Testing of the compositing algorithm for Sentinel-2 products[1]

Technical report

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February 2020

[1] This study was partly funded by the Slovenian Research Agency core funding No. P6-0079 and P2-0406, and by research projects No. J2-9251 and No. J6-9395. The view expressed herein can in no way be taken to reflect the official opinion of the financer.

Abstract

The report describes the methodology and pseudocode for compositing Sentinel-2 products and provides results of three different test cases. The compositing algorithm was designed to produce monthly temporal mosaics, however, it can also be used to produce composites of any desired time interval (e.g. two-monthly, seasonal, etc.). Based on the availability of valid observation data, the algorithm utilizes either STC or Medoid to select the most representative values on a pixel-by-pixel basis.

Contents

1. DESCRIPTION OF THE COMPOSITING ALGORITHM

The compositing algorithm presented herein is based on the Sentinel-2 Global Mosaic (S2GM) algorithm from Kirches and Brockmann (2019).

1.1. Theoretical background

The compositing algorithm selects the best pixel observation in time, which is identified through a series of empirical tests based on statistical characteristics of the spectral measurements. The selected pixel is supposed to be most representative for the selected compositing period. The pixel is kept in its original observed form, the only manipulation of the original measured values occurs during the up-sampling of images. Based on the number of valid observations, two different methods are applied in the selection process, i.e. Short Term Composite (STC) for pixels with a low number of observations and Medoid for pixels with higher number of valid observations. These two methods were chosen by Kirches and Brockmann (2019) as the most optimal, taking into account quality, documentation, applicability, robustness and implementation aspects.

1.2. Filtering

The quality of the resulting composite is sensitive to satellite image classification and pre-filtering of input based on the satellite image classification. Satellite image classification herein stands for cloud and other atmospheric noise detection. The S2GM algorithm utilizes the Sen2Cor satellite image classification algorithm, which detects clouds, their shadows, snow and other features for a total of 12 classes (Kirches and Brockmann, 2019). The algorithm described herein will be used on products from the STORM processing chain (Oštir *et al*, 2015; Zakšek *et al.*, 2015) that uses a slightly different satellite image classification method (ATCOR-2).

Table 1: Sen2Cor satellite image classification labels (Kirches and Brockmann, 2019)

Label	Value	Description
NODATA	0	No data
SATURATED_DEFECTIVE	1	Saturated or defective
DARK_FEATURE_SHADOW	2	Dark feature shadow
CLOUD_SHADOW	3	Cloud shadow
VEGETATION	4	Vegetation
BARE_SOIL_DESERT	5	Bare soil/ desert
WATER	6	Water
CLOUD_LOW_PROBA	7	Cloud (low probability)
CLOUD_MEDIUM_PROBA	8	Cloud (medium probability)
CLOUD_HIGH_PROBA	9	Cloud (high probability)
THIN_CIRRUS	10	Thin cirrus
SNOW_ICE	11	Snow or Ice

Kirches and Brockmann (2019) tested different pre-filtering set-ups, with different flag combinations. They discovered that:

Using the Medoid method, weakening the flag conditions (including classes with lower probability of being valid) resulted in "Prioritizing bare surfaces over vegetation in agricultural areas" and "Haze has more influence on the best pixel".

However, very strict filtering led to single pixels missing (over a yearly period, with even more lost pixels in shorter periods).

Using the STC method, weakening the flag conditions leads to an increase in residual clouds and in the worst case, massive clouds remain in the product.

Very strict filtering leads to immense loss in good pixels, loss of shallow water (caused by the L2A dark area flag), loss of urban areas (caused by medium and low cloud probability flags).

Table 2: Comparison of class labels between STORM and Sen2Cor products.

STORM		**Sen2cor**	
Value	**Description**	**Value**	**Description**
10	no-data/background	0	NODATA
30	ATCOR saturated	1	Saturated or defective
31	ATCOR cloud (very bright)	7, 8, 9	Cloud
32	ATCOR cirrus	10	Thin cirrus
33	*ATCOR snow*	*11*	*Snow or ice*
34	ATCOR thick haze		
35	ATCOR thin haze		
40	*ATCOR shade (water, very dark)*	*2, 6*	*Dark feature, water*
41	*ATCOR water (shade, dark)*		
47	Very dark (0 in at least one band)		
49	Radiometric shade		
50	Topographic shade		
100	*Valid (also thin haze)*	*4, 5*	*Vegetation, bare soil*

In the algorithm described herein, the user can assign a desired threshold, below which all classes are considered not valid. Regardless of the selected threshold, the pixels that classified as snow (33) are separately tested for validity.

1.3. Snow test

Snow test is performed on pixels classified as snow. "This adjustment of the snow detection has been necessary to prevent that cloudy pixels classified as snow have a negative effect on the composites" (Kirches and Brockmann, 2019). If snow test is true, the pixel is considered valid, else the pixel was erroneously classified as snow and is removed from further processing.

$$\mathrm{TCB} = 0.3029 \cdot \mathrm{B02} + 0.2786 \cdot \mathrm{B03} + 0.4733 \cdot \mathrm{B04} + 0.5599 \cdot \mathrm{B8A} + 0.508 \cdot \mathrm{B11} + 0.1872 \cdot \mathrm{B12}$$

$$\mathrm{NDSI} = (\mathrm{B03} - \mathrm{B11}) / (\mathrm{B03} + \mathrm{B11})$$

$$If \quad NDSI > 0.6 \quad and \quad TCB > 0.36 \quad then \quad isSnow = True$$

1.4. Short Term Composite (STC) method

Modified normalized difference water index (identical to the definition of normalized difference snow index, NDSI) [Du et al., 2016 and Xu, 2006]

$$mNDWI = \frac{\rho_{B3} - \rho_{B11}}{\rho_{B3} + \rho_{B11}}$$

Normalized difference vegetation index

$$NDVI = \frac{\rho_{B8} - \rho_{B4}}{\rho_{B8} + \rho_{B4}}$$

Tasseled cap transformation brightness

$$TCB = 0.3029\, \rho_{B2} + 0.2786\, \rho_{B3} + 0.4733\, \rho_{B4} + 0.5599\, \rho_{B8A} + 0.508\, \rho_{B11} + 0.1872\, \rho_{B12}$$

Brightness

$$Brigthness = \rho_{B2} + \rho_{B3} + \rho_{B4}$$

Mean of B11 and B12 values

$$Mean\ of\ B11\ and\ B12 = \frac{\rho_{B11} + \rho_{B12}}{2}$$

Mean of index X (X = NDVI, mNDWI ...)

$$\bar{X} = \sum_{i=1}^{N} \frac{X_i}{N} \quad with\ N = number\ of\ valid\ observations$$

Decision logic and thresholds for STC method are as follows:

Priority	Select the pixel with	Decision logic and thresholds
1	Max NDVI	Mean(mNDWI) < -0.55 and max(NDVI)-mean(NDVI) < 0.05
2	Max mNDWI	Mean(NDVI) < -0.3 and mean(mNDWI)-min(NDVI) < 0.05
3	Max NDVI	Mean(NDVI) > 0.6 and mean(TCB) < 0.45

4	Min TCB	Cloud test of pixel with min(TCB) is False
5	MinTCB	Snow test of pixel with min(TCB) is False and min(TCB) < 1.0
6	None	Snow test of pixel with min(TCB) is False and min(TCB) > 1.0
7	Max mNDWI	Mean(NDVI) < -0.2
8	Min NDVI	Mean(TCB) > 0.45
9	Max NDVI	None of the above

1.5. Medoid method

Medoid method is used in cases where 4 or more valid observations are available. The Medoid is the most representative object of a data set, i.e. it is the object that is the closest to the average value of the dataset. The method is robust against extreme values in the data set and works well for selecting a representative value over a season, while also reducing contamination by clouds.

The user can choose between Euclidian distance and normalized difference for calculation of Medoid.

The Medoid is defined as follows:

$$medoid(X) = \underset{x_i \in X}{\arg min} \sum_{x_j \in X} \|x_j - x_i\|$$

With the Euclidian distance

$$\|x_j - x_i\| = \sqrt{\sum_{b=1}^{n_{bands}} \left(x_{j,b} - x_{i,b}\right)^2}$$

With the normalized difference

$$\|x_j - x_i\| = \sum_{b=1}^{n_{bands}} \left|\frac{x_{j,b} - x_{i,b}}{x_{j,b} + x_{i,b}}\right|$$

The method finds the representative point from a set of points in n-dimensional space. In the case of Sentinel-2 products the dimensions correspond to available spectral bands, particularly bands B02, B03, B04, B06, B08, B11, and B12.

1.6. Up-sampling

Up-sampling to 10 m from 20 m products via nearest neighbour method for bands B06, B8A, B11, B12, and satellite image classification mask. The 20 m mask is considered more accurate since more spectral bands were used in its calculation.

