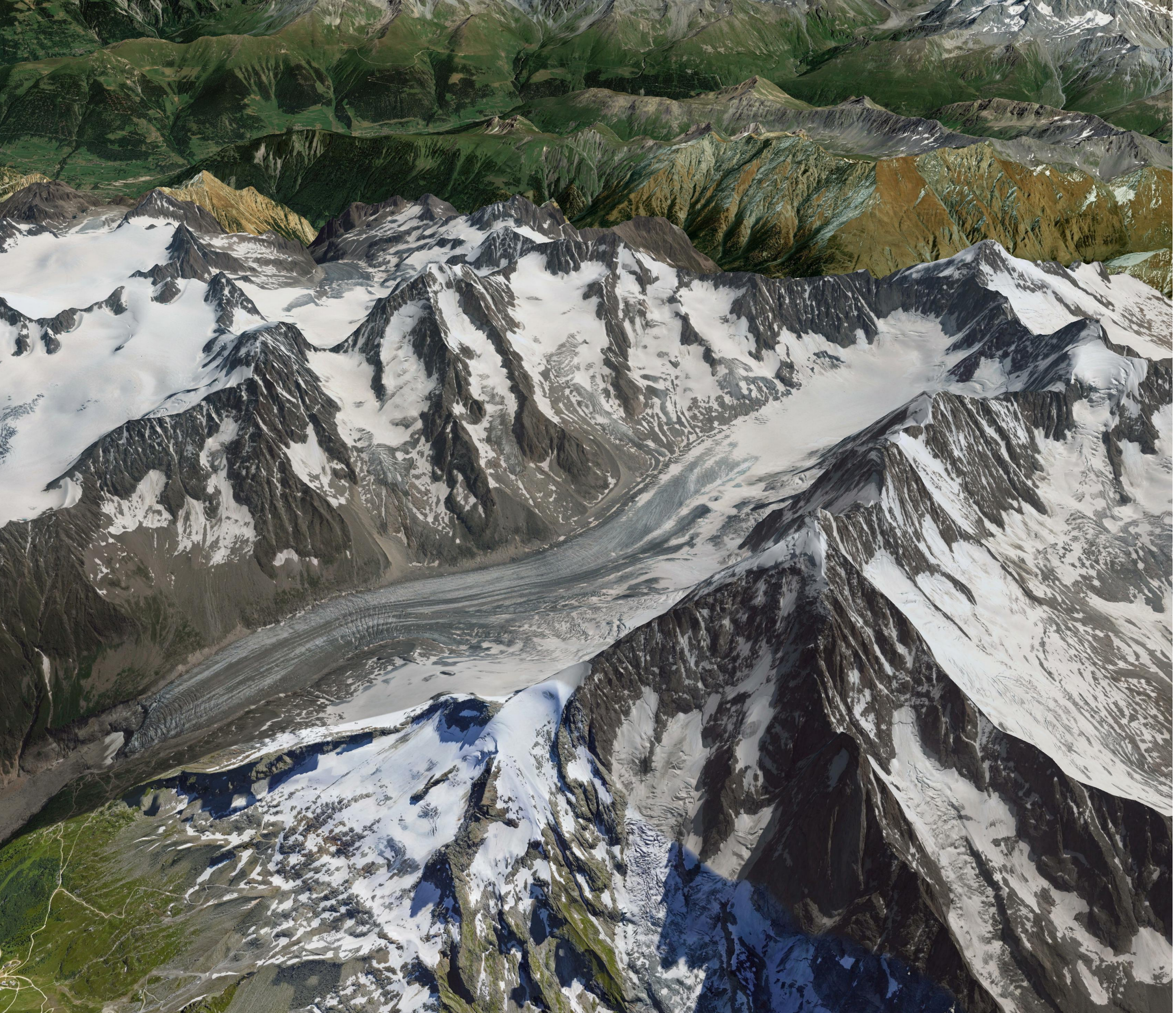

Characterizing glacial processes applying classical beamforming and supervised machine learning

European Geosciences Union
Vienna, 6th May 2020

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Motivation

ML towards complex process understanding in glacial ice

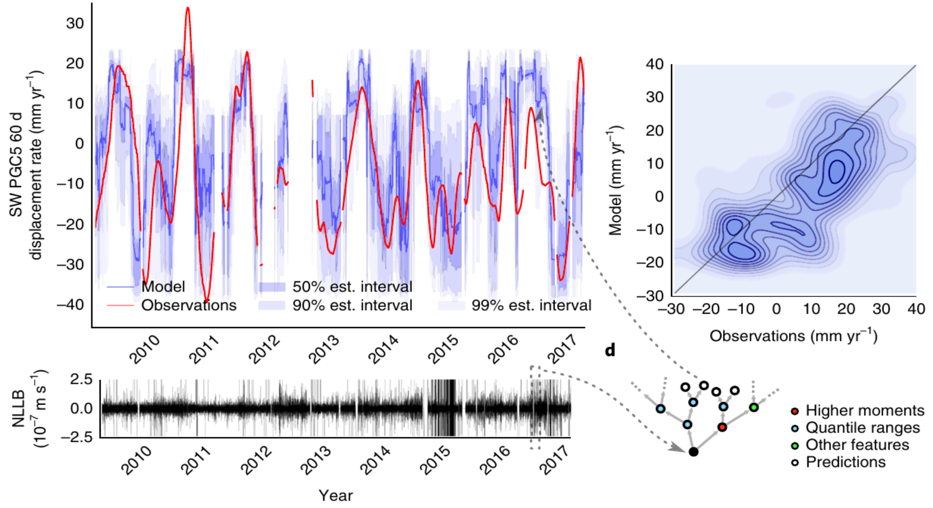
motivation

Understanding glacial movement (local surface deformation / basal motion)

Can we predict GPS movement using seismic data on a glacier ?

- We certainly can in the lab (Rouet-LeDuc et al. 2018a) and on subduction zones (Rouet-LeDuc et al. 2018b) !

- GPS movement is modulated by statistical properties of continuous seismic data (Cascadia Subduction Zone)

