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Mapping annual crops in Portugal with Sentinel-2 data

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ABSTRACT

This paper presents an annual crop classification exercise considering the entire area of continental Portugal for the 2020 agricultural year. The territory was divided into landscape units, i.e. areas of similar landscape characteristics for independent training and classification. Data from the Portuguese Land Parcel Identification System (LPIS) was used for training. Thirty-one annual crops were identified for classification. Supervised classification was undertaken using Random Forest. A time-series of Sentinel-2 images was gathered and prepared. Automatic processes were applied to auxiliary datasets to improve the training data quality and lower class mislabelling. Automatic random extraction was employed to derive a large amount of sampling units for each annual crop class in each landscape unit. An LPIS dataset of controlled parcels was used for results validation. An overall accuracy of 85% is obtained for the map at national level indicating that the methodology is useful to identify and characterize most of annual crop types in Portugal. Class aggregation of the annual crop types by two types of growing season, autumn/winter and spring/summer, resulted in large improvements in the accuracy of almost all annual crops, and an overall accuracy improvement of 2%. This experiment shows that LPIS dataset can be used for training a supervised classifier based on machine learning with high-resolution remote sensing optical data, to produce a reliable crop map at national level.

Keywords: Crop mapping, Supervised Classification, Agriculture, Sentinel-2, Portugal

1. INTRODUCTION

Mapping of agriculture using supervised classification of satellite images has been a challenge for the scientific community in the past years, and it has been emerging recently[1]. In particular, annual crop type identification is rather challenging due to its large diversity (distinct leaf composition and canopy structure), growth variability (varying from region to region due to soil properties and local climate) and distinct agriculture practices throughout the agricultural year (crop rotation over the years or within the year itself). Consequently, annual crop mapping can be greatly benefited from the existence of a consistent time series of data to monitor its dynamics[2,3]. It has been verified that different crops have similar spectral proprieties in one single acquisition but the separability among crops is greatly improved when the different stages of growth are monitored through a series of images[4]. On the other hand, derivation of information from satellite original bands, such as the combination of spectral information to produce vegetation indices or spectro-temporal metrics, allows a better characterization of the annual crops phenological properties[4,5,6].

A new paradigm has been introduced with the Sentinel-2 satellites of the Copernicus program, allowing high frequency data collection of spectral information capable of crop monitoring. Sentinel-2 provides freely accessible global data at high resolution (10 m at best). Together with the availability of these data, the evolution of technology regarding the computational power and the arising of new big data processing techniques leveraged the production of detailed land cover maps[1,5,6]. In particular, mapping crop areas for larger areas, for example at national scale, have become feasible[7]. The Sen2Agri is a good example of the application of automated methodologies with multi temporal satellite data for monitoring agriculture crops at an operational level[8].

One of the crucial phases for obtaining a land cover map is the preparation of representative reference data for training extraction and further classification. In order to reduce the heavy workload of training collection and the map production time, automatic extraction of data from already available reference datasets has already been applied in the classification of large areas[9,10]. The application of automatic filters with specific conditions for data cleansing and harmonization allows to mitigate the differences between datasets and thus reducing also class mislabeling[9]. In particular, crop map classification requires a reference database with detailed information on agricultural land use and land cover.

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The Land Parcel Identification System (LPIS) is a European mechanism for providing subsidies to farmers according to the crop type or agriculture practice of each parcel. Although not providing information on all agricultural parcels in a given European country (only for tenderers and crops eligible for payment), this dataset has been used either to train or validate several crop maps[2,7,11].

Most of the multiple crop mapping studies based on supervised classification of multi-temporal data are carried out either on relatively small areas[2,3] or with a very limited number of crops[5,12]. The main objective of this work is to assess if a crop map at national level and with an increased number of crops can be generated using an LPIS dataset to train a supervised machine learning-based classifier with high resolution multi-temporal satellite imagery data. The map reference year was the 2020 agricultural year. The thirty-one most representative crops from LPIS in continental Portugal were selected from training, together with other representative land cover classes. Automatic processes were applied to improve the training data quality and lower class mislabeling. The territory was divided into fourteen areas of similar landscape characteristics for independent training and classification. Sentinel-2 imagery and supervised classification using the Random Forest algorithm was undertaken. A LPIS dataset of controlled parcels was used to access the crop map quality.

