



# Machine learning algorithms for global modelling of Zenith Wet Delay based on GNSS measurements and meteorological data

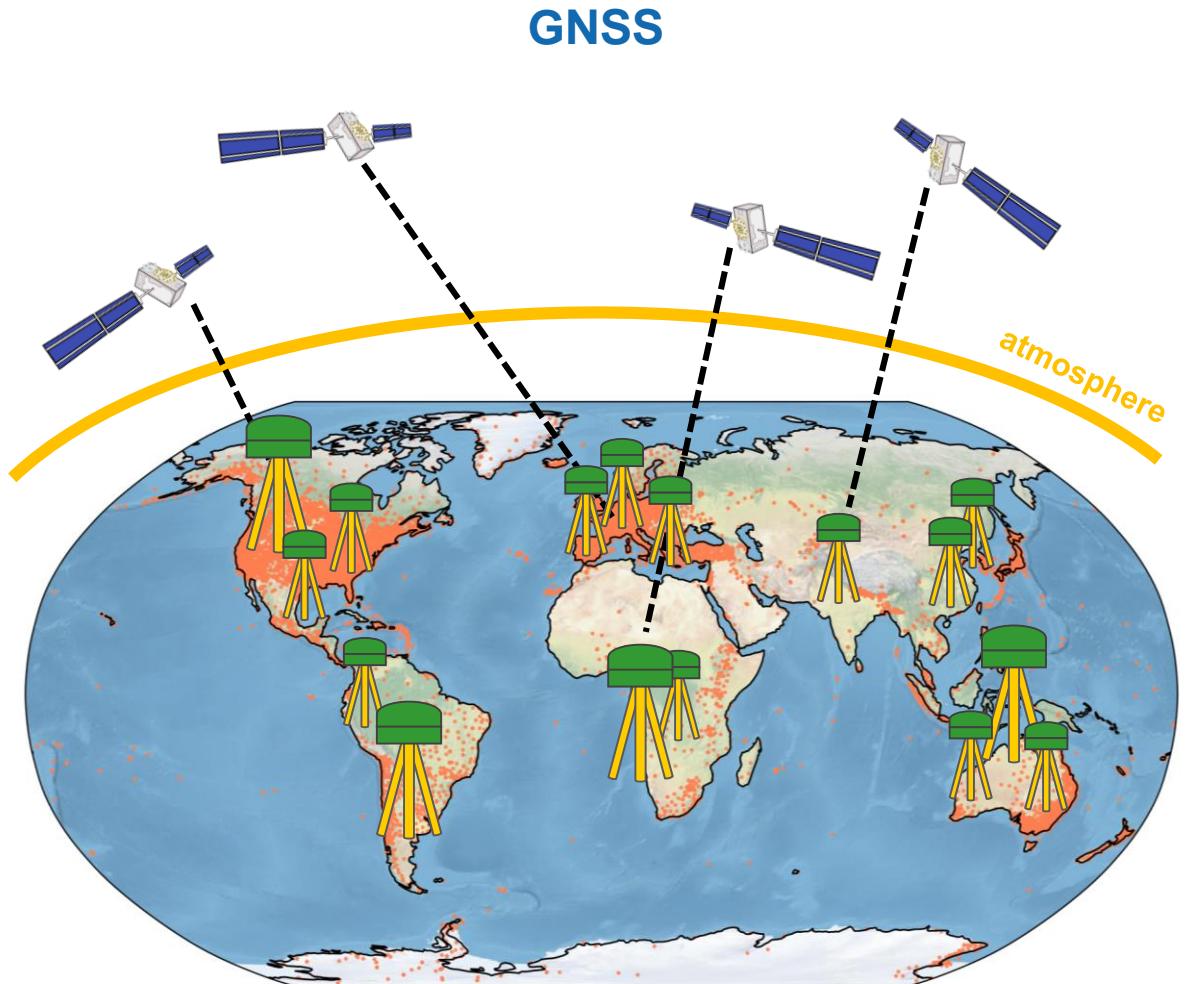
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L. See, R. Weinacker, T. Sturn, I. McCallum,  
V. Navarro

14<sup>th</sup> June 2022, D4G22



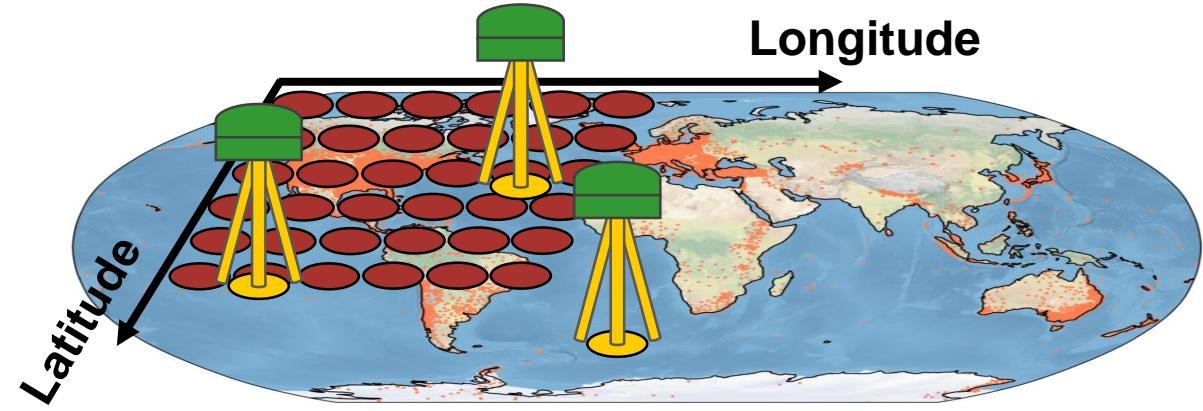
# Motivation

- Global Navigation Satellite System (GNSS)
  - find also application in atmospheric research
- GNSS signals traverse the atmosphere
- Time delays → measurements of atmospheric properties



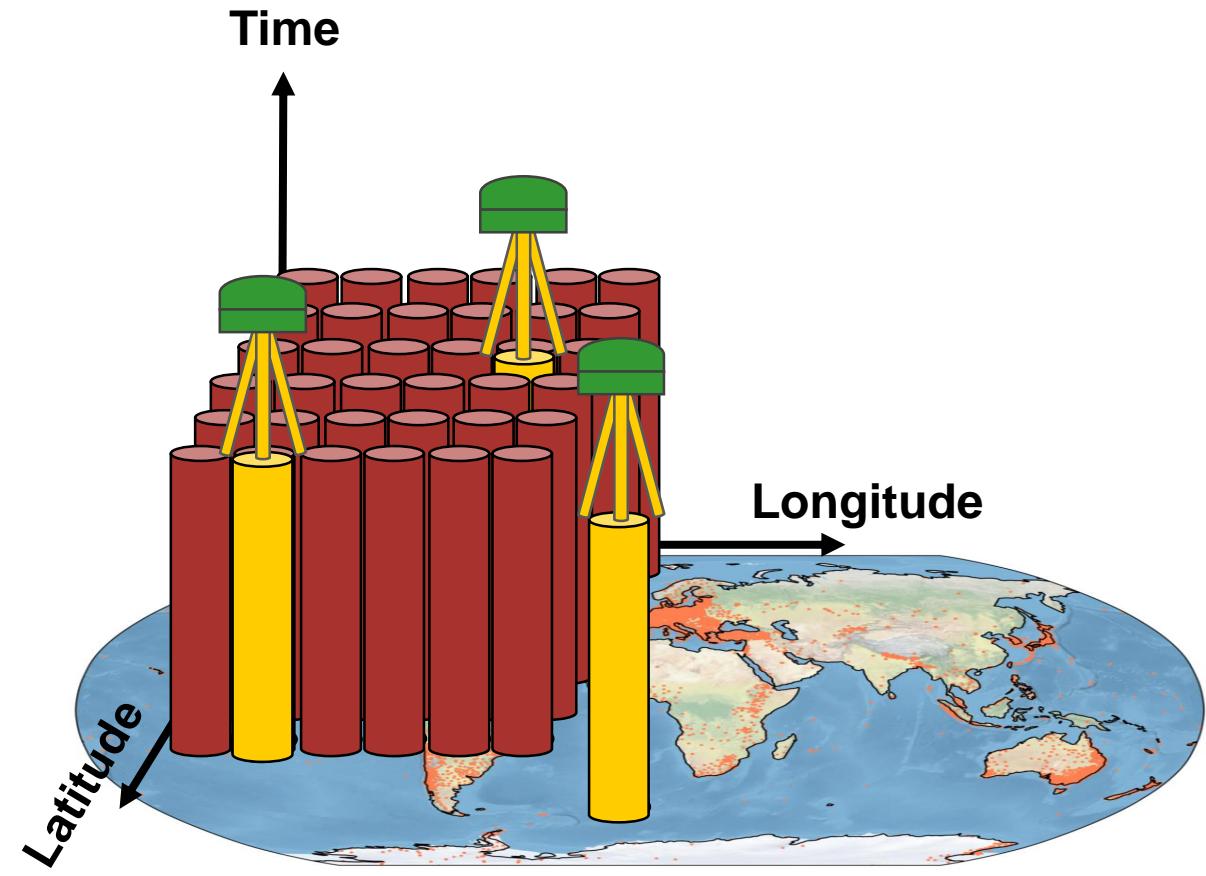
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- Model **Zenith Wet Delay** globally based on meteorological data using Machine Learning (ML)

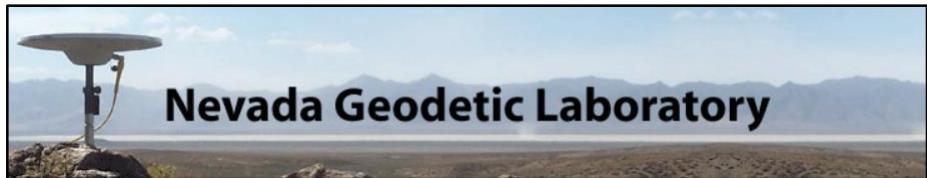


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# Data



## Zenith Wet Delay (ZWD)

### TARGET

- Source: Nevada Geodetic Laboratory (NGL)
    - More than 19.000 GPS stations available
  - Temporal resolution: 5 min → hourly resolution
  - Spatial resolution: stations distributed globally
  - Time span: year 2019
- 
- Aim: predict ZWD in space (and time) using ML algorithms



## Meteorological data

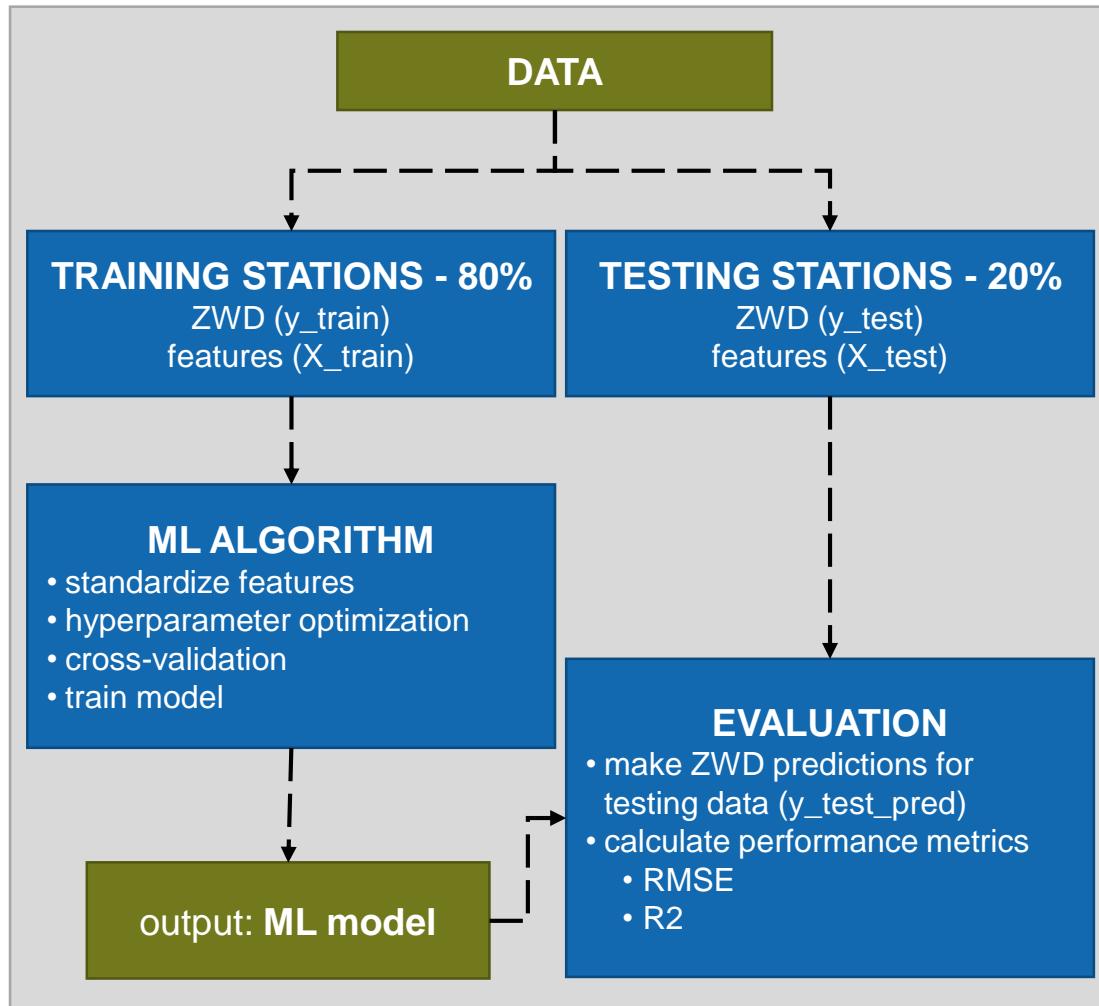
- Source: ECMWF ERA5
- Temporal resolution: hourly
- Spatial resolution: 0.25°
- Time span: year 2019
- Several variables:

