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Prediction of Alpine Foehn from timeseries of GNSS tropospheric parameters using machine learning

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Contents

Alpine Föhn: a short introduction

Characteristics:

- Strong, warm fall winds (up to 100 km/h in typical Foehn valleys, up to 200 km/h at high altitude stations)
- Large pressure gradient across the Alpine ridge
- Low pressure system south (case of South Foehn)
- Warm, dry weather north
- Strong increase/decrease in temperature/humidity

Typical Foehn locations:

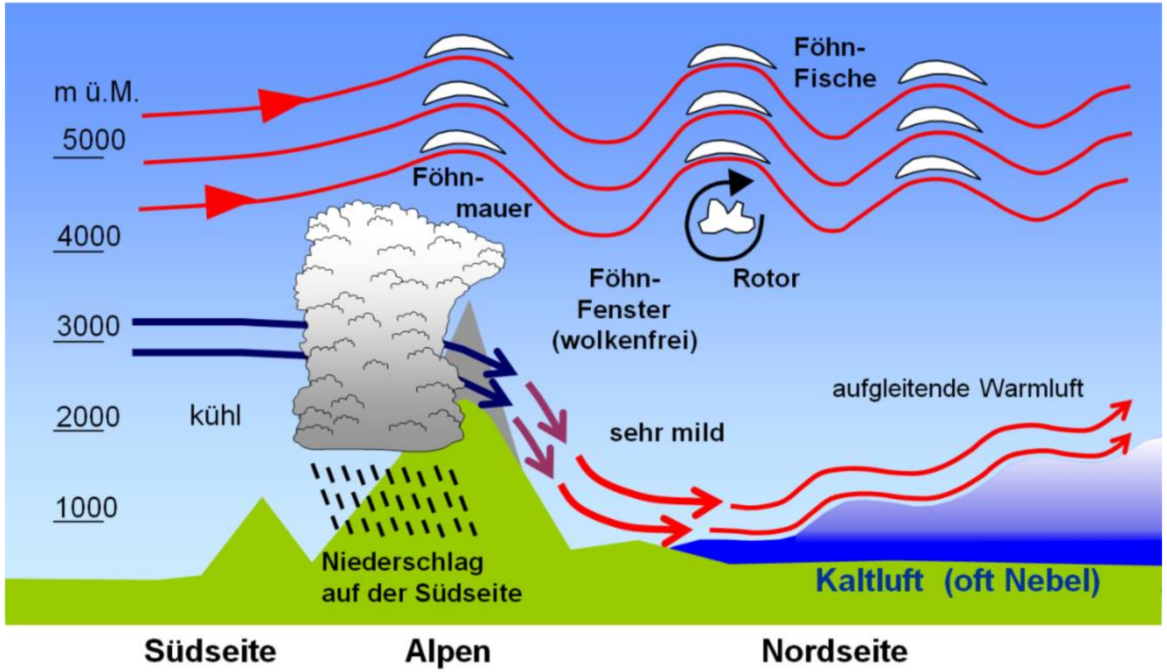
- Reuss valley (CH)
- Wipp Valley (AT)
- Rhein Valley (AT/CH)

Climatology:

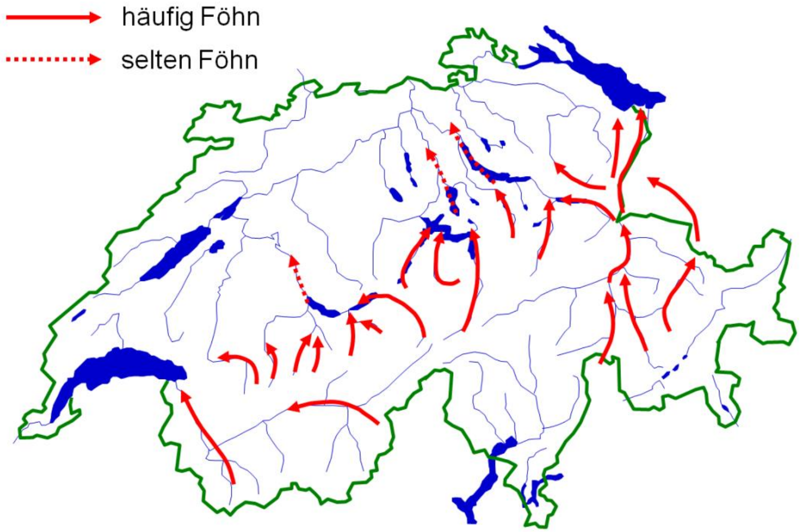
- Most events in spring/autumn
- Rare in summer

