Schweizerische Eidgenossenschaft
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Federal Department of Home Affairs FDHA
Federal Office of Meteorology and Climatology MeteoSwiss

Capstone Project Presentation:

Towards hail detection from satellite images using ML

Jordi Figueras i Ventura
Supervisor: Mohamad Dia

EPFL EXTENSION SCHOOL

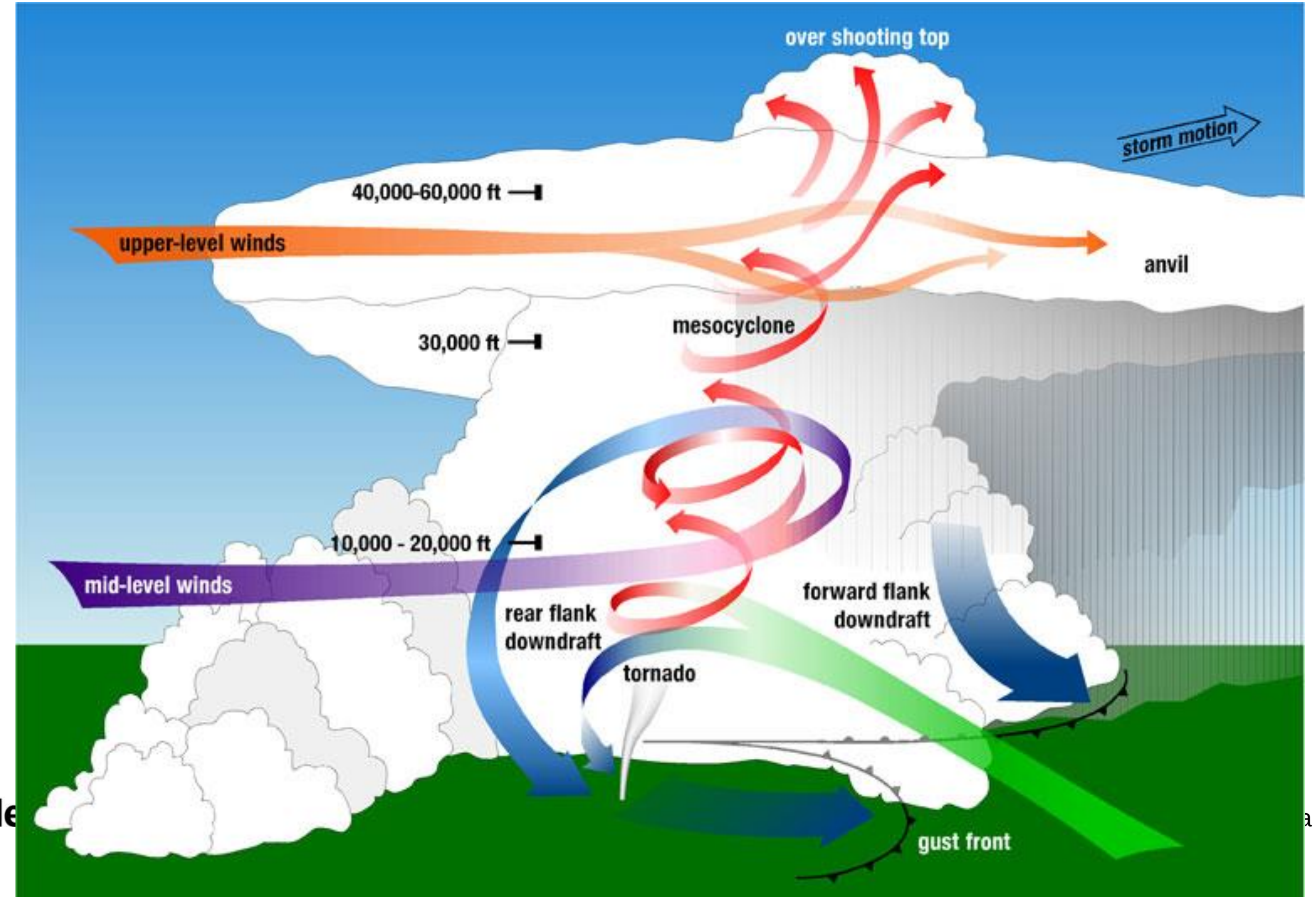
Certificate of Open Studies (COS):
Applied Data Science: Machine learning

Motivation

- Hail one of the most costly natural hazards:
  - 1.5 billion CHF paid by insurers for agriculture damage in Switzerland between 1972 and 2012
  - Significant hazard for aviation
- Very localized phenomenon, very difficult to predict

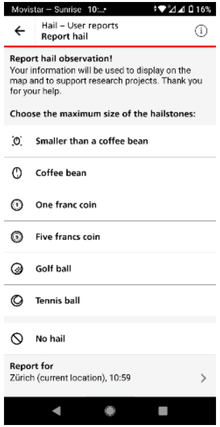


Severe storm structure



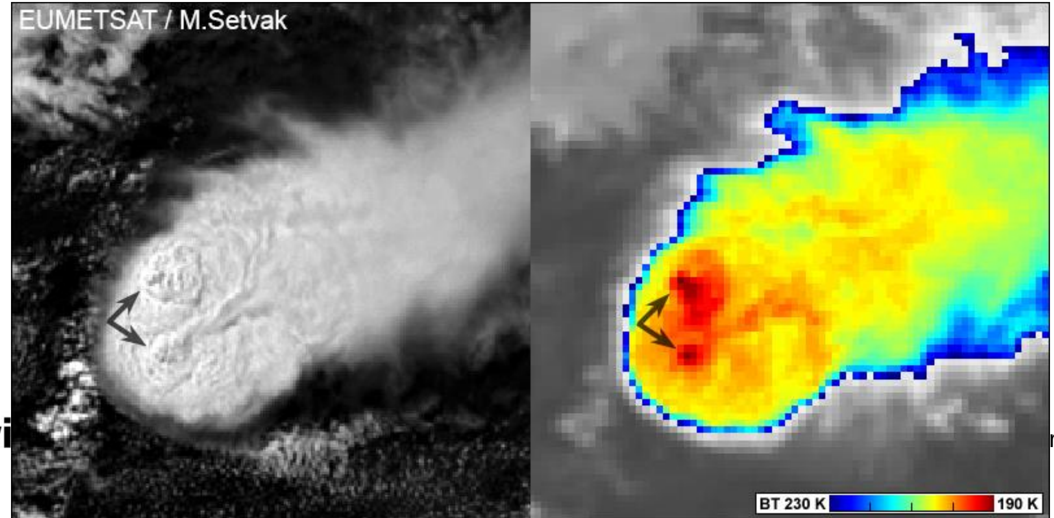
Hail detection

- Hail pads, hail sensors:
  - Precise information on hailstone size and timing ✓
  - Very sparse coverage ✗
- Crowdsourcing:
  - Good coverage (mostly in urban areas and by day) ✓
  - Timing, location and hailstone size with uncertainties ✗
- Radar:
  - Good coverage over extensive area with precise timing ✓
  - Uncertainties in hail detection and hailstone size estimation ✗