- Specific humidity
- Relative humidity
- Temperature
- Surface pressure
- Total precipitation
- Geopotential
- Wind speed

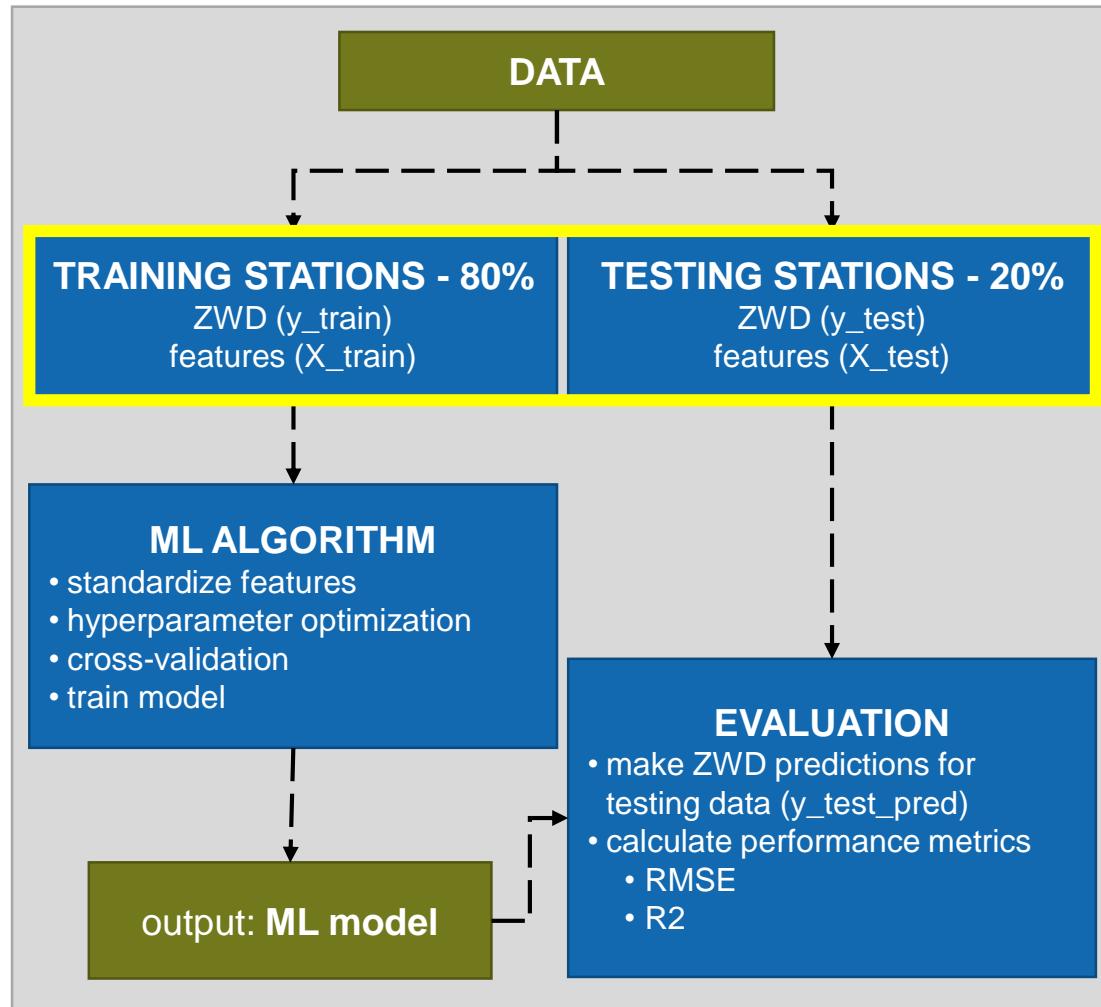
## FEATURES

- Latitude
- Longitude
- Height
- Time

# Setup

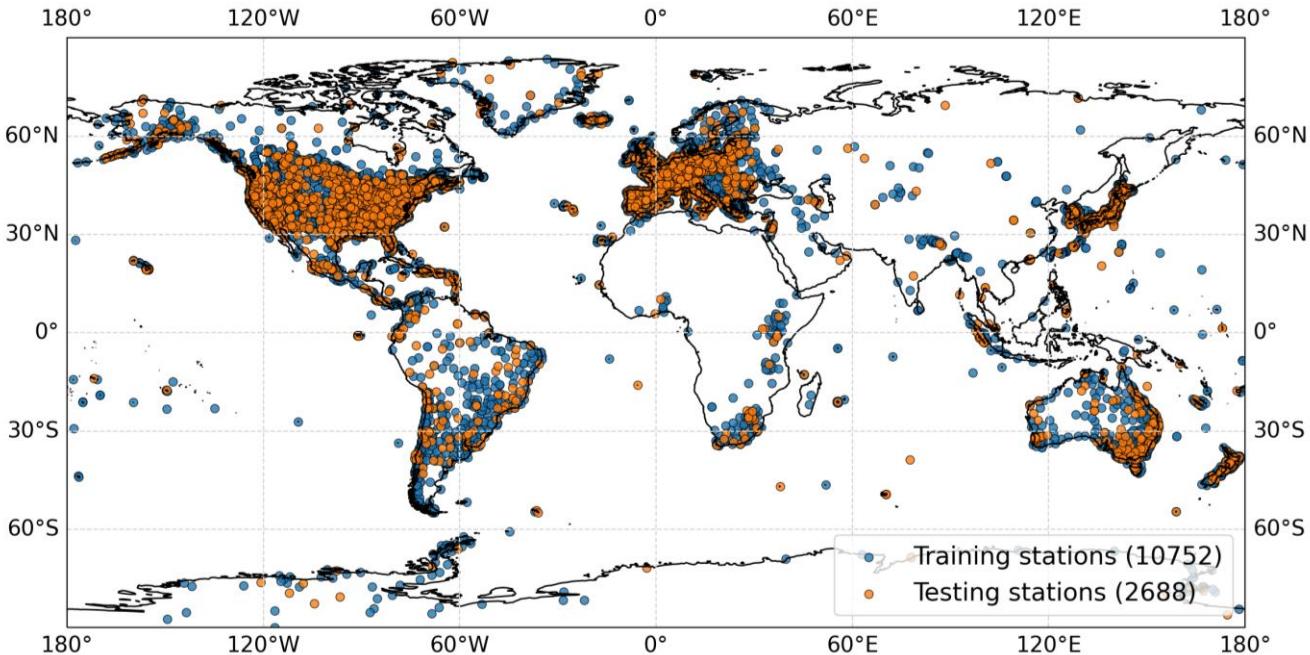


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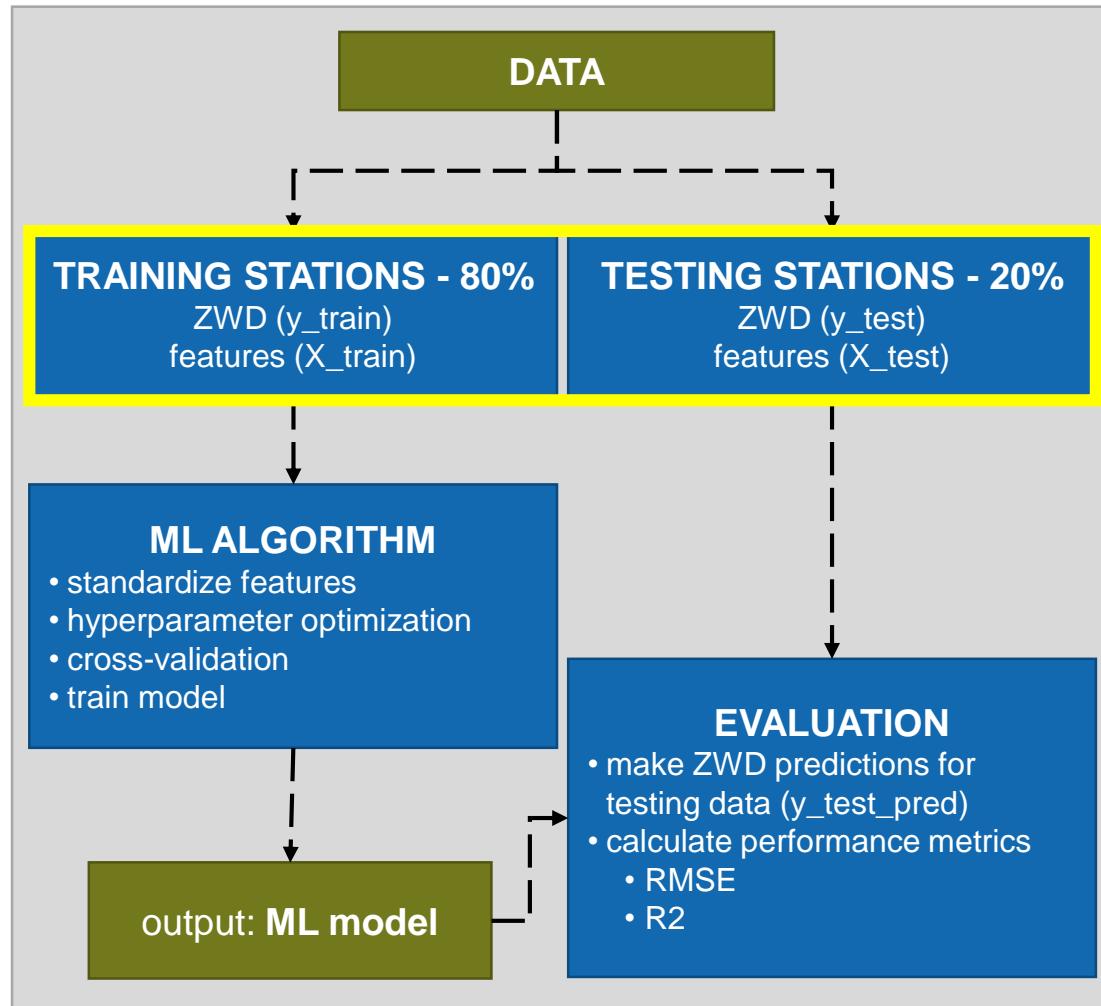


## Global model for the year 2019

Distribution of training and test stations for all available stations (2019)

