TECHNISCHE UNIVERSITÄT
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Faculty of Geosciences, Geotechnics and Mining
Institute of Mine Surveying and Geodesy

Tutorial
QGIS for remote sensing applications

Applied Spatial Data Analysis

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Contents

1 Loading Sentinel-2 data

Remote sensing is the non-contact exploration of the Earth's surface, including the Earth's atmosphere. Remote sensing data are provided, for example, by ESA's Copernicus Program. The European Union's Earth Observation Program Copernicus, formerly known as the Global Monitoring for Environment and Security (GMES), is a program set up in 1998 by the European Commission and the European Space Agency.

"Goal of the Sentinel Program is to replace the older Earth observation missions which have retired or are currently nearing the end of their operational life span. The Sentinel Program consists of six missions. Each mission focuses on a different aspect of Earth observation: Atmospheric, Oceanic and Land monitoring and the data is of use in many applications." [3]

An overview of the missions can be found here:
https://sentinels.copernicus.eu/web/sentinel/missions

For remote sensing tasks involving land use classification, **Sentinel-2 data** are used.
"Sentinel-2 provides high-resolution optical imagery for land services. It provides for example, imagery of vegetation, soil and water cover, inland waterways and coastal areas. Sentinel-2 also delivers information for emergency services. The two polar-orbiting satellites Sentinel-2A and Sentinel-2B were respectively launched on 22 June 2015 and on 7 March 2017." [3]

Additional facts about the Copernicus Sentinel-2 mission from European Space Agency - ESA are shown here:

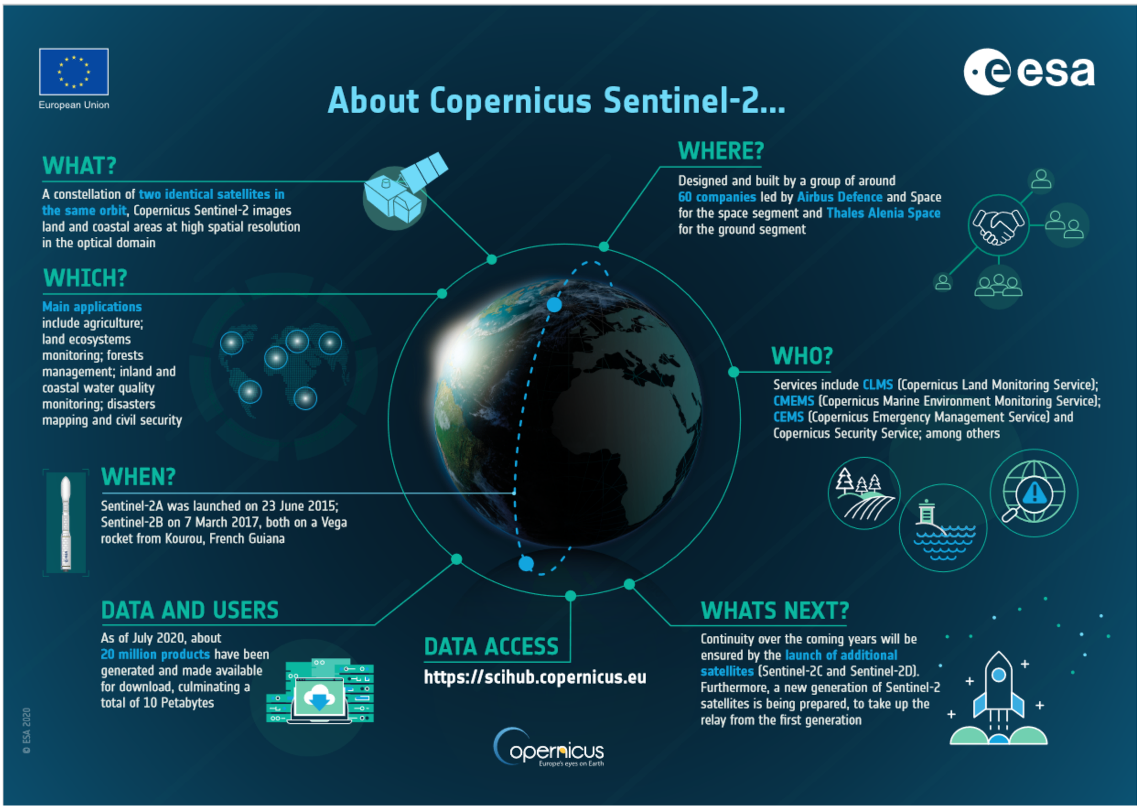

Fig. 1: Facts about Copernicus Sentinel-2 mission

Sentinel-2 offers the user two different types of products:

Name	High-Level Description	Production & Distribution	Data Volume
Level-1C	Top-Of-Atmosphere reflectances in cartographic geometry	Systematic generation and online distribution	~600 MB (each 100km x 100km^2)
Level-2A	Bottom-Of-Atmosphere reflectances in cartographic geometry	Systematic and on-User side (using Sentinel-2 Toolbox)	~800 MB (each 100km x 100km^2)

Fig. 2: Sentinel-2 product types

1.1 Load Sentinel-2 data from ESA website

Sentinel-2 data from ESA can be downloaded here:
https://scihub.copernicus.eu/dhus/#/home

On the website, an area can be selected on the map for which Sentinel data should be downloaded. In the filter, specific search criteria, such as the acquisition period or the product type and cloud cover. can be selected to narrow down the search. Care should be taken to select Level-2A data for remote sensing tasks. The satellite image should be taken during the daytime if possible, and preferably at a time of year when snow is not covering the ground. Cloud cover should be as small as possible (< 1 %).

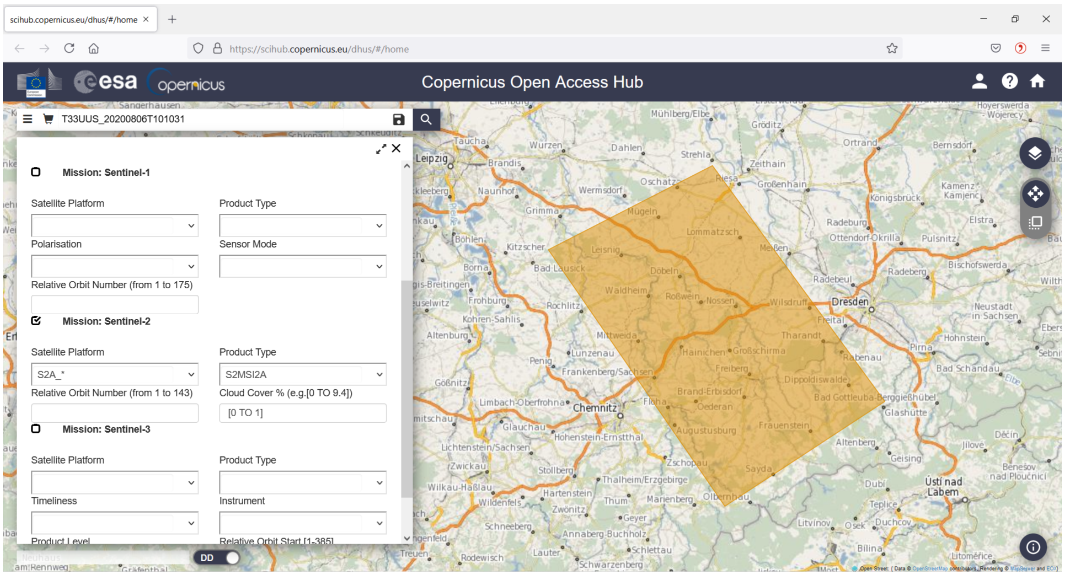

Fig. 3: Download Sentinel data from ESA website

From the results of the search, a satellite image can be selected and downloaded.

The following satellite image is used in this tutorial:
→ Filename: S2A_MSIL2A_20200806T101031_N0214_R022_T33UUS_20200806T115620

Once the sentinel data has been downloaded from the Copernicus website, the individual bands can be imported as a (raster) JP2-File.

1.2 Load Sentinel-2 data within QGIS

The Sentinel data can also be downloaded within QGIS. For this and also for the following steps the "Semi-Automatic Classification Plugin" should be installed.

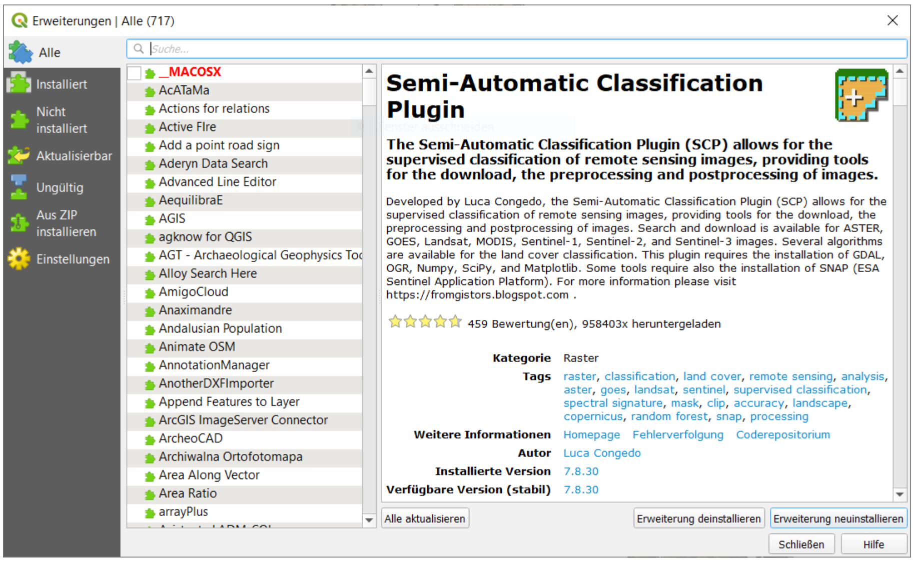

Fig. 4: Semi-Automatic Classification Plugin

The plugin provides the "Download products" tool. In the search, by entering coordinates or selecting an area on the map, it is possible to specify for which region sentinel data is searched. Also here the recording period and the cloud cover can be filtered. The run-button starts the download.

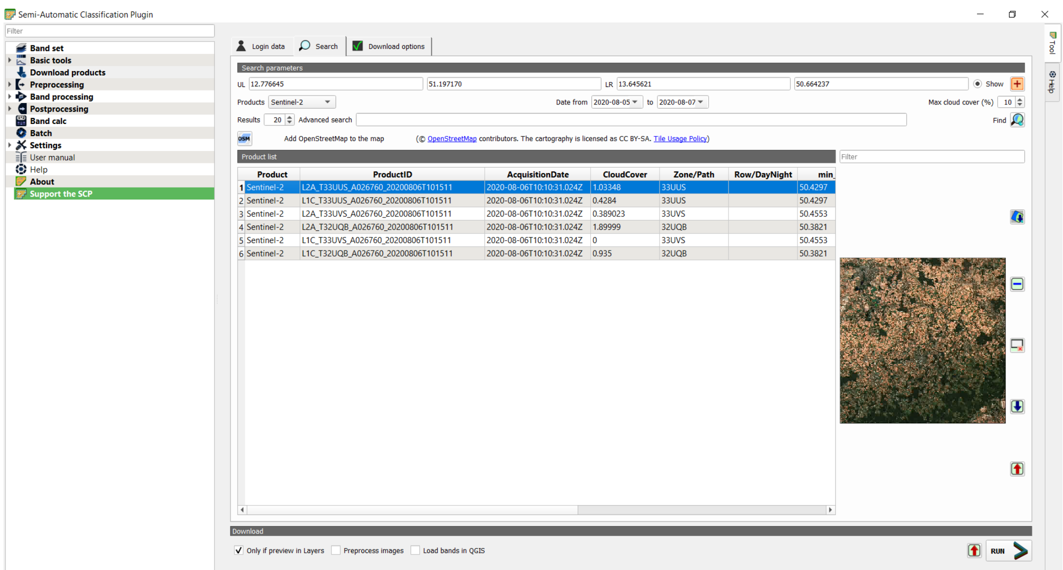

Fig. 5: Download Sentinel data in QGIS

In this tutorial the district Mittelsachsen (middle saxony) shall be examined. For this purpose, the sentinel data must be tailored to the district.

The outline of districts and municipalities can be taken from the administrative boundaries of Saxony. The administrative boundaries can be downloaded as a shapefile here: https://www.geodaten.sachsen.de/downloadbereich-verwaltungsgrenzen-4344.html

With the intersection, the raster satellite image can be applied to the layer mask of the polygon of Mittelsachsen. The blank value should be set to zero.

