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Nowcasting wind using machine learning
from the stations to the grid

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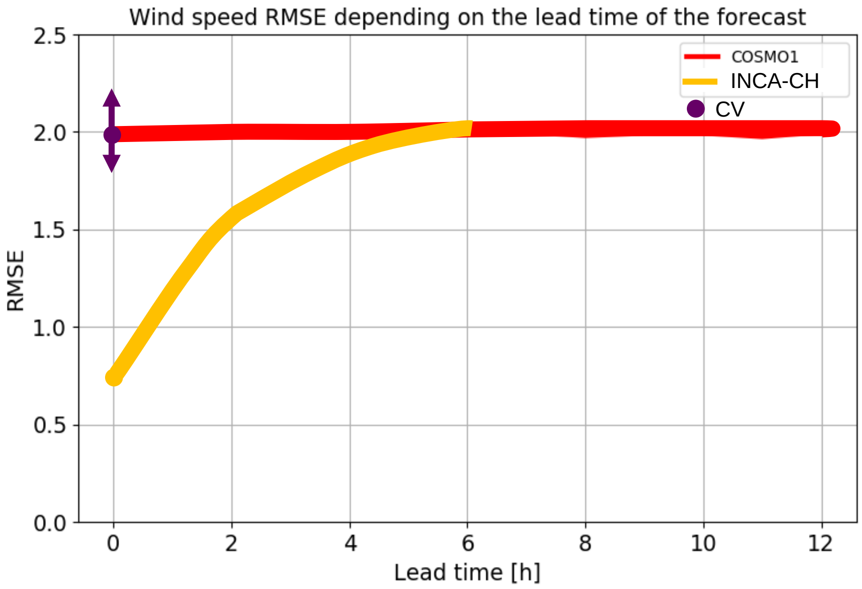
Motivation: INCA-CH seamless Nowcasting System

Current INCA-CH system for mean wind

- Analysis:
  - COSMO-1 error interpolated in space using inverse distance weighting (horizontal and vertical).
  - leave one out cross-validation: equivalent or sometimes even worse performance as COSMO-1.
- Forecast:
  - Linear blending between analysis and COSMO-1 (0-6h): unrealistic transitions.



Goal: evaluate **machine learning** techniques

- Improve analysis and nowcasting of the model on the whole grid
- Add wind gust

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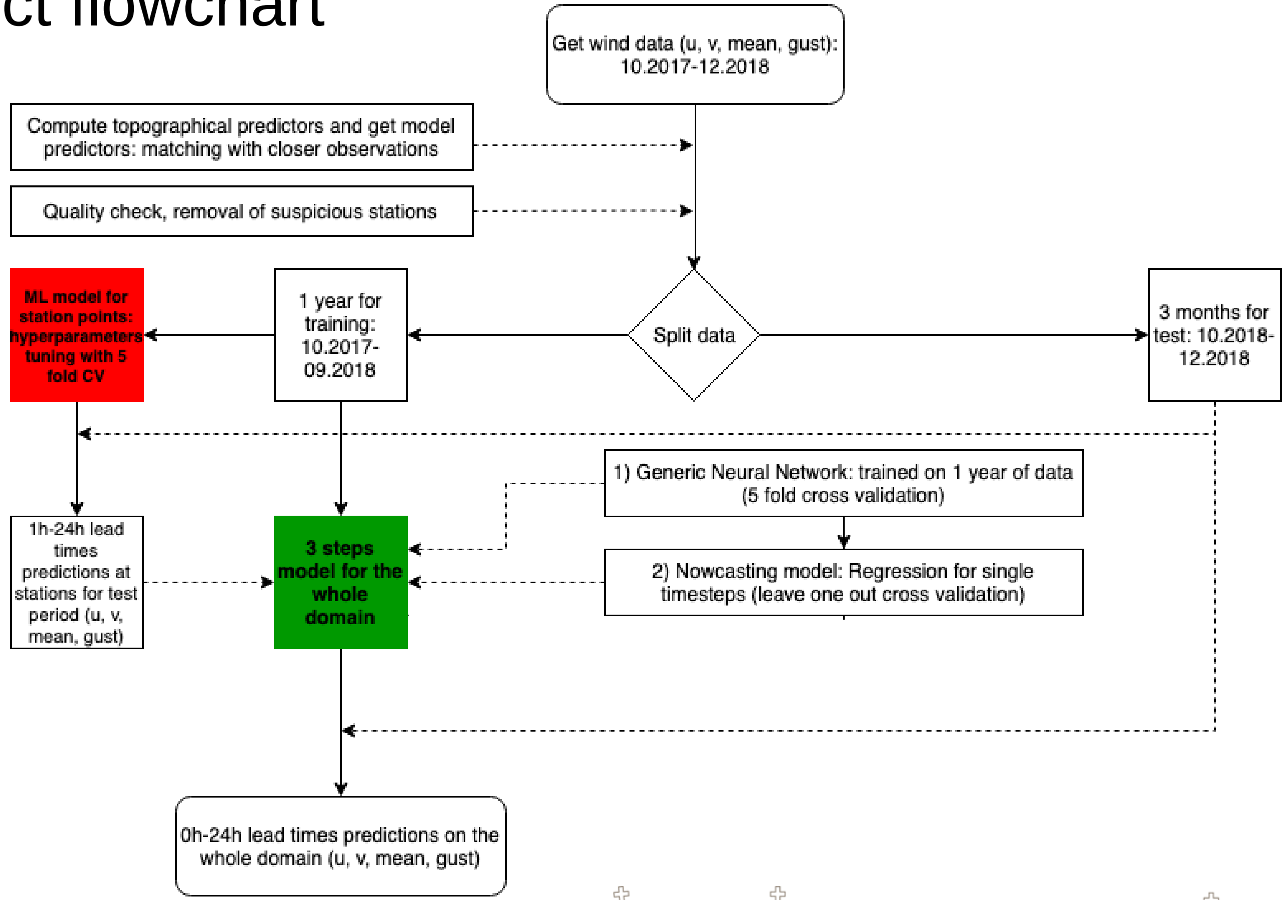
Project flowchart

