

Monitoring Land Degradation from Space

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Abstract

Unsustainable practices and increasing pressure on soil jeopardise the achievement of land degradation neutrality, targeted by 2030. Land degradation is costing billions in terms of land restoration and is heavily impacting human health and climate change. Sustainable Development Goals' (SDGs) target 15.3 focuses on the issue, and several methodologies are proposed to address land degradation. However, all present some limitations in terms of accuracy. This paper aims to present a more comprehensive approach based on the application of remote sensing technology. We show that the Copernicus Sentinel-1 and Sentinel-2 satellite imagery archives can be used on the one hand to detect the current soil conditions, on the other hand to predict the future balance of Soil Organic Carbon (SOC). A case study illustrates that SOC, tillage and bare soil are key quality indexes that can facilitate quantifying and achieving a land degradation-neutral world.

Keywords: land degradation, soil quality, soil organic carbon

1 Introduction

Soil is a complex ecosystem that hosts several organisms and influences several services and mechanisms, such as water quality, food production, and climate regulation. Moreover, soil is a crucial non-renewable resource for humankind and its economic system (European Commission, 2020).

The Sustainable Development Goals (SDGs) try to establish a transnational commitment to promoting more sustainable management of Earth resources (Mancebo, 2015). Sustainability, intended as the *“dynamic and unstable equilibrium between the natural and social systems capability to soak in shocks, keeping their functions, without collapsing (resilience), and losing that capability (vulnerability)”* (IAEG-SDGs, 2016), represents the common theme of the whole framework. Whereas the previous Millennium Development Goals presented an independent list of objectives, the 2030 Agenda establishes a systematic foundation for sustainability, where the single SDGs are not 17 separate purposes but interlinked goals requiring systemic planning and intervention.

This close interconnection is clear with regards to soil: food security (SDGs 2 and 6) and safety (SDG 3), mitigation and adaptation to climate change (SDG 13) and sustainability of terrestrial

ecosystem services (SDG 15), for instance, all directly depend on soil conditions, while indirect correlations with other SDGs (e.g., 7, 12) can be easily identified. Moreover, a specific target (15.3) has been established to combat land degradation (Tóth et al., 2018).

Land degradation represents one of the main threats for the Earth and its inhabitants: it affects at least 3.2 billion people and costs about €5.5-10.5 trillion per year and 10% of the annual global gross product in terms of biodiversity and ecosystem services. In addition, land degradation and climate change feed mutually (Keesstra et al., 2018; IPBES, 2018). According to Keesstra (2018), it is possible to identify three types of land degradation: physical, chemical, and biological. Physical degradation refers to phenomena like erosion and compaction, which imply the dislocation and relocation of soil particles without modifying their chemical composition. In contrast, chemical degradation also involves such alteration, for example, in case of overuse of fertilisers, insecticides, and herbicides, or inadequate water management, leading to salinisation of (semi)arid regions. Biological degradation refers to loss of Soil Organic Matter (SOM) connected to change in land destination (e.g., the conversion of forests in arable lands). This overview underlines, even more, the interconnection between land degradation and the entire sustainable development framework and poses an urgent challenge: on the one hand, water management (SDG 6), responsible production (SDG 11), and sustainable economic growth (SDG 8) are negatively impacted by land degradation; yet, on the other hand, the targets of other SDGs related to food, health, water, and climate, pose a high pressure on land and soil.

Looking at SDGs, target 15.3 calls for “land degradation neutrality - LDN” as “a state whereby the amount and quality of land resources necessary to support ecosystem functions and services and enhance food security remain stable or increase within specified temporal and spatial scales and ecosystem”. LDN is measured (in hectares or km²) by indicator 15.3.1 as the “proportion of land that is degraded over total land area” (IAEG-SDGs, 2016) and by three sub-indicators referring to land cover (measured as Land Cover Meta Language - LCML), land productivity (indicated as Net Primary Production - NPP) and carbon stock (expressed as Soil Organic Carbon - SOC) (UNSD, 2018).