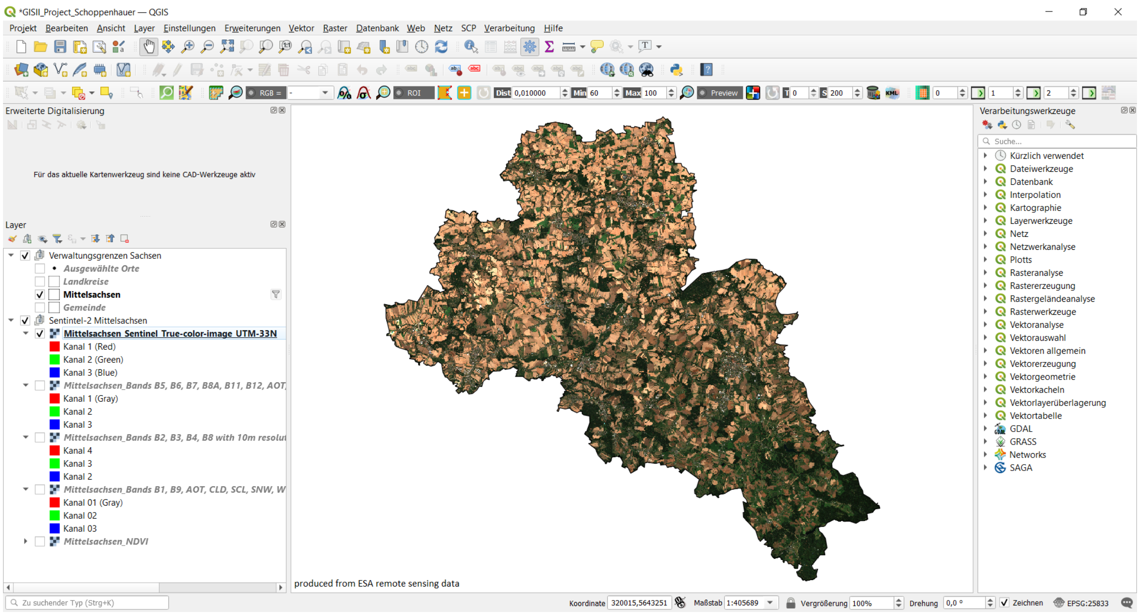

Fig. 6: Satelite image of Mittelsachsen (true color)

2 Calculating indices

Sentinel-2 provides a multispectral image with several spectral bands. The following overview of the Sentinel-2 bands (Fig. 7) refers to the L2A products:

Name	Description	Resolution
B01	Coastal aerosol, 442.7 nm (S2A), 442.3 nm (S2B)	60m
B02	Blue, 492.4 nm (S2A), 492.1 nm (S2B)	10m
B03	Green, 559.8 nm (S2A), 559.0 nm (S2B)	10m
B04	Red, 664.6 nm (S2A), 665.0 nm (S2B)	10m
B05	Vegetation red edge, 704.1 nm (S2A), 703.8 nm (S2B)	20m
B06	Vegetation red edge, 740.5 nm (S2A), 739.1 nm (S2B)	20m
B07	Vegetation red edge, 782.8 nm (S2A), 779.7 nm (S2B)	20m
B08	NIR, 832.8 nm (S2A), 833.0 nm (S2B)	10m
B8A	Narrow NIR, 864.7 nm (S2A), 864.0 nm (S2B)	20m
B09	Water vapour, 945.1 nm (S2A), 943.2 nm (S2B)	60m
B11	SWIR, 1613.7 nm (S2A), 1610.4 nm (S2B)	20m
B12	SWIR, 2202.4 nm (S2A), 2185.7 nm (S2B)	20m
AOT	Aerosol Optical Thickness map, based on Sen2Cor processor	10m
SCL	Scene classification data, based on Sen2Cor processor, codelist	20m
SNW	Snow probability, based on Sen2Cor processor	20m
CLD	Cloud probability, based on Sen2Cor processor	20m
CLP	Cloud probability, based on s2cloudless (more)	160m
CLM	Cloud masks (more)	160m

Fig. 7: Sentinel-2 bands

2.1 Band Combinations

To better understand the features in imagery band combinations are used. By using band combinations, specific information from an image can be extracted. For example, there are band combinations that highlight geologic, agricultural, or vegetation features in an image.

The **natrual color** band combination uses the red (B4), green (B3) and the blue (B2) channels. The natural color image is already seen in Fig. 6.

The **color infrared** band combination uses the near-infrared (B8), red (B4) and green (B3) band and is meant to emphasize healthy and unhealthy vegetation. By using the near-infrared (B8) band, it's especially good at reflecting chlorophyll. This is why in a color infrared image, denser vegetation is red. But urban areas are white.
The color infrared image is shown in Fig. 8.

Other useful band combinations are explained here:
https://gisgeography.com/sentinel-2-bands-combinations/

Band combinations can be displayed by collecting the desired bands in a bandset (Fig. 11) and choosing this bandset in the "Band Combination" tool of the Semi-Automantic Classification Plugin.

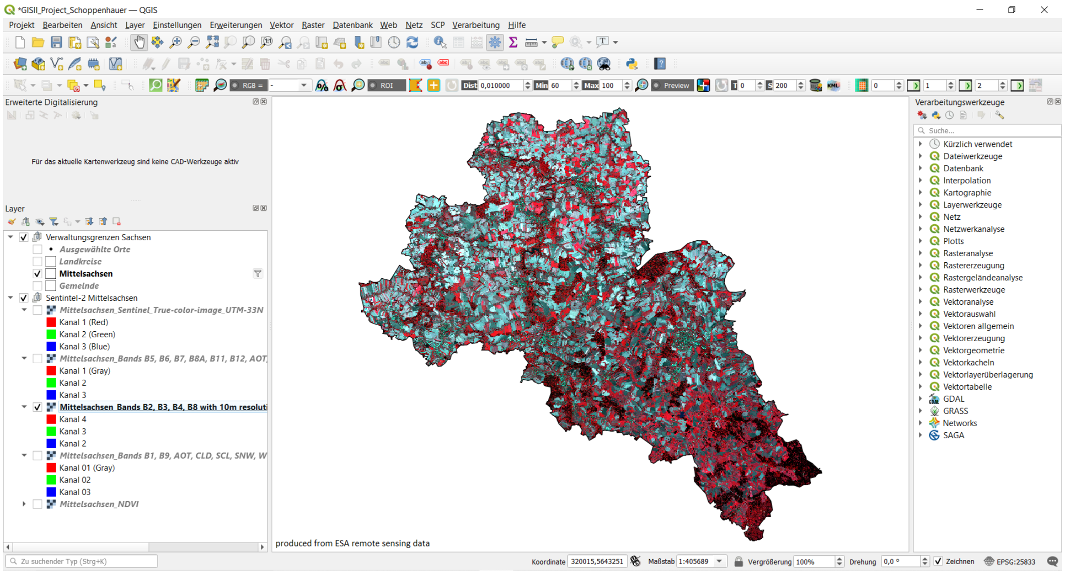

Fig. 8: Color Infrared Band Combination

2.2 Normalized Difference Vegetation Index

To understand the information of the bands even better, different indices can be calculated from band combinations. An important index in land use classification by remote sensing is the **Normalized Difference Vegetation Index** (NDVI).

"Because near-infrared (which vegetation strongly reflects) and red light (which vegetation absorbs), the vegetation index is good for quantifying the amount of vegetation." [7]

The formula for the normalized difference vegetation index is:

$$NDVI = \frac{NIR - RED}{NIR + RED} = \frac{Band\ 8 - Band\ 4}{Band\ 8 + Band\ 4} \tag{1}$$

The value range of the NDVI is -1 to 1.

"Negative values of NDVI (values approaching -1) correspond to water. Values close to zero (-0.1 to 0.1) generally correspond to barren areas of rock, sand, or snow. Low, positive values represent shrub and grassland (approximately 0.2 to 0.4), while high values indicate temperate and tropical rainforests (values approaching 1)." [7]

The NDVI can be determined in QGIS using the raster calculator. The result is a new layer with the NDVI values.

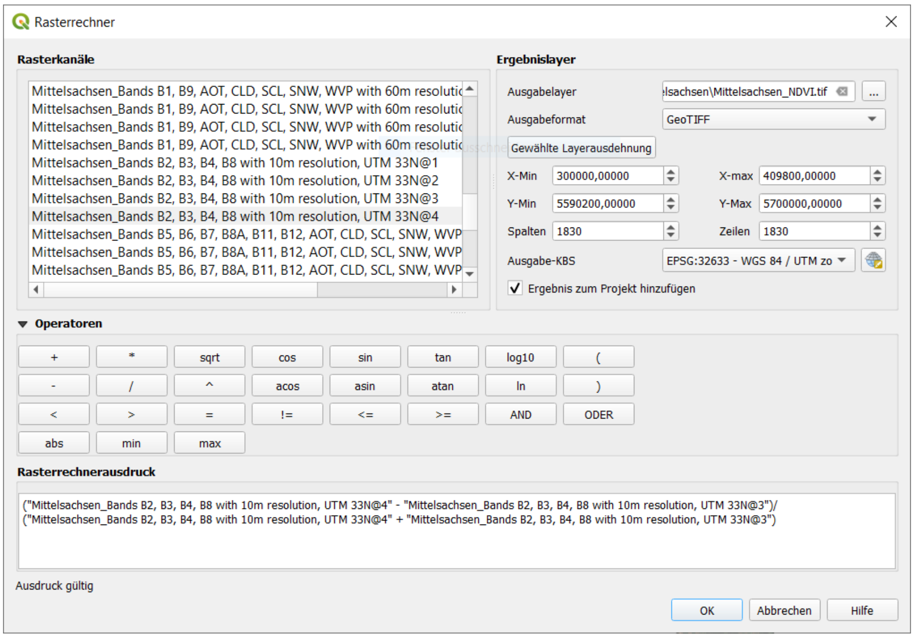

Fig. 9: Calculate NDVI

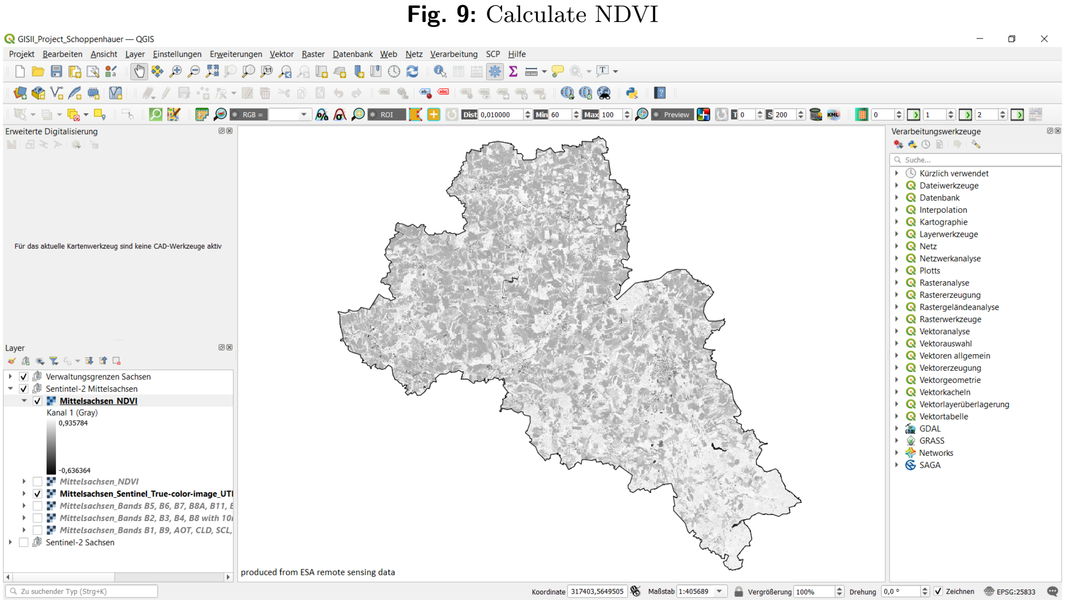

Fig. 10: Result of NDVI

The NDVI values for Mittelsachsen range from around -0,64 to 0,94.

The NDVI layer can now be used as further information for the upcoming tasks.

3 Land Use Classification

For the classification, all important bands of the sentinel data must be in one bandset. For this purpose, the "Bandset" tool of the Semi-Automatic Classification Plugin can be used. After installing the plug-in, the "SCP" tab appears in the control panels. The individual tools can be found and selected via this tab.

