

Advanced monitoring of crop traits with hyperspectral and multispectral time series

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Abstract

One part for tackling agricultural challenges such as the need for increased food production, reduced environmental impacts, and adaptation to climate change is the optimization of agricultural management. This requires improved monitoring of agricultural areas with respect to vegetation status over dense time series. The combined use of different types of satellite missions has the potential for a more detailed monitoring of agricultural fields. The increasing availability of spaceborne hyperspectral data (from EnMAP, PRISMA and upcoming CHIME) calls for fast processing chains and efficient retrieval algorithms. Therefore, this contribution aims to (i) accelerate and improve existing retrieval workflows, (ii) evaluate currently available hyperspectral EnMAP/PRISMA retrievals to monitor crops, and (iii) test the combined use of hyperspectral and multispectral Sentinel-2 data for crop monitoring.

1. Introduction

Agriculture faces a variety of challenges such as a growing population, changing climate conditions, and the need for a more sustainable production to reduce environmental impacts. A series of measures is necessary to address these challenges. One is the optimization of agricultural management which requires an improved monitoring of agricultural areas with respect to vegetation status, health, and stress via dense time series.

Hyperspectral imagery can add value to information based on multispectral imagery as it contains quasi-continuous information from the visible, near infrared, and shortwave infrared (VSWIR) spectrum. The advantages of using hyperspectral instead of multispectral data for the retrieval of biophysical and biochemical crop traits have been described several times (e.g., Hank et al. 2019). These traits provide important quantitative information on crop status and health for crop monitoring and management. Recent studies demonstrated that the hybrid approach, combining physically-based modelling and machine learning, is a promising generalized and transferable method for the retrieval of crop traits from hyperspectral reflectance data (Berger et al. 2021, Verrelst et al. 2021b, Tagliabue et al. 2022, Woher et al. 2022, Pascal-Venteo et al. 2023, Candiani et al. 2024). Due to the size of hyperspectral imagery, fast processing chains and efficient retrieval algorithms are required.

Spaceborne hyperspectral data is increasingly becoming available through scientific missions such as EnMAP and PRISMA. However, time series over the growing season of a certain area, especially over Europe are rare. The upcoming Copernicus Expansion mission CHIME – a mapping mission with a revisit time of 11 days at the equator when using two satellites – will partly close this gap. Nevertheless, the combination with multispectral data will still be desirable to achieve dense time series for an optimal monitoring of agricultural areas.

Our study addresses several of the challenges in using hyperspectral data for agriculture monitoring. The aims include (i) the acceleration and improvement of existing retrieval

workflows, (ii) the evaluation of currently available hyperspectral EnMAP/PRISMA retrievals to monitor crops, and (iii) the testing of the combined use of hyperspectral and multispectral Sentinel-2 (S2) data for crop monitoring. In the study, we apply retrieval models to a time series of EnMAP and PRISMA in combination with S2 data to demonstrate the potential of jointly using hyperspectral and multispectral time series for agricultural monitoring. With this we highlight the possibilities offered by the future CHIME and Sentinel-2 Next Generation missions.

2. Material and Methods

2.1 Data for model development and validation

In-situ data and related hyperspectral data from different campaigns across Europe were used for the development and validation of retrieval models: (i) the Munich-North-Isar (MNI) dataset, located north of Munich, Germany, includes crop traits and field spectrometer measurements from winter wheat, summer barley, and maize from 2018 – 2022 (Woher et al. 2018). (ii) The southwest Poland (SW-PL) dataset covers crop traits and field spectrometer measurements from 2024 and 2025 for winter wheat and summer barley fields close to the town of Głubczyce (50.2° N, 17.83° E). Accompanying to the SW-PL dataset from 27th March to 2nd July 2024, eight satellite scenes from EnMAP and PRISMA and twelve from S2 are available. EnMAP data was pre-processed retaining only the SWIR-detector in the overlap region. PRISMA data was spectrally resampled to EnMAP at 183 effective bands in the VSWIR domain. EnMAP and PRISMA was spatially co-registered via the tool AROSICS (Scheffler et al. 2017) using the temporally closest S2 scene spatially resampled to 30 m GSD.