Specific conditions at different locations

- Influence of topography
- Objective prediction/classification difficult



MeteoSwiss, 2021



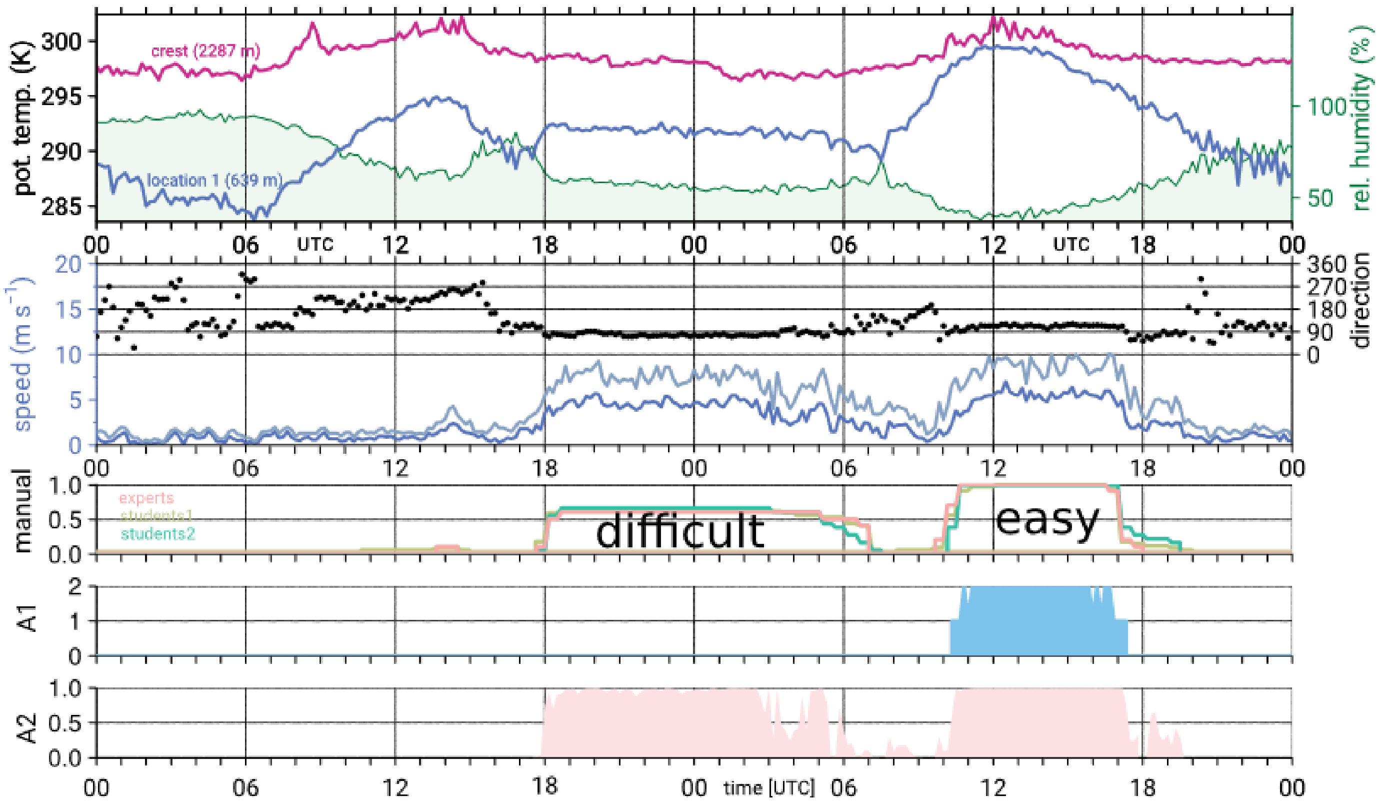
MeteoSwiss, 2021

Alpine Foehn: a short introduction

Detection and prediction:

- ❑ Subjective
  - ❑ human expert/forecaster

- ❑ Objective:
  - ❑ Index-based
  - ❑ Statistical models
  - ❑ Machine-learning



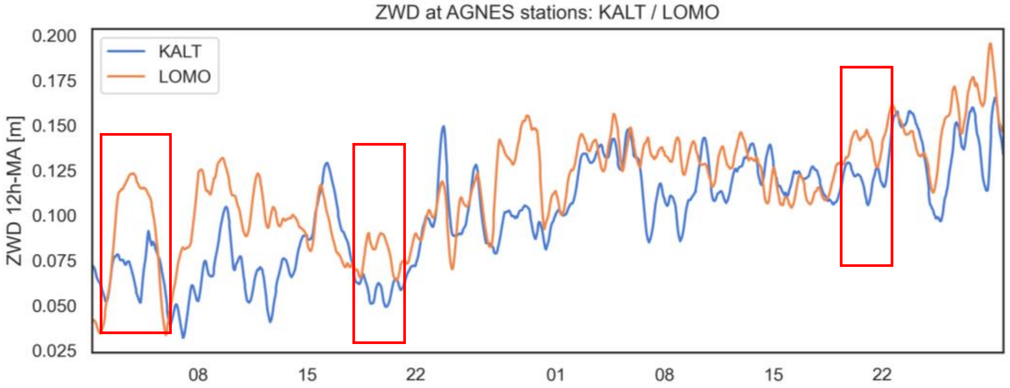
Source:
Mayr et. al (2018). The Community Foehn Classification Experiment, *Bulletin of the American Meteorological Society*, *99*(11), 2229-2235.

First try: Foehn detection in GNSS time series

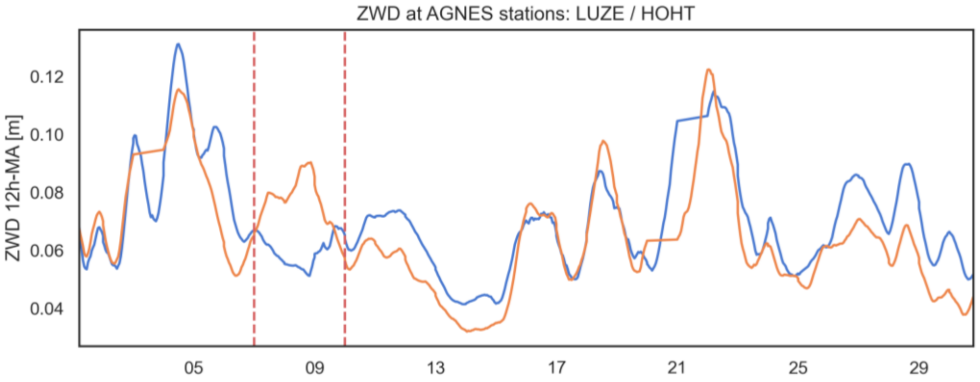
Initial ideas for detection

- ❑ Search for minima/maxima in Zenith Wet Delay (ZWD)
- ❑ Compare stations north/south of the Alpine ridge (contrary trends, also Zenith Hydrostatic Delay (ZHD)!)
- ❑ Detection: difficult task in general (even using classical meteo measurements)
- ❑ Collocated stations especially beneficial (huge changes observed in local conditions! ---> esp. for ZHD!)

