

Remote sensing retrieval of plant traits and sub-pixel constituents in agriculture

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1. Introduction

In the current decade, the agricultural sector has seen increased interest in innovation and technology transfer to address challenges related to climate change and future economic and climatic scenarios. In the perspective of European Green Deal and the UE Climate Law, the importance of ecosystems in providing services to mitigate climate impacts, to restore and maintain biodiversity, to improve food security is acknowledged.

The forthcoming Common Agricultural Policy is expected to regulate mechanisms to reward those agricultural practices capable to increase carbon sequestration in soils and biomass. The establishment of Conservative Agriculture will be based on a set of practices such as the management of plant residues and non-photosynthetic vegetation (NPV), conservative soil management (tillage), cover cropping, et al. A large technical and scientific effort will be required for developing and/or improving adequate monitoring and verification methodologies, that are trusted, transparent and verified.

Near-real time information of the crop growth and status is important both to support farm management at the field level, and for policy makers to evaluate the ecosystem services and sustainability at regional scale. Remote sensing (RS) offers an efficient alternative to manual measurements by providing frequent and georeferenced information at a field- or large-scale with repetitive coverage. Optical sensors (multi- and hyperspectral) are widely used in agriculture for crop classification, land cover mapping, yield estimation, non-photosynthetic component quantification, plant stress detection, including also soil characterisation and soil carbon content estimation (Karmakar et al., 2023). Their application in plant characterization is based on the spectral radiation absorption features of the different components (Fig. 1). However, the traditional use and interpretation of the spectral optical data is often based on vegetation indices (VIs) using few spectral bands, empirical and non-physical based, preventing direct estimation and quantification of plant traits and surface pure components. The integration of remote sensing and biogeochemical modelling in a model-data fusion approach appears the key to overcome the limitations related on each specific tool. However, this requires the capability of extracting remotely sensed information at the proper spatial and temporal scale to be assimilated into crop models, overcoming some important limitations

1.1 Limitations of optical RS in regenerative agriculture monitoring

Remote sensing of surface land cover especially in the context of precision agriculture and regenerative agriculture is facing some limitations such as:

- The spatial resolution issue: conservative agriculture practices present spatial heterogeneity at fine spatial scale, e.g plant residues are combined with variable amounts of green vegetation and soil, resulting in 'mixed' spectral signatures where the effects are combined and very difficult to disentangle. This issue becomes more pronounced with coarser spatial resolution imagers, leading to the well-known mixed pixels issue (i.e. when more than one land cover class contributes to the spectral response of a single pixel).

- The soil coverage issue: remote sensing driven soil carbon estimates require the spectral signature of the soil to be acquired; if soils are kept covered with NPV, residues, cover cropping, in conservative agriculture practices, remote sensing fail in assessing directly the SOC, and will instead be focused on the assessment of soil cover properties. In addition, before the crop achieves full canopy cover, the soil background affects the signal acquired by the sensor, making it difficult to identify the crop status at early growth stages, when it is a critical period for taking decisions related to fertilizer-rate application.

Other issues are related to optical disturbances related to off-nadir view angle and different sun illumination geometries, impacting the spectral signature, the crop parameters retrievals and the transferability of the model to different dates or locations.