In the single band list the desired bands are selected and added to the bandset with the + symbol.

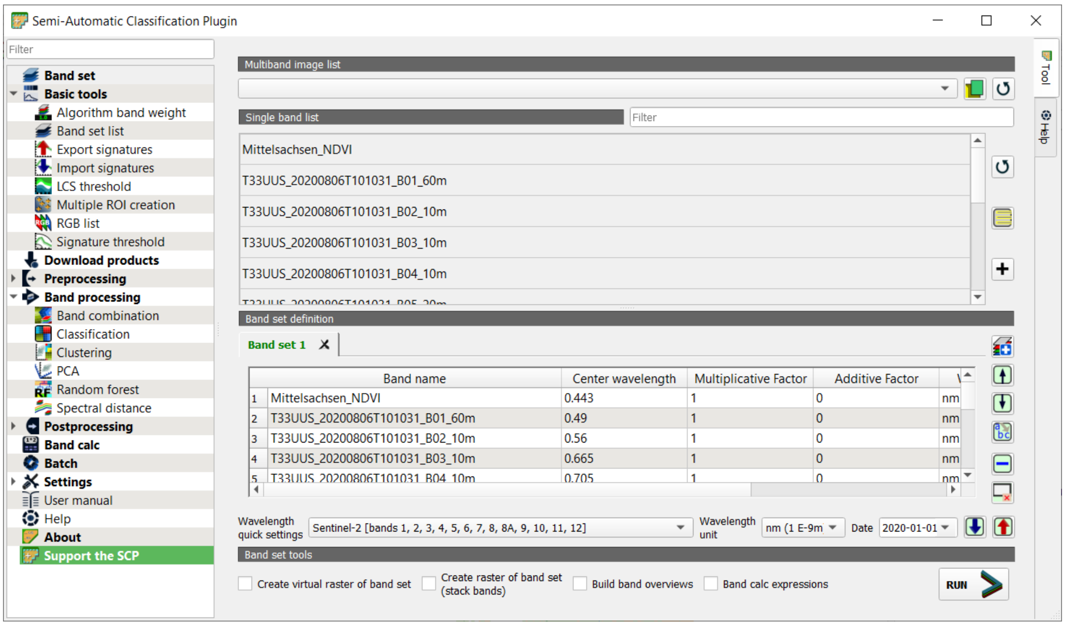

Fig. 11: Create a bandset

3.1 Unsupervised Classification (Clustering)

"Unsupervised classification is where the outcomes (groupings of pixels with common characteristics) are based on the software analysis of an image without the user providing sample classes. The computer uses techniques to determine which pixels are related and groups them into classes. The user can specify which algorism the software will use and the desired number of output classes but otherwise does not aid in the classification process. However, the user must have knowledge of the area being classified when the groupings of pixels with common characteristics produced by the computer have to be related to actual features on the ground (such as wetlands, developed areas, coniferous forests, etc.)." [4]

The unsupervised classification itself is performed with the "Clustering" tool. Input for the clustering is the created bandset. Two different methods (K-means or ISODATA algorithm) can be used.

For the example, four classes are to be created.

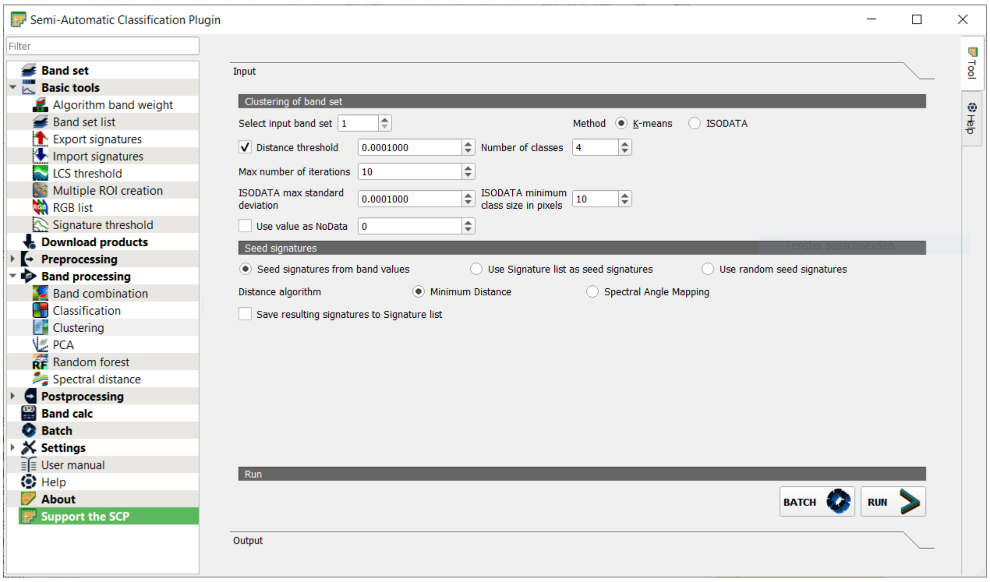

Fig. 12: Settings for clustering

The generated classes must subsequently be assigned the land use types based on the normal color image. The assignment of the result classes to specific land use types is not entirely clear. In comparison with the true-color satellite image, it can be seen that water areas are detected very well. Arable land is also recognized correctly for the most part. Forest areas, built-up areas (urban) and meadows are not clearly classified.

The result with the assigned classes can be seen here:

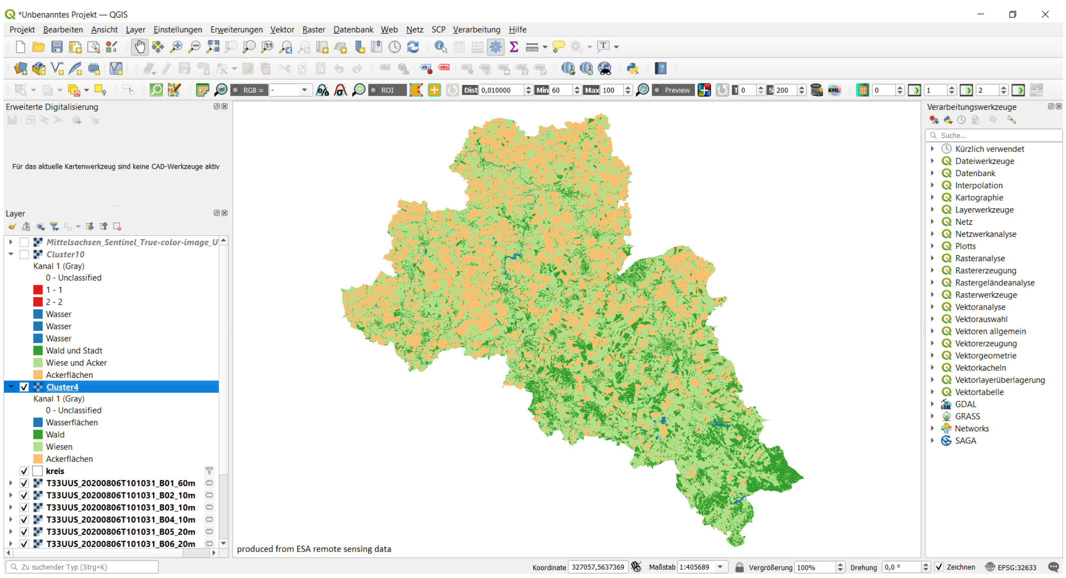

Fig. 13: Result of clustering with 4 classes

To improve the result, eight classes are to be generated in another experiment.

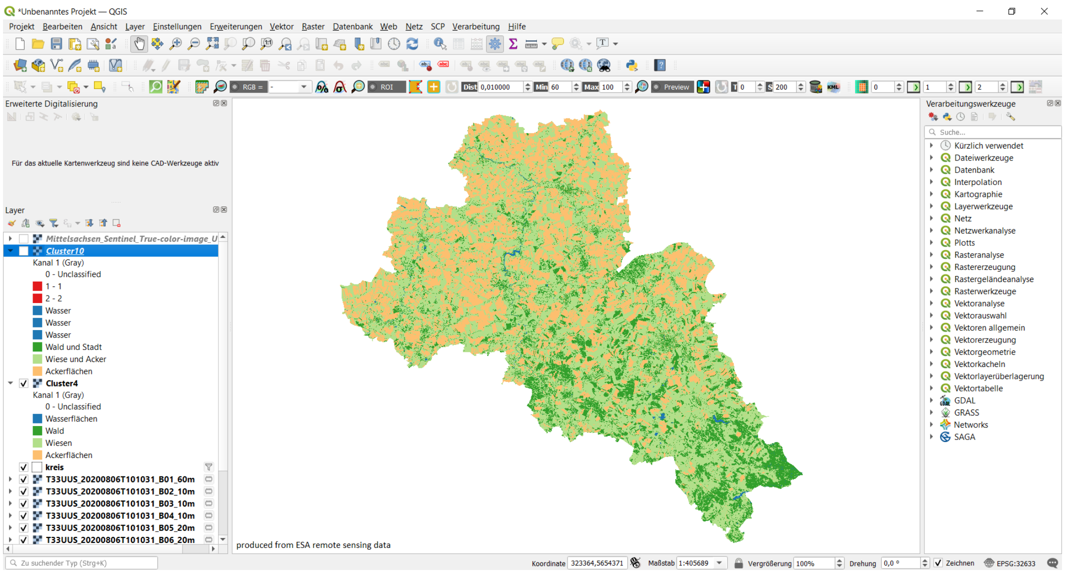

Fig. 14: Result of clustering with 8 classes

If clustering is done with more classes, the result is not necessarily better. More classes are created, however, classes can be clustered together because they are of the same land use type. In the example, 3 classes were created, all of which can be assigned to water areas.

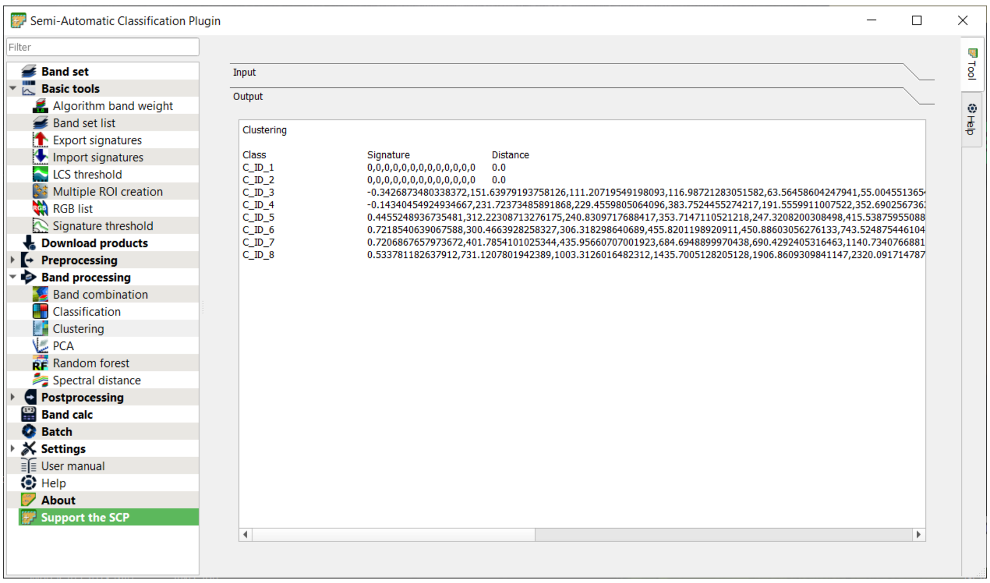

Fig. 15: Signatures of clustering with 8 classes

The class signatures show that the first two classes have no content. Merging the classes produces the same classification result as clustering with 4 classes. It is noticeable that urban areas were not recognized as a separate class.

Thus, increasing the number of classes does not necessarily improve the result.

3.2 Supervised Classification

"Supervised classification is based on the idea that a user can select sample pixels in an image that are representative of specific classes and then direct the image processing software to use these training sites as references for the classification of all other pixels in the image. Training sites (also known as testing sets or input classes) are selected based on the knowledge of the user. The user also sets the bounds for how similar other pixels must be to group them together. These bounds are often set based on the spectral characteristics of the training area, plus or minus a certain increment (often based on "brightness" or strength of reflection in specific spectral bands). The user also designates the number of classes that the image is classified into. Many analysts use a combination of supervised and unsupervised classification processes to develop final output analysis and classified maps." [4]

Usually, supervised classification provides a better result than unsupervised classification.

