GENERATING CROP MASKS FOR THE EU THROUGH LUCAS DATA, CORINE AND SPOT NDVI-IMAGERY

From point data to map units reflecting area fractions grown to major crops

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ABSTRACT

Recently, about a quarter of a million land cover data collected through the LUCAS project, at systematically pre-defined sample points, became available. These data paved the way, through an up-scaling process, to generate reference crop-masks (maps) covering systematically the whole territory of the EU, as e.g. required for improved crop monitoring (MARS project; requiring what is where maps), setting a benchmark for future change specifications, or to support annual surveys to establish variability in crop areas planted and to subsequently generate improved annual crop area statistics.

For the process of up-scaling, the point data required to be correlated with a classified spatial product, generated from hyper-temporal imagery that was assumed to have captured both spatial as temporal variability of actual land cover. Through the use of NDVI data of the SPOT-VGT archive, that captured differences in land cover phenology, density, and followed crop calendars at a 1km spatial resolution this feat could be accomplished. Additional use through data-mining of the most recent CORINE map of the EU, which specifies where broad land use categories are practiced, though without specifying the actual crop species cultivated, proved very useful to achieve a final set of crop maps that adhere to the high producer as user accuracy requirements set by the authors.

The generated temporal NDVI-profiles that link to areas where a crop is grown, the practiced cropping calendar can be deduced. Factual survey data on planting and harvesting periods remain to be integrated into the legends of the produced crop maps to make them truly comprehensive.

INTRODUCTION

Using remote sensing (RS) to monitor and report on the performance of agricultural production is by necessity crop-specific. Agricultural statistics derived from RS-imagery are often generated and reported by administrative units. All RS-based data within the administrative areas are then considered of equal importance. We however all know that the extent of areas cropped to a specific crop differs considerably from the artificially superimposed admin-boundaries.

MARS bulletins [1] generated by JRC of the EU (Agri4Cast; crop monitoring in Europe), report in principle at country level the derived yield and production estimates (Fig.1a). When possible, available masks are applied to discern areas of interest (Fig.1b). Concerning crops, specific masks are simply not available and when possible the CORINE map [2] is used to produce the required masks (Fig.1b). Though CORINE reports specific areas for major land use/cover classes, it does not report within relevant areas where exactly individual arable crops are cultivated (Fig.2). By class that may differ considerably pending on climate, weather, soil, terrain, available markets and processing facilities, land rights, economic conditions like costs and prices, plus farm and logistical specifications. Basically, a farmer decides from year to year which arable crop to grow. Overall, it is known that within a relatively homogeneous farming area, the mix of crops grown across fields remains constant, given that changes in given conditions do not alter the annual decision making.

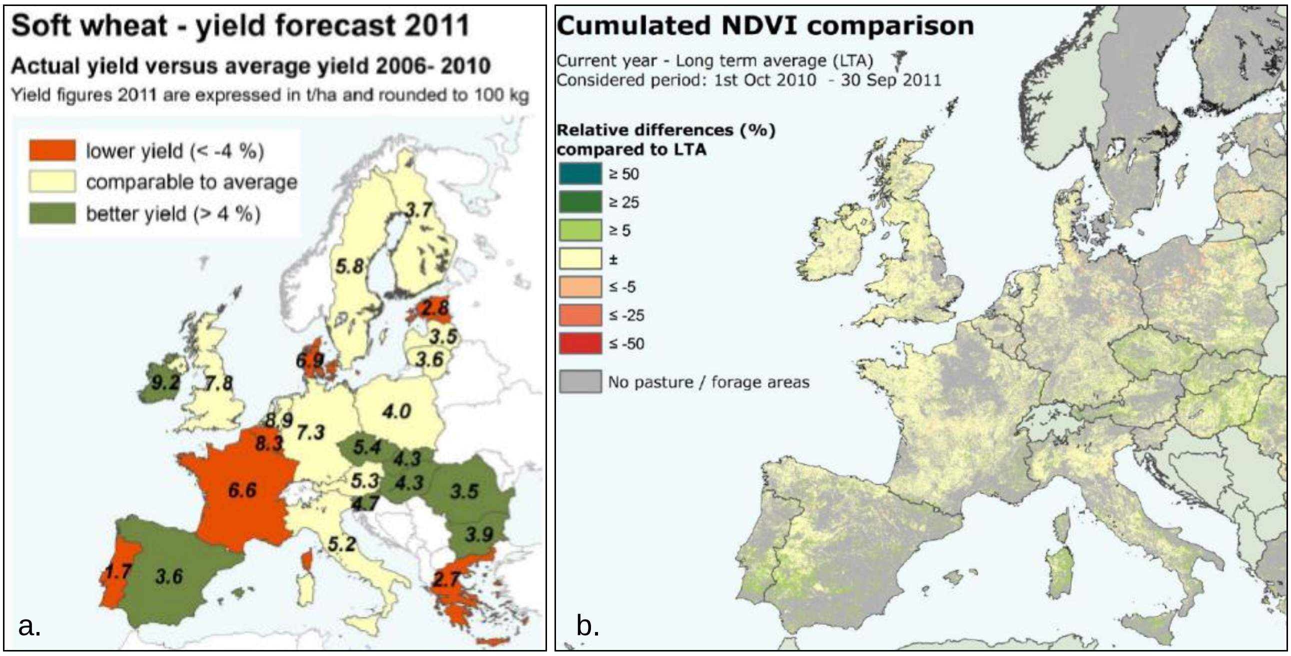


Figure 1. ***a****: MARS country level forecasts report on wheat yields (© JRC)*
b*: MARS pasture/forage anomaly report for the EU after applying a mask (© JRC).*

Maps that report for areas cultivated, crop-specific cropping intensities (crop-masks) require specific image interpretation methods plus data by ground observations [3]. Images used to cover a study area are either single frame or are multi-temporal [4,5,6,7,8]. The goal was often to make crop area assessments or to prepare land cover maps. Discussions frequently focus on resolution and scale [9]. Agro-ecosystems however show frequently a higher temporal (seasonal) variability than a spatial one [3]. This characteristic was in the past poorly used for agro-ecosystems mapping due to the general lack of high-quality imagery availability. In recent years however, free MODIS, SPOT-VGT and MERIS data offered the option to study and gain insights in temporal dynamics due to their almost daily global revisiting frequency. This gain however implied a loss in spatial resolution: 250m to 1km spatial resolution versus an 8 to 16 day temporal frequency of the supplied Maximum Value Composites (MVC) imagery.

Traditionally, vegetation monitoring based on remotely sensed data [10] has been carried out using vegetation indices like the Normalized Difference Vegetation Index (NDVI) derived by dividing the difference between infrared and red reflectance measurements by their sum; it is an effective index of photosynthetic active biomass [11,12,13,14,15,16,17,18,19,20]. Several studies indicated the suitability of temporal NDVI-profiles for studying spatial variability in land cover (phenology) and in practiced crop-calendars [21,22,23,24,25].

