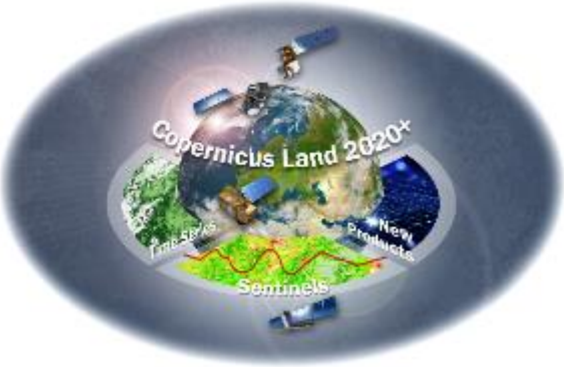
Horizon 2020

Space Call - Earth Observation: EO-3-2016: Evolution of Copernicus services

Grant Agreement No. 730008

ECoLaSS

Evolution of Copernicus Land Services based on Sentinel data



D14.1

"D44.1a – Prototype Report: Crop Area and Crop Status/Parameters"

Issue/Rev.: 1.0

Date Issued: 10.08.2018

submitted by:

UCL Université catholique de Louvain

in collaboration with the consortium partners:

SIRS · JOANNEUM RESEARCH DIGITAL · GAF AG · DLR

submitted to:

European Commission – Research Executive Agency

This project has received funding from the European Union's Horizon 2020 Research and Innovation Programme, under Grant Agreement No. 730008.

Consortium Partners

No.	Participant Organisation Name	Short name	City, Country
1	GAF AG	GAF	Munich, Germany
2	Systèmes d'Information à Référence Spatiale SAS	SIRS	Villeneuve d'Ascq, France
3	JOANNEUM RESEARCH Forschungsgesellschaft mbH	JR	Graz, Austria
4	Université catholique de Louvain, Earth and Life Institute (ELI)	UCL	Louvain-la-Neuve, Belgium
5	German Aerospace Center (DLR), German Remote Sensing Data Center (DFD), Wessling	DLR	Wessling, Germany

Contact:

GAF AG
Arnulfstr. 199 – D-80634 München – Germany
Phone: ++49 (0)89 121528 0 – FAX: ++49 (0)89 121528 79
E-mail: copernicus@gaf.de – Internet: www.gaf.de

Disclaimer:

Document Release Sheet

	Name, Function	Date	Signature
Author(s):	Pierre Defourny (UCL) Jolan Wolter (UCL) Omar Ali Eweys (UCL) Marie-Julie Lambert (UCL) Nicolas Bellemans (UCL)Katharina Schwab (GAF) Linda Moser (GAF) Benjamin Mack (GAF) Christophe Sannier (SIRS) Sophie Villerot (SIRS)	09.08.2018	
Review:	Katharina Schwab (GAF)	10.08.2018	K. Schwab
Approval:	Linda Moser (GAF)	10.08.2018	Linda Moser
Acceptance:	Massimo Ciscato (REA)		
Distribution:	public		

Dissemination Level

Dissemination Level		
PU	Public	X
CO	Confidential: only for members of the consortium (including the Commission Services)	

Document Status Sheet

Issue/Rev	Date	Page(s)	Description / Changes
1.0	10.08.2018	71	First issue of the Prototype Report: Crop Area and Crop Status/Parameters.

Applicable Documents

ID	Document Name / Issue Date
AD01	Horizon 2020 Work Programme 2016 – 2017, 5 iii. Leadership in Enabling and Industrial Technologies – Space. Call: EO-3-2016: Evolution of Copernicus services. Issued: 13.10.2015
AD02	Guidance Document: Research Needs Of Copernicus Operational Services. Final Version issued: 30.10.2015
AD03	Proposal: Evolution of Copernicus Land Services based on Sentinel data. Proposal acronym: ECoLaSS, Proposal number: 730008. Submitted: 03.03.2016
AD04	Grant Agreement – ECoLaSS. Grant Agreement number: 730008 – ECoLaSS – H2020-EO-2016/H2020-EO-2016. Issued: 18.10.2016
AD05	D7.1 : D32.1a - Methods Compendium: Time Series Preparation, Issue 1.0, Issued: February 2018. Issued: 28.02.2018
AD06	D8.1 : D33.1a - Methods Compendium: Time Series Analysis for Thematic Classification, Issue 1.0. Issued: 29.03.2018

EXECUTIVE SUMMARY

The Horizon 2020 (H2020) project, "Evolution of Copernicus Land Services based on Sentinel data" (ECoLaSS) addresses the H2020 Work Programme 5 iii. Leadership in Enabling and Industrial technologies - Space, specifically the Topic EO-3-2016: Evolution of Copernicus services. ECoLaSS is being conducted from 2017–2019 and aims at developing and prototypically demonstrating selected innovative products and methods for future next-generation operational Copernicus Land Monitoring Service (CLMS) products of the pan-European and Global Components. This will contribute to demonstrating operational readiness of the finally selected products, and shall allow the key CLMS stakeholders (i.e. mainly the Entrusted European Entities (EEE) EEA and JRC) to take informed decisions on potential procurement of the next generation of Copernicus Land services from 2020 onwards.

To achieve this goal, ECoLaSS makes full use of dense time series of Sentinel-2 and Sentinel-3 optical data as well as Sentinel-1 Synthetic Aperture Radar (SAR) data. Rapidly evolving scientific as well as user requirements is being analysed in support of a future pan-European roll-out of new/improved CLMS products, and the transfer to global applications.

This Deliverable **D11.1: "D.44.1a – Prototype Report: Crop Area and Crop Status Parameters"** is a deliverable of the WP 44 targeting capturing the phenology of the different crop types as well as the crop type mapping based on S-1 and/or S-2 time series.

Methods developed for the Crop Mask (CRM) and the Crop Type Map (CRT) prototypes are applied in this WP for the West, Central and Mali Demonstration sites in a way testing the methods under a large diversity of agrosystems and Earth Observation conditions (cloudiness in particular). Hence, the features types and the applied classifier are taken into consideration for harmonizing the protocols among across the Demonstration sites. In addition, bases of the calibration and validation differs according to the sites where the LPIS layers are used in the case of the European sites while comprehensive dataset collected on the field by partner and quality controlled by UCL is employed for the Mali Site.

Promising results are obtained. The CRM products obtained from applying the Random Forest classifier on different datasets gives very satisfactory performance with an overall accuracy much higher than 90% where the overall accuracy records (i) 98 % for site West (France) from S-2 only, (ii) 97% (F1-Score 0.97) for site Central from S-1 and S-2, 97%, and (iii) (F1-Score 0.89) for site Mali from S-2). These high accuracies obtained for all sites including the Malian smallholder cropping systems demonstrated the maturity level of this prototype. However, important aspects should be taken into consideration including the optimization of the number of features (for the site Central 28 features out of the 1246 computed were found efficient), the stratification to deal with uneven spatial distribution of the calibration data, and some specific confusion like the grassland in Germany and the bottoms of valley in Mali.

Also, promising results are obtained for the Crop Type Map (CRT) products. The accuracy assessments show that the overall accuracy ranging from 64 % in Mali (20 tiles - 6 classes) and 77 % (4 tiles together - 13 classes) in France both using only S-2 to 89 % in Germany (9 tiles together – 16 classes) to 92 % in Belgium (for the best tile – 24 classes) both combining S-2 and S-1-derived features. Employing the CRM and CRT products for masking positively impacts these results where the F1-score values for the different crops show a very large range with some crops. The associated F1-score values are beyond 0.8 (dominant crops in the agricultural landscape) while most of them below 0.8 down to 0.3 for marginal classes.

Finally, it is worth mentioning that CRM and CRT prototypes will be further developed over the West, Central and Mali Demonstration sites and, then, extended to the South France and South Africa Demonstration sites where cropland – grassland discrimination and then the year-to-year variation of the CRM prototype products will be of the first priority.

Table of Contents

List of Figures and Tables

Abbreviations

AOI	Area of Interest
BRI	Brightness Index
CLMS	Copernicus Land Monitoring Service
CMDT	Compagnie Malienne pour le Développement du Textile
Co	Cotton
CRM	Crop Mask
CRT	Cropland Type/Crop Type
CT	Classification Trees
ECoLaSS	Evolution of Copernicus Land Services based on Sentinel data
EEA	European Environmental Agency
EEE	European Entrusted Entities
EO	Earth Observation
ESA	European Space Agency
FFS	Forward Feature Selection
GIS	Geographic Information System
GRA	Grassland
GRD	Ground Range Detected
H2020	Horizon 2020
HRLs	High Resolution Layers
IRECI	Inverted Red-Edge Chlorophyll Index
ITCZ	Intertropical Convergence Zone
JRC	Joint Research Center
LC/LU	Land Cover/Land Use
LPIS	Land Parcel Identification System
Mi	Millet
MMU	Minimum Mapping Unit
Mz	Maize
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
OA	Overall Accuracy
PA	Producer’s Accuracy
Rc	Paddy rice
PHENO	Phenological Product
PIRT	Projet d’Inventaire des Ressources Terrestres
RF	Random Forest
S-1	Sentinel-1
S-2	Sentinel-2
S-3	Sentinel-3
SAR	Synthetic Aperture Radar
Sg	Sorghum
UA	User’s Accuracy
VHR	Very High Resolution
WBS	Work Breakdown Structure
WP	Work Package
XML	Extensible Markup Language

1 Introduction

The Horizon 2020 (H2020) project, "Evolution of Copernicus Land Services based on Sentinel data" (ECoLaSS) addresses the H2020 Work Programme 5 iii. Leadership in Enabling and Industrial technologies - Space, specifically the Topic EO-3-2016: Evolution of Copernicus services. ECoLaSS is being conducted from 2017–2019 and aims at developing and prototypically demonstrating selected innovative products and methods for future next-generation operational Copernicus Land Monitoring Service (CLMS) products of the pan-European and Global Components. This will contribute to demonstrating operational readiness of the finally selected products, and shall allow the key CLMS stakeholders (i.e. mainly the Entrusted European Entities (EEE) EEA and JRC) to take informed decisions on potential procurement of the next generation of Copernicus Land services from 2020 onwards.

To achieve this goal, ECoLaSS makes full use of dense time series of Sentinel-2 and Sentinel-3 optical data as well as Sentinel-1 Synthetic Aperture Radar (SAR) data. Rapidly evolving scientific as well as user requirements are analysed in support of a future pan-European roll-out of new/improved CLMS products, and the transfer to global applications.

This Deliverable **D14.1-D.44.1a – Prototype Report: Crop Area and Crop Status/Parameters (Issue 1)** is devoted for demonstrating a proof-of-concept system for delivering agriculture related products on feature pan-European scale by taking advantage of the continuous fluxes of Sentinel-1, and -2 data. This deliverable comprises a description of the provided prototype datasets of crop area and crop status/parameters (linked to D44.2a). A detailed description of the objectives are provided together with an explanation of the methodology, results and conclusions, as derived by WP44. It addresses the developed methodologies for extending S-2 processing chain to S-1 and to larger number of crop types, the implementation of a classification processing chain considering multi-annual spectral signatures, the integration of Synthetic Aperture Radar (SAR) time series into optical processing lines for mapping agricultural practices, as well as explore the algorithm potential in food insecure countries. As such, it is part of WP 44 of task 4:"Thematic proof-proof-of-Concept/Prototype on Continental/Global Scale", which aims at exploring and setting up a robust classification approach for Crop type identification based on Sentinel-2 and Sentinel-1 time series and in situ data for pan-European Land Monitoring. This report will be accompanied by the Deliverable **D14.3 - P44.2a – Data Sets of Crop Area and Crop Status/Parameters Products (Issue 1)**. This report serves as documentation for the prototype dataset.

In the ECoLaSS project a prototype is defined as a prototypic / thematic proof-of-concept implementation of an improved or newly defined potential future Copernicus Land layer, building on the methods and processing lines developed in Task 3. The consortium has selected representative demonstration sites both in Europe and Africa, covering various bio-geographic regions and biomes. All prototype products and services are prototypically implemented in these sites in the frame of the Task 4 WPs. In ECoLaSS proofs-of-concept / prototype demonstration are carried out with respect to five topics of relevance: (i) Time series derived indicators and variables, (ii) Incremental Updates of HR Layers, (iii) Improved permanent grassland identification, (iv) Crop area and crop status / parameters monitoring, and (v) New LC/LU products. This deliverable focusses on the prototype Crop Type Identification as part of WP 44.

This report comprises of six sections. Section 1 of the document structure provide comprehensive introduction with the objectives and contents of the report. Section 2 gives background information on crop type identification, prototyping phase and how they will be serve the stakeholders in the framework of Copernicus HRLs and ongoing activities. Section 3 details the demonstration sites characteristics where development and validation of the prototypes take place. Then, overview of the developed methods for crop type mapping is provided in section 4 while section 5 describes the implementation of the developed methods in a way detailing the processing chain producing crop type maps with accuracy assessment of the maps. Finally, core points of the developed methods and main results are summarized with perspectives in section 6.

2 Background and Summary of Requirements

After first methods have been tested by the Task 3 WPs (AD05, AD06, AD07, AD08, AD09) in various test sites and algorithms have been described, the demonstration activities of Task 4 have commenced to set up the developed processing lines in demonstration sites and derive first prototype versions. This will comprise establishing prototypes for: (i) deriving indicators and variables both for Continental and Global Component products and services from high-volume time series data with high spatial resolution and temporal repeat frequency; (ii) improving one of the main pan-European Copernicus Land products, i.e. the current (2012) and future (2015, 2018) HRLs on Forest and Imperviousness by developing incremental update strategies and ensuring time series consistency; (iii) improved permanent grassland identification targeting the HRL Grassland 2015 improvement; (iv) crop area and crop status/parameters monitoring targeting a potential future Agricultural service; as well as (v) further novel LC/LU products, e.g. as tested in Task 3.

The project is basing all its developments on regularly updated high-priority user requirements, and assess/benchmark all operational product candidates in view of their innovation potential and technical excellence, automation level, potential for roll-out to pan-European level and/or global scale, timeliness for operational implementation, costs versus benefits, etc. (further elaborations will be performed in Task 5).

The latest production of the Copernicus High Resolution Layers contains five thematic areas: Imperviousness, Forest, Grassland, Water and Wetness, and Small Woody Features. A layer on agriculture or arable land has not yet been part of the HRLs, and is also not foreseen for the 2018 production. ECoLaSS targets a potential new layer on agriculture for 2020+, which is proposed to contain, on the one hand a Crop Mask (CRM), and on the other hand a Crop Type (CRT) map.

Within the user and stakeholder requirements analysis, as performed as part of WP 21, a future potential Agricultural Service was most voiced by multiple users. The Joint Research Centre (JRC) emphasised the concept note entitled “Towards Future Copernicus Service Components in support to Agriculture” which has been drafted by JRC in April 2016 (JRC, 2016). A follow-up on this concept note is expected to be issued any time soon. Since up to now no clear specifications for a Copernicus HRL Agricultural Service have been set, the ECoLaSS team is proposing a Crop Mask and different setups of Crop Type maps, which have been produced for four different prototype experiments applied onto three demonstration sites in project phase one.

3 Demonstration Sites

All prototypes are implemented in selected representative demonstration sites, which cover various bio-geographic regions and biomes. The Crop mask and crop types 2016 is demonstrated in the demonstration site West, whereas for 2017 the demonstration sites Central, West and Mali are used.

3.1 ECoLaSS Demonstration Sites

The selected larger prototype sites (60,000/90,000 km² per prototype site) contain the 5 test sites from Task 3. These prototype sites are relevant in Task 4 for demonstrating the proposed candidates for a Copernicus Land Service Evolution roll-out on a larger scale. As shown in Figure 3-1, the pre-selected demonstration sites cover the Boreal, Continental, Alpine, Atlantic and Mediterranean zones (Source EEA: http://www.eea.europa.eu/data-and-maps/data/biogeographical-regions-europe-3#tab-gis-data) of the member and associated states of the EEA-39. The selected prototype sites are located in the **North of Europe, in the Alpine/Central region, in the West, in the South-West and in the South-East of Europe**. All prototype products and services will be prototypically implemented in one or more prototype sites in project phase 1, and in three prototype sites in phase 2.

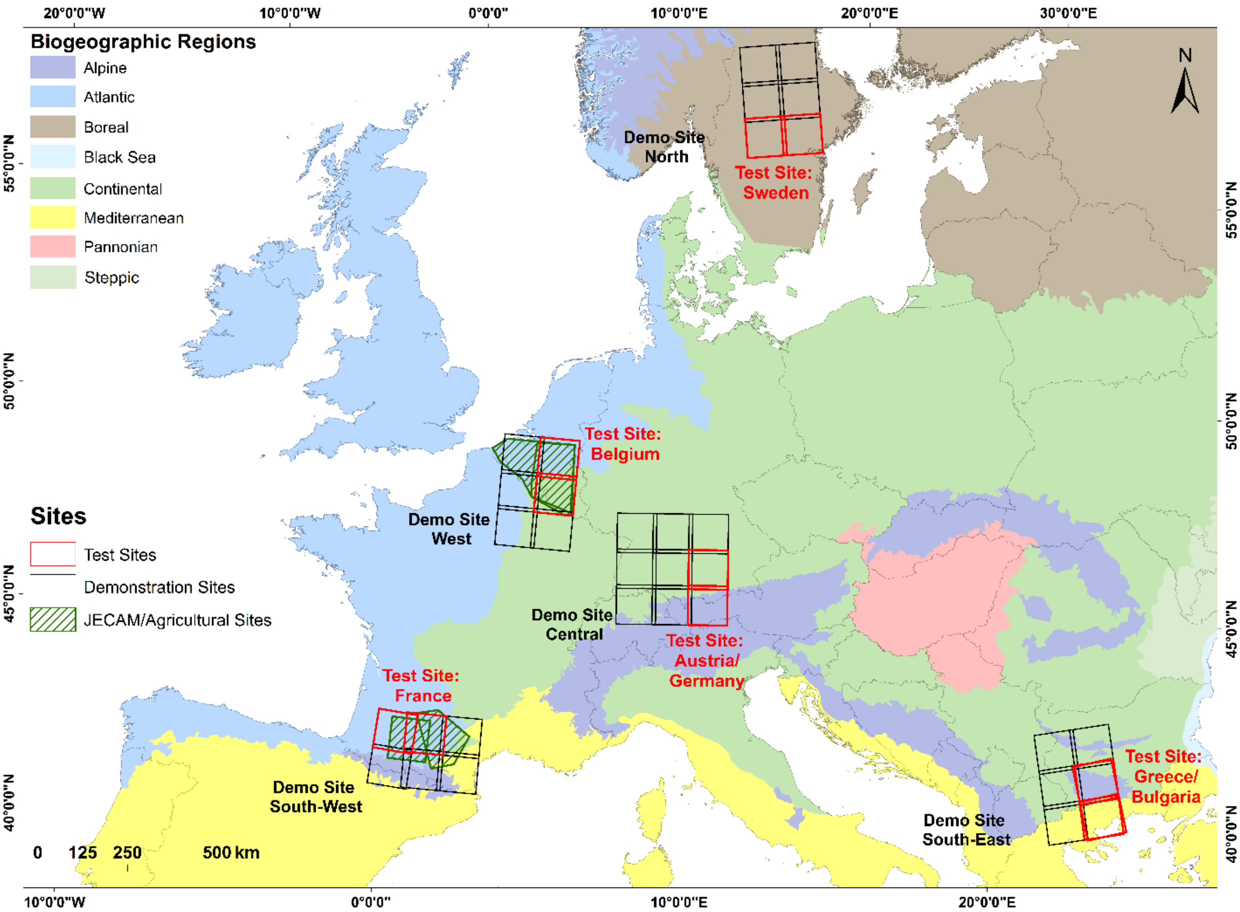


Figure 3-1: European Demonstration Sites

(Map: © European Environment Agency; administrative boundaries: ©EuroGeographics)

A short description of the different prototype sites is given in the following Table 3-1 below:

Table 3-1: Description of the selected Prototype Sites

Location	Biogeographical region(s)	Countries	Distribution of CORINE land cover classes 2012 (Level 1) per prototype site
Northern Europe	Boreal	Sweden, Norway	Artificial areas: 1,38 %, Agricultural areas: 10,54 %, Forest and semi-natural areas: 70,61 %, Wetlands: 4,25 %, Waterbodies: 13,22 %
Alpine / Central Europe	Continental, Alpine	Germany, Austria, Switzerland, Italy and Czech Republic	Artificial areas: 5,86 %, Agricultural areas: 42,96 %, Forest and semi-natural areas: 49,95 %, Wetlands: 0,24 %, Waterbodies: 0,98 %
West Europe	Atlantic, Continental	Belgium, France, Luxembourg	Artificial areas: 7,81 %, Agricultural areas: 53,75 %, Forest and semi-natural areas: 13,15 %, Wetlands: 0,25 %, Waterbodies: 25,04 %
South-East Europe	Mediterranean, Continental, Alpine	Serbia, Macedonia, Greece, Bulgaria and Kosovo	Artificial areas: 3,03%, Agricultural areas: 37,00 %, Forest and semi-natural areas: 53,95 %, Wetlands: 0,17 %, Waterbodies: 5,71 %
South-West Europe	Atlantic, Mediterranean, Alpine	France, Spain	Artificial areas: 3,26 %, Agricultural areas: 46,73 %, Forest and semi-natural areas: 49,20 %, Wetlands: 0,01 %, Waterbodies: 0,40 %

3.1.1 Demonstration site West for Crop Type Mapping

In the frame of the Task 4 where all prototype products and services are implemented, the West demonstration site has been chosen as the primary demonstration site for the improved HRL Grassland (GRA), a potentially new phenological product (PHENO) as well as a potential future Copernicus Land High Resolution Layer on Agricultural (AGRI). The demonstration site contains the test site “Belgium” that has been studied in Task 3.

For this WP44, regarding the French part, the area selected exhibits a strong heterogeneity of cropland, mixed with intensive grasslands, besides common areas such as urban areas, forest or water.

For SIRS production site, all the prototype experimentation was conducted on four Sentinel-2 tiles over France and Belgium (31UER, 31UEQ, 31UFR and 31UFR), which represents a total superficies of 40.000 km² in the south part of the demo-site West, as seen in Figure 3-2.
For UCL production site, three Sentinel-2 tiles were used for conducting the prototype experimentation. In particular, the 31UES and 31UFS tiles are over Belgium while the 31UFR tile is over Belgium and France (Figure 3-2) with a total superficies of 30.000 km² in the south part of the demo-site West.

Figure 3-2: Overview of the six tiles of the WEST demonstration site where the southern four tiles are over Belgium and France.

3.1.2 Demonstration site Central for Crop Type Mapping

The Demonstration Site Central covers the countries of Germany (mainly the provinces of Bayern and Baden-Wurttemberg), Austria (mainly the provinces of Tyrol and Vorarlberg), some parts of Switzerland, a small part of France, Italy, and Liechtenstein. This Demonstration site covers the test-site in Germany/Austria. The Central demonstration site is characterized by dominant use of cropland areas, mixed with grassland (pastures). The adjoining part towards South, covering the foothills of the Bavarian Alps, is dominated (besides forest cover) by grasslands including several habitat grassland and wetland types. Mountain-specific vegetation zones are included in the southern tiles, which contain also the Wetterstein mountain range as part of the Alps, stretching South down to the Inn valley. Also covered by the southern tiles is the Bodensee region and the lower parts of Switzerland. Besides the Alps the Black Forest as well as the Vosges are the highest regions, where forests and grassland take place instead of cropland. This site has been chosen for crops mapping due featuring diversified crop categories among different regions (e.g. in Baden-Wurttemberg and Austria), featuring topography and lowlands to high mountains and associated differences in crop types, and the availability of Land Parcel Identification System (LPIS) in-situ data for training the classification algorithm and for validations. Figure 3-3 shows the Central Demonstration site:

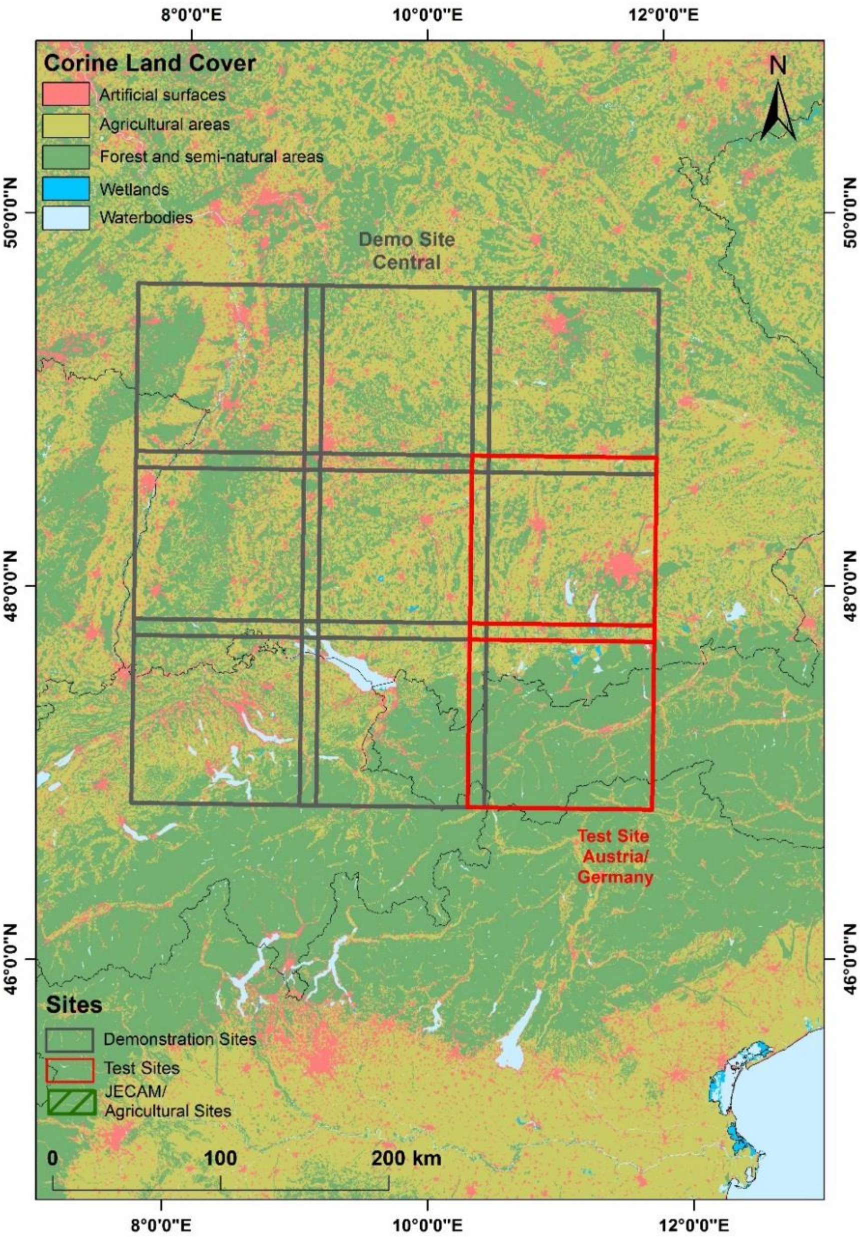


Figure 3-3: Overview of the demonstration-site Central draped over the CORINE Land Cover classes (2012).

© European Union, Copernicus Land Monitoring Service 2012, European Environment Agency (EEA).

3.1.3 Demonstration site Mali for Crop Type Mapping

The Mali demo-site corresponds to a small holder farming system typically monitored by Early Warning Systems in the context of food unsecure countries. The outstanding challenges faced by all Early Warning Systems in assessing local food insecurity, include data accuracy, timeliness and disaggregation. Those challenges are even wider in heterogeneous smallholder farming systems, such as Southern Mali, due to small field size, heterogeneity in management practices, the resulting landscape fragmentation, and the widespread presence of trees within the fields. This Malian demo-site is representative more specifically of the Sudanian region covering a large part of the food unsecure region of West Africa. This region has a strong north-south gradient linked to the movements of the Intertropical Convergence Zone (ITCZ). The climate is tropical with two distinct dry and rainy seasons. In the Sudanian region (isohyets from 500 to 1,000 mm) the growing period is longer (more than 150 days) and spans from May to November.

