

Synergistic Use of Sentinel-1, Sentinel-2, & EnMAP Data towards Advancing Agricultural Monitoring in Greece

Eleni Sofikiti^{1,2*}, Christina Karakizi^{1,2}, Olympia Gounari¹, Konstantinos Karantzalos¹

¹ Remote Sensing Laboratory, National Technical University of Athens (NTUA), 15780 Zographos, Greece

² Hellenic Space Center (HSC), 15231 Chalandri, Greece - * esofikiti@hsc.gov.gr

Keywords: Earth Observation, Land Cover/Crop Type Mapping, Classification, SAR, Multispectral, Hyperspectral

Abstract

Accurate and frequently updated land cover and crop type maps are essential for environmental monitoring, agricultural management, and informed decision-making. While multi-temporal SAR and multispectral data from various satellite sensors have been widely assessed towards this end, the potential of spaceborne hyperspectral Environmental Mapping and Analysis Program (EnMAP) data for such applications, remains largely unexplored. This study evaluates the added value of multi-temporal EnMAP observations combined with Sentinel-1 and Sentinel-2 time series for joint land cover and crop type mapping in a complex landscape of Western Greece. A detailed reference dataset comprising 32 classes (14 non-crop and 18 crop categories) was developed, and progressively richer sensor configurations were evaluated using a Random Forest classifier. Different representations of the high-dimensional EnMAP feature space were assessed, including original bands, spectral indices, Principal Component Analysis (PCA), and Minimum Noise Fraction (MNF) transformations. All experimental configurations achieved Overall Accuracy (OA) rates above 88% and average F1-score above 78%. Incorporating Sentinel-1 temporal metrics increased OA from 88.13%, using Sentinel-2 spectro-temporal metrics alone, to 89.40%, while the addition of EnMAP features further improved performance across all feature representations. The highest OA (90.27%) and average F1-score (83.45%) were achieved by combining Sentinel-2 and Sentinel-1 metrics with the MNF-transformed EnMAP features. Overall, multi-temporal EnMAP information enhanced notably the discrimination of spectrally complex and overlapping classes, particularly those with lower baseline performance, while dimensionality reduction techniques provided the greatest classification benefits. These results encourage further research on hyperspectral time series over broader spatial extents and their integration into operational land cover and crop type mapping frameworks.

1. Introduction

Addressing global food insecurity and hunger remains a major challenge within the 2030 Agenda for Sustainable Development (FAO et al., 2025). In particular, Sustainable Development Goal 2 (SDG 2) aims to end hunger, achieve food security and improved nutrition, and promote sustainable agriculture. Agriculture is a central component of these goals through its contributions to food production, rural livelihoods, employment and economic development. Thus, timely and reliable information on agricultural areas is essential for monitoring agricultural production, supporting sustainable management practices and improving long-term food security.

In this context, accurate and frequently updated land cover and crop type maps are essential for several scientific communities, as well as for public and regional authorities, supporting decision-making, spatial planning, sustainable development, and natural resource management. Continuous monitoring of agricultural areas is particularly important, as reliable information on the spatial distribution of croplands and individual crop types can support agricultural management, production assessment, and food-security-related decision-making.

Over the past decade, the increasing availability of Sentinel-1 and Sentinel-2 observations has improved high-resolution land cover mapping through the use of dense Earth Observation time series (Karakizi et al., 2021; Karakizi, 2022; Karakizi et al., 2024a; Kumhálová et al., 2026). However, cropland mapping, particularly the discrimination of individual crop types, remains challenging due to the spectral and phenological similarities among agricultural classes. Towards this end, hyperspectral data have been investigated for their potential to enhance classification performance due to their ability to capture subtle

spectral differences between classes (Karantzalos et al., 2018; Lou et al., 2025; Nikolaou-Alavanou et al., 2026).

The launch of the Environmental Mapping and Analysis Program (EnMAP), which provides spaceborne hyperspectral observations at 30 m spatial resolution, offers new opportunities in this direction (Storch et al., 2023). The high spectral resolution of EnMAP data has the potential to improve the discrimination of nuanced differences in vegetation characteristics (Ferreira et al., 2026; Karakizi et al., 2024b; Matsokane and Tesfamichael, 2026). Moreover, although EnMAP acquisitions are primarily performed on demand, a foreground mission initiated in March 2024 targets specific regions across Europe, providing repeated acquisitions throughout the vegetation period from March to October and thus enabling the generation of systematic and longer hyperspectral time series.

Recent studies have assessed the potential of EnMAP data for crop type mapping, demonstrating that the provided rich spectral information improved the discrimination of spectrally similar crop categories (Bourriz et al., 2025; Li et al., 2026). However, the potential of EnMAP data utilized in more demanding, simultaneous, land cover and crop type classification tasks remains largely unexplored, particularly for detailed thematic nomenclatures that include numerous categories and in study areas with heterogeneous landscapes, characterized by diverse climatic conditions, topography, and agricultural practices. Furthermore, the potential gain of exploiting relatively dense multi-temporal EnMAP observations in combination with Sentinel-1 and Sentinel-2 time series has yet to be comprehensively investigated.

Towards this end, this study evaluates the synergistic use of multi-temporal Sentinel-1, Sentinel-2, and EnMAP data for detailed land cover and crop type mapping in Western Greece,

with particular emphasis on assessing the added value of multi-temporal EnMAP observations. A detailed nomenclature is considered for which a highly reliable reference dataset was developed. A series of single- and multi-sensor configurations is evaluated within a Random Forest classification framework, starting with Sentinel-2 observations and subsequently incorporating Sentinel-1 and EnMAP data. Different approaches for reducing the high-dimensional EnMAP feature space were evaluated to assess the trade-off between richer spectral information and classification performance.

2. Materials

2.1 Study Area

The study area is located in the highlands of the administrative region of Western Macedonia, northern Greece, extending from south of Grevena in the west to Mount Kaimaktsalan near the country's northern border (Figure 1). The study area includes parts of the Kastoria and Kozani Basins, separated by the Askio mountain range and characterized by considerable topographic variability. Lake Vegoritida is the largest of several natural lakes in the area, while Aliakmon River crosses the region. The main urban centers within the study area include Ptolemaida and Grevena.

