ACCURACY ASSESSMENT OF A 122 CLASSES LAND COVER MAP BASED ON SENTINEL-2, LANDSAT 8 AND DEIMOS-1 IMAGES AND ANCILLARY DATA

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ABSTRACT

Castile and Leon crops and natural land map is a highly detailed land cover layer, obtained through satellite imagery, which distinguishes between 122 land cover classes and includes 50 specific crop types. The project began in 2013 by using several satellites, with the production cost greatly reduced since 2016 when Sentinel-2 imagery became freely available, and is updated annually. The classification is performed using a machine learning algorithm trained with data retrieved from Integrated Administration and Control System and some other land use databases available in Spain. This map is also proposed as an *advanced crop map,* within SENSAGRI project (Sentinels Synergy for Agriculture) drafting in response of the EO Work programme "EO-3-2016: Evolution of Copernicus Services", as one of the four advanced proof-of-concept services. The algorithm will be validated in others European agricultural test areas which, along with Castile and León, are representative enough to show an overview of the European crop diversity.

Index Terms— Sentinel-2, Landsat-8, Deimos-1, crop classification, land cover, crop mapping, decision tree, supervised classification

1. INTRODUCTION

The main aim of this work is to produce a highly detailed land cover map for 2016 that represents the changes in annual arable crops as well as permanent crops and the areas of natural vegetation.

Combining satellite images from several sensors, the ESA Sentinel-2, the US Landsat-8 and Deimos-1 from private sector between October 2015 and the end of 2016, this land-cover classification map shows different land cover classes across a country-size region of Castile and Leon (over 94,000 km^2) in Spain. Over 1.3 TB of data were used to generate a 20m GSD map, which distinguishes between 122 land cover classes and includes 50 specific crop types, being 35 of them arable crops, 7 are irrigated crops and 8 for permanent crops.

The proposed methodology is based on the US crop data layer [1] and US National Land Cover Database (NLCD). This product takes advantage of supervised classification systems based in machine learning algorithms with huge amounts of satellite images. Machine learning allows computers to become more accurate in predicting outcomes without explicit programming, using algorithms that iteratively learn from data. At its core, machine learning is the process of automatically discovering patterns in data. In particular, decision trees algorithm used here has been proved to be efficient for land cover classification [2].

The used methodology relies on the access to detailed in-situ data from Integrated Administrative Control Systems (IACS) from Common Agricultural Policy and some other databases that contain environmental inventories. The ability to discriminate a wide range of classes converts the product into a useful multipurpose tool that could be applied on administrative controls for agriculture and environmental monitoring.

2. SITE DESCRIPTION

The study area covers the whole region of Castile and León. It is the largest autonomous region in northwestern Spain with an extent of 94,223 km^2 representing one fifth of the Spanish area (see Fig. 1). It consists mainly of a dry and undulating plateau with an average altitude of 800m, surrounded by mountains.

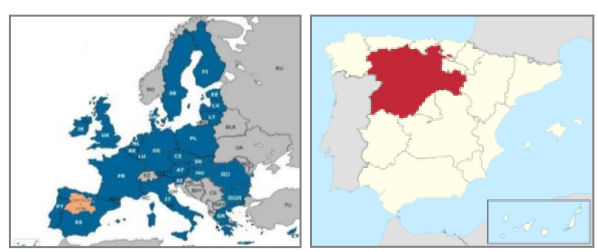

Fig. 1. Study area is the whole region of Castile and Leon.

The territory is composed mainly of areas of extensive herbaceous crops or natural vegetation. Most of the arable land (55,000 km^2) is located in the center of the plateau (see Fig. 2) where rain averages 500 mm. Dryland farming is based in winter crops such as cereals, namely wheat and barley, and also forage. Ten percent of the arable land is irrigated in summer with water stored in reservoirs. The main irrigated crops are maize, barley, wheat, sugar beet, alfalfa and potato. Among permanent crops, vineyards are the most important (see Fig. 3 showing vineyards within wine appellation of Ribera del Duero).

3. DATA SOURCES

The data sources have been divided into two groups: Satellite images, representing the core of the independent variables in the machine learning, and ancillary data. .

3.1. Satellite imagery

Satellite images from three different sensor but similar spatial resolution have been used. The initial goal for this 2016 map was to make use only of the Sentinel-2 satellite but due to the Sentinel-2B having not been launched and a considerable amount of Sentinel-2A images had to be discard due to cloud coverage, the use of other satellite were mandatory. Deimos-1 was a good choice by its spatial resolution (22m) and acquisition programming with low cloud cover and Landsat-8 was chosen by its freely availability and near spatial resolution (30m and 15m in panchromatic). Finally, we make use of 27 Landsat-8 images, three Deimos-1 cloud-free mosaics covering the whole region. 32 Sentinel-2A image compositions were incorporated from the second half of the year when the images were available. A total of 54 multiband compositions of Landsat-8 images were obtained to include three bands each: 2-3-4 or 4-6-7. As for Sentinel-2 images each image includes four bands: 2-3-4-8.

