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Limitations and future perspectives for satellite-based soil carbon monitoring

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ABSTRACT

Soil organic carbon (SOC) plays a crucial role in terrestrial C storage and ecosystem services. Agricultural management practices have the potential to increase C inputs and reduce its losses. However, uniform standard protocols for measuring, monitoring, and assessing changes using remote sensing is lacking for SOC in the scientific literature. In this discussion paper, we present techniques for collecting and analyzing ground samples and employing remote sensing to quantify SOC, along with its limitations and future perspectives. Our analysis identified a number of key limitations to advancing the science for remotely sensed terrestrial C in croplands including i) lack of consensus in sampling depth and density, ii) the absence of a standard (or universally accepted) laboratory procedure and statistical methodology, and iii) lack of details on imagery pre-processing or information on the spectral properties of the targeted soils. Establishing standard protocols for ground-truth data collection and remote sensing approaches, as well as a knowledge of the impacts of diverse soil types, land uses, and landscapes on C assessment, are all required to enhance the accuracy and reliability of future SOC assessments.

1. Introduction

Terrestrial carbon (C) comprises more than 3000 petagrams (Pg) of C (Lal, 2004), with the potential to store significantly more by absorbing CO_2 from the atmosphere. The terrestrial C component influences several ecosystem services, including soil water cycle, soil structure, plant nutrition, and plant growth (Rawls et al., 2003). The largest proportion of this pool, around 1500 Pg C, exists as soil organic C (SOC) in an equilibrium between sequestration and emissions as a sink or source. Initiatives such as “4 per 1000″ explore the potential that soil has to capture more atmospheric C (Minasny et al., 2017), helping to tackle global challenges such as climate change, land degradation, biodiversity loss, and food security (Lal, 2006). Agricultural management practices have the potential to help to achieve this goal in two fundamental ways: i) by increasing C inputs, and ii) by lowering C losses, both of which can be accomplished via implementation of best management practices such as optimal fertilization rates, use of cover crops, and no-tillage agroforestry, crop – livestock integration, amongst others (Tiefenbacher et al., 2021). However, to fully understand these dynamics and use them to contribute to the improvement of C storage, we must first be able to precisely measure and monitor changes of soil C over time, along with an accurate description of land use and management practices that are among the main drivers of SOC dynamics. This discussion paper presents a brief summary on (i) the limitations associated with soil data collection and remote sensing approaches for SOC assessments; (ii) the importance and need for standard protocols for measurements and associated issues; and (iii) future directions necessary to advance towards a more homogenous implementation of remote sensing for SOC assessment (Fig. 1).

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2. Current scenario: progress and global footprint

Globally, several attempts have been made to advance the understanding of SOC dynamics from the sky (Angelopoulou et al., 2019). This becomes particularly important when looking for solutions that: (i) allow for efficient global deployment, (ii) are non-destructive, (iii) cost effective, and (iv) can be easily updated. These studies may involve optical and/or radar sensors, soil spectral libraries, and proxies such as digital elevation models or other covariables. In recent review studies by Angelopoulou et al. (2019) and Vaudour et al. (2022) described and discussed the role of different sensors, spectral ranges, methodologies, and spatial distribution over the past decades.

From a SOC ground sampling perspective, soil data collection presents a broad range of sampling depths (0–10 cm, 0–20 cm, 0–30 cm or 0–100 cm), number of samples per unit area (0.1 samples km^{-2} to 2.7 samples km^{-2}, to 201 per field), and laboratory methodologies (wet oxidation and dry combustions) (Casa et al., 2013; Castaldi et al., 2016; Chen et al., 2019; Vaudour et al., 2022). While these studies were distributed across the world, the geographical scope has been limited to small regions and many regions/countries remain heavily under-represented or not represented at all.