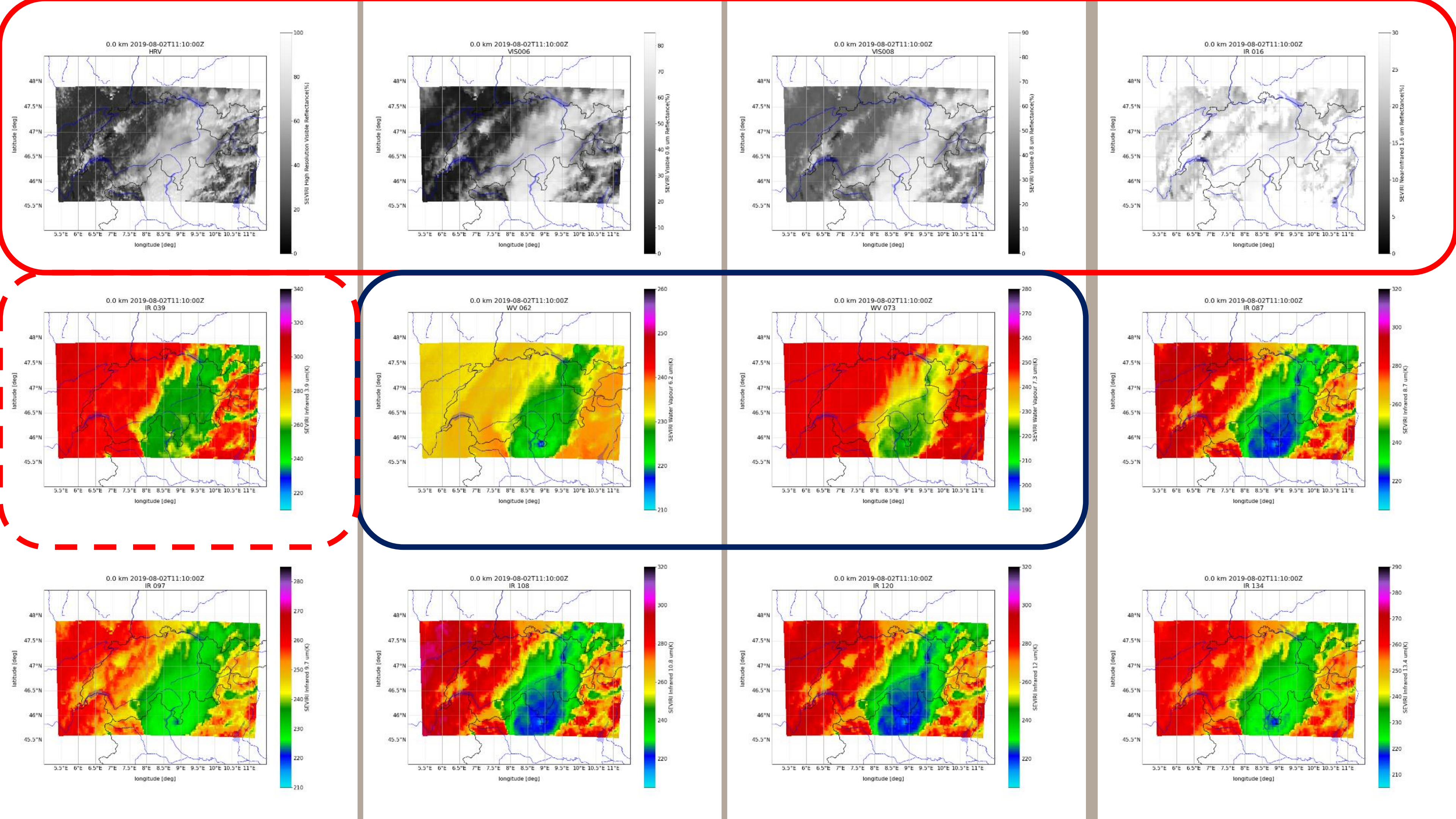
Hail detection by satellite

- 24/7 global coverage including non-instrumented areas
- Detection performed indirectly through observation of characteristic cloud structures, e.g. overshooting tops
- Currently detection performed manually by trained forecasters

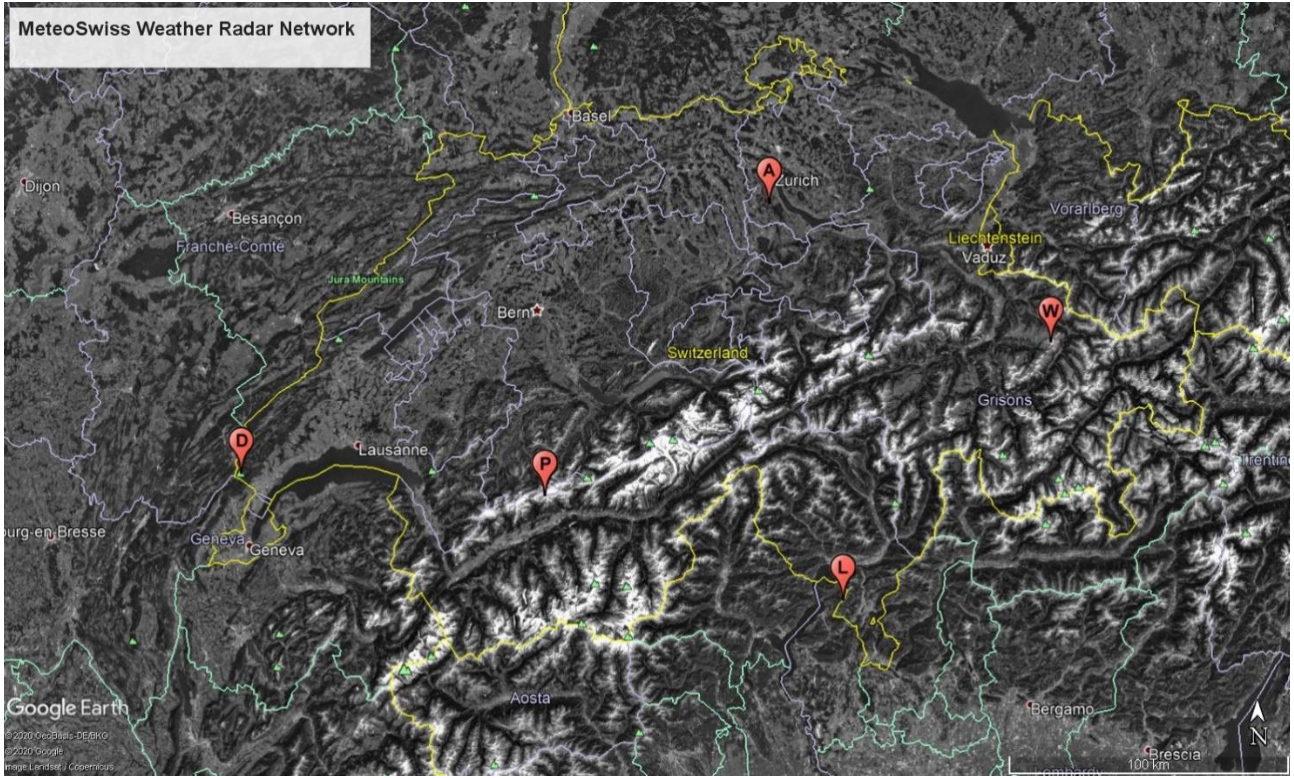


METEOSAT SEVIRI

- 12 spectral channels (4 visible-8 infrared) sensitive to different physical phenomena
- Further information from channel differences
- 3 km resolution (1 km HRV)
- 5 min temporal resolution (Fast scanning mode)

