Assessing Change Detection of Adamello Glacier Using Sentinel-2 Images

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Abstract

This study focuses on monitoring glacier changes using multispectral satellite data from Sentinel-2. The Adamello Glacier is the largest glacierized area in the Italian Alps and is analyzed to assess glacier retreat and vegetative growth in areas where the glacier has receded. Various spectral indices, including NDWI, NDSI, NDVI, and MSAVI, were computed with GEE to enhance the features of the area. Two classification methods have been performed: one unsupervised, Kmeans, and one supervised, Random Forest using Python notebook. Both methods faces some challenges in divide in clusters the area and distinguishing melting snow from rocks, vegetation and urban areas. To improve classification results, different numbers of clusters were tested. The Random Forest classifier, benefiting from labeled training data, demonstrated higher accuracy and robustness in distinguishing different land cover types. Results indicated a decrease in glacier extent, with a difference in snow and ice coverage of $1,12\,\mathrm{km}^2$ *from 2019 to 2022. The spectral indices showed changes in snow and ice cover, with indices values indicating increased melting. These results underscore the importance of using both classification methods and spectral indices to monitor glacier dynamics and highlight the impact of climate change on glacial environments.*

1. Introduction

The Adamello massif, with a maximum altitude of 3539 m a.s.l., is located in the eastern part of the Central Italian Alps. It includes the Adamello Glacier, that belongs to two different regions: the Lombardia region and the Trentino-Alto Adige region. The Glacier surface had an extension of $16.30\,\mathrm{km}^2$ in 2007 that is retreating fast in the last years. (wikipedia, 06.2024) Figure 1 shows the location and boundaries of the study area. The Adamello Glacier is the largest glacierised area in the Italian Alps and consists of five hydrographic units, the major in size being the Mandrone Glacier. (Roberto Ranzi, 2010) European Union studies have proven that glaciers have retreated by about 200 meters from 2016 to 2023 due to the effects of global warming.(UE, 08/09/2023)

Figure 1. *Study area*

The primary objective of this analysis is to determine the extent of the glacier's retreat from 2019 to 2022. The secondary objective is to assess the vegetative growth in areas where the glacier has receded.

2. Materials and method

2.1 Data

For this analysis, Sentinel-2A satellite data for the years 2019, 2022 were directly downloaded from Google Earth Engine (GEE). Sentinel-2 is an ESA mission and part of Copernicus program. It constitutes two satellites launched into orbit in June 2015 (Sentinel-2A) and March 2017 (Sentinel-2B). A new mission is planned for September 2024 (Sentinel-2CC). Sentinel-2 missions are aimed at acquiring Multi-spectrum images in 13 bands and with a resolution of 10, 20 and 60 m. It collects passive sensor imagery and the revisit time is of 5 days.

Data from both summer and winter seasons were selected to provide an overview of seasonal variations. The selected images are characterised by less than 5% of cloud coverage to ensure minimal interference from clouds. Most of the data does not contain clouds therefore, in most cases, cloud masking has a low impact on the images. Therefore the cloud coverage processing haven't been applied.

2.2 Spectral Indices

All spectral indices presented in the following were computed with GEE. A spectral index is a mathematical combination of wavelengths designed to enhance the information content of imagery data. These indices are useful for extracting specific features or properties of the Earth's surface, such as vegetation density, soil moisture, or water quality (Adisa, 23/04/2023) (L. Biagi and Oxoli, 2024). For the aim of the analysis, evaluating snow surface and vegetation growth, the following spectra indices have been selected:

- **Normalized Difference Water Index:**

$$\mathrm{NDWI} = \frac{\mathrm{Green} - \mathrm{NIR}}{\mathrm{Green} + \mathrm{NIR}} \tag{1}$$

The Normalized Difference Water Index (NDWI) is used to monitor changes related to water content in water bodies. As water bodies strongly absorb light in the visible-to-infrared range of the electromagnetic spectrum, NDWI uses green and near-infrared (NIR) bands to highlight water bodies. It can also be used for snow and ice coverage monitoring.(Sentinelhub, n.d.)