2. METHODS

2.1 Framework

The land cover classification methodology adopted for this work follows for the most part some of the stages of the methodology applied in a previous work to produce an experimental land cover map of continental Portugal relative to 2018[13]. This map was produced in raster format with a 10 m pixel size and 13 land cover classes including Agriculture. Map production also included post-classification analysis with expert knowledge. This national land cover map is included in the initiative of building a land cover and land use monitoring system to deliver frequent and up to date products. In this regard, a map for the agriculture year of 2020 has already been produced. The number of classes in this map increased to 15, by breaking down the class of Agriculture into 3 classes: annual spring/summer (SS) crops, annual autumn/winter (AW) and other agriculture (including mostly managed grassland and permanent crops). The national land cover map production goes through various processing stages but the part that provides information for the crop mapping takes place after the first automatic classification stage, not including any post-classification or expert knowledge. The crop information was possible to extract because training samples were collected from a larger set of training classes instead of the final map classes in order to ensure spectral diversity[14].

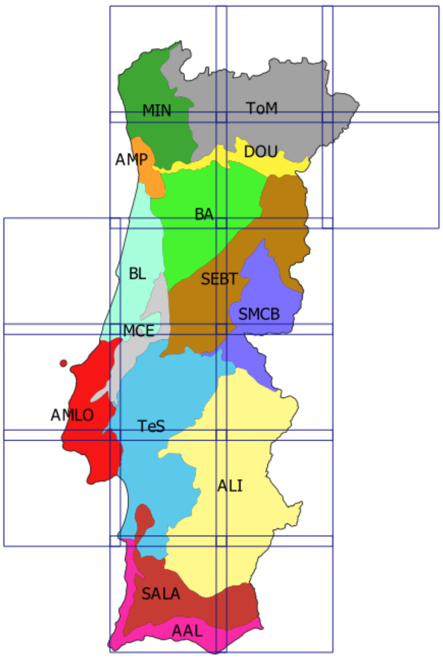

Figure 1. Continental Portugal divided by 14 mapping zones in various colors with the 17 Sentinel-2 tiles overlaid.

The study area for this work includes the continental Portugal territory (Figure 1). From a global perspective, Portugal is a relatively small country, with an area of about 90000 km^2, but diverse agricultural practices can be found throughout the territory. It is also characterized by a considerable diverse landscape that can be delimited by similar characteristics. Thus, a spatial stratification of the territory was performed dividing it into 14 mapping zones, following Costa et al.[13], facilitating the training and classification stages for the crop map production of the whole territory.

2.2 Sentinel-2 data

A time-series of Sentinel-2 images covering the Portuguese territory was gathered and prepared, following the 2020 agricultural year. In continental Portugal the agricultural year includes the months from October 2019 to September 2020. The production of an annual crop map allows to capture the phenological variability of the crops, which enables to evaluate their distinct spectral signatures and therefore likely improves supervised classification of these classes[4]. The Sentinel-2 images were obtained from the Theia Land Data Center, providing bottom of atmosphere (BOA) reflectance images with atmospheric corrections including cloud, shadow and topographic corrections using MAJA algorithm[15]. A total of 17 tiled areas were selected to allow full coverage of the territory (Figure 1) and a threshold of less than 60% cloud coverage was applied to download the images. The resulting 10 bands for each image were disaggregated to 10m spatial resolution. Synthetic composite images were created calculating for each band the pixel median using the images acquired during each month of the 2020 agricultural year. A linear interpolation through time was perform in order to fill the data gaps that resulted from areas of the images totally masked by atmospheric corrections in a whole month. A set of 5 spectral indices based on normalized differences between bands (NDVI, NBR, NDWI, NDBI, NDMIR) were also processed for the 12 monthly composite images. Additionally, 7 different spectral-temporal metrics were applied to each band of the monthly composites and each monthly spectral index using different quantile intervals (10, 25, 50, 75, 90, 75-25, 90-10). At the end a Digital Terrain Model (DTM) of 25 m was also included. Gathering all these data resulted in a Sentinel-2 based imagery dataset composed by 286 layers, including the DTM.

2.3 Training

Training data for this work was obtained from two primary datasets. One was considered for the most general land cover classes, namely the COS map, which is the national land cover land use map of Portugal. The other was considered specifically for training agriculture classes, which was the LPIS dataset. Land cover classes other than agriculture are important to identify specific landscape features usually found inside or near agricultural occupations such as roads, artificial infrastructures or water bodies, in order to exclude them from the crop map. The most recent COS map was produced in 2018 and it is based in visual interpretation of very high resolution orthophotos, being also characterized by a minimum mapping unit (MMU) of 1 ha and having a detailed nomenclature of more than 80 land cover and land use classes. The LPIS dataset is produced every year by the Portuguese Institute of Agriculture and Fisheries (IFAP), having a much smaller MMU of 100m^2. Its base information is also obtained from orthophoto interpretation but specific rules are applied to identify agricultural uses and occupations with higher detail such as temporary or permanent crop types, greenhouses or fallow lands. Its MMU also enables the identification of smaller elements such as hedges, roads or trees at the parcel boundary. Afterwards, the parcels crop type is determined through the farmers' annual declarations in the framework of the application for European funds. Its class nomenclature at parcel level allows more than 160 different occupations to be identified, including most of the crops types existing in the country. It is important to note that LPIS only provides information on agricultural parcels eligible for subsidies, not covering the entire country area.