1.7. Pseudo code

PREPARATION OF DATA

a. Set input parameters:
    i. Geographical extents (optional),
    ii. Time interval for compositing,
    iii. Product resolution (10m or 20m),
    iv. Valid pixel threshold (which mask classes to treat as valid),
    v. Medoid method (Euclidian distance or normalized difference).
b. Create a list of paths to relevant source images:
    i. Create a table where each row contains data for single observation,
    ii. Add paths to 10m image and mask (only if 10m is selected),
    iii. Add paths to 20m image and mask.
    iv. Read metadata of source images
c. Set properties of the output array (based on the input and source images):
    i. Width,
    ii. Height,
    iii. Pixel size,
    iv. Other metadata required for saving as GeoTIFF.
d. Exclude images that fall out of the selected geographic extents.
e. Open all files with Rasterio for reading (create list of Rasterio objects).

PROCESSING (PER-PIXEL)

a. Determine coordinates of the current pixel from metadata.
b. Initiate a table that will store all available instances of the same pixel (across all observations.
c. Initiate *nobs* (number of available observations) and *nok* (number of valid observations) arrays.
d. For each observation:
    i. Check if pixel exists: are coordinates within image extents?
       If yes then *nobs += 1;*
       Else skip this image.
    ii. Read pixel from Rasterio object.
    iii. Check if pixel is valid:
        Determine validity from mask.
        If classified as snow, preform snow test (with S2GM method).
       If it is valid then *nok += 1;*
       Else skip this image.
    iv. If it passed both tests add pixel as a new row in the table.
e. Select best pixel (from the table) using one of the following methods:
    i. If only one valid pixel: Keep this pixel,
    ii. If < 4 valid pixels, preform STC method (S2GM),
    iii. If >= 4 valid pixels, preform Medoid method (S2GM),
    iv. If no valid pixels set to Nan.
f. Save selected pixel (and nok, nobs) to output array.

FINISHING UP

a. Close all open files (Rasterio objects).
b. Save composite, nok and nobs arrays.

2. Test areas

2.1. Test case 01: Mura 2017-03 (March)

This test case was used to illustrate how the algorithm deals with data sets with low number of valid observations. Only 6 images were available for this period and, based on the RGB previews, only 2 of them could offer good quality observations, with other 4 heavily obscured by clouds.

Because there were less images available we also used this case study to test WEAK FILTERING, i.e. a filtering criteria where pixels classified as very bright and cirrus are also considered as valid observations.

- Monthly composite for March 2017 for the “Mura” reference area
- Geographical extents: (597580, 154390, 610635, 164960)
- Spatial resolution: 20 m

There were 6 available observations for the selected case:

- (20170302T100021_S2A_MSIL2A_20170302T100020_C122_20m\)
- 20170309T095021_S2A_MSIL2A_20170309T095021_E079_20m\
- 20170312T100021_S2A_MSIL2A_20170312T100706_C122_20m\
- 20170319T095021_S2A_MSIL2A_20170319T095021_E079_20m\
- 20170322T100021_S2A_MSIL2A_20170322T100019_C122_20m\
- 20170329T095021_S2A_MSIL2A_20170329T095024_E079_20m\

Four different filtering criteria were tested:

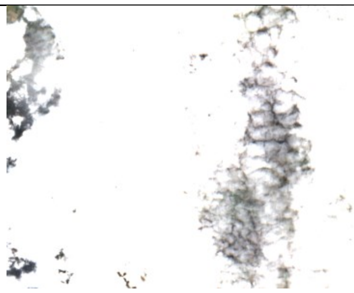
- WEAK FILTERING: valid if mask is 31 or greater (include very bright pixels, clouds, cirrus, thick and thin haze, shade, water and above)
- SEMI-WEAK FILTERING: valid if mask is 34 or greater (include thick and thin haze, shade, water and above)
- SEMI-STRICT FILTERING: valid if mask is 41 or greater (include water and above)
- STRICT FILTERING: valid if mask is 100 (only strictly valid pixels)

Runtime on a standard PC with Intel Core i7 processor, running in parallel on 7 threads:

Area:	140 km2
Spatial resolution:	20 m
Pixel count:	350,000
No. of input images:	5
Average runtime:	2176 s = 36 min

RGB of available observations

- Available 6 observations in total
- Of those, 2 are mostly free of clouds
- Because of errors in classification of image (1) (explained and illustrated in the next sub-section) only images (2) – (6) were used in March composite

(1) 2017-03-02	(2) 2017-03-09	(3) 2017-03-12
		

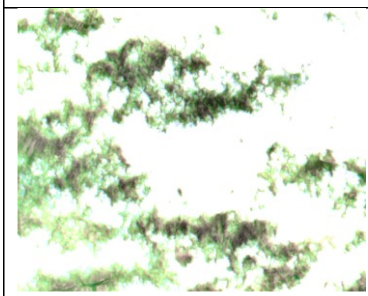
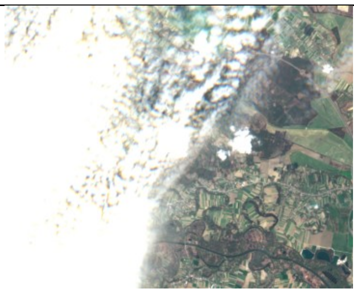
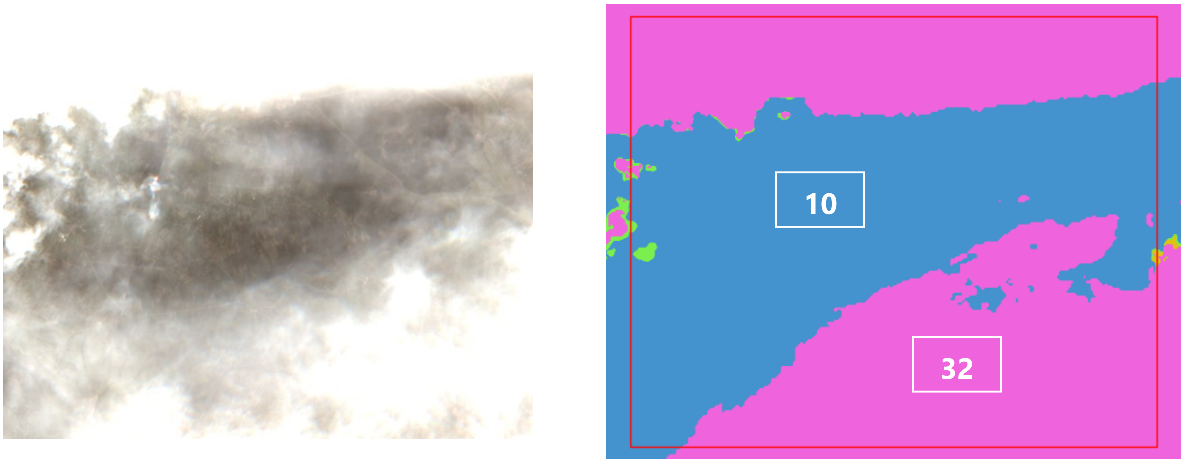
(4) 2017-03-19	(5) 2017-03-22	(6) 2017-03-29
		

Figure 1: RGBs of available S-2 products for March 2017.

Problems arising from erroneous classification 1

Results of the compositing algorithm are only as good as the initial classification of the pixels. The observations from March 2017 of Mura reference area contain one of the images in which a large area obscured by clouds was classified as valid (100) (*Figure 2*).

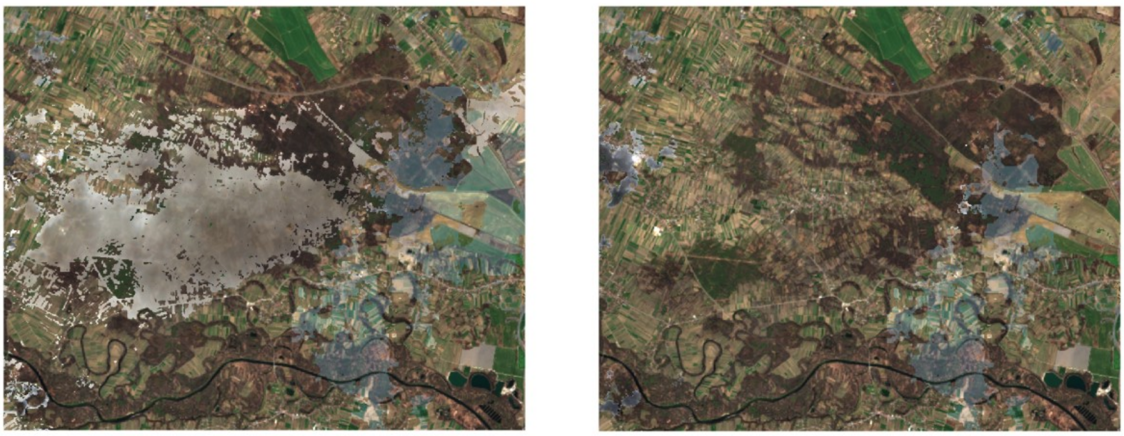


(1a) RGB on 2017-03-02

(1b) satellite image classification mask

Figure 2: Classification of image (1) from 2017-03-02 with the following classes: (32) cirrus, (100) valid.

Such error has a substantial effect on the resulting composite, primarily in situations where STC method has to be applied (i.e. 2 or 3 valid observations available). Because STC method favours brighter observations, such cloudy pixel will be selected over a "truly green" pixel (*Figure 3*).



(a) If image (1) is included in compositing

(b) If image (1) is excluded from compositing

Figure 3: The difference between including (a) and excluding (b) the erroneously classified image from the compositing algorithm.

