École Polytechnique Fédérale de Lausanne

The Diminution of Snow around Zermatt

Image Processing for Earth Observation

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ABSTRACT

Due to the rising temperatures of the earth and in the Swiss alps, the glaciers in have been decreasing in size [[5]]. In order to validate this claim, this report will investigate the diminution of snow around the Zermatt area. This is done by taking several image from the Sentinel-2 sensor and labeling them by using the Matlab image labeler. Thereafter, the images are segmented by patches and regions and then fed to a random forest (RF) classifier and a K-Nearest Neighbour (KNN) classifier. The four results are compared and it turned out that the random forest using patches returned the best results. Finally, the total amount of patches of snow over the years are compared in Figure 5.1 and it turned out that no definite trend can be found and thus no conclusion can be drawn. The reason for this is that the test set uses images from over the last four years. Sentinel-2 does not have enough historical data to analyze the effect of global warming on the diminution of snow around Zermatt and therefore, for future research, another sensor with more available images dating back more years should be used.

Contents

CHAPTER 1

INTRODUCTION

Our research question, the diminution of snow around Zermatt through the years, will be discussed in the following rapport. Firstly the data (images) will be collected via an appropriate sensor chosen by the requirements of the research. The images then need be prepared, by labelling and splitting the data into sets used for training, validation and testing. By using the validation set different classifiers and spatial supports can be compared based on their accuracy scores, and F1 scores. Based on these results the best method for snow prediction can be chosen. Using this final method, the snow fall can be compared over the years to see if there's a certain trend.

Chapter 2

Data

In the following chapter the chosen data will be discussed. Firstly, the data collection will be discussed, including the reasons for the chosen sensor in terms of the bands and resolution required. Secondly, the data preparation will be considered, inclusive of labelling and the data splits.

2.1 Data Collection

2.1.1 Choosing the Sensor

Bands

Our research question is looking at the diminution of snow around Zermatt over the years. According to our hypothesis, the reason for this so-to-say decrease in snow over the years must be due to global warming, but this will only be analyzed in the discussion (Chapter 5).
During our thought-process we decided that we wanted to collect multiple bands of the images so enough features can be extracted and analyzed later on. The first bands being RGB-IR and the extra one being the spectral index NDSI; Normalized-Difference Snow Index. To collect images with RBG-IR bands we would need multiple multi-spectral sensors.
On the EO browser we found the Sentinel-2 sensor first. It's bands can be found below in Figure 2.1. According to these bands, the NDSI can be calculated by equation 2.1.

$$\frac{B_3 - B_{11}}{B_3 + B_{11}}[[4]] \tag{2.1}$$

Band	Resolution	Central Wavelength	Description
B1	60 m	443 nm	Ultra blue (Coastal and Aerosol)
B2	10 m	490 nm	Blue
B3	10 m	560 nm	Green
B4	10 m	665 nm	Red
B5	20 m	705 nm	Visible and Near Infrared (VNIR)
B6	20 m	740 nm	Visible and Near Infrared (VNIR)
B7	20 m	783 nm	Visible and Near Infrared (VNIR)
B8	10 m	842 nm	Visible and Near Infrared (VNIR)
B8a	20 m	865 nm	Visible and Near Infrared (VNIR)
B9	60 m	940 nm	Short Wave Infrared (SWIR)
B10	60 m	1375 nm	Short Wave Infrared (SWIR)
B11	20 m	1610 nm	Short Wave Infrared (SWIR)
B12	20 m	2190 nm	Short Wave Infrared (SWIR)

FIGURE 2.1
Bands of Sentinel-2 [[2]]

RESOLUTION

Our area of interest of Zermatt and parts areas around it, is about 6,000 km^2. For results accurate enough we want to look at images of around 2500 by 2500 pixels. According to the calculation below, for an image of around 2500 by 2500 pixels, the resolution needed is 8m.

$$6,000 * 10^6/2500^2 = 960m^2$$

$$\sqrt{960m^2} \approx 31m$$

The resolution of Sentinel-2 is in the range of 10-60m [[3]] which is perfect for our application. Thus, we will extract images from the Sentinel-2 sensor.