In practical terms, the United Nations Convention to Combat Desertification (UNCCD) called for the application of remote sensing to monitor land degradation, and several satellite-based methods already provide an algorithm for calculating 15.3.1. This paper aims to promote a more comprehensive analysis for the design of supporting tools to help especially farmers turn SDGs’ commitments into agricultural practices.

2 Materials and Methods

In order to improve the understanding of the primary soil degradation dynamics, it is necessary to ensure the interconnection of a broad network of data and monitor them at a global scale. The methodology we propose differs from traditional and other satellite-based studies. It defines soil texture, weather conditions, agronomic intervention (tillage, fertilisation, etc.) and anthropic elements directly from satellites instead of using land cover maps to precisely predict carbon balance. Both historical and real-time data about carbon balances allow to forecast the impact of agricultural practices and to support the farmer in optimising their application.

In particular, data from Sentinel-1 (S1) and Sentinel-2 (S2) on agricultural areas are used, with the aim of creating binary maps of the variations in surface roughness related to tillage practices and the related loss or storage of carbon in the soil. The adopted strategy includes a pre-processing phase for both sensors and final modelling of data consolidation and correlation. The multispectral data underwent a classification and a pre-processing of some indices such as the selection of values <0.36 NDVI (normalised difference between band 8 and 4) and Normalized Burn Ratio 2 (NBR2) index thresholds from 0,05 to 0,1, which helped to identify the bare or sparsely vegetated soils where tillage practices are usually performed.

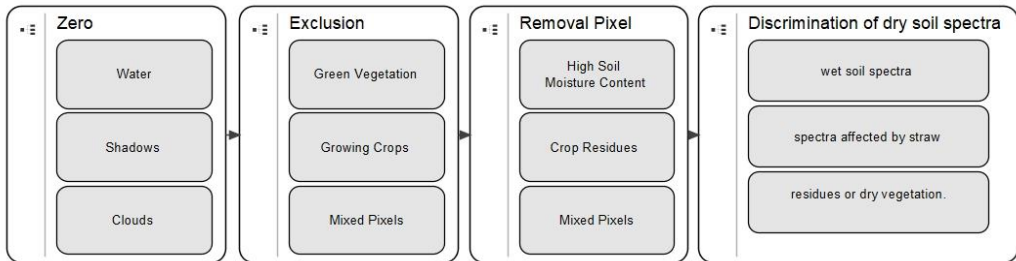


Figure 1: The image masking process

The SAR data, on the other hand, were used for detecting the processing change. The pre-processing of the S1-SLC images was accomplished using SNAP Toolbox S1. In the second phase, the adjacent meteorological stations within a radius of three km were added to the study and sorted for the hourly frequency close to the satellite pass. This allowed us to mask pixels that received more than 1 mm of rain within the five hours before image capture.

The pre-processing chain for SLC images consists of applying precise S1A orbits, calibrating, removing thermal noise, de-bursting and ground correction with SRTM 1 sec. The values of the digital numbers have been converted to dB scale with a backscatter coefficient with a resolution of 25 m. Analysing the temporal changes of S1 on the VH polarisation allowed us to identify the variations due solely to tillage practices since the roughness of the surface on agricultural land varies unevenly in space. In contrast the soil humidity usually varies uniformly (Mercier et al., 2020). The analysis of S2 data concentrated on two spectral wavelength ranges: 700-865 nm and 1375-2190 nm. These spectral ranges were selected since the Near Infra-Red (NIR), and the Short Wave Infra-Red (SWIR) regions have spectral characteristics associated with SOC (Sorenson et al., 2017). The algorithm was validated by observing various types of tillage practices collected at different sites. Among the study areas, we selected three homogeneous cereal crops farms: two practice conservation agriculture and the third traditional agriculture. In addition, 16 samples (8 before and 8 after tillage) were collected at 0-30 cm depth and used for validating the satellite data.

The temporal changes of S1 on the VH polarisation are shown in Figure 2 and allow us to identify the processing mechanisms that took place on the different soils. It is clear that traditional processing affects more the VH polarisation. On the other hand, in Figure 2, it can be seen that the unploughed soil does not go under any variation of VH polarization between one crop and another.

