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Mapping Nitrogen from Satellite Data to Improve Soil Quality - A Worked Example

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Abstract

Soils are complex ecosystems. They play a key role in providing sustainable life on Earth, meeting the needs of humans and regulating several environmental processes. The United Nation's 2030 Agenda for Sustainable Development and the related 17 Goals include a commitment to the preservation of soil quality. However, the adopted indicators lack the measurement of a key nutrient: nitrogen. The aim of this paper is to call for the integration of two nitrogen indexes to measure soil quality and to present a worked example of geospatial technologies applied to nitrogen monitoring, aiding in farmland management and decision-making. Due to their inherent time/location precision, remote sensing data can provide insight in predicting the impact of agricultural practices and optimise their application.

Keywords: land degradation, soil quality, nitrogen

1 Introduction

Soil quality is *"The capacity of a soil to function within ecosystem and land-use boundaries to sustain biological productivity, maintain environmental quality, and promote plant and animal health"* (Doran & Parkin, 1996). This definition reflects the complexity of soil ecosystems and destinations of use. The latter aspect is especially complex, as changes in land use may be slow, making it difficult to detect changes in soil quality before non-reversible damage occurs (Nortcliff, 2002). Hence, it is crucial to identify a comprehensive and practical set of indicators to support quality assessment.

An attempt to measure soil quality is represented by SDG-15 Life on Land, namely by Indicator 15.3.1, which introduces three key indexes to quantify the loss of biological or economic productivity, and complexity of land: Land Cover Meta Language (LCML); Net Primary Production (NPP), to measure land productivity; and Soil Organic Carbon (SOC), to measure carbon stock (Global Mechanism of the UNCCD, 2016). However, this framework overlooks another key indicator: nitrogen. Nitrogen is a crucial nutrient for plants, contributes to keeping water bodies and air clean, and relates to severe soil threats, such as: contamination, erosion, soil organic matter decline, and biodiversity loss (Else K., Bünemann et al., 2016). Moreover, nitrogen is positively correlated to carbon stock.

If duly integrated into the analysis, an explicit reference to nitrogen will lead to a more complete understanding of the factors that contribute to healthy soil, and therefore to appropriate actions and interventions (see Table 1).

Table 1: EU Soil Framework Directive (European Commission, 2006) soil functions and threats, SDG targets and indicators where nitrogen should be integrated.

Soil function	Soil threats	SDGs target	SDGs indicator
Biomass production; Storing, filtering, transforming nutrients,carbon pool	Sealing; Compaction; Biodiversity loss; Erosion; SOM decline	2.4	2.4.1
Physical and cultural environment for humans; Source of raw materials; Archive of geological and archaeological heritage	Contamination; Biodiversity loss	3.9	
Physical and cultural environment for humans; Source of raw materials; Archive of geological and archaeological heritage	Contamination	12.4	
Biomass production; Storing, filtering, transforming nutrients substances and water; Biodiversity pool; Physical and cultural environment for humans; Carbon pool	Erosion; SOM decline; Biodiversity loss; Landslides/floods	13.2	13.2.2
Biomass production; Storing, filtering, transforming nutrients, substances and water; Biodiversity pool; Physical and cultural environment for humans; Carbon pool	Erosion; SOM decline; Contamination; Sealing; Compaction; Biodiversity loss; Salinization	15.3	15.3.1
Storing, filtering, transforming nutrients, substances and water; Biodiversity pool; Physical and cultural environment for humans; Archive of geological and archaeological heritage	Erosion; Contamination; biodiversity loss; Salinization	15.5	

The aim of this paper is twofold:

- to underline that, in order to evaluate soil quality, it is advisable to include Soil Total Nitrogen concentration (STN) and Nitrogen Nutrition Index (NNI);
- to present a worked example of remote sensing and geospatial technologies applied to nitrogen monitoring, to aid farmland management and decision-making.

STN is a pivotal indicator of fertility and is closely related to agricultural productivity. Therefore, reliable prediction of STN is critical for supporting sustainable agricultural development (Lausch et al., 2019). Up to date STN maps are of great interest to identify spatial variation and control factors, which can help maintain soil safety and provide a reference for climate change management. NNI is a plant-based diagnostic method used to determine the crop nitrogen distribution and status, to optimize its management in farming systems.
Remote sensing allows for open, precise, real-time, and localised data to be obtained, about how nitrogen is organized in soils or used by plants. Unlike traditional in-situ methodologies, it can show the impact of agricultural practices on large areas. Furthermore, when merged with other pieces of information, remote sensing supports the identification of the most suitable practices for each given soil. A seemingly passive monitoring tool subsequently turns into a

proactive planning methodology, supporting farmers to implement good practices strictly connected with the achievement of SDGs. For example, geospatial data concerning the loss of nitrogen in the atmosphere due to tillage interventions may suggest that crop rotation stores more nitrogen in the soil and increases its quality.