An automatic processing strategy was followed using the polygons of COS and LPIS in order to extract training areas representative of the classes of interest. Previous experiences have shown that the filtering of this primary information with some auxiliary datasets in the automatic training process, such as High-Resolution Layers (HRL) from Copernicus or National burnt area maps, improved training data quality and reduced class mislabeling in the selection of training areas[16]. For example, forest training areas can be refined intersecting COS polygons for a specific tree species with other datasets including HRL characterized by appropriated thresholding (leaf type and tree coverage), burnt maps from recent years and clear-cuts from the same year to exclude those areas from training. This is a fundamental step for having up to date training information since the most recent available COS is from 2018. In the case of agriculture, previous versions of COS were used as auxiliary dataset to help identify crop types, allowing for example a more accurate identification of permanent crops and managed grassland. The data sources and filtering criteria applied in this work can be consulted in Costa et al.[13]. The land cover nomenclature consist of 15 classes, the same used in Costa et al.[13] methodology, but only areas of the agriculture class are selected for the further crop map classification. This subzone selection allows choosing a more restricted set of training classes, considering the classes likely to be present in agricultural areas, and therefore reducing the proportion of commission error. In this case, besides the temporary crops classes from LPIS, the other land cover selected classes were shrubland, natural grassland and bare soil.

LPIS from 2020 was used for selecting the crops to produce the national annual crop map. In a previous crop map experiment, the 10 most abundant annual crops at country level, also based on LPIS, were selected for training[17]. However, it was found that a significant percentage of crops not represented in training were classified in the crop map as other LPIS annual crops. A crop type that is abundant at the country level might not be abundant in a particular mapping zone. Following the country division into 14 landscape areas, the most abundant annual crops were identified for each area based on LPIS dataset. Only the crops having more than 1% of the total area of annual crops were selected for training, in order to reduce crop omission in the final map. This resulted in 31 distinct annual crops to classify at country level, which are presented in Table 1, and that were categorized in two different growing seasons following LPIS nomenclature: autumn/winter (AW) and spring/summer (SS).

Automatic random extraction was employed to derive a large amount of sampling units for each annual crop class in each landscape unit. The training areas automatically processed in the filtering stage were considered separately for each of the mapping zones. The collected samples were used to retrieve the spectral information from the dataset presented in Sentinel-2 data section. The maximum number of sampling units per class was defined to be 6000 pixels for the largest mapping zone (ALI), and varying according to the proportion of area of the remaining mapping zones until a minimum limit of 1000 pixels (DOU, AMP, MCE).

Table 1. Crop type classes for crop mapping and their growing season.

Crop type class	Growing season	Crop type class	Growing season	Crop type class	Growing season
Oat	autumn/winter	**Clover**	autumn/winter	**Carrot**	spring/summer
Ryegrass	autumn/winter	**Corn**	spring/summer	**Cabbage**	spring/summer
Wheat	autumn/winter	**Other Horticultures**	spring/summer	**Chickpea**	spring/summer
Triticale	autumn/winter	**Potato**	spring/summer	**Melon**	spring/summer
Rye	autumn/winter	**Sorghum**	spring/summer	**Beetroot**	spring/summer
Barley	autumn/winter	**Pumpkin**	spring/summer	**Onion**	spring/summer
Yellow Lupine	autumn/winter	**Bean**	spring/summer	**Zucchini**	spring/summer
White Lupine	autumn/winter	**Rice**	spring/summer	**Turnip**	spring/summer
Nitrogen-Fixing Plants	autumn/winter	**Tomato**	spring/summer	**Other Dried Leguminous**	spring/summer
Pea	autumn/winter	**Sunflower**	spring/summer		
Broad Bean	autumn/winter	**Sweet Potato**	spring/summer		

2.4 Classification

Supervised classification of Sentinel-2 data was undertaken using Random Forest algorithm[13]. Each mapping zone was classified separately and at the end the individual areas were joined together to form the land cover map at country level. This allows specific crop types to be classified only in areas of the country where there is occupation for that class. Previous preliminary classification tests in the national land cover map production[13] showed that some classes with automatic training did not produced accuracy results with the desired quality. Therefore, for those classes automatic training was replaced by manual delimitation of training areas through visual interpretation[13]. It is important to note that agriculture classes were not included in this procedure. After the final automatic classification of the land cover map at country level, the 31 annual crop classes were extracted to form the national annual crop map.