The MNI dataset and the SW-PL dataset of 2025 were used as in-situ support in the active learning step of the hybrid retrieval approach (see section 2.2.1). For model validation, the SW-PL in-situ measurements of 2024 close to the corresponding hyperspectral acquisitions were used.

2.2 Retrieval models

The retrieval of crop traits was based on two algorithms: the hybrid retrieval workflow (Steinhauser et al. 2024) to derive leaf chlorophyll a+b content (C_{ab}), LAI, and the area-based leaf nitrogen content (N_{area}) and the Plant Water Retrieval (PWR) tool (Woher et al. 2018) to derive canopy equivalent water thickness (EWT_{canopy}), i.e., the canopy water content. Originally, both algorithms are part of the Agricultural Applications of the EnMAP-Box 3 (Jakimow et al., 2023).

2.2.1 In-situ driven hybrid retrieval: The hybrid retrieval approach combines a physically based radiative transfer model (RTM) with a machine learning (ML) regression algorithm. We used the RTM PROSAIL-PRO (Féret et al., 2021) to create sensor-specific training datasets of canopy reflectance and corresponding vegetation RTM-parameters ($n = 2000$) representing a wide range of crops and growth stages in accordance with previous studies (Woher et al. 2022). For hyperspectral sensors, first 4% Gaussian noise and then principal component analysis (PCA) was applied to reduce data dimensionality using 20 PCs. Afterwards, Gaussian Process Regression (GPR; Rasmussen and Williams, 2005) models were trained for C_{ab} , LAI, and N_{area} in an active learning (AL) framework to reduce and optimize the training dataset. We applied the pool active learning (PAL) strategy (Verrelst et al., 2021a) utilizing in-situ data from the MNI and SW-PL 2025 dataset, which reduced the training dataset by ~75%. Aside from the final variable predictions GPR also provides model uncertainty estimates useful for model reliability and stability assessment. For a better whole-scene mapping result, we added SW-PL bare soil spectra to the optimized training database and retrained the GPR models. Finally, the trained models were applied to EnMAP, PRISMA and S2 data.

Compared to the EnMAP-Box implementation of the hybrid retrieval workflow the algorithm has been updated at various levels: instead of random initial sampling (2%) at the start of the AL process, PAL is applied over k randomly selected subsets to increase AL determinism. Furthermore, the runtime was optimized by parallelization of PAL while updating GPR after each added sample during AL instead of stepwise full retraining. Also, final model inversion runs in chunks of pixels and sequentially over multiple image cubes which largely speeds up and facilitates processing of satellite timeseries.

2.2.2 Inversion of Beer-Lambert law: This recursive algorithm quantifies EWT_{canopy} by extracting the optically active water layer from the Beer-Lambert law in the liquid water absorption feature at 970 nm. Note that for this method contiguous spectral coverage from 930 – 1060 nm is necessary, and the algorithm therefore is not applicable to S2 data (see Woher et al. 2018 for more details).

Compared to the original EnMAP-Box implementation, the runtime of the algorithm was drastically reduced by implementing just-in-time compilation, parallelization, and sequential processing of multiple image cubes. The increased speed also allowed to effectively refit a calibration factor in the algorithm to enable targeting of total above-ground EWT_{canopy} by recursively minimizing residuals from EnMAP-based results to SW-PL total EWT_{canopy} measurements.

2.2.3 Model validation: The final GPR models were applied to the EnMAP/PRISMA and S2 time series of 2024 from SW-PL and validated against in-situ measurements taken within ≤ 8 days. Only those pixels from the satellite data were accepted for validation that were located at least 10 pixels away from detected

clouds, based on the available cloud masks (from EnMAP and S2). In addition, the average of a 3x3 pixel matrix around the in-situ measurement point was extracted and used for validation.

2.3 Crop traits mapping

The potential of hyperspectral time series and the combination with multispectral data is demonstrated by applying the retrieval models to at least 60% cloud-free EnMAP, PRISMA, and S2 data from May to July 2024 for a field ensemble in SW Poland covering multiple crop types. The fields are also located in the SW-PL study area but are different from the fields where in-situ measurements were conducted. We show true colour (RGB) imagery, as well as retrieved C_{ab} , LAI, and N_{area} , with the corresponding model uncertainties. S2 data were resampled to a spatial resolution of 30 m to match the EnMAP/PRISMA pixel size.