- **Normalized Difference Snow Index:**

$$\mathrm{NDSI} = \frac{\mathrm{Green} - \mathrm{SWIR}}{\mathrm{Green} + \mathrm{SWIR}} \tag{2}$$

The Normalized Difference Snow Index (NDSI) is a measure of the relative magnitude of the difference in reflectivity between visible (green) and shortwave infrared (SWIR) used to detect snow covered areas. (Sentinelhub, n.d.)

- **Normalized Difference Vegetation Index:**

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}} \tag{3}$$

The Normalized Difference Vegetation Index (NDVI) is a simple, yet effective index for quantifying green vegetation. It normalizes green leaf scattering in near-infrared wavelengths with chlorophyll absorption in red wavelengths. (Sentinelhub, n.d.)

- **Modified soil adjusted vegetation index:**

$$\mathrm{MSAVI} = \frac{2\cdot\mathrm{NIR}+1-\sqrt{(2\cdot\mathrm{NIR}+1)^2-8\cdot(\mathrm{NIR}-\mathrm{Red})}}{2} \tag{4}$$

The Modified Soil Adjusted Vegetation Index (MSAVI) works where other vegetation indices do not, for example during seed germination and leaf development stages. In this analysis, it was used to quantify the growth of vegetation where the glacier retreated.

2.3 Classification Methods

Techniques, such as unsupervised and supervised classification are useful for analysing the extend of glaciers and how it changes over time. Both methods have distinct advantages and limitations. Both the analysis with unsupervised and supervised have been performed using Python Notebooks on Google Colab.

- **Unsupervised Classification** Unsupervised classification involves the automatic grouping of pixels in a remote sensing image into clusters based on their spectral properties without prior knowledge or training data. The method used in this analysis is the k-means clustering algorithm. The strength of the unsupervised method is that there is no need of labeled training data and often it requires fewer computational resources compared to supervised methods. Drawbacks are usually a lower accuracy due to the lack of training samples and that the clusters are unlabelled, leading to difficulties in interpreting their meaning.

- **Supervised Classification** Supervised classification involves training a model using labelled training data. The Random Forest algorithm builds multiple decision trees using bootstrapped samples of the training data and averages their predictions to improve accuracy and robustness. Supervised methods usually have a higher accuracy due to the use of labeled training data that guides the algorithm. This also allows for higher control on the class definition, which is particularly useful when looking for some specific feature. However, the drawbacks are: the need of the labelled training data and higher computational complexity.(L. Biagi and Oxoli, 2024)

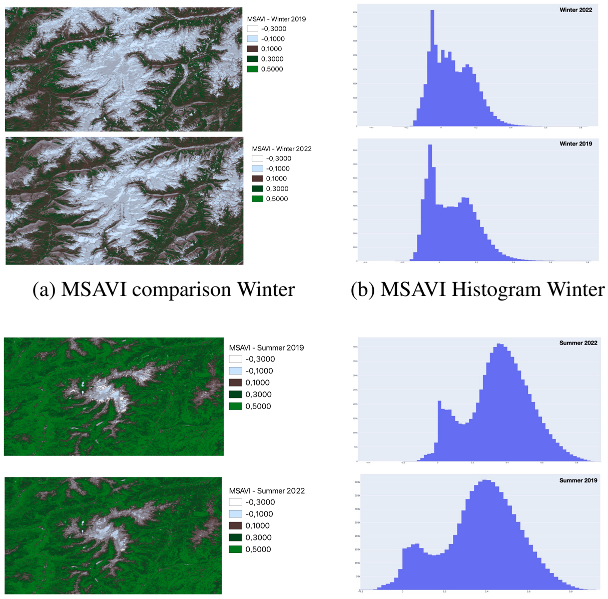
3. Results discussions

From the computation of the indices defined in 2.2 it is possible to gain insights into the changes in snow and ice cover (NDWI and NDSI), and changes in vegetation growth and healthiness (MSAVI and NDVI) over the considered time interval.

