

# Assimilation of train based ZTD observations in AROME-RUC

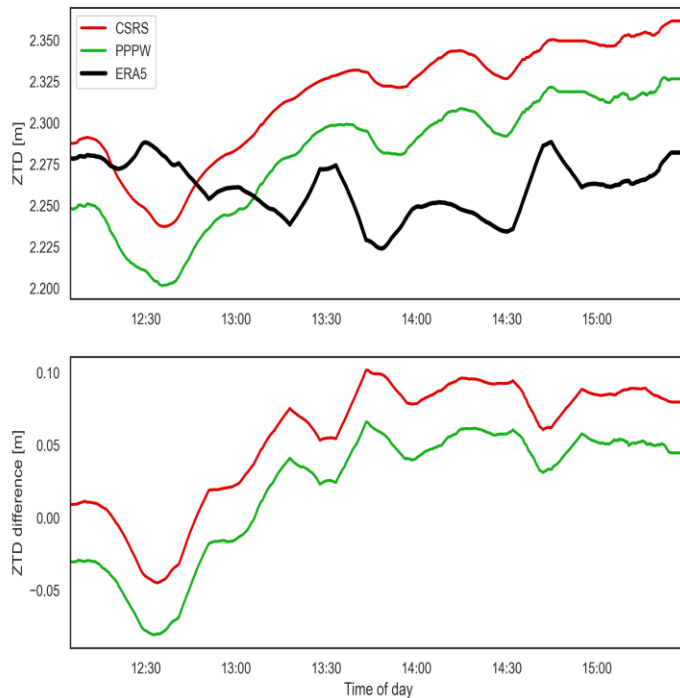
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- Introduction to the project **TRain**
  - Project triggered by PhD of Matthias Aichinger-Rosenberger at TU Vienna
  - One conclusion of PhD: Retrieval of ZTD observations based on GNSS receiver on moving trains works reasonably well
  - Start of project in September 2020
- ZTD observations from moving trains
  - Data set for a 4 weeks period in autumn 2021 was provided in summer 2022
  - How do data look like? How many trains per day, how is the coverage?
  - Usage of train data in AROME-RUC
  - Analysis of data/fg-departures to apply bias correction
- Case study (on-going work)
  - Impact of train based observations on AROME-RUC forecasts
  - Evaluation of different setups
- Conclusions/Outlook

# Motivation – Project history

- PhD at TU Vienna from Matthias Aichinger-Rosenberger dealt with the retrieval of ZTD data from GNSS-receivers on trains
- **Major challenges** have been an appropriate pre-processing and outlier detection of the data, and since only single-frequency observations are available a special treatment of the ionosphere has to be implemented. (PhD-thesis available online: <https://repositum.tuwien.at/bitstream/20.500.12708/17044/1/Aichinger-Rosenberger%20Matthias%20-%202021%20-%20Tropospheric%20parameter%20estimation%20based...pdf>)

Bad case

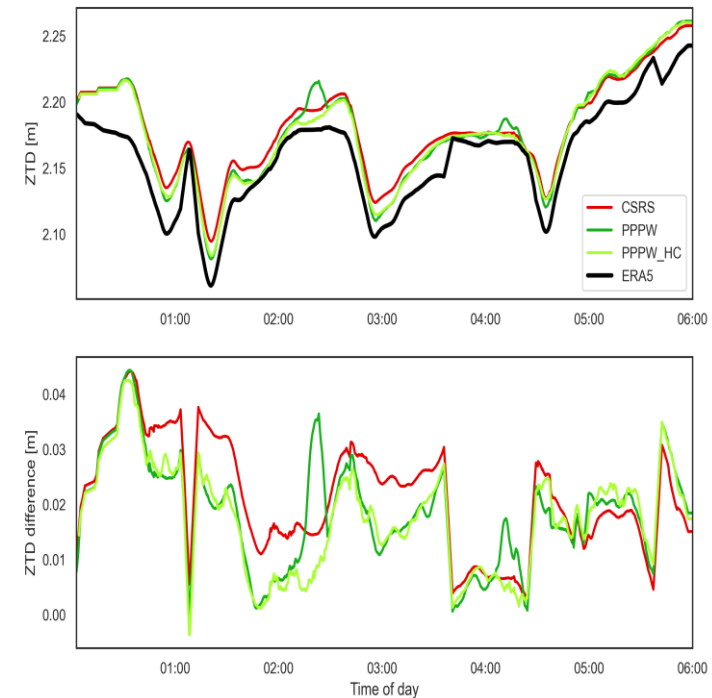


Courtesy of Matthias Aichinger-Rosenberger

3 out of 4 investigated cases showed high correlation with ERA5-ZTD data

In one case the observations were uncorrelated with ERA5 for parts of the track.  
Could also be caused by erroneous ERA5 data....