3. Results and discussion

3.1 Model training and validation

The training of the GPR models utilizing in-situ based AL resulted in light and optimized models for the estimation of different crop traits. The model performance (in terms of R^2) for testing (i.e. using field spectrometer data in the AL step) and validation (i.e. using satellite data) is presented in Table 1.

Variable	Sensor	R^2_{test}	R^2_{val}
C_{ab}	EnMAP	0.93	0.65
	S2	0.94	0.72
LAI	EnMAP	0.93	0.51
	S2	0.94	0.58
N_{area}	EnMAP	0.93	0.57
	S2	0.85	0.35
EWT_{canopy}	EnMAP	na	0.59
	S2	na	na

Table 1. R^2 -results of in-situ driven AL (R^2_{test}) and validation using SW-PL 2024 data (R^2_{val}) for EnMAP/PRISMA and S2 GPR models.

The EnMAP models reach very good results in the testing phase explaining 93% of the variance in the response variables. The S2 models reach similar R^2_{test} values for estimating C_{ab} and LAI, and a lower, but still high value for N_{area} ($R^2_{test} = 0.85$).

Figure 1 shows the validation plots of the hybrid GPR models for C_{ab} , LAI, N_{area} (EnMAP/PRISMA and S2), as well as the validation plot for EWT_{canopy} of the physical retrieval approach (only EnMAP/PRISMA). The symbols represent the crop types winter wheat (WW) and summer barley (SB), and the field numbers (ESU 1 – 3). The colour code indicates valid pairs of in-situ measurement dates and satellite overpass with the temporal distance to the corresponding satellite acquisition. The error bars in the x direction show the standard deviation from three measurements, while those in y direction illustrate the GPR's internal model uncertainty.

The validation results for the retrieval of C_{ab} are good – for both EnMAP/PRISMA ($R^2 = 0.65$; $RMSE = 8.29 \mu g cm^{-2}$) and S2 ($R^2 = 0.72$; $RMSE = 10.23 \mu g cm^{-2}$) models. The S2 model generally shows higher model uncertainties and less accurate estimates of low C_{ab} values. The estimation of LAI is characterized by only slightly lower R^2_{val} values compared to C_{ab} . The model performance of S2 ($R^2 = 0.58$; $RMSE = 1.01 m^2 m^{-2}$) is slightly better than the one of EnMAP/PRISMA ($R^2 = 0.51$; $RMSE = 1.21 m^2 m^{-2}$), which shows a tendency to underestimation of high LAI values. Model uncertainties are

generally low (but slightly higher for S2 models) but increase in the senescent plant development stage (2nd July 2024).

The EnMAP/PRISMA model for N_{area} shows a good model performance ($R^2 = 0.57$; $RMSE = 3.96 \text{ g m}^{-2}$) and low model uncertainties. However, it tends to underestimate high and overestimates low N_{area} values. The S2 model for N_{area} performs notably worse ($R^2 = 0.35$; $RMSE = 4.84 \text{ g m}^{-2}$) than the EnMAP/PRISMA model and estimates are associated with high model uncertainties. Here, the continuous SWIR coverage provided by hyperspectral data appears to demonstrate its effectiveness compared with two broad SWIR bands of S2.

The EnMAP/PRISMA model for the retrieval of EWT_{canopy} shows good performance in validation ($R^2 = 0.59$, $RMSE = 0.10 \text{ cm}$), yet tends to saturate at very high values.

Overall, the EnMAP/PRISMA GPR models show encouraging validation results despite the location change from training to validation data. Also other studies leveraged hybrid retrieval workflows in combination with AL for crop trait estimation. Tagliabue et al. (2022) validated their hybrid retrieval models with datasets from two different years but from the same area and achieved R^2 of 0.82 – 0.84 for LAI, 0.62 – 0.67 for leaf chlorophyll content (C_{ab}), and 0.62 – 0.92 for LAI-upscaled canopy nitrogen content (CNC). Candiani et al. (2024) achieved R^2 values of 0.75 for LAI and 0.52 for CNC, also with data from the same study area.