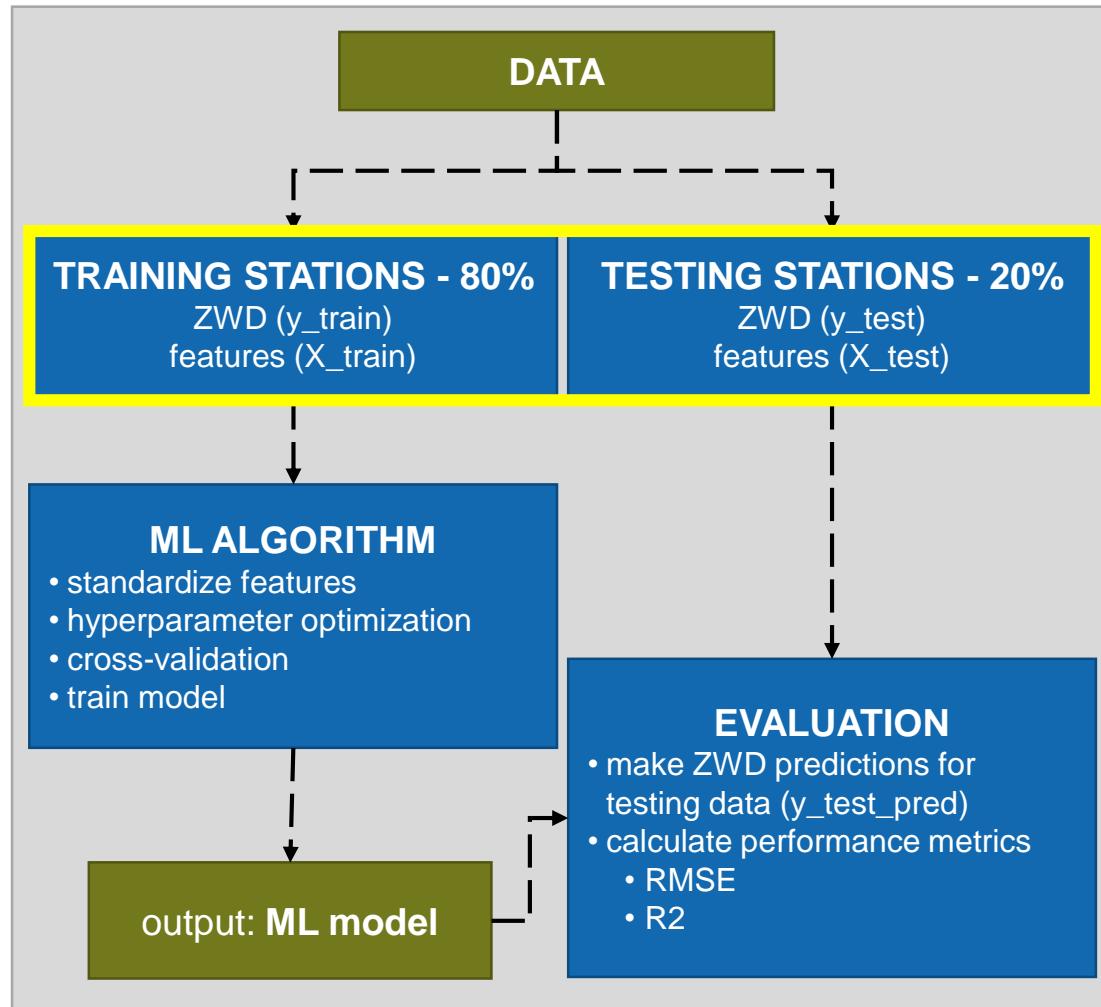


# Setup



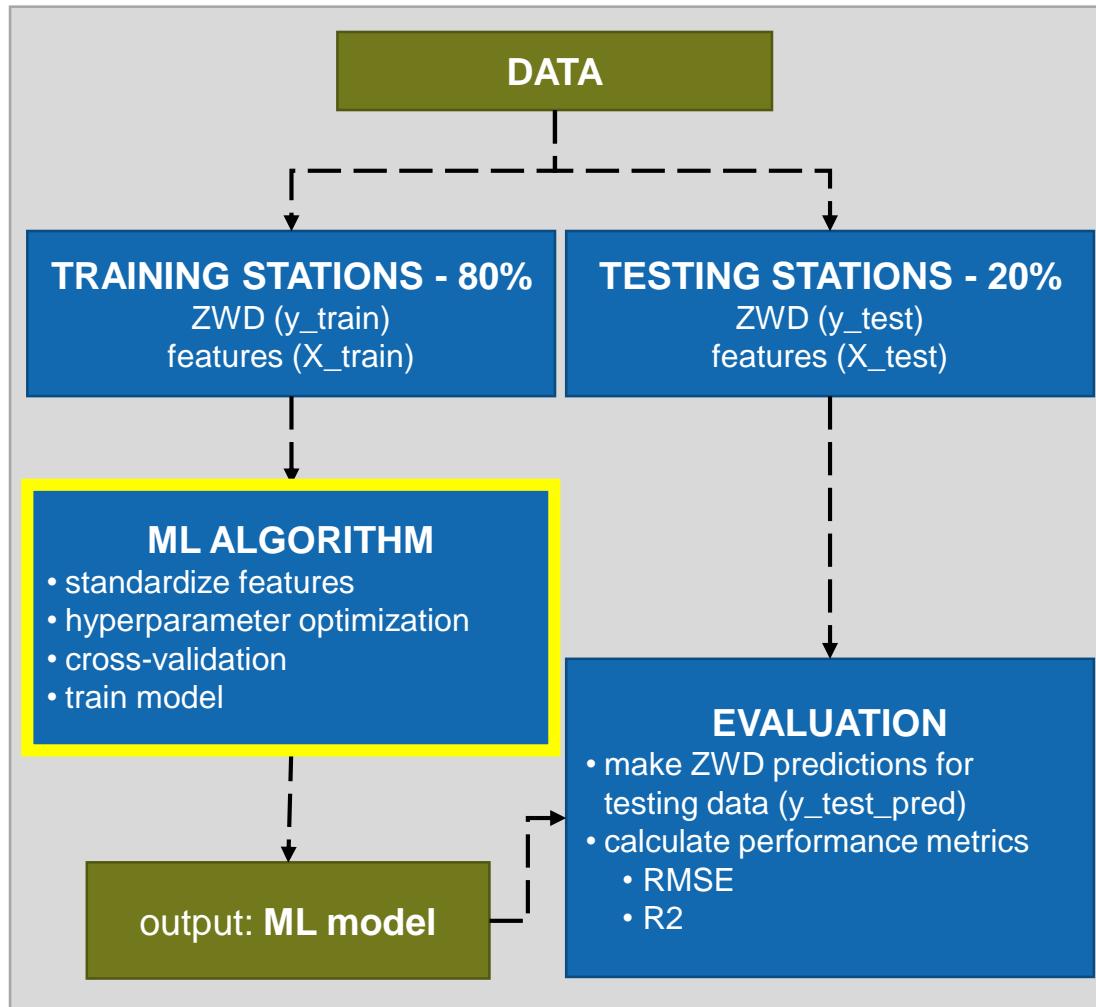
# samples	Target	Features					
		ZWD	lat	lon	time	doy	hour
1	2019-01-01 00:00:00/USAL	73.80000	40.33492	18.11149	1043136.00000	1.00000	0.00000
2	2019-01-01 01:00:00/USAL	72.40000	40.33492	18.11149	1043137.00000	1.04167	1.00000
3	2019-01-01 02:00:00/USAL	71.00000	40.33492	18.11149	1043138.00000	1.08333	2.00000
4	2019-01-01 03:00:00/USAL	68.70000	40.33492	18.11149	1043139.00000	1.12500	3.00000
5	2019-01-01 04:00:00/USAL	66.30000	40.33492	18.11149	1043140.00000	1.16667	4.00000
6	2019-01-01 05:00:00/USAL	66.50000	40.33492	18.11149	1043141.00000	1.20833	5.00000
7	2019-01-01 06:00:00/USAL	63.80000	40.33492	18.11149	1043142.00000	1.25000	6.00000
8	2019-01-01 07:00:00/USAL	60.50000	40.33492	18.11149	1043143.00000	1.29167	7.00000
9	2019-01-01 08:00:00/USAL	57.70000	40.33492	18.11149	1043144.00000	1.33333	8.00000
10	2019-01-01 09:00:00/USAL	56.70000	40.33492	18.11149	1043145.00000	1.37500	9.00000
11	2019-01-01 10:00:00/USAL	55.30000	40.33492	18.11149	1043146.00000	1.41667	10.00000
12	2019-01-01 11:00:00/USAL	52.00000	40.33492	18.11149	1043147.00000	1.45833	11.00000
13	2019-01-01 12:00:00/USAL	50.90000	40.33492	18.11149	1043148.00000	1.50000	12.00000
14	2019-01-01 13:00:00/USAL	49.30000	40.33492	18.11149	1043149.00000	1.54167	13.00000
15	2019-01-01 14:00:00/USAL	47.50000	40.33492	18.11149	1043150.00000	1.58333	14.00000
16	2019-01-01 15:00:00/USAL	48.10000	40.33492	18.11149	1043151.00000	1.62500	15.00000
17	2019-01-01 16:00:00/USAL	48.30000	40.33492	18.11149	1043152.00000	1.66667	16.00000
18	2019-01-01 17:00:00/USAL	49.20000	40.33492	18.11149	1043153.00000	1.70833	17.00000
19	2019-01-01 18:00:00/USAL	52.60000	40.33492	18.11149	1043154.00000	1.75000	18.00000
20	2019-01-01 19:00:00/USAL	56.10000	40.33492	18.11149	1043155.00000	1.79167	19.00000
21	2019-01-01 20:00:00/USAL	56.60000	40.33492	18.11149	1043156.00000	1.83333	20.00000
22	2019-01-01 21:00:00/USAL	56.80000	40.33492	18.11149	1043157.00000	1.87500	21.00000
23	2019-01-01 22:00:00/USAL	57.60000	40.33492	18.11149	1043158.00000	1.91667	22.00000
...							

# Setup



- Train model based on 10752 training stations for the year 2019
- Make predictions for 2688 testing stations for the year 2019
  - Predictions for different stations for the same time period
  - no predictions into the future

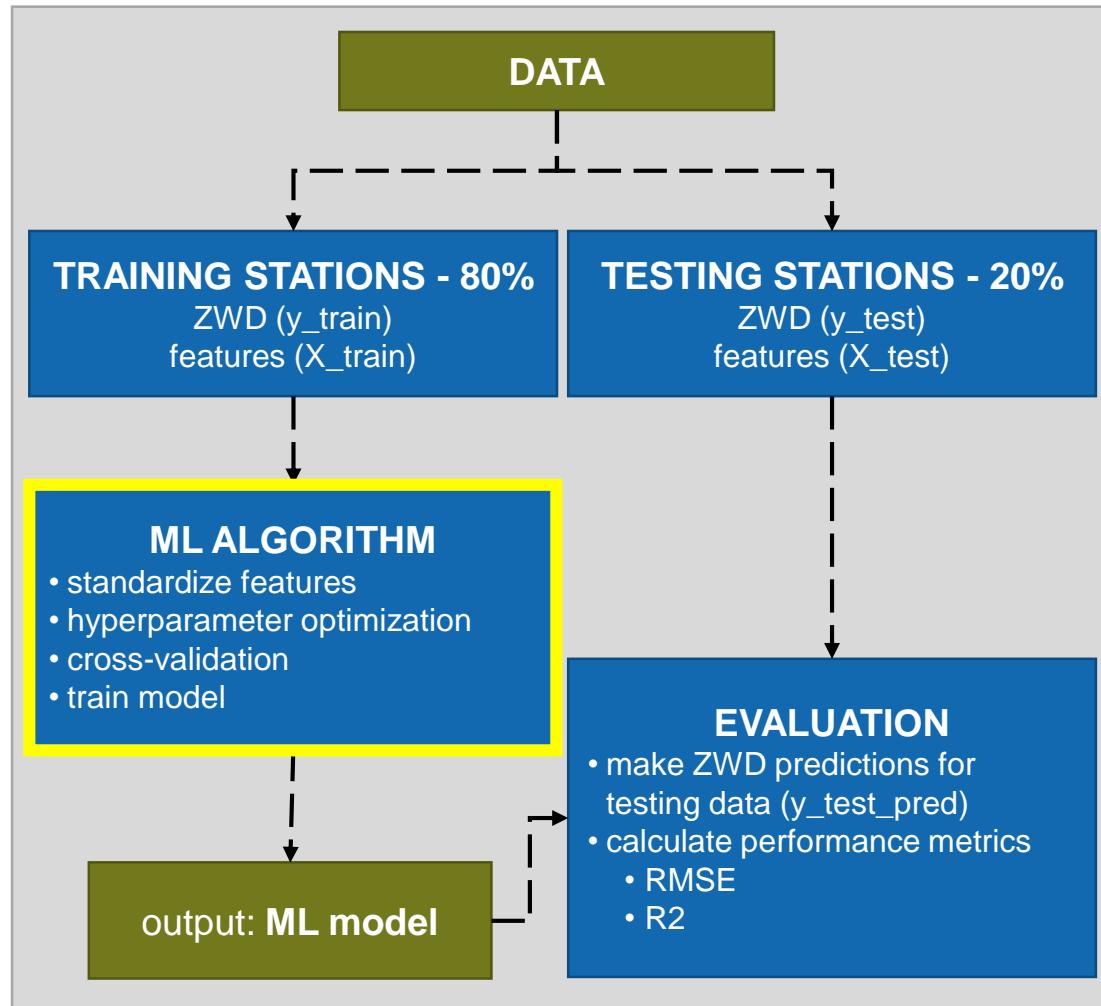
# Setup



ML algorithms:

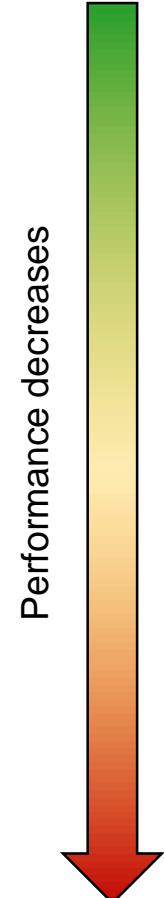
- **XGBoost**
- **Random Forest**

# Setup

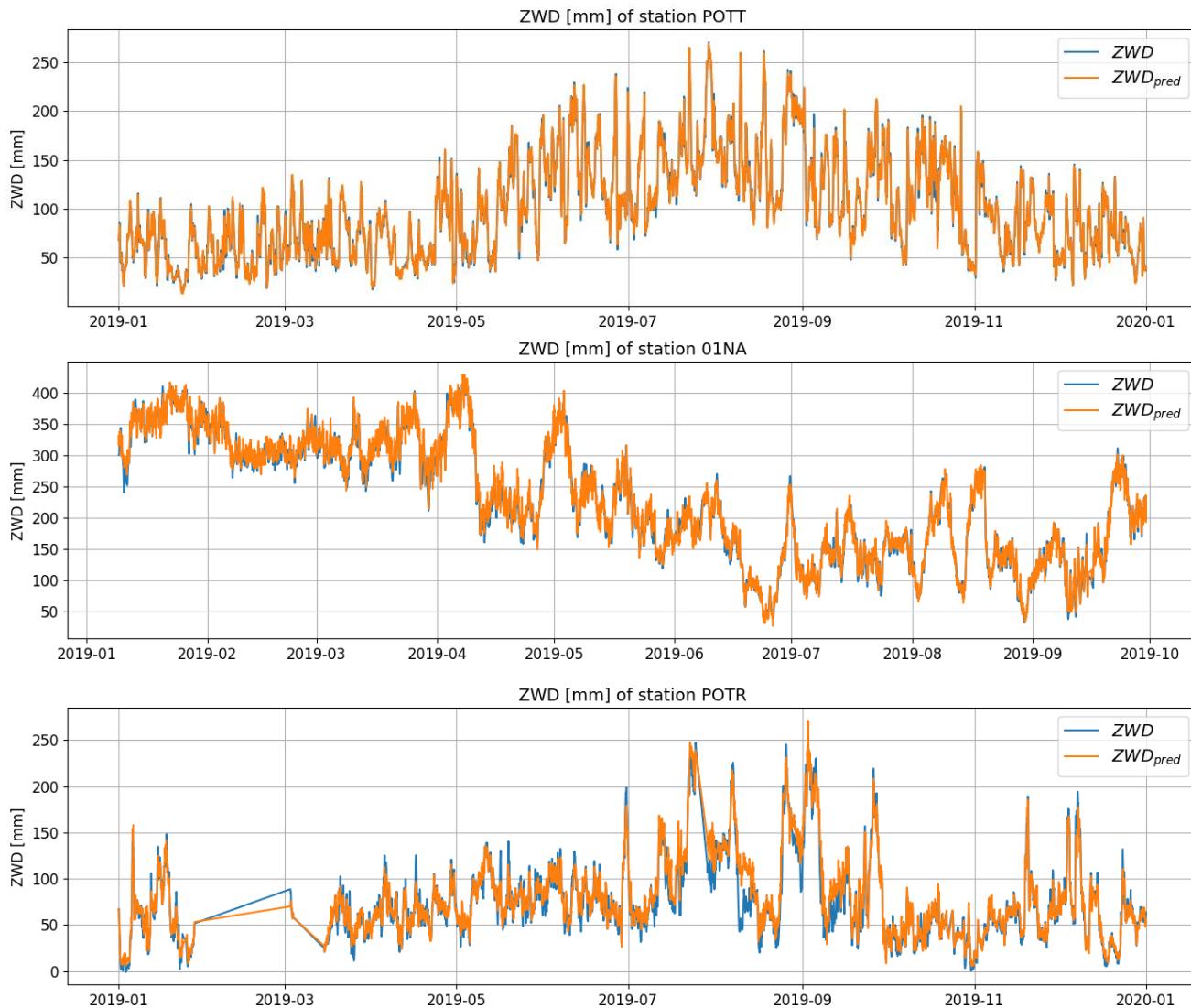
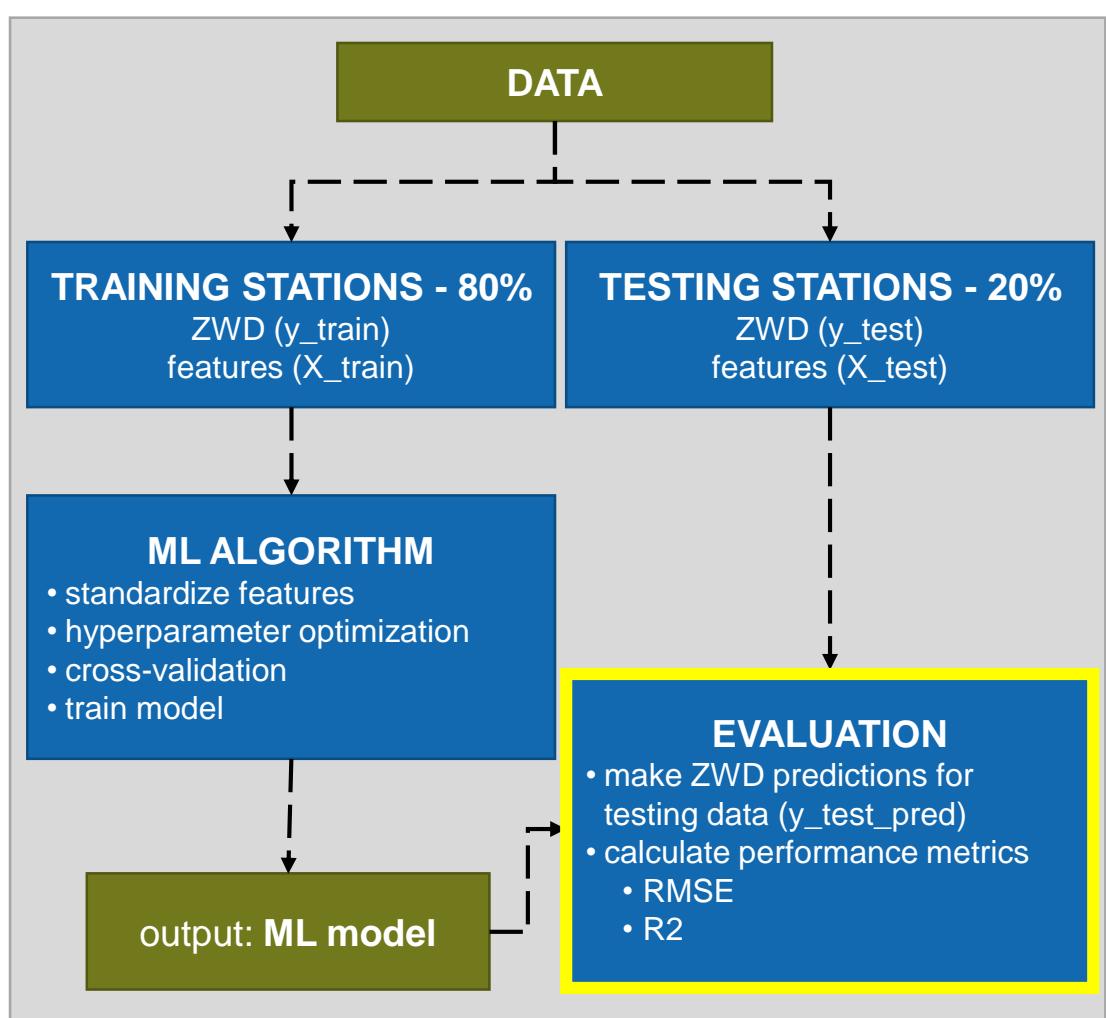


ML algorithms:

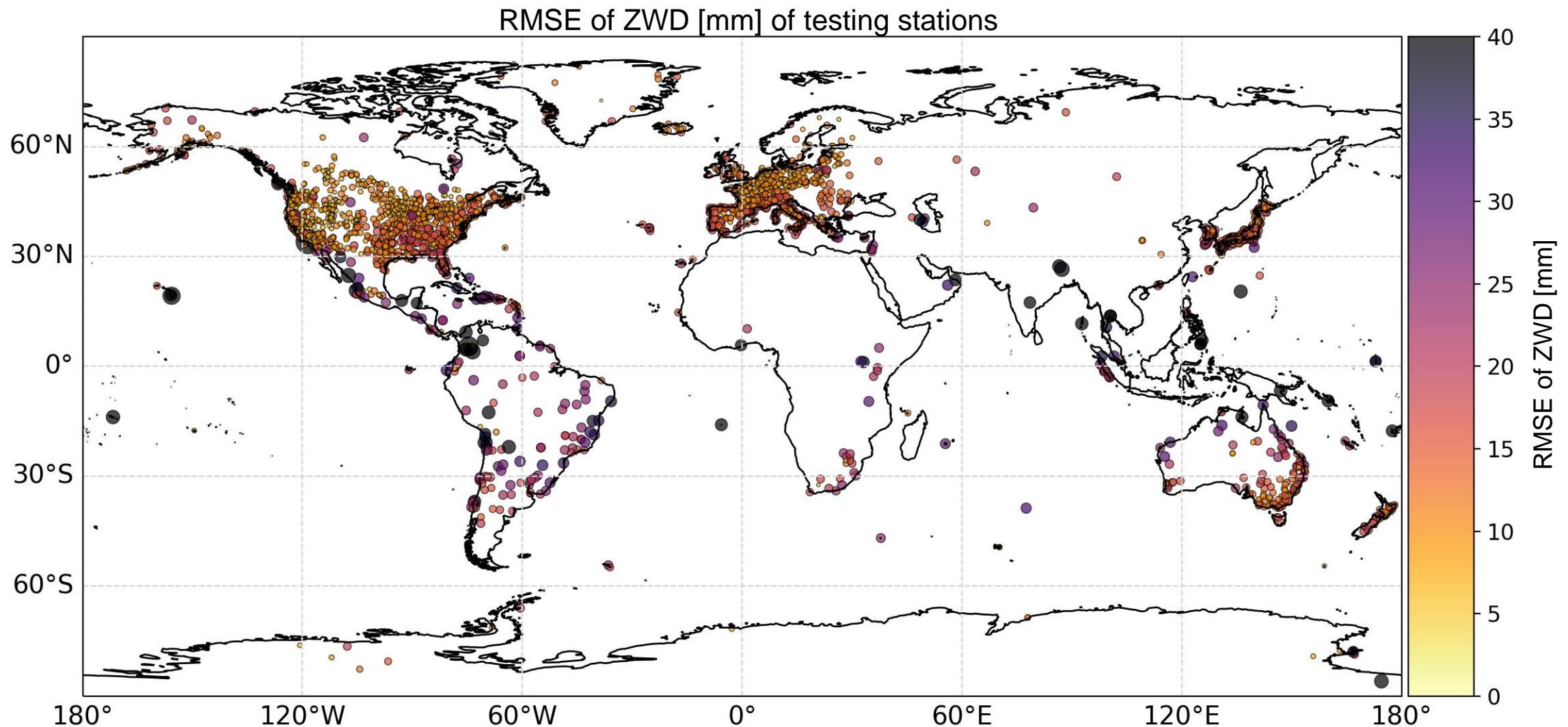
- **XGBoost**
- **Random Forest**
- HistGBoost
- Multilayer Perceptron
- Ridge Regression
- Stochastic Gradient Decent
- ElasticNet Regression
- Lasso Regression
- Linear Support Vector Machine
- AdaBoost



