DELIVERABLE 1.2

Final Report

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Executive Summary

This document is the Final Report (FR) prepared for the European Space Agency as part of the extension of Scientific Exploitation of Operational Missions project entitled Sentinel-2 Global Land Cover project (S2GLC) based on the CHANGE REQUEST No. 1 to ESRIN Contract No. 4000116197. The aim of this report is to summarise work performed during the extension of S2GLC project.

List of Acronyms and Abbreviations

Acronym	Meaning
CCI LC	Climate Change Initiative Land Cover 2010
CORINE	Co-ORdinated INformation on the Environment
CLC	CORINE Land Cover
DEM	Digital Elevation Model
EO IPT Poland	Earth Observation Innovative Platform Testbed Poland
ESA	European Space Agency
FROM-GLC	Finer Resolution Observation and Monitoring of Global Land Cover
GLC	Global Land Cover
GlobCover	Global Land Cover 2009
GUF	Global Urban Footprint
HRL	High Resolution Layers
OA	Overall accuracy
LC	Land cover
NDVI	Normalized Differential Vegetation Index
NDWI	Normalized Differential Water Index
RF	Random Forest
S2	Sentinel-2
S2GLC	Sentinel-2 Global Land Cover

1. Document overview

1.1. Purpose of the document

This document provides description of data processing and analyses performed during the S2GLC project extension . It is a summary of the classification methodology development, implementation of the methodology on the CREODIAS and the works performed in order to complete the land cover (LC) classification of the agreed part of Europe based on Sentinel-2 images. The satellite images have been processed using the S2GLC classification approach developed by CBK PAN and adapted to the CREODIAS computing environment.

1.2. Applicable and input documents

[AD-1] Technical proposal of Scientific Exploitation of Operational Missions (SEOM) S2-4Sci Land and Water" Study 3: Classification, CBK PAN, 2015

[AD-2] Scientific Exploitation of Operational Missions (SEOM) S2-4Sci Land and Water" Study 3: Classification, ESA contract No. 4000116197/15/I-SBo

[AD-3] CHANGE REQUEST No.1 to ESRIN Contract No. 4000116197 SEOM S2GLC

[AD-4] Contract Change Notice to Contract No. 4000116197

[AD-5] Mid-term Report (15/10/2018)

2. WP2 – S2GLC LC classification method adjustment to European landscape

2.1. WP 2.1. S2GLC legend extension

A three-level legend combining common LC classes and cultivated areas has been developed during the S2GLC project to be used for LC classification on a global scale. In the extension of the S2GLC project the legend has been adapted to the European landscape and climate conditions, to fully represent and visualise important LC classes. The possibility of recognition of new classes has been taken into account.

CLC

In the initial part of the S2GLC project three databases have been used as a source of reference data for classifying two European countries, i.e. Germany and Italy. Two of them are GLC databases: CCI LC and GlobeCover. The third one, CLC database, was treated as a regional LC database. In the current phase of the project this Pan-European database has been tested as a main source of training data and a possible source of information for new LC classes that could extent the existing legend.

At this stage CLC database has been evaluated in order to exclude from tests all classes representing high degree of mixture of different LC types and typical LU classes except from those related to agriculture. New classes, e.g. Vineyards and Peat bogs, have been tested whether their recognition is

possible using CLC as a training source. The tests are fully described in section 2.5. Table 1 presents CLC classes and indicates which one have been selected for testing in the S2GLC project extension. The new classes proposed for testing are marked in column 'New class for tests'. These classes have not been classified previously but in many cases they represent relatively homogenous LC types and are important considering their coverage in different parts of the Europe. As compared to the legend definition resulting from the previous phase of the S2GLC project the legend prepared for the current tests does not include class called 'Inundated vegetation'. Instead, land cover types covered previously under this name have been split and currently are represented by classes Peat bogs and Marshes. Inland marshes and Salt marshes are being classified together as Marshes.

Table 1. Lists of CLC classes proposed for extension of the S2GLC legend

CLC code	CLC class name	S2GLC class name	New class for tests
111	Continuous urban fabric	Artificial surfaces and constructions	
112	Discontinuous urban fabric		
121	Industrial or commercial units		
122	Road and rail networks and associated land		
123	Port areas		
124	Airports		
132	Dump sites		
133	Construction sites		
141	Green urban areas		
142	Sport and leisure facilities		
211	Non-irrigated arable land	Cultivated areas	
212	Permanently irrigated land		
213	Rice fields	Rice fields	✓
221	Vineyards	Vineyards	✓
222	Fruit trees and berry plantations		
223	Olive groves	Olives groves	✓
231	Pastures	Herbaceous vegetation	
321	Natural grasslands		
241	Annual crops associated with permanent crops		
242	Complex cultivation patterns		
243	Land principally occupied by agriculture, with significant areas of natural vegetation		
244	Agro-forestry areas		
311	Broad-leaved forest	Broadleaf tree cover	
312	Coniferous forest	Coniferous tree cover	
313	Mixed forest		
322	Moors and heathland	Moors and Heathland	✓

323	Sclerophyllous vegetation	Sclerophyllous vegetation	✓
324	Transitional woodland-shrub		
331	Beaches, dunes, sands	Un-consolidated areas	
131	Mineral extraction sites		
332	Bare rocks	Consolidated areas	
333	Sparsely vegetated areas		
334	Burnt areas		
335	Glaciers and perpetual snow	Permanent snow, glaciers	
411	Inland marshes	Marshes	✓
421	Salt marshes		
412	Peat bogs	Peatbogs	✓
422	Salines		
423	Intertidal flats		
511	Water courses	Water bodies	
512	Water bodies		
521	Coastal lagoons		
522	Estuaries		
523	Sea and ocean		

HRL

High Resolution Layers developed under the Copernicus Program have been also considered to be a part of the training database used for classification. Some of the classes from CLC could be replaced or combined with masks originating from HRL, which are more detailed in case of spatial resolution. With spatial resolution of 20 m HRL outperforms CLC with MMU of 25 ha and minimum width of 100 m. This assure more detailed outline of certain objects (LC classes) and less heterogeneous classes that often compose a separate polygon of CLC database. The correspondence of CLC, HRL and classes being tested in the S2GLC projects are presented in Table 2. This table shows which classes from CLC may be replaced or used in combination with HRL.

Table 2. A list and relation between LC classes classified within CORINE CL, S2GLC project and High Resolution Layers data bases.

CLC code	CLC class name	S2GLC class name	HRL
111	Continuous urban fabric	Artificial surfaces and constructions	Imperviousness
112	Discontinuous urban fabric		
121	Industrial or commercial units		
122	Road and rail networks and associated land		
211	Non-irrigated arable land	Cultivated areas	
212	Permanently irrigated land		
213	Rice fields	Rice fields	

221	Vineyards	Vineyards	
223	Olive groves	Olives groves	
231	Pastures	Herbaceous vegetation	Grassland
321	Natural grasslands		
311	Broad-leaved forest	Broadleaf tree cover	Forests Dominant Leaf Type: broadleaved or coniferous
312	Coniferous forest	Coniferous tree cover	
322	Moors and heathland	Moors and Heathland	
323	Sclerophyllous vegetation	Sclerophyllous vegetation	
331	Beaches, dunes, sands	Un-consolidated areas	
332	Bare rocks	Consolidated areas	
335	Glaciers and perpetual snow	Permanent snow, glaciers	
411	Inland marshes	Marshes	
421	Salt marshes		
412	Peat bogs	Peatbogs	
511	Water courses	Water bodies	Water and Wetness
512	Water bodies		
521	Coastal lagoons		
522	Estuaries		
523	Sea and ocean		

Table 3 presents detailed characteristics of HRL while the section below shows general description of HRL database.

HRL **Imperviousness**

A database presenting built - up areas characterized by the substitution of the original semi natural or natural cover or water surface with an artificial, often impervious cover. These artificial surfaces are mapped as a degree of imperviousness (0-100%) with a spatial resolution of 20 m. It was produced using automatic procedure based on calibrated NDVI index values. The data provided suggested the threshold of circa 30% to be applied in transforming imperviousness to built-up areas.

HRL **Grassland**

This layer represent classification of areas into grassland and non-grassland lands. The grassy and non-woody vegetation baseline product includes all kinds of grasslands: managed grassland, semi-natural grassland and natural grassy vegetation.

HRL **Forest**

This database consists of following products: Tree Cover Density - proportional crown coverage per pixel (1-100%) and Dominant Leaf Type – providing information on the dominant leaf type: broadleaved or coniferous.

HRL **Water and Wetness**

A database indicating the occurrence of water and wet surfaces over the period from 2009 to 2015.

Table 3. Main characteristics of Copernicus High Resolution Layers

Product:	Year	Spatial resolution	MMU	Accuracy	Legend and pixels coding
HRL **Imperviousness**	2015	20m	no	Minimum 90% user's / producer's accuracy	0: non sealed 1-100: Degree of Imperviousness 255: outside area
HRL **Grassland**	2015	20m	1 ha	85 % thematic accuracy to be achieved within each biogeographic region.	0: all non-grass areas 1: grassy and non-woody vegetation 254: unclassifiable 255: outside area
HRL **Forest:** Tree Cover Denstity	2012, 2015	20m	no	Minimum 90% user's / producer's accuracy	0: all non-tree covered areas 1-100: tree cover density values 254: unclassifiable 255: outside area
HRL **Forest:** Dominant Leaf Type	2012, 2015	20m	0.52 ha (equivalent to 13 pixels)	Minimum 90% user's / producer's accuracy for both, broadleaved and coniferous class	0: all non-tree covered areas 1: broadleaved trees 2: coniferous trees 254: unclassifiable 255: outside area
HRL **Water and Wetness**	2015	20m	20m	80 - 85%	0 no water/no wet areas 1: Permanent water 2: Temporary water 3: Permanently wet area 4: Temporary wet areas 254: unclassifiable 255: Sea water
HRL Permanent Water Bodies (PWB)	2012	20m	no	90 - 95%	0: All Non-Permanent Water Bodies; 1: Permanent Water Bodies;
HRL Wetlands (WET)	2012	20m	no	produced results are below the requirements of 80 % minimum thematic accuracy	0: All Non-Wetland Areas; 1: Wetland Areas;

Other databases analysed in the project

Urban atlas created by Copernicus program is a very detailed database presenting LU and LC of urban areas and its surroundings. Its usage was taken into consideration but there is no continuous coverage over Europe. Some of S2 tiles placed in less urbanised areas might have not enough training data.

GUF (Global Urban Footprint) - is a global mask of settlement with resolution of 12 m developed by DLR. It results from classification of TerraSAR-X and TanDEM-X SAR images acquired with 3 m spatial resolution. Data was classified with Support Vector Data Description (SVDD) one-class classifier. It was tested to be used as a mask for training the class Artificial surfaces.

2.2. WP 2.2. Review of Sentinl-2 data availability

Sentinel-2A and Sentinel-2B

In this task of the project the availability of S2 images has been analysed which was necessary for the selection of the test sites, preparation of S2 data selection scenario as well as preparation of a detailed schedule for the overall data processing. Images from Sentinel-2A satellite have been acquired during the whole 2017 year. Data from Sentinel-2B was available since June 2017. An increase in data acquisition frequency may be clearly noted in Figure 1 since July 2017.

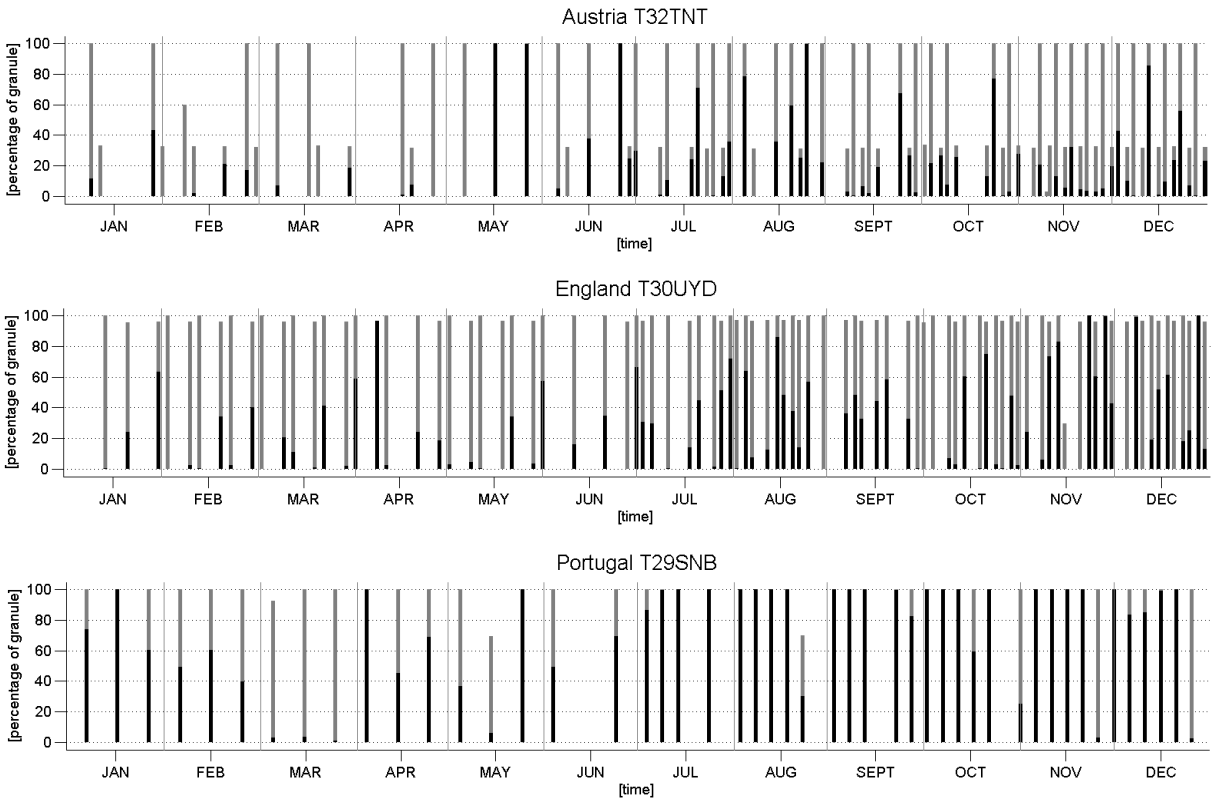

Figure 1. Sentinel-2 data images acquired in 2017 for selected tiles. Black indicates percentage of clear pixels, grey indicates cloudy pixels.

Sentinel-2 data for Europe in 2017

The availability of S2 image data was analysed considering the following features:

- Percentage of tile area covered by data from single image acquisition
- Percentage of data covered by clouds

Different thresholds have been set up for both features. We have analysed and visualized area coverage between 80% and 100% with an increment of 5% and combined it with increasing amount of clouds – from 10% to 50% with an increment of 10%. For each combination of features a total number of available images for Europe has been calculated as well as the mean number of images per tile (see Table 4). Figure 2 presents the spatial distribution of the number of images available for each tile, which fulfil two criteria:

- Area >= 90%
- Clouds <=10%

The number of images fulfilling these criteria varies from 0 to 50 for different tiles. A high number of cloudless images may be observed in the southern part of Europe, around the Mediterranean Sea.

Table 4. Cumulative sum and mean number of Sentinel-2 images acquired in 2017 over 870 preselected tiles, which fulfil the criterion of area and cloud coverage.

	Area = 100%	**Area >= 95%**	**Area >= 90%**	**Area >= 85%**	**Area >= 80%**
Clouds <= 10%	Sum: 8 788 Mean: 9.7	Sum: 10 911 Mean: 12.0	Sum: 11 693 Mean: 12.9	Sum: 12 360 Mean: 13.6	Sum: 13 032 Mean: 14.3
Clouds <= 20%	Sum: 11 435 Mean: 12.6	Sum: 14 195 Mean: 15.6	Sum: 15 211 Mean: 16.7	Sum: 16 076 Mean: 17.7	Sum: 16 934 Mean: 18.6
Clouds <= 30%	Sum: 13 624 Mean: 15.0	Sum: 16 914 Mean: 18.6	Sum: 18 155 Mean: 20.0	Sum: 19 181 Mean: 21.1	Sum: 20 210 Mean: 22.2
Clouds <= 40%	Sum: 15 674 Mean: 17.2	Sum: 19 491 Mean: 21.4	Sum: 20 922 Mean: 23.0	Sum: 22 097 Mean: 24.3	Sum: 23 290 Mean: 25.6
Clouds <= 50%	Sum: 17 848 Mean: 19.6	Sum: 22 217 Mean: 24.4	Sum: 23 887 Mean: 26.3	Sum: 25 229 Mean: 27.7	Sum: 26 576 Mean: 29.2

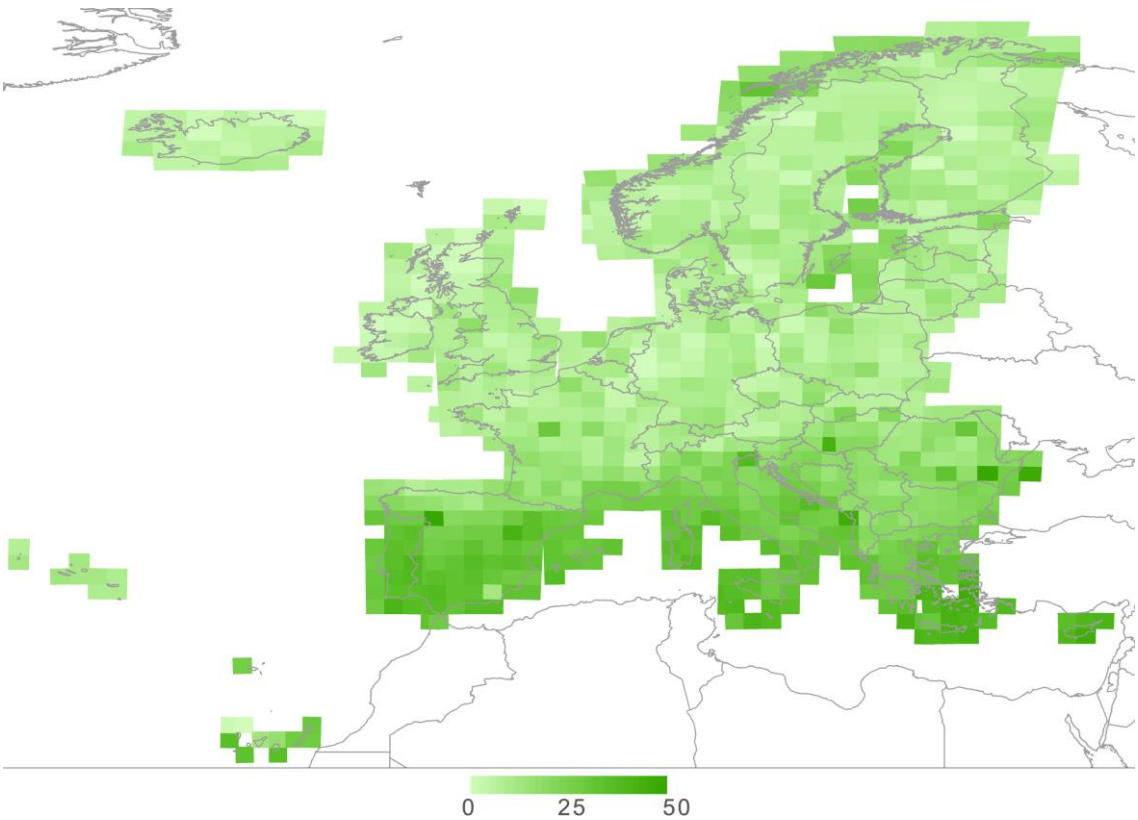

Figure 2. Quantitative distribution of Sentinel-2 images acquired in 2017 fulfilling the criteria of tile area coverage >= 90% and cloud coverage <=10%.

Test sites selection required complex analysis of data availability, climate stratification and land cover diversity at the same time. Considering data availability, the optimum scenario was to choose tiles for which the highest number of images is available with possibly at least one cloudless image for every month of a year. To facilitate test sites selection, for each tile the number of best images for each month has been checked and visualized at Figure 3.

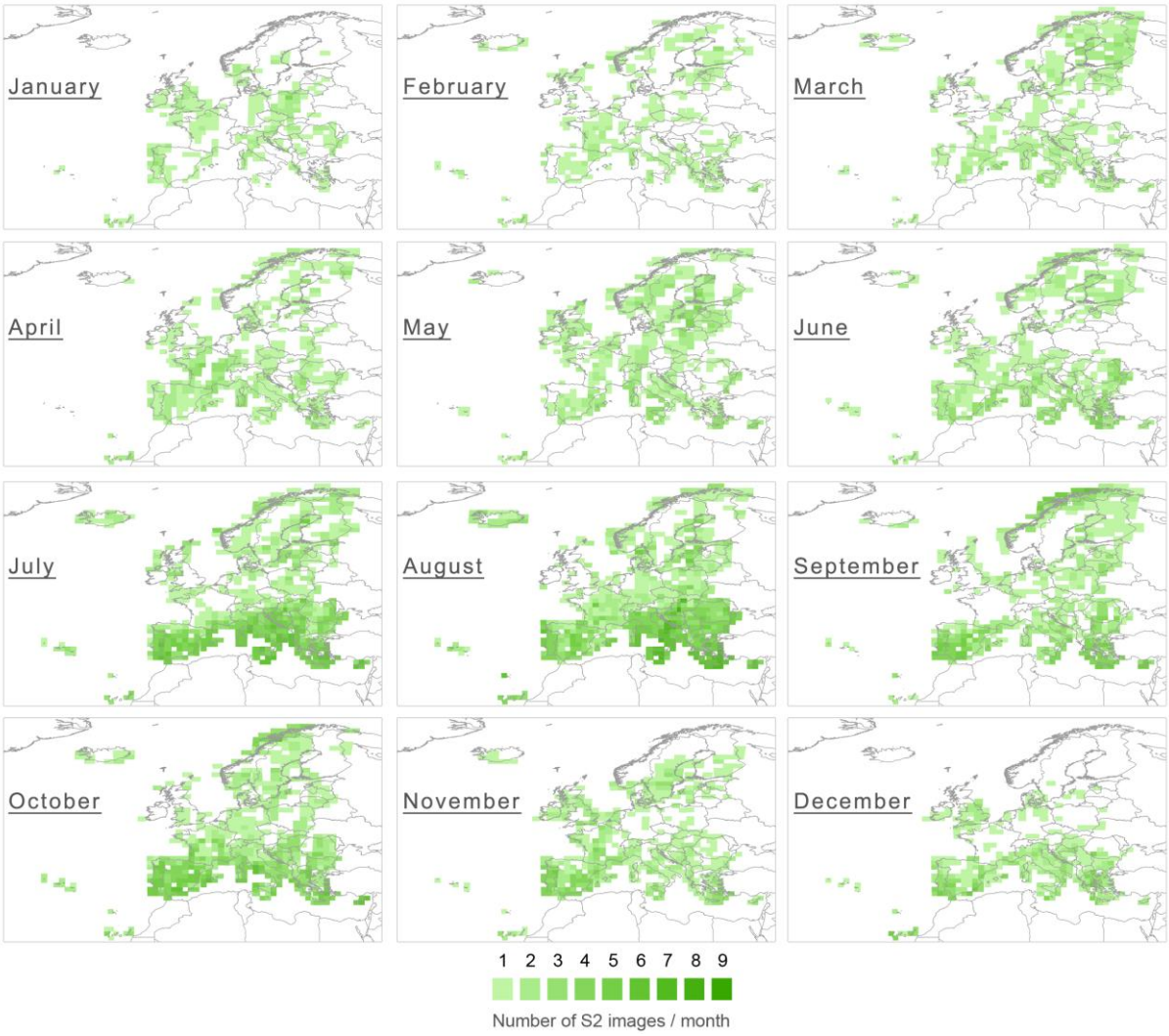

Figure 3. Number of best Sentinel-2 L1C products for each month of 2017. A tile is counted if it has at least 90% of data coverage and less than 10% of cloud coverage.

L1C and L2A products availability

The analysis of products availability presented below have been performed for the test sites selected in WP 2.3. For these test sites a number of available L1C and L2A products from 2017 has been compared and gathered in Table 5. It shows that about 48-54% of L1C products acquired in 2017 by S2 satellites have been atmospherically corrected by ESA to generate L2A products. It is not clear what is the criterion, why some images were processed and why other were not. In general it was

observed that practically data acquired before the end of March 2017 has not been processed to L2A products. Considering a period between April and June, most of the data were processed. Between July and November about 50% of data were processed and most data from December 2017 were processed. Comparison of data availability for products L1C and L2A date to date is presented in Table 6.

These conclusions are based only on the analysis of data from nine test sites listed in Table 5. Initial tests revealed that currently almost all data acquired in 2018 are available in the form of both products: L1C and L2A at ESA Open Access Hub (https://scihub.copernicus.eu/).

Table 5. Number of S2 products for selected test areas, acquired in 2017 and available at ESA Open Access Hub (https://scihub.copernicus.eu/).

	29SNB	**30SXH**	**30TWN**	**30UYD**	**32TNT**	**32TQR**	**32VLL**	**33TXM**	**35VLF**
L1C	106	102	101	98	138	103	139	157	150
L2A	51 (48%)	52 (51%)	52 (51%)	53 (54%)	73 (53%)	53 (51%)	69 (50%)	76 (48%)	73 (49%)

Table 6. List of all L1C and L2A products available at ESA Open Access Hub for the T30SXH tile. Empty line indicates lack of L2A product. In bold type images with the least cloud coverage are marked (three for each calendar month). The table is divided into four parts presenting different quarters of the year 2017.

L1C	L2A	L1C	L2A	L1C	L2A	L1C	L2A
20170116		**20170406**	20170406	20170703		20171001	
20170119		20170409	20170409	20170705	20170705	**20171003**	20171003
20170126		**20170416**	20170416	**20170710**		20171006	20171006
20170129		20170419	20170419	20170718	20170718	20171008	
20170205		**20170426**	20170426	**20170720**		20171011	
20170208		20170429	20170429	20170723		**20171013**	20171013
20170215		**20170506**	20170506	20170725		20171016	20171016
20170218		20170509	20170509	20170728	20170728	20171018	
20170225		20170516	20170516	**20170730**		20171021	
20170228		**20170519**	20170519	20170802		20171023	20171023
20170307		**20170526**	20170526	**20170804**		20171026	20171026
20170310		20170529	20170529	20170807		**20171028**	
20170317		**20170605**	20170605	**20170809**		20171031	
20170320		**20170615**	20170615	20170812		20171102	20171102
20170327		20170618	20170618	20170814	20170814	20171105	20171105
20170330	20170330	20170625	20170625	20170817	20170817	**20171107**	
		20170628	20170628	**20170819**		20171110	
		20170630		20170822		**20171112**	20171112
				20170824	20170824	20171115	20171115
				20170827	20170827	**20171117**	
				20170829		20171120	
				20170901		20171122	20171122
				20170903	20170903	20171125	20171125

20170906	20170906	20171127	
20170908		20171130	
20170911		**20171202**	20171202
20170913	20170913	20171205	20171205
20170916	20170916	20171207	
20170923	20170923	20171210	
20170926		**20171212**	20171212
20170928		20171215	20171215
		20171217	20171217
		20171220	20171220
		20171222	20171222
		20171225	20171225
		20171227	20171227
		20171230	20171230

2.3. WP 2.3. Tests of new LC classes

Test sites selection

This part of WP2 started with selection of test sites which were used to perform tests necessary for the extension of the LC legend defined in the initial part of the S2GLC project. For that purpose the area of Europe was divided into different climatic regions according to the Köppen-Geiger climate classification system updated by Peel et al. (2007). Such division aimed at assuring an analysis of different LC classes which often occur only in certain regions of Europe. The Köppen-Geiger classification map was further modified due to the limited existence of some of the classes in Europe. This modification was performed according to the stratification proposed by Olofsson et al. (2012) and consisted in merging together selected classes and removing small isolated patches of different class from inside of bigger regions of other dominant classes. This modification allowed for the reduction of 18 climatic classes originally occurring in Europe to seven main classes including boreal forest, continental forest, marine west coast, Mediterranean, steppe, temperate evergreen forest and tundra. The original Köppen-Geiger classification map of Europe and the modified one are showed in Figure 4.

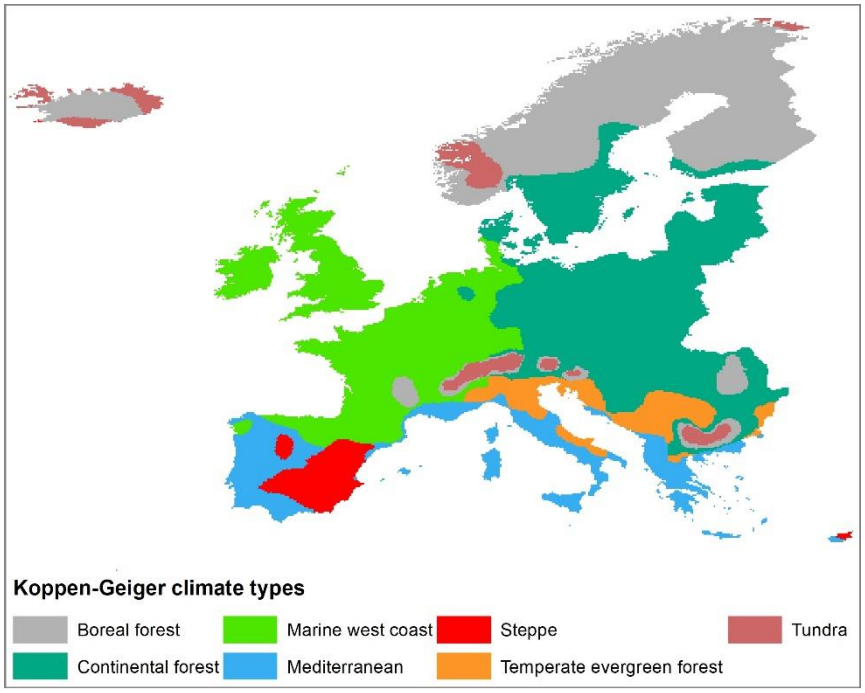

Figure 4. Köppen-Geiger climate type map of Europe modified for the need of the S2GLC project.

After modification of the climatic map it was decided to select one test site for every climatic class. Additionally two extra sites were added, one for each of the two largest climate types i.e. continental forest, marine west coast, making nine test areas in total. As a separate test site an individual tile (granules) of S2 image data was defined that represents an area of 110 km x 110 km. Possible locations of these test areas were further investigated considering the occurrences of LC classes selected for tests as well as the availability of S2 images with limited cloud coverage (analysed in section 2.2). The number of LC classes was estimated using CLC database as described in section 2.1. The idea standing behind this combination of factors was to analyse areas with possibly high number of different LC classes. At the same time it was important to choose tiles for which a relatively high number of S2 images were acquired in the analysed year (i.e. 2017), so that LC classification could be tested with different number of images acquired at different periods and time intervals, including those falling in and outside of the growing season. Therefore, besides the number of images also information about the temporal distribution of S2 images in different months were analysed. In this analysis S2 images were checked that fulfilled the condition of 90% of spatial coverage within a tile and less than 10% of cloud coverage.

Following the analyses nine test sites were selected and their distribution with climatic data is illustrated in Figure 5.

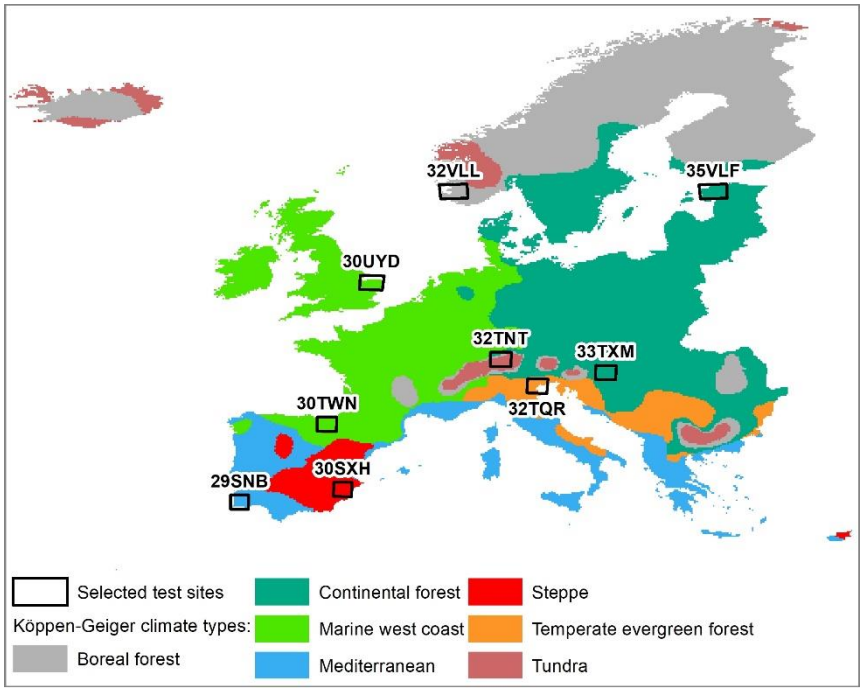

Figure 5. Distribution of the selected test sites (with their naming) with division between climatic zones in Europe.

In order to perform the planned test and provide quantitative and objective assessment a set of validation reference data were prepared for each of the selected test area using a stratified random sampling method. For the stratification purpose the CLC database was used with necessary modification that consisted in merging together all LC classes that were not being tested (see section 2.1). The sample size for LC classes being tested were estimated according to the proportion of these classes within the area of a given tile (S2 tile). The strata composed of all merged LC classes was also considered and appropriate number of samples were selected. For each test areas 2000 samples were initially set and this number was split proportionally between LC classes. However, for classes with small total area a minimum number of samples was set with the following criteria:

- a LC class receives the number of samples according to the area coverage proportion if its total area exceed 1% of a total tile area (circa 120 km^2),
- a LC class with its total area falling between 0.5% (circa 60 km^2) and 1% of a total tile area receives a fixed number of 20 samples, which is 1% of all samples,
- a LC class with its total area falling below 0.5% of a total tile area receives a fixed number of 10 samples.