From a remote sensing standpoint, sensors mounted on planes or drones tend to be costly. Add to that the requirement for highly qualified personnel to conduct the flights, the additional time for pre-processing of the images, calibration and understanding of images, and the limited scalability of the findings. On the other hand, spaceborne platforms can retrieve data from anywhere across the world, with significantly reduced cost. Spaceborne sensors deliver data with varying spatial, temporal, and spectral resolutions, such as MODIS for regional scale studies or PlanetScope images for field-level analyses. Increasing availability of analysis-ready data (ARD) and free access via government or educational initiatives are additional benefits of satellite-based sources. Significant advancements in cloud computing infrastructure (e.g., Google Earth Engine, AWS) (Gorelick et al., 2017) have also contributed to a greater uptake of satellite-based data by enabling an increasing number of images to be analyzed/processed in very little time. The past years have seen an explosion in satellite-based studies (Vaudour et al., 2022), coincident with the launch of Sentinel 2. Sentinel 2 represents a significant advance over previous sensors with improvements in both spatial, temporal, and spectral resolution, allowing for enhanced super-spectral analyses at 10 m with a 5-day revisit (Drusch et al., 2012). Add to that, studies based on other multi-spectral missions such as Landsat and MODIS (Peng et al., 2015; Sayão and Demattê, 2018) and hyperspectral systems such as HyMap, Hyperion, PRISMA, and CHRIS (Hbirkou et al., 2012; Hong et al., 2020). While multi-spectral sensors collect data in discrete bands (channels) across the electromagnetic spectrum, hyperspectral imaging (HSI) typically measures in 100′s of continuous bands. HSI has been shown to deliver more precise retrievals given access to high spectral resolution information across specific portions of the electromagnetic spectrum (Angelopoulou et al., 2019; Chabrillat et al., 2019). The disadvantage, however, is in relation to the cost per image, spatial coverage and trained personnel to process the data. The utility of spaceborne HSI has traditionally been hindered by a lack of global monitoring missions in addition to more complicated image pre-processing tasks (atmospheric correction, radiometric interferences) (Angelopoulou et al., 2019).

3. Limitations of current approaches from ground collection to remote sensing

Multiple attempts have been made on a global scale for quantifying SOC, as presented by Vaudour et al. (2022), but still large uncertainties are associated with its estimation (Stockmann et al., 2015). For the purpose of this review and discussion, these uncertainties may be divided into three major categories: those connected with i) characterizing land use and management practices, ii) soil sample collection and