3.1 Spectral Indices

For vegetation monitoring:

- **Modified soil adjusted vegetation index:**



(a) MSAVI comparison Winter

(b) MSAVI Histogram Winter

(c) MSAVI comparison Summer

(d) MSAVI Histogram Summer

Figure 2. *Comparison MSAVI spectral index*

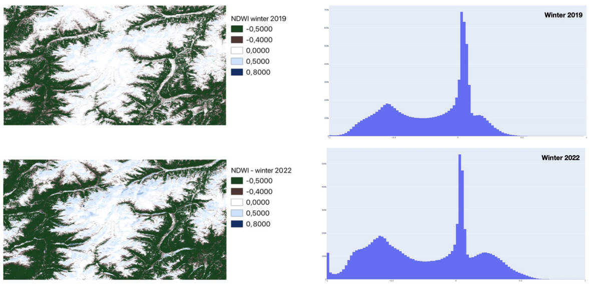
The MSAVI analysis, showed in Figure 2, have been carried out both in summer and in winter. The histograms suggest that while the overall vegetation health in the area remained relatively stable from 2019 to 2022, there are signs of increased variability and potential degradation in certain areas. The 2022 histogram shows more lower MSAVI values, indicating regions with reduced vegetation health or increased soil exposure. This could be due to the areas where the glacier retreated and the vegetation still didn't grow or area with rocks and with a low MSAVI values. From the images of the MSAVI we can also notice a retreat of the glacier, with a reduction of the ice coverage.

- **Normalized Difference Vegetation Index:**
  The analysis of NDVI confirms again the previous results, underling a progressive melting of the glacier and a growing vegetation on the margins.

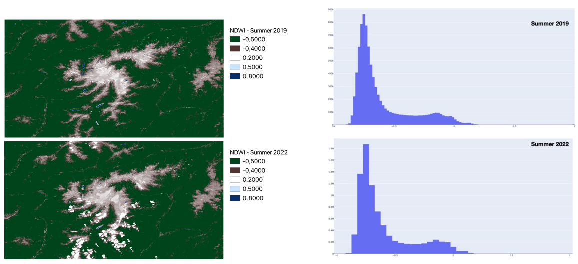
The first part of the analysis wants to be a study of the general area where the glacier is located to understand how the vegetation in summer area and how the snow precipitations in winter changed. After the vegetation analysis in the whole area, it is evident that in the summer season the glacier is restricted to a smaller area for the snow from the winter precipitations melting, therefore, in order to perform a more precise glacier retreat analysis through NDWI and NDSI indexes, the considered area for the summer periods have been cropped using GEE to a restricted area that contains the whole glacier.

For snow and ice coverage evaluation:

- **Normalized Difference Water Index:**



(a) NDWI comparison Winter (b) NDWI Histogram Winter



(c) NDWI comparison Summer (d) NDWI Histogram Summer

Figure 3. *Comparison NDWI spectral index*

Analysing the NDWI histograms showed in Figure 3 over the period from winter 2019 to 2022, a significant variation in the NDWI values can be observed, indicating changes in snow and ice coverage. In particular the following changes can be noticed: the NDWI values from winter 2019 to 2022 reveal significant changes in the snow coverage area. The peak NDWI values have decreased, with values now concentrated slightly above zero, suggesting a reduction in maximum snow and ice cover due to melting and retreat.

In 2022, there is an increase in negative NDWI values, indicating more exposed ground or vegetation, both in summer and in winter. These negative values, now peaking at a lower point compared to 2019, reflect increased heterogeneity in the glacier surface.

Positive NDWI values have also increased, indicating that some areas of the glacier have higher reflectivity, possibly due to fresh snow or less-melted ice. These values show a slower decrease over a broader range, suggesting more regions with higher reflectivity.

Overall, the concentration of NDWI values around zero indicates significant melting. Areas that previously had snow or ice cover now show mixed surfaces of snow, ice, and exposed ground, resulting in NDWI values close to zero, highlighting the ongoing retreat of the glacier. Furthermore this is even more evident in Figure 4 where is shown a zoom of the area in the Summer season comparing 2019 and 2022 and the slightly more bright white in some part underline the presence of ice instead of snow, sign of a melting process and the surface of the glacier that is reduced. In Figure 4 is also noticeable that also the water bodies shrank in the interval.