Considering the above rules the final number of samples differed between test sites and exceeded 2000 samples in some cases. The selected samples were then inspected by visual interpretation using different data sources including data from Google Earth, PlanetScope and S2 imagery, choosing the one that was the most consistent with the analysed year 2017. The visual interpretation resulted in labelling of validation data into classes selected for test, however, the final number of samples was reduced in most cases due to difficulties in recognising classes in certain cases by an interpreter or the location of a sample on the border between different classes.

This dataset was used as reference data in different tests described in the next sections.

Selection of S2 images for classification

Another task in this WP was dedicated to the improvement of a method for selection of S2 images from a time series that would be classified in the final approach (European scale). In the initial part of the S2GLC project (a global approach) a simplified method was developed that considered only information on the cloud coverage in the image and was based mostly on images from a growing season. In the current project more complex analyses were performed considering also the number of images used and the distribution of images in a whole year being analysed. A number of classification were performed based on different combinations of the input images with the maximum cloud cover reaching 80%. In each case the classification was conducted according to the method developed in the S2GLC project. This consists of separate classification of selected S2 images and the final aggregation of these separate results into one final LC map (see more details in Lewiński et al. (2017)). The final assessment of the methods tested was based on the resulting overall accuracy scores and the required workload. In this test the following combinations of images with different acquisition dates were evaluated (order according to the number of images used):

Table 7. Rules for selection of satellite data

Selection rule	Description of selected images
1	All available S2 images acquired in 2017
2	Two least cloudy images from every month - 24 images in total
3	20 least cloudy images from a year – 20 images in total
4	Two least cloudy images from each month of a growing season (April to October) and one least cloudy image for months from outside a growing season (January – March and November – December) – 19 images in total
5	15 least cloudy images from a year – 15 images in total
6	One least cloudy image from every month – 12 images in total
7	10 least cloudy images from a year – 10 images in total
8	10 least cloudy images from a growing season (April to October) – 10 images in total
9	10 least cloudy images from a grown season (April to October) divided into 10 equal length periods (one image from each period) – 10 images in total
10	10 least cloudy images from a narrowed growing season (June to September) – 10 images in total

The results derived from the tests are shown in Figure 6 and Table 8.

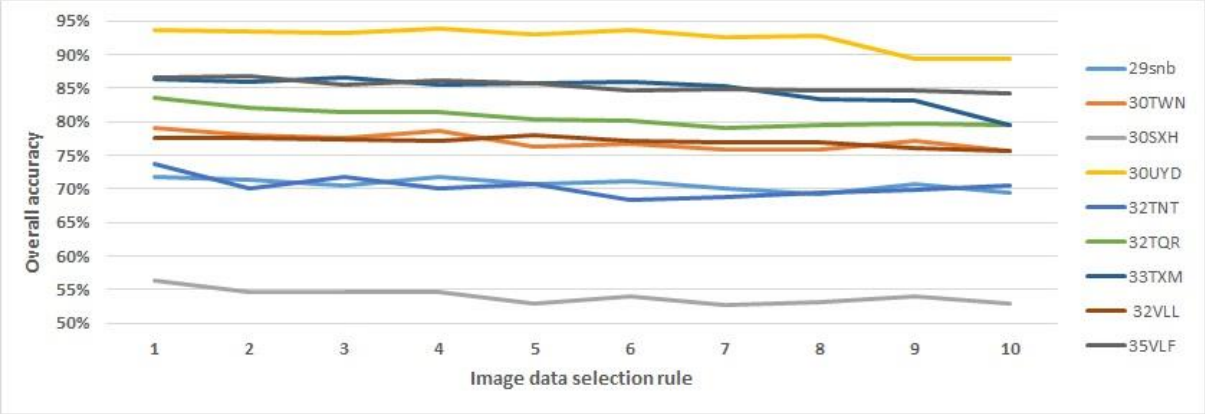

Figure 6. A graph showing overall accuracy values for different selection rules described in Table 7 for the nine testing sites.

Table 8. The values of overall accuracy received in test sites for different image selection rules described in Table 7.

	Test areas								
Selection rule	**29SNB**	**30TWN**	**30SXH**	**30UYD**	**32TNT**	**32TQR**	**33TXM**	**32VLL**	**35VLF**
1	0.7181	0.7903	0.5628	0.9377	0.7370	0.8350	0.8640	0.7751	0.8656
2	0.7132	0.7799	0.5461	0.9356	0.7013	**0.8207**	0.8599	0.7758	**0.8672**
3	0.7059	0.7754	**0.5470**	0.9316	**0.7178**	0.8148	**0.8654**	0.7739	0.8550
4	**0.7171**	**0.7860**	0.5461	**0.9383**	0.7013	0.8138	0.8558	0.7708	0.8618
5	0.7067	0.7640	0.5285	0.9296	0.7072	0.8031	0.8571	**0.7811**	0.8565
6	0.7119	0.7678	0.5408	0.9363	0.6827	0.8007	0.8591	0.7712	0.8466
7	0.7002	0.7591	0.5265	0.9262	0.6882	0.7919	0.8537	0.7695	0.8496
8	0.6917	0.7591	0.5319	0.9275	0.6950	0.7962	0.8338	0.7687	0.8473
9	0.7068	0.7716	0.5397	0.8937	0.6987	0.7982	0.8321	0.7602	0.8458
10	0.6948	0.7571	0.5295	0.8936	0.7044	0.7962	0.7948	0.7561	0.8420

The above results show that the selection rule 1 received the highest OA score in most test sites. This confirms assumption that usage of multitemporal image data and high number of images improves classification. However, in many case processing high number of images (tens or even over a hundred images) could provide computation problem and hamper operational use of the developed methodology. Therefore, the selection rule 4 was selected as the one that assure relatively high accuracy of classification and is based on limited number of images, i.e. 19. Such number is often lower than the one used in other selection rules but assures similar or higher accuracy. This method provided the highest OA in three out of nine test areas and was only slightly worst in the remaining test sites. Moreover, images used in this selection rule represent not only different parts of a growing season but are also selected from the remaining months of a year. The performed test showed that this is also a very important aspect of LC classification with multitemporal data. However, to emphasis the part of a year when most changes occur (related to vegetation growing), this selection rule assume selection

of two images from each month of a growing season (April – October). For each of the remaining months only one image is selected. This data selection method has been applied and used in most of the tests described in Table 9.

2.4. Modifications of classification methodology - tests

This section presents all the test and analyses that were carried out in order to adjust the S2GLC methodology to the European conditions and possibly to extend the existing LC legend. This required analysis of possibility of application of different training data sources and their adjustment to the project workflow. Based on the analysis described in section 2.1 a group of LC classes were identified to be tested as well as LC databases that could serve as a source of reference data for the new classification approach (new class composition). Some of the tests performed in this part of the project were repeated as compared to the first part of the S2GLC project. This was necessary due to the new LC classes and new LC databases used.

All test carried out it this experimental phase of the project are described shortly in Table 9. For some of the tests only pixels that intersect with validation points were classified instead of whole S2 images (e.g. test no. 5). This approach allowed for much faster data processing and analysis of results. In general, our tests were used to verify among other things the possibility of using different sets of S2 spectral bands, different methods for resampling of S2 bands with lower resolution to the resolution of 10 m, an application of different classification features (Table 10) as well as different training data (e.g. CLC or HRLs) and training data filtrations (Table 11). Tests 1 – 15 concerned all LC classes from Table 1 proposed for classification. This legend was defined as L0 in Table 9. Legend L1 refers to a set of LC classes that was modified after the initial tests (test 1 – 15). All details are provided in section 2.6.

Assessment of the results derived from the tests was based either on comparison of error matrixes (OA, user and producer accuracies), visual inspection of resulting thematic maps or both of them. The most important results and the derived conclusions are presented in section 2.6.

Table 9. Summary of performed tests

Test No.	**Legend**	**Description / training**	**Bands**	**Set of features** (Table 10)	**Set of time series** (Table 7)	**Main conclusion**
1	L0	All classes CLC,	all	1	10	
2	L0	All classes CLC, built-up 111	all	1	10	Reference classification
3	L0	All classes CLC, CLC built-up 111+112+ 121	all	1, 3	10	Improved built-up/artificial
4	L0	Image selection rules All classes CLC, CLC built-up 111+112+ 121 All combinations of data selection were tested	all	1	1 -10	Best results: system 1 and 4 4 less images results similar to 1
5	L0	All classes CLC, built-up 111+GUF only validation points classified	all	1	1	Built-up/artificial improved

6	L0	Test 5 performed using the whole images	all	1	1	Built-up/artificial improved
7	L0	All classes CLC, built-up 111+112+121 + features + Laplacian filter, separately and combinations only validation points classified	all	1-9	4	Best results for feature sets 1+3
8	L0	Test 7 performed using the whole images	all	1+3	4	Visual inspection confirmed results evaluated based on error matrices
9	L0	All classes CLC, built-up 111+112+121 Images 2018 only validation points classified	all	1	1	Results similar to 2017, differences at level -2%
10	L0	All classes CLC, built-up 111+GUF	all	1+3	4	Is still need to improved built-up/artificial
11	L0	All classes CLC, built-up 111+GUF training of unconsolidated and consolidated filtered by NDVI and NDWI	all	1+3	4	Classes unconsolidated and consolidated are improved
12	L0	All classes CLC, built-up 111+112+121,	10, 20m	1+3	4	Delineation of built-up/artificial is improved, vineyards are not improved
13	L0	Test 9 The whole image tiles classified	all	1+3	4	Results similar to 2017, differences at level -2%
14	L0	All classes CLC, built-up 111+112+121, Laplacian filter	10, 20m	1+3	4	Delineation of built-up/artificial is improved, vineyards are not improved
15	L0	All classes CLC, built-up 111+112+121 + features + Laplacian filter, separately and combinations The whole image tiles classified	10, 20m	1+3	4	some classes should be still improved,
16	L1	All classes CLC, built-up GUF, water divided into 2 sub classes (water/2), rice fields added to agriculture The whole image tiles classified	10, 20m	1+3	4	Agriculture improved
17	L1	All classes CLC, built-up HRL > 20%, water/2, rice fields added to agriculture The whole image tiles classified	10, 20m	1+3	4	Built-up/artificial similar to CLC training and should be more precise
18	L1	All classes CLC, built-up HRL > 20%, water/2, rice fields added to agriculture, without vineyards The whole image tiles classified	10, 20m	1+3	4	Vineyards are classified as agriculture and build-up/artificial, this class should be classified
19	L1	All classes CLC, built-up GUF, water/2, rice fields added to agriculture, without vineyards The whole image tiles classified	10, 20m	1+3	4	Built-up/artificial and other classes similar to test 18
20	L1	All classes CLC, built-up HRL > 30%, water/2, rice fields added to agriculture, without vineyards The whole image tiles classified	10, 20m	1+3	4	Built-up/artificial and other classes similar to test 18

21	L1	All classes CLC, built-up HRL > 70%, water/2, rice fields added to agriculture, without vineyards The whole image tiles classified	10, 20m	1+3	4	Built-up/artificial improved! Other classes should be improved
22	L1	All classes CLC, built-up HRL > 70%, water/2, rice fields added to agriculture, Sclerophyllous vegetation – filtered by trees from HRL	10, 20m	1+3	4	comparative analysis of tests 22-27, observation of changes in all classes
23	L1	All classes CLC, built-up HRL > 70%, water/2, rice fields added to agriculture, vineyards - filtered by GUF	10, 20m	1+3	4	comparative analysis of tests 22-27, observation of changes in all classes
24	L1	All classes, filtration rules Table 11 without trees and grass	10, 20m	1+3	4	comparative analysis of tests 22-27, observation of changes in all classes
25	L1	All classes, filtration rules Table 11, grass from CLC	10, 20m	1+3	4	comparative analysis of tests 22-27, observation of changes in all classes
26	L1	All classes, filtration rules Table 11, grass form intersection of CLC and HRL grassland	10, 20m	1+3	4	comparative analysis of tests 22-27, observation of changes in all classes
27	L1	All classes, filtration rules, grass form HRL grassland	10, 20m	1+3	4	comparative analysis of tests 22-27, observation of changes in all classes

Table 10. A list of classification features.

No. of Feature Set	Description
1	Spectral values (bands)
Spectral combinations	
2	Spectral differences
3	Spectral differences divided by spectral sums
4	Spectral sums
5	Spectral products
6	Spectral products divided by spectral sums
Spectral statistics	
7	Mean of spectral values
8	Maximum difference of spectral values
9	Mean deviation of spectral values
Edge detector	
10	Laplacian filter

2.5. WP 2.5 Assessment of tests and final conclusions

The experimental phase of the project was based on intensive tests (over 6000 separate classifications and aggregations of S2 data) that were performed for helping to modify the LC legend and classification methodology. Owing to the high number of test sites being analysed (i.e. 9) the performed tests allowed to derive highly objectives and representatives conclusions. The most important findings are presented below with short explanation of the test and their results. Finally, the

resulting classification procedure is summarised and is being implemented for performing LC classification of Europe on CREODIAS platform.

One of the initial tests was focused on finding a method for selection of S2 data from a time series that would assure the most optimal classification results, considering both the thematic accuracy and the required processing workload (test no. 4). More details of this test are provided in section 2.3 (Selection of S2 images for classification). The data selection rule indicated as the most efficient one (i.e. selection rule 4, Table 7) was used in most of the later tests and will be implemented in the final classification workflow.

Another important issue verified in the project was selection of features used for LC classification. This test (test no. 7) was based on application of various sets of input data derived from S2 images. This included usage of S2 spectral bands themselves, combinations of spectral bands, statistics derived from spectral bands as well as usage of edge detection function. The features tested are summarised in Table 10. The results of this test showed that classification based on S2 spectral bands (feature set 1, Table 10) joined with feature set 3 - Spectral differences divided by spectral sums (calculated between different combinations of bands), provides the highest accuracy in most test sites and the most stable results. Therefore, combination of feature sets 1 and 3 was selected to be used in the final approach.

The next important conclusion is resignation from use of S2 spectral bands with 60 m spatial resolution. Our test showed that classification performed with 60 m bands are characterised by the presence of blocky, pixelated objects with unnaturally regular shapes. Moreover, this influence especially the quality of classification of the Artificial surfaces class and often leads to its overestimation. Even application of different resampling methods (e.g. bi-linear interpolation) reduces only the effect of highly pixelated shapes but overestimation of objects remains apparent. This is why tests 12 and 14 – 27 were performed only using spectral bands with 10 m and 20 m resolution. This applies also to the final classification implementation.

Many tests were focused on the improvement of classification of the class Artificial surfaces. This included testing of an use of different spectral bands as explained above, but also application of edge detection filter. Additionally different sources of training data were checked, including usage of various sets of classes originating from CLC (e.g. classes 111 vs. 111+112+121) as well as other data sources such as GUF and HRL (with different sets of imperviousness level (%)). As a result HRL Imperviousness data was indicated as the most appropriate, with the imperviousness level grater then 70%. HRL data outperforms GUF dataset despite its higher spatial resolution because it includes all kind of imperviousness surfaces including both buildings and infrastructure network. GUF data do not contains infrastructure.

Similarly to the class Artificial surfaces, the classes Broadleaf tree cover, Coniferous tree cover and Herbaceous vegetation are also being classified with use of HRLs. While HRL Grassland replaces completely classes related to herbaceous vegetation from CLC, the classes broadleaf and coniferous trees are trained with data resulting from the intersection of those classes from HRLs and CLC databases. This assures higher confidence of this data source and improves thematic accuracy. Similar intersection for the Herbaceous vegetation class did not improved accuracy within the analysed test sites.

Training data for the class Water bodies is derived from NDWI with a threshold of 0.2 (a method tested in the previous part of the project). However, a modification was made that introduces division of the mask resulting from NDWI into classes of inland water and sea water. Such division is made using appropriate classes of CLC database. Following this division, the training data is selected equally from both sub-classes what assures more uniform representation of all types of water surfaces.

From all classes being selected for tests (see Table 1) only the Olives groves class was removed from the final legend. The very heterogeneous sets of olive trees in the field (varying distance between trees) makes many difficulties for automatic classification of this land use. The Rise fields class was in many cases wrongly classified as Cultivated areas, and therefore, was merged with the latter class. According to our tests the classes Un-consolidates areas and Consolidated areas were also merge into one class called Natural material surfaces. This is related to the fact that the spectral response from them are often similar and they may represent the same mineral material but in some cases in different state (i.e. solid or fragmented). The final legend of classes selected for classification of entire Europe is presented in Table 12 and the class description is provided in Table 13.

For most vegetation classes from the final legend (Table 12) an additional condition was introduced related to the area coverage of a certain class within the analysed S2 tile. A class is being classified in a given S2 tile only if its area reaches 1% of the total area of a tile, that is approximately 120 km^2. This condition results from our tests, which showed that classification of classes with relatively small coverage results in high degree of misclassification. This is related to a weak representativeness of the class in a small sample size of training data. This condition is not applied to classes of Artificial surfaces and Natural material surfaces due to their natural limited extend in most of the analysed sites. Application of such threshold for these two classes would results in their removal from considerable number of tiles at European scale.

As compared to the proposal a change was introduce into the classification approach. The final classification was supposed to be based on multiple LC databases and besides CLC data, application of CCI LC and GlobCover databases was planned. However, due to the numerous changes introduced into the composition of input data (Table 1) and the new classes originating from CLC, which often do not appear in the two other databases, the utilization of the global databases (CCI LC and GlobCover) was abandoned. In our opinion their use would not provide significant changes to the classification as it would require replacement of most classes with those already used in the presented classification method based on CLC and HRL data.

To summarise, it can be sated that the final classification legend has been modified and extended by a few classes as compared to the initial one. This modifications originate from the assumptions included in the proposal, our experience from the first phase of the S2GLC project and all the intensive tests performed in the current phase of the project. For each LC class a source database has been indicated for selecting training samples that include existing LC databases: CLC and HRLs (Table 2). The procedure, however, differs between LC classes. Training data for eight classes are derived using CLC database, in case of two other classes an intersection of CLC and HRL is used, two classes are trained using only HRLs. Moreover, it was found that the water class is best trained using NDWI index combined with CLC. Training data for most classes are further improved by filtration with different datasets of HRLs and spectral indices (i.e. NDVI and NDWI). All the rules of selecting training samples applied in the developed methodology are presented in Table 11. Selection of training data from

reference source is compatible with the procedure developed in the initial part of the S2GLC project. The samples are randomly selected for each separate classification with 1000 samples for each analysed class.

Table 11. Rules of training data selection and filtration

LC class	Training source and rules	Filtration rules				
		NDWI	HRL Imp	HRL Trees	HRL Grass	NDVI
Artificial surfaces and constructions	HRL Imp - >70%	✓	-	>10%	✓	
Cultivated areas	CLC	✓	>30%	>10%	✓	
Vineyards	CLC	✓	>30%	>10%	✓	
Herbaceous vegetation	HRL Grassland	✓	>30%	>10%		
Broadleaf tree cover	Intersection of HRL Dominant Leaf Type and CLC	✓	>30%		✓	
Coniferous tree cover	Intersection of HRL Dominant Leaf Type and CLC	✓	>30%		✓	
Moors and Heathland	CLC	✓	>30%	>10%		
Sclerophyllous vegetation	CLC	✓	>30%	>10%	✓	
Natural material surfaces	CLC	✓	>30%	>10%	✓	✓
Permanent snow, glaciers	CLC	✓	>30%	>10%	✓	
Marshes	CLC	✓	>30%	>10%	✓	
Peatbogs	CLC	✓	>30%	>10%	✓	
Water bodies	NDWI	-	-	-	-	-

Table 12. The final classification legend.

Legend S2GLC Extension		
Level 1	**Level 2**	**Level 3**
1. Non-Vegetated surfaces	**1.1.** Artificial surfaces and constructions	**1.1.1.** Artificial surfaces and constructions
	1. 2. Natural material surfaces	**1. 2.1.** Natural material surfaces
2. Vegetated surfaces	**2.1.** Tree cover	**2.1.1.** Broadleaf tree cover
		2.1.2. Coniferous tree cover
	2.2. Low vegetation	**2.2.1.** Herbaceous vegetation
		2.2.2. Moors and Heathland
		2.2.3. Sclerophyllous vegetation
3. Cultivated and managed areas	**3.1.** Cultivated and managed areas	**3.1.1.** Cultivated areas
		3.1.2. Vineyards
4. Wetlands	**4.1.** Wetlands	**4.1.1.** Marshes

		4.1.2. Peatbogs
5. Water bodies	**5.1.** Water bodies	**5.1.1.** Water bodies
6. Permanent snow covered surfaces	**6.1.** Permanent snow covered surfaces	**6.1.1.** Permanent snow covered surfaces
7. Unclassified surfaces	**7.1.** Surfaces permanently covered by clouds	**7.1.1.** Surfaces permanently covered by clouds

Table 13. The final classification legend and class description

S2GLC class name	Description
1. Non-Vegetated surfaces	Any unvegetated surfaces not covered permanently by water or snow, either covered with man-made artificial structures or geologically natural material surfaces.
1. 1. Artificial surfaces and constructions (1. 1. 1.)	All surfaces where landscape has been changed by or is under influence of human construction activities by replacing natural surfaces with artificial abiotic constructions or artificial materials.
1. 2. Natural material surfaces (consolidated and un-consolidated)	Any kind of surface material that remains in its natural state or form, including consolidated surfaces, which are in most parts impervious for water, formed by natural material and with a solid surface. It may have been modified through different man-made processes (e.g. extraction sites). It also includes any surface with loose mineral particles of any size range, either as an outcome of natural physical sedimentation processes or human activity, e.g. mountain slope debris, glacier moraines, river pebble banks, beaches, sand dunes (unvegetated) or quarries.
2. Vegetated surfaces	Naturally grown vegetated land surface.
2. 1. Tree cover	Any type of high vegetation with ligneous stems.
2. 1. 1. Broadleaf tree cover	Land covered with broadleaved tree canopy that loses leaves seasonally.
2. 1. 2. Coniferous tree cover	Land covered with needle-leaved tree canopy that do not lose needles seasonally.
2. 2. Low vegetation	Any type of low vegetation.
2. 2. 1. Herbaceous vegetation	Lands covered by herbaceous vegetation including both natural low productivity grassland and managed grassland used for grazing and/or mowing.
2. 2. 2. Moors and Heathland	Low growing vegetation with closed cover and with predominately shrub and bushy vegetation (limited herbaceous species allowed).
2. 2. 3. Sclerophyllous vegetation	Bushy sclerophyllous vegetation characteristic for the Mediterranean climate, includes maquis and garrige. May exist in both closed and discontinuous cover.
3. Cultivated and managed areas (3. 1.)	Agriculturally-used lands managed by human (including temporary bare soil).
3.1.1. Cultivated areas	Cultivated areas managed by human that include non-irrigated and irrigated arable land with different crops and land under rice cultivation. It also includes temporary bare soils (e.g. fallow lands).
3.1.2. Vineyards	Areas planted with vines.

4. Wetlands (4. 1.)	
4. 1. 1. Marshes	Low-lying areas covered with non-woody vegetation distinguished by the presence of water at the surface (waterlogged) either permanent or temporary, due to high precipitation rates or flooding by fresh or sea water.
4. 1. 2. Peatbogs	Peatlands with deposit of decomposed moss or other dead plant material (including exploited peatlands).
5. Water bodies (5. 1. and 5. 1. 1.)	Water in liquid state of aggregation regardless of location, shape, salinity and origin (natural or artificial).
6. Permanent snow covered surfaces (6. 1. and 6. 1. 1.)	Snow cover that persists throughout the year, above the climatic snow line. Persistent ice cover formed by accumulation of snow.
7. Unclassified surfaces	Pixels which are unclassified due to technical difficulties or cloud cover.
7. 1. Surfaces permanently covered by clouds (7. 1. 1.)	Areas where no land cover interpretation is possible due to obstruction caused by clouds and their shadows, smoke or haze.

Table 14 presents OA scores of the LC classification for all test sites performed with use of the defined procedures:

- classification legend – level 3 from Table 12, class descriptions: Table 13;
- rules of image selection – selection rule 4 from Table 7;
- training data selection and filtration according to rules presented in Table 11;
- post-processing - not applied.

Table 14. Classification results of test tiles

	29SNB	**30SXH**	**30TWN**	**30UYD**	**32TNT**	**32TQR**	**33TXM**	**32VLL**	**35VLF**
OA %	75.5	62.1	81.8	95.4	81.8	88.9	87.2	77.6	88.4

Thematic maps resulting from LC classification within test sites together with error matrices are presented in Appendix 1.

2.6. WP 2.4. Classification post-processing

Post-processing is the last stage of classification workflow and complements the aggregation process by removing the most common classification mistakes. The whole process of post-processing from the previous part of the S2GLC project has been adapted to meet the requirements for Europe classification. A set of processing steps is applied to the aggregation result to improve the final classification image. Values of selected pixels are analysed considering the prediction score resulting from RF classification and the values of the surrounding pixels. Typical classification errors can be reduced in the final classification map by following the prepared procedure.

Post-processing is applied to the final aggregation result after an analysis of the prediction score for each separate pixel. In most of the post-processing steps only pixels with low values of the prediction scores are considered as candidates for reclassification. An important aspect of the post-processing is that no filtration such as removal of “salt and pepper” effect is applied. Thus, the resulting thematic

map is not smoothed and spatial resolution still remains at the level of a S2 pixel (10 m × 10 m). Figure 7 shows how the prediction score of classified pixels influences the overall accuracy.

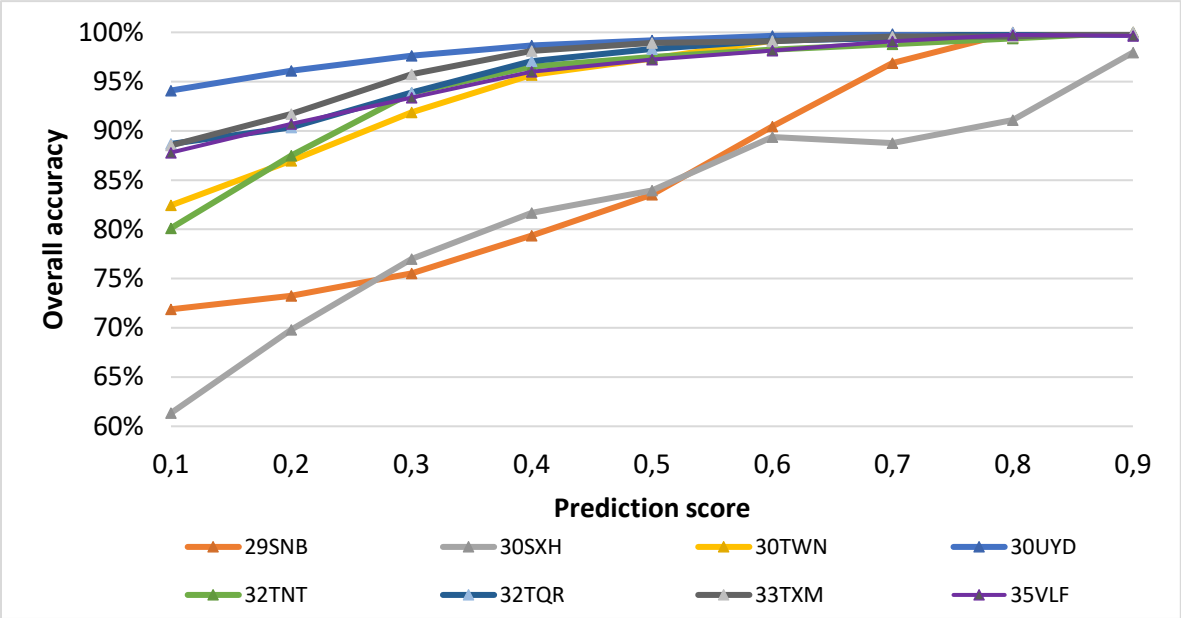

Figure 7. Changes of the overall accuracy while points with low prediction score are removed from validation data, presented for analysed test sites.

The whole post-processing consists of seven procedures that are performed in a sequence. In some of the steps only pixels classified with low prediction score can be changed. A threshold of low/high prediction score has been defined based on the performed tests. This means that classification with prediction score higher than the defined threshold will not be changed. The results presented in Figure 7 for test sites located in different parts of Europe (30TWN – Northern Spain, 30UYD - England, 32TNT – The Alps, 32TQR – Italy, 33TXM – Hungary, 35VLF – Estonia) are similar and confirm the value of threshold for the prediction score estimated in the previous part of S2GLC project, that is 0.35. The different values seen for tiles 29SNB – Portugal and 30SXH – Southern Spain result from difficulties in classifying dry landscape and distinguishing certain LC classes. In case of the drier Southern-European countries the threshold has been increased to 0.6 and can be adjusted for reclassification of different classes.

The post-processing implemented in the previous part of the S2GLC project consisted of the following steps: 1. Reclassification of pixels classified as Artificial surfaces with low prediction score, 2. Reclassification of group of pixels fenced by Artificial surfaces – elimination of shadows misclassified as water, 3. Reclassification of Artificial surfaces classified on the bank of water bodies, 4. Reclassification of Artificial surfaces in high mountains, 5. Correction of Inundated vegetation classification, 6. Reclassification of vegetation LC classes in urban areas, 7. Reclassification of cloudy pixels.

In the European extension of the project the following steps have been implemented and adjusted to the current classification and aggregation results and the operating S2GLC extension legend (Table 12):

Step 1 - Reclassification of pixels classified as artificial surfaces with low prediction score.

Considering the spatial resolution of Sentinel-2 data and the fact that buildings and other artificial surfaces are located in the direct vicinity of different types of vegetation (e.g. trees, grass), some vegetated areas are misclassified as artificial surfaces. Also due to the spectral similarity of certain LC types e.g. bare soil, rocks or other bright surfaces, the class of Artificial surfaces is occasionally overestimated. Therefore, in this step, groups of pixels classified as Artificial surfaces with the prediction score resulting from the aggregation process lower than a certain threshold are reclassified to the neighbouring class that they have the longest border with. This step corrects a lot of arable fields with bare soil misclassified as Artificial areas. Example of the results of this step of post-processing is illustrated in Figure 8.

Threshold value: prediction score < 32%

Figure 8. Example of use of step 1 of the post-processing, (a) orthophoto (Bing resources), (b) classification results before post-processing with many areas wrongly classified as Artificial surfaces (red colour) and (c) classification results after post-processing with reduced distribution of the class Artificial surfaces in rural areas (reclassification mostly to the class Cultivated areas).

Step 2 - Reclassification of Artificial surfaces classified on the bank of water bodies.

Another common classification mistake is misclassification of pixels located on the banks (at the edge) of water reservoirs as artificial areas, which may result from the mixture of spectral values of pixels representing water and other adjacent LC classes. The proposed step is based on reclassification of clusters of pixels with low prediction score that are adjacent to Water bodies and Peatbogs classes. The value of investigated group of pixels is changed to the Water bodies class if the area of neighbouring water body is larger than 5 ha. The performed changes are illustrated in Figure 9.

Threshold values: prediction score 48 %, area of a water body > 5 ha (500 pixels).

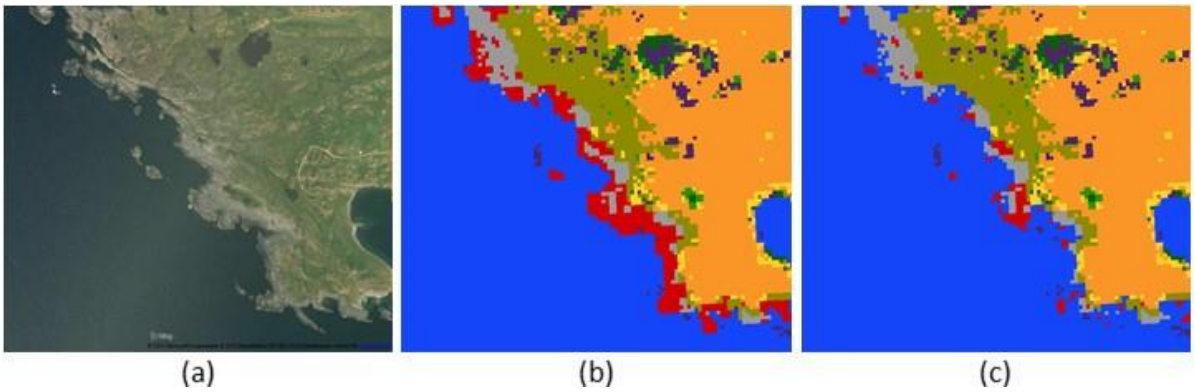

Figure 9. Example of use of step 2 of the post-processing, (a) orthophoto (Bing resources), (b) classification results before post-processing with numerous pixels representing the class Artificial surfaces (in red) on the edges of water bodies, and (c) classification results after post-processing with incorrectly classified Artificial surfaces reclassified to water (blue).

Step 3 - Reclassification of a group of pixels representing the class Artificial surface adjacent to the class Natural material surfaces

Maintaining the rocky or sandy areas classified as Natural material surfaces without misclassifying them as Artificial surfaces is a problematic part of the classification process. Due to the spectral similarity between these classes, it happens that RF algorithm misclassifies them. This results in numerous pixels of the class Artificial surfaces found within the rocky areas classified with relatively high values of prediction scores. Therefore, to be able to correct these mistakes groups of pixels representing the Artificial surfaces class surrounded by the class of Natural material surfaces are investigated. While qualifying the clusters of pixels to be reclassified to Natural material surfaces two conditions have to be met. First, the neighbouring area of the class Natural material surfaces has to be larger than 1 ha. Second, the value of the prediction score has to be lower than a empirically derived threshold. Illustration of the effect of this post-processing step is shown in Figure 10.
Threshold values: prediction score < 48 %, area of surrounding Natural material surfaces > 1 ha (100 pixels).

