Random Forest and Deep Learning for Glacier Mapping

Finse Alpine Research Centre, Norway

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September 2024

Outline

Image classification

Random forest

From convolutional networks to fully-convolutional networks

Project description

Image classification

Image classification (in the context of remote sensing) or semantic image segmentation (in the context of machine learning/deep learning) is a problem of segmenting the whole digital image into semantically meaningful classes.

There are several types of features that help to classify objects in remotely sensed images:

- spectral
- textural
- shapes
- topological

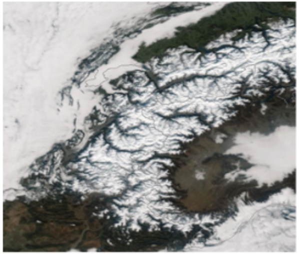




Image classification

In general, one can identify three approaches to address the classification problem:

- Pixel-to-pixel (the majority of the classification methods; can take into account only the spectral information)

$$\mathbf{y_{ij}} = f(\mathbf{x_{ij}}) + \epsilon \tag{1}$$

- Patch-to-pixel (textural analysis, convolutional neural networks, transformers)

$$\mathbf{y_{ij}} = f(\mathbf{X_{i:i+h,j:j+w}}) + \epsilon \tag{2}$$

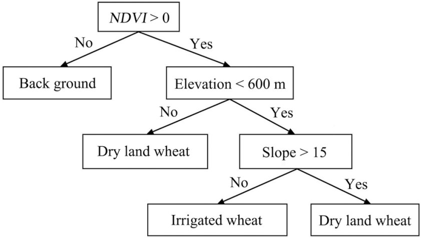
- Patch-to-patch (fully-convolutional neural networks, transformers)

$$\mathbf{Y_{i:i+h,j:j+w}} = f(\mathbf{X_{i:i+h,j:j+w}}) + \epsilon \tag{3}$$

Random forest

Random forest—an ensemble of decision trees trained to solve one problem.

Decision trees:



Source: Meng et al., 2014

- No-leaf nodes are splits (rules to build decision boundaries)
- Leaf nodes are decisions

- To make a split, compare how every feature threshold reduces 'impurity', e.g., Gini impurity
- $gini_{leaf} = 1 - p_0^2 - p_1^2$
- $gini_{split} = \frac{N_{yes}}{N_{yes}+N_{no}} gini_{yesleaf} + \frac{N_{no}}{N_{yes}+N_{no}} gini_{noleaf}$
- At each split, choose a threshold to minimize $gini_{split}$ in a greedy manner
- After every leaf is 'pure', assign labels to the leaves

Random forest

The output of a random forest model is the average prediction of the decision trees:

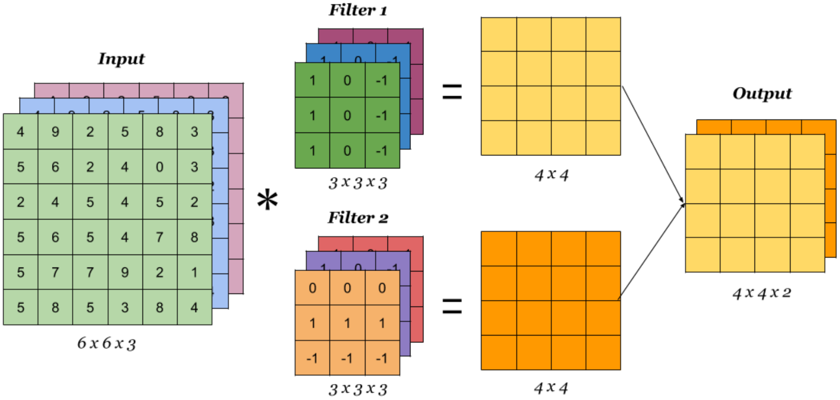
$$forest(\mathbf{x}) = \frac{1}{N_{trees}} \sum_i tree_i(\mathbf{x}). \tag{4}$$

But we do not want the decision trees to be correlated, so

- use data bootstrapping
- use feature bootstrapping at each split

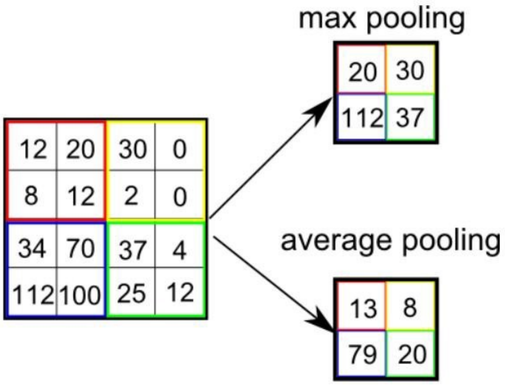
Fully-convolutional networks: convolutional layers

Let's first recall what convolutional neural networks are.