The most common use of hyper-temporal imagery is called ‘anomaly mapping’; an anomaly is defined by the difference of the current reading versus the average of the long-term readings. Operational systems [26] are e.g. the Foreign Agricultural Service (FAS) of the USDA, the Global Agricultural Monitoring (GLAM) of USDA/NASA, the MARS project of the European Joint Research Centre (JRC), the CropWatch System of the CAS in China, the Famine Early Warning System (FEWS NET) of the USAID, and the Global Information and Early Warning System (GIEWS) of UN FAO. All these systems typically do not consider area stratification concepts to monitor predefined crop-specific strata. This calls for an exploration to improve the established methods so that monitoring becomes agro-ecosystem specific. A WFP representative [27] worded this as: “This type of EO information (anomaly mapping) must be combined with other information if conclusions need to be drawn about possible impacts on rural/pastoral households, like info on land cover, crop calendars, and household livelihoods.” The argument counts equally for the generation of agricultural statistics through monitoring efforts as practiced by MARS. In short: Crop monitoring methods can substantially benefit when methods to prepare good crop-masks become available.

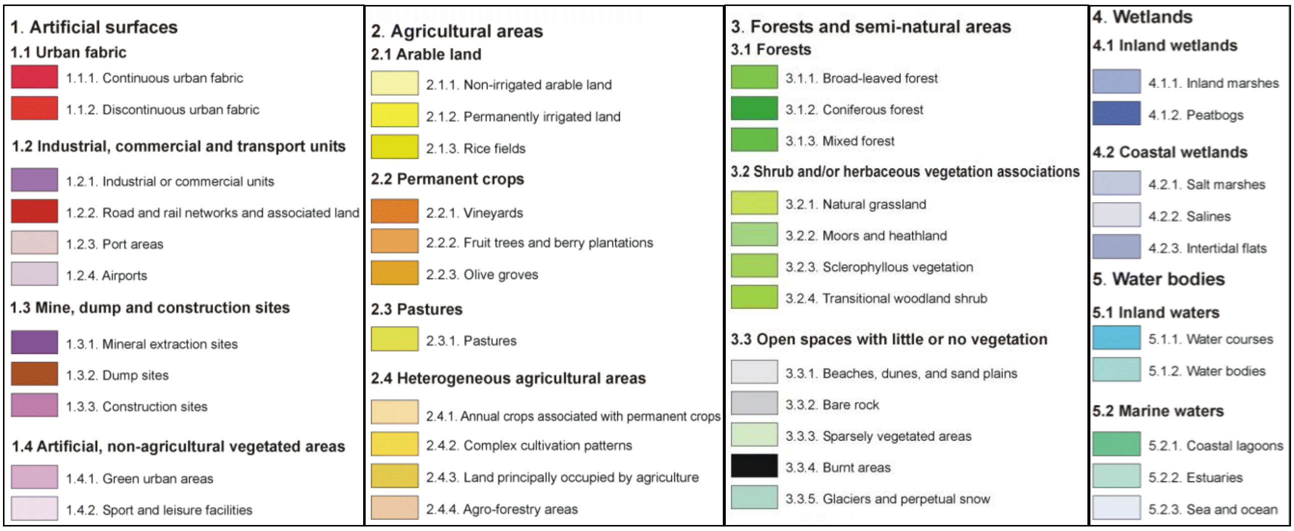


Figure 2. *The CORINE legend [2].*

METHOD

Data used

The **CORINE** Land Cover map [2] for the EU of 2006 as derived through segmentation of ETM+ 30m resolution imagery was used. It was made available by the JRC. The map covers all EU-countries and nominated EU-countries except Greece and Iceland (Fig.3a). Its legend is shown in Fig.2.

Through the JRC the **LUCAS 2009** Land Use / Cover Area Frame Survey was obtained [28,29]. For 23 European countries, it contains for some 230,000 pre-defined (geo-referenced) points, data that were collected by field surveyors (Fig.3b). The points were spaced at equal intervals of 2km, following the standard grid of the EU (Lambert Azimuthal Equal Area projection; ETRS spheroid). Randomly, within accessible areas, actually only about 6-7% of the available 2km-spaced grid points were sampled. Used for this paper was, besides the locations of all points, only data of the land cover parameter (LC1) and land use parameter (LU1).

The used **SPOT-Vegetation** data [38] cover the period 1 Jan.2006 to 31 Dec.2010 (10-day MVC's, 36 images per year, 5 years). Provided are DN-values (0 to 255) representing NDVI data (-1 to 1). Pre-processing steps executed were:

- Only pixels (area-of-interest) of the 23 countries covered by LUCAS were kept (plus pixels 10km across borders plus the whole of Switzerland; Fig.3c).
  By pixel (1km-sq) the upper envelop was generated [30,31,32,33] to remove haze & cloud effects. De-clouding of the received DN-values by pixel was carried out in two steps. Firstly, by image and pixel, based on the supplied quality record: only pixels with a 'good' radiometric quality for bands 2 (red; 0.61-0.68 µm) and 3 (near IR; 0.78-0.89 µm), and not having 'shadow', 'cloud' or 'uncertain', but 'clear' as general quality, were kept (removed pixels were labeled as 'missing'). Secondly, a modified version of ASAVGOL [30] as built in TIMESAT 2.3 [31,32,33] was used to derive the upper-envelop through application of the Savitzky Golay filter [34] on a pixel-by-pixel basis of the temporal NDVI values. Relatively low NDVI values are assumed related to haze and undetected cloud cover, while relatively high NDVI values (very few; outliers!) are assumed caused by solar reflection off clouds.
- Then, to generate an annual representative image-stack, by pixel the median was generated for each of the 5 annual data repeats.
- The image-stack (now 36 layers) was classified using ISODATA generating classified maps from 10 to 200 classes [35,36,37], and the 128 classes map was evaluated as 'best' within the set range (Fig.4). Details of this step are provided in the next section.

Figure 3d shows the territory for which, based on the available data, the required crop maps could be generated.

