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EVALUATION OF A HIGH-RESOLUTION OPERATIONAL SNOW COVER AREA CLASSIFICATION ALGORITHM

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ABSTRACT

The Let-It-Snow (LIS) algorithm generates 20m resolution maps of the snow cover area (SCA) including snow, no-snow and cloud pixels from Sentinel-2 level-2A images for the Copernicus Snow & Ice Monitoring Service. The pixel classification relies on two Normalized Difference Snow Index (NDSI) threshold parameters and two red band reflectance threshold parameters. In this study we used the Active Learning for Cloud Detection (ALCD) software to generate via supervised classification reference products from 10 Sentinel-2 images representing the snow and weather conditions over one year of the T31TCH tile (Pyrenees). Those reference products were used to evaluate both the algorithm's snow-cloud discrimination performances and the sensitivity of its threshold parameters. While it shows good performances in snow-land differentiation, the algorithm classifies transparent clouds pixels as cloud when a human eye could see the snow underneath. We tried 24167 values combinations of the threshold parameters and compared the resulting products with the reference products. The results indicate that the default parameters already give near-optimal performances and that they could be modified for a slight increase in snow detection.

Keywords: *snow; snow cover area; clouds; Sentinel-2.*

1. INTRODUCTION

Snow cover is considered as one of the 50 essential climate variables to be monitored by satellite remote sensing by the Global Observing System for Climate (GCOS). It plays an important role in water management and as a driver of natural processes in mountain regions and high latitude areas. The Copernicus Snow & Ice Monitoring Service provides operational snow cover maps at Pan European scale from Sentinel-2 data. In the context of this project, the CESBIO developed the Let-It-Snow (LIS) algorithm which first provide a binary description of the snow cover area (SCA) in the pixels of a level-2A products as output by MAJA [1], [2] (slope corrected surface reflectance images including a coarse resolution cloud and cloud shadow mask). That part of the algorithm is referenced as LIS-SCA [3]. LIS then calculates the fractional snow cover of every pixels identified as containing snow (LIS-FSC) [4].

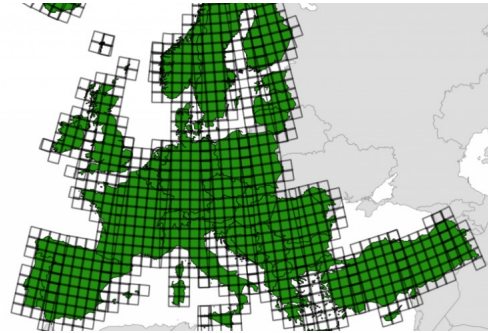


Figure 1: Sentinel 2 tiles grid covering Europe.

The main challenge in snow cover area mapping from multispectral imagery is the discrimination between clouds and snow cover as cloud and snow pixels can have similar spectral signatures in the visible and shortwave infrared bands of current spaceborne sensors [5]. Another important source of error is the lack of illumination in steep shaded slopes especially in winter when the sun elevation is low at the satellite overpass time.

To detect snow and refine the cloud mask from MAJA, the LIS-SCA algorithm relies on four threshold parameters for the differentiation between no-snow, snow, and cloud pixels. The first two parameters are used in the pass 1 of the algorithm to determine the snow line elevation (z_s) whereas the two others are used in the pass 2 to retrieve snow in pixels having an elevation value higher than z_s . The four parameters are the Normalized Difference Snow Index (NDSI) thresholds of pass 1 (n_1) and pass 2 (n_2), and the red band reflectance thresholds of pass 1 (r_1) and pass 2 (r_2) given as milli-reflectance (values between 0 and 1000). These parameters were originally defined based on previous studies [6], [7] and the visual examination of many images [3]. The results of the SCA algorithm were evaluated using in situ measurements and very high resolution (VHR) images [3], showing good performances in comparison with existing algorithms. However, the sensitivity of the parameters was not evaluated hence it remained unclear if these performances could be significantly improved by adjusting their values. In addition, the comparison with VHR images was limited to cloud-free scenes since VHR satellites are generally tasked to acquire clear-sky images, and therefore provided a limited evaluation of the snow-cloud discrimination.

In this work we further evaluate the LIS-SCA algorithm’s current performances and the sensitivity of its four main parameters by comparing its output with reference products (“ground-truth”). These reference products were obtained by supervised classification of a time series of 10 Sentinel-2 images with the Active Learning for Cloud Detection software (ALCD). This time series of classified Sentinel-2 images was created to represent the typical snow and weather conditions over an entire year in a temperate mountain region.