Regarding the amount of images, at least one coverage per month for every piece of land is required to be included.

3.2. Ancillary data

Besides satellite imagery, it is possible and advisable to include more ancillary data in order to aid the classification algorithm to determine the class properly. Those dataset constitute a complement and most of them are available with the pan-European Copernicus land services. These data are considered very stable and therefore could be used for the ongoing year. We used the following complementary data:

- LPIS land cover class information from each ongoing year.
- Digital Elevation Model (DEM) and its derivate Slopes and Aspect.
- Averaged precipitation map (over the last 30-years period, 1981-2010).
- Other dataset available at local level that could help in the discrimination. For instance, vegetation height and canopy cover fraction derived from LIDAR.

3.3. Reference data

Integrated Administration and Control System (IACS) database that contains CAP farmers' applications is the keystone from which we obtain the reference data. This database is compiled by the local Paying Agency and contains an invaluable source of training cases for crops due to the degree of detail and the overwhelming truth contained in farmers' applications.

Regarding natural and semi natural land cover cases, they have been provided by regional public administration responsible of natural resources management and control (Dirección General del Medio Natural). For forest types they rely on two data sources: the Spanish National Forest Inventory plots (except for *Populus spp, Pinus radiata, Eucalyptus spp, Castanea sativa* and *Quercus robur*, that we have generated training datasets manually with aerial photography and ancillary information), and LIDAR data.

3.4. Land cover class definition

Land cover classes should be well defined and its correspondent training cases should be well spatially distributed. The degree of aggrupation of those classes depend on the purpose of the map and the quality of the reference. Since the aim of this methodology is crop discrimination in a very detailed way, we build a detailed crop list based queries from reference database. However, in order to avoid misclassifying within minorities classes by not having the same sampling size than the rest [2, 3, 4] and by lacking enough validation data, we discard them in the proposed legend as long as they do not have a minimum samples in reference data. Therefore, these classes are not included in the training cases. Even though the main purpose of this product is crop identification, in order to avoid commission errors it is important to include in the classification process the rest of the landscape elements besides agricultural crops, that is, natural and semi-natural land cover types such as forests, grasslands, scrubland, bare soil, etc., as well as water, urban and artificial land cover types. To start with, we define a total of 122 classes in the Castile and Leon crops and natural land map of 2016 for the purpose of assessing the possibility of discriminate between not only a vast variety of crops in the community but also different forest species.

4. METHODOLOGY

4.1. Classification algorithm

The classification is carried out by using the data-mining tool C5.0, distributed freely under the GNU General Public License [5]. This C5.0 is an improvement on the previous C4.5 algorithm used to generate decision trees from a set of reference data. Actually, the algorithm selects a random sample of the reference dataset that will be the training cases and uses the rest reference data to validate the result. The algorithm C5.0 needs to set some parameters before being run in order to customize the process of classification. The setting is established to manage to get a boosted classifier using tests that require two branches with at least two cases implied and with a pruning confidence level of 25% preventing the overfitting of the decision tree learning algorithm. The final generated decision trees are applied to all pixels of every satellite images and ancillary data, obtaining the land cover classification of the whole region in a unique step. The classification has been performed using a pixel-based approach.

4.2. Postproccesing

Normally several postproccesing steps take place after classification in order to provide a more easily interpretable map: simplify (grouping) the mapped classes if required due to accuracy problems and crop identification requirements and elimination of speckle artefacts, or the "salt-and-pepper" effect common to pixel-based classifications of fine spatial resolution imagery. The procedure is carried out using the sieve command from Geospatial Data Abstraction Library (GDAL). For this study a special version without grouping has been issued in order to assess the quality of a very detailed product.

4.3. Classification accuracy assessment

The accuracy of the obtained pixel-based classification was evaluated using overall accuracy, producer's accuracy, user's accuracy metrics, F-score and kappa coefficient [6, 7], using nearly 900.000 ha as validation dataset, which comprises almost a 10% of the whole region.

5. RESULTS

5.1. Classification accuracy assessment

We obtained an overall classification accuracy of 83.94% and a kappa coefficient of 0.80 (see Table 1). The two more representative crop classes within the region, wheat and barley (see Fig. 2 and Fig. 3), representing more than the half of the arable land of Castile and León, obtained high accuracy measures, F-Score of 87.1 and 89.2, respectively, even though both cereals are very similar botanically and have slight phenological differences.

In the Table 1, results from 60 classes selected are shown in order to give a good idea about the accuracy assessment among the more frequent classes. These classes represents more than 80% of the total map area.