However, in the case of Medoid method (i.e. more than 4 valid observations) such error will generally not pose a problem, because the "cloudy pixel" would fall out of the selection as an outlier. To illustrate this we ran a test on a combined March + April composite (12 available, with 5 relatively cloud-free images), where the error in classification in one of the images did not have any effect on the resulting composite *Figure 4*.

(c) Mar + Apr with image (1) included

Figure 4: Two-month composite of March and April 2017 with 12 available images, including image (1) with the error in classification.

Problems arising from erroneous classification 2

The image from 2017-03-09 has a relatively large patch classified as 34 (thick haze) (*Figure 5*), which means it is excluded from the selection process when strict or semi-strict filtering is applied. On inspection of the RGB image the same area appears without haze, which means it should be considered in the selection process. In some cases, such errors can lead to a loss of the only potentially valid observation.

Strict filtering would also ignore waterbodies and dark shadows (41), which generally does not have any effect on the green surfaces. However, for studies in which it is important to have an accurate representation of water surfaces, strict filtering should be avoided to prevent loss of such pixels.

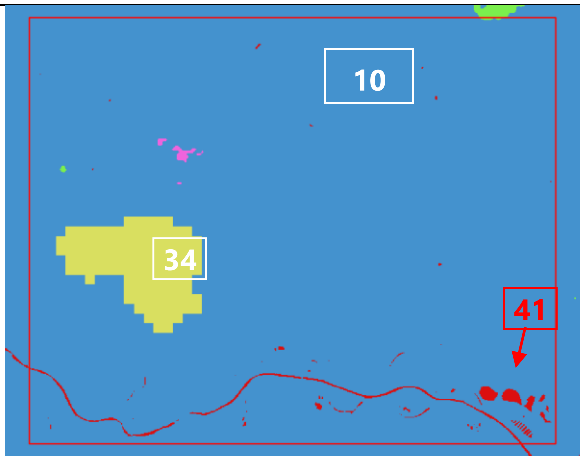
<table>
<tr><td>(1a) RGB on 2017-03-09</td><td>(1b) classification mask</td></tr>
<tr><td></td><td>
</td></tr>
</table>

Figure 5: Classification of image (2) from 2017-03-09 with the following classes: (34) thick haze, (41) water/shade, (100) valid.

Weak filtering

With weak filtering a pixel is considered valid if it was classified as (31) cloud/very bright or greater. This includes very bright pixels, clouds, cirrus, thick and thin haze, shade, water and everything above. It excludes saturated pixels, background and no-data.

Weak filtering was found to be unsuitable for compositing, as it allows to many bright/cloud pixels to be considered in the selection process (*Figure 6*). For pixels which are in majority covered by clouds (in this situation 4 out of 6), the method will choose a clouded pixel as the most representative. This shows that weak filtering is generally not suitable for compositing.

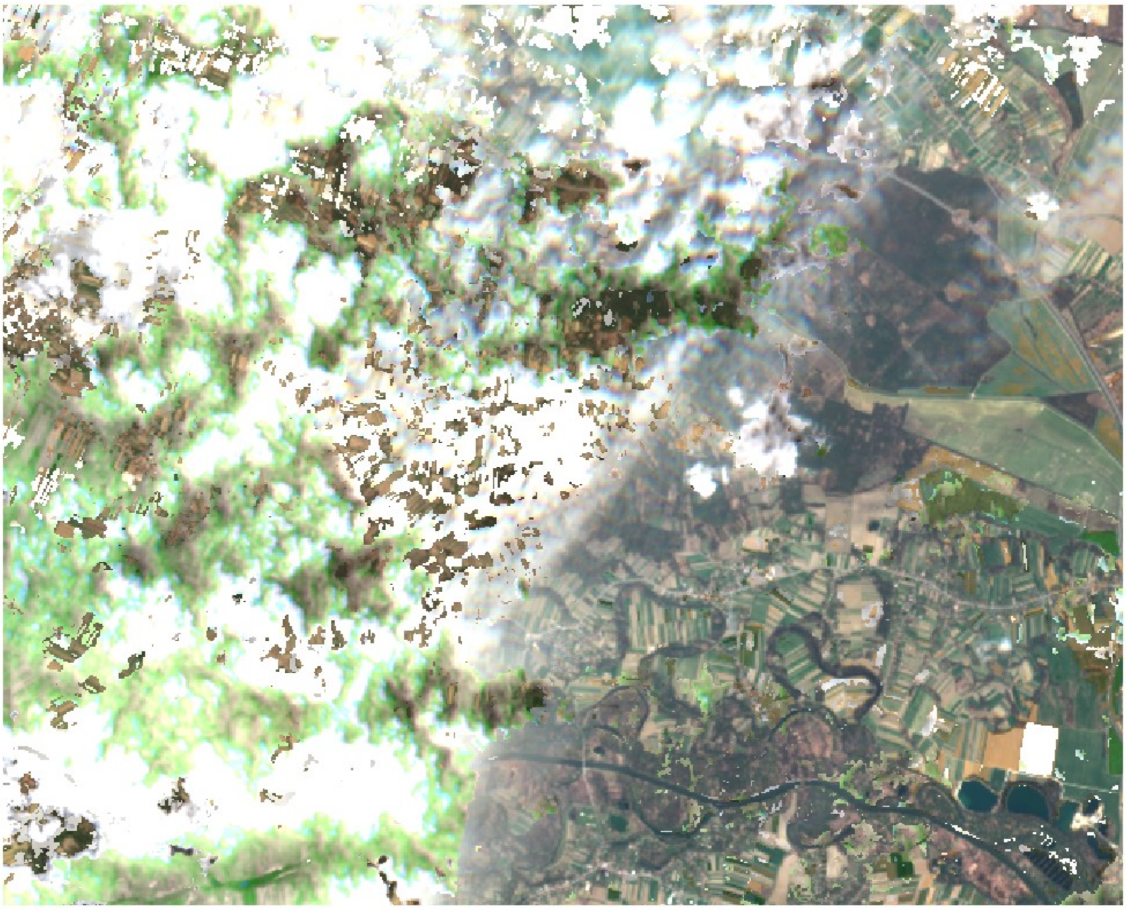


Figure 6: Monthly composite (March 2017) of Mura reference area with WEAK FILTERING.

Number of valid observations for each pixel

The image with error in classification was excluded from this test, which means that only 5 images were considered for March composite. STRICT filtering resulted in no valid observations for water surfaces (*Figure 7*). The blue patch in STRICT and SEMI-STRICT filtering means only 1 valid observation, which was in this case due to an error in classification (circled in *Figure 7* and *Figure 8*). This error was avoid by applying SEMI-WEAK filtering (*Figure 9*).

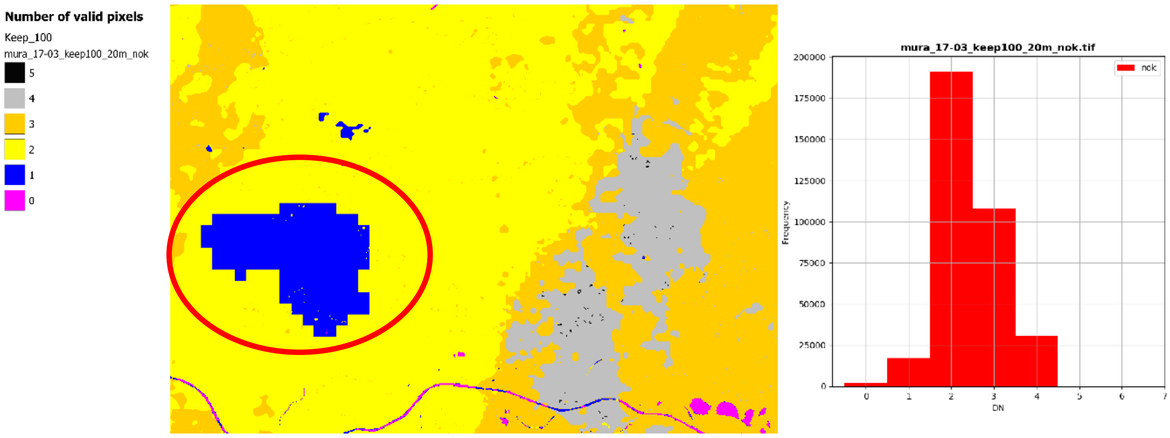


Figure 7: No. of valid observations for STRICT FILTERING.