The outcome of our work is a dynamic, real-time nitrogen map conceived to help farmers to understand where and when to use fertilizers, usually containing nitrogen, and to promote sustainable soil management practices, such as crop rotation.

2 Materials and Methods

We considered the Sentinel-1 (S1) VH (vertical transmitted, horizontal received) and VV (vertical transmitted, vertical received) polarization modes, and computed the ratio VV/VH, which is less sensitive to vegetation cover (Vreugdenhil et al., 2021). SAR images are instrumental for mapping soil properties: Yang et al. (2019) demonstrated their correlation with in-situ data and possible errors in the sensitivity of backscatter intensity, changes in soil moisture, and soil surface conditions. They found a significant correlation between SAR backscatters and various soil properties (including SOC and STN) during the growing season and demonstrated that multi-temporal SAR data are useful for predicting soil chemical properties because they can capture soil properties. Also factoring in Maynard et al. (2017), we replicated their methodologies and tested them in our case study. Firstly, we examined the temporal variation of the canopy of Sentinel-2 (S2) vegetation and the soil-to-vegetation ratio using level-1 Single Look Complex (SLC) data from S1, we then built correlation models with in-situ data to predict soil properties. A total of 28 S1 and 22 S2 images were acquired during the soils' growing season.

Two sections of land were studied in an agricultural area of Po Valley (Northern Italy). Both study sites had crops in rotation (wheat/protein pea), undergoing minimal processing for five years: one section subject to Conservation Agriculture (CA), the other an Ecological Focus Area (EFA). Each area spanned three hectares. A comparison was therefore enabled for the two areas in the same environmental and cultural conditions but with different processing approaches.

Within the study area, we sampled thirty-six surveys of SOC and STN data over three years, including land use data and various soil texture data (0-10 cm - 10-30 cm). We then integrated the ground data with the SoilGrid-250 maps and LUCAS datasets, obtaining six additional samples useful for SOC (note that LUCAS does not contain information to validate NNI).

We pre-processed the SAR data utilising the ESA open-source Sentinel Application Platform (SNAP) toolbox, as depicted in the workflow in Figure-1 (Zhou et al., 2020). Finally, the S1 data were converted to dB scale with a backscatter coefficient with a resolution of 10 m. As for optical data, we downloaded L2 images, masking clouds and shadows and homologating the grid to the S1-data using a Digital Elevation Model at 10 m as a trace. We then calculated the backscatter coefficients of the VH and VV polarizations from the S1-images.

From the S2 MultiSpectral Instrument (MSI), we extracted the B2, B3, B4, B8A, B11, and B12 bands and computed the Normalized Difference Vegetation Index (NDVI), the Modified

Chlorophyll Absorption in Reflectance Index (MCARI), the Enhanced Vegetation Index (EVI), and the Soil Adjusted Total Vegetation Index (SATVI); to be used as SOC's predictors (Gholizadeh et al., 2018).

Following Zhou (2020), we processed the S1/S2 data using machine learning models to predict and model nitrogen maps. We built three models using S1, S2, S1/S2 images across Boosted Regression Trees (BRT) and Support Vector Machine (SVM) with three validation criteria: Root Mean Square Error (RMSE), coefficient of determination (R2), and Mean Absolute Error (MAE).