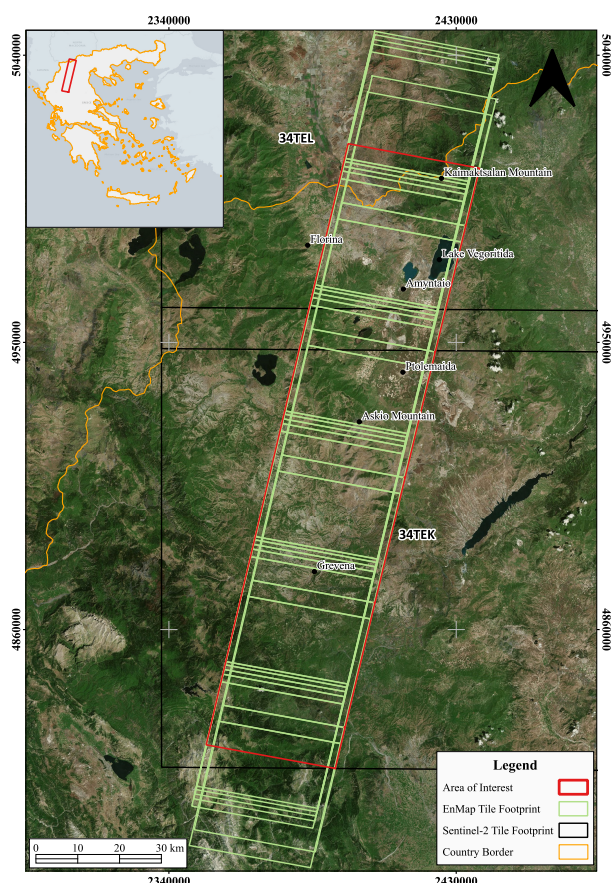


Figure 1: Study Area with footprints of the utilized EnMAP and Sentinel-2 scenes, over Bing Maps.

The region is characterized by a Mediterranean climate with pronounced continental and mountain characteristics. Winters are generally cold, with frequent frost and snowfall, whereas summers are warm and relatively dry. Average monthly temperatures in the Kozani Basin range from about 2.3 °C in January to 24.5 °C in July, while in the northern part of the

region, toward Florina, temperatures range from about 0.6 °C to 23.4 °C, respectively. Considerable spatial variability is also observed in precipitation across Western Macedonia (Grimpylakos et al., 2013). Climatic conditions become progressively colder with increasing elevation in the surrounding mountainous areas, which reach approximately 2,524 m at Mount Kaimaktsalan.

A very diverse land use/land cover landscape characterizes the area, comprising agricultural areas, forests and semi-natural vegetation, artificial surfaces, water bodies, and mining and industrial areas. Agricultural land includes a diverse range of arable and permanent crops, while forests and semi-natural areas are mainly distributed across the mountainous regions. Large-scale lignite mining and associated infrastructure further contribute to the diversity of the landscape.

In this context, the considerable environmental and landscape heterogeneity makes the study area particularly suitable for evaluating the capability of multi-temporal Sentinel-1 (S1), Sentinel-2 (S2), and EnMAP observations to discriminate among complex land cover and crop type classes.

2.2 Reference Data

A highly reliable reference dataset with 32 land cover and crop type classes, specifically adapted to the characteristics of the Greek landscape, was developed for model training and validation. It consists of 14 non-crop classes and 18 crop classes. The reference data for the agricultural classes were derived from the 2025 Land Parcel Identification System (LPIS) dataset and were filtered following the methodology developed from our team, as described in Gounari et al., 2022. The methodology combines geometric and spectral consistency criteria to identify parcels representative of their declared crop type, while minimizing the influence of erroneous declarations, inaccurate parcel geometries, mixed fields, and atypical spectral behaviour. More details are provided in section 3.1.

Reference data for the 14 non-crop classes were created primarily via manual delineation through expert photointerpretation. The reference database for these classes was built through intensive photointerpretation and supplementary integration of in-situ data and external geospatial data. Digitization was performed by photointerpretation experts on very high-resolution imagery, like Google Earth, Bing satellite data, PlanetScope data and aerial orthophotos of the Greek National Cadastre and Mapping Agency. Various geospatial datasets were used as ancillary information to support the annotation process, e.g., geospatial data from field campaigns conducted by the NTUA Remote Sensing Laboratory, national geospatial information layers and Copernicus Land Monitoring Service (CLMS) products.

2.3 EnMAP Data

For this study, atmospherically corrected Level-2A (L2A) EnMAP imagery acquired within the EnMAP foreground mission was obtained via the EOWEB GeoPortal. The study area is covered by one main EnMAP acquisition strip, comprising six tiles (Figure 1). For the agricultural year of interest (2025), nine acquisition dates were utilized (Table 1), spanning the period from October 2024 to September 2025. Of these, three acquisitions corresponded to the autumn period and six to the spring/summer growing period, providing sufficiently dense hyperspectral coverage during the main stages of crop development. Seven out of nine utilized scenes came from the

main EnMAP strip while an adjacent EnMAP strip provided two additional acquisition dates (i.e., 6/7/2025 & 2/8/2025). Since this adjacent strip presented a limited spatial coverage of the study area, these additional observations were composited with acquisitions from the primary strip obtained within the same month, to improve spatial coverage and fill data gaps caused by cloud cover. Additional EnMAP acquisitions in the studied time range were found available on the EnMAP Data Archive for some of the remaining months; however, these were excluded due to extensive cloud contamination that limited the number of usable pixels.

EnMAP preprocessing involved the removal of bands identified as ‘bad bands’ in the product specifications, as well as spectral bands strongly affected by atmospheric water absorption. This reduced the original 224 spectral bands to 204 usable bands, which were retained for subsequent analysis. The imagery was then masked for clouds and other invalid observations using the quality masks provided with the EnMAP products.

The resulting EnMAP time series, comprising the full set of 204 spectral bands, was used as the baseline EnMAP dataset for classification. In addition, three alternative representations of the EnMAP feature space were evaluated, i.e., 10 spectral indices were computed and used instead of the full spectral dataset, and two dimensionality reduction approaches, namely the Principal Component Analysis (PCA) and the Minimum Noise Fraction (MNF) were also assessed. More details on these are provided in section 3.2.

2.4 Sentinel-1 and Sentinel-2 Data

S2 Level-2A (L2A) surface reflectance data were utilized with the study area covered by tiles, 34TEK and 34TEL. Monthly spectro-temporal metrics were calculated and downloaded through Google Earth Engine (GEE), considering scenes with cloud cover below 80%. The derived metrics included the mean, standard deviation, and 10th and 90th percentiles, calculated for six spectral bands: Blue, Green, Red, Red-Edge (Band 5), NIR, and SWIR1 (Band 11) (Table 1). The same temporal metrics were also calculated for three spectral indices, proven efficient for similar vegetation mapping tasks (Karakizi et al., 2023), namely the Normalized Difference Vegetation Index (NDVI), the Modified Soil-Adjusted Vegetation Index (MSAVI2), and the Dry Bare-Soil Index (DBSI).