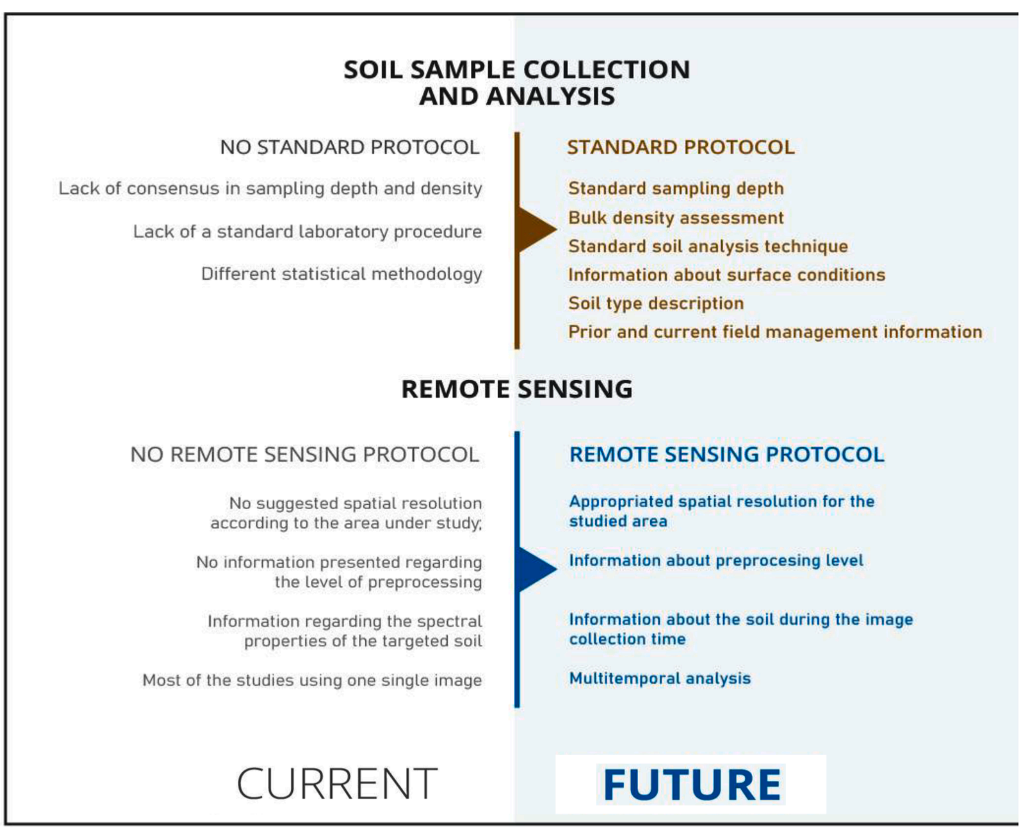

Fig. 1. Current limitations and future perspectives for soil organic carbon (SOC) assessments from soil sample collection and analysis to remote sensing.

analysis, and those linked to iii) remote sensing tools and image processing.

Land use and management practices are among the main drivers of SOC dynamics governing biomass-C inputs and outputs, diversity of organic inputs and their turnover rate associated with soil aggregation processes, abundance and diversity of soil biota that will shape the different SOC pools. Land use and management practices are usually not fully described in soil database or simply refer to generic terms such as conventional and best management practices with few descriptive elements that do not always allow an external reader to assess the nature of the practices and/or the historical path of the land use (Fujisaki et al., 2023).

Spatial distribution, sampling density (number of samples per unit of area), sample depth, bulk density, laboratory methodologies, and statistical methods are among the sources of uncertainty in the second group. The importance of sampling density for SOC prediction was studied by Long et al. (2018) who tested twenty different densities and concluded that sampling density affects the accuracy while presenting a correlation with the landscape, and soil orders ultimately affecting C stocks estimations (Sá et al., 2013). This emphasizes the complexity associated with conducting research on a worldwide scale, as the required sample density would be substantially larger in order to capture the variability. Thereby making it even more challenging, costly, and laborious to collect and analyze the data. In addition, if the propagation of error is not properly considered, scaling up field level data to regional or larger scales is likely to introduce substantial uncertainties. In this context, the spatial autocorrelation between samples plays a key role in combination with the methodology used to interpolate the values to move from sampling level to field or regional level. Few studies have been conducted covering extensive geographical areas across the globe (Vaudour et al., 2022). It is impossible for such a limited evaluation with such a low sample density to accurately portray the intricacy of this topic in its entirety.

Regarding soil sample depths, (Vaudour et al., 2022) highlighted the wide range of sample depths used in literature studies in addition to the lack of a complete characterization of other relevant management conditions. The importance of sample depth and its effect on SOC stocks has been highlighted (Olson and Al-Kaisi, 2015), concluding that optimal depth should correspond with the root zone (e.g., 1–2 m). However, this contributes to the challenge related with the cost of the analysis as well as the Intensity and laboriousness of the task.

Bulk density not only affects the flow of water and oxygen within a soil profile and the availability of nutrients but could also be source of large uncertainties when estimating SOC stocks. Overall, bulk density differed among land management uses and over time, with usually greater bulk densities under no-till cropping systems during the first years of implementation when compared with conventional management (Li et al., 2020). SOC stocks should always be estimated as an equivalent mass in order to reduce uncertainties in the results analysis (Wendt and Hauser, 2013). Unfortunately, many studies do not correct soil thickness based on difference of bulk density across management practices, resulting in one of the main reasons for high uncertainty in SOC storage estimates (Walter et al., 2016), specifically when comparing the effect of management practices (Wendt and Hauser, 2013). Attempts are also made to substitute missing bulk density data on soil database covering large scales. (Xu et al., 2016) compared several methods and reported that statistical methods involving the mean and median tend to overestimate the SOC storage by 50%, while methods using pedo-transfer functions underestimated the SOC by 8%, with a decreasing accuracy with sampling depth.