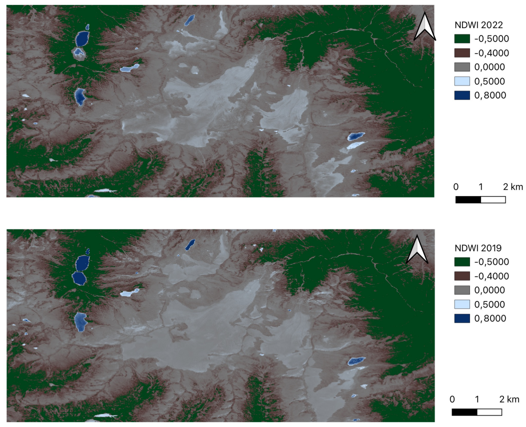


Figure 4. *NDWI maps from Summer 2019 to 2022*

- **Normalized Difference Snow Index:**
  The reduction of snow coverage is evident in Figure 5. As confirmation, the analysis of the histogram, carried out in the same way as for the NDWI, suggests a retreat of the glacier with a reflectivity that decreases and more concentration of values around 0 that hint at a more mixed and melted surface in 2022 then in 2019. Also in this case is evident a reduction of the extension of the glacier.

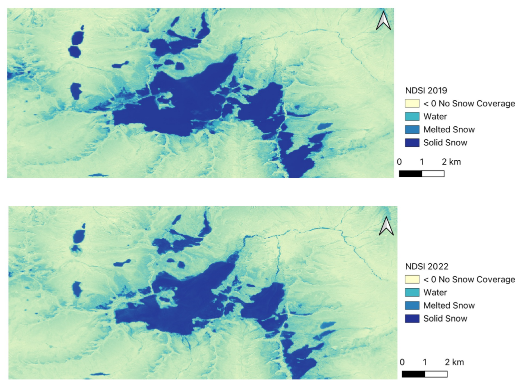


Figure 5. *NDSI maps from Summer 2019 to 2022*

3.2 Unsupervised Classification: K-means Algorithm

In this glacier monitoring, k-means clustering is used as an initial assessment tool for identifying the glacier area and other land cover types. However, k-means clustering lead to challenges in defining and distinguishing classes due to the lack of training samples. Often, melted snow and rocks are classified in the same cluster, and urban areas are mostly not be classified at all. To improve results, different numbers of clusters were tested, but increasing the number beyond 4 or 5 showed negligible differences in classification. Consequently, only 4 or 5 classes were defined for the Random Forest algorithm to have classification clarity and not waste computational time. K-means results are shown in Figure 6.

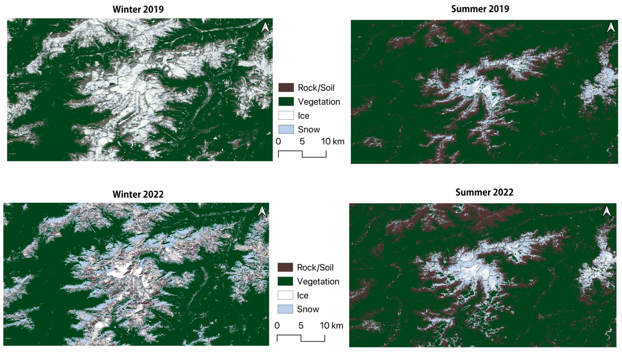


Figure 6. *Comparison Adamello Glacier Winter 2019-2022 classification with k-mean*

3.3 Supervised classification: Random Forest Algorithm

As in the index computation of the spectral indexes 2.2 also in the application of the supervised classification algorithm the focus is on the summer season, therefore in the analysis with Random Forest the maps are zoomed in, considering just the body of the glacier, to reduce the risk of miss-classification of the urban area and of mountains that doesn't characterise the glacier underlined in a first analysis and in the k-mean results. The area considered for the summer is showed in Figure 7 with a RGB representation. While for winter the area is bigger in order to have an overview of the snow precipitation in the whole area.