2.2 DATA PREPARATION

2.2.1 NUMBER OF IMAGES

As the images are quite large we decided to collect 11 images, 2 from each year from 2016 to 2021 (where 2016 only has 1 image). The images will be taken from the same day in December and in June to compare both the winter and summer conditions over the years. We included the summer periods too so that the model could also train on areas without snow so that it will differentiate well between the two on the test set.
The training set will contain 6 images, validation 2, which are December 2016 and May 2017, and the test set 3, which will be the ones from December 2017, 2019 and 2021 so we can correctly analyze the so-to-say decrease in snow over the years.

2.2.2 LABELLING

After collecting the images we needed to start labelling them. Using the Matlab image labeler app, we labeled the images ourselves. The only label used was snow, meaning the surrounding area would be classified 'not snow'. One of the labelled images can be seen in 2.2.

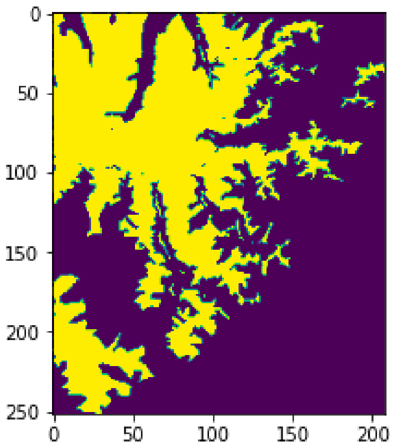

FIGURE 2.2
Ground truth

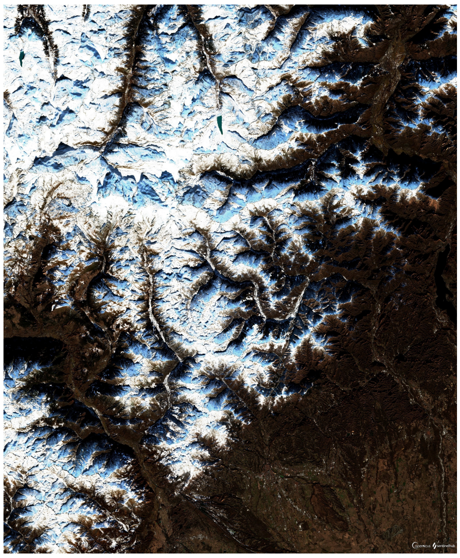

FIGURE 2.3
True color image (Dec 2017)

CHAPTER 3

METHODS

In the following chapter the different method combinations will be investigated. Firstly the different spatial support types, patches and regions will be discussed. Afterwards the usage features will be explained and then the two different classifiers will be discussed. These two classifiers, Random-Forrest and KNN, will be tested using patches and regions, which results in four different methods. For each method hyperparameters will be tuned and the final confusion matrices will be calculated.

3.1 SPATIAL SUPPORT TYPES

3.1.1 PATCH CONSTRUCTION

To extract features and group pixels into snow and 'not snow' we decided to divide the image into patches. As the image was not of a size dividable by an integer, we needed to crop them. After experimenting with sizes 6, 12, 24, and 48 we found that 24 and 48 were too pixelated so details were lost. For size 6 the computation time was too long and as the labels were drawn on by ourselves they may not be so accurate at such a small patch size. So it is found that the best patch size is 12x12 pixels.

3.1.2 REGION CONSTRUCTION

Instead of just looking at patch reconstruction we decided to also use the SLIC algorithm for region construction. As SLIC splits pixels into groups by similarity, we suspect that it should work quite well as it only has to group snow and 'not snow' which are also quite different in appearance. By using regions as well, both methods can be compared in each classifier to find the most efficient and accurate one for our predictions.

