Active Learning for Cloud Detection & Processing Chains Comparator User Manual

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Contents

1 General instructions

This is the current user manual for the Active Learning Cloud Detection (ALCD) and the Processing Chains Comparator (PCC) codes. For a quick start, you can directly go to the Tutorial parts (sections 2.4 and 3.5). This section describes the requirements, the file structure and the configuration files.

1.1 Requirements

These code requires OTB 6.0 and GDAL. It runs with Python 2.7. QGIS should be installed as well.

The Python dependencies are listed below:

otbApplication	gdal	ogr	PIL
numpy	matplotlib	pandas	

Note: before running ALCD or PCC, check that the libraries are present in the PYTHONPATH, especially the otbApplication. If this is not the case, you will get this error message:

```
ImportError: No module named otbApplication
```

1.2 File structure

The general structure of the folders and files we use in this work should be as follows.

NB: `root_dir` *is the directory where you want to have all the* `ALCD` *and* `PCC` *codes.* `Data_ALCD` *and* `Data_PCC` *can be at another place.*

```
root_dir
├── ALCD : contains the codes and parameters for the ALCD algorithm
│   ├── parameters_files : contains the configuration files for the ALCD code
│   ├── color_table : contains various files for the color scheme to use
│   └── ALCD python files
├── PCC : contains the codes and parameters for the PCC algorithm
│   ├── parameters_files : contains the configuration files for the PCC code
│   ├── color_table : contains various files for the color scheme to use
│   └── PCC python files
├── paths_configuration.json : general configuration file
├── Data_ALCD : contains the input and output for ALCD codes
└── Data_PCC : contains the input and output for PCC codes
```

The two Data directories could be renamed or placed in another place. The configuration files should be modified accordingly.

1.3 Configuration file

The file `paths_configuration.json` should be modified according to your preferences. See the default one as an example.

global__chains__paths : contains the main paths concerning the output of the processing chains

- **L1C** : the L1C products, subsequently designated as L1C product root dir
- **maja** : directory where the MAJA files are, subsequently designated as MAJA output root dir
- **sen2cor** : directory where the Sen2cor files are, subsequently designated as Sen2cor output root dir
- **fmask** : directory where the Fmask files are, subsequently designated as Fmask output root dir
- **DTM__input** : directory where the Digital Terrain Model files are, subsequently designated as DTM product root dir
- **DTM__resized** : directory where the resized Digital Terrain Model files will be stored

data__paths : in case the Data_ALCD and Data_PCC are moved or renamed, this should be modified

tile__location : specification of the tile code linked to a named place. You could add other locations here.

1.4 Input data organisation

The data organisation of each of the programs outputs is defined below, with the example of Arles on the 2nd of October, 2017. **If your structure is different, you need to change some variables in the code.** For each directory or file, the pattern to describe it follows the syntax: "General name : `ExampleForArles`". The `*` in a path indicates that the path has been truncated at this place.

1.4.1 Required for the ALCD

- L1C product structure:

```
L1C product root dir :  /mnt/data/SENTINEL2/L1C_PDGS/
└ location :  Arles
  └ date and tile folder :  S2B_MSIL1C_20171002T103009_N0205_R108*.SAFE
    └ granule folder :  GRANULE
      └ L1C product :  L1C_T31TFJ_A002994_20171002T103209
        └ image data :  IMG_data
          ├ bands files :
          ├ T31TFJ_20171002T103009_B01.jp2
          ├ T31TFJ_20171002T103009_B02.jp2
          ├ T31TFJ_20171002T103009_B03.jp2
          ├ ...
          ├ T31TFJ_20171002T103009_B11.jp2
          └ T31TFJ_20171002T103009_B12.jp2
```

The full path of the first band is therefore, in this example: `/mnt/data/SENTINEL2/L1C_PDGS/Arles/S2B_MSIL1C_20171002T103009_N0205_R108_T31TFJ_20171002T103209.SAFE/GRANULE/L1C_T31TFJ_A002994_20171002T103209/IMG_DATA/T31TFJ_20171002T103009_B01.jp2`

- DTM product structure:

  The Digital Terrain Model is specific to a tile. Therefore, there is no need to have a copy of the DTM for each date. The original DTM should be placed in the `DTM_input` directory. After the first time the ALCD is run on one location, its resized DTM will be created in the `DTM_resized` directory, so as to avoid generating it each time. The format has to be an unpacked DTM folder (.DBL).

```
Original DTM folder:  /mnt/data/home/baetensl/DTM/original
├ Tile folder (must contain the tile ref):  S2_*_T31TFJ*
│ └ Unpacked .DBL folder:  S2_*T31TFJ_*.DBL.DIR
│   └ Altitude file:  S2__TEST_AUX_REFDE2_T31TFJ_0001_ALT_R2.TIF
└ Resized DTM folder:  /mnt/data/home/baetensl/DTM/resized
  ├ Generated DTMs :
  ├ Arles_31TFJ_DTM_60m.tif
  ├ Gobabeb_33KWP_DTM_60m.tif
  ├ ...
  └ RailroadValley_11SPC_DTM_60m.tif
```

The full path of the original DTM is therefore, in this example: `/mnt/data/home/baetensl/DTM/original/S2__TEST_AUX_REFDE2_Arles_T31TFJ_0002/S2__TEST_AUX_REFDE2_T31TFJ_0001.DBL.DIR/S2__TEST_AUX_REFDE2_T31TFJ_0001_ALT_R2.TIF`. After the ALCD is run once on Arles, the resized DTM will be in /mnt/data/home/baetensl/DTM/resized/Arles_31TFJ_DTM_60m.tif.

1.4.2 Required for the PCC

- MAJA v1 and v2 output structure:

```
MAJA output root dir :  /mnt/data/SENTINEL2/L2A_MAJA/
└ location :  Arles
  └ tile :  31TFJ
    └ MAJA natif output :  MAJA_1_0_S2AS2B_NATIF
      └ date folder :  S2B_OPER_SSC_L2VALD_31TFJ____20171002.DBL.DIR
        ├ output files :
        ├ Cloud mask :  S2B_OPER_*_L2VALD_31TFJ____20171002_CLD_R2.DBL.TIF
        ├ Geo mask :  S2B_OPER_SSC_*_L2VALD_31TFJ____20171002_MSK_R1.DBL.TIF
        └ ...
```

  The full path of the cloud mask is therefore, in this example: /mnt/data/SENTINEL2/L2A_MAJA/Arles/31TFJ/MAJA_1_0_S2AS2B_NATIF/S2B_OPER_SSC_L2VALD_31TFJ____20171002.DBL.DIR/S2B_OPER_SSC_PDTANX_L2VALD_31TFJ____20171002_MSK_R2.DBL.TIF

- MAJA v3 output structure:

```
MAJA output root dir :  /mnt/data/SENTINEL2/L2A_MAJA/
└ location :  Arles
  └ tile :  31TFJ
    └ MAJA natif output :  MAJA_3_1_S2AS2B
      └ date folder :  SENTINEL2B_20171002-103209-123_L2A_T31TFJ_C_V1-0
        └ masks folder :  MASKS
          ├ output files :
          ├ Cloud mask :  SENTINEL*CLM_R2.tif
          ├ Geo mask :  SENTINEL*MG2_R2.tif
          └ ...
```

  The full path of the cloud mask is therefore, in this example: /mnt/data/SENTINEL2/L2A_MAJA/Arles/31TFJ/MAJA_3_1_S2AS2B_HOT016/SENTINEL2B_20171002-103209-123_L2A_T31TFJ_C_V1-0/MASKS/SENTINEL2B_20171002-103209-123_L2A_T31TFJ_C_V1-0_CLM_R2.tif

- Sen2cor output structure:

```
Sen2cor output root dir :  /mnt/data/SENTINEL2/L2A_SEN2COR/
└ location :  Arles
  └ date and tile :  S2B_MSIL2A_20171002T103009_N0205_R108_T31TFJ_*.SAFE
    └ granule folder :  GRANULE
      └ sub folder :  L2A_T31TFJ_A002994_20171002T103209
        └ image data :  IMG_DATA
          └ resolution :  R20m
            ├ output files :
            ├ Cloud mask :  L2A_T31TFJ_20171002T103009_SCL_20m.jp2
            └ ...
```

The full path of the cloud mask is therefore, in this example: `/mnt/data/SENTINEL2/L2A_SEN2COR/Arles/S2B_MSIL2A_20171002T103009_N0205_R108_T31TFJ_20171002T103209.SAFE/GRANULE/L2A_T31TFJ_A002994_20171002T103209/IMG_DATA/R20m/ L2A_T31TFJ_20171002T103009_SCL_20m.jp2`

- Fmask v4 output structure:

  For Fmask version 4, which is the last one, the data structure is the following.

```
Fmask output root dir :  /mnt/data/home/baetensl/Programs/Fmask4_output/
└ location tile and date :  Arles_31TFJ_20171002
  ├ Cloud mask :  L1C_T31TFJ_A002994_20171002T103209_Fmask4.tif
  └ ...
```

  The full path of the cloud mask is therefore, in this example: `/mnt/data/home/baetensl/Programs/Fmask4_output//Arles_31TFJ_20171002/L1C_T31TFJ_A002994_20171002T103209_Fmask4.tif`

- Fmask v3 output structure:

  For the previous version of Fmask, the structure is similar, only the file name of the cloud mask changes.

```
Fmask output root dir :  /mnt/data/home/baetensl/Programs/Output_fmask/
└ location tile and date :  Arles_31TFJ_20171002
  ├ Cloud mask :  Arles_20171002_cloud_mask.img
  └ ...
```

  The full path of the cloud mask is therefore, in this example: `/mnt/data/home/baetensl/Programs/Output_fmask/Arles_31TFJ_20171002/Arles_20171002_cloud_mask.img`

2 Active Learning for Cloud Detection (ALCD)

This part deals with the utilisation of the ALCD code. This code produces classification reference masks from a Sentinel-2 L1C product, and is particularly designed to detect clouds and cloud shadows. In order to get the best results as possible, while still minimizing the amount of manual work to get reference pixels, this method is only applicable to dates in a time series for which one of the next dates is cloud free.

2.1 Data organisation

For the input data, refer to the section 1.4.1.

The output structure of the code is the following, for a given location and date:

```
location and date dir : main directory; e.g. Arles_31TFJ_20171002
├─ In_data : contains the input data
│   ├─ Image : contains the different GeoTIFF files
│   └─ Masks : inside are the asks files for each class which need to be modified
├─ Intermediate : intermediate files needed for the ALCD to run smoothly
├─ Models : output models created by the OTB software
├─ Other : can contain miscellaneous files
├─ Out : main output directory
│   └─ classification map and the superimposed contours on the original TIF in true colors
├─ Previous_iterations : saves of the previous iterations
├─ Samples : reorganisation of the masks into readable format for OTB training
└─ Statistics : various statistics such as the confusion matrix
```

2.2 Configuration file

A granule is defined as a set of data specified in space and time, i.e. a location and a date. For example, a granule could be associated with Orleans, tile 31UDP, and the 13th of April 2018. In all the environment, a date is in format YYYYMMDD (the previous date becoming 20180413).

Some parameters can be tweaked in the configuration files (located in the `parameters_files` directory).

