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Volume 3

Earth Observation: current challenges and opportunities for environmental monitoring

Edited by

Associazione Italiana di Telerilevamento
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4. CONCLUSION

In this research, we have introduced a workflow, encompassing two steps, designed for mapping crop residue coverage (CRC), exploiting spaceborne imaging spectroscopy from PRISMA data. Our workflow has yielded very satisfactory findings. First, we have demonstrated the fitness for purpose of the Exponential Gaussian Optimization (EGO) model. This approach has significantly enhanced the information content of the spectral intervals of interest, as related to plant pigments, canopy water, lignin-cellulose and clay minerals, while reducing the feature space from 230 bands to 16 metrics layers. Besides, the use of machine learning played a pivotal role to find a non-linear regression between this reduced space and Crop Residue Cover information. The use of a spectral library to train the Random Forest (RF) regressive model overcomes the issue of finding a large training sample, without the use of simulated data, whereas reaching very good levels of predictive capabilities. This is proved by applying the RF to independent field datasets and satellite images. In this regard, our mapping demonstration has yielded results that align with ground observations, underscoring the robustness of our approach. Moreover, the application of the model on datasets from two different crop seasons, shows similar performance, proving the model robustness and its temporal transferability.

In summary, our discoveries proved the substantial potential of PRISMA data in monitoring and quantify NPV, spanning from individual fields to farm scales. Our overarching objective is to further advance and refine this comprehensive model, ensuring its continued effectiveness over time and expanding its adaptability to a wide range of spatial contexts. In our future works, we will focus on rigorously assessing the model performance. This assessment will involve the use of ground-level Crop Residue Cover (CRC) data at the PRISMA scale, encompassing data from 2022 and 2023. These ground-level observations will serve as a valuable benchmark to evaluate the model performance under real-world conditions. Additionally, we plan to leverage PRISMA time series data to continuously monitor CRC dynamics. This approach will provide insights into how CRC changes over time and how well our model adapts to these variations. Furthermore, we intend to enhance the model capabilities by incorporating Radiative Transfer Model (RTM) simulations. This will expand the training dataset and account for a broader range of factors that influence reflectance, including soil moisture, different mixture of target presence and sensors viewing geometry. This refinement process aims to bolster the model accuracy and broaden its applicability to various environmental conditions. In summary, our future work encompasses three key objectives: 1) Testing the robustness of the CR model against field-collected ground data from 2022 and 2023, at the PRISMA scale; 2) Leveraging RTM simulations to augment the training dataset and to consider different factors influencing reflectance, such as moisture; 3) Continuously monitoring CRC dynamics using PRISMA time series data to assess changes in time due to agro-management and target decomposition. These efforts collectively aim to advance our understanding and application of NPV mapping, contributing to more accurate and versatile environmental assessments.

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LEAF AREA INDEX AND CANOPY CHLOROPHYLL CONTENT ESTIMATION OF ARABLE CROPS FROM SENTINEL-2 WITH GAUSSIAN PROCESS REGRESSION: A MULTI-SITE, YEAR AND CROP VALIDATION

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KEY WORDS: Machine Learning; Gaussian Processes Regression; BioPar; Sentinel-2

ABSTRACT:

Spatio-temporal estimation of crop bio-parameters (BioPar) is required for agroecosystem management and monitoring. BioPar such as Canopy Chlorophyll Content (CCC) and Leaf Area Index (LAI) contribute to assess plant physiological status and health at leaf and canopy level. Remote sensing techniques are instrumental in spatially explicit CCC and LAI retrieval of arable crops across different scales. Machine Learning (ML) techniques, especially Gaussian processes regression (GPR), has outperformed traditional approaches based on Vegetation Index in BioPar estimation. However, being ML model based on data driven approach it is necessary to thoroughly evaluate the performance of GPR across different sites, seasons, and crop types to assess the exportability of the models. This study aimed to develop a transferable GPR algorithm using a large dataset collected over several years (2018-2022), on different locations (5 sites) and with different canopy conditions by sampling 10 different arable crops. The study objectives included developing a robust GPR algorithm for LAI and CCC estimation from Sentinel-2 data, validating GPR against independent datasets, and comparing results with other methods and available products. The study utilized 301 (209 crop + 92 soil spectral) CCC and 301 LAI observations for GPR model training. Validation on independent datasets (698 LAI and 364 CCC) revealed the reliability of GPR estimation, compared to Sentinel-2 Level 2 Prototype Processor (SL2P) estimates. LAI and CCC estimation metrics varied across datasets achieving coherent and similar performance between the two method (GPR and SL2P). In general, SL2P model better fits the overall data with slightly higher R^2 values with respect to GPR especially for LAI parameter. GRP estimates provided better results when accuracy analysis is performed by crops showing lower RMSE (Root Mean Square Error) and MAE (Mean Absolute Error). GPR outperforms SL2P for mais and wheat in particular for CCC parameter. These results showed the potential of GPR in BioPar estimation, especially when a robust training set was used. BioPar estimation using Sentinel 2 data provided high-quality quasi-weekly information, essential for smart crop management and early warnings in decision support systems.