3.2 FEATURES

The next step is calculating the different features. The features that will be considered are the standard deviation, average, entropy and the histogram of each band per patch/region. The histogram also includes a hyperparameter - the number of bins - this is found be most efficient and accurate at 10 bins.

3.3 CLASSIFIERS

3.3.1 RANDOM-FOREST (RF)

The first classifier that will be considered is the Random-Forest. Its main hyperparameters are the number of estimators and its maximum depth.

RF WITH PATCHES

Firstly the RF classifier will be used with patches. Using a validation set for the hyperparameter search, it is found that the maximum accuracy of 0.95 is found with 200 estimators and without a maximum depth. The confusion matrix (of the validation set) with these optimal hyperparamters is shown in Figure 3.1. At the bottom of the figure the accuracy and F1 score are also given. The accuracy is of 0.952 and an F1 score of 0.919. The F1 is the harmonic average of precision and recall. Therefore, this score takes both false positives and false negatives into account. Intuitively it is not as easy to understand as accuracy, but F1 is usually more useful than accuracy, especially if you have an uneven class distribution [[1]].

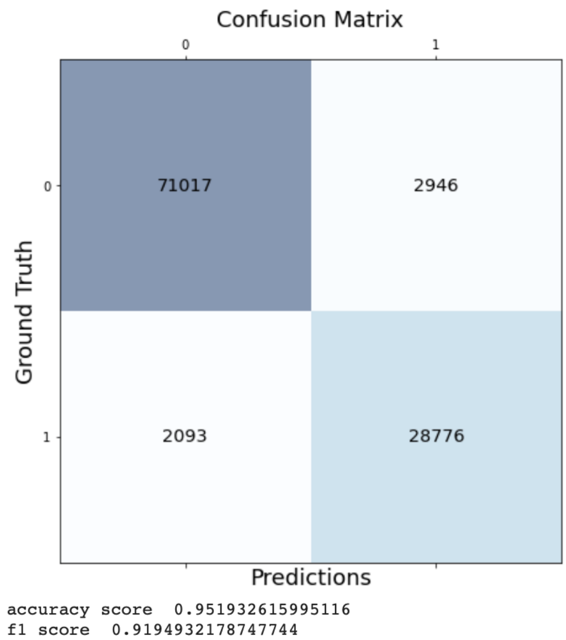

FIGURE 3.1
Confusion matrix for the RF classifier with patches

RF WITH REGIONS

Here, the same method is used to find the best hyperparameters. It is found that the optimal hyperparameters are 100 estimators and max depth of 10. In Figure 3.2 the confusion matrix is shown with an accuracy of 0.967 and a F1 score of 0.854.

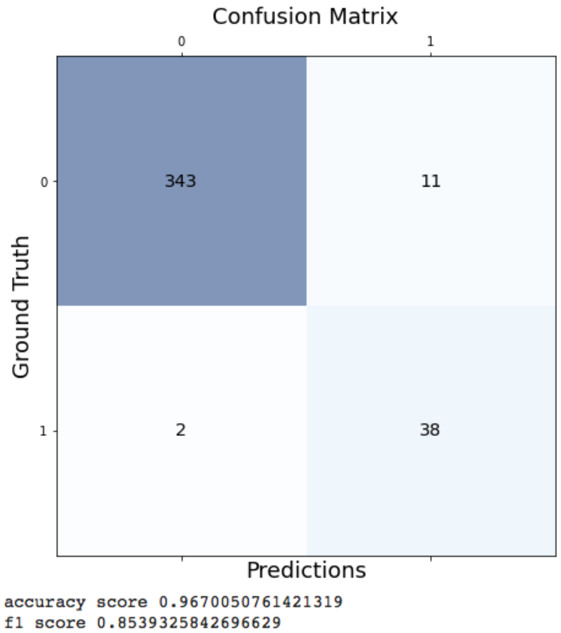

FIGURE 3.2
Confusion matrix for the RF classifier with regions

3.3.2 K-NEAREST-NEIGHBOURS (KNN)

The second classifier is the KNN model. As our input matrix, the images, is of quite a large size, using it on the KNN model directly will take a very long time. To save some calculation power it is important to reduce the number of features of our input. To do so, we use the PCA algorithm and consider the new number of features as a new hyperparameter, with a max of 65 features. The second hyperparameter in the KNN model is the number of neighbours, both will be tuned later on.