- In the `global_parameters.json`, the different parameters are described below. **The ones with a star (∗) are the ones you could consider worth changing.**

  ∗ **classification** : classification parameters

  method : which method is used (could be rf, svm, ...)

  general : output names for the files. Not necessary to change anything. The different files will be referred to with their default names afterwards

  ∗ **local_paths** : specific to your environment. It is used if you run the ALCD on a distant machine, and want to modify the masks on your local machine with QGIS. Useful if the distant machine does not have a graphic card.

copy_folder : on your local machine, where you want to edit the files
current_server : the adress of the distant machine

masks : naming and attribution of a number to each class
postprocessing : global naming for post-processing files
automatically_generated : references to the specific case you are working on. This will be modified when running ALCD, so you do not need (and should not) change it manually

∗ **training_parameters** : parameters used for the training and classification of the algorithm. The default ones are good, but you can change them.

training_proportion : the proportion of samples that will become training samples (between 0 and 1). The other part (1-training_proportion) will become validating samples.
expansion_distance : in meters, the size of the buffer zone around each sample. This buffer zone will be used to augment the data, i.e. take the neighboring pixels
regularization_radius : in pixels (should be an integer), the radius for the regularization of the classification map. Typical values are between 1 and 5.
dilatation_radius : in pixels (should be an integer), the radius for the dilatation of the contours for the visualisation. Typical values are between 1 and 5.
Kfold : for the K-fold cross-validation, which k to use (usually 5 or 10).

∗ **features** : which features will be used for the classification.

original_bands : list of the bands from the cloudy date to use. It is recommended to use all of them.
time_difference_bands : list of the bands from which the difference will be made, between the cloudy and clear date. It is recommended to use all of them apart the band 10, which is noisy.
special_indices : list of peculiar indices. Can be composed of NDVI, NDWI, NDSI for the moment.
ratios : list of ratios. Each item should have the format "a_b", where *a* and *b* are bands numbers (e.g. "2_4" will produce the ratio B2/B4).
DTM : boolean, whether you want to use the Digital Elevation Model or not.
textures : boolean, whether you want to create the two texture features (coefficient of variation and contours density are available for the moment).

- The specific model parameters can be modified in the `model_parameters.json` file. They are directly referring to the OTB ones, and you can therefore see the OTB documentation for this purpose (`https://www.orfeo-toolbox.org/CookBook/Applications/app_TrainVectorClassifier.html`)

2.3 Code workflow and overview

The ALCD framework is based on multi-spectral and multi-temporal features. The user will have to choose two images separated by a few days: a reference cloud free image, it usually happens from time to time in a time series, and an image to classify. The latter should have been acquired before the reference image, otherwise MAJA, which is also multi-temporal will be favoured as it uses cloud free pixels in the past to classify the pixels. The user should select an image which is as cloud-free as possible, along the cloudy image which he wishes to classify. The closer the two dates, the better.

Firstly, the different features are compiled into two GeoTIFF. The features described below are the one created if you use the recommended parameters.

- The main TIF contains all the 12 bands of the cloudy date, the NDVI and NDWI computed from them, the difference between the bands of the cloudy date and the cloud-free date, and the Digital Terrain Model (DTM) of the area, with a coarse resolution (60 meters).
- The second TIF, so-called 'heavy', contains the bands 2, 3, 4, 10, the NDVI and the NDWI of the cloudy image, with a full resolution (10 or 20 meters). This allows the user to conveniently select the samples.

Then, the user is asked to put some points in a vector format, such that it labels the image.

Then, the user is asked to manually add reference points with QGIS. Each wanted class should have at least 3 references points. One empty layer per class is created in the previous step, such that the user needs to populate them, or leave some of them empty if the class is not present in the image (e.g. with snow).

The OTB workflow is then put into motion, training a model and classifying the image. The classification is the output of the ALCD algorithm.

The user can afterwards add new vector points to refined the model, in an iterative way.

The flowchart is exposed in figure 2.2, with the nomenclature being in figure 2.1.

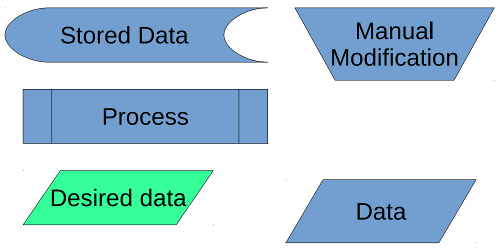


Figure 2.1: Flowcharts nomenclature

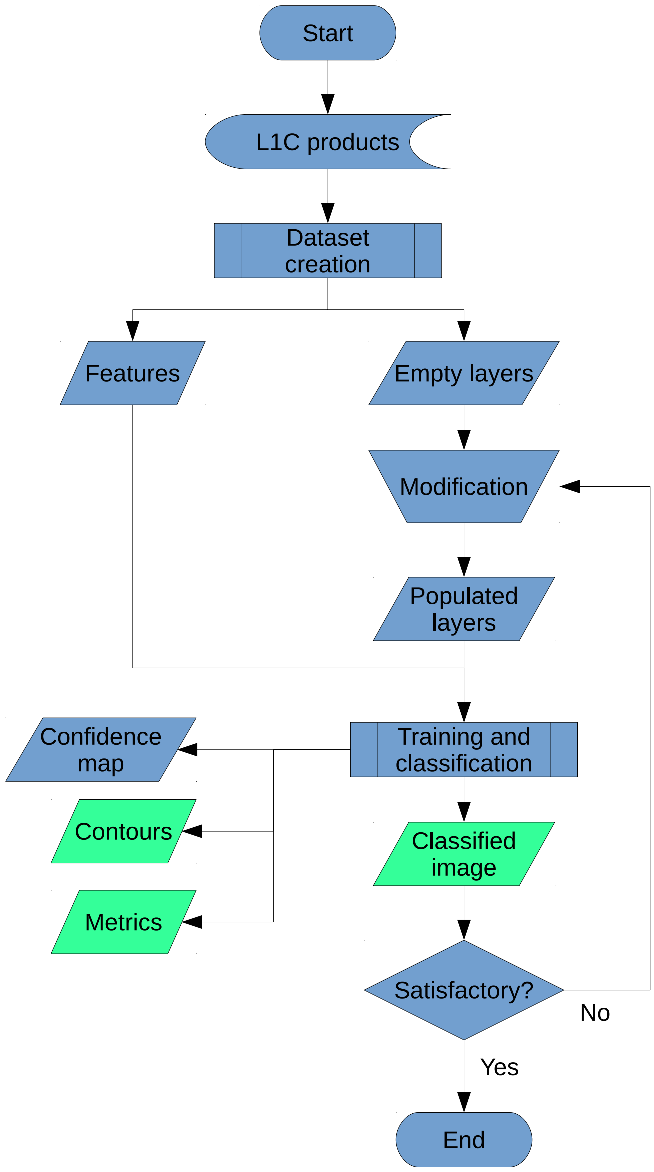
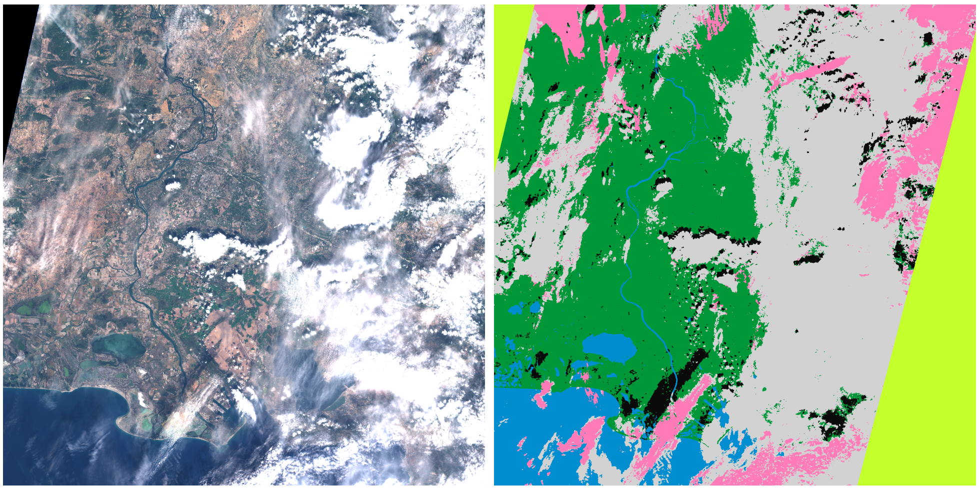


Figure 2.2: ALCD flowchart

2.4 Tutorial

This is a step-by-step tutorial, to help you use the ALCD algorithm. Here, we will classify the clouds on the image of Arles, on the 2^{nd} of October, 2017.

The expected result is the following:



(a) Image to classify (b) Final classification

Figure 2.3: Classification of Arles, 20171002

Change to the `ALCD` directory. The program that you should use is `all_run_alcd.py`. You can display the help with

```
python all_run_alcd.py -h
```

The available options are:

`-l` : the **location**. The spelling should be consistent with the names in the L1C directory (e.g. Pretoria or Orleans)

`-d` : the (cloudy) **date** that you want to classify (e.g. 20180319)

`-c` : the **clear date** that will help the classification (e.g. 20180321)

`-f` : if this is the **first iteration** or not. If set to True, it will compute and create all the features, and create the empty class layers. Set it to True for the first iteration, and thereafter to False.

`-s` : the **step** you want to do, the choice is between 0 and 1. 0 will create all the needed files if this is the first iteration, otherwise it will save the previous iteration. 1 will run the ALCD algorithm, i.e train a model and classify the image. For each iteration, you should set it to 0, modify the masks, and then set it to 1.

`-kfold` : boolean. If set to True, ALCD will perform a **k-fold** cross-validation with the available samples.

`-dates` : boolean. If set to True, ALCD will display the available **dates** for the given location.

2.4.1 Summary of the commands

The detailed steps are given after this part. We give here the summary of the commands to use, so you can come back here if you forget how to use ALCD.

See the available dates.

```
python all_run_alcd.py -l Arles -dates True
```

Initialisation and creation of the features.

```
python all_run_alcd.py -f True -s 0 -l Arles -d 20171002 -c 20171005
```

Edit the shapefiles to populate them with manually labeled samples. Then run the algorithm.

```
python all_run_alcd.py -f True -s 1
```

While the results are not satisfactory:

Visualize the results. Save the current iteration.

```
python all_run_alcd.py -f False -s 0
```

Edit the shapefiles to your convenience. Run the algorithm again.

```
python all_run_alcd.py -f False -s 1
```

2.4.2 Paths preparation

Before running anything, you need to set the correct paths and parameters.

In the `paths_configuration.json`:

- Add the tile code linked to the location you want to add
- Create the output directory for ALCD, and set its path in the "data_alcd" variable
- Set the correct paths for the L1C directory and the DTM_input

In the `global_parameters.json`, if you use a distant and a local machine, set the `local_paths` variables accordingly.

2.4.3 Step 1

First of all, you must pick the date you are interested in. As the code will run on the L1C product, you can list all the available dates with the command

```
python all_run_alcd.py -l Arles -dates True
```

You should get a list like

```
['20151202', '20151230', ..., '20180319', '20180321']
```

A good practice is to visualise the two dates we want to use beforehand. This can be facilitated by the code `quicklook_generator.py`, which generates quicklooks for a given location. The user can therefore make sure that the cloud-free image is indeed cloud-free, and that the image to be classified is interesting.

As stated above, the date we will use here is 20171002. This date was acquired just before a cloud free date: 20171005.

Therefore, initialize the environment by running

```
python all_run_alcd.py -f True -s 0 -l Arles -d 20171002 -c 20171005
```

This will create the concatenated .tif with all the bands, and empty shapefiles for each class, among other things.