2. METHODOLOGY

ALCD allows the generation of reference cloud masks from Level-1C sentinel-2 images (12 bands in the visible and infrared) by using an iterative active learning procedure with the random forest method [1]. While ALCD’s primary objective was to identify cloud pixels, it can also be used for snow detection.

We used ALCD to produce 10 ground-truth scenes of the same tile in a mountainous region (tile T31TCH in the Pyrenees) and covering every season between April 2019 and March 2020.

For each scene, we first calculated a confusion matrix and its performance metrics (Cohen’s Kappa and the F1 scores) between the snow, land, and cloud (including cloud shadows) pixels of both ALCD and LIS-SCA products. We then repeated the calculation by cross-masking the cloud pixels from both images to evaluate the algorithm ability to discriminate snow and snow-free pixels.

Then, to evaluate the sensitivity of the parameters, we ran LIS with different values for each of them:

r_1 : 6 milli-reflectance values above and 6 below the initial value of 200 with a step of 10.

r_2 : 6 milli-reflectance values above and 4 below the initial value of 40 with a step of 10.

n_1 : 6 NDSI values above and 6 below the initial value of 0.4 with a step of 0.01.

n_2 : 6 NDSI values above and 6 below the initial value of 0.15 with a step of 0.01.

This represented $13 \times 13 \times 13 \times 11 = 24167$ possible combinations for each of the ten scenes, for a total of $13 \times 13 \times 13 \times 11 \times 10 = 241670$ LIS products. This massive calculation (about 2 years of CPU time) was done in parallel with the CNES high performance computer.

For each of the 24167 combinations we calculated a confusion matrix and its performance metrics between ALCD and LIS and combining the pixels count of the ten scenes. We then used the results to determine how the parameters affected the LIS-SCA algorithm’s performances.

3. RESULTS

Figure 2 shows, for each scene, the pixel distribution between the snow, land, and cloud (cloud + shadows) classes in the output classification maps of both ALCD and LIS. The scenes 30/06/2019 to 03/10/2019 exhibit very small snow (<1%) as compared to other scenes.

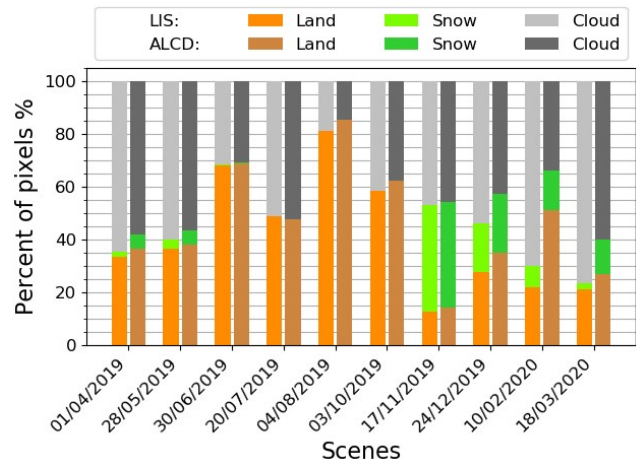


Figure 2: Pixel repartitions between snow, land, and cloud classes by ALCD and LIS.

LIS starts with the MAJA coarse cloud mask that it refines by reclassifying some of its cloud pixels as either snow or no-snow. LIS was designed to preferentially falsely classify a pixel as cloud rather than to falsely classify a pixel as snow or no-snow. On the other hand, with ALCD the training points are manually selected, hence pixels of transparent or semi-transparent clouds can be identified by the user as the class (snow or land) underneath the cloud. Those two points explain why a LIS product generally contains more cloud pixels and less snow or land pixels than an ALCD product of the same scene. Figure 3 shows an extreme case with the 10/02/2020 scene.

The differences between ALCD and LIS cloud detection methods generally affect snow pixels in a larger proportion than land pixels because, as seen in figure 2, the snow class tends to be the smallest. This leads to a smaller snow F1 score and explains the results in figure 4, which show in the top histogram, for each scene, the Kappa and F1 scores of the confusion matrix between the classification maps of ALCD and LIS. The scene 10/02/2020 seen in figure 4 differentiates itself with a remarkably low kappa because a large portion of pixels labeled as land by ALCD are labeled as cloud by LIS.