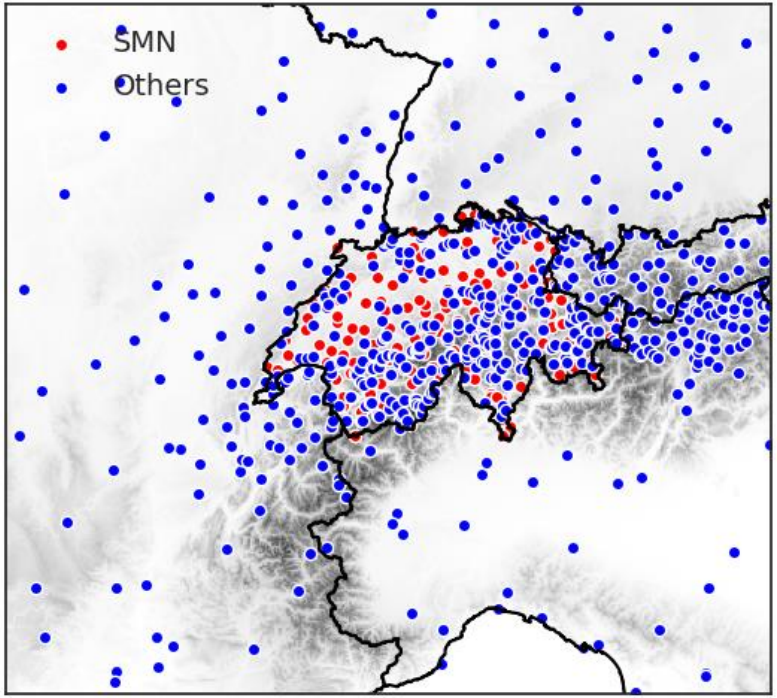


Dataset description: observation

- Hourly mean wind, wind gusts
- 10.2017 and 12.2018
- Instruments at 10 m from the ground
- Switzerland
  - SMN
  - IMIS (SLF)
  - Private network, Cantonal network
- France (FR), Italy (IY), Germany (DL), Austria (OS)

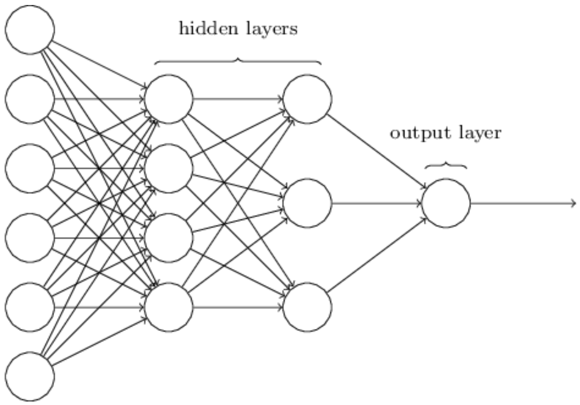
- Data quality check: removed suspicious stations