Supervised classification begins with the selection of training areas. In this example, the same classes that were generated in the unsupervised classification are to be recognised: water, forest, arable and urban areas. The SCP Dock where the training areas are selected and the classification is performed is opened by "Show plugin" of the SCP tab.

If a file with training data already exists, it can be imported via the Training Input of the SCP Dock. When training data is defined for the first time, a new file must be created in which the training data is to be stored (1). The training area can be selected as a "Region of Interests" (ROI) polygon (2). With a right click the polygon is closed.

A masterclass and a subclass can then be assigned to the polygon (3). With the save symbol (4) the training areas are added to the training data files.

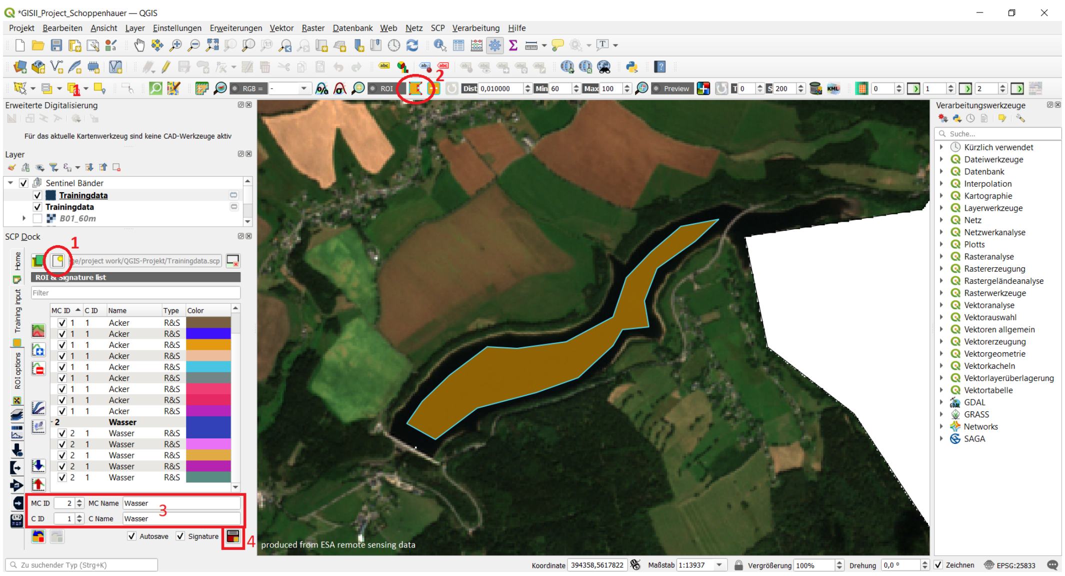

Fig. 16: Selecting the training areas

Each class should contain unique typical sample areas of the class, this should be done very accurately. Create at least 20 representative training areas for each class.

Once all training areas are selected, the supervised classification can be performed in the Semi-Automatic Classification Plugin under "Band processing", "Classification". In this example, only the master classes are relevant for the classification.

3.2.1 Minimum Distance Classification

“The Minimum Distance Classification uses the mean vectors of each endmember and calculates the Euclidean distance from each unknown pixel to the mean vector for each class. All pixels are classified to the nearest class unless a standard deviation or distance threshold is specified, in which case some pixels may be unclassified if they do not meet the selected criteria.” [6]

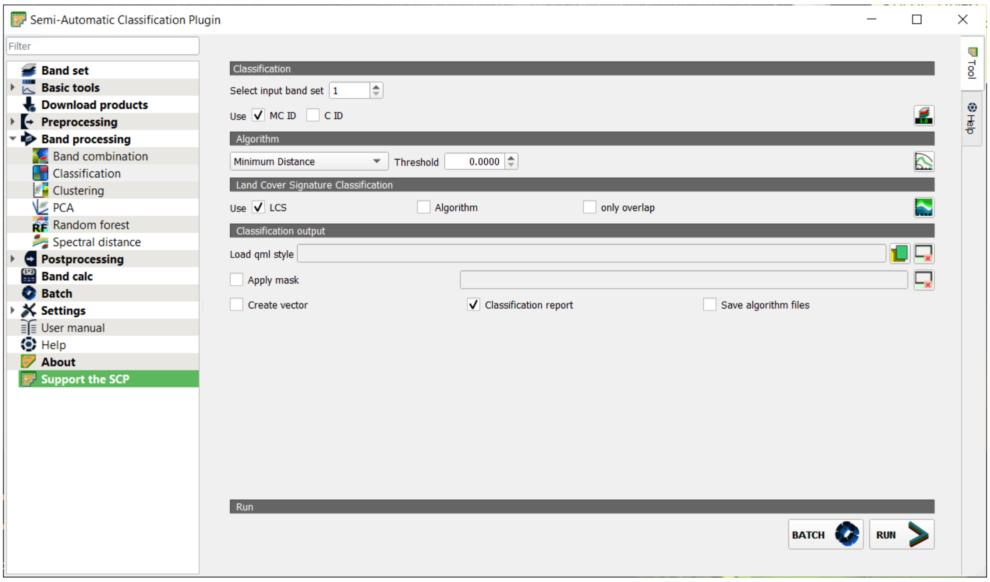

Fig. 17: Classification Settings for Minimum Distance

The result of the supervised classification with minimum distance has some gaps, but the land use classes were mostly correctly assigned. Improvement of the result is possible by adding more training areas or changing treshholds.

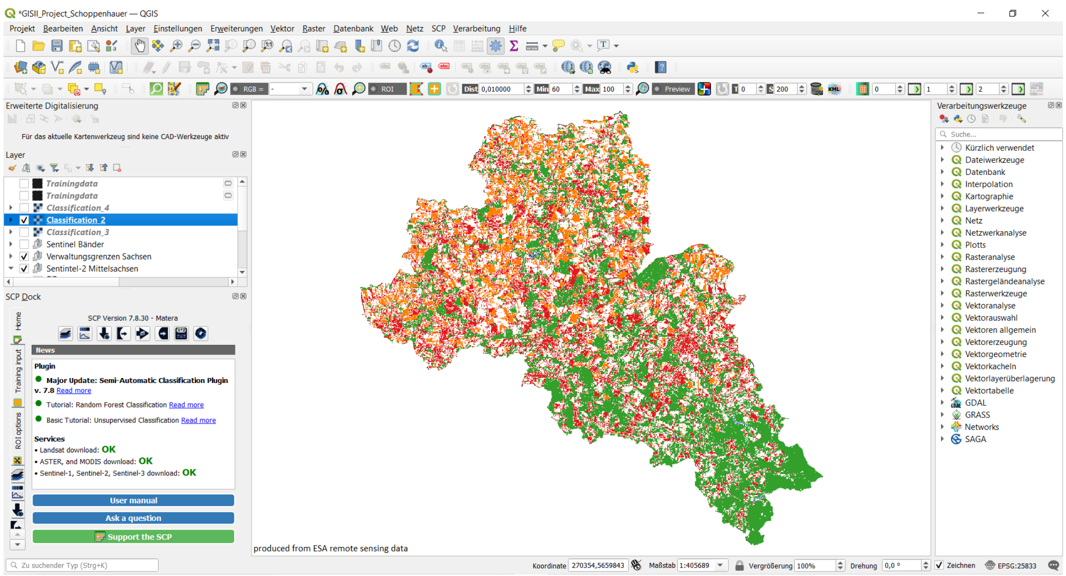

Fig. 18: Result of Classification with Maximum Likelihood

3.2.2 Maximum Likelihood Classification

"The Maximum Likelihood Classification assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Unless you select a probability threshold, all pixels are classified. Each pixel is assigned to the class that has the highest probability. If the highest probability is smaller than a threshold you specify, the pixel remains unclassified." [6]

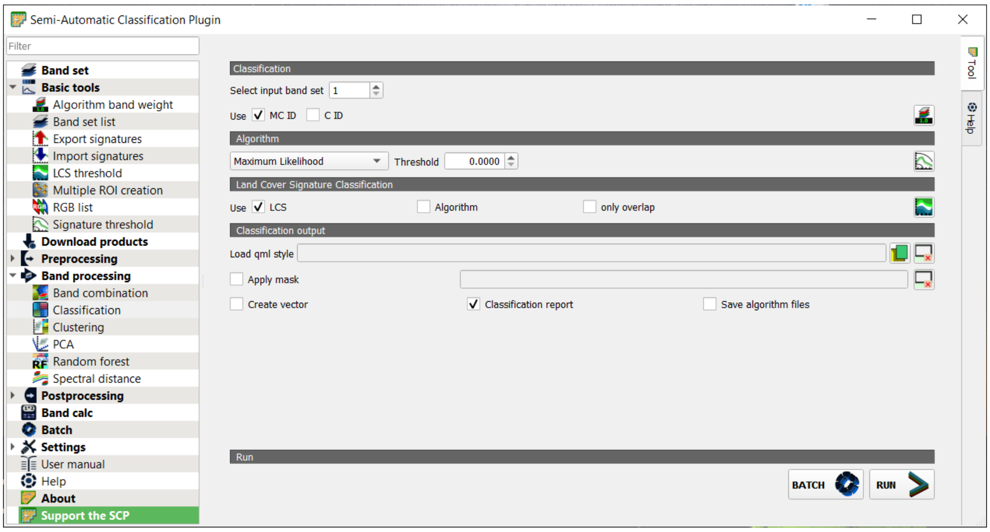

Fig. 19: Classification Settings for Likelihood

The result of the supervised classification with maximum likelihood agrees relatively well with the stallite image.

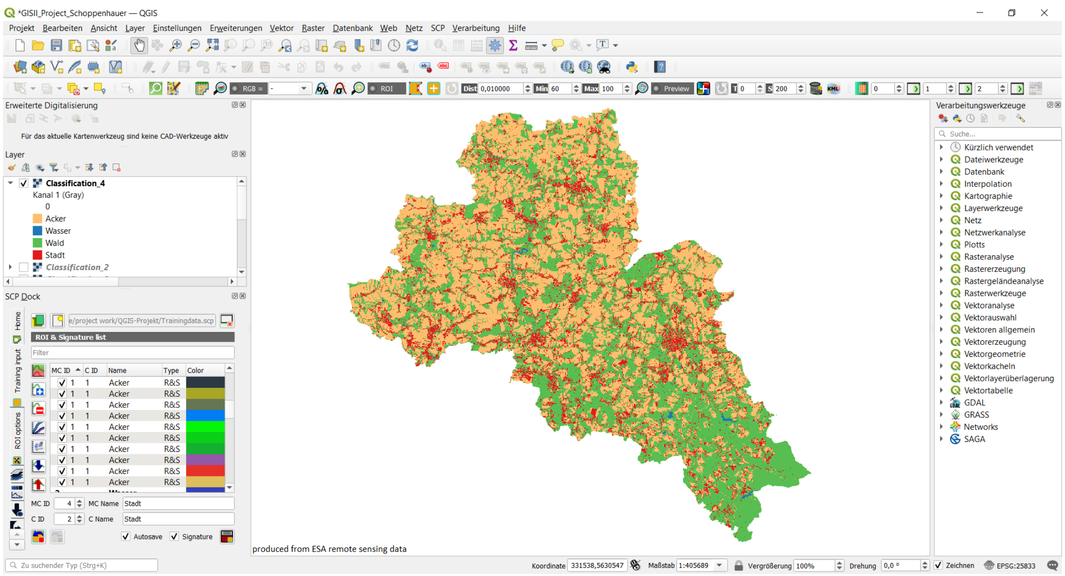

Fig. 20: Result of Classification with Maximum Likelihood

With more classes (which must be significantly different), the result would probably be even closer to reality.

3.3 Accuracy Assessment

The SCP plugin offers the possibility to output a classification report in postprocessing. The input for this is the classification result. The result is shown here as an example of the result of the supervised classification with the most likelihood method.