Monthly differences:
April (2-3 Föhn events) vs May (1)



Special case: Guggiföhn (07-08.01.2018)



Machine-learning for Foehn detection/prediction

Machine-learning

- Data-driven algorithms for classification and prediction problems
- Large field of applications in geosciences, i.e.:
  - Atmospheric/climate sciences: Time series analysis/forecasting
  - Remote sensing: Data processing/Image classification/…
  - Seismology: Event detection (earthquakes)
  - Gaining importance in geodetic science

Initial studies on Foehn

- Only little number of investigations (even for meteorological data)
- Sprenger et. al (2017):
  - Three years (2000–02) of hourly data from Consortium for Small-Scale Modeling's (COSMO) numerical weather prediction (NWP) model and corresponding foehn wind observation
  - **Results:**
    - **Probability of detection (POD): 88.2%, probability of false detection (POFD): 2.9%**
    - **Correct alarm ratio (CAR): 66.2%, missed alarm ratio (MAR): 0.8%**

Benchmark

Machine-learning for Foehn detection/prediction

Why?

- Visual/analytical detection in ZWD time series challenging
- Nevertheless: Foehn signal visible

- Need for:
  - Automation of detection process (using specific features, e.g. ZWD)
  - Ability for prediction of Foehn event from previous epochs

- Idea: **Classic task for Machine-learning classification algorithms!**

- Objectives:
  - Learn event characteristics from a large amount of data
  - Choose and train appropriate algorithm
  - Assess ability of algorithm to predict event
    - Apply shift to respective time series of Foehn observations

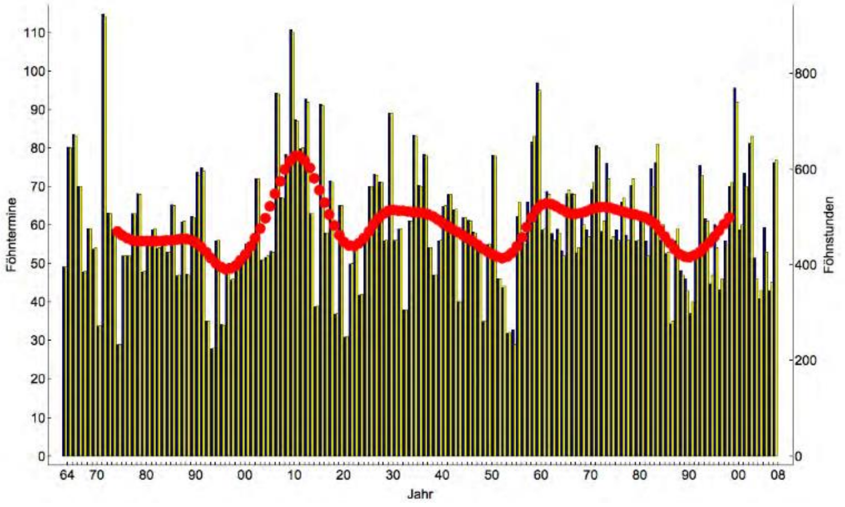
Machine-learning for Foehn detection/prediction

How?

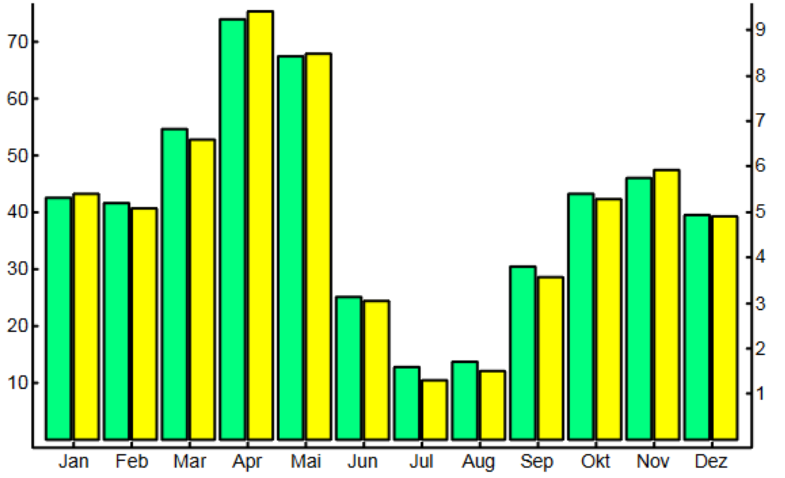
- Collect large data sets
  - GNSS troposphere products
  - Foehn index (Dürr, 2008) observations at Altdorf
- Apply well-established classification algorithms

Challenges?

- GNSS troposphere time series:
  - Long-term record
  - High quality
- Highly unbalanced data set (~ 4-7% of annual hours == Föhn)
- Foehn index has flaws ------> not unrestricted "truth"
- Experiment settings:
  - Best algorithm?
  - Optimal set of features? (tropo parameters, station distribution, …)
  - Hyperparameter tuning
  - Performance metric? -----> classical metrics might not be reasonable



Source: Gutermann et. al (2014)



Source: Gutermann et. al (2014)