The study site has been extended to largely correspond to the cotton's belt and covers about 135,500 km². From an administrative perspective, this includes the entire Sikasso's region and part of the Koulikoro (Koulikoro, Kati, Kangaba and Dioila circles) and Ségou's (Bla, San, Tominiam, Baroueli circles) regions with a North limit around 14° in latitude following the circles limits. It is covering most of the Compagnie Malienne pour le Développement du Textile (CMDT) region. The study areas includes two main agro-climatic zones: the Sudanese and the Sudano-Guinean zones that contrast mainly in the annual amount of rainfall. Two major natural regions from the Projet d'Inventaire des Ressources Terrestres (PIRT) are observed in the study regions: Haut Bani-Niger and Koutiala. Pearl millet (Pennisetum glaucum (L.) R. Br.), sorghum (Sorghum bicolor (L.) Moench), maize (Zea mays L. ssp.), paddy rice and cotton (Gossypium sp.) are the major crops in the study area covering respectively 29%, 20%, 13%, 11% and 9% of the cultivated land. A map of the selected prototype site of Mali for the Crop type map is provided in Figure 3-4:

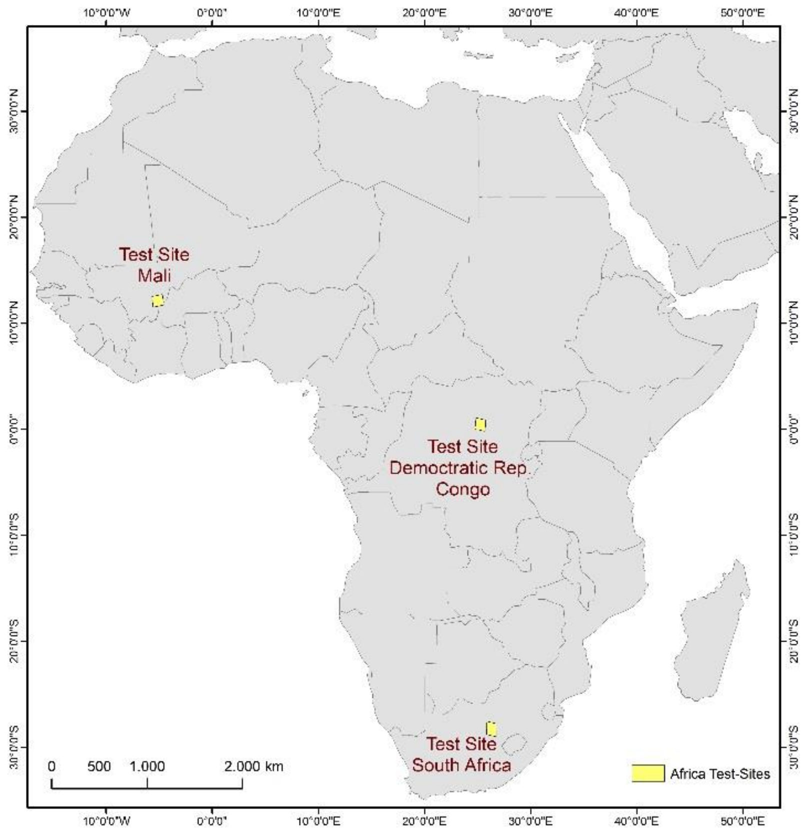


Figure 3-4: Africa Sites

The main crops are the millet (29%), sorghum (20%), maize (13%), paddy rice (11%), and cotton (9%) with a field size typically ranging from 1 to 5 ha. Table 3-2 reports the crop calendar (1-2-3 corresponding to decades) of the main crops.

Table 3-2: Crop calendar for the main crops of the site in Mali (1-2-3 corresponding to decade).

	May			June			July			August			September			October			November		
	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Co			Sowing			Growing							Harvest								
Mz			Sowing				Growing						Harvest								
Mi			Sowing						Growing										Harvest		
Sg			Sowing						Growing						Harvest						
Rc					Sowing					Growing							Harvest				
Gr					Sowing				Growing				Harvest								

4 Overview of applied methods

Each cropland type has its own growing period, it is then necessary to work with time series analysis to discern the phenological dynamics associated. Moreover, since grassland and cropland can show similitudes throw time, it seems important to work on time series indicators on which the phenological distinction should be optimized. Thus, this chapter will present the spectral indicators and the time features associated used to generate this prototype, the pre-classification steps, the classification algorithm employed in the processing chains, and finally, the validation analysis procedure.

4.1 Method for crop type map – Demo-site West

The chapter 4.1 contains information about feature computation and selection, the pre-classification steps, the classification algorithm and the validation procedure.

FEATURES COMPUTATION AND SELECTION

Many spectral indices have already been defined in the WP31 [AD05]. The ones used for the cropland type prototype generation will be specified in this paragraph.

NDVI – Normalized Difference Vegetation Index:

The "Normalized Difference Vegetation Index" (Rouse Jr. et al., 1974; Tucker, 1979) is used as an indicator to monitor vegetation health, and can be used as a proxy for photosynthetic activity and primary production from vegetation biomass. It is calculated as the difference in the reflectance between the NIR region and the red region – a rapid change in the spectral response of vegetation known as the "red edge" – then normalized by the sum of the reflectance in both channels:

$$\mathrm{NDVI} = \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{Red}}}{\rho_{\mathrm{NIR}} + \rho_{\mathrm{Red}}}$$

NDWI – Normalized Difference Water Index:

The “Normalized Difference Water Index” (Gao, 1996) is defined as the ratio

$$\mathrm{NDWI} = \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{SWIR}}}{\rho_{\mathrm{NIR}} + \rho_{\mathrm{SWIR}}}$$

where ρ is the reflectance of each spectral channel. Both wavelengths are localized in the part of the spectrum reflected by vegetation canopies. The NIR channel is linked to a negligible absorption of light by the water content present in the vegetal, while the SWIR channel present a weak liquid absorption. The NDWI is therefore sensitive to slight changes in the liquid water absorbed by vegetation canopies, giving an indication on the vegetation water stress.

BRI – Brightness Index:

The brightness Index (BI) can expressed as (Mathieu et al., 1998):

$$\mathrm{BI} = \sqrt{\frac{\rho_{\mathrm{Red}} + \rho_{\mathrm{Green}} + \rho_{\mathrm{Blue}}}{3}}$$

which is a measure of the average reflectance magnitude in the visible bands, used to quantify the soil color effect.

Temporal features:

Furthermore, temporal statistics on those derived indices have been applied, based on the seasonal time intervals. They are especially useful for determining vegetated classes (Esch et al., 2018). On the prototype generation only nine of them have been generated, for each index, on each considered period, at pixel-level:

- maximum value,
- mean value,
- minimal value,
- standard deviation,
- 10^{th}, 25^{th}, 50^{th} (i.e. the median), 75^{th} and 90^{th} percentiles.

For UCL, the coefficient of variation has been computed in addition to the previously mentioned temporal features on Sentinel 1 data.

<u>**PRE-CLASSIFICATION STEPS**</u>

The Pre-classification steps sub-chapter addresses the image generation and furthermore LPIS data as reference data.

Image generation

For SIRS, A composite of 81 bands was produced by SIRS. The cropland types prototype generation was established with three different time-windows: January to March, April to June and July to September, in order to find a balance between the amount of valid data and the temporal constraints to create a meaningful time series for the phenology, thanks to spectral features as the NDVI, NDWI and brightness, which highlight different characteristics of the vegetation.

For UCL, two time series of bands were used. The fist was composed of 374 bands representing Sentinel-2 data (b3:b8 and b11:b12) in addition to the calculated spectral features (NDVI, NDWI and BRI). Sentinel-2 data were cloud masked and, then, a gap-filling algorithm based on linear interpolation (every 10 days) was applied from January to December. The second time series was composed of 288 bands of Sentinel-1 data representing the backscattering (VV, VH, VV/VH) based calculated features such as mean, standard deviation, coefficient of variations, 10th, 25th, 50th, 75th and 90th percentiles. Each temporal feature has been computed on a 2 months period from January to December.

LPIS as reference data

Two LPIS were used to generate the cropland type product (one on France and another on Belgium). These datasets will be used as a reference for the year 2016. The polygons differentiate several agricultural areas such as croplands and grasslands.

These reference data will be used for three different steps of the processing chain:

1. Samples selection on the most represented cropland types (as the classifications will be distributed on two countries, the classes need to be in common)
2. Homogenization of the results at the parcel levels (attribution of the majority number of pixels to the fields, by statistics zonal computation)
3. Qualitative comparison (i.e. look and feel) for the assessment of the cropland type product

The Belgian LPIS for the year 2017 was used by UCL for the training and validation of the classification.

CLASSIFICATION ALGORITHM

As explained in previous WPs of Task 3, Random Forest (RF) classification combines many decision trees to obtain better predictive performance. Each decision tree is calibrated on a selection of random subset. Algorithms such as RF have recently received increasing interest (Rodriguez-Galiano, Ghimire, Rogan, Chica-Olmo, & Rigol-Sanchez, 2012) because they have proved to be more accurate and more robust to noise than single classifiers (Shang & Breiman, 1996). Ensemble classifier, like the multitudes of decision trees in RF, are known to perform better than an individual classifier can. Breiman (Breiman, Random Forests, 2001) introduced RF in 2001 which presents many advantages for its application in remote sensing:

- Efficiency on large data bases;
- Thousands of input variables without variable deletion;
- Estimation of which variables are important in the classification;
- Relative robustness to outliers and noise;
- Computational lightness compared to other tree ensemble methods (e.g. Boosting);
- Much less sensitivity to overtraining or over fitting.

A RF consists of a combination of classifiers where each one of those contributes with a single vote to the assignation of the most frequent class detected for the input vector. This grant RF special characteristics which make it substantially different to traditional classification trees (CT). In fact, a RF increases the diversity of the trees by making them grow from different training data subsets created through the process.

VALIDATION PROCEDURE

Thematic accuracy is presented in the form of an error matrix made from the results of the samples interpretation, with 50% of them used for the calibration and the other 50% for the validation.

The thematic accuracy is also defined by several quality indices:

- The Overall Accuracy (also called Recognition Rate) is measured by the sum of the diagonal of the Confusion Matrix divided by the total number of controlled points. It assesses the overall agreement between the classified and reference data set.
- The User Accuracy is measured by dividing the diagonal number of pixels by the row total. It assesses the commission error (or contamination risk), i.e. the errors due to the wrong allocation of an observation to a class.

Producer Accuracy is measured by dividing the diagonal number of pixels by the column total. It assesses the omission error.

The F-score was utilized as a measure of accuracy where the precision and recall were considered to calculate the score. Specifically, the precision is the number of correct positive results divided by the number of all positive results returned by the classifier while the recall is the number of correct positive results divided by the number of all samples identified as positive.

4.2 Method for crop type map – Demo-Site Central

During the testing and benchmarking performed in the frame of WP33 (AD06) one of the main results was that for the crop mask as well as the crop types, the accuracies of the classifications based on S-2 are significantly higher than those based on S-1. Using both S-1 and S-2 increases the accuracies only marginally in the Germany/central test site. It was decided to use both Sentinel-1 and Sentinel-2 data for the agricultural prototype, in the light of implementation and comparison on the larger demonstration site, a future pan-European roll out into areas of high cloud cover or short growing season, and further testing of the advantages of optical/SAR sensor integration.

After the data selection, several pre-processing steps are necessary to prepare the EO data (see section 5.1.2 and AD05).

FEATURES COMPUTATION AND SELECTION

As preceding tests in the frame of Task 3 (AD06) of this project have shown that the time-features approach is an appropriate method to prepare the data for crop type classification this method is used for the calculation of the agricultural prototype in the demonstration site Central. The feature extraction step consists of computing the most discriminant variables from the time series to be used as input for the classification algorithm. These features may be of various natures: (1) spectral, such as the multispectral reflectance from S-2 or the backscatter coefficient from S-1, as well as derived indices, such as the NDVI or any other vegetation, chlorophyll or soil index, as well as SAR band rations; (2) temporal, such as the minimum, maximum or amplitude of a variable over a given time period; and (3) textural, such as the local contrast, entropy or any other variable derived from the co-occurrence matrix. More details on the time-features and their background are given in the AD06 (pp. 74).

PRE-CLASSIFICATION STEPS (FORWARD FEATURE SELECTION)

Building a large set of features for the whole raster data is computationally expensive and it is desirable to reduce this cost by only computing features that turn out to be informative for the respective classification task. However, the optimal set of features is usually not known in advance. In order to tackle this problem the classification workflow applied in this study explicitly addresses feature selection, which is computed (i) for a subset of the data, e.g. for a proportion of the training polygons, and thereafter (ii) only the selected features are calculated for the complete raster data (not only for the training data locations). Therefore, the calculated features for the training data are analysed first, and they are reduced in number by applying a forward feature selections (FFS) approach. Feature selection aims on reducing a pre-defined set of potential features but without reducing the accuracy of the model. The forward feature selection is an iterative feature selection approach where the most informative features are selected. In the first iteration the classification accuracy is estimated for all single features and the one which has the highest accuracy is selected. In the second iteration, the accuracies are calculated for each of the remaining, i.e. not yet selected, features combined with the selected feature. Based on these calculations the new feature, which leads to the highest accuracy is selected and added to the already selected one. This can be done until all features are selected or until the accuracy does not improve anymore significantly.

In the developed feature selection approach used for the crop classification two runs of the FFS are applied. The first one uses feature groups which are defined by all features derived for a specific band and time period, e.g. all features derived from the NDVI in the period mid-March to mid-May. After the first

FFS the resulting reduced set of features builds the basis for the second FFS run, which selects single features in contrary to the first group-based run.

The advantage of this approach is two-fold. First, for a given number of features to be calculated, the processing cost decreases with the number of feature groups which are composed out of single features. This is on one hand due to the reduced loading-from-disc-in-memory cost and on the other hand because the derivation of two or more features from the same feature group is often less computationally expensive than the derivation of two features where each comes from a different feature group. For example, for the percentiles, the valid values of each pixel time series have to be ordered. Once ordered, the derivation of two different percentiles, e.g. the 10th and 25th percentile, is less expensive than the computation of the 10th percentile from one group and the 25th from another group since the pixel values from two groups need to be ordered. The second advantage of a group-based FFS is that it is faster compared to the single-feature-based FFS. Although both group- and single-feature-based FFS are containing the same features, the focus lies in a reduced amount of groups compared to the single-feature-based FFS, which leads to a reduced duration of computation.

The finally selected features were then calculated for the whole raster data and used to train the final classification model. An independent accuracy assessment was then performed based on the test polygons, which have not been used at any point during model training (including FFS).

CLASSIFICATION ALGORITHM (RANDOM FOREST CLASSIFIER)

The classifications (crop type, crop mask, FFS) themselves consist of one or many numerical processes to finally allocate every pixel (in terms of a pixel-based classification) to one of the classes of a defined land cover typology. At the moment many different methods exist, which can be, e.g., parametric/non-parametric or supervised/unsupervised. The applied non-parametric random forests approach was selected for the agricultural prototype. The algorithm is robust to data reduction and doesn't overfit. Moreover, it has its strengths in the capacity to determine variable importance. One of the negative aspects is a high computational effort. However, due to the higher accuracies compared to other classification methods it has been chosen for the calculation of the agricultural prototype. For further details on the classification method please see AD06 (pp. 82). The outcome of the classification are different layers depending on the number of classes: one layer for the predictions (classes), the class-probabilities (one layer per class), and three reliability layers (max. probability, breaking ties, entropy), which is combined to one single reliability layer.

For the validation of the classification result a confusion matrix is created which compares the final classification with a reference data set via cross-correlation. In this context the Producer's (PA) and User's Accuracies (UA) are analyzed as well as the Overall Accuracy (OA) and the F-Score.

POST-PROCESSING

The final result is a pixel based product representing the most probable crop type per pixel. As users of such data are more familiar with vector based products, where each vector patch represents a parcel with a certain crop type, several tests were conducted to enhance the overall look-and-feel of the product. The most common method to harmonize such pixel based products is a filtering of neighbouring pixels and an elimination of pixel cluster below a specified size, the minimum mapping unit.

At a first step a majority filter has been applied. In a kernel of 3x3 pixels the majority of the classes is determined to define the center pixel value. With that method single pixel and small lines of pixel, which mostly represents parcel borders, which couldn't been interpreted due to spectral mixture with other land use and land cover like tracks between fields or the land use of an adjacent parcel, can be removed.

In a second step the filtered results have been eliminated to cluster of pixel with a certain amount of pixel. A threshold was set to a parcel size of 15 pixel or 1500 m², as this size allowed the removal of small patches with uncertain class predictions (just from visual inspection) by keeping an accurate mapping of the agricultural fields. This threshold will be further investigated in the second project phase, as it will differ from region to region over Europe.

After these two steps of filtering the final product appears much more harmonized but still fulfilling the request of a pixel based product. The overall accuracy only slightly differs from the pixel based analyses while the overall look-and-feel is increased tremendously.

The overall filtering of the product will also be further investigated in the second project phase to determine the most appropriate way of product post-processing to not lose too much information from the pixel based crop type classification but to improve the look-and-feel of the product and receive the most user friendly end-product with great acceptance on user side.

4.3 Method for crop type map – Demo-site Mali

The proposed method for the demo-site Mali is based on the ESA Sen2-Agri system which has been supported by ESA and recently developed as a generic free and open-source operational tool for crop mapping. It was demonstrated in several countries but never for crop type mapping over a large area in a smallholder cropping system. This standalone processing system made of modules generates a series of four agricultural products from Sentinel-2 (S2) and Landsat 8 (L8) time series acquired along the growing season of interest. It allows handling large volume of EO data in near real time and easily scale up to cover countrywide products. Two modules were tested over the demo-site Mali: (i) the dynamic cropland mask and (ii) the cultivated crop type map for the main crop types.

Features computation and selection

As described by Valero et al. (2016) and Inglada et al. (2015), the Sen2_Agri system uses as input features for the classifier, 10-day gap-filled time series of S2 and L8 surface reflectance values. This means that a S2-interpolated image is computed every 10-day at 10 and 20 m resolution according to the S2 bands by a weighted linear interpolation. The no-data values were determined thanks to available missing value masks provided by the data preprocessing step, detecting pixels affected by clouds, cloud shadows or saturation effects. The weights used for the linear interpolation were computed by measuring the temporal linear distance between the interpolated date and the valid observations. In addition to the 10 spectral bands of S2, other features such as NDVI, Normalized Difference Water Index (NDWI), and brightness are computed for each of these S2-interpolated image. Unlike for the other demo-sites, the Brightness index is defined by Sen2-Agri as follows:

$$\mathrm{Sen2Agri} = \sqrt{{\rho_{\mathrm{Green}}}^2 + {\rho_{\mathrm{Red}}}^2 + {\rho_{\mathrm{NIR}}}^2 + {\rho_{\mathrm{SWIR}}}^2}$$

Therefore 13 features compiled for the 25 dates of the time series corresponding to the growing period are available for the classification process. All are used in the crop type classification process. For the cropland extent mapping, 17 phenological metrics derived from the NDVI profile (Valero et al., 2016) and 5 statistical metrics respectively computed from the NDWI and the Brightness time series (Valero et al., 2016) are compiled as input data.

Pre-classification step (Cropland mask)

As a preliminary step for the crop type mapping, the detection of the cropland extent is required and completed using a supervised Random Forest (RF) classifier exploiting a set of 27 temporal and statistical features specifically designed to depict the growing cycle. This cropland mask is mandatory as no LPIS exists in most of the food unsecured countries. The training data are composed of a set of cropland and non-cropland spatial polygons spread over the demo-site. The methodology applied to map the cropland class relies on the “cropland” definition proposed by the JECAM network in the framework of GEOGLAM. According to this definition, the “annual cropland from a remote sensing perspective is a piece of land of a minimum 0.25 ha (minimum width of 30 m) that is sowed/planted and harvested at least once within the 12 months after the sowing/planting date. The annual cropland produces an herbaceous cover and is sometimes combined with some tree or woody vegetation” (JECAM, 2017). In this definition, perennial crops and fallows are excluded from the cropland class.

CLASSIFICATION ALGORITHM (RANDOM FOREST CLASSIFIER)

The crop type map is a map of the main crop types at 10 m resolution. Similarly to the cropland mask, the processing chain for the generation of the crop type map follows a supervised RF classification approach built on field data. The identification of individual crop types is conducted within the previously created cropland mask. All the features, i.e. the surface reflectance for the 10 S2 spectral bands and the 3 spectral indices are considered as input to establish the RF model at the stratum level. Indeed, to cope with the agro-ecological gradients and the diversity of cropping systems, a stratification layer is defined to reduce the heterogeneity observed for each main crop of interest. As the demo-site Mali covers two main agro-climatic zones: the Sudanese and the Sudano-Guinean zones that contrast mainly in the annual amount of rainfall. The two major natural regions depicted by the Projet d'Inventaire des Ressources Terrestres (PIRT) are used as stratification: Haut Bani-Niger and Koutiala.

ACCURACY ASSESSMENT

The in situ information were split randomly between training samples (75%) used to feed the classification process and validation samples (25 %) used to assess the product accuracy through the computation of several well-known criteria (Overall Accuracy, and F1-Score of individual crops). In addition, a spatially independent validation data set has been prepared to further assess the quality of the cropland mask.

5 Prototype Implementation

This chapter shows the prototypical implementation of the agricultural prototype, consisting of a crop mask (CRM) and a crop type (CRT) map. Firstly, the integrated EO and ancillary data is described (section 5.1), followed by the demonstration of the results of the actual prototype in the demonstration site as well as the validation (section 0), and lastly, the description of the dataset properties and its metadata, referring to **D14.3: "D44.2a – Data Sets of Crop Area and Crop Status/Parameters Products"**. For a description see section 0.

5.1 Data and Processing Setup

The following subchapters will give further details on the creation of a prototype for a potential future HRL Agriculture, implemented on the Central demonstration site. The following sections include the input data and their integration (section 5.1.1) as well as the several pre-processing steps (section 5.1.2) and the experimental setup for preparing and performing the classification (section 5.1.3).

5.1.1 Input Data

In the following sections, the input data of the Demonstration Sites West, Central and Mali are described. This contains the image data, reference and field data as well as Copernicus HRL 2015 data.

5.1.1.1 Demo-site West

For SIRS, the LPIS dataset for the reference year 2016 only was available over France, and the next version for the year 2017 should become available this summer 2018, hence the use of images dated from the year 2016 only. Since no SAR image covering this time window has been provided, and a complete re-processing of the raw archive of S-1 images was deemed too time-consuming, the process only used optical data from 2016. Regarding these optical data, it has been decided to split them into three trimesters – January to Mars, April to June and July to September. The aim of this approach was to establish a spectral signature over the study year (2 January of 2016 to 28 September of 2016) for the different classes, through several indices such as NDVI, NDWI or BRI (the description of the indices and their time features are available in the methodology section in chapter 4.

For all those reasons, the dataset used was restricted to 91 S-2 images, after applying the cloud mask to put aside the unexploitable captures. Those images are composed of 10 bands at 10m and 20m and are atmospherically corrected. In order to increase the accuracy of the results for further classification, it should be useful to integrate S-1 in the next iteration of the task 4.

In contrast to SIRS, UCL used the LPIS datasets dated from the year 2017 which was concurrent to sufficient observations acquired by Sentinel-1 and Sentinel-2 satellites. For Sentinel-1, scenes of the co-polarized (VV), and cross-polarized (VH) backscattering acquired between January and December 2017 were used for calculating the backscattering ratio (VV/VH) which, then, used together (VV, VH, VV/VH) as added sources of information (to optical data acquired by Sentinel-2) for increasing the ability of crop identification. For Sentinel-2 data, observations acquired between January 3rd and December 2nd, 2017 and composed of bands 3:8 and bands 11:12 in addition to NDVI, NDWI and BRI were used after being atmospherically corrected and cloud masked. Hence, the crop type identifications was applied on features fundamentally originated from optical and Synthetic Aperture Radar (SAR) datasets after being undergone to various steps of pre-processing chain detailed in section 5.1.2

Two LPIS datasets were necessary to cover the study area: one over Belgium, called LPIS_OPENDATA_PARC_AGRI_2016 and a second over France referred to as LPIS_Registre_Parcellaire_Graphique_2016. As previously mentioned, the French LPIS for reference year 2016 was used since France has not provided the 2017 version yet at the time of the production of this layer. It is also worth underlining that this LPIS does not contain vineyard parcels, so this class will not show up in the results.

Two of the four Sentinel-2 tiles also covered part of Luxembourg but the LPIS was not complete on this zone. Only the geographical information could be exploited but no information appears in the attribute table.

Besides, the use of the LPIS fulfills two main objectives:

- To select training samples of different cropland types;
- To homogenize the results on the parcels.

The Copernicus 2015 High-Resolution layers (HRL) provide information for the whole of the EEA-39 area on 5 specific land covers: the level of sealed soil (imperviousness), tree cover density and forest type, grasslands, wetness and water, and finally, small woody features. What is more, these products were automatically computed from time series satellite imagery from 2015, before being manually enhanced and finally validated using very high-resolution (VHR) imaging. This is the reason why they are used here to generate 4 layers of non-cropland samples: urban areas, forest, water and grassland. In the final product, these non-cropland classes will be merged in a unique class to establish an overall accuracy of the prototype as detailed in section 5.2.1.

5.1.1.2 Demo-site Central

The prototype calculation for the demo-site Central (see chapter 0) is based on both S-1 and S-2 data covering a time period from 2017/15/03 to 2017/14/11. In case of the S-2 images the cloud cover was constrained to a maximum of 90%. Table 5-1 shows the resulting distribution of images per tile and satellite.

Table 5-1: Number of S-1 and S-2 images per tile used for the calculation of the agricultural prototype for the demonstration site Central.

	32TMT	32TNT	32TPT	32UMU	32UMV	32UNU	32UNV	32UPU	32UPV	SUM
S-1	38	105	66	54	37	115	103	92	103	**713**
S-2	46	47	45	47	45	49	44	42	44	**409**
SUM	**84**	**152**	**111**	**101**	**82**	**164**	**147**	**134**	**147**	**1122**

The differences in number of scenes per tile are mainly caused by the respective point in time and the location of the demonstration site. Regarding the point in time, since data acquisition starts in mid-March, where the cloud cover in the Central demo-site is typically very high, there are a lot of Sentinel-2 scenes which don't fulfil the requirement of less than 90% cloud cover. In terms of location, the differences in Sentinel-1 coverage can be explained by the overlapping swaths (see Figure 5-1). The 32UNU and the 32TNT tile for example have the highest number of scenes and as the Figure 5-1 shows, the two swaths have the biggest overlap there, so there are more images available that mostly cover these tiles.