1. INTRODUCTION

Remote sensing, with its capacity to provide near real-time and comprehensive information, has emerged as an indispensable tool for monitoring crop health and growth (Defourny et al., 2019; Weiss et al., 2020). In the context of precision farming, the accurate estimation of vegetation biophysical parameters through remote sensing techniques (Verrelst et al., 2019) plays a key role in the effective management of agricultural crops.
Two of the most critical biophysical parameters in this context are Leaf Area Index (LAI) and Canopy Chlorophyll Content (CCC). LAI represents the extent of foliage cover, aiding in the assessment of crop density and growth, while CCC is an indicator of photosynthetic activity. These parameters are central in decision-making processes because offering insights into crop health and vigor. The incorporation of LAI and CCC estimates into operational workflows enables farmers to make informed decisions about fertilization, thereby optimizing crop management and reducing environmental impact. However, achieving accurate parameter estimations is no simple task and a variety of retrieval methods for BioPar extraction (Verrelst et al., 2019) have been applied to optical data (multi and hyperspectral). The theoretical framework of the multitude of retrieval methods was accurately given by Verrelst et al., 2015 with four main methodological categories: i) Parametric regression methods (Clevers et al., 2017; Crema et al., 2020); ii) Nonparametric regression methods (Campos-Taberner et al., 2016; De Peppo et al., 2021; Upreti et al., 2019); iii) Physically based model inversion methods (Berger et al., 2018; Sehgal et al., 2016) and iv) Hybrid regression methods (Candiani et al., 2022; Ranghetti et al., 2022; Rossi et al., 2022). All these categories are not rigid and definitive and we are witnessing new development together with improvements in the computational capacity and the progress in new imaging sensors.
In order to meet the increasing demand for tools to support the site-specific management of crops, we need to improve estimation accuracy but also systems operations. For this reason, the data provided by Sentinel-2 represent an optimal solution due to the spatial (10-20m) and temporal resolution of the sensor that allow to have BioPar maps at a suitable scale for operational practices (Bontemps et al., 2015; Defourny et al., 2019; Segarra et al., 2020) .
In this study, we evaluated the potential of non-parametric approaches and robustness of ML methods for multi-temporal BioPar retrieval by Sentinel-2 multispectral data. The specific objectives were: (i) develop a transferable GPR algorithm for LAI and CCC estimation by exploiting a robust multi-crop, multi-year and multi-site dataset; (ii) assess GPR BioPar retrieval performance against ground measurements acquired over independent dataset; (iii) compare result with the product freely available from Sentinel Application Platform (SNAP) using SL2P.

2. MATERIALS AND METHODS

2.1 Study area and Dataset

Data collection aimed to assess the robustness of non-parametric methods concerning diverse sources of variability of BioPar, including specific conditions related to crop species, agronomic

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practices (density) growth stages, farms, and years. With the objectives of effectively capture the site-specific differences in BioPar variability, LAI and CCC ground-measurements were collected during several field campaigns. The measures, performed contemporary to S2 data acquisition, were collected on an Elementary Sampling Units (ESU) of 20x20 m according to the Validation of Land European Remote Sensing Instruments (VALERI) sampling strategy (Baret et al. 2005).

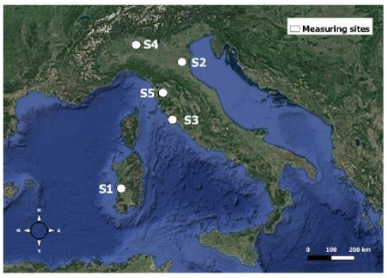

Figure 1:Study areas of ground measurements: S1 (Arborea); S2 (Ferrara); S3 (Grosseto); S4 (Milano); S5 (Pisa)

Different study areas located in central and northern part of Italy (Figure 1) were investigated collecting data of ten different crops: alfalfa, maize, wheat, emmer, pea, sugarbeet, barley, rice, sorghum and soybean. In particular, to achieve a robust multi-crop, multi-year and multi-site dataset, the ground BioPar measurements were conducted over different growing seasons from 2018 and 2022 (Table 1) characterized by different growing periods and canopy structures and considering different agronomic conditions. A total of 907 (573) LAI (CCC) observations were collected with standard instrumentation like LAI2200 (MC100) (Tagliabue et al., 2022), hemispherical photography (Dualex) (Crema et al., 2020) and SunScan (De Peppo et al., 2021) during the campaigns. Grubbs' test for data anomalies was performed to identify potential outliers.