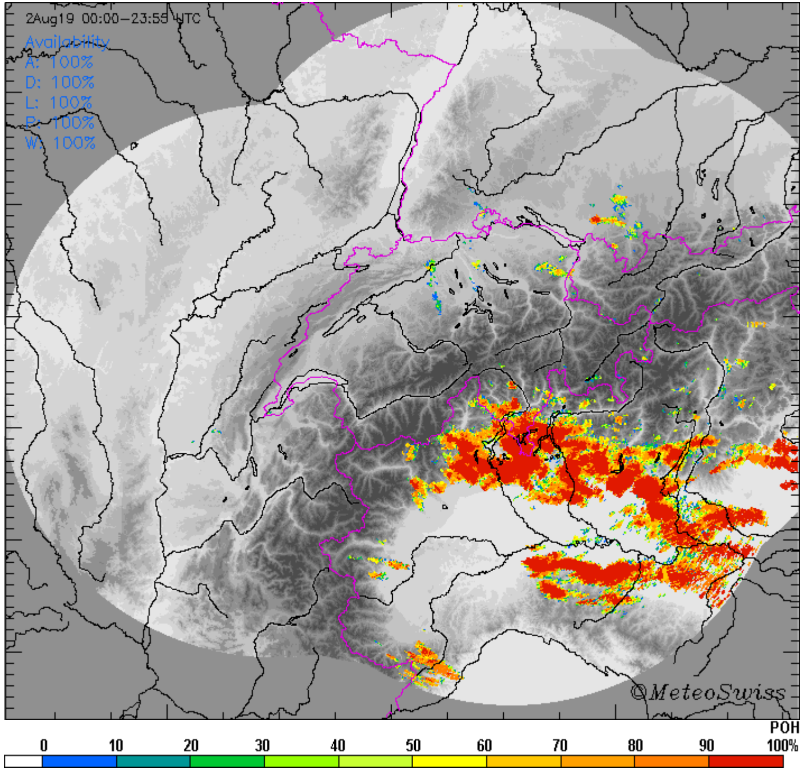

0.0 km 2019-08-02T11:10:00Z
HRV
SEVIRI High Resolution Visible Reflectance(%)
0.0 km 2019-08-02T11:10:00Z
VIS006
SEVIRI Visible 0.6 um Reflectance(%)
0.0 km 2019-08-02T11:10:00Z
VIS008
SEVIRI Visible 0.8 um Reflectance(%)
0.0 km 2019-08-02T11:10:00Z
IR 016
SEVIRI Near-Infrared 1.6 um Reflectance(%)
0.0 km 2019-08-02T11:10:00Z
IR 039
SEVIRI Infrared 3.9 um(K)
0.0 km 2019-08-02T11:10:00Z
WV 062
SEVIRI Water Vapour 6.2 um(K)
0.0 km 2019-08-02T11:10:00Z
WV 073
SEVIRI Water Vapour 7.3 um(K)
0.0 km 2019-08-02T11:10:00Z
IR 087
SEVIRI Infrared 8.7 um(K)
0.0 km 2019-08-02T11:10:00Z
IR 097
SEVIRI Infrared 9.7 um(K)
0.0 km 2019-08-02T11:10:00Z
IR 108
SEVIRI Infrared 10.8 um(K)
0.0 km 2019-08-02T11:10:00Z
IR 120
SEVIRI Infrared 12 um(K)
0.0 km 2019-08-02T11:10:00Z
IR 134
SEVIRI Infrared 13.4 um(K)
latitude [deg]
longitude [deg]

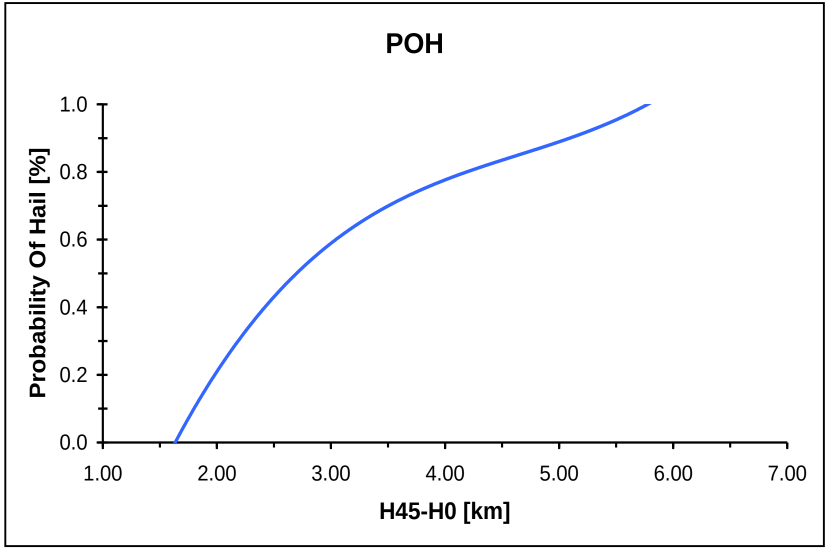
Hail detection with radar: POH algorithm



Echotop 45 dBZ: Maximum altitude at which the radar reflectivity is 45 dBZ or higher

Hail detection with radar

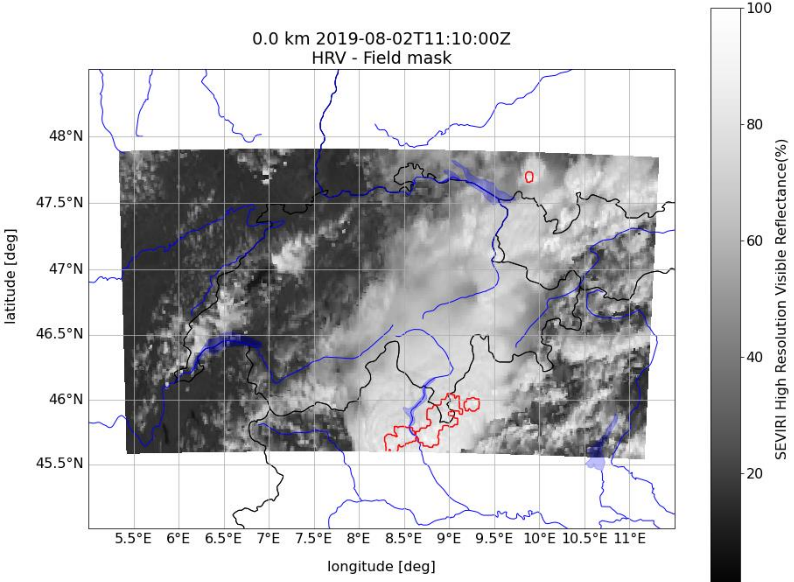




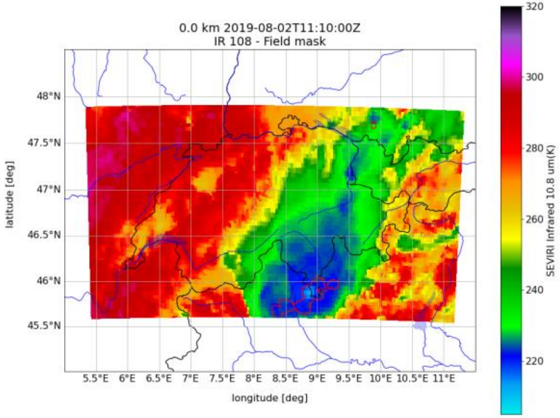
POH ≥ 90%: Hail on the ground very likely

This is our target!

