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Document sheet

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Document Status

Issue/Rev.	Date	Reason
0.1	20/02/2023	Initial version of the deliverable
1.0	28/02/2023	First version submitted to ESA - Demo products cycle 1
2.0	10/04/2024	Second version submitted to ESA - Demo products cycle 2 added
2.1	25/03/2025	Update of the second version based on ESA RIDs

Detailed record sheet

From version 2.0 to 2.1

Comment	Section	Problem description	Change
ESA RID	2.1.2	Blurry text in figure	Figure 2-8: better quality for the crop class legend
ESA RID	2.1.2	Blurry text in figure	Figures 2-10 to 2-13: better quality of the graphics captions
ESA RID	2.4	Blurry text in figure	Figures 2-20 to 2-22: better quality of the graphics captions
ESA RID	3.1.1.1	Blurry text in figure	Figures 3-1, 3-5, 3-6, 3-10, 3-14, 3-15: better quality of the graphics captions
ESA RID	3.1.1.2	Blurry text in figure	Figures 3-18, 3-23, 3-24: better quality of the graphics captions

ESA RID	3.1.2.1	Blurry text in figure	Figures 3-29, 3-31, 3-33, 3-35: better quality of the graphics
ESA RID	3.2.1.1	Blurry text in figure	Figure 3-42: French present in the figure has been removed
ESA RID	3.2.1.2	Blurry text in figure	Figure 3-43, 3-47: French present in figures has been removed
ESA RID	3.2.1.3	Blurry text in figure	Figure 3-48, 3-49: better quality of the graphics
ESA RID	3.2.1.3	Blurry text in figure	Figure 3-50: French present in the figure has been removed
ESA RID	3.2.2.1	Blurry text in figure	Figure 3-51
/	From 3.2.2	Document structure	Numbering of figures
ESA RID	All	Typos	Review of the document

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1 Introduction

1.1 Purpose and scope

This document is the 1st version of the Validation Report (VR) of the Sentinels for Agricultural Statistics (Sen4Stat) project funded by the European Space Agency (ESA).

The overall objective for the Sen4Stat project is to facilitate the uptake of Earth Observation (EO) information in the National Statistical Offices (NSO) supporting the agricultural statistics. Special attention shall be given to develop and demonstrate EO products and best practices for agriculture monitoring relevant for Sustainable Development Goals (SDG) reporting and monitoring their progress at national scale

The VR-v2 is one of the key outputs of the Task 5 (WP 5000) of the Sen4Stat project, named “Full-scale demonstration” (Figure 1-1). It presents and documents the accuracy of the EO products of the two cycles of the demonstration phase, and it shows their impacts on the statistical use cases when relevant.

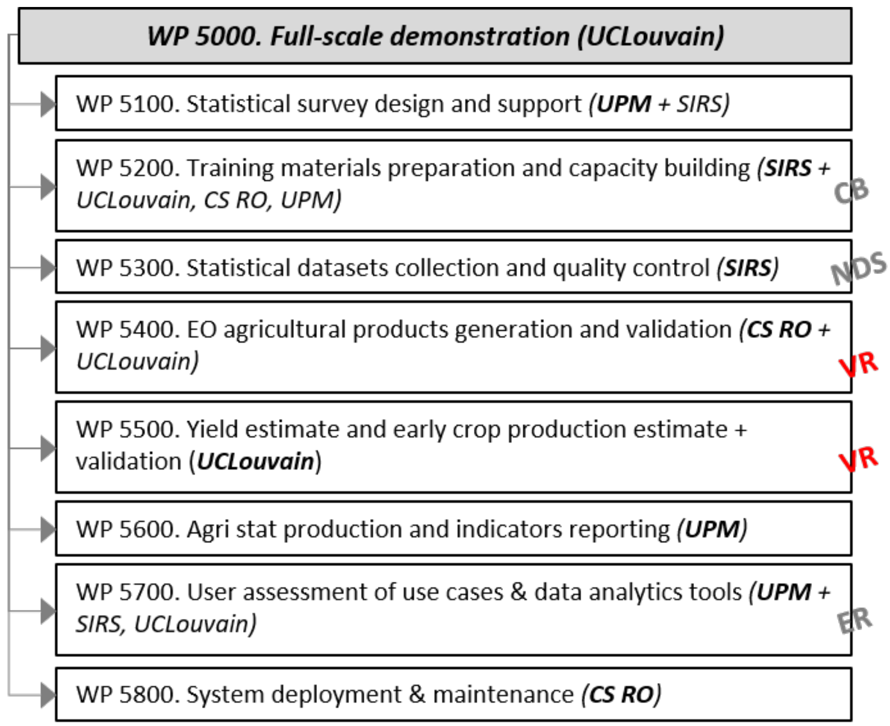


Figure 1-1. Organization of the Task 5 activities (from [AD.2])

1.2 Structure of the document

After this introduction, this document contains 3 sections:

- A section **2** dedicated to the description of the demonstration sites and available in situ datasets;
- A section **3** presenting the validation of the EO products for each site;
- An section **4** showing how the generated EO products can support the agricultural statistics through dedicated use cases.

1.3 References

1.3.1 Applicable documents

ID	Title	Reference	Issue/Rev.	Date
AD.1	Statement of Work for ESA Sentinels for Agricultural Statistics	EOEP-EOPS-SW-17-015	1.0	15/03/2017
AD.2	Sen4Stat Implementation Proposal - Chapter 5		1.0	12/05/2017

Table 1-1. Applicable documents

1.3.2 Reference documents

ID	Title
RD.1	Copernicus4GEOGLAM D2.1 Field Campaign for Tanzania – Successful completion statement, Issue 1.0 - 11/06/2021
RD.2	Copernicus4GEOGLAM D2.4 Field Campaign for Tanzania – Methodology applied, Issue 1.0 - 11/06/2021

Table 1-2. Reference documents

1.3.3 Acronyms and abbreviations

Acronym	Definition
AAS	Annual Agricultural Survey
AD	Applicable Document
DAPSA	Direction de l'Analyse, de la Prévision et des Statistiques Agricoles
EO	Earth Observation
ESA	European Space Agency
ESU	Elementary Sampling Unit
FAO	Food and Agriculture Organization
GPS	Global Positioning System

ha	hectares
ID	Identifier
LPIS	Land Parcel Identification System
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NSO	National Statistical Office
ODK	Open Data Kit Collect
RD	Reference Document
RF	Random Forest
S1, S2	Sentinel-1, Sentinel-2
SDG	Sustainable Development Goal
Sen4Stat	Sentinels for Agricultural Statistics
SMOTE	Synthetic Minority Oversampling Technique
VR	Validation Report

Table 1-3. List of acronyms and abbreviations

2 Demonstration sites and dataset

2.1 Spain

2.1.1 Cycle 1

The first cycle of the demonstration focuses on two provinces: Castilla y Leon and Andalusia (Figure 2-1). These two provinces have been selected by the NSO because they are both important from the economic point of view and they have very different agro-climatic conditions and agricultural practices: Castilla y Leon is one of the major winter cereals productor in Europe, is quite flat and has big fields while Andalusia is dominated by olive trees with an arid climate. The area of Castilla y Leon is of 94.226 km² and the area of Andalusia is of 87.599 km².

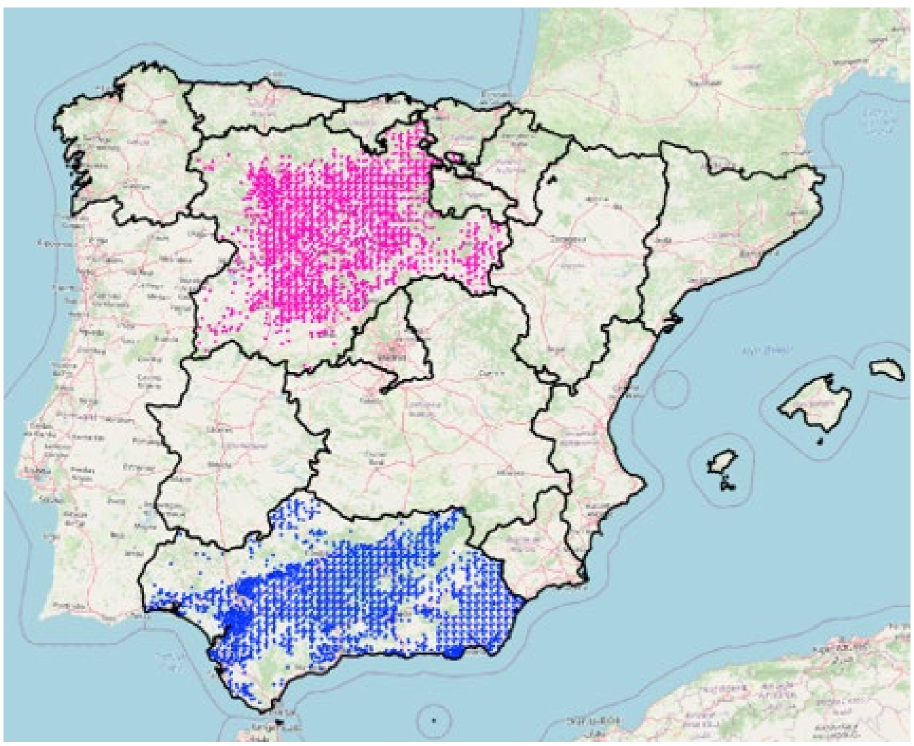


Figure 2-1. Area of Interest in Spain (cycle 1)

The NSO dataset is named ESYRCE. ESYRCE is an integrated list and area frame survey over all Spain, with a master frame that is the same since 2006-2007. Elementary Sampling Units (ESU) of the survey are generally of 49 hectares (700x700 m) and exceptionally of 25 ha (500x500 m). They have no link with the Land Parcel Identification System dataset used in the Common Agricultural Policy context.

Each ESU, also called segment, is composed of plots (or polygons) representing agricultural parcels (Figure 2-2). All crops present in the ESUs are identified and the yield is estimated over 1/3 of the ESU. GPS coordinates are recorded at parcel-level, including plot outlines.

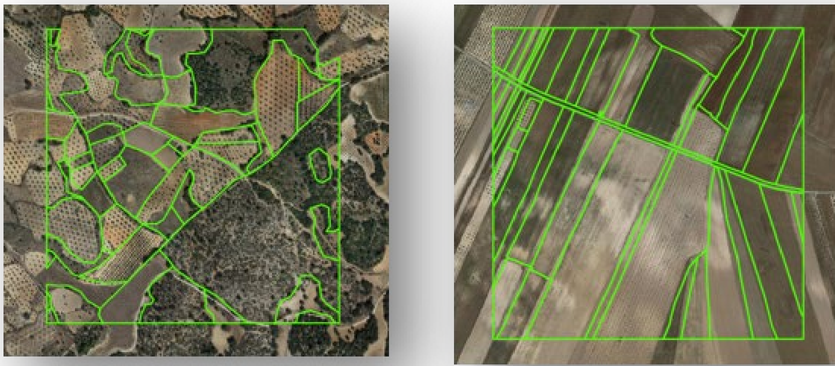


Figure 2-2. Example of ESYRCE segments in 2020

The distributions of crops in the ESYRCE samples for the regions of Castilla y Leon and Andalusia (expressed in terms of surface) are shown in Figure 2-3 and Figure 2-4, showing the specificities of each region. There are 60.666 polygons in Castilla y Leon, which are mainly annual crops while Andalusia counts 58.583 polygons which are mainly permanent crops.

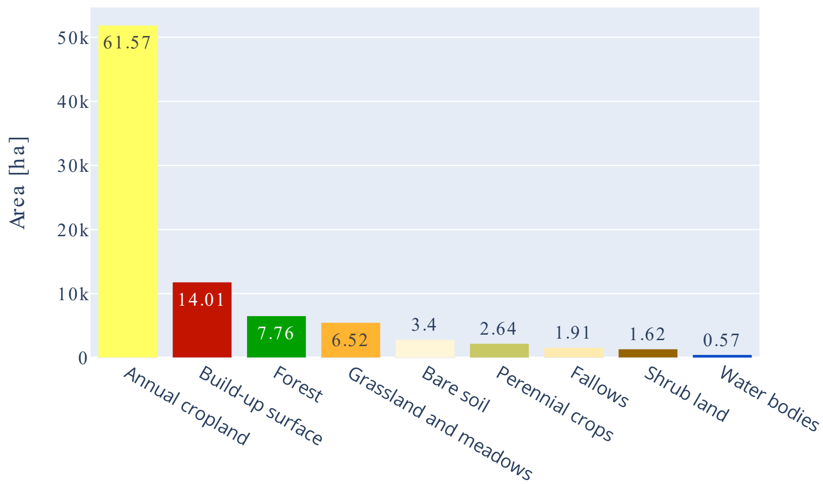


Figure 2-3. Land cover classes representation in the ESYRCE dataset in Castilla y Leon (2020)

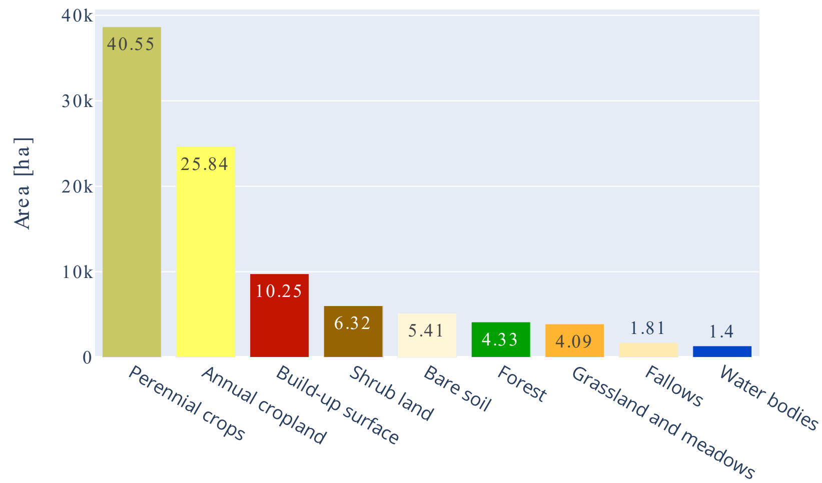


Figure 2-4. Land cover classes representation in the ESYRCE dataset in Andalusia (2020)

2.1.2 Cycle 2

The second phase of the demonstration extends the study area to the whole country. It relies on the entirety of the ESYRCE dataset in mainland Spain (Figure 2-5) to produce a crop type map at national scale.

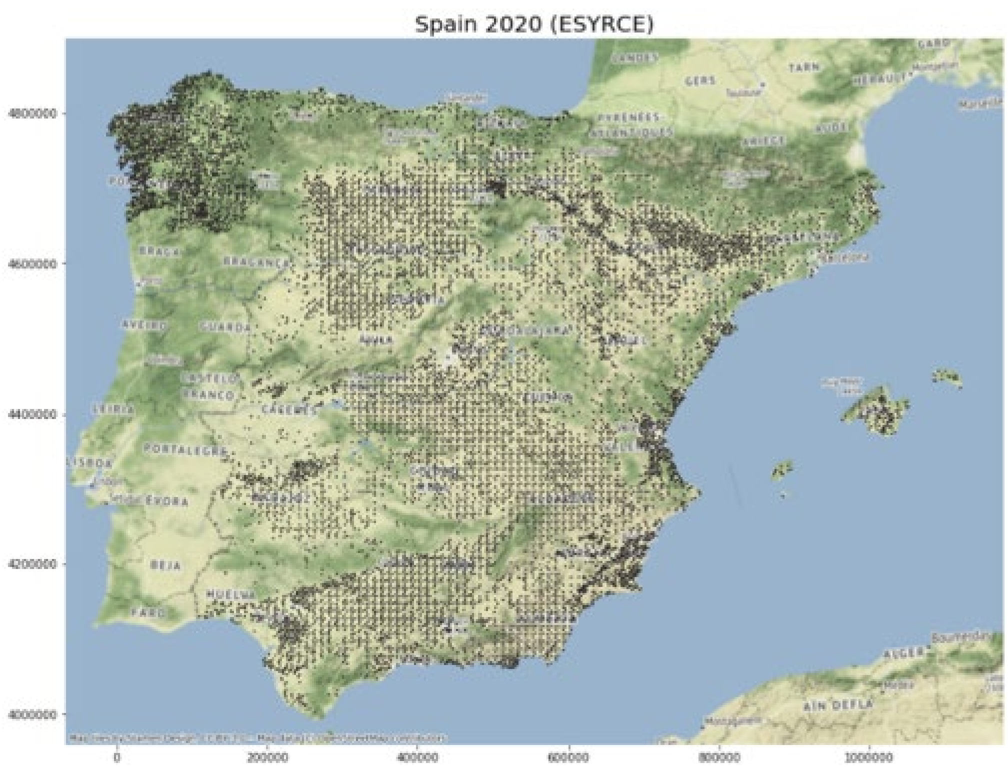


Figure 2-5. National ESYRCE dataset in 2020

In 2020, ESYRCE counts 496.182 polygons. The different classes represented in the ESYRCE dataset at national scale is shown in Figure 2-6 (distribution expressed in terms of surface).

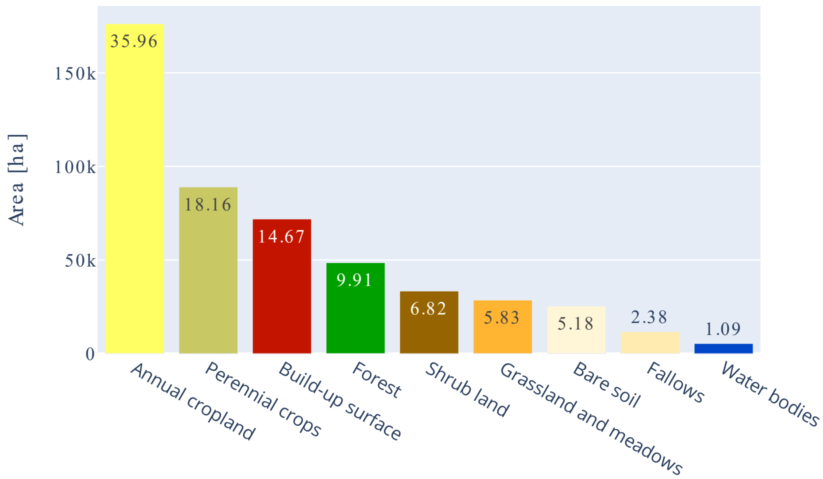


Figure 2-6. Land cover classes representation in the ESYRCE national dataset in 2020

This second cycle also aims at combining the ESYRCE dataset irrigation attribute (Figure 2-7) with farmers' yearly parcel declarations and parcel delineations (Figure 2-8) to produce an irrigation map at national scale.

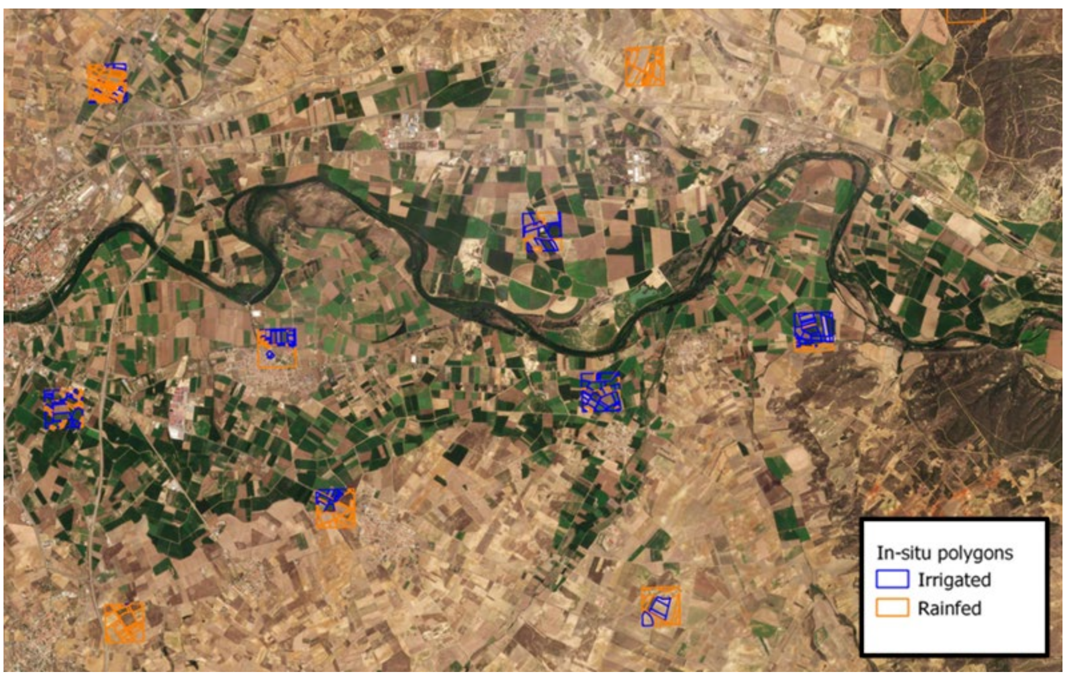


Figure 2-7. Sample of polygons with rainfed and irrigated attributes in the ESYRCE dataset in Castilla-y-Leon (2020)

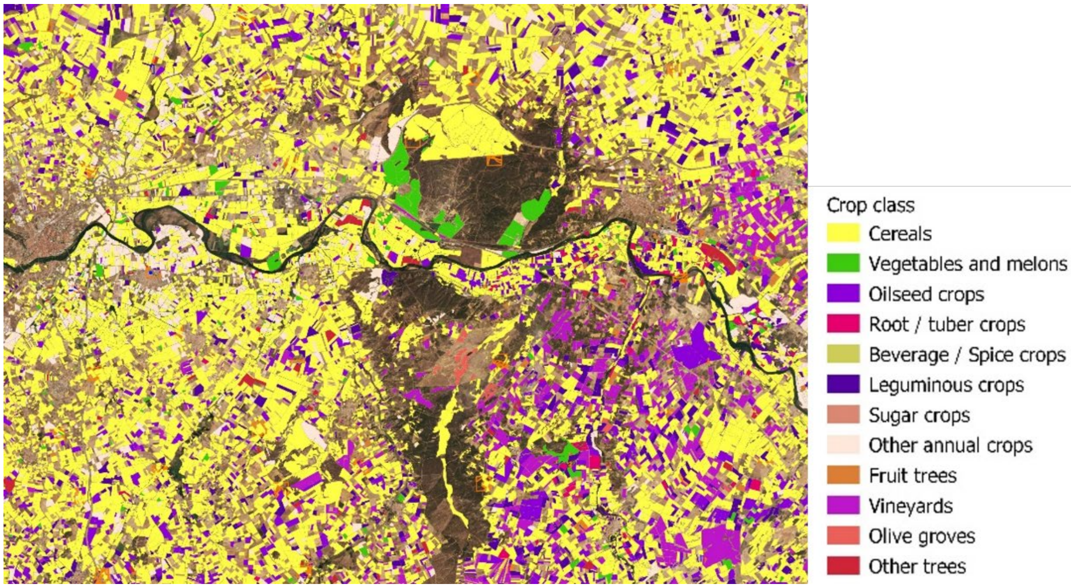


Figure 2-8. Sample of polygons from the 2020 farmers' declaration and parcel delineations.

A stratification module was implemented in the system in the framework of this cycle 2 in order to divide the whole country in smaller and more homogeneous regions in terms of agricultural practices. This stratification is displayed in Figure 2-9. The four strata were defined according to agroecological zones, landscape elements, meteorological variables and major crop distribution in the country. The distribution of crop types within each stratum is displayed in Figure 2-10 to Figure 2-13.

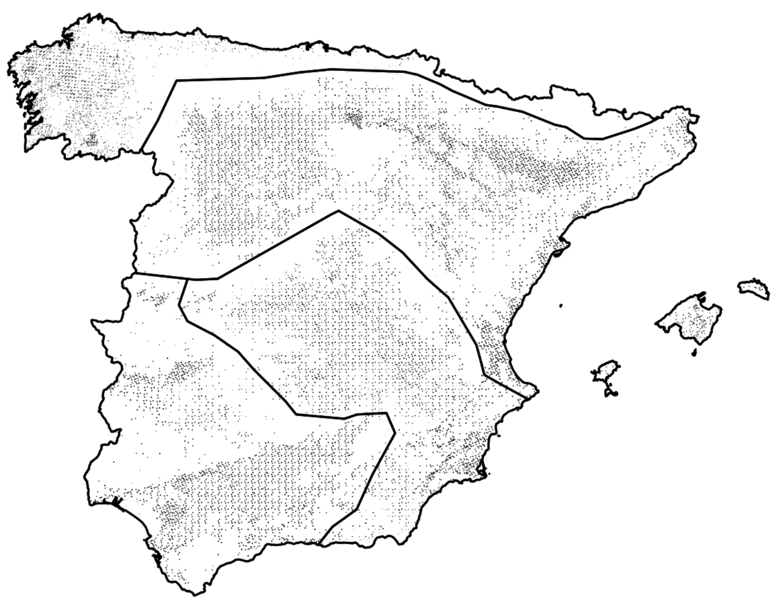


Figure 2-9. Stratification of Spain defined in the framework of the cycle 2 demonstration

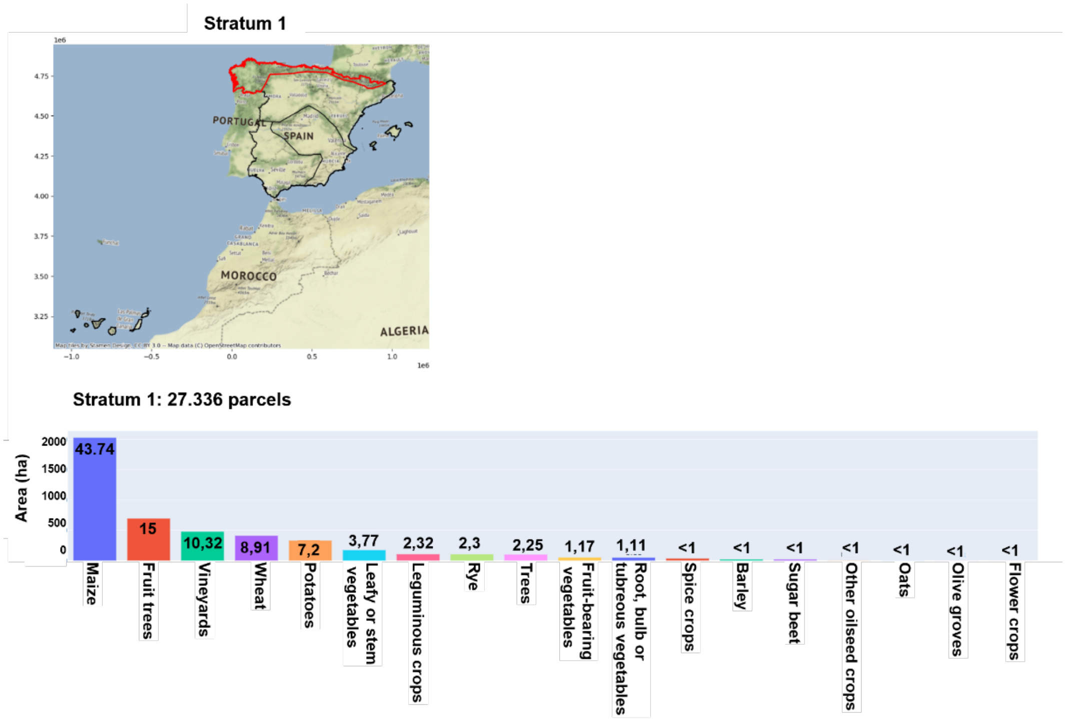


Figure 2-10. Distribution of crop types in terms of surface in the ESYRCE dataset in stratum 1

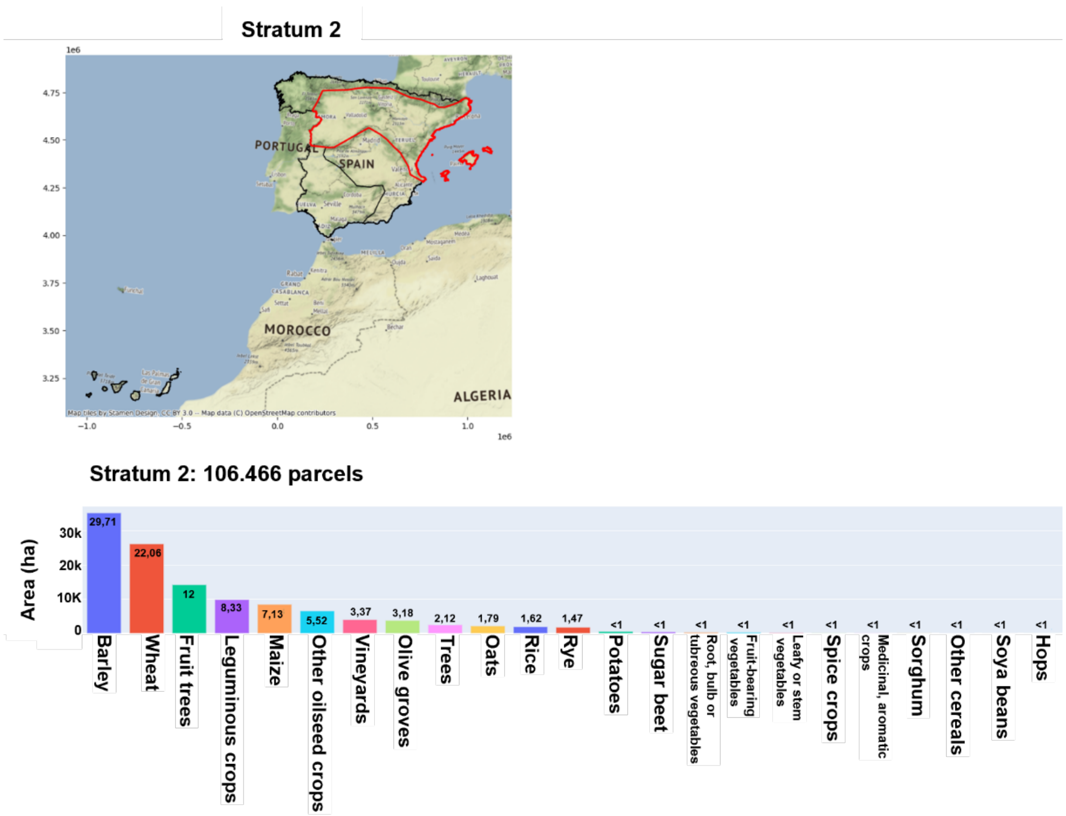


Figure 2-11. Distribution of crop types in terms of surface in the ESYRCE dataset in stratum 2

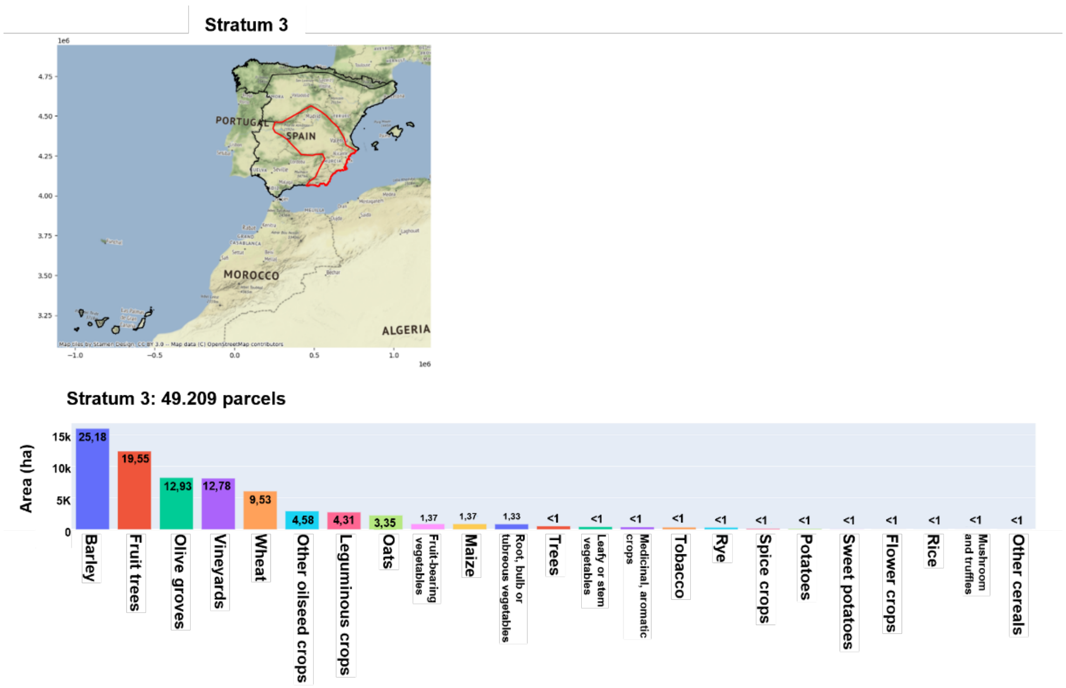


Figure 2-12. Distribution of crop types in terms of surface in the ESYRCE dataset in stratum 3

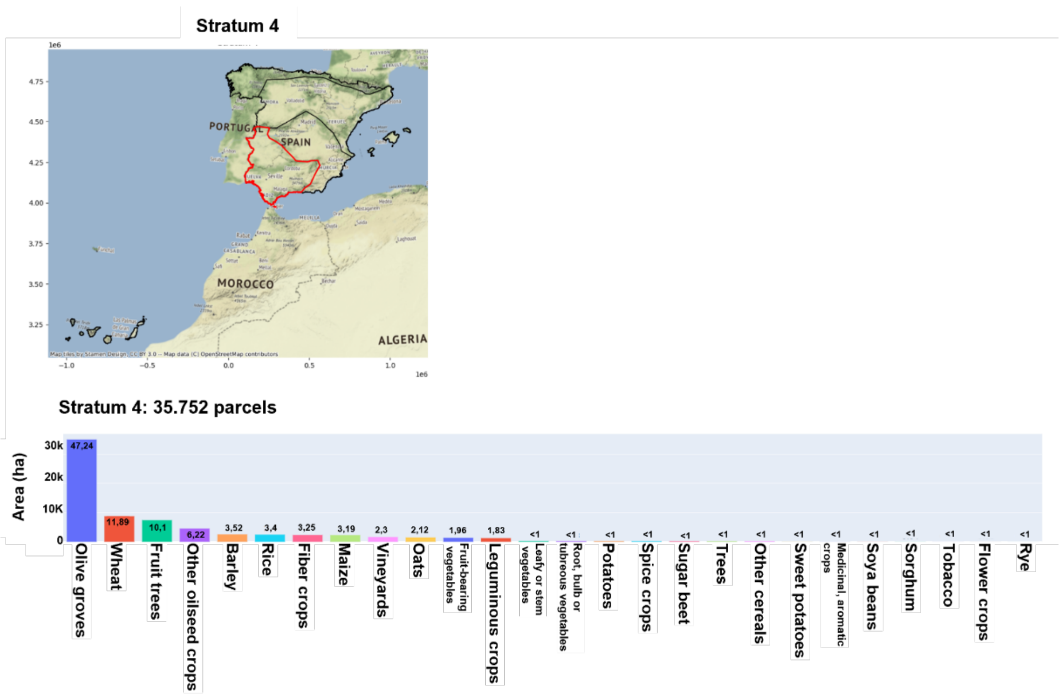


Figure 2-13. Distribution of crop types in terms of surface in the ESYRCE dataset in stratum 4

2.2 Senegal

2.2.1 Cycle 1

The first cycle of the demonstration focuses on a regional pilot area, which is the department of Nioro du Rip (Figure 2-14). The department of Nioro du Rip is one of the 46 departments of Senegal and one of the 3 departments of the Kaolack region. Its area is of 2302 km².