Study setup: Data

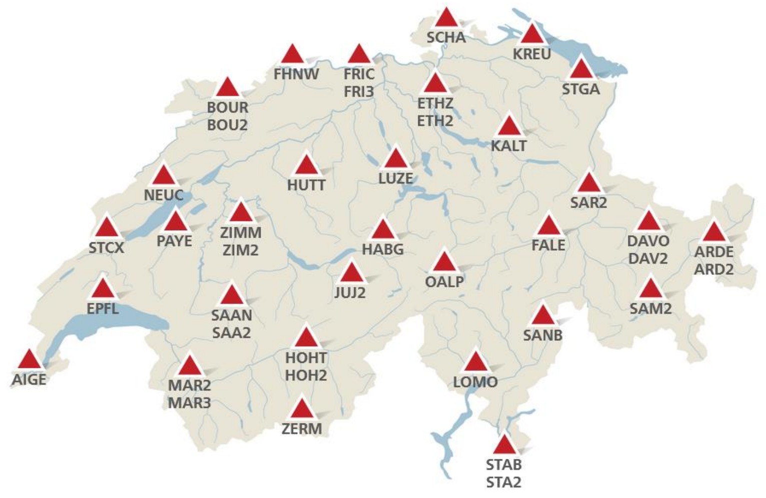
GNSS troposphere products

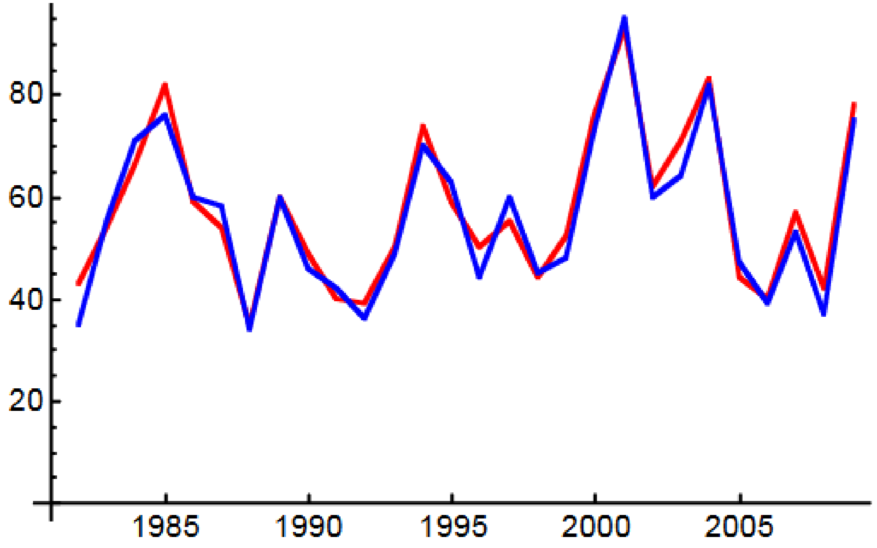
- AGNES reprocessed troposphere products
  - Time span: 1997 - 2021
  - High quality, post-processing estimates
- AGNES near-real-time (NRT) troposphere products
- Provided by swisstopo

Foehn observations at Altdorf

- Index-based classification/observation
- Algorithm proposed by Dürr et. al(2008)
- Automated classification based on thresholds (at Altdorf and various other stations) for:
  - Wind speed/direction
  - (Potential) temperature
  - Relative humidity
  - Surface pressure
- Matches well with human (expert) classification

Automated GNSS Network for Switzerland (AGNES)





Source: Gutermann et. al (2014)

Study setup: algorithms and data

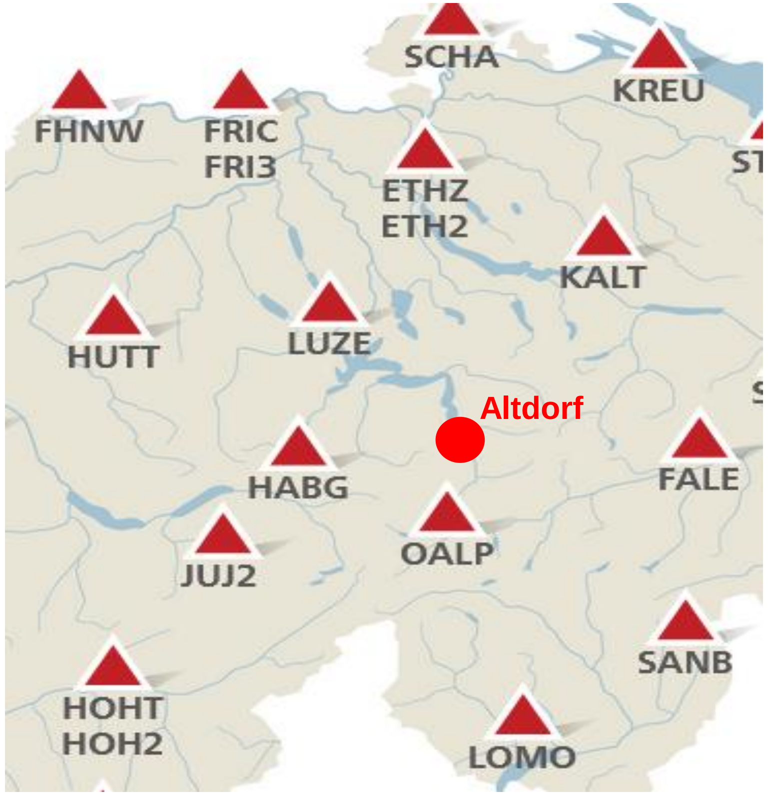
Tested algorithms

- ❑ Adaptive Boosting (ADB)
- ❑ Gradient Boosting (GB)
- ❑ Multi Layer Perceptron (MLP)
- ❑ Random Forest Classifier (RF)
- ❑ Support Vector Classifier (SVC)
- ❑ K-Nearest Neighbor (KNN)
- ❑ Decision Tree (DT)

Stations

❑ Attributes to look for:

- ❑ North/south distribution: stations experience very different weather conditions
- ❑ Height distribution: stations at higher altitudes (e.g. passes) important?!



Study setup: feature and station selection

Data set

- ❑ Training data + cross-validation: 2010 – 2018
- ❑ Test data: 2019 – 2020
- ❑ Hourly data

Features from troposphere time series (predictors)

- ❑ Intuitive choices:
  - ❑ ZWD
  - ❑ ZWD differences for stations north/south of Alpine ridge (humidity deviations)
  - ❑ North/south gradients
  - ❑ ZHD differences for stations north/south of Alpine ridge (pressure deviations)

Metrics: following Sprenger et. al (2017)