KNN WITH PATCHES

Again as before, the validation set is used for hyperparameter search. It is found that the optimal hyperparameters are 10 features and 9 neighbours. The confusion matrix is given in Figure 3.3, with an accuracy of 0.909 and a F1 score of 0.850.

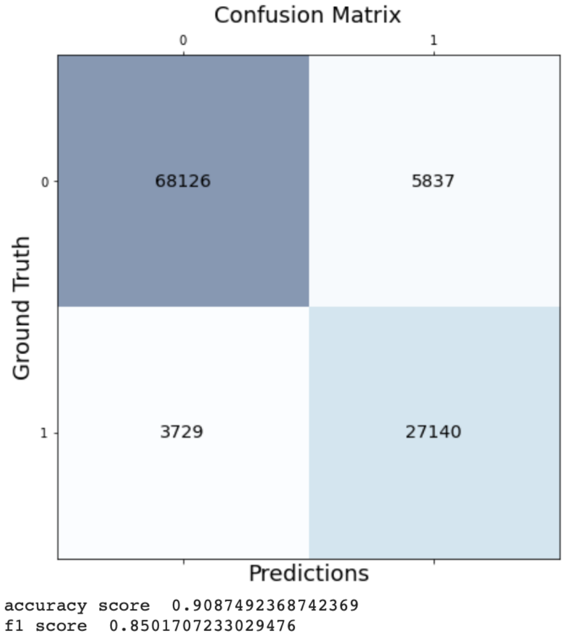

FIGURE 3.3
Confusion matrix for the KNN classifier with patches

KNN WITH REGIONS

Finally, the KNN model with regions has the optimal hyperparameters at 35 features and 39 neighbours. In Figure 3.4 the confusion matrix is given with an accuracy score of 0.856 and a F1 score of 0.1515. We can already see that this method combination of KNN with regions is very much less accurate than the others due to the very low F1 score compared to the rest.

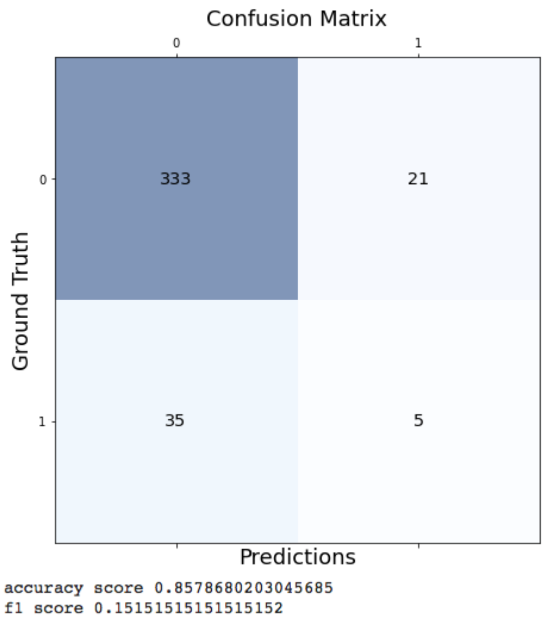

FIGURE 3.4
Confusion matrix for the KNN classifier with regions

CHAPTER 4

EVALUATION OF RESULTS

In the following chapter, the results of all the used methods are evaluated and discussed. The used methods are compared by their metrics, accuracy and F1-score, for both segmentation methods with their respective machine learning models to find the optimal combination. Afterwards, the prediction maps are plotted amongst the true colour and ground truth.