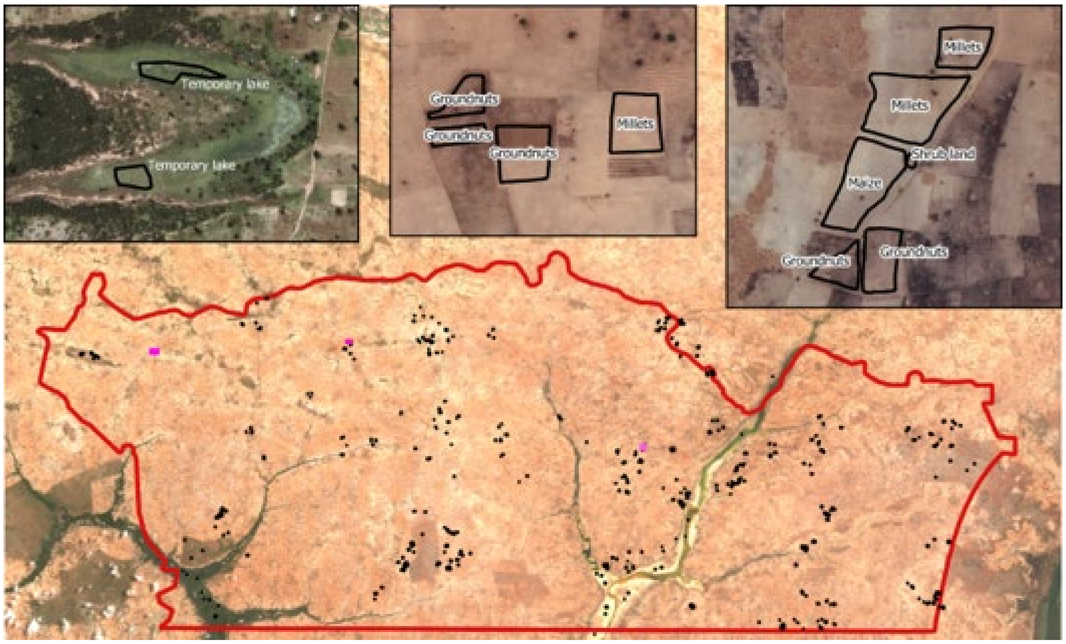


Figure 2-14. Area of Interest in Senegal (cycle 1)

The survey in place in Senegal is a list frame survey over all country, with a master frame that is the same since 2013. In 2013, an agriculture census took place, which allowed listing all active farmers (identifying new ones and removing the ones who stopped since the previous census). In parallel, a mapping exercise aimed at listing the active farmers by village, resulting in a map of agricultural households by village.

2000 holdings are selected thorough a stratified sampling from the 526.000 holdings in Senegal, which corresponds to ~ 0.4%. These 2000 holdings are spread in all the Senegalese departments, in direct ratio to the size of these departments. The same holdings are visited during 2 consecutive years and then, a new sample of holdings is drawn (2015-2016, 2017-2018, 2019-2020).

In each holding, farmers are interviewed and GPS measurements are done in all fields belonging to the household. GPS coordinates are recorded at the parcel-level in the form of points and the parcel area is measured (but outlines are not recorded). For the main season crops (not off-season crops), information is collected about crop type, crop area and production (no crop cutting, only farmers' estimates). Surveys are conducted annually, during the second half of the season (i.e. starting in August) and in any case, before the harvest. The surveys are carried out using a decentralized approach, through regional offices.

The reference year for this first cycle of the demonstration is 2021, during which a dedicated field data campaign is implemented between August and November 2021. The 2021 dataset is not presented here because it is part of the demonstration product. It will be presented in detail in section 4.2.

2.2.2 Cycle 2

The second cycle of the demonstration in Senegal focuses on the upscaling of the first pilot described in section 2.2.1 to 6 distinct administrative units: the regions of Kolda and Tambacounda and the departments of Nioro, Mbacke, Koungheul and Dagana.

This second cycle of demonstration will rely on in situ data collected through a survey protocol **specifically adjusted by and for the project**. This adjusted protocol should enhance compatibility of collected data with Earth Observation data, with the ultimate objective to improve agricultural statistics estimation. The new protocol involves two phases.

- In the first phase, field data collection occurs using Garmin 64 GPS devices to delineate parcel boundaries, with additional GPS points recorded via SurveySolutions software to ensure data consistency. The Directorate of Agricultural Statistics and Agricultural Planning (DAPSA) oversees protocol adherence and quality control, including geometry validation of parcel data;
- The second phase involves visiting yield crop cutting subplots, where GPS points are taken and yield assessments conducted, with data transmitted to UCLouvain.

Collected polygons for which data could be retrieved (not all geometries could be linked to collected data) are displayed in Figure 2-15.

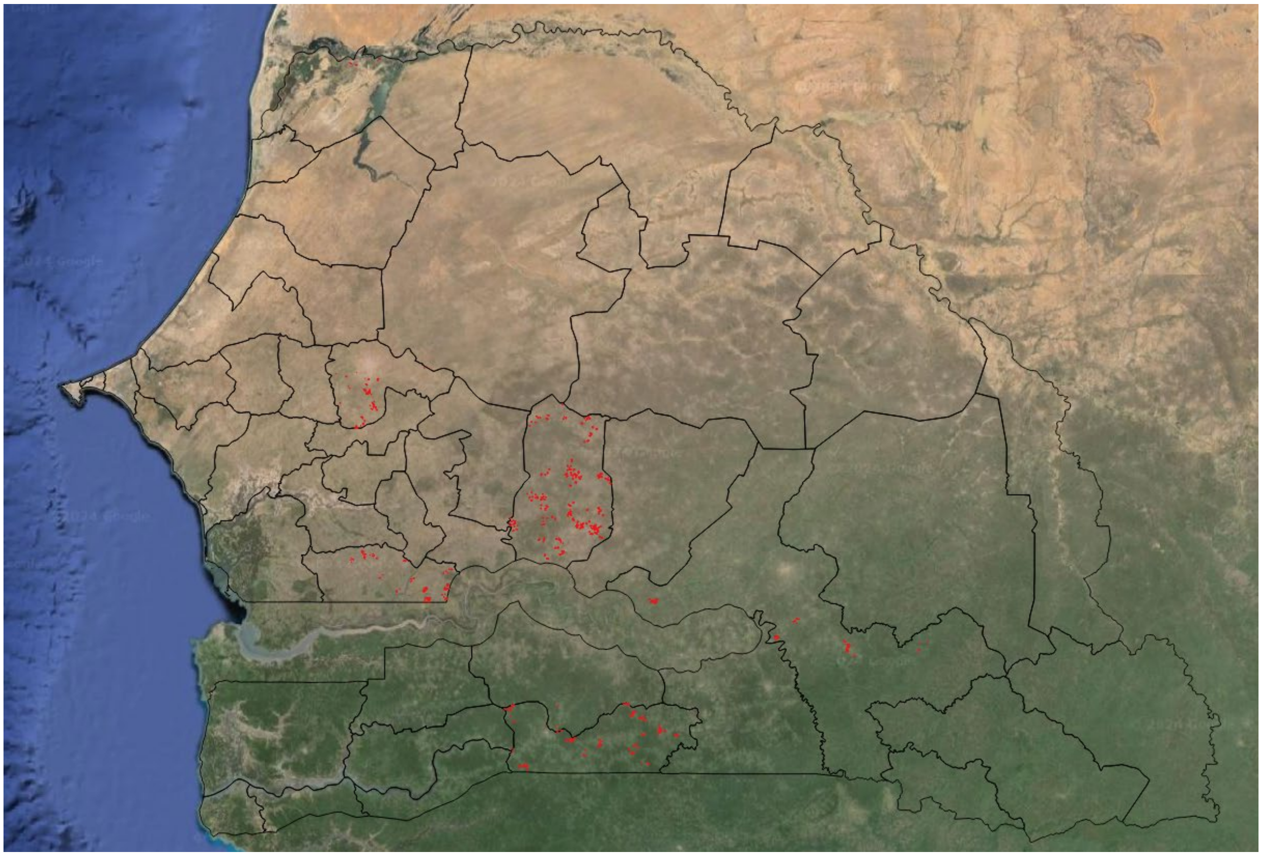


Figure 2-15. Polygons (highlighted in red) collected during the 2023 field campaign

2.3 Ecuador

The first cycle of the demonstration focuses on the same area as the benchmarking because the benchmarking results did not allow to scale-up the production. This area counts 4 Sentinel-2 tiles, which cross the country following a longitudinal transect (Figure 3-8).

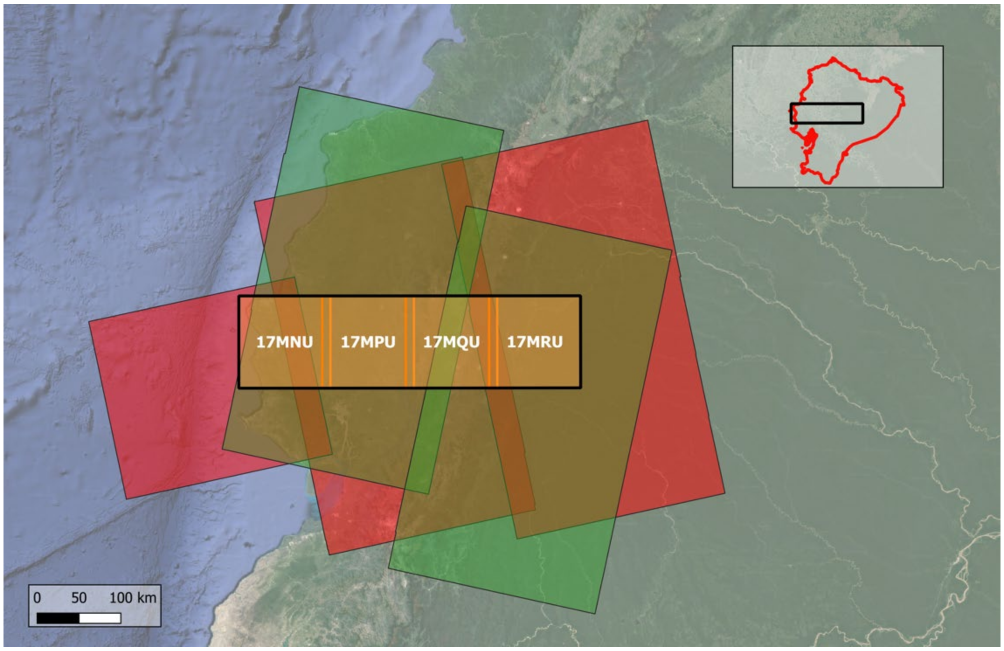


Figure 2-16. Area of Interest in Ecuador (cycle 1)

The survey in place in Ecuador is an integrated list and area frame survey over all country (Figure 3-9). The main input to define the sample frame is a land use map generated every 5 years (partnership with the Ministry of Agriculture and Ministry of Environment).

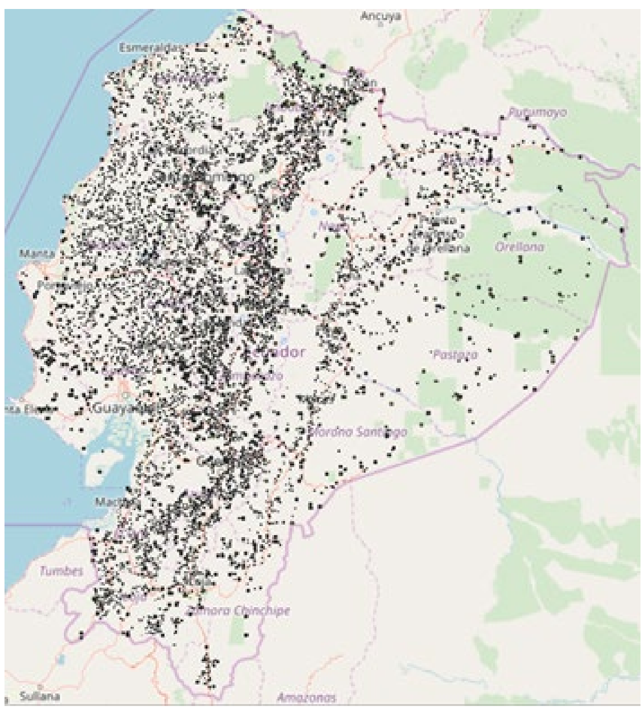


Figure 2-17. Overview of the Ecuador INEC dataset

Around 2% of the country is specifically surveyed for agriculture. Surveys take place each year, with visits on the fields during and after the harvest. Depending on the crop, it occurs along September, October and November.

The sample unit is the segment and the size of the segment depends on an a priori stratification: 9 or 36 ha in intensive strata, 145 ha in medium intensity and 576 ha in low intensity (Figure 3-10). Until 2018, all parcels intersecting the block were surveyed while from 2019, all holdings intersecting the block are surveyed (i.e. parcels outside the block may also be surveyed).

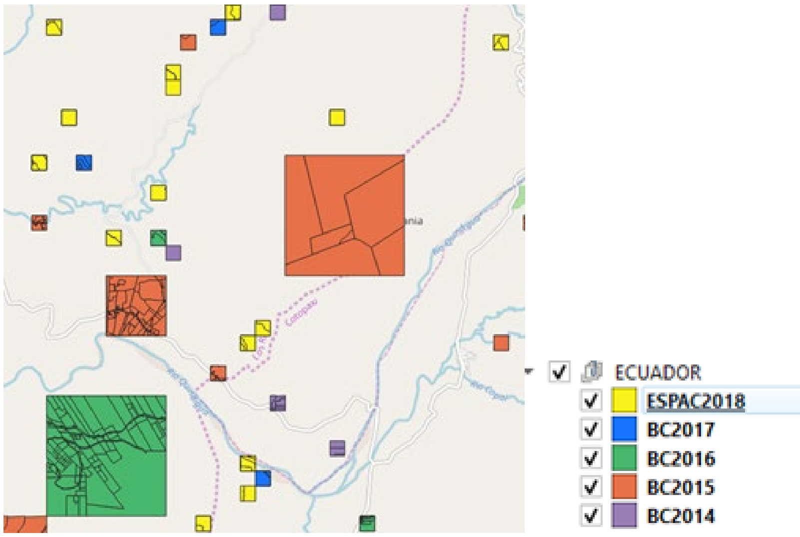


Figure 2-18. Example of INEC segments

Every plot inside the segment is outlined and has a specific code. The land use of the plot is categorized by the type (permanent crop, temporary crop, fallow, pastures, grassland, bushes, other uses). For the plots that contain crops or pasture, the following information is collected by crop and cycle: production (farmers' estimates by parcel and by crop), harvested area, lost area, type of seed, irrigation, fertilizers/pesticides, tillage.

One GPS point is recorded and that point could be taken in the farm, office of the farm or household producer. Plot outlines are drawn on orthophoto images from the last years during the field visit and they are later digitalized in the office. This plot outline digitization is made using all available sources of remote sensing: Landsat images (but the 30m resolution is not really useful for plots outlines), RapidEye images, Google Earth imagery.

The quality of the in situ data could not be improved between cycles 1 and 2; no more activities were carried out in cycle 2.

2.4 Tanzania

In Tanzania, the project was no more in contact with the NSO at the time of the cycle 1 demonstration. Therefore, the project is working with in situ data shared by the "Copernicus4GEOGLAM" project. These data cover the three administrative regions of Dodoma, Manyara and Tanga (Figure 3-10). The areas are located in the Central extending to the northeastern part of the country. The total area occupied by the three regions is covering approximatively 116,190 km² (representing 12% of the country).

Figure 2-19. Area of Interest in Tanzania (cycle 1) (from [RD.1] and [RD.2])

The three regions usually act as swing regions for food security and availability of data from these areas will be an important step towards food security forecast in the country. Majority of the regions lie in the semi-arid characterized by bi-modal rainfall regime receiving from 500 mm to 800 mm annual rainfall for Dodoma, 450 mm and 1,200 mm annual rainfall for Manyara, and 750 mm to 1400 mm for Tanga.

Sample units were selected based on a stratified systematic and random sampling selection (two stage approach). The first stage was implemented by applying a 20 x 20 km grid over the overall area of the AOI. In a second stage, multiple sample units were randomly selected in sequence for each grid cell based on the 500 x 500 m sub-grid, resulting with 400 segments selected. The spatial distribution of the sample units over the crop and non-crop strata are is shown in Figure 3-12.

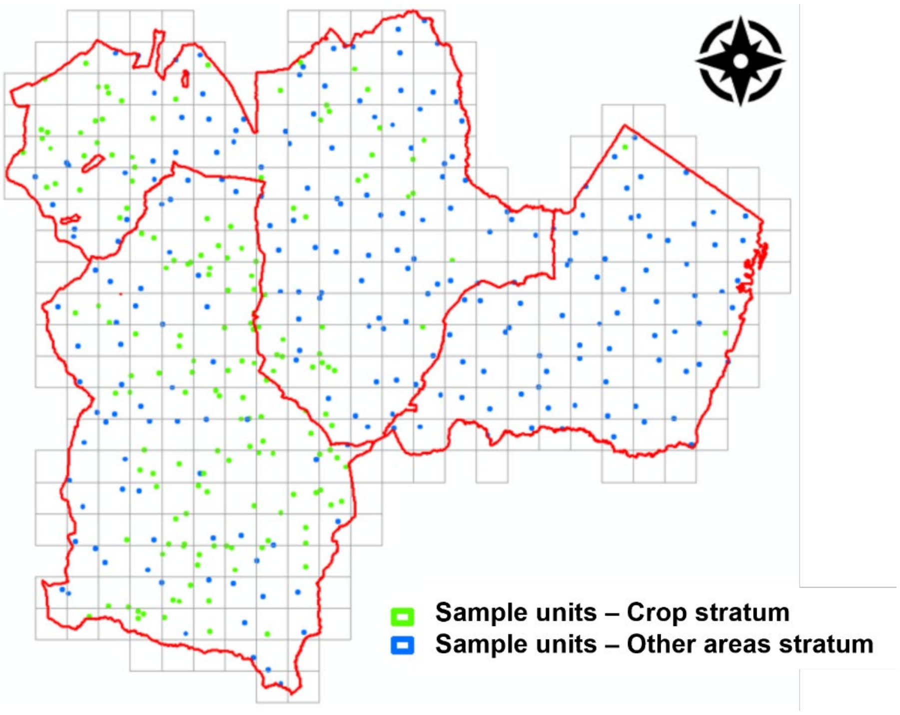


Figure 2-20. Spatial distribution of the sample units per aggregated stratum (from [RD.2])

In total out of the overall sample of 400 segments, 247 segments were identified to contain field parcels and therefore were to be surveyed (Figure 3-13).

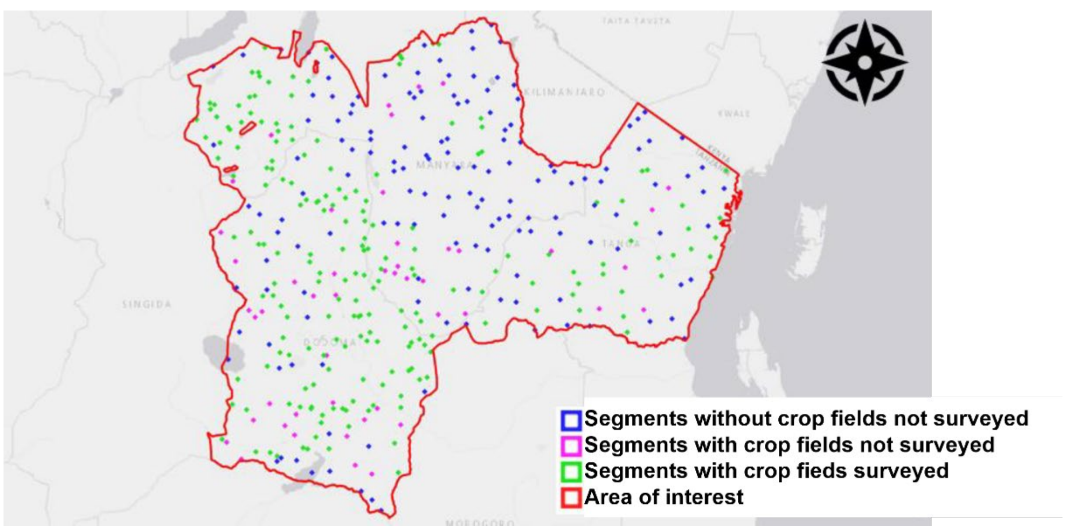


Figure 2-21. Final spatial distribution of the surveyed segments (from [RD.2])

The different classes represented in the Copernicus4GEOGLAM dataset is shown in Figure 3-14 (distribution expressed in terms of surface).

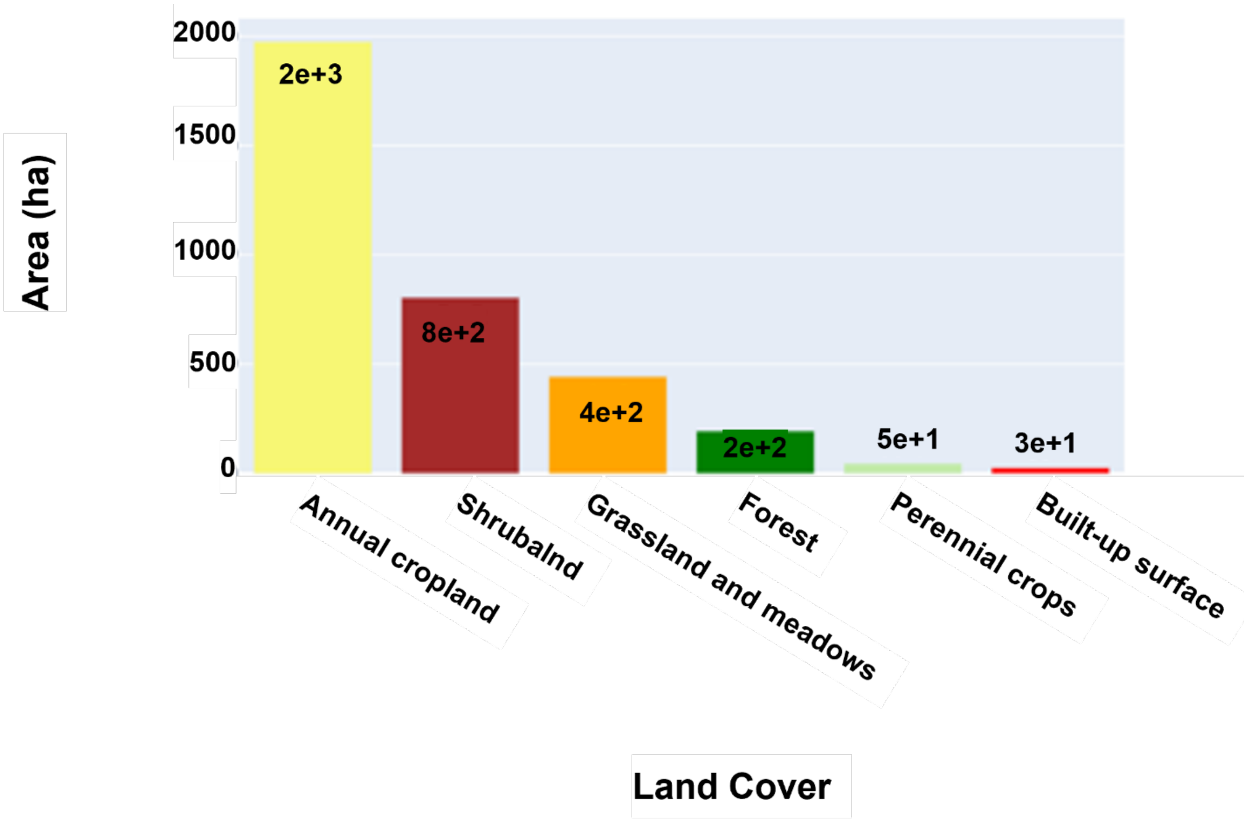


Figure 2-22. Land cover classes representation in the Copernicus4GEOGLAM dataset in 2020

No new data were acquired for the cycle 2 of the demonstration; no specific activities were conducted during the cycle 2.

3 Quantitative validation

3.1 Spain

3.1.1 Cycle 1

Two use cases were addressed during the first cycle of demonstration: cost-efficiency and sampling design (through the generation of a map of irrigation areas to support a new sampling). With this aim in view, two kinds of EO products were generated: crop maps and irrigation map.

3.1.1.1 Crop type maps

Figure 4-1 presents the crop type map obtained over the region of Castilla y Leon, the legend counting 28 different crop types. The map is based on Sentinel-2 (S2) time series from January to December. A Random Forest (RF) algorithm was applied on the S2 bands B03-04-05-06-07-08-11-12 and on the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) and Brightness. A Synthetic Minority Oversampling Technique (SMOTE) algorithm was used to increase the number of samples of the minor crops and therefore increase their representativeness. The overall accuracy of the map is of 76%.

The legend of the map can be simplified to have a map of the main crop groups (Figure 4-2). In this case, the overall accuracy increases up to 91% (97% if non-cropland classes are not considered).

Figure 4-3 presents a zoom of the crop type map, showing that the map is very smooth despite the fact that this is a per-pixel classification: no a posteriori filtering was applied and the parcels are clearly visible on the map. In addition, the same kind of performance is obtained both for small (right) and larger (left) parcels.