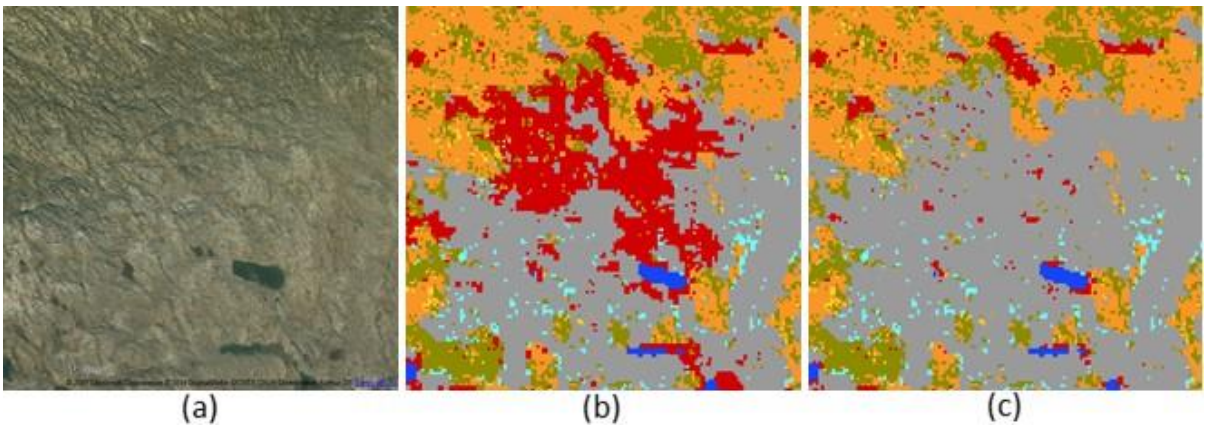

Figure 10. Example of use of step 3 of the post-processing, (a) orthophoto (Bing resources), (b) classification results before post-processing with numerous pixels representing the class Artificial surfaces (in red) in the mountainous (rocky) areas, and (c) classification results after post-processing with incorrectly classified artificial areas reclassified to the class of Natural mineral surfaces (in grey).

Step 4 - Reclassification of cloudy pixels.

The initial classification of satellite images with RF classifier uses a cloud mask that is generated during the process of atmospheric correction of S2 data. It has been noticed, that the mask incorrectly indicates clouds in urban areas. Many large and bright artificial surfaces are misinterpreted as clouds. Moreover, during the classification process, an additional buffer is being created around the clouds from the mask to reduce possible errors of incorrect recognition of cloud edges. This may result in masking out small areas of vegetation that are located in buildings vicinity. The areas incorrectly indicated as clouds appear on every classified images, therefore, even after aggregation of numerous images the "clouded" areas remain unclassified (cloud-covered areas are excluded from classification by default). This issue is even more problematic on the south of Europe (e.g. Athens) where buildings are characterised by bright roofs and appear in the classified image almost completely covered by clouds (Figure 11).

Figure 11. Example of buildings misclassified as clouds in the area of the city of Athens: (a) a cloud-free S2 image, (b) results of classification of a cloud-free S2 image (the same as shown in (a)) with the cloud mask used. White colour represents cloud extent resulting from the cloud mask.

In reality, for vast majority of S2 tiles there are cloud free images available what is opposite to the information about the cloud cover derived from a cloud mask. To solve or at least minimize this problem the least-cloudy image is being selected for every analysed S2 tile and classified without using a cloud mask. Then, in the next step, the "clouded" pixels on the aggregated image are filled with the results of classification performed on the S2 image without applying erroneous cloud mask. The effect of this step is shown in Figure 12.

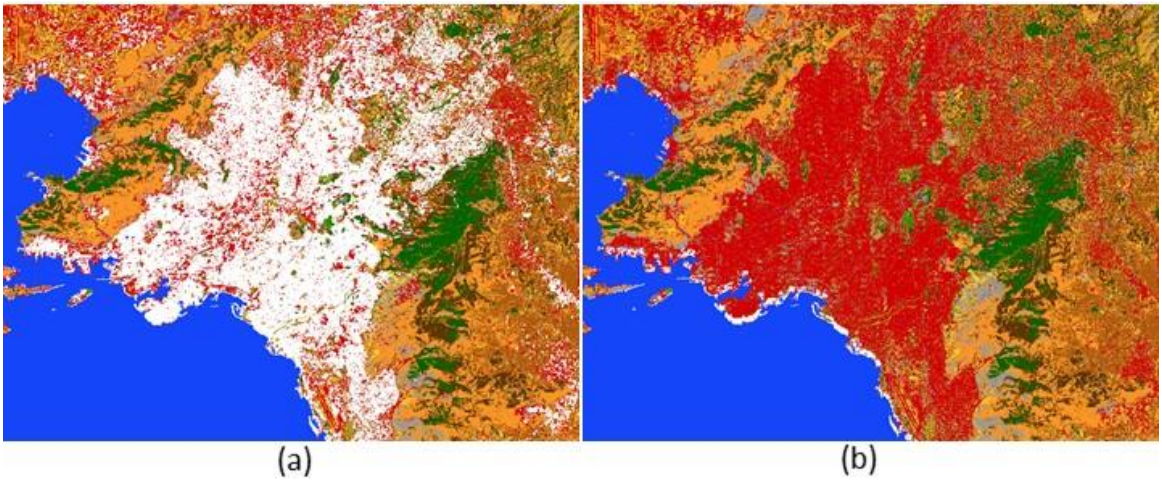

Figure 12. Example of use of step 4 of the post-processing shown on the example of the city of Athens: (a) classification results before post-processing with an enormous part of a urbanized area masked out as clouds (in white), (b) classification results after post-processing with cloudy pixels reclassified to the class of artificial surfaces (red colour).

Step 5 - Reclassification of artificial surfaces in high mountain regions.

Large areas of rocky mountains are often incorrectly classified as Artificial surfaces due to the spectral similarity of both classes. Also the pixels which contain both Natural material surfaces and vegetation are similar to pixels containing Artificial surfaces and vegetation. Misclassification often occur on the edges of large rocky areas and on steep slopes. Some of these errors can be corrected by using DEM of the analysed terrain. In this step, the pixels classified as Artificial surfaces located above certain altitude or on steep slopes, are reclassified to the second class according to the prediction score ranking originating from the aggregation. If the second class is not available a pixel is changed straight to the class Natural material surfaces. This procedure is adopted to different mountainous areas in Europe so the thresholds vary in order to fit the terrain being analysed. Figure 13 shows an example of application of step 5 to a selected mountainous area.

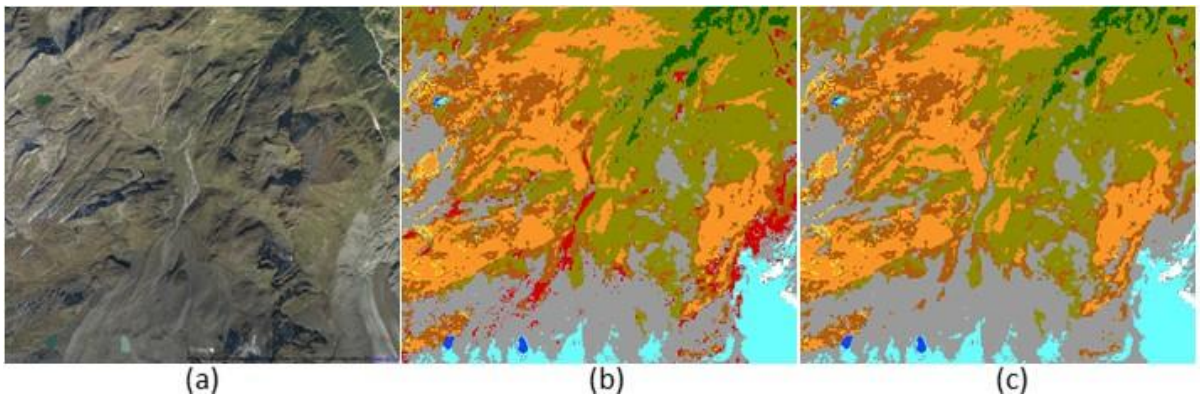

Figure 13. Example of use of step 5 of the post-processing applied: (a) orthophoto (Bing resources), (b) classification results before post-processing with numerous pixels representing the class Artificial surfaces (in red) in the mountainous (rocky) areas, and (c) classification results after post-processing with incorrectly classified artificial areas reclassified to the second most probable class.

Additional modifications - Correction mountain shadows classified as water

It has been noticed that in the mountainous areas shadows are sometimes classified as water surfaces. To minimize this effect, some S2 images acquired during winter or autumn months had to be excluded from the aggregation process. This is related to a lower Sun illumination angle that results in more shadowed areas and is the most problematic in mountainous regions. In order to fit this idea to different latitudes, the area of Europe has been divided into two sub-regions according to the UTM grid system (see Figure 14).

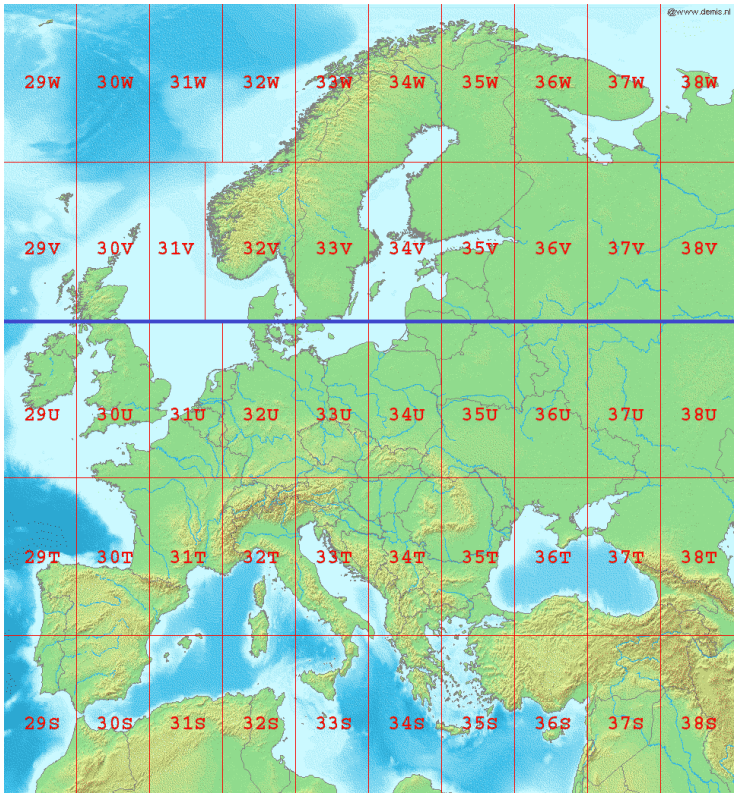

Figure 14. UTM grid for Europe with the division line (bold blue) between different schemes of image selection. Data source: https://commons.wikimedia.org/wiki/File:LA2-Europe-UTM-zones.png.

For S2 tiles located in the northern part of Europe and named with letters V and W, the S2 images acquired between 1st of October and 31st of March have not been used in the aggregation. For the Central and Southern Europe S2 images acquired between 1st of November and 28th of February have been excluded.

The removal of images from the aggregation process was applied only to the mountainous tiles in the number of 171. The list of all excluded tiles is available in Table 15. An example of improvements of the classification result by applying this modification is illustrated in Figure 15.

Table 15. The list of S2 tiles representing mountainous areas for which selected S2 images acquired in autumn and winter periods have not been used for the aggregation.

S2 Tile	Mountain Range	Excluded months	S2 Tile	Mountain Range	Excluded months
26WPT	Iceland	I,II, III, X, XI, XII	32WNT	Scandinavia	I,II, III, X, XI, XII
26WPU	Iceland	I,II, III, X, XI, XII	32WPA	Scandinavia	I,II, III, X, XI, XII

27WVM	Iceland	I,II, III, X, XI, XII	32WPS	Scandinavia	I,II, III, X, XI, XII
27WVN	Iceland	I,II, III, X, XI, XII	32WPT	Scandinavia	I,II, III, X, XI, XII
27WVP	Iceland	I,II, III, X, XI, XII	32WPU	Scandinavia	I,II, III, X, XI, XII
27WWM	Iceland	I,II, III, X, XI, XII	32WPV	Scandinavia	I,II, III, X, XI, XII
27WWN	Iceland	I,II, III, X, XI, XII	33TUM	Alps	I,II, XI, XII
27WWP	Iceland	I,II, III, X, XI, XII	33TUN	Alps	I,II, XI, XII
27WXM	Iceland	I,II, III, X, XI, XII	33TVM	Alps	I,II, XI, XII
27WXN	Iceland	I,II, III, X, XI, XII	33TVN	Alps	I,II, XI, XII
27WXP	Iceland	I,II, III, X, XI, XII	33TWH	Dinaric Alps	I,II, XI, XII
28WDS	Iceland	I,II, III, X, XI, XII	33TXH	Dinaric Alps	I,II, XI, XII
28WDT	Iceland	I,II, III, X, XI, XII	33TYJ	Dinaric Alps	I,II, XI, XII
28WDU	Iceland	I,II, III, X, XI, XII	33VUJ	Scandinavia	I,II, III, X, XI, XII
28WES	Iceland	I,II, III, X, XI, XII	33VUK	Scandinavia	I,II, III, X, XI, XII
28WET	Iceland	I,II, III, X, XI, XII	33VVK	Scandinavia	I,II, III, X, XI, XII
28WEU	Iceland	I,II, III, X, XI, XII	33VVL	Scandinavia	I,II, III, X, XI, XII
29TPG	Cantabrian Mountains	I,II, XI, XII	33WVM	Scandinavia	I,II, III, X, XI, XII
29TPH	Cantabrian Mountains	I,II, XI, XII	33WVN	Scandinavia	I,II, III, X, XI, XII
29TPJ	Cantabrian Mountains	I,II, XI, XII	33WVP	Scandinavia	I,II, III, X, XI, XII
29TQG	Cantabrian Mountains	I,II, XI, XII	33WVQ	Scandinavia	I,II, III, X, XI, XII
29TQH	Cantabrian Mountains	I,II, XI, XII	33WVR	Scandinavia	I,II, III, X, XI, XII
29VNE	Grampian Mountains	I,II, III, X, XI, XII	33WWN	Scandinavia	I,II, III, X, XI, XII
29VPD	Grampian Mountains	I,II, III, X, XI, XII	33WWP	Scandinavia	I,II, III, X, XI, XII
30SUF	Baetic Mountains	I,II, XI, XII	33WWQ	Scandinavia	I,II, III, X, XI, XII
30SVF	Baetic Mountains	I,II, XI, XII	33WWR	Scandinavia	I,II, III, X, XI, XII
30SVG	Baetic Mountains	I,II, XI, XII	33WWS	Scandinavia	I,II, III, X, XI, XII
30SWF	Baetic Mountains	I,II, XI, XII	33WWT	Scandinavia	I,II, III, X, XI, XII
30SWG	Baetic Mountains	I,II, XI, XII	33WXQ	Scandinavia	I,II, III, X, XI, XII
30SWH	Baetic Mountains	I,II, XI, XII	33WXR	Scandinavia	I,II, III, X, XI, XII
30SYH	Baetic Mountains	I,II, XI, XII	33WXS	Scandinavia	I,II, III, X, XI, XII
30TUN	Cantabrian Mountains	I,II, XI, XII	33WXT	Scandinavia	I,II, III, X, XI, XII
30TUP	Cantabrian Mountains	I,II, XI, XII	34SDJ	Dinaric Alps	I,II, XI, XII
30TXM	Pyrenees	I,II, XI, XII	34SEF	Dinaric Alps	I,II, XI, XII
30TXN	Pyrenees	I,II, XI, XII	34SEH	Dinaric Alps	I,II, XI, XII
30TYN	Pyrenees	I,II, XI, XII	34SEJ	Dinaric Alps	I,II, XI, XII
30VUH	Grampian Mountains	I,II, III, X, XI, XII	34SFF	Dinaric Alps	I,II, XI, XII

30VUJ	Grampian Mountains	I,II, III, X, XI, XII	34SFG	Dinaric Alps	I,II, XI, XII
30VUK	Grampian Mountains	I,II, III, X, XI, XII	34SFH	Dinaric Alps	I,II, XI, XII
30VVH	Grampian Mountains	I,II, III, X, XI, XII	34SFJ	Dinaric Alps	I,II, XI, XII
30VVJ	Grampian Mountains	I,II, III, X, XI, XII	34SGE	Dinaric Alps	I,II, XI, XII
31TCG	Pyrenees	I,II, XI, XII	34SGH	Dinaric Alps	I,II, XI, XII
31TCH	Pyrenees	I,II, XI, XII	34TCK	Dinaric Alps	I,II, XI, XII
31TDG	Pyrenees	I,II, XI, XII	34TCL	Dinaric Alps	I,II, XI, XII
31TDH	Pyrenees	I,II, XI, XII	34TCN	Dinaric Alps	I,II, XI, XII
31TFK	Alps	I,II, XI, XII	34TDK	Dinaric Alps	I,II, XI, XII
31TGJ	Alps	I,II, XI, XII	34TDL	Dinaric Alps	I,II, XI, XII
31TGK	Alps	I,II, XI, XII	34TDM	Dinaric Alps	I,II, XI, XII
31TGL	Alps	I,II, XI, XII	34TDN	Dinaric Alps	I,II, XI, XII
32TLP	Alps	I,II, XI, XII	34TEL	Dinaric Alps	I,II, XI, XII
32TLQ	Alps	I,II, XI, XII	34TFK	Dinaric Alps	I,II, XI, XII
32TLR	Alps	I,II, XI, XII	34TFL	Dinaric Alps	I,II, XI, XII
32TLS	Alps	I,II, XI, XII	34TFM	Dinaric Alps	I,II, XI, XII
32TMP	Alps	I,II, XI, XII	34TFN	Dinaric Alps	I,II, XI, XII
32TMR	Alps	I,II, XI, XII	34TFR	Carpathian Mountains	I,II, XI, XII
32TMS	Alps	I,II, XI, XII	34TGL	Dinaric Alps	I,II, XI, XII
32TNR	Alps	I,II, XI, XII	34TGM	Dinaric Alps	I,II, XI, XII
32TNS	Alps	I,II, XI, XII	34TGN	Dinaric Alps	I,II, XI, XII
32TNT	Alps	I,II, XI, XII	34TGR	Carpathian Mountains	I,II, XI, XII
32TPS	Alps	I,II, XI, XII	34TGS	Carpathian Mountains	I,II, XI, XII
32TPT	Alps	I,II, XI, XII	34UCV	Tatra Mountains	I,II, XI, XII
32TQS	Alps	I,II, XI, XII	34UDV	Tatra Mountains	I,II, XI, XII
32TQT	Alps	I,II, XI, XII	34WDB	Scandinavia	I,II, III, X, XI, XII
32VKN	Scandinavia	I,II, III, X, XI, XII	34WDC	Scandinavia	I,II, III, X, XI, XII
32VKP	Scandinavia	I,II, III, X, XI, XII	34WDD	Scandinavia	I,II, III, X, XI, XII
32VLK	Scandinavia	I,II, III, X, XI, XII	34WEB	Scandinavia	I,II, III, X, XI, XII
32VLL	Scandinavia	I,II, III, X, XI, XII	34WEC	Scandinavia	I,II, III, X, XI, XII
32VLM	Scandinavia	I,II, III, X, XI, XII	34WED	Scandinavia	I,II, III, X, XI, XII
32VLN	Scandinavia	I,II, III, X, XI, XII	34WFB	Scandinavia	I,II, III, X, XI, XII
32VLP	Scandinavia	I,II, III, X, XI, XII	34WFC	Scandinavia	I,II, III, X, XI, XII
32VLQ	Scandinavia	I,II, III, X, XI, XII	34WFD	Scandinavia	I,II, III, X, XI, XII
32VML	Scandinavia	I,II, III, X, XI, XII	35SKV	Dinaric Alps	I,II, XI, XII
32VMM	Scandinavia	I,II, III, X, XI, XII	35SLA	Dinaric Alps	I,II, XI, XII
32VMN	Scandinavia	I,II, III, X, XI, XII	35SLB	Dinaric Alps	I,II, XI, XII

32VMP	Scandinavia	I,II, III, X, XI, XII	35SLC	Dinaric Alps	I,II, XI, XII
32VMQ	Scandinavia	I,II, III, X, XI, XII	35SLU	Dinaric Alps	I,II, XI, XII
32VMR	Scandinavia	I,II, III, X, XI, XII	35SLV	Dinaric Alps	I,II, XI, XII
32VNM	Scandinavia	I,II, III, X, XI, XII	35SMB	Dinaric Alps	I,II, XI, XII
32VNN	Scandinavia	I,II, III, X, XI, XII	35SNA	Dinaric Alps	I,II, XI, XII
32VNP	Scandinavia	I,II, III, X, XI, XII	35TLH	Dinaric Alps	I,II, XI, XII
32VNQ	Scandinavia	I,II, III, X, XI, XII	35WMT	Scandinavia	I,II, III, X, XI, XII
32VNR	Scandinavia	I,II, III, X, XI, XII	35WMU	Scandinavia	I,II, III, X, XI, XII
32VPP	Scandinavia	I,II, III, X, XI, XII	35WNU	Scandinavia	I,II, III, X, XI, XII
32VPQ	Scandinavia	I,II, III, X, XI, XII	35WPT	Scandinavia	I,II, III, X, XI, XII
32VPR	Scandinavia	I,II, III, X, XI, XII	35WPU	Scandinavia	I,II, III, X, XI, XII
32WNS	Scandinavia	I,II, III, X, XI, XII			

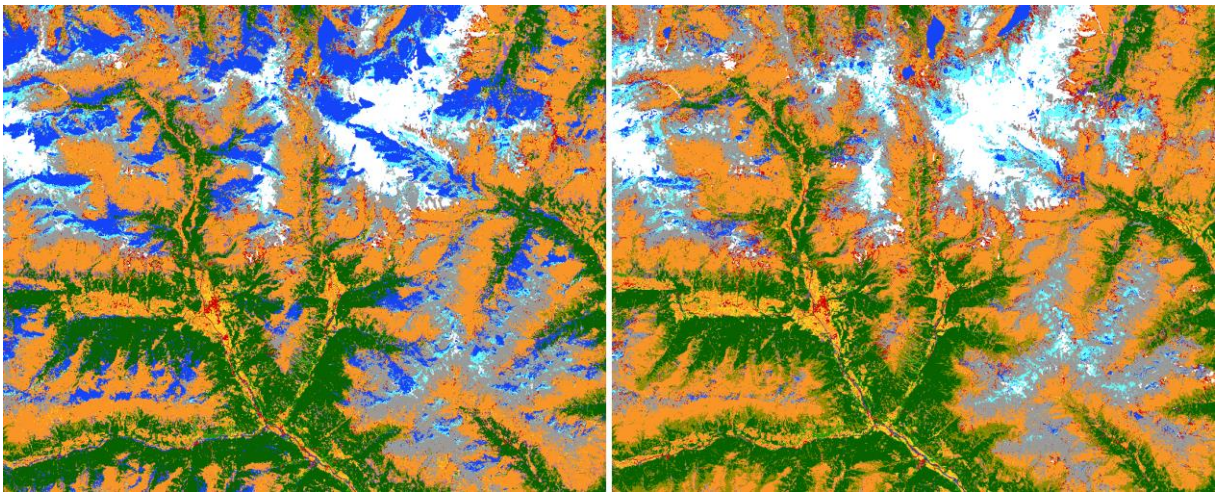

Figure 15. Results of aggregation process performer using different schema of image selection, in which some S2 images originating from the autumn and winter periods were excluded: (a) classification result with all available S2 images that shows misclassification of shadows as Water bodies (in dark blue), (b) classification results after the aggregation performed with S2 images limited to those acquired during spring and summer months, with majority of errors removed.

3. WP3 - Implementation of the classification algorithm to the EO IPT environment

While working on implementation of the classification method, all the previously created tools had to be modified in order to match the calculation process in the cloud environment, and more specifically the environment of the CREODIAS platform. In addition, it was necessary to create a system that manages all the calculations.

Completion of this WP involved implementation and assemblage of eight independent tools used to perform separate tasks that together compose the complete processing system. These tasks, also referred to as processes, are the most important parts of the data processing chain, and are necessary

to complete the classification process in an automated mode. The tasks of the processing system and their order are presented in Figure 16.

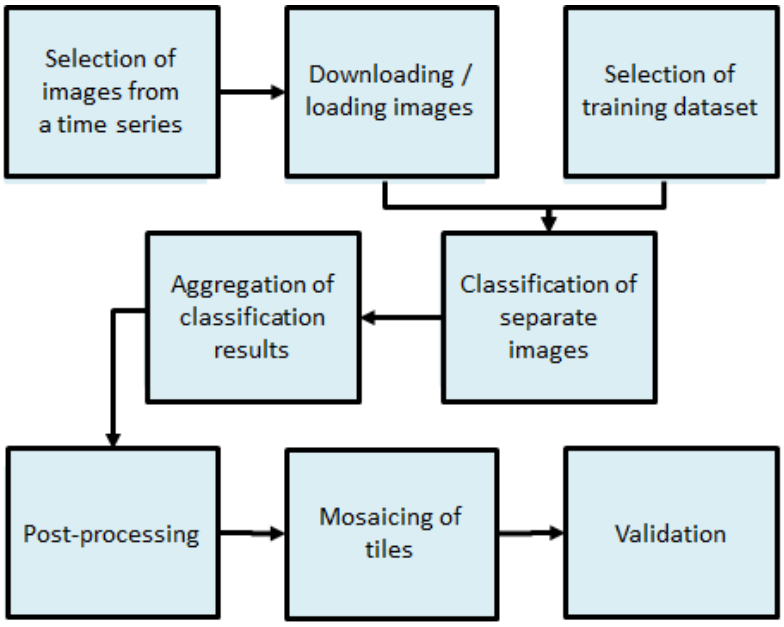

Figure 16. Data processing workflow illustrating successive tasks of the LC classification system implemented in the CREODIAS environment.

Selection of images from a time series

Implementation of this process was done in a Python code. The aspect of selection of dates of S2 images that also considers cloud coverage was investigated in in the initial part of the project and described in section 2.3 (Selection of S2 images for classification) of this report. The data selection rule that was found the best was implemented and used in the processing system. The code implemented for this purpose also addressed the issue of selecting images with appropriate data content. Due to the fact that information about data coverage within separate S2 images acquired in 2017 was not available in metadata files neither on the CREODIAS nor the Copernicus Open Access Hub, it was necessary to obtain it from a different source. Initially, the percentage of data coverage was approximated from the size of a data file (measured in megabytes), but the results were found ambiguous. Another idea was to calculate the image area based on the coordinates of the polygon representing image data coverage that is available in the metadata. Finally, information provided by external data provided by the project partner, IABG mbH, in the form of tables with statistics for S2 images for the whole Europe was used. This information was acquired from the Amazon Web Services. It is important to mention that for S2 images from the year 2018 and later, information on the data coverage is available from the Copernicus Open Access Hub and could be easily accessed from the CREODIAS server using API. To use such option, however, it would be necessary to adjust the existing script.

Downloading / loading image data

One of the main idea of the project was to perform LC classification utilizing infrastructure provided by CREODIAS. To enable this and avoid downloading of image data to local repository as it was done in the first phase of the S2GLC project, the tool developed for this task was modified and adjusted so that the conversion of S2 data format (SAFE) to TIFF was not necessary anymore. With the new code the original image data in JPEG2000 format was directly read and used for processing, which made the phase of data pre-processing faster.

Selection of training data

Selection of training samples is a process composed of many steps. The optimal format of training data for the implemented classifier is a raster image with a grid of pixels precisely matching pixels from S2 data (10 m resolution). Additionally, the values of pixels of the training raster must be consistent with the codes of the final legend (Table 12). The CLC dataset representing the highest level of details is available in a vector format. Therefore, the tool implemented to perform this task enable to rasterize selected classes from CLC dataset and also resample HRL data into a raster format matching the 10 m grid of pixels of S2 images. Finally, the tool enables to combine information from CLC and HRL datasets into a single raster that addresses the thematic data selection rules presented in Table 11. A raster data prepared in this way is an entry to the classification algorithm.

Classification of separate images

The most important part of the entire processing system is the classifier. The part of the script implementing the classifier was written in the MATLAB language and, therefore, it requires dedicated MATLAB Runtime environment. The first part of the tool is responsible for selection of training samples. Similarly as in the initial part of the project the classification is carried out on a tile by tile basis. This means that each S2 image tile is being classified separately with its own training dataset that covers strictly the same area (i.e. a tile). The tool selects randomly a new set of training samples for every separate classification from the training dataset prepared in the previous step (i.e. Selection of training dataset). It also utilizes for that purpose information derived from spectral indices including NDVI and NDWI, which are calculated in parallel, and the cloud mask of a given S2 image. In the next step the script starts RF algorithm and performs the learning and classification phases. The results of classification are written to the corresponding pixels in the output image. The resulting files, along with the learned classifier, are saved in a container available in the CREODIAS environment. The task of a file saving was written in Python language with the boto3 library.

Aggregation

The overall concept of the aggregation algorithm has not changed as compared to the initial part of the S2GLC project and the general idea may be found in (Lewiński *et al.*, 2017). The difference is only in the number of used. In some regions, only results from the summer months were aggregated, despite the fact that classification was performed on data acquired in other parts of a year. This is due to large classification errors in S2 images with numerous shadowed areas. The program code was written in C ++.

Post-processing

The schema and rules of post-processing are described in section 2.6. The script related to this part of the processing executes each post-processing step one after another, and saves results to a new file to enable comparison between the steps. The code was written in C ++ and is partly shared with the aggregation program.

Mosaicing of separate tiles

Outputs of the post-processing process, still divided into separate S2 tiles are combined together by a series of simple, static scripts containing names of selected S2 tiles. The gdalwarp and the gdal_merge programs from the GDAL library are used for this purpose. The final output representing LC classification over Europe was saved into GeoTIFF files, each representing different latitude and longitude zone of the Universal Transverse Mercator coordinate system as shown in the Figure 14. The mentioned scripts might be modified if the classification output is to be merged in a different way than it was performed in the project.

Validation

The script for performing validation of the classification output has been improved in the current project phase. In general it is written in C ++ but additional functionality was added (written in Python) for generating cumulative error matrices and charts for illustrating the validation results with division into countries and also for the whole of Europe.

As mentioned before a tool for managing the classification process, called CalcManager was created. It consists of two components: a server and a computing station. In addition, CalcManager uses a database server where all computing tasks and logs files are saved. The tasks of both components of the program are shown in Figure 17. An important feature of the CalcManager program is its ability to run on Windows and Linux systems. It also enables integration and use of own and cloud computing resources (e.g. CREODIAS) together. Communication between the server and station is done using the REST API and the http protocol.

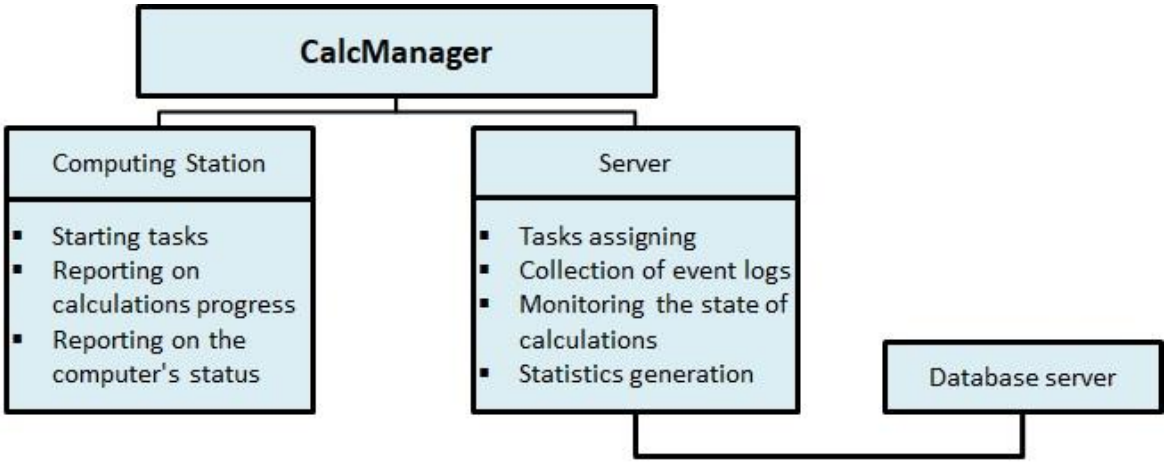

Figure 17. A structure and tasks of the CalcManager tool used for managing the classification processes.

4. WP4 – LC classification on EO ITP

As planned in the project proposal most of the calculations were carried out on the CREODIAS platform. CREODIAS is a successor of the EO Cloud platform.
All data processing on the CREODIAS platform was postponed by over a month due to a delay in downloading S2 images for Europe to the platform and performing atmospheric correction.
Once S2 data were fully prepared data processing and classification has started. During the phase of data processing on CREODIAS, several problems were encountered, which originated from errors in the programing codes. This was unavoidable despite the numerous tests that were performed. However, most of the problems resulted from minor errors that were rather easily eliminated. Following these, the S2 tiles were classified in groups and checked regularly by visual inspection of the outcomes.