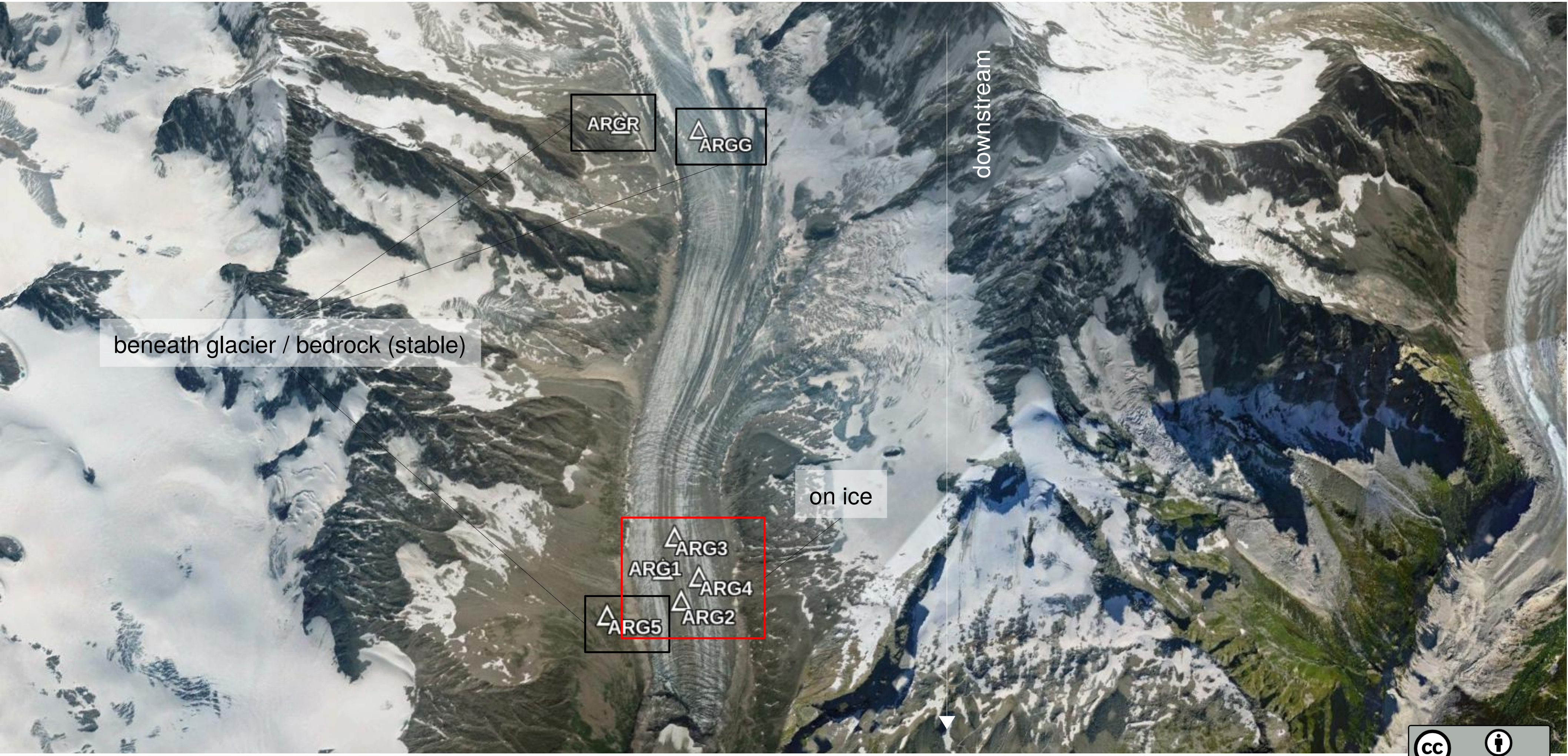


Rouet-LeDuc et al. (2018a), Nature Geosciences

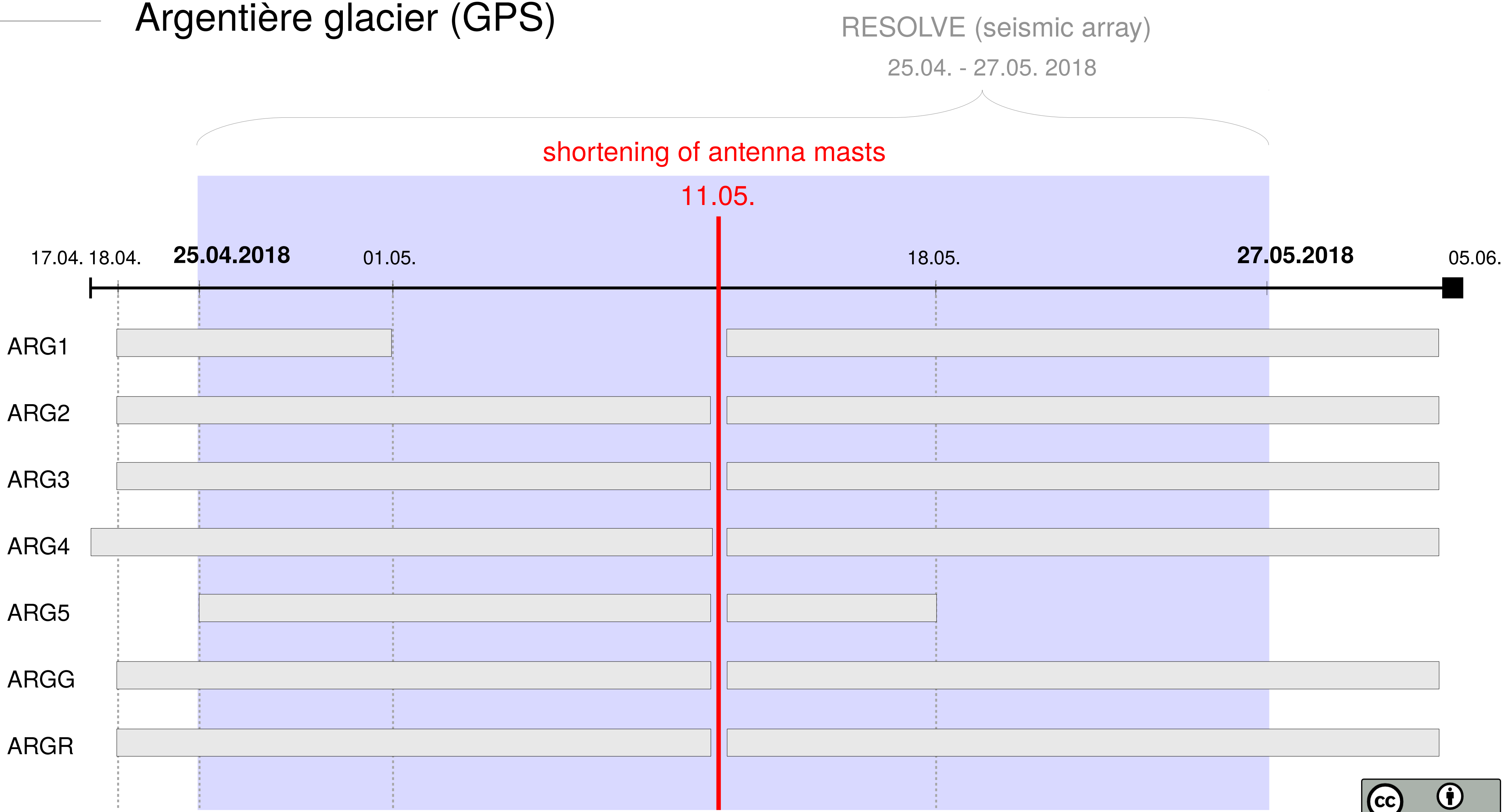
RESOLVE

‘High-Resolution imaging in subsurface geophysics:
development of a multi-instrument platform for interdisciplinary research’

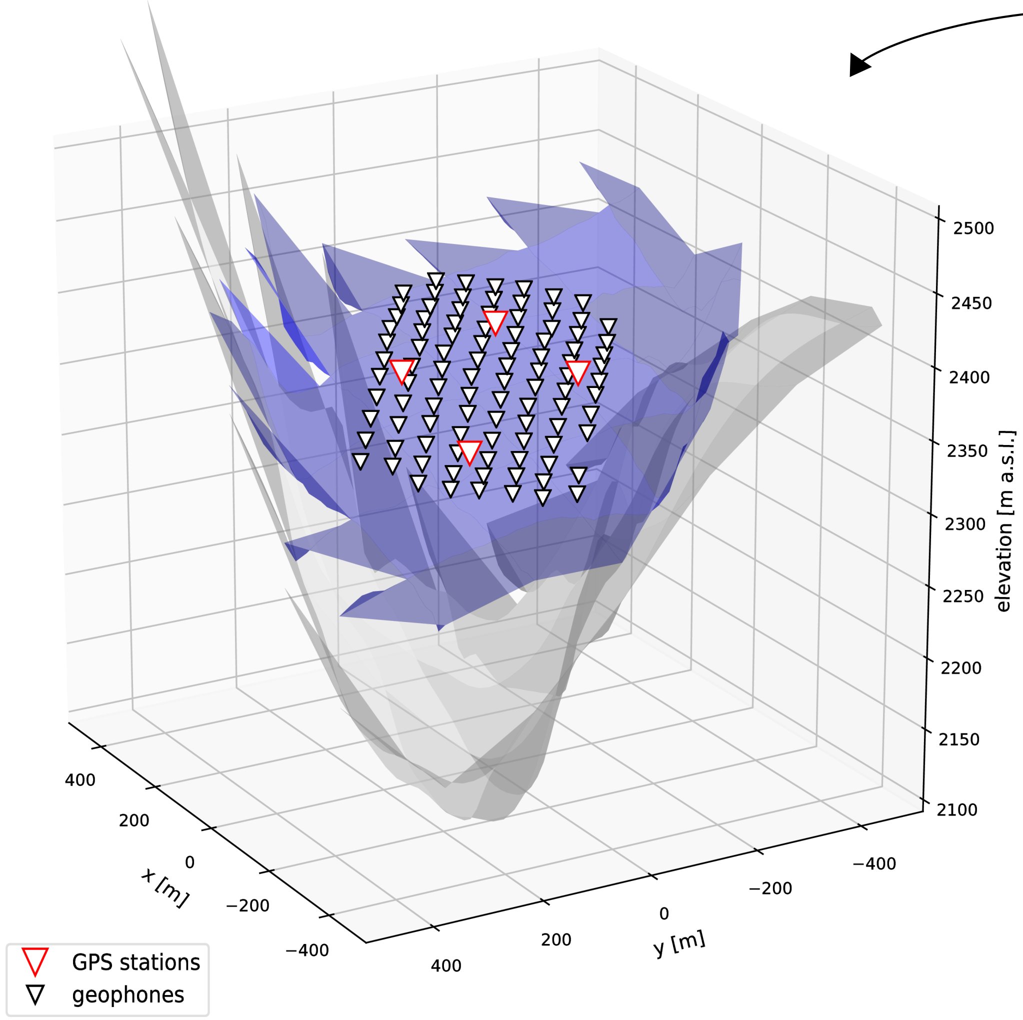
Argentière glacier (GPS)