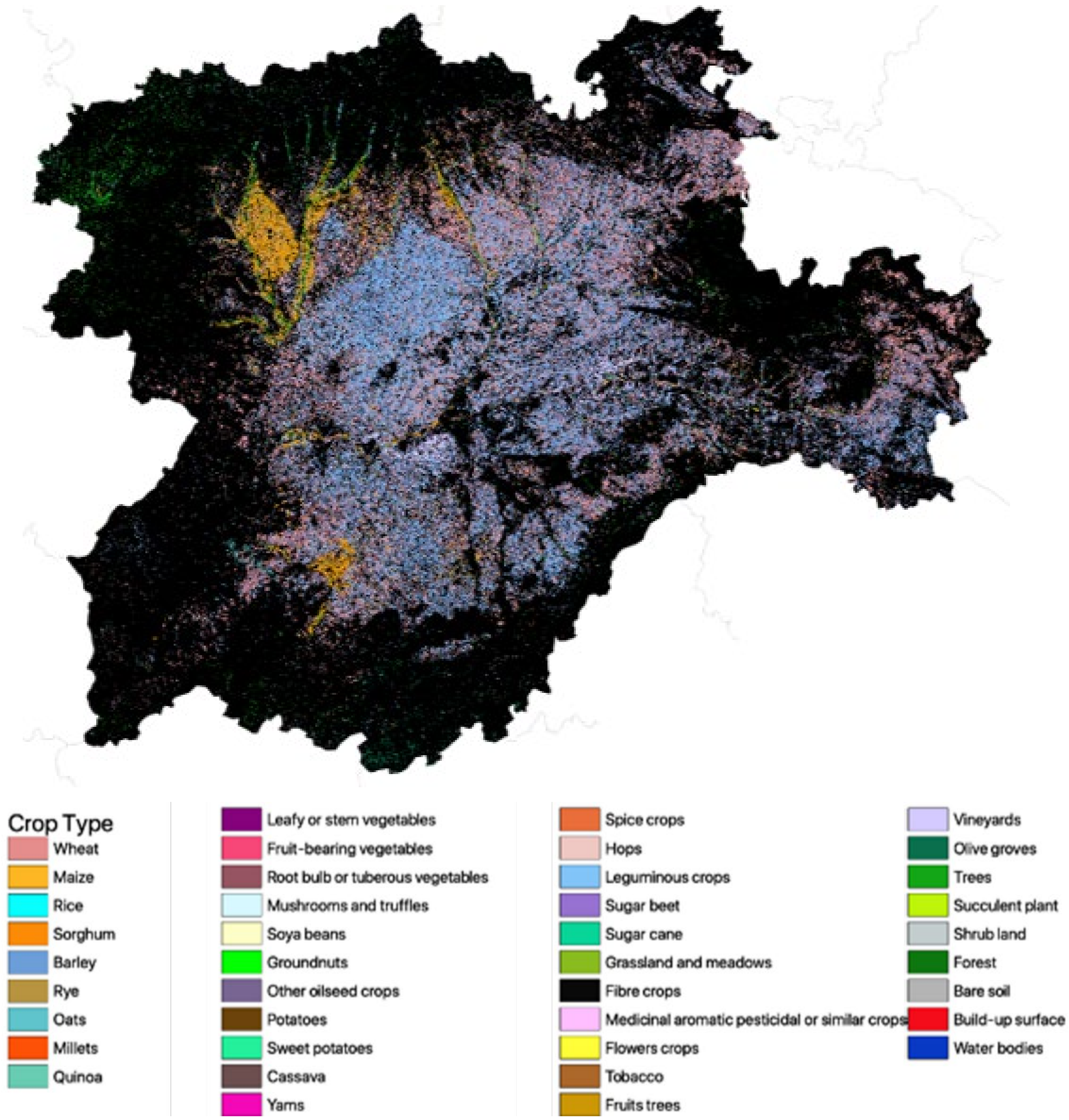


Figure 3-1. Crop type map in Castilla y Leon

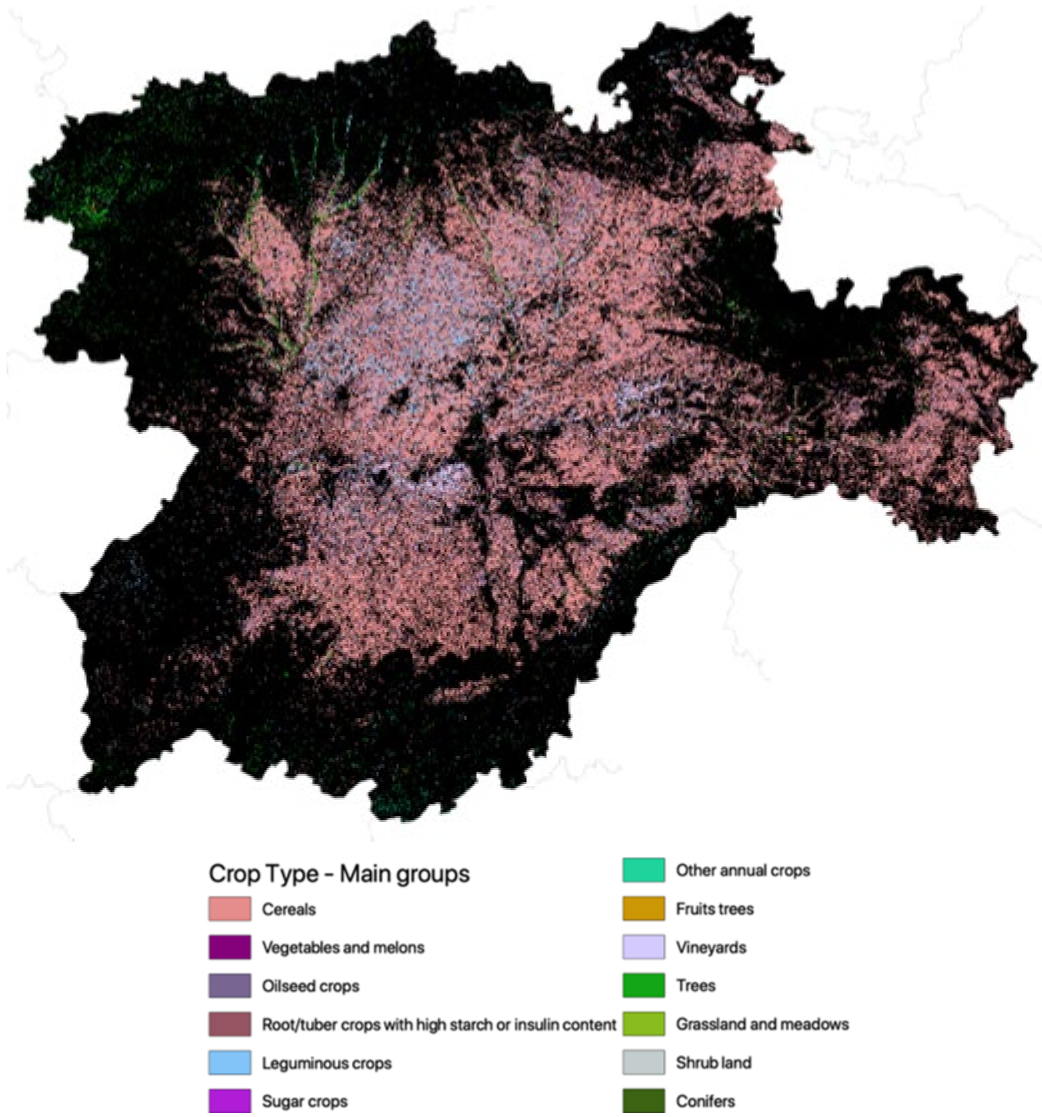


Figure 3-2. Crop group map in Castilla y Leon

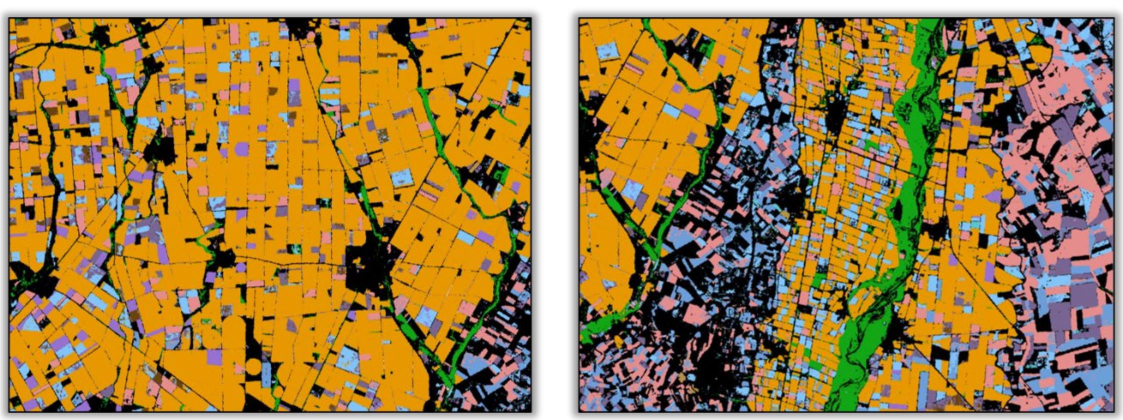


Figure 3-3. Zoom of the crop type map in Castilla y Leon

The confusion matrix of the crop type map (including the non-cropland classes) is presented in Figure 4-4. It can be observed that the highest confusion between crops is between wheat and barley, which are two classes very similar, having a low thematic distance. The discrimination between maize and sunflower is very good. Looking at the non-cropland classes, the matrix reveals some confusion between them (especially between bare soil, built-up and grassland) and some confusion between the crop classes and the grassland and built-up classes.

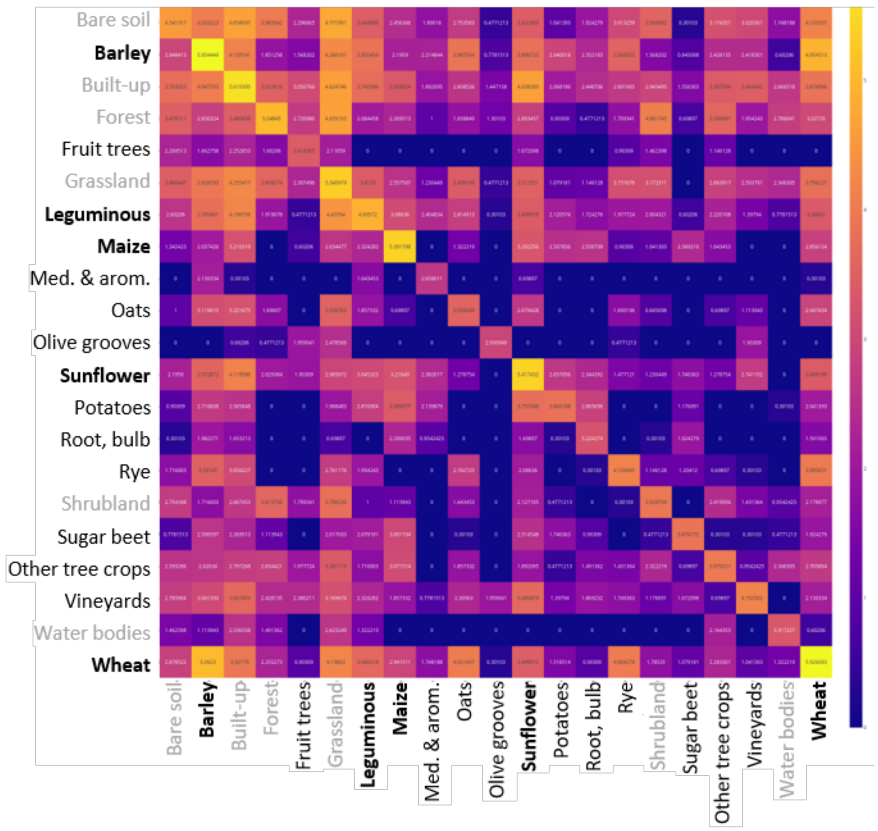


Figure 3-4. Confusion matrix of the crop type map (main crop types being shown)

In order to complete the quantitative accuracy assessment, F-Score by classes are computed: Figure 4-5 shows them for individual crop types while Figure 4-6 show the results obtained after a first grouping of crop types.

All main crops (barley two row, soft wheat, sunflower and maize) have a F-Score higher than 0.8. Logically, the accuracy increases when grouping the different varieties of barleys and of wheats.

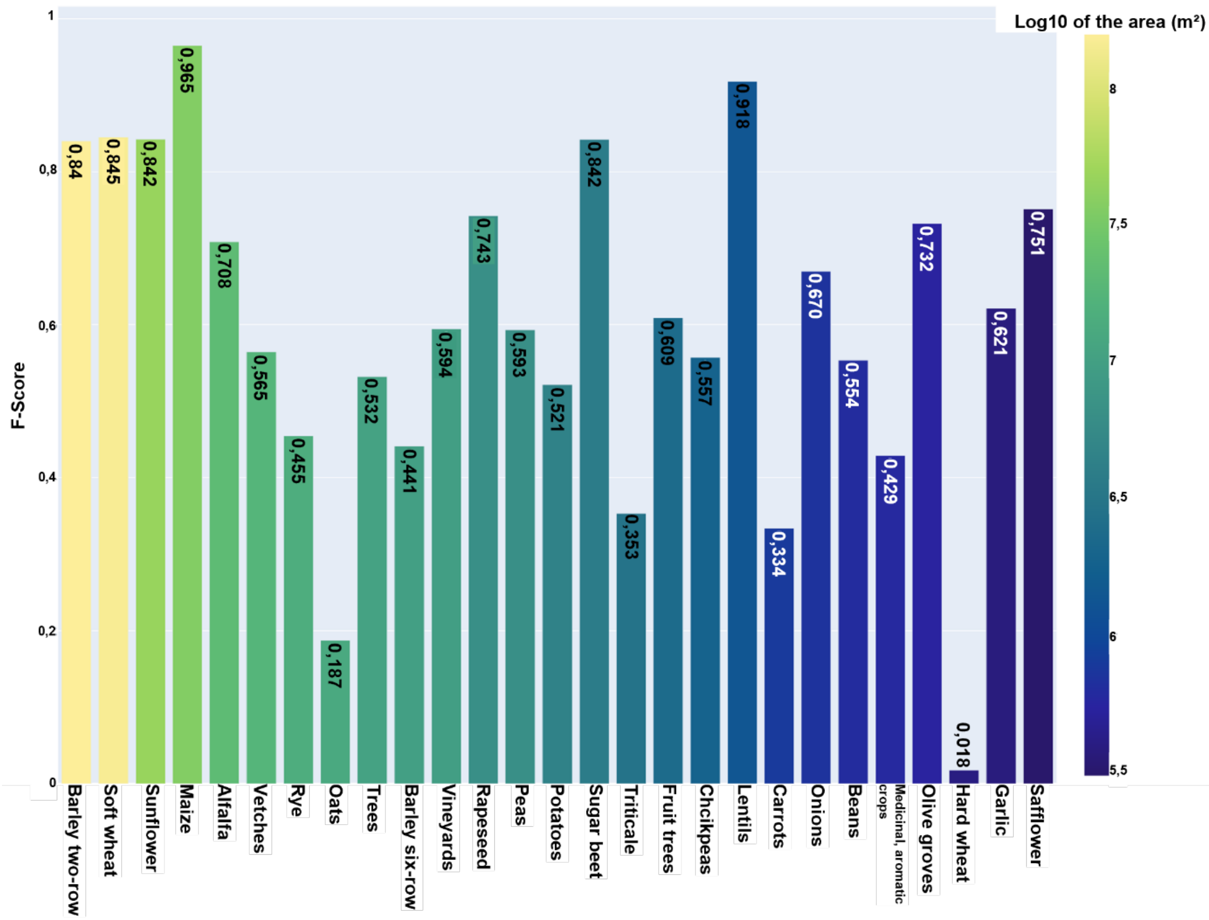


Figure 3-5. F-Score by class sorted by area (largest to smallest) of the crop type map in Castilla y Leon

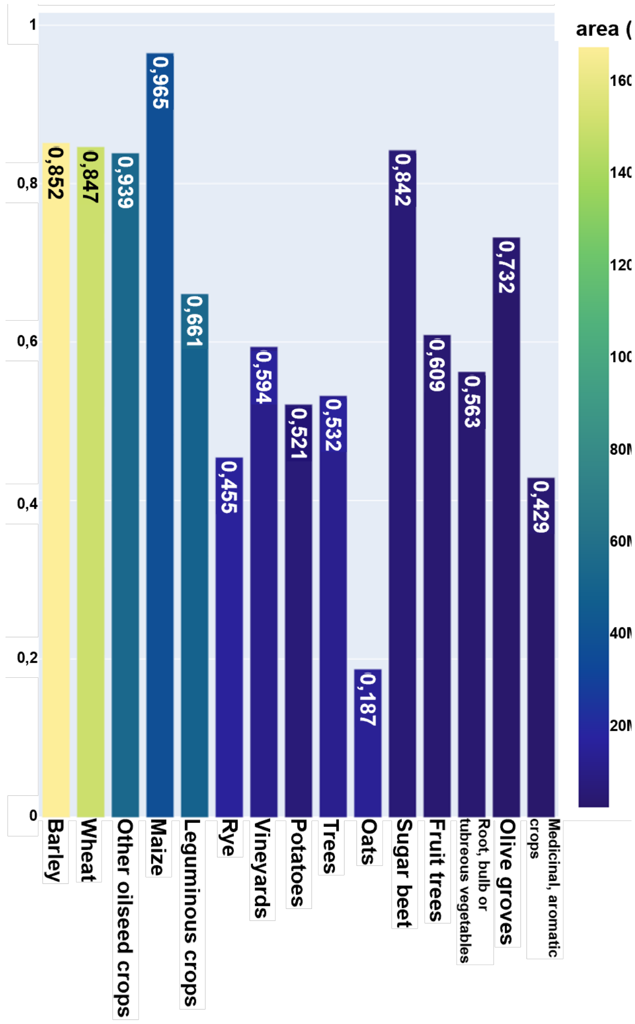


Figure 3-6. F-Score by aggregated class sorted by area (largest to smallest) of the crop type map in Castilla y Leon

The Broceliande algorithm was also applied over a smaller test area in Castilla y Leon (Figure 4-7). This algorithm aims at improving the discrimination of permanent crops. In general, class change areas are well defined (Figure 4-8 - left) and vineyard inside fallow, forest and "no cropland" class are well classified (Figure 4-8 - right). Yet, it should be noted that the Broceliande algorithm has issues with mixed pixels and does not recognize patterns at the parcel-level, which creates a salt-and-pepper effect in the map.

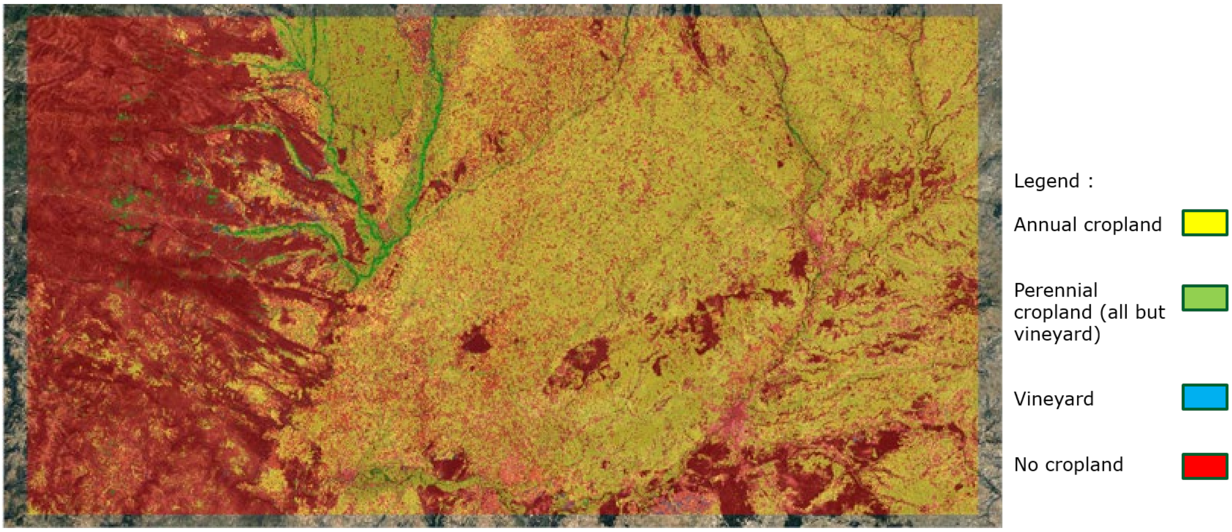


Figure 3-7. “Broceliande” crop type map in Castilla y Leon

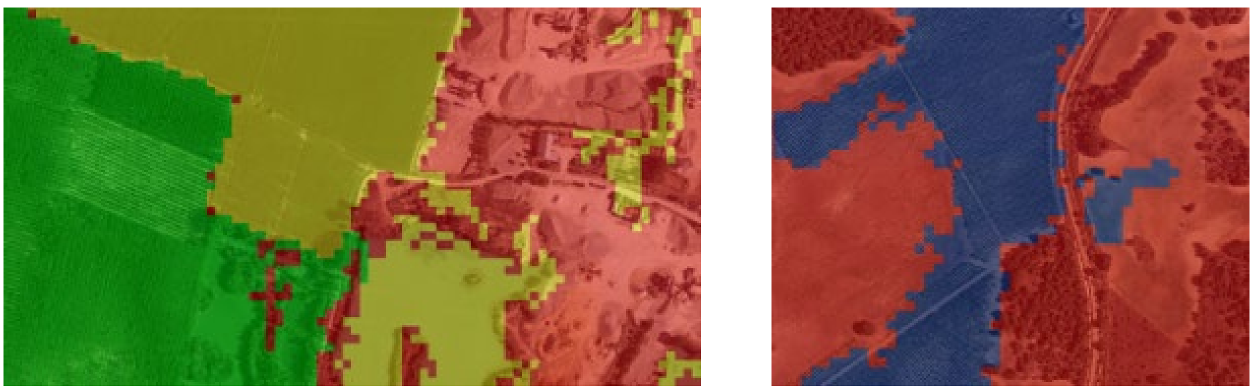


Figure 3-8. Zoom of the “Broceliande” crop type map in Castilla y Leon

The confusion matrix over the two S2 tiles included in the test site is shown in Figure 4-9.

The presence of forests often leads to confusion with the perennial croplands. This confusion affects the two tiles, resulting in a significant omission rate.

Additionally, fallows have a significant impact on the classification process, as their spectral response can be very similar to the one of annual crops, leading to many "annual crops" being misclassified as “fallows”, therefore as “non-cropland”.

30TTM

Truth data

Classifier results	Class 1	Class 2	Class 3	Class 4	Classification overall	User's accuracy (Precision)
Class 1	404484	8712	2545	37901	453642	89.164%
Class 2	627	11703	80	793	13203	88.639%
Class 3	32	14	953	42	1041	91.547%
Class 4	14022	6141	3332	51569	75064	68.7%
Truth overall	419165	26570	6910	90305	542950	
Producer's accuracy (Recall)	96.498%	44.046%	13.792%	57.105%		

Overall accuracy (OA): 86.326%

Kappa[1]: 0.587

30TUM

Truth data

Classifier results	Class 1	Class 2	Class 3	Class 4	Classification overall	User's accuracy (Precision)
Class 1	979534	587	1083	47489	1028693	95.221%
Class 2	2225	5792	0	5974	13991	41.398%
Class 3	54	0	1488	18	1560	95.385%
Class 4	20403	367	135	71059	91964	77.268%
Truth overall	1002216	6746	2706	124540	1136208	
Producer's accuracy (Recall)	97.737%	85.858%	54.989%	57.057%		

Overall accuracy (OA): 93.106%

Kappa[1]: 0.642

Legend :

Annual cropland (class 1)

Perennial cropland (all but vineyard) (class 2)

Vineyard (class 3)

No cropland (class 4)

Figure 3-9. Confusion matrix of the “Broceliande” crop type map over the 2 test tiles

Figure 4-10 presents the crop type map obtained over the region of Andalusia, the legend counting 34 different crop types. The map is based on S2 time series from January to December. A RF algorithm was applied on the S2 bands B03-04-05-06-07-08-11-12 and on the NDVI, NDWI and Brightness. A SMOTE algorithm was used to increase the number of samples of the minor crops and therefore increase their representativeness. The overall accuracy of the map is of 73%.

The legend of the map can be simplified to have a map of the main crop groups (Figure 4-11). In this case, the overall accuracy increases up to 84% (93% if non-cropland classes are not considered).

Figure 4-12 presents a zoom of the crop type map, showing like in Castilla y Leon that the parcels are clearly visible on the map, without too much noise, despite the fact that this is a per-pixel classification without a posteriori filtering. The map is quite good both in very intensive areas with small adjacent parcels having different crops (left illustration) and in more extensive areas fully covered by olive groves (right illustration).

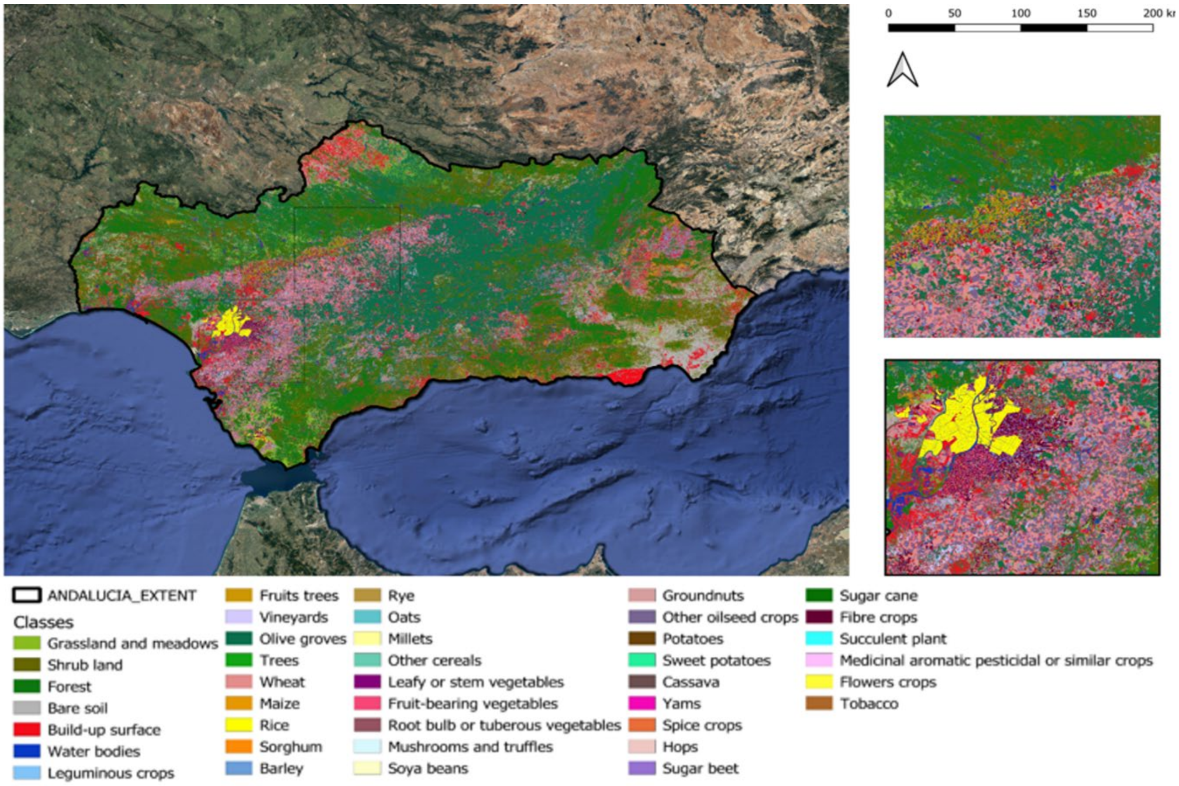


Figure 3-10. Crop type map in Andalusia

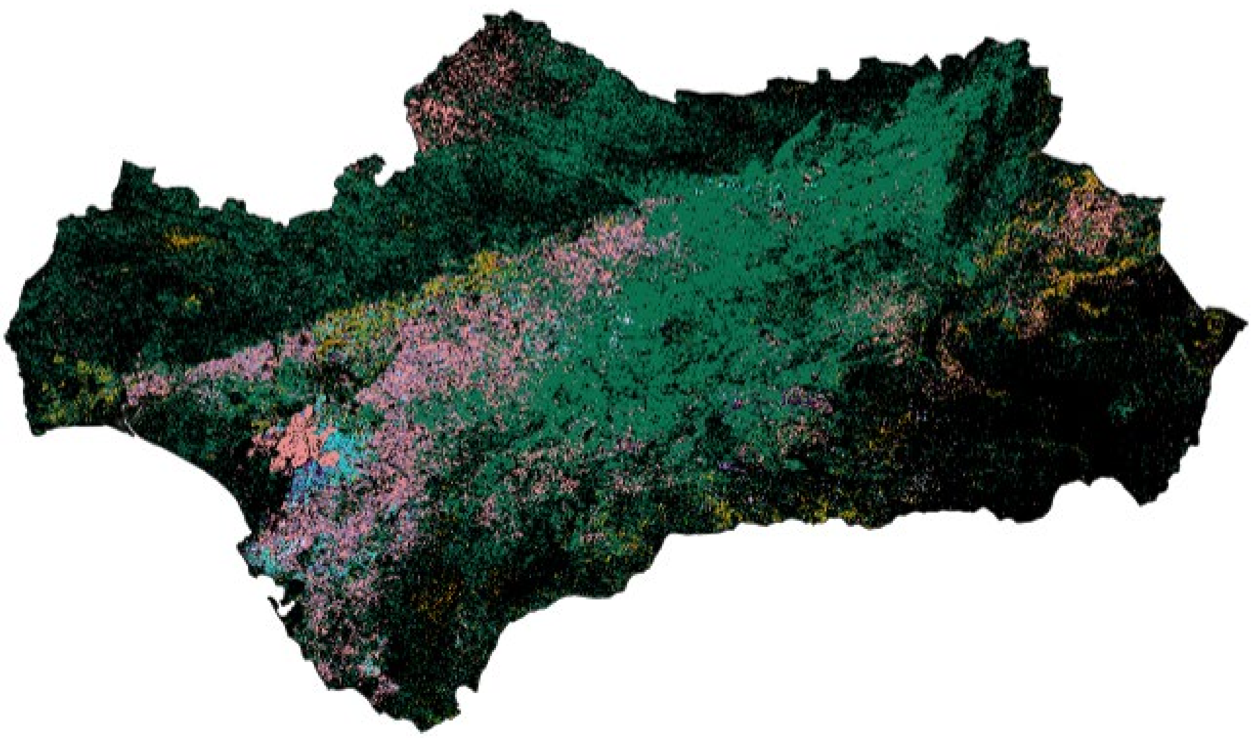


Figure 3-11. Crop group map in Andalusia

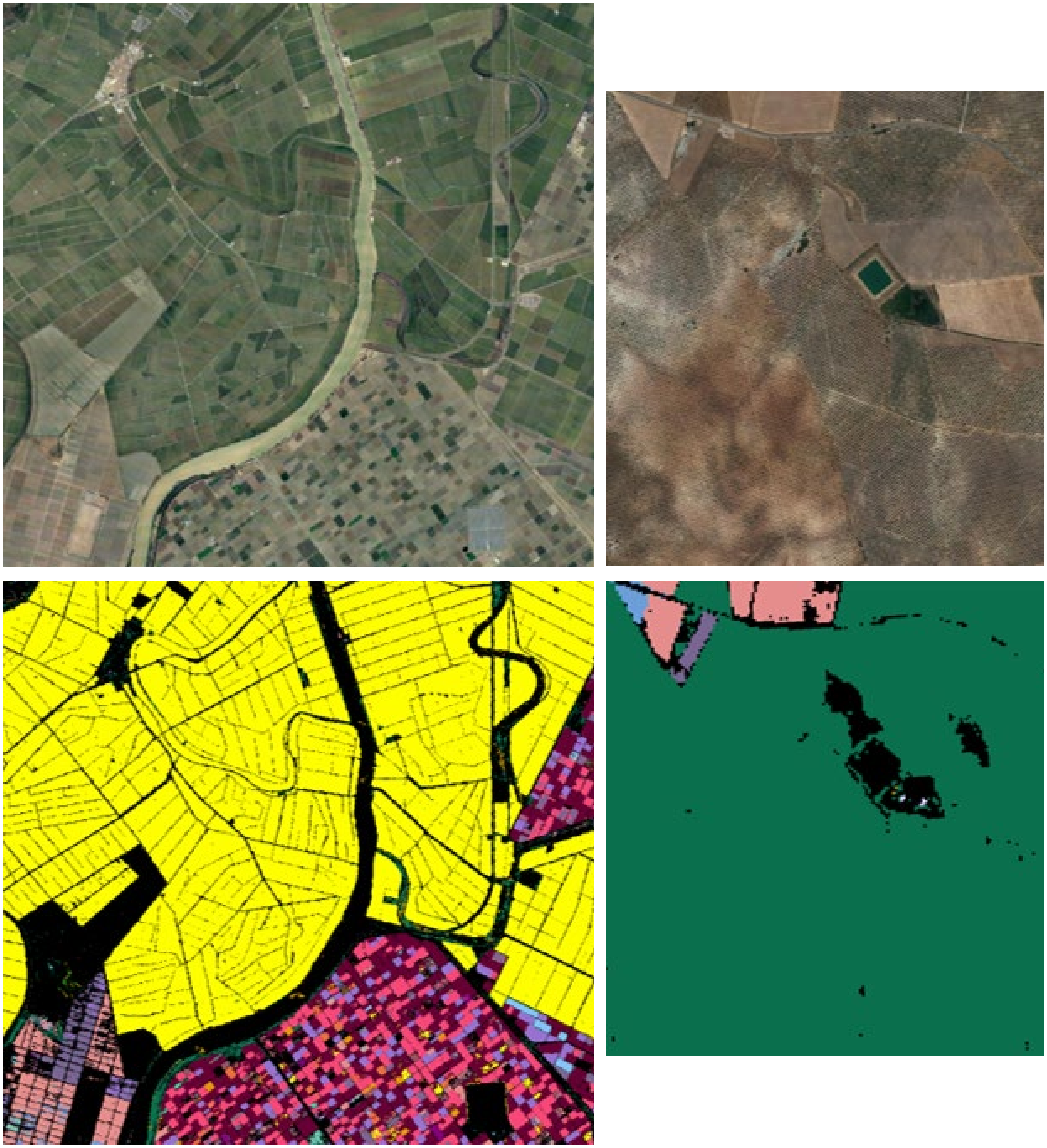


Figure 3-12. Zoom of the crop type map in Andalusia

The confusion matrix of the crop group map (including the non-cropland classes merged in a single group) is presented in Figure 4-13. It can be observed that the annual crops are well discriminated, especially the maize and sunflower which are the main ones. To some extent, there is a small confusion between olive groves and fruit trees. There exists also some confusion between the non-cropland and crop classes: bare soil is sometimes confused with cereals, grassland and built-up are also confused with the different crop types.