Table 1: Multicrop, multiyear and multisite database with ground measurements cardinality. T indicates training dataset; V indicates validation dataset

Site	Location	Year	Crop	LAI	CCC	Use	Reference
S1_1	Arborea	2021	alfalfa barley	52	40	V	
S1_2	Arborea	2022	alfalfa	35	34	V	
S2_1	Ferrara	2018	maize	71	71	T	Crema et al. 2020
S2_2	Ferrara	2019	wheat	20	40	V	Crema et al. 2020
S2_3	Ferrara	2020	alfalfa maize pea soybean sugarbeet wheat	47	47	T	Tagliabue et al 2022
S2_4	Ferrara	2021	barley emmer maize soybean rice wheat sugarbeet	91	91	T	Tagliabue et al 2022
S2_5	Ferrara	2021	maize soybean	71	67	V	
S2_6	Ferrara	2022	barley wheat	71	68	V	
S2_7	Ferrara	2022	maize rice sorgum soybean	30	28	V	
S3	Grosseto	2018	maize	87	87	V	Candiani et al. 2022
S4	Milano	2022	maize	54	0	V	
S5_1	Pisa	2018	maize	173	0	V	De peppo et al 2021
S5_1	Pisa	2019	wheat	105	0	V	De peppo et al 2021

The S2 Level 2A (L2A) images over the growing seasons were acquired using sen2r R package (Ranghetti et al., 2020) providing seasonal time-series of Bottom of Atmosphere (BOA) reflectance. All cloud-free images, collected in correspondence with the in situ monitoring period (±5 days from ground data collection), were used to analyse the relationship between measured ground BioPar and S2 data. A zonal statistic was performed to extract S2 pixels values using the centroid of each ESU as reference. S2 bands at10 m (B02, B03, B04, and B08) and 20 m (B05, B06, B07, B08A, B11, and B12) were selected for the analysis, resampling all bands to 20 m spatial resolution.

2.2 Machine learning model

Among the different available MLR algorithms, GPR is considered promising for LAI and CCC mapping (Campos-Taberner et al., 2016; Verrelst et al., 2013, 2012) and in general this is also the algorithm more exploited in hybrid approaches (Candiani et al., 2022; Tagliabue et al., 2022). GPR is a non-linear non-parametric regression algorithm that learn the relationship between the input (e.g. reflectance) and output (e.g. LAI or CCC) fitting a flexible model directly from the data and providing both a predictive mean and a predictive variance (uncertainty). The theoretical aspects of GPR are deeply described in Rasmussen, 2004 and in Verrelst et al., 2019 and in studies that applied this approach with hyperspectral (Caicedo et al., 2014; Verrelst et al., 2012) and multispectral data (Estévez et al., 2020).. In addition, the model is trained and validated relatively fast Following De Peppo et al., 2021, GPR was selected as the best-performing algorithm for LAI prediction for arable crops. Few studies have examined the performance of GPR in predicting crop parameters when applied to different site, season and crop typology (i.e. validation using independent dataset).Moreover, the retrieved BioPar were also compared against LAI and CCC generated by the Neural Network (NN) model implemented into the S2LP of the Sentinel Application Platform (SNAP) (Weiss and Baret, 2016) for all the S2 images.

2.2.1 Training and cross validation performance

We first generated 301 (209 from vegetation + 92 soil) data pairs (reflectances-BioPar values) from valuable multiyear data set (S2_1, S2_3, S2_4) with the simultaneous presence of LAI and CCC data (Crema et al., 2020; Tagliabue et al., 2022) for model training, and then evaluated model performance with the remaining 698 (364) LAI (CCC) samples (Table 1). The accuracy of the model in cross validation was assessed using K-fold approach (Kohavi, 1995), where the dataset was randomly split into k = 10 subsets of equal size repeated 5 times. The coefficient of determination (R^2), the mean absolute error (MAE) and root mean square error (RMSE) were calculated to assess the prediction accuracy.

2.2.2 Independent validation to assess model exportability

A robust model validation was performed using nine independent datasets (Table 1). BioPars estimated using the GPR model were compared with LAI and CCC values collected in different sampling areas and years to test the transferability of the developed model.