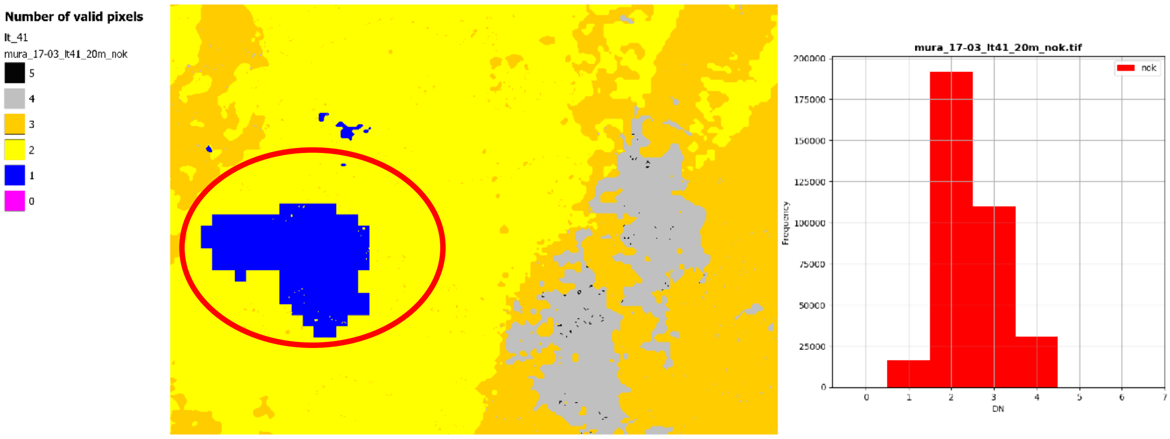


Figure 8: No. of valid observations for SEMI-STRICT FILTERING.

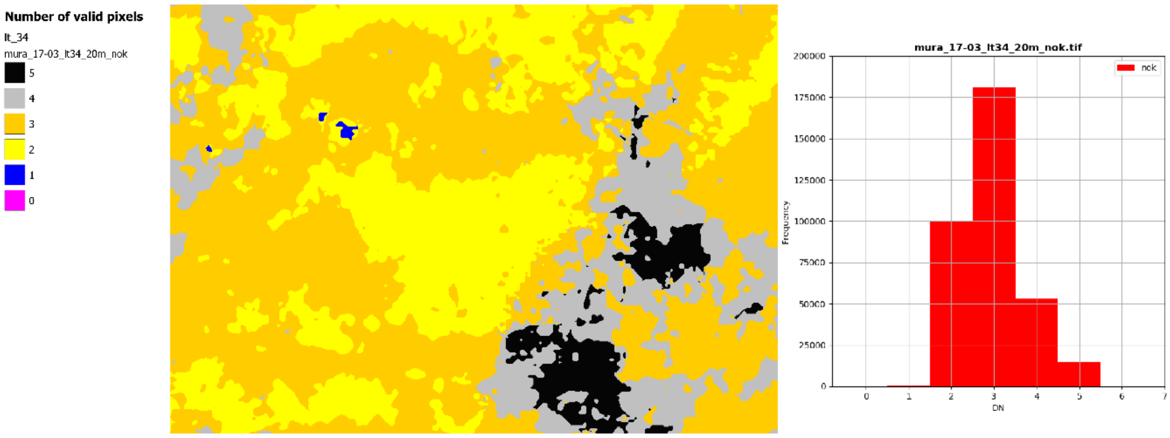


Figure 9: No. of valid observations for SEMI-WEAK FILTERING.

Selected pixels

The majority of the pixels were selected from image (2). In STRICT and SEMI-STRICT filtering, the pixels from the blue area (from previous images) were selected from image (6) (*Figure 10* and *Figure 11*). In the place where Medoid method was applied (grey area from previous images), selected pixels came from image (5), shown in red. SEMI-WEAK filtering allowed some pixels from image (4) (in light blue) to be selected over other visually clearer observations.

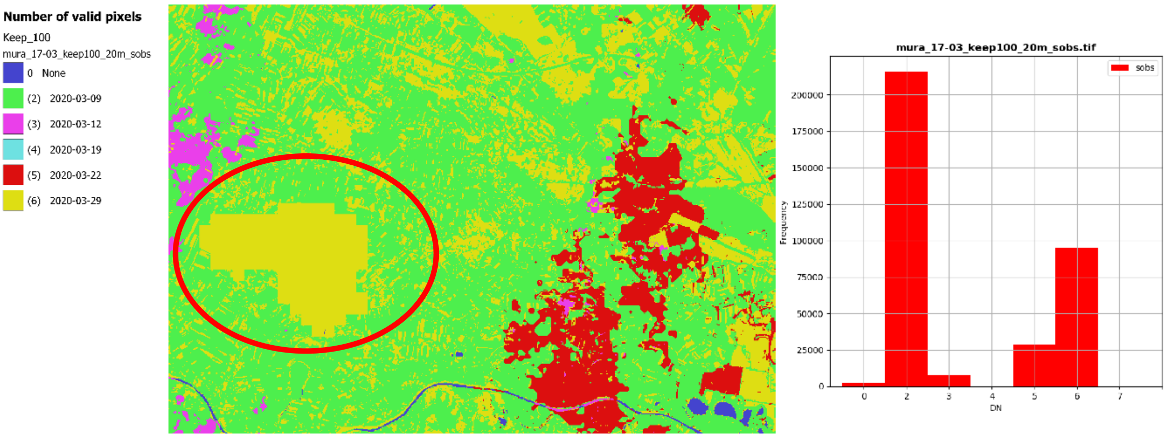


Figure 10: Observation date of the selected pixel for STRICT FILTERING.

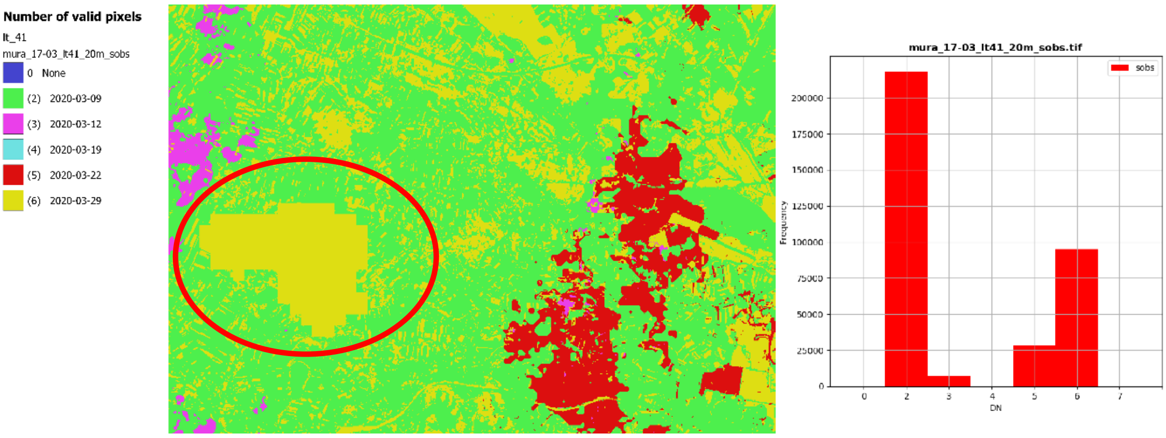


Figure 11: Observation date of the selected pixel for SEMI-STRICT FILTERING.

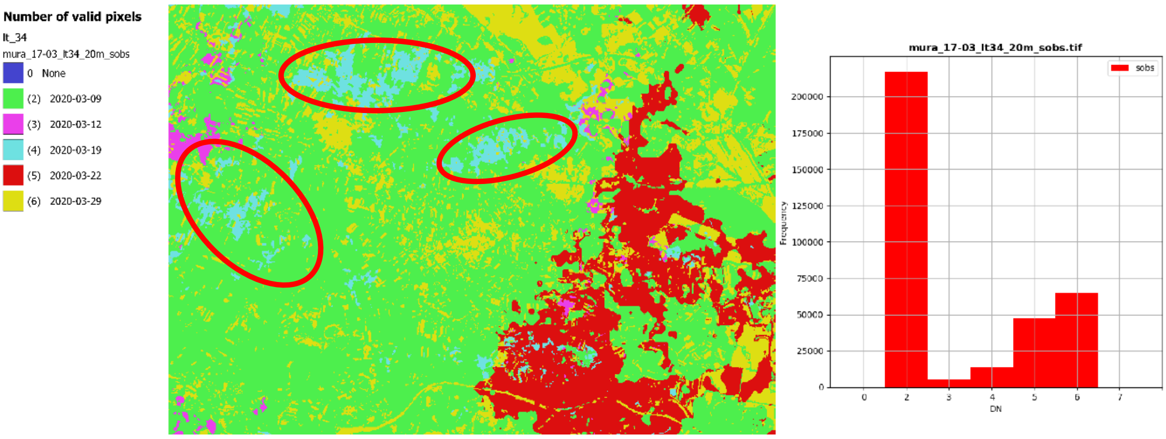


Figure 12: Observation date of the selected pixel for SEMI-WEAK FILTERING.

Resulting composites

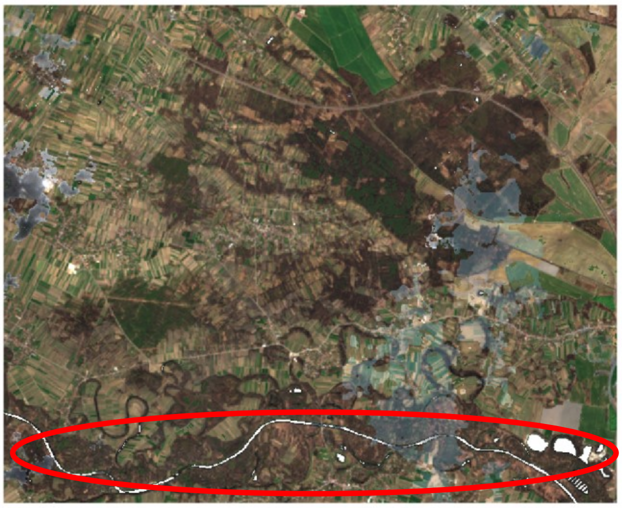


Figure 13: Composite from STRICT FILTERING. No-data in the location of larger water bodies (circled).