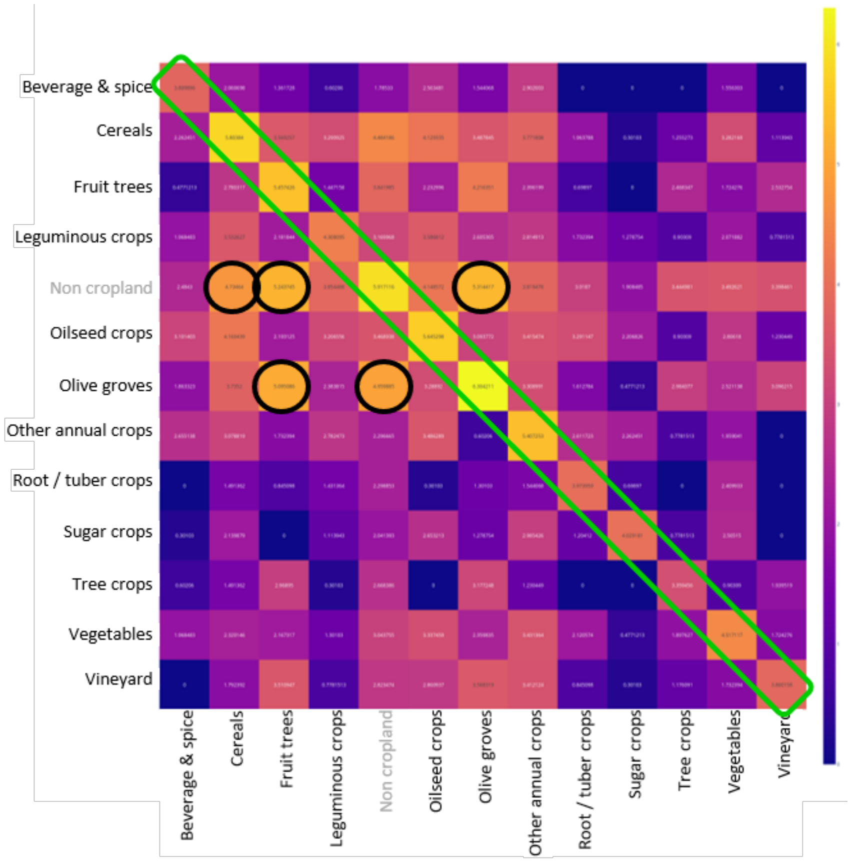


Figure 3-13. Confusion matrix of the crop group map

In order to complete the quantitative accuracy assessment, F-Score by classes are computed: Figure 4-14 shows them for individual crop types while Figure 4-15 shows the results obtained after a first grouping of crop types.

Looking at the main individual crop types (Figure 4-14), olive groves, sunflower, cotton and rice are well identified and the metric is lower for fruit trees, hard wheat and soft wheat. The performance increases for the wheat when grouping the hard and soft wheats (Figure 4-15); some confusion remains with the barley but this is mainly due to the low thematic distance with the wheat. The accuracy of the fruit trees and vineyards is significantly lower than the olive one; but this can be explained by the fact that there are minor classes in the permanent crops group.

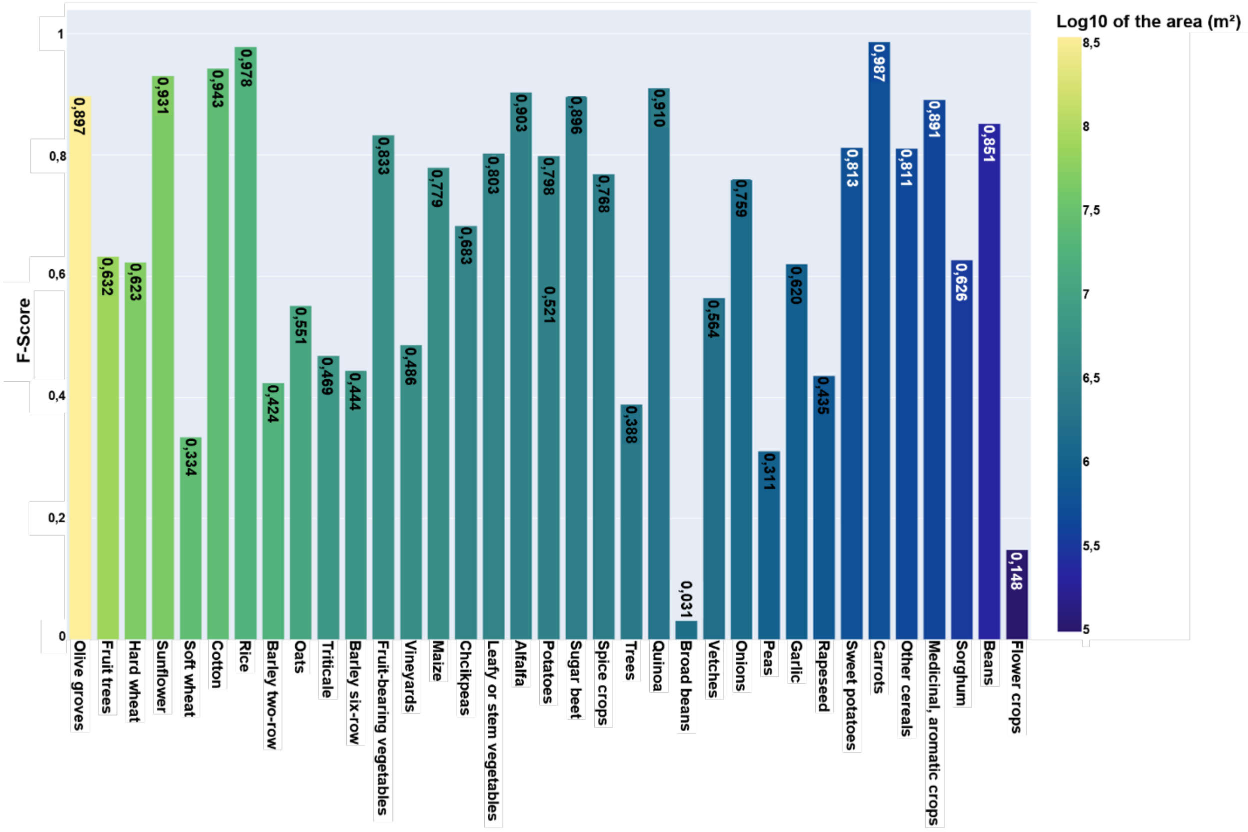


Figure 3-14. F-Score by class sorted by area (largest to smallest) of the crop type map in Andalusia

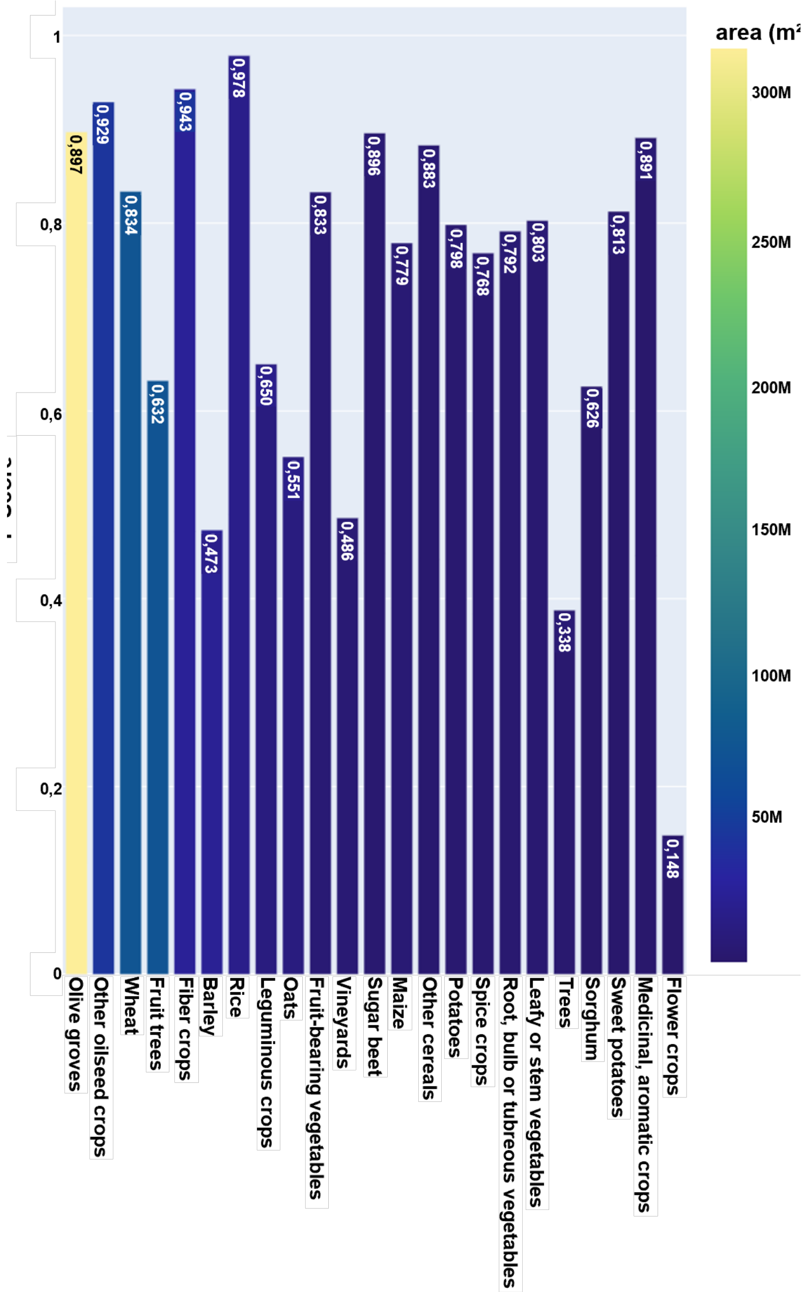


Figure 3-15. F-Score by aggregated class sorted by area (largest to smallest) of the crop type map in Andalusia

Like in Castilla y Leon, the Broceliande algorithm was also applied over a smaller test area in Andalusia (Figure 4-16). Since there are more permanent crops in Andalusia than in Castilla y Leon, the potential of this algorithm is higher here. Yet, the results are somehow disappointed. Maps are also affected by the mixed pixels issue and it does not allow to distinguish well between the different types of permanent crops. These conclusions are supported by the confusion matrix shown in Figure 4-17.

Like in Castilla y Leon, forests cause significant commission errors in the permanent crops. The classification of vineyards (class 3) is improved due to the fact that they are more numerous in the region, resulting in fewer omission errors.

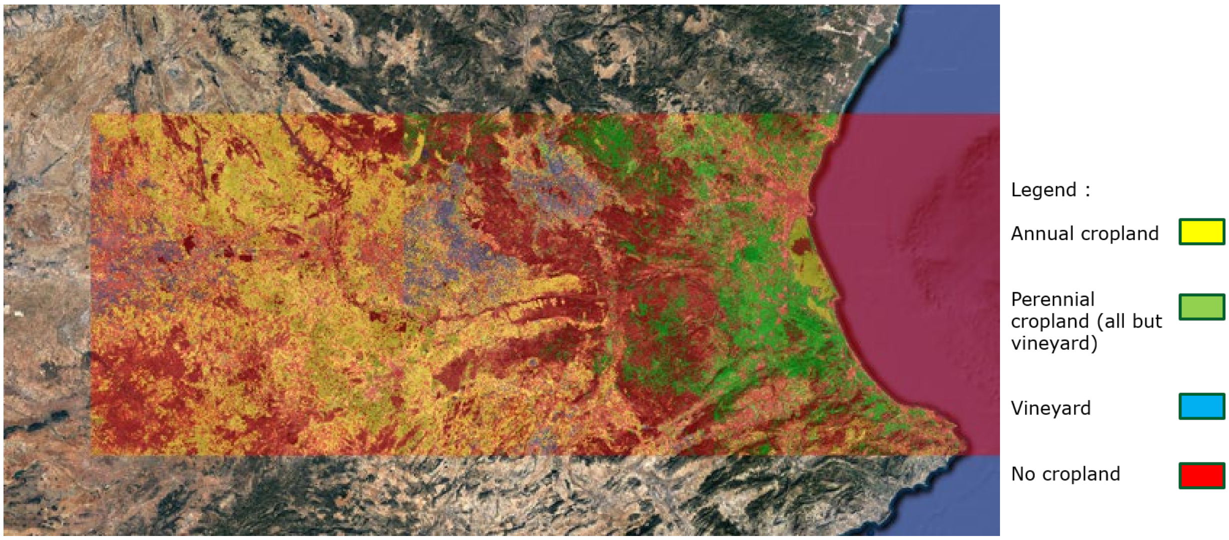


Figure 3-16. “Broceliande” crop type map in Andalusia

30SWJ

Truth data

Classifier results	Class 1	Class 2	Class 3	Class 4	Classification overall	User's accuracy (Precision)
Class 1	314150	582	148	4735	319615	98.29%
Class 2	8852	7930	2417	11233	30432	26.058%
Class 3	8994	958	68978	969	79899	86.331%
Class 4	6605	218	30	82700	89553	92.348%
Truth overall	338601	9688	71573	99637	519499	
Producer's accuracy (Recall)	92.779%	81.854%	96.374%	83.001%		

Overall accuracy (OA): 91.195%
Kappa[1]: 0.838

30SXJ

Truth data

Classifier results	Class 1	Class 2	Class 3	Class 4	Classification overall	User's accuracy (Precision)
Class 1	22124	17	17	285	22443	98.579%
Class 2	467	956	2174	721	4318	22.14%
Class 3	351	78	10006	81	10516	95.15%
Class 4	1261	1034	11	11139	13445	82.849%
Truth overall	24203	2085	12208	12226	50722	
Producer's accuracy (Recall)	91.41%	45.851%	81.963%	91.109%		

Overall accuracy (OA): 87.191%
Kappa[1]: 0.809

30SYJ

Truth data

Classifier results	Class 1	Class 2	Class 3	Class 4	Classification overall	User's accuracy (Precision)
Class 1	24645	4815	7	4100	33567	73.42%
Class 2	4576	66010	126	9448	80160	82.348%
Class 3	338	1249	1422	594	3603	39.467%
Class 4	7463	30503	11	52405	90382	57.982%
Truth overall	37022	102577	1566	66547	207712	
Producer's accuracy (Recall)	66.569%	64.352%	90.805%	78.749%		

Overall accuracy (OA): 69.559%
Kappa[1]: 0.525

Legend :
Annual cropland (class 1)
Perennial cropland (all but vineyard) (class 2)
Vineyard (class 3)
No cropland (class 4)

Figure 3-17. Confusion matrix of the “Broceliande” crop type map over the 3 test tiles

3.1.1.2 Irrigation map

The need for this map comes from a specific request from the Spanish NSO: they would like to be able to distinguish between irrigated and non-irrigated areas to know the big areas of potential irrigation and stratify their country to help in the update of the future sampling frame.

In order to answer this request, we have relied on the Land Parcel Identification System (LPIS) from 2020 on top of the ESYRCE data. Using the LPIS allows us to know where the different crops are growing and thus, to develop irrigation mapping methodology which are crop-specific (Figure 4-18). In the future, it would be possible to replace the LPIS data by the crop type map presented in section 4.1.1.

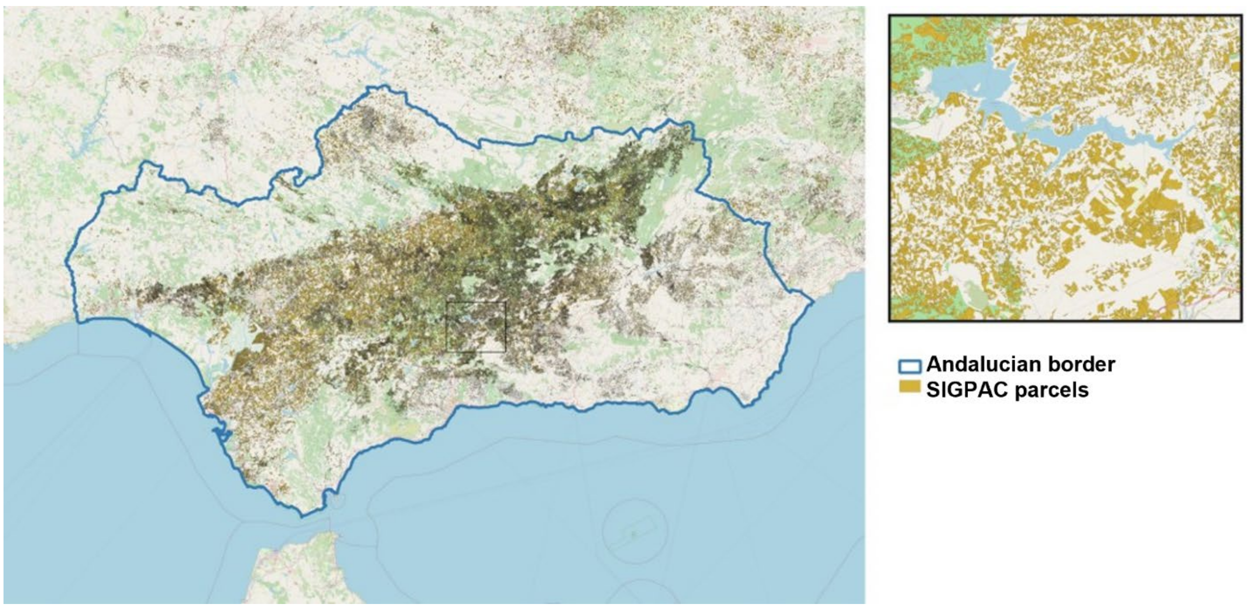


Figure 3-18. SIGPAC - Spanish LPIS - in Andalusia from 2020

The method applied to obtain the irrigation map is slightly different from the one implemented in the Sen4Stat system, since it works by crop type and it combines local and global classification models (Figure 4-19). The classification algorithm runs by S2 tile. For crop types where there are enough training samples, the model is local, i.e. by tile. On the other hand, the model is trained globally, i.e. over the whole region.

The obtained map is shown in Figure 4-20. Figure 4-21 and Figure 4-22 presents two zooms of the map, that give confidence in the irrigation detection. Irrigated areas are located around rivers and in the most intensive places of the region.

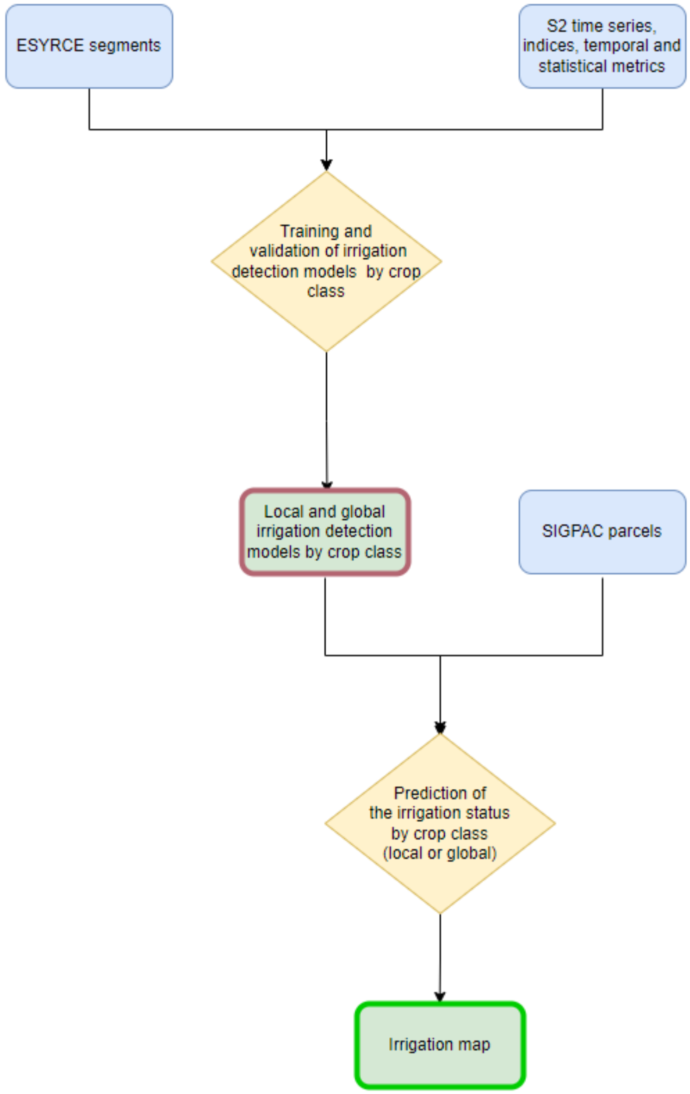


Figure 3-19. Methodology developed to map irrigation in Andalusia

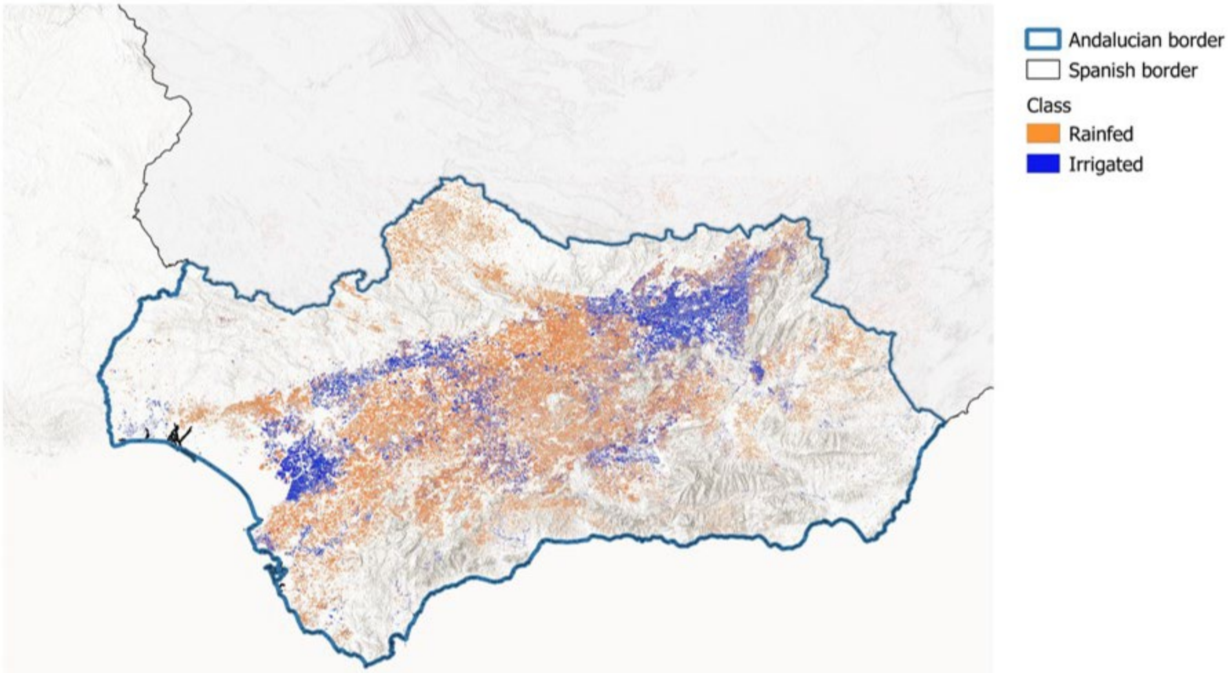


Figure 3-20. Irrigation map in Andalusia

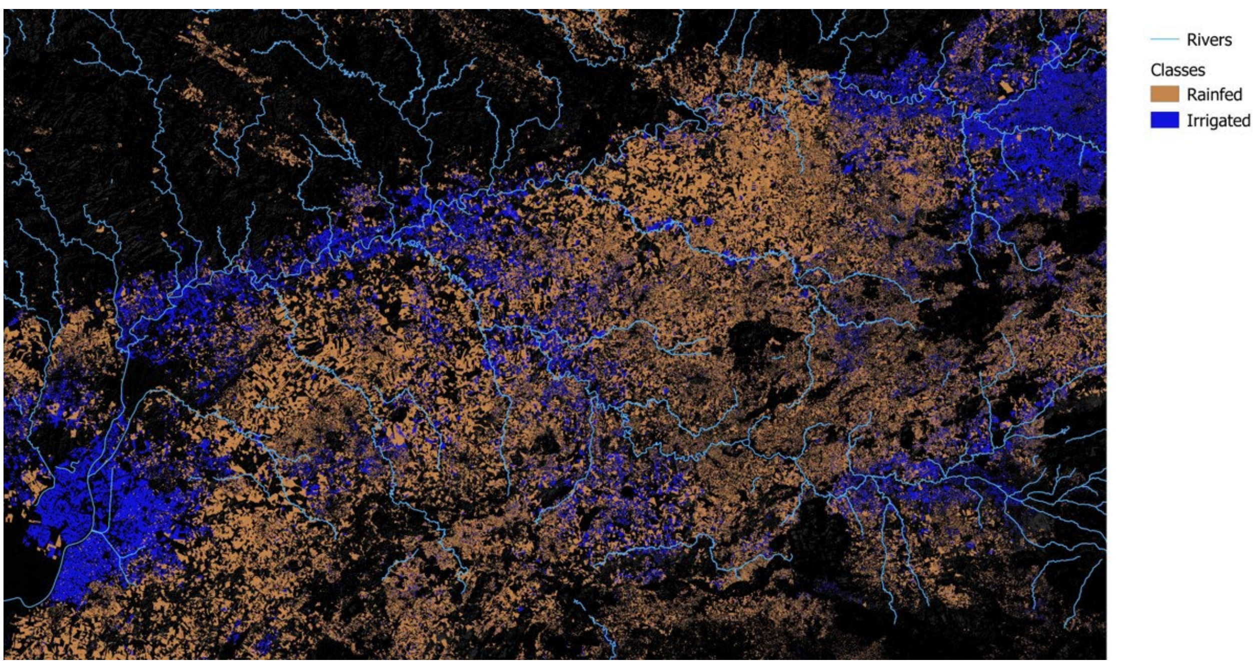


Figure 3-21. Zoom on the irrigation map in Andalusia

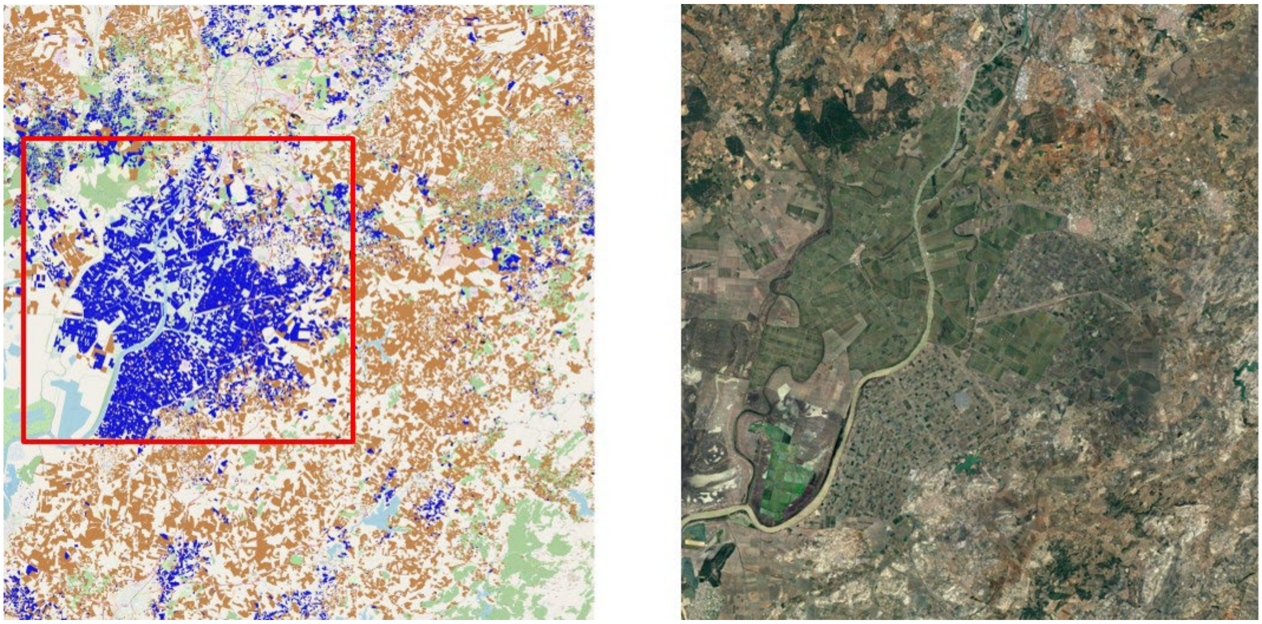


Figure 3-22. Zoom on the irrigation map in Andalusia over an intensive area of agriculture (red square)

F-Scores were calculated for the main crop types based on the local and global classification models (Figure 4-23 and Figure 4-24), and the high values confirm the good impression gained from the visual assessment.

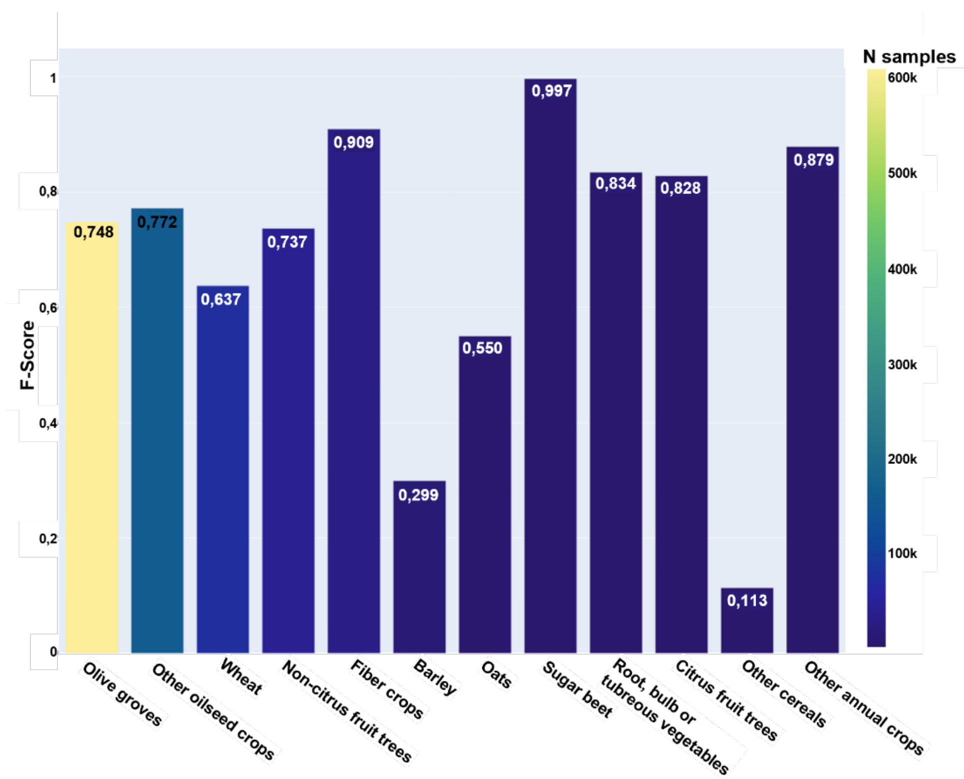


Figure 3-23. F-Score by class sorted by area (largest to smallest) of the irrigation map in Andalusia obtained by the local models

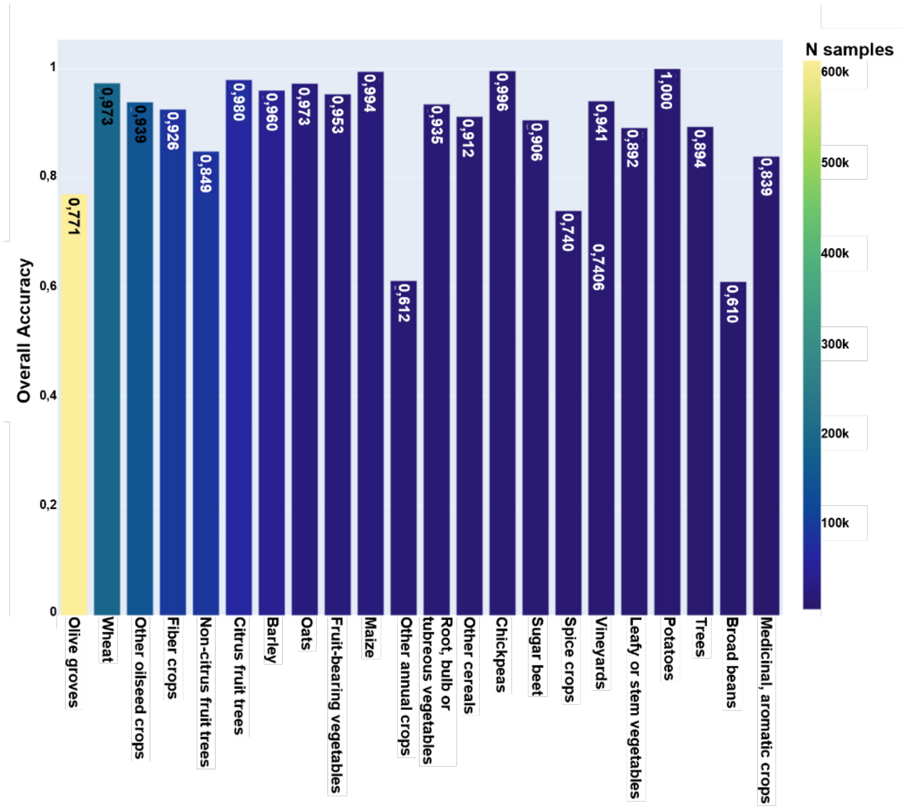


Figure 3-24. F-Score by class sorted by area (largest to smallest) of the irrigation map in Andalusia obtained by the global models

3.1.2 Cycle 2

3.1.2.1 Crop type maps

Figure 3-25 presents the crop type map obtained at national scale (continental Spain and Balearic Islands), the legend counting 38 different classes, including distinct non crop classes. The same map with a unique non crop class is shown in Figure 3-26, and a map showing the aggregation into crop groups is displayed in Figure 3-27. The national crop type map is the result of the aggregation by mosaicking of the 4 classified strata (Figure 2-9). Each stratum was classified using Sentinel-2 time series with different season start and end dates depending on the major crops within the stratum. A Random Forest algorithm was applied on the Sentinel-2 bands B03-04-05-06-07-08-11-12 and on the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) and Brightness. A Synthetic Minority Oversampling Technique (SMOTE) algorithm was used to increase the number of samples of the minor crops and therefore increase their representativeness.

