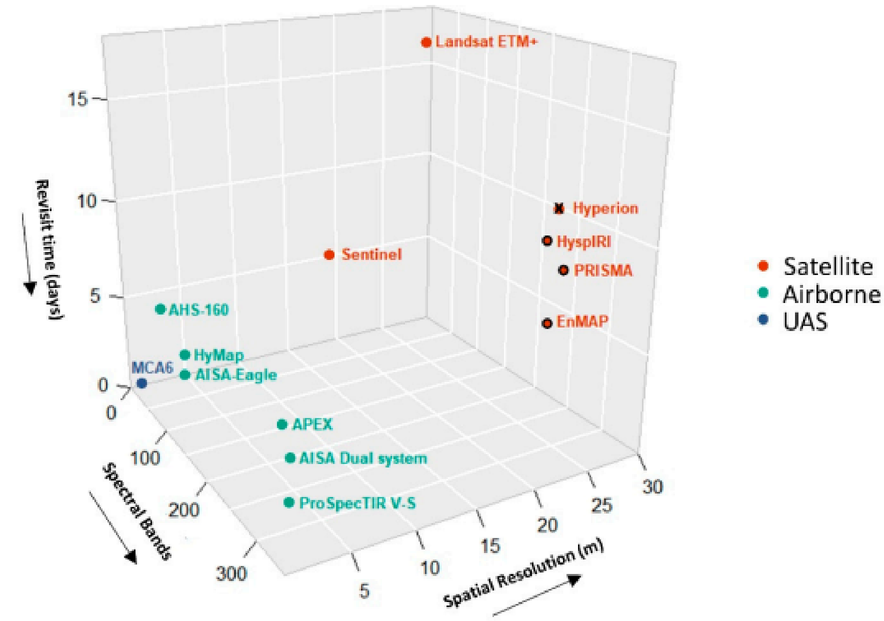

Fig. 1. An overview of various RS practices founded on their three-dimensional, spectral, chronological as well as radiometric resolution for SOC estimation. Black bordered signs represent upcoming remote sensing systems whereas x symbol represent that Hyperion is not in working position. Reproduced with permission from (Angelopoulou, Tziolas et al. 2019).

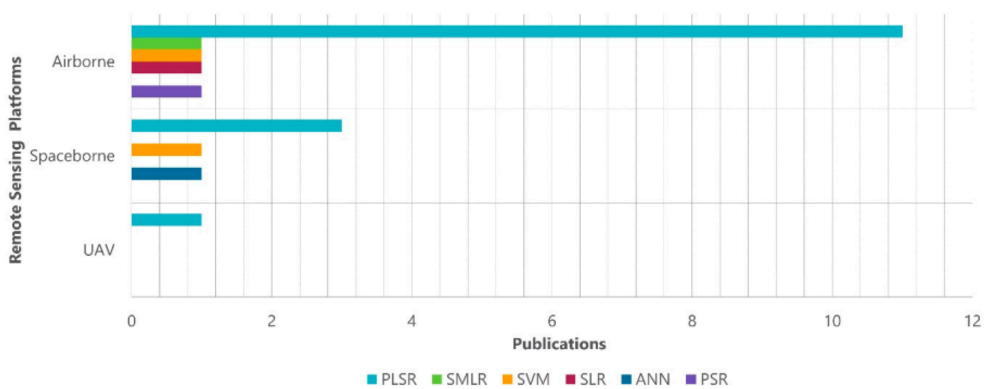

Fig. 2. Number of articles involving use of multivariate calibration technique in each EO domain (PLSR stands for Partial Least Squares Regression, SMLR stands for Stepwise Multiple Linear Regression, SVM stands for Support Vector Machines, SLR stands for Simple Linear Regression, ANN stands for Artificial Neural Networks, PSR stands for Penalized-spline Signal Regression and MLR stands for Multiple Linear Regression). Reproduced with permission from (An-

gelopoulou, Tziolas et al. 2019)