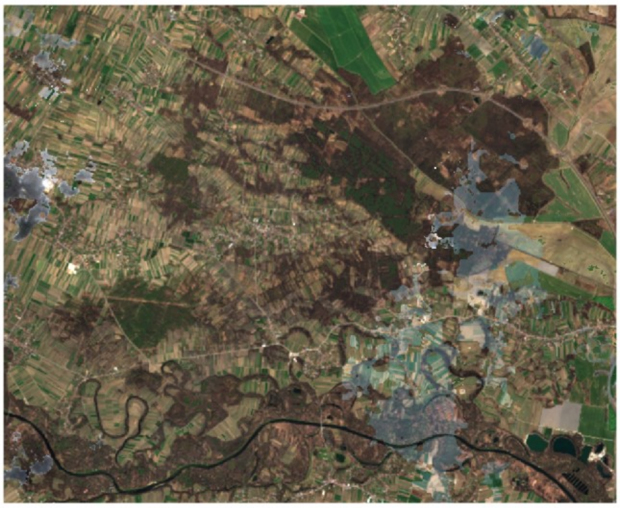


Figure 14: Composite from SEMI-STRICT FILTERING.

Figure 15: Composite from SEMI-WEAK FILTERING. "Brighter patches" selected from image (4), which was partially obscured by clouds.

2.2. Test case 02: Mura 2017-04 (April)

Another test case to illustrate how the algorithm deals with data sets with low number of valid observations. Only 6 images were available for this time period and based on the previews only 2 of them could offer good quality observations, with other 4 heavily obscured by clouds.

- Monthly composite for April 2017 for the "Mura" reference area
- Geographical extents: (597580, 154390, 610635, 164960)
- Spatial resolution: 20 m

There were 6 available observations for the selected case:

- 20170401T100021_S2A_MSIL2A_20170401T100022_C122_20m\
- 20170408T095031_S2A_MSIL2A_20170408T095711_E079_20m\
- 20170411T100031_S2A_MSIL2A_20170411T100025_C122_20m\
- 20170418T095031_S2A_MSIL2A_20170418T095718_E079_20m\
- 20170421T100031_S2A_MSIL2A_20170421T100541_C122_20m\
- 20170428T095031_S2A_MSIL2A_20170428T095704_E079_20m\

Three different filtering criteria were tested:

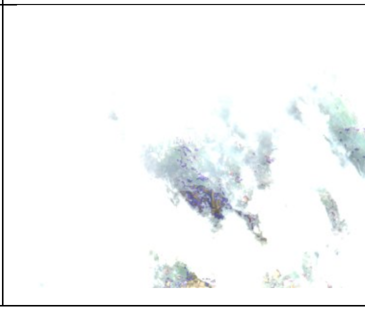
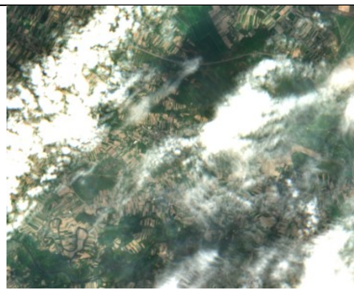
- SEMI-WEAK FILTERING: valid if mask is 34 or greater (include thick and thin haze, shade, water and above)
- SEMI-STRICT FILTERING: valid if mask is 41 or greater (include water and above)
- STRICT FILTERING: valid if mask is 100 (only strictly valid pixels)

Runtime on a standard PC with Intel Core i7 processor, running in parallel on 7 threads:

Area:	140 km2
Spatial resolution:	20 m
Pixel count:	350,000
No. of input images:	5
Average runtime:	2254 s = 38 min

RGB of available observations

- Available 6 observations in total
- Of those, 2 are mostly free of clouds

(1) 2017-04-01	(2) 2017-04-08	(3) 2017-04-11
		

(4) 2017-04-18	(5) 2017-04-21	(6) 2017-04-28
		

Figure 16: RGBs of available S-2 products for April 2017.

Number of valid observations for each pixel

Again, STRICT FILTERING resulted in 1 or less valid observations for water surfaces (circled in *Figure 17*). SEMI-WEAK filtering meant that Medoid method was used on a patch in the eastern part of the image (circled in *Figure 19*).

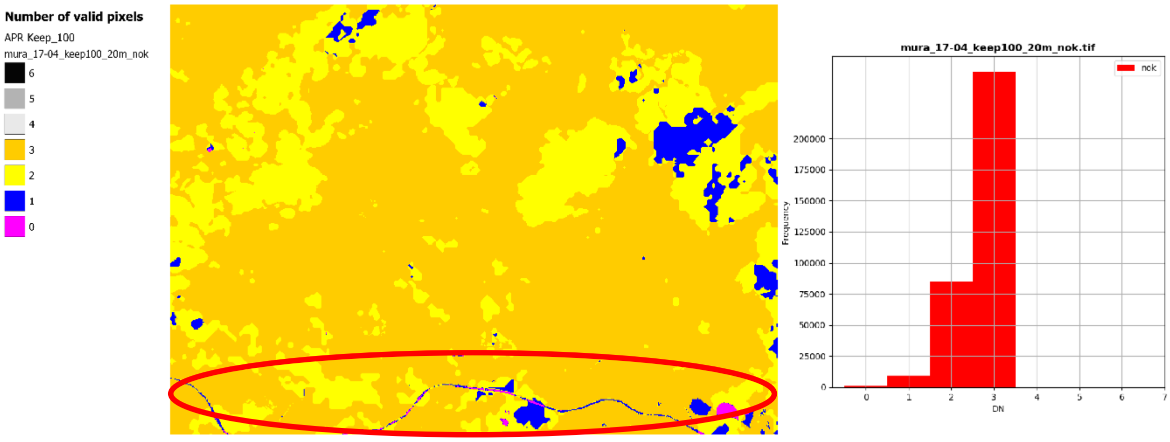


Figure 17: No. of valid observations for STRICT FILTERING. Water surfaces (circled) have 1 or less valid observations.

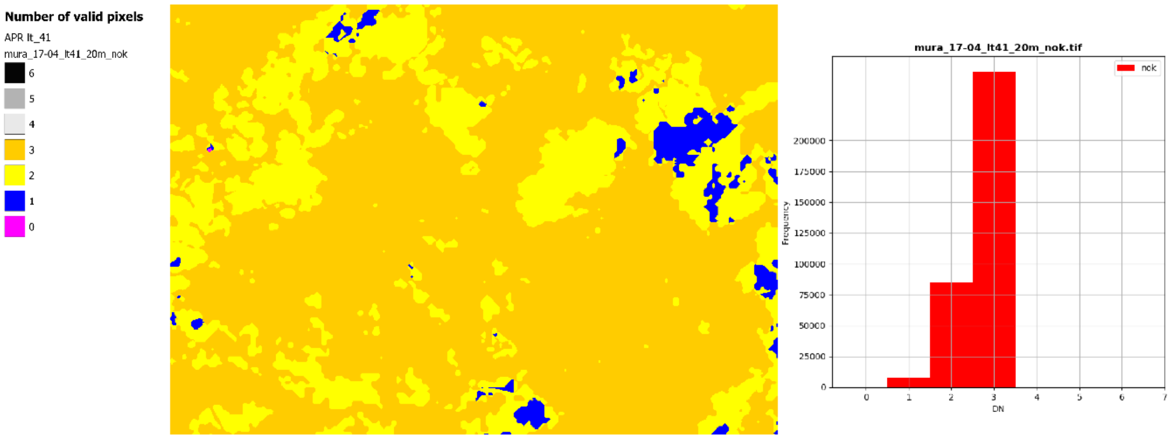


Figure 18: No. of valid observations for SEMI-STRICT FILTERING.

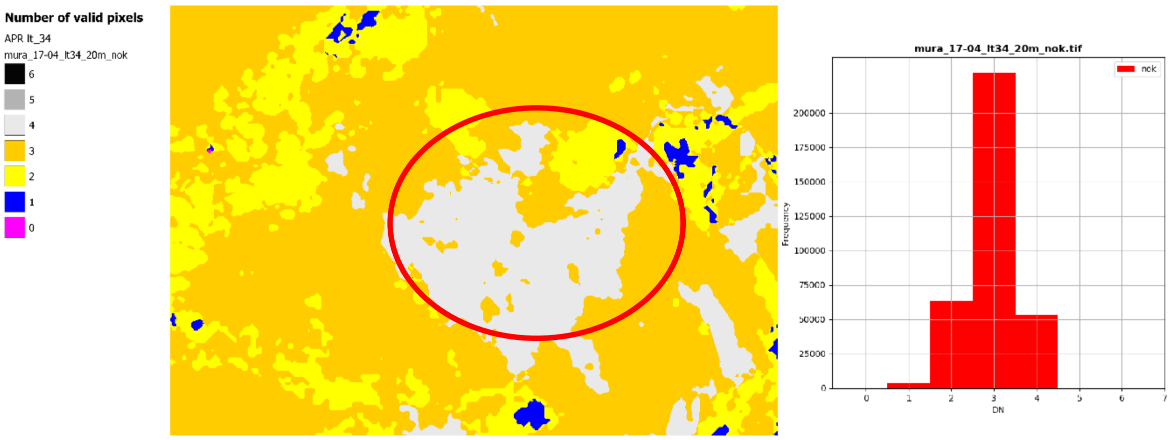


Figure 19: No. of valid observations for SEMI-WEAK FILTERING. Medoid method (circled) only used if this filtering is selected.