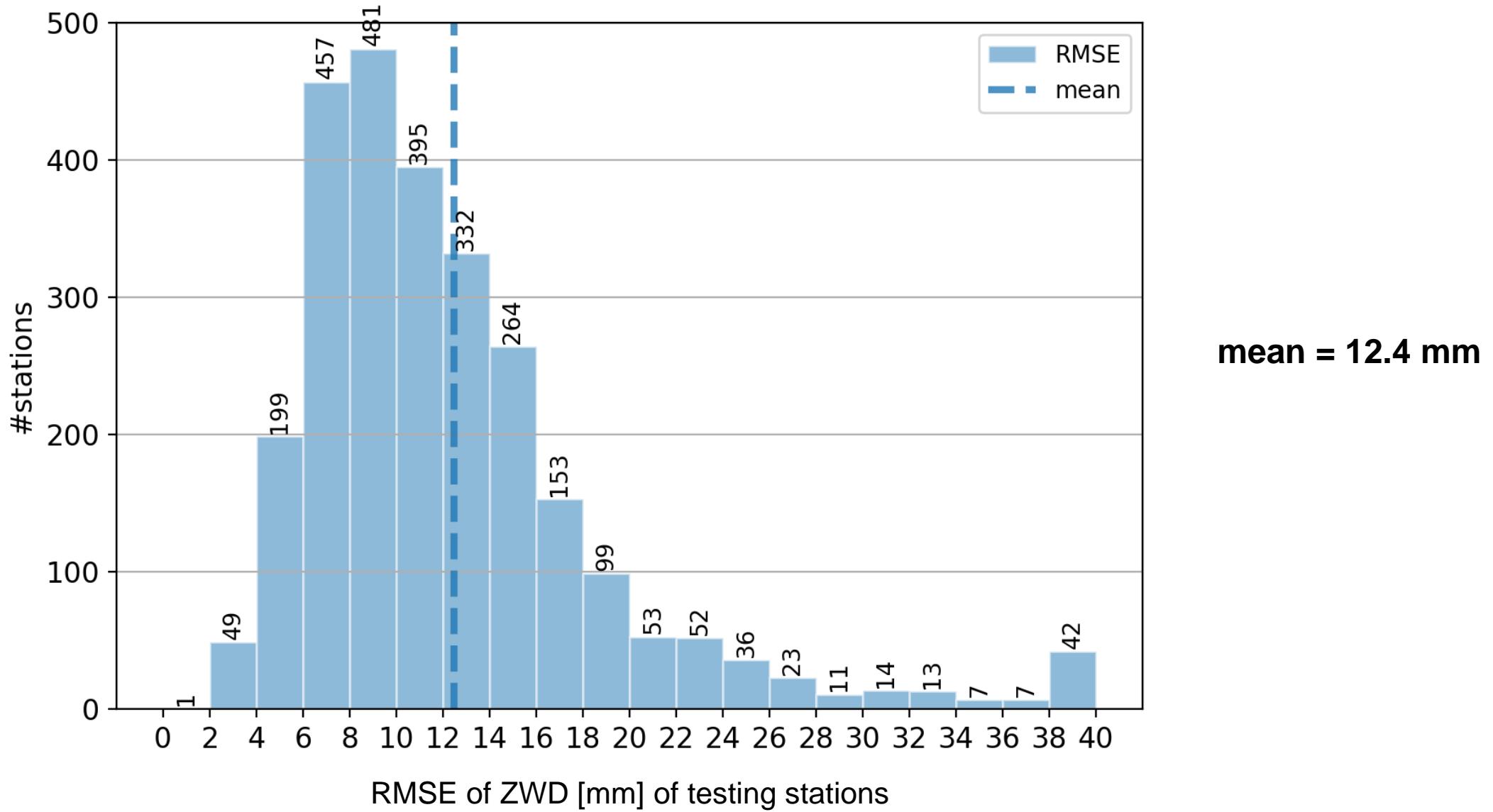
# Setup



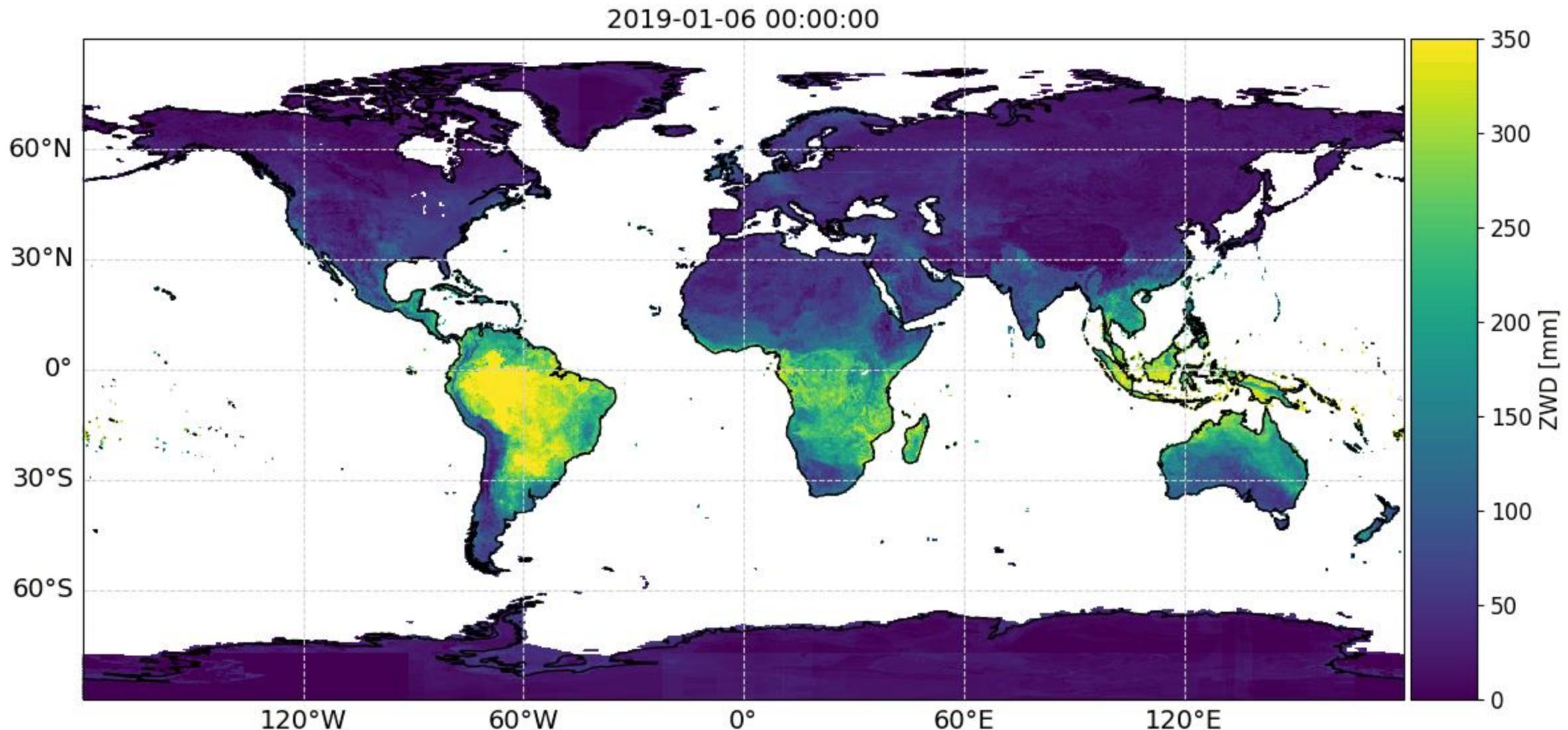
# Performance of individual test stations



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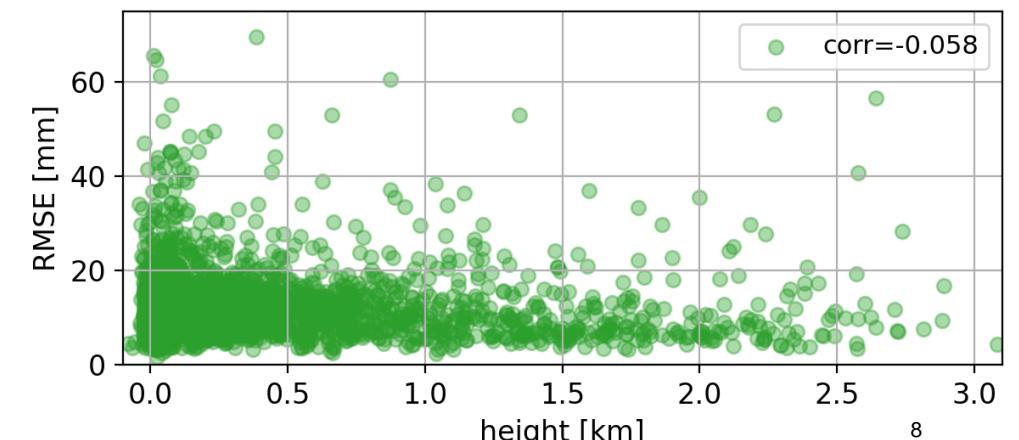
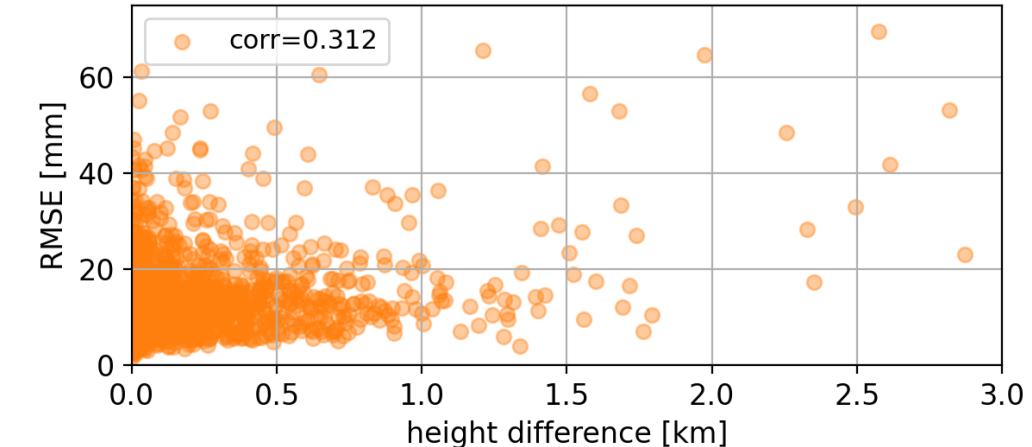
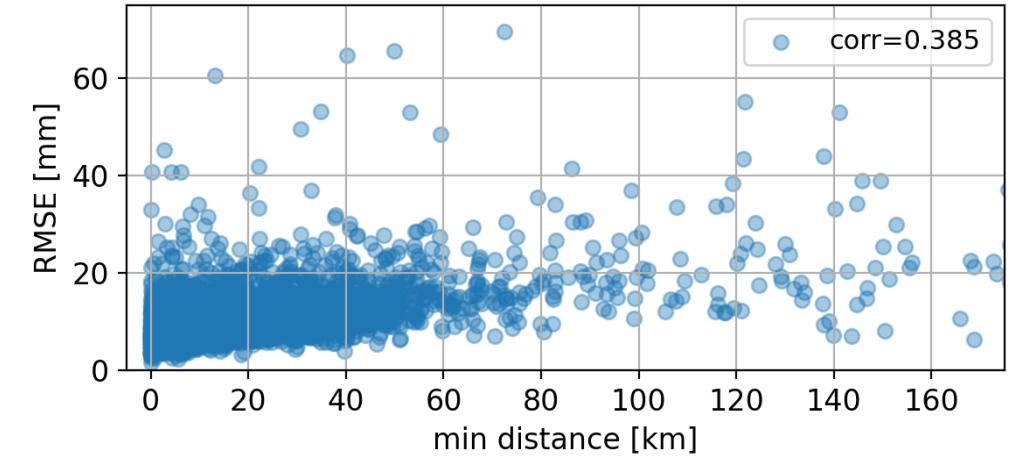
# ZWD predictions for 2019