Source: `https://bit.ly/3eoHAJd`

Fully-convolutional networks: pooling/downsampling layers



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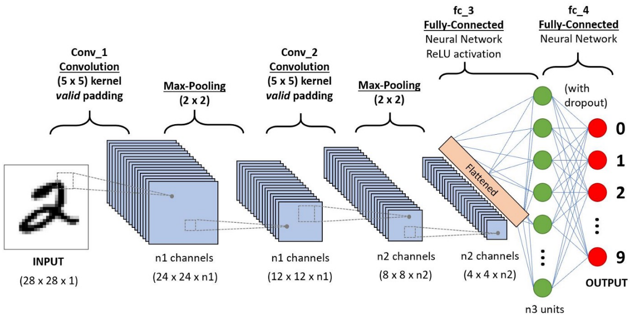
Fully-convolutional networks: typical convolutional network topologies

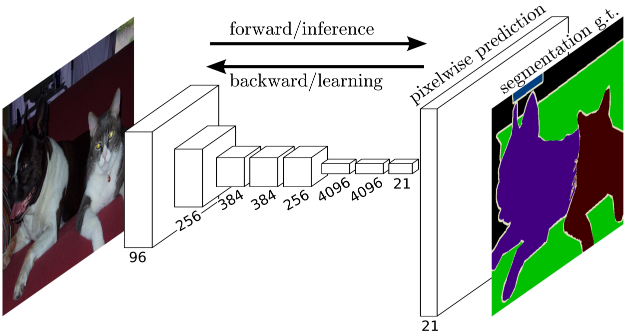


Source: `https://bit.ly/3wU3ryu`

- One inference to classify one pixel
- Computationally intensive
- Still can neglect some spatial correlations producing ‘noisy’ results

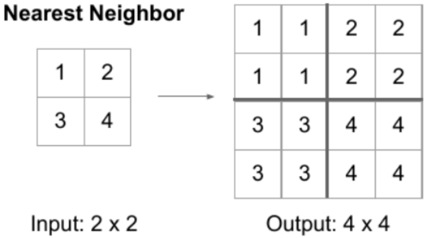
Fully-convolutional networks

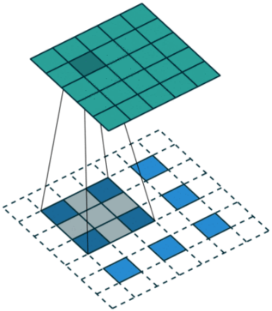
Can we do better? Yes!