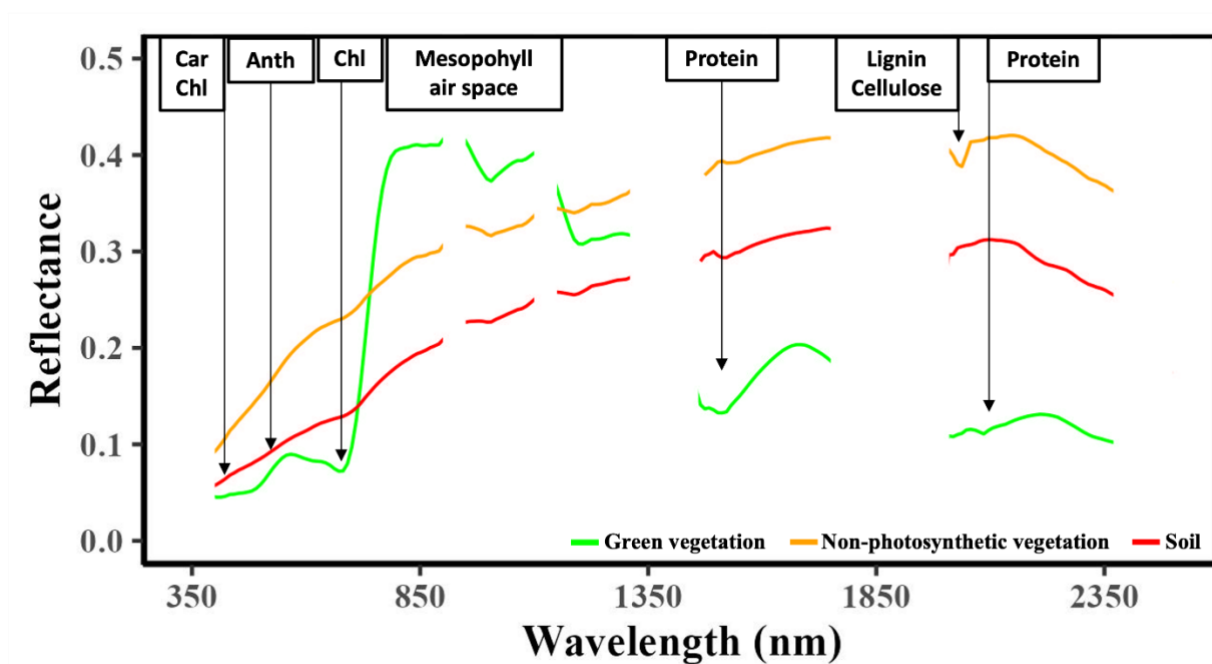


Figure 1. Reflectance spectrum (350 – 2350 nm) of green vegetation, non-photosynthetic vegetation and bare soil. Arrows indicate the absorption peaks of some important plant constituents. Car, Anth and Chl mean carotenoid, anthocyanin and chlorophyll, respectively.

In this perspective, a data fusion approach capable of retrieving plant traits, soil traits and carbon traits of surface and vegetation, disentangling spectral signatures from the different contributions, reducing the limitations of traditional RS techniques and potentially feeding data into biogeochemical is presented here.

2. Approach

This study aims to develop and validate a crop trait estimation pipeline based on integrating a hybrid artificial neural network and a radiative transfer model with satellite images.

Plant traits and carbon traits retrieval

Physical-based quantification of crop traits from a canopy reflectance spectrum was made with hybrid machine learning (ML) biophysical radiative transfer model (RTM) approaches. This technique relies on simulated spectra developed by the RTM that are used to train a ML model used to estimate the plant and carbon traits of observed spectral signatures (Feret et al., 2021).

The RTM PROSAIL-PRO model is used to provide information of key plant and carbon traits, such as leaf area index (LAI), chlorophyll content (Cab; $\mu\text{g}/\text{cm}^2$), water content (EWT; g/cm^2) or Carbon-based constituents (CBC; g/cm^2). PROSAIL-PRO also considers the external factors affecting the spectral signal of crops, such as the viewing and illumination geometry or the soil spectra.

The experimental design was based on a winter wheat field experiment with 16 plots, established during two consecutive years with 4 levels of nitrogen (N) and two levels of water. The model was applied to a time series of the multispectral Sentinel-2 bands acquired in each plot. The validation was performed by comparing the retrieved Cab and LAI with ground-truth data collected at three key growth stages. The chlorophyll content was measured with a Dualex leaf-clip sensor and LAI was obtained with a ceptometer. More detailed description of the experiment can be found at Pancorbo et al., 2021.

Spectral unmixing

To address the mixed pixel problem and quantify pure surface components at a sub-pixel level, spectral mixture analysis (SMA) techniques, especially the optimized Multiple Endmember SMA (MESMA) approach, have been proposed. MESMA assumes each pixel's spectrum is a mixture of signals from different components, providing a physical framework for disentangling land use contributions. The MESMA approach was tested in this study by monitoring the trends of agricultural practices followed by farmers during an exceptional multi-year drought period. The model was applied to yearly hyperspectral AVIRIS images (350 – 2500 nm) collected on the peak of the summer crops (July) between 2013 and 2018 over 2334 km^2 of the Central Valley, California. The land cover classes selected for this study were : bare soil, green vegetation (GV) and non-photosynthetic vegetation (NPV). The endmembers were selected from the pure pixels extracted for each class and date to develop a spectral library used to produce the fractional cover maps. The accuracy of the MESMA products was evaluated by comparing the temporal trends of the fractional covers of the crop fields with the official crop reports of the region. More information of the study can be found at Pancorbo et al., 2023.

3. Results

The Cab and LAI values estimated with the hybrid ML-RTM showed a good correlation with the Dualex and ceptometer measurements, allowing the identification between N levels (Fig. 2) even at early growth stages while outperforming the accuracy of the traditional VIs. In addition, the temporal dynamics of the retrieved crop traits matched the physiological development of the crop by correctly describing the growing and senescence seasons (Fig. 3). The retrieved values showed differences between N levels from early growth stages, even earlier than the traditional VIs. These results validate the capacity of the hybrid model of accurately retrieving specific plant traits.