In summary, over 21,000 classifications of separate S2 images have been made. For that purpose 49 virtual machines with Windows Server 2016 system were used as computing station. Each of them had 8 VCPUs with clock speeds of about 2.5 GHz, 32 GB of RAM, 128 GB of SSD and a direct connection to the EO data repository.

5. WP5 – Product validation

The goal of this section is to present the standards and the validation approach applied to the geospatial product accuracy assessment. The definition of the sample size and sample distribution, the validation mechanism and the set of validation measures, the reference dataset and the validation outcomes are presented in the following sections respectively: 5.1, 5.2, 5.2.2.

5.1. WP 5.1 Development of validation methodology

The S2GLC project aims at providing LC classification of the whole Europe based on S2 images. Figure 18 shows the S2 image classification workflow with the delineation of the final geospatial product subjects to the validation processes.

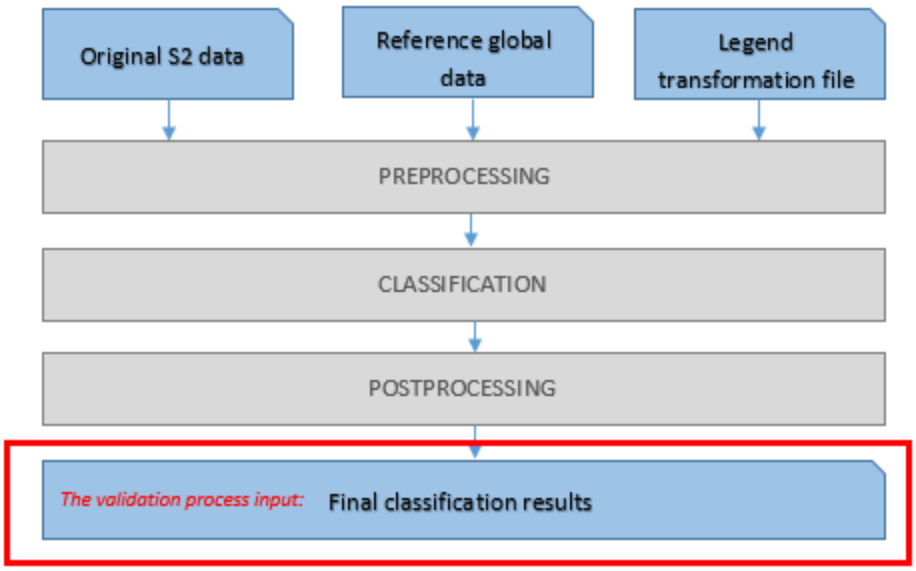

Figure 18. General S2GLC classification workflow.

The main objective of the validation in this project is to perform an accuracy assessment to derive a quantitative description of the quality of the produced land cover map. Selecting a suitable method requires to consider map specifications, constraints of the data as well as the purpose of its usage. The following issues had to be considered:

- Thematic reference data used and expert personnel involved shall be independent from any data and staff employed during production;
- Reference data should encompass the same time period as the classification product under validation;
- Validation approaches must consider characteristics of a product, including technical product specifications (e.g. generalization criteria), production methods and limitations of the base data (e.g. geometric mis-registrations of EO data);
- Regional information and knowledge are very important factors.

An accuracy assessment itself consists of three consecutive steps: sampling design, response design and analysis (see Figure 19).

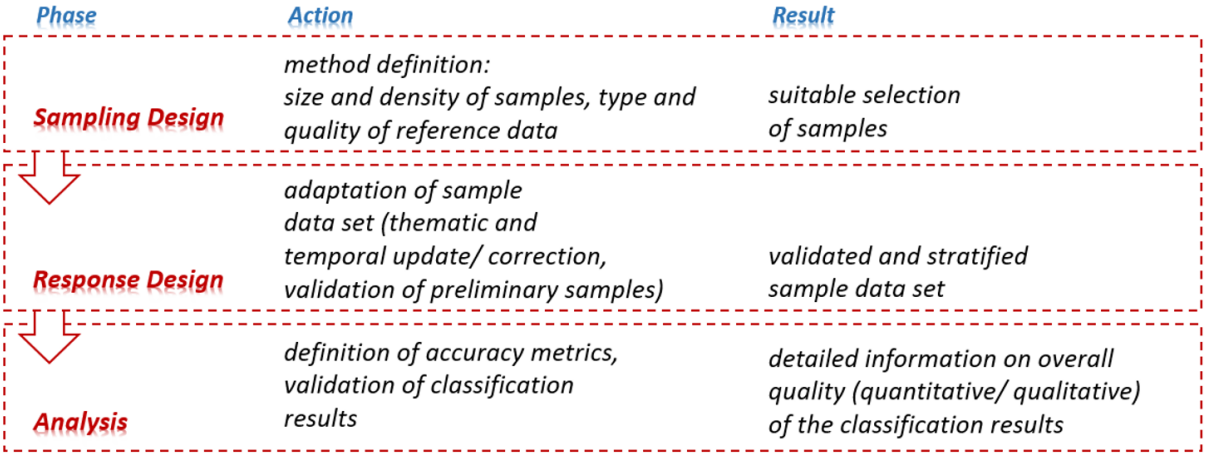

Figure 19: Workflow of the general validation method.

The sampling design specifies the locations at which the map information will be validated and where reference data will be collected (and – if needed – verified), and comprises of the selection of strata as well as the definition of sampling units and sampling size.

The response design is the protocol to obtain the ground situation (i.e. selection, preparation and information retrieval from ground or reference data) for each sample unit. Access to consistent in-situ data (even collected by means of “virtual truthing”) is a key success factor for validation.

Finally, analysis of the derived results consists of suitable aggregation and valuing with respect to the context resp. pre-requisites.

The following chapter describes the methodology of the whole validation process considering the above-listed points.

5.1.1. Sampling Design - Site selection

Validation refers to the thematic accuracy assessment of the time-series classification aggregation. The final LC classification outcome consists of the 13 thematic classes presented in Table 12.

The selected validation sites are distributed all over Europe. In the designed sampling strategy the size of a single area sample refers to the S2 image tile (granule) covered by land area with more than 75% (project proposal [AD-4], WP5 – Product validation). The thematic accuracy assessment is performed for approximately 10% of all Sentinel-2 image tiles covering each of the mapped country, except Andora, Vatican, San Marino and Lichtenstein (Figure 20). Luxemburg is presented in a part of one of the three sites selected for Germany (Figure 20). The summary will refer to the validation sample of Germany and Luxemburg, as a one area of interest (Figure 21, case c). For some of the countries 10% of the number of covering S2 tiles gives near-zero values. In that case, it has been decided to select randomly one single tile fulfilling the condition of providing the accuracy assessment on the country level (Figure 20). This set of tiles are referred to as “added” sites. Table 16 presents the summary of the randomly selected sites.

Table 16. The summary of the randomly selected sites.

No. of “base” sites (10 % per country)	No. of “added” sites	Total No. of sites	Mean country area coverage
45	10	55	21%

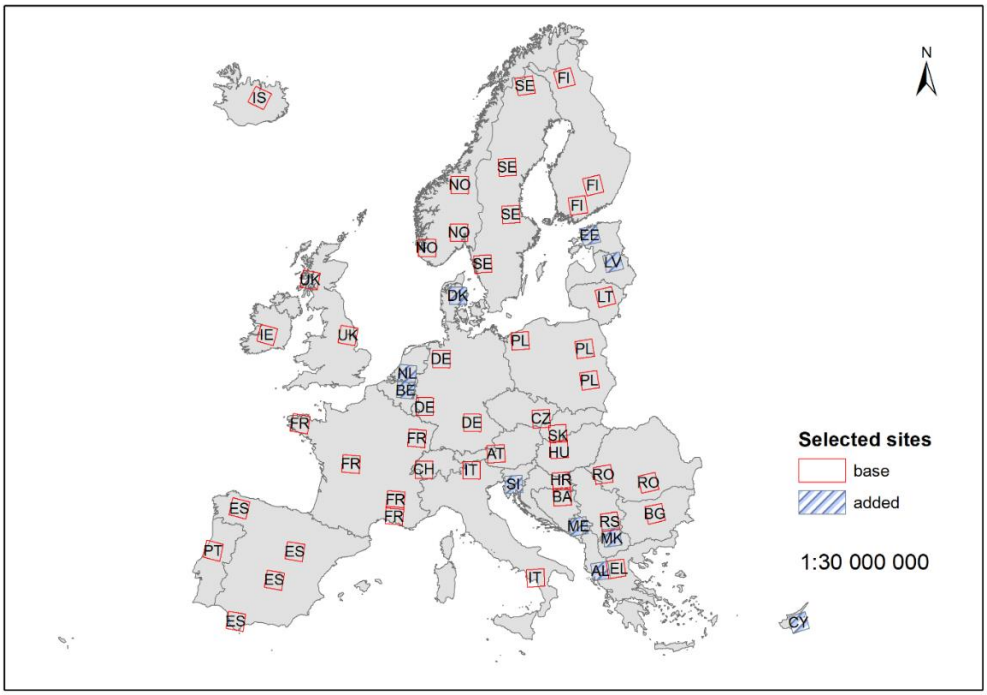

Figure 20. The map of randomly selected sites labelled with codes for the names of countries they represent; “base” - 10% of tiles per country; “added” – one tile per country for those countries where 10% gives near-zero value.

From the set of the "added" sites, two sites are located at the country's borders (Figure 21, case a and b). Those sites are merged with the sites selected for the neighbourhood country and are represented in the summary as the validation sites of two countries. This is a case for the following pairs: Albania and Greece; Croatia and Slovenia.

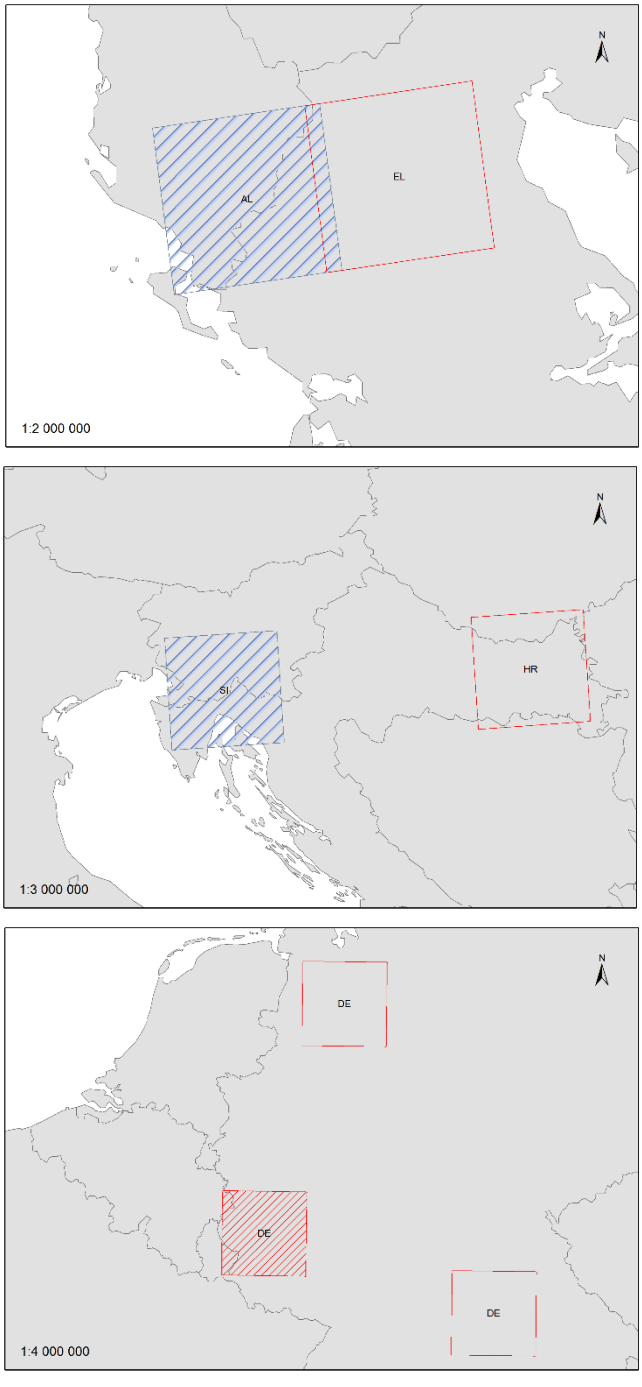

Figure 21. The example of the merged country sites for: a) Albania and Greece, b) Croatia and Slovenia, c) Germany and Luxemburg.

5.1.2. Sampling Design – Initial sample dataset selection

Within the initial sampling design phase, methods were set-up containing a concept on the data to be used and the technology applied. It also comprised the selection of strata, the definition of sampling units and sampling size.

To obtain an appropriate set of samples, the sampling design requires sufficient samples, which are on the one hand representative, which means that their composition must include all relevant information the sampling is supposed to check, and on the other hand significant, which means that their dimension must be sufficient to ensure with high probability that the results are reliable.

The samples must be well distributed across the area of interest. The samples may be randomly selected using a random automatic generator. However, the sample points must be identifiable on the classification results being assessed, as well as on the reference data.

To meet the requirements a stratified random sampling was performed, assuring sufficient accuracy estimation for all classes according to their frequency of occurrence.

There are two aspects to a sampling strategy: the items to be sampled (area or feature), and the manner by which the items are selected (probability or judgement) (Figure 22). Figure 23 present the selected sampling approach: Stratified Random Sampling, in respect to the most commonly used procedures.

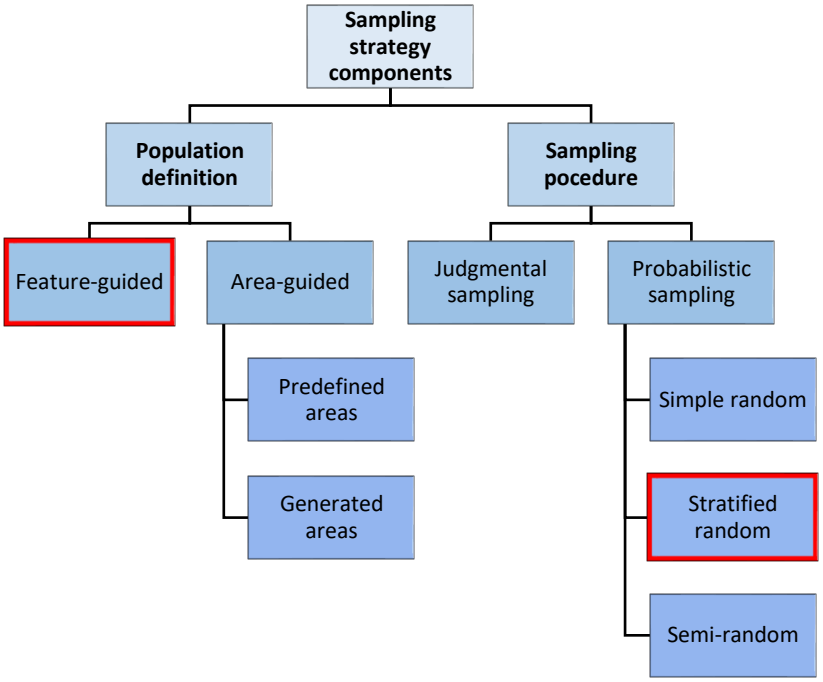

Figure 22. Sampling strategy relationship with the delineation of selected strategy (ISO 19157:2013).

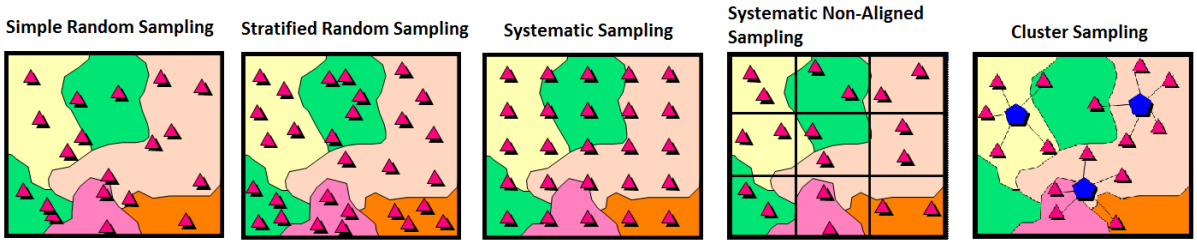

Figure 23. Sampling Methods (Oregon State University).

The stratification was done based on the available reference data, i.e. CLC. Based on the legend provided in WP2.5 (Table 12), the LC classes of interest were selected. One additional LC class was prepared by merging the remaining classes from CLC in one single class, hereinafter referred to as Not Applicable – NA, class. The samples were randomly selected within the strata according to the proportion of a given class within the area of a S2 tile and were provided without pre-determined LC class in the attribute table. Figure 24 shows an example of validation samples selected for the tile 29TNE (Portugal).

As the number of reference samples may vary depending on a number of several factors, e.g. scale of generated map, size of the area of interests (Congalton and Green, 2009), the total number of selected samples has been estimated as n = 800. The number of selected samples results from the time and resources constrains. The selected set of points provides the statistically representative sample of LC classes.

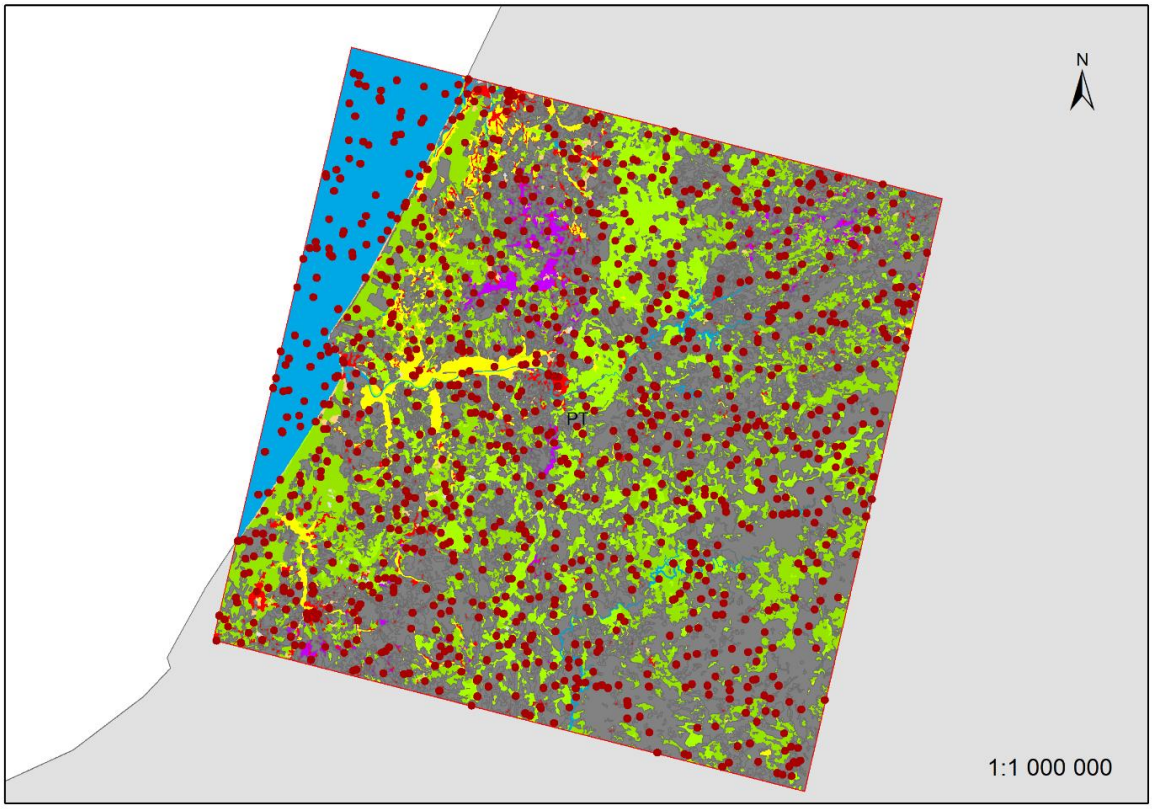

Figure 24. The example of randomly selected validation points, 29TNE S2 tile. The colours in the presented image corresponds to those presented in Table 12, grey colour represents the NA class.

Following the assumption of the selected samples clear identification in respect to the assessed outcome and reference data (section 5.1.2), the number of initially selected samples was increased to the level of 1000. This approach is driven by the fact that some of the samples could be eliminated due to the following reasons:

- a location of a sample on the border of LC classes;
- difficulty of an interpreter in class distinction.

In addition, during the stratification process several conditions have been imposed:

- LC classes which cover less than 0.95% of a tile (granule) area have been excluded from validation process, no validation samples have been selected for them;
- For LC classes which cover 0,95% to 2% of a tile (granule) area, the minimum number of validation samples has been adjusted manually. Following the requirements listed in the project proposal (WP 2.5) the minimum number of validation samples is 20;
- For LC classes: Artificial surfaces and constructions and Natural material surfaces, the minimum number of validation points has been provided by default (20 points), even if the LC class covers less than 0,95% of a tile (granule) area.

Finally, 55 separate files containing approximately 55.000 initial sample points were produced.

5.1.3. Response Design – Verification of selected sample dataset

The response design contains all actions related to increasing thematic and geometric quality of the initially selected validation samples.

Using Sentinel-2 data, geometric co-registration errors in multi-temporal images may occur (see Figure 25) (Kukawska *et al.*, 2017).

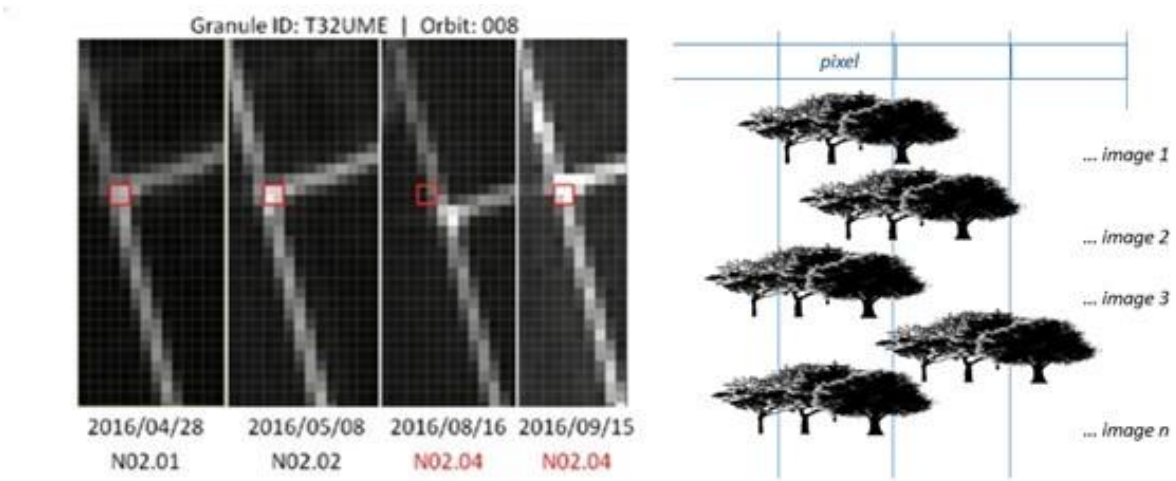

Figure 25: Example of a geometric co-registration error in S2 images acquired for the tile T32UME, from orbit 008 with different baselines (N02.02, N02.02, N02.04).

These errors can be caught by a special sample structure. To avoid quality losses of the reference samples during verification in case of mis-registration, the initial sample points and their nearest neighbourhood were verified by drawing a 3 x 3 pixel-window (30 m x 30 m matrix, see Figure 26).

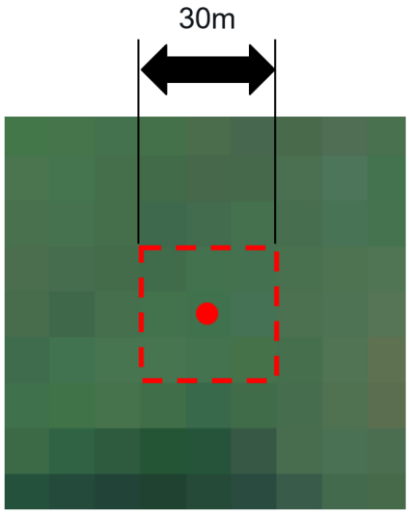

Figure 26: Example of the window area considered as the randomly selected sample with the nearest neighbourhood (3x3 window).

The sample polygons were slightly shifted, if necessary. Thus, the final locations show an explicit occurrence and definite class appearance.

The verification of the initial sample data was based on reference data, that had to fulfil high standards in order to compensate missing 'ground truth' derived by in-situ surveys. Selection criteria for suitable and eligible reference data are availability, accessibility (if possible at no/low cost), technical relevance (with respect to temporal, thematic and geometric resolution – ideally being of higher quality than the data set under validation), consistency (with comparable quality across the globe), and independency (as it should have not been used during production). In case of identical data sources, the technology of creating the reference classification should be of a different method and more accurate than the process of creating the map.

Further criteria include strategies to guarantee access to independent reference data in adequate quality (i.e. thematic relevance, high resolution, homogeneous coverage, timelines) and to ensure a homogeneous quality across a team of validation experts, including methods for resolving issues from ambiguous results (e.g. the use of multiple interpretations of the layer in question). Key element of the interpretation is a sufficient number of experts with local knowledge and expertise in high resolution data interpretation independent from the production team. Differences in image interpretation when working with many analysts was avoided by providing a comprehensive signature catalogue and by carrying out interpretation workshops at the beginning of the response design phase. Naturally, the verification used the same legend as the classification under validation.

The reference data were of different type, selected according to the criteria listed above. Both EO image data and thematic land cover data were preliminarily considered within this project and are described in detail below.

The main objective was the verification of the samples against real world carried out as virtual truthing with EO imagery, which was ideally of independent kind, of higher resolution and of the same time frame compared to the data used for the classification of the land cover map. To ensure and improve the classification of classes with seasonal changes, multi-temporal images were used.

Table 17 lists the EO data sources that were taken into account.

Table 17: EO data sources considered as virtual truth

	Short description	Way of use
PlanetScope	• RGBNIR; ~3 m • >175 satellites in orbit/ global coverage, daily update	• Important independent data source, up-to-date, very high resolution
	• Land monitoring	• Primary source as WMTS
Sentinel 2	• 13 Bands in VIS, NIR, SWIR; 10/ 20/ 60 m • Two satellites/ global coverage over land and coastal areas, 5 days repeat cycle	• Up-to-date data source and classification base
	• Land monitoring, freely available	• Cross-checking source

PlanetScope data were accessed via WMTS (Web Map Tiles Service), as IABG is an official sales partner and a service provider of PlanetScope data products. The Planet Explorer Beta platform is a browser-based viewer, which allows the user to search, visualize and analyse areas of interest. Planet operates more than 175 Dove, 13 SkySat and 5 RapidEye satellites that provide a versatile data set for geospatial analysis of markets, environments and global change. Due to Doves' daily revisit, the multispectral data is made available in near-real time. In combination with the very high spatial resolution of PlanetScope satellite images (3 m), a resistant, solid and independent sample data quality could be ensured.

In fact, the usage of PlanetScope data is partially commercial and therefore not practicable when dealing with global sampling data sets. The utilization within this project focused on finding a logic in building up a robust validation database for the European land cover. The processed sampling points were thus as well cross-checked with freely accessible multi-temporal S2 data.

Global land cover datasets act as an important overall reference source. However, it is obvious that global reference datasets show a high variety and a limited scale within the global context. It is therefore, of advantage to include, at least within a development stage, regional or national sources for validation purposes.

To support the visual verification of the initial samples several thematic land cover databases were used:

- Existing European land cover data sets:
  - HRL 2015 (Imperviousness, Forest, Grassland, Water and Wetness)
  - CLC 2012
  - GUF 2016
- Existing Global land cover data sets:
  - FROM-GLC 2015
  - ESA CCI 2015
  - GlobCover 2009

Figure 27: Specific reference land cover datasets: HRL, CORINE, FROM-GLC.

The existing data sets were downloaded and reviewed with respect to their potential benefit for this project. The objective within this process was to identify thematic and geometric applicability of medium scale sources for validation purposes of large-scale classification products. Furthermore they were valued regarding restrictions of use, usability and suitability for S2GLC classification issues, following characterization including:

- data type (raster, vector, text),
- spatial extent (point, line, polygon, pixel),
- spatial resolution,
- detail and structure of thematic classification (nomenclature),
- frequency of data collection,
- possible restrictions on data availability,
- spatial data coverage.

Table 18 gives an overview on reference classifications considered as suitable, and how they had been included in the process. The following sub-sections describe their structure and layout.

Table 18: Overview of regional and global land cover data sets with respect to this project.

	Short description	Applicability
HRL	• 2015, raster/ 20 m (and 100 m) • EEA, 5 products (Imperviousness, 2 x forest, grassland, water and wetness) • European countries, free access	• Artificial class, forest, grassland, water and wetness • Primary reference layers for supporting visual verification
GUF	• 2016, raster/ 12 m • DLR, Binary mask • Based on Sentinel-1 and other • European countries	• Artificial class • Primary reference layer for supporting visual verification
CLC	• 2012, vector/ > 25 ha • EC, 44 classes (L3), >85 % accuracy • Visual interpretation • 27 European countries, free access	• S2GLC classes • Primary reference layer for supporting visual verification
FROM GLC	• 2015, raster/ 30 m • 11 classes (L1); 29 subclasses (L2) • Global, free access	• S2GLC classes • Sparsely used for supporting visual verification due to insufficient quality

	• Suitable for global validation, unsatisfactory overall accuracy	
CCI	• 2015, raster/ 300 m • ESA, 23 classes (FAO-LCCS) , 80 % accuracy • Supervised and unsupervised classification • Global, free access • Well established global classification • Under updating process (date ranges available)	• S2GLC classes • Hardly used for supporting visual verification due to coarse resolution
GlobCover	• 2009, raster/ 300 m • ESA, 23 classes (FAO-LCCS) , 67.5 % accuracy • Supervised and unsupervised classification • Global, free access	• S2GLC classes • Hardly used for supporting visual verification due to coarse resolution

The LUCAS database, which is a common source of reference data used for training and validation purposes were not used in the project, since the given initial samples hardly met the locations of the LUCAS validation points.

Within the S2GLC project the four HRL layers of imperviousness, forest, grassland as well as water and wetness were used for primarily supporting the visual verification procedure (see Figure 28).

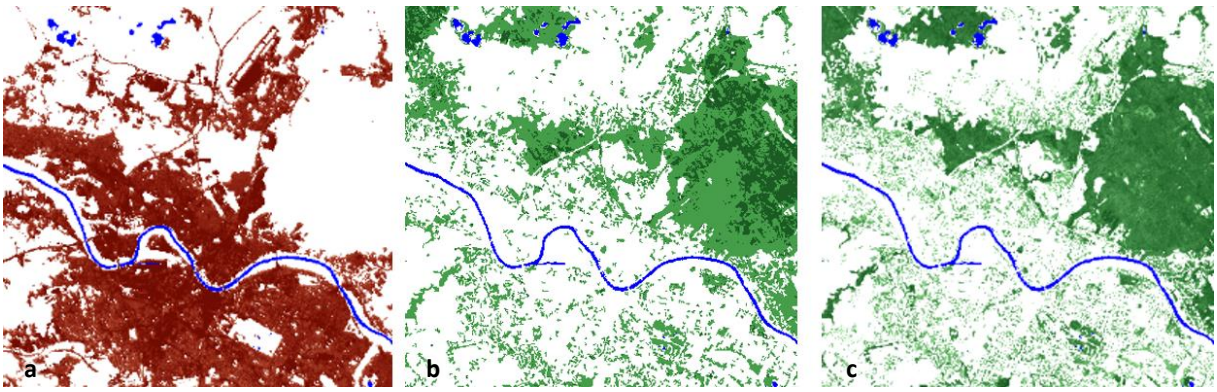

Figure 28: Selected layers of HRL data (a) imperviousness, (b) forest type, (c) crown density, (all) water and wetness.

Figure 29 illustrates the high-resolution settlement mask (red) laid over the CLC urban land cover polygons (rosé).

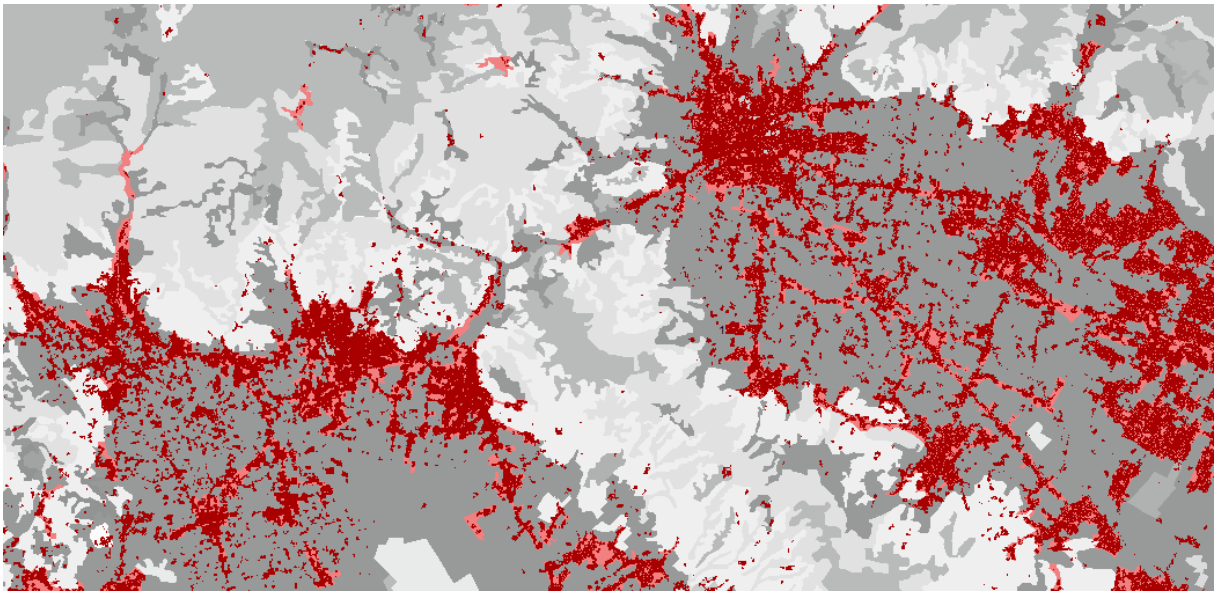

Figure 29: GUF on CLC urban land cover.