Relationship POH-Satellite images

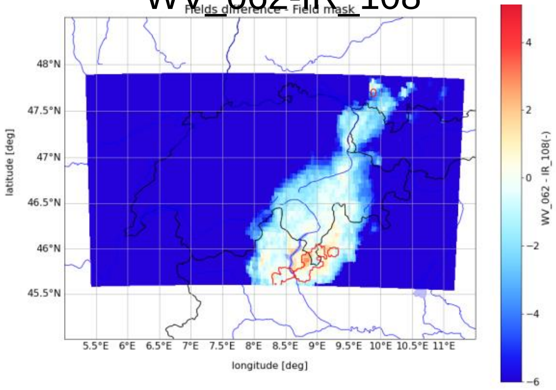


Used by humans to detect overshooting tops
We normalize by sun zenith angle



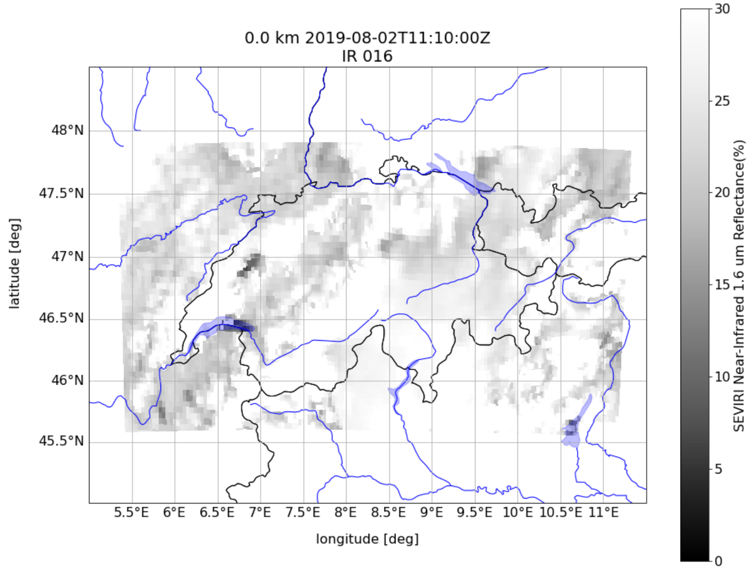
Cloud top height

WV_062-IR_108



Cloud water content

Feature added later on

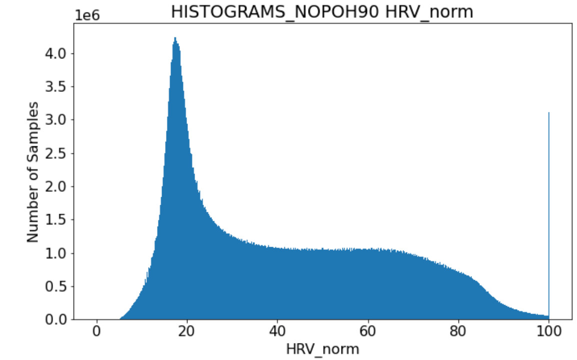


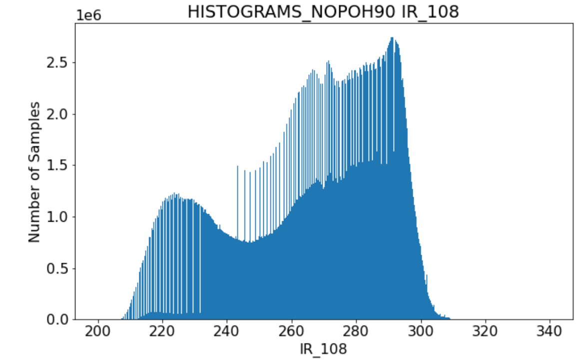
Cloud top phase

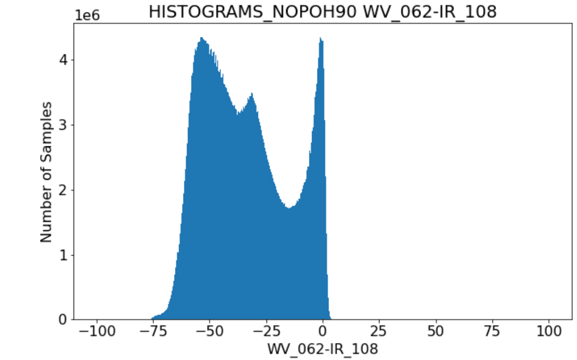
Dataset

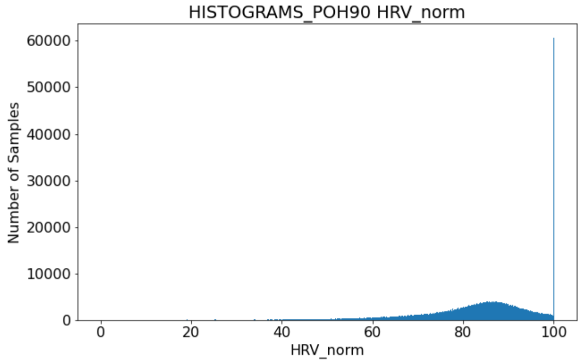
- Convective season (April-September) of 2018, 2019, 2020 (Until July)
- 448x256 1km-resolution images
- Daylight only, images containing at least 1 POH90 pixel
- Missing images due to gaps in the satellite archive and corrupted data
- **4351** images available!