Using the hybrid retrieval approach for S2 data was also demonstrated by other studies. Pancorbo et al. (2025) combined PROSAIL with an artificial neural network to retrieve C_{ab} and LAI. The validation with in-situ data from a two year winter wheat field experiment at one study area yielded an $R^2 = 0.39$ for C_{ab} , and an R^2 of 0.50 for LAI. Estévez et al. (2022) implemented an AL optimized hybrid model (PROSAIL and atmospheric model 6SV combined with GPR) for processing S2 level 1C top of atmosphere reflectance data to retrieve LAI and LAI-upscaled leaf-level traits. The validation with an independent maize dataset showed an R^2 of 0.78 for LAI and 0.65 for LAI* C_{ab} .

The joint use of retrieved traits from EnMAP/PRISMA and S2 in time series in our study (chapter 3.2) is supported by the comparable performances of the models for LAI and C_{ab} . Monitoring N_{area} is not supported by S2 due to the low performance of the S2 model. Here, the associated uncertainties of S2 based retrievals provide clear indications of the low reliability when evaluating these time series.

3.2 Mapping examples

RGB images as well as estimated crop traits and associated model uncertainties are shown for LAI, C_{ab} , and N_{area} for a selected field ensemble in SW-Poland (Figure 2–4). The time series encompasses retrievals from EnMAP/PRISMA and S2 imagery demonstrating plant development from May to July 2024.

Overall, the retrieved crop traits show plausible developments over varying crop types and over time. Winter wheat and summer barley in the northern part first show an increase in LAI and C_{ab} and then a decrease with beginning senescence. The sugar beet and potato fields start to emerge from end of May which is correctly reflected by growing LAI. Before, the absence of plants (and hence C_{ab} and LAI) on bare soil is correctly represented, due to the addition of bare soil spectra in the retraining step. In the EnMAP scene of 2nd July 2024, some clouds and cloud shadow pixels over the southern fields were missed by the detection algorithm leading to unreliable trait estimates and high uncertainties. Such uncertainty outliers could be used to mask out unreliable results which constitutes a practical application of the GPR internal uncertainty measure.

Despite the overall plausibility of the mapping results, there are some sensor specific characteristics. S2 estimates for C_{ab} and N_{area} generally show higher associated uncertainties than the hyperspectral estimates indicating lower model stability. For C_{ab} , uncertainties in S2 retrievals reveal unnatural variations in the estimations. For N_{area} the S2 model uncertainties are very high and in combination with the validation results, it is not meaningful to include S2 based estimates in practical nitrogen monitoring.

The comparison between EnMAP and PRISMA retrievals for the match-up on 5th May 2024 also shows interesting differences. While EnMAP indicates no C_{ab} in the bare soil fields in the south, PRISMA partly shows low C_{ab} content with high uncertainty. Knowing that the added bare soil spectra were extracted from EnMAP acquisitions only, uncertainties in PRISMA retrievals point out insufficient training samples. In addition, LAI and N_{area} estimates of PRISMA are generally higher than those of EnMAP. More in-situ data with corresponding satellite data and match-up scenes are needed to better assess the differences between the retrievals from different sensors. This data would also allow to develop transfer functions between the retrievals of different sensors in the future to better integrate multi-sensor data for time series analysis.

4. Conclusions

Spatio-temporal maps of crop traits can be used to monitor plant development over time and to optimize agricultural management. In this study, we increased the efficiency of retrieval algorithms in the EnMAP-Box, estimated C_{ab} , LAI, N_{area} , and EWT_{canopy} , and validated these traits with in-situ and corresponding satellite data. We then applied the final models to a time series of diverse crop types from different satellite sensors (EnMAP, PRISMA, and S2).

The speed improvements of the retrieval workflows help to improve the efficiency of the model development process and to handle an ever-growing number of acquisitions from different missions.

The validation of the developed EnMAP/PRISMA and S2-based models with in-situ and associated satellite data showed robust results for C_{ab} and LAI, supporting the joint use of hyperspectral and multispectral data in time series analysis for these variables. Considering N_{area} , the validation results for the EnMAP/PRISMA model were good, but not satisfying for the S2 model, which was also reflected by large model uncertainties. The GPR internal uncertainties are a valuable measure to assess the robustness of mapping results across various crop types and sensors.