Selected pixels

There is almost no difference in selected pixels amongst the three cases, apart from no-data for water surfaces in STRICT FILTERING (*Figure 20*) and small patches where Medoid method was used in SEMI-WEAK filtering (*Figure 22*).

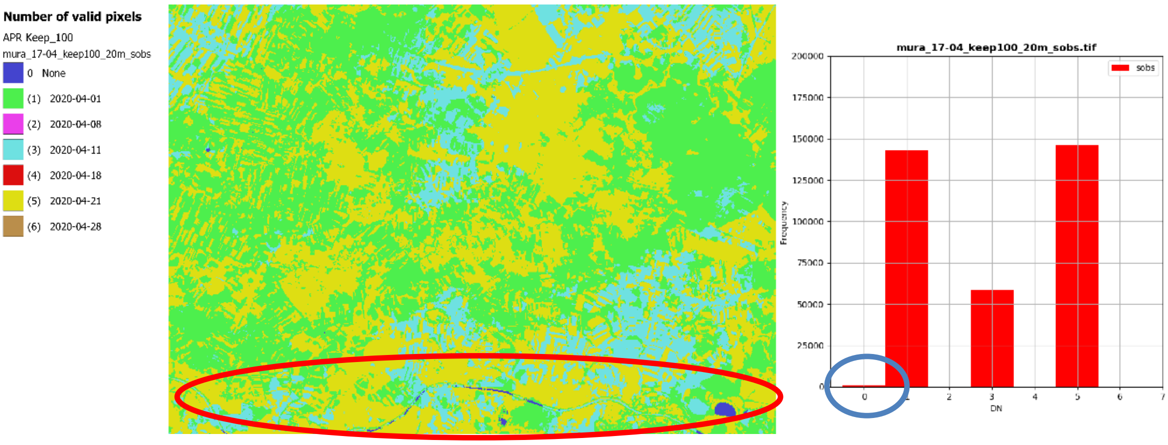


Figure 20: Observation date of the selected pixel for STRICT FILTERING.

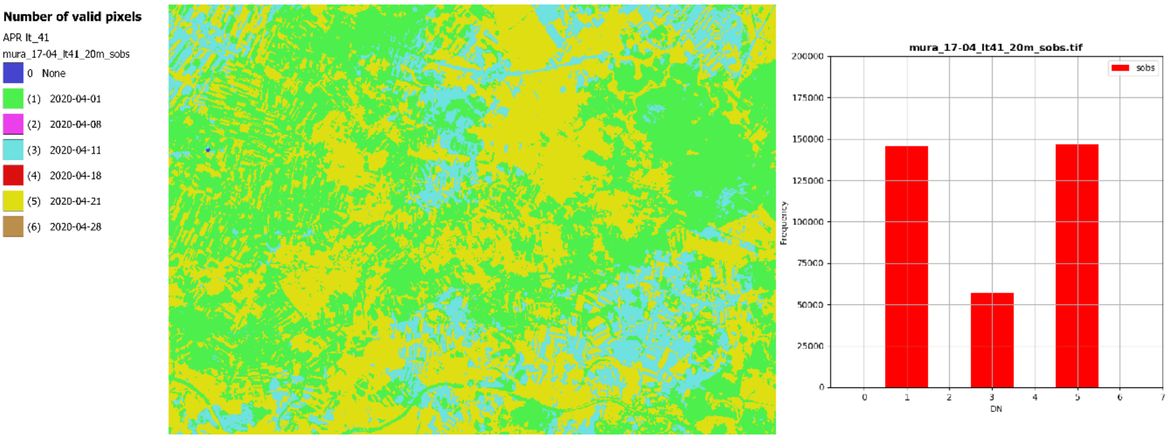


Figure 21: Observation date of the selected pixel for SEMI-STRICT FILTERING.

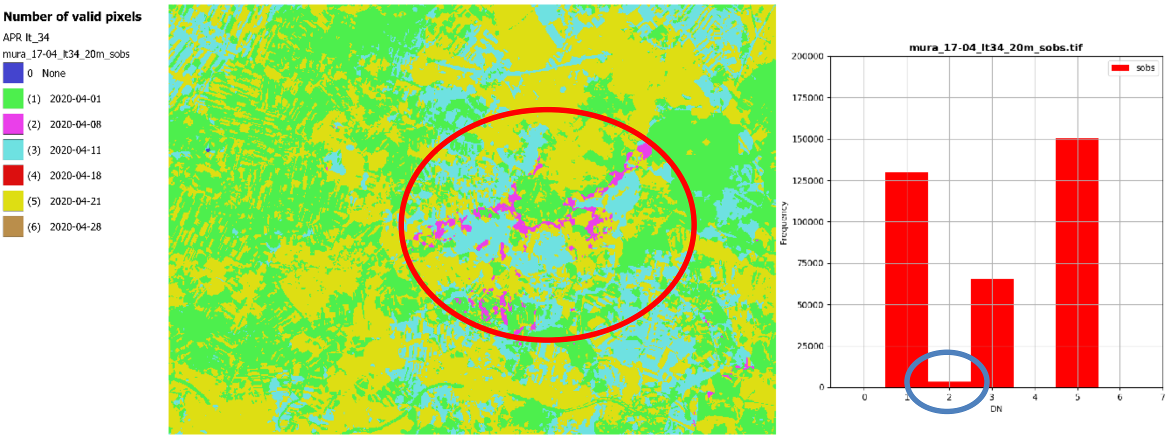


Figure 22: Observation date of the selected pixel for SEMI-WEAK FILTERING.

Resulting composites

Figure 23: Composite from STRICT FILTERING. No-data in the location of larger water bodies (circled).

Figure 24: Composite from SEMI-STRICT FILTERING.

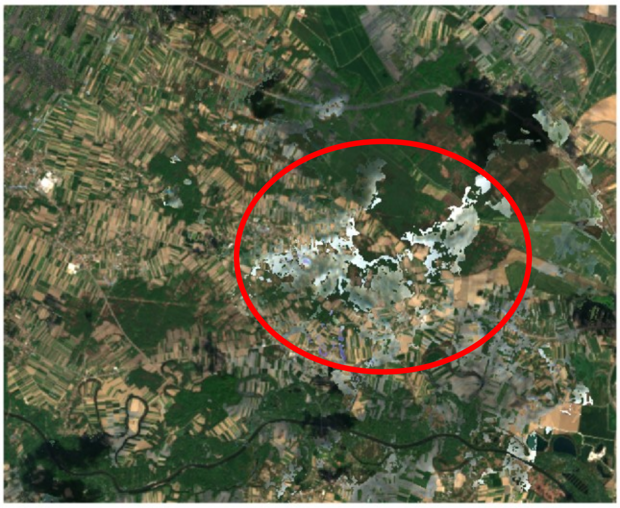


Figure 25: Composite from SEMI-WEAK FILTERING. "Brighter patches" selected from image (2), which was obscured by clouds.

2.3. Test case 03: Mura 2017-07 (July)

This test case illustrates the performance of the algorithm where there is a large number of observations available. In total there were 12 observations available for July 2017 and majority of them cloud-free, which means that Medoid method was predominantly used for compositing.

Test case for compositing algorithm for Sentinel-2 products:

- Monthly composite for July 2017 for the "Mura" reference area
- Geographical extents: (597580, 154390, 610635, 164960)
- Spatial resolution: 20 m

There were 12 available observations for the selected case:

- 20170702T095029_S2B_MSIL2A_20170702T095713_E079_20m\
- 20170705T100029_S2B_MSIL2A_20170705T100026_C122_20m\
- 20170707T095031_S2A_MSIL2A_20170707T095257_E079_20m\
- 20170710T100031_S2A_MSIL2A_20170710T100540_C122_20m\
- 20170712T095029_S2B_MSIL2A_20170712T095623_E079_20m\
- 20170715T100029_S2B_MSIL2A_20170715T100026_C122_20m\
- 20170717T095031_S2A_MSIL2A_20170717T095631_E079_20m\
- 20170720T100031_S2A_MSIL2A_20170720T100027_C122_20m\
- 20170722T095029_S2B_MSIL2A_20170722T095521_E079_20m\
- 20170725T100029_S2B_MSIL2A_20170725T100536_C122_20m\
- 20170727T095031_S2A_MSIL2A_20170727T095429_E079_20m\
- 20170730T100031_S2A_MSIL2A_20170730T100535_C122_20m\

Three different filtering criteria were tested:

- SEMI-WEAK FILTERING: valid if mask is 34 or greater (include thick and thin haze, shade, water and above)
- SEMI-STRICT FILTERING: valid if mask is 41 or greater (include water and above)
- STRICT FILTERING: valid if mask is 100 (only strictly valid pixels)