The classification is generally homogeneous and effectively distinguishes crop types, but some artifacts can be observed over strata borders. This can be explained by some Sentinel-2 tiles belonging to multiple strata, and by very contrasted agricultural landscapes between strata not being correctly classified in overlapping areas.

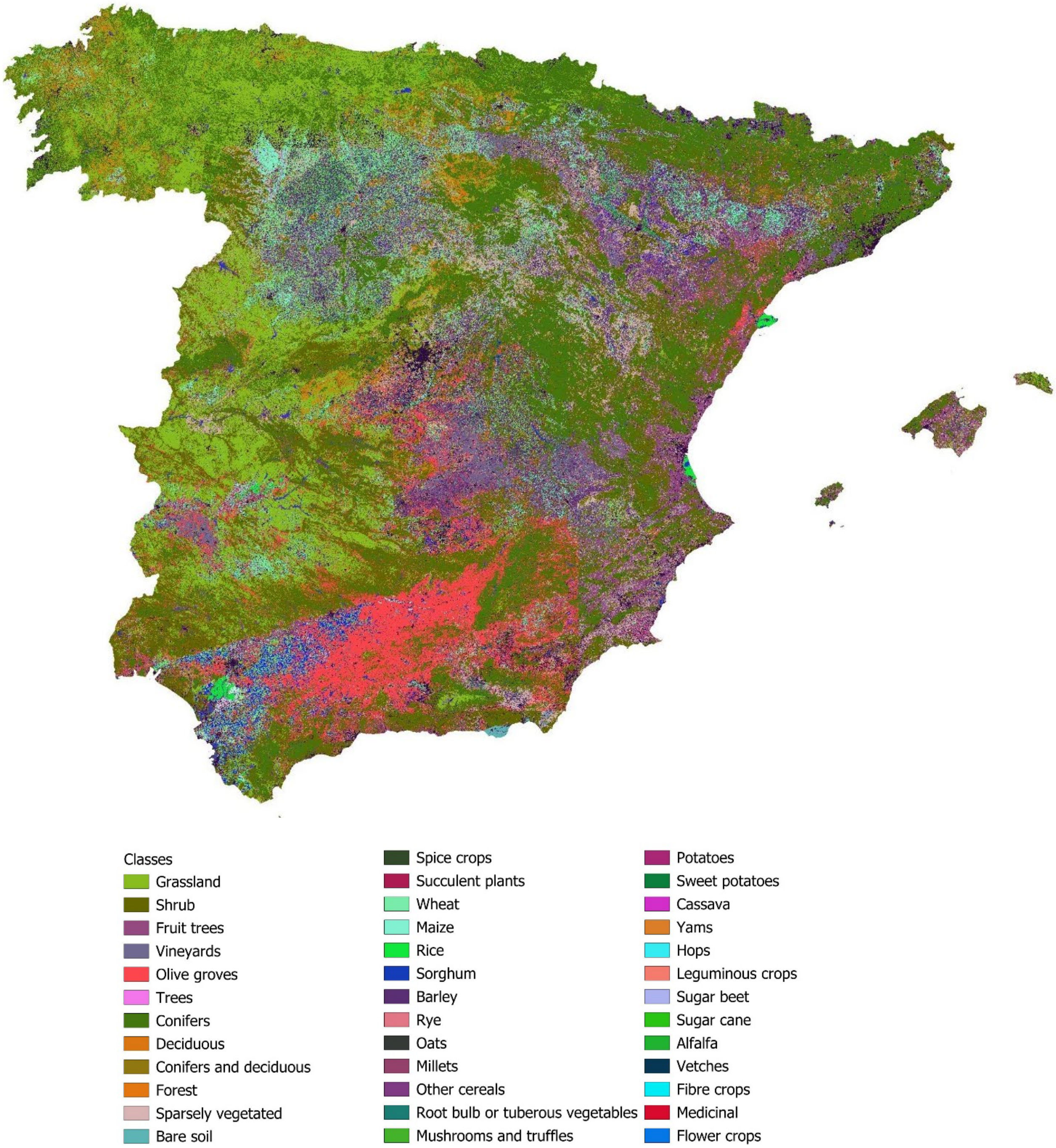


Figure 3-25. National scale crop type map in Spain

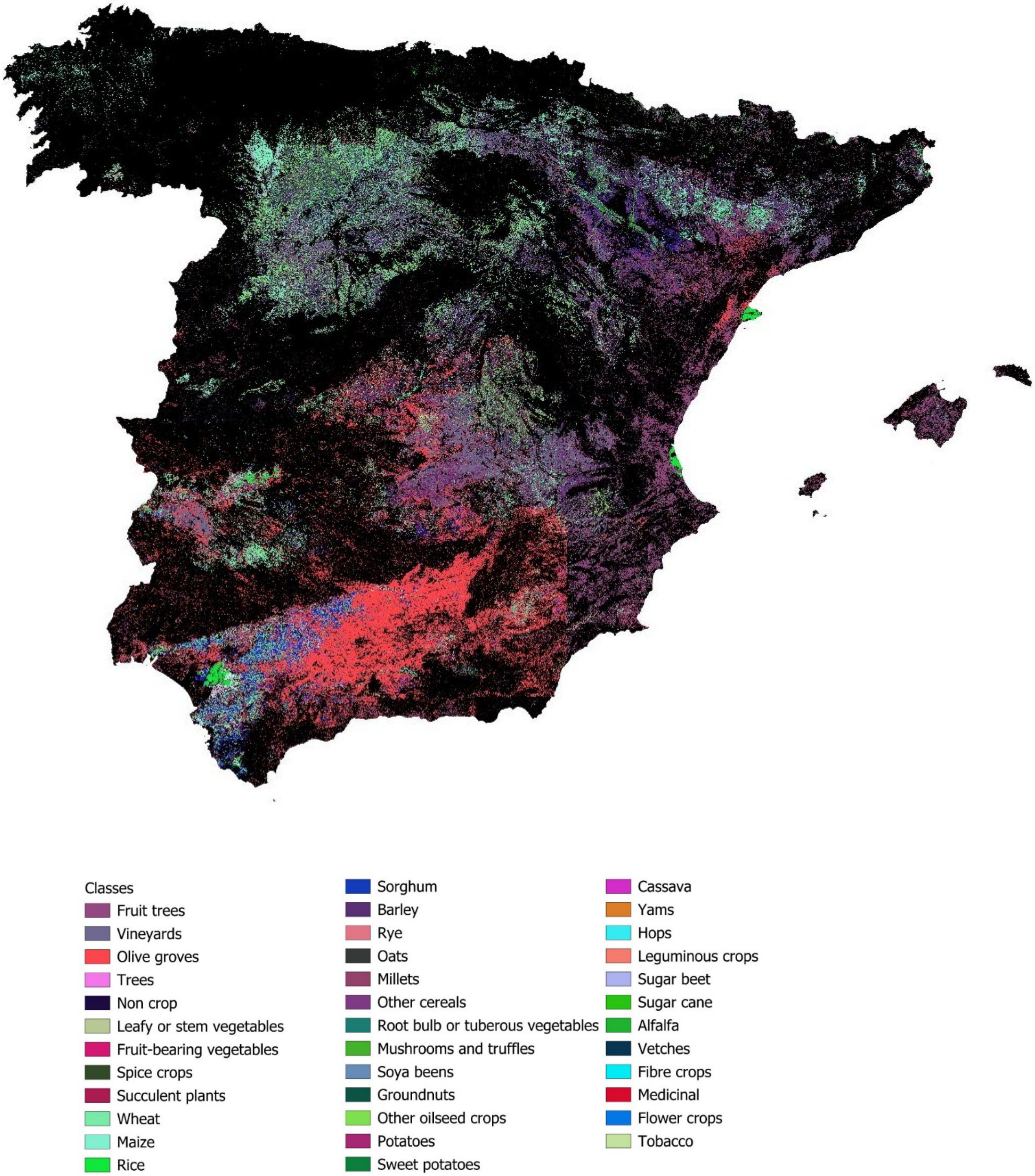


Figure 3-26. National scale crop type map in Spain (non-distinctive non crop class)

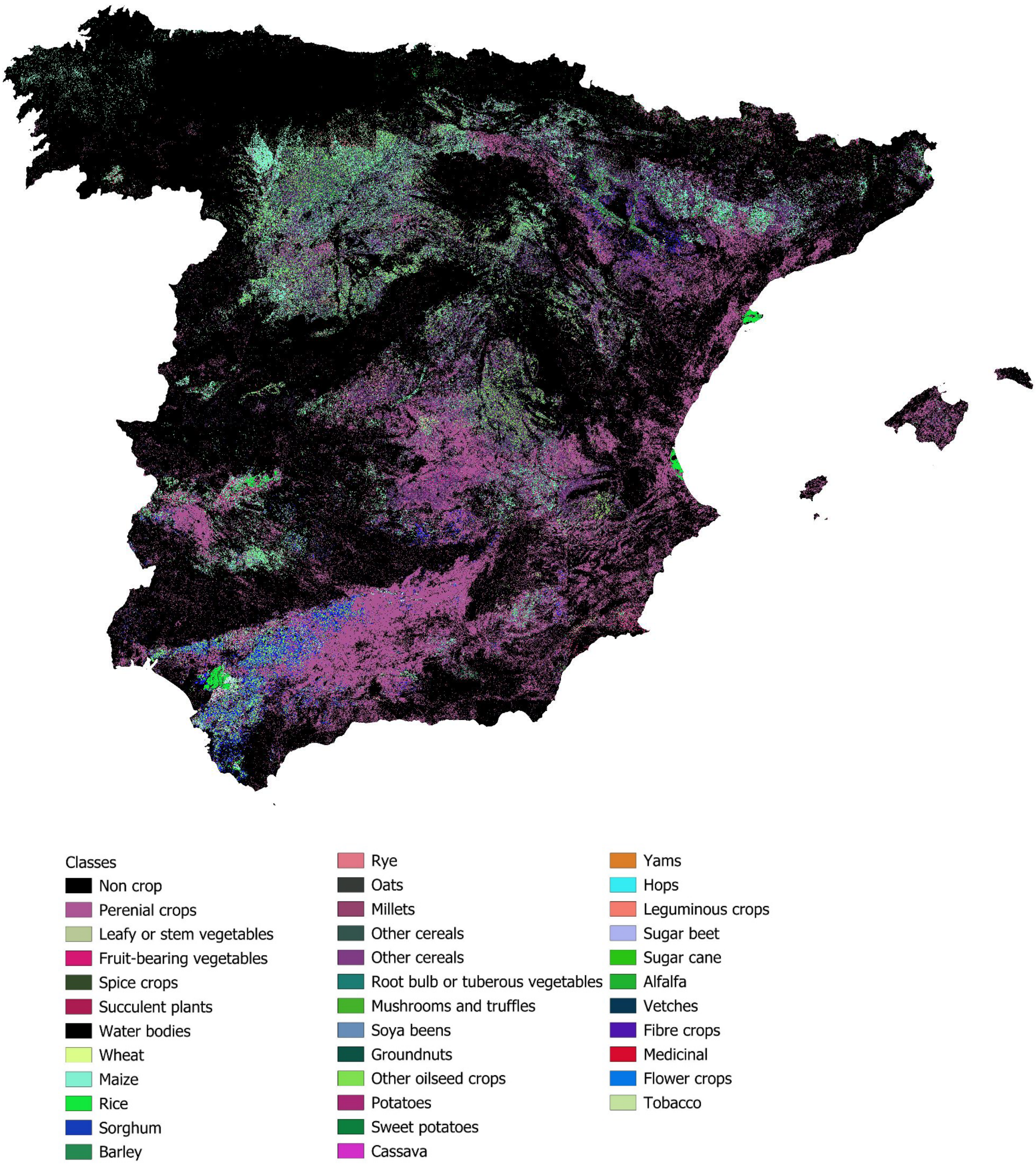


Figure 3-27. National scale crop type map in Spain (aggregated classes)

A quantitative assessment of the classification was conducted for each stratum, based on the confusion matrix of the model and on the accuracy metrics derived from it. The F-score sorted by class prevalence and confusion matrix are shown for each stratum below.

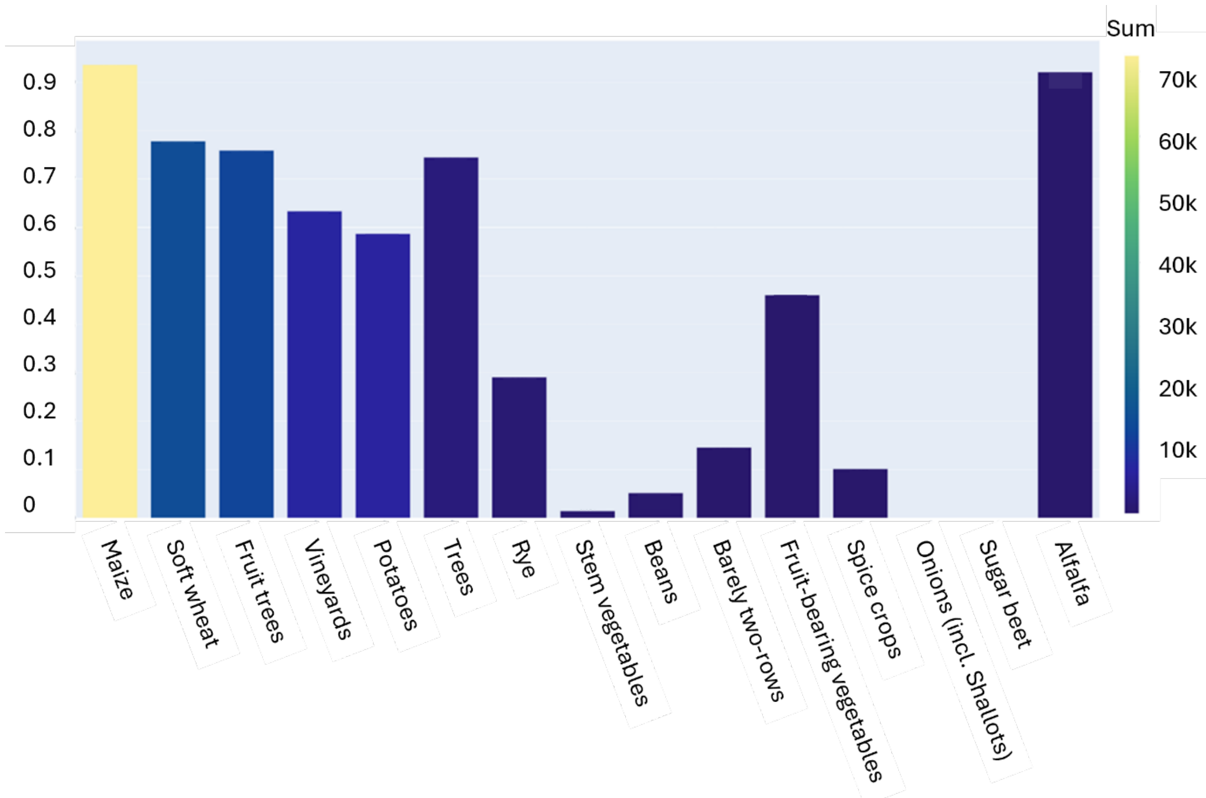


Figure 3-28. F-Score by class sorted by area (largest to smallest) of the crop type map in stratum 1

Stratum 1 is situated along the Atlantic coastline and is characterized by a landscape that is notably dominated by maize, wheat and fruit trees, which were well classified. The remaining crops were found to be of significantly minor proportion and therefore were less classified (Figure 3-28 and Figure 3-29).

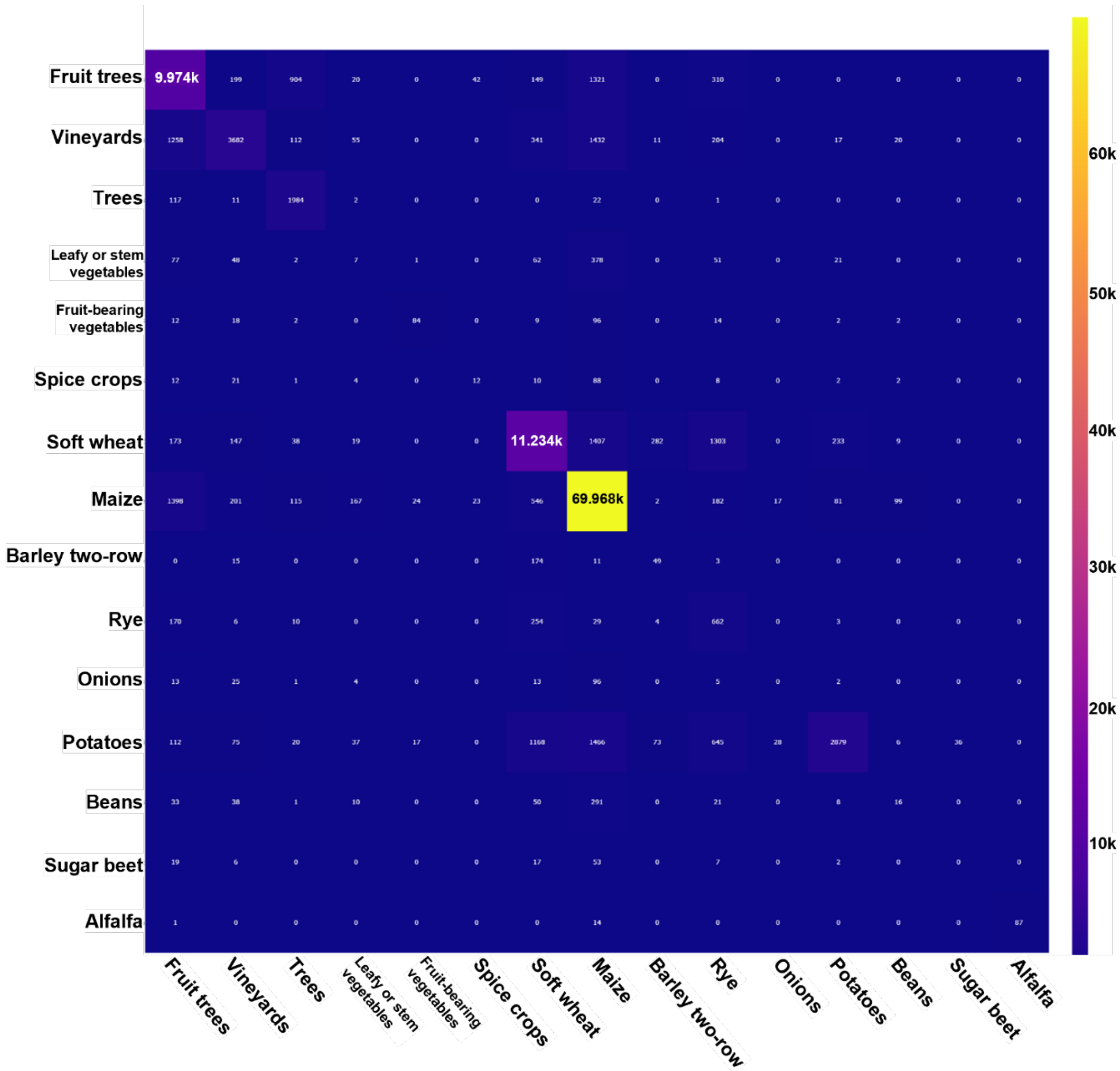


Figure 3-29. Confusion matrix of the classification in stratum 1

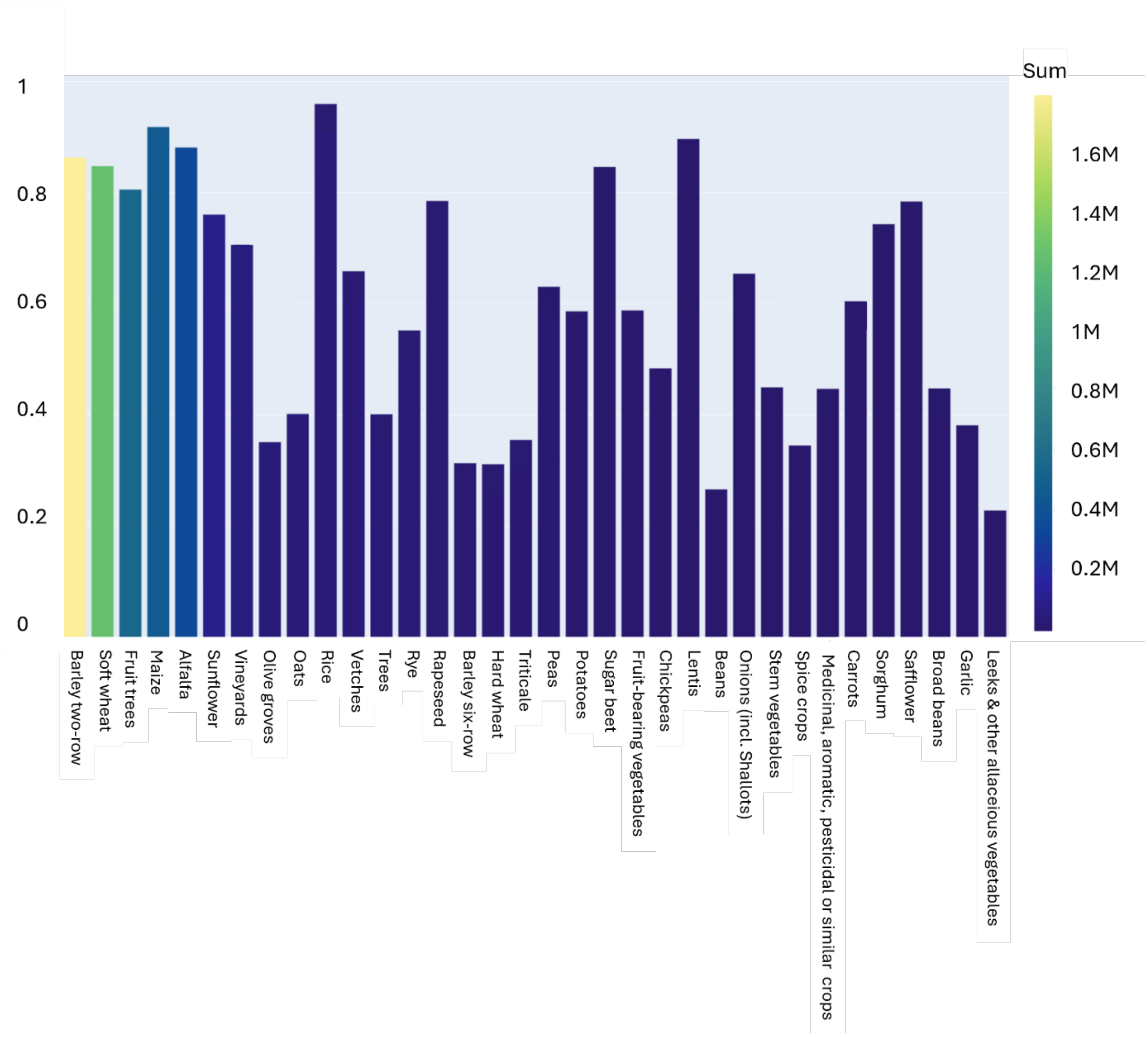


Figure 3-30. F-Score by class sorted by area (largest to smallest) of the crop type map in stratum 2

Stratum 2 spans over Castilla-y-Leon, Aragon and Catalonia. These autonomous communities are notable for their cereal, perennial fruit tree, fodder and oilseed crop production. The F-scores for each crop (Figure 3-30) and the confusion matrix (Figure 3-31) show that the primary source of confusion in the classification of stratum 2 is observed between barley and wheat and between olive groves, vineyards and orchards. These confusions are expected when considering the thematic proximity of these classes. Nevertheless, these classes were accurately classified.

Except for rice, the minor classes were less accurately classified, the confusions often taking place between similar classes (e.g. between hard wheat and soft wheat, two-rows barley and six-rows barley, and so forth).

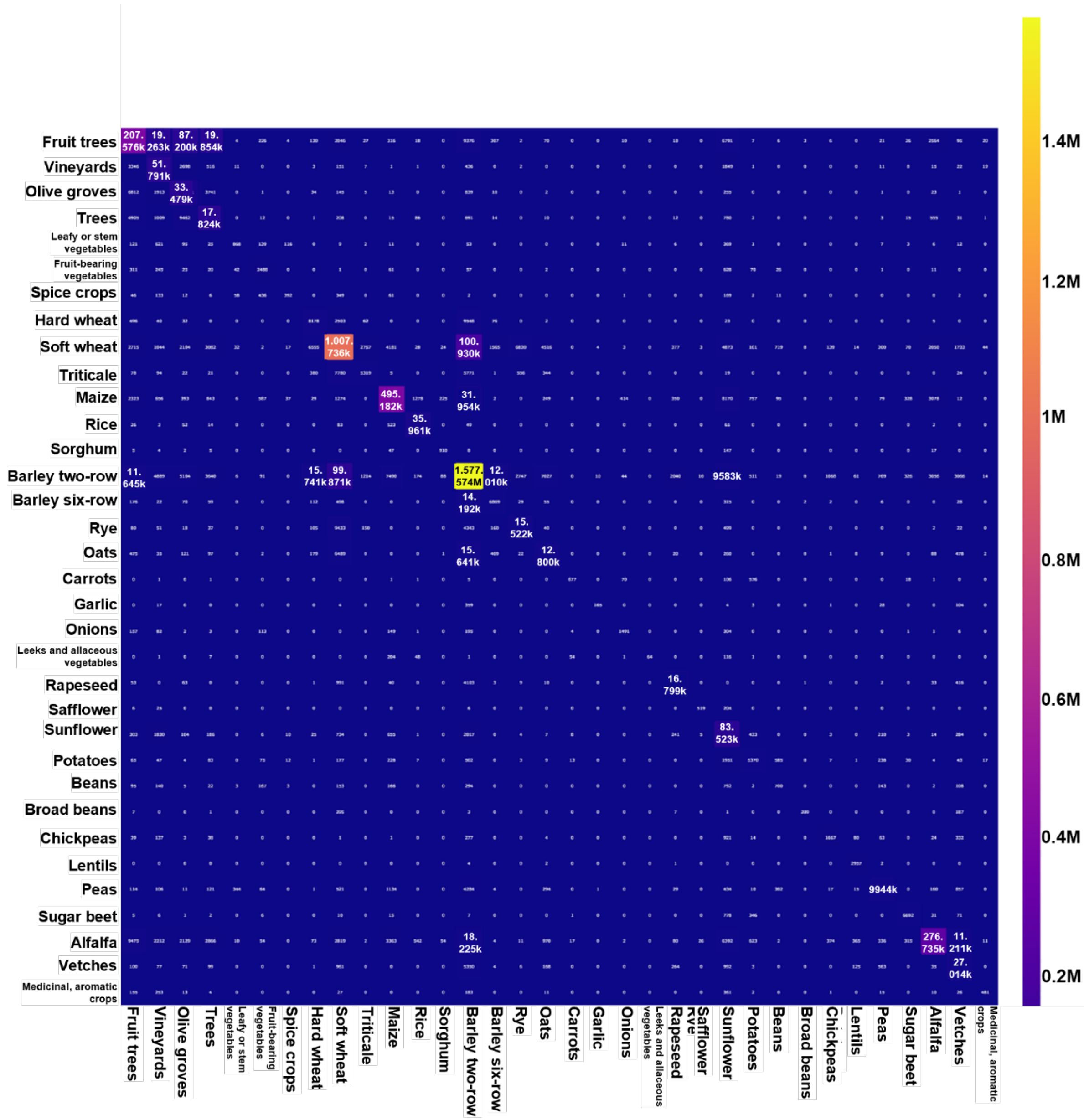


Figure 3-31. Confusion matrix of the classification in stratum 2

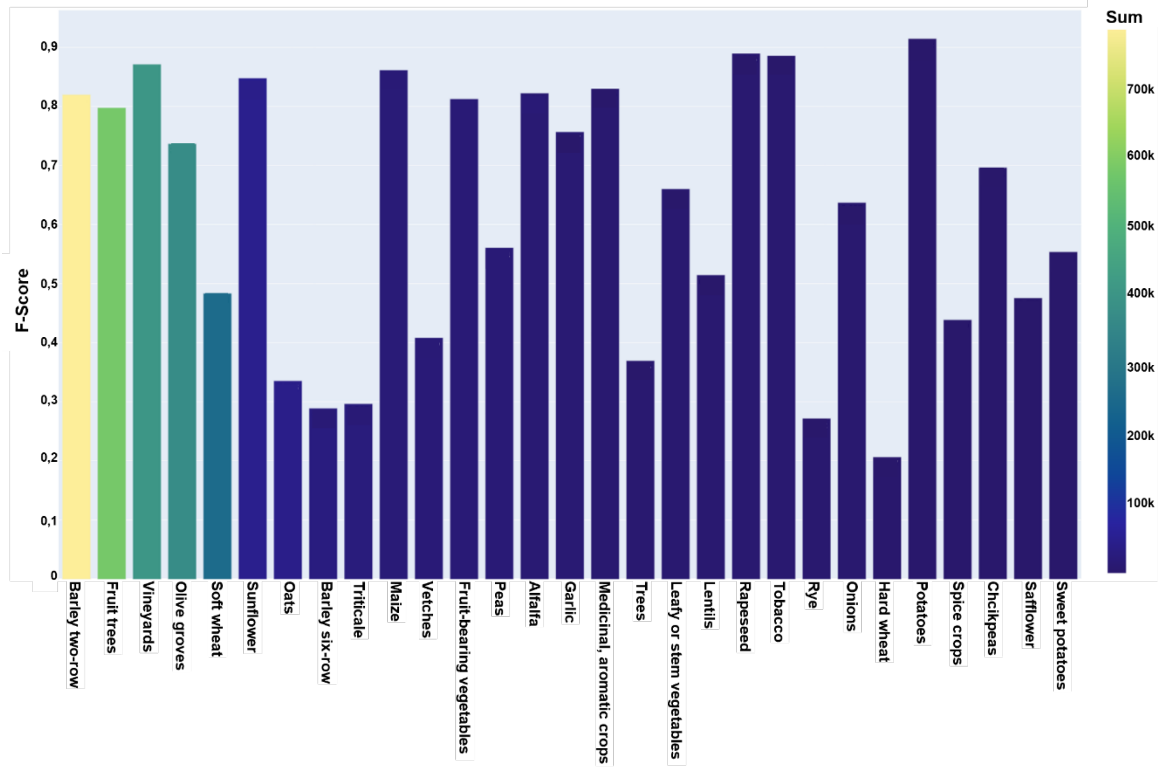


Figure 3-32. F-Score by aggregated class sorted by area (largest to smallest) of the crop type map in stratum 3

Stratum 3 spans over Castilla-la-Mancha, Murcia, and Valencian Community, where the major crops are barley and perennial fruit trees. The same type of thematic confusion between barley and wheat as in stratum 2 is observed and is geographically located over the overlapping areas between the northern part of stratum 2 and stratum 3. As can be seen in the confusion matrix (Figure 3-32) Commissions are also observed for oat, which is mixed with barley.