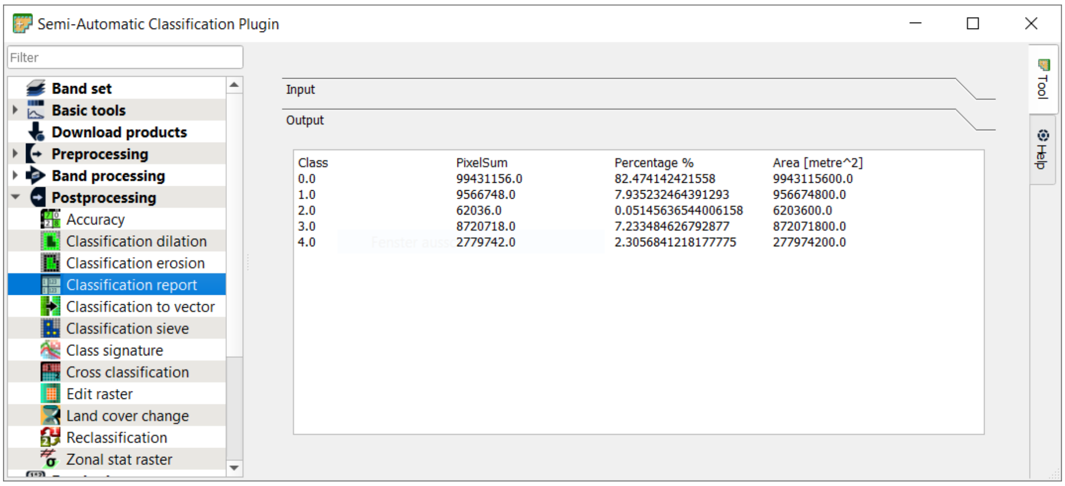

Fig. 21: Classification Report

The class IDs are to be assigned to the following land use types:
1 - Agricultural areas
2 - Water bodies
3 - Forest areas
4 - Urban areas

The zero class in this case is the area of the satellite image that lies outside Mittelsachsen (shown in black).

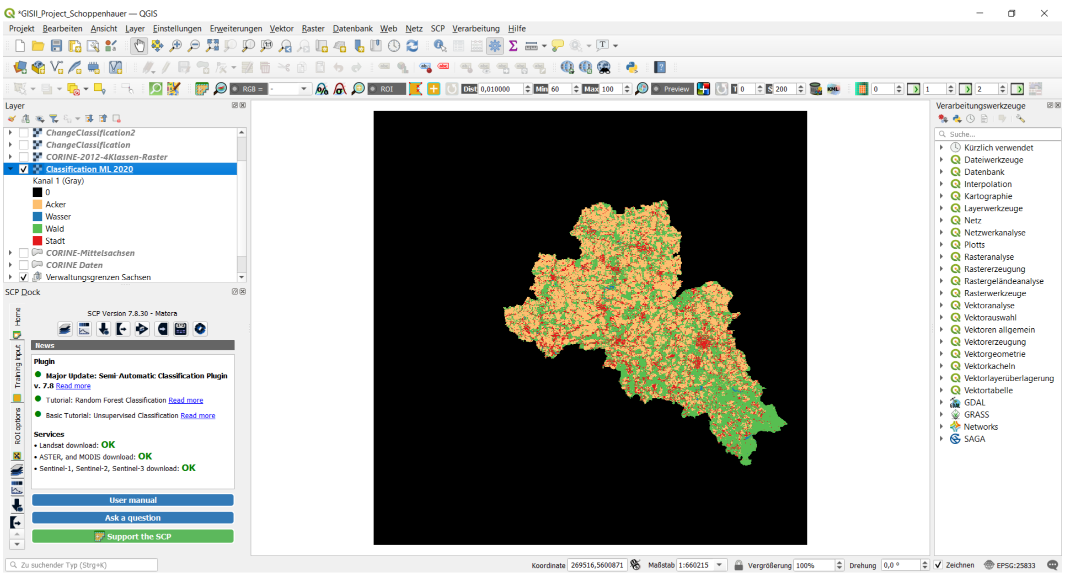

Fig. 22: Classification Zero Class

To estimate the accuracy of the land cover classification, a sample of reference observations from the study area shall be selected and compared with the result of the classification.

For this purpose, a new training input file must be created (see supervised classification). Only the single layer of the classification may now be in the bandset. On the start screen, the min and max size of the ROIs must be set to 1. The reference observations are then only one pixel in size.

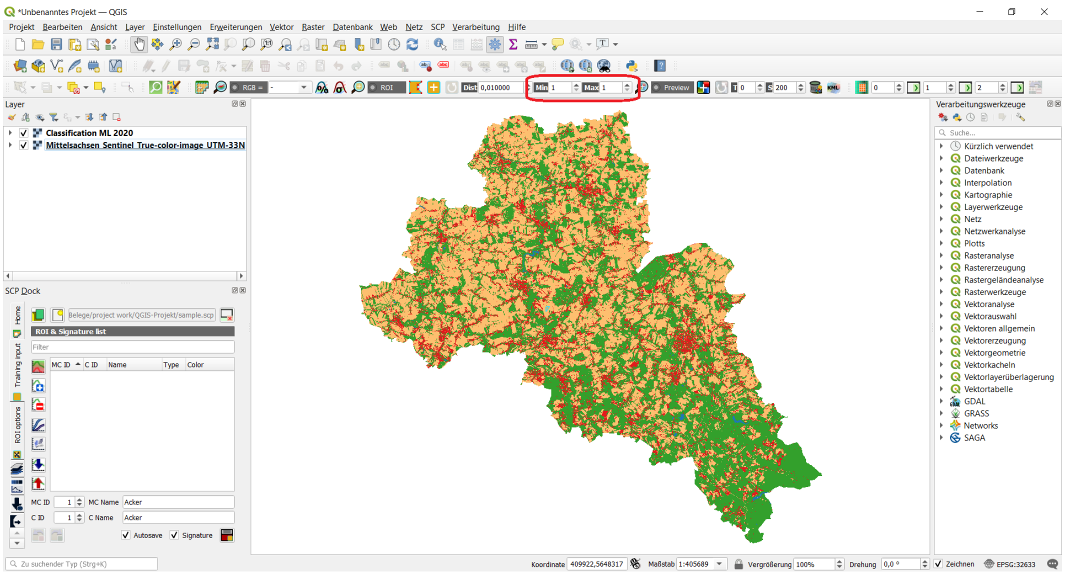

Fig. 23: Define size of ROI samples

The random samples are created with "Multiple ROI creation". A sufficient number of samples should be created for each class. Here 10 are created per class. In order to determine the class, raster == 1 or raster == 2 etc. must be used. The samples are created with "create points".

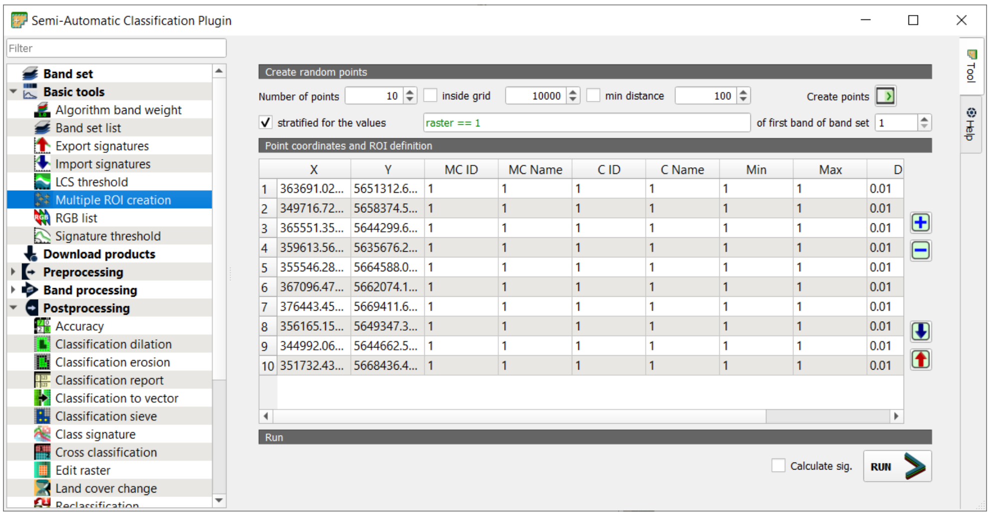

Fig. 24: Multiple ROI creation - random samples

The signatures do not have to be calculated now, as the spectral signatures are not to be calculated here. With RUN the samples are transferred to the training file.

Each ROI is then assigned the true land use type using a satellite image. For this purpose, the value of the masterclass MC ID can be selected and changed by entering the ID of the true class.

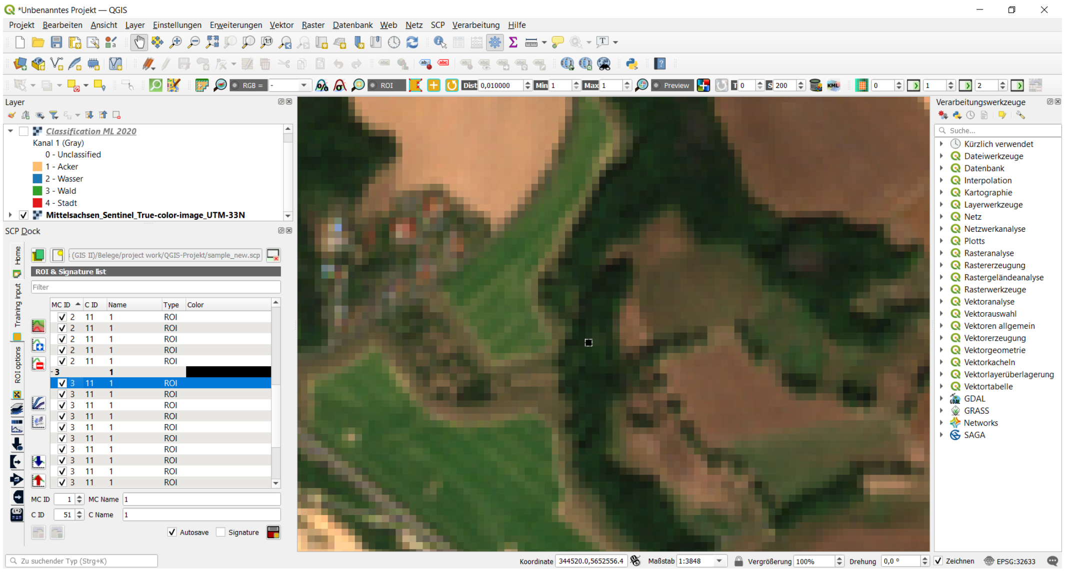

Fig. 25: Multiple ROI creation - random samples

This ROI, for example, is located in a forest and is therefore assigned Master Class ID 3.

The accuracy of the classification can then be checked with the tool “Accuracy” in the post-processing of the SCP plugin. Input is on the one hand the result of the classification as and the samples just defined. The vector field MC ID must be selected, as this identifies the land use class.

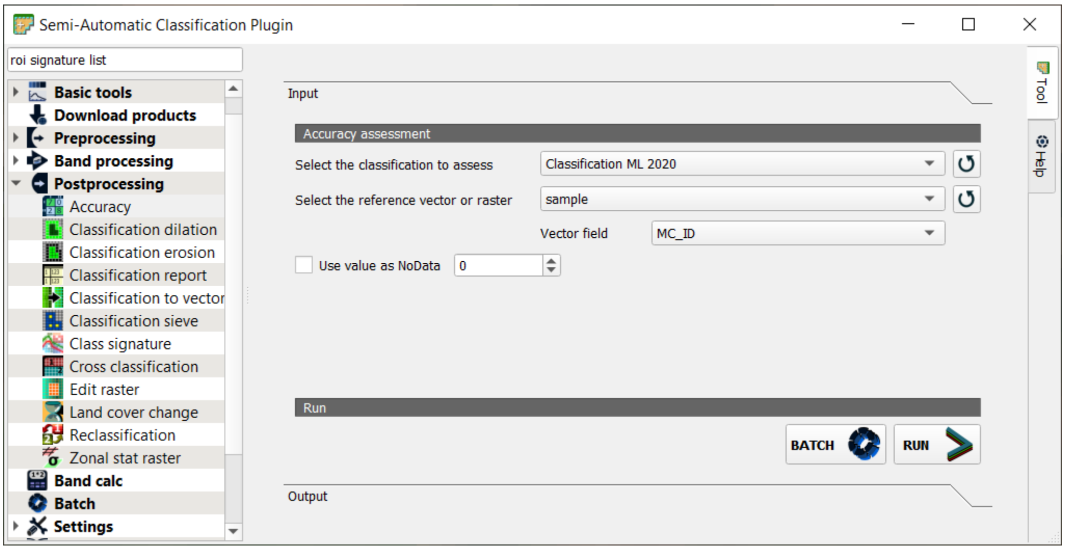

Fig. 26: Input for Accuracy Assessment

The output of the accuracy analysis is an pixel based and an area based error matrix. It can be seen how many reference observations were actually assigned correctly and which were assigned to an incorrect land use type during classification.