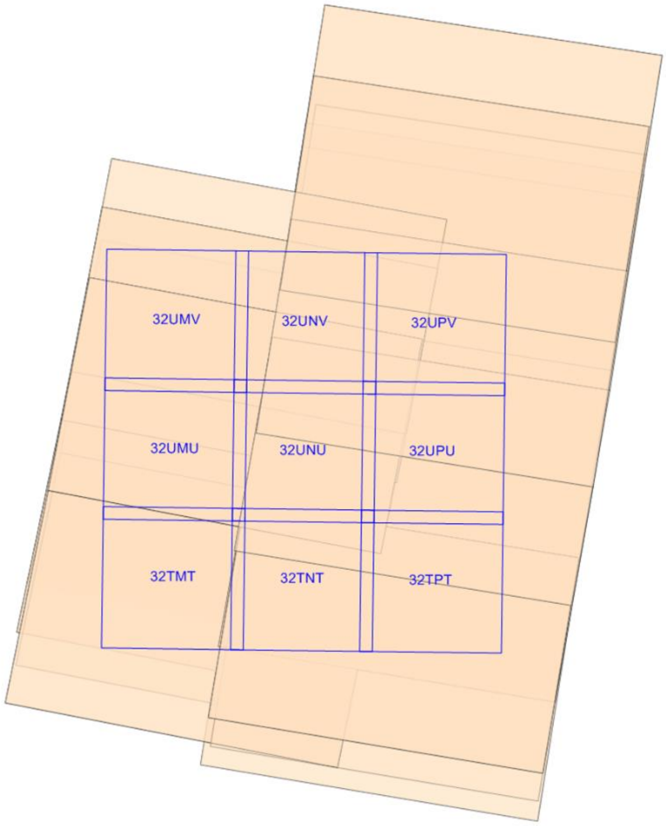


Figure 5-1: Coverage of the Demo-Site Central with Sentinel-1 data (orange) and Sentinel-2 data tiles (blue).

Besides the EO data for the classification, reference data were necessary for the calibration of the classification model as well as for the validation of the classification results. Therefore Land Parcel Identification System (LPIS) data were used for most of the analysed tiles, where LPIS data was available. The LPIS data on Grassland (e.g. represented by the sub-classes of meadows, alps and orchards etc.) as well as some very small and not meaningful classes (e.g. sweet potatoes, field margins, agricultural roads) were excluded from the LPIS dataset. The result of the selected LPIS polygons is visualized in Figure 5-2. This remaining LPIS data was grouped into meaningful crop groups (see section 5.1.3)

A further step in the processing chain of the Agricultural prototype is to explore the utilised reference data. The area covered by the central demonstration site includes parts of two different countries (Southwest-Germany and West-Austria) with different crop type nomenclatures, which led to several compatibility challenges when merging the data into joint classes and, thereafter, groups of classes. After some adjustments 16 classes (15 crop groups plus one rest group for "others"; see (Table 5-2) could be identified, based on logical considerations of similar crop types, and their spectral characteristics and temporal appearance. The derived crop group classes served as input to the prediction in a further step.

Table 5-2: Number and name of crop groups and their abbreviation.

ClassID	Crop Group	Crop Group Abbreviation
1	Agrarian Grass	AgrGrass
2	Fallow	Fallow
3	Fruit Trees	FruitTrees
4	Legume	Legume
5	Maize	Maize
6	Others	Others
7	Potatoes	Potatoes
8	Strawberries	Strawberries
9	Sugar Beets	SugarBeets
10	Summer Crop	SummerCrop
11	Summer Rape	SummerRape
12	Sunflowers/Topinambour	SunflTopinamb
13	Vegetables	Vegetables
14	Winegrowing	Winegrowing
15	Winter Crop	WinterCrop
16	Winter Rape	WinterRape

As can be seen in Figure 5-2, the majority of the tiles of the demo-site is covered well by the reference data. Due to LPIS data use for Bavaria (tile 32UPV and 32UPU) not being granted by the Bavarian Ministry of Food, Agriculture and Forestry, and for Switzerland not being available to the consortium, it was not possible to retrieve and use the reference data for Bavaria until now. For the second project phase repeated efforts will be undertaken to hopefully being allowed to use the data also for the missing two to three tiles. Nevertheless, the prototype was developed for all nine tiles with training data distributed within the area of Baden-Wurttemberg and western Austria.

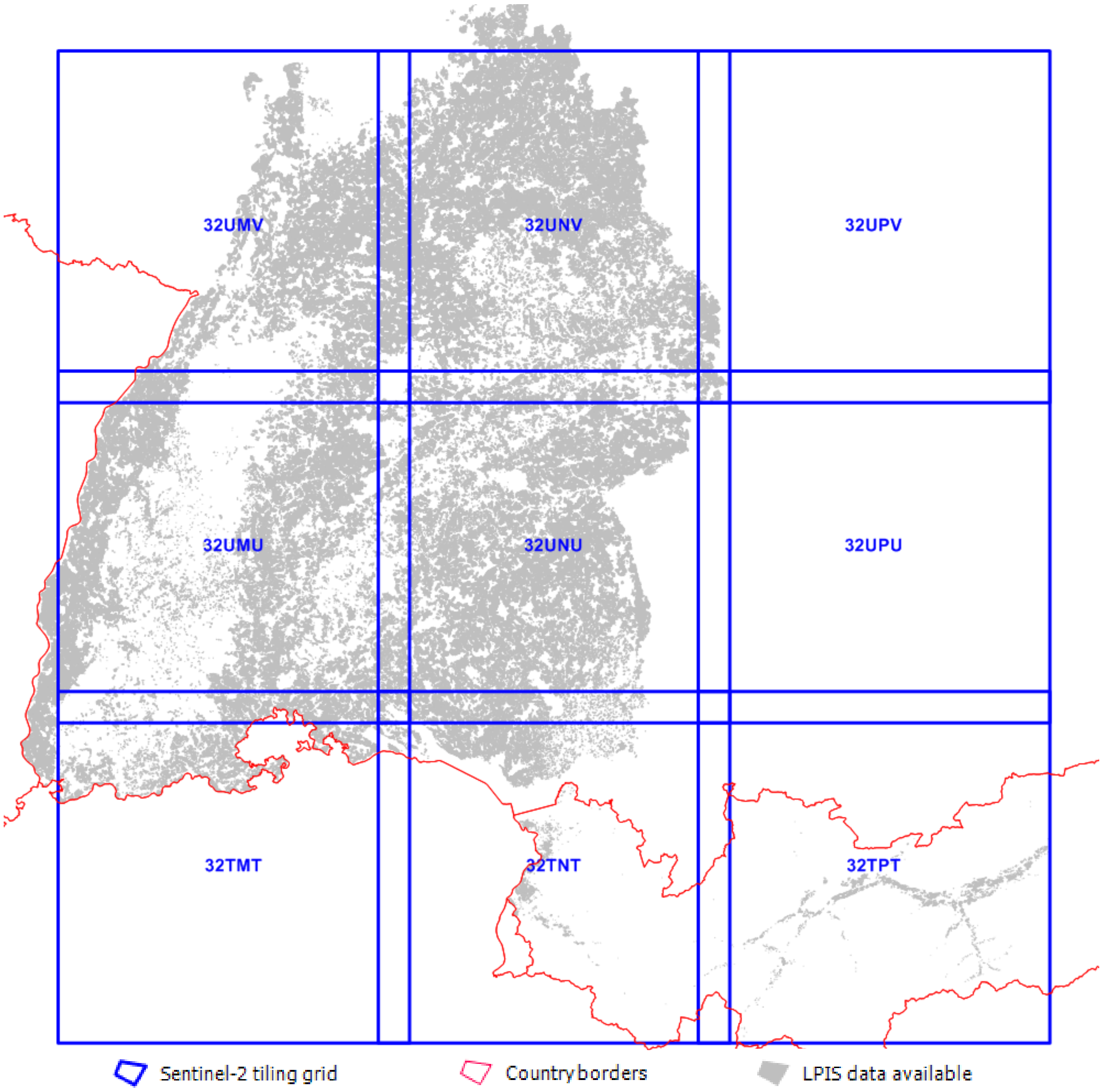


Figure 5-2: Coverage of the Demo-Site Central with LPIS data (Grassland excluded) used for training and validation.

© EuroGeographics; © Agrarmarkt Austria © MLR BW

5.1.1.3 Demo-site Mali

As proposed in the Sen2A-Agri system, all S2 and L8 imageries acquired over the demo site during the 2017 growing season starting on the 1st April and ending on the 15 December 2017 were automatically downloaded from the ESA's Scientific data Hub (https://scihub.copernicus.eu/) and United States Geological Survey (USGS) (https://landsat.usgs.gov/) data provider platforms. The total number of images acquired by S2 and L8 were 1811 and 273 images respectively with less than 90% cloud cover while no Sentinel-1 data have been used over Mali.

Crop type data were collected in situ by the Institut d'Economie Rurale (IER), a UCLouvain partner in Bamako, during the 2017 growing season. A comprehensive field campaign was organized over the demo-site in 27 villages spread covering all regions and circles to capture most of the diversity of the main crop types (Figure 5-3). The crop type field data set is composed of 6591 cultivated fields including both major and minor crop types (Table 5-3). The data were collected along the roads associated with crop type information following the JECAM guidelines (JECAM, 2017).

Table 5-3: Description of the in situ datasets in terms of number of samples per class.

Site	Cropland samples / ha	Non-cropland samples / ha
Koutiala	4205	322
Haut-Bani Niger	2386	698

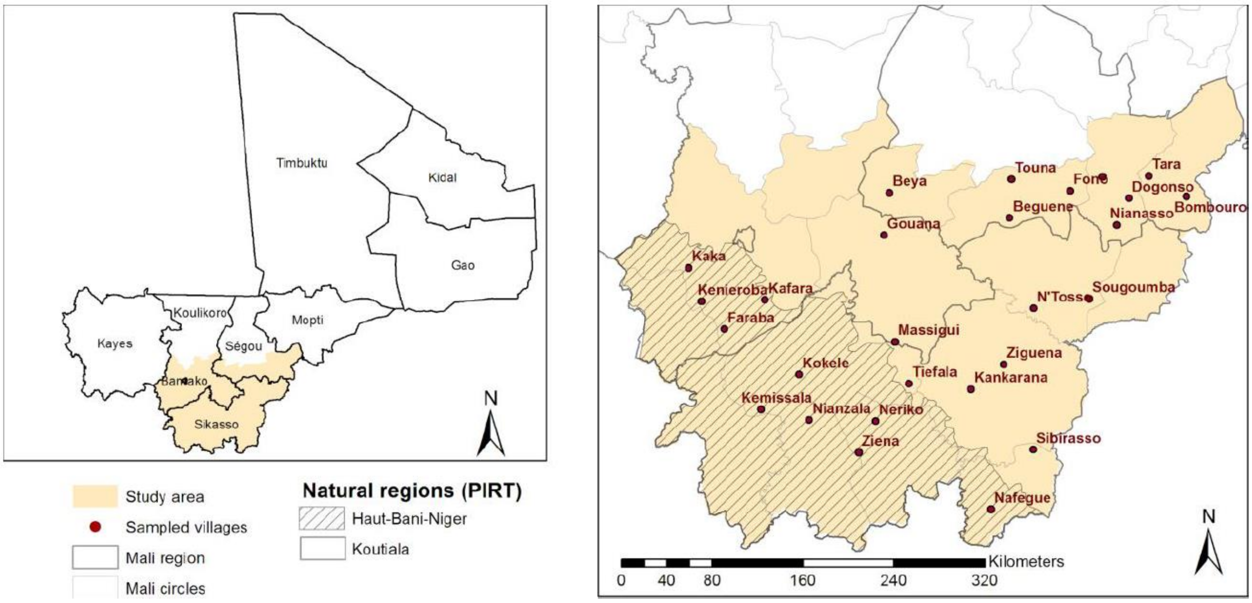


Figure 5-3: Demonstration site (in color) covering all the Sikasso region and part of the Segou and Koulikoro administrative regions. Field data were collected around 27 villages spatially distributed over the demo site (presented in red). The natural regions of the PIRT are presented in stripped line for the Haut-Bani-Niger region and in transparent for the Koutiala region.

In each sampled village, a team of field operators collected geotrace (polylines) on the border of the fields alongside vehicule roads and secondary roads (Figure 5-4), following the JECAM guidelines. Field operators traveled on motorbikes to be able to take the small paths. When fields were too small to record geotrace, operators collected georeferenced points in the middle of the parcels. All visible fields along the major roads were sampled while a minimum of 30% of the fields were collected along secondary roads or paths. For each collected sample, the field operators were asked to identify and encode the crop type as well as the relative position of the field with regards to the geotrace, i.e. left or right. The data collection was performed using the GeoODK data collection free app (http://geoodk.com/) on smartphones with GPS. On a daily basis, all collected data were sent to a web platform for near real time quality control.

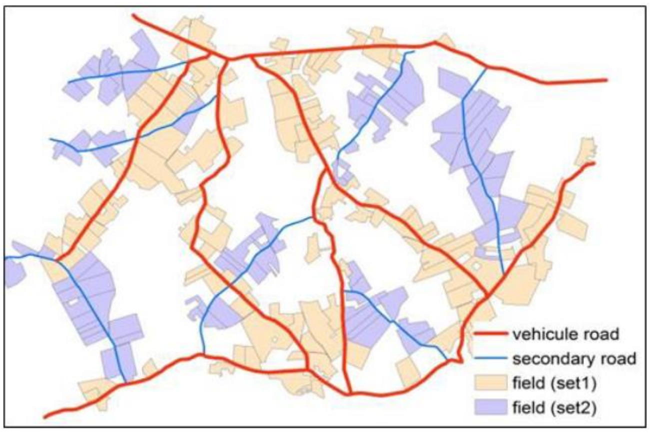


Figure 5-4: JECAM protocol to sample fields along main and secondary roads (JECAM, 2017)

In order to transform geotraces into polygons delineating individual fields, visual digitalization on recent Sentinel-2 data was completed. When no field limits were visible on the Sentinel-2 image, the operators were asked to draw a polygon of 20m width following the geotrace to limit the errors. The same methodology was applied to field points. Nevertheless, as field points were often collected in area with very small fields (e.g. bottom of valley, rice fields, peanut fields), the operators were asked to draw a small polygon of 20 X 20 m (400^2 m) around the field point.

In order to complement this very comprehensive in situ crop type survey, a non cropland dataset including +2,100 polygons corresponding to all land cover types except cropland, was built by visual interpretation of Sentinel-2 and various freely available very high resolution imagery such as from Google map or Bing. Those polygons were pre-selected based on a stratified random sampling over strata derived from a land cover map (GlobeLand30). GlobeLand 30 provides a generic land cover map of 10 classes at 30-m derived from Landsat images for 2010 (Chen et al, 2015). The stratified random sampling guarantees the representativeness and the good spatial distribution of all classes in the non-cropland dataset (including grassland, forest, water, urban, wetland, bare soil).

5.1.2 Pre-processing

The Pre-processing chapter provides an overview of the pre-processing steps for the Demo-site West, Central as well as Mali. Therefore information about the Image-data and the HRLs 2015 are given.

5.1.2.1 Demo-site West

For SIRS, the WEST demonstration site data, over the 6 S-2 tiles (31UES, 31UER, 31UFS, 31UFR, 31UFQ and 31UEQ) has been pre-processed by the Joanneum Research for the year 2016, as described in the report of WP32.

Due to the strong cover in the time series, only 91 images could be deemed exploitable after cloud mask application.

For UCL, the level-2A processor named as MACCS; Multi-sensor Atmospheric Correction and Cloud Screening; was used in processing Sentinel-2 data (tiles 31UES, 31UFS and 31UFR) for detecting clouds and their shadows, estimating aerosol optical thickness (AOT), water vapor and correcting for the atmospheric effects. MACCS was jointly developed by CESBIO and CNES. CESBIO developed the methods and a prototype, while CNES funded the operational version of the processor, with a strong support from CESBIO for the validation. A gap-filling algorithm employing a linear interpolation was applied every 10 days in order to obtain time series of bands 3:8, bands 11:12 having the resolution of 10 and 20 m. Bands of 20 m resolution were resampled to 10 m resolution and, then, NDVI, NDWI and BRI were calculated.
Also, the Sentinel-1 backscattering datasets (VV, VH, VV/VH) were undergone to various steps of pre-processing chain including calibration, radiometric normalization, terrain correction and speckle filtering. Then, pixel based statistics were calculated a time interval of two months from the backscattering time series resulting in input features of mean, standard deviation, coefficient of variation and the 10th, 25th, 50th, 75th and 90th quantiles.

It is worthy mentioning that the pre-processing of the backscattering was constrained to Sentinel-1 data acquired within the Belgian borders. Thus, the input features originated from Sentinel-2 data and, hence, the classification results were constraints to the same extent LPIS (SIRS)
For SIRS, As the LPIS dataset comes from farmers' declarations and from different production sites, the French and the Belgium datasets require an harmonization step. Indeed, nomenclatures from both zones do not match due to divergence in the agricultural policy of each country. This leads to the impossibility of combining certain different classes issued from those incompatible LPIS together.
Decision has been made to take into account only the most representative cropland types to circumvent this difficulty. The classification is therefore not made on all the declared classes, which minimizes the

confusion on exceptionally rare classes. For future production deployment at larger scale, this step will have to be done for each kind of landscaping set.

Once this harmonization is made, several criteria for the set of samples per class have been drawn:

- Containing approximately 50 elements;
- Geographically well-defined over the all area of interest (AOI), using a regular fishnet;
- As pure as possible in order to restrain the mixed pixel effect, ensuring a more precise classification.

After the generation of points for each part of the fishnet, a buffer is made on those points and the zonal statistics are computed – this step requires the clearest image, without atmospheric veil that could have been missed by the cloud masking.
It is worth noting that LPIS is based on declaration only, resulting in potentially mixed or flawed class assignation, making the third and last criterium a crucial step in the sampling design process. Thus, for each set of samples per class, the mean and the standard deviation is calculated. Only samples within one standard deviation of the mean are selected, and assumed to be of the "purest" form. This step is closely intertwined with a visual check of those samples, to assess the effective selection inside a parcel, or the absence of any remaining cloudy veil, for each temporal window. The Table 5-4 below shows two examples of samples which can't be keep because of calibration or validation issues.

Table 5-4: Example of visual check on the samples.

	The sample collected is not pure enough, statistically and visually: it is then remove of the selection.
	The sample should normally be keep for the set, if the decision was based only on statistics and on the look and feel. However, on the right image, the sample obscured by the shadow of a cloud; this will alter the image statistics in the time series during classification. It is then removed from the selection.

Finally, the samples are randomly selected in order to keep one sample per class in each part of the fishnet. For UCL, the Belgian datasets of the tiles 31UES, 31UFS and 31UFR of the year 2017 were used with some constraints which are 1) applying a buffer of 15 meters from the polygons borders for avoiding mixels, 2) ignoring fields of small areas which are represented by few (sometimes scattered) pixels (less than 50) in a way distorting the classifier performance and 3) splitting the dataset into two equal parts (50% of the data each) for training and classification.

The sampling design for the HR layers is the same as the one mentioned in the previous section. A selection of samples from zonal statistics analysis is followed by a visual check of the sample relevance and then a random selection over the fishnet is applied.

The only divergence can be found in the thematic accuracy. Indeed, to gain processing time, the HRL samples are created for one year and then re-used for the next year while being also completed with new ones. This still implies a visual checking, to also ensure that the samples used are still valid. The prototype product for the cropland type is based on 2016 data while using HRL samples based on 2015 data.

5.1.2.2 Demo-site Central

The selected EO data (see chapter 5.1.1) were generally pre-processed as described in the Deliverables AD05 (pp. 18) and AD06.

There are five main processing steps to prepare the used Sentinel-1 data: The Sentinel-1 Ground Range Detected (GRD) data (VV and VH polarisation) were pre-processed to Gamma0 values and a multi-temporal speckle filter was applied on the time series. Furthermore, the data are radiometrically calibrated and a terrain flattening as well as a terrain correction has been performed. The pre-processing was done using the ESA SNAP toolbox. Only data of the descending orbit 66 was used for the analysis.
The major processing steps for all S-2 images are the atmospheric correction, cloud, cloud shadow and snow masking, as well as topographic normalisation and geometric accuracy tests. The software used for all these pre-processing steps is the Sen2Cor provided by ESA.

5.1.2.3 Demo-site Mali

S2 and L8 satellite data were atmospherically-corrected using the Multisensor Atmospheric Correction and Cloud-Screening (MACCS) algorithm (Hagolle et al., 2008; Hagolle et al., 2010), included in the Sen2-Agri system. That method associates to each pixel one of the following status: “Land”, “Cloud”, “Cloud shadow”, “Water” or “Snow”. The consecutive classification methods are applied only over “Land” and “Water”.

These so called missing values were determined by value masks provided by the MACCS preprocessing step, detecting pixels affected by clouds, cloud shadows or saturation effects. The gap-filling method is a weighted linear interpolation on a 10-day time step for S2. These interpolated reflectance are used to extract the features and compute the indices.

5.1.3 Experimental Setup

In the following subsections the experimental setup will be described following the three different experiments carried out in the demo-site West (Belgium/France), Central (Germany/Austria), and Mali.

5.1.3.1 Demo-site West

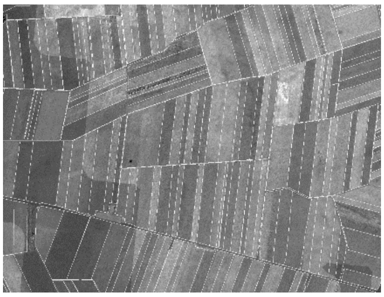
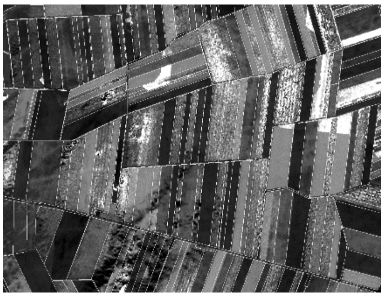
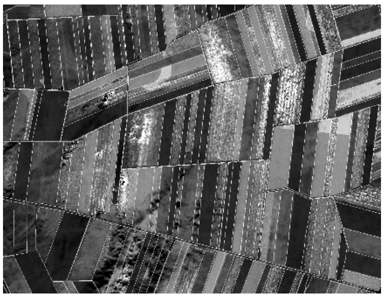
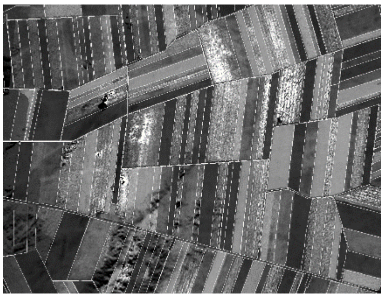
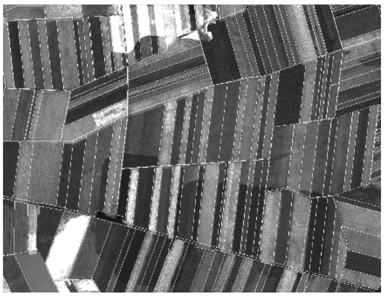
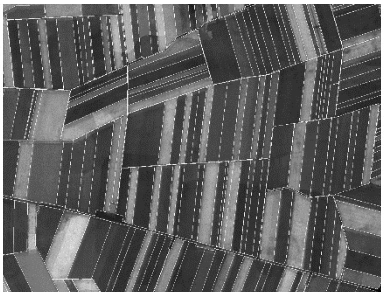
The following sections describe the time features methodology applied in the production of the cropland type prototype. The preliminary set of implemented features will be explained in the following sections, along with a description of the consecutive classification workflow implementing those time features.

PRELIMINARY SET OF IMPLEMENTED FEATURES

For SIRS, several indices have been used for the classification of the different cropland types: NDVI (Normalized Difference Vegetation Index), NDWI (Normalized difference water index) and BRI (brightness). Moreover, for each index, 9-time features have been generated: maximum, mean, minimum, percentiles (10^{th}, 25^{th}, 50^{th}, 75^{th}, 90^{th}) and standard deviation. As the yearly time window was divided on three three-month periods, 81 indices have been therefore computed for each S-2 tile, and then stacked. Those 81-band images has then been fed as input data to the classifier.

The choice of the indices is employed to discriminate different cropland types over all the S-2 tiles, which exhibit at least one cloudless value per pixel for each the three-month period. Those three trimesters three periods are therefore used to build a spectral signature for each cropland type.
The
Table 5-5 below represents some examples of time features (mean, maximum and minimum) for the NDVI on the three-time periods on the working units 31UEQ.

Table 5-5: Temporal features associated with the NDVI extracted from the tile 31UEQ. The delineation represents LPIS dataset parcels.

		
(a) Period 1: maximal NDVI	(b) Period 1: mean NDVI	(c) Period 1: minimal NDVI
		
(d) Period 2: maximal NDVI	(e) Period 2: mean NDVI	(f) Period 2: minimal NDVI
		
(g) Period 3: maximal NDVI	(h) Period 3: mean NDVI	(i) Period 3: minimal NDVI

The second period, from April to June, exhibits more phenological variability than the first period from January to March. Those darker or brighter fields are a sign of a more complex and disparate range of value linked to the chlorophyll activity of the present vegetation. Due to the restrained number of available images, there is still some secondary effects linked to the cloud mask application, as can be seen, for

example, on the image (c). The footprint of the cloud mask is noticeable. On the third period, the variability of the NDVI is less significant, but it still brings information on the phenology of the different crop types.
For UCL, the input features were produced from datasets of Sentinel-1 and Sentinel-2 satellites. In particular, 374 features were originated from Sentinel-2 datasets where a stuck of eleven layers (8 bands: "b3:8 b11:12", NDVI, NDWI and BRI) was produced every 10 days over the acquisition period (January 3rd-December 2nd, 2017). In addition, 288 features were originated from the Sentinel-1 data where the mean, standard deviation, coefficient of variation and five quantiles (10th, 25th, 50th, 75th and 90th quantiles) were produced from the co-polarized (VV), the cross-polarized (VH) and polarization ratio (VV/VH) of the backscattering at a constant time interval (every two months) of the time series.

Classification workflow (Demonstration Site West)

The main processing steps for the generation of this prototype product rely on the classification computation. The processing chain is composed of four successive steps:

1. Computing of the images statistics;
2. Generation of class features;
3. Classification with random forest algorithm;
4. Application of a majority filter to harmonize the results;
5. Calculation of an automatic confusion matrix.

The 81-band image is fed to the algorithm which computes various spatial statistics, such as mean and standard deviation for each band. Those statistics are used to establish a classification model, according to each cropland and non-cropland class. The classes' signature are computed from the selected samples, whose 50% are used for calibration while the other 50% reserved for validation. The random forest algorithm, chosen after the tests conducted in WP33, can finally be applied to classify the different classes. A majority filter is also applied to the classification. This final step presents two advantages:

- to harmonize the results, since it smooth's the pixel-based classification and lets a more naturel landscape appear;
- to merge isolated pixels into larger parcels.

Once the classification generated, a first confusion matrix is automatically generated to estimate the accuracy of the results for each tile.
It is worth mentioning that UCL applied the same classification workflow (steps 1:5 in addition to the majority filter) using 374 and 288 features/tile originated from Sentinel-2 and Sentinel-1 datasets respectively. The classification was performed in two ways where the first trained and applied the RF classifier for each tile individually while the second trained the classifier on the 31UFR tile and then applied on other tiles. The 31UFR was selected in the second case based on accuracy assessment of the first case. In addition, the classification results were constrained to the LPIS polygons within the Belgian borders, which means that all non-agricultural land covers produced by the classifier were grouped in one class named as "other land cover". Finally, 24 classes were selected for representing the classification results in a way grouping similar classes (e.g. the summer cereals class includes mixed protein crops, summer Triticale, Quinoa, summer Rye and Sorghum).

The developed processing chain is able to treat a large amount of input data within a reasonable temporal window to provide two cropland-related layers, without manual enhancement. The achieved level of automation ensures the effective application of the process to map different cropland types at pan-European level.