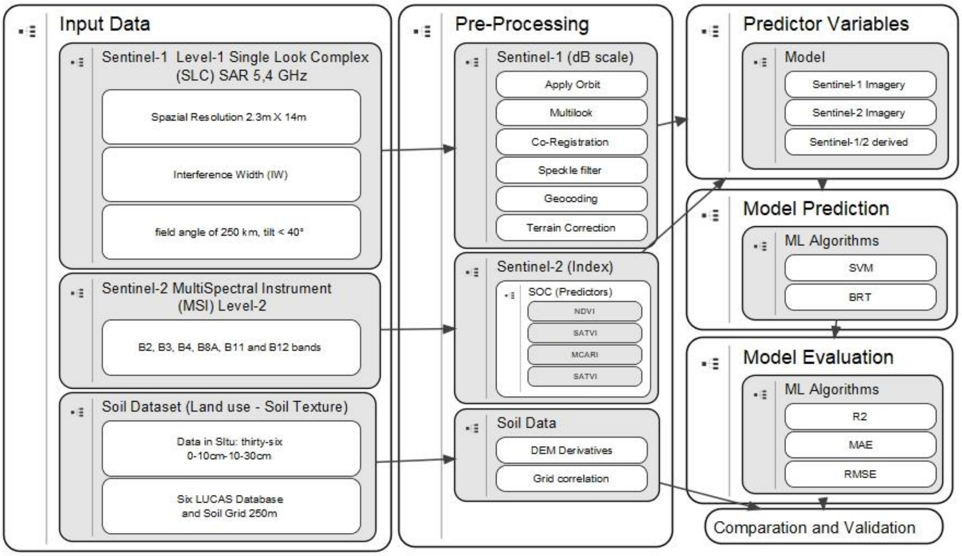

Figure 1: Summary of input data and related pre-processing workflow

The results in Table 2 confirmed the in-situ sampling data: crop rotation, applied on both areas, increases the SOC and STN levels, as foreseen by the literature. Both the EFA and the CA areas increased their nitrogen and carbon stocks over the three years. However, due to higher temporal sampling and a shorter review time, the satellite data highlight an additional dynamic, undetected by in-situ samples. Between one crop rotation and the next, the satellite can show the actual nitrogen loss, mainly due to processing, washout, and wind. For example, even if the EFA area did not undergo tillage in 2018, it suffered a substantial loss of nitrogen, unobserved by in-situ samplings, only highlighting the overall nitrogen and carbon balance, but not helping farmers to understand where to improve or identify any cause. Instead, the satellite shows what happens in a specific time frame and allows, using machine learning, to correct errors based on data and problems faced in the past. For example, in the EFA case, we could report to the farmer that the sowing process on sod was inaccurate in 2018; in addition, we could signal to postpone sowing for a week, due to very wet soil, resulting in abrupt losses due to ground runoff and wind. In the CA area, we could warn against the use of compost in 2018, postponing it to 2019, when it was needed, resulting in a positive balance of nitrogen in 2020.

Maximum prediction accuracy was achieved for S1/S2 models, suggesting that multi-source approaches may be preferable for monitoring soil properties. Notably, SVM gave better results for CA, whereas BRT did for EFA.

Table 2: Model outputs for three years on the two case study areas, rotating wheat (grey) and protein pea (white) culture. The best correlations of satellite data with in-situ data are in green. The validation data in the two rightmost columns were obtained from the LUCAS database and in-situ data.