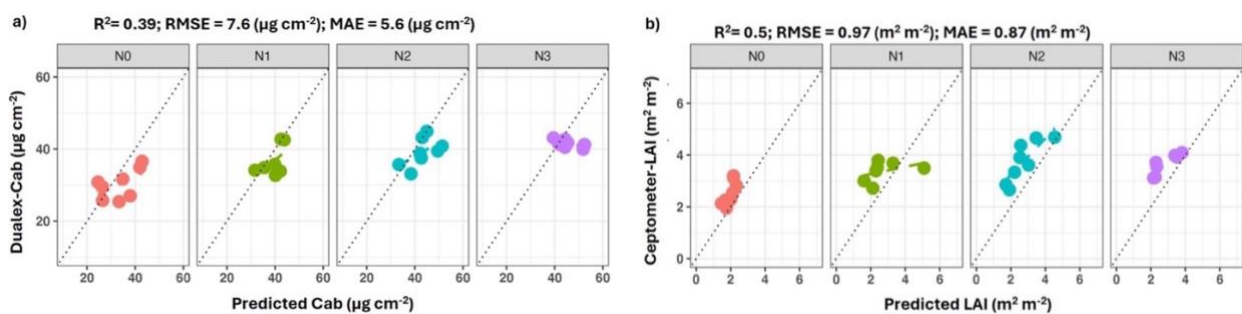


Figure 2. Relationships between a) chlorophyll content measured with Dualex and predicted with the hybrid model and b) leaf area index (LAI) measured with the ceptometer and with the hybrid model. Points represent the mean value of each plot and year grouped by N levels (N0, N1, N2, N3). The dotted line indicates 1:1.

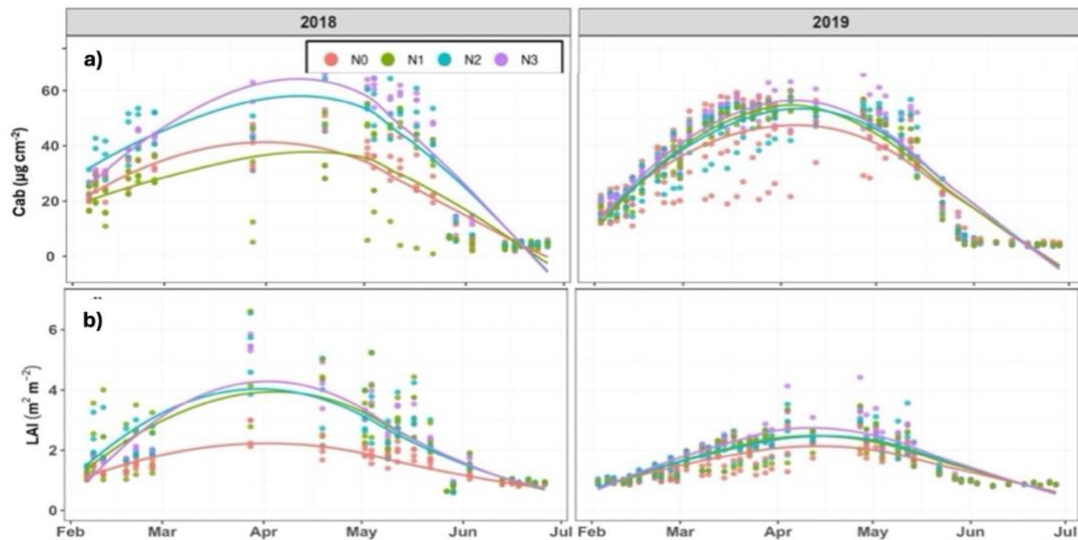


Figure 3. Temporal series of a) Chlorophyll content (Cab) and d) leaf area index (LAI) retrieved with the hybrid artificial neural network-PROSAIL model applied to Sentinel-2 in the 2018 and 2019 experimental years. Each dot represents the value of a plot, with colors representing the N level.

The performance of the MESMA approach for monitoring the pixel fractional covers showed a good agreement with official crop reports. Both datasets showed a reduction in GV area in the crop fields during the drought years, attributed to an increase in non-cultivated or abandoned fields due to water restrictions (Fig. 4). Additionally, RS data revealed an increase in bare soil area during the drought period, that was not provided by the official crop reports. The narrow shortwave infrared (SWIR) bands offered by the AVIRIS sensor, and in general by state of the art hyperspectral imagers, showed to be fundamental in distinguishing between bare soil and NPV.