The workflow for the production of the Imperviousness Prototype is listed hereafter:

1. Layer stacking of the bands from the data pre-processing by Joanneum Research
2. Application of the cloud mask

3. Regrouping of data per time-windows to balance cloud presence and phenological variability
4. Computation of spectral indices, such as NDVI, NDWI and BRI
5. Computation of time features, such as maximum, mean, minimum, median and percentiles (10th, 25th, 75th, 90th) and standard deviation
6. Concatenation of all the previously generated data
7. Classification – which could be divided into the following subtasks:
    a. Computation of bands spatial statistics
    b. Generation of class features with 50% of the samples used for calibration and the remaining 50% kept for validation
    c. Classification with RF algorithm
    d. Application of a majority filter to smooth the results
    e. Computation of an automatic confusion matrix for validation, using the other half of the samples
8. Aggregation of the results at field parcel level according to the LPIS shapefile
9. Mosaicking of the results obtained over each S-2 tile
10. Merge of isolated pixels into larger ensembles (especially in the corridors between two parcels of the LPIS)
11. Formatting of the metadata

5.1.3.2 Demo-site Central

For the calculation of the agricultural prototype the used S-1 and S-2 images were grouped into 10 different scene sets based on different time steps, five for S-2 and five for S-1 (see Table 5-6). The results of the tests regarding the respective start and end date further described in WP33 (AD06) were taken into account here. There are 5 scene sets per sensor on which the feature extraction (see section 4.2) is performed: one of them covering the whole growing season from mid-March until mid-November and four others each covering a two-month period starting from mid-March until mid-September.

Table 5-6: Start and end date of the 10 different scene sets and the number of S-1/S-2 images they contain including the maximum amount of cloud cover (%).

Sensor	Sceneset Name	Start Date	End Date	Number of Scenes per Tile	Max. Cloud Cover (%)
S-1	EL_S1_2017-03-15TO2017-05-14_CC00	2017-03-15	2017-05-14	9-30	0
	EL_S1_2017-05-15TO2017-07-14_CC00	2017-05-15	2017-07-14	8-26	0
	EL_S1_2017-07-15TO2017-09-14_CC00	2017-07-15	2017-09-14	10-31	0
	EL_S1_2017-09-15TO2017-11-14_CC00	2017-09-15	2017-11-14	9-29	0
	EL_S1_2017-03-15TO2017-11-14_CC00	2017-03-15	2017-11-14	37-115	0
S-2	EL_S2_2017-03-15TO2017-05-14_CC90	2017-03-15	2017-05-14	5-7	90
	EL_S2_2017-05-15TO2017-07-14_CC90	2017-05-15	2017-07-14	10-12	90
	EL_S2_2017-07-15TO2017-09-14_CC90	2017-07-15	2017-09-14	13-15	90
	EL_S2_2017-09-15TO2017-11-14_CC90	2017-09-15	2017-11-14	10-16	90
	EL_S2_2017-03-15TO2017-11-14_CC90	2017-03-15	2017-11-14	42-49	90

For the crop mask classification, reference samples that cover the basic LC types (Forest, Cropland, Grassland, Urban Areas, and Waterbodies) were available from the HRL 2015 layer production. In order to derive a crop mask independent from LPIS – since LPIS is not available in all European countries – the LPIS data are not part of the samples for cropland.

Splitting the dataset into a training- and test set was also performed for the crop mask classification, meaning that approx. 50% (~400–1300 polygons for each class) were used for training and the remaining 50% for testing. This led to a total of ~7300 sample polygons for all classes amounting to more than 1 million pixels. In order to reduce the amount of samples for training, 50,000 random pixels were extracted out of the full trainset. For the urban areas the amount of pixels in the full trainset was <50,000. Therefore, all available pixels of the urban areas (~31,000) were used (see Table 5-7).

Table 5-7: Number of polygons for each LC type in the reference data for the crop mask: All, Trainset (for model training), and Testset (for validation).

LC Type	All (polygons)	Trainset (pixels)	Testset (polygons)
Forest	2672	50000	1336
Cropland	1129	50000	565
Grassland	1538	50000	769
Urban areas	1142	31300	571
Waterbodies	846	50000	423
SUM	**7327**	**231300**	**3664**

Regarding the sampling dataset for the crop type classification the complete LPIS reference data was randomly split in training (30%) and test (70%) polygons. For the model training, in order to derive a balanced and reduced training/calibration data set, a random sample of 10,000 pixels was drawn for each crop group (the trainset).

The following Figure 5-5 and the Table 5-8 shows the referring classes and the number of LPIS polygons they contain (number of total LPIS polygons and their respective size (km²), as well as number of 70% of polygons per class: the testset). Winter Crop has by far the most polygons in the demonstration site Central whereas Summer Rape or Sunflowers/Topinambour cover the least area. Both large in polygons as well as field size are Maize, Summer Crop and Agrarian Grassland, whereas fruit trees and vegetables cover small areas in relation to their amount of polygons. Regarding the mean parcel size Sugar Beets and Winter Rape have remarkable big parcel sizes compared to their amount of reference parcels. Winter Crop and Maize are again both large in number of reference parcels and mean parcel size. The smallest mean parcel size of all classes has winegrowing.

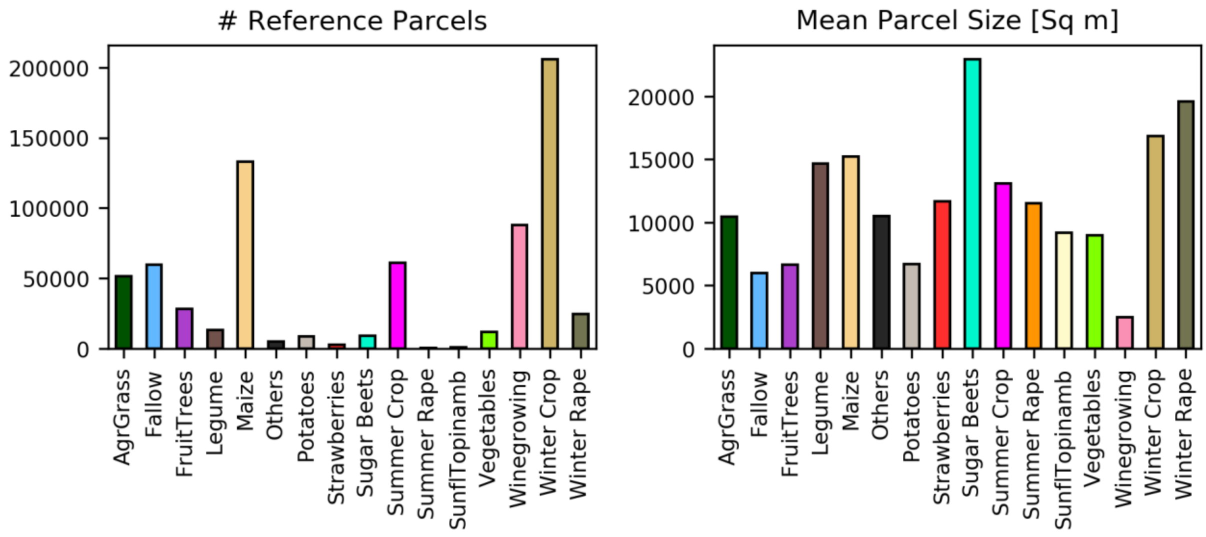


Figure 5-5: Number of Reference Parcels and the Mean Parcel Size per class.

Table 5-8: Number of polygons for each crop group in the reference data (All), their area, and the number of polygons used for validation (Testset).

Crop Group	All (polygons)	Area of All (km²)	Trainset (Pixels)	Testset (polygons)
Winter Crop	205861	3471,1	10000	144103
Maize	132789	2018,83	10000	92952
Winegrowing	87831	219,68	10000	61482
Summer Crop	61150	801,66	10000	42805
Fallow	59729	355,97	10000	41810
Agrarian Grass	51493	538,86	10000	36045
Fruit Trees	24932	169,59	10000	17452
Winter Rape	24484	479,42	10000	17139
Legume	13217	193,85	10000	9252
Vegetables	9701	79,23	10000	6791
Sugar Beets	9053	207,67	10000	6337
Potatoes	8708	58,33	10000	6096
Strawberries	2715	31,63	10000	1901
Others	1844	22,89	10000	1291
Sunflowers/Topinambour	767	7,03	10000	537
Summer Rape	256	2,94	10000	179
SUM	**694530**	**8658,68**	**160000**	**486172**

Another important step is the calculation of spatially contiguous features from the pre-processed and stacked input data. A feature is a statistical metric which is derived for each band/index and pixel from a set of valid (i.e. cloud/cloud shadow free) observations over a specific time range, e.g. the median of all valid NDVI values of the defined period from 2017-03-17 to 2017-05-14. Table 5-9 lists the bands/indices and the derived time features from them. For more information on the features please refer to AD06. These features were calculated for all periods listed in Table 5-6 which lead to a total of 1246 features. But as mentioned in section 4.2 it is more efficient to reduce the number of features for the following reasons: (i) to keep the computational effort as low as possible, and (ii) to avoid redundant information and reduce noise. For the selection of the most relevant features the FFS was applied. For the feature selection the 10,000 training samples were split in a 50% training and 50% validation set for classifying and evaluating the feature performance with the Random Forest (RF). The final model with the selected features was then trained with the full training samples.

Table 5-9: Overview over the relevant bands/indices and the derived time features used for training and classification.

Sensor	Bands/Indices	Time Features Groups
Sentinel-1a/b	• VV (Gamma0) • VH (Gamma0) • Norm. Difference VV/VH (NDVVVH) • Ratio VV/VH (RATIOVVVH)	activity, cov, dif, max, maxmean, mean, median, min, percentiles (p010, p025, p050, p075, p090), std, trend
Sentinel-2a/b	• Brightness (derived through summation of the values of the bands Green, Red, NIR and SWIR1) • IRECI (Inverted Red Edge Chlorophyll Index) • NDVI (Normalized Difference Vegetation Index) • NDWI (Normalized Difference Water Index, based on SWIR and NIR) • B03, B04, B08, B11, B12	

Both for the crop mask and crop type classification, the RF classifier was used as classification approach for the final model training as well as for the classification approach used for the FFS and the classification of the final products. The parameters were the same during FFS, crop mask classification and the crop type classification (number of trees: 500, 'gini' criterion for measuring the split quality, number of features to consider when looking for the best split: square root of the number of features, no constrain at the depth of the trees; for further information see AD06 (pp. 82).

The crop mask was validated with the sample dataset as described in section 5.1.1, taking all pixels of the testset into account. For validating the results of the crop type map, a buffer was applied on the selected 70% of the LPIS dataset (the reference data) where all pixels with a distance ≤2 pixels from the polygon border (which represent boarders between agricultural fields) were not considered for validation.

5.1.3.3 Demo-site Mali

The Sen2-Agri products were processed and specifically assessed with regards to three questions: delivery time versus accuracy for the cropland mask along the season, the importance of the stratification, and the impact of the validation dataset.
First, the Sen2-Agri system was run along the season to deliver cropland masks along the season. Indeed this cropland mask can be used to focus on the crop monitoring activities or the early warning system based on daily MODIS or PROBA-V NDVI time series. Therefore, the accuracy evolution of the cropland mask along the accumulation of S2 observation is assessed for four different periods all starting in April to September, October, November and, December.
While the stratification seems to have an impact on the product accuracy, three different levels of stratification have been assessed: no stratification over the demo-site Mali, the aggregated PIRT zoning and the aggregated strata of Vintrou (Vintrou et al, 2012) (Figure 5-6).

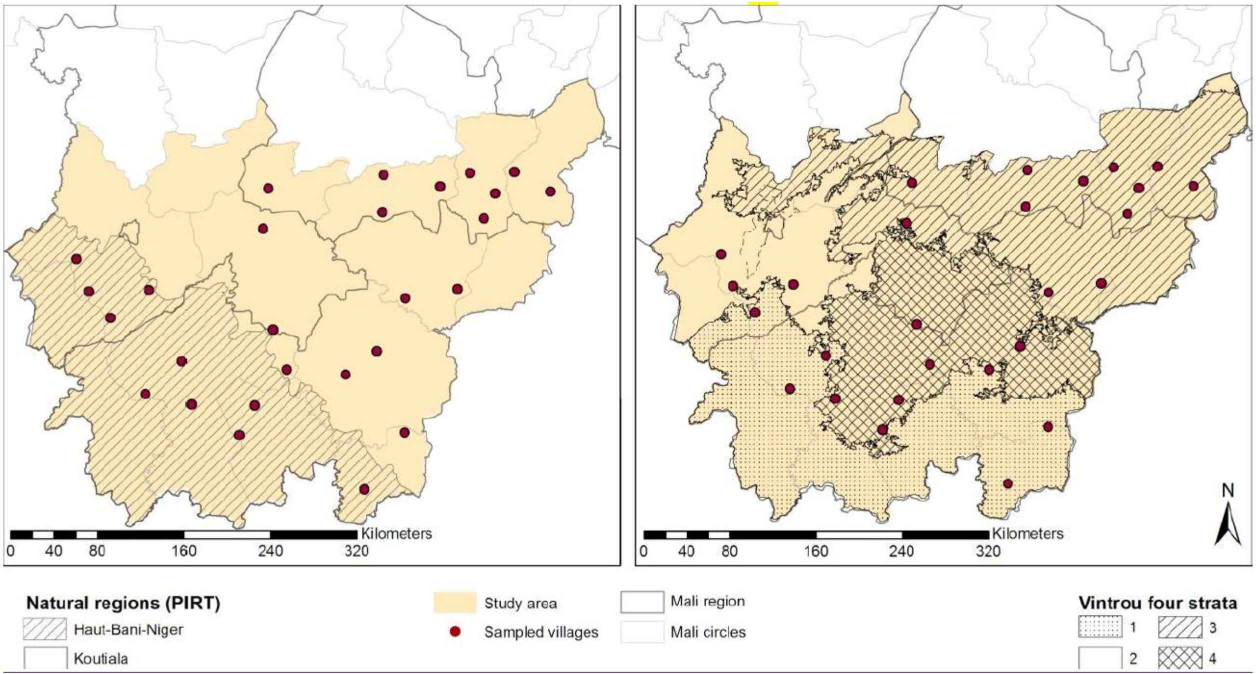


Figure 5-6: Two stratification datasets: aggregated PIRT natural zones on the left and aggregated Vintrou strata on the right based on cropping systems analysis.

Splitting randomly the in situ dataset into training and validation subset is quite valid when the entire region of interest is systematically covered. While the comprehensive field data campaign insured a widely distributed sampling, only 27 villages and their surroundings where samples for 135 000 km². Therefore, a randomized sample of cropland points selected with the cropland class of the GlobeLand30 should provide a validation set spatially independent of the training set. A set of 500 cropland samples have been photo-interpreted on screen by an field expert using Google maps and Bing.

5.1.4 Post-processing

Demo-site West (French part)

The look and feel gives a first qualitative impression on the prototype product, based on its proximity with the LPIS dataset. The confusion matrix automatically generated for the filter classification leads to a first quantitative assessment of the results.
Using those two combined techniques, the classification has been launched on several occasions - for each iteration, the classes have been re-arranged differently (through fusion, suppression or addition) until a final nomenclature of 16 classes (12 cropland classes and 4 non-cropland classes) has been selected, whose details are shown in the Table 5-10 as well as in Table 5-11.

Table 5-10: Cropland labels, characterizing 12 types of culture.

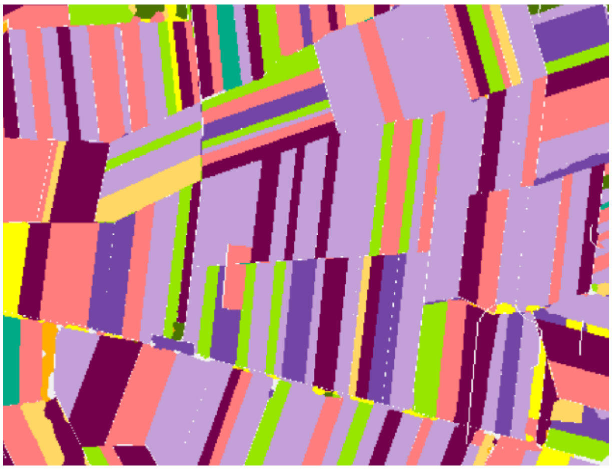
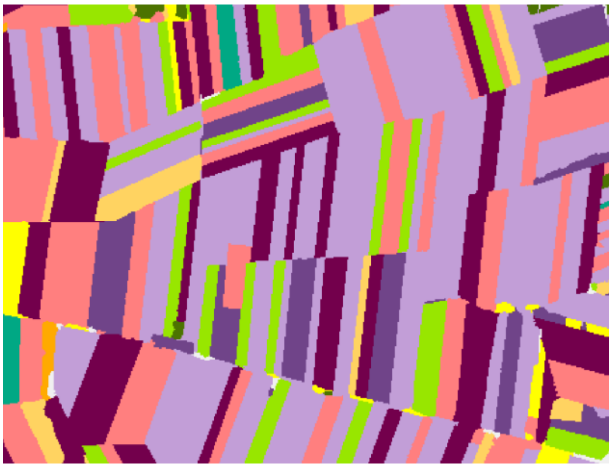
Class ID	11	31	40	61	71	81	91	101	131	141	151	161
Category	Cropland type											
Class	Winter Wheat	Winter Barley	Spring Cereals	Peas	Winter Rape	Maize	Agrarian Grassland	Beets	Potatoes	Fallow	Linen	Chicory

Table 5-11: Non-cropland class labels.

Class ID	1	2	3	4
Category	Other Land Cover (Non-Cropland)			
Class	Grassland	Urban areas	Forest	Water

There may still be room for improvement by refining the quality of the samples for example, or by integrating S-1 data, as demonstrated in the WP43. It should be noted that one of the S-2 tile was more difficult to classify. Several reasons could explain this, from the availability of the S-2 data or the quality of the LPIS in this region.
However, the overall final prototype product reached a satisfying level, with this configuration of 16 classes.
The following step in the post-processing lies in the aggregation of pixels at field-level according to the LPIS shapefile. This leads to a harmonization of the processed layer for all the cropland classes, resulting from a majority occurrence re-classification of pixel at field level.
Each S-2 tile classification has then been mosaicked to obtain one unique layer over the whole demonstration site. In the overlapping area between two adjacent tiles (a corridor of 10km by 100km), a majority vote has been applied, based on the number maximal number of observations leading to a particular label. For example, a considered pixel identified as belonging to a particular class, as the result of a classifier using only 3 images will be overruled by a classifier result made from 6 optical images identifying the pixel as containing another kind of crop.
Finally, the last part of the post-processing merges isolated pixels into larger ensembles, especially on the corridors between two adjacent field shapes, as taken from the LPIS. A comparative oversight is displayed in the Table 5-12 below.

Table 5-12 - Before and after the cleaning of isolated pixels.

	
Results before the cleaning of the isolated pixels between two contiguous parcels of the LPIS	Results after the cleaning of the isolated pixels between two contiguous parcels of the LPIS

The layer name is set following naming convention: layer_year_resolution_demosite_EPSGC_version.tif, as discussed between partners. Two products, named respectively CRT_2016_010m_WE_03035_prototype_v01.tif for the detailed cropland type prototype layer and CRM_2016_010m_WE_03035_prototype_v01.tif for the derived binary mask between cropland and non-cropland pixels are conformed to the following specifications inTable 5-31.

DEMO-SITE WEST (BELGIUM PART)

As a first post-processing step, the LPIS polygons was used as a cropland mask to constrain the classification results to the actual agricultural parcels.

A majority filter based on the LPIS polygons was then applied as a second post-processing step to produce a coherent result in the form of one crop type class per field parcel (Table 5-13).

Table 5-13: Before and after majority filtering.

	
Results before applying the majority filter	Results after applying the majority filter

5.2 Results and Validation

This Chapter contains the main results. It contains information about the Crop mask (CRM) and Crop Type (CRT) maps of the Demonstration-Sites West, Central as wells as Mali.

5.2.1 Crop type map of Demo-Site West

Several tests were conducted over each S-2 tile until the handling of the number of cropland classes gave satisfying. After various addition, suppression or fusion of classes, the following tables (Table 5-14 to Table 5-17) present the confusion matrices for each tile.

Table 5-14: Confusion matrix for tile 31UEQ.

31UEQ		REFERENCE LABELS														
		Other Land Cover	Winter Wheat	Winter Barley	Spring Cereals	Peas	Winter Rape	Maize	Agrarian Grassland	Beets	Potatoes	Fallow	Linen	Chicory	User Accuracy	Commission
PRODUCED LABELS	Other Land Cover	3186	0	0	12	0	28	130	8	0	0	0	36	0	93.71%	6.29%
	Winter Wheat	3	811	23	223	46	193	0	0	0	0	0	3	0	62.29%	37.71%
	Winter Barley	0	101	518	0	48	59	0	16	0	0	0	27	0	67.36%	32.64%
	Spring Cereals	29	405	0	680	0	552	13	2	0	0	13	0	0	40.14%	59.86%
	Peas	3	0	111	155	321	168	0	0	0	0	7	0	0	41.96%	58.04%
	Winter Rape	0	170	58	193	12	656	0	1	0	17	5	0	0	58.99%	41.01%
	Maize	107	0	0	43	0	5	1287	100	0	19	73	0	7	78.43%	21.57%
	Agrarian Grassland	0	26	4	106	0	125	143	1266	0	23	52	0	0	72.55%	27.45%
	Beets	115	0	0	0	0	0	40	0	1319	0	0	0	2	89.36%	10.64%
	Potatoes	0	0	0	0	6	46	0	0	0	393	3	0	0	87.72%	12.28%
	Fallow	56	0	0	0	3	220	218	398	0	82	946	0	0	49.19%	50.81%
	Linen	50	49	0	109	62	50	3	121	0	16	143	1253	0	67.51%	32.49%
	Chicory	0	0	0	0	0	18	27	0	0	103	146	0	269	47.78%	52.22%
Producer Accuracy		89.77%	51.92%	72.55%	44.71%	64.46%	30.94%	69.16%	66.21%	100.00%	60.18%	68.16%	95.00%	96.76%	69.03%	
Omission		10.23%	48.08%	27.45%	55.29%	35.54%	69.06%	30.84%	33.79%	0.00%	39.82%	31.84%	5.00%	3.24%		

Table 5-15: Confusion matrix for tile 31UER.

31UER		REFERENCE LABELS														
		Other Land Cover	Winter Wheat	Winter Barley	Spring Cereals	Peas	Winter Rape	Maize	Agrarian Grassland	Beets	Potatoes	Fallow	Linen	Chicory	User Accuracy	Commission
PRODUCED LABELS	Other Land Cover	4137	79	0	14	0	0	69	105	0	26	11	0	1	93.13%	6.87%
	Winter Wheat	0	1328	172	87	0	1	0	0	0	0	0	0	0	83.63%	16.37%
	Winter Barley	0	209	1233	0	0	61	0	23	0	0	0	0	0	80.80%	19.20%
	Spring Cereals	0	175	25	979	0	20	10	6	0	55	3	92	103	66.69%	33.31%
	Peas	0	0	0	0	0	0	0	0	0	0	0	0	0	-	-
	Winter Rape	0	99	65	0	0	94	0	0	0	0	0	0	0	36.43%	63.57%
	Maize	94	8	20	58	0	0	1056	207	0	33	11	0	164	63.96%	36.04%
	Agrarian Grassland	6	62	59	89	0	25	54	1641	0	0	30	0	0	83.47%	16.53%
	Beets	0	0	0	0	0	0	57	5	1710	0	0	40	0	94.37%	5.63%
	Potatoes	48	86	0	219	0	8	8	120	0	466	111	13	35	41.83%	58.17%
	Fallow	119	4	0	33	0	0	7	3	0	30	637	4	0	76.11%	23.89%
	Linen	0	0	0	0	0	0	16	0	5	0	0	1249	184	85.90%	14.10%
	Chicory	0	0	32	91	0	0	0	0	0	679	1	0	1305	61.91%	38.09%
Producer Accuracy		93.94%	64.78%	76.77%	62.36%	-	44.98%	82.69%	77.77%	99.71%	36.15%	79.23%	89.34%	72.82%	78.30%	
Omission		6.06%	35.22%	23.23%	37.64%	-	55.02%	17.31%	22.23%	0.29%	63.85%	20.77%	10.66%	27.18%		

Table 5-17: Confusion matrix for tile 31UFR.

31UFQ		REFERENCE LABELS													User Accuracy	Commission
		Other Land Cover	Winter Wheat	Winter Barley	Spring Cereals	Peas	Winter Rape	Maize	Agrarian Grassland	Beets	Potatoes	Fallow	Linen	Chicory		
PRODUCED LABELS	Other Land Cover	3741	0	0	6	0	0	1	0	4	0	11	0	0	99.42%	0.58%
	Winter Wheat	14	1054	79	304	0	0	0	0	0	0	48	0	0	70.31%	29.69%
	Winter Barley	17	223	666	57	17	0	0	5	0	2	13	0	0	66.60%	33.40%
	Spring Cereals	71	0	0	3329	358	58	35	69	0	0	218	0	0	80.45%	19.55%
	Peas	137	35	31	42	1535	0	0	79	0	10	176	0	0	75.06%	24.94%
	Winter Rape	0	0	78	0	0	1667	0	0	0	0	0	0	0	95.53%	4.47%
	Maize	0	0	0	0	3	0	482	34	1	57	14	0	0	81.56%	18.44%
	Agrarian Grassland	5	84	0	141	3	93	111	1235	0	11	168	0	0	66.72%	33.28%
	Beets	0	0	0	0	0	0	25	0	691	79	0	0	0	86.92%	13.08%
	Potatoes	0	0	0	0	0	0	92	0	60	86	0	0	0	36.13%	63.87%
	Fallow	37	18	0	8	0	135	99	698	0	0	542	0	0	35.26%	64.74%
	Linen	0	0	0	0	0	0	0	0	0	0	0	0	0	-	-
	Chicory	0	0	0	0	0	0	0	0	0	0	0	0	0	-	-
Producer Accuracy		93.01%	74.54%	77.99%	85.64%	80.11%	85.36%	57.04%	58.25%	91.40%	35.10%	45.55%	-	-	78.26%	
Omission		6.99%	25.46%	22.01%	14.36%	19.89%	14.64%	42.96%	41.75%	8.60%	64.90%	54.45%	-	-		

Table 5-16: Confusion matrix for tile 31UFQ.

31UFR		REFERENCE LABELS													User Accuracy	Commission
		Other Land Cover	Winter Wheat	Winter Barley	Spring Cereals	Peas	Winter Rape	Maize	Agrarian Grassland	Beets	Potatoes	Fallow	Linen	Chicory		
PRODUCED LABELS	Other Land Cover	3732	0	0	0	0	0	0	0	0	0	0	0	0	100.00%	0.00%
	Winter Wheat	0	982	152	85	0	0	0	48	0	0	0	0	0	77.51%	22.49%
	Winter Barley	0	9	1269	172	0	53	0	50	0	0	0	0	0	81.71%	18.29%
	Spring Cereals	121	25	47	183	0	0	92	3	0	0	0	232	0	26.03%	73.97%
	Peas	0	0	0	0	0	0	0	0	0	0	0	0	0	-	-
	Winter Rape	37	0	2	25	0	930	0	0	0	0	0	24	0	91.36%	8.64%
	Maize	0	4	51	131	0	0	1612	71	74	3	0	1	32	81.46%	18.54%
	Agrarian Grassland	30	0	111	0	0	0	0	1564	0	0	0	5	0	91.46%	8.54%
	Beets	0	0	0	0	0	0	21	0	834	0	0	0	0	97.54%	2.46%
	Potatoes	0	0	0	0	0	0	49	4	31	130	0	43	0	50.58%	49.42%
	Fallow	0	0	0	0	0	0	0	0	0	0	0	0	0	-	-
	Linen	0	73	0	179	0	0	0	0	0	0	0	531	0	67.82%	32.18%
	Chicory	0	0	0	0	0	0	156	0	0	1	0	0	295	65.27%	34.73%
Producer Accuracy		95.20%	89.84%	77.76%	23.61%	-	94.61%	83.52%	89.89%	88.82%	97.01%	-	63.52%	90.21%	84.30%	
Omission		4.80%	10.16%	22.24%	76.39%	-	5.39%	16.48%	10.11%	11.18%	2.99%	-	36.48%	9.79%		

Those results are quite promising, especially for the tile 31UFR, where the overall accuracy is near 85%. However, the tile 31UEQ overall accuracy remains below the 70% threshold, despise various attempts to improve the classification results. The final confusion matrix for the four demonstrations tiles is shown in Table 5-18. According to this matrix, some classes are well identified, such as beets, while others, in particular potatoes and linen, still exhibit strong confusion with other classes. The rest of the classes are identified at an acceptable producer accuracy (between 63% and 77%) and a user accuracy between 60% and 78%.