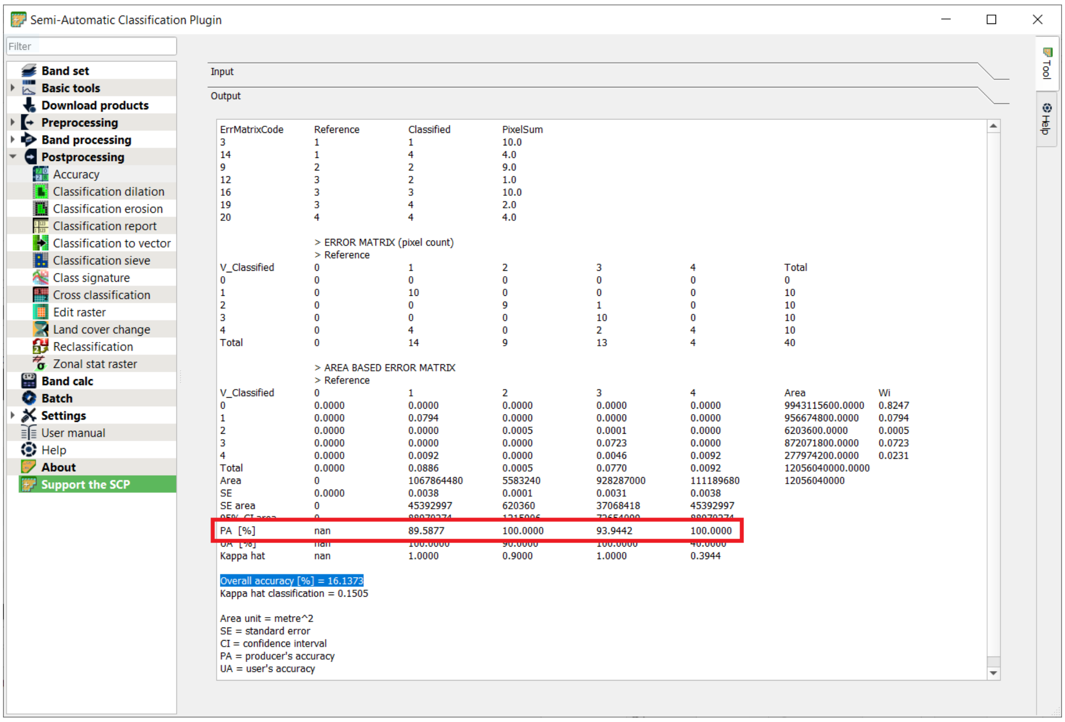

Fig. 27: Output of Accuracy Assessment

It can be seen that all land use classes in the classification are correct with about 90 % probability or more (values in the red rectangle).

From the error matrix, an overall accuracy is calculated, which in this case corresponds to only 16.14 %. The overall accuracy is so low here because the reference observations of the zero class are also included in the calculation. However, no reference samples were generated for the zero class and could therefore not be correctly or incorrectly assigned.

The accuracy of the individual classes shows that the classification provides a good result.

4 Data Analysis

4.1 Spectral Signatures

Spectral signatures are generated using the band information presented by the satellite image. Spectral signature indicate the reflectance as a function of the wavelength. Classification algorithms use spectral signatures to label the pixels of the image. [5]

In the SCP Dock, a spectral signature plot can be created for the selected training areas.

The spectral signatures can be displayed individually for each training area. For reasons of clarity and understanding, only one spectral signature per class should be displayed. For this purpose, all training areas of a class are selected in the SCP Dock and these items are merged (via right mouse click).

The following image shows that each land cover type has a unique signature, therefore, this spectral signature can be used for the classification of materials such as agriculture, vegetation, water and built-up areas.

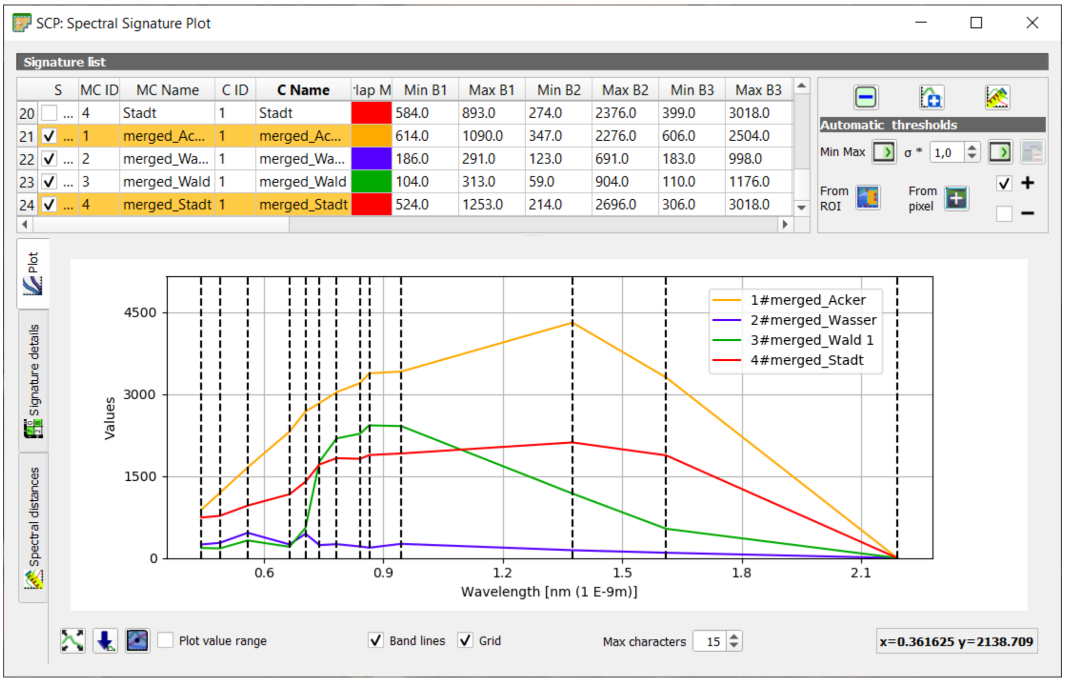

Fig. 28: Spectral signatures of merged training classes

The spectral signatures of the land use classes should be as different as possible at the respective wavelengths of the bands so that the classes can be easily distinguished.

The value range also shows how equal or unequal the properties of the respective class are. For the best possible results of the classification, the values should scatter as little as possible.

More details of the spectral signatures are shown in the table:

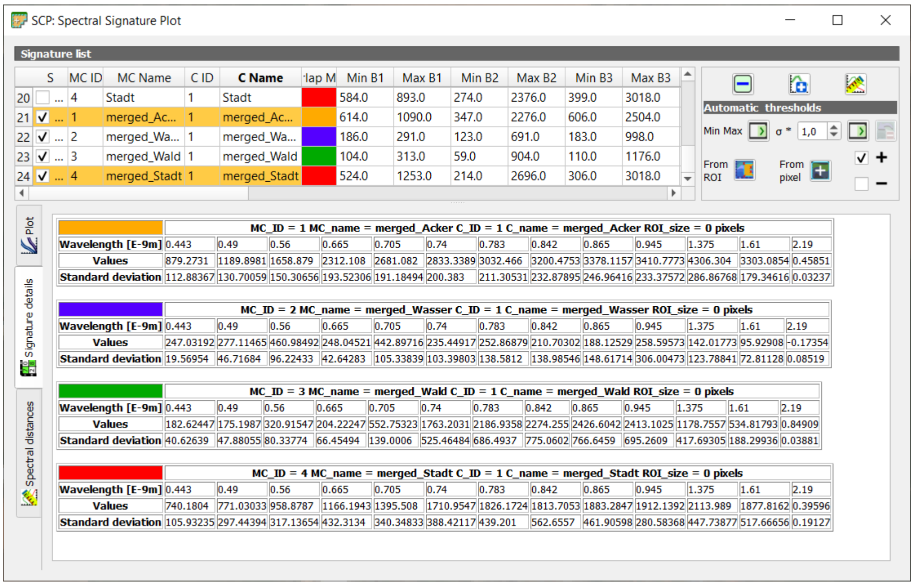

Fig. 29: Details of the spectral signatures of merged training classes

The spectral distances between the classes, which can be calculated from the spectral signatures, should preferably have the value two, so that the classification alogithm can distinguish the classes.

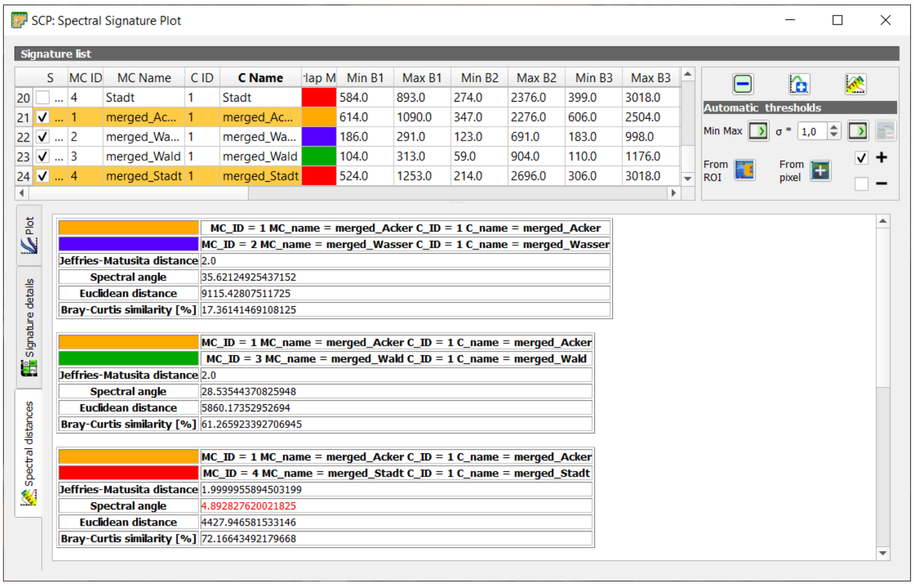

Fig. 30: Spectral distances of merged training classes

4.2 Correlations between input channels

Correlations between the input channels can be made clear with the help of a scatterplot.

The Semi-Automatic Classification Plugin contains a tool that can be used to generate scatterpolts. It is possible to select which input bands are to be compared with each other. In addition, the scatterplot can be calculated for a temporary region of interest (ROI), the current image section or the entire image.

Desired ROIs can be selected from the training areas and added to the scatterplot (here one ROI per land use class). The scatterplot then looks as follows, for example:

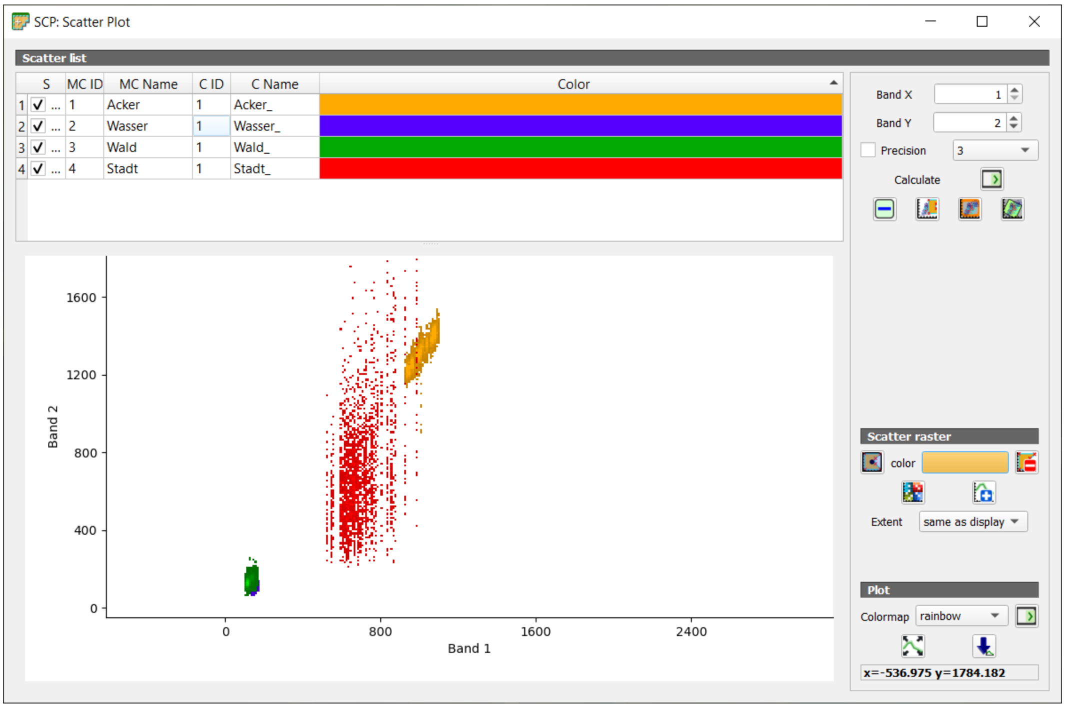

Fig. 31: Scatterplot of training areas

Similar to the spectral signatures, it can be seen here how the land use classes differ.

