CROP MAPPING FOR A FUTURE COPERNICUS AGRICULTURAL SERVICE

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ABSTRACT

The ECoLaSS project: "Evolution of Copernicus Land Services based on Sentinel data" is developing innovative methods and algorithms for next-generation prototypes of improved or novel operational Copernicus Land services from 2020 onwards. This paper introduces the ECoLaSS project and focusses on developments and first results particularly in view of a new pan-European agricultural service. Dense time series of optical (Sentinel-2) and SAR (Sentinel-1) data are analyzed by means of high-volume data processing chains. Prototype crop mask and crop type maps were successfully derived for a test site in Baden-Württemberg, Germany. The agricultural prototype products are compared with the operational Copernicus High Resolution Layer (HRL) 2015 Grassland product. An outlook presents the next steps towards fit-for-purpose prototypes for pan-European roll-out.

Index Terms— agriculture; Copernicus; CLMS; grassland; HRL; LCLU; Sentinel; time features; time series

1. INTRODUCTION

Copernicus is the European Commission's ambitious program for earth observation (EO), building on the fleet of Sentinel satellites. The Copernicus Land Monitoring Service (CLMS) is one of six thematic service components, which provides EO and in-situ data based monitoring of the earth's land surface, serving both a global, a European and a more local-scale perspective [1].

The goal of the Horizon2020 project, "Evolution of Copernicus Land Services based on Sentinel data" (ECoLaSS) – http://www.ecolass.eu – is to develop and test innovative methods and algorithms for various prototypes of improved or novel next-generation operational Copernicus Land services. The targeted implementation schedule is from 2020 onwards, and the spatial focus is on pan-European scale with a secondary focus on global level [2].

The pan-European CLMS High Resolution Layers (HRLs) 2015 are in their final production phases, addressing Imperviousness, Forest, Grassland, Water & Wetness and Small Woody Features [3]. An agricultural (arable land) layer is considered another potential future pan-European HRL, for which one possible prototype is currently being developed in the frame of ECoLaSS, comprising a consistent European-wide crop mask and crop types. Hereunder the agricultural prototype products are compared with the operational HRL Grassland, a thematically complementary dataset freely available for Europe (EEA39 area) [3].

The ECoLaSS project is built upon four pillars (Fig. 1):

- analysis of user, data and infrastructure requirements;
- methods development, testing and benchmarking;
- prototype development and benchmarking; and
- operativeness assessment & stakeholder consultation.

Accordingly, the initial steps of the project are to assess the main users' requirements for service evolution for which, amongst others, a series of detailed interviews with key users and stakeholders has been carried out. Moreover, the future needs for EO and in-situ data as well as processing and storage infrastructure are being analyzed.

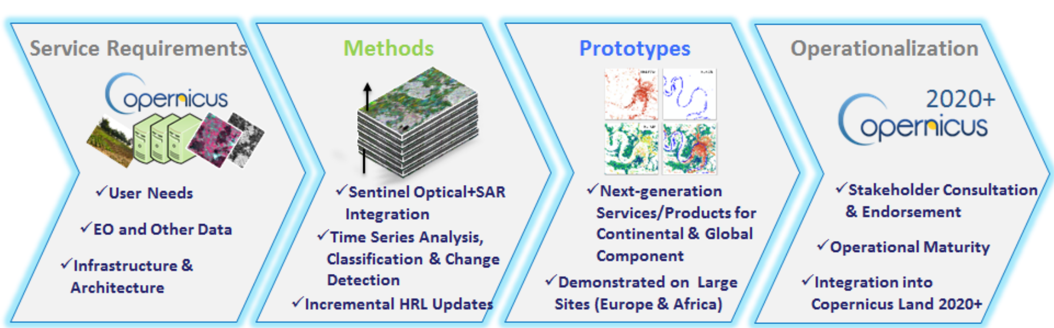

Fig. 1. ECoLaSS workflow: service requirements, methods, prototypes, operationalization

Secondly, dense Sentinel-1 (SAR) and Sentinel-2 (optical) time series are analyzed by means of high volume data processing chains for, e.g., image pre-processing, optical and SAR data integration, time series classification and change detection, and Copernicus HRL updating. These methods are automated, customizable for different products, and scalable to be fit for pan-European roll-out. They will be used to establish several prototypes in terms of time series-based indicators and variables, HRL forest and imperviousness incremental updates, improved grassland characterization, and crop area and crop status/monitoring. These prototypes will be demonstrated on larger sites representing the various biogeographic regions of Europe (Fig. 2).