The final classification statistics are the following:

- Overall accuracy of 77%
- Producer accuracy between 46% and 96%
- User accuracy between 49% and 96%
- Kappa at 0.70
- F-Score between 0.27 and 0.47.

Table 5-18: Global confusion matrix for the four S-2 tiles.

DEMO-SITE WEST (4 WUs) GLOBAL ASSESSMENT		REFERENCE LABELS													User Accuracy	Commission
		Other Land Cover	Winter Wheat	Winter Barley	Spring Cereals	Peas	Winter Rape	Maize	Agrarian Grassland	Beets	Potatoes	Fallow	Linen	Chicory		
PRODUCED LABELS	Other Land Cover	14796	79	0	32	0	28	200	113	4	26	22	36	1	96.47%	3.53%
	Winter Wheat	17	4175	426	699	46	194	0	48	0	0	48	3	0	73.82%	26.18%
	Winter Barley	17	542	3686	229	65	173	0	94	0	2	13	27	0	76.03%	23.97%
	Spring Cereals	221	605	72	5171	358	630	150	80	0	55	234	324	103	64.61%	35.39%
	Peas	140	35	142	197	1856	168	0	79	0	10	183	0	0	66.05%	33.95%
	Winter Rape	37	269	203	218	12	3347	0	1	0	17	5	24	0	80.98%	19.02%
	Maize	201	12	71	232	3	5	4437	412	75	112	98	1	203	75.69%	24.31%
	Agrarian Grassland	41	172	174	336	3	243	308	5706	0	34	250	5	0	78.47%	21.53%
	Beets	115	0	0	0	0	0	143	5	4554	79	0	40	2	92.22%	7.78%
	Potatoes	48	86	0	219	6	54	149	124	91	1075	114	56	35	52.26%	47.74%
	Fallow	212	22	0	41	3	355	324	1099	0	112	2125	4	0	49.45%	50.55%
	Linen	50	122	0	288	62	50	19	121	5	16	143	3033	184	74.10%	25.90%
	Chicory	0	0	32	91	0	18	183	0	0	783	147	0	1869	59.85%	40.15%
Producer Accuracy		93.09%	68.23%	76.70%	66.70%	76.88%	63.57%	75.04%	72.39%	96.30%	46.32%	62.83%	85.36%	77.97%	77.08%	
Omission		6.91%	31.77%	23.30%	33.30%	23.12%	36.43%	24.96%	27.61%	3.70%	53.68%	37.17%	14.64%	22.03%		

Several improvements can be explored in the next phase of task 4, such as different fusion/separation combinations between classes and a between refinement of the samples, with ancillary data cross-checking. Textural indices should also be coupled with spectral indices in order to take spatial coherence into account – this can also be reinforced with the use of S-1 data.

The relative look and feel of one of the tile is shown below, in Figure 5-7. A clear coherence in the landscape is visible.

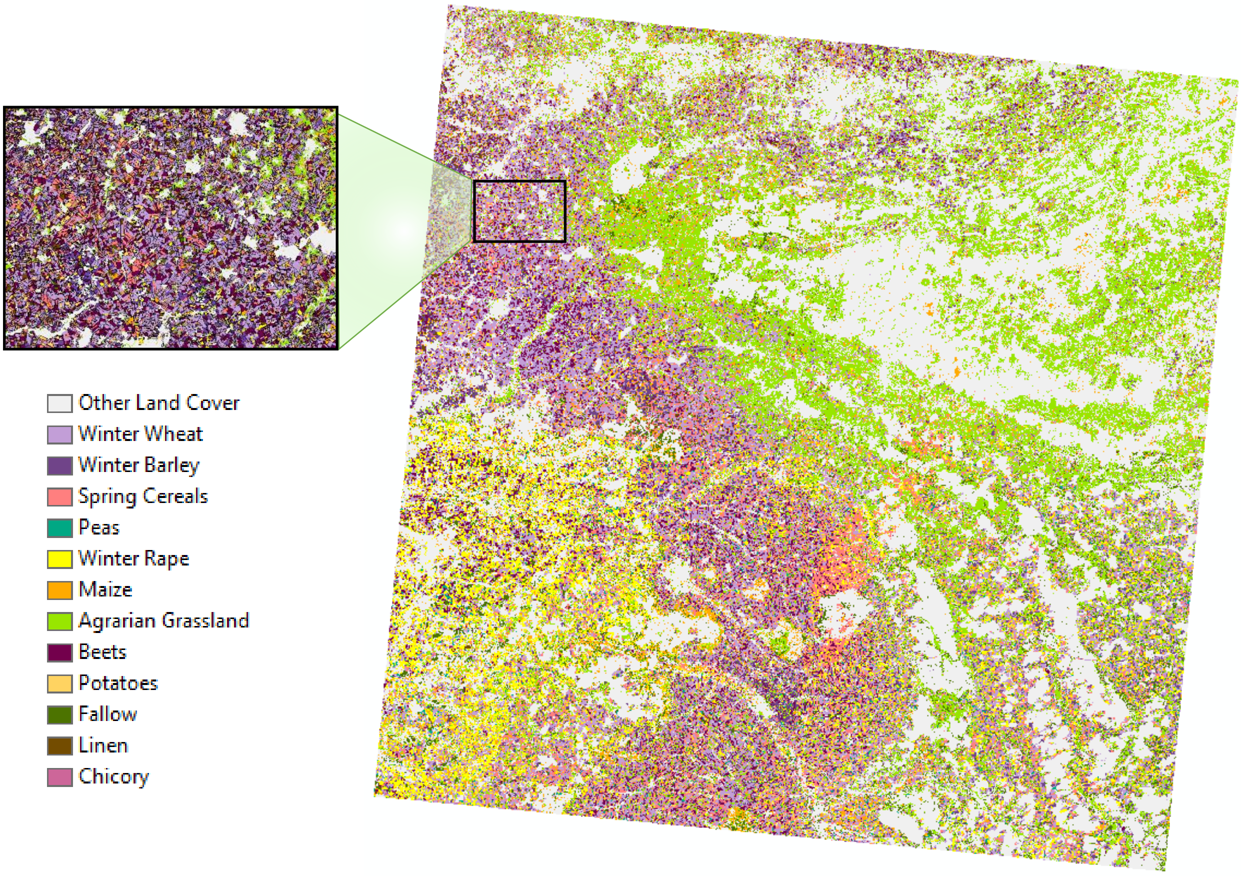


Figure 5-7: Tile look and feel.

The derived product from this first prototype, the cropland mask, can be also used for validation. This secondary product is a reclassification of the first one, but a different quantitative approach for validation was conducted: a set of stratified random points was generated over the 4 tiles, and the following confusion matrix was extracted, see Table 5-19.

Table 5-19: Confusion matrix for the derived crop mask, over the 4 tiles.

CROPLAND MASK (plausibility)		REFERENCE LABELS			
		Non-Cropland	Cropland	User Accuracy	Commission
PRODUCT LABELS	Non-Cropland	245.19	15.92	93.90%	6.10%
	Cropland	4.51	134.38	96.75%	3.25%
	Producer Accuracy	98.19%	89.41%	94.89%	
	Omission	1.81%	10.59%		

This leads to another proposition to improve the two products: a reclassification could be performed over the first product classes, only present in the cropland mask. A reprocessing step could be added at the end of the workflow on the composite image at 81 bands – this should be tested in the next iteration of task 4. The Table 5-20 summarizes the assessment of this section.

Table 5-20: Overall Accuracy (OA) on both products over the 4 tiles.

	31UEQ	31UER	31UFQ	31UFR	Cropland Type	Cropland Mask	Remarks
OA	69.03%	78.30%	78.26%	84.30%	77.08%	98.89%	Could be improved with: - a modification of the classes, - better samples - use of textural indices - use of S-1 data - reclassification of the cropland types on the cropland mask only

For UCL, as detailed in section 5.1.3.1, the RF classifier was applied in two ways. The first is by training and applying RF on each tile individually while the second is by training RF on the 31UFR only.

For the first case, the overall accuracy was computed for each tile before and after grouping the crop type classes as well as after applying the majority filtering (Table 5-21). The 31UFR tile recorded the highest overall accuracy (88.81%) followed by the 31UFS (84.13%) and 31UES (82.99%) in case of not grouping similar classes. The overall accuracy has improved after grouping similar classes with an increase between 3% and 8% while the highest overall accuracies for all tiles (> 90%) are obtained after applying the majority filter.

Table 5-21: Overall Accuracy (OA) of classification results based on specific model per tile. OA is presented before and after grouping crop classes and applying majority filter on for the 31UFR, 31UFS and 31UES tiles.

Tile	OA before grouping classes (up to 159 different classes)	OA for classes grouped (24 classes)	OA after majority filtering (24 classes)
31UFR	88.81 %	92.35 %	93.92 %
31UFS	84.13 %	88.55 %	90.76 %
31UES	82.99 %	91.13 %	93.55 %

For the second case, the accuracy assessment detailed in table 5-22 show that the classifier has lower performance on the tiles not used for the training (which is expected). Thus, the final product of the tiles are kept separated.

Based on the abovementioned accuracy assessment, the final products are considered as the maps produced from training and applying the RF classifier along with applying the post processing steps including the majority filter (Figure 5-8).

Table 5-22: Overall Accuracy (OA) of classification results based on a single model trained on 31UFR tile for the 31UFR, 31UFS and 31UES tiles.

Tile	OA for classes grouped (24 classes)
31UFR	92.35 %
31UFS	68.59 %
31UES	59.71 %

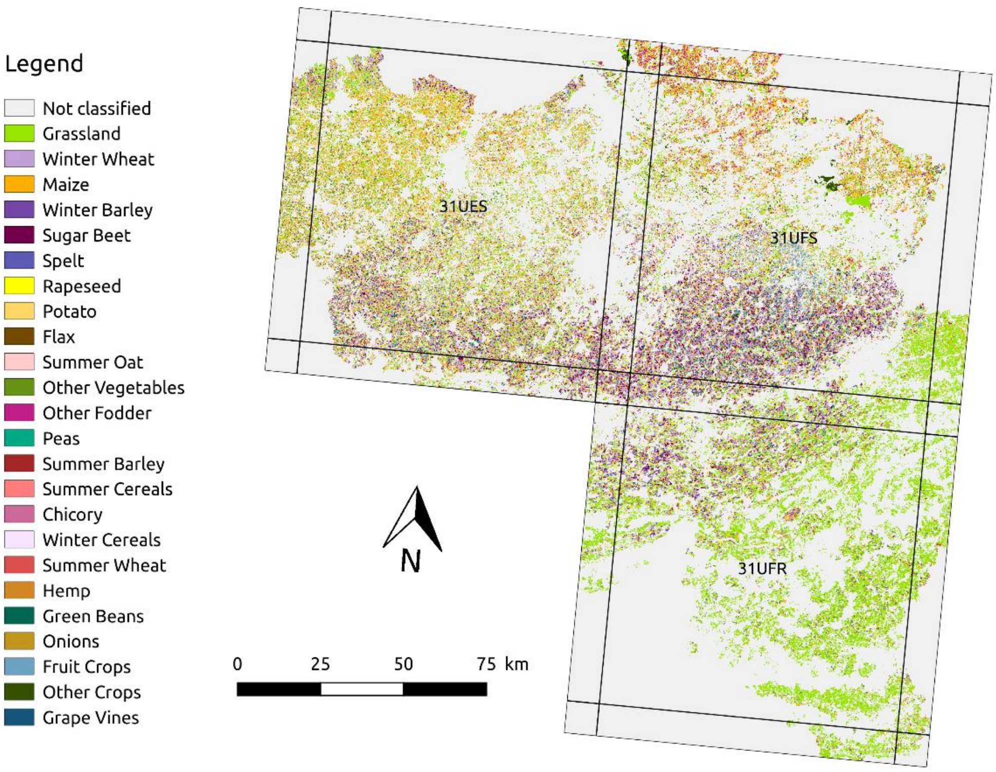


Figure 5-8: Classification results on UFR-UFS-UES tiles after majority filtering.

For reliable assessment of the methods core, confusion matrices were built for all the tiles after grouping similar classes and without applying the majority filtering (Table 5-23 to Table 5-25). Then. The F1-score was computed for each crop type class and tile. Figure 5-9 depicts the F1-score where the classes are ordered based on decreasing area coverage. Overall the classifier was able to differentiate several of the minority classes. The differences in accuracy between the tiles can be explained by the occurrence of these classes in the training dataset between tiles (for example the absence of Grape Vines in the 31UES tile).

Table 5-23: Confusion matrix for tile 31UFR.

31UFR		REFERENCE LABELS																								User Accuracy (%)	Commision (%)
		Grassland	Winter Wheat	Maize	Winter Barley	Sugar Beet	Spelt	Rapeseed	Potato	Flax	Summer Oat	Other Vegetables	Other Fodder	Peas	Summer Barley	Summer Cereals	Chicory	Winter Cereals	Summer Wheat	Hemp	Green Beans	Onions	Fruit Crops	Other Crops	Grape Vines		
	Grassland	6103301	5949	6510	628	140	5728	621	55	88	8292	23795	123750	3243	6700	20752	76	5434	853	130	7	1	2939	282	116	96.58	3.42
	Winter Wheat	4390	1143800	1913	13393	238	107024	1101	685	1737	10906	8246	715	1589	6574	2042	0	4267	4278	0	0	0	0	123	0	87.11	12.89
	Maize	12911	2701	670736	572	559	466	390	431	0	2272	1763	2103	642	2604	2698	121	804	2918	16	32	32	6	526	6	95.1	4.9
	Winter Barley	3532	17004	511	462851	24	7342	35	33	17	638	5395	469	194	824	807	0	4395	344	0	1	0	0	2	0	91.76	8.24
	Sugar Beet	43	77	791	0	316880	3	9	3580	5	13	378	5348	100	10	16	632	4	1	0	0	17	1	9	0	96.63	3.37
	Spelt	3592	41929	801	2778	0	215417	25	50	478	5933	7066	421	200	4089	1418	0	4721	2100	0	5	0	0	491	0	73.9	26.1
	Rapeseed	178	105	47	224	2	26	277863	0	0	11	468	3	361	0	73	0	33	0	0	0	0	0	0	0	99.45	0.55
	Potato	517	275	1060	0	1499	55	18	229337	476	216	585	115	2707	101	61	1143	44	133	7	42	196	0	418	1	95.95	4.05
	Flax	1	4	684	0	0	4	0	316	95935	882	18	0	164	100	10	0	0	5	0	0	0	0	0	0	97.77	2.23
	Summer Oat	3977	1013	1025	64	528	1069	18	25	1018	47527	1762	1153	325	10302	1514	2	143	774	116	0	0	0	14	0	65.67	34.33
	Other Vegetables	10857	3481	2386	2748	125	3346	68	1448	185	4889	36271	4519	1570	3317	6051	434	4921	2349	0	1	13	181	341	1	40.53	59.47
PRODUCED LABELS	Other Fodder	46008	535	1468	9	4381	296	9	88	129	874	4005	37421	767	1570	3578	108	616	64	5	40	0	2	14	1	36.69	63.31
	Peas	366	5	662	73	8	113	53	43	4	288	2067	298	50971	319	1401	34	51	93	112	564	0	0	9	0	88.59	11.41
	Summer Barley	2870	1163	228	975	0	784	1	26	545	9714	916	465	104	17209	1032	0	49	697	0	0	0	0	15	0	46.77	53.23
	Summer Cereals	1672	1503	1204	15	0	494	5	139	23	2512	4203	892	1469	1220	10687	0	1033	112	52	0	0	0	11	0	39.22	60.78
	Chicory	0	0	146	0	215	0	0	14	0	0	22	4	5	0	0	17115	0	0	0	255	0	0	0	0	96.28	3.72
	Winter Cereals	3006	7865	885	3931	1	3288	179	0	11	1620	6402	326	13	791	1400	2	8160	217	0	0	0	0	6	0	21.42	78.58
	Summer Wheat	532	3525	536	835	0	786	0	3	947	5251	1418	95	52	2637	668	22	533	1780	0	0	0	0	7	0	9.07	90.93
	Hemp	119	0	219	0	0	0	0	5	0	12	91	0	19	1	111	0	0	0	6574	0	0	0	0	0	91.93	8.07
	Beans	0	0	63	0	0	0	0	16	1	0	215	0	814	3	0	0	0	0	0	2300	0	0	9	0	67.23	32.77
	Onions	0	0	73	0	0	0	0	0	31	1	1053	0	226	0	0	0	0	1	0	4	1101	0	0	0	44.22	55.78
	Fruit Crops	2986	6	0	0	0	114	3	0	0	0	3	1	0	0	0	0	0	0	0	0	0	1164	0	0	27.22	72.78
	Other Crops	815	527	1006	16	28	191	12	725	205	172	813	292	207	29	455	46	98	64	2	0	0	8	1166	0	16.96	83.04
	Grape Vines	112	0	1	0	2	0	0	0	0	0	7	5	0	0	52	0	0	0	0	0	0	0	0	368	67.28	32.72
Producer Accuracy (%)		98.41	92.88	96.79	94.63	97.61	62.16	99.09	96.76	94.21	46.58	33.91	20.98	77.53	29.47	19.49	86.72	23.11	10.61	93.73	70.75	80.96	27.06	33.87	74.65	92.35	
Ommision (%)		1.59	7.12	3.21	5.37	2.39	37.84	0.91	3.24	5.79	53.42	66.09	79.02	22.47	70.53	80.51	13.28	76.89	89.39	6.27	29.25	19.04	72.94	66.13	25.35		

Table 5-24: Confusion matrix for tile 31UFS.

31UFS		REFERENCE LABELS																								User Accuracy (%)	Commision (%)
		Grassland	Winter Wheat	Maize	Winter Barley	Sugar Beet	Spelt	Rapeseed	Potato	Flax	Summer Oat	Other Vegetables	Other Fodder	Peas	Summer Barley	Summer Cereals	Chicory	Winter Cereals	Summer Wheat	Hemp	Green Beans	Onions	Fruit Crops	Other Crops	Grape Vines		
PRODUCED LABELS	Grassland	2806586	4138	14865	696	66	925	121	1107	795	1625	6294	370741	2217	6606	1430	20	20	930	174	473	421	45872	271640	753	79.32	20.68
	Winter Wheat	2536	2321667	2510	12538	889	69267	5	1505	6618	1210	2061	68	2407	1565	57	143	387	1448	0	85	50	227	1071	18	95.61	4.39
	Maize	13370	3302	1873125	447	1548	421	0	5654	37	92	3104	5302	722	156	51	652	389	685	12	516	1410	2228	8328	183	97.47	2.53
	Winter Barley	1603	22876	292	424251	544	6282	56	0	447	792	551	1006	316	2811	0	0	56	170	0	8	0	238	522	1	91.67	8.33
	Sugar Beet	48	1858	2165	580	974834	12	0	14014	689	0	873	36841	146	0	6	1944	7	0	0	3	75	68	229	98	94.23	5.77
	Spelt	148	14822	4	2546	0	71265	6	0	849	81	474	1	280	74	0	2	72	8	0	3	0	11	134	11	78.49	21.51
	Rapeseed	94	20	318	5	2	122	122506	4	0	4	121	33	121	26	12	0	1	0	0	0	1	9	25	0	99.26	0.74
	Potato	202	580	7238	371	2499	43	0	910028	11	4	3774	4681	6550	10	36	3944	0	33	7	1587	3046	25	963	12	96.23	3.77
	Flax	287	1793	62	221	8	257	0	15	261492	336	157	74	1713	63	0	0	1	10	577	20	19	1	117	7	97.85	2.15
	Summer Oat	301	216	247	35	1	2	0	0	1265	5132	51	7	48	753	13	0	8	200	0	0	1	0	161	0	60.8	39.2
	Other Vegetables	3739	706	6697	1128	589	1569	53	3543	509	593	173026	2139	21831	2577	195	8007	313	609	143	11794	4485	303	6322	39	68.96	31.04
	Other Fodder	77740	439	1649	168	5063	20	0	685	31	5	1831	171455	170	1788	0	136	51	158	0	114	60	1064	9474	21	63.01	36.99
	Peas	610	5	3046	0	94	11	0	593	12	92	3003	899	222835	1247	80	908	0	10	55	3444	841	20	555	9	93.48	6.52
	Summer Barley	242	314	256	2197	2	54	0	6	336	1203	223	99	65	10307	111	0	3	743	0	4	15	19	632	1	61.23	38.77
	Summer Cereals	92	0	558	330	2	4	0	356	46	9	205	37	225	126	2139	0	1	0	0	0	2	0	129	21	49.95	50.05
	Chicory	0	0	117	42	1054	0	0	3594	705	0	4120	461	20	0	0	140648	0	0	28	343	63	6	273	2	92.85	7.15
	Winter Cereals	1031	3404	525	2477	59	3476	10	0	0	208	402	1281	221	38	0	0	2370	56	0	2	42	111	199	1	14.89	85.11
	Summer Wheat	9	2044	166	539	3	85	0	43	244	1021	72	87	67	2410	0	0	0	1574	0	2	3	0	341	0	18.07	81.93
	Hemp	52	4	324	0	0	2	0	19	5	1	73	0	50	86	30	0	2	2	4334	3	8	1	66	16	85.35	14.65
	Beans	463	2	1362	1188	5	0	1	3052	91	0	7176	262	15039	442	0	767	0	124	1	46094	1045	4	477	9	59.4	40.6
	Onions	2	37	1020	0	129	0	0	496	37	0	872	1	1469	13	0	43	0	0	0	65	32078	0	404	0	87.49	12.51
	Fruit Crops	11124	483	395	0	17	21	0	27	19	0	4164	102	304	392	0	0	1	271	0	234	43	320311	17514	1022	89.86	10.14
	Other Crops	43302	962	3607	277	164	179	47	569	93	135	3012	1270	1141	578	209	92	1	147	0	822	422	2778	94422	259	61.12	38.88
	Grape Vines	232	1	646	0	0	2	0	58	0	0	270	32	20	1	0	0	0	72	0	95	56	481	1559	455	11.43	88.57
Producer Accuracy (%)		94.7	97.56	97.5	94.27	98.71	46.27	99.76	96.26	95.32	40.92	80.14	28.73	80.16	32.14	48.96	89.41	64.35	21.71	81.3	70.15	72.6	85.7	22.72	15.49	88.55	
Ommision (%)		5.3	2.44	2.5	5.73	1.29	53.73	0.24	3.74	4.68	59.08	19.86	71.27	19.84	67.86	51.04	10.59	35.65	78.29	18.7	29.85	27.4	14.3	77.28	84.51		

Table 5-25: Confusion matrix for tile 31UES.

31UES		REFERENCE LABELS																								
		Grassland	Winter Wheat	Maize	Winter Barley	Sugar Beet	Spelt	Rapeseed	Potato	Flax	Summer Oat	Other Vegetables	Other Fodder	Peas	Summer Barley	Summer Cereals	Chicory	Winter Cereals	Summer Wheat	Hemp	Green Beans	Onions	Fruit Crops	Other Crops	Grape Vines	User Accuracy (%)	Commision (%)
	Grassland	2851861	2104	9249	5400	20	2056	24	2288	1459	411	12622	197752	433	4776	0	146	174	579	22	7640	768	24540	225201	18	85.14	14.86
	Winter Wheat	890	2067699	2084	11520	754	41541	6	300	8028	1241	2501	289	837	452	8	15	76	6495	0	930	361	62	2251	0	96.25	3.75
	Maize	7668	1887	2396243	1049	1212	233	12	8893	298	54	7013	4391	1142	42	0	1869	98	128	70	9779	2894	256	15277	2	97.39	2.61
	Winter Barley	627	10482	389	308061	0	4309	2	61	105	141	478	284	1	756	0	5	2	38	0	28	0	40	470	0	94.42	5.58
	Sugar Beet	133	840	1315	155	661805	2	0	9362	19	3	790	30569	244	0	0	919	0	1	0	387	190	17	259	0	93.61	6.39
	Spelt	326	9373	7	1221	186	26994	0	0	303	190	10	11	38	1	0	0	2	42	0	26	0	5	168	0	69.39	30.61
	Rapeseed	31	0	113	2	13	2	21076	42	0	0	34	23	223	16	0	0	61	0	0	12	0	0	332	0	95.89	4.11
	Potato	1176	360	8180	77	1528	29	0	1419829	51	3	3760	3109	5927	22	0	4970	0	56	13	4723	5645	19	2373	0	97.13	2.87
	Flax	57	315	86	99	0	50	0	33	153362	123	532	8	53	301	0	0	0	102	0	1097	155	3	623	0	97.68	2.32
	Summer Oat	139	315	0	132	0	128	0	31	2186	3139	19	12	21	300	0	0	0	352	0	64	5	0	80	0	45.34	54.66
	Other Vegetables	1539	1164	4353	977	417	1073	120	5856	758	511	311747	1558	4836	1175	9	11053	234	144	1	9092	3357	31	10141	0	84.22	15.78
PRODUCED LABELS	Other Fodder	64336	174	2011	298	5834	184	2	1008	78	58	4343	98434	208	958	0	736	61	91	11	1527	80	780	5050	0	52.85	47.15
	Peas	6	7	86	0	370	4	2	588	72	69	2232	154	114871	223	0	529	0	35	0	2916	569	0	267	0	93.39	6.61
	Summer Barley	76	826	267	1045	0	46	0	7	295	346	35	14	40	5282	0	0	0	883	0	358	42	7	256	0	53.76	46.24
	Summer Cereals	383	2	120	1	0	0	0	104	50	6	207	688	0	95	0	160	0	154	0	31	20	2	214	0	0	100
	Chicory	4	286	426	0	140	0	0	937	0	0	10957	68	7	0	0	76750	0	0	0	478	129	0	160	0	84.95	15.05
	Winter Cereals	175	1547	116	1299	0	1090	0	0	18	4	22	63	1	52	0	0	504	0	0	273	5	0	45	0	9.67	90.33
	Summer Wheat	160	1420	444	58	0	34	0	12	1127	578	15	13	35	792	0	0	0	2939	0	2	4	0	139	0	37.82	62.18
	Hemp	0	0	319	0	0	0	0	419	0	0	1025	1	88	0	0	0	0	0	1654	16	1	0	56	0	46.21	53.79
	Beans	1114	234	1243	1586	7	153	1	2115	511	19	11758	768	1733	40	0	180	0	50	0	132869	1676	1	3095	0	83.49	16.51
	Onions	27	3	52	0	0	12	0	1765	95	9	595	1	2083	4	0	110	0	2	0	929	79290	4	575	0	92.68	7.32
	Fruit Crops	2363	0	33	69	0	0	0	6	0	0	187	6	5	0	0	3	0	0	0	93	78	51338	5001	0	86.75	13.25
	Other Crops	18491	488	3984	179	89	45	1	1724	318	0	5201	1334	200	106	0	908	0	55	3	2751	494	1375	75139	100	66.5	33.5
	Grape Vines	795	0	0	0	0	0	0	0	0	0	122	1	0	0	0	0	0	0	0	42	0	63	647	1	0.06	99.94
Producer Accuracy (%)		96.6	98.48	98.57	92.45	98.43	34.61	99.2	97.56	90.68	45.46	82.87	28.99	86.35	34.31	0	78.04	41.58	24.2	93.24	75.47	82.8	65.36	21.6	0.83	91.30	
Ommision (%)		3.4	1.52	1.43	7.55	1.57	65.39	0.8	2.44	9.32	54.54	17.13	71.01	13.65	65.69	100	21.96	58.42	75.8	6.76	24.53	17.2	34.64	78.4	99.17		

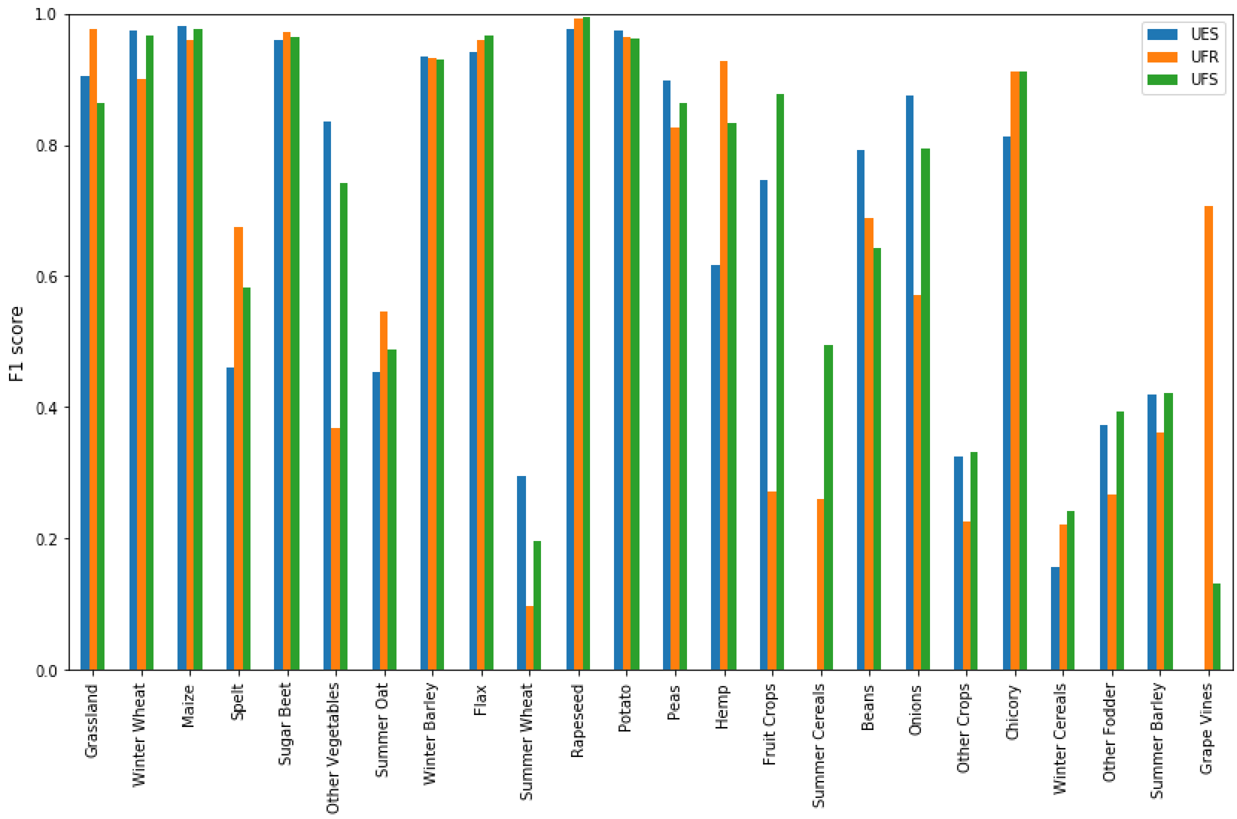


Figure 5-9: F1-score per crop type for UFR, UFS and UES tiles. Ordered by decreasing area over the 3 tiles.