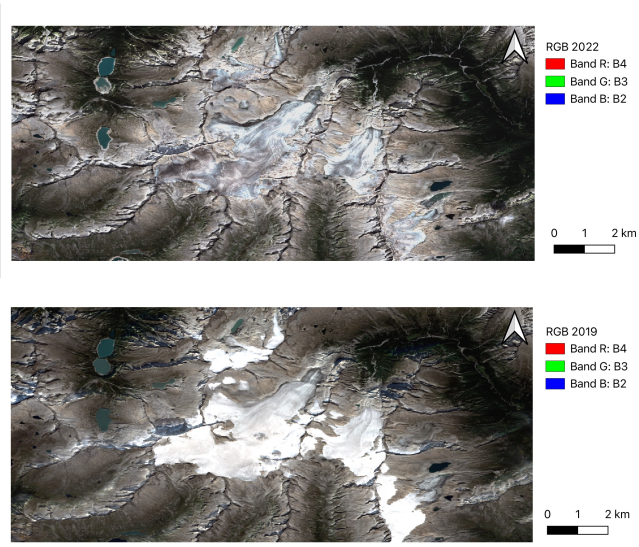


Figure 7. *RGB images Summer 2022-2019*

The performance of Random Forest classifier highlights several key points. The study is performed on images characterised by all the available bands, in this way the classifier has all the information of the different wavelength.

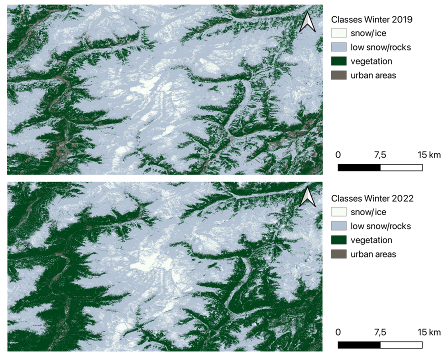


Figure 8. *Comparison Adamello Glacier Winter 2019-2022 classification with Random Forest*

3.3.1 Winter Analysis: In Figure 8 are shown the results of the classification in Winter. The results corroborate what the index analysis underlined, a smaller snow covered area and a increase of the vegetation. The dominant class in winter is, as expected, low snow, followed by vegetation. The presence of snow at the bottom of the valleys makes it challenging for the classifier to distinguish between urban areas and snow-covered landscapes, but this can be useful to notice where it snowed in the different years. The proportion of vegetation also differs significantly between the two winters, with 38.8% (for RGB and 25.13% for RGB + NDSI) in 2022 compared to 25.2% (for RGB and 19.29% for RGB + NDSI) in 2019. This could be due to varying winter conditions, such as snow cover duration and different level of vegetation's growth. In particular in the results Table 1 are described in details the performance of the classifier. The accuracy is low and that can be caused by different factor such as the different illuminations of the valleys that can lead to a miss-classification between rocks and vegetation areas, but also the similar reflectivity of melting or dirty snow and rocks.

Classes	Winter 2019	Winter 2022
Snow/Ice	6.9%	7.3%
Low snow	62.4%	51.2%
Vegetation	25.2%	38.8%
Urban Areas	5.2%	2.7%
Accuracy*	75.63%	66.54%

Table 1. *Comparison of Winter 2019 and 2022 Random Forest results. *Accuracy computed with accuracy score from sklearn with the value for testing (from the geometry defined and labeled previously and the predicted by the classifier)*

3.3.2 Summer Analysis and Glacier Retreat Assesment Comparing the summer classifications of 2019 and 2022 as can be seen in Figure 9, the ice percentage suffers of a large decrease in favor of an increase in snow coverage and rocks percentage. This show that the glacier is suffering of a fast melting process of the snow on the glacier showing the ice underneath. The vegetation cover had a small increase as well as the water bodies suffered of a decrease of their surface.