# Understanding the performance

## Comparison between RMSE and ...

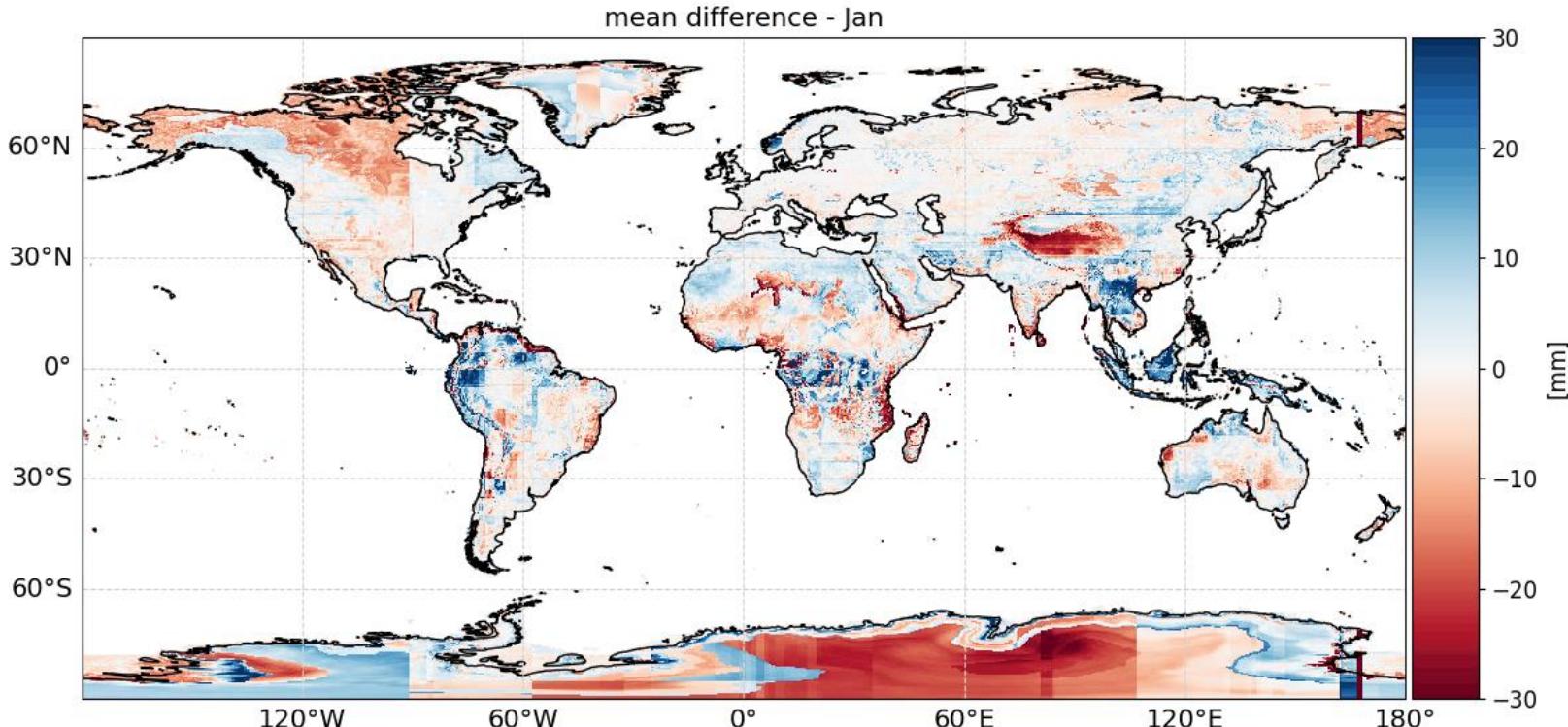
- minimum distance to next training station  
→  $\text{corr} = 0.34$
- height difference to next training station  
→  $\text{corr} = 0.31$
- height of GNSS station  
→  $\text{corr} = -0.06$



# Comparison between RF and XGBoost

## Mean difference over each month for the year 2019

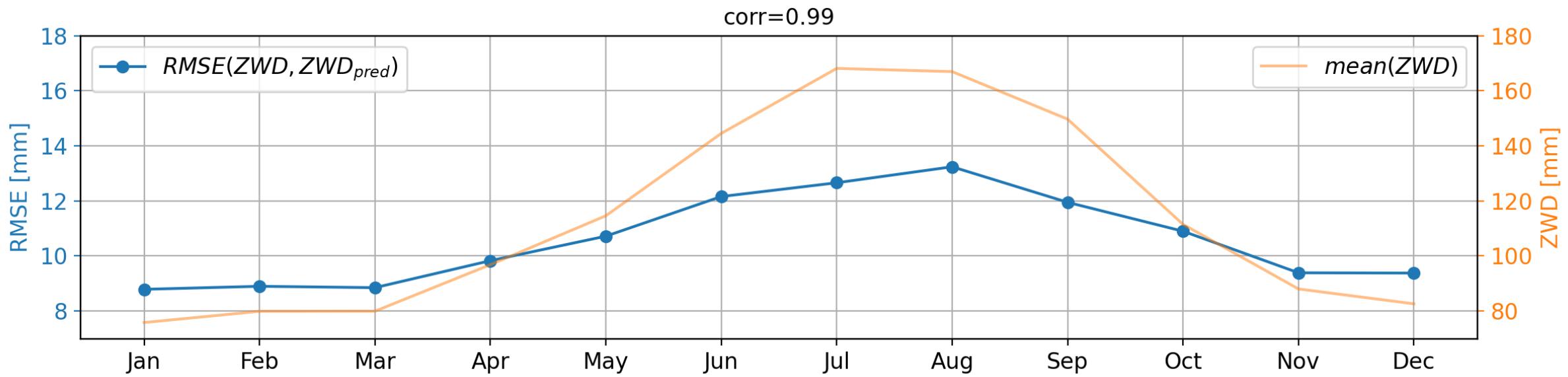
- Calculated ZWD predictions for year 2019, once with RF and once with XGBoost
- Took differences between RF predictions and XGBoost predictions
- Took mean over the differences for each month



# Monthly models – performance for testing stations

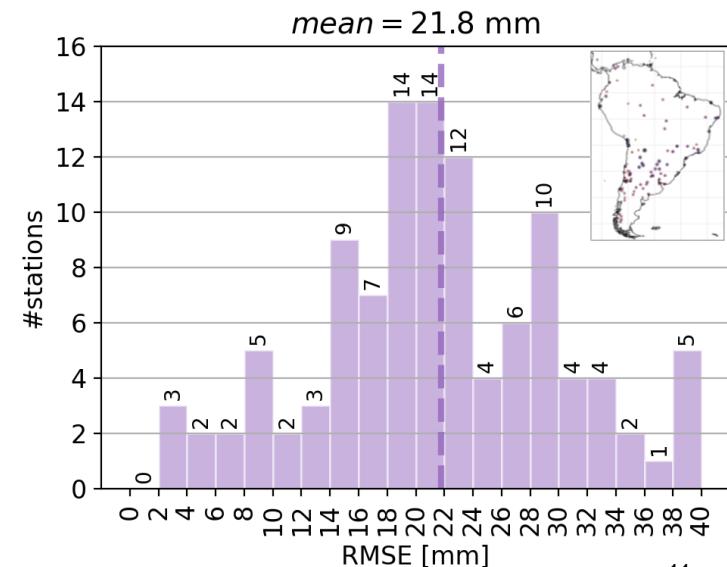
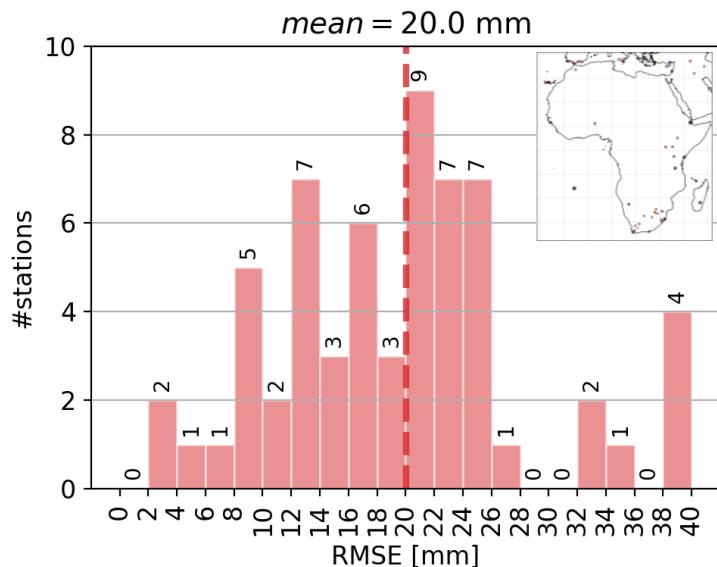
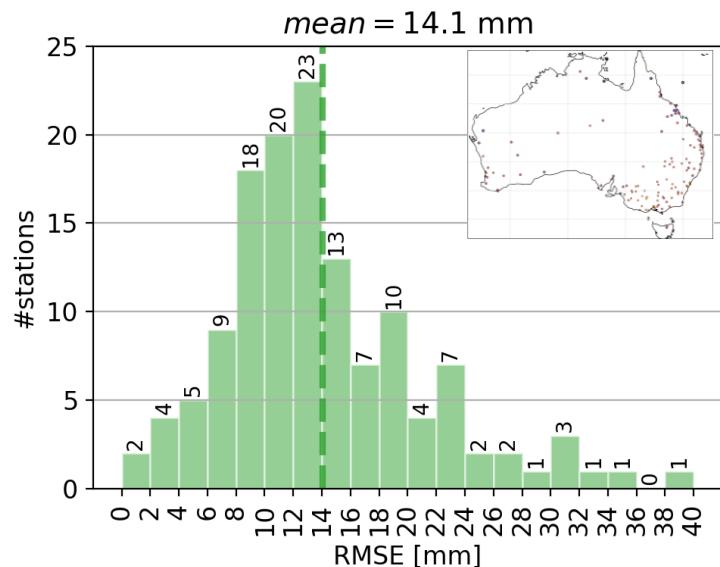
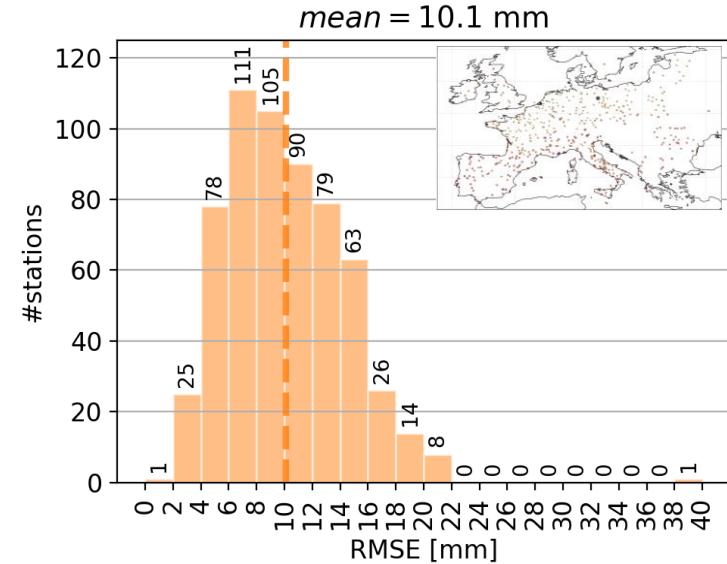
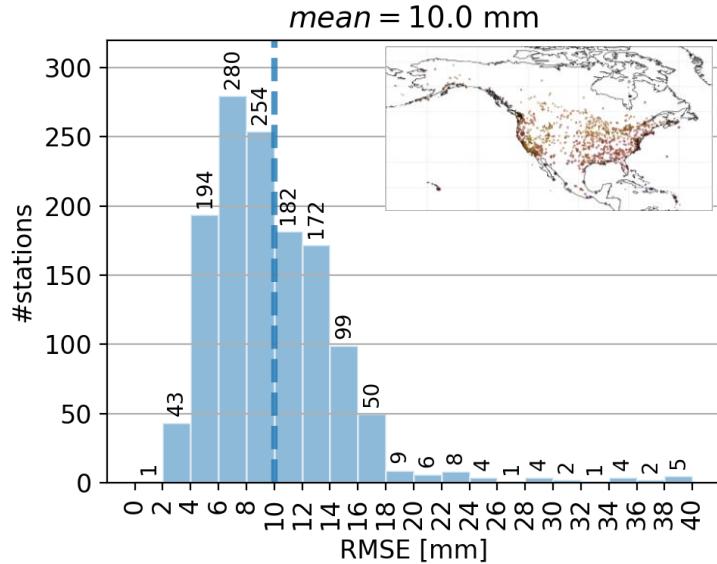
World 2019