2.5 Validation

A subset of the LPIS dataset containing controlled parcels was used to validate the annual crop map. This dataset corresponds to about 5% of the total LPIS and was obtained by means of photo-interpretation of very high-resolution satellite images and verification of some crops through fieldwork. Although the LPIS is targeted at agricultural land cover and land uses, the dataset contains all types of uses and occupations observed in the country. LPIS validation dataset covers an area of 3632 km^2, representing approximately 4% of continental Portugal area. A confusion matrix between the areas of the classified crop map and the LPIS validation dataset was generated and an overall accuracy at national level was estimated. Producer's accuracy (PA) and User's accuracy (UA) were also estimated considering the 31 annual crops separately and by grouping them into categories of growing season (AW and SS).

3. RESULTS AND DISCUSSION

The classified annual crop map for continental Portugal concerning the 2020 agricultural year represents about 12% of the total area of the national 2020 land cover map, covering a considerable part of the territory, where all agriculture covers about 45% of the continental country. An overview of the annual crop map is presented in Figure 2 a).

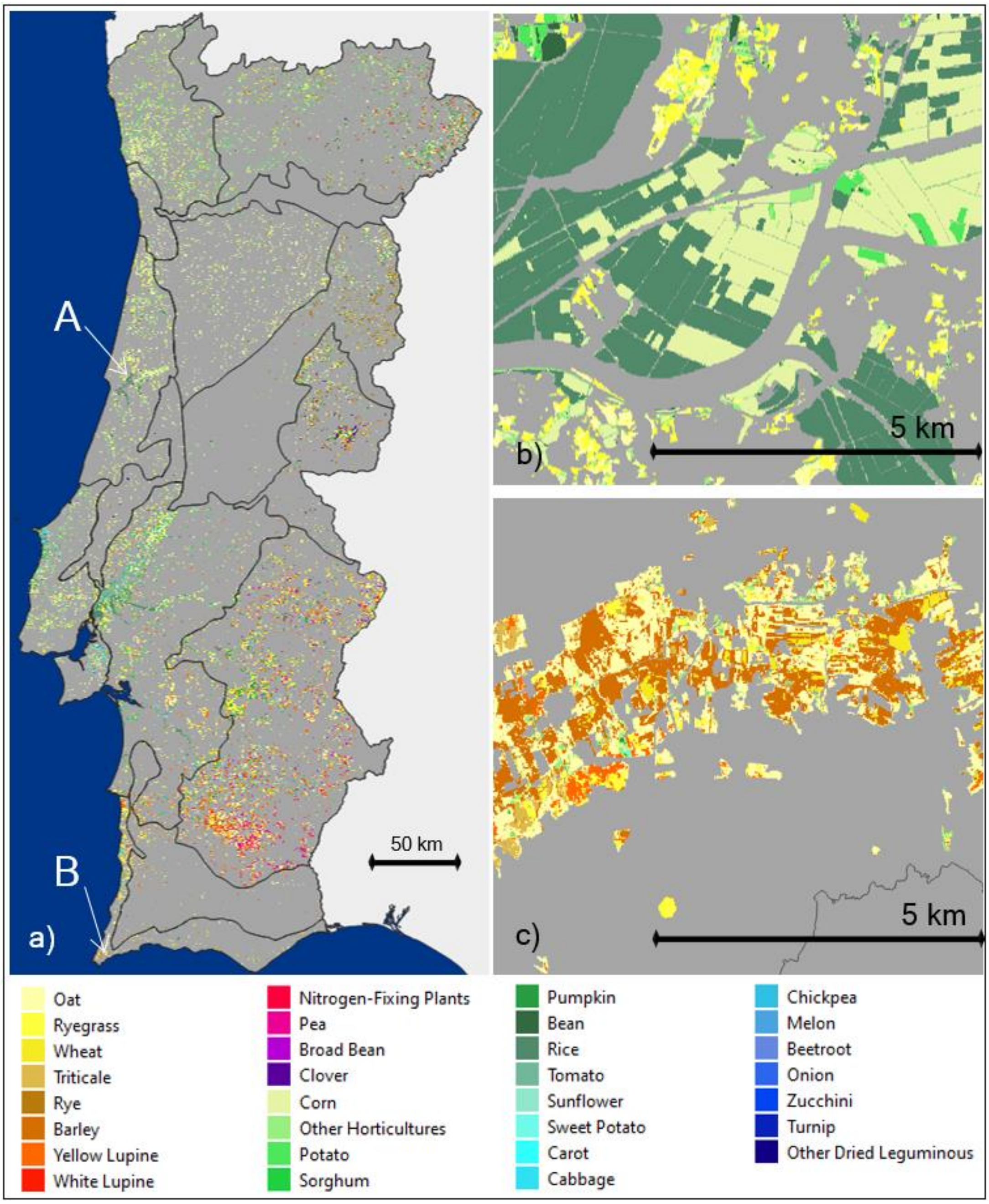

Figure 2. Overview of the produced annual crop map of 2020 (a), close-up example in area A (b) and a close-up example in area B. Crop type legend is presented at the bottom (yellow to dark purple for AW crop types and light green to dark blue for SS crops types).