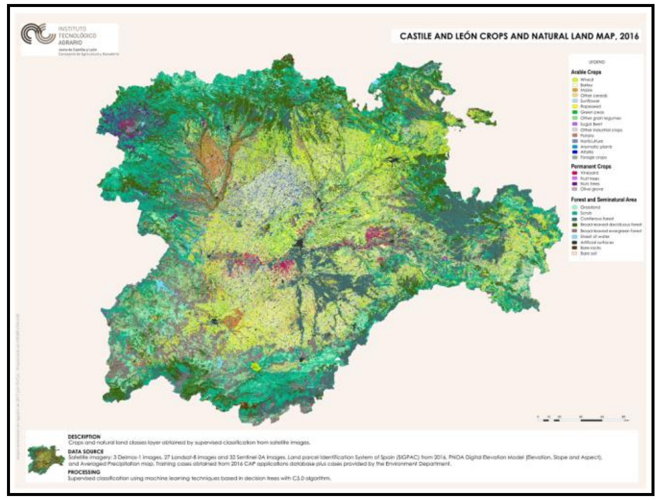

Fig. 2. Crop and natural land classification map over the test site of Castile and León for 2016.

The highest accuracies were achieved by crops and forest species resulting rather good accuracy indexes as shown in the table 1. In particular, maize class (F-Score 96.8), followed by sugar beet, sunflower, barley and wheat are the classes better classified among crops. The lowest accuracy measures among crops was obtained by triticale and forage classes (F-Score 38.22 and 38.36, respectively). Triticale is a product developed in the last century by crossing wheat and rye; therefore, as might be expected, it is misclassified in the latter classes, mostly to wheat class. As for forage, the low index is because of the confusion with the alfalfa class, what suggests us that these two categories should be integrated into only one. Likewise, triticale might be included in the wheat class to prevent misclassification errors or future inaccuracies in these minor classes.

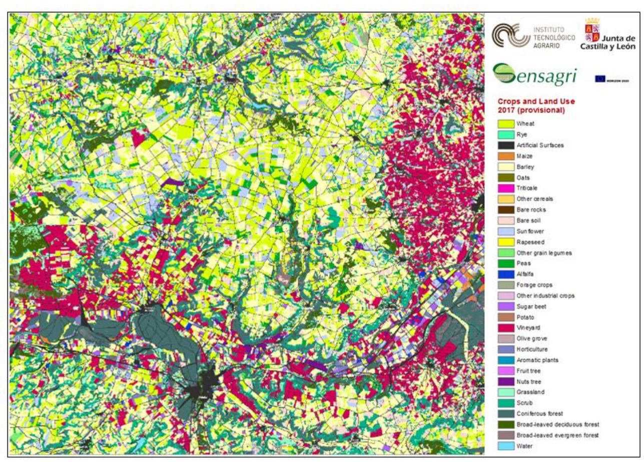

Fig. 3. Example of crop and natural land classification map over a mixed area with natural vegetation, arable land and permanent crops along the Duero River (Spain).

Concerning the irrigated arable crops, we obtained satisfactory results expect for oats class, and also, for rye and triticale (not shown in the table), being the less extended one. This suggests that we might be able to discriminate only the main irrigated crops: wheat, barley, alfalfa and sunflower, being wheat the best classify by far. It is important to mention that reliability of ground truth for irrigated crop is under concern, especially for crops that are not first priority due to its productivity or market value (such as barley).

Regarding to forest classes, most of them yielded very acceptable accuracy measures even though there are some errors when we try to discriminate some classes in terms of their density. The high misclassification rates of the forest classes were caused by this reason. Thus, it is highly advisable to take this into account in future classification maps and consider each forest class as a whole without regarding their canopy cover fraction.

Table 1. Accuracy measures for each crop type in the classification map 2016.