CLC datasets was used as a primary reference database for suggesting land cover within Europe.

The CCI LC and GlobCover data were hardly used for supporting visual verification due to its coarse resolution.

Using external sources demands a transformation of the individual thematic structure into the targeting nomenclature concept. All integrated existing land cover database values were translated into S2GLC-codes. As a next step, reference data information was extracted at sample locations and served as a suggestion during the visual interpretation (Figure 30). Besides, the interpreters had the opportunity to enable the layers during the editing process for supporting the embedding of the sample points into the environment.

Figure 30: Examples of initial sample polygons to be verified.

The verification process was carried out as a stable, manual driven but efficient workflow. A multi-user working environment (ArcGIS SDE) was set up and sample polygons were edited using an established Review Toolbar.

The interpreters were working using a tailored environment supported by

- effective shifting between initial sampling points per class,
- working climate zones wise (interpreters as experts for certain zones),
- defining simple and standard mapping specifications to support constant quality and effective work.

Figure 31 illustrates main elements of the workflow applied for all sample polygons. The well-experienced interpreters, trained in selected European climate zones, were guided through the single pre-selections polygon-by-polygon using a “pan to next” functionality.

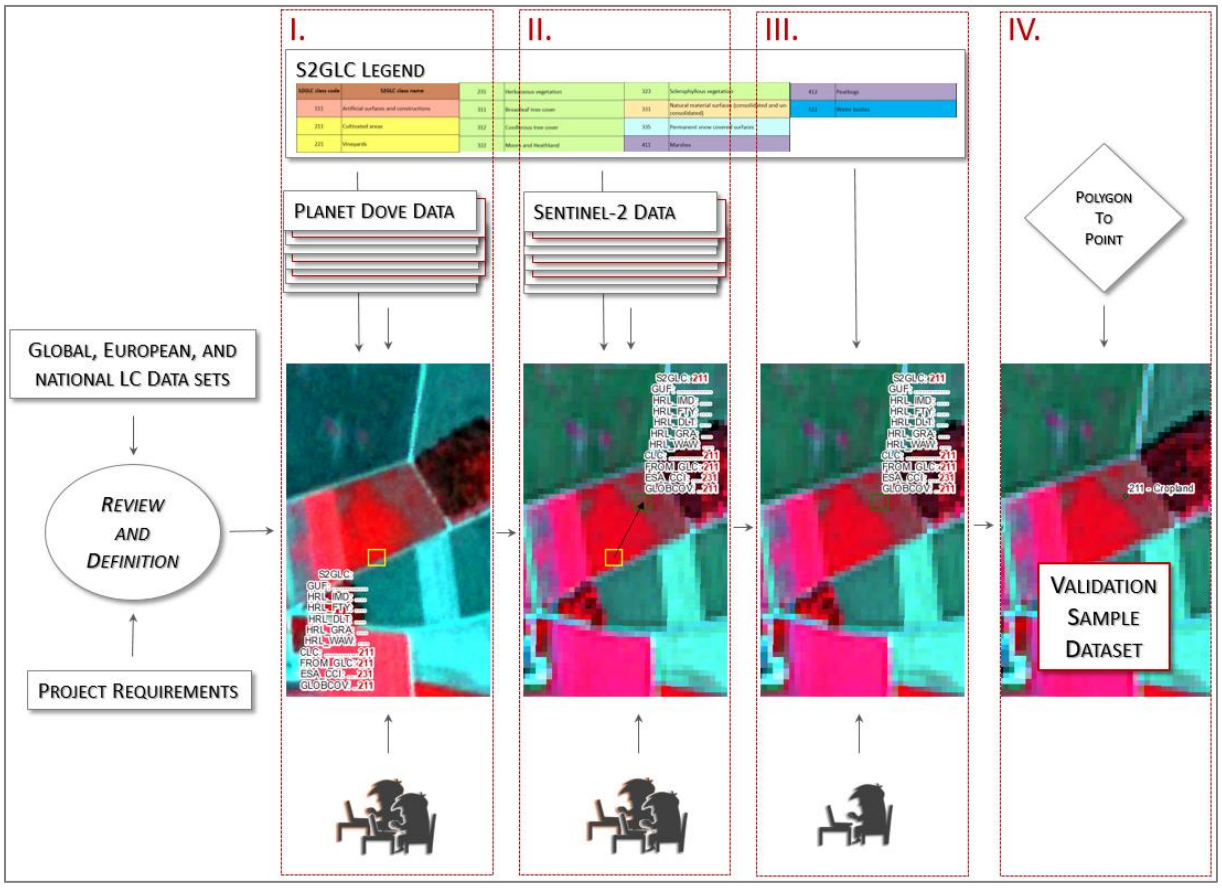

Figure 31: Manual verification workflow.

The working instruction prepared took experiences made within prior mappings into consideration. The workflow consisted of the following consecutive steps:

I. Verification of land cover suggestion of the initial sample polygon using PlanetScope (including possible shifting of polygons in case of locations outside appropriate areas, inconsistent signature behaviour or touching class edges/ boundaries, in order to prevent features of mixed classes due to the possible spatial offset of S2 data).
II. Crosscheck of assigned LC code by different interpreters using S2 data.
III. Quality Check by a specialist (including visual random sample check, attributes check, logical check (e.g. snow class in Mediterranean area), topology check (e.g. inside tile area).
IV. Transformation of polygon features into point features.

The following figures demonstrate some area shifting and/ or classification of initial samples.

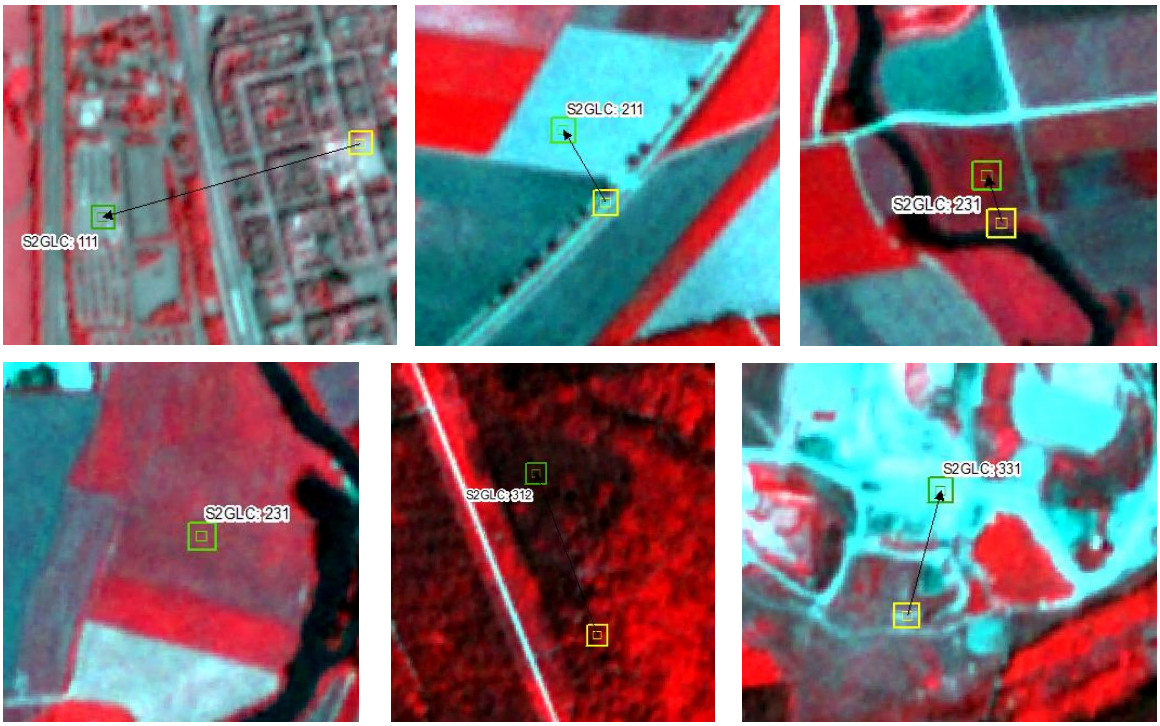

Figure 32: Shifting and classification of initial sample polygons using PlanetScope.

When verifying the samples, a prospective global classification process was always in mind, in which case there is no area-wide LC map in a high resolution and relatively good quality, like CLC or HRL, existent. The approach was to manually and visually classify the samples almost exclusively using available satellite imagery (PlanetScope and S2). Taking this into account, a few classes occurred which turned out to be problematic during visual classification without using any ancillary data.

The problematic classes are listed below:

1. In some regions Vineyards patterns look similar to Fruit Trees. These signatures are only classifiable with the help of (aerial) photos and/or in-situ data (see Figure 33).

Figure 33: The vineyard signature in Portugal and Spain, which is not feasible when satellite images are interpreted without ancillary date.

2. The wetlands classes including Marshes and Peatbogs are characterized by fuzzy class boundaries. It is very difficult to distinguish these classes and assign them consistently (see Figure 34), especially when they coexist in the same regions. Besides, the Marsh class is a complex class including subclasses like mosses, herbaceous plants, woody plants, scattered trees, non-vegetated peat surfaces under exploitation, piled up heaps of extracted peat, and water surfaces (EEA 2018[1]), all of which can be extracted for themselves by (very) high resolution image interpretation.

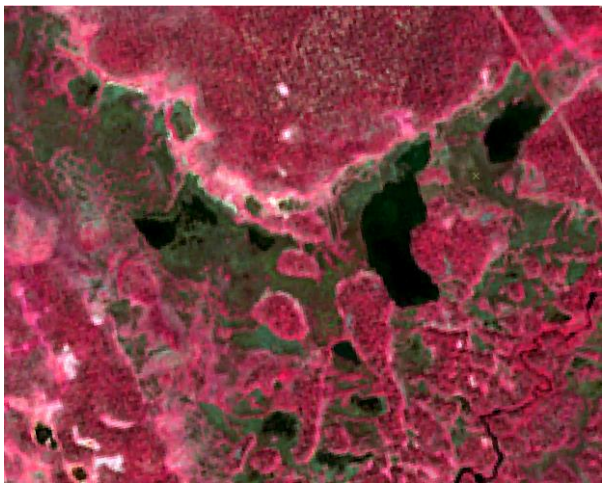

Figure 34: Coexistence of Marsh and Peatbogs classes pictured on S2 imagery (CIR - false colour composition).

3. In the S2GLC the shrub or sparse vegetation class has not been extracted as individual classes. This is a consequence of the input data spatial resolution. The above mentioned classes are used in databases of 25 ha MMU, where the type of a vegetation cover is hardly specified. In case of S2GLC, the reference samples collected on shrub should be verified in a wider context by an interpreter and assigned to the proper class which includes a specific shrub types: Herbaceous vegetation, Moors and Heathland or Sclerophyllous vegetation. The appropriate selection of the representative class may generate the conflicts between the validation data and the classification outcome.

The analyses of the results summarise statistics of the numbers of initial samples per tile, numbers of classified samples, shifted samples, and selected class distributions per tile.

Figure 35 presents the amount of classified samples per tile. Only a few samples were rejected, over 93% of all samples were classified and a number of over 900 of classified samples was reached for most of the tiles.

[1] https://land.copernicus.eu/user-corner/technical-library/corine-land-cover-nomenclature-guidelines/docs/pdf/CLC2018_Nomenclature_illustrated_guide_20170930.pdf, page 106

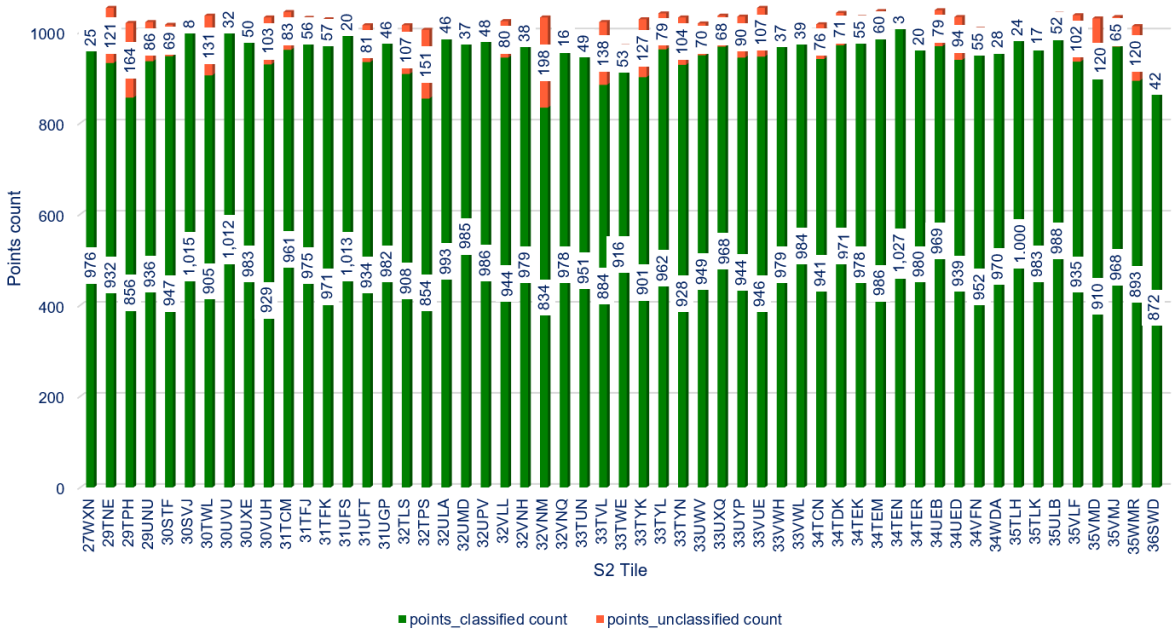

Figure 35: The number of classified and unclassified samples per tile.

Figure 36 shows the number of classified and shifted samples per tile, while Figure 37 presents the most occurring shift distance. There was a very high number of shifted samples, what in fact, was not expected in that amount before. Due to the fact that the samples were chosen using coarser CLC database, many mixed pixels and inhomogeneous areas appeared. Besides, the 3 x 3 pixel window (required for possible -co-registration errors of S2) made it necessary to shift more points. An example of this issue was demonstrated in snapshots in Figure 32. Finally, only with that high number of shifted samples, a reliable and sound validation dataset could be generated.

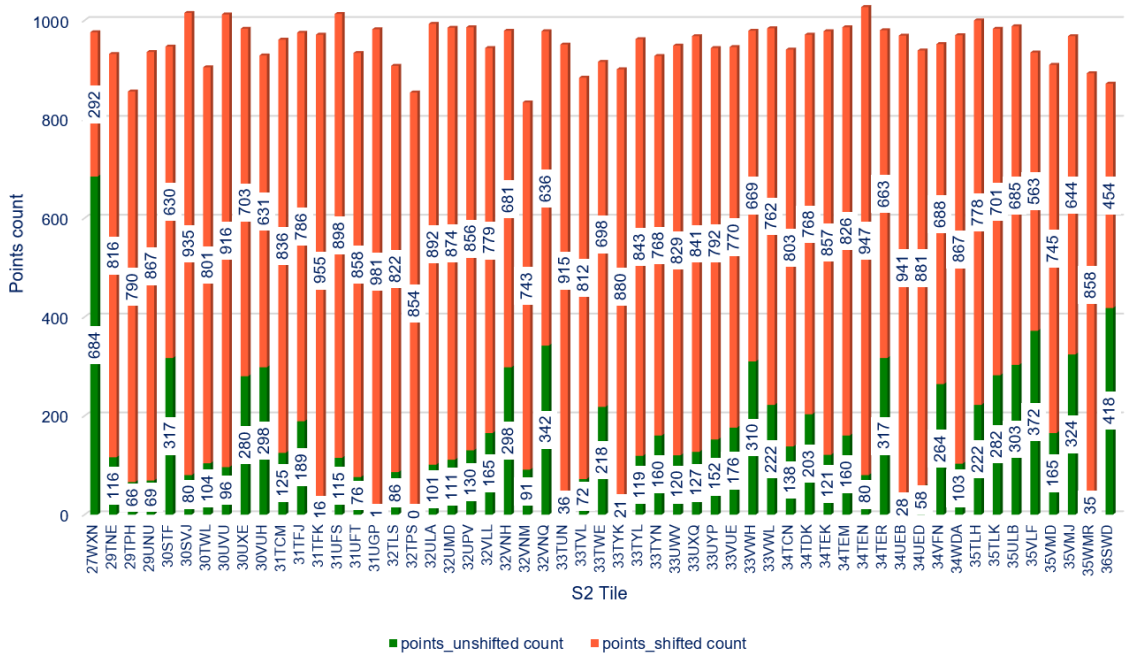

Figure 36: Amount of classified and shifted samples per tile.

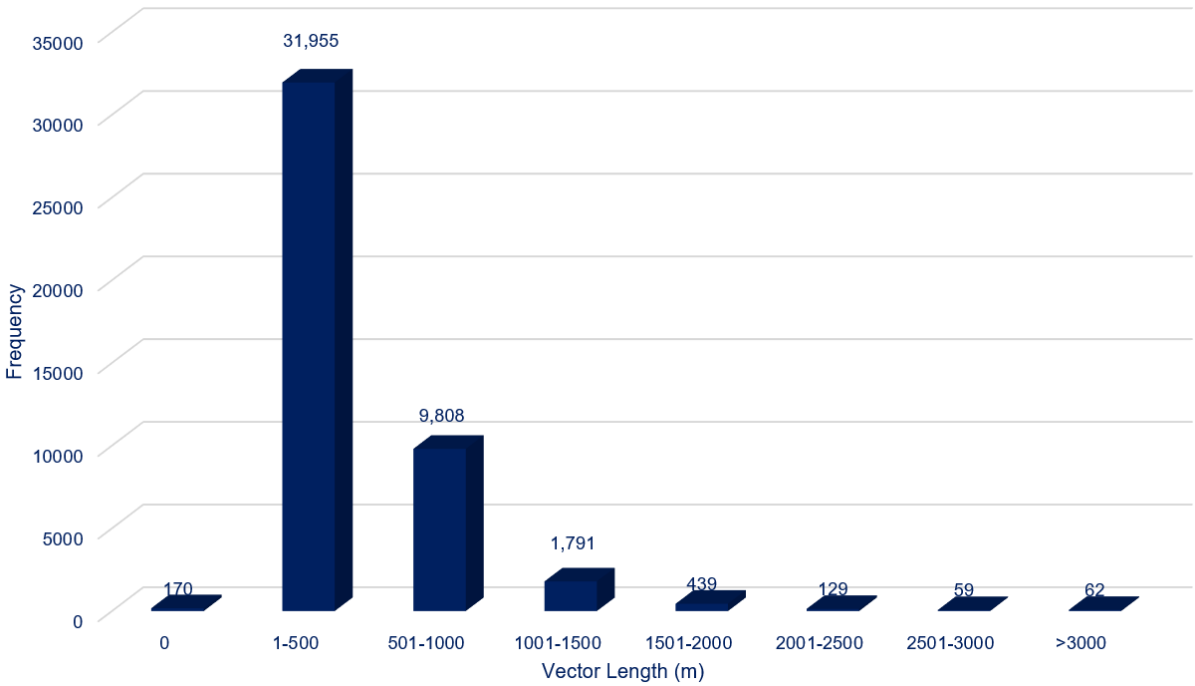

Figure 37: Length of the shift vectors in meters.

The review of the data was supported by statistics of the class distributions per each tile. The numbers helped to check logical classification in line with regional characteristics. Below, specific climatic areas are chosen and presented graphically.

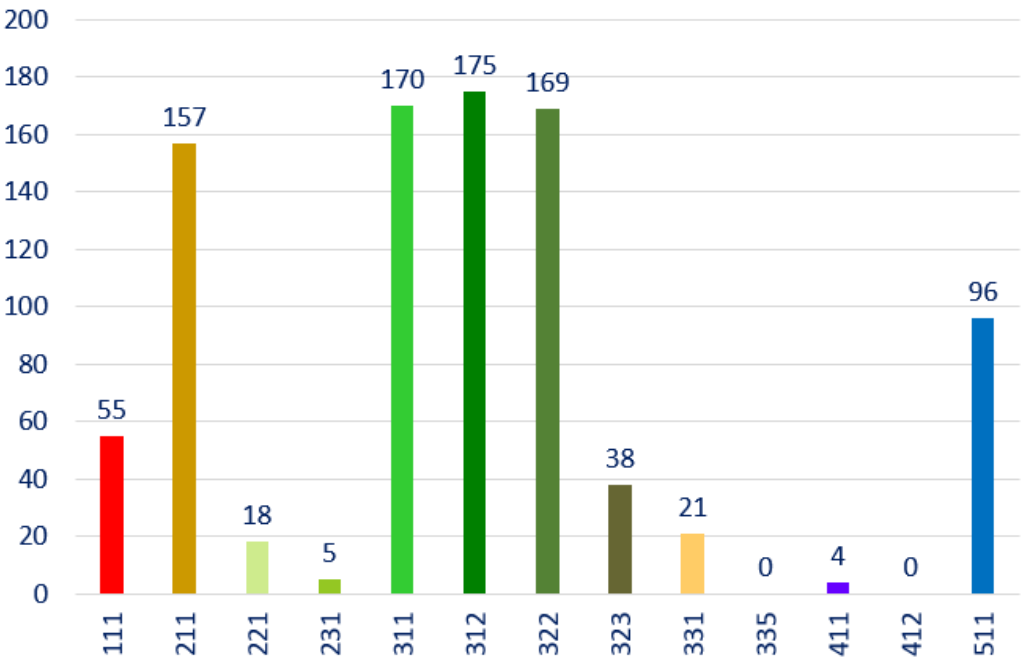

Figure 38: S2 tile 29TNE - Portugal: Class distribution.

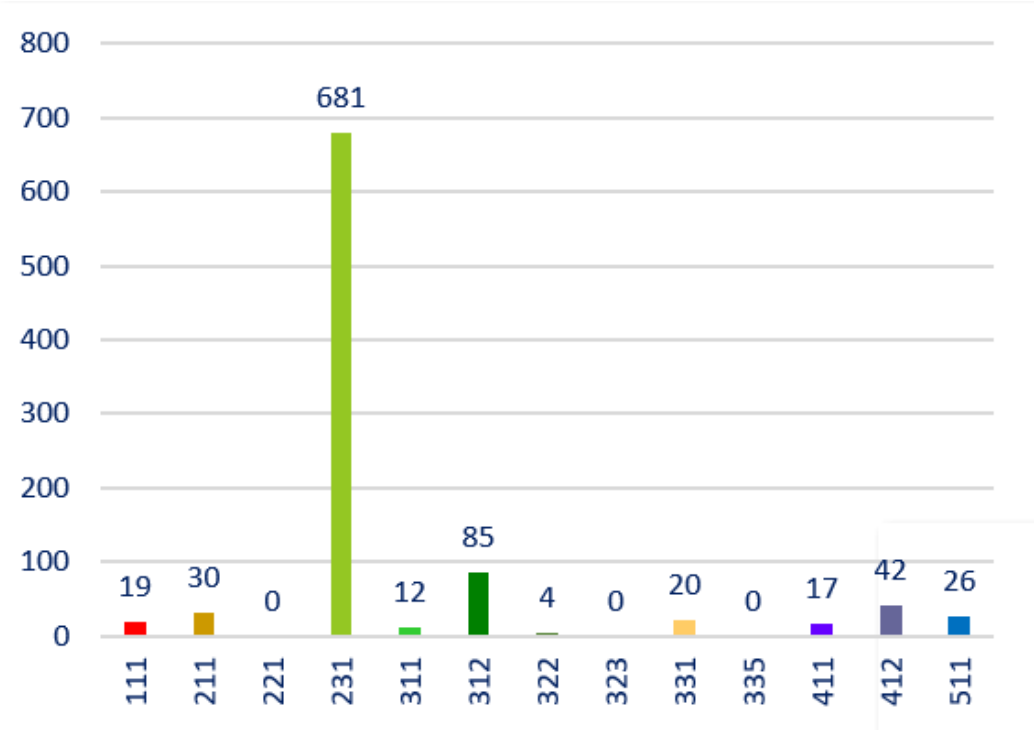

Figure 39: S2 tile 29UNU - Ireland: Class distribution.

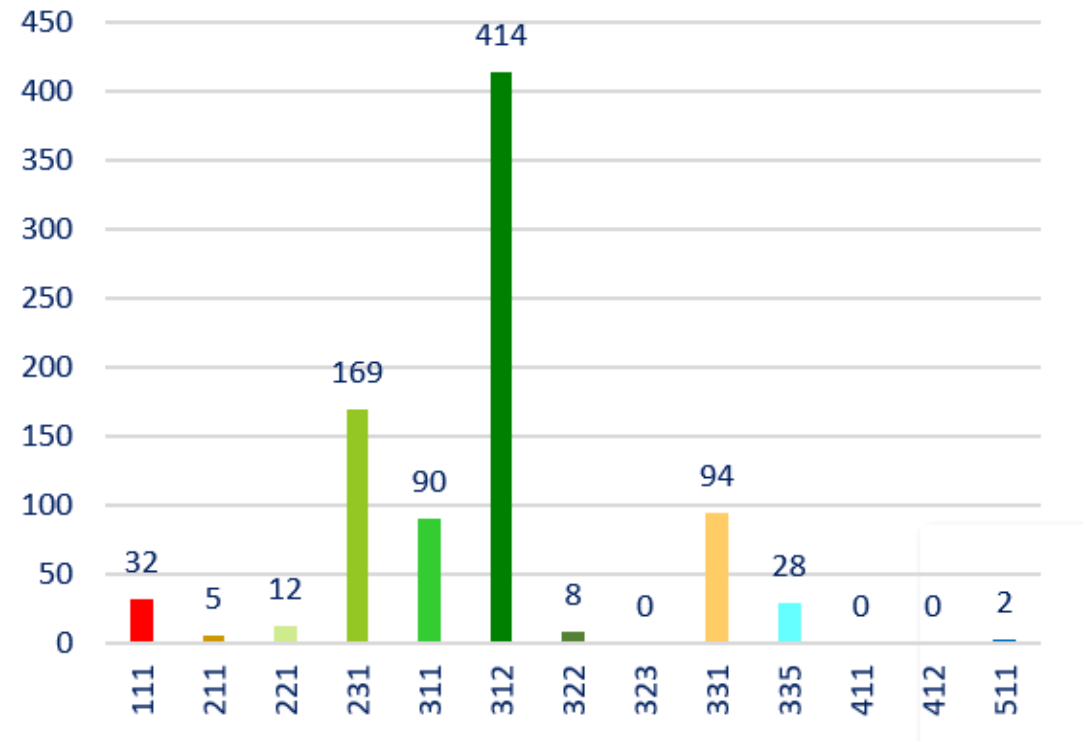

Figure 40: S2 tile 32TPS - Italy: Class distribution.

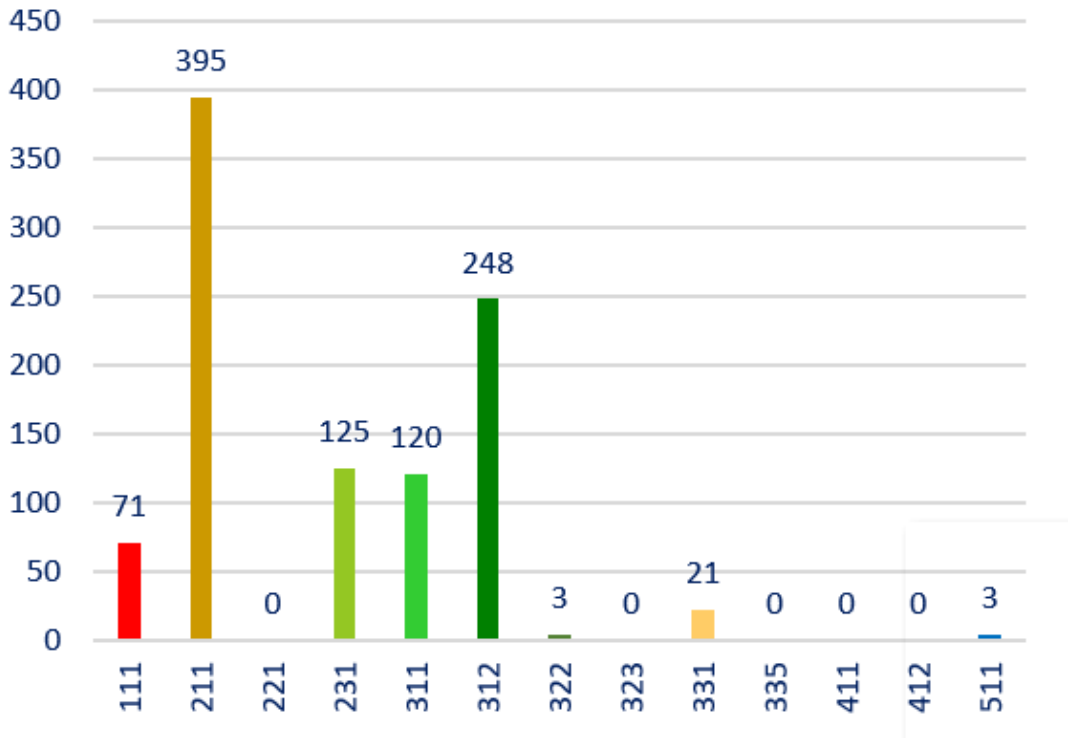

Figure 41: S2 tile 32UPV - Germany: Class distribution.

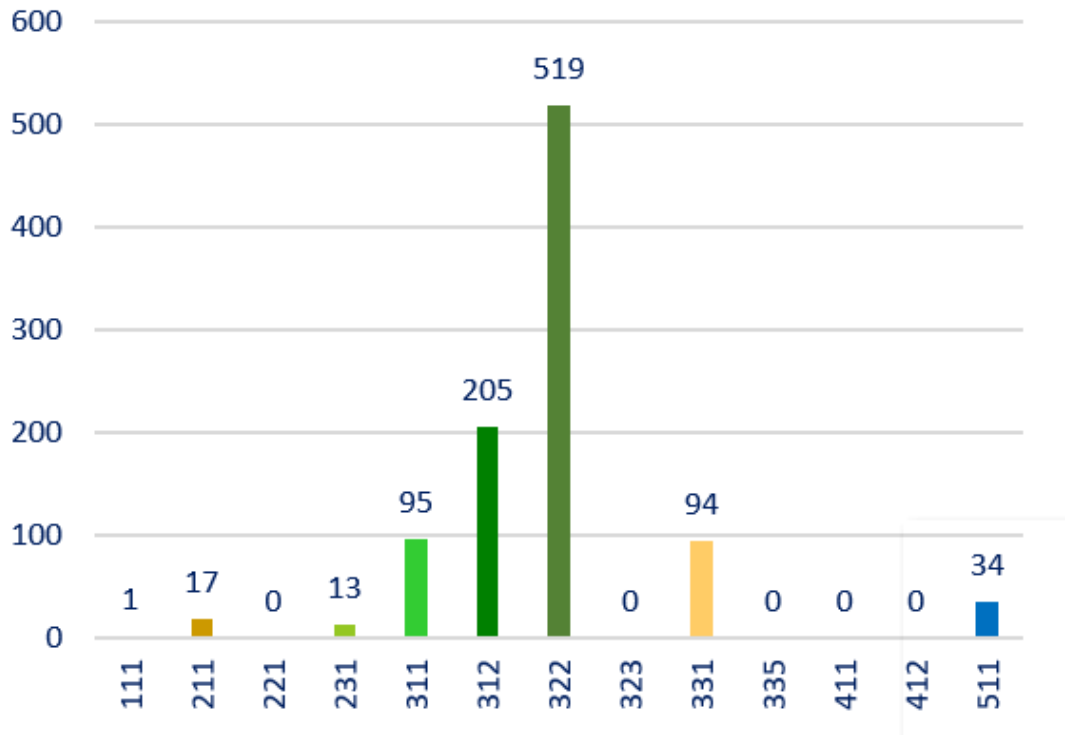

Figure 42: S2 tile 32VNQ - Norway: Class distribution.