It invites you to copy those created files to your local machine, to accelerate the process in QGIS (on our processing computer, visualisation is slow, so we use QGIS on a different computer). You can also modify the files directly, in this case, you can skip the manual copy of the files and go to Step 2. Otherwise, copy the files on your machine with QGIS, and go to Step 2.

2.4.4 Step 2

You can now open QGIS. Open the raster `In_data/Image/Arles_bands_H.tif` (H stands for Heavy, as it is in full resolution of 20m per pixel), and `In_data/Image/Arles_bands.tif`. The `Arles_bands_H.tif` bands refer to the band 2 (blue), 3 (green), 4 (red), 10 (the band at 1375nm), the NDVI and the NDWI. The bands for the `Arles_bands.tif` are quite numerous, but the content of each band is documented in the .txt file corresponding to each .tif.

Now, adjust the style in QGIS such that you see the image in true colors. For that, you can load the file `color_tables/heavy_tif_true_colors_style.qml` on the Heavy .tif. You should get :

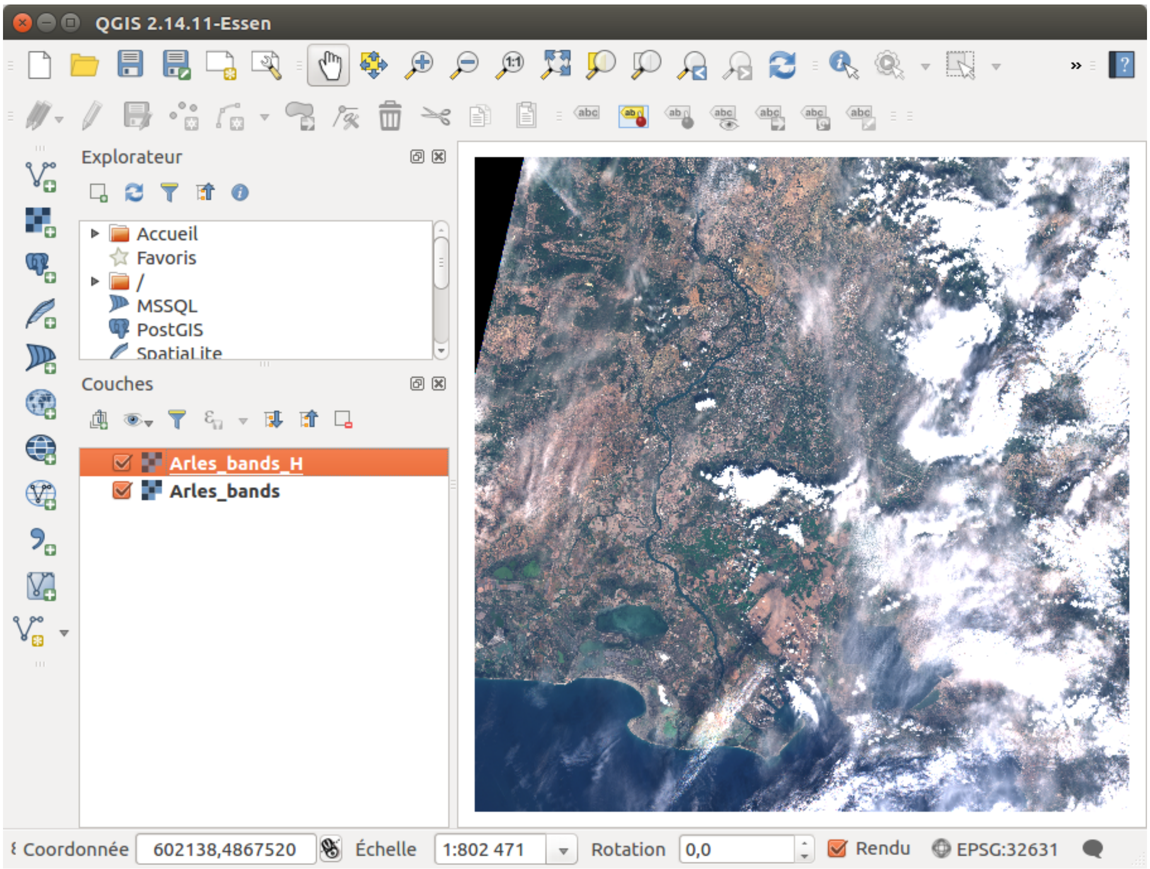


Figure 2.4: QGIS window with the scene displayed in true colors

Now, load all the empty shapefiles from the directory `In_data/Masks`.

If you display a band being a time difference (for example the 20th band of `Arles_bands.tif`), you will observe that there was no data on the bottom-right corner for the clear date. The same is true with the top-left corner for the cloudy date.

Thus, the `no_data` file already has some data (which is the case if one or both of the original images have no_data pixels). As you can see, on figure 2.4 the top-left and bottom-right corners are covered by the no-data mask. If you are not satisfied with the mask, you can edit it manually.

You should get something along the lines of the following :

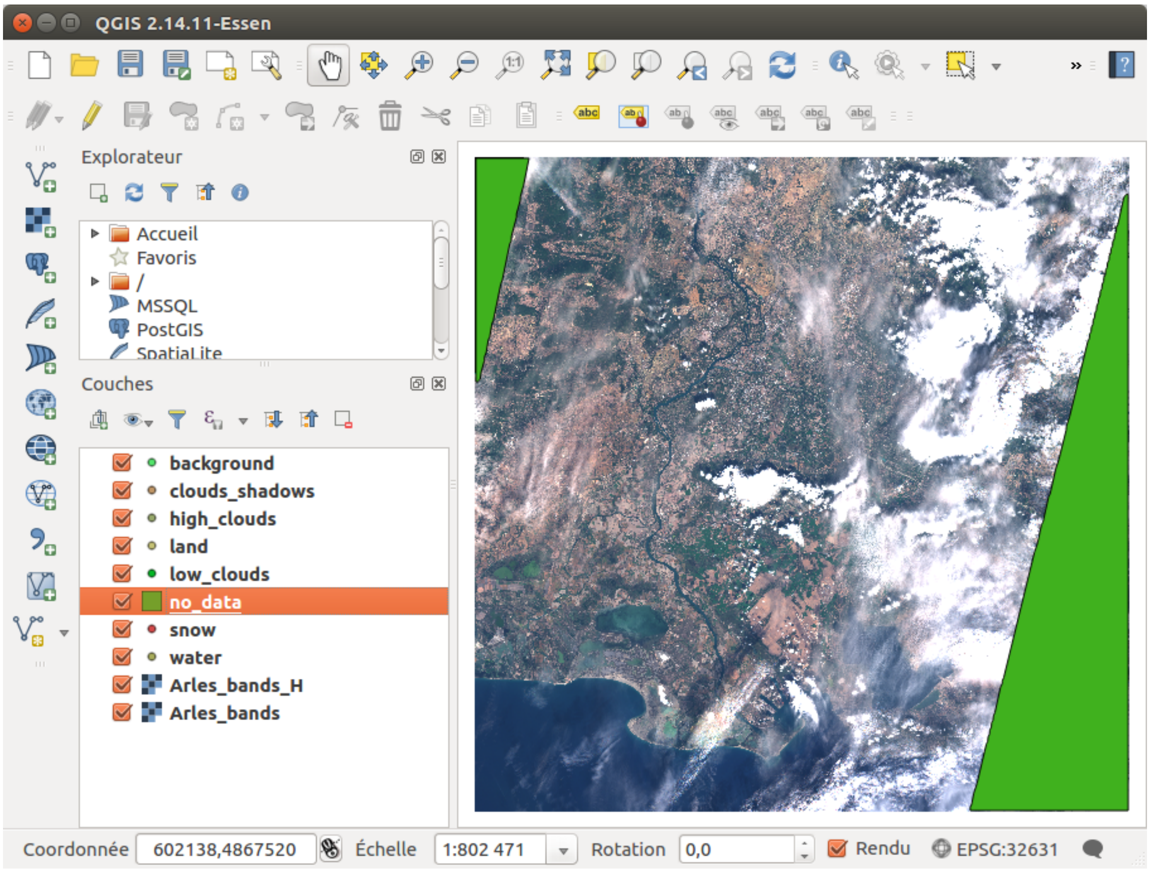


Figure 2.5: No-data areas are automatically computed

This no-data layer is used to discard the areas under it, be it for the classification, or if the user add samples in these areas by mistake.

2.4.5 Step 3

It is now time to edit the masks layers. For each class (*land*, *low clouds*, etc), edit the corresponding layer. Add the points that you want to take as samples, by clicking on the image and pressing Enter for each point. We have found more efficient to use points rather than polygons, we later dilate the points by 3 pixels assuming the neighbourhood is homogeneous in terms of class, so you should avoid to use a pixel just at the edge of a feature (*cloud*, *land*).

The high clouds can be visible with the 1375nm band (i.e. the band number 4 of the heavy .tif). You can load the style `heavy_tif_clouds_green_style.qml` to see them quickly.

The figure 2.6 shows the image with the high clouds highlighted, and the steps to add points.

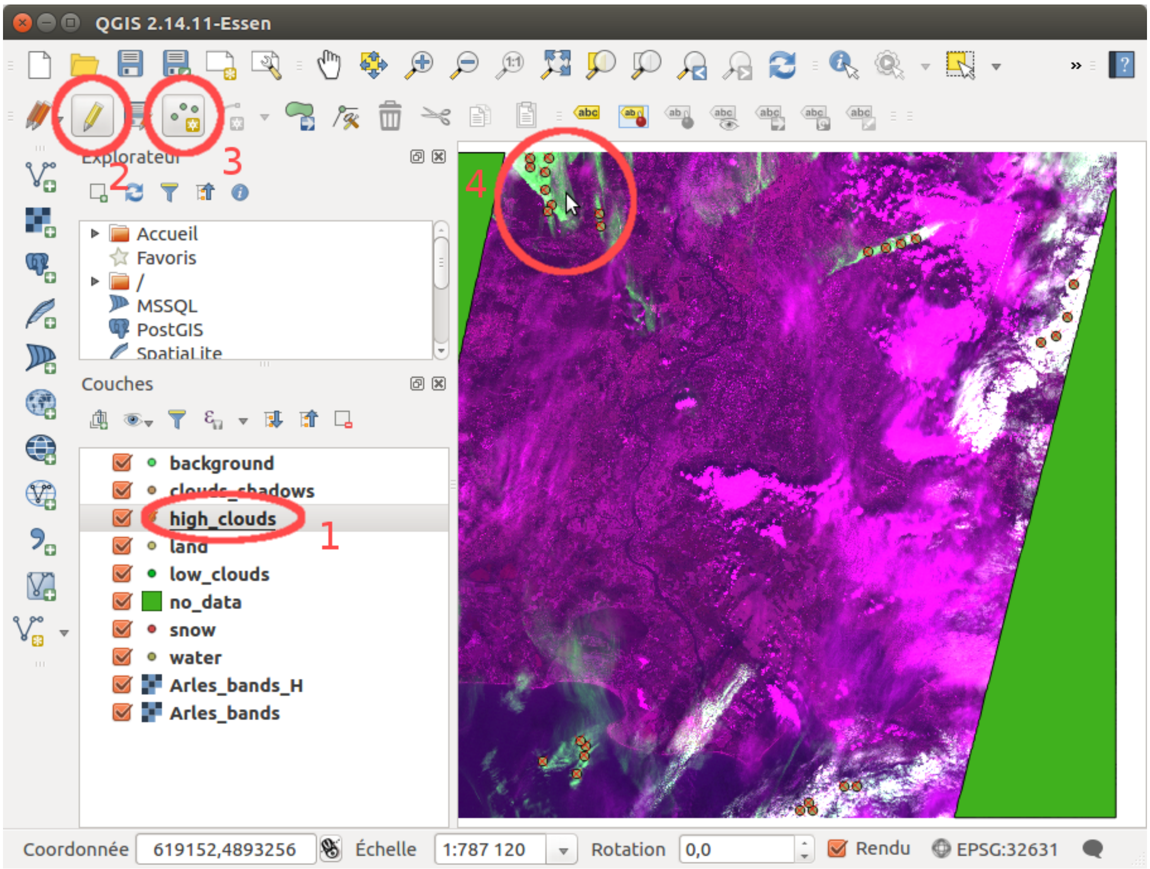


Figure 2.6: Steps to add data points with QGIS

Note: the 1375nm band is not to be trusted blindly. The principle of this band is that the water vapour in the atmosphere usually absorbs the photons in this wavelength. However, in dry conditions, or with high altitudes terrains (such as mountains), the photons can be reflected back. This can be misleading, so the user should take precautions. A typical way to detect such artefacts is to see if the potential cirrus shape is strongly correlated with that of the underlying terrain.