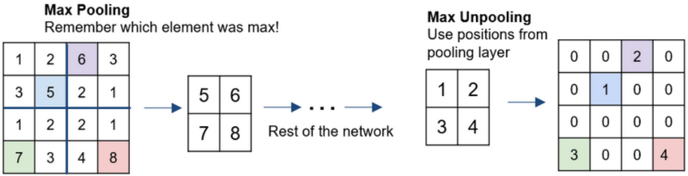


Source: Long et al., 2014

Fully-convolutional networks: upsampling layers







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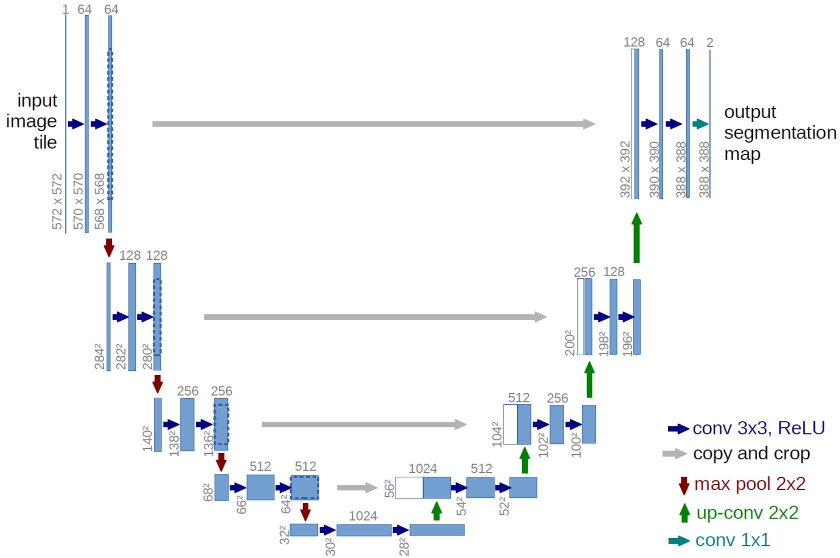
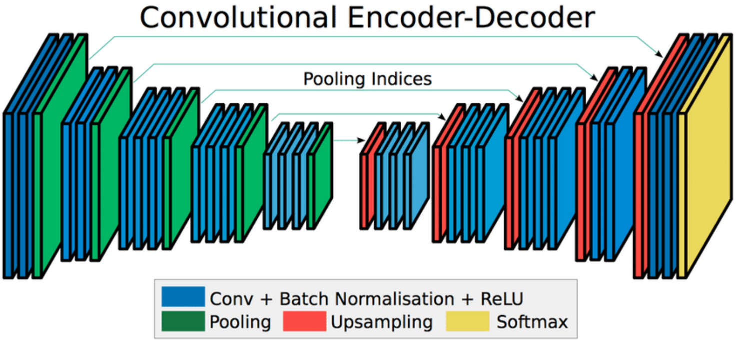
Fully-convolutional networks: U-Net



Source: Ronneberger et al., 2015

Fully-convolutional networks: SegNet



Source: Badrinarayanan et al., 2015

Fully-convolutional networks: DeepLab

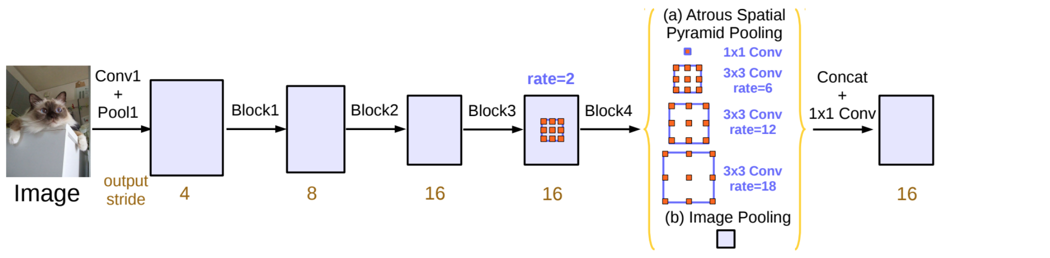
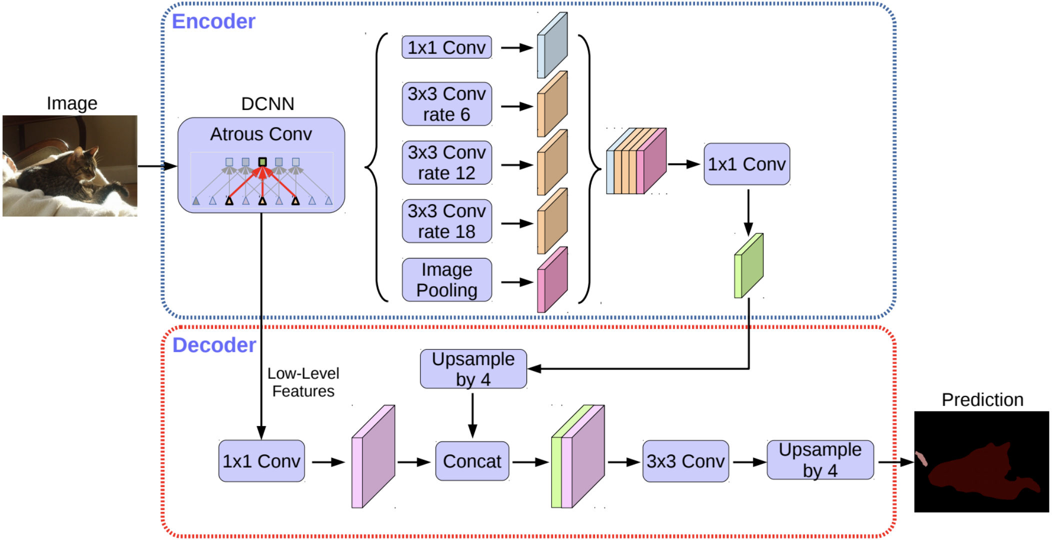


Figure 5. Parallel modules with atrous convolution (ASPP), augmented with image-level features.