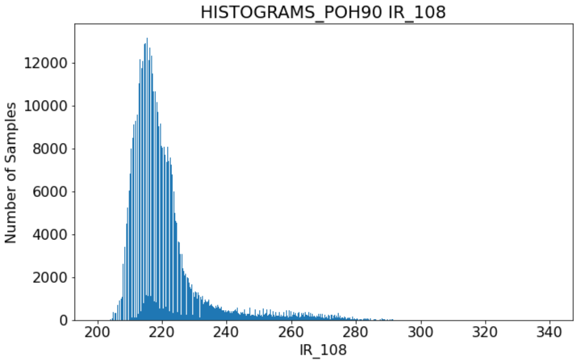
EDA

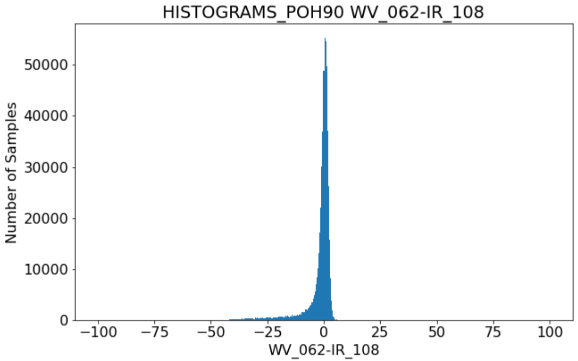

HISTOGRAMS_NOPOH90 HRV_norm
1e6
Number of Samples
HRV_norm


HISTOGRAMS_NOPOH90 IR_108
1e6
Number of Samples
IR_108

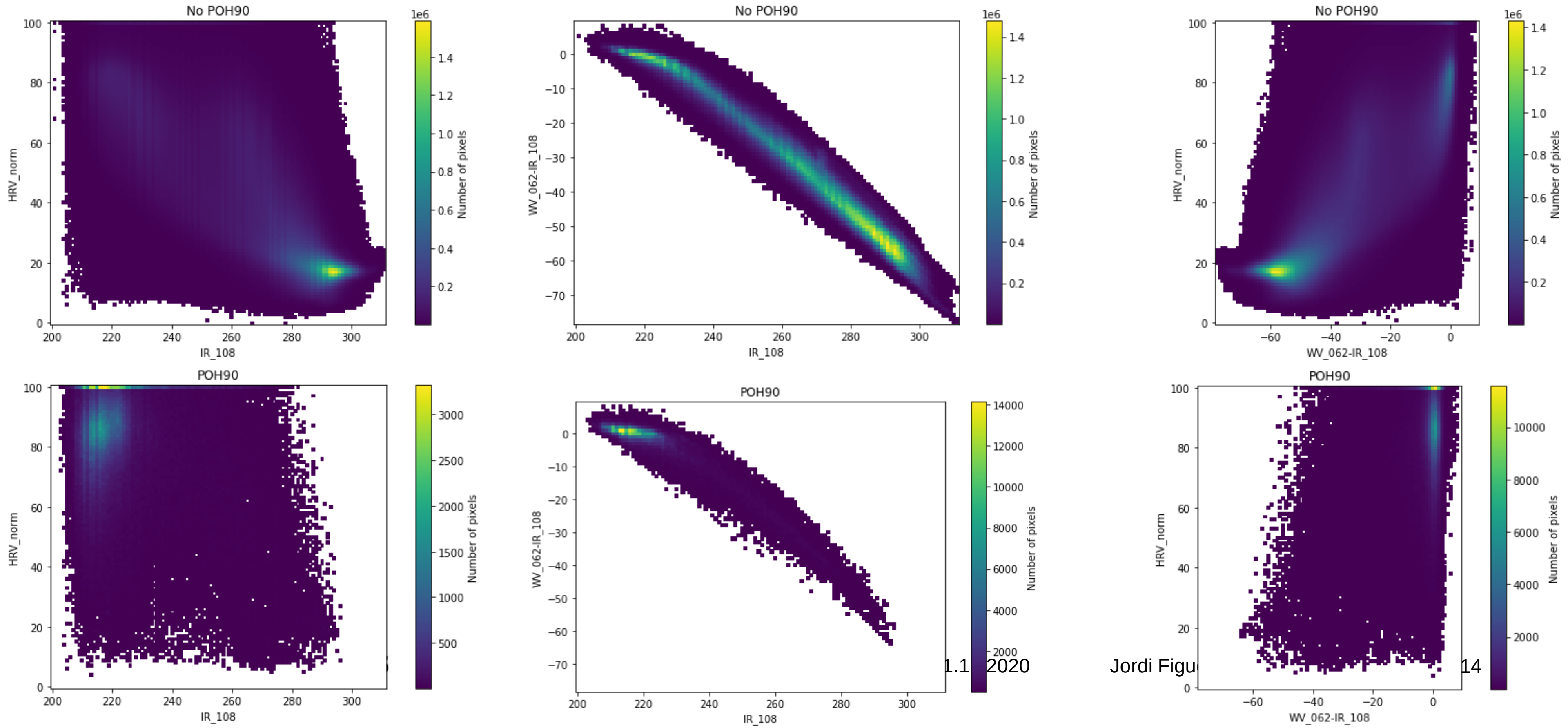

HISTOGRAMS_NOPOH90 WV_062-IR_108
1e6
Number of Samples
WV_062-IR_108


HISTOGRAMS_POH90 HRV_norm
Number of Samples
HRV_norm


HISTOGRAMS_POH90 IR_108
Number of Samples
IR_108


HISTOGRAMS_POH90 WV_062-IR_108
Number of Samples
WV_062-IR_108

EDA

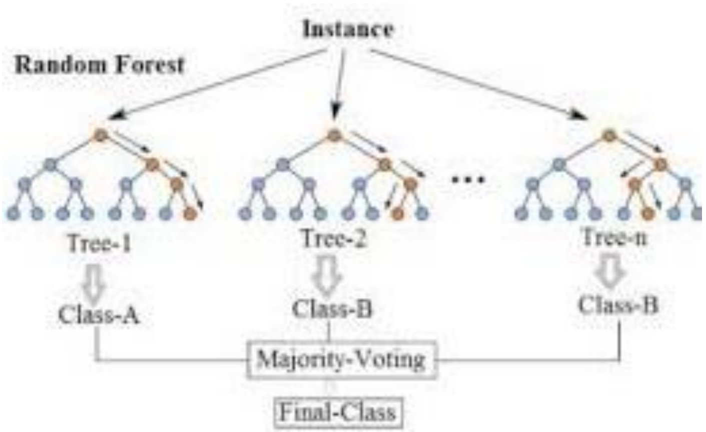

No POH90
HRV_norm
IR_108
1e6
Number of pixels
No POH90
WV_062-IR_108
IR_108
1e6
Number of pixels
No POH90
HRV_norm
WV_062-IR_108
1e6
Number of pixels
POH90
HRV_norm
IR_108
Number of pixels
POH90
WV_062-IR_108
IR_108
Number of pixels
POH90
HRV_norm
WV_062-IR_108
Number of pixels

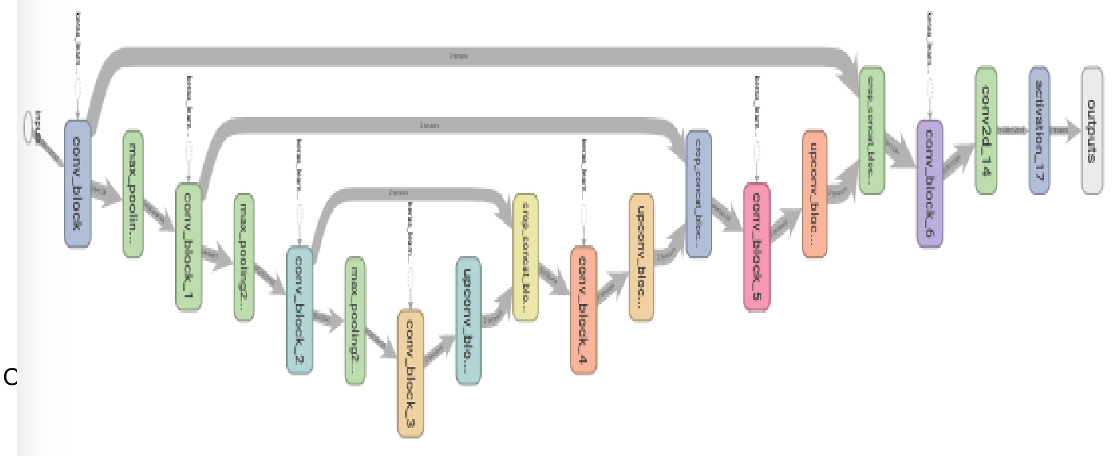
EDA conclusions

- Extremely large imbalance: Hail pixels 0.1% of total
- Distinct distributions of hail/no hail features BUT large overlap

Proposed models

- **Random Forests family:**
  - Deals with non-linear data
  - Scalable
  - Pixel-based
  - Contribution of each feature easily measurable
- **U-net architecture:**
  - CNN for semantic image segmentation=> learns spatial structure
  - Large amount of data needed for training





Pre-processing

- **Random Forests family:**
  - Thresholds to keep only areas of interest:
    - IR_108 < 240 k
    - Window > -50 K
  - 7-km texture of each variable to get information of spatial structure
  - Remove pixels with NaN values in the texture

- **U-net architecture:**
  - Min-max scaling
  - One-hot encoding of the target

Random Forest models

- 7,432,290 pixels used (0.8% contain hail):
  - 10% for test
  - 10% of remaining for validation
- Grid search with 5-fold random shuffle validation
- Parameter to optimize: Number of trees from 1 to 50