Sensor	Product	Period	Temporal Sampling	Spatial Res.	Bands used	Derived Features
EnMAP	L2A surface reflectance	Oct 2024 – Sep 2025	13/10/2024 6/7/2025*	30 m	204 bands	204 bands, Spectral Indices, PCA components, MNF components
			9/11/2024 2/8/2025* 20/04/2025 6/8/2025 13/06/2025 2/9/2025			Mean, StdDev, P10, P90, correlation, entropy, contrast, dissimilarity
Sentinel-1	GRD scenes IW mode	Oct 2024 – Oct 2025	12 monthly composites	10 m	VV VH VHV	Mean, StdDev, P10, P90, NDVI, MSAVI2, DBSI
Sentinel-2	L2A Surface Reflectance	Oct 2024 – Oct 2025	12 monthly composites	10 m	2,3,4,5,8,11	Mean, StdDev, P10, P90, NDVI, MSAVI2, DBSI

*Additional acquisitions

Table 1: Characteristics of EnMAP, S1, and S2 datasets used in this study and their derived features.

For S1, the calibrated and ortho-corrected Ground Range Detected (GRD) scenes available through GEE were utilized. Monthly composites were generated and downloaded for the VV and VH polarizations and their ratio (VH/VV). Similarly to S2, the monthly metrics included the mean, standard deviation, and

10th and 90th percentiles. In addition, several Grey-Level Co-occurrence Matrix (GLCM) texture metrics were calculated from the monthly mean VV, VH, and VH/VV images. These included Correlation, Entropy, Contrast, and Dissimilarity, providing additional information on the spatial characteristics of the radar backscatter.

3. Methodology

3.1 Preprocessing of the Reference data

The LPIS preprocessing workflow (Gounari et al., 2022) was applied starting with the removal of parcels with ambiguous crop declarations, as well as records corresponding to mixed or sequential cropping. An inward buffer was then applied to parcel boundaries to reduce boundary effects and the occurrence of mixed pixels. Very small or highly elongated parcels were also excluded using geometric criteria based on their minimum rotated rectangles. Finally, the spectral consistency of the remaining parcels was assessed using multi-temporal NDVI profiles derived from S2 observations. More specifically for each S2 tile and crop class, a representative median temporal NDVI profile and class-specific variability thresholds were calculated, and parcels exhibiting atypical temporal behaviour were identified as potential outliers or erroneous records and removed.

The resulting dataset therefore retained only parcels exhibiting both geometric and spectral consistency, providing a high-quality subset of the 2025 LPIS database for crop type classification. This filtered agricultural dataset was subsequently combined with the manually delineated reference data for the non-crop classes to form the complete 32-class reference dataset. The resulting crop and non-crop reference datasets were integrated, clipped to the study area, and rasterized to the same spatial grid as the satellite observations, ensuring direct spatial correspondence between the reference labels and feature data.

3.2 EnMAP feature extraction

Besides the original spectral information, ten spectral indices (Table 2) were derived from the pre-processed EnMAP imagery to investigate whether a substantially reduced EnMAP feature space could provide comparable classification performance to the full hyperspectral information. The selected indices cover the focus on vegetation, soil, built-up areas, and water, and were calculated following the implementation of the ‘Create spectral indices’ tool of the EnMAP-Box open source QGIS Plugin (Jakimow et al., 2023). Four vegetation-related indices were used: TCARI, which is sensitive to vegetation chlorophyll content (Haboudane et al., 2002); NDREI, which exploits the red-edge region for vegetation characterization (Gitelson and Merzlyak, 1994); EVI, which provides increased sensitivity in areas of high vegetation biomass (Huete et al., 1997); and SAVI, which reduces the influence of soil background on the vegetation signal (Huete, 1988).

Three indices related to soil and non-photosynthetic vegetation were employed: CAI, for the identification of non-photosynthetic vegetation (Nagler et al., 2003), MBI for enhancing bare-soil information (Nguyen et al., 2021), and BI (Mathieu et al., 1998). The NDBI was included for built-up areas detection (Zha et al., 2003), while two water-related indices were considered: MNDWI, which enhances open water while suppressing other land cover types such as built-up surfaces (Xu, 2006), and AWEI, designed to improve the separation of water from shadows and other dark surfaces (Feyisa et al., 2014). This resulted in a substantially reduced EnMAP feature space of 10 features per

acquisition date, which was subsequently benchmarked against the rest of representations of the EnMAP data.

Index	Full name	Application	EnMAP formula
TCARI	Transformed Chlorophyll Absorption in Reflectance Index	Vegetation	$3[(B_{54} - B_{48}) - 0.2(B_{54} - B_{30})] \times (B_{54} / B_{48})$
NDREI	Normalized Difference Red Edge Index	Vegetation	$(B_{71} - B_{54}) / (B_{71} + B_{54})$
EVI	Enhanced Vegetation Index	Vegetation	$g(B_{71} - B_{48}) / (B_{71} + C_1 B_{48} - C_2 B_{16} + L)$
SAVI	Soil-Adjusted Vegetation Index	Vegetation	$(1 + L)[(B_{71} - B_{48}) / (B_{71} + B_{48} + L)]$
CAI	Cellulose Absorption Index	Vegetation	$0.5(B_{174} + B_{194}) - B_{181}$
MBI	Modified Bare Soil Index	Soil	$[(B_{150} - B_{193} - B_{71}) / (B_{150} + B_{193} + B_{71})] + 0.5$
BI	Brightness Index	Soil	$\sqrt{[(B_{16}^2 + B_{30}^2 + B_{48}^2) / 3]}$
NDBI	Normalized Difference Built-Up Index	Urban	$(B_{150} - B_{71}) / (B_{150} + B_{71})$
MNDWI	Modified Normalized Difference Water Index	Water	$(B_{30} - B_{150}) / (B_{30} + B_{150})$
AWEI	Automated Water Extraction Index	Water	$4(B_{30} - B_{150}) - (0.25B_{71} + 2.75B_{193})$

Table 2: The selected spectral indices derived from EnMAP data. Parameters were set to $L=1.00$, $g=2.50$, $C_1=6.00$ and $C_2=7.50$.