Despite the presented map scale it is possible to note some diversity of the crop types according to the defined mapping zones. SS crops are more concentrated in coastal regions and along larger rivers while AW crops are more scattered throughout the territory, with some clustered areas where cultivation is more concentrated (mostly in the interior of the country). Figure 2 b) and c) show two close-up examples of different areas, the first showing an area dominated by SS crop types in area A, located in the center of the country near the coastline, and the second an area dominated by AW crops in area B, located in the south also near coastline.

Validation of the annual crop map was performed through the intersection with LPIS dataset of controlled parcels. A confusion matrix was produced to evaluate the accuracy of each classified crop type. Table 2 presents the main types of uses and occupations by area and percentage observed in the LPIS validation parcels. Grassland is the most represented class with about 50% of the total area. Analyzing the classes of agricultural use, the annual crop types represent only 11.1%, with a balanced proportion between SS and AW (about 5% each), while the other agriculture occupations together cover 62.8% (from Fallow to Grassland) and the remaining non-agriculture classes 26.1%. Other AW crops and Other SS crops are the LPIS crop types that do not have a corresponding crop type in the map. They represent only 0.1% of LPIS validation. For sake of simplicity, all the all classes not representative of annual crops (from Other AW crops to Other surfaces) were grouped together in the validation process under the designation of “Other Classes”.

Table 2. Area and percentage of coverage for the LPIS validation dataset main uses and occupations.

	Area (ha)	**Area (%)**
Annual AW crops	19053	5.2
Annual SS crops	20836	5.7
Other AW crops	173	0.0
Other SS crops	350	0.1
Fallow	9517	2.6
Vine	7179	2.0
Olive grove	17153	4.7
Permanent crops	11927	3.3
Other crops	111	0.0
Grassland	182088	50.1
Shrubland	28911	8.0
Forest	58859	16.2
Water	2533	0.7
Other surfaces	4523	1.2

The confusion matrix is presented in Table 3, showing the annual crop map and other land cover classes row wise and the LPIS validation classes column wise. The PA and UA percentages calculated for each annual crop are also represented. Class names are colored as follows: annual AW crop types in light brown, annual SS crop types in light green and other classes in red. Bold and underline values represent concordant values between the datasets for the same class. Values colored in light yellow represent values between discordant classes greater than 100 ha. The value 0 indicates intersected areas smaller than 1 ha.

A large amount of confusion is seen for AW crop type classes, which is notable by the presence of most of the light yellow areas in the matrix. Oat shows high omission and commission errors mostly with other AW crops, despite commission with Corn being larger than 100 ha. The same is observed for Wheat but in smaller proportions, but again showing high commission with Corn. The best UA for AW crops are found for Barley and Wheat, despite the high level of confusion registered for the later, whereas the best PA is obtained again for Barley and for Ryegrass. Some AW crops have poor UA or PA percentages, namely Pea (UA), Broad Bean (UA), Ryegrass (UA), Nitro-Fixing Plants (UA and PA), White and Yellow Lupine (UA and PA) and Clover (UA and PA). Omission errors with the SS crops are present for some of the most abundant crop types such as Oat, Ryegrass, Triticale and Rye.

Table 3. Confusion matrix of the annual crop map and other land cover classes (in rows) with the LPIS validation dataset (in columns). Areas are in ha. PA and UA are presented for each class.