You can now go back to true colors, and continue by editing all the wanted classes. The *background* class can be used if you do not want to discriminate between *land* and *water* for example, but its use is not recommended.

At the end, you obtain figure 2.7

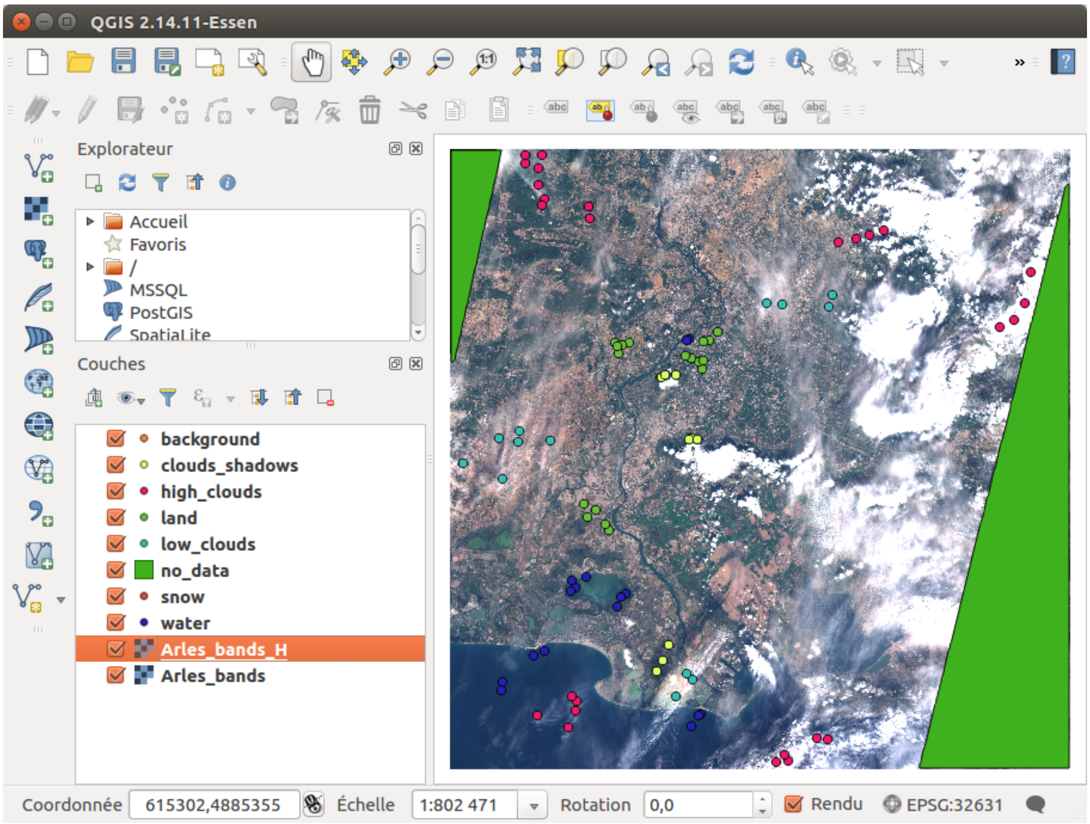


Figure 2.7: Samples placed manually after the first iteration

2.4.6 Step 4

Now, copy back the edited masks to the distant machine, or skip this if you work on one machine.

It is time to train the model, and classify the image! Do it with

```
python all_run_alcd.py -f True -s 1
```

The results can be seen in the `Out` directory. The regularized classification map is `labeled_img_regular.tif`. You can also see the contingency table in the `Statistics` directory.

As you can see on the classification map, figure 2.8, some pixels are not well classified. Moreover, the confidence is low in numerous places, as seen on figure 2.9 (more information about it in part 2.4.9). Therefore, we will take part of the advantage of this program: the active learning.

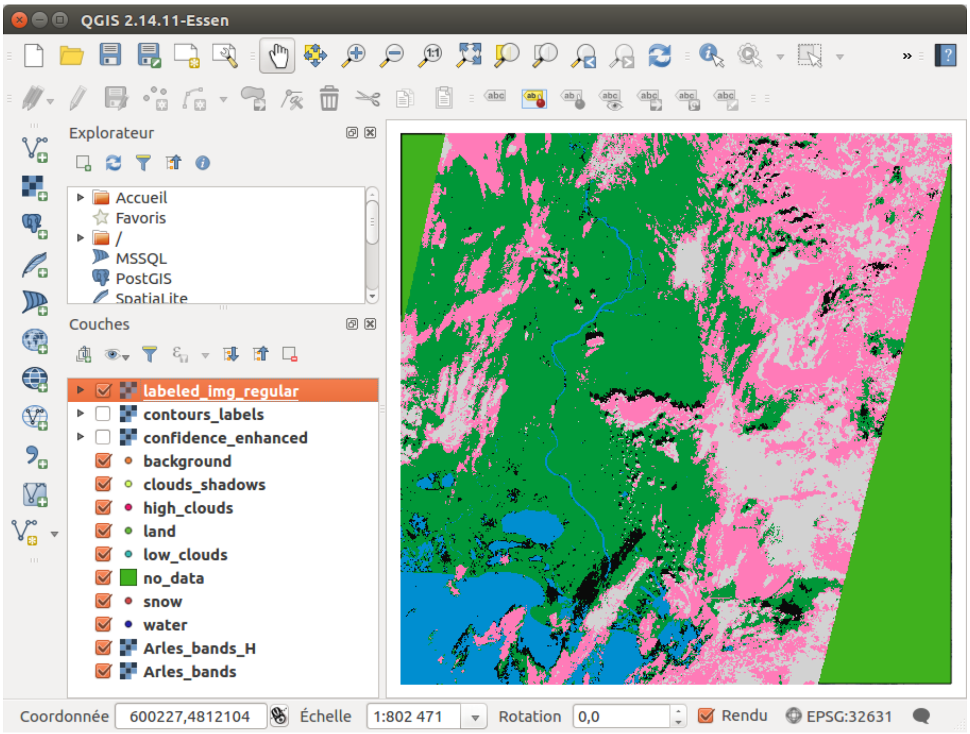


Figure 2.8: Result of the first classification

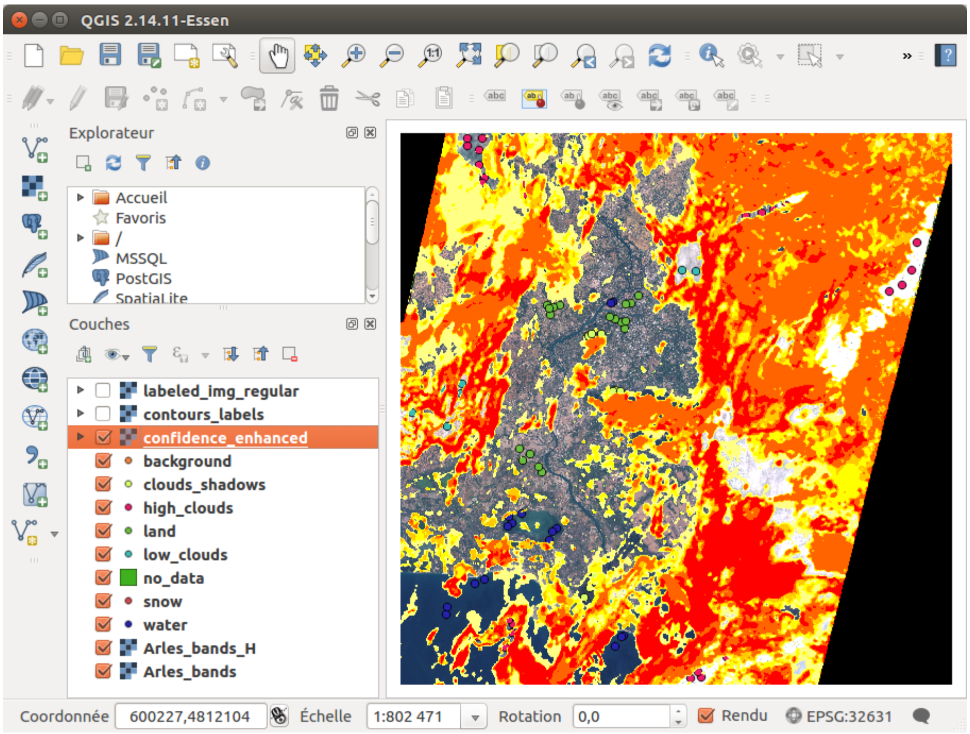


Figure 2.9: Confidence map of the first classification

2.4.7 Step 5

Do an new iteration, by running

```
python all_run_alcd.py -f False -s 0
```

It will save the previous iteration, and you can now edit the class layers, by adding new points (and also remove some if you made an error previously). You can copy on your local machine the outputs of the previous iteration (the bash command is given when you run the command above).

We suggest to open the files `Out/contours_labels.tif` and `Out/labeled_img_regular.tif`, and to apply to them the `contours_labeled_contrasted_style.qml` and the `labeled_img_regular_style.qml` styles respectively. It gives each class a recognisable color, which are given in table 2.1.