The physical based retrieval of EWT_{canopy} leveraging the Beer-Lambert law approach was recalibrated to target total water content. The recalibration was enabled by major speed improvements of the original algorithm. Nevertheless, the approach is restricted to hyperspectral data where it showed good validation results. A combination with S2 for denser temporal monitoring of plant water content would only be enabled by an index proxy.

In general, more in-situ and corresponding satellite data is needed to improve the accuracy of current models, validate retrieval models over different crops, regions and times, and establish tailored retrieval models for specific crop types (e.g., sugar beet). A promising initiative is the CaRMA campaign which was conducted in 2025 west of Munich, Germany by the LMU Munich with support from ESA (ESA 2026; LMU 2026). The data is currently being processed, and the publication of the dataset is planned for 2027. In combination with match-up scenes from different sensors, this kind of datasets will enable the further improvement of methods to combine retrievals from various spaceborne sensors for a dense monitoring of agricultural areas.

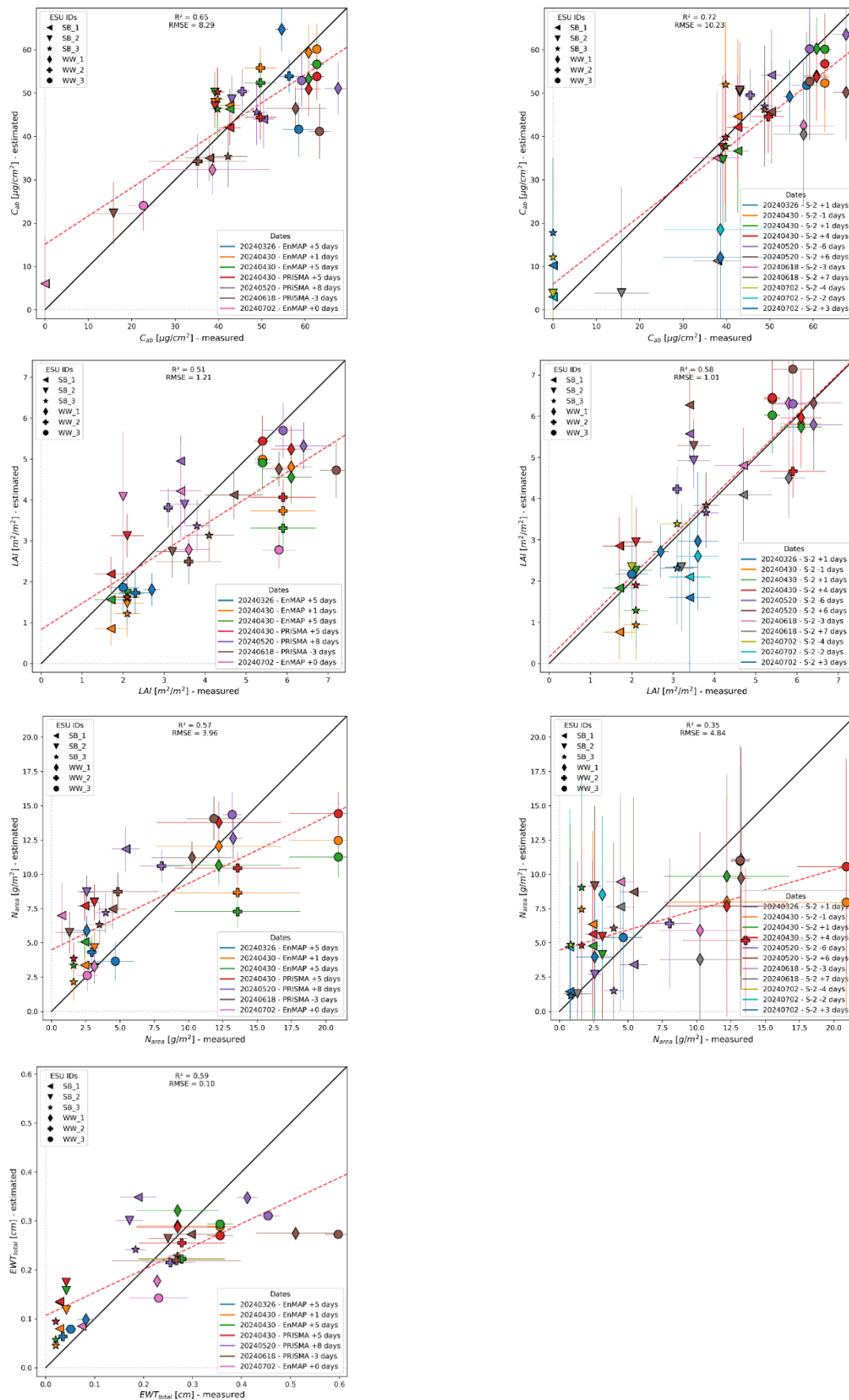


Figure 1. Validation of GPR models for C_{ab} (1st row), LAI (2nd row), N_{area} (3rd row), and EWT (4th row) based on EnMAP/PRISMA (left) and S2 data (right) using SW-PL 2024 data.

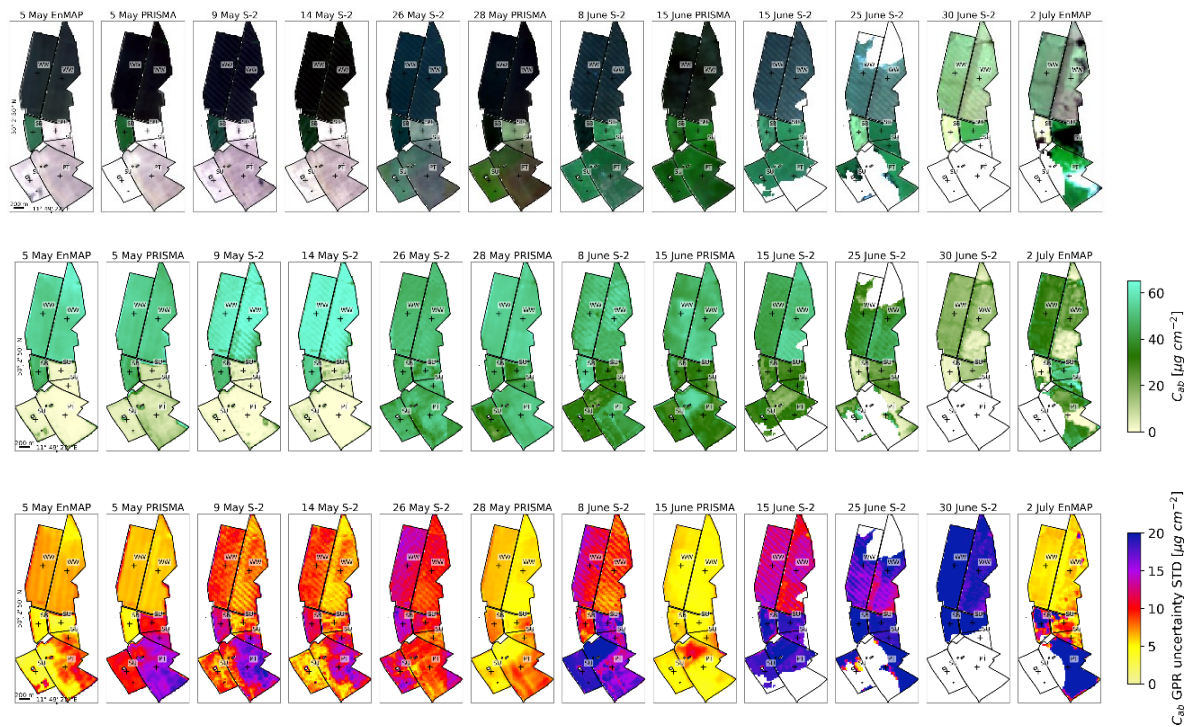


Figure 2. EnMAP/PRISMA and S2 true color (top), mapped C_{ab} (middle), and related GPR uncertainties (bottom) of fields in SW-PL 2024. WW = winter wheat, SB = summer barley, SU = sugar beet, PT = potato.