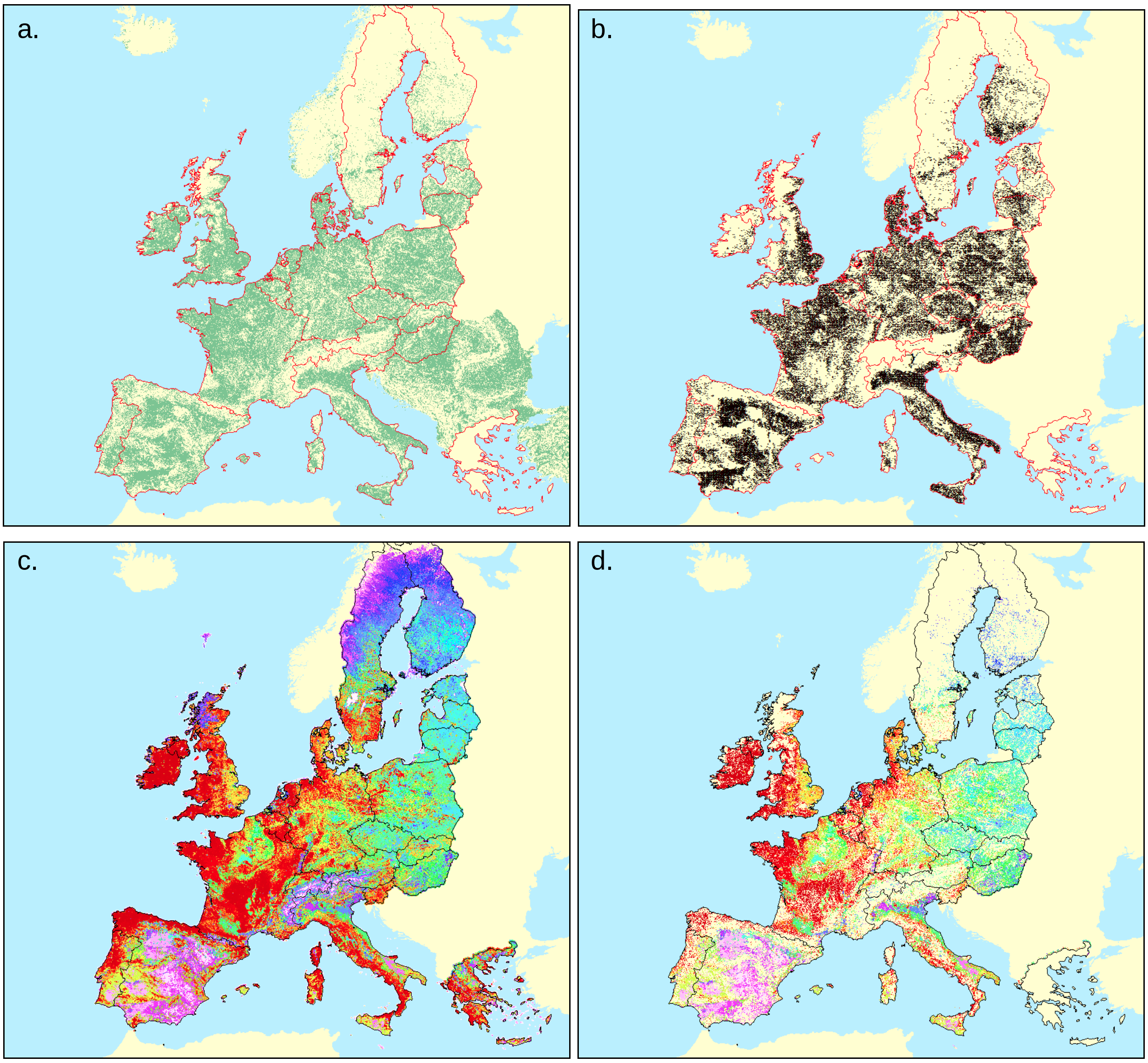


Figure 3. *Data layers available for the territories of the European Union (EU):*

- ***a.*** *Agricultural areas (code=2xx) as mapped by CORINE (2006).*
- ***b.*** *Within **a**: Locations of the 56,221 LUCAS (2009) point observations on cropland (code=Bxx).*
- ***c.*** *The classified SPOT-VGT product (128 classes; colors used are random).*
- ***d.*** *The intersection between **a** and **c** (same colors as **c**), to be related to **b**.*

SPOT-NDVI imagery classification

The free 10-daily MVC NDVI-images of SPOT-VGT for 5 years [38], constitute an image stack of 180 layers. The stack of NDVI values is extremely data-rich and multi-dimensional. A data-implosion through classification leading to a 2-dimensional map having classes described by temporal NDVI-profiles brings out exactly where (spatial) and when (temporal) the major part of the variability in NDVI is for the area and time-span studied.

Thus, using the ISODATA clustering algorithm of Erdas-Imagine software [39] and all compiled and stacked NDVI images (36x) many unsupervised classification runs were carried out to generate maps with a series of pre-defined number of classes. Unsupervised indicates that no additional data were used or expert's guidance applied, to influence the classification approach. The maximum number of iterations was set to 50 and the convergence threshold to 1.0. One 'run' performed an entire classification, and was "self-organizing" regarding the way in which it located the clusters that are inherent in the data; the ISODATA algorithm minimizes the Euclidian distances to form clusters [39,40]. Of each produced map, of classes generated, the NDVI-profiles can be presented graphically and matched to their spatial extent. Also their separability statistics can be retrieved; they indicate how different classes are amongst one-another. A graphical presentation of these separability statistics is used to select which map produced, having 'what' number of pre-defined classes, can be the 'best' map of choice. This choice presents almost always a no-win solution between: (i) keep the number of classes low to gain maximum data-reduction, and (ii) optimize separability between classes without information loss. Figure 4 presents this trade-off dilemma faced.

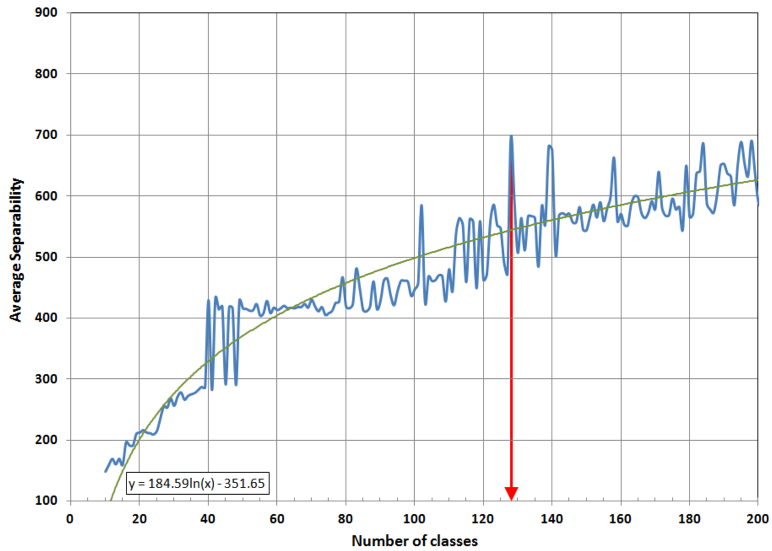


***Figure 4**. Average separability statistics, as derived from the iteration to classify (unsupervised) the NDVI-imagery into 10 to 200 classes. At 128 classes, the positive deviation from the shown trend line (green) indicates a natural 'state of balance' between the variability in NDVI-data and the classification results.*

Thus, a preliminary agro-ecological map is realized for the EU that uses both spatial as temporal information regarding the greenness of the Earth's surface, therefore stratifying variability in vegetation abundance and phenology as of crop calendars practiced (Fig.3.c). In fact the map represents the overall result of geology, landform, terrain, soil, climate plus weather, and land use on the vegetative land cover. It is definitely an integrated index that captures the variability of the real situation while not explaining exactly what the true differences are or why they are different. The intermediate legend consists only of NDVI-profiles that are indicative of when what (which mix) is where. Considering the low spatial resolution of the input imagery, the NDVI-profiles almost always represent land cover/use complexes. Only use of additional data will translate the intermediate legend into a practical and informative legend.

Preparation of the crop maps

The following procedure was followed to generate the required crop maps containing frequency statistics (=cropping intensity) by map unit:

- The 128 classes SPOT raster map (Fig.2c) was converted to a polygon map with identical geo-referencing specifications as the LUCAS (2009) and CORINE (2006) datasets, being the Lambert Azimuthal Equal Area projection (in meters) on the ETRS (1989) spheroid with the ETRS (1989) zero-datum (false easting=4321000; false northing=3210000; central meridian=10; latitude of origin=52).
- Through the spatial-join operation in ArcGIS, to each of the LUCAS (2009) point-based record, the proper CORINE (2006) and SPOT class-identifier codes were added (Table 1).