RMSE [mm]													
Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	all months	
8.8	8.9	8.9	9.8	10.7	12.1	12.7	13.2	12.0	10.9	9.4	9.4	12.5	



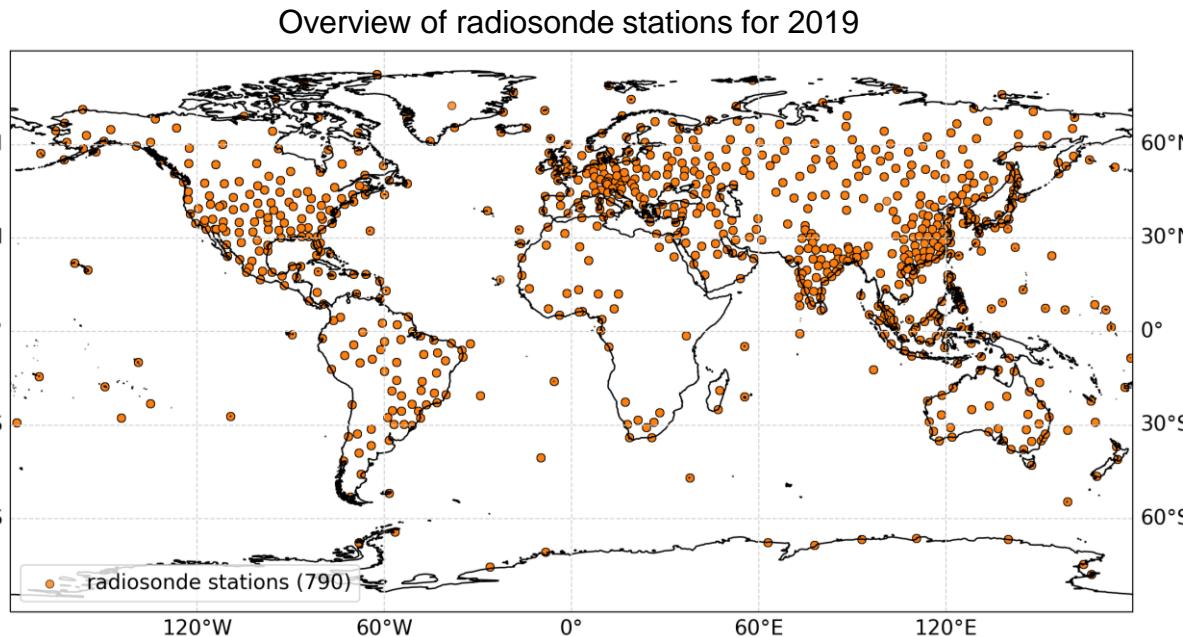
# Regional models for the year 2019

	RMSE [mm]	#stations
<b>North America</b>	10.0	6605
<b>Europe</b>	10.1	3004
<b>WORLD</b>	<b>12.5</b>	<b>13440</b>
<b>Australia</b>	14.1	665
<b>Africa</b>	20.0	302
<b>South America</b>	21.8	542



# Validation of ZWD predictions with independent methods

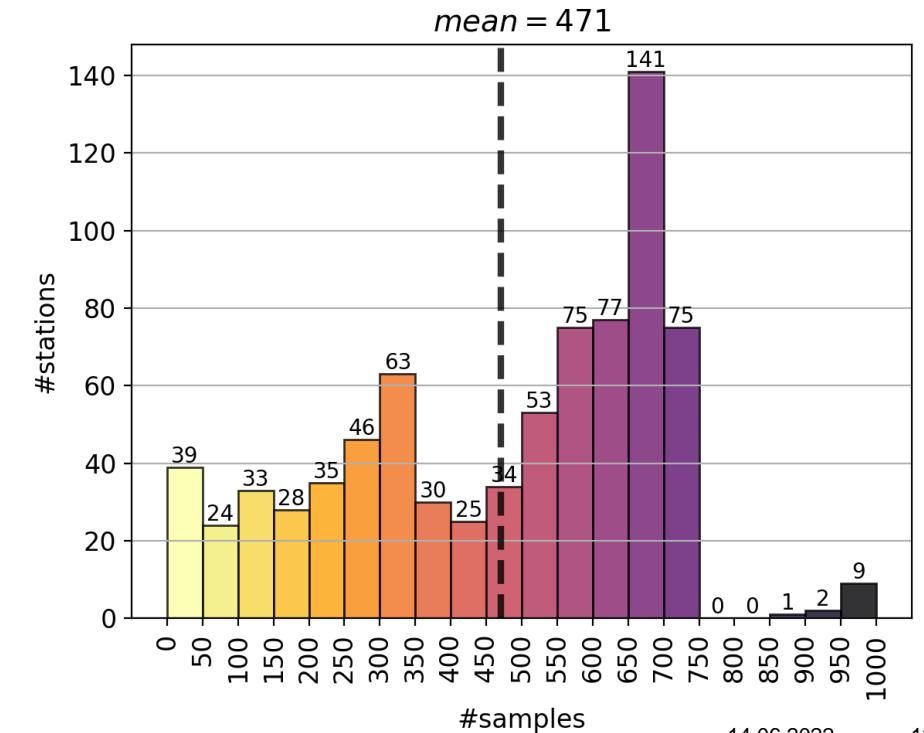
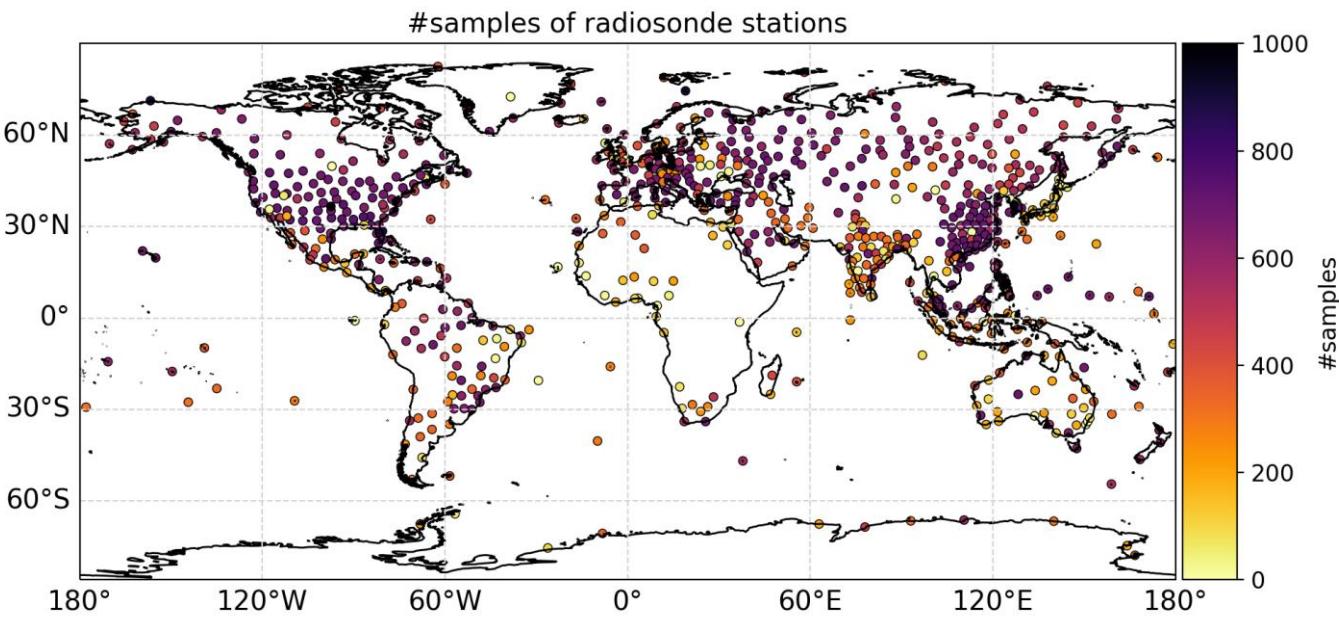
- Use **radiosonde data** to calculate ZWD
- Several options for validation:
  - Compare ZWD at locations where radiosonde data are available
  - Compare ZWD at locations where additionally a GNSS station is available



- 790 radiosonde stations available for 2019
- source:
  - Integrated Global Radiosonde Archive (IGRA)
  - <https://www.ncei.noaa.gov/pub/data/igra/>
- #samples differs for the stations

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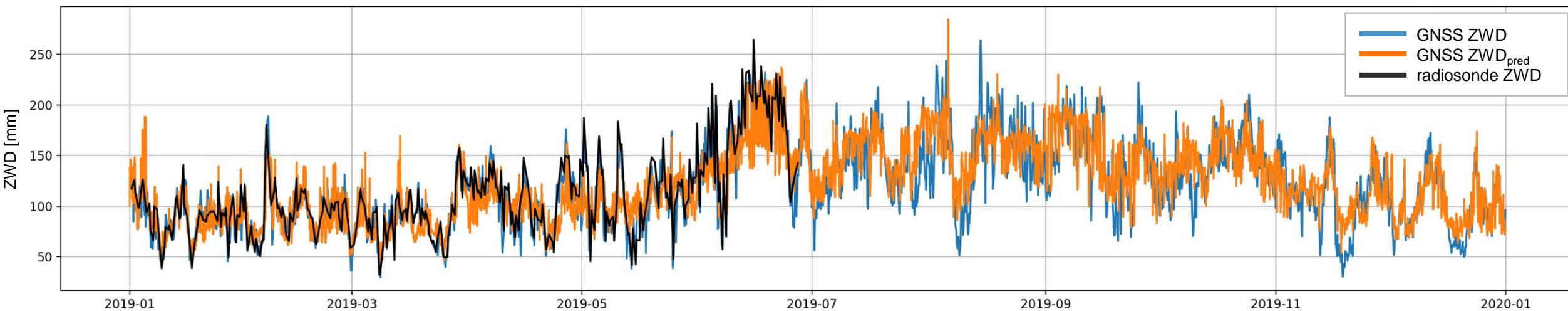


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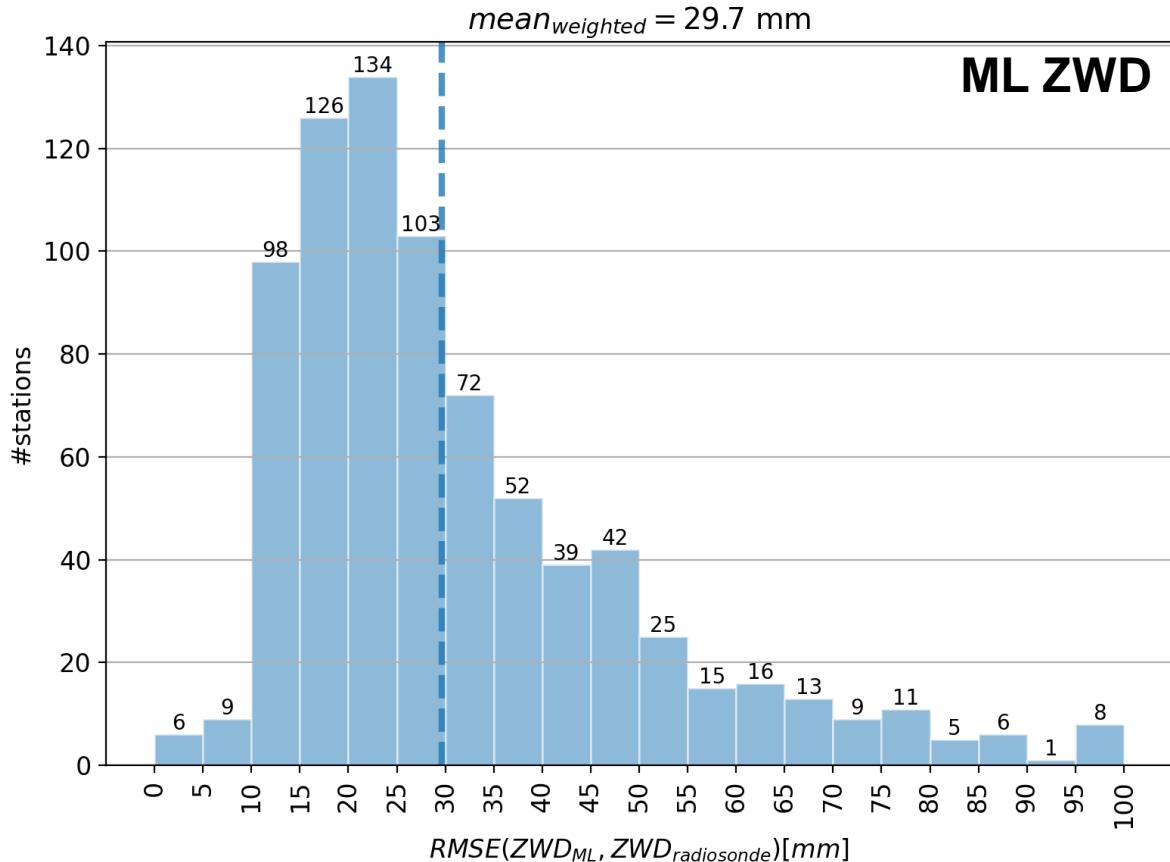
## Example time series