In addition to the spectral-index representation, two widely used dimensionality reduction techniques, PCA and MNF, were evaluated to reduce the high dimensionality and spectral redundancy of the EnMAP hyperspectral data. Initially, 100 components were generated for each method, and a series of EnMAP-only classification experiments was performed using different numbers of retained components. Based on these preliminary experiments, the results supported that the first 20 components provided the best classification performance for both PCA and MNF and were therefore retained in the subsequent multi-sensor experiments.

The PCA and MNF transformations were applied independently to each EnMAP acquisition date. For PCA, the spectral features were first standardized and subsequently projected onto the principal-component space. The transformation was fitted exclusively using the training samples, and the fitted standardization and PCA transformation were then applied unchanged to the corresponding held-out test samples and to the EnMAP imagery during inference. This ensured that no information from the test data was introduced during model training.

For MNF, the EnMAP data were first subjected to a noise-whitening transformation, followed by PCA, allowing the resulting components to be ordered according to their signal-to-noise characteristics rather than spectral variance alone. The noise covariance was estimated from spatially neighbouring training pixels, and the MNF transformation was fitted using the training data only. As with PCA, the fitted transformation was subsequently applied without refitting to the test data and corresponding EnMAP imagery during inference. For both approaches, the first 20 components per EnMAP acquisition date were retained as classification features.

3.3 Experimental setup

Pre-processed images from all three sensors were integrated into a common tiling system and resampled using nearest-neighbour interpolation to match the 10 m spatial resolution of S2. To account for potential geometric misalignments among the different datasets, all images were co-registered using the open-source AROSICS software (Scheffler et al., 2017). The grid of

the common tiling system used for the experiments of this work consisted of 20×20 Km tiles, having the study area covered by a total of 11 tiles.

The Random Forest (RF) classifier, proven robust and efficient for such detailed classification tasks (Karakizi, 2022) was employed for all performed experiments. To comprehensively evaluate the contribution of the different sensor's data, a series of progressively richer single- and multi-sensor configurations was investigated. S2 was initially evaluated independently (S2), followed by the combined use of S2 and S1 (S2-S1). EnMAP information was then incorporated together with the Sentinel observations using four alternative hyperspectral representations: the entire set of valid EnMAP bands (Raw), the 10 selected spectral indices (Indices), the 20 PCA components (PCA-20), and the 20 MNF components (MNF-20), retained per EnMAP acquisition date.

This experimental design therefore enabled direct comparison of S2, S2-S1, S2-S1-EnMAP Raw, S2-S1-EnMAP Indices, S2-S1-EnMAP PCA-20, and S2-S1-EnMAP MNF-20 classification feature datasets, allowing the quantification of the incremental value of integrating SAR data, hyperspectral information, and alternative hyperspectral feature representation strategies.

3.4 Evaluation

To provide a robust and spatially independent assessment of the classification performance, a polygon-based train-test partitioning procedure of the reference data, was applied independently to each class and common grid tile, targeting a 70-30 split of the labelled area between the training and held-out test subsets.

Spatially contiguous labelled regions were first identified as individual polygons using connected-component labelling (Zuo and Zhang, 2023), and their areas were determined from the corresponding number of labelled pixels. Entire sample polygons, rather than individual pixels, were then randomly allocated to the training subset until approximately 70% of the total reference area for each class was reached, with all remaining polygons assigned to the independent test set. Where the target proportion could not be achieved because of the number or size distribution of the available polygons, the acceptable deviation from the 70% target was progressively relaxed up to a predefined maximum of 600 iterations. For the majority of class-tile combinations, the targeted 70% training proportion was achieved or closely approximated. Nevertheless, the train-test proportions remained well balanced when considered across the entire study area. Importantly, polygons were never divided between the two subsets, thereby preventing pixels belonging to the same spatially contiguous reference region from occurring in both training and testing data and, in this way, reducing spatial dependence between the two subsets.

The spatial distribution of the reference dataset, to begin with, was broad, with every class represented in at least three of the 11 investigated common grid tiles and most classes absent from only one or two tiles. This balanced spatial coverage, together with the polygon-based partitioning strategy, provided a geographically distributed reference dataset and ensured a robust and representative partitioning between the training and independent testing subsets.

Training was performed on the entire train dataset and validation on the held-out test dataset, both of which remained the same across all experiments performed, to enable direct comparison

between the different experimental setups. Best performing models were used to inference classification maps, that were meticulously assessed for qualitative evaluation. Model performance was evaluated quantitatively by forming Confusion Matrices and calculating standard accuracy metrics, i.e., User's Accuracy (UA), Producer's Accuracy (PA), F1-score, and Overall Accuracy (OA).

4. Results

4.1 Models' Performance and Comparison

Classification results on the held-out test set for the different feature configurations (Figure 2) demonstrated that incorporating S1 temporal metrics improved classification performance over the S2 only model, with OA reaching 89.40% in comparison to 88.13%. The addition of the EnMAP features (En) resulted in further OA improvement, regardless of the feature representation. Highest OA value, i.e., 90.27%, was achieved when using the S2-S1 combination along with EnMAP and the MNF transformation (S2-S1-En MNF-20). Second best performing model was recorded when using the S2-S1 combination along with EnMAP and the PCA transformation (S2-S1-En PCA-20). When incorporating EnMAP indices to the S2-S1 setup (S2-S1-En Indices), a slightly lower OA was achieved, i.e., 89.94% and lastly when using all EnMAP bands (S2-S1-En Raw) the OA rate reached 89.75%. Regardless of the EnMAP feature space representation the results demonstrated that the inclusion of EnMAP in the S2-S1 models, improved the classification performance.

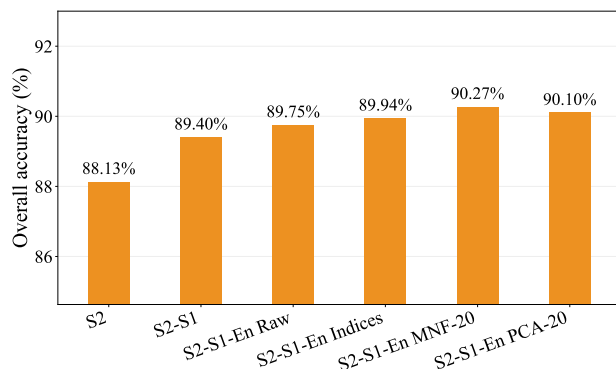


Figure 2: Overall Accuracy rates for the RF models with different combinations of feature sets.