- The CORINE (2006) and SPOT maps were intersected, and only map units of CORINE×SPOT combinations where LUCAS stated that crops were grown were kept (Fig.2d). As a result, well-known SPOT data inconsistencies for areas at very high latitudes became non-relevant.
- From the updated LUCAS attribute table, series of pivot-tables were prepared through the parse-operation in MS-Excel (Table 1). Frequency counts of LUCAS records by CORINE× SPOT combination were used to prepare summary tables. Compared by combination were frequency data of:
  - (**c**) land cover (LC1) is equal to one of the cropland codes (code=Bxx; 40 different codes).
  - (**a**) land cover (LC1) is equal to any cropland code (code=Bxx) and the land use code (LU1) and equal to any agriculture, forestry, fishing, mining, or hunting code (code=U1xx). Only 60,614 records qualified (26%; Fig.3b). In total only 33 cropland points fell beyond the U1xx-condition.
  - (**l**) any LUCAS record (total of 234,709 records).
- Using (**c**)/(**a**) and (**c**)/(**l**), tables with ratio-data evolved (in %). During made calculations, author-defined thresholds were set (otherwise the ratio was set to "0"):
  - The sum of the (**c**) count for all SPOT cases by CORINE class must be higher than 5.
  - The sum of the (**c**) count for all CORINE cases by SPOT class must be higher than 5.
  - The (**a**) count for any CORINE×SPOT combination must be higher than 10. The count of (**l**) was not considered.
  - The derived (**c**)/(**a**) and (**c**)/(**l**) percentages must be higher than 1%. Lower values represent inclusions that are rarely shown on maps.
- To the generated tables, by CORINE×SPOT class, the sum of all (**c**)/(**a**) and (**c**)/(**l**) values were added, to denote respectively the 'tabulation success' and the 'unit specific cropping-intensity'.
- The data of the summary tables were then added to the CORINE×SPOT map.
- Note: no results were produced for Greece as for the Faroe and Shetland islands. Through extrapolation, results were however produced for Switzerland, the Balearic Islands and Malta.

***Table 1**. Tabular data and parse-operations:*

a. *Section of the LUCAS table to which CORINE and SPOT class codes were added. The CORINE-classes are reported under 'code-06' and the SPOT-classes under 'gridcode'.*

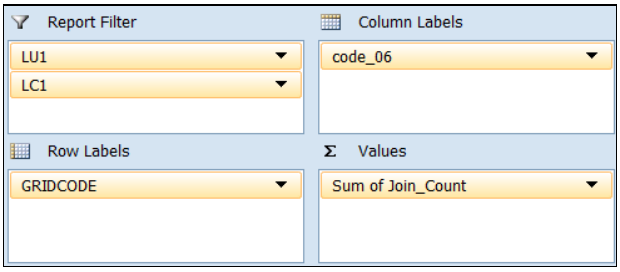
b. *The used parse-command in MS-Excel.*

c. *Section of the parse results with counts for a specific crop (left) and for all crops (right).*

Join_Count	POINT_ID	LC1	LU1	code_06	GRIDCODE
1	26501948	B76	U111	243	22
1	26521992	B55	U111	242	7
1	26561964	B16	U111	242	90
1	26561986	B21	U111	221	99
1	26581954	B41	U113	243	7
1	26581962	B21	U111	242	90
1	26581984	B82	U111	221	99
1	26602000	B55	U111	243	99
1	26621956	B55	U111	243	22
1	26621992	B55	U111	242	79
1	26641984	B82	U111	221	99
1	26661818	B23	U111	212	83
1	26661926	B55	U111	243	99
1	26661998	B16	U111	242	116
1	26662006	B43	U111	242	83
1	26681768	B81	U112	241	86
1	26681804	B55	U111	212	99
1	26681918	B82	U111	221	109
1	26681984	B82	U111	221	99
1	26701960	B12	U111	212	83
1	26701970	B55	U111	242	99
1	26701978	B21	U111	242	90
1	26721828	B83	U111	212	90
1	26722008	B21	U111	242	99
1	26741820	B74	U111	212	99

a.

b.



LU1 (All) Only Agriculture
LC1 B11 (make a Bxx selection)

Sum of Joi Colun												
Row Lab	**211**	**212**	**213**	**221**	**222**	**223**	**231**	**241**	**242**	**243**	**244**	**Sum**
3	31	3	0	1	0	0	0	0	5	0	0	40
7	80	5	0	1	0	0	0	0	2	4	2	94
8	66	3	0	0	0	0	0	0	1	1	8	79
9	151	13	0	2	0	0	0	0	5	7	0	178
13	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0
15	27	1	0	0	0	1	0	0	1	3	1	34
16	3	0	0	0	0	0	0	0	0	1	0	4
17	0	0	0	0	0	0	0	0	0	0	0	0
19	35	1	0	2	1	0	0	0	2	2	1	44
20	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0
22	4	1	0	0	0	1	0	0	0	1	1	8
23	3	2	0	0	0	0	0	0	0	0	0	5
24	1	0	0	0	0	0	0	0	0	0	0	1
25	0	0	0	0	0	0	0	0	0	0	0	0
26	24	5	1	0	0	0	1	0	3	2	0	36
27	0	0	0	0	0	0	0	0	0	0	0	0
28	50	0	6	0	0	0	0	0	1	0	0	57
29	3	3	0	0	0	0	0	0	0	0	0	6
30	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0
33	8	1	0	0	0	0	0	0	1	0	0	10
34	14	0	0	0	0	0	1	0	0	0	0	15
35	0	0	0	0	0	0	0	0	0	0	0	0
36	50	0	0	1	1	0	1	0	0	1	0	54

LU1 (All) Only Agriculture
LC1 (All) All crops

c.

Sum o Col												
Row	**211**	**212**	**213**	**221**	**222**	**223**	**231**	**241**	**242**	**243**	**244**	**Sum**
3	593	39	1	145	19	57	0	1	308	49	4	1216
7	854	80	1	11	14	71	1	4	105	17	9	1167
8	352	19	0	5	3	46	1	6	38	16	40	526
9	1314	110	0	11	0	0	2	1	36	40	5	1519
13	0	0	1	0	0	0	0	0	0	0	0	1
14	0	0	1	0	0	0	0	0	0	0	0	1
15	695	19	0	2	1	11	1	12	22	18	7	788
16	12	0	0	0	0	0	0	0	0	3	0	15
17	4	0	0	0	0	0	0	0	0	3	0	7
19	457	94	0	99	45	290	0	4	298	60	7	1354
20	1	0	1	0	0	0	0	0	0	0	0	2
21	6	3	1	71	0	0	0	0	21	0	0	102
22	105	51	0	23	66	413	0	4	142	28	16	848
23	83	32	182	0	3	0	0	0	1	1	0	302
24	4	0	0	0	0	0	0	0	0	0	0	4
25	4	0	2	0	0	0	0	0	0	0	0	6
26	164	118	5	55	26	16	1	0	101	38	2	526
27	1	0	2	0	0	0	0	0	0	0	0	3
28	437	41	44	1	4	0	1	0	30	0	0	558
29	21	40	4	37	6	0	1	0	8	1	0	118
30	2	0	0	0	0	0	0	0	1	0	0	3
32	2	0	0	0	0	0	0	0	0	0	0	2
33	48	36	14	41	2	1	1	0	15	4	0	162
34	110	0	0	0	1	0	2	0	7	0	0	120
35	19	0	0	0	0	0	1	0	0	18	0	38
36	339	1	1	17	20	0	12	0	28	17	0	435

RESULTS

The essential result of tabulating crop-wise the frequencies of LUCAS points by NDVI and CORINE classes resulted in a table that listed by crop the required cropping intensities (Table 2). These records were successively linked to the map containing the CORINE×SPOT map units.