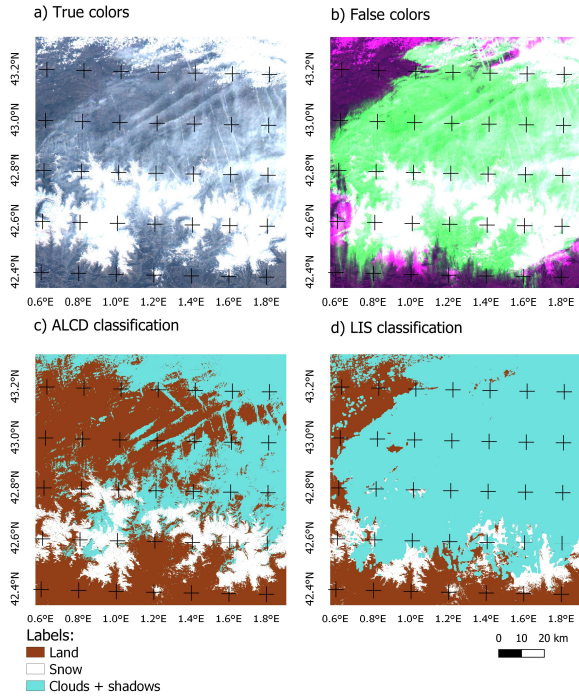


Figure 3: 10/02/2020 scene with a RGB combination of (a) the red, green, and blue S2 LIC bands, of (b) the green, cirrus (1375 nm), and blue bands to better visualize high clouds (green color in image), (c) classified with ALCD, and (d) classified with LIS.

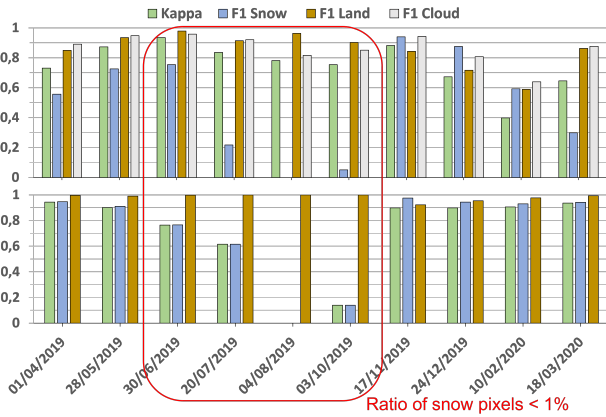


Figure 4: For each scene, the Kappa and F1 scores for the snow/land/cloud tri-classes confusion matrix (above) and for the snow/land bi-classes confusion matrix (below).

The bottom histogram of figure 4 shows the Kappa and F1 scores of the snow and land labels after cross-masking the cloud pixels. The results show an improvement of the two labels' F1 scores, both being above 0.9 except for the snow label at the scenes 30/06/2019 to 03/10/2019 which have small (or zero) amounts of snow pixels compared to the amounts of land pixels.

Figures 5 to 8 show the effects r_1 , r_2 , n_1 and n_2 individually have on the Kappa and F1 scores between the 10 LIS classification maps and the 10 ALCD classification maps. The red dot on each graph represents the performance metric calculated with the default threshold values.

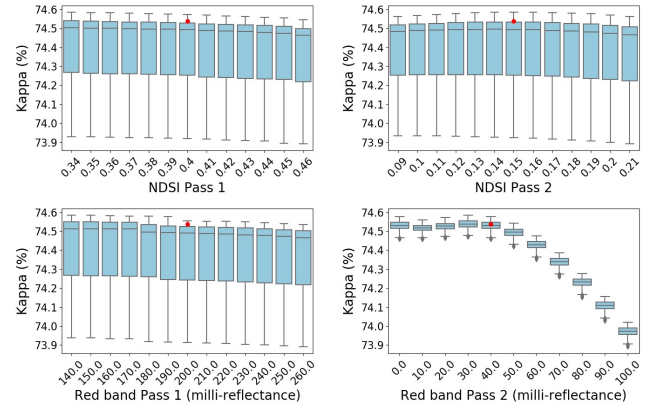


Figure 5: Individual effects of the threshold parameters r_1 , r_2 , n_1 , and n_2 on the Kappa score. The red dots correspond to the default parameters.