781 station measurements

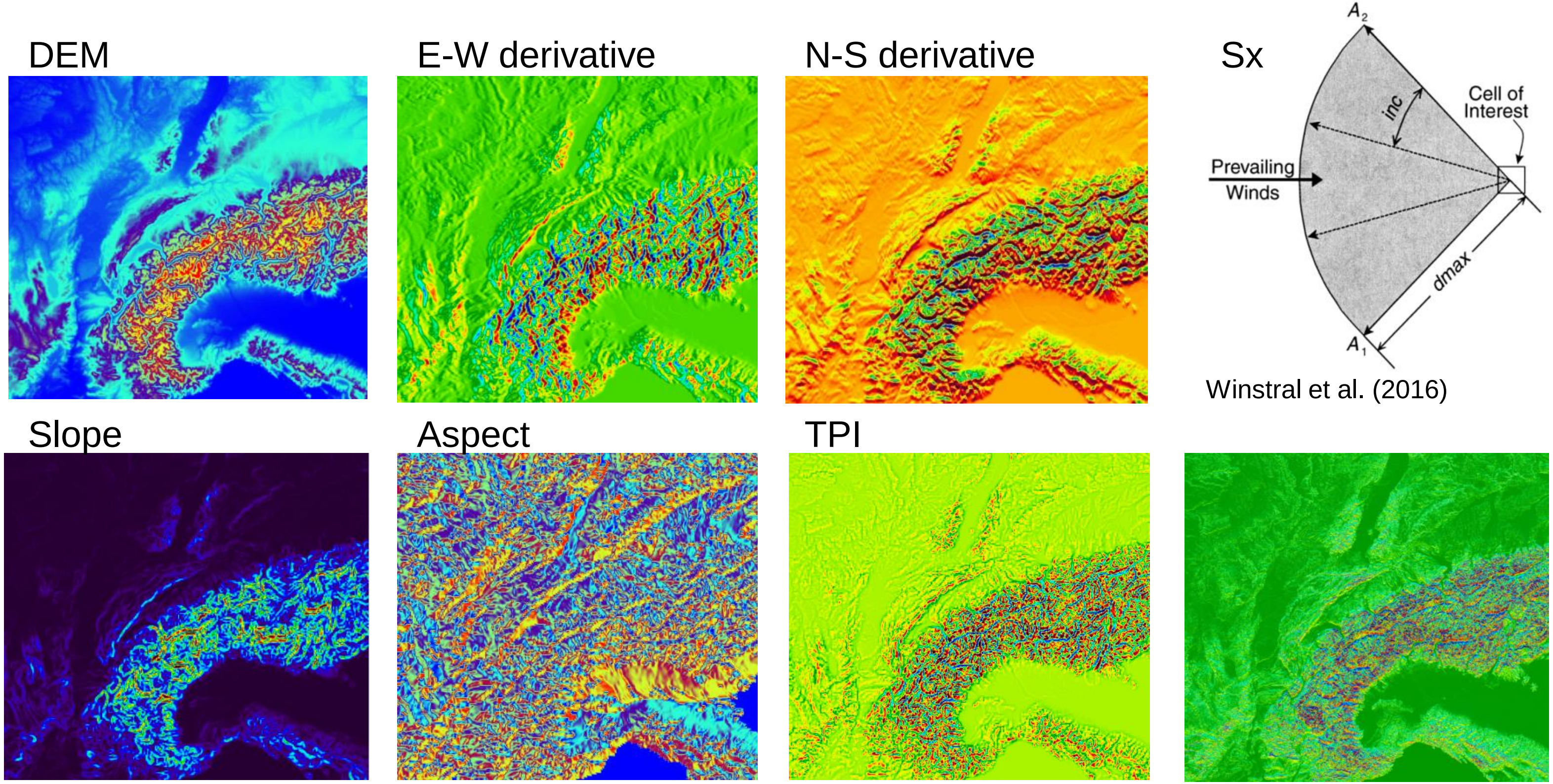


Dataset description: predictors

- COSMO-1 variables:
  - Hourly mean wind, gust, u, v
  - Pressure
  - Boundary layer height
  - Relative humidity
  - …
- Seasonality parameters:
  - Hour and Day of the year
- Topographical parameters (resolutions 15 km – 100 m):
  - Altitude
  - Slope
  - Aspect
  - Directional derivatives
  - Topographic Position Index
  - Maximum slope dependent on wind direction