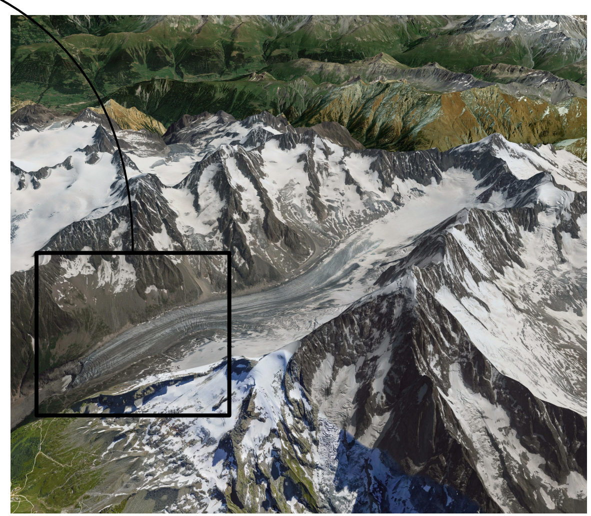


Argentière glacier (GPS)



Argentière glacier (seismic array)





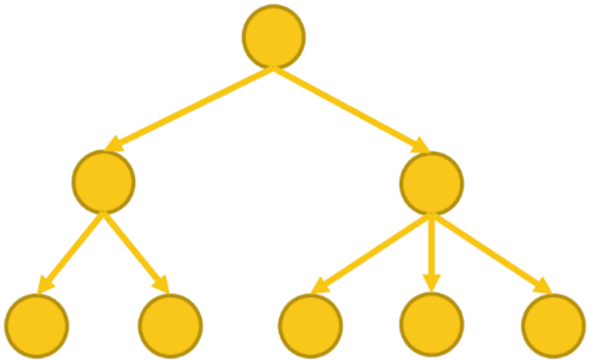
- array of 98 seismic nodes
- 1 month of continuous seismic records (May 2018)
- dense aperture on ice (Ø 700 m)
- f_s = 400 Hz

Random Forest

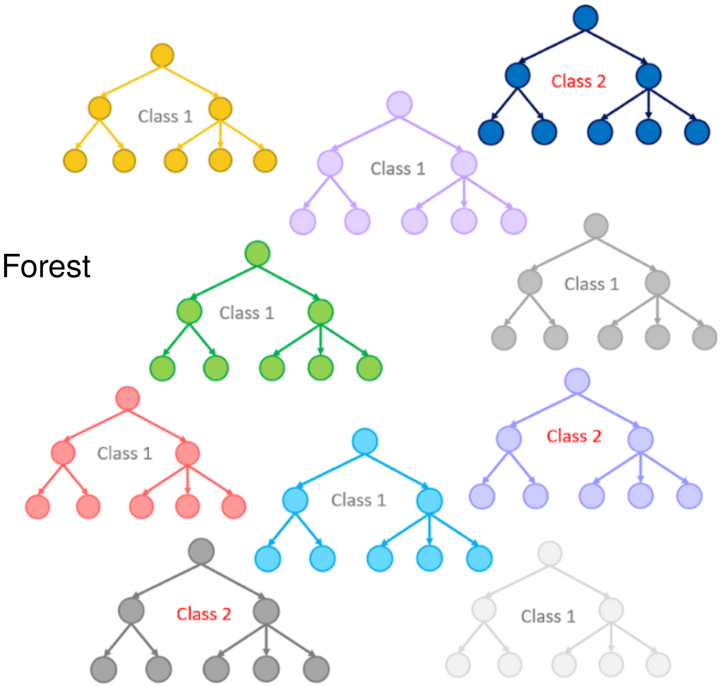
Supervised Machine Learning

random forest in a nutshell

Single Decision Tree

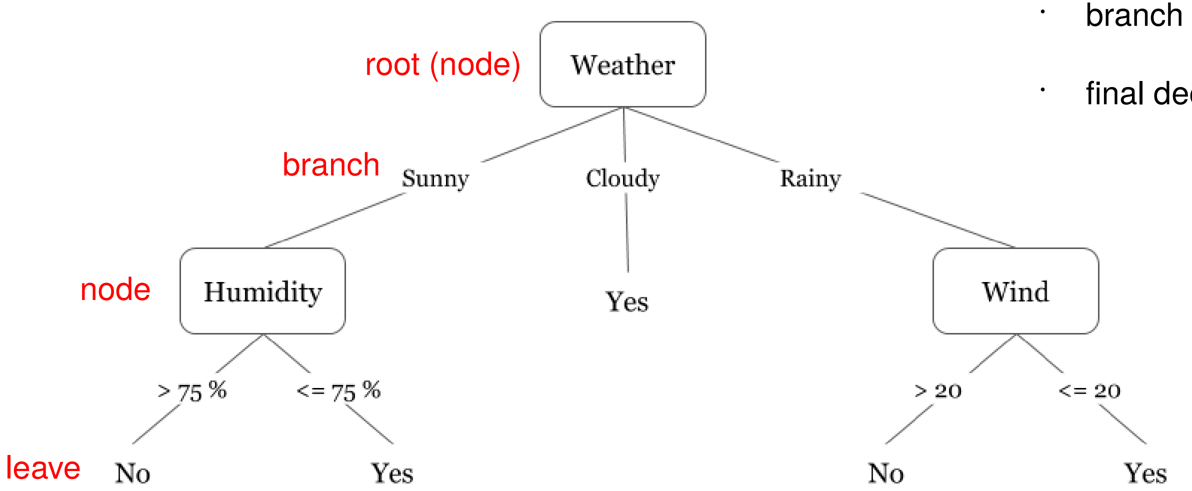


Random Forest



- randomized decision tree approach (forest classifier / regressor)
- multiple single decision trees are randomly constructed following the same design (depth, nodes) / diverse set of classifiers
- outputs are averaged (handles data gaps/ high dimensionality, won't overfit)

random forest in a nutshell



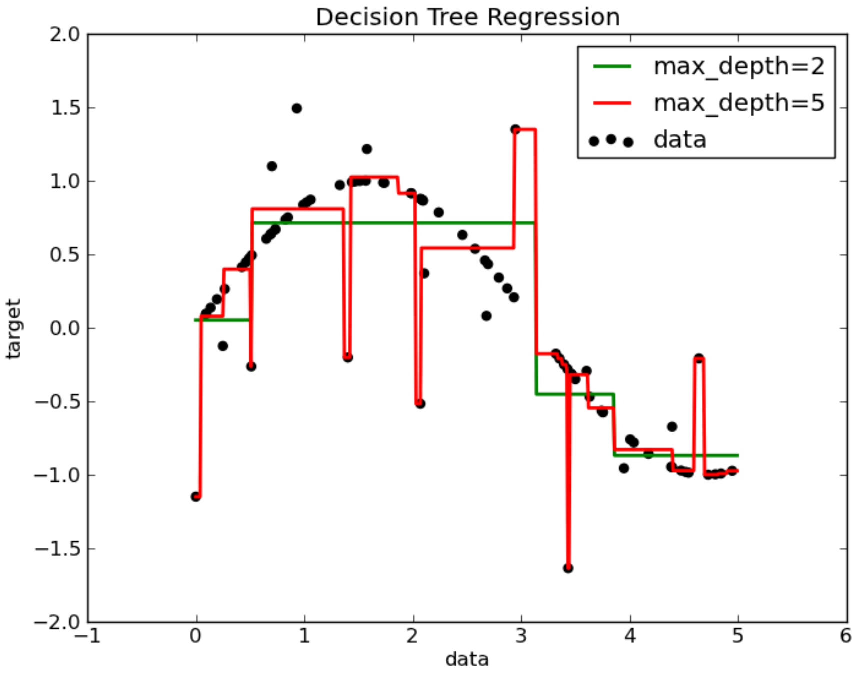
Play Badminton today?

classification problem

- nodes are features
- branch from each node represents outcomes of that node
- final decisions are made at the leaves of the tree

random forest in a nutshell

labels



features

fitting with two arrays

- sparse or dense array X of size [n_samples, n_features] holding the **data** (training samples)
- array Y of size [n_samples] holding the **target** values (class labels) for the training samples

model set up

data == features

- statistical characteristics of seismic signals
- meteorological data
- beamforming catalogue

target == labels

- GPS (velocity/ displacement)

1. Features to choose

   (find attribute that splits the data)

2. Conditions for splitting

   (ask relevant question)