In terms of laboratory procedures for determination of soil C concentration, wet oxidation and dry combustion are the two most often used procedures (Davis et al., 2018; Meersmans et al., 2009), despite efforts to establish the latter one as the norm. This leads to another source of uncertainty when comparing soil libraries and samples from various times and years. Wet oxidation methods fail to completely oxidize SOC, resulting in an underestimation of the SOC content. A recovery factor of 1.33 is usually found in the literature, and used to estimate the total SOC, however this factor must be changed based on land use, soil type, climate, depth, and other variables (Tivet et al., 2012). Vaudour et al. (2022) advise adding this information to the metadata in order to compare varied sources and the same source across different periods in order to partially mitigate this issue. In addition, the intrinsic error associated with the laboratory (equipment and technicians) is another factor that should be included in the metadata, especially if data from different laboratories will be compared (Mountier et al., 1966).

The selection of an appropriate model of SOC estimation, has a significant impact on the uncertainties associated with the final estimate. Various modeling techniques can be employed. Many published studies use multivariate methods, with partial least squares regression as the most prevalent option. In recent years more complex algorithms such as support vector machine, artificial neural networks, random forest, Bayesian analysis, hybrid and ensemble models have become increasingly common due to enhanced computer power and cloud computing (Tajik et al., 2020). These machine learning methods can effectively account for nonlinear data relationships and integrate supplementary variables in the learning process. Due to the fact that SOC dynamics and correlations with other variables are often non-proportional and even non-monotonic (Croft et al., 2012), nonlinear techniques become a core requirement for analyzing SOC dynamics. The proper model selection, hence, is determined by the available data, objectives, and level of understanding of underlying processes.

The remote sensing-based uncertainties (i.e., last group) are associated with (i) spatial resolution, (ii) image pre-processing, (iii) the spectral properties of the targeted soil (soil moisture, cover, soil type, etc.), and (iv) temporal analysis when assessing SOC. Insufficient spatial resolution can significantly limit the accuracy of SOC estimates via remote sensing. Remote sensing data may lack the granularity to differentiate between various SOC levels on the ground and this type of pixel mixing can result in erroneous estimations (Zhou et al., 2021).

In addition, image pre-processing steps such as atmospheric correction, absorption effects, and topographic effects are frequently implied but not explicitly stated in the literature. Differences in pre-processing procedures and lack of universal ARD (analysis ready data) standards can contribute to wrongful assessments, especially when looking at the same area at different times.

Soil moisture may alter the precision of remote sensing based SOC estimates (Jiang et al., 2016). The reflectance of the soil surface, depends on soil moisture that may indirectly control SOC retrievals via impacts on surface reflectivity (Nocita et al., 2013). Similarly, the presence of surface cover may further influence the precision of SOC estimates via its impact on surface reflectivity (Angelopoulou et al., 2019; Chabrillat et al., 2019). Variations in the spectral reflectance signature of the soil may also impact the precision of SOC given the influence of soil type, mineralogy, texture and SOC concentration, (Dematte et al., 2009; Liu et al., 2018; Castaldi et al., 2016; Gholizadeh et al., 2018). These potentially confounding features and complexities become even more relevant when the assessments are extrapolated to larger areas, since heterogeneity is more likely to be part of the landscape.

In terms of temporal analysis (i.e., intra and inter-year) the literature is considerably scarce on the topic. For example from the perspective of the resolution and time of satellite data acquisition, Vaudour et al. (2019) found that the image date has an impact on the SOC assessment, while Shi et al. (2022) highlighted that a multitemporal composite consistently outperformed single-date images.

To quantify changes in-field SOC and the impact of different management practices over C stocks, long term analysis is required along with diachronic assessments to improve the accuracy of SOC accumulation rates (Costa Junior et al., 2013). The Food and Agriculture Organization of the United Nations (FAO), for example suggest 5 to 10 years before impacts can be measured (Lefevre, 2017). In this sense the literature is still scarce even with decades old satellite missions, such as Landsat, being available. In addition, the conversion rate of biomass inputs to SOC can be highly variable based on management practices. For example, Fujisaki et al. (2018) assessing 48 tropical studies observed a mean conversion rate of C inputs to SOC of 8.2% with a range from −7.3 to 35.6% with biomass-C inputs being the main predictor of SOC accumulation rate. The conversion rate of biomass to C could depend on factors such as no-tillage, use of cover crops, rotation, restitution of biomass inputs, and years of implementation. This highlights the need to have a clear description of agricultural practices along with soil attributes.