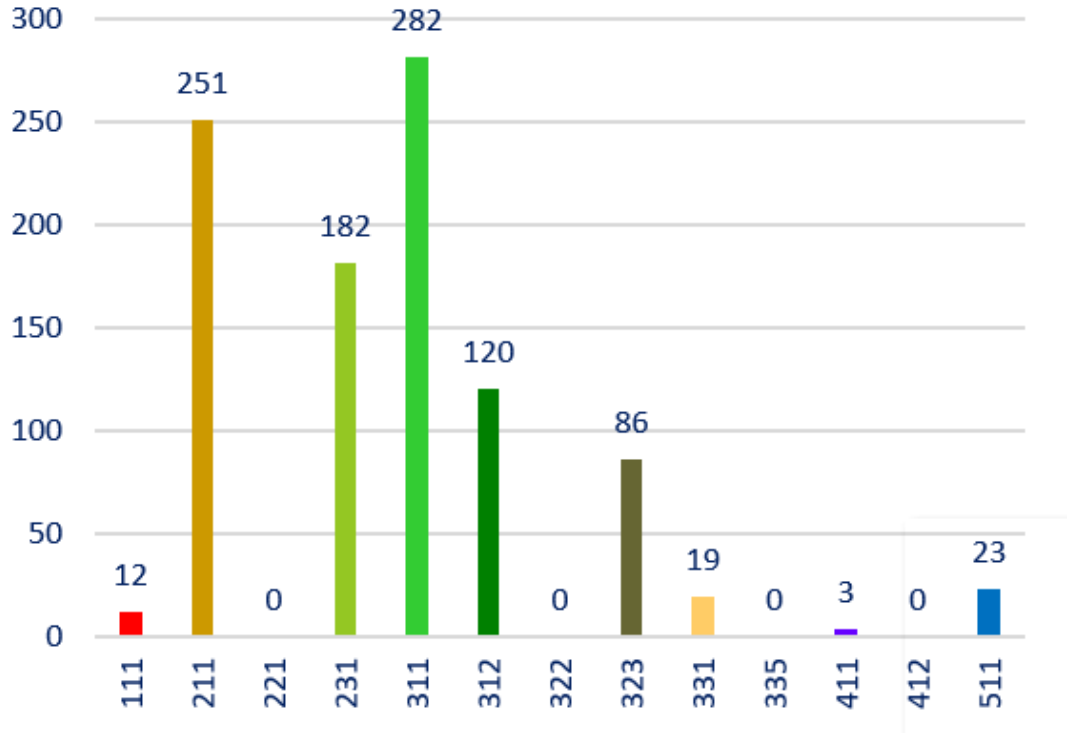

Figure 43: S2 tile 34TEK - Greece: Class distribution.

Table 19 presents the summary of the validation sites and sample selection.

Table 19. The summary of the validation sites and samples selection.

Country	Country code	No. of validation sites	% country area	No. of validation samples	No. of samples excluded due to the cloud mask occurrence	Final no. of validation points	No. of validated classes
Albania, Greece	AL, EL	2	15%	1949	14	1935	9
Austria	AT	1	14%	951	25	926	9
Bosnia and Herzegovina	BA	1	24%	901	11	890	9
Belgium	BE	1	39%	1013	34	979	9
Bulgaria	BG	1	11%	999	10	989	8
Switzerland	CH	1	29%	908	25	883	10
Cyprus	CY	1	46%	872	27	845	8
Czechia	CZ	1	15%	968	17	951	9
Germany, Luxemburg	DE	3	10%	2963	55	2908	11
Denmark	DK	1	28%	979	1	978	9

Estonia	EE	1	27%	935	6	929	10
Spain	ES	4	10%	3531	32	3499	12
Finland	FI	3	11%	2765	1	2764	10
France	FR	5	9%	4901	47	4854	12
Croatia, Slovenia	HR, SI	2	32%	1846	17	1829	9
Hungary	HU	1	13%	928	19	909	9
Ireland	IE	1	17%	936	7	929	10
Iceland	IS	1	12%	976	23	953	7
Italy	IT	2	8%	1770	43	1727	11
Lithuania	LT	1	19%	988	10	978	10
Latvia	LV	1	19%	910	0	910	10
Montenegro	ME	1	87%	941	1	940	9
North Macedonia	MK	1	48%	986	27	959	8
Netherlands	NL	1	32%	934	30	904	10
Norway	NO	2	7%	2732	11	2721	10
Poland	PL	2	8%	2856	195	2661	10
Portugal	PT	1	13%	908	18	890	11
Romania	RO	2	10%	1963	7	1956	10
Serbia	RS	1	14%	1052	33	1019	9
Sweden	SE	4	11%	3848	5	3843	10
Slovakia	SK	1	25%	944	14	930	9
United Kingdom	UK	2	10%	1906	24	1882	10

5.2. WP 5.2 Validation of LC maps

5.2.1. The validation measures

Within the S2GLC project only the reliability of the classification outcomes will be subject to the validation performance. Thus, this document focuses only on the metrics which refers to the thematic accuracy as a part of effectiveness and reliability of the information content group.

Based on the Confusion Matrix and the Kappa Coefficient the validation measures will be reported (Table 20, Table 21). The Confusion Matrix is a very effective way to represent map accuracy in that the individual accuracies of each category are plainly described along with both the User's accuracy (commission errors) and the Producer's accuracy (omission errors) present in the classification. The set of the Confusion Matrices is presented in the Appendix 3.

Table 20. Misclassification matrix description (ISO 19157:2013).

Component	Description
Name	Misclassification matrix
Alias	Confusion matrix

<table>
<tr><td>Element name</td><td>Classification correctness</td></tr>
<tr><td>Definition</td><td>Matrix that indicates the number of items of class (i) classified as class (j)</td></tr>
<tr><td>Description</td><td>The misclassification matrix (MCM) is a quadratic matrix with n columns and n rows. n denotes the number of classes under consideration.
MCM (i,j) = [# items of class (i) classified as class (j)]
The diagonal elements of the misclassification matrix contain the correctly classified items, and the off diagonal elements contain the number of misclassification errors.</td></tr>
<tr><td>Value type</td><td>Integer</td></tr>
<tr><td>Example</td><td>
<table>
<tr><td></td><td colspan="5">Dataset class</td></tr>
<tr><td rowspan="5">True class</td><td></td><td>A</td><td>B</td><td>C</td><td>Count</td></tr>
<tr><td>A</td><td>7</td><td>2</td><td>1</td><td>10</td></tr>
<tr><td>B</td><td>1</td><td>2</td><td>2</td><td>5</td></tr>
<tr><td>C</td><td>1</td><td>1</td><td>3</td><td>5</td></tr>
<tr><td>Count</td><td>9</td><td>5</td><td>6</td><td>20</td></tr>
</table>
Overall Accuracy = (7+2+3)/20 = 60%
Producer’s Accuracy User’s Accuracy
A: 7/9 = 78% 7/10 = 70%
B: 2/5 = 40% 2/5 = 40%
C: 3/6 = 50% 3/5 = 60%
Omission Error Commission Error
A: 2/9 = 22% 3/10 = 30%
B: 3/5 = 60% 3/5 = 60%
C: 3/6 = 50% 2/5 = 40%
</td></tr>
</table>

Table 21. The Kappa coefficient description (ISO 19157:2013).

Component	**Description**
Name	Kappa coefficient
Element name	Classification correctness
Definition	Coefficient to quantify the proportion of agreement of assignment to classes by removing misclassifications
Description	With the elements of misclassification matrix MCM(*i,j*) given as data quality measure in Table 20 the kappa coefficient (κ) can by calculated by: $$\kappa = \frac{n\sum_{i=1}^{r} MCM(i,i) - \sum_{i=1}^{r}\left(\sum_{j=1}^{r} MCM(i,j) * \sum_{j=1}^{r} MCM(j,i)\right)}{N^2 - \sum_{i=1}^{r}\left(\sum_{j=1}^{r} MCM(i,j) * \sum_{j=1}^{r} MCM(j,i)\right)}$$ *N* – number of classified items
Value type	Real

5.2.2. Validation summary

The result of LC classification performed in the project over the whole Europe is presented in Figure 44. This final map is composed of 815 separately classified S2 tiles. Validation of this finial map was performed according to the assumptions presented in section 5.1. Table 22 presents the obtained results with division into countries (or groups of countries). The accuracies are expressed by OA and the Kappa coefficient. Moreover, Table 22 contains values of OA that represents the accuracy of classification with and without the post-processing rules applied as well as comparison of the classification with CCL database (where possible).

Figure 44. The final result of land cover classification of the whole Europe with division into 13 classes and clouds. The light grey colour represents Eastern European countries not covered by the classification within the S2GLC project. The classified open sea waters represent a buffer area of 1 km.

The post-processing is an integral part of the proposed classification chain and was designed to correct the most common classification errors. As expected, the differences between the results of classification with and without the post-processing rules applied are not significant in the validation

results. The greatest improvement in OA values was obtained for Poland, North Macedonia, Austria and Italy, respectively 2.6 %, 1.8 %, 1.7 %, 1.3 %. The largest decrease of OA was observed in Bulgaria (1.4%) while in other ten countries the decrease was clearly below 1%. Nevertheless, improvement of the LC classification by applying the proposed post-processing rules is clearly visible during visual inspection of the resulting maps. The LC classification map with the post-processing applied is treated as the final results of the S2GLC classification.

According to the presented results OA for 12 out of 32 European countries (or groups of countries), exceeded a value of 90%. Other 13 countries fall in the range of 80% to 90% of OA, for other 5 countries the OA fall in the range of 75% to 80% and only for two countries OA less than 75% was achieved. Germany is the country with the best OA of 95.8%, while classification of Portugal received the lowest OA measure (66.9%).

Table 22 also presents comparison of OA values between the S2GLC classification and CLC2012 database. Such comparison is provided only for selected countries because of different rules of grouping the analysed countries. In the S2GLC project, European countries were grouped according to the location of S2 tiles used for the validation purpose (more details can be found in section 5.1). The results of comparison between the S2GLC classification and CLC2012 database, however, should be assessed very roughly because of the different classification methodology, differing number of LC and land use classes and also because of almost a seven-years-long span of time between their release. Out of 15 compared countries, particularly large differences are observed for Finland and Norway: 17.1%, 18.9%, respectively. In case of Finland better result has been reached by the S2GLC classification (91.4%). As opposite, in Norway better result was achieved for CLC2012 database at the level of 93.2% with 74.3% for the S2GLC classification. In other countries consistency of results is in the range of 2% to 13% with no apparent advantage for any of the classifications.

On a scale of the whole Europe the accuracy of the S2GLC classification was calculated based on 55 selected S2 tiles (see Table 16) combined together. The error matrix generated for the whole Europe for the result with the post-processing procedure applied is presented in Table 23 and shows that accuracy was estimated at the level of 86.1% of OA and 0.83 of the Kappa coefficient. Table A.3 - 1 presented in Appendix 3 provides also the accuracy estimates for the results without post-processing applied. The difference between results with and without post-processing is at the level of 0.3% (OA) with higher accuracy achieved for the result with post-processing.

Table 22. The accuracy assessment measures of the S2GLC classification at the country level.

Country		**S2GLC post-processing**					**Comparison to CLC2012**	
Name	**Country code**	**OA %**			**Kappa**			
		before	**after**		**before**	**after**	**CLC2012**	
		a	*b*	*b – a*			*c*	*b – c*
Albania, Greece	AL EL	71.2	**70.8**	- 0.4	0.65	0.64	80.2	- 9.4
Austria	AT	82.8	**84.5**	1.7	0.76	0.78		
Bosnia and Herzegovina	BA	92.5	**92.7**	0.2	0.89	0.89		
Belgium	BE	87.3	**87.6**	0.3	0.84	0.84		

Bulgaria	BG	90.6	**89.2**	- 1.4	0.86	0.84	86.9	2.3
Switzerland	CH	89.5	**90.1**	0.6	0.87	0.88		
Cyprus	CY	83.4	**83.5**	0.1	0.76	0.77		
Czechia	CZ	94.1	**94.1**	0.0	0.91	0.91		
Germany, Luxemburg	DE	95.6	**95.8**	0.2	0.94	0.94	82.8	13.0
Denmark	DK	93.7	**94.0**	0.3	0.91	0.91		
Estonia	EE	89.2	**89.0**	- 0.2	0.87	0.87		
Spain	ES	78.2	**78.7**	0.5	0.74	0.75	85.1	- 6.4
Finland	FI	91.3	**91.4**	0.1	0.88	0.88	74.3	17.1
France	FR	88.4	**88.5**	0.1	0.86	0.86	86.3	2.2
Croatia, Slovenia	HR SI	92.2	**92.6**	0.4	0.89	0.90		
Hungary	HU	92.5	**93.0**	0.5	0.89	0.90	86.1	6.9
Ireland	IE	95.0	**95.0**	0.0	0.89	0.89		
Iceland	IS	83.3	**82.7**	- 0.6	0.68	0.67	85.1	- 2.4
Italy	IT	86.7	**88.0**	1.3	0.84	0.85	76.0	12.0
Lithuania	LT	82.7	**82.5**	- 0.2	0.76	0.76		
Latvia	LV	84.8	**84.8**	0.0	0.81	0.81		
Montenegro	ME	77.7	**77.4**	- 0.3	0.68	0.68		
North Macedonia	MK	75.5	**77.3**	1.8	0.67	0.69		
Netherlands	NL	87.4	**87.6**	0.2	0.84	0.84		
Norway	NO	74.9	**74.3**	- 0.6	0.70	0.70	93.2	- 18.9
Poland	PL	90.3	**92.9**	2.6	0.86	0.90	92.1	0.8
Portugal	PT	66.4	**67.0**	0.6	0.61	0.62	75.9	- 8.9
Romania	RO	89.4	**89.1**	- 0.3	0.83	0.83	78.9	10.2
Serbia	RS	92.0	**92.0**	0.0	0.85	0.85		
Sweden	SE	79.9	**80.0**	0.1	0.74	0.74	87.9	- 7.9
Slovakia	SK	95.3	**95.4**	0.1	0.92	0.92		
United Kingdom	UK	86.4	**85.7**	- 0.7	0.83	0.82	87.1	- 1.4

Table 23. The error matrix for the S2GLC classification result for the whole Europe with the post-processing procedure applied.

Land Cover map of Europe after post-processing 13 LC classes	1.1.1. Artificial surfaces and constructions	2.1.1. Cultivated and managed areas	2.2.1. Vineyards	2.3.1. Herbaceous vegetation	3.1.1. Deciduous broadleaf tree cover	3.1.2. Evergreen coniferous tree cover	3.2.2. Moors and Heathland	3.2.3. Sclerophyllous vegetation	3.3. Natural material surfaces	3.3.5. Permanent snow and glaciers	4.1.1. Marshes	4.1.2. Peatbogs	5. 1. 1. Water bodies	Total	User's accuracy
Clouds, snow, ice, mask	11	1	0	0	0	0	0	0	28	56	0	0	1	97	
1.1.1. Artificial surfaces and constructions	**1548**	65	1	7	0	0	5	2	430	0	0	0	6	2064	75,00%
2.1.1. Cultivated and managed areas	37	**11774**	26	574	32	5	12	23	46	0	4	0	1	12534	93,94%
2.2.1. Vineyards	8	426	**445**	58	12	1	10	26	7	0	0	0	1	994	44,77%
2.3.1. Herbaceous vegetation	15	886	20	**5592**	127	6	689	289	72	7	88	13	0	7804	71,66%
3.1.1. Deciduous broadleaf tree cover	5	44	1	40	**10436**	202	165	113	4	0	12	5	1	11028	94,63%
3.1.2. Evergreen coniferous tree cover	8	16	2	12	171	**8374**	82	60	1	0	3	6	2	8737	95,85%
3.2.2. Moors and Heathland	10	65	1	249	53	24	**760**	50	49	0	5	58	2	1326	57,32%
3.2.3. Sclerophyllous vegetation	3	26	0	39	54	10	53	**181**	3	0	4	0	0	373	48,53%
3.3. Natural material surfaces	96	73	2	86	2	0	38	64	**1319**	7	1	2	7	1697	77,73%
3.3.5. Permanent snow and glaciers	4	0	0	0	0	0	0	0	73	**9**	0	0	0	86	10,47%
4.1.1. Marshes	37	76	2	55	40	3	58	7	18	0	**140**	83	79	598	23,41%
4.1.2. Peatbogs	5	17	0	62	16	4	197	0	5	0	61	**578**	55	1000	57,80%
5. 1. 1. Water bodies	42	1	0	4	2	1	2	0	63	6	6	0	**3558**	3685	96,55%
Total	1818	13469	500	6778	10945	8630	2071	815	2090	29	324	745	3712	51926	
Producer's accuracy	85,15%	87,42%	89,00%	82,50%	95,35%	97,03%	36,70%	22,21%	63,11%	31,03%	43,21%	77,58%	95,85%	**OA**	**86,11%**
														Kappa	0,83

The error matrix presented in Table23 contains all 13 LC classes selected for classification after experimental tests and the accuracy was estimated on the basis of 51,926 samples distributed across Europe (more details provided in section 5). Taking into account the highly automated mode of the classification process, the OA at the level of 86.1% is being considered as very high and promising.

Unsurprisingly, the accuracy of classification of individual LC classes are at different levels. The most accurate results were obtained for highly represented classes (the number of validation samples expresses the class proportion) such as Cultivated and managed areas, Deciduous broadleaf tree cover, Evergreen coniferous tree cover, Herbaceous vegetation and Water bodies. These classes received high values of both Producer's and User's accuracies, predominately well above 80% and often exceeding 90% for both or one of them. The class Artificial surfaces and constructions also received good results despite its much lower spatial coverage. It was very well recognised by the classifier (less than 15% of omission error) and is characterised by relatively low level of commission error (approx. 25%). Other classes represented by lower number of validation samples (close or lower than 1000) are often classified with lower quality. This is an important aspect in case of an automated algorithms, but of course, the main reason for incorrect classification is the spectral similarity between classes. All classes used were carefully investigated during the experimental phase of the project extension but the transfer of classification rules to a larger area is always associated with a risk of obtaining results of lower quality. Examples of such classes are Moors and Heathland, Sclerophyllous vegetation, Marshes and Peatbogs that occurred to be very difficult to map accurately. They are characterised often by high commission or omission errors.

A pair of classes Marshes and Peatbogs were mapped together in the initial part of the S2GLC project as a class named Inundated vegetation. The test performed in the project extension, however, suggested that it is possible to separate these classes with relatively good accuracy. This has not been confirmed in a case of classification of the whole Europe. These classes are mixed not only with each other but also with other types of vegetation including cultivated areas.

Similar problems were met while classifying Moors and Heathland and Sclerophyllous vegetation classes. Both of them are often composed on different herbaceous and small woody (shrubs) vegetation, and therefore, heaving similar spectral signature they might be mixed with other LC classes. This is a case in the S2GLC classification, in which Moors and Sclerophyllous classes are misclassified in most cases with either herbaceous vegetation or woodlands, both broadleaves and coniferous (Table 23). Additionally, the class Moors and Heathland can be confused with the class Peatbogs (Table23), which fact is also indicated in the description of the CLC classification nomenclature.

The most serious problem was encountered with the class Permanent snow and glaciers. This class received the lowest User's accuracy and one of the lowest Producer's accuracy. This low accuracy may be explained by the quality of training data and spectral similarity of the class to the Natural material surfaces class. Considering that the classification quality heavily relays on the quality of training data, it must be remembered that CLC, the main source of training data, represents the state from before the year 2012. Since that time, the area covered by permanent snow and glaciers could have changed considerable. Finally, it has to be mentioned that this class was represented by the lowest number of validation samples which fact may indicate less accurate estimate of the assessment quality.

After the analysis of the classification results, another modification to the legend was proposed, in which selected classes were combined together. The classes were combined considering their thematic and spectral similarity. The mentioned modification included joining together classes Vineyards and

Cultivated and managed areas, Moors and Heathland and Herbaceous vegetation, as well as Marshes and Peatbogs. The recalculated validation results are presented in Table 24 and show that OA increased from 86,1% to 89.0 %. The LC classification with a reduced number of classes, from 13 to 10, provides better and more equalized classification results for all classes (except the Permanent snow and glaciers and Sclerophyllous vegetation). It is recommended to combine the indicated classes after the classification process.

Table 24. The error matrix for the S2GLC classification result for the whole Europe with modified legend and selected classes merged.

Land Cover map of Europe 10 LC classes	1.1.1. Artificial surfaces and constructions	2.1.1. Cultivated and managed areas 2.2.1. Vineyards	2.3.1. Herbaceous vegetation 3.2.2. Moors and Heathland	3.1.1. Deciduous broadleaf tree cover	3.1.2. Evergreen coniferous tree cover	3.2.3. Sclerophyllous vegetation	3.3. Natural material surfaces	3.3.5. Permanent snow and glaciers	4.1.1. Marshes 4.1.2. Peatbogs	5. 1. 1. Water bodies	Total	User's accuracy
Clouds, snow, ice, mask	11	1	0	0	0	0	28	56	0	1	97	
1.1.1. Artificial surfaces and constructions	**1548**	66	12	0	0	2	430	0	0	6	2064	75,00%
2.1.1. Cultivated and managed areas 2.2.1. Vineyards	45	**12671**	654	44	6	49	53	0	4	2	13528	93,66%
2.3.1. Herbaceous vegetation 3.2.2. Moors and Heathland	25	972	**7290**	180	30	339	121	7	164	2	9130	79,85%
3.1.1. Deciduous broadleaf tree cover	5	45	205	**10436**	202	113	4	0	17	1	11028	94,63%
3.1.2. Evergreen coniferous tree cover	8	18	94	171	**8374**	60	1	0	9	2	8737	95,85%
3.2.3. Sclerophyllous vegetation	3	26	92	54	10	**181**	3	0	4	0	373	48,53%
3.3. Natural material surfaces	96	75	124	2	0	64	**1319**	7	3	7	1697	77,73%
3.3.5. Permanent snow and glaciers	4	0	0	0	0	0	73	**9**	0	0	86	10,47%
4.1.1. Marshes 4.1.2. Peatbogs	42	95	372	56	7	7	23	0	**862**	134	1598	53,94%
5. 1. 1. Water bodies	42	1	6	2	1	0	63	6	6	**3558**	3685	96,55%
Total	1818	13970	8849	10945	8630	815	2090	29	1069	3712	51927	
Producer's accuracy	85,15%	90,70%	82,38%	95,35%	97,03%	22,21%	63,11%	31,03%	80,64%	95,85%	OA	**89,06%**
											Kappa	0,87

6. Summary and final conclusions

The main objective of the extension of the S2GLC project was to verify operability of the LC classification methodology developed during the first phase of the project. This was supposed to be done by performing LC classification over a major portion of the European continent on the EO IPT infrastructure. To accomplish this objective the methodology had to be adjusted to the European landscape and undergone full automation of all processes. Additionally, an investigation of possibility of the legend extension for new LC classes was foreseen.

For realization of the project assumptions S2 data from the year 2017 was selected. According to the rules established in the initial part of the S2GLC project training samples were derived from existing LC databases and the final classification result was calculated from multi-temporal S2 data using the developed aggregation formula. Adaptation of the S2GLC classification method was based on tests conducted within selected S2 tiles representing various bio-geographical regions of Europe. The performed experimental tests enabled construction of the final legend composed of 13 LC classes and selection of European LC databases (i.e. CLC and HRL) as a source of trainings data. The process of selection of training samples was enhanced by introducing additional mutual filtration between the selected databases and use of spectral indices (NDWI and NDVI). Additionally, the rules of selection of images for classification have also been improved, which in general assume usage of approx. 20 images per S2 tile representing all seasons. The post-processing approach was also modified and adjusted so that it fits the European landscape.

The most important elements of the overall classification workflow include:

- selection of S2 images,
- selection of training samples,
- classification of separate images for every analysed tile,
- aggregation of classification results for individual tiles,
- classification post-processing,
- validation,
- mosaics of S-2 tiles (possibility of execution depending on the needs)

All the above processes were carried out on the CREODIAS platform that is a successor of the EO IPT. This required adaptation of all the previously created S2GLC algorithms and also development of a tool for managing all computations performed by multi-processors virtual machines.

Nearly fifteen thousand of S2 images representing 815 S2 tiles have been processed to map the selected area of Europe. Validation of the final map was performed based on a large set of 51,926 randomly distributed samples representing 55 S2 tiles spread across Europe. Distribution of these tiles allowed to perform validation on both European and a country level. The overall accuracy of the complete map with 13 LC classes was estimated to be over 86%. Due to lower accuracy achieved for some of the classes, additional merging of selecting vegetation classes was proposed. This merging resulted in redaction of the number of LC classes in the legend but assured OA increase up to 89%. The accuracy assessment on a country level revealed very good quality of the LC map with majority of countries exceeding 80% of OA.

An important advantage of the applied approach is the separate classification of S2 images on a tile by tile basis, which reduces influence of climatic differences and discrepancy in atmospheric correction between neighbouring areas. Additionally, the applied aggregation procedure once again was

confirmed to be an effective means of utilizing multi-temporal data by increasing accuracy of the final product and allowing for considerable reduction of cloudiness in the resulting LC map.

In general, the LC classification performed on a continental scale confirmed the eligibility of the S2GLC approach as a tool dedicated to global mapping.

Developed solutions may be applied to automatically generate new editions of European Land Cover map with 10 m resolution every year.

7. References

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List of appendixes:

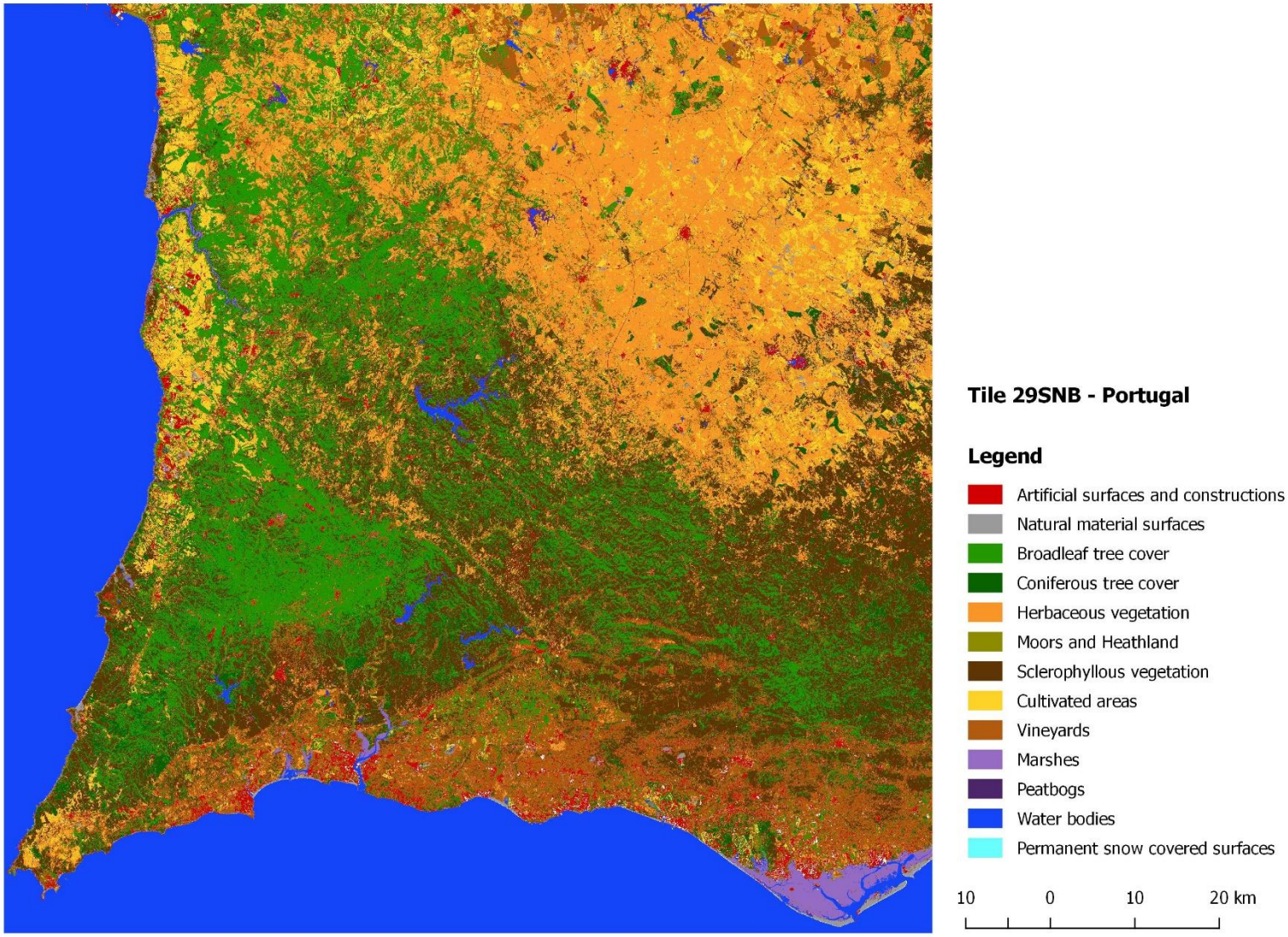
Appendix 1. Classification maps and error matrices of tested tiles.

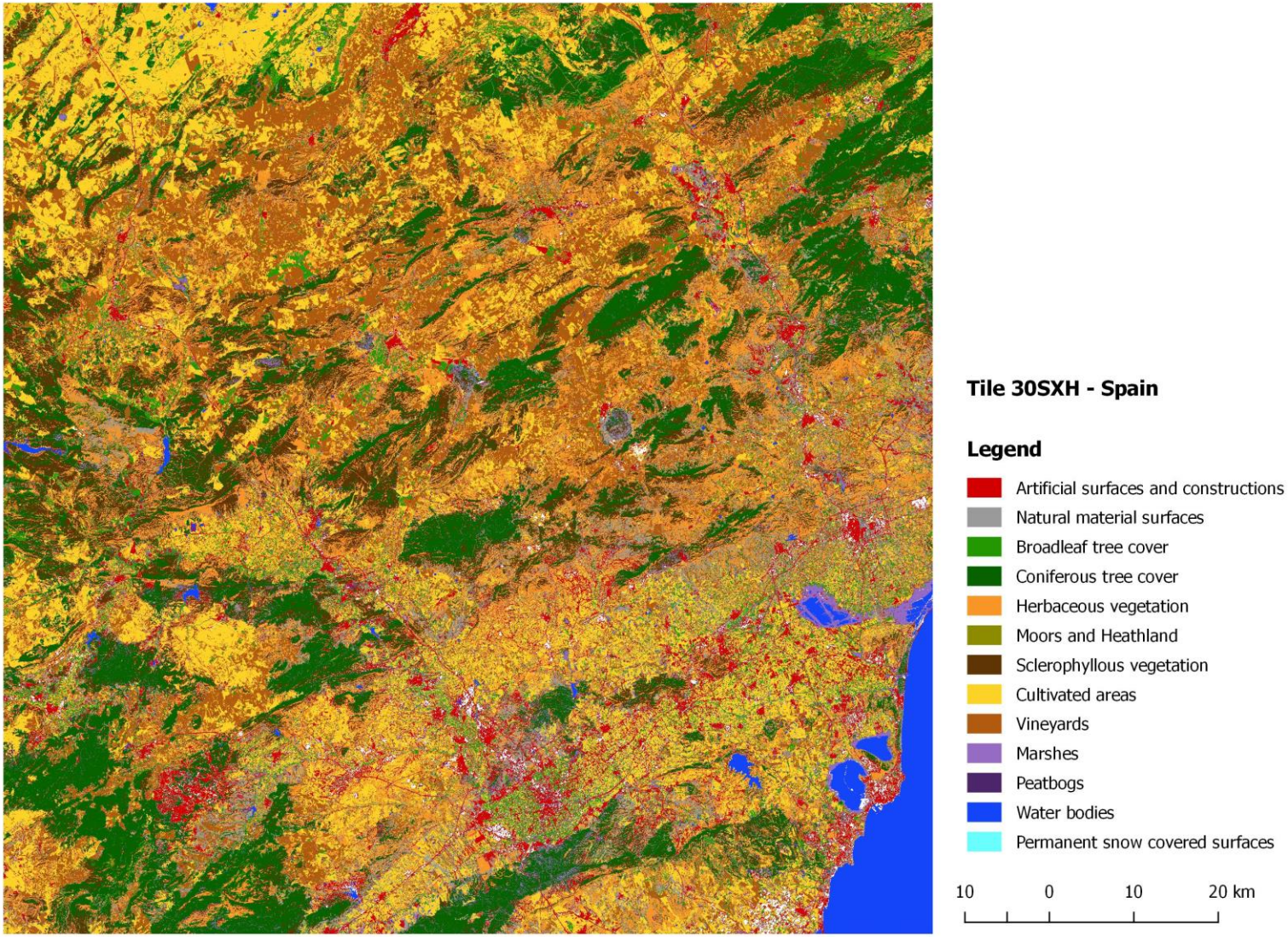
Appendix 2. List of classified Sentinel-2 tiles and performed LC classifications.