4.1 BEST METHOD COMBINATION

Now that we've seen all the different method combinations and their confusion matrices the results can be summed below to compare.
RF with patches:

- Accuracy score = 0.951932615995116
- F1 score = 0.9194932178747744

RF with regions:

- Accuracy score = 0.9670050761421319
- F1 score = 0.8539325842696629

KNN with patches:

- Accuracy score = 0.9087492368742369
- F1 score = 0.8501707233029476

KNN with regions:

- Accuracy score = 0.8578680203045685
- F1 score = 0.15151515151515152

Overall we can see that the RF classifier scores better. Then comparing patches to regions in the RF classifier, the patches have a higher F1 score while there isn't a big difference between the accuracy's in comparison. Additionally, the F1 score is more important and therefore, the best method for snow prediction is using an Random Forrest classifier with patches as the spatial support. Moreover, looking at Figure 4.1, through visualization we can also see that the prediction labels by RF-patches is much more accurate than the rest.

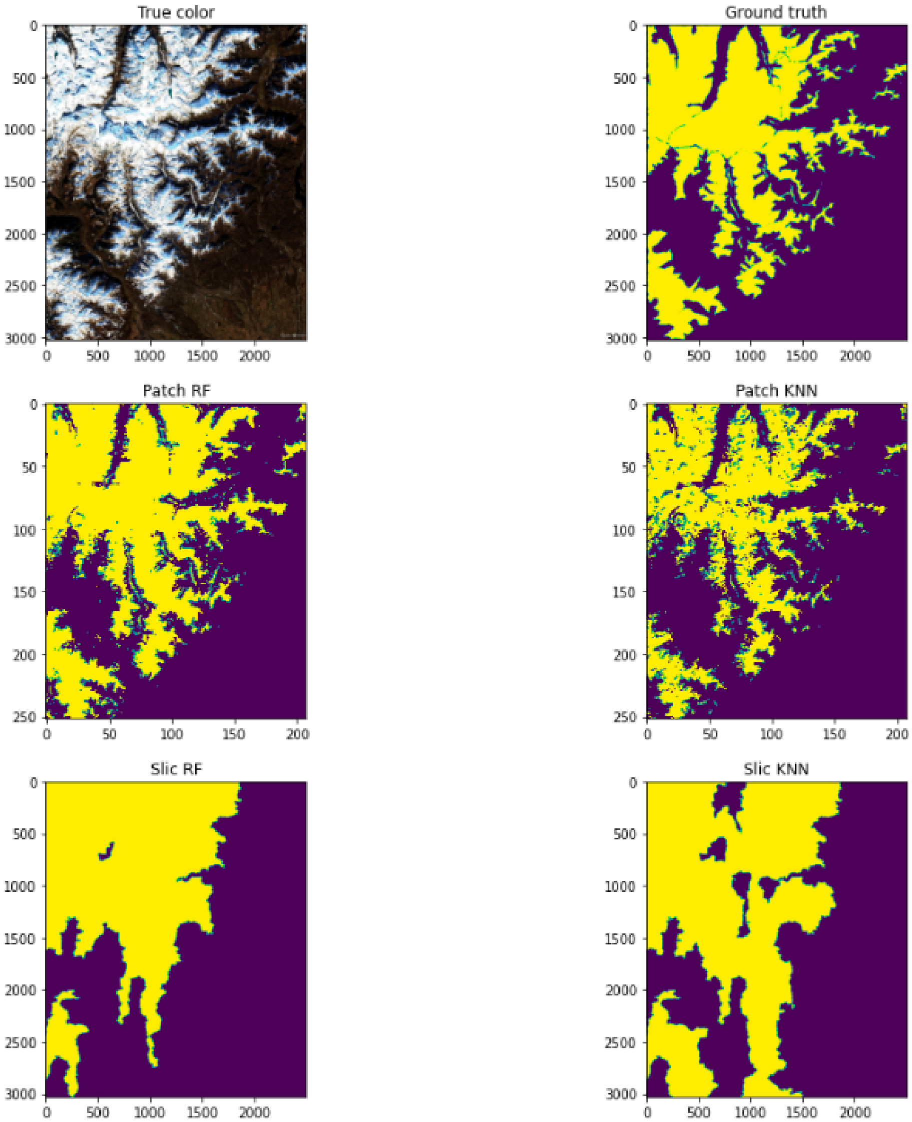

FIGURE 4.1
The true color and ground truth compared to all the prediction maps for December 2017.