5.2.2 Crop type map of Demo-Site Central

This chapter focusses on the results of the crop mask and crop type classification in the Central demonstration site. The results of the features selection are described, followed by the crop mask and crop types results and accuracies, and finally, a comparison with the HRL Grassland 2015 is provided.

During the group-based FFS the accuracy reached its plateau with 13 selected feature groups which comprise 228 features, out of a total of 1246 features. After the first FFS 172 of the 228 selected features had their origin in the optical data. 56 features were derived from the radar data. In the second FFS the 228 were further reduced to 28 features.

After the two runs of FFS the selected 28 features, which are listed below in Table 5-26, were used for the crop mask and the crop type classification for the demonstration site Central. Most of these features could be derived from the optical data (20 out of 28), 8 from SAR data (4 derived from indices and 4 derived from VV and VH bands). The 20 optical feature consisted of 17 features derived from indices (only NDVI and NDWI whereas BRIGHTNESS- and IRECI-based features were not selected), and only 3 features derived from spectral bands.

Table 5-26: Selected time features used for training and classification.

Feature No.	Scene Set (Start Date TO End Date)	Sensor	Band/Index	Featuretype
1	2017-03-15 TO 2017-11-14	S1	NDVVVH	std
2	2017-03-15 TO 2017-05-14	S2	NDVI	p090
3	2017-07-15 TO 2017-09-14	S2	NDWI	p050
4	2017-05-15 TO 2017-07-14	S1	VV	median
5	2017-03-15 TO 2017-11-14	S2	B08	p090
6	2017-05-15 TO 2017-07-14	S2	NDWI	p075
7	2017-07-15 TO 2017-09-14	S2	B03	p050
8	2017-05-15 TO 2017-07-14	S2	NDWI	actn0t42
9	2017-09-15 TO 2017-11-14	S2	NDWI	mean
10	2017-03-15 TO 2017-05-14	S2	NDVI	cov
11	2017-05-15 TO 2017-07-14	S2	NDVI	p025
12	2017-03-15 TO 2017-11-14	S1	VH	std
13	2017-03-15 TO 2017-05-14	S1	RATIOVVVH	mean
14	2017-03-15 TO 2017-11-14	S2	NDVI	max
15	2017-07-15 TO 2017-09-14	S2	NDWI	pdiff075025
16	2017-03-15 TO 2017-11-14	S2	NDVI	median
17	2017-09-15 TO 2017-11-14	S2	NDWI	std
18	2017-05-15 TO 2017-07-14	S2	NDWI	min
19	2017-03-15 TO 2017-11-14	S1	NDVVVH	pdiff090010
20	2017-05-15 TO 2017-07-14	S2	NDVI	difmax3mean
21	2017-07-15 TO 2017-09-14	S2	NDWI	actn0t42
22	2017-05-15 TO 2017-07-14	S2	NDVI	min
23	2017-03-15 TO 2017-11-14	S1	NDVVVH	mean
24	2017-03-15 TO 2017-11-14	S1	VH	mean
25	2017-03-15 TO 2017-11-14	S2	B08	std
26	2017-05-15 TO 2017-07-14	S1	VV	cov
27	2017-05-15 TO 2017-07-14	S2	NDVI	p075
28	2017-05-15 TO 2017-07-14	S2	NDWI	difdif3mean

Four selected time features based on optical and radar data are shown in Figure 5-10 (for Sentinel-1) and Figure 5-11 (for Sentinel-2). For the S-1 derived time features the indices are RATIOVVVH, NDVVVH, and VV from different time steps. The features based on S-2 in Figure 5-11 are derived from the NDVI, NDWI, and one single band (B08), also from different time steps.

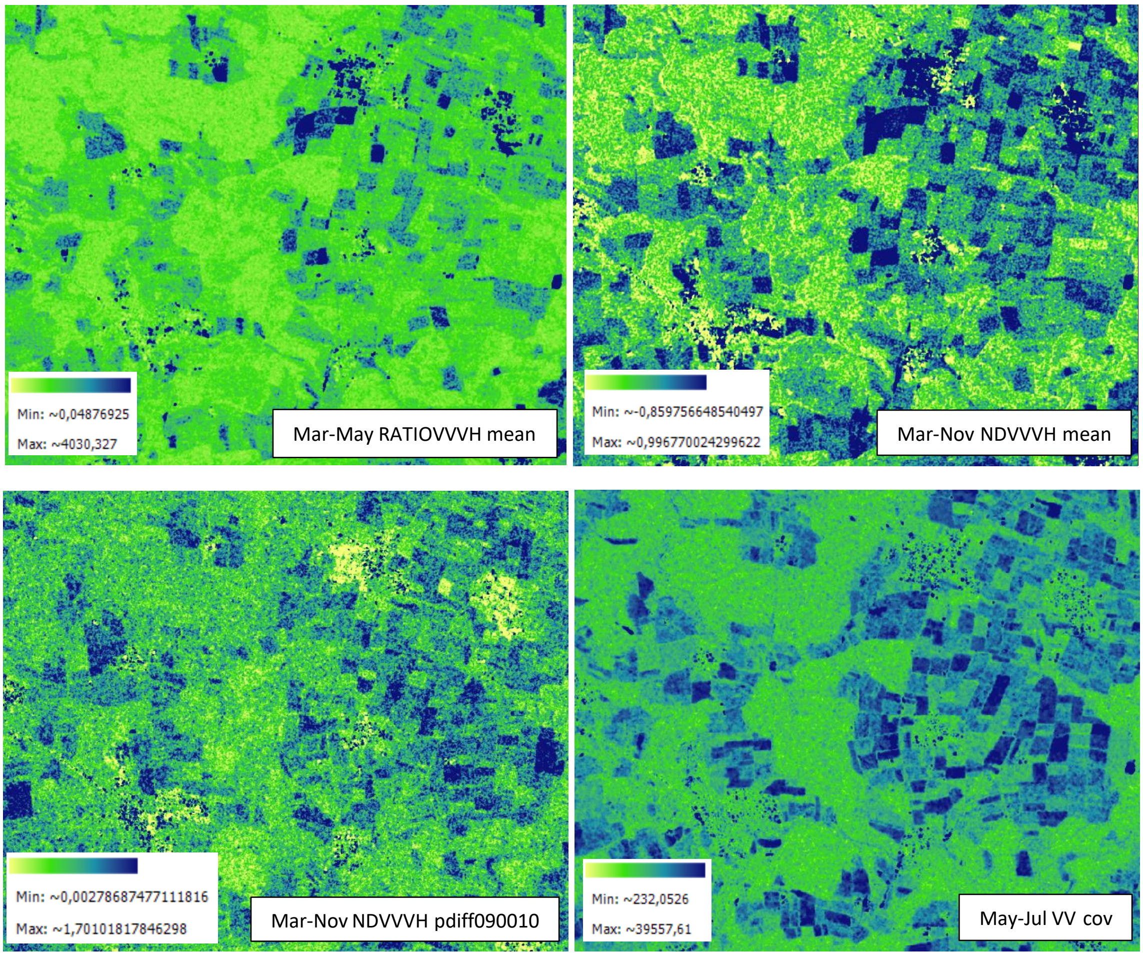


Figure 5-10: Results of the single features mean, std, pdiff090010, and cov derived from different Sentinel-1 based indices.

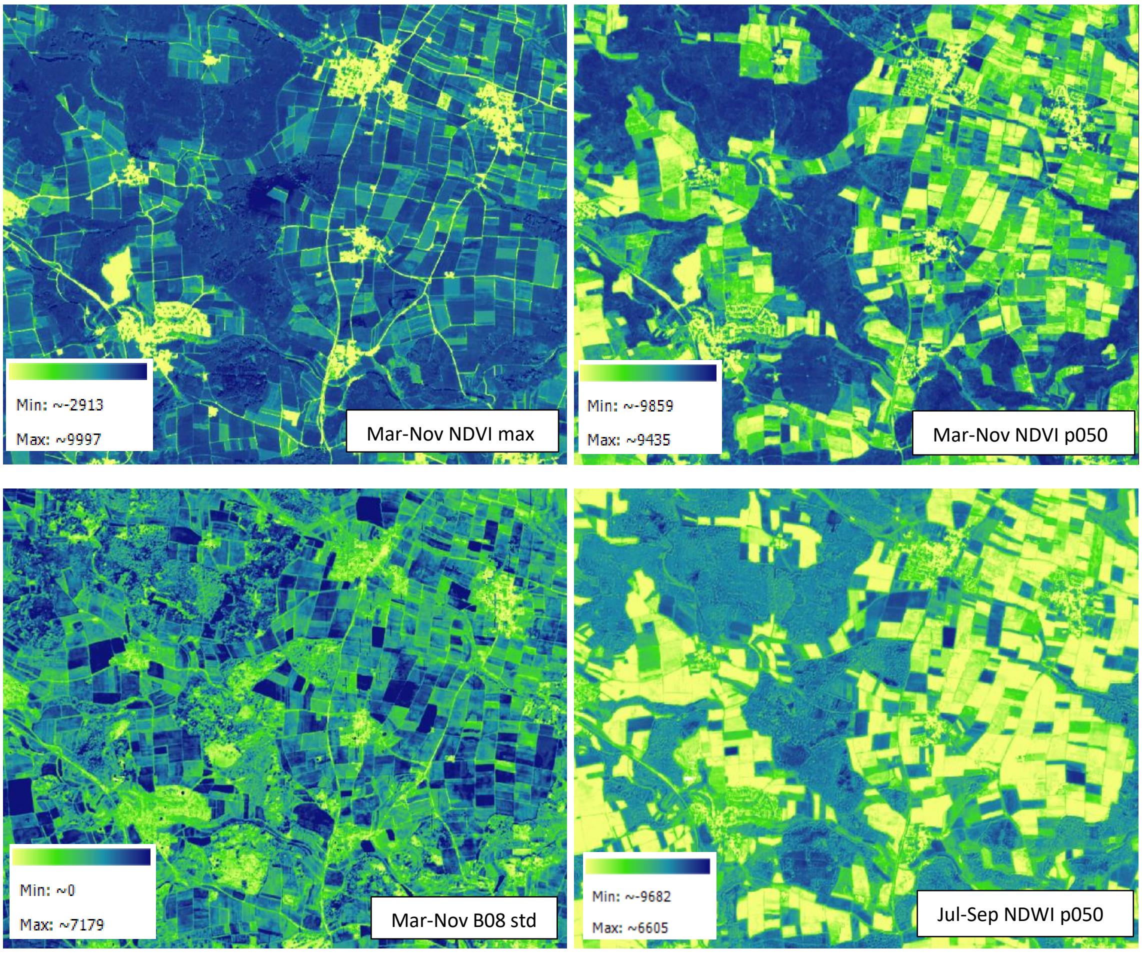


Figure 5-11: Results of the single features max, p050 and std derived from different Sentinel-2 based indices/bands.

Before the results of the crop mask and the crop type classification will be described it should be mentioned that the whole prototype product was created pixel-based and until now no MMU filter has been applied. This means that single classified pixels are still kept in the product. Such an MMU filter, as it is applied for some of the current HRLs, will be subject of future definitions of a potential agricultural HRL.

The 28 selected features were also used for the derivation of the crop mask. The cross-validation yielded an Overall Accuracy of 97% (F1-Score 0.97). As can be seen in the results shown in Table 5-27 the classification model for the distinction between cropland and non-cropland works well in general. Producer's and User's Accuracies of the non-crop class are very high (between 96% and 98%) as well as the Producer's Accuracy for the crop class (93%) whereas the User's Accuracy of the crop class is lower (85%). The latter value signalizes that 15% of the cropland is wrongly classified as non-crop.

Table 5-27: Confusion matrix of the CRM prototype in the demonstration site Central.

		Reference Data		
		0	1	
Class Name	**CRM 2017**	Non-cropland	Cropland	Totals
Non-cropland	0	**445929**	15625	461554,00
Cropland	1	6224	**94850**	101074,00
		452153,00	110475,00	562628,00

Figure 5-12 shows the whole crop mask for the demonstration site Central with the location of the examples described hereafter. It is visible that in the higher regions the cropland gets less compared to the lower parts, e.g. in the Black Forest or in the Alps in Austria and Switzerland.

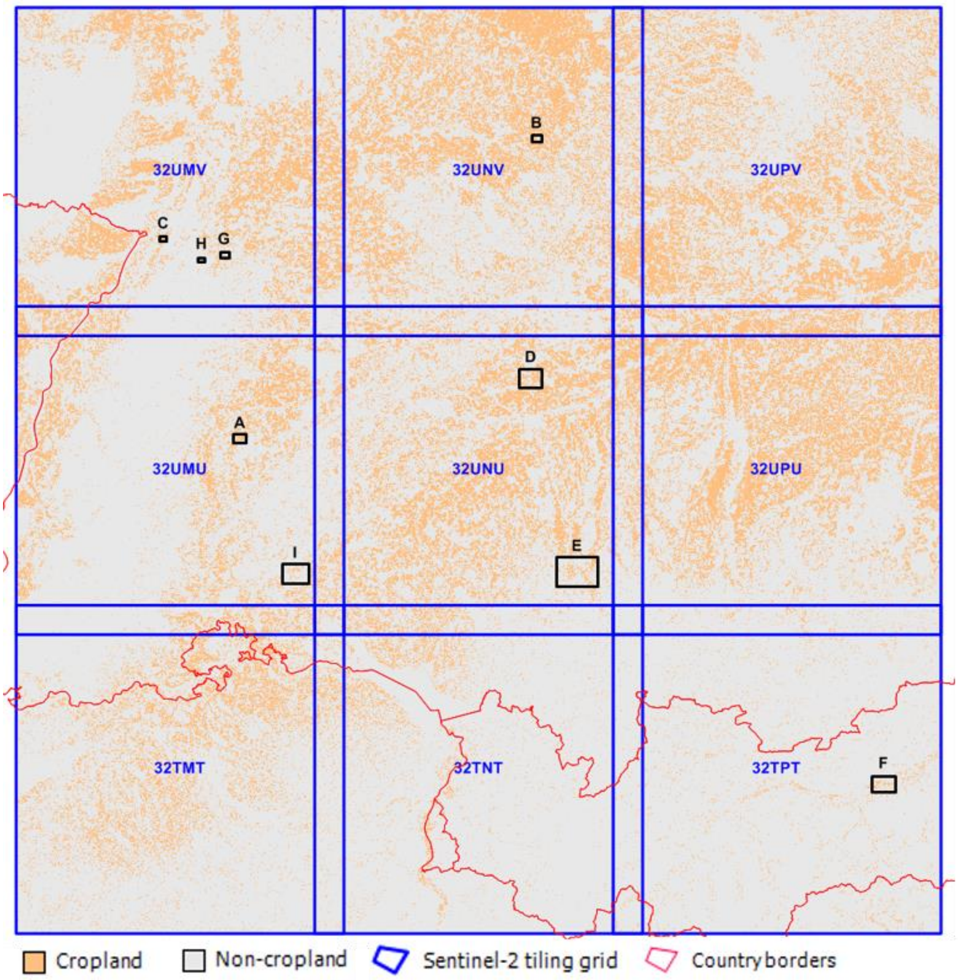


Figure 5-12: Overview over the resulting crop mask in the demonstration site Central.

A closer look on the crop mask is given in Figure 5-13. Forest areas as well as waterbodies, grassland and urban areas are masked very precisely. Only some parts of gardens and green areas in urban areas are wrongly classified as cropland and therefore not masked out. In order to address this problem, the whole pixel-based product was filtered as it is described in chapter 4.2. The resulting crop mask fixes the problem of wrongly unmasked urban areas for the most part.

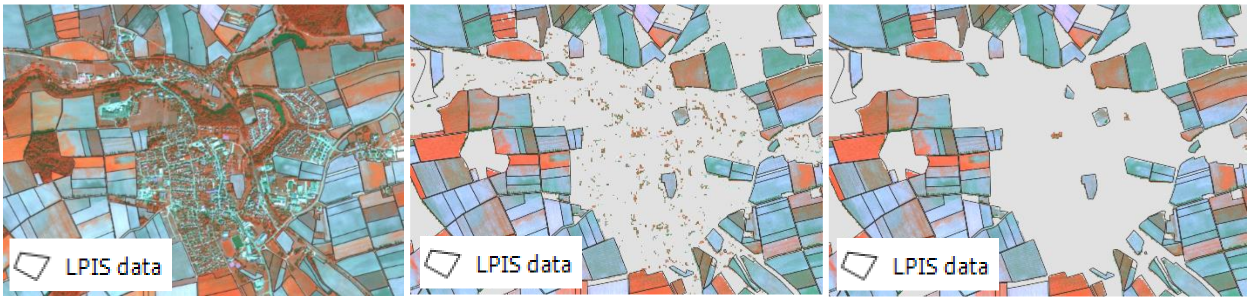


Figure 5-13: Results of the crop mask classification (middle: unfiltered, right: filtered, in grey) in NW Baden-Wurttemberg (location B) over a Spot-6 image of 2016 in combination with the reference data.

However, predominantly in the Austrian part of the demonstration-site the crop map does not only include some green areas within cities but also a lot of grassland in rural and mountainous areas (see Figure 5-14). Therefore, in particular grassland areas are sometimes recognized as cropland in the mask and not masked out, some potential for improvement is identified regarding this issue. The example below from Austria shows that forests and water are mostly cut out by the mask but some grassland areas that should have been masked out are not covered by the mask.

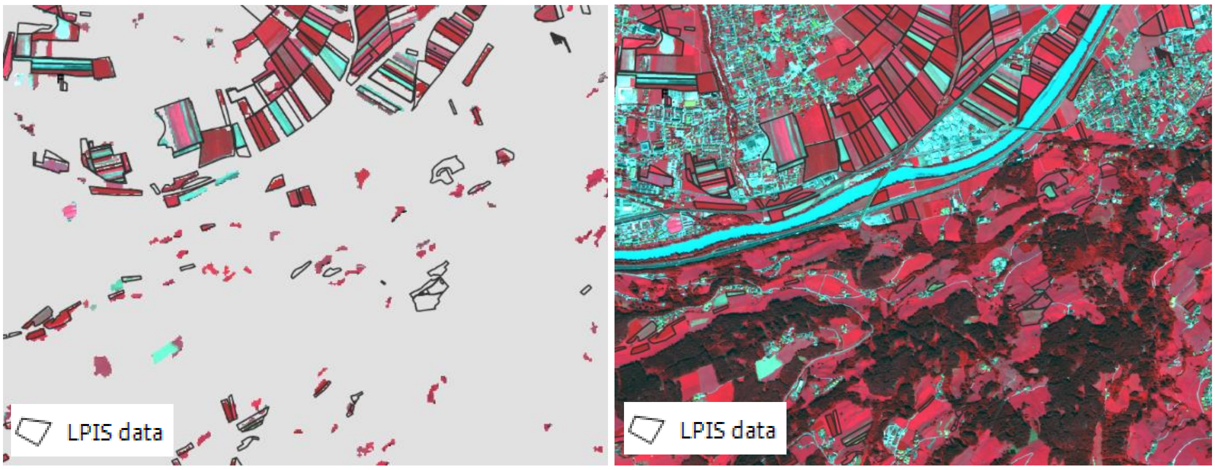


Figure 5-14: Results of the crop mask classification (in grey) near Innsbruck (AT, location F), draped over a Worldview-1 image of 2015 in combination with the LPIS reference data.

In contrary to the previous case of over-estimation of cropland, another fact that should be addressed in the future is that some fields which are present in the reference data get cut out by the crop mask, which leads to under-estimation in some areas (see Figure 5-15). This, however, primarily happens with the class Agricultural Grassland and Fallow, and especially when these fields are surrounded by a lot of Grassland, which was excluded from the prototype classification and thereby is correctly masked out in the figure below. This effect has not been largely observed for other crop types. In chapter 0 a potential way forward will be presented in order to improve the crop mask.

Figure 5-15: Results of the crop mask classification (in grey) in W Baden-Wurttemberg (location H) over a Deimos image of 2016 in combination with the reference data. Grassland (dark blue) is correctly masked out by the crop mask, Agricultural grassland (green lines) and Fallow (light blue lines) areas are wrongly masked out.

The results of the crop type classification are very promising. The overall accuracy is at 89%. A closer look into the several classes and their accuracy results reveals some differences in performance. Table 5-28 shows that many classes (e.g. Maize, SugarBeets, WinterCrop, WinterRape) are very well distinguished with Producer's and User's accuracies between 91% and 98%. Several other classes, e.g. FruitTrees, Legume and SummerCrop still show acceptable User's and Producer's accuracies (around 71 – 86%). Classes such as strawberries and vegetables show high Producer's accuracies (around 65 – 80%) but low

Producer's accuracies (around 40 – 50%) which is explainable by the fact that most reference pixels are correctly classified but many other classes are confused with these classes. Only some predominantly smaller classes, e.g. SummerRape and SunflTopinamb could not be classified very precisely, characterized by low Producer's accuracies. The class others, which provides a mix of all remaining under-represented crop types is by definition very inhomogeneous and amounts to accuracies above 50%.

Table 5-28: Accuracy results per class.

Crop Group	PA (%)	UA (%)
AgrGrass	58	74
Fallow	49	71
FruitTrees	75	71
Legume	76	75
Maize	94	95
Others	53	73
Potatoes	51	59
Strawberries	79	41
SugarBeets	95	91
SummerCrop	86	82
SummerRape	46	21
SunflTopinamb	64	28
Vegetables	68	48
Winegrowing	96	95
WinterCrop	94	94
WinterRape	98	93

The following Table (Table 5-29) shows the confusion matrix of the crop type classification on a polygon level, with 70% of the LPIS dataset used as reference pixels (see Table 5-8 for comparison), and the reference dataset being represented in the columns. One has to take into account, however, that the total number of polygons strongly varies among the classes In general, the accuracy levels can be closely related to the size of the referring classes: High-accuracy classes such as WinterCrop, WinterRape, SummerCrop and Maize occur more often in the demonstration site, whereas SummerRape, SunflTopinamb, Strawberries and Others are underrepresented and are therefore of lower importance for the crop type discrimination in the Central demonstration site.

The confusion matrix shows that some classes, e.g. Maize, WinterCrop, WinterRape and SugarBeets could be classified very well. Their User's Accuracies are between 91% and 95%, whereas the Producer's Accuracies are between 94% and 98%. In case of SummerCrop which has a PA of 86% and a UA of 82% it is noticeable that nearly all of the scattering goes towards WinterCrop. Reasons for this confusions will be further investigated, potentially they are in the timing of the crop growth phenology of particular summer crops.

It is also demonstrated that for example 22% of the polygons classified as SunflTopinamb are actually Fallow and 16% are Maize in the reference data. Furthermore the SummerRape, which was less successfully classified has many omission errors. Nearly 80% of the SummerRape in the reference data was wrongly classified as Fallow (21%), SummerCrop (16%), or WinterRape (12%). This leads to a low User's Accuracy of 28% (SunflTopinamb) and 21% (SummerRape) respectively. While the SunflowerTopinamb class has an acceptable Producer's Accuracy of 64% the SummerRape is also problematic with a PA of 46%. One reason for that is the rather small size of the classes (see Table 5-8 and Figure 5-5).

Table 5-29: Confusion matrix of the CRT prototype in the demonstration site Central.

		Reference Data																
Class Name		1	3	5	8	9	10	11	13	14	15	16	17	18	19	20	21	
	CRT 2017	AgrGra	Fallow	Fruit Trees	Legume	Maize	Others	Pota-toes	Straw-berries	Sugar Beets	Summer Crop	Summer Rape	Sunfl/ Topinamb	Vege-tables	Wine-growing	Winter Crop	Winter Rape	**Totals**
AgrGra	1	**4997**	240	18	70	232	47	84	5	4	220	5	0	51	2	757	6	**6738**
Fallow	3	390	**5892**	44	188	628	55	161	19	16	363	5	13	79	21	412	12	**8298**
FruitTrees	5	52	119	**3235**	3	50	12	6	12	0	15	0	0	31	949	56	3	**4543**
Legume	8	198	416	12	**5921**	236	104	108	11	10	507	15	2	78	1	272	28	**7919**
Maize	9	528	849	99	216	**75207**	105	362	22	35	516	5	12	234	12	1170	41	**79413**
Others	10	12	51	11	21	156	**1046**	5	4	0	21	0	4	55	1	46	0	**1433**
Potatoes	11	177	312	12	165	191	51	**1985**	14	33	63	4	13	306	1	35	3	**3365**
Strawberries	13	115	182	51	73	106	48	64	**933**	5	78	1	3	219	59	326	20	**2283**
SugarBeets	14	41	172	12	9	81	8	32	2	**5785**	53	1	1	100	4	76	3	**6380**
SummerCrop	15	331	460	22	399	427	83	311	7	35	**30689**	4	7	105	4	4488	21	**37393**
SummerRape	16	2	54	0	26	9	0	5	0	1	40	**51**	0	3	0	27	29	**247**
Sunfl/Topinamb	17	21	136	1	22	99	17	41	1	30	32	1	**174**	18	0	17	2	**612**
Vegetables	18	398	557	120	205	861	225	275	109	52	221	7	24	**3260**	222	186	5	**6727**
Winegrowing	19	114	570	499	10	125	39	17	20	2	25	0	2	77	**28302**	40	11	**29853**
WinterCrop	20	1102	1643	187	433	1342	126	416	23	69	2680	5	11	193	34	**122950**	187	**131401**
WinterRape	21	114	275	9	38	153	16	61	2	6	160	7	4	23	4	273	**15396**	**16541**
Totals		**8592**	**11928**	**4332**	**7799**	**79903**	**1982**	**3933**	**1184**	**6083**	**35683**	**111**	**270**	**4832**	**29616**	**131131**	**15767**	**343146**

The following Figure 5-16 gives an overview over the crop type classification in the demonstration site Central. Marked in black and numerated from A-I are the examples, which will be presented afterwards.