Detection-based

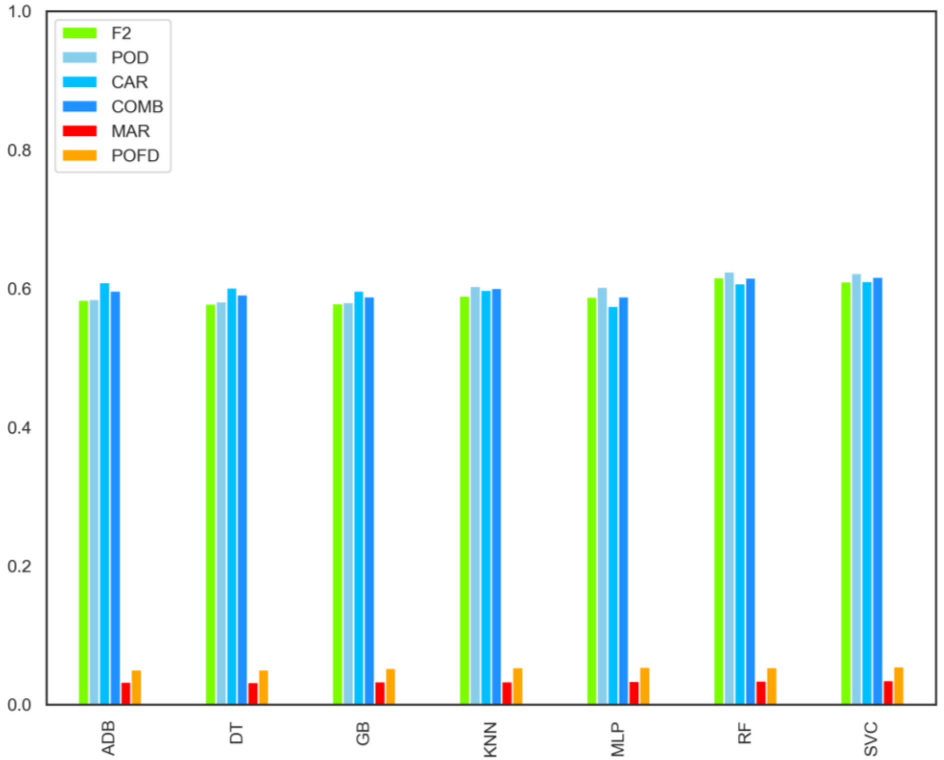
Probability of detection	POD	P(predicted | observed)
Probability of false detection	POFD	P(predicted | not observed)
Missing rate	MR	P(not predicted | observed)

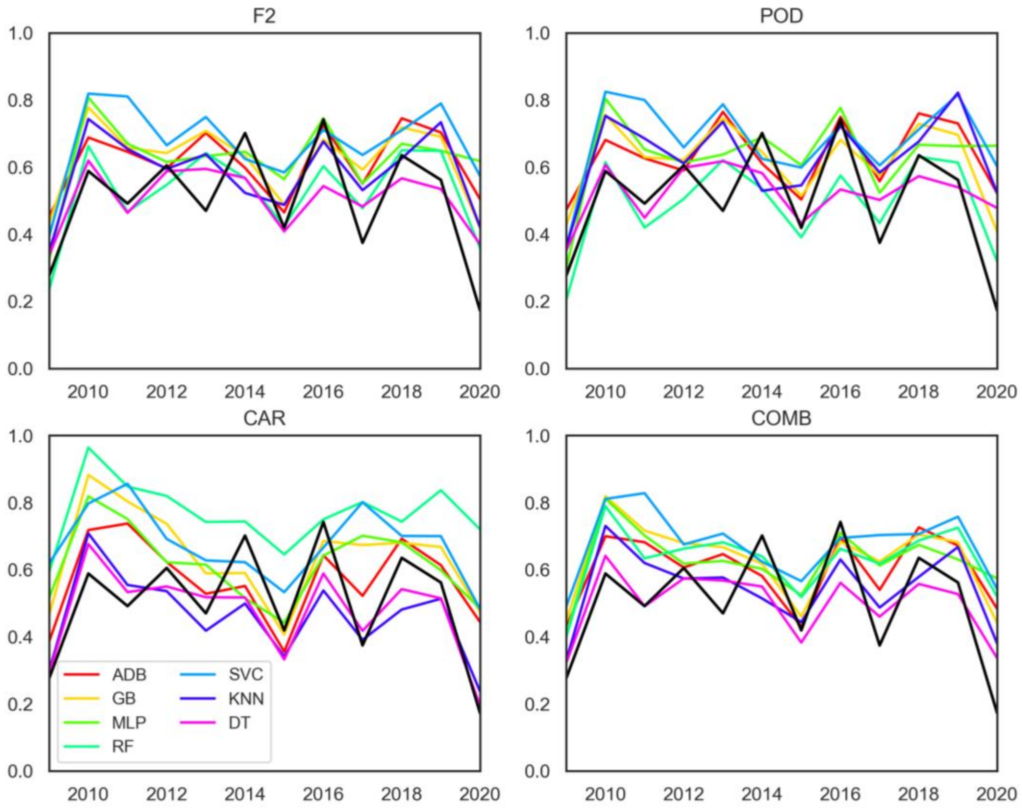
Alarm-based

Correct alarm ratio	CAR	P(observed | predicted)
False alarm ratio	FAR	P(not observed | predicted)
Missing alarm ratio	MAR	P(observed | not predicted)

Results: Cross-validation

- Time period: 2009 – 2020
- ~50-100 simulations performed
- Strategy:
  - evaluate performance iteratively every year using classifiers trained on other years
  - E.g: 2010
    - Training data 2011-2020
    - Test data: 2010