In Figure 3, average F1-score values for non-crop and crop classes are presented when EnMAP's different feature representations were incorporated along with S2-S1. Above each bar, the average F1-score gain is presented, as the increase in accuracy over the S2-S1 baseline model. As presented, all models performed better, for the non-crop classes compared to the crop ones. This observation is to some extent expected, as the non-crop classes are more distinctively differentiated from each other, while the crop ones present more overlaps in the spectral space.

Delving deeper, when considering each model individually, results became more interesting. The model utilizing EnMAP Raw (S2-S1-En Raw), achieved the lowest average F1-score and lowest gain for the crop classes, but achieved competitive average F1-score and larger gains, very close to the results achieved by S2-S1-En PCA-20, for the non-crop classes. The use of indices achieved a moderate but still considerable gain for both sets of classes, but when compared to the rest of the models, fell short in performance for the non-crop classes. S2-S1-En PCA-20

and S2-S1-En MNF-20 performed well for both crop classes and non-crop classes, with the latter presenting the highest F1-score rates, similarly with the OA results.

An interesting remark is that the dimensionality reduction techniques (S2-S1-En MNF/PCA-20) applied on EnMAP data, were proven slightly more beneficial for the crop classes, compared to the non-crop ones. Moreover, the use of spectral indices (S2-S1-En Indices) considerably improved the results for crop classes, but the specific set of indices fell short to significantly improve the classification accuracy, for the non-crop ones, compared to gains achieved with PCA and MNF.

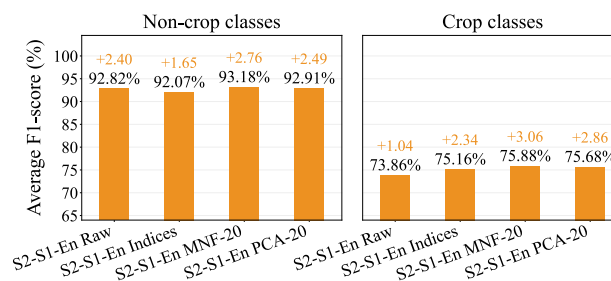


Figure 3: Average F1-score for non-crop and crop classes and gain over the S1-S2 baseline model, when EnMAP's different feature representations are incorporated.

In Table 3 average UA, PA and F1-score for all classes are presented. For all accuracy metrics, best rates were achieved from the S2-S1-En MNF-20 model (highlighted with bold in the table). A more detailed examination reveals that UA benefited less by the inclusion of EnMAP data, regardless of the representation of the feature space, compared to PA. In particular, employing the S2-S1-En MNF-20 model achieved an average PA rate of 79.27%, i.e., 3.89% higher compared to that of the baseline S2-S1 model (highlighted with italics in the table), while the respective gain for UA was recorded at 0.54%.

Features	Accuracy metrics (%)		
	avUA	avPA	avF1
S2	90.96	72.62	78.52
<i>S2-S1</i>	91.47	75.38	80.52
S2-S1-En Raw	91.41	77.87	82.15
S2-S1-En Indices	91.39	78.34	82.56
S2-S1-En MNF-20	92.01	79.27	83.45
S2-S1-En PCA-20	91.80	79.03	83.22

Table 3: Average (av) UA, PA and F1-score metrics for the RF models with different combinations of feature sets.

4.2 Per-class Analysis

In general, larger improvements were observed for classes that exhibited lower baseline performance and, consequently, had greater potential for improvement, whereas classes that were already accurately classified by the S2-S1 model presented more limited gains (Table 4). This suggests that the contribution of hyperspectral information is particularly important for spectrally complex or overlapping classes for which the multispectral and SAR information alone was proven less sufficient for discrimination. This pattern was observed for both crop and non-crop classes.

Among the non-crop classes, the largest F1-score improvement was observed for *Beaches, dunes, sands*, which gained 12.11% over the S2-S1 baseline reaching a rate of 80.93%. This class is characterised by considerable intra-class spectral variability and potential spectral overlap with other sparsely vegetated and bare

surfaces, for which the increased spectral detail provided by EnMAP appears particularly beneficial. A considerable improvement (F1 gain of 8.81%) was also documented for *Industrial and commercial units* while for *Photovoltaic units*, also a significant F1 gain of over 4% was recorded. Classes *Urban fabric* and *Road/Asphalt networks*, also benefited, albeit less markedly, from the incorporation of EnMAP features. Both classes are spatially heterogeneous and frequently comprise mixed pixels containing combinations of built-up surfaces, bare soil and vegetation, particularly within the sparsely developed rural settlements, typical of the study area. The additional hyperspectral information was associated with improved discrimination of these mixed and spectrally heterogeneous surfaces from neighbouring artificial and natural classes.

Natural grasslands also exhibited a notable F1-score improvement of 3.50%, reaching a rate of 90.21% for the best performing model. Examination of the class mixings on the confusion matrix, indicated that *Natural grasslands* were predominantly confused with *Grassfodders* and *Fallow*, which can exhibit similar spectro-temporal behaviour. The inclusion of EnMAP reduced these misclassifications, although confusion with *Grassfodders* remained to some extent. This residual confusion may partly reflect spectral similarity but is also likely associated with differences in seasonal development that are not fully represented by the available EnMAP acquisitions. Winter observations would be useful for capturing the senescent stage of *Natural grasslands*, when their loss of greenness provides a stronger distinction from managed *Grassfodders*. Some additional confusion with *Broad-leaved forest* was also observed after incorporating EnMAP features, indicating the importance of a full timeseries used for such vegetation classes.

For crop classes, the contribution of EnMAP was proven similarly correlated with the spectral and temporal characteristics of the individual crop types. More specifically, notable gains were recorded for *Horticultural summer*, *Nut trees*, *Horticultural fall*, *Legumes*, *Beans*, *Vineyards*, and *Potatoes*. *Nut trees*, for example, were frequently confused with *Stone-fruit trees*, when the baseline S2-S1 model was employed, as both classes consist of deciduous tree crops with similar seasonal development. The incorporation of EnMAP features provided additional spectral information that facilitated their separation. Nevertheless, residual confusion with *Grassfodders* and *Fallow* remained, suggesting that part of the classification difficulty is related to the temporal and within-class variability of these classes rather than to spectral separability alone.