Color for the classification	**Color for the contours**	**Class #**	**Class name**
		0	null value
		1	background
		2	low clouds
		3	high clouds
		4	clouds shadows
	Transparent	5	land
		6	water
		7	snow

Table 2.1: Available classes and colors

For example, you can display the contours of the classes to see were the classifier was wrong. Here, we obtained a false detection of *clouds shadows* on the left of the image, which can be seen with the yellow contours:

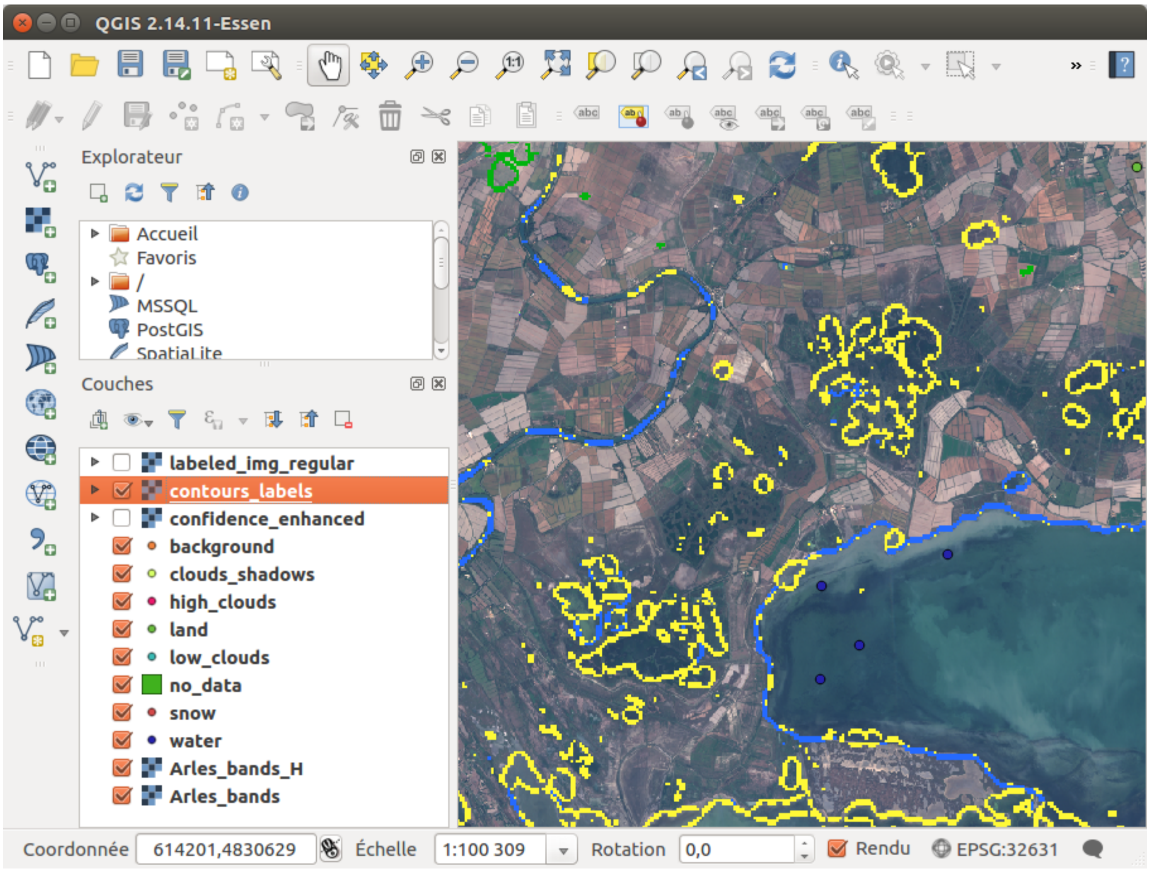


Figure 2.10: Contours of the shadows, in yellow

Therefore, we will add some points of *land* class in this region to increase the accuracy of our output, as shown in figure 2.11.

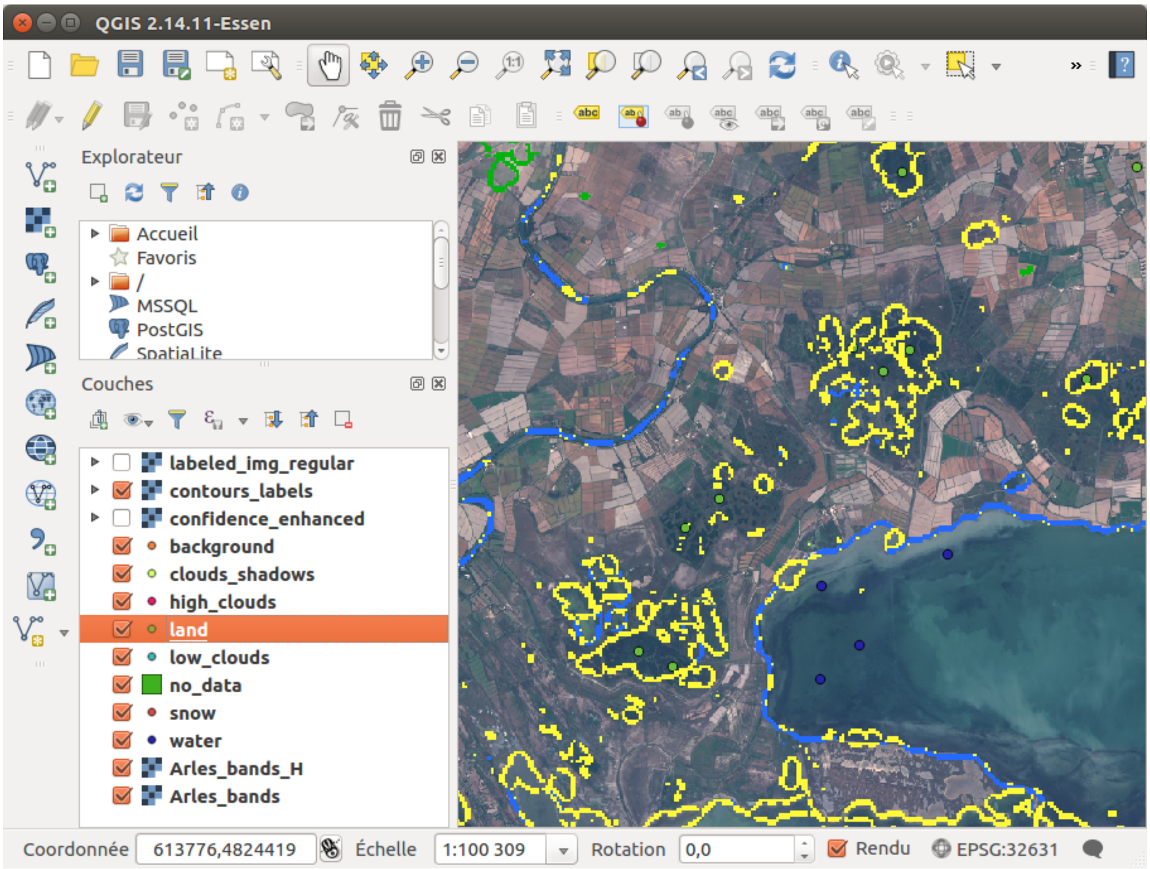


Figure 2.11: Some *land* samples are added where the wrong classification is visible

Do this for the areas where a misclassification is visible.

Once the wanted points in each class have been added, you can copy back the layers to the distant machine with the appropriate command.

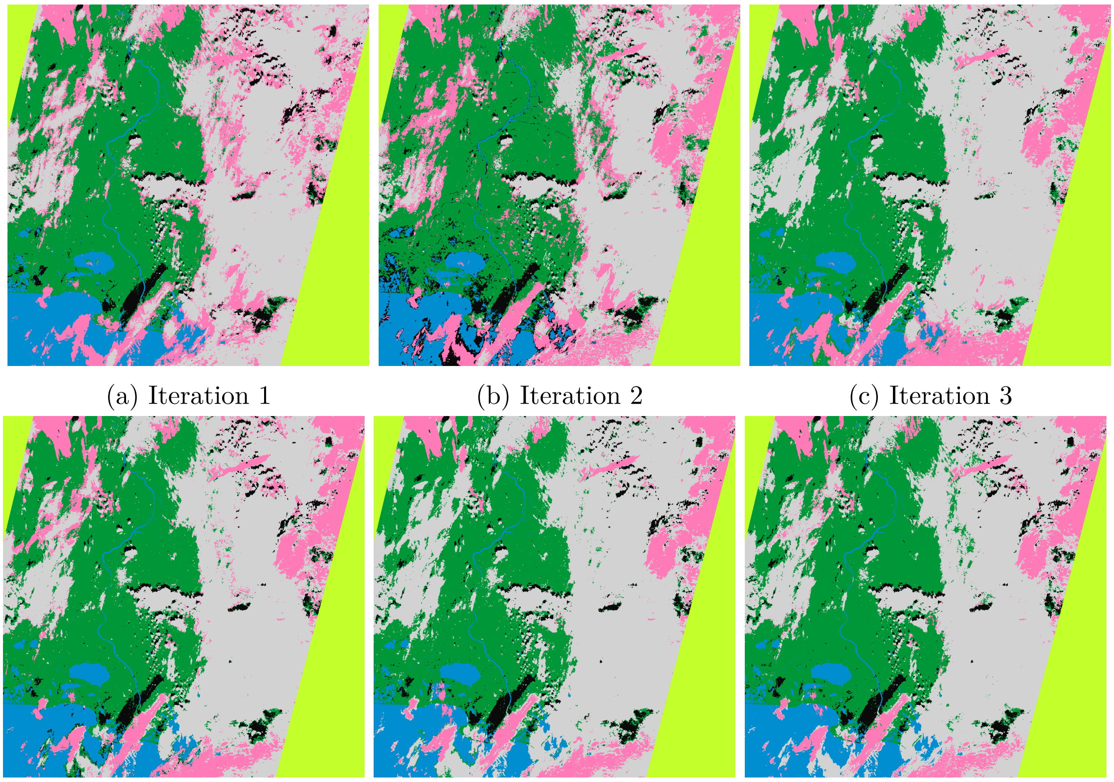
Finally, you run once again the training and the classification with

```
python all_run_alcd.py -f False -s 1
```

2.4.8 Step 6

Repeat the Step 5 until you are satisfied with the classification the ALCD algorithm returns. *Quick tip: some data (30% by default) are used for the validation of the model, i.e. just to compute statistics. If you want to have more samples that you add manually to be taken into account for the training part, you can increase the* `training_proportion` *in the* `global_parameters.json`.

Here is an example of the classification that you could obtain after each iteration. The 6th one is considered to be good (by myself), so you can stop there.



(a) Iteration 1 (b) Iteration 2 (c) Iteration 3

(d) Iteration 4 (e) Iteration 5 (f) Iteration 6

Figure 2.12: Evolution of the classification

As a reference, the QGIS windows at the last iteration with all the samples, with the labeled classification, and with the confidence map, are given in figures 2.13, 2.14 and 2.15.