2. MATERIALS

2.1. Data and Pre-processing

We used all available Sentinel-2A and -2B scenes with a cloud cover below 50% between March and October 2017 (Table I). This resulted in 34 scenes for both tiles T32UNU and T32UNV. The data have been topographically normalized, geometrically corrected, and atmospherically processed including cloud and cloud shadow masking using the Sen2Cor package [4]. The 20m bands were resampled to 10m pixel resolution. Indices such as the NDVI, NDWI, Brightness and IRECI were computed for every selected scene. 37 Sentinel-1A and -1B Ground Range Detected (GRD) data (VV and VH polarisation) from orbit 66 (Table II) were pre-processed to Gamma0 values and were multi-temporally filtered using the ESA SNAP toolbox [5].

TABLE I. OPTICAL EO DATA

Sensor	**Sentinel-2A / -2B**		
Data type	Optical HR2	*Spatial res.*	10m,20m,60m
No of bands	13	*Utilized bands*	B1–8, 11
Revisit time	5 days	*Data interval*	Mar – Oct 2017

TABLE II. SAR EO DATA

Sensor	**Sentinel-1A / -1B**		
Data type	SAR HR2	*Spatial sampl.*	10m
No of bands	2	*Utilized bands*	VV, VH
Revisit time	6 days	*Data interval*	Mar – Oct 2017

2.2. Study Area

Five ECoLaSS study sites are defined across Europe, representing different biogeographic regions. Each site comprises a smaller (~20,000 km²) test site within a larger (60,000–90,000 km²) demonstration site. This work was carried out in the Central test site (southern Germany), to be rolled out to the full demonstration site (Fig. 2).

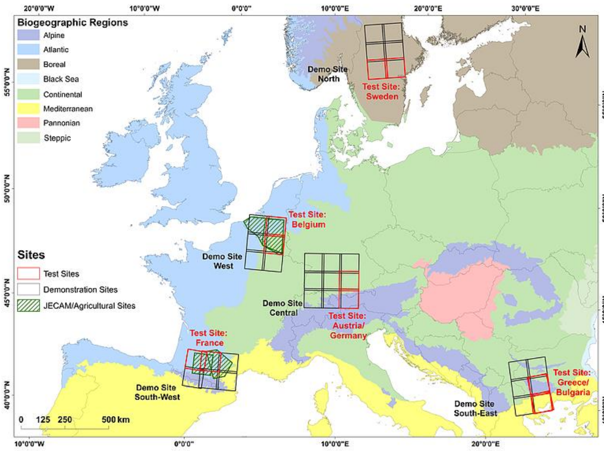

Fig. 2. ECoLaSS study sites

3. METHODOLOGY

The most important methodological aspects, i.e. the computation of time features, crop mask/type classification and complementary development of the HRL Grassland 2015 are described: In a nutshell, we first calculated a large set of 187 candidate time features for LPIS-based training samples only. Subsequently, we performed a statistical feature selection to determine the key time features comprising the most relevant information. Since the calculation of time features is computationally intensive and the relevance of features for a given classification task is not entirely known in advance, we performed the feature selection based on the training data, and calculated only those selected features for the full raster data. With the selected features, we then built the final model, and performed the mapping and accuracy assessment.

3.1. Time Features

Time features derived from Sentinel-1 and -2 data were used as input for crop mask and crop type classifications. Time features are a method of temporal analysis which can capture the intensity of significant change information and statistical time series properties. They are powerful input features for various classification or regression tasks. Time features do not require manual scene selection or prior knowledge of change event dates and can be flexibly computed from reflectance or index data. Due to the iterative calculation over a time stack, they are suitable for dynamic change detection systems which require frequent updates, such as future dynamic agricultural services [6].