3. Knowing when to stop

   (following answer path)

uncover underlying function that relates seismic features to GPS displacement rate and thus, formulates the problem as a regression

model set up

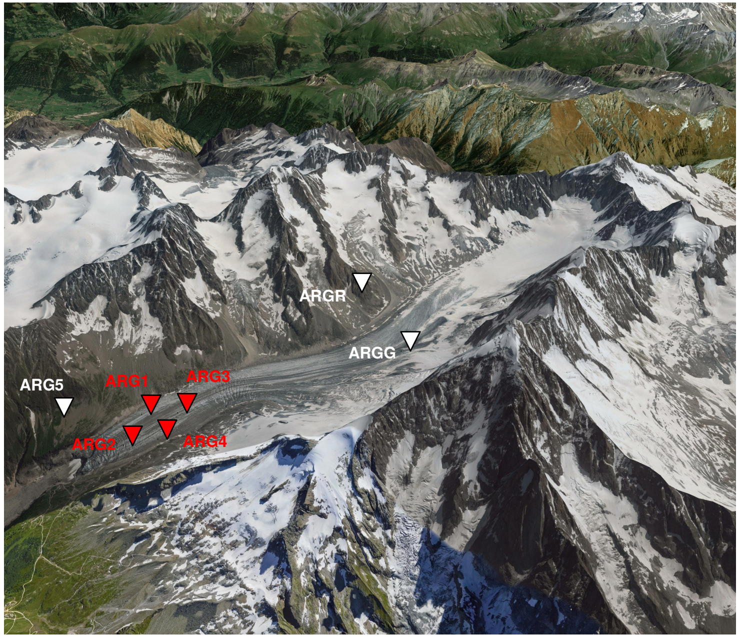
features

label

1-5 Hz ... 15-20 Hz

	k_1	k_2	k_n	v_n	q_n (0.025 – 0.95)	beams_n (counted)	beampower_n (summed)	meteo data	GPS (velocity / displacement)
1 hr x_1									
x_2									
x_n									

label (GPS data)

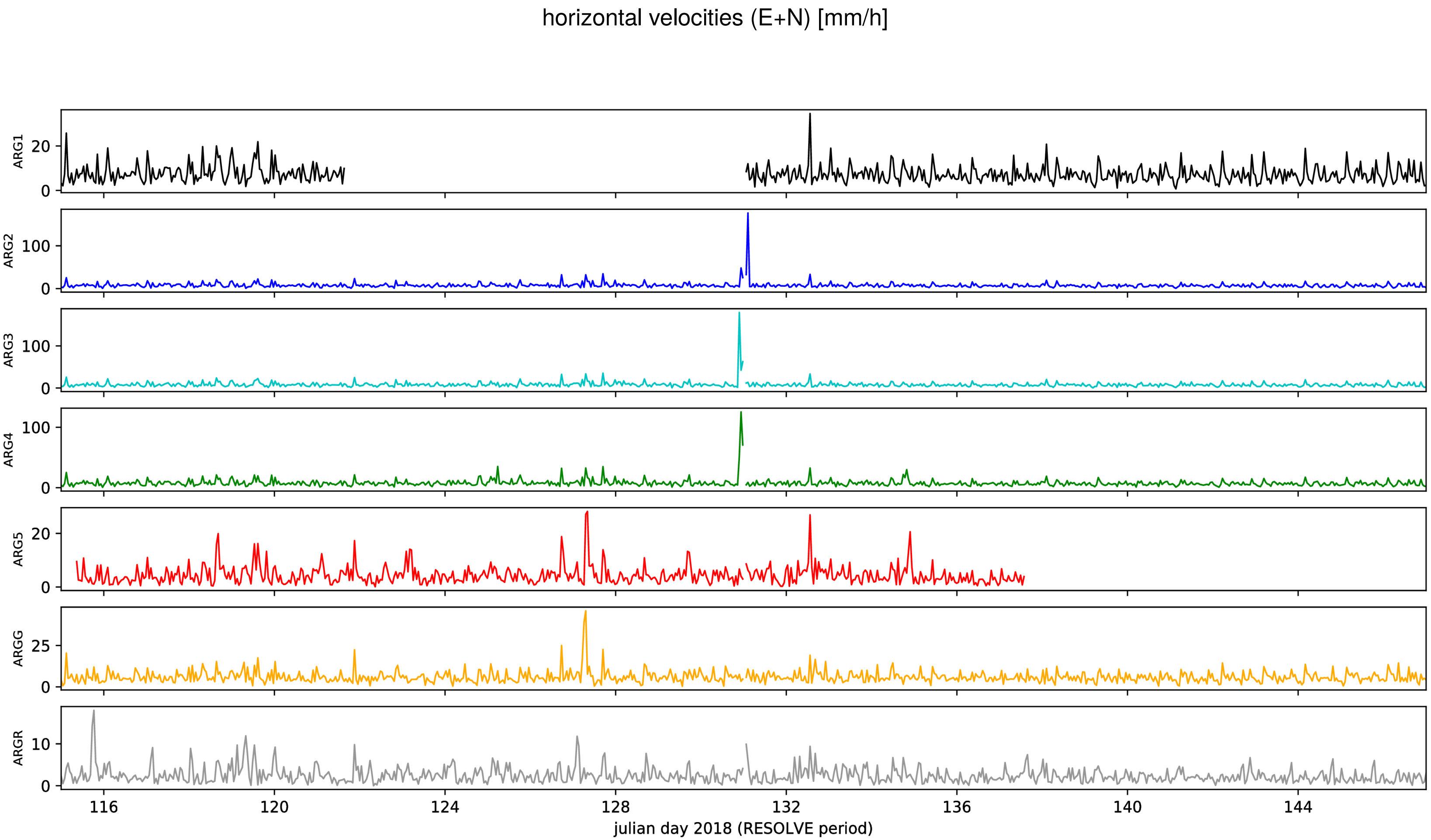


7 GPS stations on the Argentière Glacier

- 4 stations on-ice (within the array aperture)
- 3 stations off-ice on the bedrock

- 1 hr sampling (6 hrs moving average)
- some data gaps / some outliers (partially removed)
- components: vertical, horizontal (E+N, E and N individual)

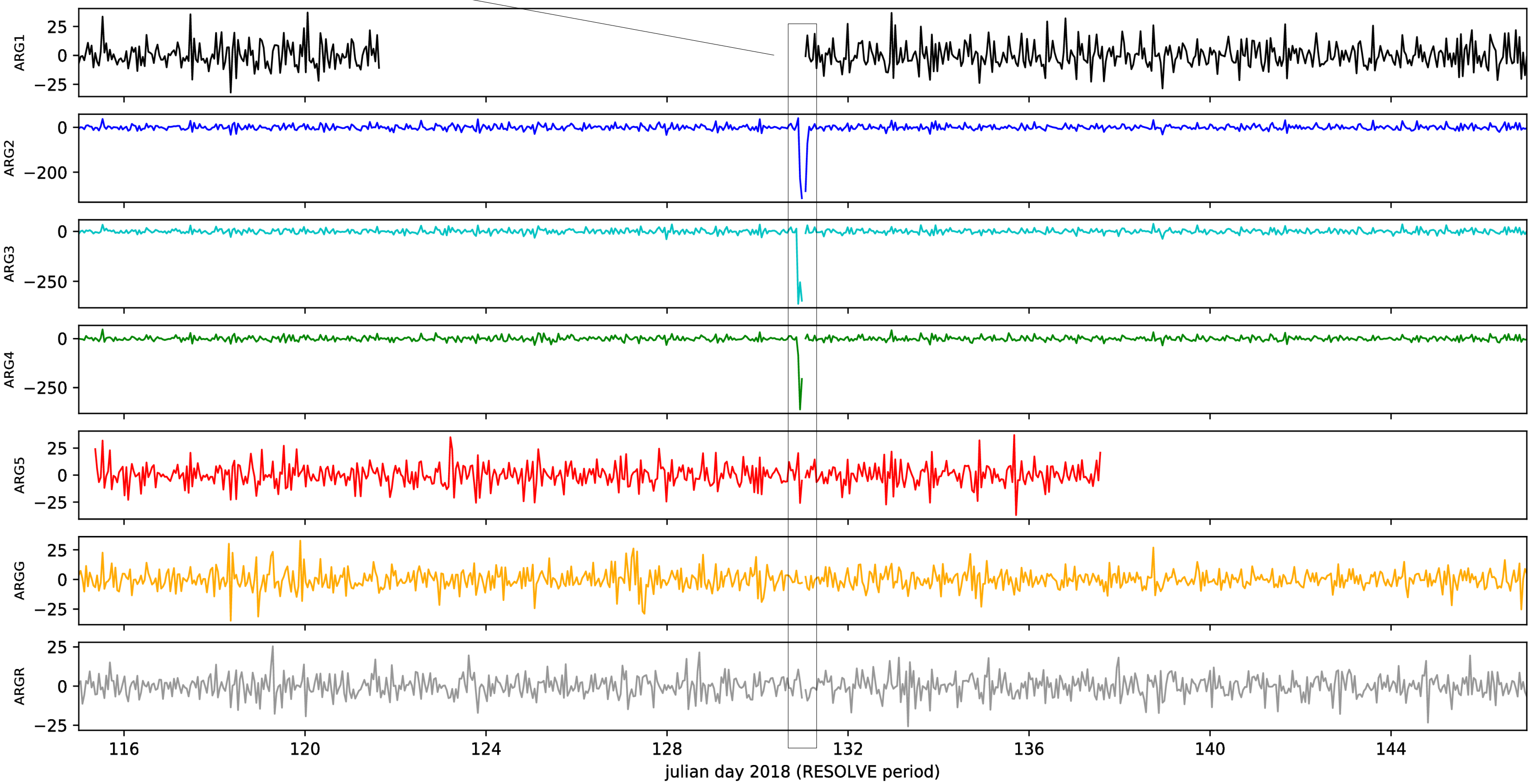
label (GPS data)