A similar behaviour was observed for several annual and horticultural crops. *Tobacco*, *Grassfodders*, *Beans*, *Legumes*, *Melons* and *Horticultural spring* continued to show confusion cases with *Fallow* despite the inclusion of EnMAP. *Fallow* represents a particularly heterogeneous class, encompassing fields at different stages of vegetation cover, senescence and bare-soil exposure, and can therefore resemble several crop types at different periods of the agricultural cycle. Consequently, hyperspectral information alone cannot completely compensate for temporal overlap among these classes.

This is particularly evident for *Melons* and *Horticultural spring*, which retained low PA values of 21.29% and 22.05%, respectively, and despite the additional EnMAP information, confusion with *Fallow* remained. These classes therefore represent cases where the classification limitation appears to be driven also by temporal and intra-class variability rather than by spectral information alone.

Class	Classification metrics (%)				
	UA	PA	F1	F1 Gain	Support
Non Crops					
Urban fabric	93.46	96.97	95.18	2.62	1090
Industrial and commercial units	94.48	76.00	84.24	8.81	675
Road/Asphalt networks	97.48	95.24	96.35	2.05	1177
Photovoltaic units	100.00	79.84	88.79	4.83	224
Broad-leaved forest	98.99	99.31	99.15	0.30	68517
Coniferous forest	99.32	99.28	99.30	0.90	11467
Natural grasslands	99.74	82.34	90.21	3.50	2299
Sclerophyllous vegetation	89.97	84.40	87.09	0.53	6257
Sparsely vegetated areas	94.45	97.85	96.12	0.55	15522
Beaches, dunes, sands	94.89	70.55	80.93	12.11	5579
Bare rocks	94.79	94.18	94.48	0.97	1564
Wetlands	99.10	98.30	98.70	0.67	9234
Water courses	98.30	94.29	96.26	0.81	368
Water bodies	95.41	100.00	97.65	-0.07	12105
Crops					
Vineyards	84.35	81.24	82.77	4.00	9784
Pome Trees	93.26	68.83	79.20	2.53	4299
Stone-fruit trees	83.66	93.26	88.20	0.76	12181
Nut trees	67.35	52.44	58.97	8.48	7496
Cereals	92.73	94.10	93.41	0.06	75423
Maize	99.37	96.23	97.77	0.13	53942
Tobacco	79.88	57.62	66.95	1.59	689
Sunflower	93.54	94.21	93.87	1.15	53610
Rapeseed	98.64	80.51	88.66	1.73	7644
Grassfodders	88.05	87.62	87.84	1.40	60824
Beans	99.05	66.57	79.62	4.15	1714
Legumes	84.43	70.14	76.62	4.59	11027
Potatoes	89.41	80.92	84.96	3.44	3580
Melons	88.66	21.29	34.33	0.73	404
Horticultural fall	97.17	62.16	75.81	6.51	3200
Horticultural spring	98.60	22.05	36.03	2.85	3198
Horticultural summer	99.33	60.57	75.25	8.95	246
Fallow	56.50	78.24	65.62	2.05	30786
Overall Accuracy	90.27%				

Table 4: Class-wise UA, PA and F1-score metrics for the S2-S1-En MNF-20 model, along with F1-score gain over the S2-S1 baseline model. Sample support of test set is also provided.

Horticultural fall also provides an example of a challenging class for which hyperspectral information was proven more effective. Despite its considerable intra-class variability (a group of many horticultural sub-species), its F1-score increased by 6.51% with the incorporation of EnMAP data. The additional spectral information was found to reduce confusion with several other crop classes, although some misclassification with *Sunflower* and *Potatoes* remained. *Horticultural summer* presented an even larger F1-score gain of 8.95%, but its relatively small sample support should be considered when interpreting this result.

Categories that already had high F1-score showed limited additional benefit from EnMAP data. *Broad-leaved forest*, *Coniferous forest*, *Sparsely vegetated areas*, *Wetlands*, *Water courses* and *Water bodies* all achieved F1-scores above 96%, with comparatively small gains. A similar saturation effect was evident for two major crop classes, particularly *Cereals* and *Maize*, which reached F1-scores of 93.41% and 97.77%, respectively. These classes have distinctive spectral and temporal characteristics that were already effectively captured by the multi-temporal S2 and S1 dataset. Consequently, little additional improvement was possible through the incorporation of hyperspectral information. Overall, the results demonstrated that the addition of the EnMAP multi-temporal information further improved classification performance for most classes, especially for those with lower baseline classification performance.

4.3 Qualitative results

Best performing models were used to inference classification maps, and then a meticulous visual assessment was conducted. Visual comparison revealed that the optimal qualitative output was achieved by the model that also gave the best quantitative results, i.e., the S2-S1-En MNF-20 model.

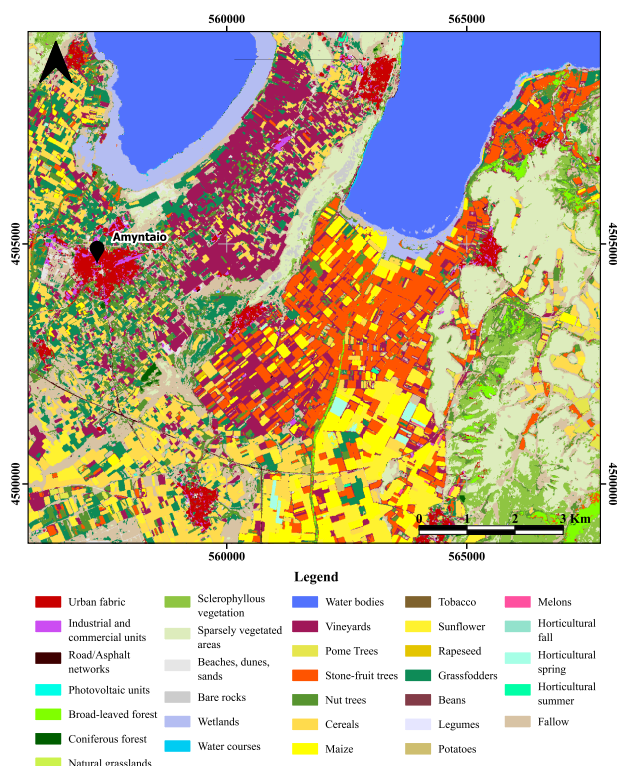


Figure 2: Zoomed part of the produced land cover and crop type map, employing the S2-S1-En MNF-20 model.