“Simple” and “complex” time features were derived from S-1 and S-2 index time series. Simple time features are commonly used statistical metrics, which are calculated over time using all valid (particularly cloud/cloud shadow free) observations. We considered the minimum, maximum, mean, standard deviation, different percentiles: 10th, 25th,

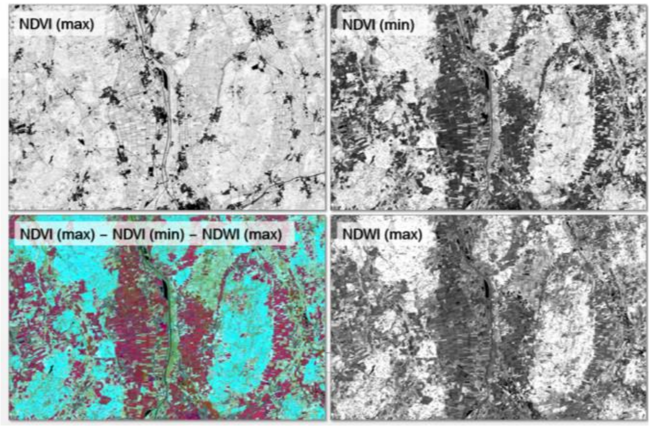

Fig. 3. Selected time features and RGB composition

75^{th} and 90^{th}, as well as the differences between the 90th and 10^{th}, and 75^{th} and 25^{th} percentiles. We also calculated complex time features as proposed by Valero et al. (2016) [6], applying a temporal sliding window and updating the information of the final feature layer by iteratively applying feature-specific mathematical operations. We selected and computed the maxmean, dif_max, dif_min, and difdif_mean features. All above-mentioned features were derived from S1 & S2 full period (March–October 2017) time series. Additionally, we calculated the median and mean time features for all consecutive two-month periods (March/April, May/June, etc.). Fig. 3 illustrates three selected simple time features (NDVI_MAX, NDVI_MIN, NDWI_MAX) and an RGB composition thereof.

3.2. Classification of crop mask/type

For the crop mask classification, training samples of agricultural fields (from LPIS data) as well as from forest, grassland, urban and water land cover classes (derived from HRL 2012/2015 datasets) were used. The subsequent crop type classification was limited to the crop mask area, using only the agricultural LPIS training samples.

The feature selection step was performed with the recursive feature selection approach wrapped around the Random Forest (RF) classifier. Consequently, RF was also used to build the final classification model. This algorithm was chosen (i) since tests have shown that it yields higher accuracy levels than other classifiers, (ii) due to its capability to process higher-dimensional data and (iii) since it provides a homogeneous appearance of the results. The accuracy assessment was carried out on pixel level as well as on aggregated field level based on LPIS-polygons.

3.3. HRL Grassland 2015 Development

The HRL Grassland 2015 product provides a consistent map of all managed and (semi-)natural grasslands in Europe (EEA39) with 20m spatial resolution (Fig. 5).

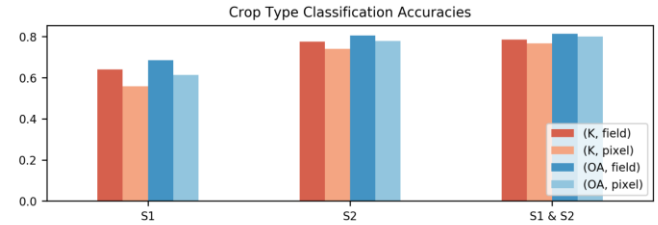

Fig. 4. Barplot of Kappa (K) and Overall Accuracy (OA) for crop types

It has recently been produced on behalf of the European Environment Agency (EEA) in a combined optical/SAR data analysis approach. Image segments derived from multi-temporal optical EO data and training samples of the main land cover/land use classes were utilized for supervised classifications of both, optical (Sentinel-2/Landsat) and SAR (Sentinel-1) dense time series, resulting in intermediate scene-based grassland masks and a single SAR-based classification layer.

A subsequent rule-based evaluation and combination approach of the optical classification results – by weighting each independent, scene based classification according to the attainable classification accuracy in a rule-based combination with the SAR result – resulted in the final grassland mask. It is a harmonized product covering Europe and Turkey (EEA39) with a 1 ha minimum mapping unit.

4. RESULTS

This section presents the results of the RF-based classification of crop mask and crop types in the ECoLaSS test site in southern Germany, and compares them with the HRL Grassland 2015.

Our final classification model in the ECoLaSS Central test site was built based on 50 of the potential 187 S1 and S2 time features and provided encouraging results. We also compared the combined S1- and S2-based classification performance with classification scenarios using S1 or S2 features separately. The crop mask and type classification accuracies on pixel and field level based on S2 were significantly higher than based on S1. Their combination improved the accuracies only marginally (Fig. 4).