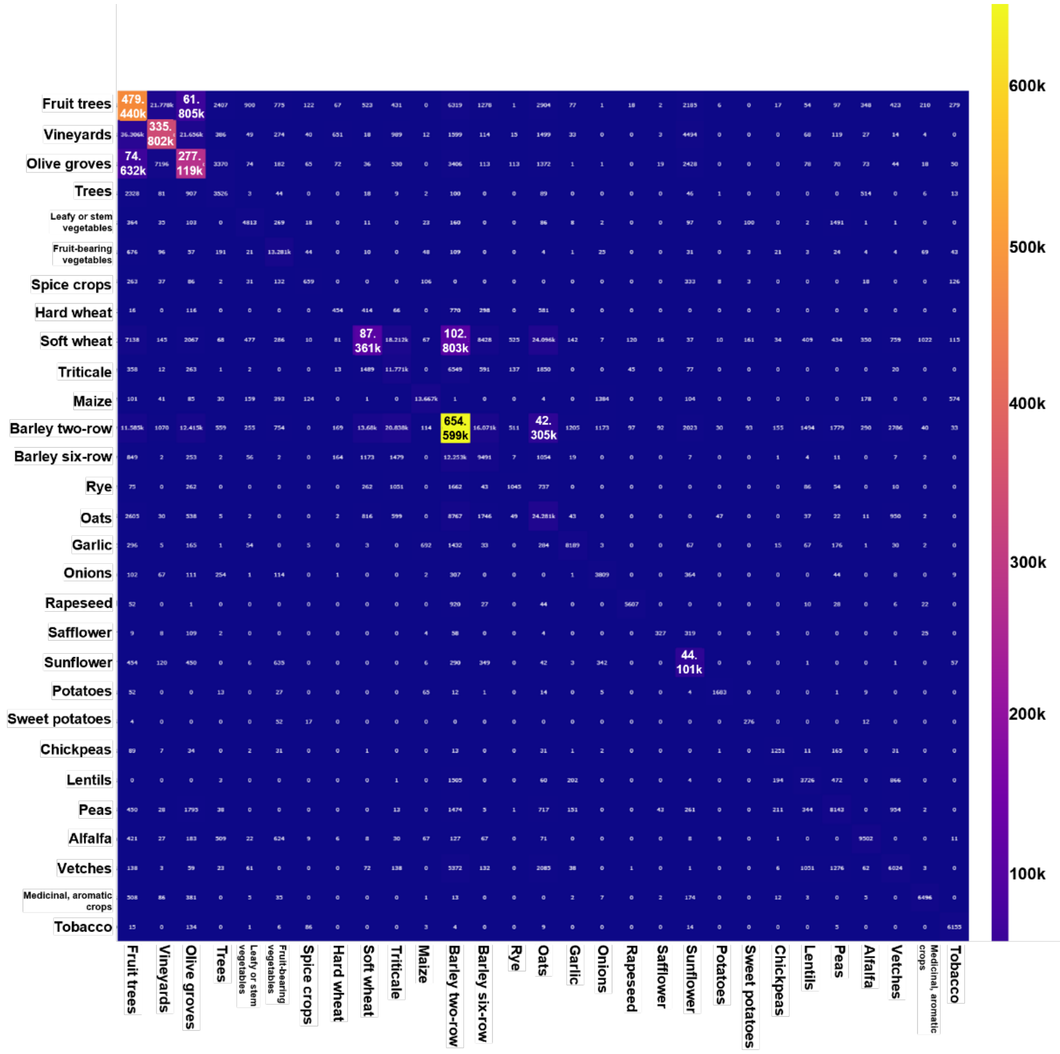


Figure 3-33. Confusion matrix of the classification in stratum 3

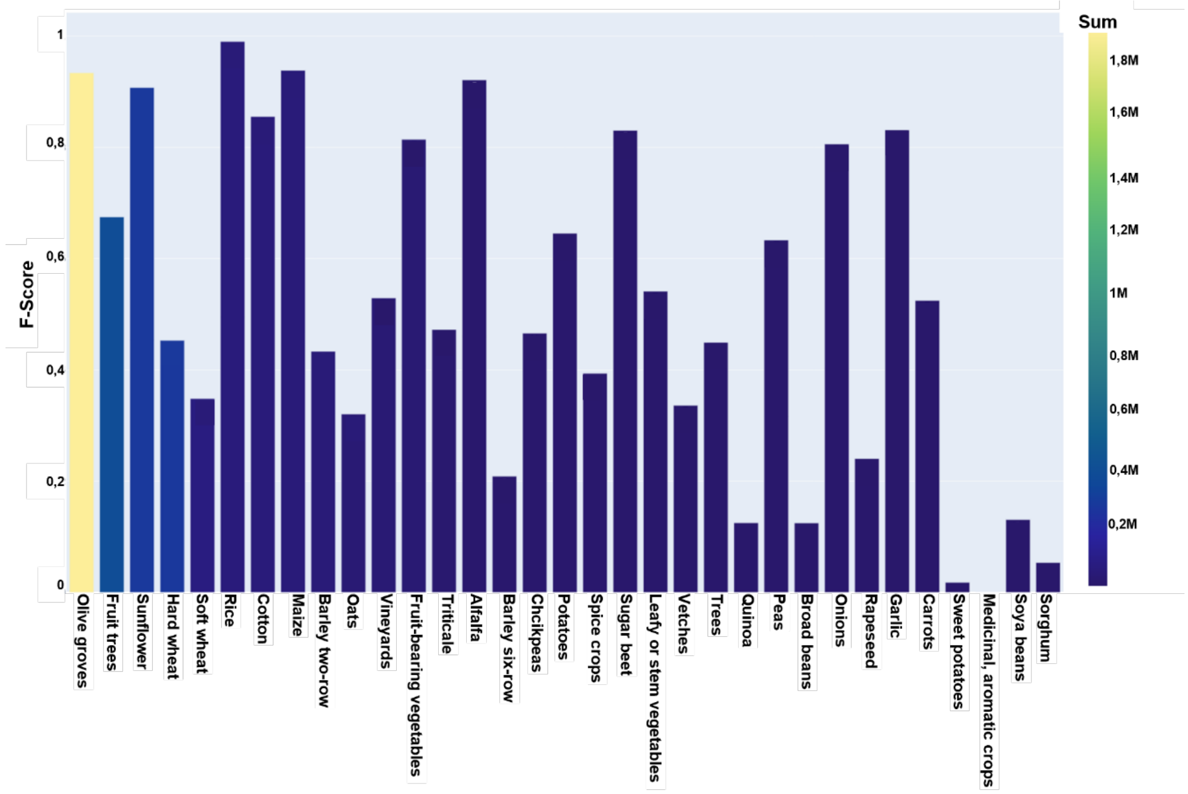


Figure 3-34. F-Score by aggregated class sorted by area (largest to smallest) of the crop type map in stratum 4

Stratum 4 spans over Andalucia and Extremadura and its agricultural landscape is largely dominated by perennial fruit trees (mainly olive groves). Omissions of fruit trees classified as olive groves can be noted when looking at the confusion matrix (Figure 3-35) as well as expected thematic classification errors between soft and hard wheat. Olive groves are well classified but generate the most confusion with minor classes due to the proportion of crops in the stratum.

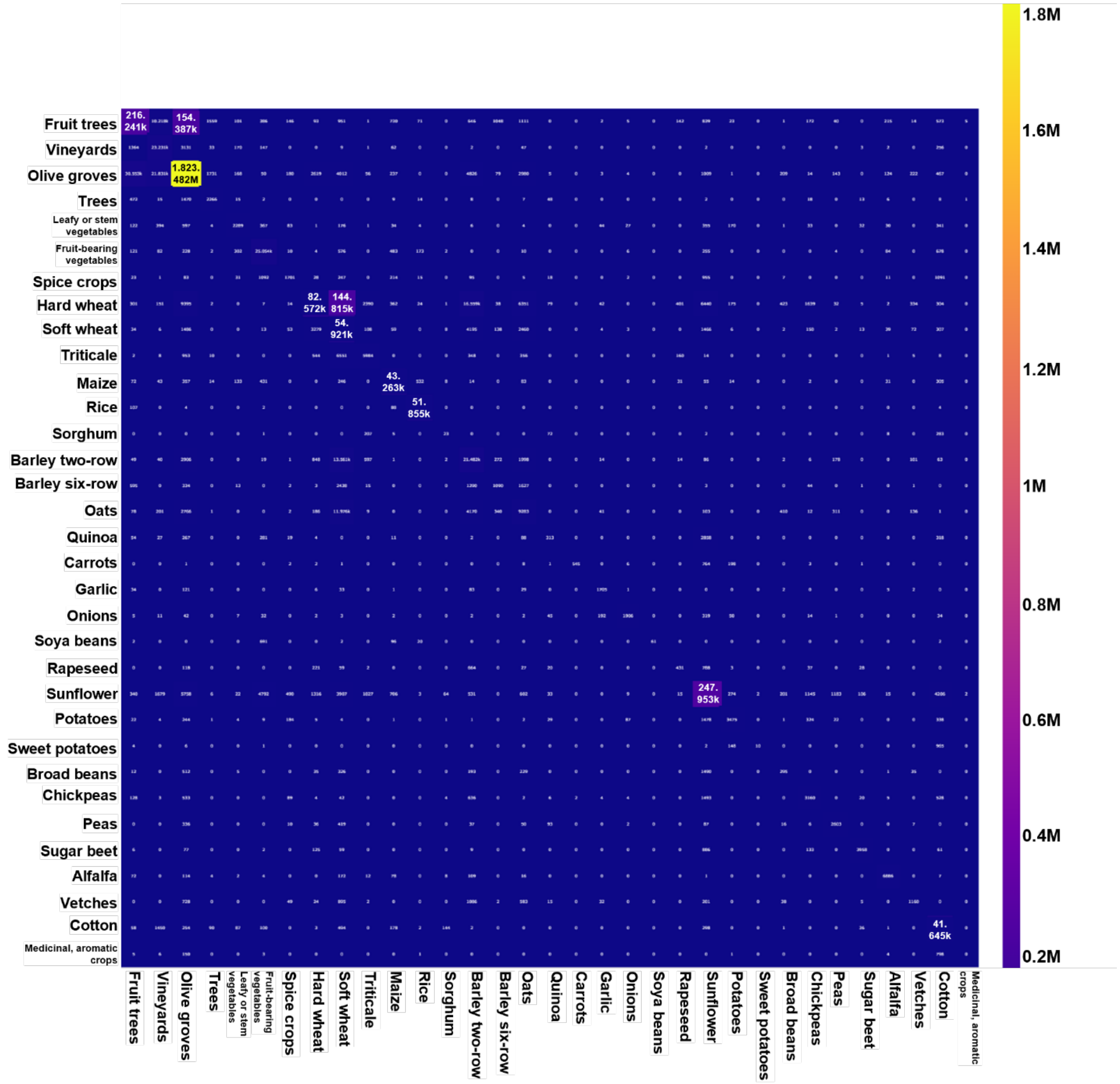


Figure 3-35. Confusion matrix of the classification in stratum 4

3.1.2.2 Crop yield

This case study was set up to show the effect of yield estimation from model at field level using remote sensing can be useful for estimating yield on a larger statistical scale. The idea was to show that estimating yield on a larger sample of data can improve confidence in aggregate statistics by virtually increasing the number of data points collected in the survey.

To do so, the Sen4stat yield processor was run on all the two-row barley plots recorded in the ESYRCE survey in the Autonomous Community of Castillà Y leon.

Table 3-1 shows that yield values are estimated for only about 30% of the ESYRCE plots. Yield values are mainly measured by visual observation by experts and, to a lesser extent, by cutting the crop and measuring the weight of the grain.

Table 3-1. Summary of barley two row fields in the ESYRCE survey for each Province of Castilla y Leon. On the left; the number of parcels containing a yield estimated by expert, on the right ; the total number of parcels censed in the survey.

	$ESYRCE_{yld}$	$ESYRCE_{crop}$
Àvila	151	330
Burgos	446	2530
Leòn	52	276
Palencia	304	1068
Salamanca	122	279
Segovia	294	775
Soria	275	662
Valladolid	460	1556
Zamora	206	624
Castilla Y Leòn	2310	8100

At first, 30% of the ESYRCE parcels containing a yield value, randomly selected, are removed from the dataset. Two estimation models based on the remaining 70% are then compared. Their results simulate the estimate that would be given by an incomplete ESYRCE survey.

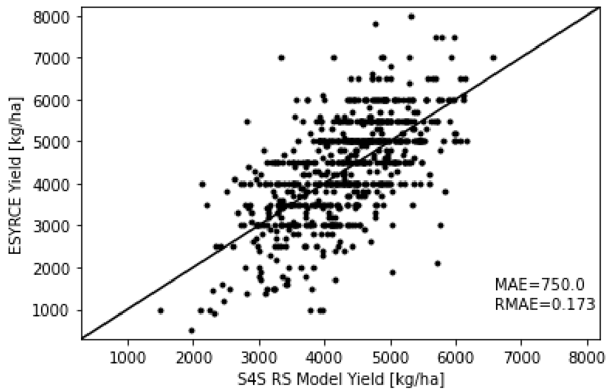
The first model (null model), currently used by the NSO, is based on the yield value measured in the field during the incomplete survey. The aggregation at the provincial level is done by weighting the area. In this way, the agricultural production of each field visited in each province is summed. Their respective average yield is equal to the sum of the production of their field divided by the total area of the visited fields in the province.

The second model (RS model) uses the S4S field level yield estimation module. The retained data (70%) from ESYRCE are used to train a regression model using the yield explanatory variables derived from the Yield Characteristics module. The regression model was then applied to all fields (70%+30%) to increase the amount of data used for aggregation. The estimates on the training plots (70%) provide information on any biases in the estimates for each province. These biases were used to correct the model estimates.

For the study, the algorithm selected was gradient boosting regressor (sklearn default setting) and all S4S features are used without pre-selection.

10 repetitions of this method were carried out, reiterating the 70-30 split. Table of Figure 3-36 shows the average performance of the 10 regressions and their standard deviations. Graph of Figure 3-36 display the performance of a randomly selected model from the 10 replications. In both cases, the performance is assessed on the basis of the 30% of plots not used for calibration.

Finally, all yield data referenced in ESYRCE were also aggregated (weighted by area) at the provincial level and used as a baseline for comparing the estimation models in the study.



	Mean	sd
MAE	744.5	24.6
RMAE	0.172	0.004

Figure 3-36. Performance of the S4S RS model estimation produced by the 10 repetitions of the 70/30 dataset partition, graphical comparison between one set of estimation and the ESYRCE reference yield.

The average provincial yields calculated with both models, their standard deviations and the MAE of the ten repetitions are presented in Table 3-2 and compared with the baseline model. Figure 3-37 presents the results

Table 3-2 and Figure 3-37 identify three points of discussion. For the majority of provinces, the use of the RS model significantly reduces the standard deviation of the ten estimates. The robustness of the estimate can be increased by reducing the confidence interval through synthetic augmentation of the data.

The RS model tends to bias the estimates moderately. A slight underestimation is observed in all provinces except Lèon. This underestimation remains relatively small, with the largest difference being 88 Kg/ha in the most productive province (Burgos).

Finally, it should be noted that the improvement in the mean absolute error over the ten estimates between the two models seems to be related to the amount of data. The use of the RS model degrades the quality of the estimate in three of the nine provinces (Burgos, Soria and Valladolid). These are the three provinces where the bias is most pronounced. Burgos and Valladolid are also the provinces with the highest number of barley observations. On the other hand, Avila and Leon, two of the three provinces with the lowest number of observations, benefit most from the use of the RS model. Thus, by synthetically increasing the data from 37 to 52 observations, the average error in the estimates for the province of Leon is reduced by about 50 kg/ha and the standard deviation around this average is reduced by about 46 kg/ha.

Table 3-2. Yield estimation of the provinces of Castilla-y-Lèon (kg/ha) given by ESYRCE and both models (Null and RS). The average yield, the standard deviation, and the mean absolute error computed on the ten repetitions of estimation are presented.

	ESYRCE		Null Model (10x)				S4S RS Model			
	N	Yield	N	Mean	Sd	MAE	N	Mean	Sd	MAE
Àvila	151	4250.2	107	4241.5	83.0	84.7	150	4232.4	34.9	37.9
Burgos	446	4852.4	315	4826.8	64.9	69.6	446	4764.3	38.2	88.1
Leòn	52	3792.7	37	3822.0	103.8	109.7	52	3817.5	57.0	59.2
Palencia	304	4585.6	211	4602.1	32.3	39.2	302	4557.5	17.0	29.9
Salamanca	122	4204.3	87	4155.8	63.1	81.5	122	4155.8	57.9	72.3
Segovia	294	4169.5	206	4168.0	52.5	52.8	294	4134.1	35.4	50.1
Soria	275	3617.5	192	3640.1	35.2	40.3	275	3542.6	26.8	74.9
Valladolid	460	4588.2	320	4574.6	37.8	41.4	459	4531.1	26.5	57.1
Zamora	206	4600.0	142	4586.8	65.0	67.2	204	4569.1	54.7	60.4
Castilla Y Leòn	2310	4437.2	1617	4426.5	16.5	20.8	2304	4391.9	14.0	45.3

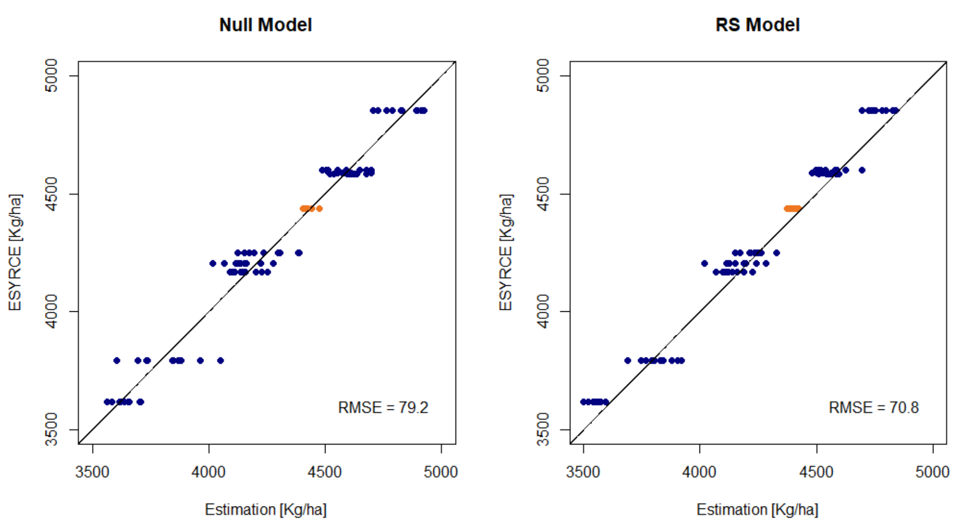


Figure 3-37. Repetition of estimates aggregated at province level for both methods (Null and RS model)

This study shows that the model incorporating the remote sensing variables, although not capable of accurately estimating yields at the plot scale, can be used to synthetically augment data in poorly represented statistical units and thus improve the robustness of estimates at this scale. Since the use of the RS model greatly reduces the standard deviation of the estimates, it is likely that improving the performance of the estimation model at the field level would allow the number of samples to be measured in the field to be reduced while maintaining the same confidence in the estimates.

For this exercise, the model trained on the yield data collected in ESYRCE was applied to all the Barley fields censed in the survey. This method, used with a high-performance RS model, is intended to limit sampling bias, by producing an estimate for all plots spread over a territory. This exercise was carried out as an example, but could not be correctly validated. The results are presented in Table 3-3.

It can be seen that the estimate given by our model for the provinces of Segovia and Valladolid is significantly higher than ESYRCE. In the previous exercise, our models showed a tendency to underestimate yields in these provinces. The addition of estimates on a larger number of plots (~500 for Segovia and 1150 for Valladolid), undoubtedly better distributed over the territory, has probably highlighted a sampling bias implying an underestimation of yields in these two provinces.

Table 3-3. Comparison of ESYRCE Yield estimation given by Province with the S4S RS yield estimation model applied on all the barley fields of the survey.

	ESYRCE		S4S RS Model	
	N	Yield [kg/ha]	N	Yield [kg/ha]
Àvila	151	4250.2	330	4297.8
Burgos	446	4852.4	2530	4678.7
Leòn	52	3792.7	276	4077.1
Palencia	304	4585.6	1068	4541.2
Salamanca	122	4204.3	279	4193.0
Segovia	294	4169.5	775	4327.8
Soria	275	3617.5	662	3611.5
Valladolid	460	4588.2	1556	4676.4
Zamora	206	4600.0	624	4462.6
Castilla Y Leòn	2310	4437.2	8100	4483.0

3.1.2.3 Irrigation map

The national scale irrigation map presented in Figure 3-31 was computed based on the same principles as the one presented in cycle 1. However, the method was optimized to limit computing needs in terms of volume and processing time. The method described in cycle 1 made use of distinct models at two spatial scales for each crop type, which yielded good results, but is impossible to scale up without substantial computing power.

To account for varying phenological response to irrigation across crop types at national scale, we employed a pixel-based categorical gradient boosting model. This model classified each pixel with known crop types (information from the farmers' declarations) as rainfed or irrigated. Meaning a single model could be used, considering the crop type of classified pixels as categorical feature and Sentinel-2 bands and spectral indices computed by the Sen4Stat system as continuous features. Specific statistical and temporal metrics were also designed to highlight phenological differences between irrigated and rainfed parcels at specific dates and throughout the growing season. A schematic summary of the method is shown in Figure 3-38.

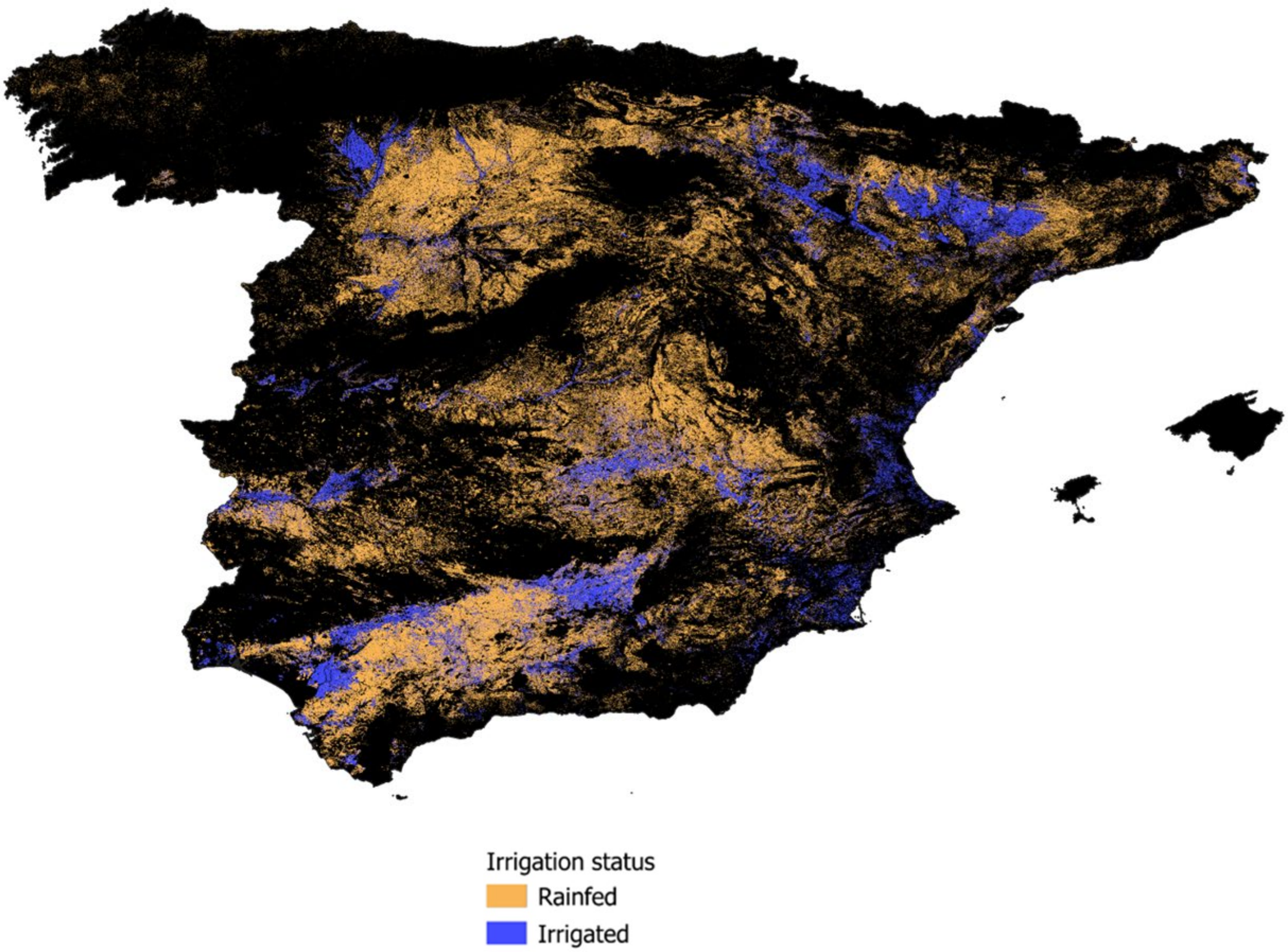
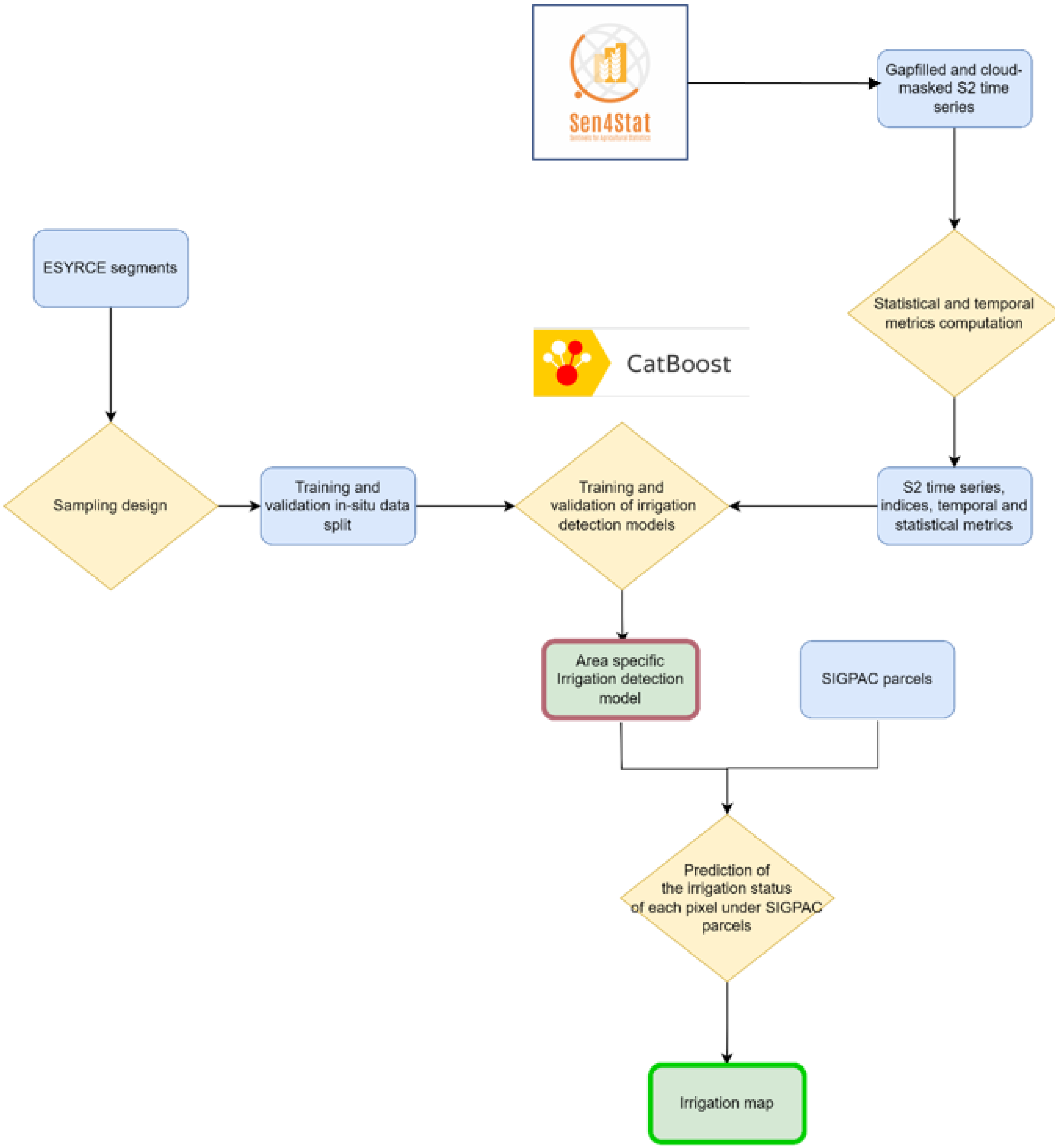


Figure 3-38. Irrigation map in Spain



s

Figure 3-39. Methodology developed to map irrigation

Accuracy metrics of the classification were computed separately for each crop type in Spain (Figure 3-40). Good F-scores were attained for the major classes, including those with irrigation proportions that were neither notably abundant nor scarce.

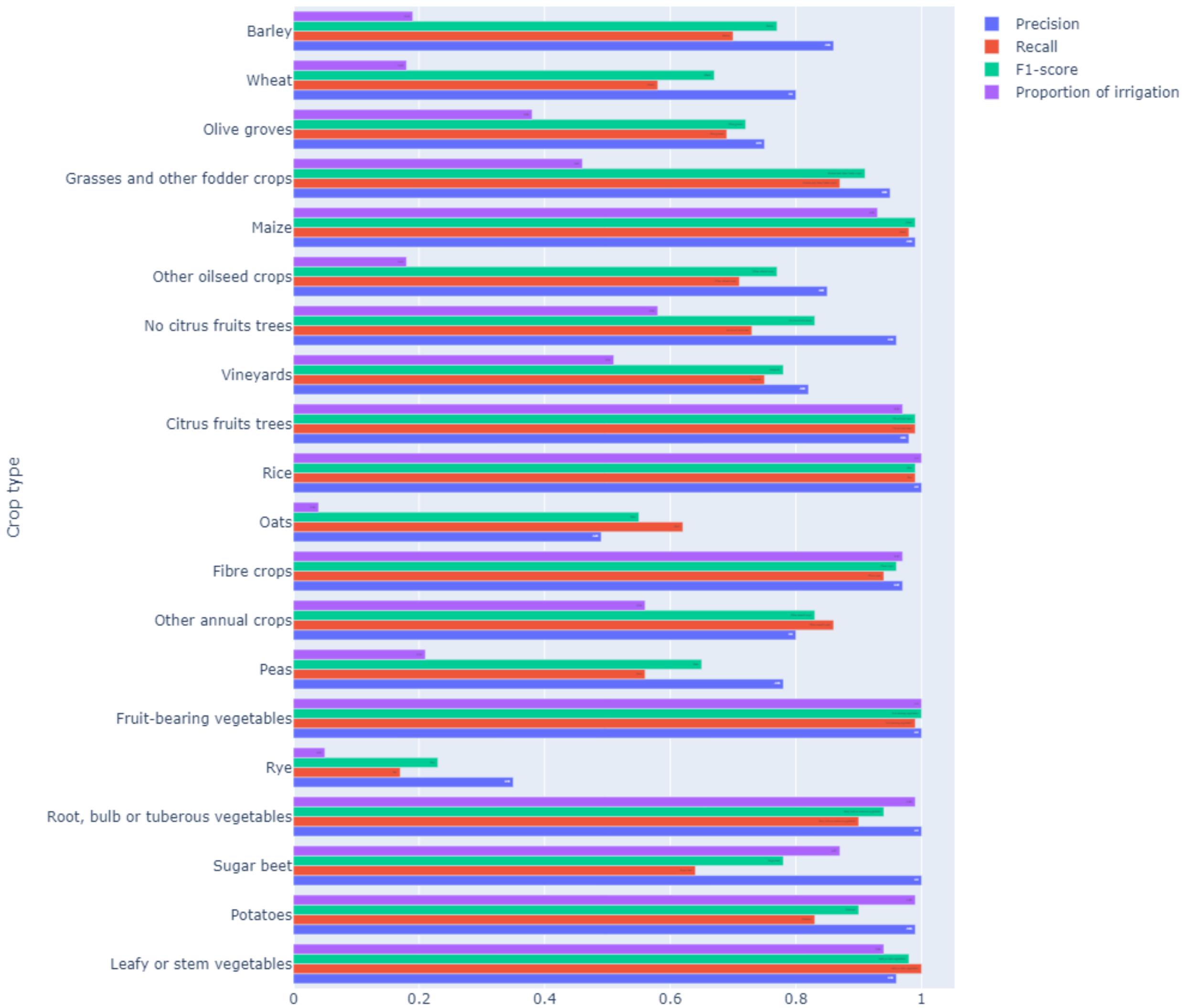


Figure 3-40. F-Score, Precision, Recall and irrigation proportion in validation data by class sorted by area (largest on top to smallest on the bottom) of the irrigation map in Spain.