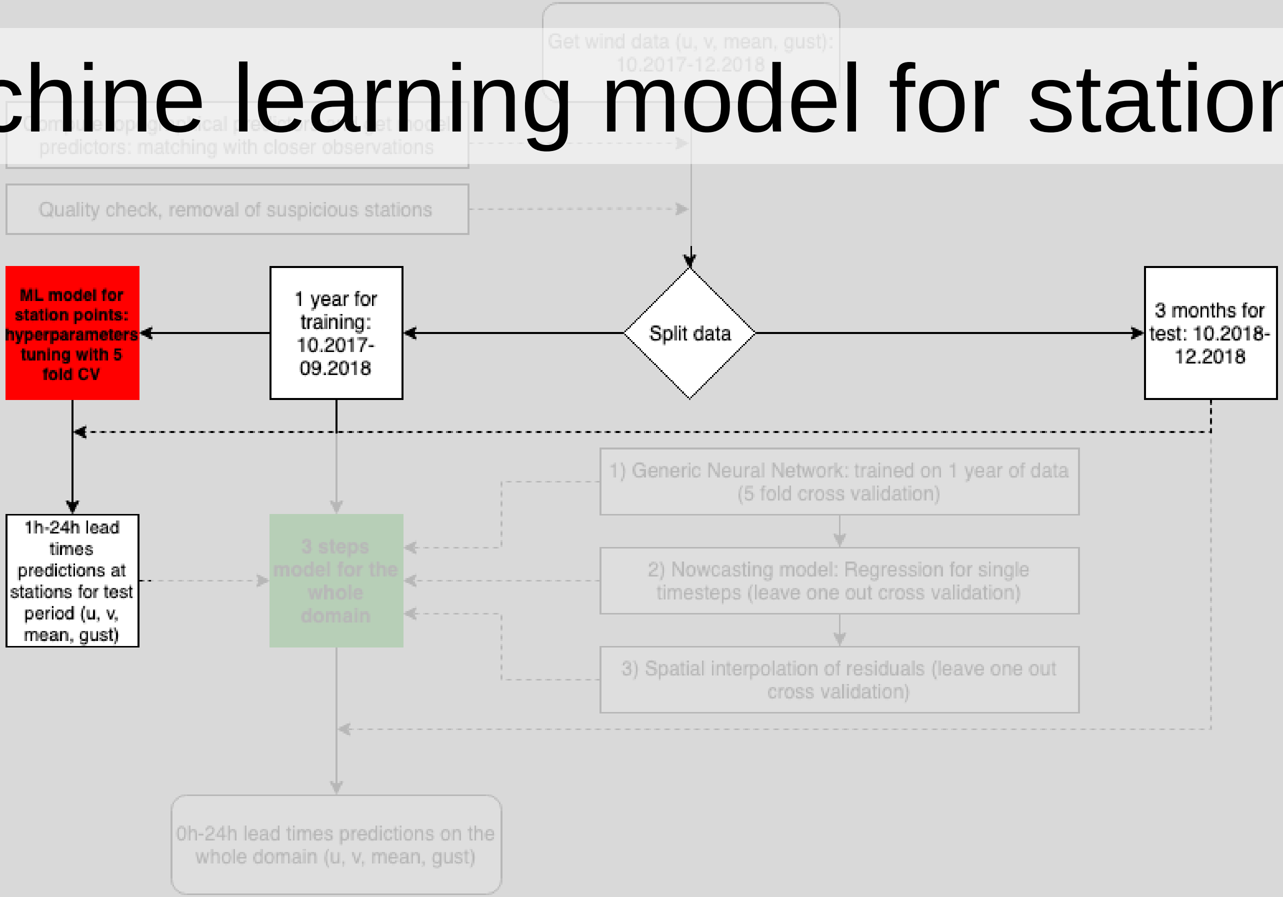


Dataset description: topographical predictors



Resolutions:
15km, 7km, 3km, 1km, 500m, 250m, 100m

Machine learning model for stations

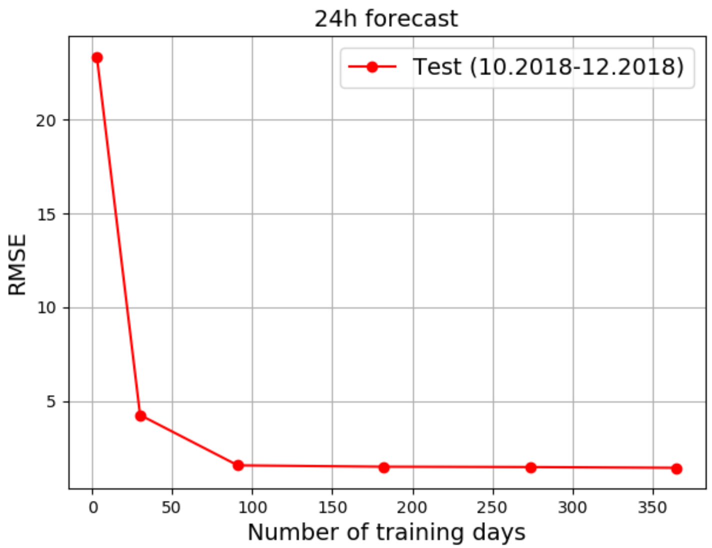


Model for stations

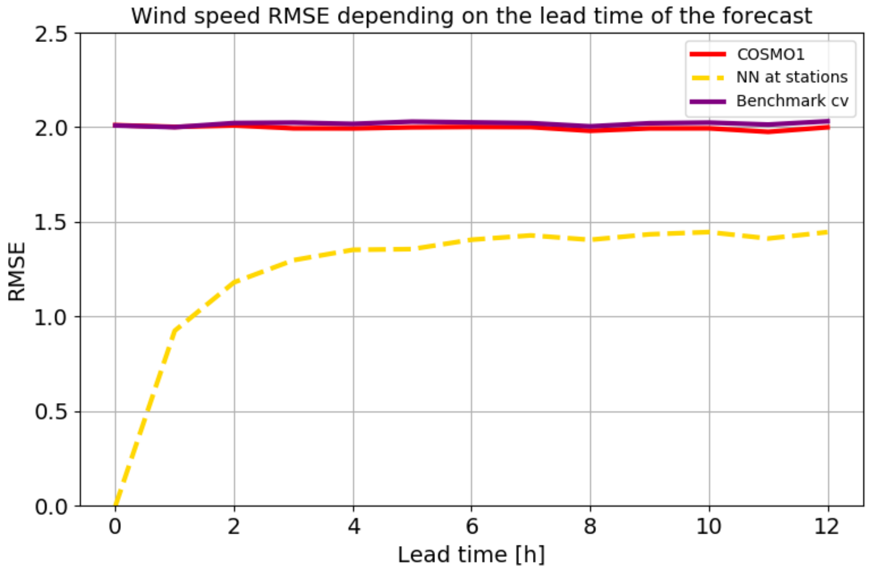
Feedforward Artificial Neural Network:

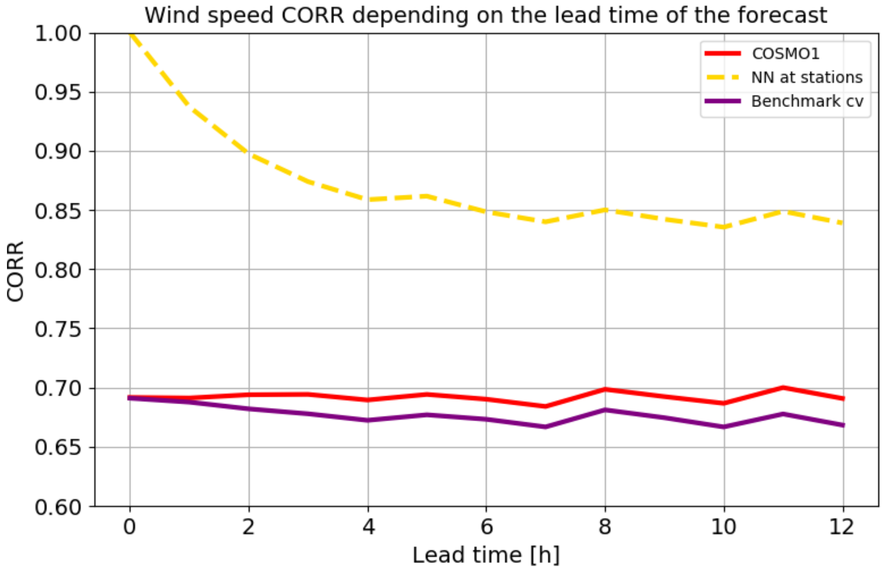
- Multi-layer perceptron
- Number of observations > 1 billion (365 days)
- 38 predictors (10 COSMO-1, 4 seasonality, 20 topographical, 4 observations)
- 2 hidden layers with (200,100) neurons
- Loss function: Mean Squared Error
- 5-fold cross-validation with grid-search for hyperparameter tuning
- Early-stopping to avoid overfitting
- Test independent in TIME
- Training: 10.2017-09.2018 (30 % for validation); Test: 09.2018 – 12.2018
- Feature importance from Random Forest

Learning curve:

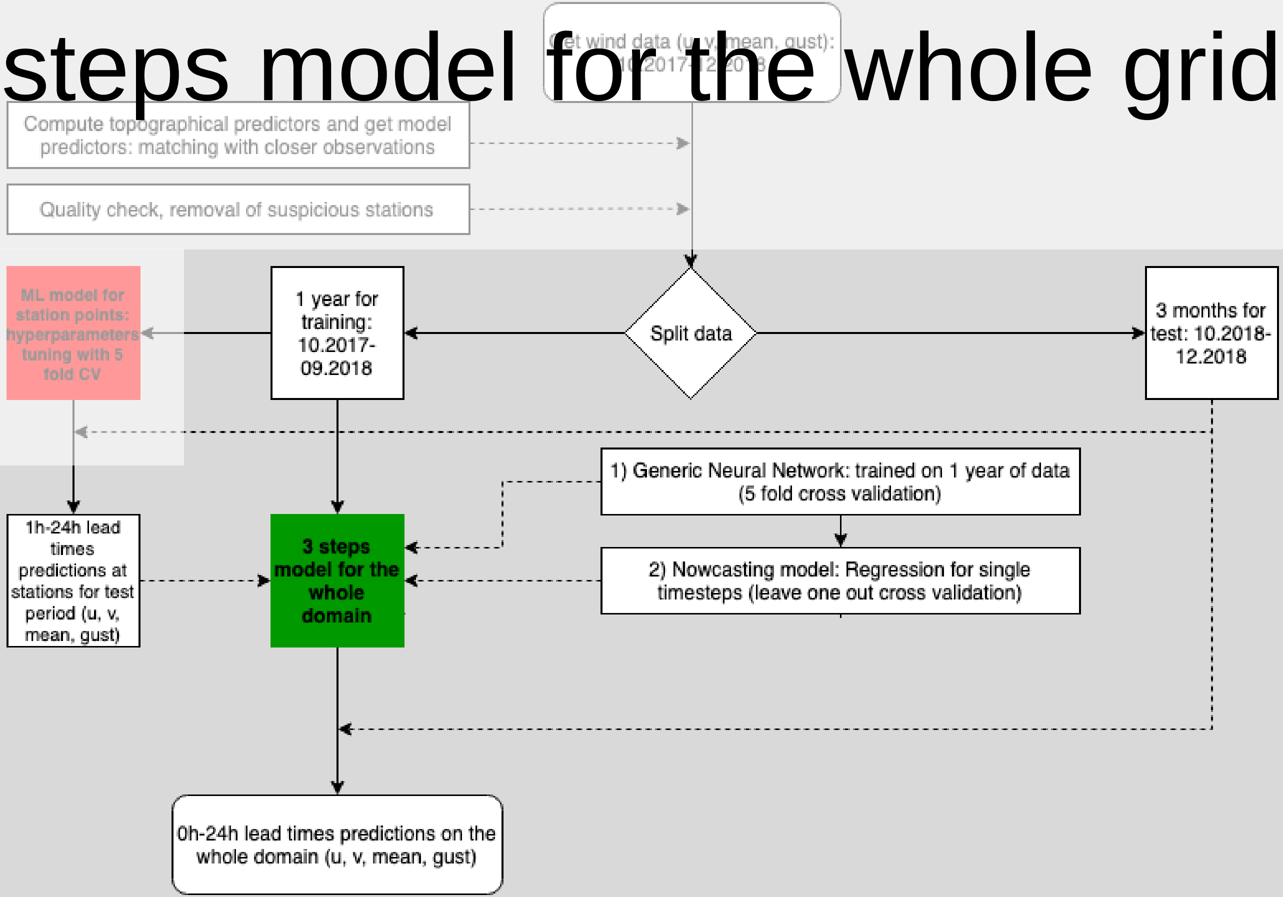


Results at stations: mean wind performance





2 steps model for the whole grid

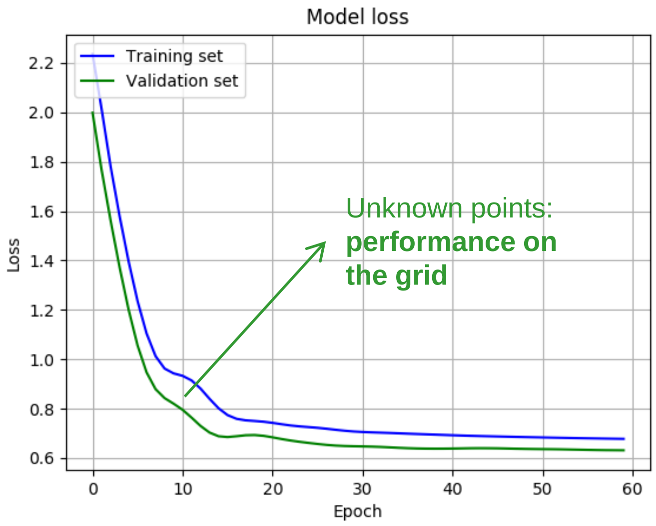


Model on the grid: step 1

Generic model trained on 1 year of data

- **Correction of the systematic error**
- Trained not only on independent period of time, but also on **independent stations** (unknown points, 20-fold cross-validation)
- Trying to keep the same performance at stations included and not included (grid), avoiding overfitting
- Loss function: Logarithm of the hyperbolic cosine of the prediction error
  - $\log(\cosh(x)) \cong \begin{cases} x^2 \; for\ small\ x \\ abs(x) - \log(2) \; for\ large\ x \end{cases}$
  - Mostly like MSE, but less affected by the occasional wildly incorrect prediction
- The validation curve shows the same performance on known and unknown points, early-stopping to avoid overfitting at stations