3. RESULTS AND DISCUSSION

The GPR model assessment was performed considering the average of coefficient of determination estimated between ground-and predicted BioPar and the average value of RMSE and MAE from the cross-validation. Overall estimation metrics in cross validation ranges from R^2=0.89 (MAE=0.49; RMSE=0.74) for LAI variable to R^2=0.83 (MAE=0.28; RMSE=0.43) for CCC (Figure 2).

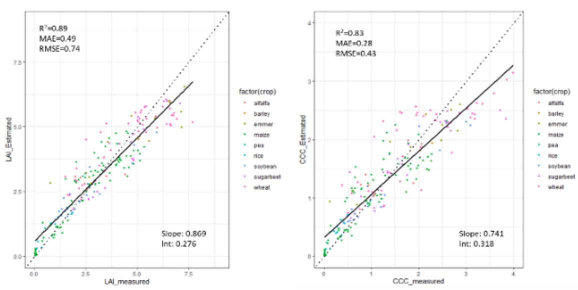

Figure 2: Cross-validation results of LAI (m^2 m^{-2}) and CCC (g m^{-2} estimation from GPR. (p-values < 0.05)

In order to evaluate and compare the accuracy of predictions at pixel level (i.e. for available ESU) both for data driven GPR and NN of S2LP, validation results on independent data were evaluated considering the single crops (Table 1).

Table 2: CCC GPR and CCC SL2P metrics derived from independent validation (p-values < 0.05)

Crop	Methods	R2	MAE	RMSE
alfalfa	CCC GPR	0.07	0.65	0.76
alfalfa	CCC SL2P	0.12	0.65	0.78
barley	CCC GPR	0.58	0.57	0.64
barley	CCC SL2P	0.62	0.73	0.86
maize	CCC GPR	0.59	0.43	0.56
maize	CCC SL2P	0.5	0.78	1.21
soybean	CCC GPR	0.85	0.28	0.41
soybean	CCC SL2P	0.87	0.36	0.63
wheat	CCC GPR	0.78	0.53	0.64
wheat	CCC SL2P	0.84	1.07	1.31

Table 3: LAI GPR and LAI SL2P metrics derived from independent validation (p-values < 0.05)

Crop	Methods	R2	MAE	RMSE
alfalfa	LAI GPR	0.08	1.03	1.3
alfalfa	LAI SL2P	0.08	1.44	1.77
barley	LAI GPR	0.53	1.3	1.59
barley	LAI SL2P	0.56	1.12	1.51
maize	LAI GPR	0.51	0.94	1.16
maize	LAI SL2P	0.46	0.96	1.39
rice	LAI GPR	0.47	1.1	1.3
rice	LAI SL2P	0.73	1.2	1.36
sorghum	LAI GPR	0.8	0.45	0.52
sorghum	LAI SL2P	0.9	0.39	0.45
soybean	LAI GPR	0.69	0.98	1.37
soybean	LAI SL2P	0.89	0.68	1
wheat	LAI GPR	0.49	0.93	1.18
wheat	LAI SL2P	0.4	1.05	1.38