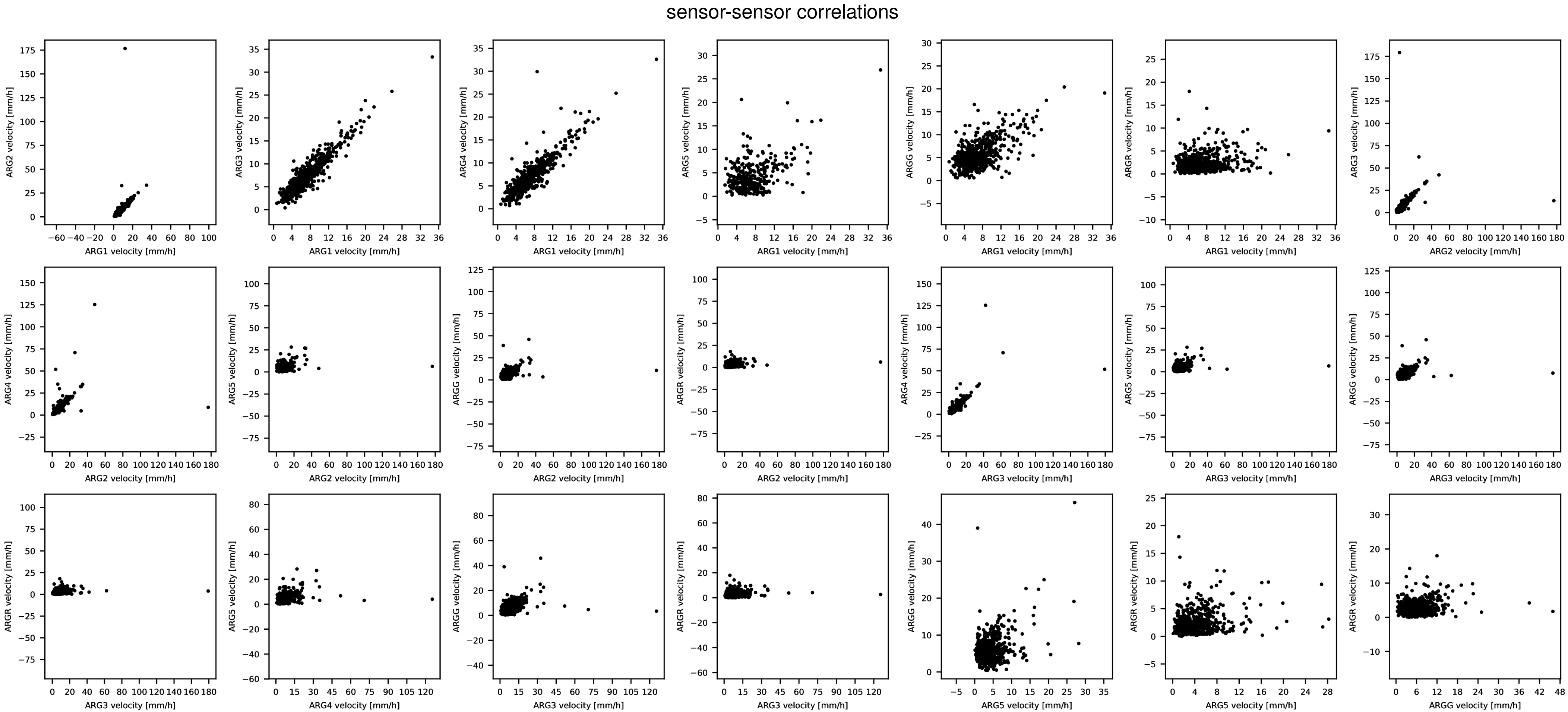
label (GPS data)

very likely related to shortening of antenna masts
(removed)

vertical velocities [mm/h]

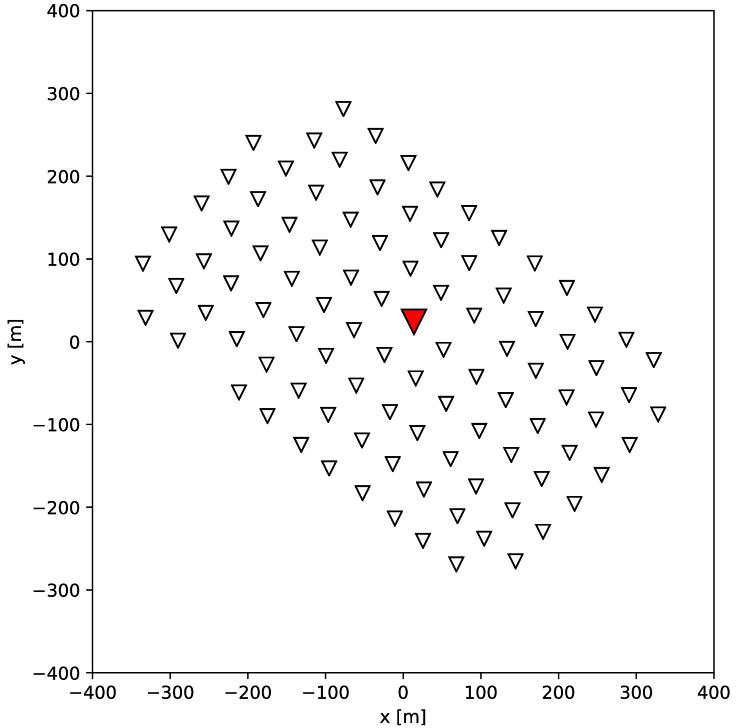


label (GPS data)



features

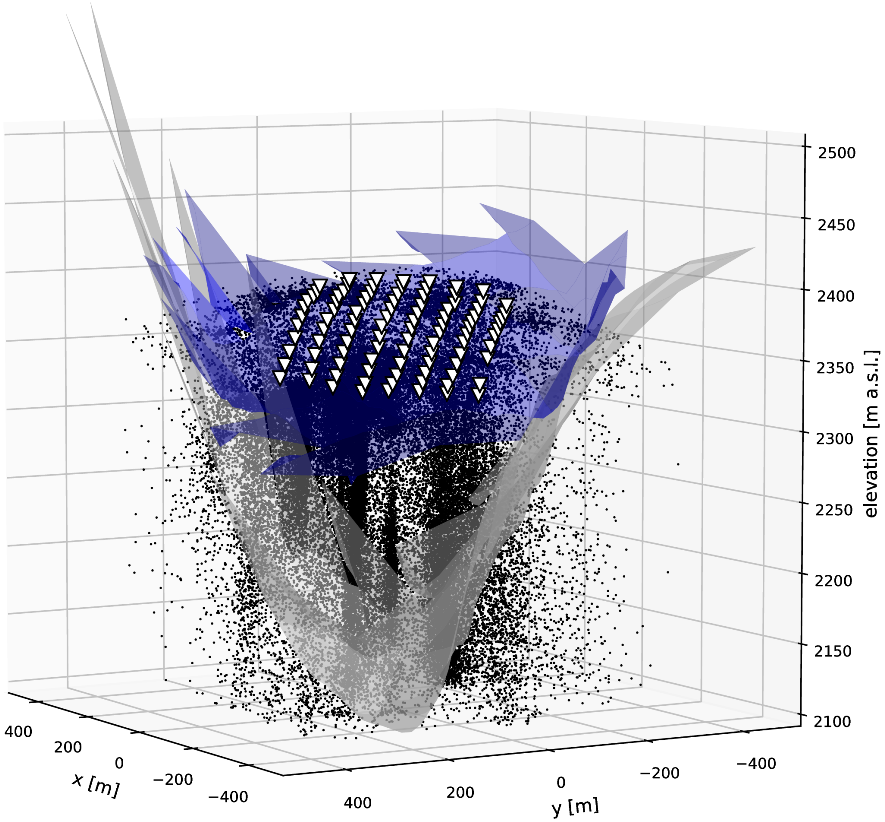
- seismic data - 1 station (center of array)
  - 1 hr sampling (6 hrs moving average)
    - 4 frequency bands (1-20 Hz) each for
      - kurtosis
      - variance
      - quantiles (0.025, 0.25, 0.5, 0.75, 0.95)
      - counted beam sources within definite areas (grid)
      - summed beam power within that grid