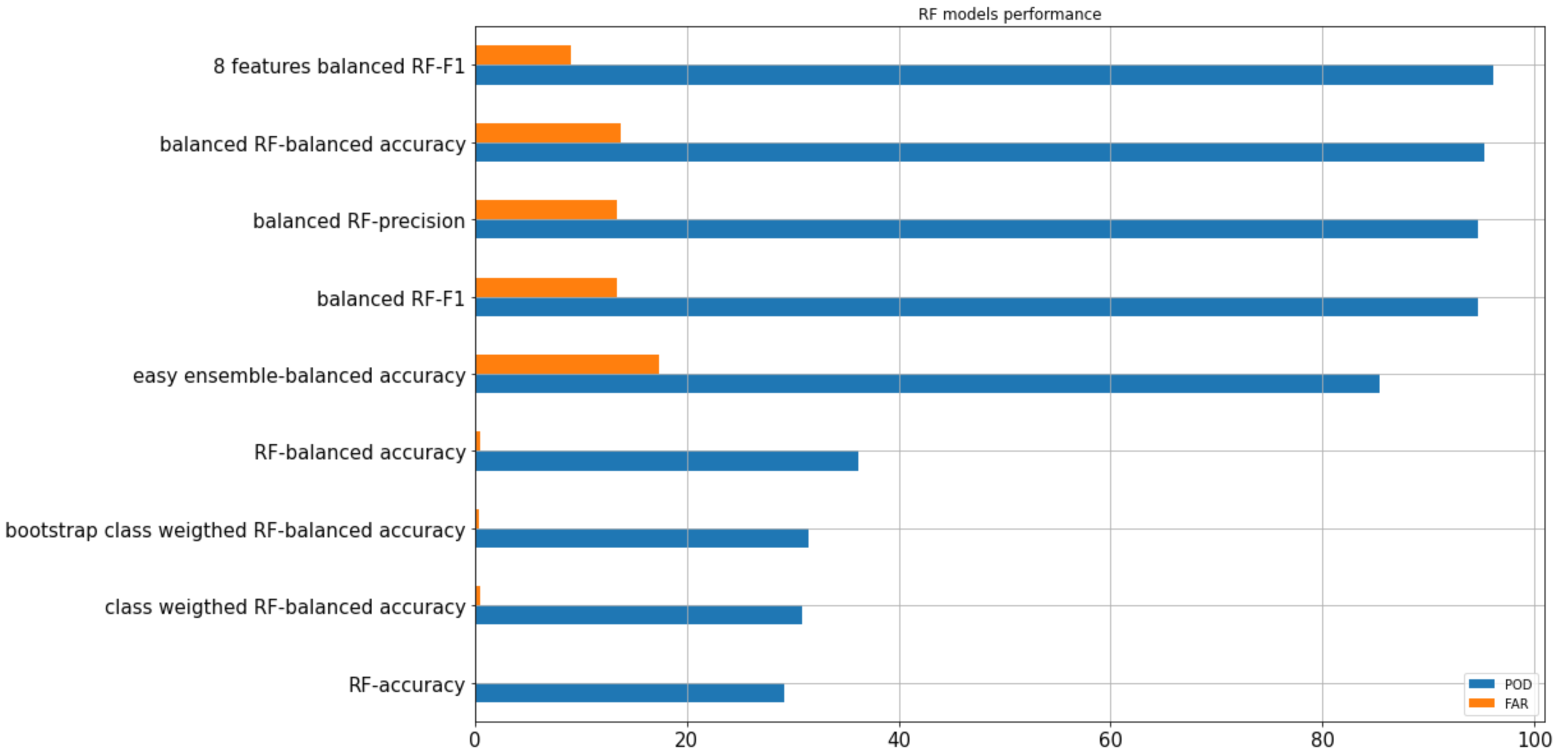
RF models tested

- [1] Classic RF
- [2] Class weighted RF
  - We penalize more misclassification of the less frequent class (frequency computed over whole dataset)
- [3] Bootstrap class weighted RF:
  - As previous but frequency computed over each bootstrap sample
- [4] Balanced RF:
  - We perform random under-sampling of the majority class in each bootstrap sample to equilibrate the class frequency
- [5] Easy Ensemble for imbalanced classification:
  - We create multiple datasets consisting of all samples of the minority class and a random selection of the majority class

Score optimized

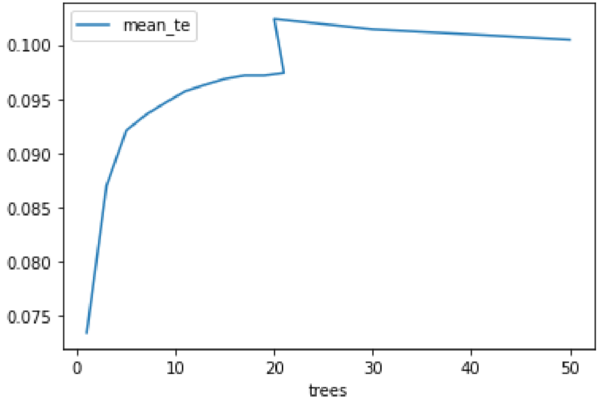
- Accuracy [1]:
  - (TP + TN)/(TP + TN + FP + FN)
- Balanced accuracy [1, 2, 3, 4, 5]:
  - The average of the recall of each class:
  - 1/2[TP/(TP+FN)+TN/(TN+FP)]
- Precision [4]:
  - TP/(TP+FP)
- F-score [4]:
  - Harmonic mean of precision and recall
  - TP/[TP+0.5(FP+FN)]

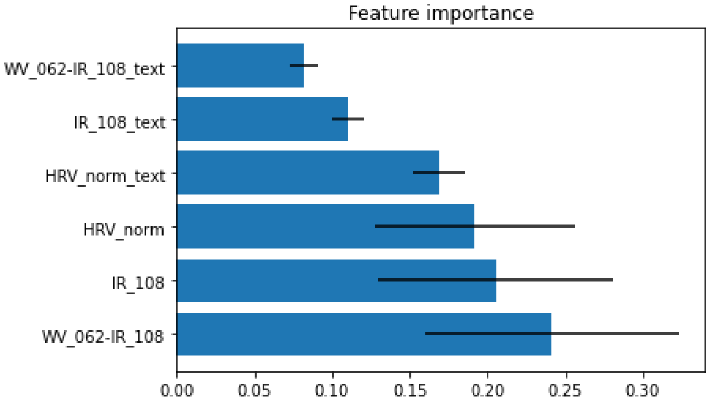
Results


RF models performance
8 features balanced RF-F1
balanced RF-balanced accuracy
balanced RF-precision
balanced RF-F1
easy ensemble-balanced accuracy
RF-balanced accuracy
bootstrap class weigthed RF-balanced accuracy
class weigthed RF-balanced accuracy
RF-accuracy
POD
FAR
0
20
40
60
80
100