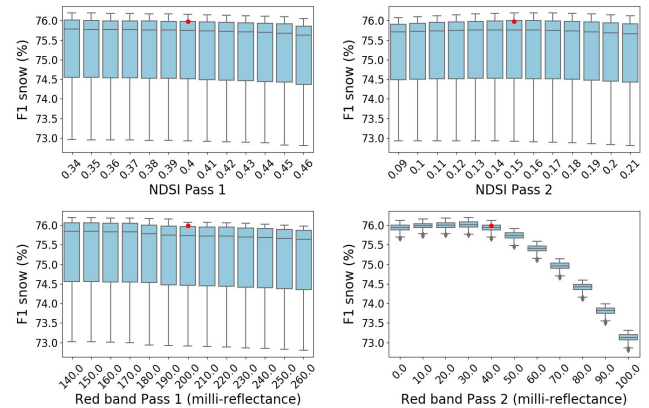


Figure 6: Individual effects of the threshold parameters r_1 , r_2 , n_1 , and n_2 on the snow F1 score.

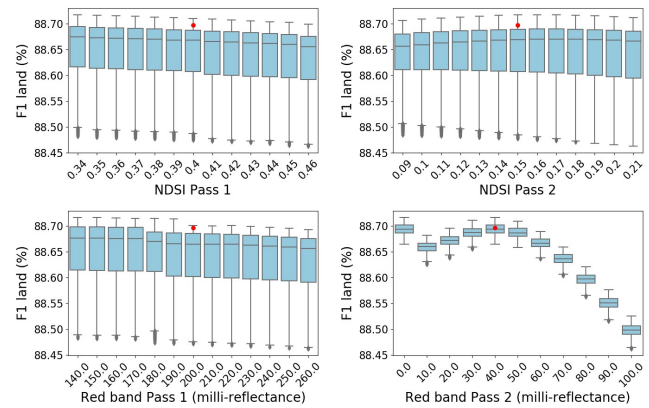


Figure 7: Individual effects of the threshold parameters r_1 , r_2 , n_1 , and n_2 on the land F1 score.

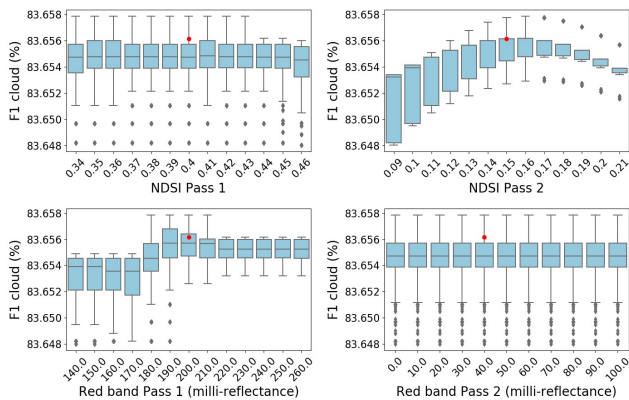


Figure 8: Individual effects of the threshold parameters r_1 , r_2 , n_1 , and n_2 on the cloud F1 score.

From figure 8 we can tell that LIS’s performance in cloud detection is the most stable and only slightly affected by a change of the threshold parameters, mostly from the NDSI pass 2 (n_2) and the red band pass 1 (r_1), with a difference of only 0.01 % between the minimum and the maximum F1 score.

A larger effect is seen with the other metrics (figure 5 to 7) with the red band pass 2 (r_2) having the biggest influence. Snow detection is the most affected with a difference of 3% between the minimum and the maximum F1 score.

4. CONCLUSION

From this sensitivity study we can see that the default thresholds used by LIS-SCA are already close to giving optimal results for every metrics but a slight increase in performance was obtained with the following set of parameters ($n_1=0.34$; $n_2=0.16$; $r_1=140$; $r_2=30$). r_1 and n_1 being optimized at their lowest values, it could be worth repeating the analysis with an extended range at their lower ends.

LIS-SCA also shows good performances in differentiating between snow and land for scenes with significant snow amounts. Where transparent or semi-transparent clouds are present, LIS-SCA conservatively classifies them as cloud pixels, mostly where snow pixels could have been identified instead. This represents a loss of information which could be avoided to get a more complete coverage of the snow cover area. However, thin cloud pixels have a mixed snow-cloud spectral signature which presumably would deteriorate the snow fraction retrieval as the LIS-SCF algorithm is applied to every pixel marked as snow by LIS-SCA [4].

MAJA and LIS are licensed under the Apache License 2.0. ALCD is licensed under the Apache License 3.0. The source codes can be obtained from the following repositories:

<https://github.com/CNES/MAJA/>
https://gitlab.orfeo-toolbox.org/remote_modules/let-it-snow/
<https://github.com/CNES/ALCD/>

5. ACKNOWLEDGEMENTS

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