- meteorological data (temperature, precipitation, water discharge, bicycle wheel)

beam sources

- catalogue of located beam sources for 15 frequencies (5-20 Hz)
- matched field processing in 5D (x, y, z, velocity, time) using a simple phase match replica (steering vector)
- time window: 1 sec (0.5 sec overlap)
- 28 starting points at depth using monte carlo sampling in array environment → 28 locations / 0.5 sec
- selection of best location according to beampower → 1 location / 0.5 sec



beam sources (matched field processing)

DATA

$$\boxed{K_{ij}(\omega) = d_i(\omega)d_j^*(\omega)}$$

cross-spectral density matrix

SYNTHETICS

$$\boxed{\hat{d}_i(\omega, a) = exp^{\frac{-i\omega a}{c}}}$$

replica vector

monte carlo sampling (simulated annealing)

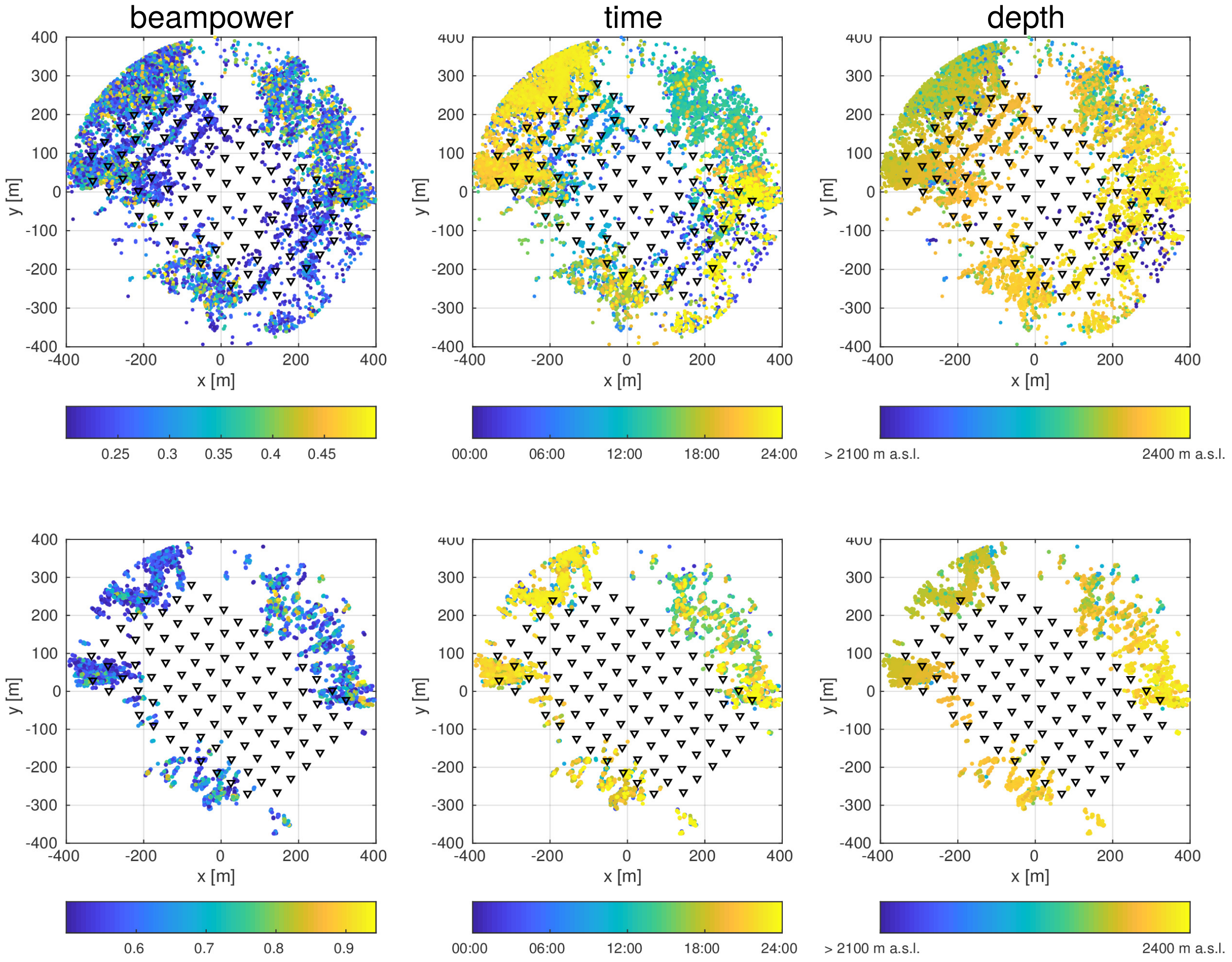
$$B(a) = \sum_{\omega} \boxed{\hat{d}^*{}_i(\omega, a)}\boxed{K_{ij}(\omega)}\boxed{\hat{d}_j(\omega, a)}$$

bartlett processor

beam sources

low beamformer [0.2 - 0.5]

high beamformer [0.5 - 1.0]