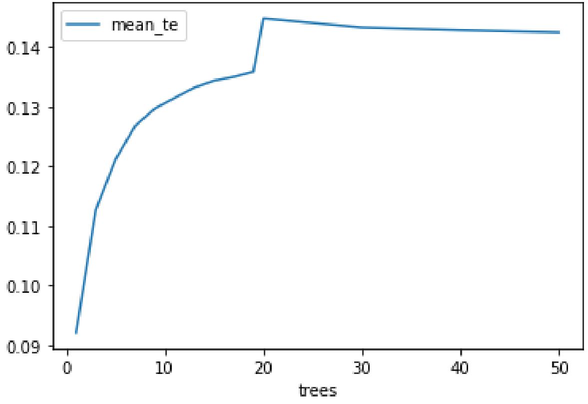
Balanced RF with F-score optimization

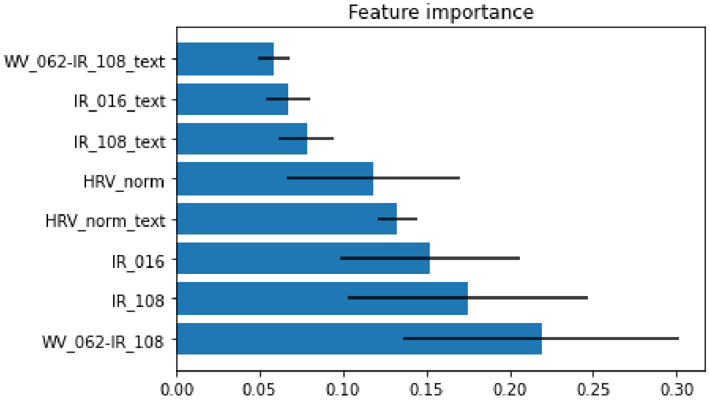
6 features





8 features

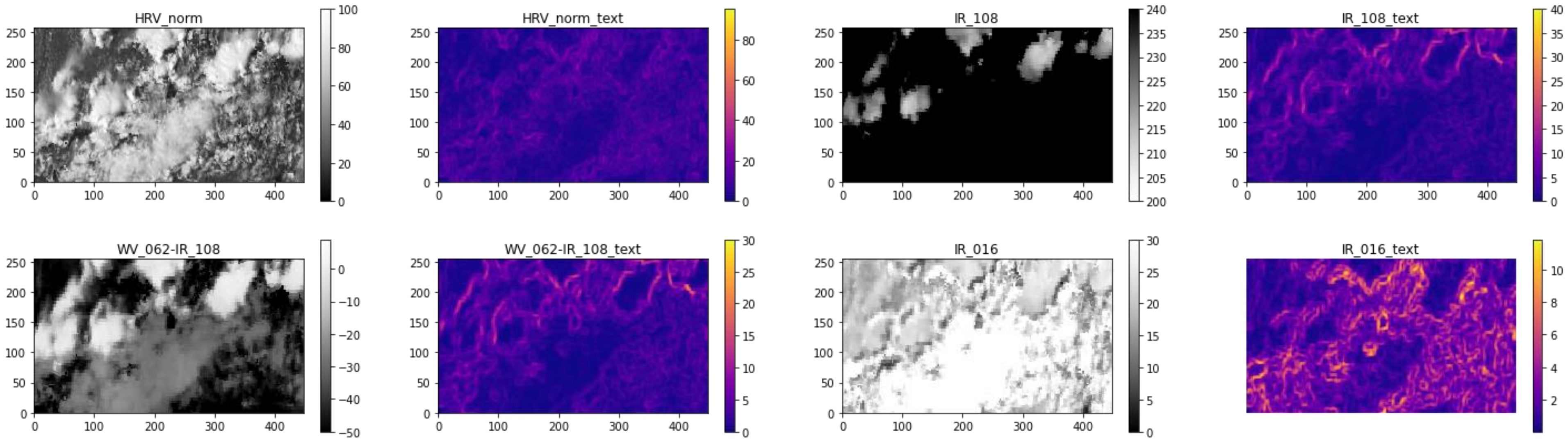




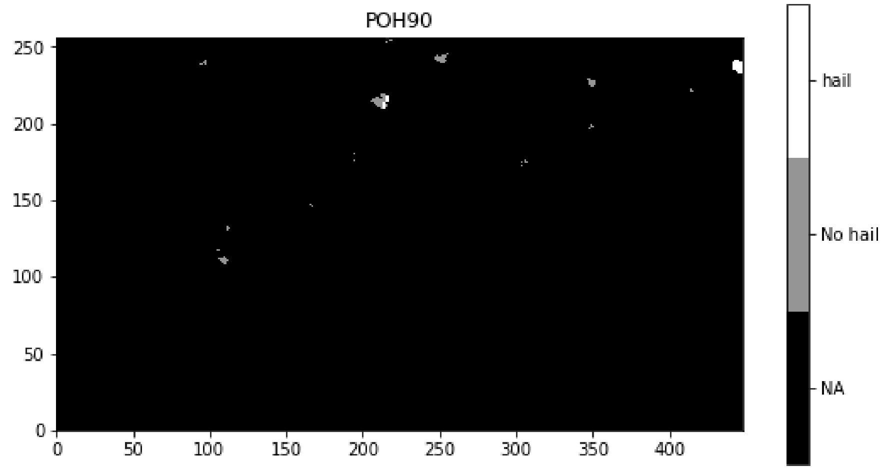
MeteoSwiss

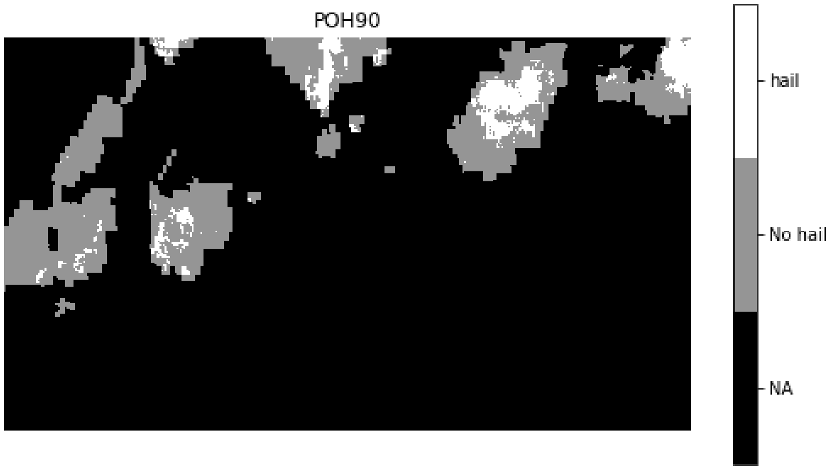
Results on individual image

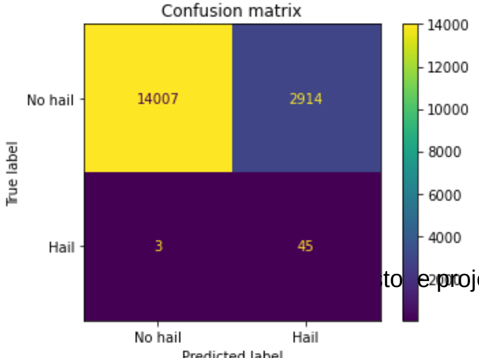
2018-06-08 13:45 UTC



Results on individual image







POD: 93.75%
FAR: 17.22%

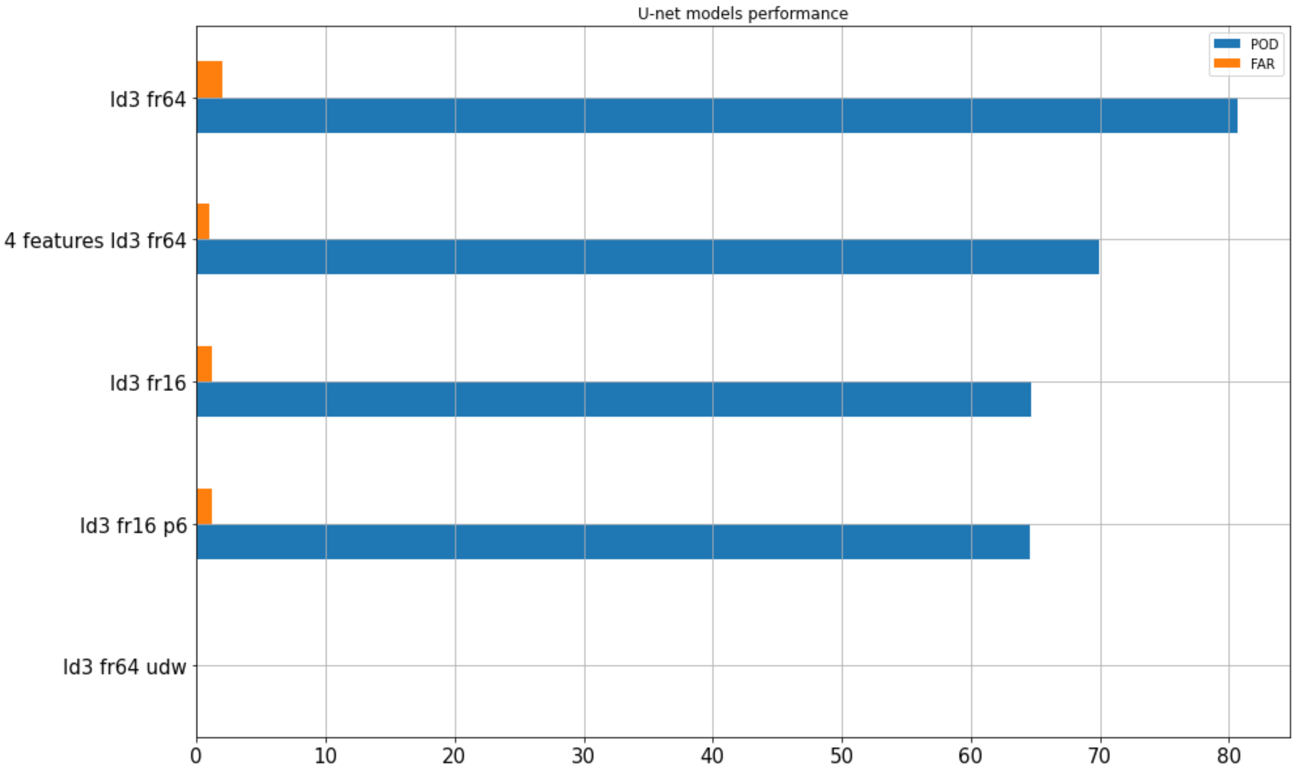
U-NET model

- 4351 images used (0.1% of pixels contain hail):
  - 351 Test
  - 400 Validation
- Loss function: Weighted binary cross-entropy
  - Weights inversely proportional to class frequency (0.5 no hail/456 hail)

U-NET architectures tested

- 3 layers, 16 filters in first layer (patience 3 epochs and 6 epochs)
- 3 layers, 64 filters in first layer (patience 3 epochs)
- 3 layers, 64 filters with user defined weights (1/10) in the binary cross-entropy
- 5 layers => Problems with image size
- 3 layers, 64 filters, 4 channels