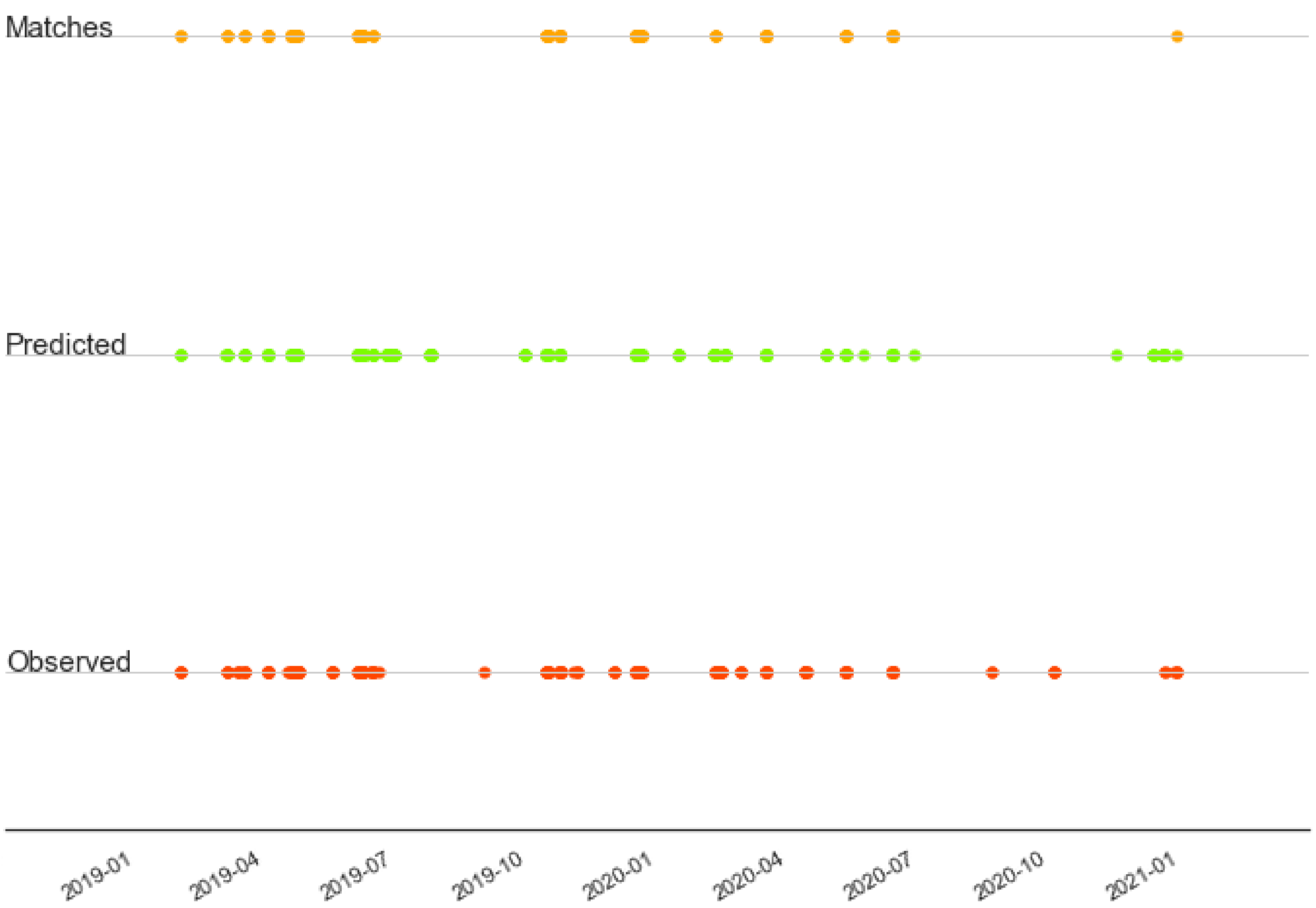


Results: Test cases

- ❑ Test case: **2019-2020**
- ❑ RF algorithm

POD	CAR	F2	POFD	MAR
0.63	0.61	0.62	0.03	0.02

Station	Features
KALT	ZWD, ZWD_DIFF, ZHD_DIFF
LOMO	ZWD, ZWD_DIFF, ZHD_DIFF
HABG	ZWD, ZWD_DIFF
SANB	ZWD, ZWD_DIFF
LUZE	ZWD, ZWD_DIFF, ZHD_DIFF
ETH2	ZWD
FALE	ZWD
STA2	ZWD, ZHD_DIFF