4. Future perspectives

Fujisaki et al. (2023) called for a harmonized thesaurus to give genericity to the terms describing land use and management practices across large soil database for the evaluation of soil carbon storage. The authors proposed a hierarchical tree based on three main management practices (i.e., annual and perennial croplands, grasslands, and forest and tree plantations) subdivided on land managers' point of view including plant, biomass, amendments management but also erosion, fire, and land clearing management. This being one example, the absence of a uniform and well-established ground-based protocol for SOC estimation is one of the major obstacles in the field. This is owing to a wide range of sampling strategies (such as sample depth, density, and bulk density) and laboratory tests (such as dry combustion and wet oxidation), which have led to inconsistent methodologies for SOC measurement and evaluation. This prevents us from accounting for unbiased estimations and from establishing a foundation for more knowledgeable contributions of each biome, ecosystem, crop, and activity to the overall C system. A first step to help accelerate and upscale the use of remote sensing tools to address C dynamics, should lean towards a deeper understanding of the effect of sampling density to cover the variability and diversity of soil type at catena scale, sampling depth, soil thickness corrected by bulk density, sampling dates, historical information, management practices, and laboratory methods for different soil types around the world (Fig. 1).

The increasing presence and potential democratization of hyperspectral systems such as the Environmental Mapping and Analysis Program (EnMAP) launched on April 2022 and emerging HIS systems such as Copernicus Hyperspectral Imaging Mission for the Environment (CHIME, collaboration between European Space Agency and US National Aeronautics and Space Administration, ESA-NASA), Tanager (Planet), and TD-2 (Pixxel) embrace the opportunity for significant science innovations. These systems have the potential to deliver higher resolution and accuracy in SOC evaluations, playing an essential role in enhancing our comprehension of the effects that agricultural management practices have on the terrestrial storage of carbon. Still, uncertainties presented previously, associated with spatial resolution, image pre-processing, and temporal assessment hold valid for this technology as well.

The estimation of SOC is a complex and multidimensional issue, affected by various factors as highlighted in this discussion paper. To achieve more accurate and consistent SOC estimations, it is necessary to establish uniform protocols, generate consensus, and develop true transdisciplinary efforts to better account for the complexity of biological processes, variability and diversity of agricultural landscapes around the world. A concerted effort by the scientific community to tackle these challenges and develop a more comprehensive approach is crucial for achieving sustainable goals and moving forward relevant efforts on long-term food security.

5. Conclusions

This study discussed the current challenges, limitations, and next steps related to advancing the use of remote sensing to monitor terrestrial C in croplands. The major limitations for expanding this discipline are linked to: (i) lack of consensus in sampling density and depth, (ii) lack of proper bulk density assessment, (iii) lack of standard laboratory procedures, (v) lack of details on imagery pre-processing steps, (vi) missing information on the spectral properties of the targeted soil, and (vii) lack of multi-temporal approaches. Our ability to accurately quantify SOC and its dynamics in space and time comes down to how well we can address and resolve these obstacles.

In summary, this study highlights the need for standardized protocols in terms of ground-truth data collection and remote sensing approaches, along with an improved understanding of the interlinked impacts of differences in soil types, land use, and landscape heterogeneity on C assessment.

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CRediT authorship contribution statement

Luciana Nieto: Conceptualization, Data curation, Investigation, Project administration, Resources, Writing – original draft, Visualization, Writing – review & editing. **Rasmus Houborg:** Writing – review & editing. **Florent Tivet:** Writing – review & editing. **Brad J.S.C. Olson:** Writing – review & editing. **P.V. Vara Prasad:** Writing – review & editing. **Ignacio A. Ciampitti:** Conceptualization, Funding acquisition, Project administration, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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