ZWD [mm] of radiosonde station 17607 and closest GNSS station NICO

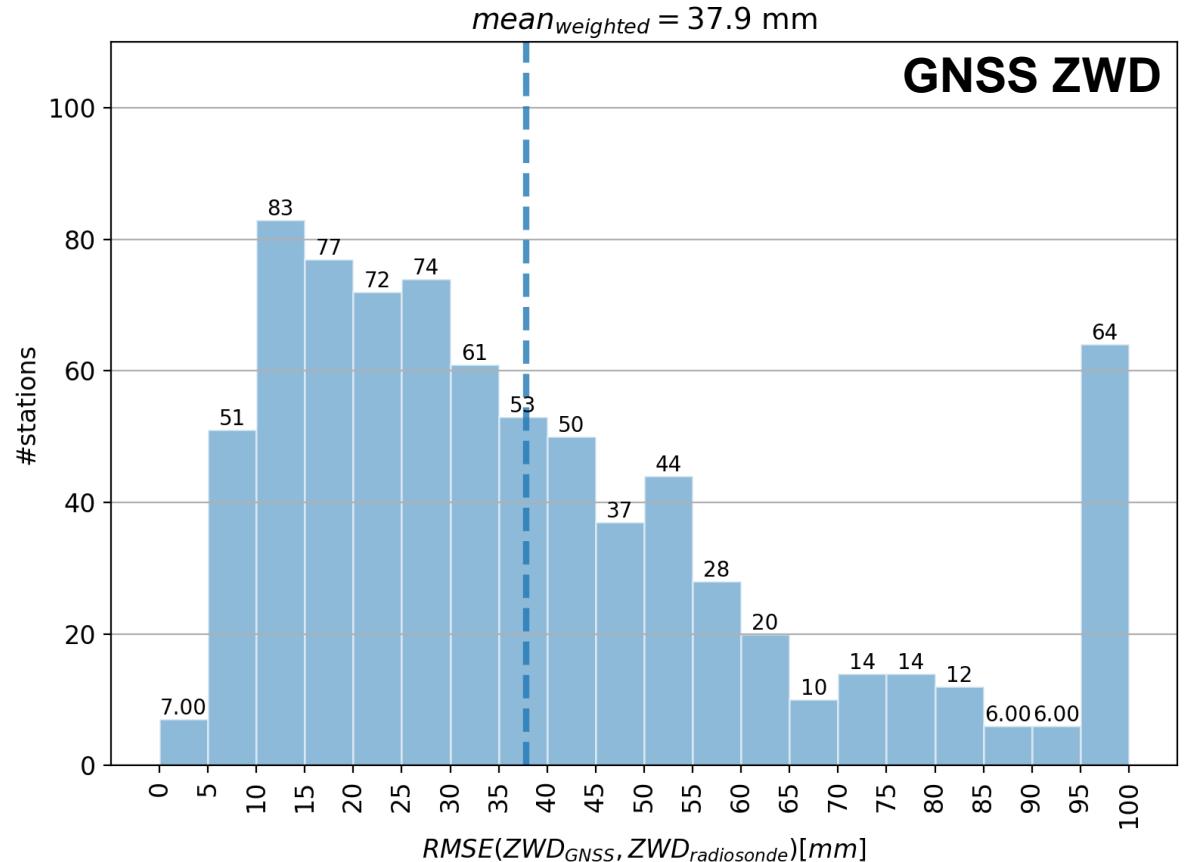


# RMSE between ZWD of ...

... radiosonde station and ML prediction



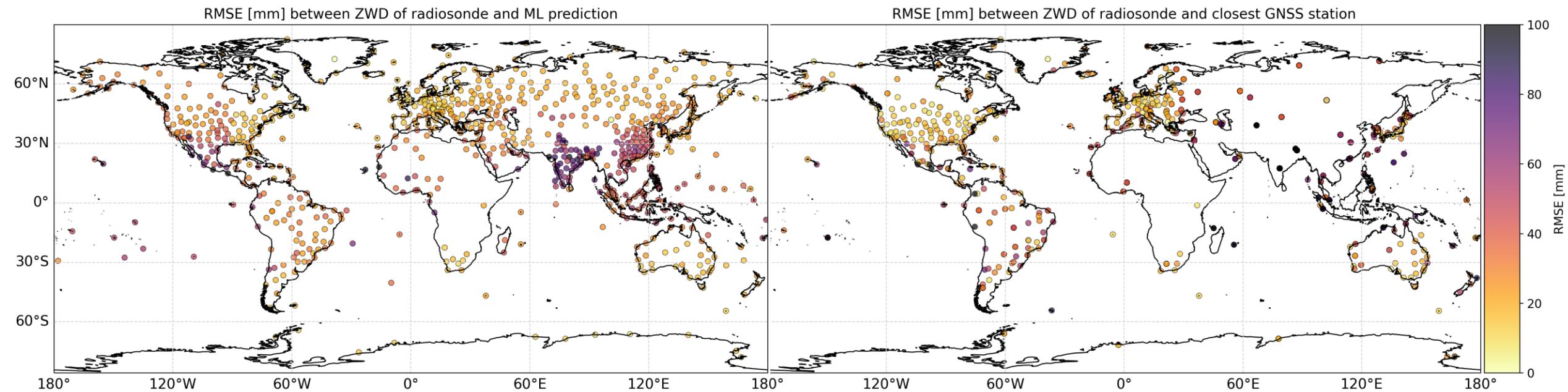
... radiosonde station and closest GNSS station



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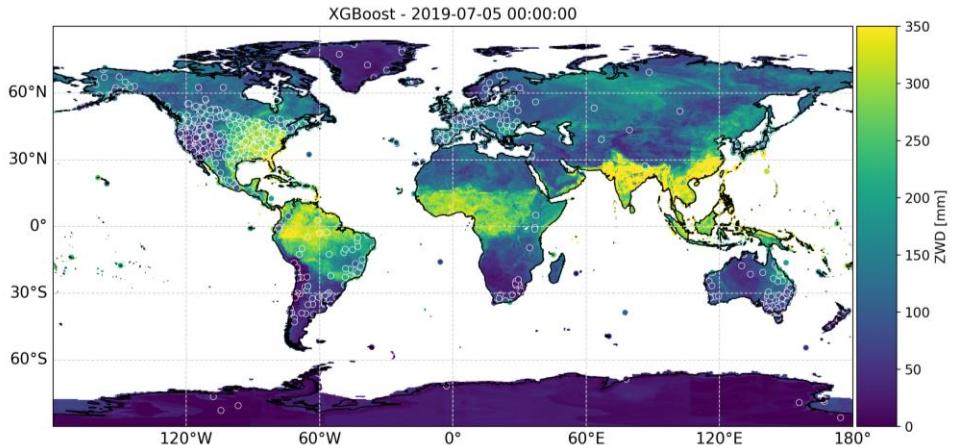
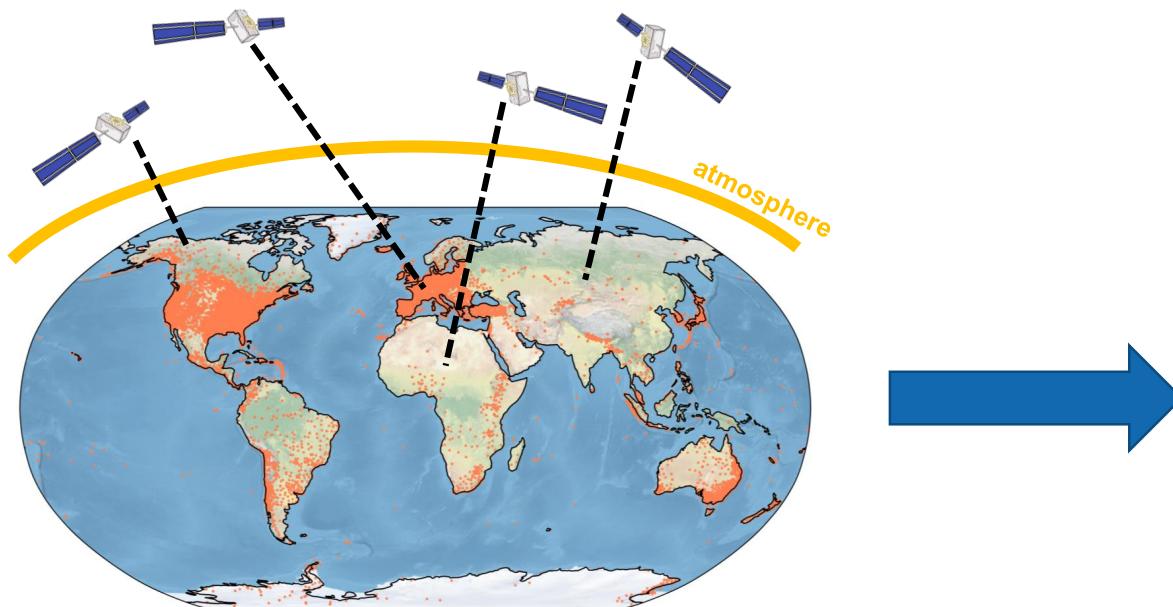
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... radiosonde station and closest GNSS station



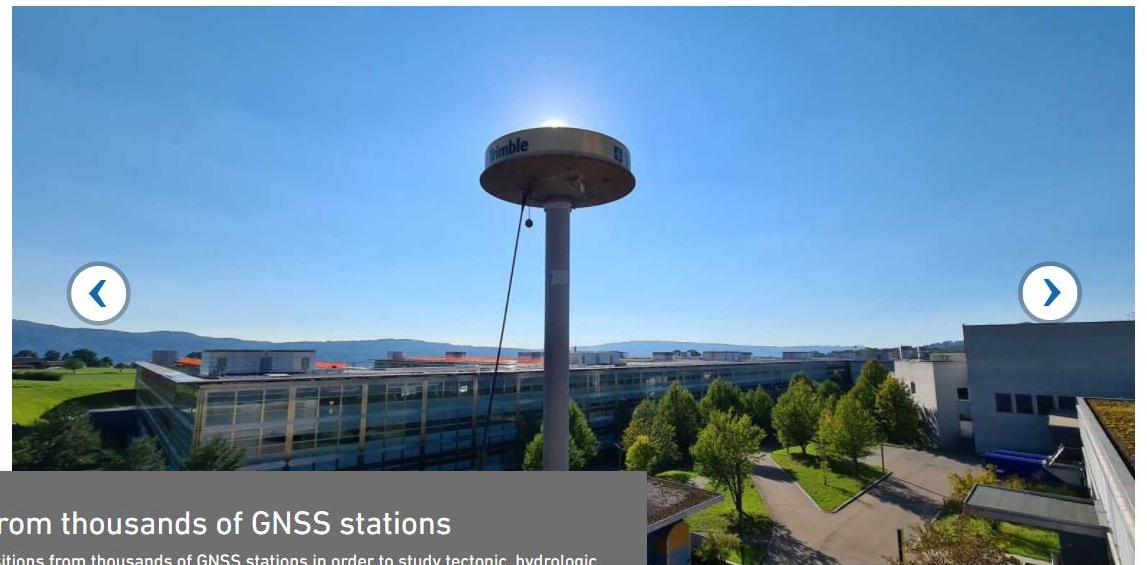
# Summary

- Global ML-based ZWD model based on meteorological data
- Can make predictions of ZWD for every point on Earth (assuming meteorological data is available)
- Achieves an average RMSE of **12.4 mm**
- ML algorithms: **XGBoost** and Random Forest



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#### Learning from thousands of GNSS stations

We analyse the positions from thousands of GNSS stations in order to study tectonic, hydrologic and other geophysical effects with machine learning.