The presented methodology allows to create soil tillage change maps from S1 data. The methodology based on multiscale time change detection on S-1 VH-backscatter on bare soil areas or poorly vegetated areas has an overall accuracy of tillage/no-tillage land identification of 90%. Based on the observations collected for the three agricultural lands, errors were found on the perimeter areas of the land due to delimitation trees or anthropogenic objects.

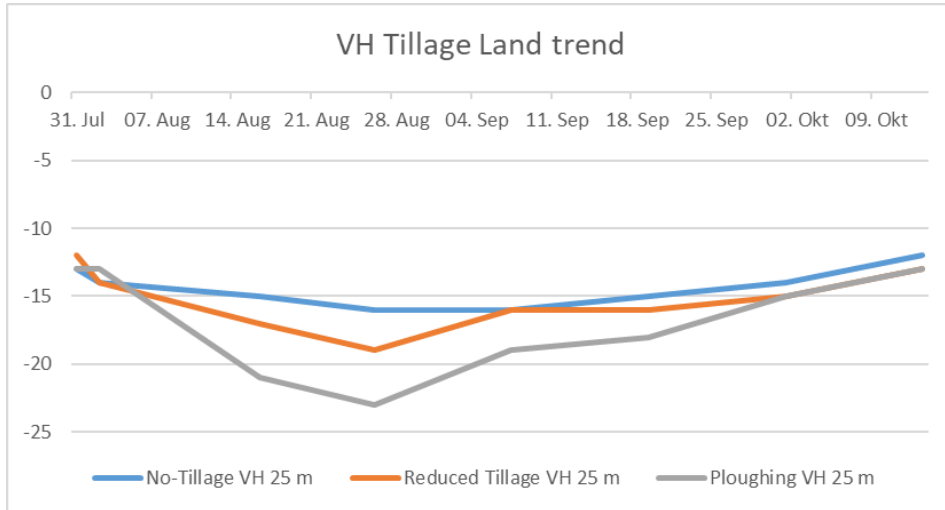


Figure 2: Monitoring of agricultural operations with the S1 VH polarisation in the pre-sowing period.

Once tillage was identified from the satellite, two models were developed based on Random Forest (RF) and Support Vector Machine (SVM) neural networks that use S2 images on the VNIR and NIR-SWIR bands. Each spectrum was pre-processed using Continuous Wavelet Transform (CWT) within the WMTSA package in R (Percival et al., 2016). Spectral data were calibrated against a pre-and post-processing SOC calibration dataset (Table-1).

Table 1: Summary of S2 elaboration and related validation of in-situ data.

Sensor	Parameter	SOC content %											
		No-Tillage				Reduced Tillage				Ploughing			
		SVM		RF		SVM		RF		SVM		RF	
		Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
	Bare Soil	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Data in Situ	SOC Validation Standard Deviation	0.26	0.26	/	/	0.28	0.23	/	/	0.29	0.18	/	/
S2	VNIR	0.27	0.29	0.32	0.3	0.31	0.24	0.29	0.24	0.28	0.19	0.32	0.21
	NIR-SWIR	0.22	0.21	0.25	0.24	0.25	0.19	0.23	0.14	0.22	0.13	0.26	0.17

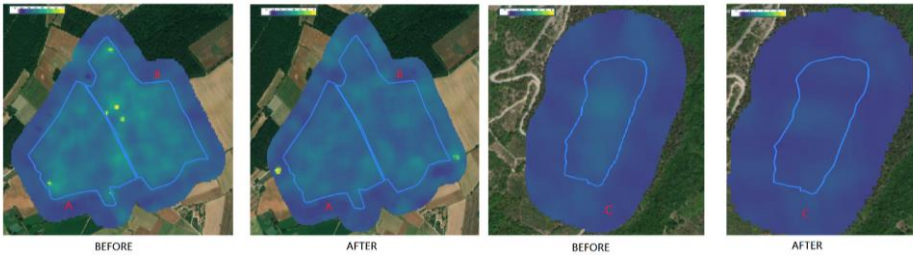


Figure 3: Annual graphical representation of S2 SOC data. The complete charts are available by [name deleted to maintain the integrity of the review process]. Study area A: No-Tillage; Study area B: Reduced Tillage; Study area C: Ploughing