Table 2. *Section of the frequency table showing by crop, SPOT-class (NDVI) and CORINE-class (Cor-06) the respective frequency statistics (%) after applying the set thresholds.*

		Common wheat	Durum wheat	Barley	Rye	Oats	Maize	Rice	Triticale	Other cereals	Potatoes	Sugar beet	Other root crops	Sunflower	Rape and turnip seeds	Soya
NDVI	**Cor06**	**B11**	**B12**	**B13**	**B14**	**B15**	**B16**	**B17**	**B18**	**B19**	**B21**	**B22**	**B23**	**B31**	**B32**	**B33**
3	211	5.2	18.2	49.6	0.0	7.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
7	211	9.4	17.9	36.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	16.5	0.0	0.0
8	211	18.8	18.8	14.2	0.0	13.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	7.1	0.0	0.0
9	211	11.5	0.0	59.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	9.0	0.0	0.0
13	211	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
14	211	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
15	211	0.0	42.4	22.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	9.8	0.0	0.0
16	211	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
17	211	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
19	211	7.7	6.8	45.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	10.9	0.0	0.0
20	211	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
21	211	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
22	211	0.0	14.3	24.8	0.0	5.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.7	0.0	0.0
23	211	0.0	0.0	0.0	0.0	0.0	75.9	8.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
24	211	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
25	211	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
26	211	14.6	0.0	37.2	0.0	5.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	7.3	0.0	0.0
27	211	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
28	211	11.4	0.0	0.0	0.0	0.0	65.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.9
29	211	14.3	0.0	19.0	0.0	0.0	14.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
30	211	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
32	211	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
33	211	16.7	0.0	0.0	0.0	0.0	35.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
34	211	12.7	0.0	6.4	0.0	0.0	33.6	0.0	0.0	0.0	15.5	0.0	0.0	6.4	0.0	0.0
35	211	0.0	0.0	31.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
36	211	14.7	0.0	7.4	0.0	0.0	37.8	0.0	0.0	0.0	6.8	0.0	0.0	0.0	0.0	0.0

To the CORINE×SPOT map also the sum of all (**c**)/(**a**) and (**c**)/(**l**) values were added to denote respectively the 'tabulation success' and the 'unit specific cropping-intensity'; Table 3 presents the (**c**)/(**l**) values. Unexpectedly, certain CORINE×SPOT combinations displayed that cropping took place for CORINE classes that were basically considered non-agricultural, i.e.: 112, 321, 323, 324 and 333. The cropping intensities for these units however remained low.

***Table 3**. Cropping intensity for each CORINE×SPOT class combination as defined by the fraction of all crop point counts over all LUCAS point counts for that combination (%; (**c**)/(**l**)). The numbers represent the 'unit specific cropping-intensity'.*

	112	211	212	213	221	222	223	231	241	242	243	244	311	312	313	321	323	324	333
3		60	40		73	46	87			66	22						9		6
7		66	68			63	93			63	41								
8		46	64				71			50	22	14				8	10		
9		75	76							61	52						20		
15		73	61				69		60	76	60								
19		63	51		71	57	88			61	28						6		7
21		56			88					70									
22		47	45		65	65	88			47	25	29					5		
23		77	68	86															
26		48	64		55	59	67			46	33						10		
28		71	73	79						54									
29		43	55		73														
33		55	51	67	59					36									
34		59																	
35		33									35								
36	5	55			54	75		19		30	24								
38	16	78									30								
39		55									66								
40		32																	
41		60									47								
42		47	63	75	61	47				32									
43		58									46								
44		81	89	83						65									
45		65									43								
46		45									48								
47		72									51			4					
48	14	83								53	37								
49		46								28	39				5				
50		47	79		58					26									
51		43						31			14								
52		49	62		56					42	27								
53		77								46	35								
54	7	53						7		19	14								
55		56									43				2				
56	20	79								34	34								
57		24																	
58		52									42				3				
59		84	63								57								
60		19																	
61	15	77			85			45		36	31								
62		50						7		18	18								
63		27						2		14	5								
64	6	74			58			14		44	22								
65		24									43								
66	12	49				85		6		35	11								
67	23	67						18		28	21			7					
68		69	72							65	51								
69		72	77			85				63									
70		21								15									
71		58			59	56				33									
72	17	77								50									
73	14	82						32		47	30								
74		39								24	13								
75		66	79		60			37		53	28								
76	10	63			76	67		9		37	20								
77		60	73				58		48	46	24								
78		36				69				26	4								
79		37	51		58	67	77		54	54	29						3	3	
80		28				82		3		24									
81		83								67									
82		50			67	64		9		36	16								
83		37	56		67	67	72		41	42	21						2		
84		82																	
85		53						11		40	16								
86		41	62				70		36	46						2	6		
87		44	55		53	70	63			31	19								
88		74						24		44	43								
89	5	68						19		42	13								
90		38			78	69	69		55	43	21					4	2		
91		57						10		34	20								
92		71						21		27	34								
93		53			77	50		15		30	14								
94		78						33											
96		51	32		62	48				32	12								
97		51						14		35									
98		47				91		8		31	14								
99		46	68		62	67	73		37	42	24						2	2	
100		66						19		41	30		8						
101		65								54									
102		35						7		28	11								
103		64						24		36	26								
104		9																	
105	6	49				68		12		26	10								
106		58	73		66	57		24		44	25		4						
107		52						7		33	11								
108		63						17		28	21								
109		41	36		62	71	59		52	39	20						2	2	
110		28						11											
111	3	48			50	71		19		32	17								
112		50				59		11		27	12								
113		58					43	22		33	26								
114		3																	
115		49						11		22	13								
116		33			76	73	74		40	45	28								
117		50			66			15		32	10								
118		27						6		22	6								
119		53			41	50	58		27	35	20			2					
120		27						8		15									
121		52					55	16		34	18		3						
122		37	73			55	65		38	35	22								
123		46						11	31	24	4								
125		42					58	11		25	13								
126		26						7		15	6								
127		20						4		14	5								
128							60			20	8								

The unit specific cropping-intensity map ((**c**)/(**l**)), e.g. for Spain, is displayed in Fig.5. It shows that agricultural areas are concentrated to specific regions (orange-red tones), while other regions contain none (grey-tones) or hardly any cropping (light-blue tones). Consequently, generating monitoring data for Spain should consider only areas where crops are cultivated, and not be a general average data compilation/estimation for all areas without using the displayed stratification. Such stratification should in fact be crop-specific. Figures 8 and 9 show for Spain that within the cropped areas, still very clear differentiations occur between e.g. where olive-groves occur versus where rice is cultivated. Further examples of crop-specific cropping intensity maps are shown in Figures 6, 7 and 9. These maps further confirm that areas differ considerably concerning their crop-specific relevance.