Modelling technique / Sensor	Year	Farmland	STN BRT MAE	STN BRT RMSE	STN BRT R2	STN SVM MAE	STN SVM RMSE	STN SVM R2	SOC BRT MAE	SOC BRT RMSE	SOC BRT R2	SOC SVM MAE	SOC SVM RMSE	SOC SVM R2	Analysis Standard Deviation SOC	Analysis Standard Deviation STN
Sentinel-1, Incident Angle ~44, SLC, IW, Descending VV/VH	2016 Balance	CA	0.26	0.33	0.09	0.22	0.28	0.08	0.21	0.28	0.08	0.22	0.34	0.05	0.34	0.22
			0.28	0.39	0.07	0.26	0.30	0.15	0.22	0.34	0.13	0.24	0.36	0.07		
		EFA	0.23	0.22	0.16	0.24	0.21	0.05	0.30	0.33	0.13	0.29	0.40	0.04	0.39	0.21
			0.29	0.28	0.12	0.25	0.22	0.06	0.32	0.35	0.14	0.26	0.41	0.06		
	2018	CA	0.41	0.48	0.24	0.37	0.43	0.23	0.36	0.43	0.23	0.37	0.49	0.20	0.36	0.23
			0.27	0.39	0.07	0.26	0.30	0.14	0.22	0.33	0.13	0.24	0.36	0.07		
		EFA	0.31	0.30	0.25	0.32	0.30	0.13	0.38	0.41	0.21	0.37	0.48	0.12	0.42	0.26
			0.31	0.30	0.14	0.27	0.24	0.08	0.34	0.37	0.16	0.28	0.43	0.10		
	2020	CA	0.50	0.57	0.33	0.46	0.52	0.32	0.45	0.52	0.32	0.46	0.58	0.29	0.37	0.25
			0.27	0.39	0.06	0.25	0.29	0.14	0.21	0.33	0.13	0.24	0.36	0.07		
		EFA	0.31	0.30	0.25	0.32	0.30	0.14	0.38	0.41	0.21	0.37	0.48	0.13	0.43	0.27
			0.35	0.34	0.18	0.31	0.28	0.12	0.38	0.41	0.20	0.32	0.47	0.14		
Sentinel-2, L2A, No clouds, B2, B3, B4, B8A, B11 e B12	2016 Balance	CA	0.24	0.29	0.11	0.22	0.28	0.08	0.21	0.28	0.08	0.22	0.34	0.05	0.34	0.22
			0.22	0.24	0.14	0.19	0.27	0.04	0.21	0.23	0.05	0.21	0.31	0.03		
		EFA	0.21	0.21	0.17	0.24	0.19	0.04	0.31	0.32	0.12	0.31	0.35	0.06	0.39	0.21
			0.27	0.26	0.14	0.23	0.21	0.05	0.32	0.35	0.13	0.27	0.27	0.07		
	2018	CA	0.38	0.42	0.29	0.37	0.43	0.23	0.36	0.43	0.23	0.37	0.49	0.20	0.36	0.23
			0.22	0.24	0.13	0.19	0.27	0.04	0.21	0.23	0.04	0.20	0.31	0.03		
		EFA	0.28	0.29	0.25	0.32	0.26	0.10	0.39	0.40	0.20	0.40	0.42	0.17	0.42	0.26
			0.28	0.27	0.16	0.24	0.22	0.06	0.34	0.37	0.14	0.29	0.28	0.12		
	2020	CA	0.46	0.50	0.40	0.46	0.52	0.32	0.45	0.52	0.32	0.46	0.58	0.29	0.37	0.25
			0.22	0.24	0.13	0.19	0.26	0.04	0.21	0.23	0.04	0.20	0.31	0.03		
		EFA	0.29	0.29	0.26	0.32	0.26	0.10	0.40	0.40	0.20	0.40	0.42	0.17	0.43	0.27
			0.32	0.31	0.20	0.28	0.26	0.10	0.38	0.41	0.18	0.33	0.31	0.16		
Sentinel-1-2	2016 Balance	CA	0.19	0.21	0.19	0.21	0.31	0.10	0.19	0.24	0.19	0.22	0.28	0.21	0.34	0.22
			0.23	0.32	0.05	0.21	0.21	0.14	0.18	0.27	0.12	0.20	0.27	0.37		
		EFA	0.28	0.17	0.36	0.29	0.28	0.08	0.37	0.43	0.14	0.36	0.48	0.24	0.39	0.21
			0.34	0.23	0.32	0.30	0.29	0.09	0.39	0.45	0.15	0.33	0.49	0.26		
	2018	CA	0.46	0.43	0.44	0.42	0.50	0.26	0.43	0.53	0.24	0.44	0.57	0.40	0.36	0.23
			0.32	0.34	0.27	0.31	0.37	0.17	0.29	0.43	0.14	0.31	0.44	0.27		
		EFA	0.36	0.25	0.45	0.37	0.37	0.16	0.45	0.51	0.22	0.44	0.56	0.32	0.42	0.26
			0.36	0.25	0.34	0.32	0.31	0.11	0.41	0.47	0.17	0.35	0.51	0.30		
	2020	CA	0.55	0.52	0.53	0.51	0.59	0.35	0.52	0.62	0.33	0.53	0.66	0.49	0.37	0.25
			0.32	0.34	0.26	0.30	0.36	0.17	0.28	0.43	0.14	0.31	0.44	0.27		
		EFA	0.36	0.25	0.45	0.37	0.37	0.17	0.45	0.51	0.22	0.44	0.56	0.33	0.43	0.27
			0.40	0.29	0.38	0.36	0.35	0.15	0.43	0.51	0.21	0.39	0.55	0.34		

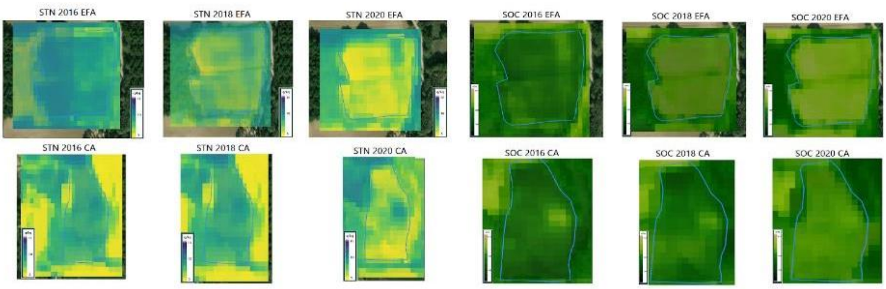

Figure 2: Annual graphical representation of STN-SOC data. The complete charts are available by [name deleted to maintain the integrity of the review process].