Source: Chen et al., 2017

Fully-convolutional networks: DeepLabV3+



Source: Chen et al., 2018

Case studies: GlaViTU

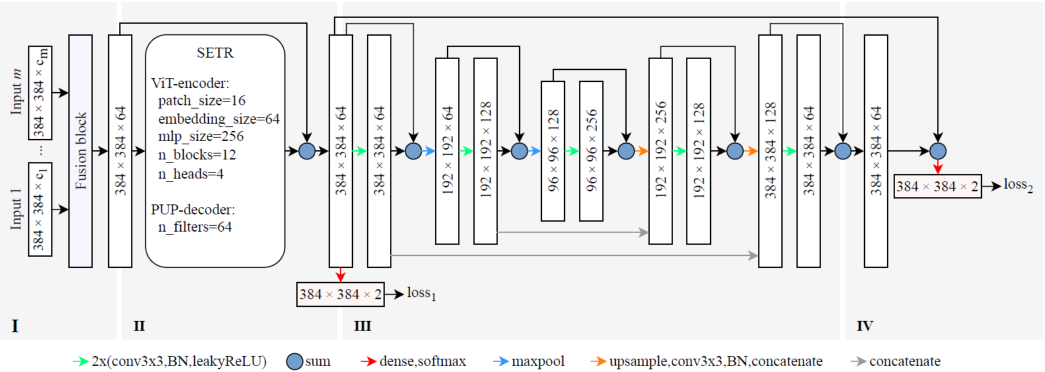


Fig. S10 Glacier-VisionTransformer-U-Net (GlaViTU). Boxes and numbers in them represent tensors and their shapes in the height × width × channels format, and arrows indicate operations and data flow. GlaViTU **I** fuses multi-modal inputs such as satellite images and elevation models, **II** extracts global features with a vision transformer, **III** refines local features with a convolutional subnet and **IV** yields the final classification map.

Case studies: GlaViTU

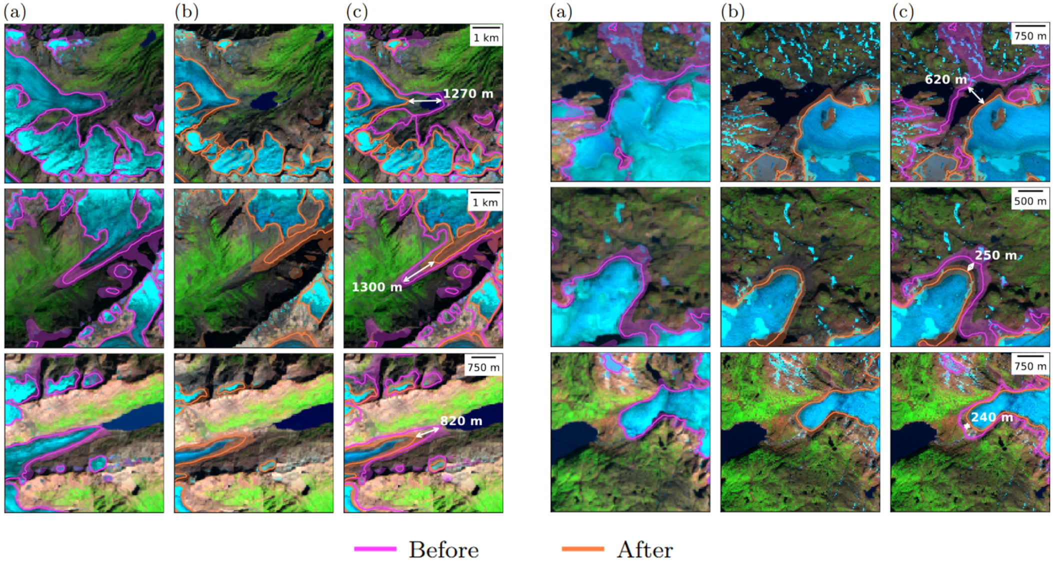
Fig. 2 Semantic segmentation results for the independent acquisition test data as derived using GlaViTU with regional encoding and bias optimisation: a, b the Swiss Alps, c, d Southern Norway, e, f, g Alaska and h, i Southern Canada. The satellite images are presented in a false colour composition (R: $SWIR_{\approx 2.2\mu m}$, G: NIR, B: R). Landsat images courtesy of the U.S. Geological Survey. Copernicus Sentinel data 2019.