The scale (resolution) of the displayed maps is based on the used input maps. CORINE is based on 30m resolution imagery interpretation while the SPOT layer originates from 1km^2 imagery. Thus, the shown maps pretend to have a spatial accuracy that is basically over-rated. Accordingly the generated crop maps must be re-sampled to a 1km resolution on the basis of the weighted contribution of the concerned polygons within that grid. This exercise is still pending, and only when completed, the created crop intensity maps will be made available widely through the internet.

Also the displayed crop intensity data still require statistical screening and validation on the basis of number of LUCAS points used by CORINE×SPOT combination as through the use of external data sources, e.g. to address the question: does unit size influence accuracy? Till this work is completed, the generated cropping intensity data remain tabulated results.

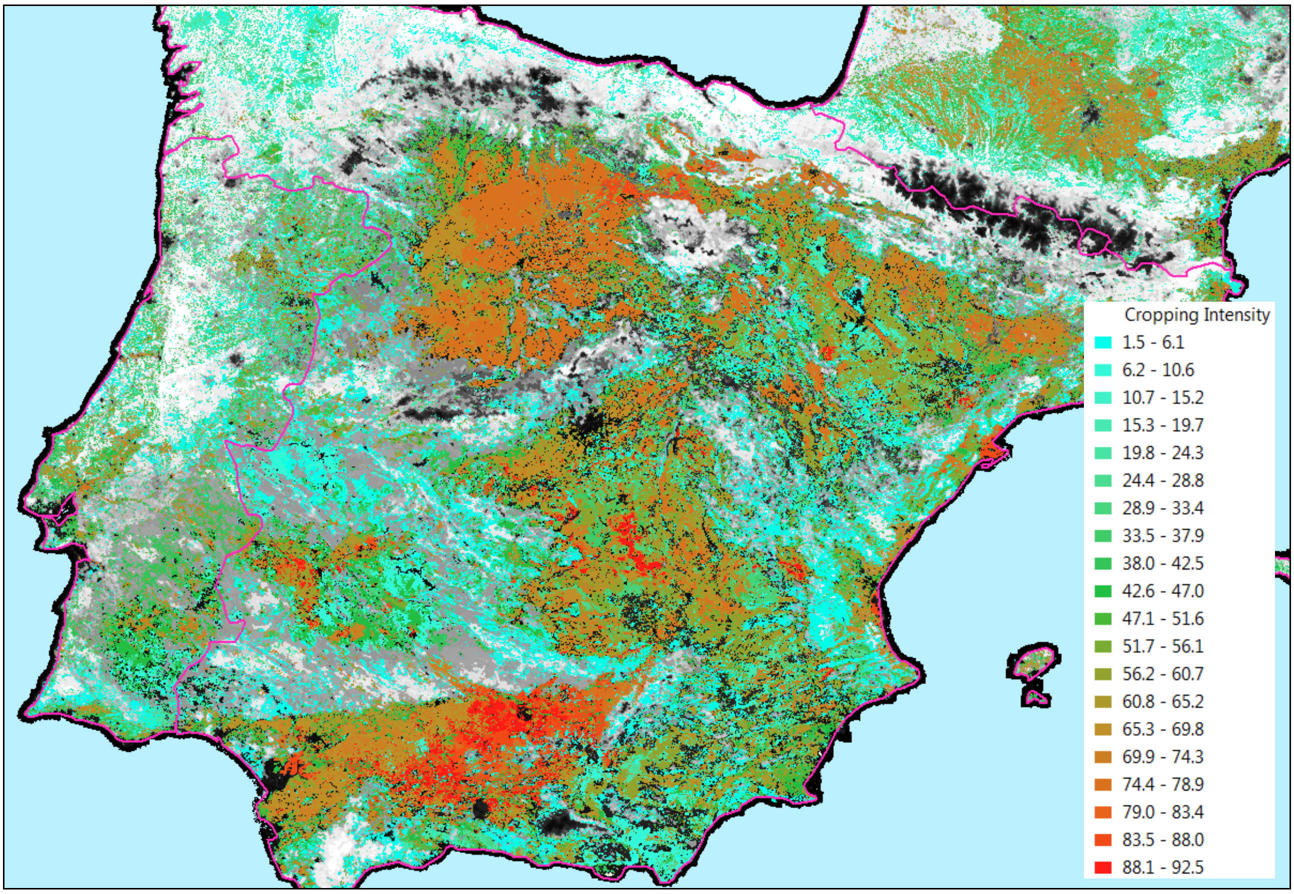


Figure 5. *Cropping intensity in Spain and Portugal as defined by the fraction of all crop point counts over all LUCAS point counts (%). The cropping intensity is specific for each CORINE×SPOT class as specified in Table X.*

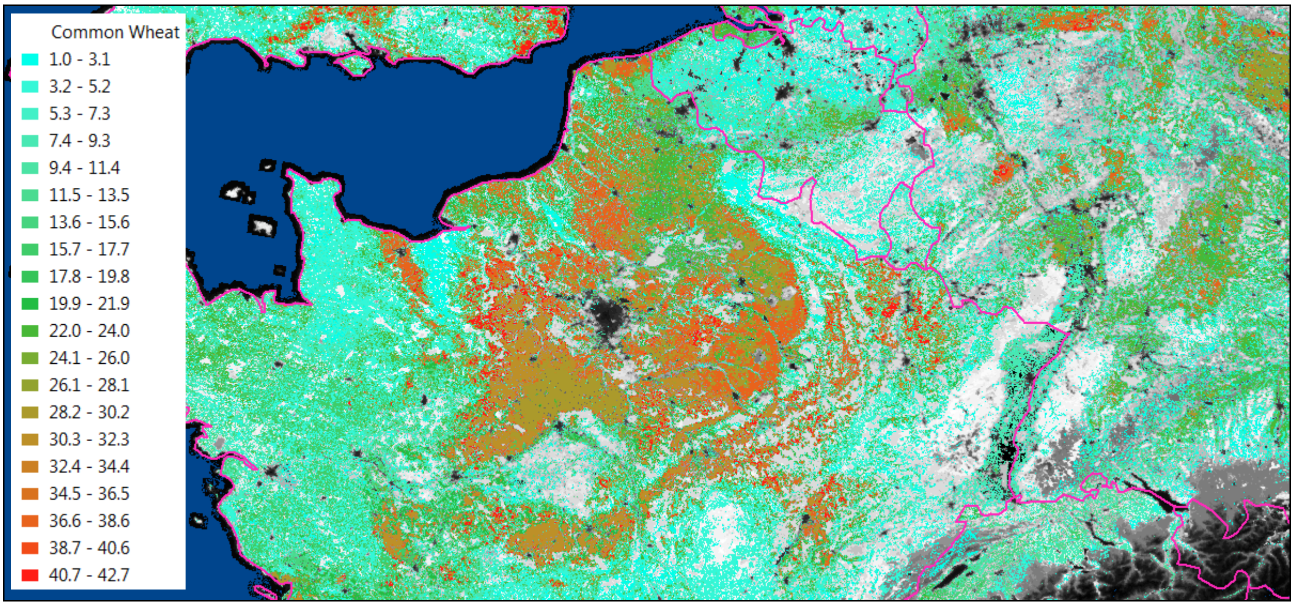


Figure 6. *Common wheat cropping intensity in N-France, Belgium and SW-Germany as defined by the fraction of common wheat point counts over all LUCAS point counts (%). The fraction is specific for each CORINE×SPOT class.*