Overall, the Random Forest classification results highlight the challenges also in summer in the classification of ice, frequently miss-classified with rocks as well as the melting ice/snow. In the Figures 10 are shown the Confusion matrices for the two different years for the summer. The performance of Random Forest are again with an accuracy around 73% and 78%, that

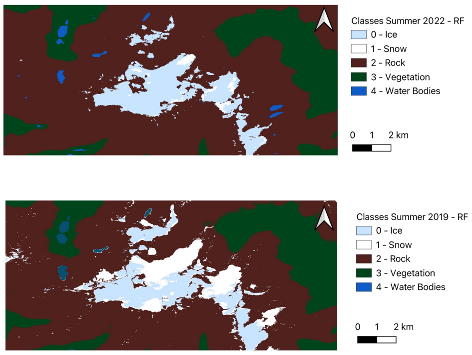


Figure 9. *Comparison Adamello Glacier Summer 2019-2022 classification with Random Forest*

Classes	Summer 2019	Summer2022
Clean snow/Ice	4.20%	2.27%
Melting Snow	7.70%	8.35%
Rock	63.79%	61.94%
Vegetation	23.57%	26.72%
Water	0.75%	0.71%
Accuracy*	72.78%	77.54%

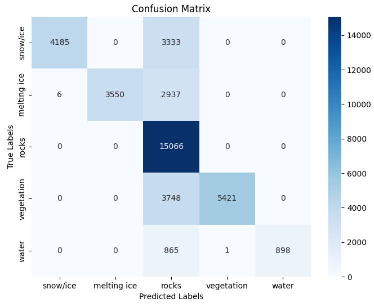
Table 2. *Comparison of Summer 2019 and 2022 Random Forest results.*

can lead to an imprecise evaluation of the glacier extent. This problem persist changing the polygons on which the classifier is trained. This can be caused by the same reasons listed before in 3.3.1; the wavelength of rocks, melting snow and ice are similar and therefore they can be miss-classified and lead to a lower accuracy. This problem is supported by the confusion matrices that show that the classes the algorithm finds more challenging to classify are ice, snow and rocks.

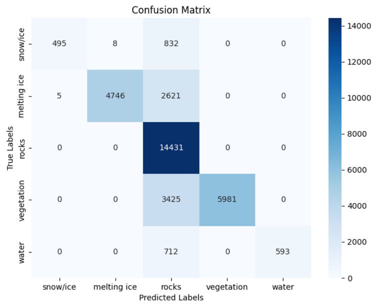
In the end, an estimation of the glacier retreat has been performed using the results form the Random Forest classifier. The analysis is performed only in the summer season in order to avoid the inaccuracy due to the influence of the snow coverage and variation of snow precipitation on the glacier surface. The numerical evaluation have been carried out taking into account both the snow and the ice classes. The results shows a glacier extension reduced from the 2019 to the 2022. Looking at the computed percentage of pixels for each class is evident a reduction in the layer of clean snow in favor of the melting and dirty snow; the results are clearly visible both in the plot of the Random Forest classification, Figure 9, and from the confusion matrices, Figure 10. Moreover, this is evident also in Table 2 where the clean snow percentage goes from 4.20% to 2.27%, and the melting snow from 7.70% to 8.35% underling an increase in the melting snow and a large decrease in clean snow. Using the total surface and the conversion of the pixels in km^2 can be find out that the glacier suffered of a reduction of $1,12\,\mathrm{km}^2$.

4. Conclusion

The analysis proved, consistently with current literature (Maggi, 2024), (Fondazione Cariplo, 12/03/2024), that the Adamello glacier is facing a melting process for climate changes. Spectral indices analysis have been fundamental to



(a) Confusion Matrix Summer 2019



(b) Confusion Matrix Summer 2022

Figure 10. *Confusion Matrixes SUmmer 2019-2022*

asses the glacier state both for the vegetation and for the snow and ice coverage. The results showed by the unsupervised classification confirms that the glacier retreated of $1,12\,\mathrm{km}^2$. The final evaluation can be affected by inaccuracies due to the low classification accuracy obtained by the Random Forest but it is in line with the current studies. A suggested further analysis could test different algorithm and perform analysis using digital terrain model (DTM) to improve the understanding of the topography. Another analysis that could be carried out is to analyse and compare the melting process from Winter 2019 to Summer 2019 with the melting from Winter 2022 to Summer 2022. This further analysis could give more evidence and quantification of how the melting process change over years.

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