Validation curve



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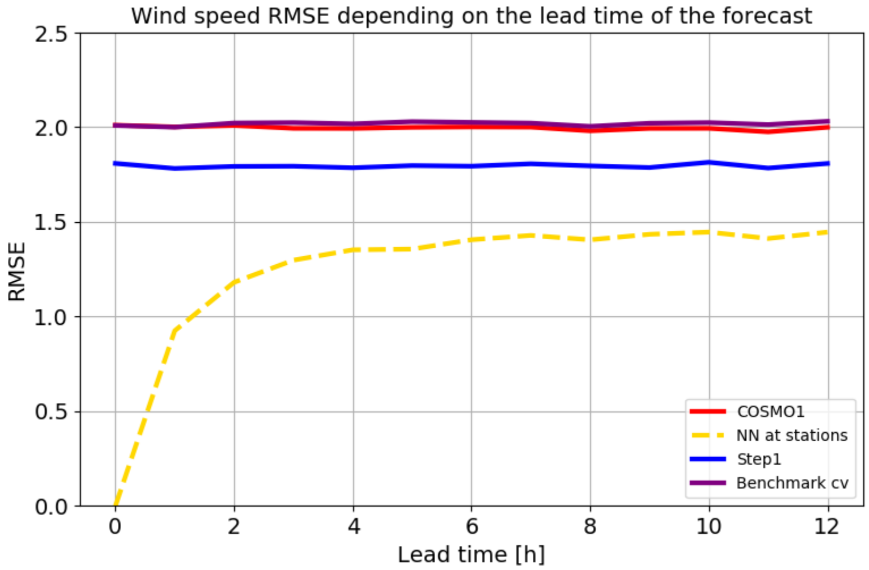
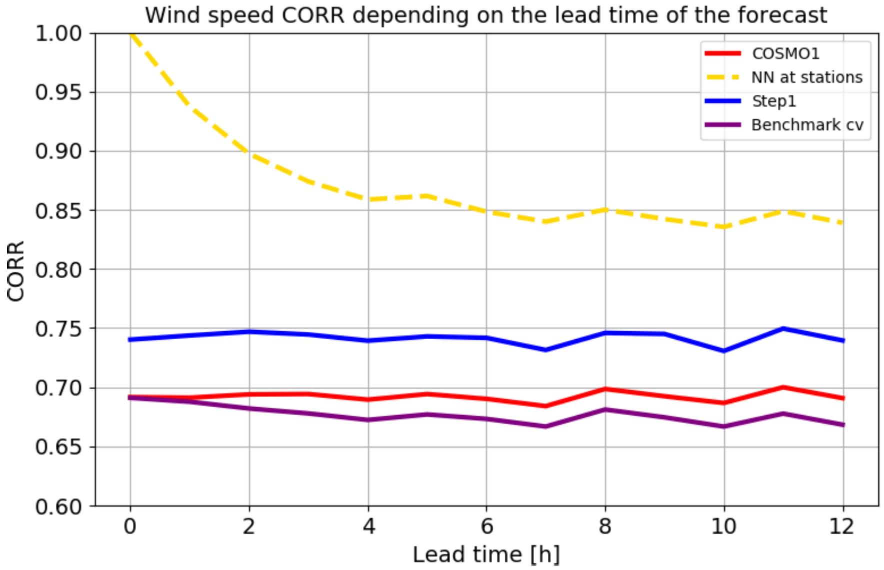
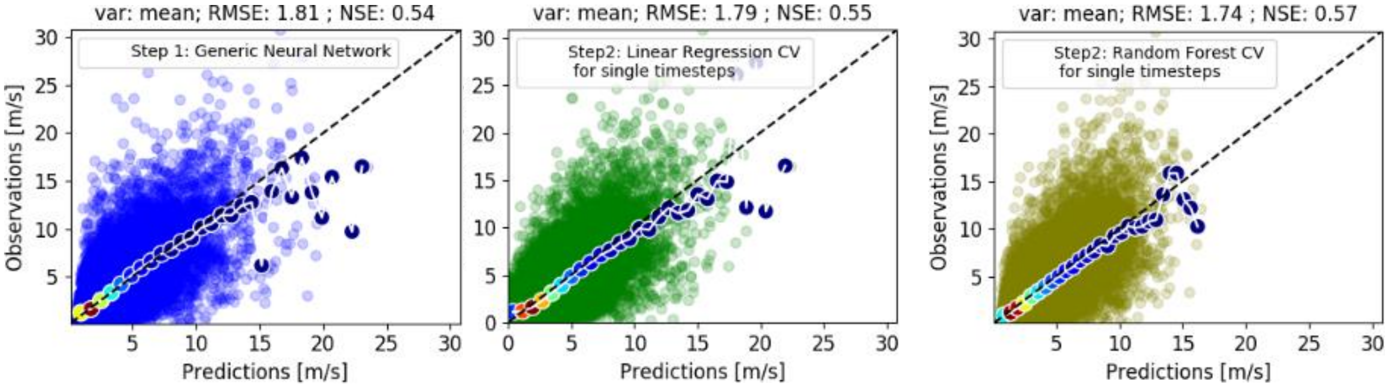
Results step 1: mean wind performance