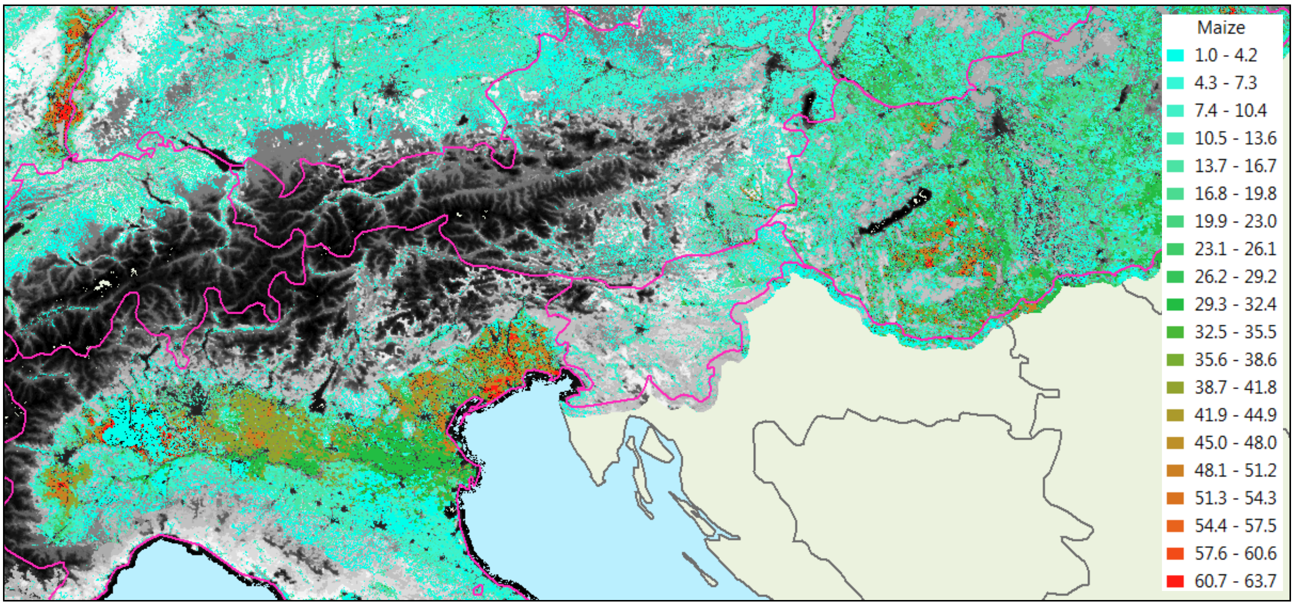


Figure 7. *Maize cropping intensity in N-Italy,Switzerland, and parts of Austria and Hungary as defined by the fraction of maize point counts over all LUCAS point counts (%). The fraction is specific for each CORINE×SPOT class.*

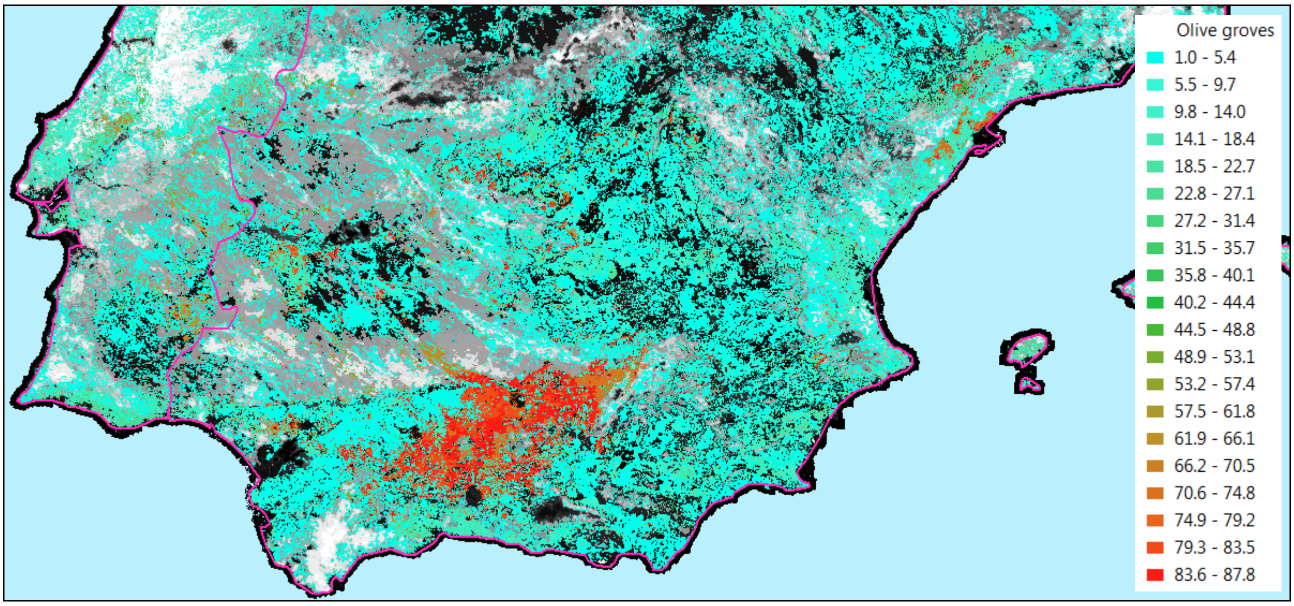


Figure 8. *Olive-groves cropping intensity in S-Portugal and S-Spain as defined by the fraction of olive-groves point counts over all LUCAS point counts (%). The fraction is specific for each CORINE×SPOT class.*