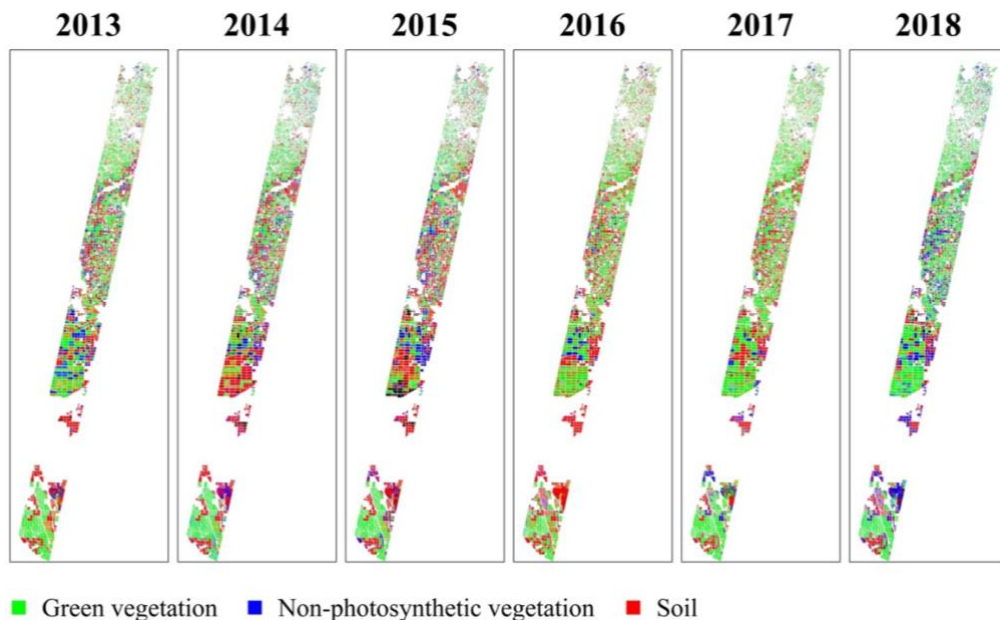


Figure 4. MESMA results of the AVIRIS images showing the fractional covers of green vegetation (green), non-photosynthetic vegetation (blue) and soil (red) in the field crops each year.

4. Conclusions

The hybrid models based on the biophysical RTM PROSAIL-PRO, allow the quantitative estimation of plant traits and carbon traits, while the MESMA spectral unmixing approach was able to discriminate the amount of NPV in terms of fractional cover per unit of area.

Despite good results were obtained when testing the hybrid model in the multispectral Sentinel-2 images, better results are expected when applying the model to other sensors with enhanced spectral and spatial resolution. This method will be applied on centimeter scale UAV full range hyperspectral sensing.

Finally, a framework to assimilate RS data into biogeochemical models will be adopted, since RS it is not able to estimate those carbon fluxes to the atmosphere, that result from heterotrophic and autotrophic respiration and decomposition of soil organic carbon. These aspects are expected to improve agricultural practices planning and obtain more reliable estimates of production and C and N fluxes in crop systems in the perspective of climate mitigation.

References

Féret, J.-B., Berger, K., de Boissieu, F. y Malenovsky, Z. (2021) "PROSPECT-PRO for estimating content of nitrogen-containing leaf proteins and other carbon-based constituents", *Remote Sensing of Environment*, 252, p. 112173. doi:10.1016/j.rse.2020.112173.

Karmakar, P., Teng, S.W., Murshed, M., Pang, S., Li, Y. and Lin, H., 2023. Crop monitoring by multimodal remote sensing: A review. *Remote Sensing Applications: Society and Environment*, p.101093.

Pancorbo, J. L., Camino, C., Alonso-Ayuso, M., Raya-Sereno, M. D., Gonzalez-Fernandez, I., Gabriel, J. L., Zarco-Tejada, P. J., & Quemada, M. (2021). Simultaneous assessment of nitrogen and water status in winter wheat using hyperspectral and thermal sensors. *European Journal of Agronomy*, 127, 126287. <https://doi.org/10.1016/j.eja.2021.126287>

Pancorbo, J. L., Quemada, M., and Roberts, D. A. (2023). Drought impact on cropland use monitored with AVIRIS imagery in Central Valley, California. *Science of The Total Environment*, 859, 160198. DOI: <https://doi.org/10.1016/j.scitotenv.2022.160198>