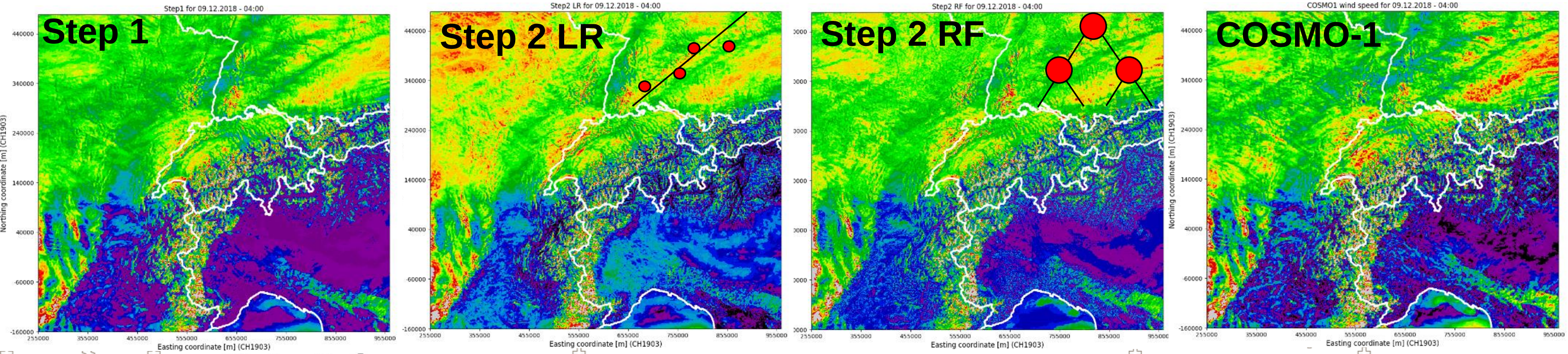




Results step 2: mean wind



- Prediction values limited for Random forest
- Better at stations but cross validation doesn't improve consistently:
- RMSE LR at stations = 1.62
- RMSE RF at stations = 1.40
- LR improves the dispersion, distribution closer to observations



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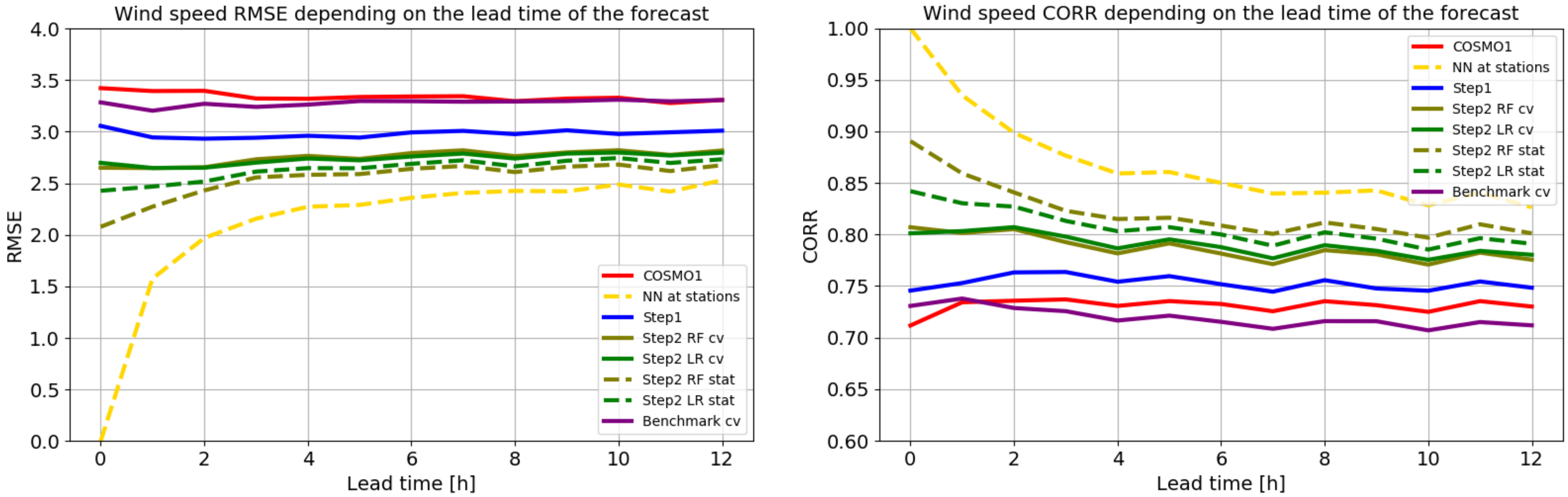
Results step 2: wind gust



Summary and Outlook

Model at stations

- 1 unique ML model leads to a strong improvement for all lead-times (0-24h).
- Persistence of wind is very important for nowcasting.

Model on the grid

- Machine learning for wind on locations without measurements remains a very difficult task in the Alpine region.
- Multi-step approach aims to correct systematic and forecasting errors on the whole grid.
- The efficacy of step 2 is evident for wind gusts, less significant for mean wind.

Possible improvements

- Step 1: data size vs performance (learning curve)
- Step 1: further optimisation of the Neural Network
- Step 1: convolutional Neural Networks (better representativeness of topographical parameters) or/and more realistic ground model (accounting for buildings and vegetation)
- Step 2: increase the number of high quality stations, try to give more importance to coordinates

Future work

- Implementation of the model in real time and evaluate performance

Thanks for the attention!

Results step 2: mean wind