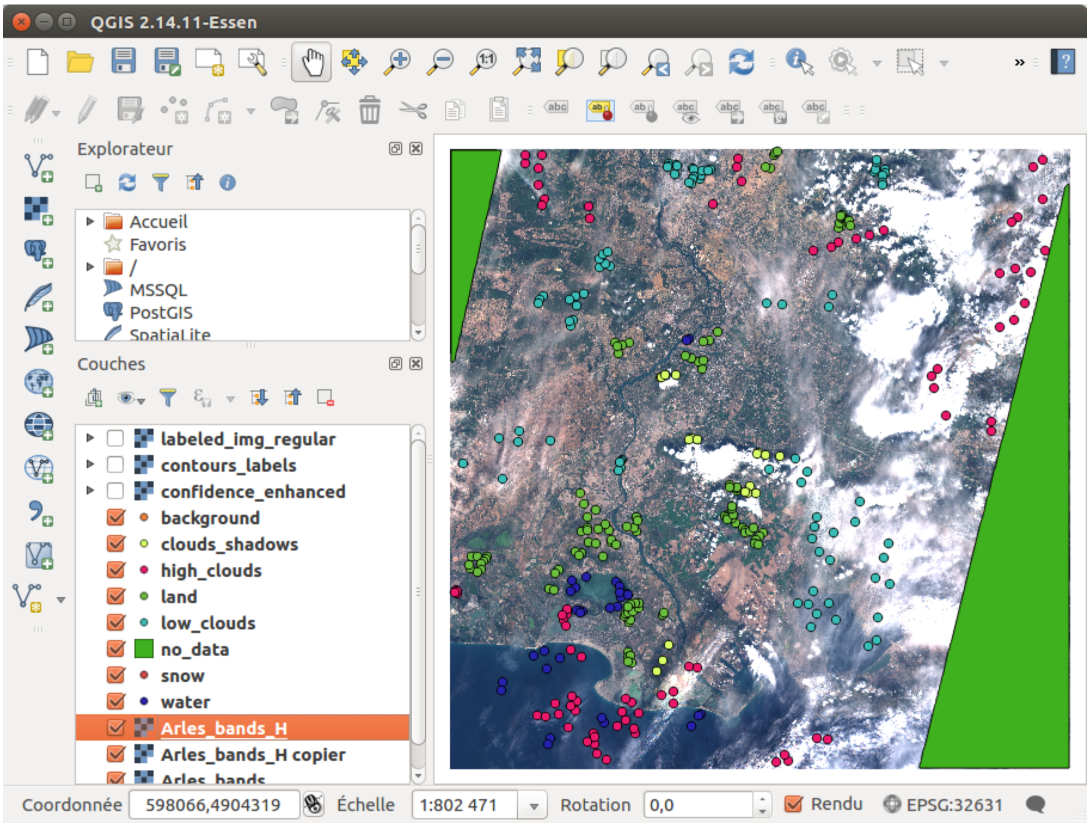


Figure 2.13: All samples present for the last iteration

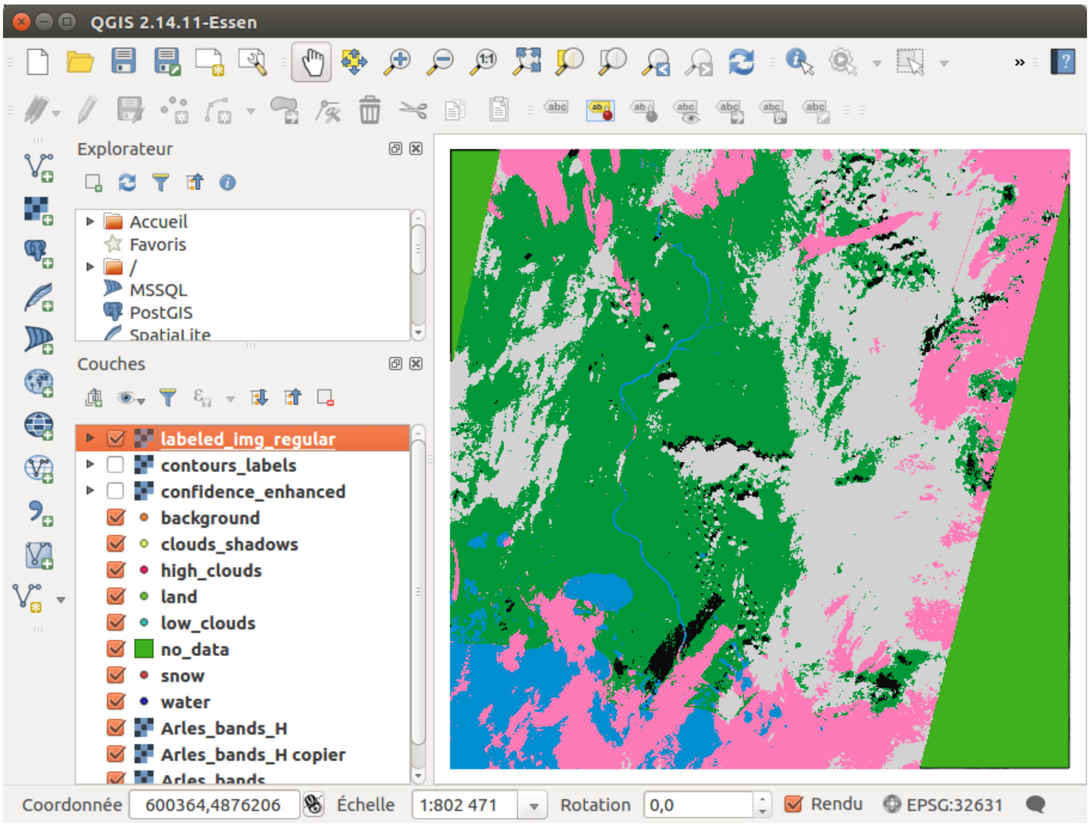


Figure 2.14: Labeled classification as seen in QGIS window for the last iteration

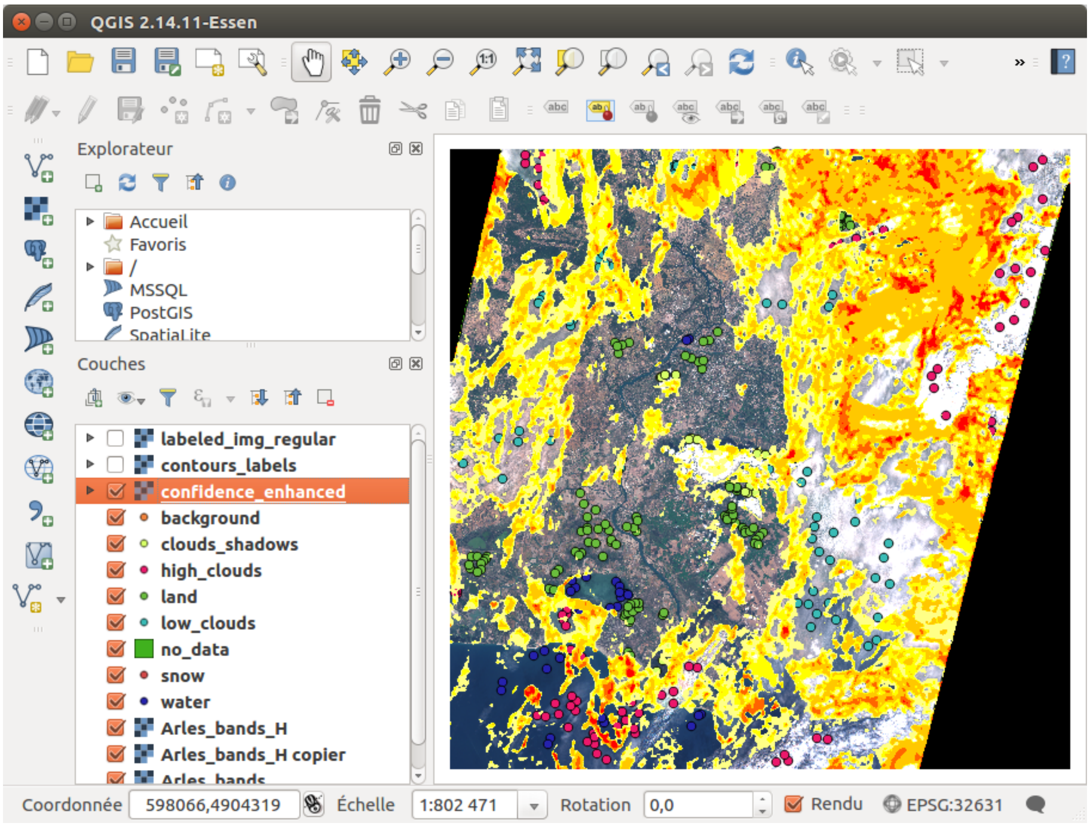


Figure 2.15: Confidence map as seen in QGIS for the last iteration

2.4.9 Tips and advice

Here are some advice that you could consider to achieve a better and faster classification.

A. Samples positioning

If you want to achieve a great classification, a good thing to do is to have a wide variety of samples. This means samples that are well distributed spatially (do not take all your samples in a radius of 1km), but also from a feature point of view, especially for the *land* class. If your image contains grass, forests, sand and mountains, place samples on all these classes, and not just on the grass one. For the *low clouds* and the *high clouds* classes, put samples on the centre of the clouds, but also where they are thin. For the *clouds shadows*, select shadows over the land, over the water, and so on.

B. Proportion between classes

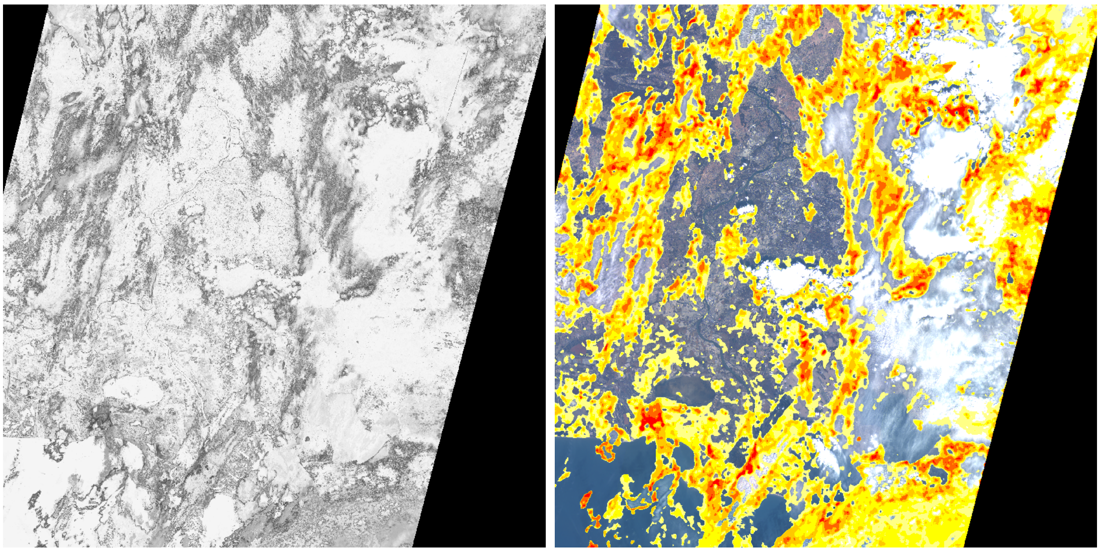
It is a good practice to keep a balanced number of samples between classes. Therefore, you should try not to put 10 times more *land* samples than *water* ones, or vice versa. It is sometimes difficult to find enough samples that are well distributed spatially (see point above), especially for *water* and *snow*. In this case, you can add points not far apart, so as to increase their number, even if it could lead to redundant information.

C. Confidence map

Generally speaking, the user wants to add relevant points at each iteration. The recommendation is to check on the files `Out/contours_labels.tif` and `Out/labeled_img_regular.tif` if the classification seems correct.

However, the confidence map is also provided. It allows to see where the classifier experiences difficulties to make a clear choice between two classes. For the Random Forest (the default classifier), the confidence of a pixel is the proportion of votes for the majority class. For other classifiers, see the OTB Cookbook [1]. The confidence map has values between 0 and 1, 1 being the best confidence. The user will therefore try to add samples in the low confidence zones. The original confidence map can be a bit difficult to read at first, mostly due to the fact that isolated pixels of low confidence are often hard to classify even for a human observer. Therefore, a modified confidence map is provided, consisting of zones of low confidence, rather than pixels. To do so, a median filter is simply applied to the original confidence map. The result are given in figure 2.16. To obtain the same result, apply the style `confidence_enhanced_style.qml` on the `Out/confidence_enhanced.tif` file.

Warning: is it important to note that a high confidence does not imply a good classification. Therefore, the classification should be checked visually first. However, a low confidence often implies a bad classification, or at least an unstable one.