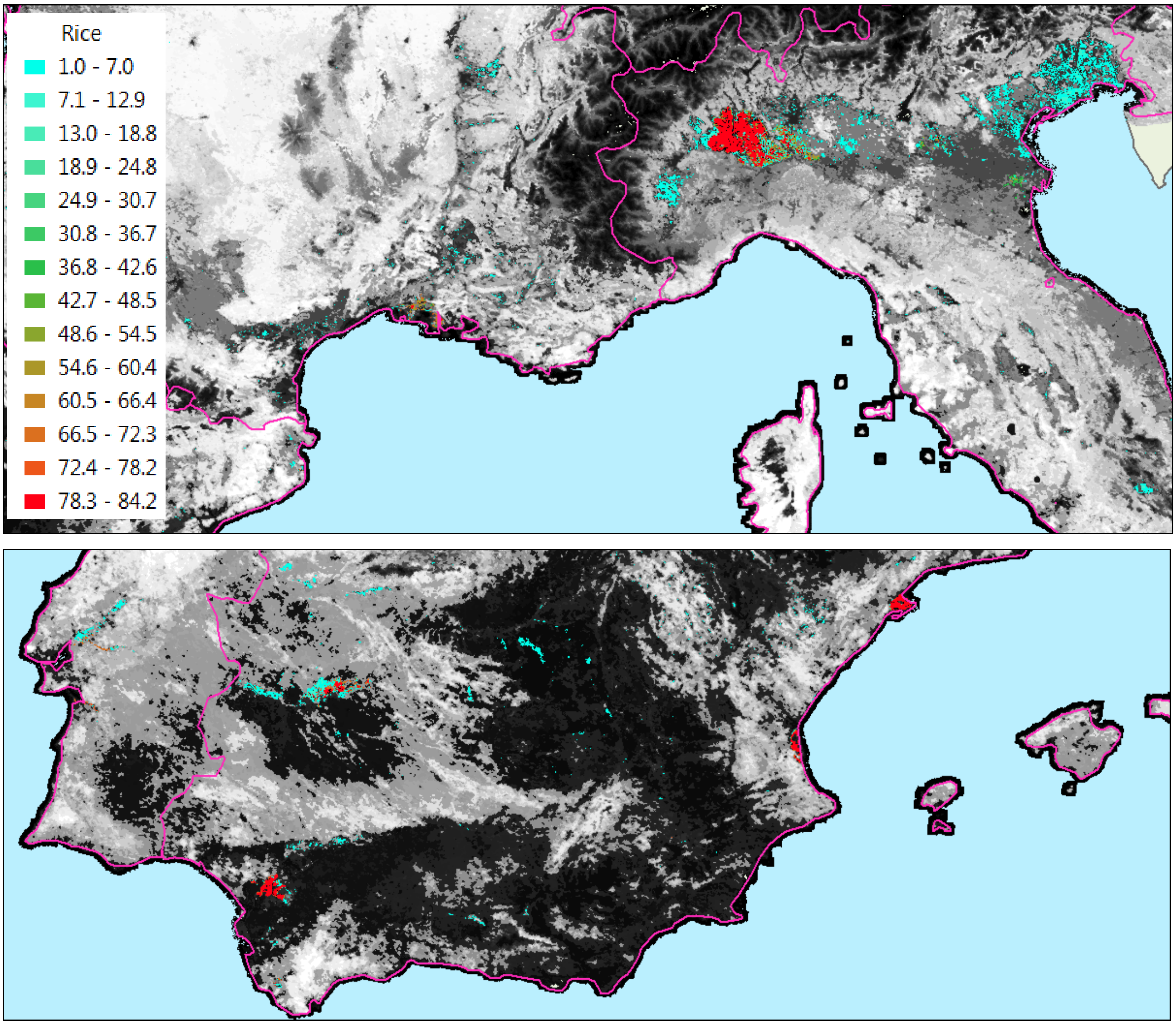


Figure 9. *Rice cropping intensity in N-Italy, S-Portugal and S-Spain as defined by the fraction of rice point counts over all LUCAS point counts (%). The fraction is specific for each CORINE×SPOT class.*

DISCUSSION AND CONCLUSIONS

The CORINE layer differentiates land cover patterns in the landscape that are clearly distinguishable on high resolution satellite imagery. Such patterns are in the first place based on spatial homogeneity (heterogeneity) of the infrastructure ‘agricultural fields’ by map unit, and successively on the reflectance as seen in the imagery. Using imagery-based reference keys, field data and expert knowledge, interpreters are thus able to distinguish basic patterns that are link to the classes provided in Fig.2. Differentiations which crops are actually grown, or even an assessment on the dominant crops cultivated, is not possible through this method unless by unit hard field data are collected to further subdivide or annotate the used legend keys. On the other hand, by grid-cell, the differences in temporal NDVI-profiles are related to differences in land cover, being differences in phenology of natural vegetation or crops grown plus the man-influenced aspects of the followed cropping-calendars. For the 1km^2 grids, various mixtures of land covers (=crops) do occur and as complex they display as a whole specific greenness behavior over time. Seasonal variability due to weather impacts on this behavior, but assumed can be that taking the median readings over a 5 year period consolidates the characteristic differences between signals of different land cover mixtures as occur in space for the study area. Through ISODATA analysis, 128 different mixtures were differentiated for the EU, and their temporal NDVI-profiles were assumed correlated to cover-specific (crop-specific) greenness characteristics. As such, such classes complement information as captured through CORINE and the combination of both could be assumed proper spatial representations of different crop-areas. Identification of the relationships between the generated CORINE×SPOT classes and the actual land cover mosaics they represent is only possible when additional information is available. The LUCAS area frame survey delivered the needed data, and made it possible to describe the content of the delineated CORINE×SPOT units through ample ground-truth data. Earlier studies already proved successful use of stratifying areas based on hyper-temporal NDVI data for crop-mapping [3,35,36,37].

Combining CORINE and SPOT information was assumed useful based on the promise that each contained complimentary (unique) information. Results would thus show that different CORINE×SPOT classes differentiate land cover mosaics beyond their individual merits. Table 3 displays that this is indeed the case, and that the combined use of SPOT and CORINE allowed the differentiation needed to make this exercise successful.

The issue of scale is first of all a mapping question, but it also relates to the natural patterns of crops grown to individual fields in an area. Argued is that farmers decisions creates over years high variability of crops grown to individual parcels, but that for specific areas, the total area grown to a specific crop remains more static. Based on that logic, detailed mapping (large-scale) would become a hopeless exercise. The used 1km^2 grid resolution of the SPOT layer actually coincides best to the described requirement that crop-maps must be area specific. For the current exercise, the aim was clearly not to prepare annual crop maps at field level that require annual updating, but a reference series of crop-masks that can be assumed static for e.g. a period of 5-years. Changes do happen to environments (social and bio-physical), and re-creating the prepared crop-masks at a 5-year interval seems thus logical to monitor the impacts of such changes.

Sources of errors concerning the prepared crop-masks relate to the artificial grid of 1km^2 used for the SPOT layer, to possible misclassification of various CORINE units (crops are clearly cultivated in various non-agricultural land cover/use classes; Table 3), and to the non-use of the LUCAS sample scheme of area-frames leading to less data for smaller CORINE×SPOT and ample data for larger ones. In addition, a major problem remains that the LUCAS data are basically point based. In case that the selected grid would refer to e.g. 500x500m areas, and the survey did complete spatial inventories of such areas (=segments), improved crop-area estimates would follow as use of accuracy statistics formulae developed over time for the so-called ‘double-frame agricultural survey’ method [41,42,43,44,45,46,47].

This study is not yet completed. The unit-based crop maps need conversion to a 1km^2 grid following the standard projection system of the EU, crop-specific maps containing accuracy indicators that reflect the number of points sampled by unit are required, statistical tests to report on the merit of the CORINE and SPOT layers must be added, validation of the prepared crop-maps using external data-sources is needed, and besides all these, also maps on pastures and grass-lands must be prepared.

The expected use and utility of the prepared crop-maps for the EU is considerable. The MARS project can directly upgrade their production line by adding weights (crop-intensity data) to the grid-cells evaluated regarding their performance, so that consecutive administrative area reports can be generated based on areas that matter. Beyond the EU, clarity must exist that space-time products can be generated through remotely sensed imagery that reflect the space-time cube that matters to distinguish land cover and cropping systems mosaics. Using such an area-stratification forms in turn a basic input to the design of area-frame surveys for successive ground-truth data collection, legend preparation and statistics generation. This logic not only suits preparation of crop-masks, but also supports annual surveys to estimate variability in cropped areas as currently carried out by many countries.

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