LAI and CCC estimation metrics varies across datasets (Table 2;Table 3) . The results showed that for both LAI and CCC, GPR retrieval is reliable and comparable with SL2P estimates for all crops and in some cases better. The estimates of vegetation biophysical variables given by the toolbox S2LP embedded in SNAP represented the reference product. NNs are the most widely-used tools and SNAP Biopar have been evaluated in previous studies with diverse results (Estévez et al., 2020; Kganyago et al., 2020; Xie et al., 2019).
The estimates showed an agreement between the GPR and S2LP results on single crops/dataset. In general, the two models showed no partialities for individual crops and were consistent in performance except for lower errors in GPR_CCC retrieval. Regarding CCC, GPR showed a higher coefficient of determination only for maize (CCC_GPR R^2=0.59; CCC_S2LP R^2=0.50) but MAE and RSME (i.e., ~0.4 to ~0.75) were always better than S2LP (RMSE ~0.6 to ~1.3) for all the crops. S2LP estimates for wheat and maize resulted significantly overestimated (data not shown) when compared to ground data showing MAE and RMSE value almost double than GPR (see table 2).
With regard to LAI, GPR presented a better coefficient of determination for maize (LAI_GPR R^2=0.51; LAI_S2LP R^2=0.46) and wheat (LAI_GPR R^2=0.49; LAI_S2LP R^2=0.4) together with MAE and RSME while for the remaining crops S2LP performs better. Also on rice, the LAI estimated by GPR has lower R^2 but better MAE and RMSE than S2LP. These results confirmed the tendency of SNAP-derived products to have higher errors as found by Kganyago et al., 2020 with MAE and RMSE > 2 and Fernandes et al., 2014 with reasonably unbiased LAI estimates with acceptable error (<;1 unit) and validation sites with larger (>1 unit) error.
The satisfactory error metrics confirm the substantial robustness of the GPR prediction and its consistency with existing products as found in other validation studies (Brown et al., 2021; Campos-Taberner et al., 2018). The GPR model performed well for most crops despite the diversity of species and locations and alfalfa was the only crop to have unsatisfactory results for both retrieval approaches (R^2=0.08), probably due to the law quality of ground data (LAI) with LAI max data higher respect to the literature (Verger et al., 2009).
Applying the GPR model to an independent data we highlighted the prediction robustness over different areas both globally and by single crop. In general, we noted that the performance was less influenced by the training data set as usually observed (Mao et al., 2019; Verrelst et al., 2019). Estévez et al., 2020 demonstrated the feasibility of LAI retrieval from S2 in a hybrid machine learning framework using GPR with higher accuracies and lower uncertainties (R^2=0.78, RMSE= 0.60) compared to the SNAP toolbox. However, as mentioned by Upreti et al., 2019, the accuracies found by most of the studies using GPR with ML or hybrid were not validated against independent ground data, such as in the present work.
However, despite an overestimation of low-LAI values with GPR, the positive linear relationship between the measured and predicted values was confirmed by the slope values close to 1as found also by (De Peppo et al., 2021). This finding is in agreement with the outcomes of Verrelst et al., 2015 that indicated how GPR was the most effective algorithm for LAI retrieval.

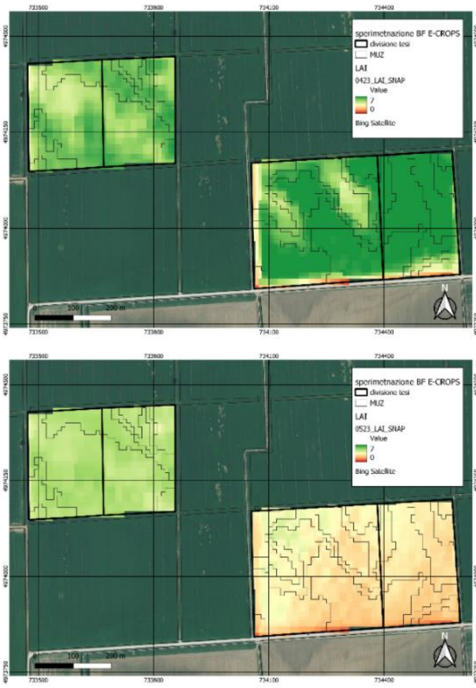

Figure 3: LAI maps of winter wheat of S2 farm in 2023. Black lines represent the boundaries of management zones derived from a soil map. above 23rd of april; below 23th of may.

The BioPar maps generated by the prediction allowed to highlight the spatial patterns present within the field during the season as shown for LAI in Figure 3. Spatial and temporal variability correctly pointed out crop (wheat) growth differences according to a soil map of the farm situated in S2 farm. This study allowed us to leverage all available information from a multi-year multisite and multicrop dataset, thus providing greater accuracy in BioPar prediction than ML model trained with local training datasets.

4. CONCLUSION

Overall the results demonstrated the potentiality of a data driven GPR machine learning approach in LAI and CCC estimations of arable crops when a robust training set is exploited, such condition guarantee a spatial-temporal transferability. The results of cross-validation confirm the theoretical GPR retrieval performance of this ML method. In addition, this work verified the model stability when applied to an independent data set and compared the performance with existing products as generated by the SNAP toolbox, which is framed in an hybrid approach using radiative transfer model simulation and neural network as retrieval algorithm. This analysis allowed for a full assessment of the robustness and exportability of the developed model and the results were in line with other studies with independent model simulations. It is important to remark that, despite medium high R_2, S2LP shows overestimation for CCC in particular for wheat and corn as highlighted by high MAE and RMSE values. Being LAI and CCC quantitative crops Biopar, the lower values of errors of the GPR model can lead to prefer this model even for R_2 slightly lower than the S2LP model. In addition, this ML technique is faster and more easily applied than NNs that are closed balck-box that require a relatively long time for training. Such maps (decametric quasi-weekly) are a fundamental input for decision support systems devoted to smart crop management and early warning indication. Many precision agriculture techniques could thus benefit from information generated with ideal quality and frequency for site-specific practices aimed at reducing inputs and improving the use-efficiency of fertilizers.

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