It can also be seen here that the urban class occupies a very large area. This is because the urban areas have very different characteristics, as there are built-up areas as well as trees and partly parks. The diversity of urban areas results in the fact that they are often not well recognised and classified in the classification.

5 Change Detection with CORINE-Data

CORINE Land Cover (CLC) is a project for the uniform classification of the most important forms of land cover that was initiated by the EU Commission. CORINE stands for Coordination of Information on the Environment. "The CORINE Land Cover (CLC) inventory was initiated in 1985 (reference year 1990). Updates have been produced in 2000, 2006, 2012, and 2018. It consists of an inventory of land cover in 44 classes. CLC uses a Minimum Mapping Unit (MMU) of 25 hectares (ha) for areal phenomena and a minimum width of 100 m for linear phenomena." [1]

More information you will find at: https://land.copernicus.eu

After the CORINE data (vector data) has been imported, the official style according to the 44 land cover and land use classes can be selected in the layer properties (right mouse click on layer).

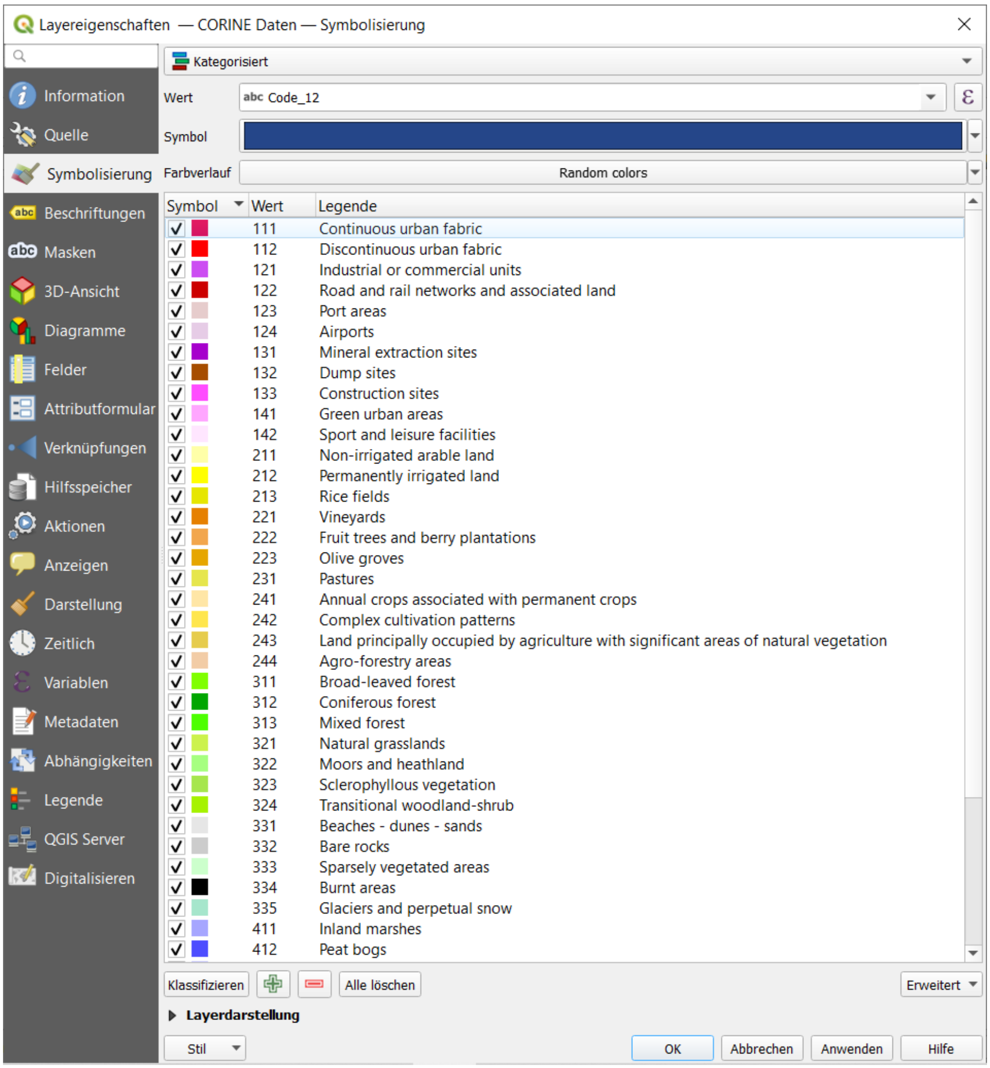

Fig. 32: CORINE classes

Each CORINE land use class is assigned a unique code. The code values are divided into three levels, which groups the land use classes into master classes and subclasses.
For example, all classes whose code starts with a 1 belong to the artificial surfaces and all classes with a 2 as the first digit belong to the agricultural areas. The second digit of the code divides the master classes into subclasses.
Thus, land use areas with a code beginning with 11 belong to urban fabric and those beginning with 12 to industrial, commercial and transport units. Both subclasses belong to the agricultural surfaces master class.
The third level of the code contains the actual land use classes.

Level 1	Level 2	Level 3
1 Artificial surfaces	11 Urban fabric	111 Continuous urban fabric
		112 Discontinuous urban fabric
	12 Industrial, commercial and transport units	121 Industrial or commercial units
		122 Road and rail networks and associated land
		123 Port areas
		124 Airports
	13 Mine, dump and construction sites	131 Mineral extraction sites
		132 Dump sites
		133 Construction sites
	14 Artificial, non-agricultural vegetated areas	141 Green urban areas
		142 Sport and leisure facilities
2 Agricultural areas	21 Arable land	211 Non-irrigated arable land
		212 Permanently irrigated land
		213 Rice fields
	22 Permanent crops	221 Vineyards
		222 Fruit trees and berry plantations
		223 Olive groves
	23 Pastures	231 Pastures
	24 Heterogeneous agricultural areas	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
3 Forest and semi natural areas	31 Forests	311 Broad-leaved forest
		312 Coniferous forest
		313 Mixed forest
	32 Scrub and/or herbaceous vegetation associations	321 Natural grasslands
		322 Moors and heathland
		323 Sclerophyllous vegetation
		324 Transitional woodland-shrub
	33 Open spaces with little or no vegetation	331 Beaches, dunes, sands
		332 Bare rocks
		333 Sparsely vegetated areas
		334 Burnt areas
		335 Glaciers and perpetual snow
4 Wetlands	41 Inland wetlands	411 Inland marshes
		412 Peat bogs
	42 Maritime wetlands	421 Salt marshes
		422 Salines
		423 Intertidal flats
5 Water bodies	51 Inland waters	511 Water courses
		512 Water bodies
	52 Marine waters	521 Coastal lagoons
		522 Estuaries
		523 Sea and ocean

Fig. 33: CORINE classes nomenclatur

[2]

A change detection can be used to show the evolution of land use of two time epochs or to compare two classification results. As an example, the classification result of the monitored classification with the maximum likelihood method (Sentinel data from 2020) is compared with the CORINE data from 2012.

For Change Classification, the first step is to tailor the CORINE data to the extent of Mittelsachsen. This can be done with the tool “Crop”.

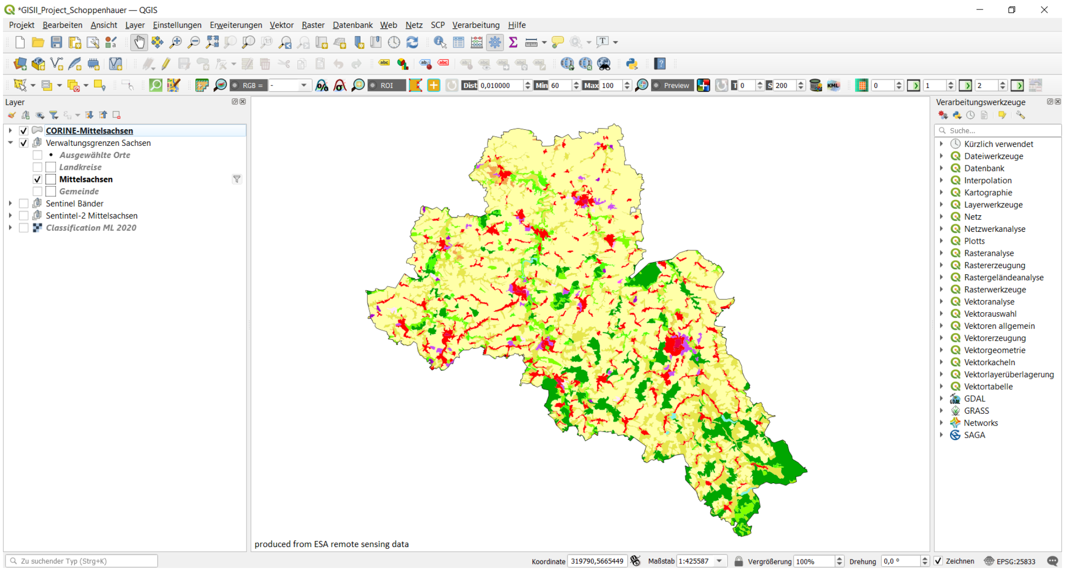

Fig. 34: CORINE data from 2012 of Mittelsachsen

The CORINE data are much more accurate than the own classification due to a large number of classes. In order for the comparison to be meaningful, the CORINE Classes are combined to the extent that only the four classes that were also created by the own classification are included.

The first level of the code of the CORINE classes already groups them into five superclasses, of which the fourth class (wetlands) does not occur in Central Saxony. In order to group the CORINE classes according to level 1 of the code, the code can be divided by 100 and stored as an integer (so that the decimal places are truncated). This can be realised in the attribute value table of the CORINE layer with the field calculator (see Fig. 35). The resulting value (level 1 of the code) is output in a new column.

This results in the following IDs for the CORINE master classes:
1 - Artificial surfaces
2 - Agricultural areas
3 - Forest areas
5 - Water bodies

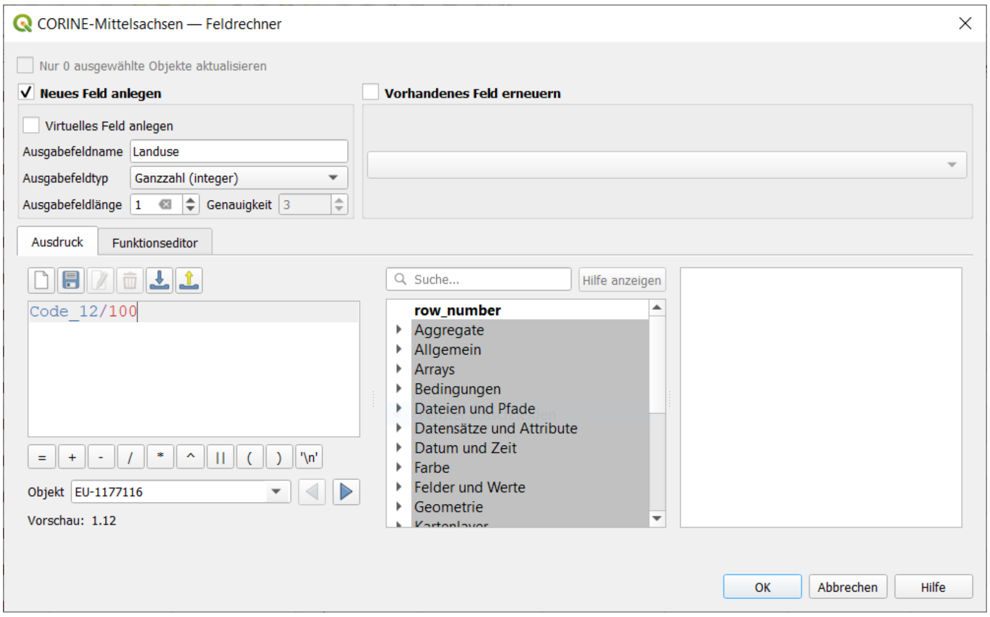

Fig. 35: Combine CORINE classes to 4 land use classes

The combined CORINE Classes then look like the following.
The style must now be adapted to the just calculated level 1 values of the class.