Runtime on a standard PC with Intel Core i7 processor, running in parallel on 7 threads:

Area:	140 km2
Spatial resolution:	20 m
Pixel count:	350,000
No. of input images:	5
Average runtime:	7588 s = 126 min

RGB of available observations

- Available 12 observations in total
- Of those, 6 are mostly free of clouds, 3 with partial cloud cover and 3 mostly obscured by clouds

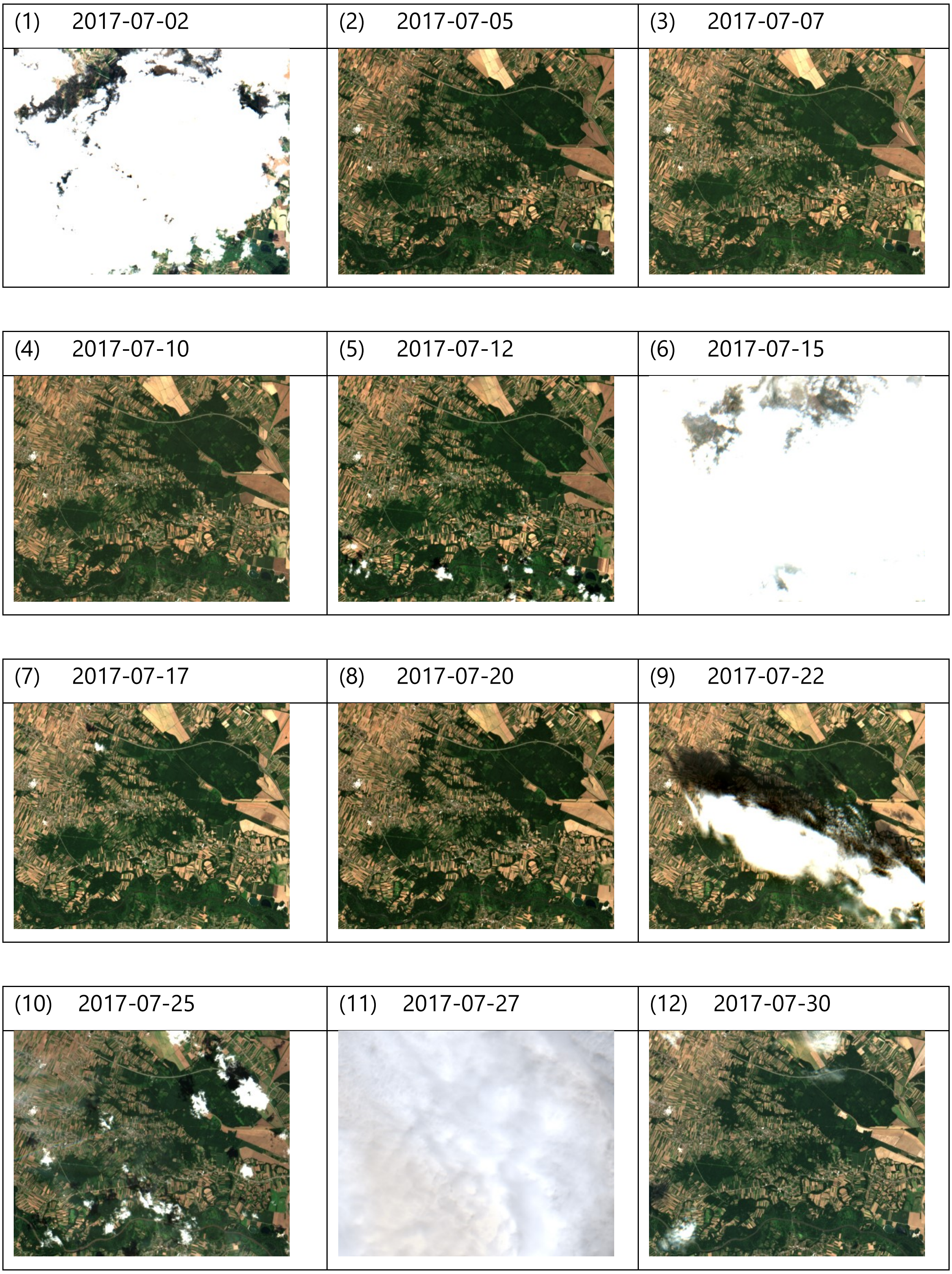


Figure 26: RGBs of available S-2 products for July 2017.

Number of valid observations for each pixel

- Pixels in grey (4 and above) are selected with Medoid method
- Pixels in yellow (2 and 3) are selected with STC method
- Majority of the pixels were selected using Medoid, regardless of the selected filtering.
- In the strict filtering scenario (a), STC method was used over water bodies in the lower part of the image.

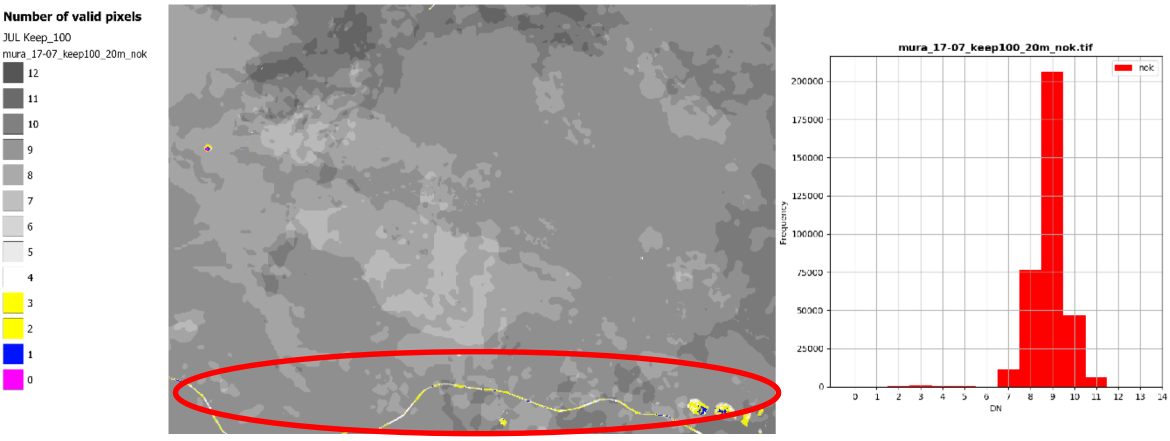


Figure 27: No. of valid observations for STRICT FILTERING. Water surfaces (circled) are selected with STC method.

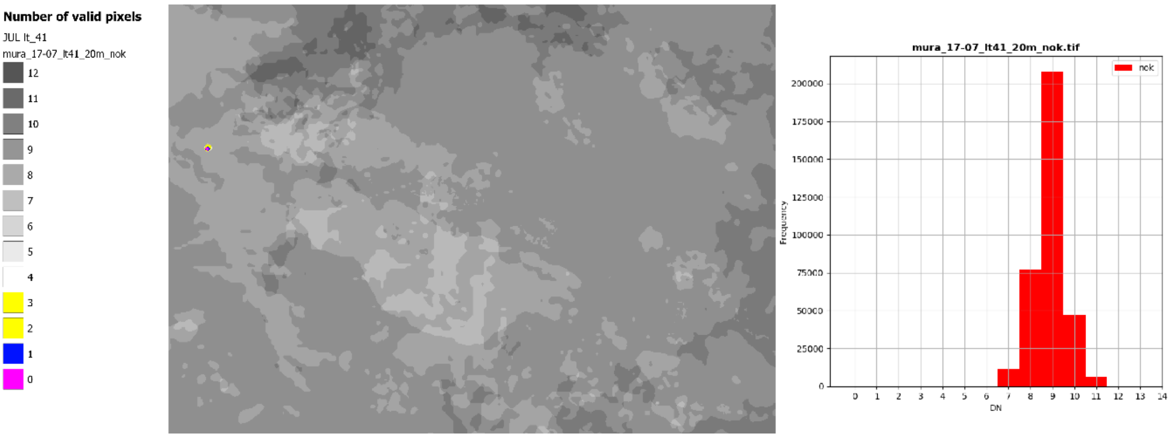


Figure 28: No. of valid observations for SEMI-STRICT FILTERING.

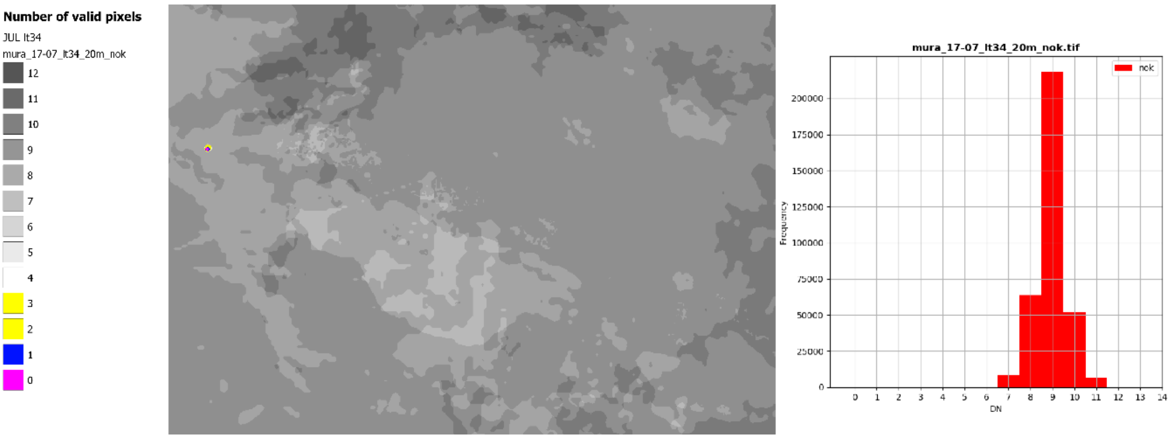


Figure 29: No. of valid observations for SEMI-WEAK FILTERING.