(a) Initial Confidence map (b) Modified Confidence map

Figure 2.16: Enhancement of the confidence map

2.4.10 Complementary information

Some information about the performed classification can be retrieved.

A. Samples and confidence evolutions

You can run the `confidence_map_exploitation.py` easily with

```
python confidence_map_exploitation.py
```

It will generates two files in the `Statistics` directory.

The first one is the evolution of samples you manually placed at each iteration (example in figure 2.17). As you can see here, the evolution is almost linear, and it is a good practice to follow to obtain quick results. Of course, in some difficult cases, the last iterations will have less added points, to finely tune the classification.

[1] https://www.orfeo-toolbox.org/CookBook/Applications/app_TrainVectorClassifier.html

The second one is the confidence evolution. The mean confidence of all the pixels should generally increase. The confidence of the samples you placed will probably slightly decrease, as you will place more difficult points at each iteration.

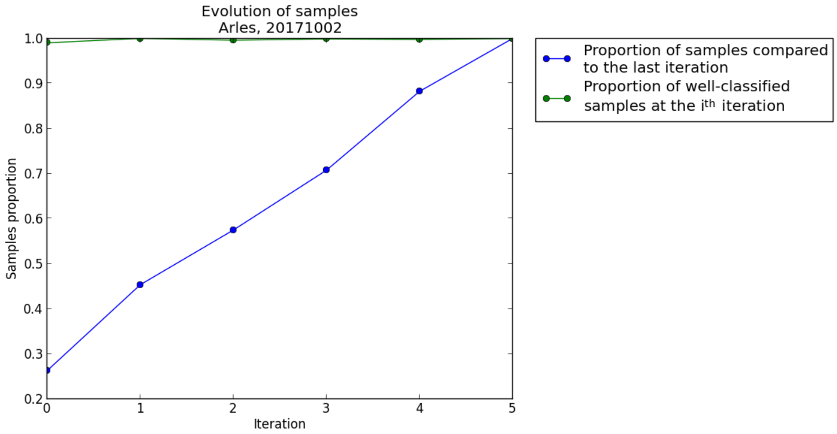


Figure 2.17

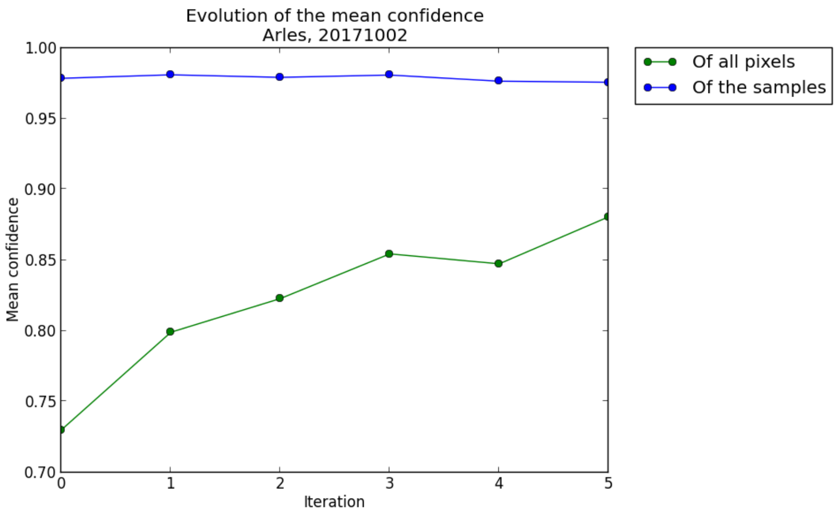


Figure 2.18

B. K-fold cross-validation

At any point, you can perform a K-fold cross-validation with the samples you placed, by running

```
python all_run_alcd.py -f false -s 0 -kfold true
```

Go to the `Statistics` directory to see the result, notably the `k_fold_summary.json` file, or the more eloquent `kfold_metrics.png` figure, an example of which is shown in figure 2.19. To have a stable classification, the four scores should be as close to 1 as possible, for each fold.

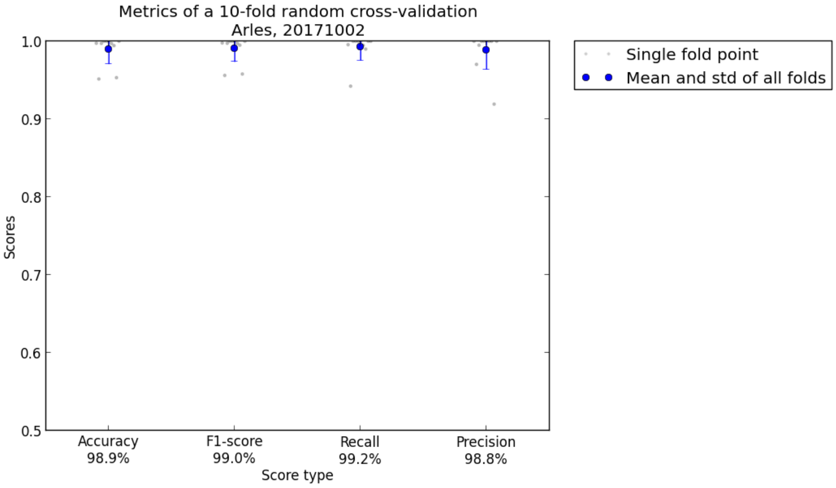

Metrics of a 10-fold random cross-validation
Arles, 20171002
Single fold point
Mean and std of all folds
Scores
1.0
0.9
0.8
0.7
0.6
0.5
Accuracy
98.9%
F1-score
99.0%
Recall
99.2%
Precision
98.8%
Score type

Figure 2.19

3 Processing Chains Comparator (PCC)

This part deals with the utilisation of the PCC code. In the following, PC stands for Processing Chain, i.e. MAJA, Sen2Cor or Fmask.

3.1 Data organisation

For the input data, refer to the section 1.4.2.

The output structure of the code is the following, for a given location and date:

`location and date dir : main directory; e.g. Arles_31TFJ_20171002`

- `Binary_classif : conversion of the masks to binary classification`
- `Binary_difference : binary difference between a reference mask and a PC mask`
  - `ALCD_dilated : the reference mask is with the dilation of the cloud masks`
  - `ALCD_initial : the reference mask is the initial ALCD output`
- `Intermediate : intermediate files needed for the PCC to run smoothly`
- `Multi_classif : conversion of the masks to multi-class classification`
- `Multi_difference : multi-class difference between a reference mask and a PC mask`
  - `ALCD_dilated : the reference mask is with the dilation of the cloud masks`
  - `ALCD_initial : the reference mask is the initial ALCD output`
- `Original_data : contains the original masks of the different PC`
- `Out : png conversion of the binary differences and quicklook of the site`
- `Statistics : various statistics such as the metrics about the binary differences`

3.2 Configuration file

Some parameters can be tweaked in the configuration files (located in the `parameters_files` directory).

- In the `comparison_parameters.json`, the different parameters are described below. **There should be no need to change them, as it is mostly definitions for the output names.** Exception is made for the ones with an ∗.

  general : parameters regarding the output names of the ALCD code. They should be the same as the ones in `root_dir/ALCD/parameters_files/global_parameters.json`

  processing : various definitions for the different processing chains.

  automatically_generated : references to the specific case you are working on. This will be modified when running PCC, so you do not need (and should not) change it manually

  ∗ **alcd_output** **dilatation_radius_meters** : the radius, in meters, for the dilatation of the clouds masks in the Dilate mode. See 3.4.

  erosion_radius_meters : the radius, in meters, for the erosion of the clouds masks in the Erode mode. See 3.4.

labeled_img_name : should be the output name of the ALCD program.
resolution : the output resolution, in meters.

maja_parameters : name of the MAJA sub directory and the MAJA version. They are automatically changed when running the code, so you should not modify them here.

3.3 Code workflow and overview

The PCC framework is mostly a comparator of georeferenced data. Therefore, its main steps are to convert the data such that they can be compared, and then to compare them.

3.3.1 Equivalences between processing chains outputs

First, the framework converts the outputs of the different processing chains to a standard format, namely that of ALCD, i.e. it changes the class numbers or flags of the original program output to the ALCD standard. The equivalence between the original classes and the ALCD ones is given in the following.

It should be noted that this conversion is necessary so as to produce a multi-class classification, and not just a valid / not-valid one. However, the interpretation and the philosophy of each program being different, one could argue about the pertinence of the equivalences. For example, should a pixel labeled as 'cloud_low_probability' by Sen2Cor translate into a land or a low cloud class? Luckily, one can change them directly in the code.

A. Sen2Cor and ALCD equivalence

For Sen2Cor, a direct conversion can be applied between the classes, as shown in table 3.1.

ALCD		Sen2Cor	
Label	**Classification**	**Label**	**Classification**
0	null value	0	NO_DATA
0	null value	1	SATURATED_OR_DEFECTIVE
5	land	2	DARK_AREA_PIXELS
4	clouds shadows	3	CLOUD_SHADOWS
5	land	4	VEGETATION
5	land	5	BARE_SOILS
6	water	6	WATER
5	land	7	CLOUD_LOW_PROBABILITY
2	low clouds	8	CLOUD_MEDIUM_PROBABILITY
2	low clouds	9	CLOUD_HIGH_PROBABILITY
3	high clouds	10	THIN_CIRRUS
7	snow	11	SNOW

Table 3.1: Sen2cor equivalence

B. MAJA and ALCD equivalence

MAJA works with a flag system. Therefore, one pixel can be flagged in different categories, for example in ALL CLOUDS and in CIRRUS. Each flag is encoded on one bit. The description of each bit can be found in the MAJA ATBD [2]. Therefore, to have a direct

[2] MAJA's ATBD, O Hagolle, M. Huc, C. Desjardins; S. Auer; R. Richter, `https://doi.org/10.5281/zenodo.1209633`

relation between the MAJA and the ALCD output, each class corresponds to a set of valid and invalid bits. Moreover, two files produced by MAJA are actually used: a Cloud mask (thereafter referred to as C) and a Geophysical mask (thereafter referred to as G). The classification conversion is based on both. The condition C5 means that the 5^{th} bit of the Cloud mask is 1. The combination $C1 \wedge \neg\ G6$ means that the 1^{st} bit of the cloud mask is 1, and the 6^{th} bit of the Geophysical mask is 0. The summary is in table 3.2.

To make it clearer, the condition 'this pixel is cloudy' is noted C_any. It is formally noted: $C\_any = (C1 \vee C2 \vee C3 \vee C4 \vee C5 \vee C6 \vee C7 \vee C8)$

ALCD		**MAJA**
Label	**Classification**	**Bits logic rules**
0	null value	If it belongs to no other class
1	background	Not available
2	low clouds	$(C5 \vee C6 \vee C7) \wedge\neg\ (C8)$
3	high clouds	C8
4	clouds shadows	$(C3 \vee C4) \wedge\neg\ (C5 \vee C6 \vee C7 \vee C8)$
5	land	$\neg\ C\_any \wedge \neg\ (G6 \vee G7)$
6	water	$\neg\ C\_any \wedge G1$
7	snow	$\neg\ C\_any \wedge G6$

Table 3.2: MAJA equivalence

C. Fmask and ALCD equivalence

Fmask equivalence is pretty straight-forward. However, it does not make the difference between the low clouds and the high clouds classes.