	Oat	Ryegrass	Wheat	Triticale	Rye	Barley	Yellow Lupine	White Lupine	Nitrogen-Fixing Plants	Pea	Broad Bean	Clover	Corn	Other Horticultures	Potato	Sorghum	Pumpkin	Bean	Rice	Tomato	Sunflower	Sweet Potato	Carrot	Cabbage	Chickpea	Melon	Beetroot	Onion	Zucchini	Turnip	Other Dried Leguminous	Other Classes	***UA (%)***
Oat	**2577**	115	165	160	50	104	12	5	43	22	6	1	111	16	5	17	7	14	1	1	1	0	2	1	12	0	0	0	0	1	1	6803	**25**
Ryegrass	185	**1370**	29	66	11	22	14	1	40	11	1	7	125	10	3	17	8	9	1	2	1	1	5	11	2	0	0	0	0	4	3	8106	**14**
Wheat	146	5	**1693**	126	44	61	1	1	9	2	1		3	1	0	0	1	5	0	8	1	0	6	1	0	0	0	3		0	0	491	**65**
Triticale	101	6	152	**1081**	4	37	2	6	8	6	2	0	2	0	0	1	0	3		0	0	0		0	5	0	0	0		0	0	1394	**38**
Rye	142	11	27	5	**396**	1		1	0	1	0	5	40	5	2	4	1	4			0			0	1			0		0	0	1440	**19**
Barley	86	16	102	40	0	**1879**	1	0	0	51	1	0	11	0	1	1	1	0	0	1	2	0	0	1	2	1	0	0	0	0	2	670	**65**
Yel. Lupine	138	26	37	52	1	41	**152**	9	3	10	11	2	2	1	0	3	1	3	1	1	1	0	0	0	2	0	0	0	0	1	7	6308	**2**
Whi. Lupine	33	2	11	2	18	0		**15**				0	3	2	0	1	3	0							0						0	602	**2**
Nitro-Fixing	0	0	0	0	0				**9**				0	0		0											1					109	**8**
Pea	89	2	46	30	0	52	6	0	2	**486**	6	0	2	2		6	1	2	0	0	11			0	6	0		1	0	0	5	2281	**16**
Broad Bean	30	1	21	13		7	1	0	1	4	**144**	1	0	0		0	0	1		0	1				1	0				0	1	800	**14**
Clover	0	0		0	1				1			**1**	0	0		0		0							0		0					380	**0**
Corn	31	21	3	12	24	1		0	0	6	0	1	**8129**	41	14	64	8	12	137	13	1	0	2	4	0	0	3	0		1	1	792	**87**
Other Horticult.	93	37	15	5	44	6	0	2	2	0	1	1	376	**210**	50	48	37	17	4	1	0	5	3	17	4	1	3	8	3	1	1	2107	**7**
Potato	7	16	2	0	8	1	1	0	4	6	3	0	281	40	**265**	2	2	3	0	6	15	0	73	64	0	0	4	9	0	0		502	**20**
Sorghum	44	26	18	25	13	15	1	1	1	10	1	1	339	54	4	**449**	27	21	84	41	15	0	2	12	7	6	12	7	0	9	0	2196	**13**
Pumpkin	59	16	7	47	7	2	2	2	1	5	2	1	58	17	4	45	**368**	13	1	9	35	4	2	3	2	3	2	12	6	9	1	2621	**11**
Bean	18	0	2	0	8	0		0	0	0		0	62	3	1	15	2	**154**	0	0		0		4	3	0	0	2		3	1	482	**20**
Rice	0	0	0	0		0				0			13	0	0	1	0		**2934**	1	0			0		0						115	**96**
Tomato	0	2	1			0				0			42	3	2	0	3		6	**1230**	30		2	38		3	1	1	0	1		80	**85**
Sunflower	0	0	1	1		2				2	2		11	0	1	5	1	1	2	87	**646**				3	2		51	0		0	139	**68**
Sweet Potato	0	2	1	0		0		0			0		1	1	1	0	1	0		0		**13**	1	0				0	3			36	**22**
Carrot	0	0	1										0	1	21		0					0	**96**					0	0			13	**72**
Cabbage	0	3	0	1		0							0	0	0		1	0		0			0	**11**				0				8	**45**
Chickpea	3	4	11	1		6	1	0	0	18	3		14	8	1	7	2	2	1	5	15	0	0	11	**165**	1	1	3	1	2	4	802	**15**
Melon	0		1	0		2				0			5	2		1	5		1	150	7			0	0	**124**		3				32	**37**
Beetroot																																0	
Onion	0	0	1			0							1	0	4	0	0			0		0	3	0				**18**	0			10	**47**
Zucchini																																0	
Turnip	0				1							0	0	0		0		0									0			**16**		118	**12**
Oth. Dried Leg.	0		0			0							0				0														**1**	3	**26**
Other Classes	2368	438	508	566	454	311	420	61	21	202	83	73	789	473	72	260	243	232	95	30	65	3	5	6	71	75	1	8	1	41	3	**283882**	**97**
PA (%)	**42**	**65**	**59**	**48**	**37**	**74**	**25**	**15**	**7**	**58**	**54**	**1**	**78**	**24**	**59**	**47**	**51**	**31**	**90**	**78**	**76**	**48**	**47**	**6**	**57**	**57**	**0**	**14**	**0**	**18**	**4**	**88**	

Analyzing the SS crop types one can verify that a large amount of commission is also notable for some classes. In particular, Corn shows high amount of omission errors, some of them with AW crop types (Oat and Ryegrass) and a large amount of commission error with Rice. However, it is important to note that the large number of well-graded parcels far exceeds the errors previously indicated (high PA and UA). Other notable confusion with large commission error occurs between Melon and Tomato. Both best UA and PA for SS crops are found for Rice, Tomato, Corn and Sunflower. The SS crops with poorer UA or PA scores are Other Horticultures (UA and PA), Sorghum (UA), Pumpkin (UA), Chickpea (UA), Turnip (UA and PA), Cabbage (PA), Beetroot (PA), Onion (PA), Zucchini (PA) and Other Dried Leguminous (PA). In particular, for Beetroot and Turnip no pixel classified in the crop map was found in the validation dataset.