Although the study analyses the variants that represent a different soil tillage system, it can be concluded that the no-tillage system is characterised by less impact on the soil and therefore favours a higher presence of organic carbon. Taking tillage into account, the use of reduced tillage compared to a no-tillage soil resulted in a 22% decrease in SOC. On the other hand, the land that has undergone conventional ploughing resulted in a 36% reduction in SOC, which means nearly twice the emissions of no-tillage. While in the case of a comparison between reduced tillage and conventional tillage, the latter is responsible for increasing 14% of soil organic carbon.

We believe that time series are fundamental to determine causes of carbon loss that are not visible with annual coring: SOC/soil ratio and soil tillage must be monitored over a medium/long period of time, and the satellite guarantees constant monitoring over the soil. In conclusion, as shown in Figure 4, the entire research is based on a 3D map adding an additional time dimension that enables to correlate the processing of agricultural land and SOC. The first dimension consists of a binary map (full 1-byte raster images) containing an information class on the cultivated/uncultivated land, the second dimension refers to the tillage monitored by S1 “tillage/no-tillage”. The third and last dimension contains the variation of the organic substance detected by S2 through a linear correlation between reflectance indices and in-situ data.

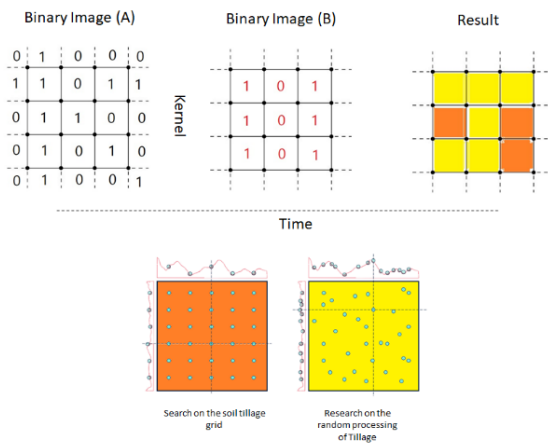


Figure 4:

Graphic representation of 3D map + Time. From the top left: cultivated/uncultivated land map; tillage/no-tillage grid; S2 SOC grid. The bottom part shows the resampling methods for homologating the different data resolutions.

Satellite data has helped demonstrate that farmers who implement these practices can significantly reduce soil erosion rates and indirectly increase the amount of organic matter in the soil. The same data can help farmers create a monitoring system of their land and their practices to further reduce the impact of agriculture on climate change. Further analyses will be carried out on the phenological cycles of 2020 and 2021 to train the neural networks better and reduce the error with in-situ data.

3 Conclusion

Many scholars and the United Nations themselves noted that the Millennium Development Goals (MDGs) missed a chance both in terms of purposes and methodology (Death & Gabay, 2015; United Nations, 2015). The post-2015 debate promoted vivacity for the definition of the “post”, which resulted in the creation of 17 new goals, the Sustainable Development Goals (SDGs), with 169 targets to be achieved by 2030.

Although several initiatives at transnational and European level have been launched, such as the Common Agriculture Policy (CAP) and the Zero Pollution Action Plan for Air, Water and Soil, to achieve the commitment on land degradation neutrality, there is no consensus about how to effectively pursue it. Our research (still ongoing in three areas in Italy and Germany) wants to contribute to the implementation of the SDGs framework with a bottom-up approach: while SDGs targets directly address governments, most land degradation processes take place in the private sphere, where farmers play a key role (Keesstra et al., 2018). The solution proposed in this paper suggests that this realignment can be facilitated by introducing an innovative monitoring system that promotes sustainable use and management of soil among farmers. The facilitation of soil monitoring and management at the farmers’ level will, on the one hand, improve SDGs accessibility and applicability. On the other hand, promote a uniform methodology, compliant to the international commitments (the 2030 Agenda) and the internationally recognised strategies to contrast global change, like the Intergovernmental Panel on Climate Change Guidelines.

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