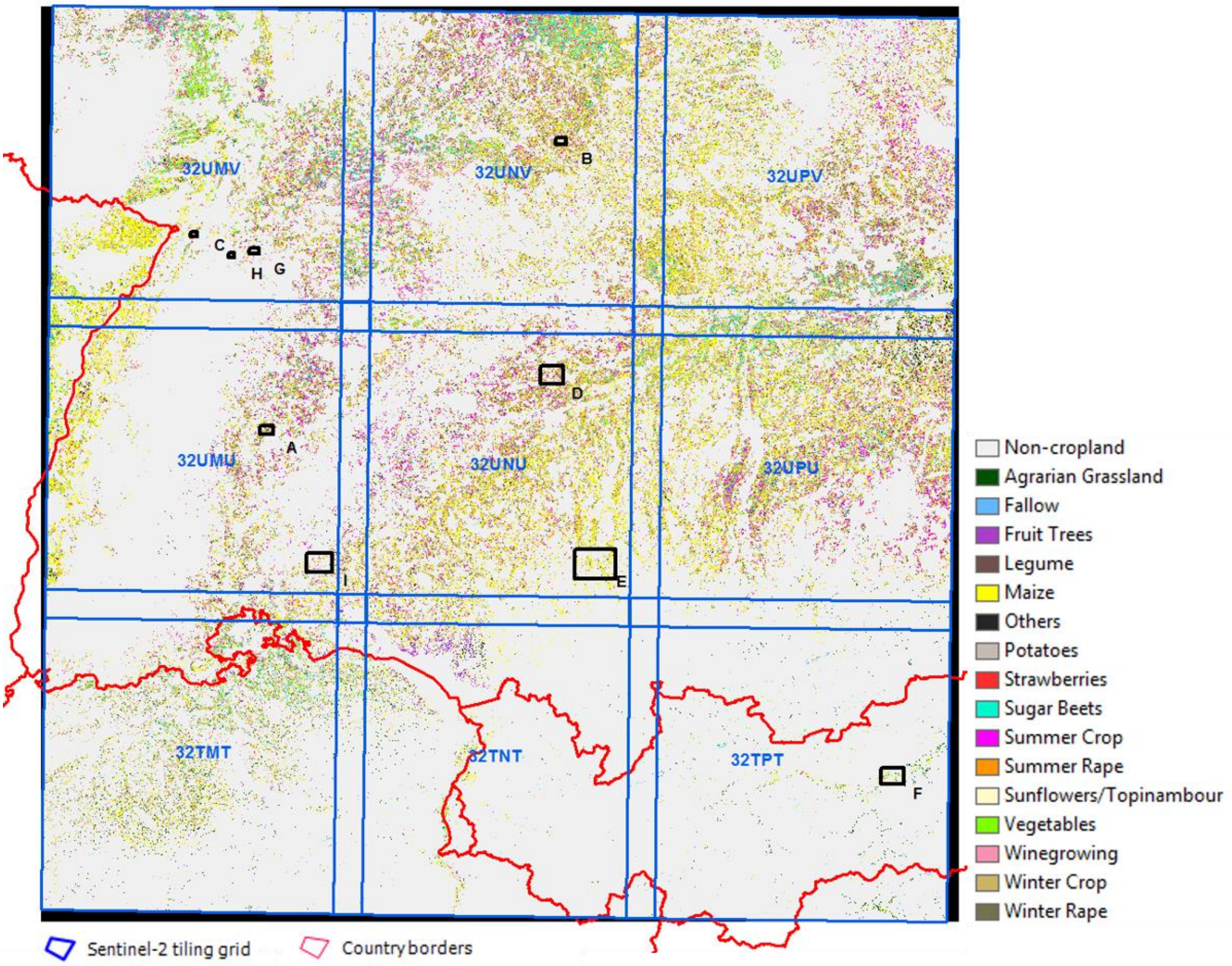
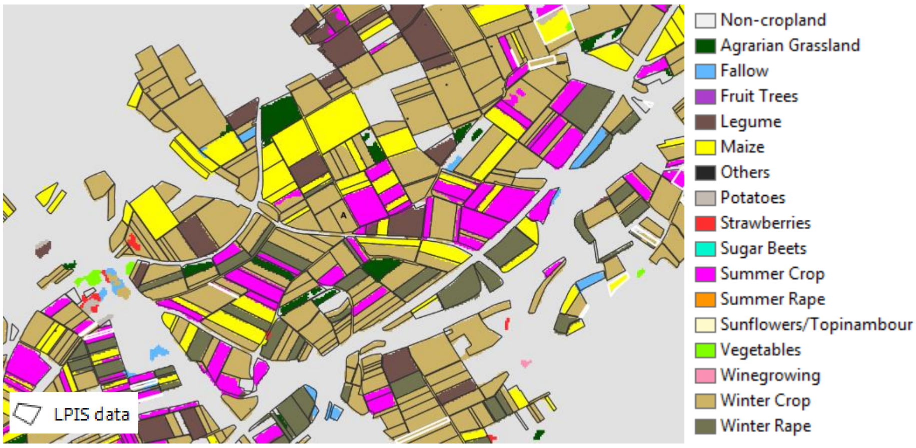


Figure 5-16: Overview over the results of the crop type classification in the demonstration site Central with the locations of the examples marked in black.

© EuroGeographics



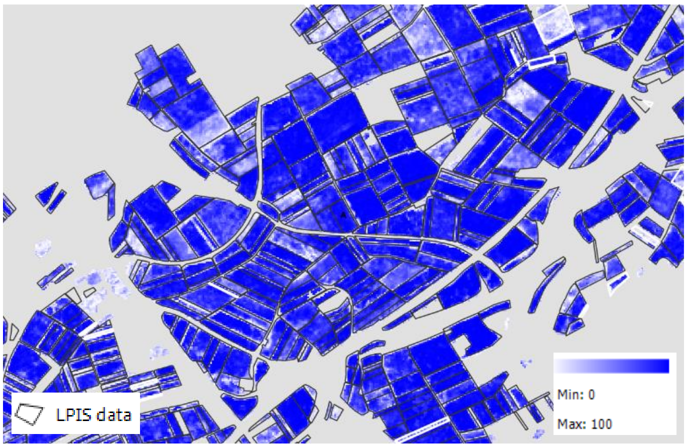


Figure 5-17: Results of the crop type classification (left) in central Baden-Wurttemberg (location A) with high breakties (right) and the classification errors (highlighted in white).

© MLR BW

Figure 5-17 depicts an example for a successful crop type classification. The upper figure shows the classification results and the one below shows the breakties of the results. Darker blue areas and higher values stand for higher breakties and thereby reliability of a crop type belonging to a certain class in the reference dataset. Additionally, field polygons where classification errors occurred are highlighted in white. Most of the fields in this area are classified correctly and only a few errors are visible.

The following example also shows good results regarding the crop type classification. Besides that the crop map problems of the unfiltered prototype within urban areas are obvious as there are a lot of pixels defined as cropland which actually aren't cropland. As already described previously in this section a filter was applied to the pixel-based product. The results are shown in the upper right Figure (see Figure 5-18).

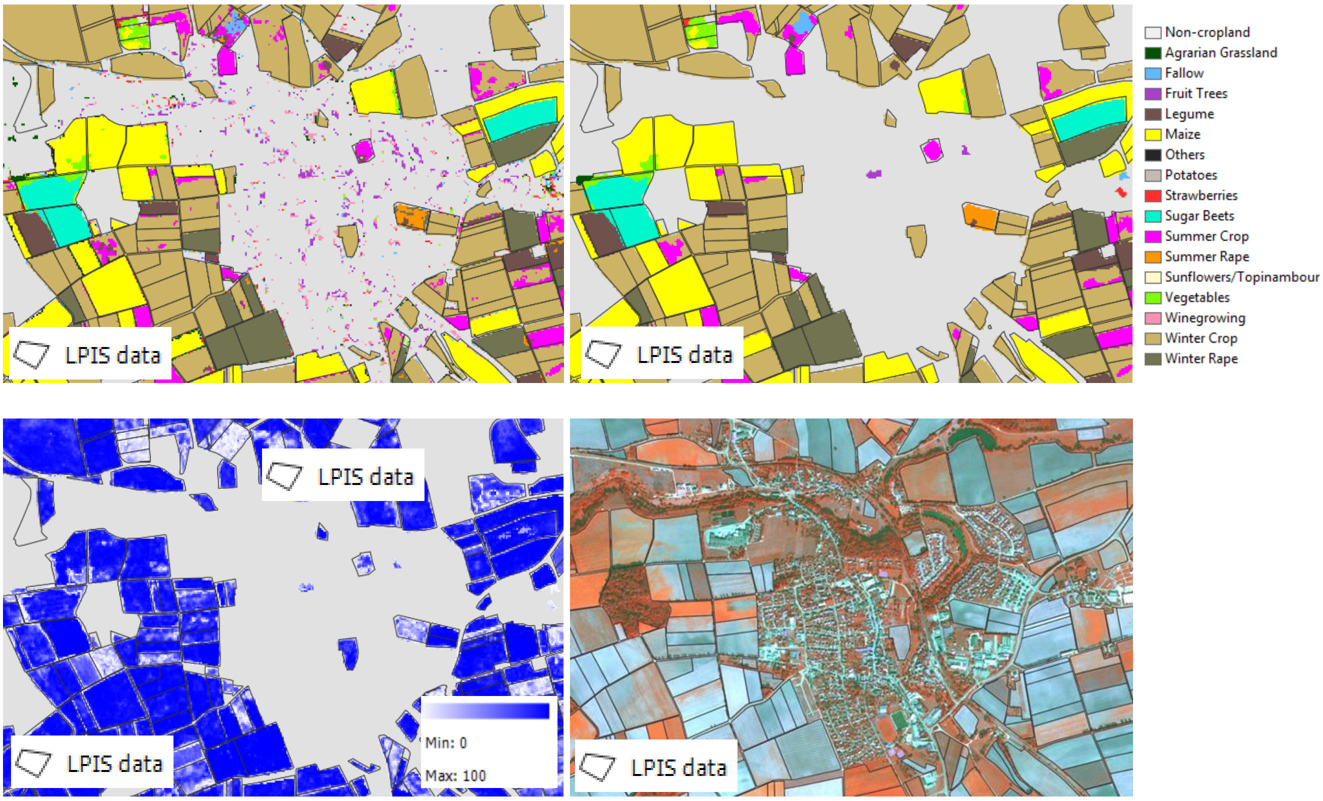


Figure 5-18: Results of the crop type classification on a pixel base (upper left figure) and after filtering (upper right figure) in NW Baden-Wurttemberg (location B) with high breakties (central figure) and a corresponding Spot-6 image (lower figure).

In some other cases the classification didn't yield as good results as in the previous examples. As the following Figure 5-19 clearly shows, the model works better for larger crop fields. If the field parcels are very narrow confusions with other classes are more likely and therefore crop type classification errors. Lower breakties in terms of crop types in this area of narrower fields can be depicted from the lower part of Figure 5-19. In the eastern part of the image some omission errors of the crop mask are visible.

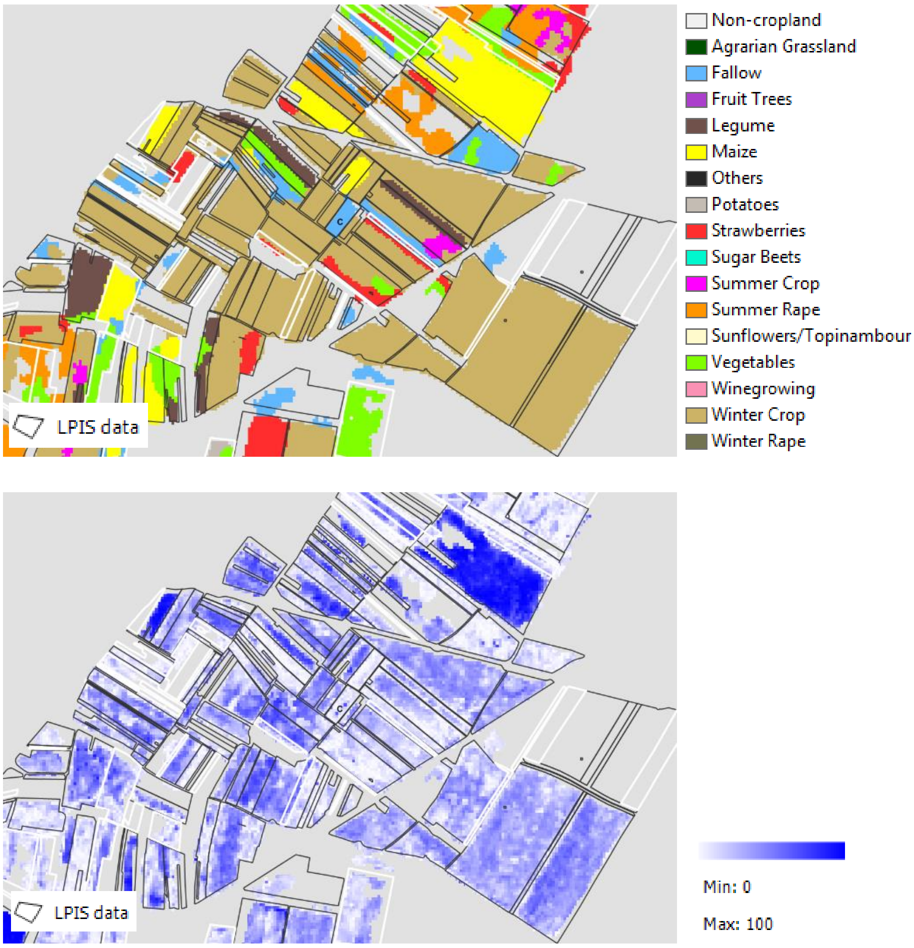


Figure 5-19: Results of the crop type classification (upper figure) in W Baden-Wurttemberg (location C) with low breakties (lower figure) and wrongly classified polygons (highlighted in white).

© MLR BW

The following figure shows the crop mask and the results of the crop type classification in combination with the HRL Grassland 2015 in southern Baden-Wurttemberg. A comparison of the crop type map with the HRL Grassland 2015 shows that the two datasets are complementary to a high degree, with a low degree of overlap. Some of the possible inaccuracies are due to the fact that all HRL 2015 products have a pixel size of 20m whereas the pixel size of the ECoLaSS prototypes is 10m.

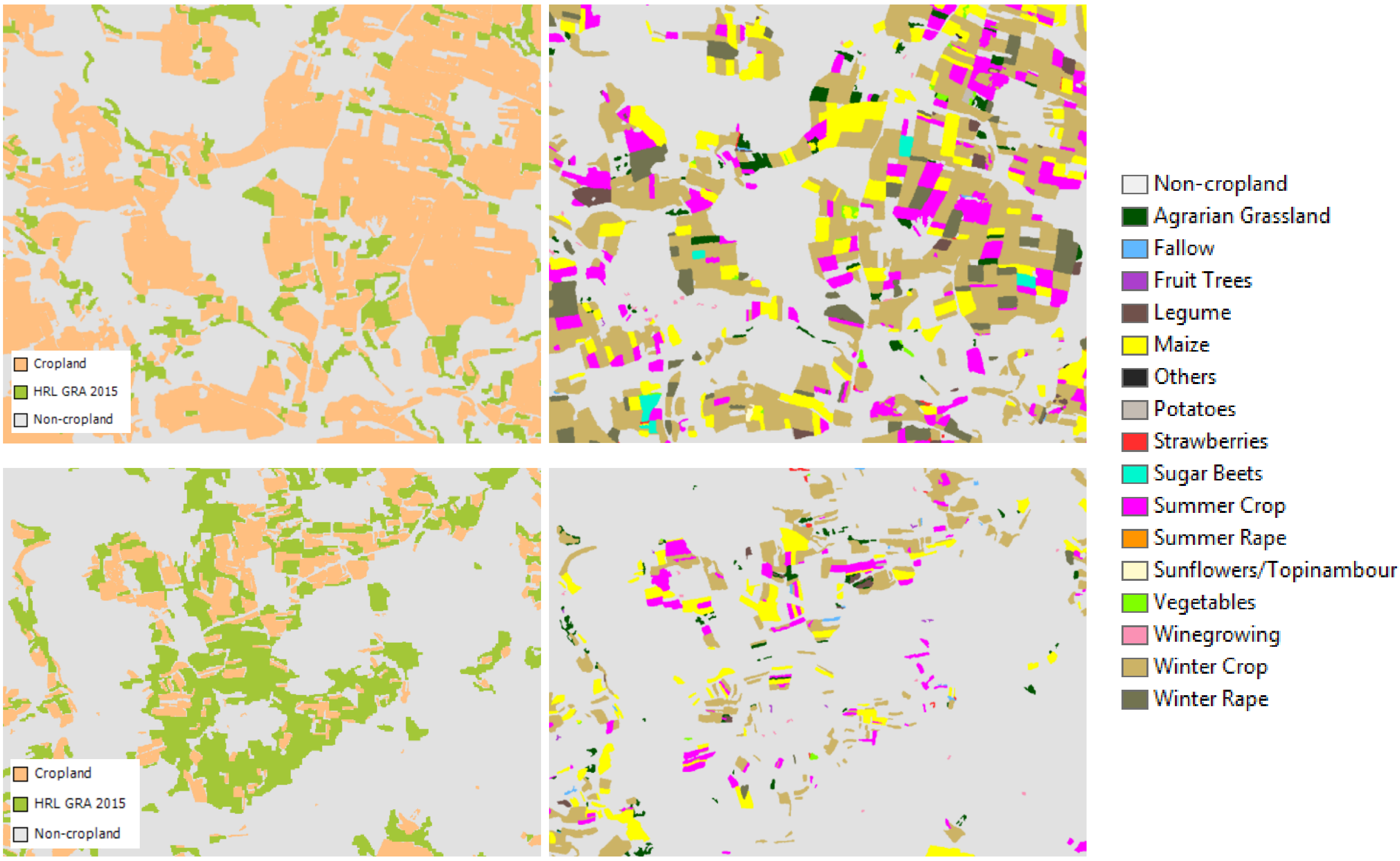


Figure 5-20: Results of the crop map classification in combination with the HRL Grassland 2015 in central (location D, upper Figures) and southern Baden-Wurttemberg (location I, below).

© European Union, Copernicus Land Monitoring Service 2015, European Environment Agency (EEA).

5.2.3 Crop type map of Demo-Site Mali

This chapter contains information about the cropland masks, the crop type map as well as the prototype specifications.

5.2.3.1 Cropland masks

Firstly, the overall accuracy of the cropland mask produced for the whole growing season has been estimated as high as 97% with a F1-Score of respectively 98% and 89% for non cropland and cropland (Table 5-30). The Figure 5-22 presents the overview of the 10-m cropland mask obtained over the south of Mali at the end of the season (December 2017). This result largely outperforms the product obtained during the demonstration phase of the Sen2-Agri mainly because of the sampling strategy and the quality of the in situ data campaign. The first Sen2-Agri obtained in the ESA project was based on the field survey completed regularly by officers for the agriculture statistics.

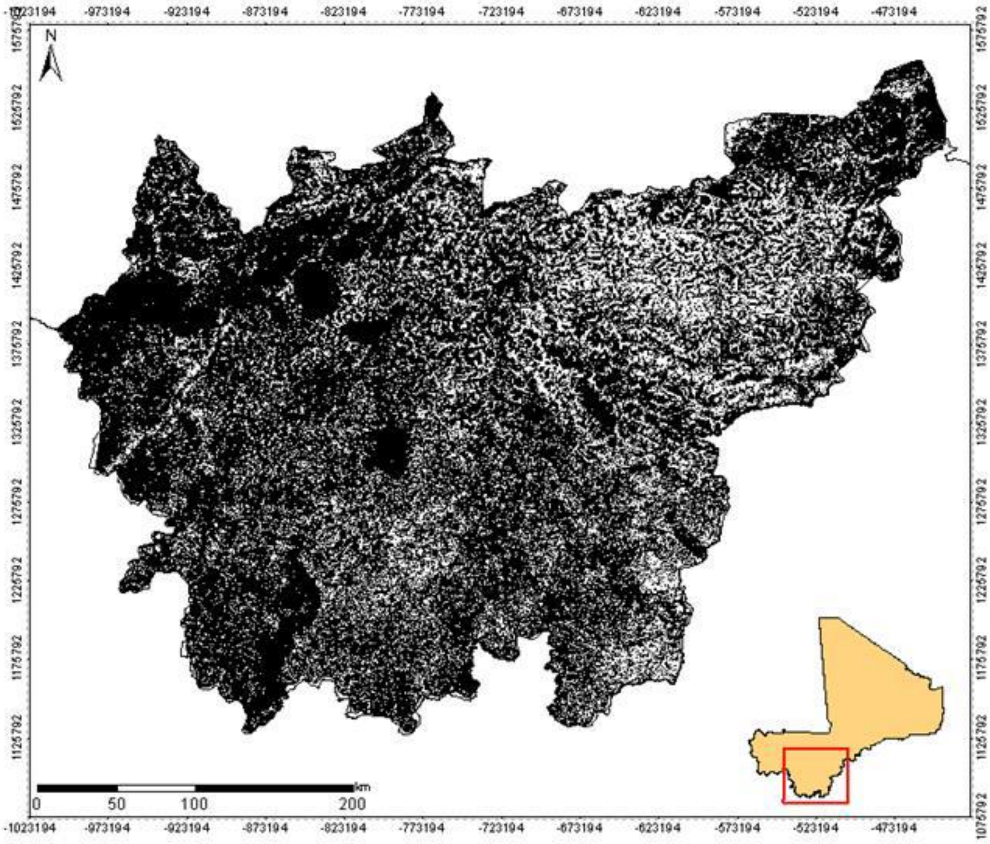


Figure 5-21: **10-meter cropland mask over south of Mali for 2017 growing season, obtained at the end of the season using S2 and L8 data. White and black represent cropland and non-cropland classes respectively.**

The evolution of the accuracy throughout the year is quite interesting. The figure highlights the fact that the cropland mask already nearly saturates from September and the addition of the December month reduces the quality of the product. This could be due to the fire season, the burned areas introducing some confusion in the cropland discrimination.

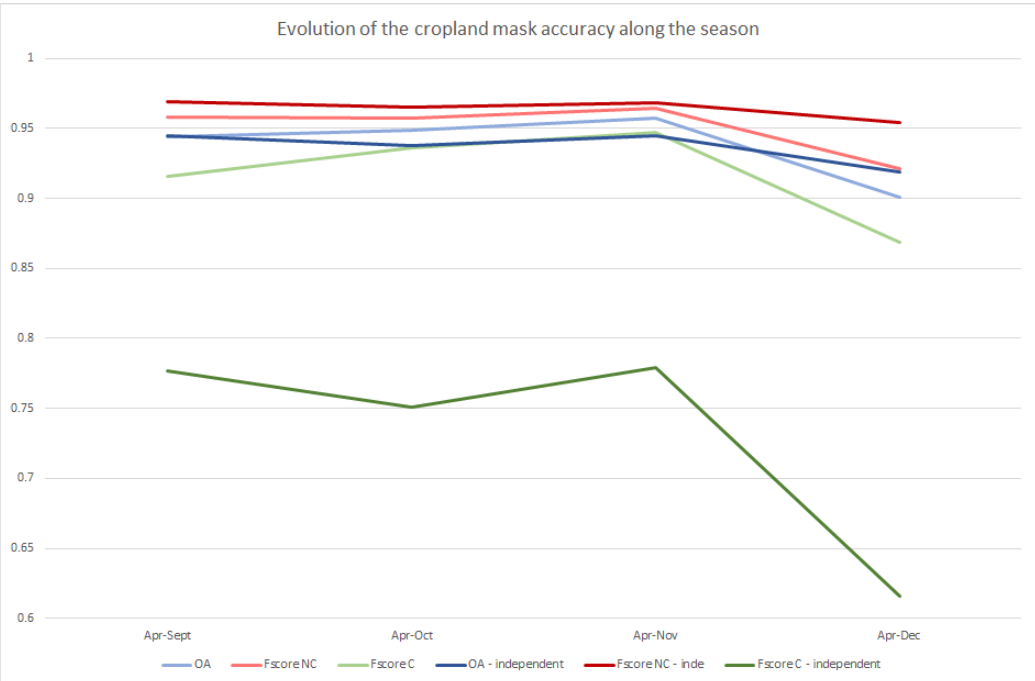


Figure 5-22: **Evolution of the accuracy metrics of the different cropland mask produced along the season over south of Mali for 2017. Four periods were considered to respectively include all the S2 observations acquired first from April to September, then from April to October, April to November and, finally from April to December 2017.**

The table 5-30 reports the impact of the stratification level on the quality of the cropland mask. The OA, kappa and F-score are computed for each strata. The F1-score for the cropland is below 0.9 without stratification while four strata maintained the F1-score higher than 0.94 for each stratum. Some strata even showed F1-score for cropland as high as for non cropland. It is worth mentioning that the OA is not really reflecting the accuracy for binary maps.

However, the classification performed with Vintrou strata outperformed the classification with no strata according to Table 5-30. A visual analysis balanced this conclusion as the figure 5-23 shows a larger under-estimation with Vintrou stratification. This was observed only on 3 small areas where very high resolution images were acquired at the end of the 2017 season.