In general, better UA and PA are obtained for SS crop types when compared to AW crops. The Other Classes in the classified map show higher commission areas for AW crop types, with Oat contributing the most, whereas for the SS crops the commission is more equally spread by the main classes, with Corn in first place. However, UA for Other Classes is very high (97%), meaning that crop commission with other types of classes at national level is relatively low. The PA obtained for Other Classes considering LPIS dataset, shows a somewhat lower percentage (88%), indicating a higher level of omission with the largest contribution coming from AW crops.

Although the most representative annual crops at country level have been trained using a reliable database that allows the identification of the type of crop, their cropping characteristics throughout the year may not be as well captured by the spectral signature of Sentinel-2 multi-temporal data. Spatial resolution of the images may not be sufficient for the classification of some crop types, particularly those from very small parcels (a common practice especially in the North of Portugal), often close to the Sentinel-2 pixel size and UMC of LPIS dataset. Classification errors can also be attributed to the fact that the class Other Classes includes several classes that often have similar spectral properties to those of annual crops, namely between annual AW crops and natural grassland or sparse vegetation, and between annual SS crops and managed grassland or wetlands. Nevertheless, the overall accuracy of the classified annual crop map at national level is 85%, suggesting that the applied methodology can be useful to identify and characterize most of these crop types.

Evaluation of the accuracy of the classes was estimated by aggregating the annual classes into their two growing season types (Table 4). First, LPIS annual crops classes are grouped column wise by type, that is AW or SS, and the UA for each class of the map class is recalculated (UA with LPIS crop aggregation). Second, the same logic is applied to the map classes but aggregating row wise the two different types of annual crops to estimate the new PA (PA with Map crop aggregation). At the end, the differences between UA and PA without and with aggregation are calculated to evaluate the level of improvement, and the average score between UA and PA with aggregation is presented.

Improvements in the UA and PA of almost all annual crop types are noticeable. The most noticeable improvements in UA percentage are observed for classes with previous low scores (e.g. Melon, Potato and Sorghum). Smaller scale improvements are also obtained for classes with previously high UA (e.g. Tomato, Sunflower and Wheat). However, some annual crop classes maintains a low accuracy level (e.g. Clover, Turnip and both Lupines). Generally, the improvements observed in the PA with aggregation of the map classes are even higher. Most noticeable increases in PA are obtained again for classes with previous low scores (e.g. Zucchini, Cabbage and Nitrogen-Fixing Plants). The classes with the lowest PA values after aggregation are Clover, Other Dried Leguminous, White Lupine and Yellow Lupine, being registered accuracy values above 40 % for all the other classes. Despite the satisfactory overall improvements seen by aggregating the data into AW or SS, the mean score between UA and PA with aggregation shows that some annual crop classes still shows low accuracy results (8 classes in 31 below 40 %). This could be related to a high level of heterogeneity that still exists in the categorization of some crop types (e.g Other Horticules and Other Dried Leguminous) which may contain different types of spectral signatures that difficult classification.

Another confusion matrix was produced following Table 3 strategy but aggregating all the annual classes into their two growing season types (AW or SS). Results are presented in Table 5, including the same features from the confusion matrix of Table 3 plus the total area for each intersection. The PA of both crop classes are higher than the UA, with the opposite being true for the Other Classes. Commission error of AW Crops with Other Classes is significantly large, resulting in only 30% of UA for the former. This is possibly due to the inclusion of grassland and permanent crops in the Other Classes. On the other hand, omission error of AW Crops with Other Classes is also larger than the omission of SS Crops with Other Classes, but both have good PA rating (67% and 85%). The smaller errors in the matrix are reported for confusions between both crop types. The overall accuracy of the map with the aggregated crops by type improved only to 87%. If the confusion matrix is calculated without considering the Other Classes the accuracy is greatly improved: the UA of AW Crops and SS Crops improve to 95% and 96%, and the PA accuracies improve to 94% and 97%, respectively. The overall accuracy of the map also increases to 96%. This shows that although the methodology does not efficiently separate crop types from other types of classes, it can separate fairly consistently AW crops from SS crops.

Table 4. UA and PA percentages for all the classes obtained in the previous validation compared with UA with aggregation of LPIS crop types (AW and OW) and with PA with aggregation of Map crop types (AW and OW). Improvement of accuracy is shown through differences and the mean UA and PA aggregation score are also presented.