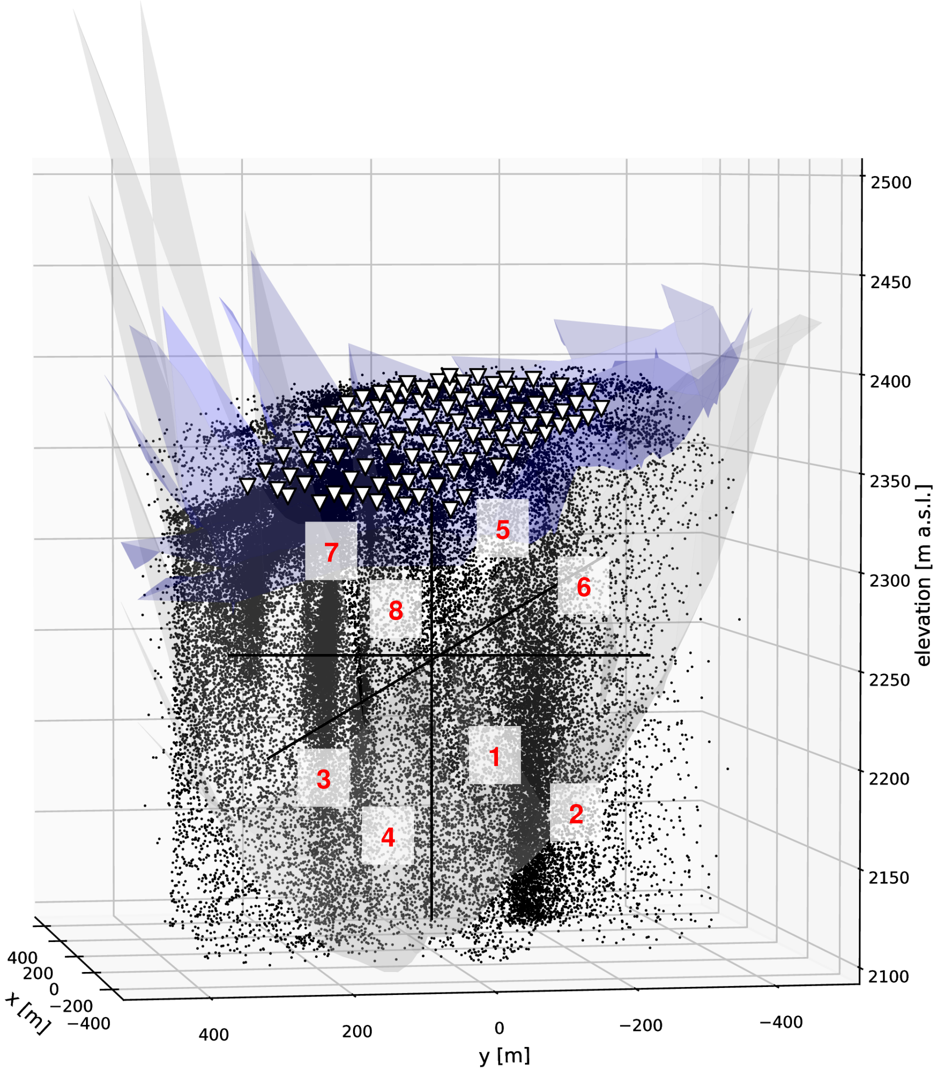


beam sources

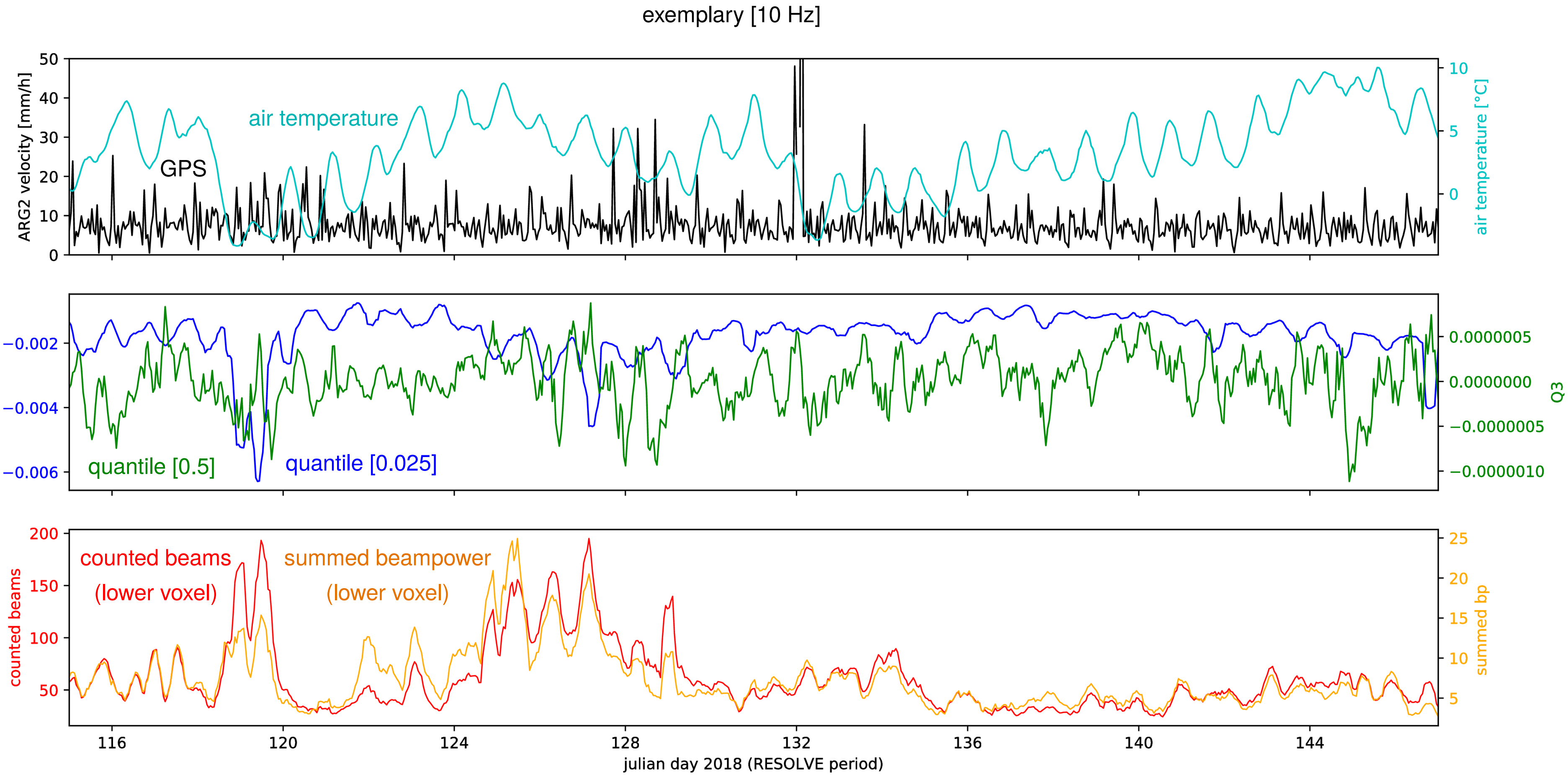
- thresholding source catalogue by
  - beampower [0.2 - 1.0] for 5, 10, 15, 20 Hz
  - beampower [0.05 - 0.2] for 5 Hz
  - x,y,z = glacier dimensions
  - velocity [1300 - 3800 m/s]

- binning sources (voxels)
  - count sources / octant / hr
  - sum beampower / octant / hr

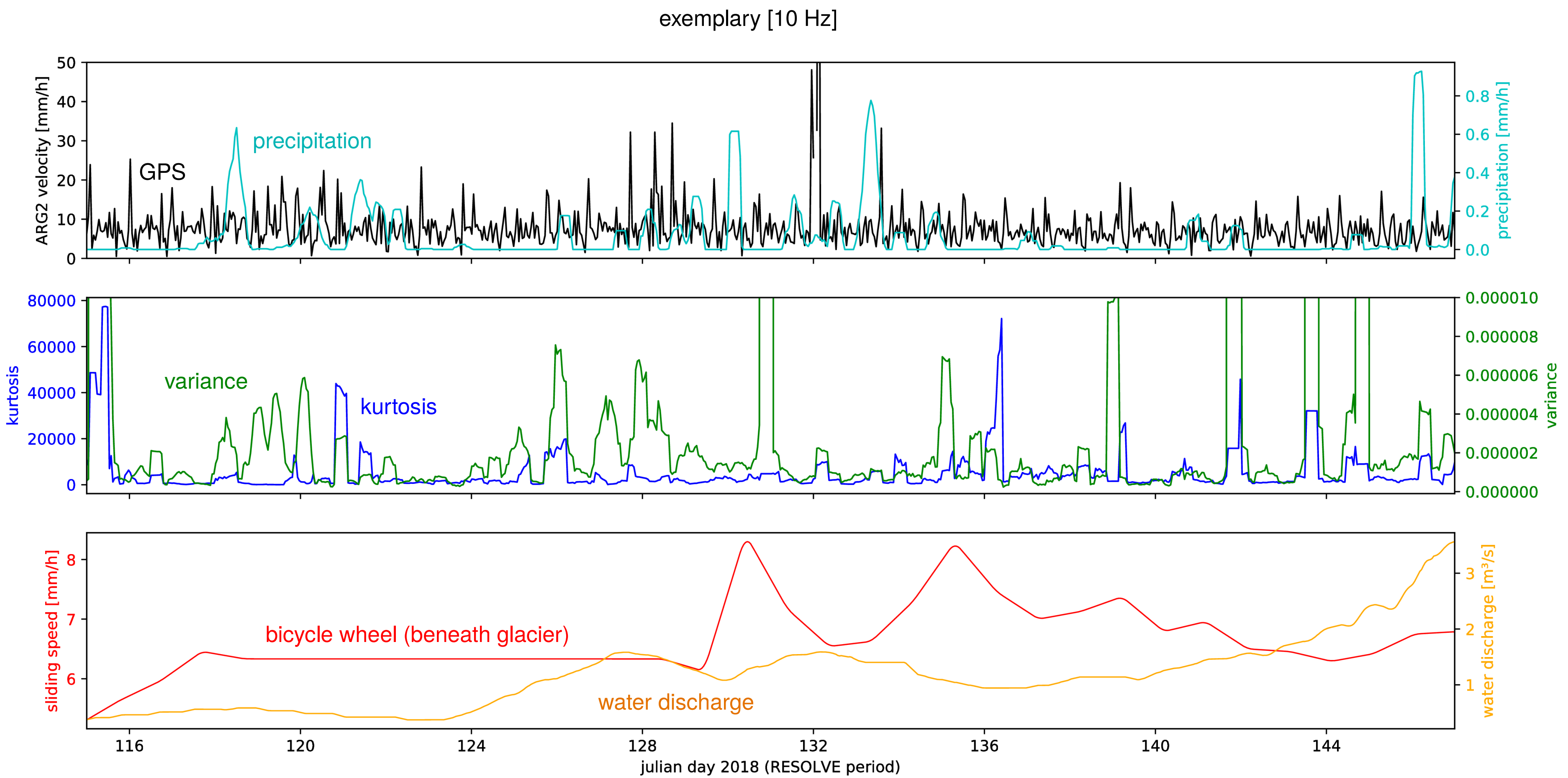
$\underbrace{\hspace{6cm}}_{\text{features}}$



model


exemplary [10 Hz]
ARG2 velocity [mm/h]
air temperature
GPS
air temperature [°C]
Q1
Q3
quantile [0.5]
quantile [0.025]
counted beams
(lower voxel)
summed beampower
(lower voxel)
summed bp
julian day 2018 (RESOLVE period)

model



exemplary [10 Hz]
ARG2 velocity [mm/h]
GPS
precipitation
precipitation [mm/h]
kurtosis
variance
kurtosis
variance
sliding speed [mm/h]
bicycle wheel (beneath glacier)
water discharge
water discharge [m³/s]
julian day 2018 (RESOLVE period)