Case studies: GlaViTU

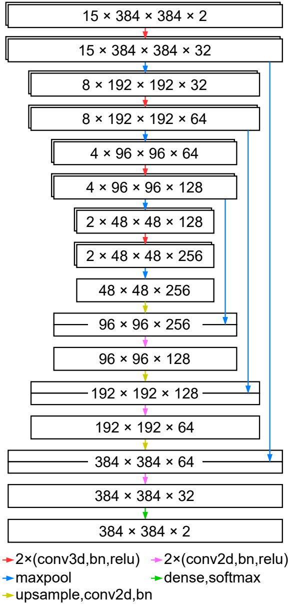
Glacier	Debris coverage, %	Pixel size, m	Area, km^2 Reference	Area, km^2 Predicted	Area deviation, km^2	Area deviation, %	Distance deviation, m Mean	Distance deviation, m Median	Distance deviation, m 95th percentile	IoU
Brattbreen	11.58	10	0.153	0.135	−0.018	−11.90	37.25	5.00	226.75	0.865
Gamchigletscher	76.09	30	1.458	1.549	+0.090	+6.19	44.69	32.02	123.96	0.797
Tundraskarsbreen	3.20	10	3.231	3.163	−0.068	−2.12	7.95	5.00	32.02	0.969
Langgletscher	18.94	30	9.115	8.973	−0.142	−1.55	52.83	30.00	183.78	0.883
Dorothy glacier	9.33	30	9.185	9.995	+0.809	+8.81	40.92	26.12	142.33	0.870
Oberaletschgletscher	35.92	30	18.938	19.644	+0.706	+3.73	44.22	30.00	152.13	0.858
Kilippi glacier	3.14	30	22.397	22.687	+0.291	+1.30	13.87	10.01	45.63	0.967
Unteraargletscher	36.40	30	24.632	24.831	+0.199	+0.81	53.79	32.15	205.31	0.869
Tonsina glacier	13.92	30	40.688	39.657	−1.031	−2.53	50.62	22.87	251.40	0.932
Scimitar glacier	16.73	30	41.038	47.692	+6.654	+16.21	52.30	26.89	188.85	0.854
Tunsbergdalsbreen	2.02	10	46.045	45.800	−0.245	−0.53	18.91	5.00	109.66	0.984
Stephens glacier	25.53	30	49.793	46.794	−3.000	−6.02	46.26	24.28	174.88	0.915
Tiedemann glacier	16.90	30	58.890	63.823	+4.933	+8.38	47.38	28.55	160.81	0.891
Aletschgletscher	9.55	30	82.278	83.934	+1.656	+2.01	39.54	30.31	103.34	0.937
Marcus Baker glacier	23.51	30	173.756	166.776	−6.979	−4.02	45.03	20.01	200.08	0.925
Matanuska glacier	17.54	30	319.142	299.263	−19.878	−6.23	59.93	15.43	209.33	0.927
Klinaklini glacier	1.84	30	469.910	474.177	+4.267	+0.91	41.33	11.51	118.16	0.970

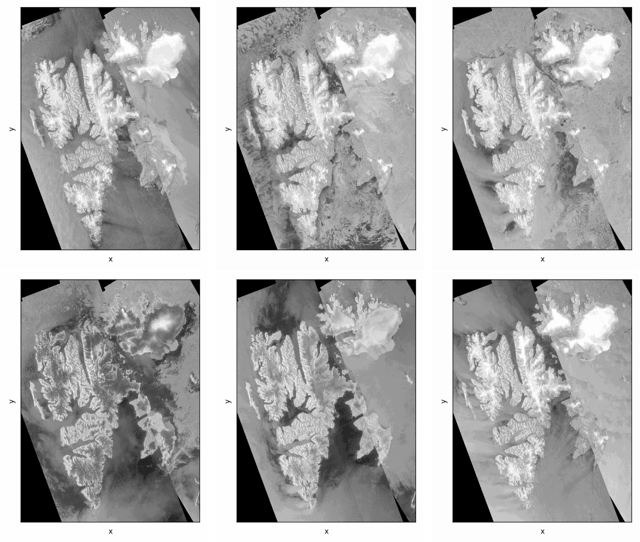
- The delineation accuracy of GlaViTU generally matches human expert uncertainty reported by Paul et al. 2013, Raup et al. 2014 and Linsbauer et al. 2021

Case studies: GlaViTU



Case studies: ICEmapper





Case studies: ICEmapper

Table. 1: Comparison of the models and the number of acquisitions per year used.