Land cover (treshold)	Class description	nº	Map area (%)	Ref. area (%)	CI UA	CI PA	FS	Est. K
Arable Crops (>0.25% map area & >0.34% reference data)	Wheat	1	11.95	29.20	84.46±0.14	89.94±0.12	87.12	0.78
	Maize	4	1.29	3.20	99.01±0.12	94.7±0.26	96.81	0.99
	Barley	5	9.82	27.67	87.21±0.13	91.22±0.11	89.17	0.82
	Rye	6	0.71	2.94	83.31±0.67	39.44±0.6	53.54	0.83
	Oats	8	0.72	3.80	78.12±0.67	34.53±0.51	47.89	0.77
	Triticale	13	0.48	0.81	51.98±1.54	30.21±1.08	38.22	0.52
	Fallow	21	1.92	1.55	77.53±0.66	87.4±0.56	82.17	0.77
	Sunflower	33	3.87	8.96	92.42±0.19	92.22±0.19	92.32	0.92
	Rape	35	0.47	1.47	90.5±0.54	81.46±0.67	85.74	0.90
	Green Peas	40	0.38	1.48	86.34±0.64	75.34±0.74	80.46	0.86
	Vicia sativa	52	1.11	4.57	87.33±0.36	70.45±0.45	77.99	0.87
	Alfalfa	60	0.74	3.34	92.34±0.34	74.24±0.5	82.3	0.92
	Forage	61	0.63	0.34	25.98±0.94	73.25±1.59	38.36	0.26
	Raygrass	69	1.15	0.48	42.68±1.14	74.08±1.33	54.16	0.42
	Sugar beet	82	0.27	0.38	92.69±0.87	97.22±0.57	94.9	0.93
	Potatoes	94	0.26	0.37	80.27±1.3	90.27±1.03	84.98	0.80
Irrigated Arable Crops (>0.15% map & >0.10% ref)	Irrigated wheat	70	0.38	1.48	82.42±0.84	50.61±0.87	62.71	0.82
	Irrigated barley	71	0.16	0.55	61.14±1.59	46.39±1.42	52.75	0.61
	Irrigated alfalfa	72	0.44	0.72	70.27±1.02	86.44±0.85	77.52	0.70
	Irrigated sunflower	73	0.23	0.47	70.3±1.38	73.37±1.36	71.8	0.70
	Irrigated oats	76	0.17	0.12	37±1.94	81.34±2.32	50.86	0.37
Permanent crops (>0.14 & >0.08%)	Vineyard	100	0.96	1.14	98.28±0.26	96.86±0.34	97.56	0.98
	Olive groves	101	0.14	0.09	99.1±0.67	99.26±0.62	99.18	0.99
Forest Areas with different canopy cover fraction expressed in % (>0.1% map area & >0.01% reference data)	Pinus sylvestris (>70%)	120	2.50	0.09	91.36±1.99	91.36±1.99	91.36	0.91
	Pinus nigra (>70%)	124	0.83	0.01	63.44±7.63	94.99±4.23	76.07	0.63
	Pinus pinaster (>70%)	126	2.29	0.10	83.31±2.53	83.83±2.51	83.57	0.83
	Pinus pinaster (40-70%)	127	0.56	0.03	71.68±6.73	50.75±6.28	59.42	0.72
	Pinus pinaster (10-40%)	128	0.62	0.01	51.76±10.55	46.15±9.94	48.8	0.52
	Pinus radiata (>70%)	134	0.15	0.03	96.82±2.03	99.38±0.92	98.09	0.97
	Quercus ilex (>70%)	143	1.39	0.02	52.48±6.38	69.62±6.76	59.85	0.52
	Quercus ilex (40-70%)	144	1.87	0.04	38.99±4.25	61.08±5.32	47.6	0.39
	Quercus ilex (10-40%)	145	2.37	0.04	42.64±4.45	59.67±5.23	49.74	0.43
	Quercus pyren. (40-70%)	186	0.92	0.02	52.85±9.27	43.7±8.37	47.84	0.53
	Quercus pyren. (>70%)	187	3.36	0.06	72.99±3.57	86.7±2.98	79.25	0.73
	Quercus pyren. (10-40%)	188	2.10	0.02	42.16±7.08	54.01±8.09	47.36	0.42
	Populus plantat. (>70%)	198	0.62	0.27	93.63±0.97	98.6±0.48	96.05	0.94
	Quercus rubber (>70%)	241	0.50	0.23	93.89±1.02	97.9±0.62	95.85	0.94
	Quercus rubber (40-70%)	242	0.10	0.03	85.59±6.89	39.33±6.5	53.89	0.86
	Castanea sativa (>70%)	243	0.45	0.17	93.83±1.2	97.64±0.77	95.7	0.94
	Castanea sativa (40-70%)	244	0.12	0.02	84.2±7.27	46.31±7.37	59.76	0.84
Other (>0.5% & >0.05%)	Rocky areas	9	0.79	0.06	98.35±1.11	98.11±1.18	98.23	0.98
	Artificial and urban areas	3	1.31	0.09	95.97±1.33	99.99±0.08	97.94	0.96
	Water cover	255	0.67	1.50	99.86±0.07	98.74±0.19	99.3	1.00
Overall accuracy								**83.94**
Kappa index								**0.80**

6. CONCLUSION

This study showed that this approach is very useful to crop and natural land mapping from satellite images, LIDAR and other ancillary data, in a very large area (9.4 million hectares), achieving an overall accuracy of 83.94% and a kappa coefficient of 0.80. We conclude that agricultural crops and many forests can be well classified by means of this pixel-basis approach. On the other hand, we have verified that open forests and non-forested natural areas (shrubs, scrubland, grassland, etc. not shown in the table 1) are not easily classified with this methodology.

However, what is even more important is that it proved that crop discrimination in Castile and León is accurate enough to support the proposed monitoring approach within European Common Agriculture Policy.

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