Chapter 5

Discussion

5.1 Results

Our final results have shown that the Random Forrest classifier with the spatial support as patches is the best method. We can even debate that it's prediction for snow might even be better than our hand-drawn labels. For example, when looking at Figure 4.1, we can see that in the top right corner of the true color image there is some snow, very faint, and this area is also shown in the RF-patch method's prediction while we didn't draw it on the ground truth image; human error.

5.2 Prediction of Snow over the Years

Now that we have finally chosen the most efficient and accurate classifier and spatial support, the test set can be used to predict the snow fall over the years 2017, 2019 and 2021 in December, in the same week. The result is given in Figure 5.1.

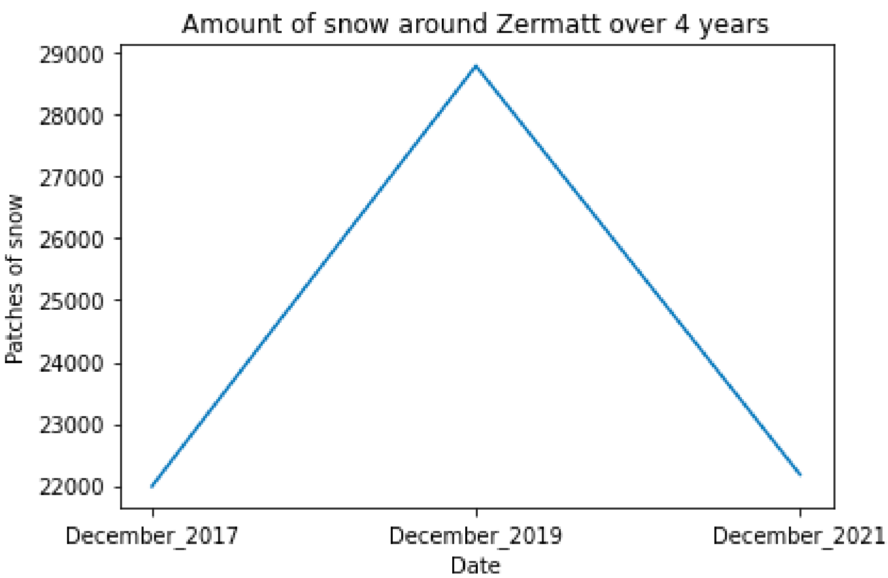

Figure 5.1
Snow fall over the years

As we can see there isn't really a trend in snow fall over the past 4 years. Overall, we can say that as a future improvement we should look at more data over a wider year-span so that a more accurate trend can be found. This was partially a problem with our chosen sensor, as Sentinel-2 only had images from 2016 onward. So we could also say, that another sensor should be used with more data.

5.3 SNOW FALL VS GLOBAL WARMING

As we said in the second chapter, the results would be compared to the effect of global warming. Though as already mentioned above there isn't really a trend as of the lack of test data. When comparing it with recent findings, there has been an increase in temperature in the Swiss Alps according to studies done by Swiss Info [[5]]. There seems to be a link between global warming and the decrease of snow through the years, however our data cannot support this yet.

CHAPTER 6

CONCLUSION

The research question was looking at the diminution of snow around Zermatt through the years. As discussed in chapter 5, due to the lack of data we don't have a concrete trend and hence cannot answer if there is a definite decrease of snow. However when comparing it to other studies there does seem to be a decrease of snow, we just can't support this trend yet.

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