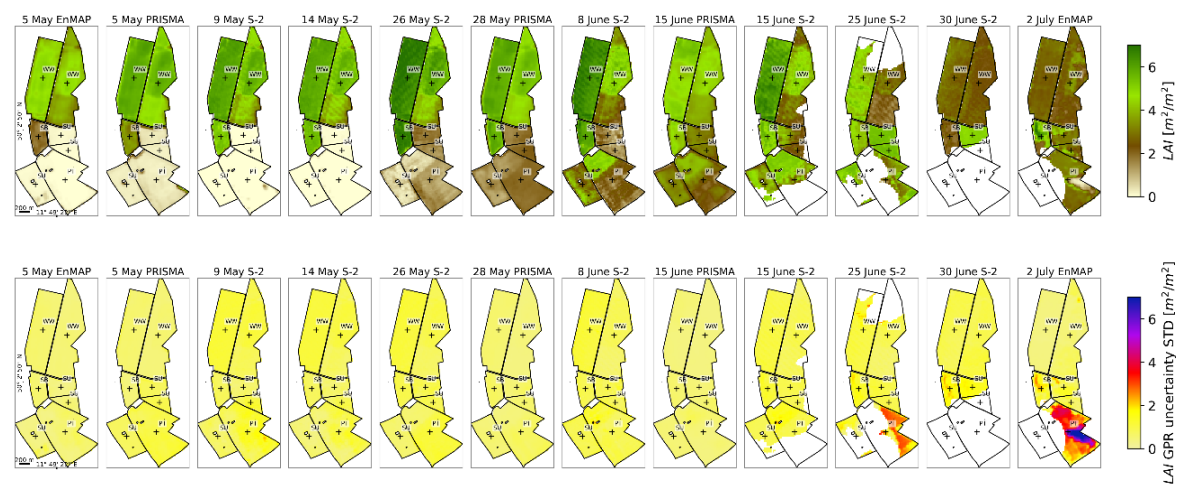


Figure 3. EnMAP/PRISMA and S2 mapped LAI (top) and related GPR uncertainties (bottom) of fields in SW-PL 2024.

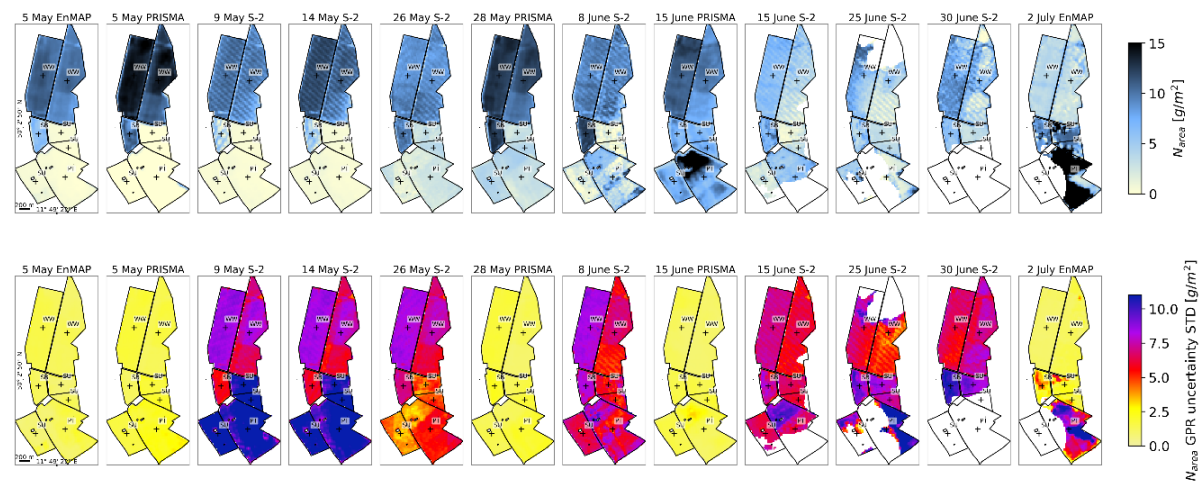


Figure 4. EnMAP/PRISMA and S2 mapped N_{area} (top) and related GPR uncertainties (bottom) of fields in SW-PL 2024.

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