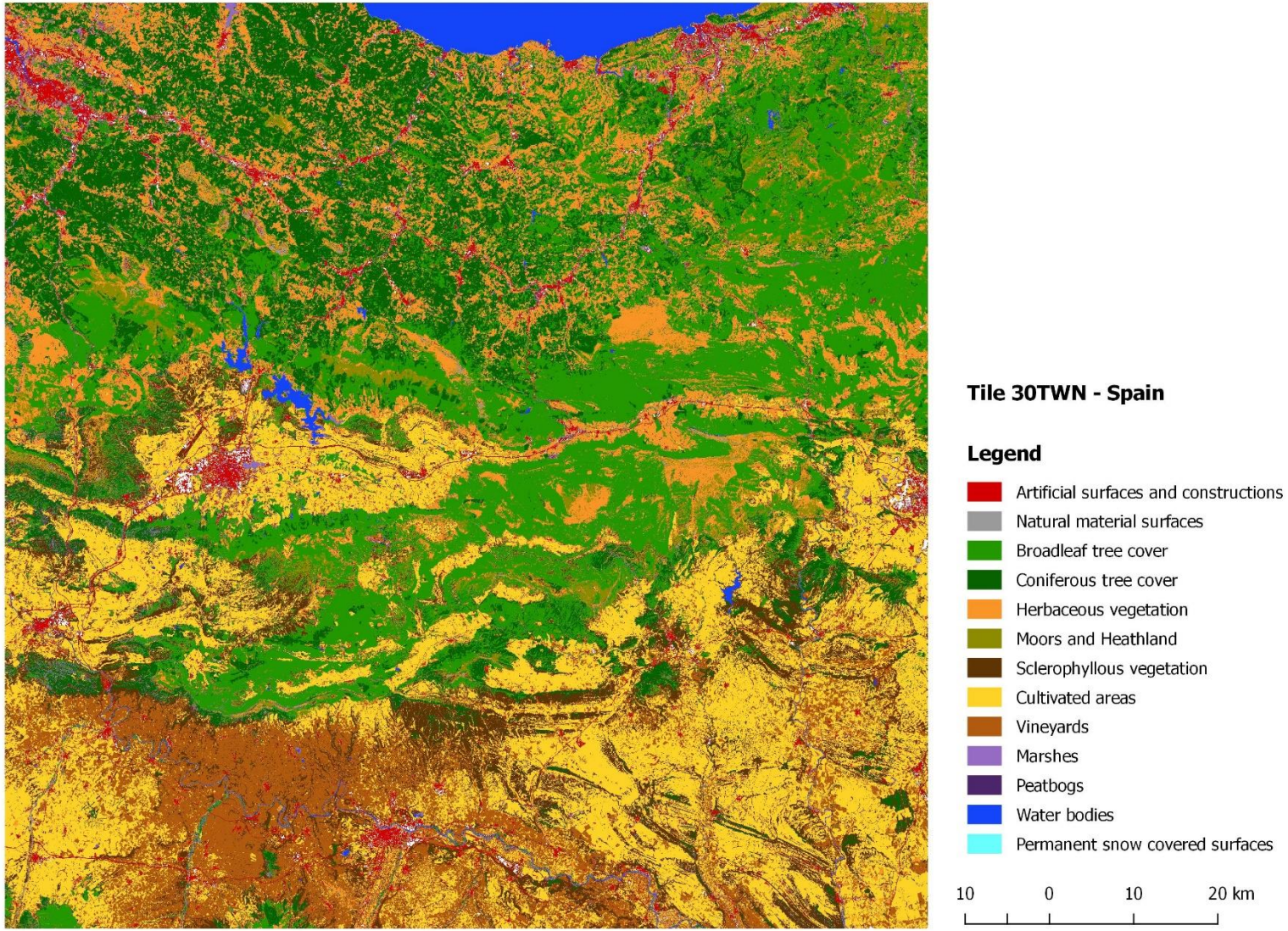
Appendix 3. Error matrices for the whole Europe computed before and after post-processing

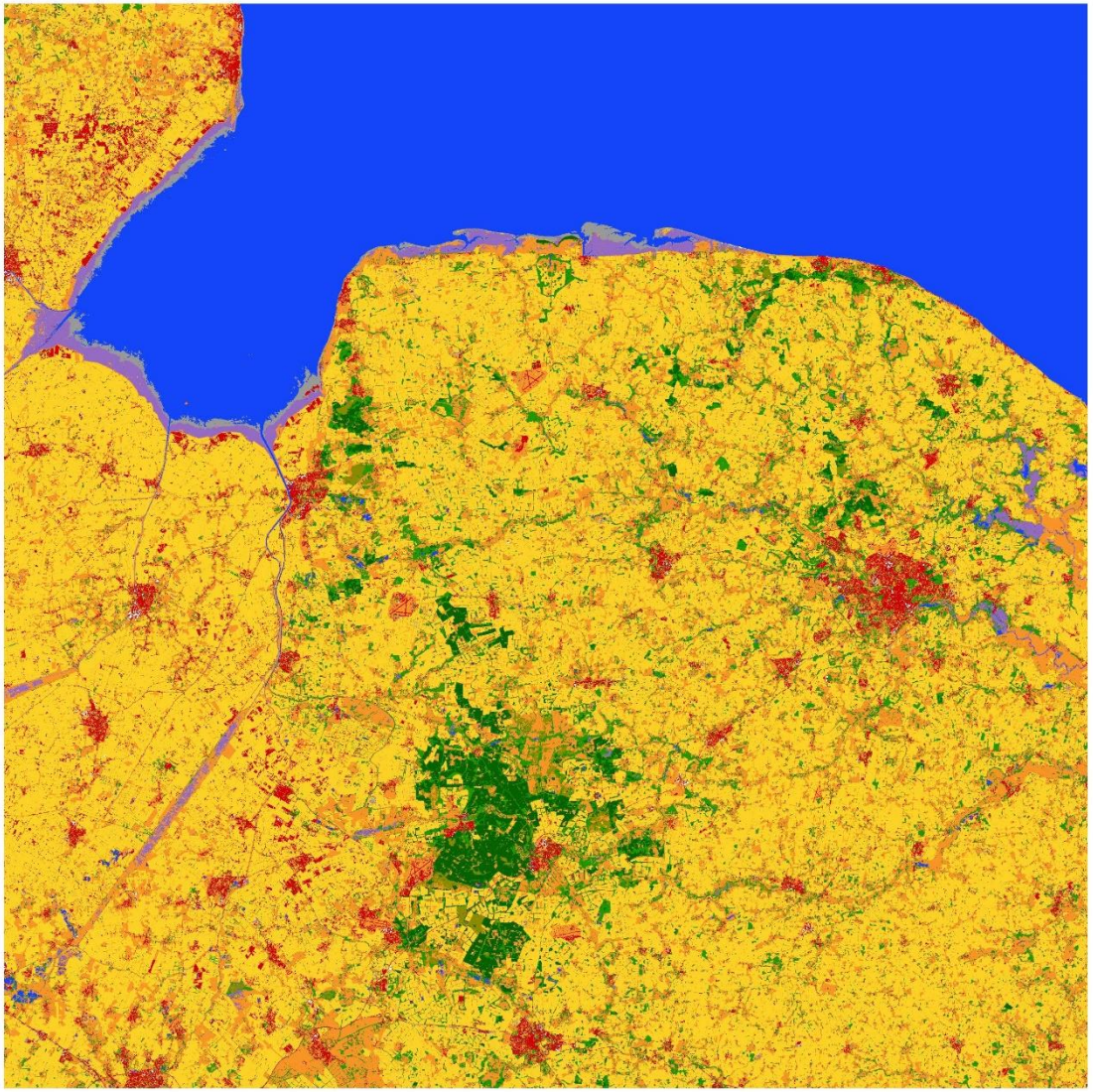
Appendix 1.

Classification maps and error matrices of tested tiles
29SNB, 30SXH, 30TWN, 30UYD, 32TNT, 32TQR, 32VLL, 33TXM, 35VLF


Tile 29SNB - Portugal
Legend
Artificial surfaces and constructions
Natural material surfaces
Broadleaf tree cover
Coniferous tree cover
Herbaceous vegetation
Moors and Heathland
Sclerophyllous vegetation
Cultivated areas
Vineyards
Marshes
Peatbogs
Water bodies
Permanent snow covered surfaces
10
0
10
20 km


Tile 30SXH - Spain
Legend
Artificial surfaces and constructions
Natural material surfaces
Broadleaf tree cover
Coniferous tree cover
Herbaceous vegetation
Moors and Heathland
Sclerophyllous vegetation
Cultivated areas
Vineyards
Marshes
Peatbogs
Water bodies
Permanent snow covered surfaces
10 0 10 20 km


Tile 30TWN - Spain
Legend
Artificial surfaces and constructions
Natural material surfaces
Broadleaf tree cover
Coniferous tree cover
Herbaceous vegetation
Moors and Heathland
Sclerophyllous vegetation
Cultivated areas
Vineyards
Marshes
Peatbogs
Water bodies
Permanent snow covered surfaces
10
0
10
20 km

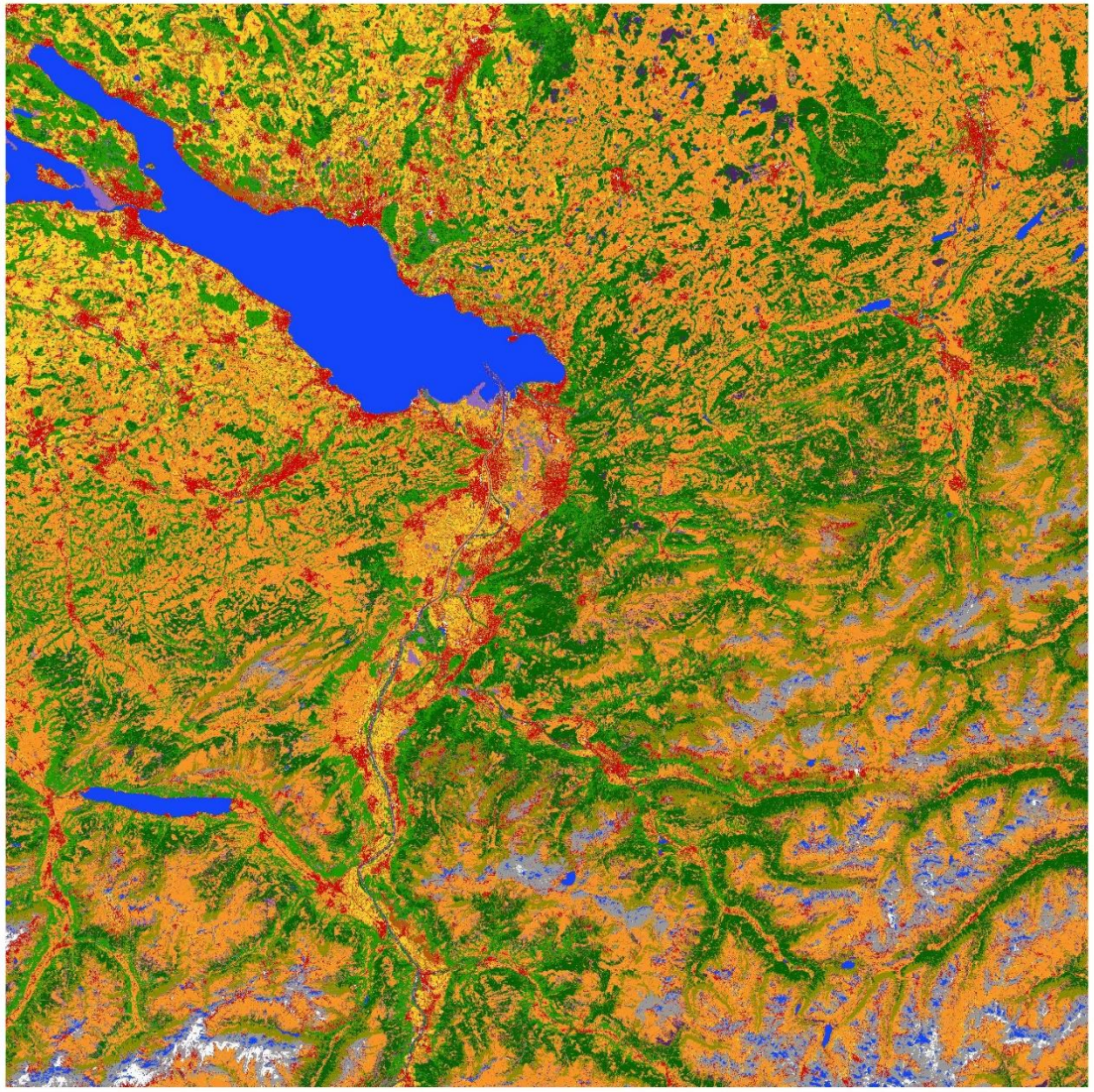


Tile 30UYD - United Kingdom

Legend

- Artificial surfaces and constructions
- Natural material surfaces
- Broadleaf tree cover
- Coniferous tree cover
- Herbaceous vegetation
- Moors and Heathland
- Sclerophyllous vegetation
- Cultivated areas
- Vineyards
- Marshes
- Peatbogs
- Water bodies
- Permanent snow covered surfaces

10 0 10 20 km

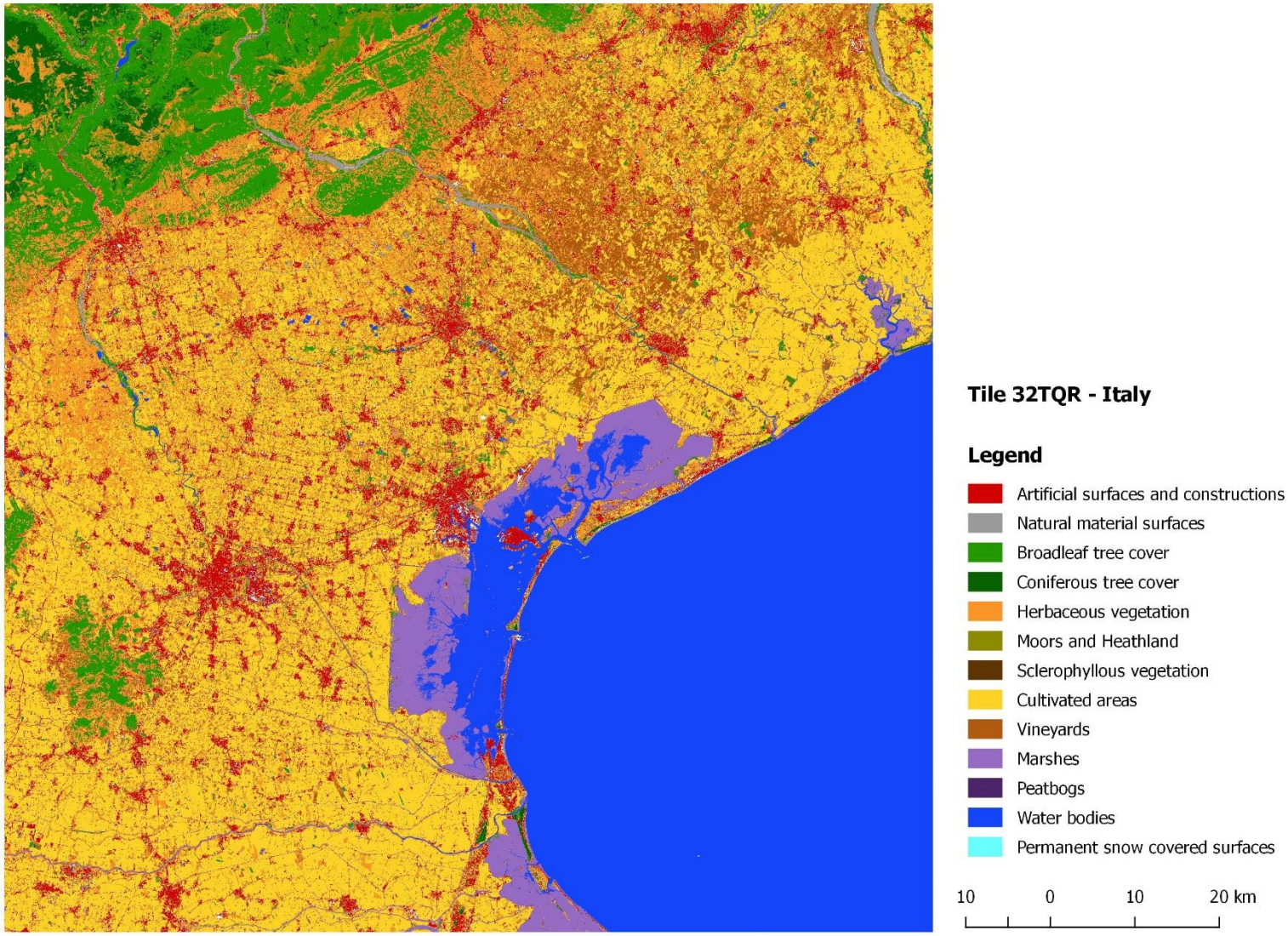


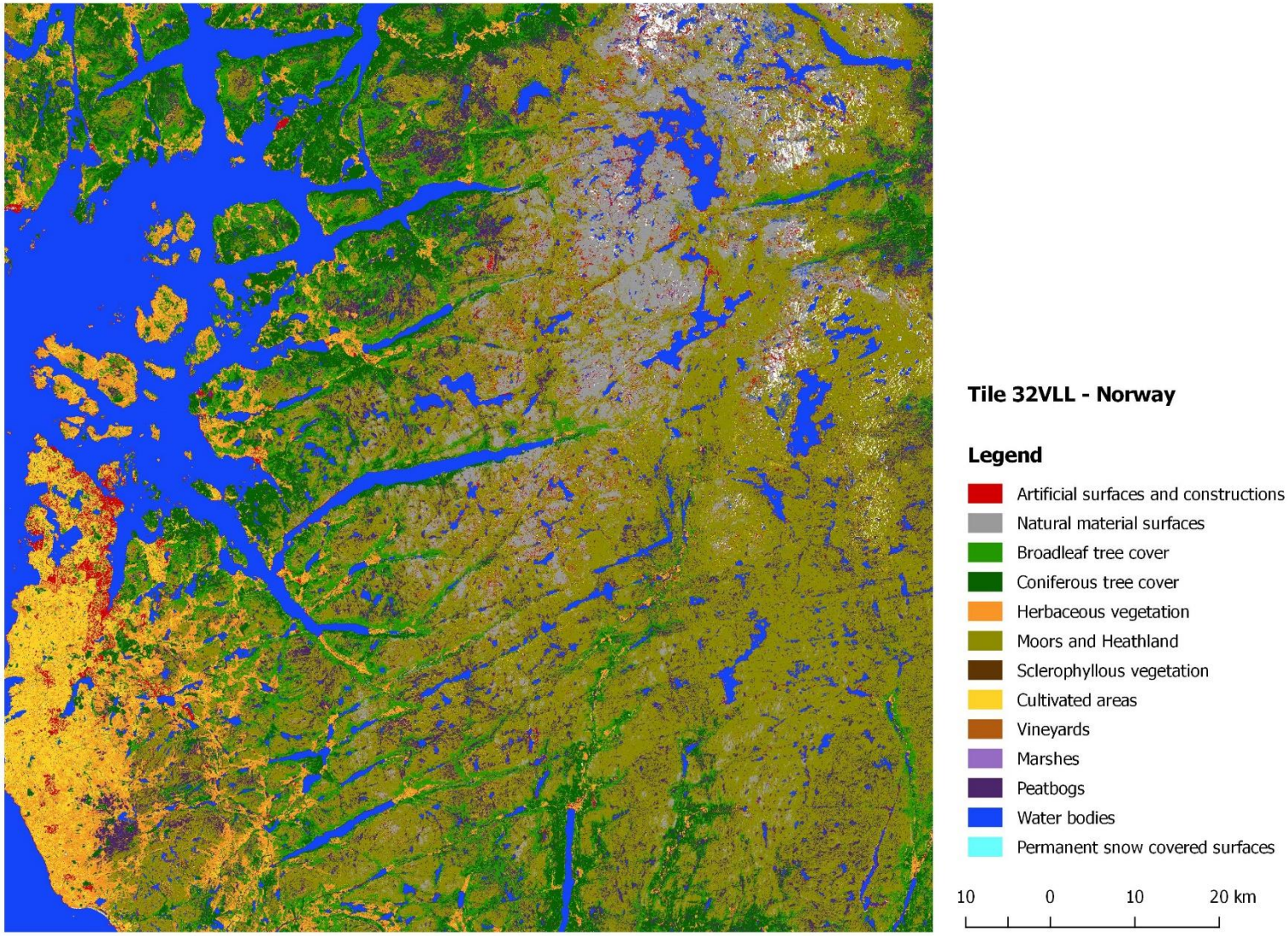
Tile 32TNT - Austria, Switzerland, Germany, Liechtenstein

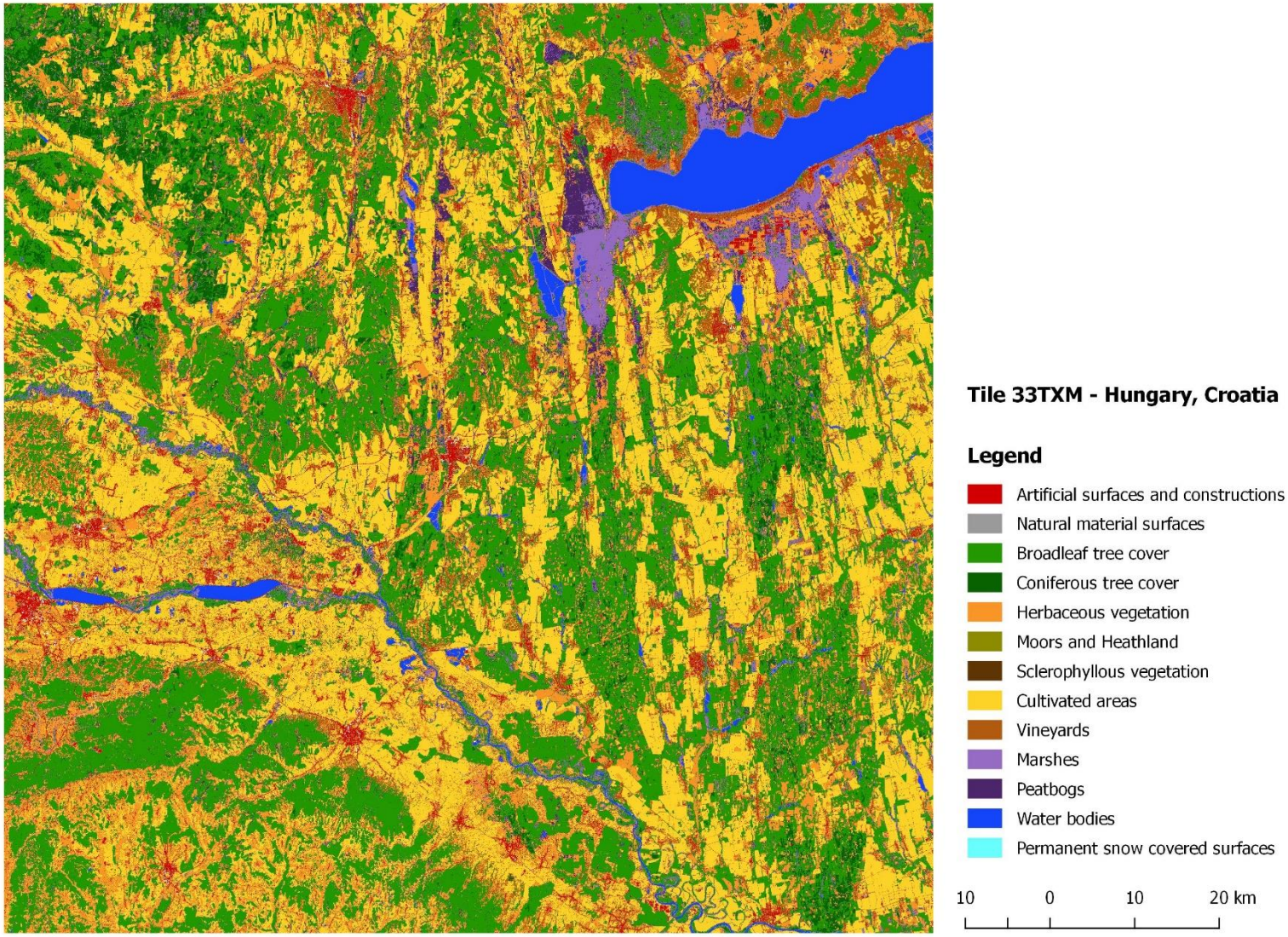
Legend

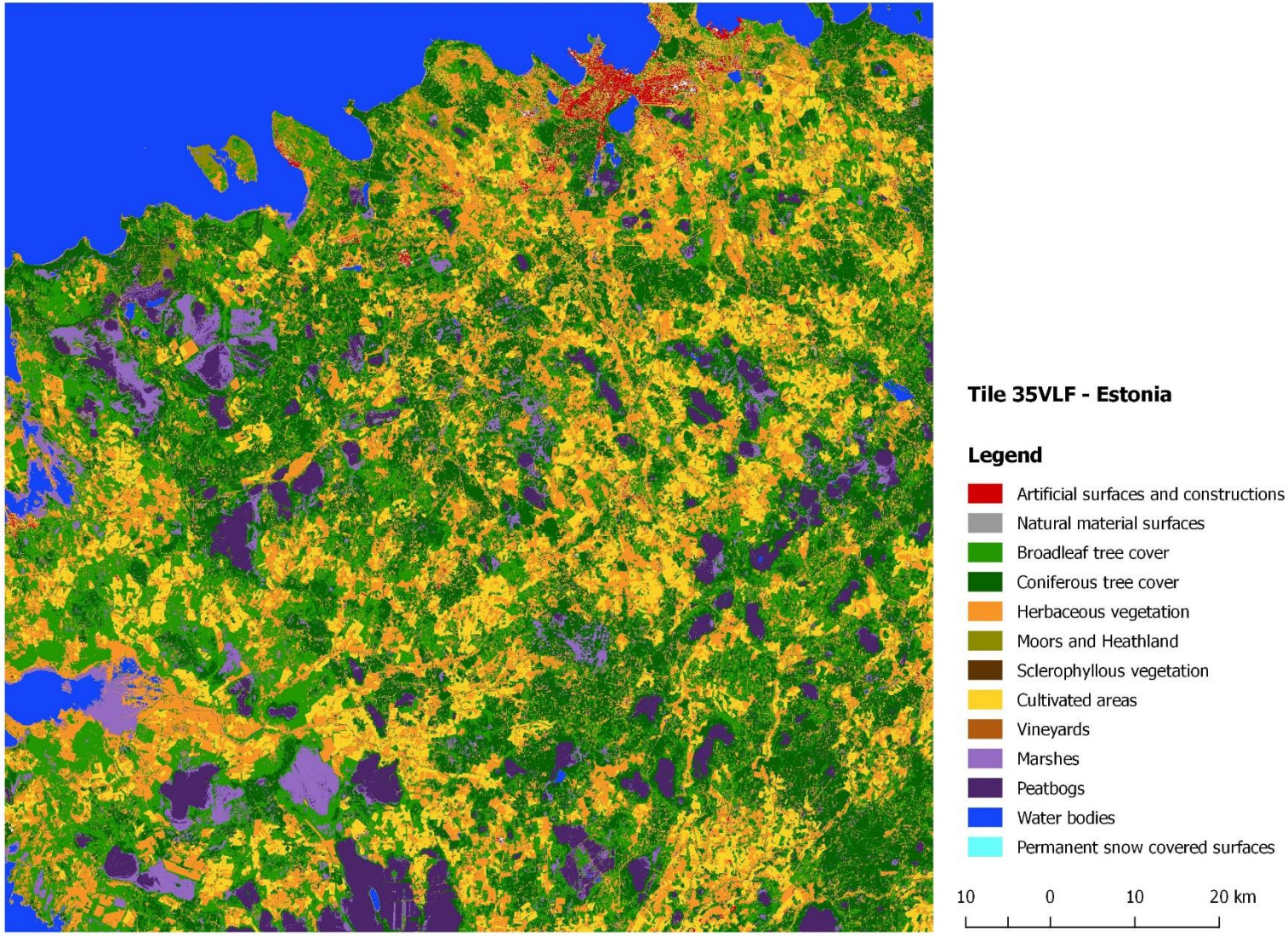
- Artificial surfaces and constructions
- Natural material surfaces
- Broadleaf tree cover
- Coniferous tree cover
- Herbaceous vegetation
- Moors and Heathland
- Sclerophyllous vegetation
- Cultivated areas
- Vineyards
- Marshes
- Peatbogs
- Water bodies
- Permanent snow covered surfaces

10 0 10 20 km


Tile 32TQR - Italy
Legend
Artificial surfaces and constructions
Natural material surfaces
Broadleaf tree cover
Coniferous tree cover
Herbaceous vegetation
Moors and Heathland
Sclerophyllous vegetation
Cultivated areas
Vineyards
Marshes
Peatbogs
Water bodies
Permanent snow covered surfaces
10 0 10 20 km


Tile 32VLL - Norway
Legend
Artificial surfaces and constructions
Natural material surfaces
Broadleaf tree cover
Coniferous tree cover
Herbaceous vegetation
Moors and Heathland
Sclerophyllous vegetation
Cultivated areas
Vineyards
Marshes
Peatbogs
Water bodies
Permanent snow covered surfaces
10
0
10
20 km


Tile 33TXM - Hungary, Croatia
Legend
Artificial surfaces and constructions
Natural material surfaces
Broadleaf tree cover
Coniferous tree cover
Herbaceous vegetation
Moors and Heathland
Sclerophyllous vegetation
Cultivated areas
Vineyards
Marshes
Peatbogs
Water bodies
Permanent snow covered surfaces
10 0 10 20 km


Tile 35VLF - Estonia
Legend
Artificial surfaces and constructions
Natural material surfaces
Broadleaf tree cover
Coniferous tree cover
Herbaceous vegetation
Moors and Heathland
Sclerophyllous vegetation
Cultivated areas
Vineyards
Marshes
Peatbogs
Water bodies
Permanent snow covered surfaces
10
0
10
20 km

29SNB	1.1.1. Artificial surfaces and constructions	2.1.1. Cultivated and managed areas	2.2.1. Vineyards	2.3.1. Herbaceous vegetation	3.1.1. Deciduous broadleaf tree cover	3.1.2. Evergreen coniferous tree cover	3.2.3. Sclerophyllous vegetation	3.3. Natural material surfaces	4.1.1. Marshes	5. 1. 1. Water bodies	Total	User's accuracy
Clouds, snow, ice, mask	3	0	0	0	0	0	0	0	0	0	3	
1.1.1. Artificial surfaces and constructions	**9**	2	0	0	0	0	0	2	0	0	13	**69,23%**
2.1.1. Cultivated and managed areas	0	**28**	0	60	0	0	0	1	0	0	89	**31,46%**
2.2.1. Vineyards	0	11	**3**	17	2	0	3	0	0	0	36	**8,33%**
2.3.1. Herbaceous vegetation	0	63	0	**153**	0	0	0	0	0	0	216	**70,83%**
3.1.1. Deciduous broadleaf tree cover	0	1	0	6	**42**	15	37	0	0	0	101	**41,58%**
3.1.2. Evergreen coniferous tree cover	0	0	0	1	1	**11**	1	0	0	0	14	**78,57%**
3.2.3. Sclerophyllous vegetation	0	0	0	8	1	0	**95**	0	0	0	104	**91,35%**
3.3. Natural material surfaces	0	3	0	0	0	0	0	**6**	0	0	9	**66,67%**
4.1.1. Marshes	0	1	0	0	0	0	0	0	**2**	2	5	**40,00%**
5. 1. 1. Water bodies	0	0	0	0	0	0	0	0	0	**452**	452	**100,00%**
Total	11	109	3	245	47	26	139	10	3	454	1047	
Producer's accuracy	**81,82%**	**25,69%**	**100,00%**	**62,45%**	**89,36%**	**42,31%**	**68,35%**	**60,00%**	**66,67%**	**99,56%**	OA	**76,50%**
											Sum diag	801
											Kappa	0,6814

30SXH	1.1.1. Artificial surfaces and constructions	2.1.1. Cultivated and managed areas	2.2.1. Vineyards	2.3.1. Herbaceous vegetation	3.1.1. Deciduous broadleaf tree cover	3.1.2. Evergreen coniferous tree cover	3.2.3. Sclerophyllous vegetation	3.3. Natural material surfaces	4.1.1. Marshes	5. 1. 1. Water bodies	Total	User's accuracy
Clouds, snow, ice, mask	9	2	0	1	0	2	1	1	0	3	19	
1.1.1. Artificial surfaces and constructions	**45**	18	1	1	0	0	6	3	0	0	74	**60,81%**
2.1.1. Cultivated and managed areas	1	**195**	6	1	6	0	3	9	0	0	221	**88,24%**
2.2.1. Vineyards	2	30	**70**	1	0	0	5	4	0	0	112	**62,50%**
2.3.1. Herbaceous vegetation	0	18	0	**26**	0	4	120	1	0	0	169	**15,38%**
3.1.1. Deciduous broadleaf tree cover	0	7	2	5	**3**	6	17	0	0	0	40	**7,50%**
3.1.2. Evergreen coniferous tree cover	0	0	0	2	4	**155**	83	1	0	0	246	**63,01%**
3.2.3. Sclerophyllous vegetation	1	0	0	3	0	10	**166**	2	0	0	182	**91,21%**
3.3. Natural material surfaces	4	9	1	6	0	0	24	**4**	0	0	48	**8,33%**
4.1.1. Marshes	2	0	0	0	0	2	3	1	**5**	1	14	**35,71%**
5. 1. 1. Water bodies	1	0	0	0	0	0	0	0	0	**44**	45	**97,78%**
Total	56	277	80	45	13	177	427	25	5	45	1151	
Producer's accuracy	**80,36%**	**70,40%**	**87,50%**	**57,78%**	**23,08%**	**87,57%**	**38,88%**	**16,00%**	**100,00%**	**97,78%**	OA	**61,95%**
											Sum diag	713
											Kappa	0,5490

30TWN	1.1.1. Artificial surfaces and constructions	2.1.1. Cultivated and managed areas	2.2.1. Vineyards	2.3.1. Herbaceous vegetation	3.1.1. Deciduous broadleaf tree cover	3.1.2. Evergreen coniferous tree cover	3.2.2. Moors and Heathland	3.2.3. Sclerophyllous vegetation	3.3. Natural material surfaces	4.1.1. Marshes	5. 1. 1. Water bodies	Total	User's accuracy
Clouds, snow, ice, mask	7	0	0	0	0	0	0	0	1	0	0	8	
1.1.1. Artificial surfaces and constructions	**17**	5	1	1	0	0	0	0	5	0	0	29	**58,62%**
2.1.1. Cultivated and managed areas	0	**337**	4	4	2	0	0	1	3	0	0	351	**96,01%**
2.2.1. Vineyards	3	34	**80**	1	1	0	0	3	0	0	0	122	**65,57%**
2.3.1. Herbaceous vegetation	0	4	3	**147**	13	0	0	7	0	0	0	174	**84,48%**
3.1.1. Deciduous broadleaf tree cover	0	1	0	1	**368**	13	1	1	0	0	0	385	**95,58%**
3.1.2. Evergreen coniferous tree cover	1	0	0	2	45	**172**	0	0	0	0	0	220	**78,18%**
3.2.2. Moors and Heathland	0	0	0	25	14	2	**5**	4	0	0	0	50	**10,00%**
3.2.3. Sclerophyllous vegetation	1	3	0	16	22	0	0	**48**	0	0	1	91	**52,75%**
3.3. Natural material surfaces	3	0	0	0	0	0	0	1	**2**	0	1	7	**28,57%**
4.1.1. Marshes	0	1	1	3	12	0	1	0	0	**7**	1	26	**26,92%**
5. 1. 1. Water bodies	0	0	0	0	0	0	0	0	0	0	**40**	40	**100,00%**
Total	25	385	89	200	477	187	7	65	10	7	43	1495	
Producer's accuracy	**68,00%**	**87,53%**	**89,89%**	**73,50%**	**77,15%**	**91,98%**	**71,43%**	**73,85%**	**20,00%**	**100,00%**	**93,02%**	OA	**81,81%**
												Sum diag	1223
												Kappa	0,7766