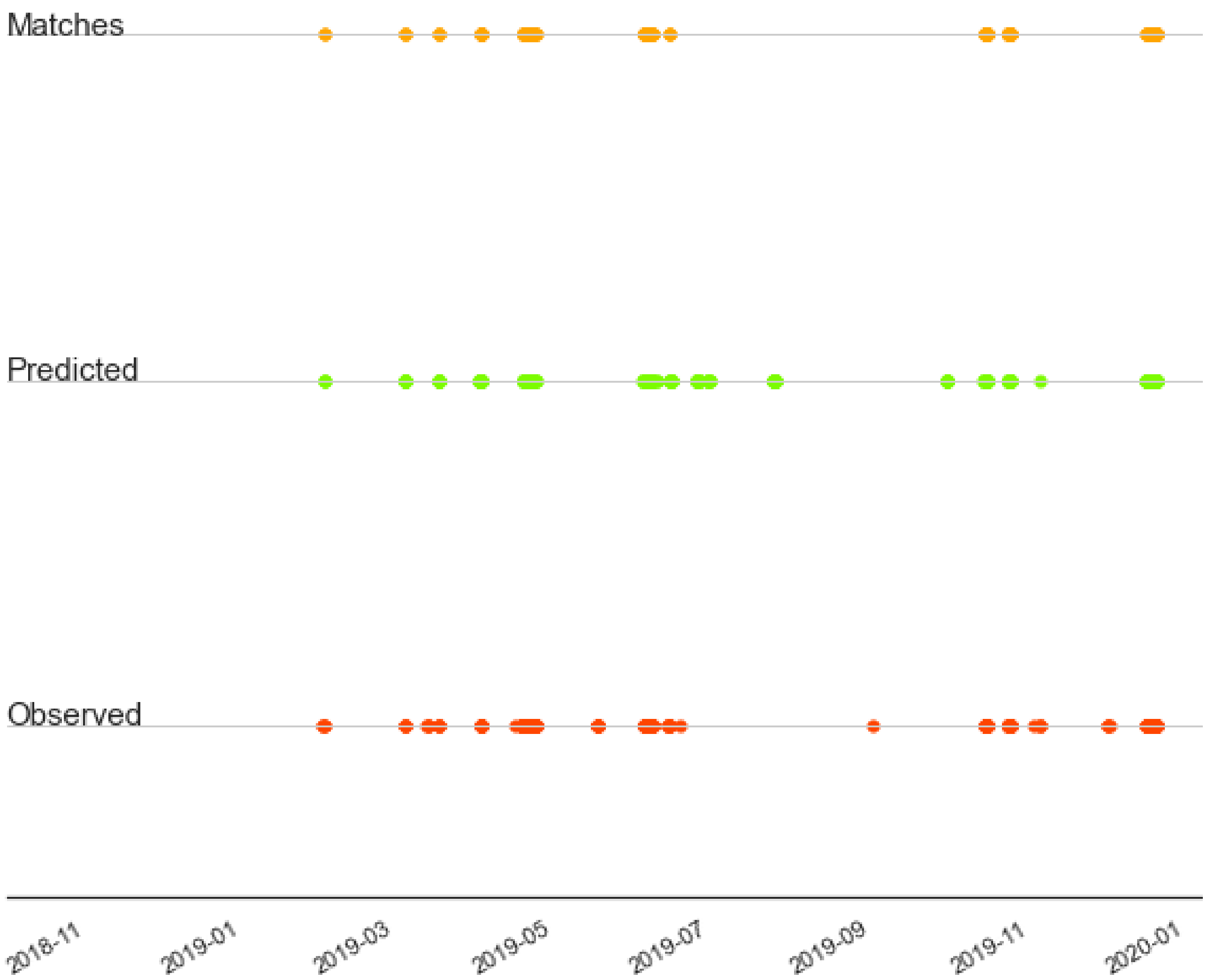


Results: Test cases

- Test case: **2019**

- Same settings as before

POD	CAR	F2	POFD	MAR
0.65	0.68	0.65	0.04	0.05



Station	Features
KALT	ZWD, ZWD_DIFF, ZHD_DIFF
LOMO	ZWD, ZWD_DIFF, ZHD_DIFF
HABG	ZWD, ZWD_DIFF
SANB	ZWD, ZWD_DIFF
LUZE	ZWD, ZWD_DIFF, ZHD_DIFF
ETH2	ZWD
FALE	ZWD
STA2	ZWD, ZHD_DIFF

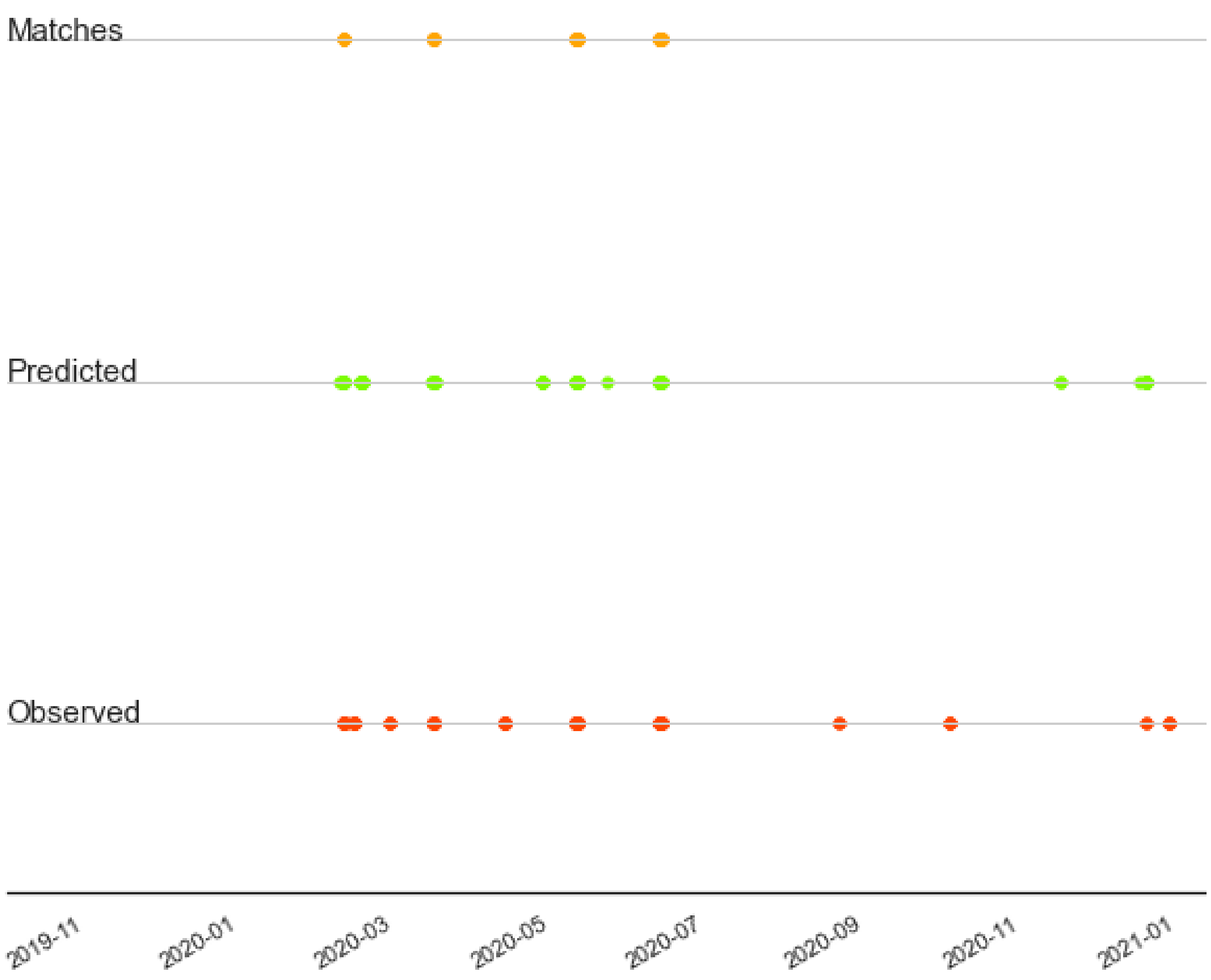
Results: Test cases

- Test case: **2020**

- Same settings as before

Station	Features
KALT	ZWD, ZWD_DIFF, ZHD_DIFF
LOMO	ZWD, ZWD_DIFF, ZHD_DIFF
HABG	ZWD, ZWD_DIFF
SANB	ZWD, ZWD_DIFF
LUZE	ZWD, ZWD_DIFF, ZHD_DIFF
ETH2	ZWD
FALE	ZWD
STA2	ZWD, ZHD_DIFF