	UA	*UA w/ LPIS crop aggreg.*	*UA difference*	*PA*	*PA w/ Map crop aggreg.*	*PA difference*	*Mean UA and PA aggreg.*
Oat	**25**	**32**	*7*	**42**	**57**	*15*	**45**
Ryegrass	**14**	**17**	*4*	**65**	**73**	*9*	**46**
Wheat	**65**	**80**	*15*	**59**	**80**	*21*	**80**
Triticale	**38**	**50**	*12*	**48**	**71**	*22*	**60**
Rye	**19**	**28**	*9*	**37**	**49**	*12*	**38**
Barley	**65**	**76**	*10*	**74**	**86**	*13*	**81**
Yellow Lupine	**2**	**7**	*5*	**25**	**31**	*6*	**19**
White Lupine	**2**	**12**	*9*	**15**	**36**	*21*	**24**
Nitro-Fixing Plants	**8**	**8**	*0*	**7**	**80**	*73*	**44**
Pea	**16**	**24**	*8*	**58**	**70**	*13*	**48**
Broad Bean	**14**	**23**	*8*	**54**	**65**	*11*	**44**
Clover	**0**	**1**	*1*	**1**	**18**	*17*	**10**
Corn	**87**	**90**	*3*	**78**	**90**	*12*	**90**
Other Horticultures	**7**	**25**	*19*	**24**	**43**	*19*	**34**
Potato	**20**	**58**	*38*	**59**	**81**	*23*	**70**
Sorghum	**13**	**32**	*19*	**47**	**67**	*20*	**51**
Pumpkin	**11**	**18**	*7*	**51**	**63**	*12*	**41**
Bean	**20**	**33**	*12*	**31**	**45**	*14*	**39**
Rice	**96**	**96**	*1*	**90**	**97**	*7*	**97**
Tomato	**85**	**94**	*9*	**78**	**97**	*20*	**97**
Sunflower	**68**	**85**	*17*	**76**	**90**	*14*	**88**
Sweet Potato	**22**	**35**	*13*	**48**	**85**	*37*	**60**
Carrot	**72**	**89**	*17*	**47**	**91**	*44*	**90**
Cabbage	**45**	**53**	*8*	**6**	**89**	*83*	**72**
Chickpea	**15**	**22**	*7*	**57**	**64**	*7*	**44**
Melon	**37**	**89**	*52*	**57**	**65**	*8*	**79**
Beetroot				**0**	**91**	*91*	**46**
Onion	**47**	**70**	*23*	**14**	**90**	*76*	**80**
Zucchini				**0**	**93**	*93*	**46**
Turnip	**12**	**12**	*0*	**18**	**47**	*29*	**30**
Other Dried Leg.	**26**	**31**	*5*	**4**	**26**	*22*	**28**

Table 5. Confusion matrix of the crop map and other land cover classes (in rows) with LPIS validation dataset (in columns), with aggregation of crop classes by growing season. Areas are in ha. PA and UA are also presented.

	AW Crops	SS Crops	Other Classes	Total area	***UA (%)***
AW Crops	**12793**	591	29386	42622	**30**
SS Crops	755	**17775**	10057	28287	**62**
Other Classes	5504	2471	**283882**	291780	**97**
Total area (ha)	19053	20836	323324	363213	
PA (%)	**67**	**85**	**88**		

4. CONCLUSIONS

The methodology here presented supports the idea that producing an annual crop map at national level using automatic training and classification of Sentinel-2 multi-temporal imagery is feasible. Training extraction from LPIS annual crop declarations provided reliable information for the classification of a large diversity of annual crops types. The use of a large amount of sampling units combined with automatic filtering and processing of general land cover auxiliary dataset helped to direct the classification towards areas of annual crops. The overall accuracy of the obtained annual crop map at national level is 85%. The map has a reduced level of omission in both growing season crop types, but a large level of commission, particularly for AW crops. This could be related to the fact that the Other Classes includes several classes such as grassland and permanent crops, that can be confused with AW crops. In general, better UA and PA are obtained for SS crop types when compared to AW crops. However, some of the 31 crop classes showed poor UA or PA percentages. This could be caused by a high level of heterogeneity of some crop types. Nonetheless, class aggregation of the annual crop types by the two types of growing season resulted in large improvements in the accuracy of almost all annual crops. However, the overall accuracy of the map with the aggregated crops by type only improved to 87%. As a future work, accuracy comparisons can be performed at the mapping zone level to access regionally the annual crop map quality. Assessment of crop type without considering all the other classes is also important to better verify individually the crop type accuracy. Categorization or aggregation of some lower accuracy annual crop types can be tested and also different crop type features can be used in the nomenclature rather than simply using the two growing seasons. The inclusion of additional non-optical satellite data (e.g. Sentinel-1) could improve the discrimination of some crop types. The results demonstrated that this methodology can be applied to fairly large regions, characterized by diverse landscapes with many distinct annual crop practices, in order to produce an annual crop map able to identify and characterize most of these crop types with great detail and reliability.

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