The accuracies varied strongly between different crop types. For example, the field level-based combined S-1 and S-2 accuracies for maize and winter rapeseed are as high as 90% and for winter barley, summer barley, winter wheat, peas and agricultural grassland 75–85%. For summer oat, winter triticale, fallow land and potatoes, however, accuracies only at 50–60% due to similar spectro-temporal characteristics as compared to other crop types. Summer wheat and winter rye were under-represented in the study site. A comparison of the crop type map with the HRL Grassland 2015 showed that the two datasets are complementary to a high degree, with a low degree of overlap (Fig. 6).

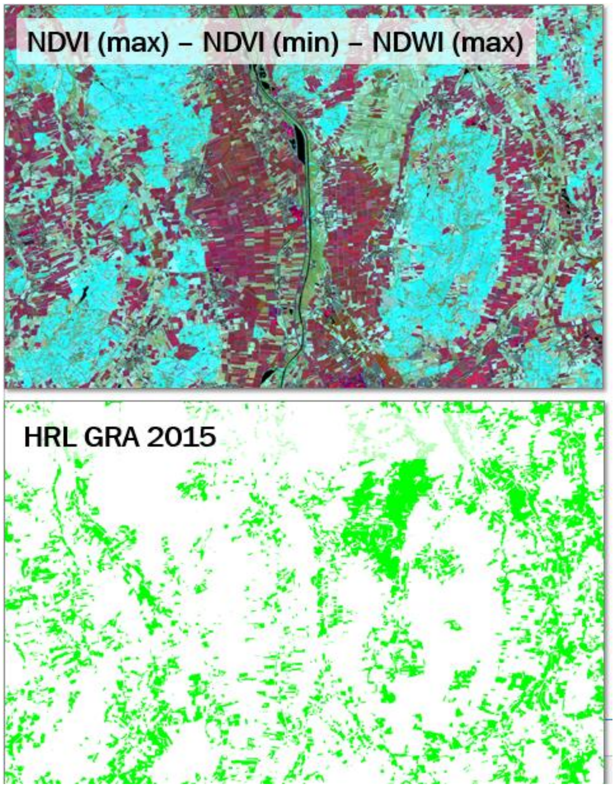

Fig. 5. RGB of Sentinel-2 time features, Grassland mask: HRL GRA 2015

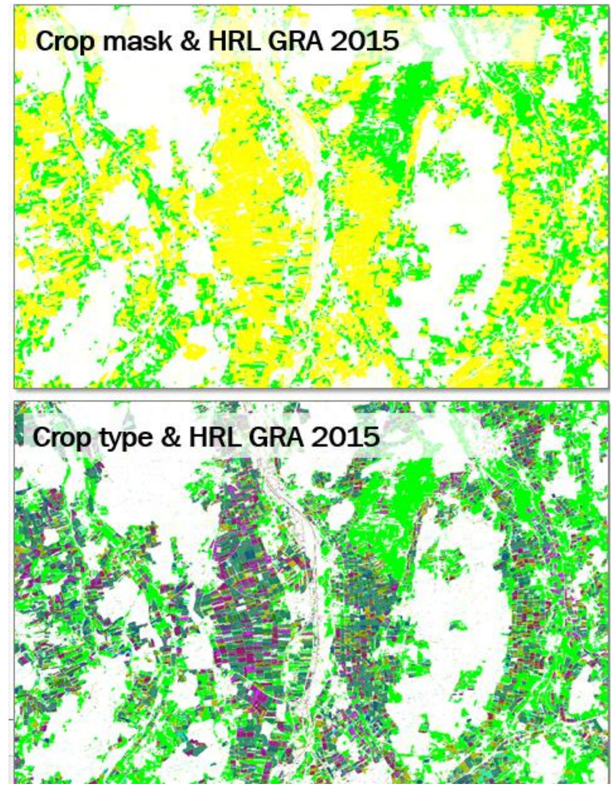

Fig. 6. Grassland mask, crop mask, crop type

5. CONSLUSIONS AND OUTLOOK

This work shows the potential of Sentinel-1 and -2 time series for highly automated classification of crop area and crop type maps, e.g. for a potential future Copernicus Land Monitoring Services on agriculture/arable land. The HRL Grassland 2015 dataset proved to be highly complementary. Future developments for crop area/type classification will concentrate on extending the input EO data with Sentinel-1 coherence data. An improved sample base is planned, further indices and time features will be developed and tested, and an enhanced feature selection and further statistical analysis will be performed.

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