3.2 Senegal

3.2.1 Cycle 1

3.2.1.1 Pilot survey design and data quality control

3.2.1.1.1 Implementation of the pilot survey

A pilot survey complementary to the official Annual Agricultural Survey (AAS) was designed and organized in the department of Nioro du Rip with the help of the FAO facilitator and the national stakeholder, the Direction de l'Analyse, de la Prévision et des Statistiques Agricoles (DAPSA).

The objective was to ensure the link between field data and remote sensing data. The initial protocol (2020) of the DAPSA survey campaign consists in the use of the GPS Garmin 64 and a survey form on the CSEntry application. The use of the 2020 field data throughout the country highlighted the difficulties of linking them with remote sensing:

- in terms of field delineation, a Garmin GPS is used to calculate the area of the fields, but little or no record is kept of the GPS tracks obtained. The geometries are often truncated. It was therefore impossible to know the exact boundaries of the fields and the part of the AAS related;
- following the protocol, a GPS point is taken in each field. Unfortunately, it is often not located inside it. Having the points, drawing the crop outline is difficult manually from very high resolution images because plot boundaries can shift from year to year.

Based on the 2 tools (Garmin GPS and tablet), the pilot survey in the Nioro department was proposed to ensure that field polygons are systematically recorded to obtain data compatible with remote sensing. The use of CSEntry is subject to an agreement between the DAPSA and the FAO and was not easily modifiable for field data collection in 2021 (e.g. addition of polygon recording and new questions for integration into remote sensing). The Open Data Kit Collect (ODK) tool installed on an Android tablet is chosen as additional tool for collecting information about the heterogeneity of plots, the presence or not of mixed crops, the crop cutting for yield information and for ensuring the recording of parcels delineation.

The defined pilot protocol discussed with the DAPSA consists in tracing the plots on one hand with the Garmin GPS and on the other hand with the tablet via the ODK Collect application. The data are sent daily to a server accessible by both protagonists.

Many points were discussed with the DAPSA to ensure the feasibility of the survey and various tests were conducted in that regard.

3.2.1.1.2 Description of the collected data

Five teams worked on the field and simultaneously, the DAPSA and UCLouvain did a quick quality control of the data each day in order to adjust the survey in real time if necessary. For example, it was difficult for some investigators to properly delimit the fields at the beginning of the campaign. It was necessary to redefine the way points were taken.

The data were to be used to produce a crop type map and a yield prediction map, both disaggregated by municipality.

- ***ODK data***

A total of 231 plots were investigated with the new ODK survey out of the 396 inventoried by the initial CSEntry survey. This difference is due to a communication error during data collection: taking measurements with two different tools on all parcels complicated the task for the investigators. In order to simplify the protocol, it was suggested to plot the first parcel of each household on the ODK app, while the other ones continue to be plotted by the GPS Garmin. What was not foreseen in the protocol was that the entire ODK survey was then omitted for the other parcels.

Some geometries taken with the tablet via ODK Collect have poor delineation. The plots were taken in a manual mode on the tablet, i.e. the surveyor manually encodes the points at the inflection points of the plot. On the other hand, some are very well delineated (better than GPS) especially after redefining the way of taking polygons when collecting data in the field (Figure 3-41).

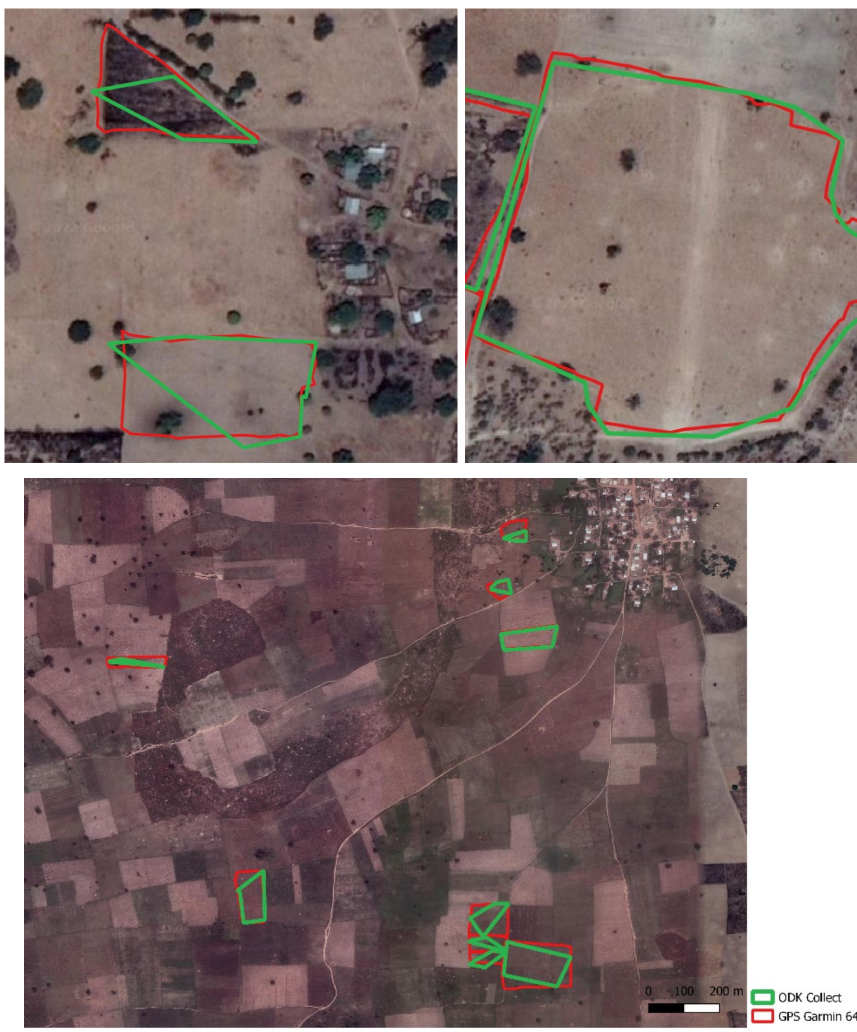


Figure 3-41. Parcel's polygons from Garmin GPS in red and from the tablet's GPS in green

- ***GPS data***

357 Garmin GPS tracks were recorded at the end of the field data collection. The difference with the 396 plots from CSEntry is explained by:

i. plot naming errors in the Garmin GPS (29 polygons). The link between the field data and the Garmin GPS is done through a unique name manually encoded in the GPS, which leads to errors. However, dozens of polygons were recovered after manual work;
ii. the loss of GPS tracks between the measurement and the sending. Some lines of field data could not be linked in any way to a polygon.

- ***Yield data***

A key feature of the Nioro pilot survey is the measurement of yields of selected crops through a crop cut square to produce a yield prediction map. The results of the crop cut and the yield per crop arrived a few months after the field survey (Figure 3-42). Some problems detected in the data made it difficult to use the data:

i. the data were aggregated by household without plot information. It was therefore impossible to relate yield predictions to measured yields;
ii. the names used to link the different data were sometimes incorrect (naming and reporting problems).

Since the results were not usable for remote sensing, one solution could have been to use the exact location of the crop cutting square requested in the ODK Collect survey. However, it appears that the location point was not taken on the crop cut but at the edges of the plots. They could not be used to improve the yield prediction results.

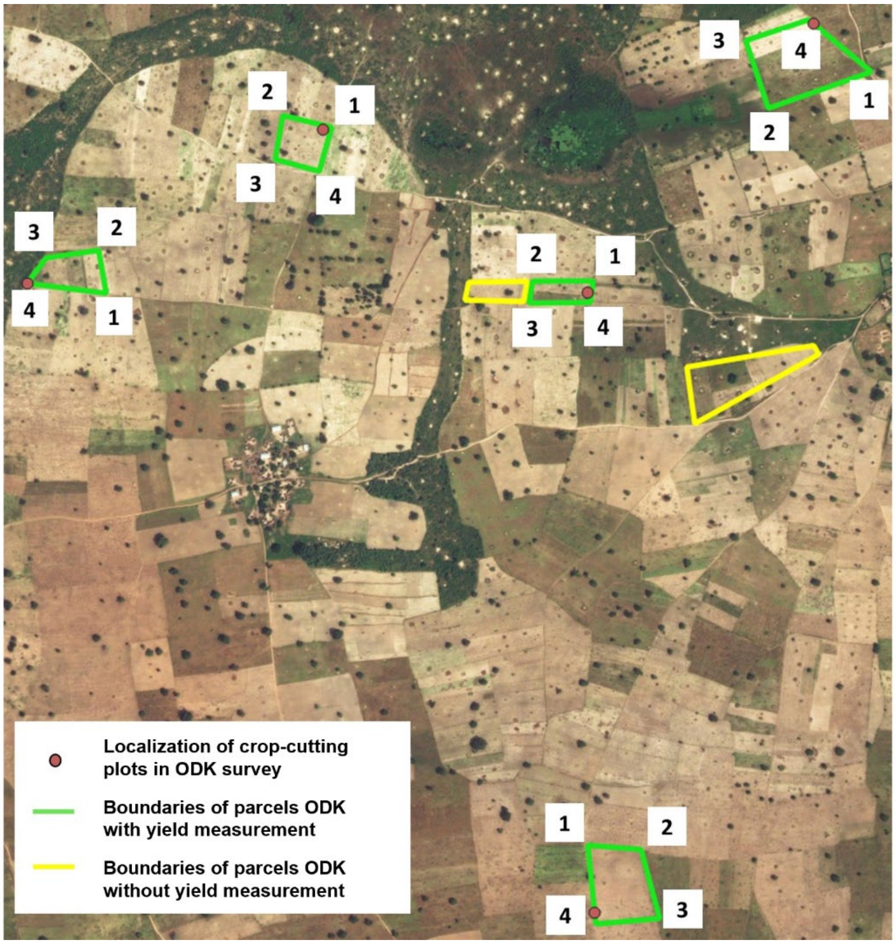


Figure 3-42. Location of crop cutting squares

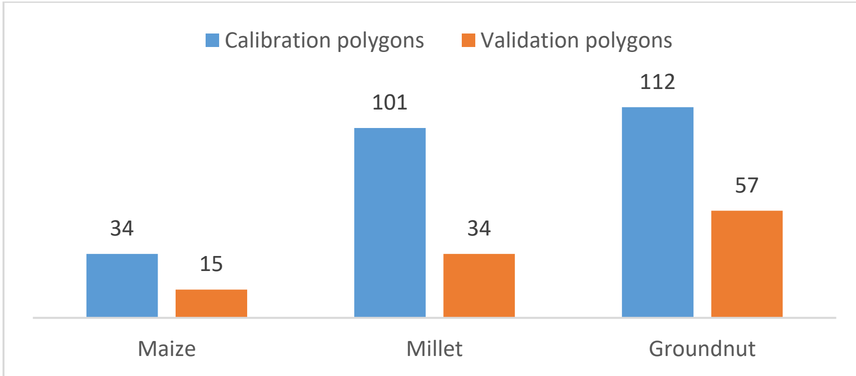
- ***Non-crop class data***

The ODK Collect survey included the creation of polygons representing non-crop classes. Few were recorded, but some classes were not represented. The information on non-crop classes was finally obtained by hand using very high resolution images. In total, 50 polygons were available for the non-crop classes.

Based on this data quality analysis and after discussion during the final workshop, it would be useful to further investigate for the next campaign (2022) the best methods to implement to obtain field data easily compatible with remote sensing.

3.2.1.2 Crop type map and estimates for Nioro district 2021

The crop type map was generated at the end of the season from May 1, 2021 to December 31, 2021. The training dataset used contains the 50 non-crop polygons and the 247 crop polygons obtained after joining and cleaning the ODK dataset as in situ input data (Figure 3-43 – calibration polygons). The distribution of observations is very uneven for the different crops and insufficient for maize.



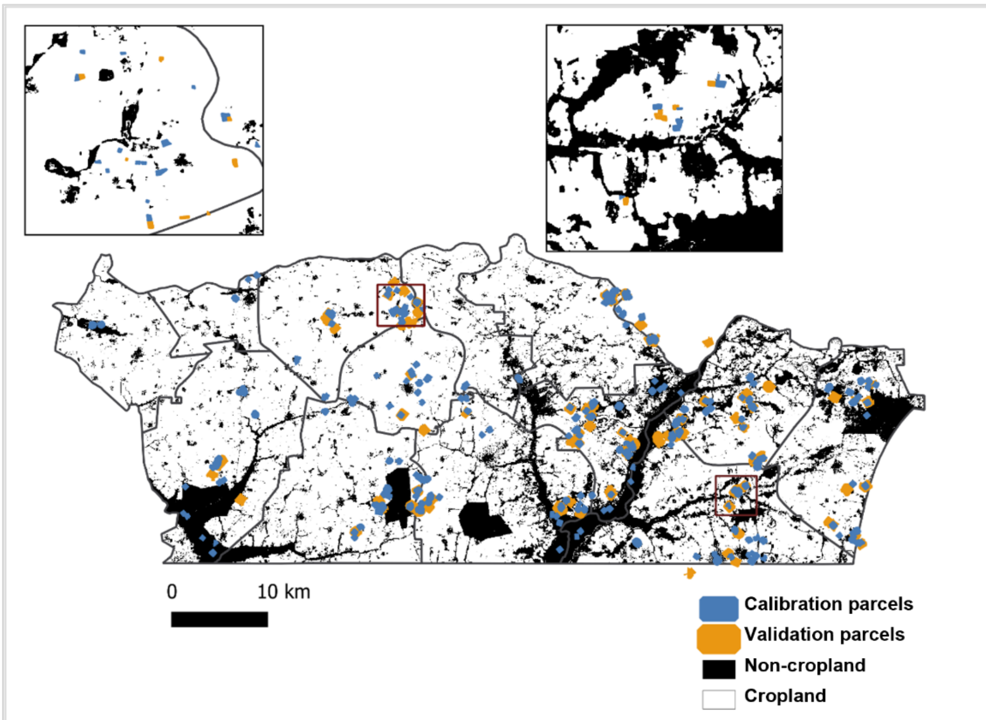


Figure 3-43. Distribution of in-situ data into a calibration data set and a validation data set

The crop type map was obtained using both S2 and Sentinel-1 (S1) time series. The obtained crop type map is shown in Figure 3-44.

The confusion matrix is presented in Figure 3-45. The overall accuracy of the crop mask is 97.1% and it is of 88.2% for the crop type. The F-Score values for cropland and non-cropland are 98% and 95% respectively. The F-score values are 54.8% for maize, 83.8% for millet, and 95.2% for groundnut. There is a very strong omission of maize. Millet is both contaminating and omitted.

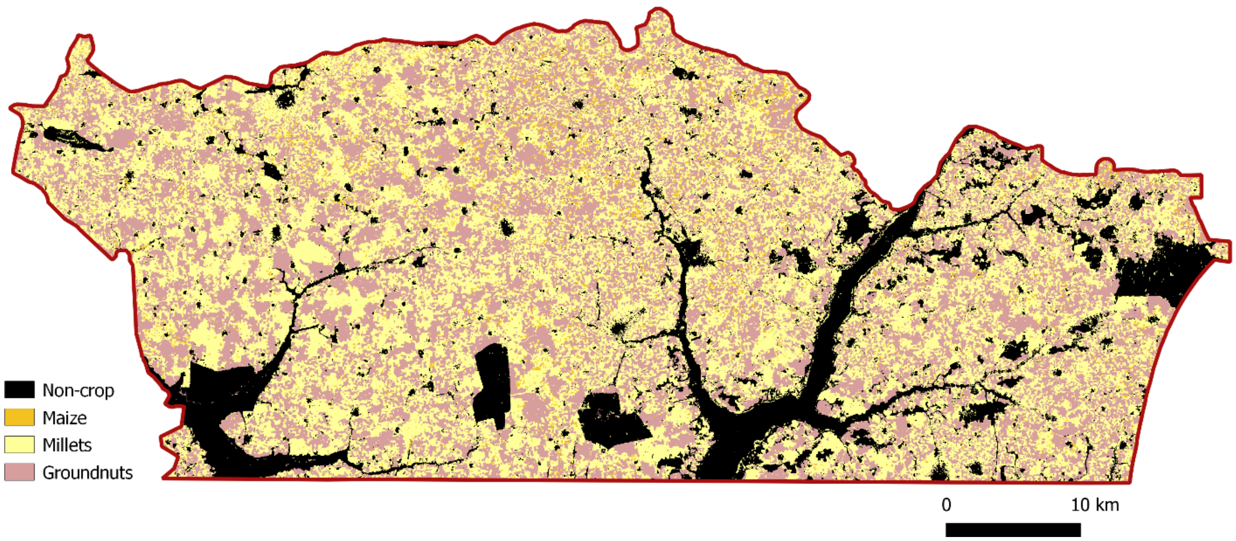


Figure 3-44. Crop type classification of the Nioro department based on S1 and S2 time series from May 1, 2021 to December 31, 2021

Expressed in number of pixels		Field survey						
		Non-crop	Maize	Millet	Groundnut	UA	Contaminations (%)	Omissions (%)
Crop type map	Non-crop	2205	0	34	17	97.7	2.3	9.3
	Maize	0	325	10	0	97.0	3.0	47.9
	Millet	202	265	2755	3268	80.5	19.5	12.6
	Groundnut	25	34	354	3487	88.8	11.2	6.3
	PA	90.7	52.1	87.4	93.7			

Figure 3-45. Confusion matrix (expressed in number of pixels) for the crop type map, with contamination and omission values for each crop, UA as user accuracy and PA as producer accuracy

The crop area indicators were derived directly from the crop type map. Figure 3-46 shows an estimation of the areas per crop using only the remote sensing data per municipality in the Nioro du Rip department. The surfaces are calculated by counting the pixels and after correcting the bias by the confusion matrix.

Figure 3-46. Estimation of the crop area per municipality in the Nioro du Rip department (in percent), based on remote sensing data

Figure 3-47 gives an estimation of the area cultivated in each municipality by the same remote sensing approach.

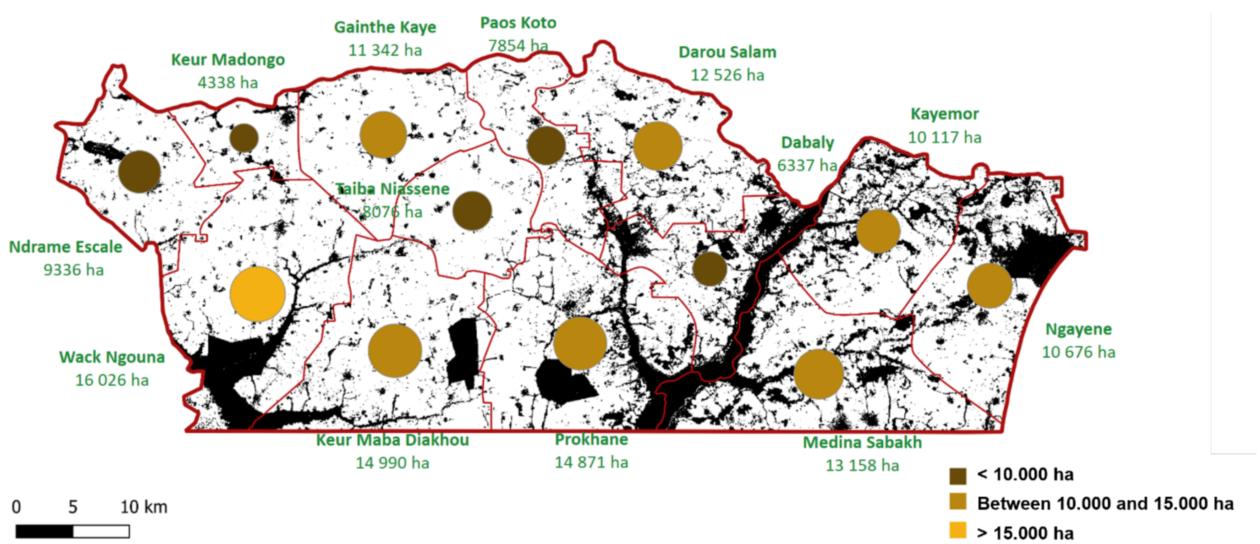


Figure 3-47. Estimation of the cultivated area for each municipality in the Nioro du Rip department (ha), based on remote sensing data

3.2.1.3 Crop yield estimates for Nioro district 2021

Remote sensing-based yield estimation requires the availability of a geo-located reference yield dataset to train and calibrate the models. Yield measurements were collected from hundreds of crop plots in the Nioro landscape. Depending on the crop, the size of the measurement square varies between 5 and 25 m². In the first investigation, the yield squares were considered georeferenced with the field ID and measurement square in the ODK application.

On basis of these affirmations, the yield's potential explanatory features were computed and extracted for each reference field. As Sen4Stat yield module was not available yet, the precursor of the yield module is been used.

During the final meeting in Dakar and after discussion with experts, it shows that measurement squares were not properly georeferenced, explaining the weak correlations between features and the measured yields at pixel level (Figure 3-48). As only one measure was taken by fields and due to the field heterogeneity, squares of measurement were not representative of the entire fields either. That explains the bad correlations at field level (Figure 3-49). These relations, neither at pixel nor field level, do not allow training a yield model providing satisfactory performance.

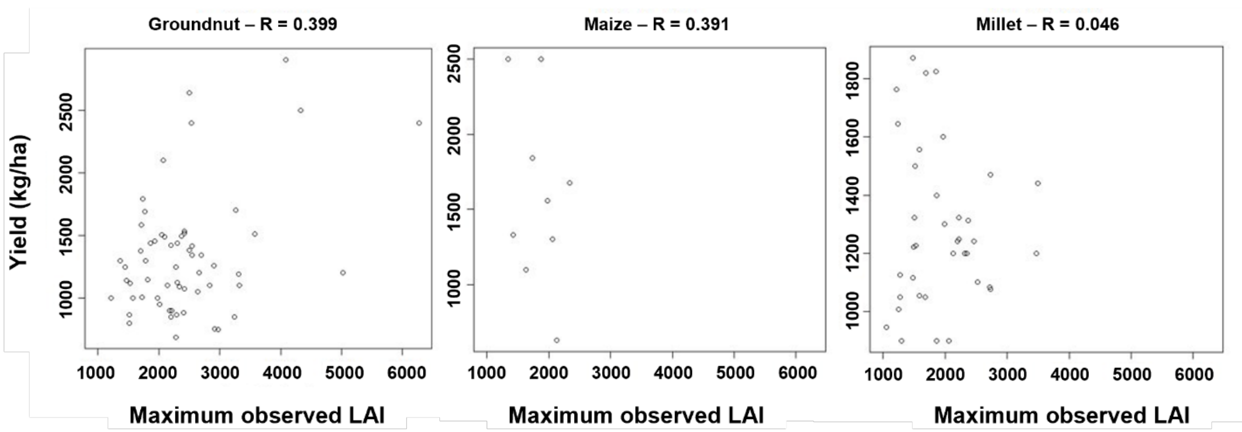


Figure 3-48. Maximum LAI observed on the pixel associated to the measurement square, compared to measured yield for the three main crops of Nioro

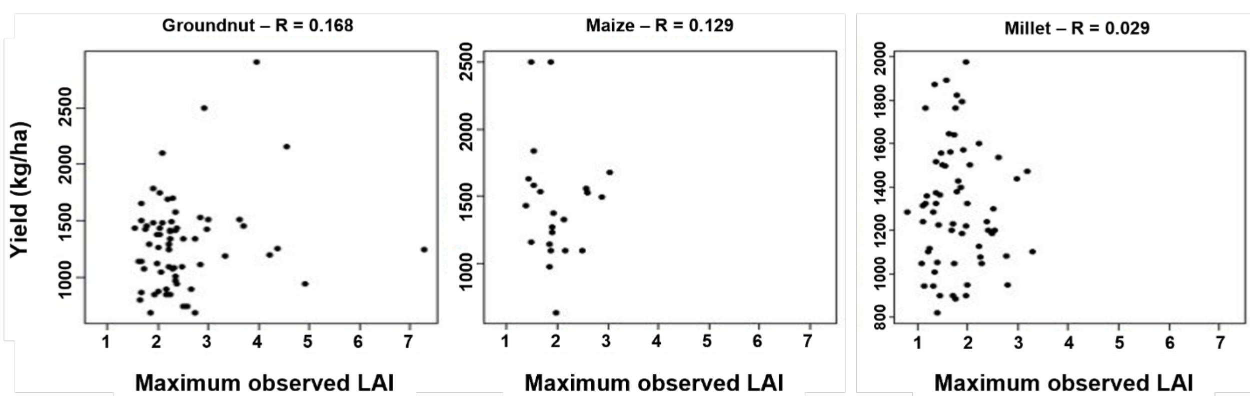


Figure 3-49. Maximum LAI observed on the field associated to the measurement square, compared to measured yield for the three main crops of Nioro

Heterogeneity analysis was applied to work with the most heterogeneous fields. It did not improve the correlation as expected. For the need of illustration, several groundnuts parcels were selected to build a standard linear relation between the peak of vegetation and the measured yield. The equation was applied to the maximum of LAI observed on each pixel classified as groundnut, providing an illustrative yield map for the groundnuts (Figure 4-34).

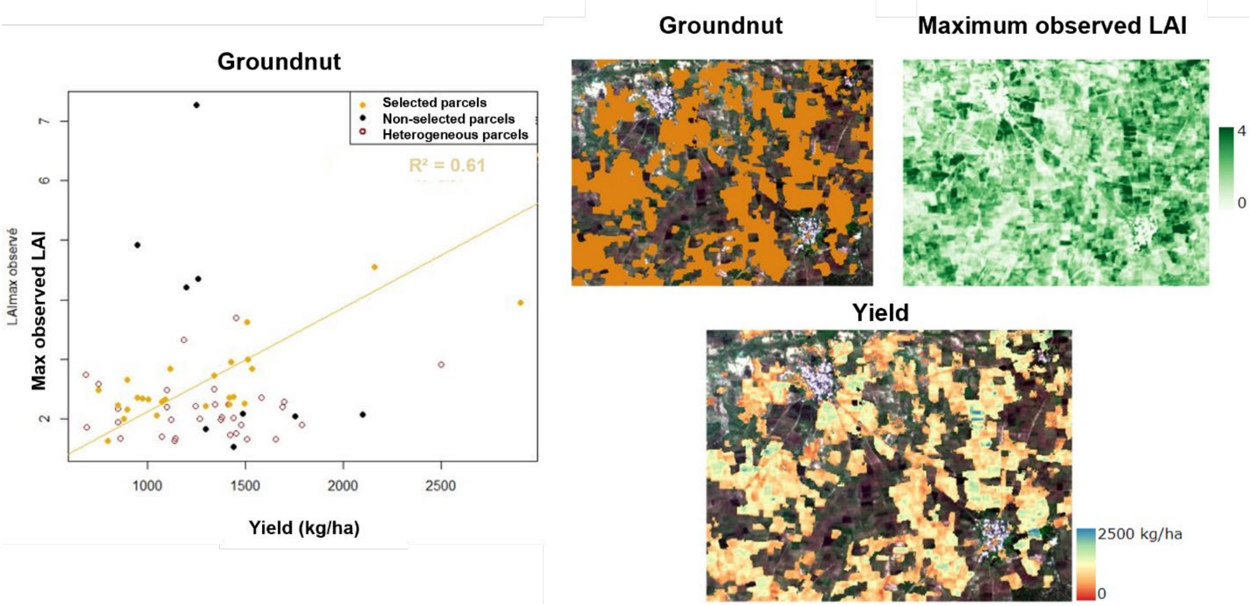


Figure 3-50. Illustration of the Groundnuts yield estimation based on a hypothetical linear relation between the measured yield and the maximum of vegetation.

An improvement is needed to relate the yield squares measured on the ground and by satellite. It is planned with the future AAS of the DAPSA.

3.2.2 Cycle 2

3.2.2.1 Pilot survey design and data quality control

Table 3-4 provides a quantitative insight about this field campaign, providing the collected data (in SurveySolution and in the form of GPX) and the remaining data after the quality control. The quality control includes the following steps: keeping only IDs existing both in SurveySolution and in GPX, keeping only valid crop class, removing duplicated geometries.

Table 3-4. Number of data collected and after quality control

	Number of samples in AAS	Number of GPX	Number of samples after quality control
Total	12827	3925	2215
Dagana		10	8
Kolda		785	430
Kongheul		1231	598
Mbacke		1264	678
Nioro		462	334
Tambacounda		173	167

A significant loss of data comes from the absence of link between the SurveySolution database and the GPX data. The shared dataset contained detailed information on each field visited during their in-situ campaign, alongside corresponding GPX tracks delineating the boundaries of crop polygons (i.e., parcels). The GPX files represent the precise geospatial extents of these fields, while the attribute data contains identifiers and other descriptive information about the crops within each field.

Initial analysis of this dataset revealed inconsistencies between the crop identifiers (IDs) listed in the attribute file and those associated with the GPX tracks. These discrepancies included instances of duplicate entries and mismatches between the crop IDs in the attribute table and those embedded in the GPX metadata. Such inconsistencies posed challenges for data integration, potentially leading to data loss or misinterpretation of field boundaries, ultimately reducing the reliability and usability of the dataset.

To resolve this, first, duplicate crop identifiers in both the attribute data and the GPX metadata were identified and systematically removed. Once the dataset was cleaned of duplicates, a spatial join method was applied, wherein the crop center point coordinates, provided in the attribute data, were matched to the GPX polygons based on spatial proximity. This process used the longitude and latitude of each crop's center point to determine the nearest polygon representing the field boundary. The join operation ensured that each crop record was spatially linked to its correct field.

Although this distance-based matching method introduced some uncertainty, particularly in areas where fields were densely packed or irregular in shape, it was the most effective solution available. By ensuring that each crop identifier was paired with its corresponding field boundary, the dataset was rendered more reliable.

The distribution of the crops within the collected data is shown in Figure 3-51.

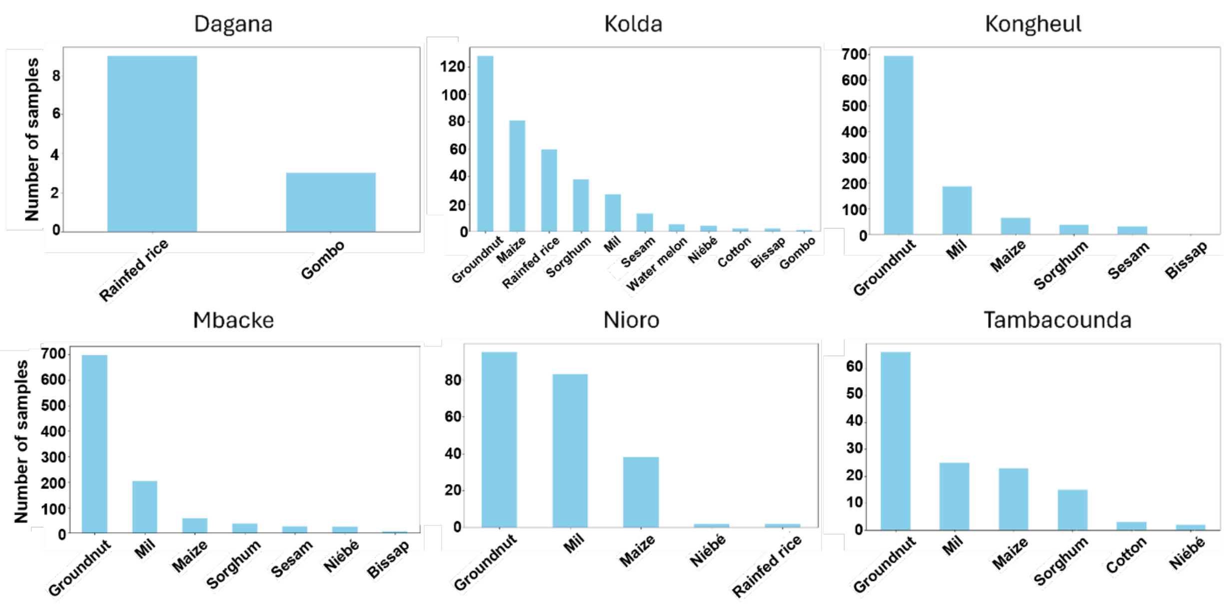


Figure 3-51. Crop distribution in the dataset collected in each department during the 2023 field campaign

3.2.2.2 Crop type map and estimates

The collected in situ data were used to calibrate the random forest algorithm included in the Sen4Stat toolbox.