To produce NNI maps, we first pre-processed the satellite data to obtain biophysical variables such as: Leaf Area Index (LAI), Fraction of Vegetation Cover (FVC), and Chlorophyll Content of the Canopy (CCC). We used the biophysical processor inside SNAP to retrieve the variables: LAI_S2, CAB_S2, CCC_S2, which include all the green parts of the Green Area Index (GAI) plant. We assumed a linear relationship from the biophysical indices with the Actual quantity of Vegetable Nitrogen (PNUa) and the specific BioMass above ground (BM) to derive the Critical absorption of Vegetable Nitrogen (PNUc), according to a specific dilution curve of the crop. The methodology consists of calculating PNUa directly from CCC using linear relationships and then obtaining PNUc by estimating BM from the GAI data. NNI can then be calculated from the PNUa and PNUc estimations. We finally calculated the soil quality at the end of each phenological cycle as the sum of the total nitrogen in the crop (NNI) and in the soil (STN).

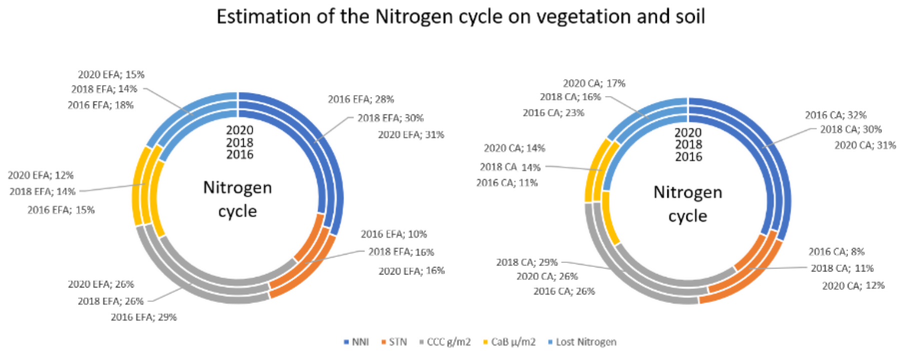

Figure 3: The graphs show an estimated "nitrogen cycle" for the CA (left) and EFA (right) areas over the three years of satellite monitoring. The cycle takes into account the nitrogen fixed by the crops, the nitrogen volatilization and the nitrogen in the soil.

In general, both fields were composed of very fertile clayey soil (67%), indicated in Table 1 by the high content of SOC (6-8%). Figure 3 highlights the importance of crop rotation, which helped to strengthen the biological, physical, and chemical components in both soils. Figures 2 and 3 suggest that no-tillage (EFA) may ensure better soil conservation than reduced tillage (CA), but the yield, vigour, and nitrogen supply of both practices are similar. The biological components are responsible for various processes such as: atmospheric nitrogen fixation, disintegration and degradation of the soil and its organic components, increase of organic substance, and simultaneously greater vigour to the crops. In conclusion, with soils richer in SOC and nitrogen, the quality of "fertile" soil improved by 6% and 4% respectively for the EFA and CA areas over the three-years period.

3 Conclusion

Although limited to the presented worked example, the nitrogen map promotes a more accurate definition of soil quality, demonstrating the relevance of nitrogen, proved to increase the soil capacity to stock carbon. The study shows that high levels of SOC and nitrogen increase the fertility of soils, improve the production, and reduce the need for fertilizers. Moreover, by measuring the most relevant physical, chemical, and biological soil indicators, including nitrogen, the map offers an effective management tool for farmers, supporting them in implementing more sustainable practices.

Remote sensing proved to be a valuable ally in monitoring the entire phenological year for different farmlands. Satellite datasets allow access to historical data on a global scale every 6-days, and with a resolution precise enough (10 m) for monitoring the state of the soil. These datasets not only complement or enhance national and regional official data sources, especially when the latter are missing or incomplete, but also validate them due to satellites' time/location accuracy. The great advantage is having access to precise, historical, and locally calibrated data on a frequent schedule, which enables predicting the soil attitude to a specific treatment, supporting decision-making and management tools for farmers, such as the nitrogen map. In the future, we plan to present this tool to governments, to support countries in meeting their commitments in monitoring and reporting key soil quality indicators.

As shown in Table 1, several SDGs' targets and indicators are heavily interlinked with nitrogen functions, therefore should be integrated with its indicators to obtain a comprehensive overview of SOC stocks processes. By including one or more nitrogen indicators, the framework for the implementation of soil-related SDGs would better address the complexity of the soil ecosystem and its dynamics, facilitating the achievement and consolidation of Agenda 2030 both for farmers and policy makers. The former would be supported in applying sustainable practices; the latter would create more localised policies based on calibrated thresholds and indicators of soil quality.

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