Selected pixels

- Because of a high number of valid observations there was little difference between the results from different filtering thresholds.
- No pixels were selected from observations 1, 6 and 11 because they were heavily obscured by clouds.

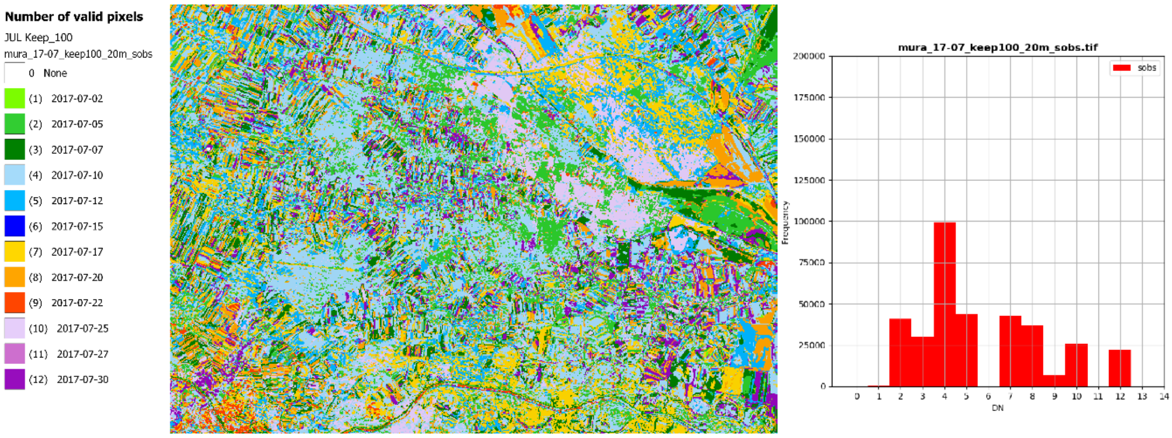


Figure 30: Observation date of the selected pixel for STRICT FILTERING.

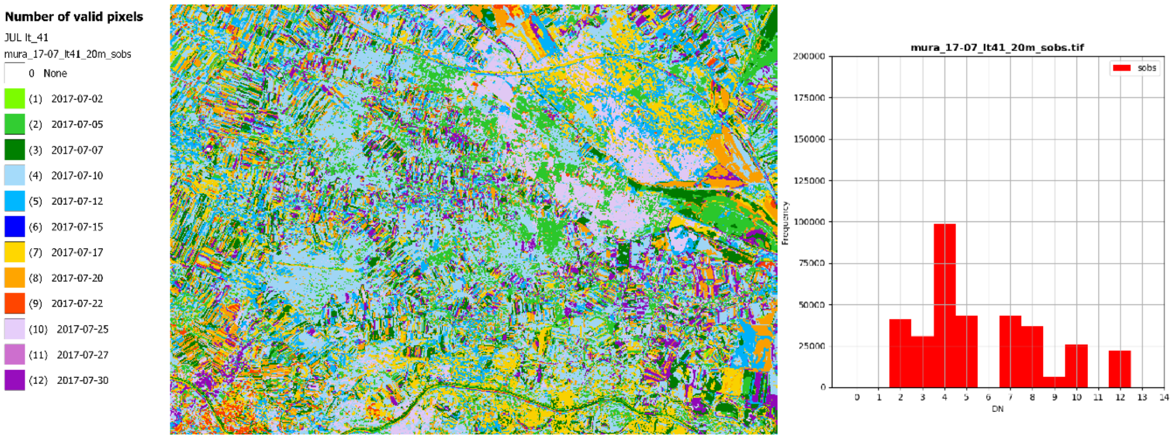


Figure 31: Observation date of the selected pixel for SEMI-STRICT FILTERING.

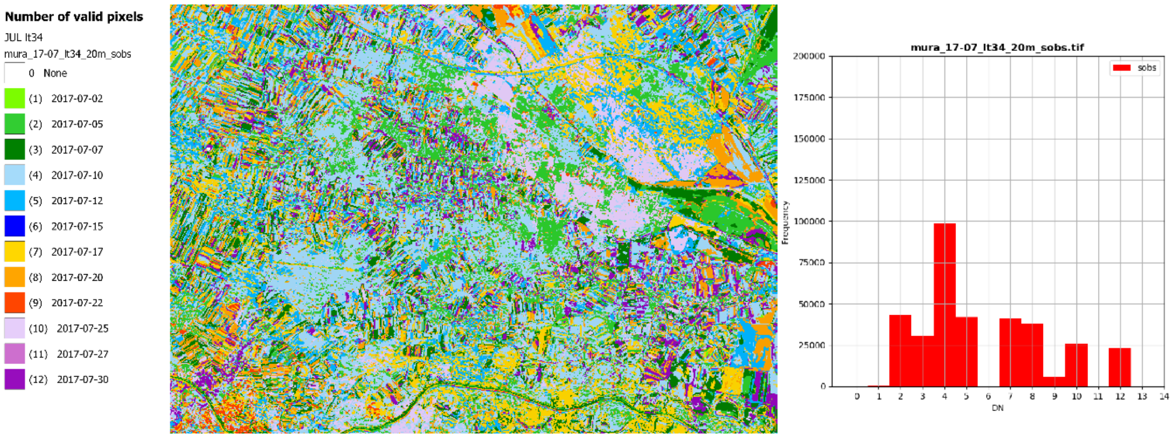


Figure 32: Observation date of the selected pixel for SEMI-WEAK FILTERING.

Resulting composites

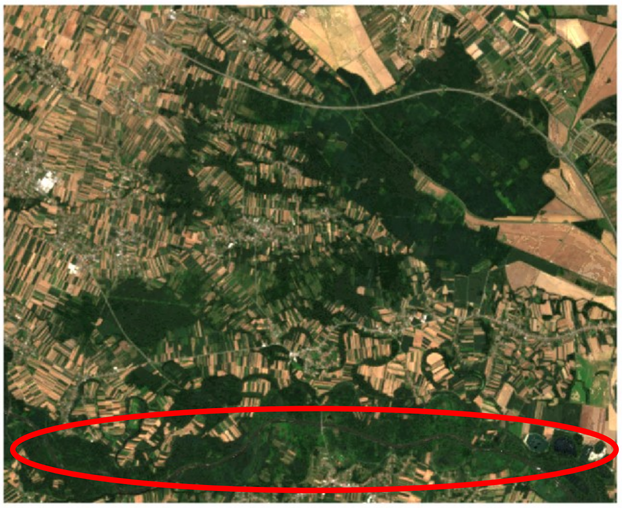


Figure 33: Composite from STRICT FILTERING. Still managed to capture water surfaces (circled), even though there were less valid pixels available to choose from.

Figure 34: Composite from SEMI-STRICT FILTERING.

Figure 35: Composite from SEMI-WEAK FILTERING.

3. CONCLUSIONS

The report describes the methodology and pseudocode for compositing Sentinel-2 products and provides results on three different test cases. The compositing algorithm was designed to produce monthly temporal mosaics, however, it can also be used to produce composites of any desired time interval (e.g. two-monthly, seasonal, etc.). Based on the availability of valid observation data, the algorithm utilizes either STC or Medoid to select the most representative values on a pixel-by-pixel basis.

The initial tests showed that the quality of the results is sensitive to pre-filtering criteria of the observations based on the classification mask. The test cases were used to investigate four different pre-filtering criteria. The results were consistent with findings from Kirches and Brockmann (2019), on which the presented compositing method is based on:

- STRONG filtering: presents higher probability of losing potentially good pixels due to classification errors,
- SEMI-STRONG filtering: showed good results in all cases,
- SEMI-WEAK filtering: while it showed no problems when a high number of observations were available (see July), this criterion proved to be problematic in the situations where a lower number of images are available. Mainly because a weakened threshold means that brighter pixels are added into consideration, which can shift the mean towards potentially cloudy pixels if Medoid method is used,
- WEAK filtering: was found to be unsuitable for compositing, as it allowed too many bright/cloud pixels to be considered in the selection process.

Based on the findings presented in this report, the semi-strict filtering (where water, shade and classes above that are considered valid) should be suitable for monthly composites, i.e. for time intervals with at least 5 available observations.

4. REFERENCES

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Kirches G., Brockmann C., 2019. Algorithm Theoretical Basis Document Sentinel-2 Global Mosaics. p. 49. Available online: https://usermanual.readthedocs.io/en/stable/_downloads/fe714f8693d5a208b3684847d762192f/S2GM-SC2-ATBD-BC-v1.3.2.pdf

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