Model	#acquisitions	Precision	Recall	F1	IoU
3D conv	1	0.822	0.941	0.877	0.781
3D conv	3	0.973	0.949	0.961	0.924
3D conv	5	0.981	0.955	0.968	0.937
3D conv	15	0.984	**0.979**	**0.982**	**0.964**
LSTM	15	**0.986**	0.976	0.982	0.964

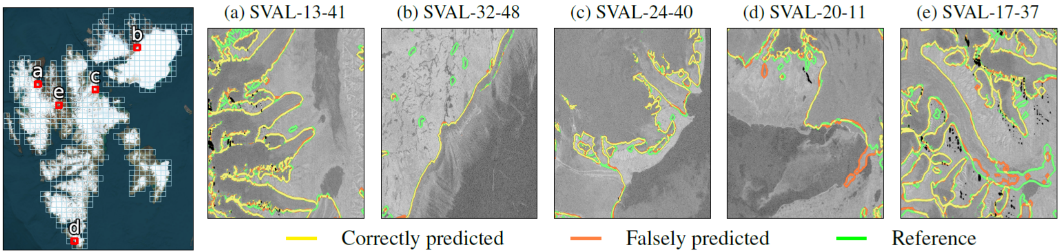
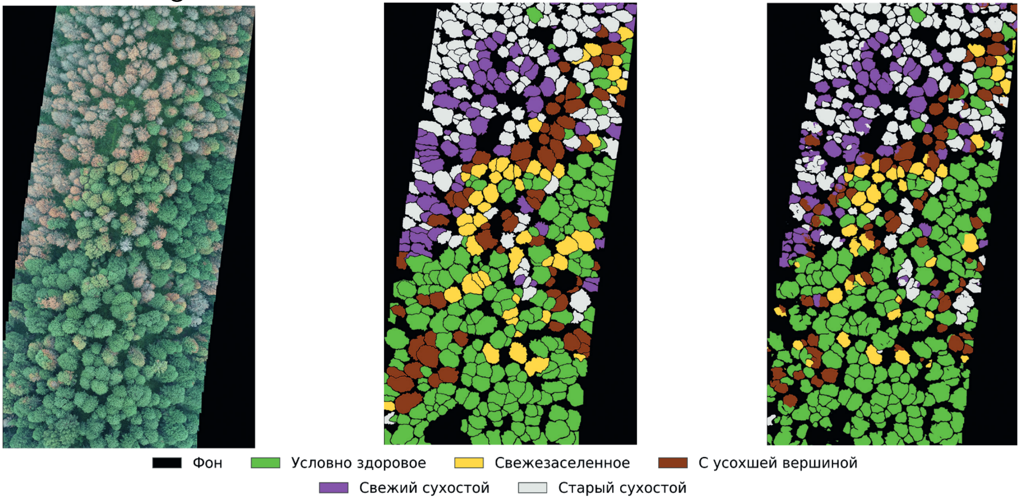


Fig. 2: (**Left**) Svalbard and tile grid. (**Right**) Predictions of the 3D convolutional model. ASF DAAC 2023, contains modified Copernicus Sentinel data 2016, processed by ESA.

Case studies: mapping forests damaged by pests in Western Siberia

UAV image | Groundtruth | U-Net–based



- Just to note that the methods can be relatively easily adapted for solving other problems

Project

In the project, we suggest going deeper with random forests and several deep learning models for glacier mapping in different world regions.

What we can offer for the beginning:

- A Jupyter notebook with the data preparation process
- A Jupyter notebook showing how to classify images with random forest
- A Jupyter notebook with fully-convolutional networks, from training to producing vector outputs
- Two pretrained models—U-Net, DeepLabV3+ (slightly modified)
- $\approx$ 200 GB dataset with optical imagery, SAR and DEM data that covers some of the Alps, Southern Andes, New Zealand and two areas in the Himalayas

You can also use other resources, e.g., GlaViTU

Project: options

- Applying the pretrained models to your regions of interest
- Glacier change analysis
- Labelling snow cover and training multi-class classification models
- Tweaking the deep learning models
- Modifying the training routines
- Hyperparameter tuning for random forest
- Exploring how different feature sets affect classification performance
- Diving deeper into XAI

  And more...

- Do not hesitate to suggest your ideas!

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