30UYD	1.1.1. Artificial surfaces and constructions	2.1.1. Cultivated and managed areas	2.3.1. Herbaceous vegetation	3.1.1. Deciduous broadleaf tree cover	3.1.2. Evergreen coniferous tree cover	3.2.2. Moors and Heathland	3.3. Natural material surfaces	4.1.1. Marshes	5. 1. 1. Water bodies	Total	User's accuracy
Clouds, snow, ice, mask	2	0	0	0	0	0	0	0	0	2	
1.1.1. Artificial surfaces and constructions	42	12	0	0	0	0	1	0	0	55	**76,36%**
2.1.1. Cultivated and managed areas	0	716	2	1	0	0	0	0	0	719	**99,58%**
2.3.1. Herbaceous vegetation	6	25	142	2	0	0	0	1	0	176	**80,68%**
3.1.1. Deciduous broadleaf tree cover	0	4	0	50	3	0	0	0	1	58	**86,21%**
3.1.2. Evergreen coniferous tree cover	0	0	0	0	24	0	0	0	0	24	**100,00%**
3.2.2. Moors and Heathland	1	0	2	0	0	8	0	1	0	12	**66,67%**
3.3. Natural material surfaces	0	0	0	0	0	0	4	0	3	7	**57,14%**
4.1.1. Marshes	0	1	2	0	0	0	0	16	1	20	**80,00%**
5. 1. 1. Water bodies	0	0	0	0	0	0	0	0	443	443	**100,00%**
Total	49	758	148	53	27	8	5	18	448	1514	
Producer's accuracy	**85,71%**	**94,46%**	**95,95%**	**94,34%**	**88,89%**	**100,00%**	**80,00%**	**88,89%**	**98,88%**	OA	**95,44%**
										Sum diag	1445
										Kappa	0,9311

32TNT	1.1.1. Artificial surfaces and constructions	2.1.1. Cultivated and managed areas	2.2.1. Vineyards	2.3.1. Herbaceous vegetation	3.1.1. Deciduous broadleaf tree cover	3.1.2. Evergreen coniferous tree cover	3.2.2. Moors and Heathland	3.3. Natural material surfaces	4.1.1. Marshes	4.1.2. Peatbogs	5. 1. 1. Water bodies	Total	User's accuracy
Clouds, snow, ice, mask	2	0	0	0	0	0	0	10	0	0	0	14	
1.1.1. Artificial surfaces and constructions	**37**	2	0	0	0	0	0	10	0	0	1	50	**74,00%**
2.1.1. Cultivated and managed areas	3	**64**	5	29	0	0	0	2	0	0	0	103	**62,14%**
2.2.1. Vineyards	0	0	**12**	19	2	0	0	0	0	0	0	33	**36,36%**
2.3.1. Herbaceous vegetation	1	11	2	**454**	3	1	1	1	0	1	0	475	**95,58%**
3.1.1. Deciduous broadleaf tree cover	0	2	2	3	**66**	22	0	0	0	0	0	95	**69,47%**
3.1.2. Evergreen coniferous tree cover	0	0	0	6	5	**182**	0	0	0	0	0	193	**94,30%**
3.2.2. Moors and Heathland	1	0	0	26	1	15	**1**	2	0	0	0	46	**2,17%**
3.3. Natural material surfaces	2	0	0	1	0	0	0	**57**	0	0	0	60	**95,00%**
4.1.1. Marshes	0	0	3	14	1	0	0	0	**9**	0	0	27	**33,33%**
4.1.2. Peatbogs	0	0	0	4	1	4	0	0	0	**4**	1	14	**28,57%**
5. 1. 1. Water bodies	1	0	0	1	0	0	0	5	0	0	**92**	100	**92,00%**
Total	45	79	24	557	79	224	2	77	9	5	94	1196	
Producer's accuracy	**82,22%**	**81,01%**	**50,00%**	**81,51%**	**83,54%**	**81,25%**	**50,00%**	**74,03%**	**100,00%**	**80,00%**	**97,87%**	OA	**81,77%**
												Sum diag	978
												Kappa	0,7607

32TQR	1.1.1. Artificial surfaces and constructions	2.1.1. Cultivated and managed areas	2.2.1. Vineyards	2.3.1. Herbaceous vegetation	3.1.1. Deciduous broadleaf tree cover	3.1.2. Evergreen coniferous tree cover	3.2.2. Moors and Heathland	3.3. Natural material surfaces	4.1.1. Marshes	5. 1. 1. Water bodies	Total	User's accuracy
Clouds, snow, ice, mask	5	0	0	0	0	0	0	0	0	0	5	
1.1.1. Artificial surfaces and constructions	**71**	8	0	0	0	0	0	0	0	0	79	**89,87%**
2.1.1. Cultivated and managed areas	5	**415**	4	5	1	0	0	0	0	0	430	**96,51%**
2.2.1. Vineyards	1	13	**35**	5	1	0	0	0	0	0	55	**63,64%**
2.3.1. Herbaceous vegetation	0	20	24	**74**	0	0	0	0	0	0	118	**62,71%**
3.1.1. Deciduous broadleaf tree cover	0	0	2	0	**50**	1	0	0	0	0	53	**94,34%**
3.1.2. Evergreen coniferous tree cover	0	0	0	0	0	**12**	0	0	0	0	12	**100,00%**
3.2.2. Moors and Heathland	0	0	0	4	3	1	**2**	0	0	0	10	**20,00%**
3.3. Natural material surfaces	3	4	0	0	0	0	0	**9**	0	0	16	**56,25%**
4.1.1. Marshes	1	0	0	0	0	0	0	0	**12**	29	42	**28,57%**
5. 1. 1. Water bodies	0	0	0	0	0	0	0	0	0	**404**	404	**100,00%**
Total	81	460	65	88	55	14	2	9	12	433	1219	
Producer's accuracy	**87,65%**	**90,22%**	**53,85%**	**84,09%**	**90,91%**	**85,71%**	**100,00%**	**100,00%**	**100,00%**	**93,30%**	OA	**88,93%**
											Sum diag	1084
											Kappa	0,8489

32VLL	1.1.1. Artificial surfaces and constructions	2.1.1. Cultivated and managed areas	2.3.1. Herbaceous vegetation	3.1.1. Deciduous broadleaf tree cover	3.1.2. Evergreen coniferous tree cover	3.2.2. Moors and Heathland	3.3. Natural material surfaces	4.1.1. Marshes	4.1.2. Peatbogs	5. 1. 1. Water bodies	Total	User's accuracy
Clouds, snow, ice, mask	0	0	0	0	0	0	1	0	0	3	4	
1.1.1. Artificial surfaces and constructions	**6**	1	2	0	0	0	6	0	0	5	20	**30,00%**
2.1.1. Cultivated and managed areas	2	**3**	23	1	2	1	0	1	0	5	38	**7,89%**
2.3.1. Herbaceous vegetation	0	0	**50**	1	0	8	0	0	0	6	65	**76,92%**
3.1.1. Deciduous broadleaf tree cover	0	0	0	**42**	10	4	0	0	0	6	62	**67,74%**
3.1.2. Evergreen coniferous tree cover	0	0	1	7	**79**	0	0	0	0	5	92	**85,87%**
3.2.2. Moors and Heathland	0	0	9	2	0	**74**	3	0	0	5	93	**79,57%**
3.3. Natural material surfaces	0	0	0	0	0	0	**20**	0	0	0	20	**100,00%**
4.1.1. Marshes	0	0	0	0	0	0	0	**0**	0	0	0	**0,00%**
4.1.2. Peatbogs	0	0	8	1	0	23	0	0	**2**	31	65	**3,08%**
5. 1. 1. Water bodies	0	0	0	0	0	0	1	0	0	**346**	347	**99,71%**
Total	8	4	93	54	91	110	30	1	2	409	802	
Producer's accuracy	**75,00%**	**75,00%**	**53,76%**	**77,78%**	**86,81%**	**67,27%**	**66,67%**	**0,00%**	**100,00%**	**84,60%**	OA	**77,56%**
											Sum diag	622
											Kappa	0,6943

33TXM	1.1.1. Artificial surfaces and constructions	2.1.1. Cultivated and managed areas	2.2.1. Vineyards	2.3.1. Herbaceous vegetation	3.1.1. Deciduous broadleaf tree cover	3.1.2. Evergreen coniferous tree cover	3.3. Natural material surfaces	4.1.1. Marshes	4.1.2. Peatbogs	5. 1. 1. Water bodies	Total	User's accuracy
Clouds, snow, ice, mask	2	0	0	0	0	0	0	0	0	0	2	
1.1.1. Artificial surfaces and constructions	**25**	5	0	0	0	0	0	0	0	0	30	**83,33%**
2.1.1. Cultivated and managed areas	0	**523**	0	1	1	0	1	0	0	0	526	**99,43%**
2.2.1. Vineyards	6	29	**6**	6	13	0	0	0	0	0	60	**10,00%**
2.3.1. Herbaceous vegetation	4	46	4	**103**	5	0	0	1	0	0	163	**63,19%**
3.1.1. Deciduous broadleaf tree cover	0	1	0	3	**485**	4	0	0	0	0	493	**98,38%**
3.1.2. Evergreen coniferous tree cover	0	0	1	0	1	**55**	0	0	0	0	57	**96,49%**
3.3. Natural material surfaces	1	0	0	0	0	0	**1**	0	0	0	2	**50,00%**
4.1.1. Marshes	1	1	0	3	13	1	0	**12**	0	2	33	**36,36%**
4.1.2. Peatbogs	0	0	0	15	6	0	0	9	**1**	0	31	**3,23%**
5. 1. 1. Water bodies	0	0	0	0	0	0	0	0	0	**61**	61	**100,00%**
Total	37	605	11	131	524	60	2	22	1	63	1456	
Producer's accuracy	**67,57%**	**86,45%**	**54,55%**	**78,63%**	**92,56%**	**91,67%**	**50,00%**	**54,55%**	**100,00%**	**96,83%**	OA	**87,36%**
											Sum diag	1272
											Kappa	0,8228

35VLF	1.1.1. Artificial surfaces and constructions	2.1.1. Cultivated and managed areas	2.3.1. Herbaceous vegetation	3.1.1. Deciduous broadleaf tree cover	3.1.2. Evergreen coniferous tree cover	3.2.2. Moors and Heathland	3.3. Natural material surfaces	4.1.1. Marshes	4.1.2. Peatbogs	5. 1. 1. Water bodies	Total	User's accuracy
Clouds, snow, ice, mask	1	0	0	0	0	0	0	0	0	0	1	
1.1.1. Artificial surfaces and constructions	**10**	0	0	0	0	0	1	0	0	0	11	**90,91%**
2.1.1. Cultivated and managed areas	7	**144**	10	1	0	0	1	0	1	0	164	**87,80%**
2.3.1. Herbaceous vegetation	0	15	**187**	3	1	0	0	0	0	0	206	**90,78%**
3.1.1. Deciduous broadleaf tree cover	0	0	3	**200**	21	0	0	1	0	0	225	**88,89%**
3.1.2. Evergreen coniferous tree cover	0	0	2	2	**277**	0	0	1	0	0	282	**98,23%**
3.2.2. Moors and Heathland	0	0	20	4	3	**0**	0	1	0	0	28	**0,00%**
3.3. Natural material surfaces	3	1	0	0	0	0	**3**	0	0	1	8	**37,50%**
4.1.1. Marshes	1	0	3	1	12	0	0	**27**	5	0	49	**55,10%**
4.1.2. Peatbogs	1	2	1	0	7	0	0	13	**63**	2	89	**70,79%**
5. 1. 1. Water bodies	0	0	1	0	0	0	0	1	0	**249**	251	**99,20%**
Total	22	162	227	211	321	0	5	44	69	252	1313	
Producer's accuracy	**45,45%**	**88,89%**	**82,38%**	**94,79%**	**86,29%**	**0,00%**	**60,00%**	**61,36%**	**91,30%**	**98,81%**	OA	**88,35%**
											Sum diag	1160
											Kappa	0,8606

DELIVERABLE 1.2

Appendix 2.

List of classified Sentinel-2 tiles and performed LC classifications

UTM Zone 25:

25SFD

UTM Zone 26:

26SLH, 26SMH, 26SMJ, 26SPF, 26SPG, 26WPS, 26WPT, 26WPU

UTM Zone 27:

27RYL, 27VVL, 27VWL, 27VXL, 27WVM, 27WVN, 27WVP, 27WWM, 27WWN, 27WWP, 27WXM, 27WXN, 27WXP

UTM Zone 28:

28RBS, 28RCS, 28RDR, 28RDS, 28RES, 28RFS, 28RFT, 28SBB, 28SCA, 28SCB, 28VDR, 28WDS, 28WDT, 28WDU, 28WES, 28WET, 28WEU

UTM Zone 29:

29SMC, 29SMD, 29SNB, 29SNC, 29SND, 29SPB, 29SPC, 29SPD, 29SQA, 29SQB, 29SQC, 29SQD, 29TME, 29TMH, 29TNE, 29TNF, 29TNG, 29TNH, 29TNJ, 29TPE, 29TPF, 29TPG, 29TPH, 29TPJ, 29TQE, 29TQF, 29TQG, 29TQH, 29TQJ, 29ULT, 29UMA, 29UMT, 29UMU, 29UMV, 29UNA, 29UNB, 29UNT, 29UNU, 29UNV, 29UPA, 29UPB, 29UPR, 29UPT, 29UPU, 29UPV, 29VND, 29VNE, 29VPC, 29VPD, 29VPE, 30STE

UTM Zone 30:

30STF, 30STG, 30STH, 30STJ, 30SUF, 30SUG, 30SUH, 30SUJ, 30SVF, 30SVG, 30SVH, 30SVJ, 30SWF, 30SWG, 30SWH, 30SWJ, 30SXG, 30SXH, 30SXJ, 30SYH, 30SYJ, 30TTK, 30TUK, 30TUL, 30TUM, 30TUN, 30TUP, 30TVK, 30TVL, 30TVM, 30TVN, 30TVP, 30TVT, 30TWK, 30TWL, 30TWM, 30TWN, 30TWP, 30TWS, 30TWT, 30TXK, 30TXL, 30TXM, 30TXN, 30TXP, 30TXQ, 30TXR, 30TXS, 30TXT, 30TYK, 30TYL, 30TYM, 30TYN, 30TYP, 30TYQ, 30TYR, 30TYS, 30TYT, 30UUA, 30UUB, 30UUC, 30UUD, 30UUE, 30UUF, 30UUG, 30UUU, 30UVA, 30UVB, 30UVC, 30UVD, 30UVE, 30UVF, 30UVG, 30UVU, 30UVV, 30UWA, 30UWB, 30UWC, 30UWD, 30UWE, 30UWF, 30UWG, 30UWU, 30UWV, 30UXA, 30UXB, 30UXC, 30UXD, 30UXE, 30UXF, 30UXU, 30UXV, 30UYA, 30UYB, 30UYC, 30UYD, 30UYE, 30UYU, 30UYV, 30VUH, 30VUJ, 30VUK, 30VVH, 30VVJ, 30VVK, 30VVL, 30VWH, 30VWJ, 30VWL, 30VWM, 30VWN, 30VXM, 30VXN

UTM Zone 31:

31SCC, 31SCD, 31SDD, 31SED, 31TCF, 31TCG, 31TCH, 31TCJ, 31TCK, 31TCL, 31TCM, 31TCN, 31TDE, 31TDF, 31TDG, 31TDH, 31TDJ, 31TDK, 31TDL, 31TDM, 31TDN, 31TEE, 31TEG, 31TEH, 31TEJ, 31TEK, 31TEL, 31TEM, 31TEN, 31TFE, 31TFH, 31TFJ, 31TFK, 31TFL, 31TFM, 31TFN, 31TGH, 31TGJ, 31TGK, 31TGL, 31TGM, 31TGN, 31UCP, 31UCQ, 31UCR, 31UCS, 31UCT, 31UDP, 31UDQ, 31UDR, 31UDS, 31UDU, 31UEP, 31UEQ, 31UER, 31UES, 31UET, 31UFP, 31UFQ, 31UFR, 31UFS, 31UFT, 31UFU, 31UFV, 31UGP, 31UGQ, 31UGR, 31UGS, 31UGT

UTM Zone 32:

32SMJ, 32SNJ, 32TLP, 32TLQ, 32TLR, 32TLS, 32TLT, 32TMK, 32TML, 32TMM, 32TMN, 32TMP, 32TMQ, 32TMR, 32TMS, 32TMT, 32TNK, 32TNL, 32TNM, 32TNN, 32TNP, 32TNQ, 32TNR, 32TNS, 32TNT, 32TPM, 32TPN, 32TPP, 32TPQ, 32TPR, 32TPS, 32TPT, 32TQN, 32TQP, 32TQQ, 32TQR, 32TQS, 32TQT, 32ULA, 32ULB, 32ULC, 32ULD, 32ULE, 32ULU, 32ULV, 32UMA, 32UMB, 32UMC, 32UMD, 32UME, 32UMF, 32UMG, 32UMU, 32UMV, 32UNA, 32UNB, 32UNC, 32UND, 32UNE, 32UNF, 32UNG, 32UNU, 32UNV, 32UPA, 32UPB, 32UPC, 32UPD, 32UPE, 32UPF, 32UPG, 32UPU, 32UPV, 32UQA, 32UQB, 32UQC, 32UQD, 32UQU, 32UQV, 32VKL, 32VKM, 32VKN, 32VKP, 32VKQ, 32VLK, 32VLL, 32VLM, 32VLN, 32VLP, 32VLQ, 32VMH, 32VMJ, 32VMK, 32VML, 32VMM, 32VMN, 32VMP, 32VMQ, 32VMR, 32VNH, 32VNJ, 32VNK, 32VNL, 32VNM, 32VNN, 32VNP, 32VNQ, 32VNR, 32VPH, 32VPJ, 32VPK, 32VPL, 32VPM, 32VPN, 32VPP, 32VPQ, 32VPR, 32WNS, 32WNT, 32WPA, 32WPS, 32WPT, 32WPU, 32WPV

UTM Zone 33:

33STA, 33STB, 33STC, 33STV, 33SUB, 33SUC, 33SVA, 33SVB, 33SVC, 33SVV, 33SWA, 33SWB, 33SWC, 33SWD, 33SXC, 33SXD, 33TTG, 33TUF, 33TUG, 33TUH, 33TUJ, 33TUK, 33TUL, 33TUM, 33TUN, 33TVE, 33TVF, 33TVG, 33TVH, 33TVJ, 33TVK, 33TVL, 33TVM, 33TVN, 33TWE, 33TWF, 33TWG, 33TWH, 33TWJ, 33TWK, 33TWL, 33TWM, 33TWN, 33TXE, 33TXF, 33TXH, 33TXJ, 33TXK, 33TXL, 33TXM, 33TXN, 33TYE, 33TYF, 33TYH, 33TYJ, 33TYK, 33TYL, 33TYM, 33TYN, 33UUA, 33UUB, 33UUP, 33UUQ, 33UUR, 33UUS, 33UUT, 33UUV, 33UVA, 33UVB, 33UVP, 33UVQ, 33UVR, 33UVS, 33UVT, 33UVU, 33UVV, 33UWA, 33UWB, 33UWP, 33UWQ, 33UWR, 33UWS, 33UWT, 33UWU, 33UWV, 33UXA, 33UXP, 33UXQ, 33UXR, 33UXS, 33UXT, 33UXU, 33UXV, 33UYP, 33UYQ, 33UYR, 33UYS, 33UYT, 33UYU, 33UYV, 33VUC, 33VUD, 33VUE, 33VUF, 33VUG, 33VUH, 33VUJ, 33VUK, 33VVC, 33VVD, 33VVE, 33VVF, 33VVG, 33VVH, 33VVJ, 33VVK, 33VVL, 33VWC, 33VWD, 33VWE, 33VWF, 33VWG, 33VWH, 33VWJ, 33VWK, 33VWL, 33VXD, 33VXE, 33VXF, 33VXG, 33VXH, 33VXJ, 33VXK, 33VXL, 33WVM, 33WVN, 33WVP, 33WVQ, 33WVR, 33WVS, 33WWM, 33WWN, 33WWP, 33WWQ, 33WWR, 33WWS, 33WWT, 33WXM, 33WXN, 33WXP, 33WXQ, 33WXR, 33WXS, 33WXT

UTM Zone 34:

34SCJ, 34SDG, 34SDH, 34SDJ, 34SEF, 34SEG, 34SEH, 34SEJ, 34SFF, 34SFG, 34SFH, 34SFJ, 34SGE, 34SGG, 34SGH, 34SGJ, 34TCK, 34TCL, 34TCM, 34TCN, 34TCP, 34TCQ, 34TCR, 34TCS, 34TCT, 34TDK, 34TDL, 34TDM, 34TDN, 34TDP, 34TDQ, 34TDR, 34TDS, 34TDT, 34TEK, 34TEL, 34TEM, 34TEN, 34TEP, 34TEQ, 34TER, 34TES, 34TET, 34TFK, 34TFL, 34TFM, 34TFN, 34TFP, 34TFQ, 34TFR, 34TFS, 34TFT, 34TGK, 34TGL, 34TGM, 34TGN, 34TGP, 34TGQ, 34TGR, 34TGS, 34TGT, 34UCA, 34UCB, 34UCC, 34UCF, 34UCU, 34UCV, 34UDA, 34UDB, 34UDC, 34UDD, 34UDE, 34UDF, 34UDG, 34UDU, 34UDV, 34UEA, 34UEB, 34UEC, 34UED, 34UEE, 34UEF, 34UEG, 34UEU, 34UEV, 34UFA, 34UFB, 34UFC, 34UFD, 34UFE, 34UFF, 34UFG, 34UFU, 34UFV, 34UGA, 34UGB, 34UGU, 34VCJ, 34VCK, 34VCL, 34VCM, 34VDH, 34VDM, 34VDN, 34VDQ, 34VDR, 34VEH, 34VEJ, 34VEK, 34VEL, 34VEM, 34VEN, 34VEP, 34VEQ, 34VER, 34VFH, 34VFJ, 34VFK, 34VFL, 34VFM, 34VFN, 34VFP, 34VFQ, 34VFR, 34WDA, 34WDB, 34WDC, 34WDD, 34WDS, 34WDT, 34WDU, 34WDV, 34WEA, 34WEB, 34WEC, 34WED, 34WES, 34WET, 34WEU, 34WEV, 34WFA, 34WFB, 34WFC, 34WFD, 34WFS, 34WFT, 34WFU, 34WFV

UTM Zone 35:

35SKA, 35SKB, 35SKC, 35SKD, 35SKU, 35SKV, 35SLA, 35SLB, 35SLC, 35SLD, 35SLU, 35SLV, 35SMA, 35SMB, 35SMC, 35SMD, 35SMU, 35SMV, 35SNA, 35SNV, 35SPA, 35TLE, 35TLF, 35TLG, 35TLH, 35TLJ,

35TLK, 35TLL, 35TLM, 35TLN, 35TMF, 35TMG, 35TMH, 35TMJ, 35TMK, 35TML, 35TMM, 35TMN, 35TNG, 35TNH, 35TNJ, 35TNK, 35TNL, 35TNM, 35TNN, 35TPJ, 35TPK, 35TPL, 35TQL, 35ULA, 35ULB, 35ULP, 35ULV, 35UMA, 35UMB, 35UMP, 35UNB, 35UNP, 35VLC, 35VLD, 35VLE, 35VLF, 35VLG, 35VLH, 35VLJ, 35VLK, 35VMC, 35VMD, 35VME, 35VMF, 35VMG, 35VMH, 35VMJ, 35VMK, 35VML, 35VNC, 35VND, 35VNE, 35VNF, 35VNG, 35VNH, 35VNJ, 35VNK, 35VNL, 35VPH, 35VPJ, 35VPK, 35VPL, 35WMM, 35WMN, 35WMP, 35WMQ, 35WMR, 35WMS, 35WMT, 35WMU, 35WNM, 35WNN, 35WNP, 35WNQ, 35WNR, 35WNS, 35WNT, 35WNU, 35WPM, 35WPN, 35WPP, 35WPQ, 35WPR, 35WPT, 35WPU

UTM Zone 36:

36SVD, 36SVE, 36SWD, 36SWE, 36SXE, 36VVQ, 36VVR

DELIVERABLE 1.2

Appendix 3. Error matrices for the whole Europe computed before and after post-processing

Table A.3 - 1. Error matrix of land cover classification of Europe before post-processing

Land Cover map of Europe before post-processing 13 LC classes	1.1.1. Artificial surfaces and constructions	2.1.1. Cultivated and managed areas	2.2.1. Vineyards	2.3.1. Herbaceous vegetation	3.1.1. Deciduous broadleaf tree cover	3.1.2. Evergreen coniferous tree cover	3.2.2. Moors and Heathland	3.2.3. Sclerophyllous vegetation	3.3. Natural material surfaces	3.3.5. Permanent snow and glaciers	4.1.1. Marshes	4.1.2. Peatbogs	5. 1. 1. Water bodies	Total	User's accuracy
Clouds, snow, ice, mask	484	54	0	9	21	59	0	0	76	53	1	0	7	764	
1.1.1. Artificial surfaces and constructions	**1185**	181	3	25	1	2	10	11	470	0	2	0	13	1903	62,27%
2.1.1. Cultivated and managed areas	15	**11608**	23	555	31	4	12	20	36	0	5	0	1	12310	94,30%
2.2.1. Vineyards	3	416	**447**	57	13	1	11	27	6	0	1	0	1	983	45,47%
2.3.1. Herbaceous vegetation	7	898	19	**5595**	128	7	690	287	64	5	88	14	0	7802	71,71%
3.1.1. Deciduous broadleaf tree cover	4	47	1	35	**10412**	194	165	113	0	0	13	6	1	10991	94,73%
3.1.2. Evergreen coniferous tree cover	4	17	2	10	174	**8314**	82	60	0	0	3	6	0	8672	95,87%
3.2.2. Moors and Heathland	7	65	1	235	54	25	**763**	50	42	0	5	58	3	1308	58,33%
3.2.3. Sclerophyllous vegetation	1	24	0	37	51	10	48	**180**	3	0	4	0	0	358	50,28%
3.3. Natural material surfaces	57	65	2	75	0	0	36	60	**1225**	5	0	2	3	1530	80,07%
3.3.5. Permanent snow and glaciers	2	0	0	0	0	0	0	0	68	**8**	0	0	0	78	10,26%
4.1.1. Marshes	9	75	2	51	42	3	55	7	16	0	**135**	85	73	553	24,41%
4.1.2. Peatbogs	2	19	0	65	16	4	193	0	4	0	61	**574**	56	994	57,75%
5. 1. 1. Water bodies	49	1	0	29	2	7	6	0	108	14	6	0	**3555**	3777	94,12%
Total	1345	13416	500	6769	10924	8571	2071	815	2042	32	323	745	3706	51259	
Producer's accuracy	88,10%	86,52%	89,40%	82,66%	95,31%	97,00%	36,84%	22,09%	59,99%	25,00%	41,80%	77,05%	95,93%	**OA**	**85,84%**
														Kappa	0,83

Table A.3 - 2. Error matrix of land cover classification of Europe after post-processing

Land Cover map of Europe after post-processing 13 LC classes	1.1.1. Artificial surfaces and constructions	2.1.1. Cultivated and managed areas	2.2.1. Vineyards	2.3.1. Herbaceous vegetation	3.1.1. Deciduous broadleaf tree cover	3.1.2. Evergreen coniferous tree cover	3.2.2. Moors and Heathland	3.2.3. Sclerophyllous vegetation	3.3. Natural material surfaces	3.3.5. Permanent snow and glaciers	4.1.1. Marshes	4.1.2. Peatbogs	5. 1. 1. Water bodies	Total	User's accuracy
Clouds, snow, ice, mask	11	1	0	0	0	0	0	0	28	56	0	0	1	97	
1.1.1. Artificial surfaces and constructions	**1548**	65	1	7	0	0	5	2	430	0	0	0	6	2064	75,00%
2.1.1. Cultivated and managed areas	37	**11774**	26	574	32	5	12	23	46	0	4	0	1	12534	93,94%
2.2.1. Vineyards	8	426	**445**	58	12	1	10	26	7	0	0	0	1	994	44,77%
2.3.1. Herbaceous vegetation	15	886	20	**5592**	127	6	689	289	72	7	88	13	0	7804	71,66%
3.1.1. Deciduous broadleaf tree cover	5	44	1	40	**10436**	202	165	113	4	0	12	5	1	11028	94,63%
3.1.2. Evergreen coniferous tree cover	8	16	2	12	171	**8374**	82	60	1	0	3	6	2	8737	95,85%
3.2.2. Moors and Heathland	10	65	1	249	53	24	**760**	50	49	0	5	58	2	1326	57,32%
3.2.3. Sclerophyllous vegetation	3	26	0	39	54	10	53	**181**	3	0	4	0	0	373	48,53%
3.3. Natural material surfaces	96	73	2	86	2	0	38	64	**1319**	7	1	2	7	1697	77,73%
3.3.5. Permanent snow and glaciers	4	0	0	0	0	0	0	0	73	**9**	0	0	0	86	10,47%
4.1.1. Marshes	37	76	2	55	40	3	58	7	18	0	**140**	83	79	598	23,41%
4.1.2. Peatbogs	5	17	0	62	16	4	197	0	5	0	61	**578**	55	1000	57,80%
5. 1. 1. Water bodies	42	1	0	4	2	1	2	0	63	6	6	0	**3558**	3685	96,55%
Total	1818	13469	500	6778	10945	8630	2071	815	2090	29	324	745	3712	51926	
Producer's accuracy	85,15%	87,42%	89,00%	82,50%	95,35%	97,03%	36,70%	22,21%	63,11%	31,03%	43,21%	77,58%	95,85%	**OA**	**86,11%**
														Kappa	0,83

Table A.3 - 3. Error matrix for land cover classification of Europe after merging from 13 to 10 LC classes

Land Cover map of Europe 10 LC classes	1.1.1. Artificial surfaces and constructions	2.1.1. Cultivated and managed areas 2.2.1. Vineyards	2.3.1. Herbaceous vegetation 3.2.2. Moors and Heathland	3.1.1. Deciduous broadleaf tree cover	3.1.2. Evergreen coniferous tree cover	3.2.3. Sclerophyllous vegetation	3.3. Natural material surfaces	3.3.5. Permanent snow and glaciers	4.1.1. Marshes 4.1.2. Peatbogs	5. 1. 1. Water bodies	Total	User's accuracy
Clouds, snow, ice, mask	11	1	0	0	0	0	28	56	0	1	97	
1.1.1. Artificial surfaces and constructions	**1548**	66	12	0	0	2	430	0	0	6	2064	75,00%
2.1.1. Cultivated and managed areas 2.2.1. Vineyards	45	**12671**	654	44	6	49	53	0	4	2	13528	93,66%
2.3.1. Herbaceous vegetation 3.2.2. Moors and Heathland	25	972	**7290**	180	30	339	121	7	164	2	9130	79,85%
3.1.1. Deciduous broadleaf tree cover	5	45	205	**10436**	202	113	4	0	17	1	11028	94,63%
3.1.2. Evergreen coniferous tree cover	8	18	94	171	**8374**	60	1	0	9	2	8737	95,85%
3.2.3. Sclerophyllous vegetation	3	26	92	54	10	**181**	3	0	4	0	373	48,53%
3.3. Natural material surfaces	96	75	124	2	0	64	**1319**	7	3	7	1697	77,73%
3.3.5. Permanent snow and glaciers	4	0	0	0	0	0	73	**9**	0	0	86	10,47%
4.1.1. Marshes 4.1.2. Peatbogs	42	95	372	56	7	7	23	0	**862**	134	1598	53,94%
5. 1. 1. Water bodies	42	1	6	2	1	0	63	6	6	**3558**	3685	96,55%
Total	1818	13970	8849	10945	8630	815	2090	29	1069	3712	51927	
Producer's accuracy	85,15%	90,70%	82,38%	95,35%	97,03%	22,21%	63,11%	31,03%	80,64%	95,85%	OA	**89,06%**
											Kappa	0,87

DELIVERABLE 4.1

Access to LC map of Europe and validation data in a digital format

All results are available on FTP server:

ftp://ftp.cbk.waw.pl/

User: cbk_npd1

Password: gj7n2

Please use FTP Client (e.g. FileZilla)

Structure of folders:

S2GLC_Extension\Classifications_of_S2_Tiles – contains final results of classification for S2 tiles saved into GeoTIFF files

S2GLC_Extension\Mosaics_of_classifications – contains LC classification over Europe saved into GeoTIFF files, each representing different latitude and longitude zone of the Universal Transverse Mercator coordinate system

S2GLC_Extension\Preview_of_LC_map_of_Europe – contains the preview of the final LC map of Europe

S2GLC_Extension\Validation – error matrices for validation tiles, countries and final LC map