Table 5-30: F1-Score, Kappa and OA achieved by the end of the season cropland mask generated using S2 and L8 time series over south of Mali

	Overall accuracy (%)	Kappa (%)	F1-Score	
			Non cropland	Cropland
CM no strata	97	88	0.98	0.9
CM 2 (PIRT) Strata 0	95	75	0.97	0.78
CM 2 (PIRT) Strata 2	94	72	0.97	0.76
CM 4 strata (Vintrou)	96.7	92.9	0.973	0.956
Strata 1	96.5	91.1	0.975	0.944
Strata 2	99.1	97.0	0.995	0.975
Strata 3	95.6	91.0	0.959	0.951
Strata 4	96.8	93.7	0.969	0.967

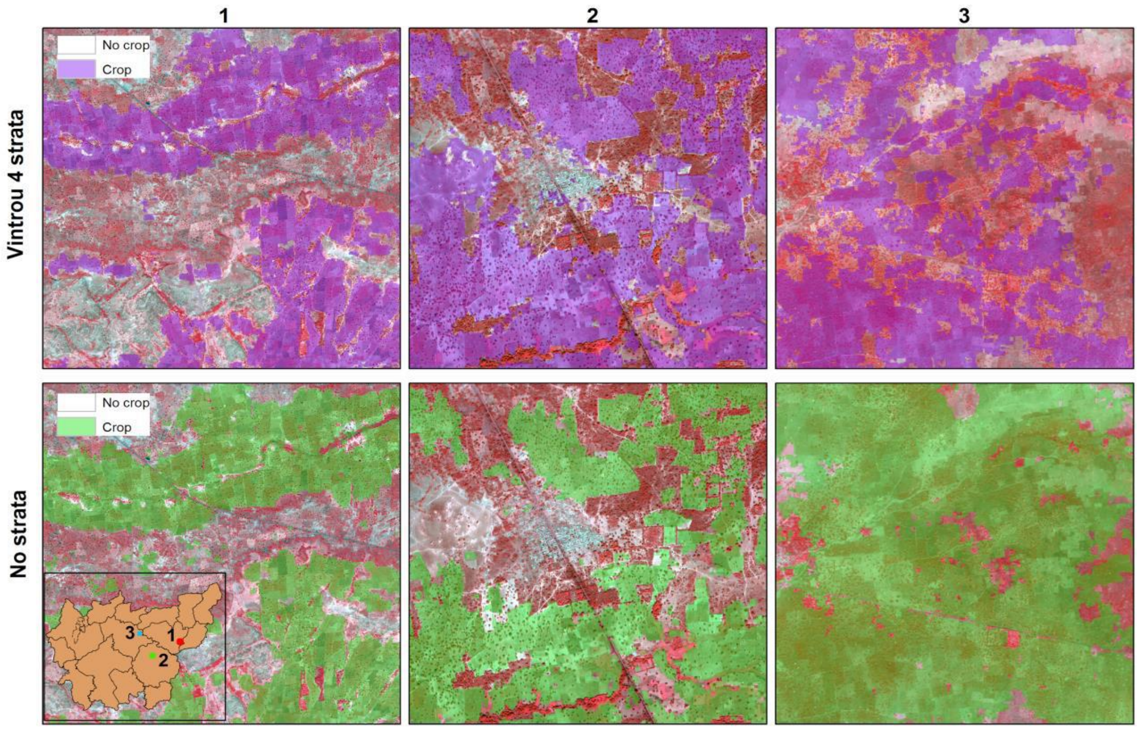


Figure 5-23: Overlay of the cropland mask on the 2017 very high resolution color composite. The upper subsets corresponds to the results with the 4 strata and the lower ones to the those without strata. over 3 small regions.

Last but not least, the validation dataset fully independent to the training set (no spatial autocorrelation) reports a significant reduction of the F1-score for the cropland, unlike the F1-score for the non cropland which increases.

5.2.3.2 Crop type maps

The accuracy of the crop type maps produced using the two strata is presented in the Figure 5-26. The crop type map reaches an OA of 63% in the northern strata (Figure 5-26 (a)) and 54.6% OA in the southern strata (Figure 5-26 (b)). In the northern strata, cotton crop yields to higher accuracy with a F1-score of 80% and is followed by millet (71%), sorghum (64%), maize (62%), rice (59%), other crops (43%) and groundnut (22%). In the southern strata, rice presents the higher F1-score of 89% and is followed by maize, cotton, sorghum, groundnut, other crops and millet with a F1-score of respectively 69%, 59%, 56%, 41%, 30%.

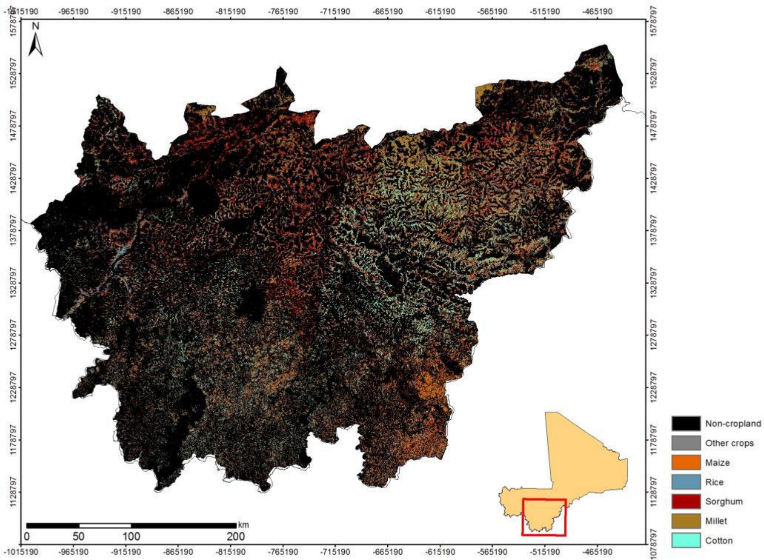
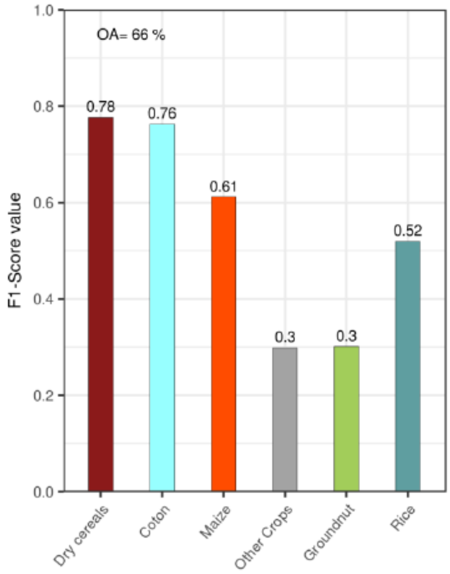


Figure 5-24: 10-meter cultivated croptype map over south of Mali for 2017 growing season, obtained at the end of the season using S2 and L8 data.



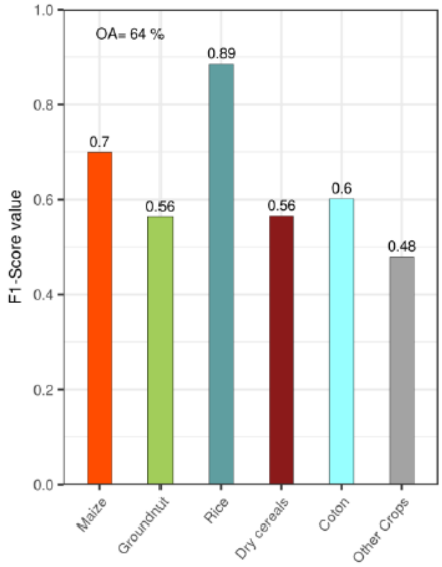


Figure 5-25: Crop map accuracy for the main crop types over the demo-site Mali (a) Koutiala strata (on the left) (b) Haut-Bani-Niger strata (on the right). Sorghum and Millet are merged into the Dry Cereals class.

A major confusion is observed between millet and sorghum which looks rather similar for a long period of the growing season and both common in the region. Combining the two crops into a dry cereals crops provided a better overall accuracy and higher F1-score. While the OA remains too low to derive useable crop area estimate, some crops are already well detected and maps of the rice, cotton and dry cereals seems becoming relevant from users perspective.

In spite of the accuracy metrics which must be improved, the spatial pattern of the crop type map resulting from a pixel-based classification is very promising as it seems to depict precisely the different fields in the complex smallholder cropping system. This is obviously a potential major Sentinel-2 contribution but still to be confirmed.

It is also of paramount importance to mention that these results are hardly included the contribution of Sentinel-2b satellite which should largely enhance the quantity of the satellite observation.

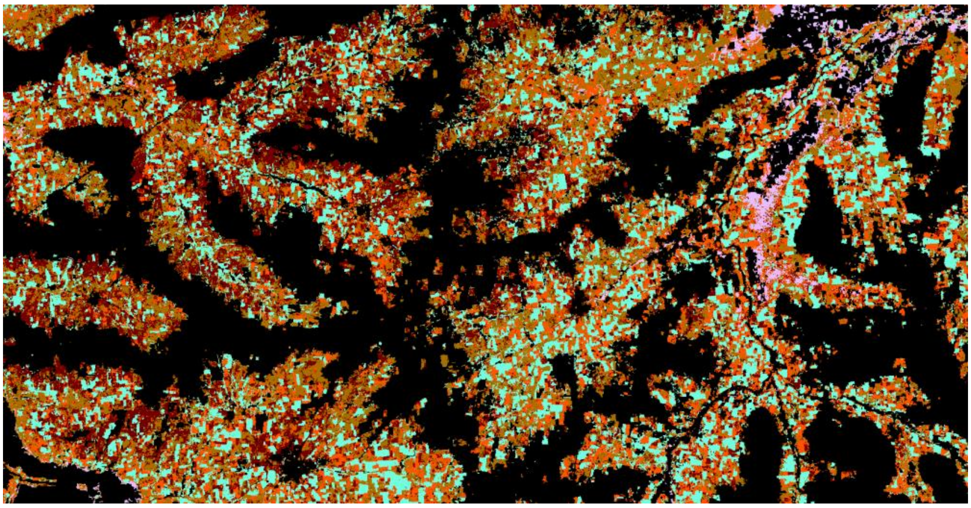


Figure 5-26: Close-up of the 2017 crop map for the main crop types including the cropland mask the over the demo-site Mali - region of Koutiala.

5.3 Prototype Specifications

This section provides a description of the dataset properties and metadata for the implemented prototypes, also referring to "*P44.2a - Data Sets of Crop Area and Crop Status/Parameters Products*".

Within ECoLaSS, a standardised and harmonised product file naming convention for all prototypes has been developed which is oriented along the already existing naming convention of the CLMS High Resolution Layers. The naming convention consists of the following 7 descriptors:

THEME YEAR RESOLUTION EXTENT EPSG TYPE VERSION
as follows:

THEME

3 letter abbreviation for main products (DLT (dominant leaf type), TCC (tree cover change), GRA (grassland), IMD (imperviousness degree), IMC (imperviousness change classified), CRT (crop type), CRM (crop mask) and NLC (new land cover products).

REFERENCE YEAR

2017 in four digits; change products in four digits (e.g. 1517)

RESOLUTION

Four-digit (020m and 010m)

EXTENT

2-digit code for demonstration-sites (CE (central), NO (north), WE (west), SW (southwest), SE (southeast), SA (South Africa), ML (Mali))

EPSG

5-digit EPSG code (geodetic parameter dataset code by the European Petroleum Survey Group) "03035" for the European LAEA projection

TYPE

prototype

VERSION

3-digit code "v01"

EXAMPLE:

"CRM_2017_010m_CE_03035_prototype_v01.tif" stands for: Crop Mask, 2017 reference year, 10m, Demonstration-site Central, European projection (EPSG: 3035), prototype, version 01

"CRT_2017_010m_CE_03035_prototype_v01.tif" stands for: Crop Type, 2017 reference year, 10m, Demonstration-site Central, European projection (EPSG: 3035), prototype, version 01

The raster products of the ECoLaSS prototypes are delivered as GeoTIFF (*.tif) with world file (*.tfw), pyramids (*.ovr), attribute table (*.dbf) and statistics (*.aux.xml), enabling an instant illustration and analysis of the products within Geographic Information System (GIS) software. Each product is accompanied with a product-specific colour table (*.clr) and INSPIRE-compliant metadata in XML format.

Metadata are provided together with the products as INSPIRE-compliant XML files according to the EEA Metadata Standard for Geographic Information (EEA-MSGI). EEA-MSGI has been developed by EEA to meet needs and demands for inter-operability of metadata. EEA's standard for metadata is a profile of the ISO

19115 standard for geographic metadata and contains more elements than the minimum required to comply with the INSPIRE metadata rules. Detailed conceptual specifications of the EEA-MSGI and other relevant information on metadata can be found at http://www.eionet.europa.eu/gis.

The following six prototypes files as part of ***D14.3 - P44.2a – Data Sets of Crop Area and Crop Status/Parameters Products (Issue 1)*** were submitted:

The specifications of the product created by the SIRS group for the West demonstration site (French part) for the year 2016 are listed in table 5-31 and the associated color palettes can be found in table 5-32 and 5-33.

- **CRM_2016_010m_WE_03035_prototype_v01.tif**
- **CRT_2016_010m_WE_03035_prototype_v01.tif**

Furthermore, one product was produced by the UCL group over the West demonstration site (Belgium part) for 2017. This product is conformed to the specifications detailed in Table 5-34 with associated colour palette listed in table 5-35.

- **CRT_2017_010m_WE_03035_prototype_v01.tif**

Product specifications for classification on MALI site are listed in table 5-36 with associated colour palettes of table 5-37.

- **CRT_2017_010m_ML_32630_prototype_v01.tif**

Detailed specifications for primary 10m CRM and CRT status layers of the demonstration site Central (produced by GAF group) are listed in table 5-38 and 5-39.

- **CRM_2017_010m_CE_03035_prototype_v01.tif**
- **CRT_2017_010m_CE_03035_prototype_v01.tif**

Table 5-31: Product specifications for CRT_2016_010m_WE_03035_prototype_v01.tif and for CRM_2016_010m_WE_03035_prototype_v01.tif

<table>
<tr><td colspan="2">Products</td></tr>
<tr><td>Cropland types 2016 – CRT_2016_10m</td><td>Cropland mask 2016 – CRT_2016_10m</td></tr>
<tr><td colspan="2">Extent
Demo site West</td></tr>
<tr><td colspan="2">Geometric resolution
Pixel resolution 10m, grid to fully conform to the EEA Reference Grid.</td></tr>
<tr><td colspan="2">Coordinate Reference System
European ETRS89 LAEA projection</td></tr>
<tr><td colspan="2">Geometric accuracy (positioning scale)
Less than one pixel, according to the quality report on S-2 products</td></tr>
<tr><td colspan="2">Thematic accuracy
77% of overall accuracy</td></tr>
<tr><td colspan="2">Data type
8bit unsigned Raster, compressed with LZW</td></tr>
<tr><td colspan="2">Minimum mapping unit (MMU)
One pixel (10m)</td></tr>
<tr><td colspan="2">Necessary attributes
Raster value, count, class name,</td></tr>
<tr><td colspan="2">Raster coding (Thematic pixel values)</td></tr>
<tr><td>Cropland types 2016 – CRT_2016_10m

0: Other Land cover (settlements, forest, grassland and water)
11: Winter Wheat
31: Winter Barley
40: Spring Cereals
61: Peas
71: Winter Rape
81: Maize
91: Agrarian grassland
101: Beets
131: Potatoes
141: Fallow
151: Linen
161: Chicory
254: unclassifiable (no satellite image available, or clouds, shadows, or snow)
255: outside Area</td><td>Cropland mask 2016 – CRM_2016_10m

0: Non-cropland
1: Cropland mask
254: unclassifiable (no satellite image available, or clouds, shadows, or snow)
255: outside Area</td></tr>
<tr><td colspan="2">Metadata
XML metadata files are to be produced according to INSPIRE metadata standards</td></tr>
<tr><td colspan="2">Delivery format
GeoTIFF</td></tr>
</table>

Table 5-32: Color palette for CRT_2016_010m_WE_03035_prototype_v01.tif

Cropland type 2016 – CRM_2016_10m					
Class Code	**Class Name**	**Red**	**Green**	**Blue**	
0	Other Land Cover	240	240	240	
11	Winter Wheat	195	160	215	
31	Winter Barley	115	70	165	
40	Spring Cereals	255	125	125	
61	Peas	0	170	135	
71	Winter Rape	255	255	0	
81	Maize	255	175	0	
91	Agrarian Grassland	150	230	0	
101	Beets	115	0	75	
131	Potatoes	255	215	100	
141	Fallow	75	115	0	
151	Linen	115	75	0	
161	Chicory	205	105	155	
254	unclassifiable (no satellite image available, or clouds, shadows, or snow)	153	153	153	
255	outside Area	0	0	0	

Table 5-33: Color palette for CRM_2016_010m_WE_03035_prototype_v01.tif

Cropland mask 2016 – CRM_2016_10m					
Class Code	**Class Name**	**Red**	**Green**	**Blue**	
0	Non- Cropland	240	240	240	
1	Cropland Mask	245	225	45	
254	unclassifiable (no satellite image available, or clouds, shadows, or snow)	153	153	153	
255	outside Area	0	0	0	

Table 5-34: Product specifications for CRT_2017_010m_WE_03035_prototype_v01.tif

Products	
Cropland types 2017 : CRT_2017_010m_WE_03035_prototype_v01.tif	
Extent Demo site West	
Geometric resolution Pixel resolution 10m, grid to fully conform to the EEA Reference Grid.	
Coordinate Reference System European ETRS89 LAEA projection	
Geometric accuracy (positioning scale) Less than one pixel, according to the quality report on S-2 products	
Thematic accuracy More than 90% of Overall Accuracy	
Data type 8bit unsigned Raster, compressed with LZW	
Minimum mapping unit (MMU) One pixel (10m)	
Necessary attributes Raster value, count, class name,	
Raster coding (Thematic pixel values)	
Cropland types 2017 – CRT_2017_10m 0: Other Land cover 1: Grassland 2: Winter Wheat 3: Maize 4: Winter Barley 5: Sugar Beet 6: Spelt 7: Rapeseed 8: Potato 9: Flax 10: Summer Oat 11: Other Vegetables 12: Other Fodder	13: Peas 14: Summer Barley 15: Summer Cereals 16: Chicory 17: Winter Cereals 18: Summer Wheat 19: Hemp 20: Green Beans 21: Onions 22: Fruit Crops 23: Other Crops 24: Grape Vines
Metadata XML metadata files are to be produced according to INSPIRE metadata standards	
Delivery format GeoTIFF	

The color palette from the 3 products is identical and represented in Table 5-18.

Table 5-35: Color palette for CRT_2017_010m_WE_03035_prototype_v01.tif

Cropland type 2016 – CRM_2016_10m					
Class Code	**Class Name**	**Red**	**Green**	**Blue**	
0	Other Land Cover	240	240	240	
1	Grassland	150	230	0	
2	Winter Wheat	195	160	215	
3	Maize	255	175	0	
4	Winter Barley	115	70	165	
5	Sugar Beet	115	0	75	
6	Spelt	91	91	180	
7	Rapeseed	255	255	0	
8	Potato	255	215	100	
9	Flax	115	75	0	
10	Summer Oat	255	203	203	
11	Other Vegetables	104	147	21	
12	Other Fodder	192	29	136	
13	Peas	0	170	135	
14	Summer Barley	164	39	39	
15	Summer Cereals	255	125	125	
16	Chicory	205	105	155	
17	Winter Cereals	245	227	255	
18	Summer Wheat	220	79	79	
19	Hemp	210	135	35	
20	Green Beans	0	103	83	
21	Onions	193	150	27	
22	Fruit Crops	108	162	194	
23	Other Crops	52	80	0	

24	Grape Vines	23	86	123	

Table 5-36: Product specifications for CRT_2017_010m_ML_32630_prototype_v01.tif

Products
Cropland types 2017 – CRT_2017_10m CRT_2017_010m_ML_32630_prototype_v01.tif
Extent Demo site MALI
Geometric resolution Pixel resolution 10m, grid to fully conform to the EEA Reference Grid.
Coordinate Reference System WGS84 – UTM zone 30 South
Geometric accuracy (positioning scale) Less than one pixel, according to the quality report on S-2 products
Thematic accuracy >90% of overall accuracy
Data type 8bit unsigned Raster, compressed with LZW
Minimum mapping unit (MMU) One pixel (10m)
Necessary attributes Raster value, class name
Raster coding (Thematic pixel values)
0: Non-Cropland 1: Millet 2: Sorghum 3: Cotton 4: Maize 5: Other Crops 6: Groundnuts 7: Rice
Metadata XML metadata files are to be produced according to INSPIRE metadata standards
Delivery format GeoTIFF

Table 5-37: Color palette for CRT_2017_010m_ML_32630_prototype_v01.tif

Cropland type 2016 – CRM_2016_10m					
Class Code	**Class Name**	**Red**	**Green**	**Blue**	
0	Non-Cropland	0	0	0	
1	Millet	164	89	20	
2	Sorghum	139	26	26	
3	Cotton	151	255	255	
4	Maize	255	76	0	
5	Other Crops	163	163	163	
6	Groundnuts	162	205	90	
7	Rice	95	158	160	

Table 5-38: Product Specifications an color palette for CRT_2017_010m_CE_03035_prototype_v01.tif

Crop Type 10m	**Acronym** CRT	**Product category** Primary Status Layer
Reference year 2017		
Extent Demonstration site Central		
Geometric resolution Pixel resolution 10m x 10m, fully conform to the EEA reference grid.		
Coordinate Reference System European ETRS89 LAEA projection		
Geometric accuracy (positioning scale) Less than one pixel. According to ortho-rectified satellite image base delivered by ESA.		
Thematic accuracy 85%		
Data type 8bit unsigned Raster, with LZW compression		
Minimum mapping unit (MMU) Pixel-based (no MMU)		
Necessary attributes Raster value, count, class name, area (in km2), area percentage (taking outside area not into account)		
Raster coding (Thematic pixel values) 0: Non-cropland		

1: Agrarian Grassland

3: Fallow

5: Fruit Trees

8: Legume

9: Maize

10: Others

11: Potatoes

13: Strawberries

14: Sugar Beets

15: Summer Crop

16: Summer Rape

17: Sunflowers/Topinambour

18: Vegetables

19: Winegrowing

20: Winter Crop

21: Winter Rape

255: Outside area

Metadata
XML metadata files are to be produced according to INSPIRE metadata standards

Delivery format
GeoTIFF

Colour Table
ArcGIS *.clr format

Class Code	Class Name	Red	Green	Blue	
0	Non-cropland	240	240	240	
1	Agrarian Grassland	0	82	0	
3	Fallow	97	184	255	
5	Fruit Trees	171	63	204	
8	Legume	112	81	75	
9	Maize	255	255	0	
10	Others	38	38	38	
11	Potatoes	196	188	179	
13	Strawberries	255	46	46	
14	Sugar Beets	0	247	206	
15	Summer Crop	255	0	255	
16	Summer Rape	255	149	0	
17	Sunflowers/Topinambour	255	250	204	

18	Vegetables	128	255	0	
19	Winegrowing	250	145	180	
20	Winter Crop	204	179	102	
21	Winter Rape	114	115	80	
255	Outside Area	0	0	0	

Table 5-39: Product Specifications and color palette for CRM_2017_010m_CE_03035_prototype_v01.tif

Crop Mask 10m	**Acronym** CRM	**Product category** Primary Status Layer
Reference year 2017		
Reference year 2017		
Extent Demonstration site Central		
Geometric resolution Pixel resolution 10m x 10m, fully conform to the EEA reference grid.		
Coordinate Reference System European ETRS89 LAEA projection		
Geometric accuracy (positioning scale) Less than one pixel. According to ortho-rectified satellite image base delivered by ESA.		
Thematic accuracy 90%		
Data type 8bit unsigned Raster, with LZW compression		
Minimum mapping unit (MMU) Pixel-based (no MMU)		
Necessary attributes Raster value, count, class name, area (in km2), area percentage (taking outside area not into account)		
Raster coding (Thematic pixel values) 0: Non-cropland 1: Cropland 255: Outside area		
Metadata XML metadata files are to be produced according to INSPIRE metadata standards		
Delivery format GeoTIFF		
Colour Table ArcGIS *.clr format		

Class Code	Class Name	Red	Green	Blue	
0	Non-cropland	240	240	240	
1	Cropland	0	82	0	
255	Outside Area	0	0	0	

6 Conclusion and Outlook

As reported in the Deliverable D3.1: "D21.1a – Service Evolution Requirements Report" of the WP 21: "WP 21 – Assessment of Service Evolution Requirements", the agriculture is one of the two thematic gaps in the current Copernicus Land Service portfolio. As clearly expressed in this report, the most frequently voiced new service was a pan-European Agricultural Service. As expected, this service are potentially interlinked with the phenology service as a key target is to capture the phenology of the different crop type also mapped by Sentinel data. While a preliminary document has been prepared by JRC and circulated to various partners, the "Concept note for a Copernicus Agricultural Service" also prepared by JRC is under examination by the Copernicus office and not available yet for the ECoLaSS partners. Therefore the targeted prototype at this stage is the crop type mapping based on S1 and S2 time series.

The Crop Mask (CRM) and the Crop Type Map (CRT) prototypes have been extensively tested in this WP 44 for three different Demonstration site (West, Central and Mali) to encompass a large diversity of agrosystems and Earth Observation conditions (cloudiness in particular). The harmonization of the protocols across the Demonstration sites concerned mainly the type of features, the Random Forest classifier and the accuracy assessment report. In addition for the European sites, the calibration and validation datasets were derived from the respective LPIS layers. At the opposite, the study in the Mali site relied on a comprehensive dataset collected on the field by Malian partner and quality controlled by UCL.

The Crop Mask (CRM) products obtained for the three Demonstration sites provided very satisfactory results with an overall accuracy far beyond 90 % (98 % for site West (France) from S-2 only, 97% (F1-Score 0.97) for site Central from S-1 and S-2, 97% (F1-Score 0.89) for site Mali from S-2). These high accuracy including in the Malian smallholder cropping systems demonstrated the maturity level of this prototype. Nevertheless, few elements should be further investigated: the optimization of the number of features (for the site Central 28 features out of the 1246 computed were found efficient), the stratification to deal with uneven spatial distribution of the calibration data, and some specific confusion like the grassland in Germany and the bottoms of valley in Mali.

The Crop Type Map (CRT) products obtained for three Demonstration sites provided promising results with the overall accuracy ranging from 64 % in Mali (20 tiles - 6 classes) and 77 % (4 tiles together - 13 classes) in France both using only S-2 to 89 % in Central (9 tiles together – 16 classes) to 92 % in Belgium (for the best tile – 24 classes) both combining S-2 and S-1-derived features. These results could be further improved by masking using the CRM the CRT products. The F1-score values for the different crops show a very large range with some crops with F1-score beyond 0.8 (dominant crops in the agricultural landscape) but most of them below 0.8 down to 0.3 for marginal classes. Furthermore the performance metrics for the different sites are apparently also driven by the fraction of validation corresponding to the (agrarian) grassland class. In France, the poor discrimination of this class reduces the metric value while the large fraction of grassland in the validation dataset for Belgium improves the metric value.

The development of these two essential CRM and CRT prototypes will further continue over the three Demonstration sites (West, Central and Mali) and further extend to the Demonstration site South Africa. First the focus will concern the improvement of cropland – grassland discrimination and then the year-to-year variation of the CRM prototype products will be assessed for several sites. For the CRT prototype products, the crop type discrimination (F1_score) will be further improved thanks to (i) an advanced exploitation of the S-1 time series (possibly using an object-based approach), (ii) a tuning of the crop type distribution in the calibration dataset, the use of stratification to improve the tile mosaicking process, and (iii) a complementarity of the CRT product with the CRM product or the GRA HRL in the European sites.

References

Chen, J., Chen, J., Liao, A., Cao, X., Chen, L., Chen, X., He, C., Han, G., Peng, S., Lu, M., et al.. 2015. Global land cover mapping at 30 m resolution: A POK-based operational approach. ISPRS Journal of Photogrammetry and Remote Sensing, 103(0):7 – 27. Global Land Cover Mapping and Monitoring.

Defourny P., Bontemps S., Bellemans N., et al. (2018) Sentinel-2 near real-time agriculture monitoring at parcel level thanks to the Sen2-Agri automated system: methods and demonstration from local to national scale for cropping systems around the world. Remote Sensing of Environment (under revision).

Hagolle, O., Dedieu, G., Mougenot, B., Debaecker, V., Duchemin, B., & Meygret, A. (2008). Correction of aerosol effects on multi-temporal images acquired with constant viewing angles: Application to Formosat-2 images. Remote Sensing of Environment, 112(4), 1689-1701.

Inglada, J., Arias, M., Tardy, B., Hagolle, O., Valero, S., Morin, D., Dedieu, G., Sepulcre, G., Bontemps, S., Defourny, P., et al.. 2015. Assessment of an operational system for crop type map production using high temporal and spatial resolution satellite optical imagery. Remote Sensing, 7(9):12356–12379.

Valero, S., Morin, D., Inglada, J., Sepulcre, G., Arias, M., Hagolle, O. & Koetz, B. (2016). Production of a dynamic cropland mask by processing remote sensing image series at high temporal and spatial resolutions. Remote Sensing, 8(1), 55.