In Figure 2 a zoomed part of the classified labelled map from the best performing model is presented. The zoomed area is located near the Amyntaio town, between lake Petron and lake Vegoritida. The area is well known for its agricultural and viticultural activity, particularly for its high-quality *Vineyards*, which appear in the crop type map in burgundy color. These grape-vine cultivations benefit from the unique microclimate created by the surrounding lakes. Further east, areas marked in bright orange correspond to *Stone-Fruit trees* cultivations, with peaches being the dominant crop. Moving toward the southwest, the landscape becomes more diverse, including scattered *Grassfodders* (in green), *Cereals* (in orange/beige), and *Maize* fields (in yellow), forming a mixed agricultural system adapted to both climatic and soil variability.

5. Conclusions

This study investigated the added value of multi-temporal EnMAP hyperspectral observations integrated with Sentinel-1 and Sentinel-2 time series for joint land cover and crop type classification in a heterogeneous landscape of Western Greece. Emphasis was placed on assessing how different representations of the high-dimensional EnMAP feature space affect classification performance.

The results demonstrated that incorporating EnMAP information consistently improved classification performance compared with

the Sentinel-1 and Sentinel-2 baseline, regardless of the employed feature representation. The greatest benefit was achieved using MNF-transformed EnMAP features, which yielded the highest overall and class-level accuracy and the best qualitative classification map. The contribution of hyperspectral information varied across classes, with larger improvements observed for land cover and crop type classes characterized by lower baseline performance and greater spectral complexity or overlap, whereas classes already effectively discriminated by Sentinel-1 and Sentinel-2 multi-temporal information showed limited gains. Remaining confusion among certain crop types indicated that hyperspectral information cannot fully compensate for strong temporal overlap and intra-class variability.

The results also highlighted the importance of effectively managing the high dimensionality of hyperspectral time series. Both PCA and MNF provided substantial benefits, with MNF transformation leading to the best overall performance, while the selected spectral indices were particularly beneficial for certain crop classes. Overall, these findings demonstrate the potential of multi-temporal EnMAP data to enhance detailed land cover and crop type mapping with satellite imagery. Further research should focus on efficient hyperspectral feature exploitation at larger spatial scales and across different ecological and agricultural landscapes, paving the way towards future integration into operational mapping frameworks.

References

- Bourriz, M., Laamrani, A., Ait Abdelali, H., Bourzeix, F., El Bouanani, N., Chehbouni, A., 2025. Assessing hyperspectral sensor capabilities: PRISMA vs EnMAP for crop type mapping in a semi-arid region. *Remote Sens. Appl. Soc. Environ.* 40, 101815. <https://doi.org/10.1016/j.rsase.2025.101815>
- FAO, IFAD, UNICEF, WFP, WHO, 2025. The State of Food Security and Nutrition in the World 2025 – Addressing high food price inflation for food security and nutrition. FAO, Rome. <https://doi.org/10.4060/cd6008en>
- Ferreira, M.P., Fuza, M.S., Viveiros, J.M.S.M., Ferranti, T., Oliveira, D., Santoro, G.B., Molin, P.G., Torres de Almeida, C., Resende, A.F., de Almeida, D.R.A., Zeng, Y., Rodrigues, R.R., Brancalion, P.H.S., 2026. Exploring EnMAP hyperspectral images and ensemble deep learning for classifying forest land-cover types in Brazil. *Int. J. Remote Sens.* 3213–3238. <https://doi.org/10.1080/01431161.2026.2628300>
- Feyisa, G.L., Meilby, H., Fensholt, R., Proud, S.R., 2014. Automated Water Extraction Index: A new technique for surface water mapping using Landsat imagery. *Remote Sens. Environ.* 140, 23–35. <https://doi.org/10.1016/j.rse.2013.08.029>
- Gitelson, A., Merzlyak, M.N., 1994. Quantitative estimation of chlorophyll-a using reflectance spectra: Experiments with autumn chestnut and maple leaves. *J. Photochem. Photobiol. B* 22, 247–252. [https://doi.org/10.1016/1011-1344\(93\)00693-4](https://doi.org/10.1016/1011-1344(93)00693-4)
- Gounari, O., Karakizi, C., Karantzalos, K., 2022. FILTERING LPIS DATA FOR BUILDING TRUSTWORTHY TRAINING DATASETS FOR CROP TYPE MAPPING: A CASE STUDY IN GREECE. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* XLIII-B3-2022, 871–877. <https://doi.org/10.5194/isprs-archives-XLIII-B3-2022-871-2022>
- Grimpylakos, G., Karacostas, T.S., Albanakis, K., 2013. Spatial and temporal distribution of rainfall and temperature in Macedonia, Greece, over a thirty year period, using GIS. *Bull. Geol. Soc. Greece* 47, 1458–1471. <https://doi.org/10.12681/bgsg.10984>