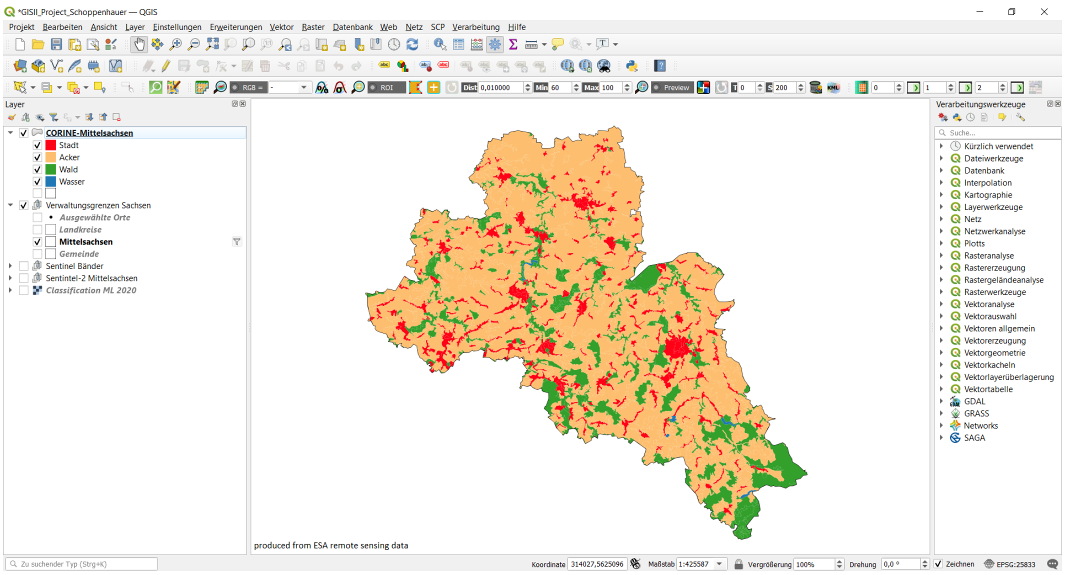

Fig. 36: Combined CORINE classes of Mittelsachsen

Afterwards the vector CORINE data are converted into raster data, so that both classifications are available as raster data and can be compared. The calculated land use value is decisive for this.

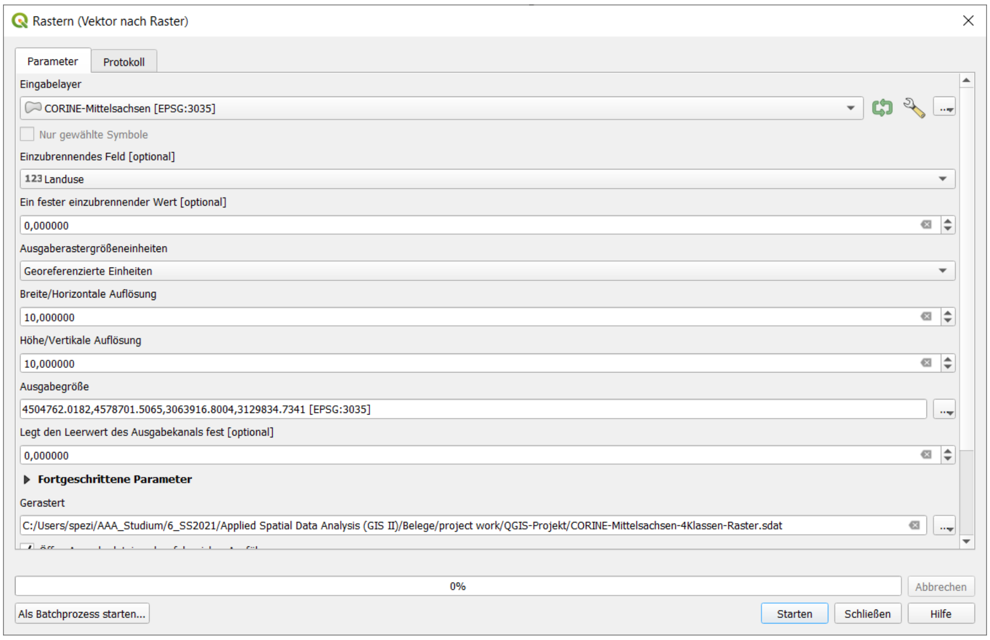

Fig. 37: Convert CORINE vector data to raster data

The actual Change Detection can be performed with the "Land cover change" tool in the post-processing of the Semi-Automatic Classification plugin.

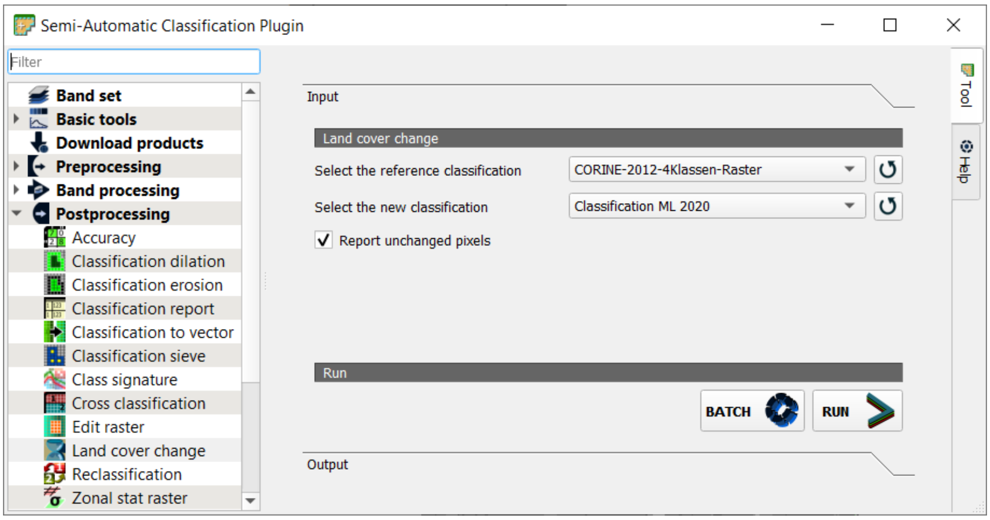

Fig. 38: Land cover change detection

The output indicates which classes have changed to which other classes.

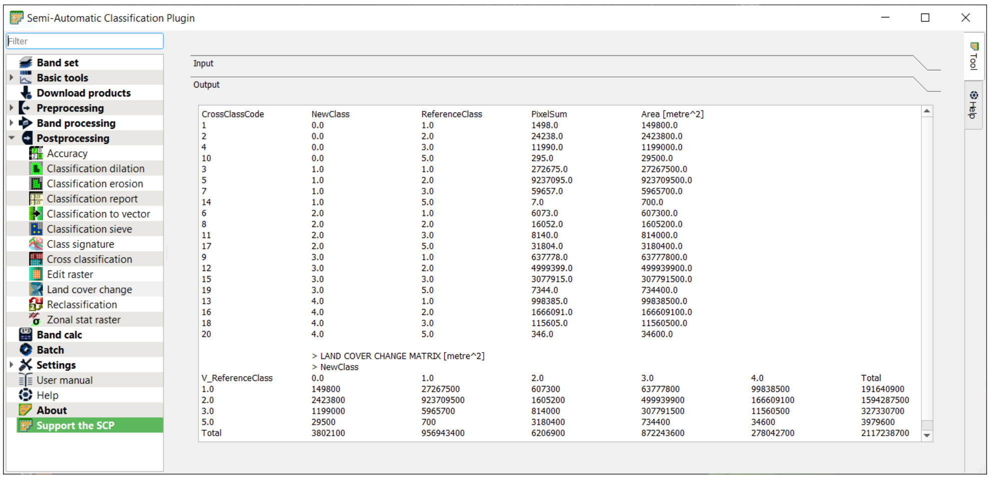

Fig. 39: Output of land cover change detection

Since only the changes are to be shown on the map later, all cross class codes are removed where the Reference Class corresponds to the New Class.

You have to pay attention to the numbering of the classes in the reference and the new file!

The Cross Classes are then named in such a way that the nature of the change is clear.

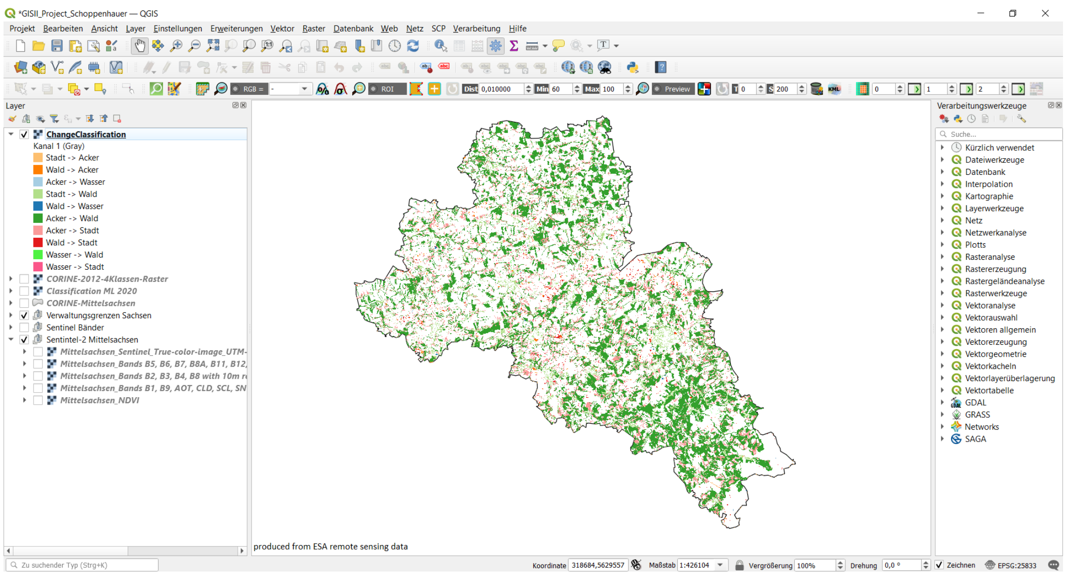

Fig. 40: Land cover change from 2012 to 2020

It can be seen that on very many areas, land use has changed from 2012 to 2020. However, the result must be viewed very critically. Since the many CORINE classes were combined to only four very coarse classes and the own supervised classification does not exactly match the true land use forms this result also shows changes in places where the classification is inaccurate or wrong.

In order to perform accurate land cover change detection, the classifications used for this purpose must be as realistic as possible!

References

[1] CLMS. *CORINE Land Cover — Copernicus Land Monitoring Service*. 2021. URL: https://land.copernicus.eu/pan-european/corine-land-cover (visited on 07/02/2021).

[2] CLMS. *CORINE Land Cover nomenclatur conversation to Land Cover Classification system*. 2010. URL: https://land.copernicus.eu/eagle/files/eagle-related-projects/pt_clc-conversion-to-fao-lccs3_dec2010 (visited on 07/11/2021).

[3] ESA. *Sentinel Overview*. 2021. URL: https://sentinels.copernicus.eu/web/sentinel/missions (visited on 07/02/2021).

[4] Mapasyst. *What's the difference between a supervised and unsupervised image classification?* 2019. URL: https://mapasyst.extension.org/whats-the-difference-between-a-supervised-and-unsupervised-image-classification/ (visited on 07/02/2021).

[5] S. Montoya. *Land cover spectral signatures determination with QGIS 3 and Semi-Automatic Classification Plugin - Tutorial*. 2018. URL: https://hatarilabs.com/ih-en/land-cover-spectral-signatures-determination-with-qgis-3-and-semi-automatic-classification-plugin-scp-6-tutorial (visited on 07/02/2021).

[6] J.A. Richards. *Remote Sensing Digital Image Analysis*. Springer Verlag, 1999, p. 240.

[7] Sentinel-Hub by Sinergise. *Normalized difference vegetation index — Sentinel-Hub custom scripts*. 2021. URL: https://custom-scripts.sentinel-hub.com/custom-scripts/sentinel-2/ndvi/ (visited on 07/02/2021).

Fig. 1: https://sentinels.copernicus.eu/web/sentinel/missions/sentinel-2

Fig. 2: https://sentinels.copernicus.eu/web/sentinel/missions/sentinel-2/data-products

Fig. 7: https://docs.sentinel-hub.com/api/latest/data/sentinel-2-l2a/

List of Figures