ALCD		**Fmask**	
Label	**Classification**	**Label**	**Classification**
0	null value	0	null value
5	land	1	clear land
2	low clouds	2	cloud
4	clouds shadows	3	cloud shadow
7	snow	4	snow
6	water	5	water

Table 3.3: Fmask equivalence

D. Multiclass and binary-class equivalence

As seen above, the different programs do not make the same distinction between the classes. To alleviate this problem, and make a fair comparison, the multiclass classification can be transformed into a binary classification.

The standard ALCD multi-class equivalence to the binary classification is in table 3.4.

ALCD multiclass classification		Binary classification	
Label	**Classification**	**Label**	**Classification**
0	null value	0	null value
1	background	1	background
2	low clouds	2	cloud
3	high clouds	2	cloud
4	clouds shadows	2	cloud
5	land	1	background
6	water	1	background
7	snow	1	background

Table 3.4: Multiclass and binary classification equivalence

3.3.2 Comparison between the masks

Once the chain masks are converted, it is possible to compare them to the ALCD output. Two modes are available: the multiclass and the binary-class classification.

Each of them is performed (firstly the multiclass, and then the binary one). The multiclass difference returns poor results in most of the cases, and for every chain. This is due to the fact that there is not a bijective relation for the various equivalence, as seen in 3.3.1. Therefore, statistics (`Statistics` directory) and quicklook of the differences (in the `Out` directory) are only computed for the binary difference. However, the multiclass differences GeoTIFF can be found in the `Multi_difference` directory.

3.3.3 Flowchart

The summary of the flowchart is given in figure 3.1, with the legend from the figure 2.1.

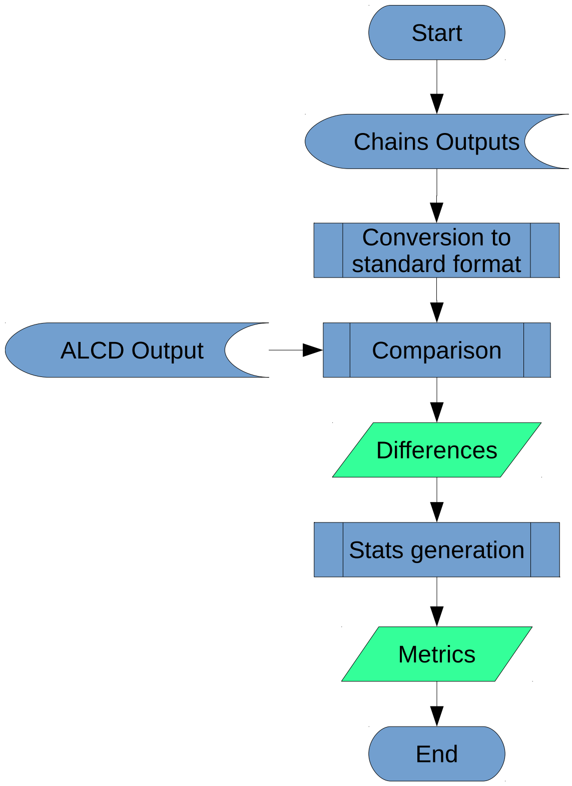


Figure 3.1: PCC flowchart

3.4 Possible variations for the comparison

The traditional way to compare is with the output of the ALCD framework. However, it is possible to use different modes.

3.4.1 ALCD Original

The original, or 'initial' mode. The chains can be compared to it on a multiclass and binary classification fashion.

3.4.2 ALCD Dilation mode

The MAJA cloud mask being dilated, it can be interesting to see what the comparison would be with the ALCD output being dilated as well. In this case, only the binary comparison makes sense and is provided.

3.5 Tutorial

The Processing Chains Comparator is pretty straight-forward. We will use the output of the ALCD code, and therefore use the classification of Arles previously obtained as a reference.

Change to the `PCC` directory. The program that you should use is `all_run_pcc.py`. You can display the help with

```
python all_run_pcc.py -h
```

The available options are:

`-l` : the **location**. The spelling should be consistent with the names in the L1C directory (e.g. Pretoria or Orleans)

`-d` : the (cloudy) **date** that you want to classify (e.g. 20180319)

`-s` : if you want to output your data to a sub-directory, add this option with a name, e.g. MAJA_v3. This will put the results in `Data_PCC/MAJA_v3/location_tile_date` instead of `Data_PCC/location_tile_date`. Useful to run multiple version of the same processing chain and compare the results afterwards.

`-m` : if the masks from MAJA, Sen2Cor and Fmask have already been converted to a standard format. If you ran the algorithm once, it should be the case. Thus, you can set it to True to reduce the computation time

`-r` : which mode you want to set as a reference. It is a combination of the letter 'i' (initial, the original ALCD output) and 'd' (for a dilation of the cloud masks). Can be 'i' or 'id' for example. Several letters will compare with each mode subsequently.

`-b` : if you only want the binary and not the multi-class comparison, you can set it to True. It will save some computation time.

`-mdir` : the name of the MAJA natif output directory you want to use, e.g. MAJA_3_1_S2AS2B_HOT0 See 1.4.2 to understand the MAJA data structure.

`-mver` : the version of MAJA you use, which has to be coherent with the -mdir option. It is needed to automatically fetch the good files, and apply the suitable bits-to-class equivalence

3.5.1 Step 1

Run the different processing chains on the original image. Their different outputs should be in a structured way. At the moment, three chains are taken into account: MAJA, Sen2cor, Fmask.

The paths of the output should be well-defined in the `root_dir/paths_configuration.json`. As a reminder, by default, the main paths for each chain are:

- L1C product root dir: `/mnt/data/SENTINEL2/L1C_PDGS`
- MAJA output root dir: `/mnt/data/SENTINEL2/L2A_MAJA`
- Sen2cor output root dir: `/mnt/data/SENTINEL2/L2A_SEN2COR`
- Fmask output root dir: `/mnt/data/home/baetensl/Programs/Output_fmask`

3.5.2 Step 2

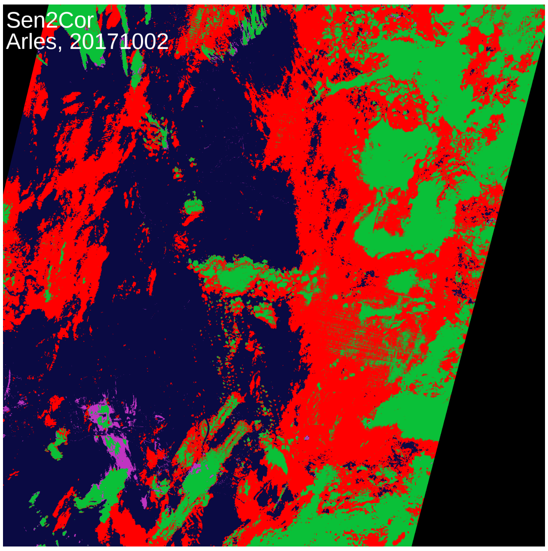
Simply run the PCC code, with the command

```
python all_run_pcc.py -l Arles -d 20171002
```

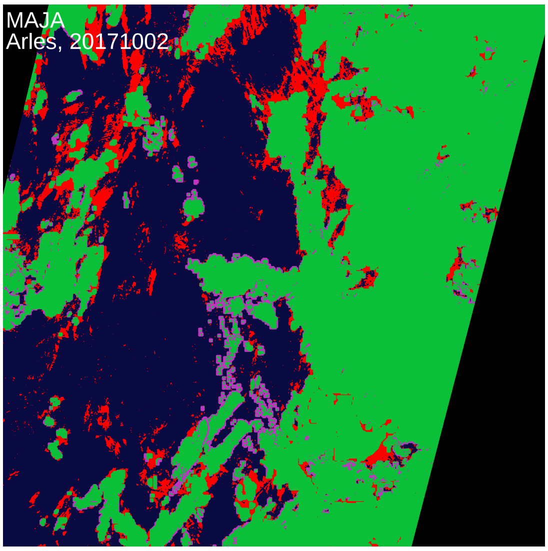
You now have the outputs in the Data_PCC directory.

3.5.3 Step 3

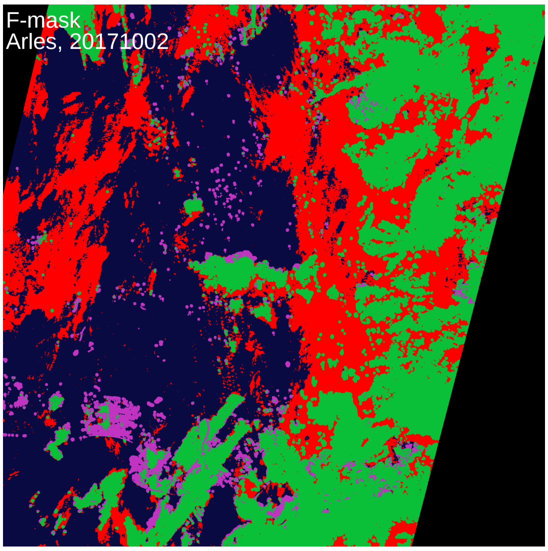
You can now analyse the results. For example, in the `Out/ALCD_initial` directory, are the quicklooks of the binary differences. You should obtain something along the lines of the figure 3.2. You can also open the GeoTIFF directly in QGIS, and apply the style `color_tables/diff_processes_style.qml` to get the same results.



(a) Sen2Cor difference



(b) MAJA difference



(c) Fmask difference

Figure 3.2

The legend is given in table 3.5.

Color	Class #	Class name	Predicted class	Actual class	Meaning
	0	null value	-	-	-
	1	True Positive	cloud	cloud	Good cloud detection
	2	False Negative	¬ cloud	cloud	Cloud Sub-detection
	3	False Positive	cloud	¬ cloud	Cloud Over-detection
	4	True Negative	¬ cloud	¬ cloud	Good background detection

Table 3.5: Available classes and colors

Therefore, it is possible to visually see where the main difference are for each chain output. From these results, statistics are computed.

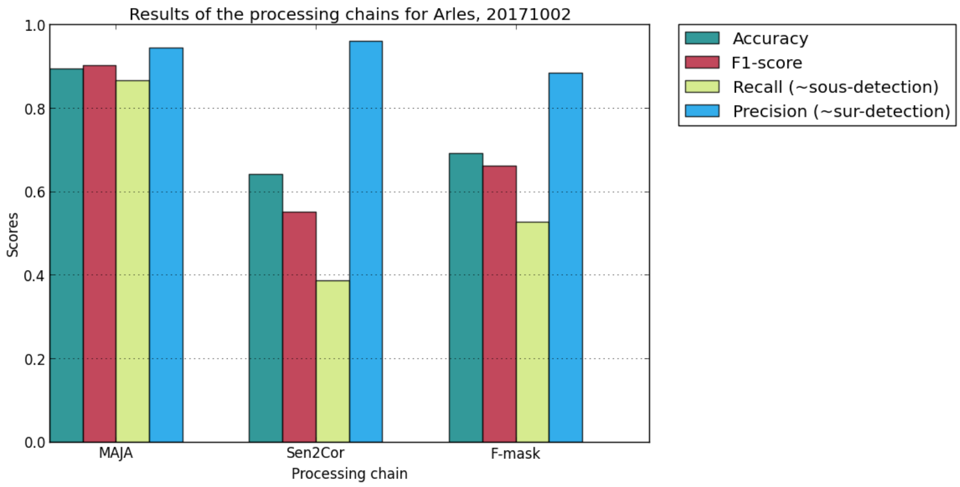


Figure 3.3: Statistics for each chain on Arles, 20171002