- Haboudane, D., Miller, J.R., Tremblay, N., Zarco-Tejada, P.J., Dextraze, L., 2002. Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. *Remote Sens. Environ.* 81, 416–426. [https://doi.org/10.1016/S0034-4257\(02\)00018-4](https://doi.org/10.1016/S0034-4257(02)00018-4)
- Huete, A.R., 1988. A soil-adjusted vegetation index (SAVI). *Remote Sens. Environ.* 25, 295–309. [https://doi.org/10.1016/0034-4257\(88\)90106-X](https://doi.org/10.1016/0034-4257(88)90106-X)
- Huete, A.R., Liu, H.Q., Batchily, K., van Leeuwen, W., 1997. A comparison of vegetation indices over a global set of TM images for EOS-MODIS. *Remote Sens. Environ.* 59, 440–451. [https://doi.org/10.1016/S0034-4257\(96\)00112-5](https://doi.org/10.1016/S0034-4257(96)00112-5)
- Jakimow, B., Janz, A., Thiel, F., Okujeni, A., Hostert, P., van der Linden, S., 2023. EnMAP-Box: Imaging spectroscopy in QGIS. *SoftwareX* 23, 101507. <https://doi.org/10.1016/j.softx.2023.101507>
- Karakizi, C., 2022. Land cover and crop type mapping at national scale from multitemporal high resolution satellite data. National Technical University of Athens, Athens. <https://doi.org/10.12681/eadd/51551>
- Karakizi, C., Gounari, O., Sofikiti, E., Begkos, G., Karantzalos, K., Symeonakis, E., 2023. Assessing the Contribution of Optical and SAR Data for Fractional Savannah Woody Vegetation Mapping, in: IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium. Presented at the IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium, IEEE, Pasadena, CA, USA, pp. 3118–3121. <https://doi.org/10.1109/IGARSS52108.2023.10282969>
- Karakizi, C., Kandylakis, Z., Vaiopoulos, A.D., Karantzalos, K., 2021. Joint Land Cover and Crop Type Mapping Using Multi-Temporal Sentinel-2 Data from Various Environmental Zones in Greece. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. XLIII-B3-2021*, 319–326. <https://doi.org/10.5194/isprs-archives-XLIII-B3-2021-319-2021>
- Karakizi, C., Karantzalos, K., Kandylakis, Z., 2024a. Exploiting Multitemporal Multispectral High-resolution Satellite Data toward Annual Land Cover and Crop Type Mapping, in: Multitemporal Earth Observation Image Analysis. John Wiley & Sons, Ltd, pp. 81–122. <https://doi.org/10.1002/97811394306657.ch3>
- Karakizi, C., Okujeni, A., Sofikiti, E., Tsironis, V., Psalta, A., Karantzalos, K., Hostert, P., Symeonakis, E., 2024b. Mapping Savannah Woody Vegetation at the Species Level with Multispectral Drone and Hyperspectral EnMAP Data, in: IGARSS 2024 - 2024 IEEE International Geoscience and Remote Sensing Symposium. IEEE, Athens, Greece, pp. 4447–4451. <https://doi.org/10.1109/IGARSS53475.2024.10641996>
- Karantzalos, K., Karakizi, C., Kandylakis, Z., Antoniou, G., 2018. HyRANK Hyperspectral Satellite Dataset I. <https://doi.org/10.5281/zenodo.1222202>
- Kumhállová, J., Sedlák, J., Marčan, J., Vandírková, V., Novotný, P., Kohútek, M., Kumhála, F., 2026. Monitoring of Agricultural Crops by Remote Sensing in Central Europe: A Comprehensive Review. *Remote Sens.* 18, 1075. <https://doi.org/10.3390/rs18071075>
- Li, W., Liang, S., Zhang, Y., Liu, L., Chen, K., Chen, Y., Ma, H., Xu, J., Ma, Y., Guan, S., Shi, Z., 2026. Fine-grained hierarchical crop type classification from integrated hyperspectral EnMAP data and multispectral Sentinel-2 time series: A large-scale dataset and dual-stream transformer method. *Remote Sens. Environ.* 344, 115525. <https://doi.org/10.1016/j.rse.2026.115525>
- Lou, C., Al-qaness, M.A.A., AL-Alimi, D., Dahou, A., Abd Elaziz, M., Abualigah, L., Ewees, A.A., 2025. Land use/land cover (LULC) classification using hyperspectral images: a review. *Geo-Spat. Inf. Sci.* 28, 345–386. <https://doi.org/10.1080/10095020.2024.2332638>
- Mathieu, R., Pouget, M., Cervelle, B., Escadafal, R., 1998. Relationships between Satellite-Based Radiometric Indices Simulated Using Laboratory Reflectance Data and Typic Soil Color of an Arid Environment. *Remote Sens. Environ.* 66, 17–28. [https://doi.org/10.1016/S0034-4257\(98\)00030-3](https://doi.org/10.1016/S0034-4257(98)00030-3)
- Matsokane, K., Tesfamichael, S.G., 2026. Mapping Ecologically Disruptive Invasive Acacia Species Using EnMAP Hyperspectral and Sentinel-1 Radar Data. *Sustainability* 18, 1599. <https://doi.org/10.3390/su18031599>
- Nagler, P.L., Inoue, Y., Glenn, E.P., Russ, A.L., Daughtry, C.S.T., 2003. Cellulose absorption index (CAI) to quantify mixed soil–plant litter scenes. *Remote Sens. Environ.* 87, 310–325. <https://doi.org/10.1016/j.rse.2003.06.001>
- Nguyen, C.T., Chidthaisong, A., Kieu Diem, P., Huo, L.-Z., 2021. A Modified Bare Soil Index to Identify Bare Land Features during Agricultural Fallow-Period in Southeast Asia Using Landsat 8. *Land* 10, 231. <https://doi.org/10.3390/land10030231>
- Nikolaou-Alavanou, E., Petropoulos, G.P., Kalogeropoulos, K., 2026. Combining ENMAP Hyperspectral Imaging and Machine Learning for Land Use/Cover Classification. *Remote Sens. Earth Syst. Sci.* 9, 19. <https://doi.org/10.1007/s41976-026-00271-6>
- Scheffler, D., Hollstein, A., Diedrich, H., Segl, K., Hostert, P., 2017. AROSICS: An Automated and Robust Open-Source Image Co-Registration Software for Multi-Sensor Satellite Data. *Remote Sens.* 9, 676. <https://doi.org/10.3390/rs9070676>
- Storch, T., Honold, H.-P., Chabrilat, S., Habermeyer, M., Tucker, P., Brell, M., Ohndorf, A., Wirth, K., Betz, M., Kuchler, M., Mühle, H., Carmona, E., Baur, S., Mücke, M., Löw, S., Schulze, D., Zimmermann, S., Lenzen, C., Wiesner, S., Aida, S., Kahle, R., Willburger, P., Hartung, S., Dietrich, D., Plesia, N., Tegler, M., Schork, K., Alonso, K., Marshall, D., Gerasch, B., Schwind, P., Pato, M., Schneider, M., de los Reyes, R., Langheinrich, M., Wenzel, J., Bachmann, M., Holzwarth, S., Pinnel, N., Guanter, L., Segl, K., Scheffler, D., Foerster, S., Bohn, N., Bracher, A., Soppa, M.A., Gascon, F., Green, R., Kokaly, R., Moreno, J., Ong, C., Sornig, M., Wernitz, R., Bagschik, K., Reintsema, D., La Porta, L., Schickling, A., Fischer, S., 2023. The EnMAP imaging spectroscopy mission towards operations. *Remote Sens. Environ.* 294, 113632. <https://doi.org/10.1016/j.rse.2023.113632>
- Xu, H., 2006. Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *Int. J. Remote Sens.* 27, 3025–3033. <https://doi.org/10.1080/01431160600589179>
- Zha, Y., Gao, J., Ni, S., 2003. Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. *Int. J. Remote Sens.* 24, 583–594. <https://doi.org/10.1080/01431160304987>
- Zuo, Y., Zhang, D., 2023. Connected Components Labeling Algorithms: A Review, in: 2023 9th International Conference on Computer and Communications (ICCC). Chengdu, China, pp. 1743–1748. <https://doi.org/10.1109/ICCC59590.2023.10507420>