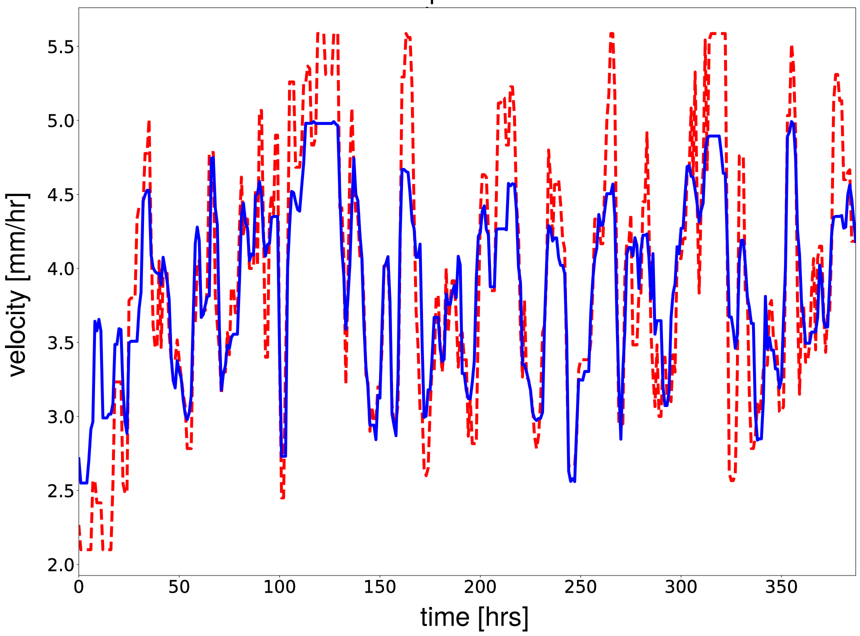
preliminary predictions (50/50 split, boosted tree)

ARG5GR_mean

average over all **off-ice** (bedrock) stations

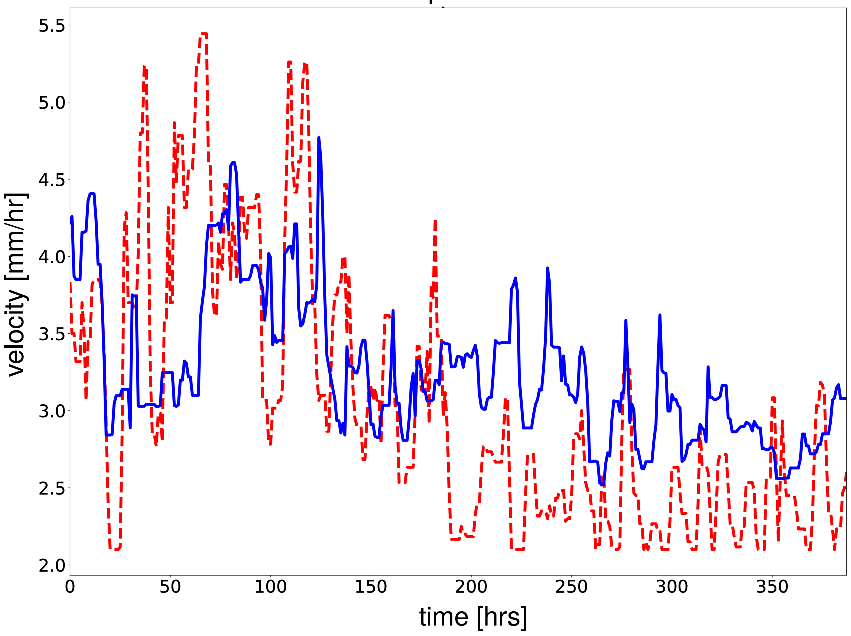
training

in sample: CC: 0.889



testing

out of sample: CC: 0.509



25.04.2018

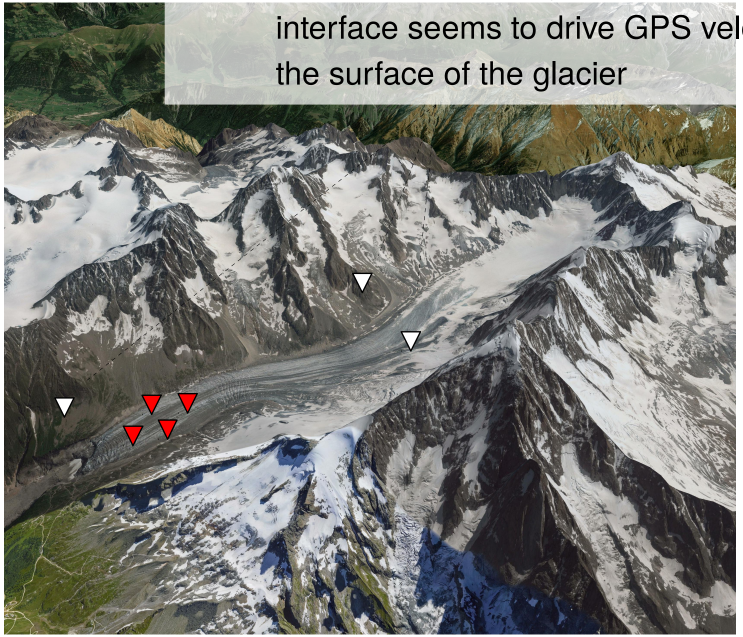
RESOLVE experiment

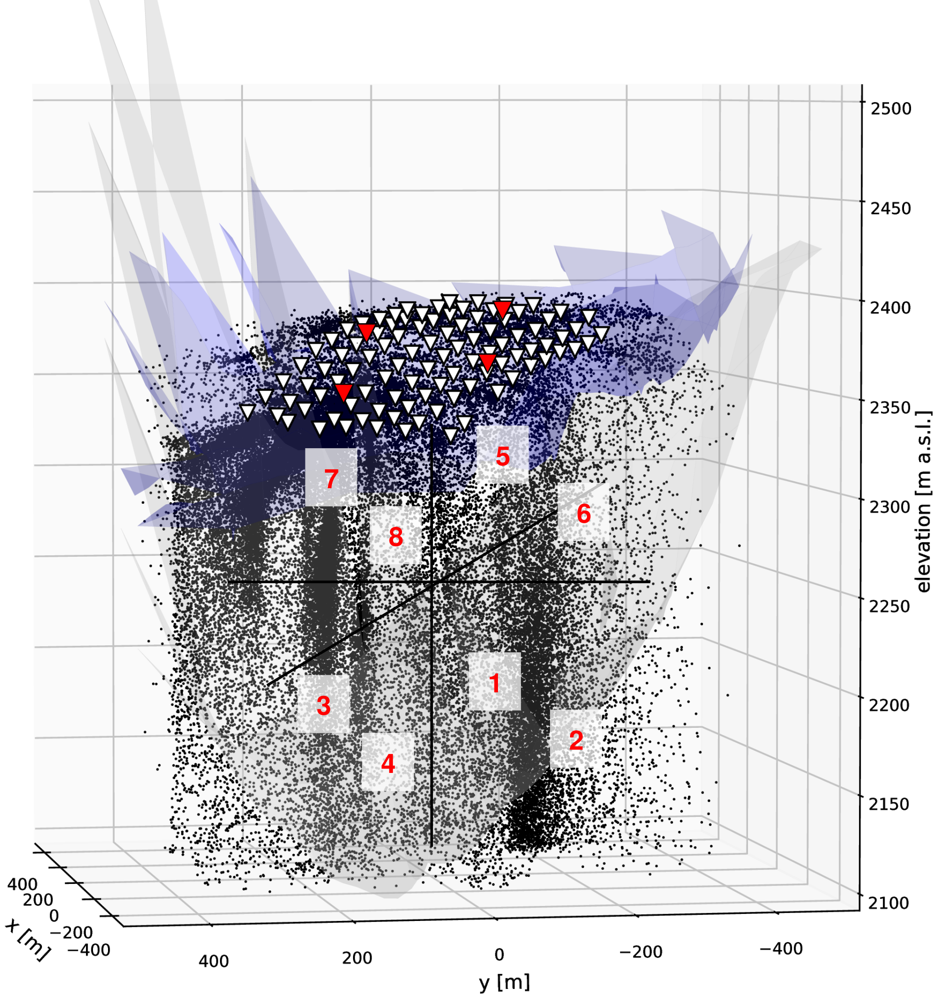
27.05.2018

feature importance evaluation and hyperparameter tuning

off-ice stations

- best fit was derived using only the lower voxels (1-4) of the beamformer catalogue
- noise source activity at the ice-bed-interface seems to drive GPS velocity at the surface of the glacier





conclusions

Can we predict GPS movement using seismic data on a glacier?

- very early state (work in progress), promising observations and findings though!
- model seems to be fairly able to capture not only daily fluctuations, but also longer-term behavoir of the GPS velocity
- beamformer catalogue seems to be very valuable, as it is by far the most important feature for the prediction of the GPS velocity on the glacier
- if true, feature importance would reveal 'active areas' within the glacier, that drive the GPS movement (local deformation at the surface vs. interactions on the ice-bedrock-interface)
- Can we learn about basal motion here?

What comes next ...

- xgboost (iterative feature dropping) / hyperparameter tuning
- other seismic stations/ GPS components and stations
- long time series (1 borehole sensor, 3 years of data // no beam catalogue)

Thank you!

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