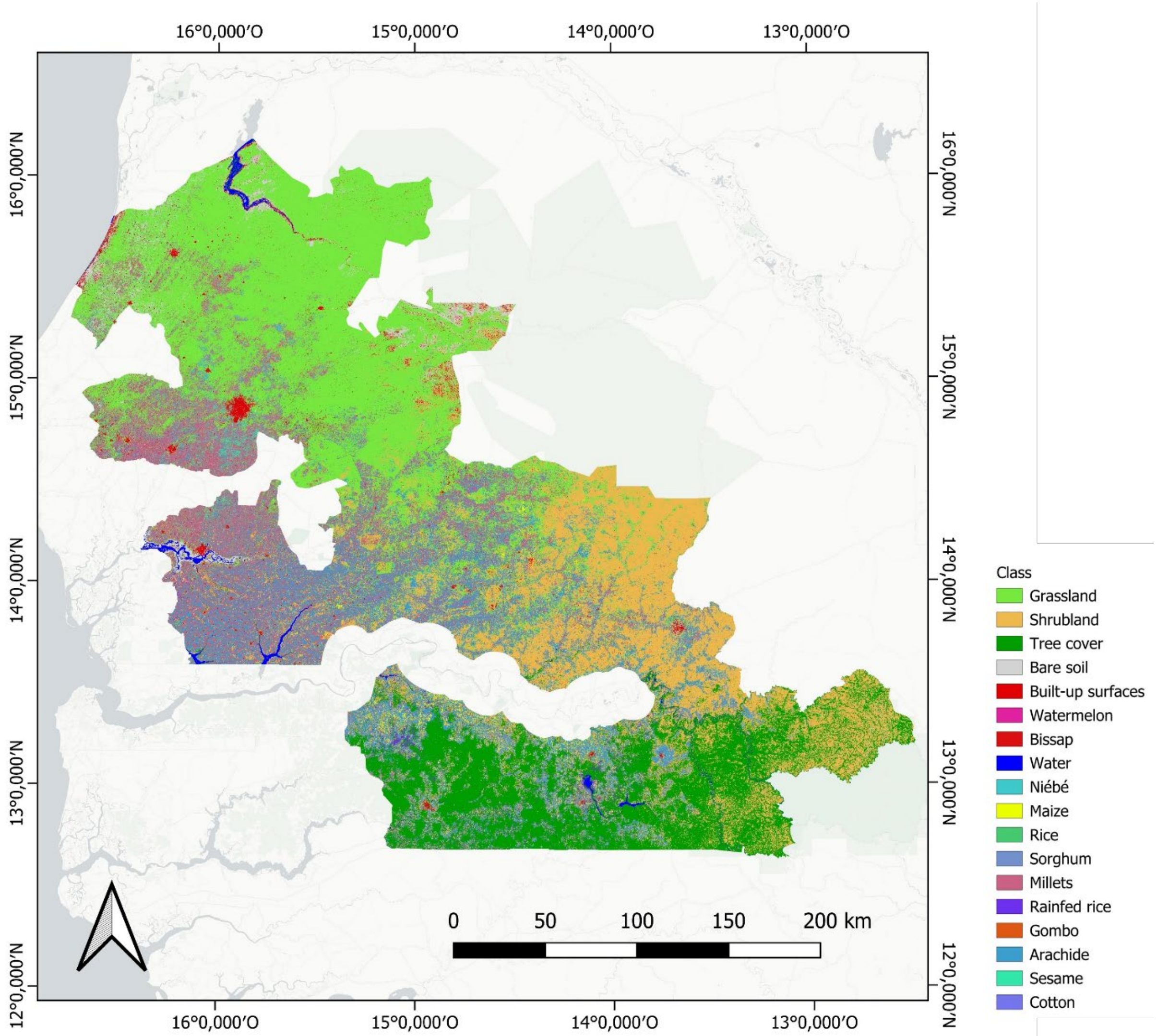


Figure 3-52. Crop type map 2023 over the 6 pilot departments

When looking at individual crop types (Figure 3-53), the ones that are best classified are groundnut (F-Score of 0,82), millets (F-Score of 0,72) and rice (F-Score of 0,972). The aggregation at the crop group levels allows significantly increasing the accuracy (Figure 3-54), showing a good accuracy for both the oilseed crops and cereals.

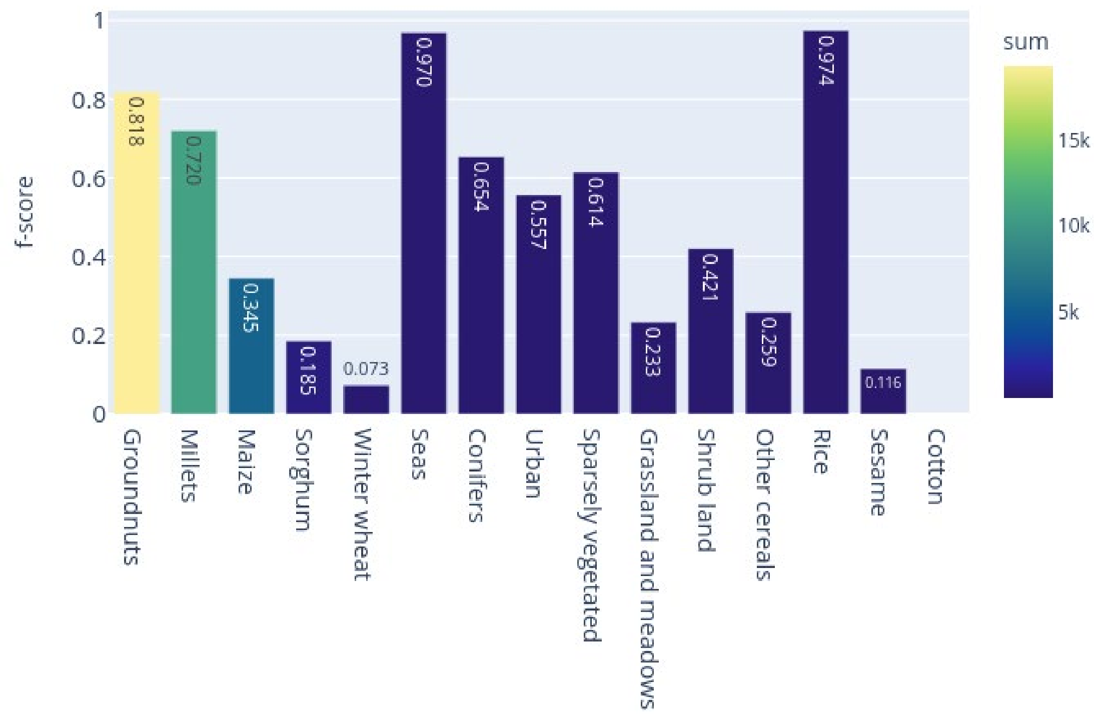


Figure 3-53. Accuracy metrics of individual crop and land cover types

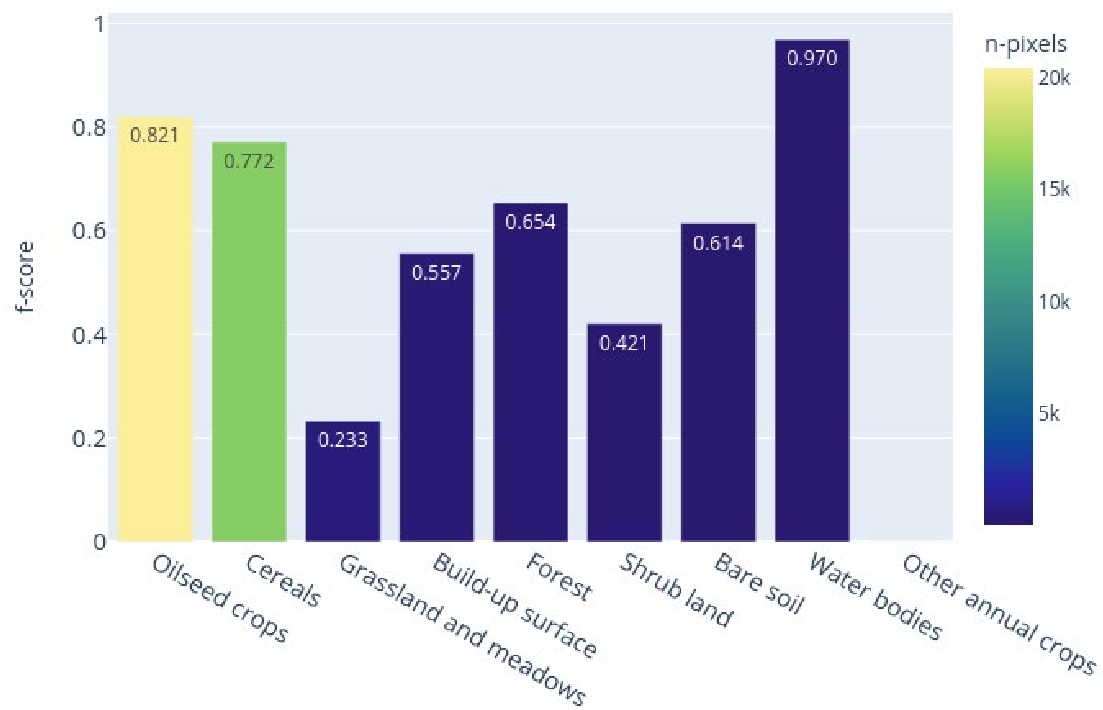


Figure 3-54. Accuracy metrics of crop and land cover groups

3.3 Ecuador

Several attempts were made to generate an accurate crop type map over the benchmarking area, but without any success. We were facing four parallel issues and so far, it has not been possible to solve them. These four issues are:

1. **Dense cloud cover**

The cloud cover is very dense over this country. There are very few cloud-free images spread along the year, which makes the use of the temporal dimension very challenging.

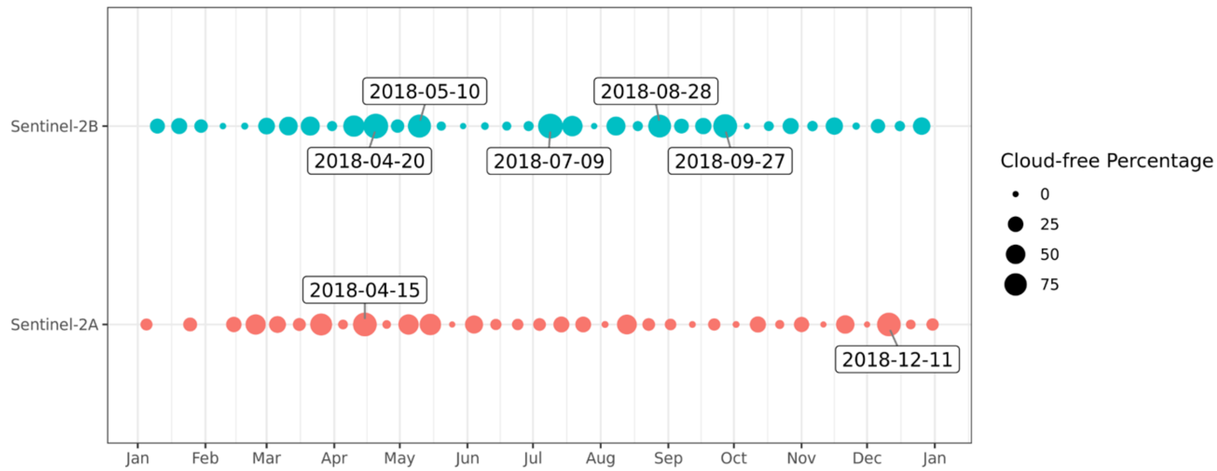


Figure 3-55. Cloud-free images over the tile 17MNU (one of the four tiles of the benchmarking area)

2. **Relief**

S1 data could be the solution to face the cloud cover issue. Unfortunately, Ecuador is crossed by the Andes cordillera and this strong relief impacts the use of Synthetic Aperture Radar data (Figure 3-56). The solution to better handle the relief is to apply a terrain flattening correction (Figure 3-57). This correction is implemented in the Sen4Stat system but was not run because it is highly time consuming. A test will be done over one tile in the near future.

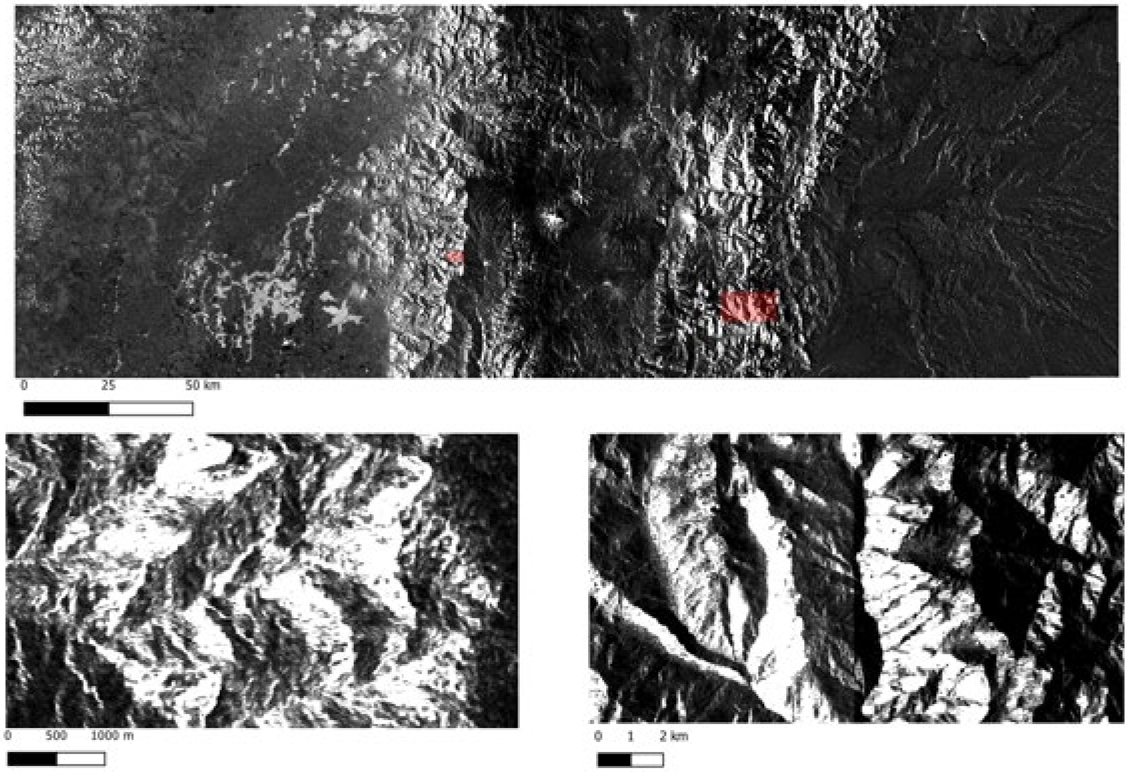


Figure 3-56. Relief impact on S1 time series

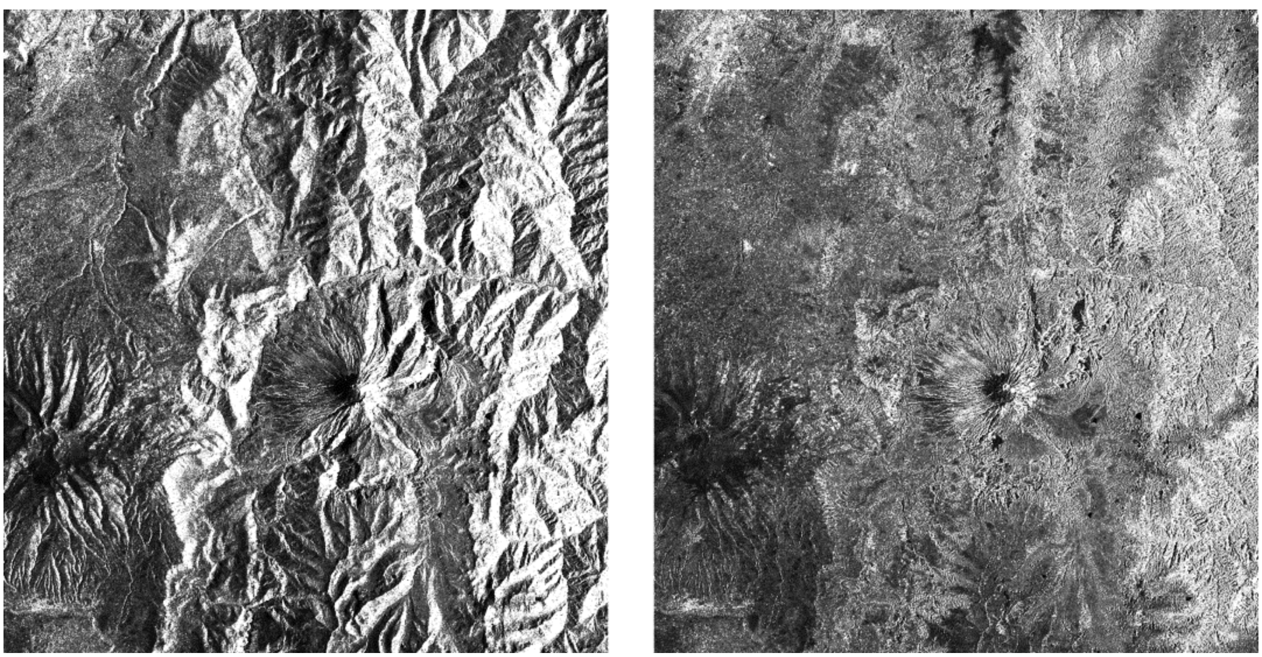


Figure 3-57. Added-value of applying a terrain flattening correction

3. Quality of NSO in situ data

During the benchmarking, several quality issues were observed in the NSO dataset. Boundaries of the plots did not seem consistent with the landscape and labels were not always coherent (Figure 3-58).

Figure 3-58. Quality issues observed in the NSO dataset.

Quality control procedure was implemented in order to increase the usability of the database and facilitate the automation of classification processes (Figure 3-59). The procedure mainly concerned the non-cropland classes: grassland & meadows, shrub land, forest, bare soil, build-up surface and water bodies. Polygons boundaries were adjusted when needed and labels were associated to "empty" segments through visual interpretation. Out of the 1397 segments of the benchmark area, 993 were treated, which correspond to 14.860 plots. Figure 3-60 shows the distribution of the different classes present in the database at the end of the procedure (distribution expressed in terms of surface).

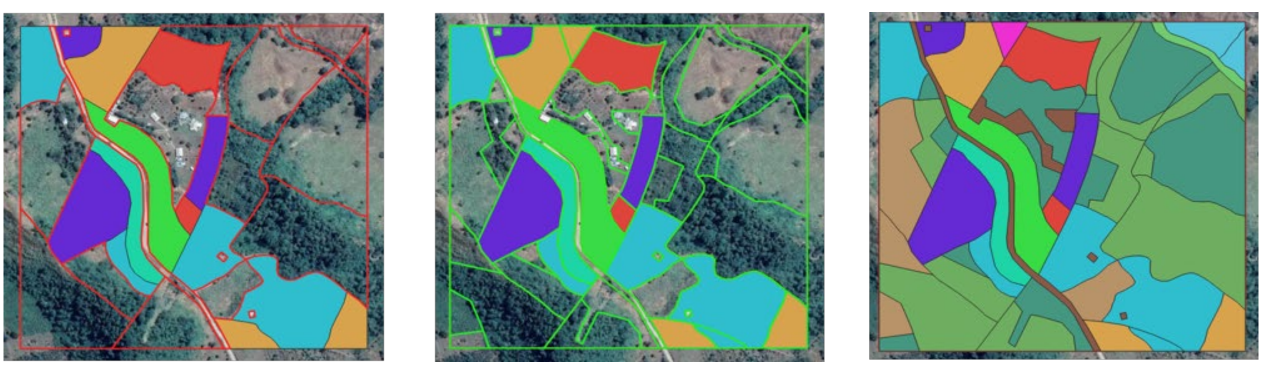


Figure 3-59. Quality control procedure implemented on the INEC database over the benchmarking area

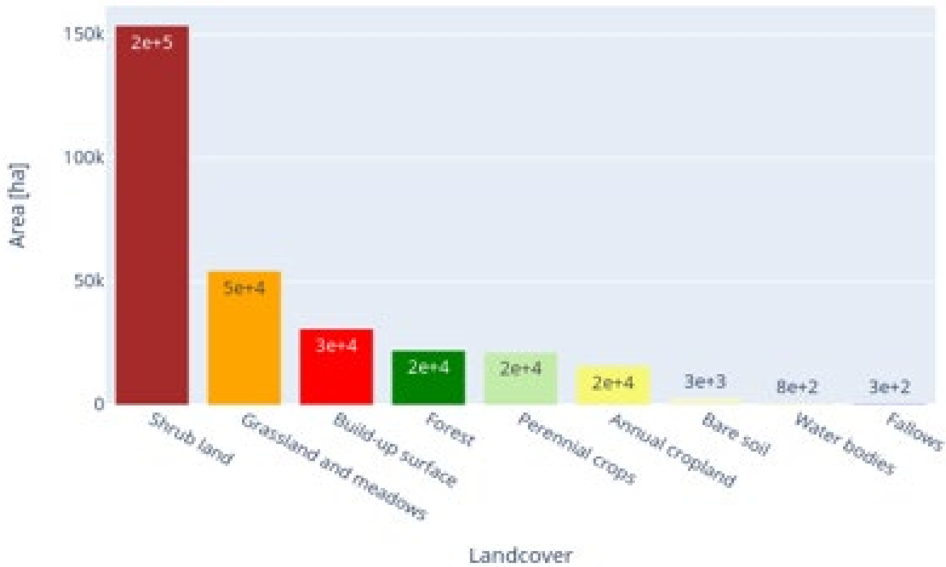


Figure 3-60. Land cover classes representation in the INEC database after the quality control procedure

4. **Complex agricultural practices**

Agriculture in Ecuador is dominated by permanent crops and often, annual crops are grown under the permanent crops. There might also be associated annual crops, i.e. more than one annual crop on the same field. In addition, there are successive crops over the same field during the year and the season depend on the crop type and on the area.

More investigation is needed and the next steps are: testing the terrain flattening correction, testing a classification based on a temporal composite, better understanding the seasonality.

3.4 Tanzania

A first crop type map was generated using S2 time series (January - December 2021). This is shown in Figure 3-61, despite the fact that the quality is not good enough. For this reason, quantitative validation figures are not presented in this report.

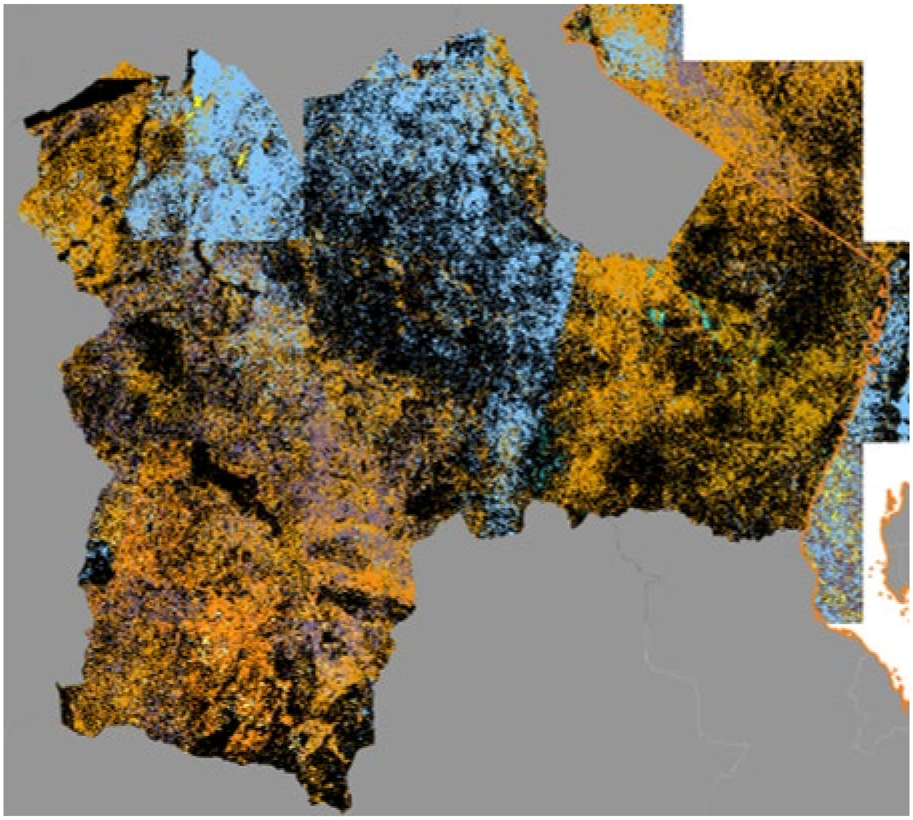


Figure 3-61. Draft version of the crop type map over the 3 regions of Dodoma, Manyara and Tanga in Tanzania

When zooming in (Figure 3-62), it can be seen that the product captures well the parcels and that the landscape structure is well described in the map. Nevertheless, the northern part of the crop type map is impacted by residual cloud and tile effects (northern region). Better dealing with the cloud cover in the S2 dataset and/or integrating the S1 time series will be tested in the near-future to see how it can help resolving this issue.

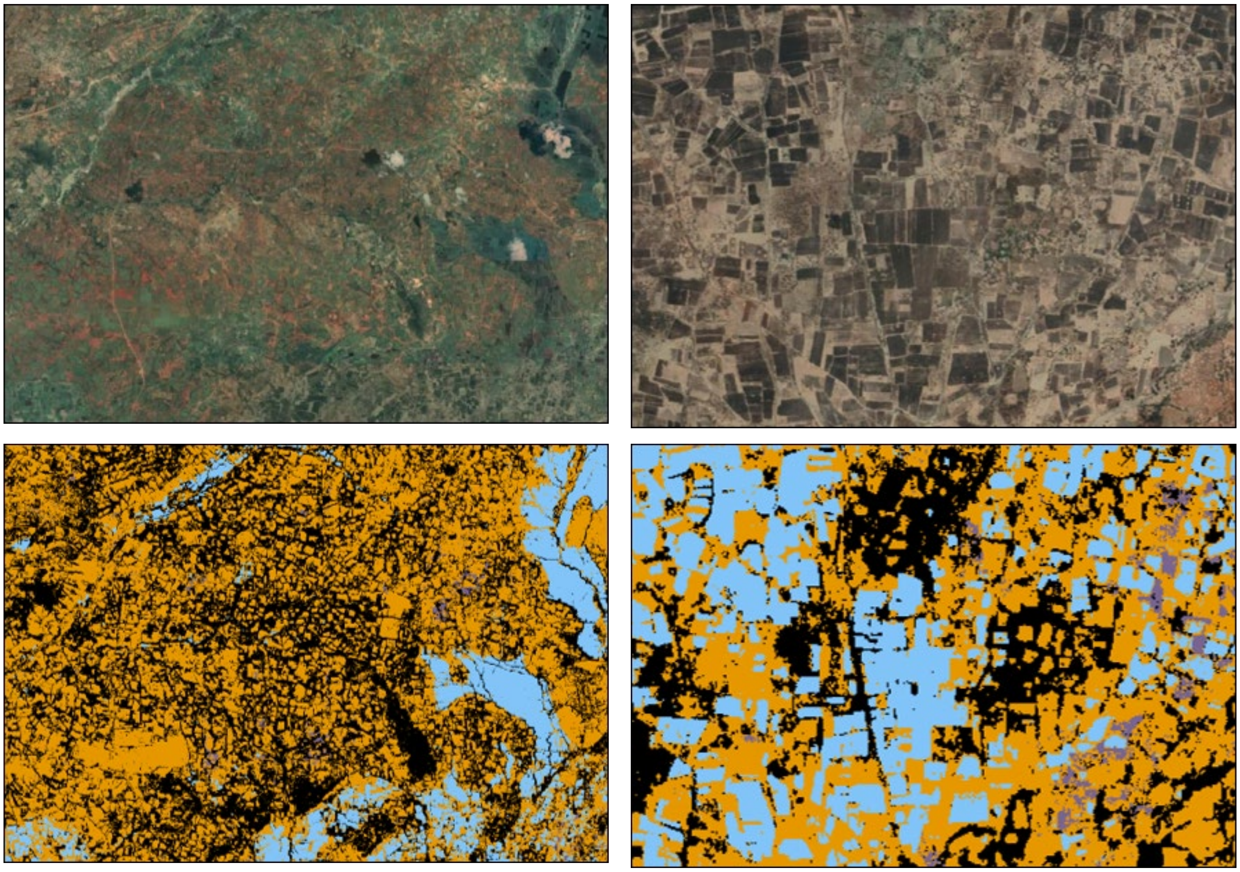


Figure 3-62. Zooms of the draft crop type map in Tanzania

For the sake of comparison, the crop type map generated by the Copernicus4GEOGLAM project is show in Figure 3-63.

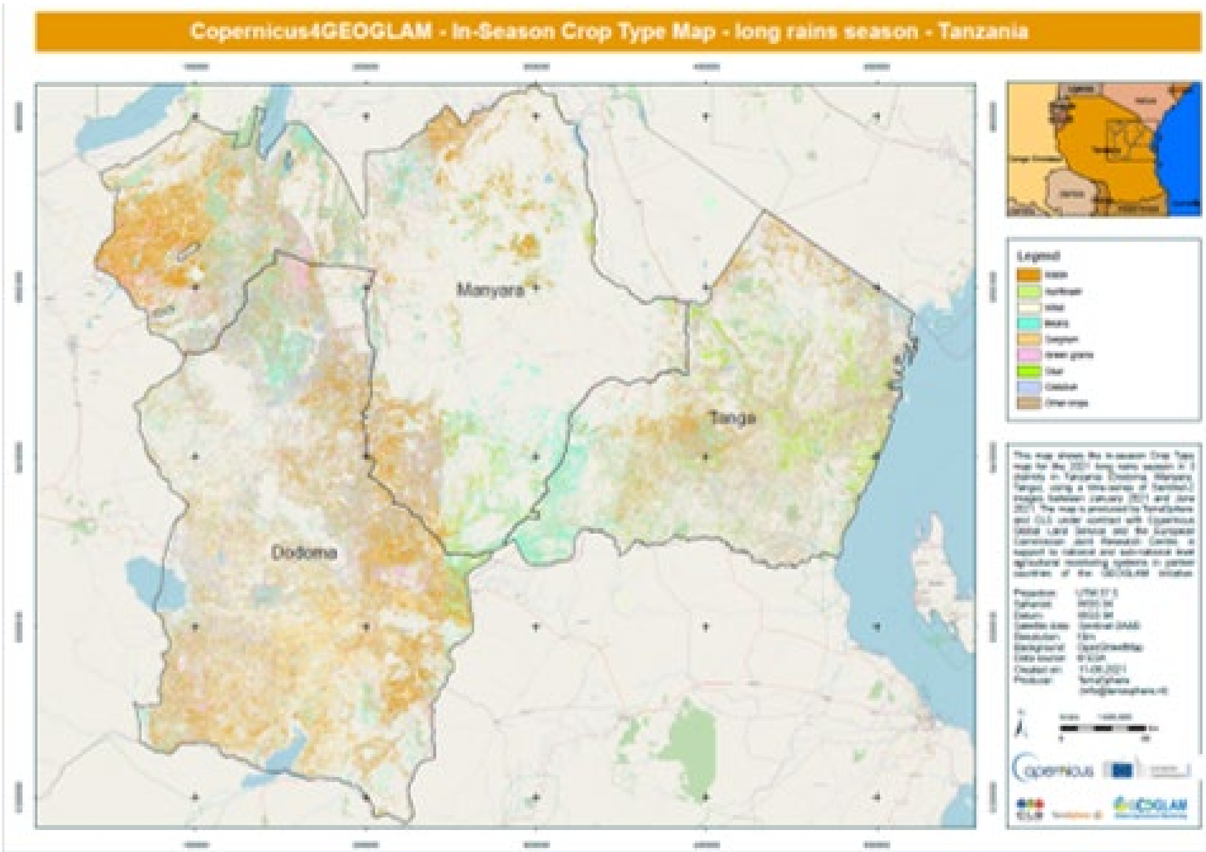


Figure 3-63. Copernicus4GEOGLAM crop type map