POD	CAR	F2	POFD	MAR
0.49	0.52	0.50	0.02	0.01

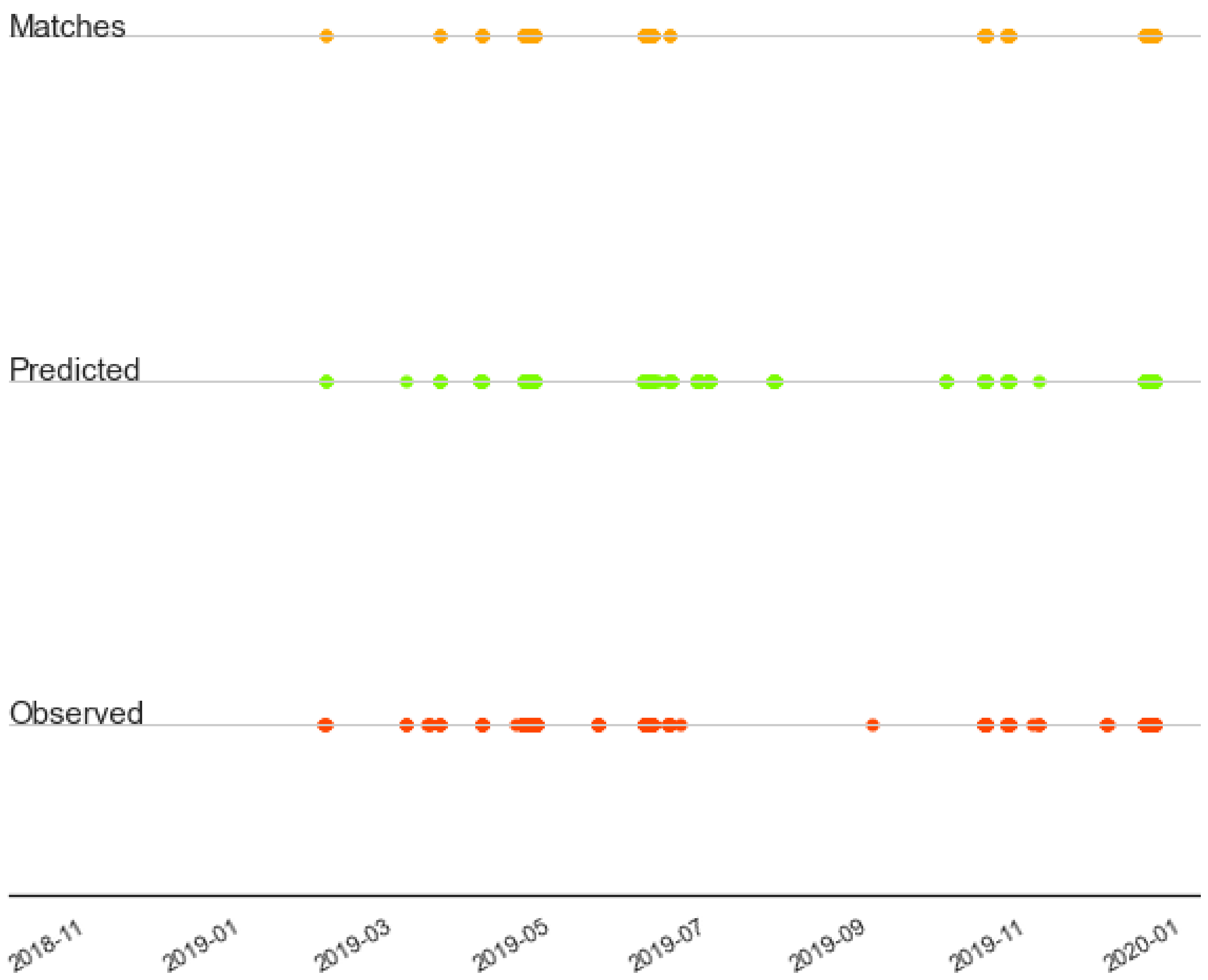


Results: Prediction

POD	CAR	F2	POFD	MAR
0.65	0.64	0.65	0.05	0.04

- Test case: **NRT 2019**
- NRT tropo parameters
- FI time series shifted by one hour

Station	Features
KALT	ZWD, ZWD_DIFF, ZHD_DIFF
LOMO	ZWD, ZWD_DIFF, ZHD_DIFF
HABG	ZWD, ZWD_DIFF
SANB	ZWD, ZWD_DIFF
LUZE	ZWD, ZWD_DIFF, ZHD_DIFF
ETH2	ZWD
FALE	ZWD
STA2	ZWD, ZHD_DIFF



Conclusions

- ML-based Foehn classification using GNSS troposphere products can provide encouraging results
- However: yearly performance of classification strongly dependent on:
  - Probability for Foehn (observed Foehn hours) ----> imbalance
  - Length of events (large events easier to detect)
  - Often not exact prediction but neighboring time steps
- Always trade-off between detection probability (POD) and false detections (POFD) / alarms (CAR)
  - More detections lead to more mishits ----> less detection to more missing alarms
  - Balance tricky to find
  - Decision for optimization towards one parameter? -----> depends on actual usage/application
- Foehn prediction using GNSS possible
  - NRT data (latency ~ 30 min) shows equal performance -----> suggests usage for prediction
  - Evaluation with shifted time series shows equal or even better results -----> predictive ability
  - Usage as additional and independent decision tool for human forecasters

Outlook

- ❑ Ideas for performance improvement:
  - ❑ Refined hyperparameter tuning
  - ❑ More sophisticated algorithms?
  - ❑ Threshold optimization
  - ❑ Use collocation approach to derive tropospheric delays at Altdorf or other relevant SMN station for usage in classification/prediction

- ❑ Real-time tropo products to be tested as well

- ❑ Several more in-depth results in preparation

- ❑ Publication in preparation (meteorological journal)