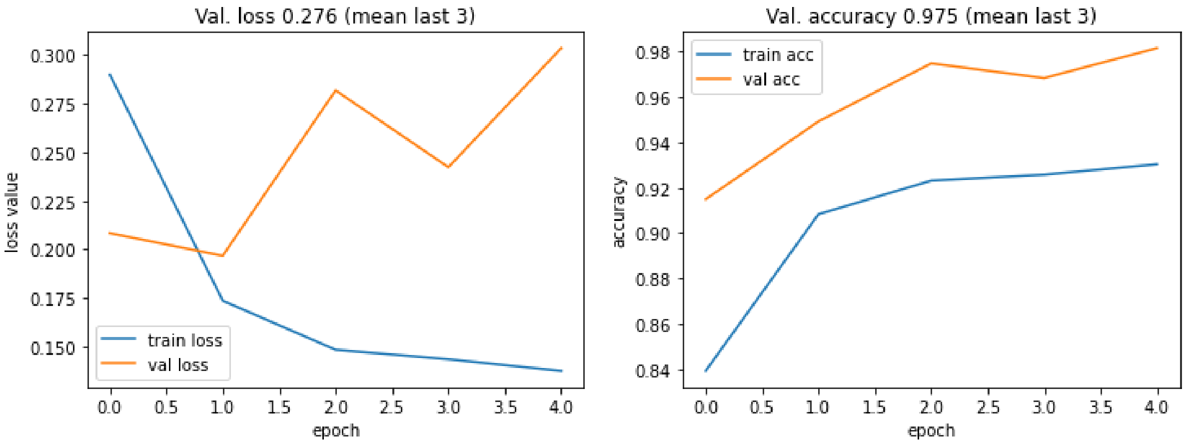
Results



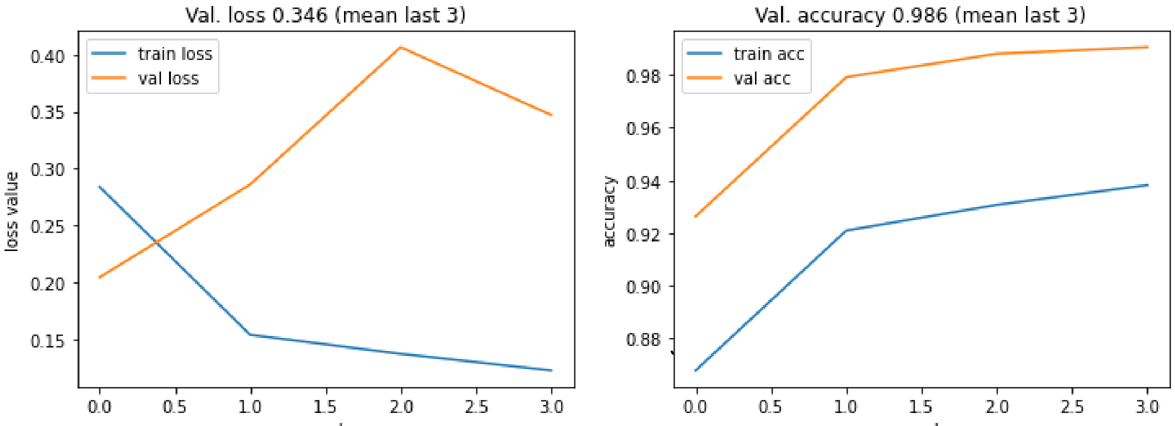
U-net models performance
POD
FAR
ld3 fr64
4 features ld3 fr64
ld3 fr16
ld3 fr16 p6
ld3 fr64 udw
0
10
20
30
40
50
60
70
80

Training results

3 channels

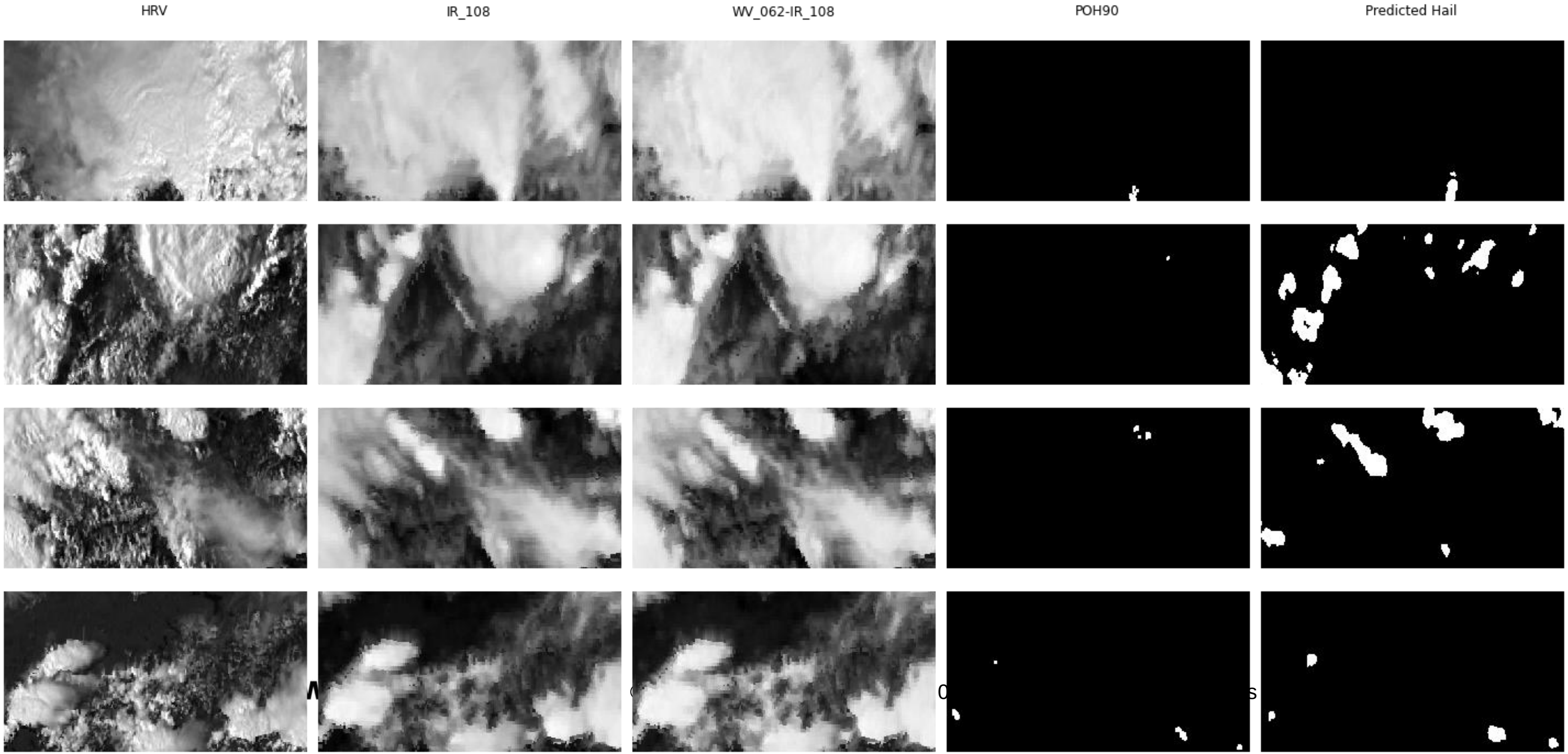


4 channels



MeteoSwiss

Results on individual images



Conclusion

- Large imbalance between classes and overlap of class distributions major challenges
- Best classical model investigated : Balanced Random Forest with 8 features
- Best u-net model investigated: 3 layers, 64 filters at first layer, 3 channels
- Likely overfitting of u-net model
- Balanced RF better performance than u-net
- Long training times for u-net: consider use of GPUs

Future work

- Increase the number of features:
  - All channels
  - Combination of channels
  - Metadata (solar time, day of the year, satellite viewing angle, etc.)
- Investigate the sensitivity to POH threshold
- Train a night time model
- Use/train the model(s) over a wider area: All Europe? All Rapid Scan Service area? All METEOSAT viewing field?


Thank you!
Grazie!
Danke schön!
Merci!
Moltes gràcies!