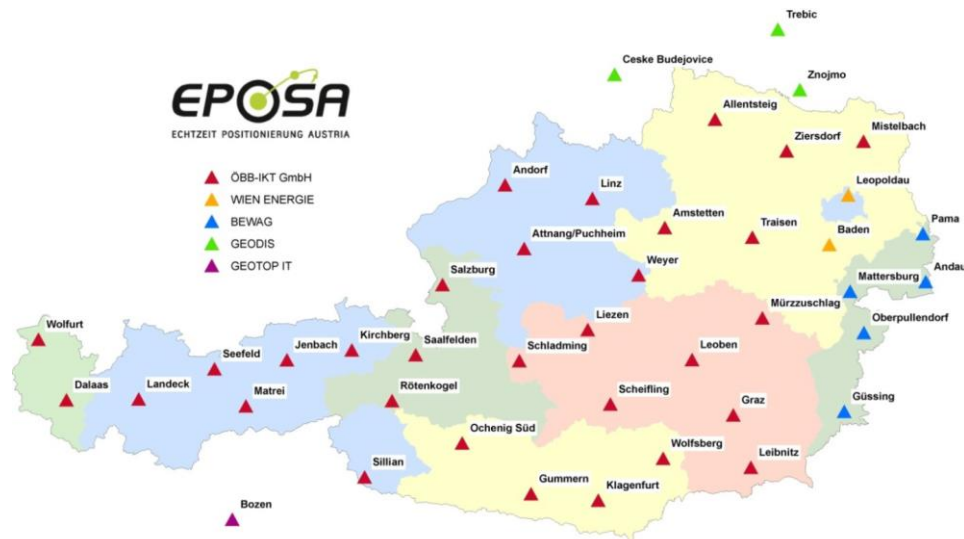
Example of good cases



Courtesy of Matthias Aichinger-Rosenberger

# Motivation – Project history

- Approx. 1500 Trains (freight and passenger trains) of federal railway company equipped with GNSS receivers and the number will even increase in the next years
- ZTD profiles with high resolution in space and time can be generated -> **Potential to increase the number of ZTD observations**
- Project started September 2020 and was prolonged to August 2023
- Delay in delivery of train based observations, data for one month period from Sep/Oct 2021 were provided in summer 2022

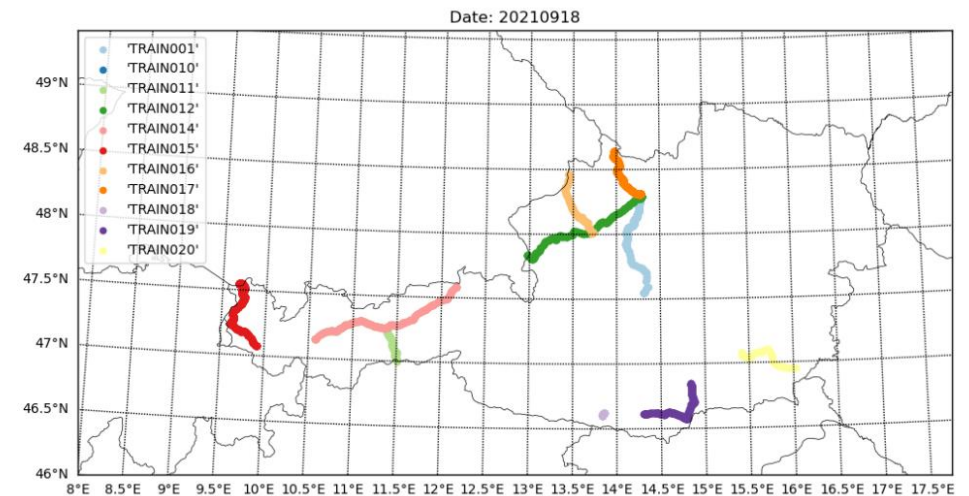
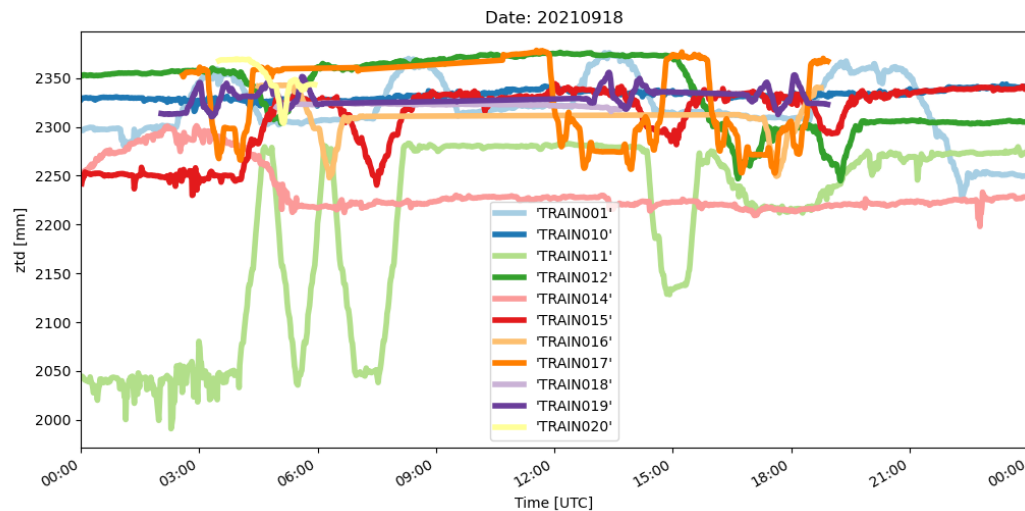


Source: OEBB 2017



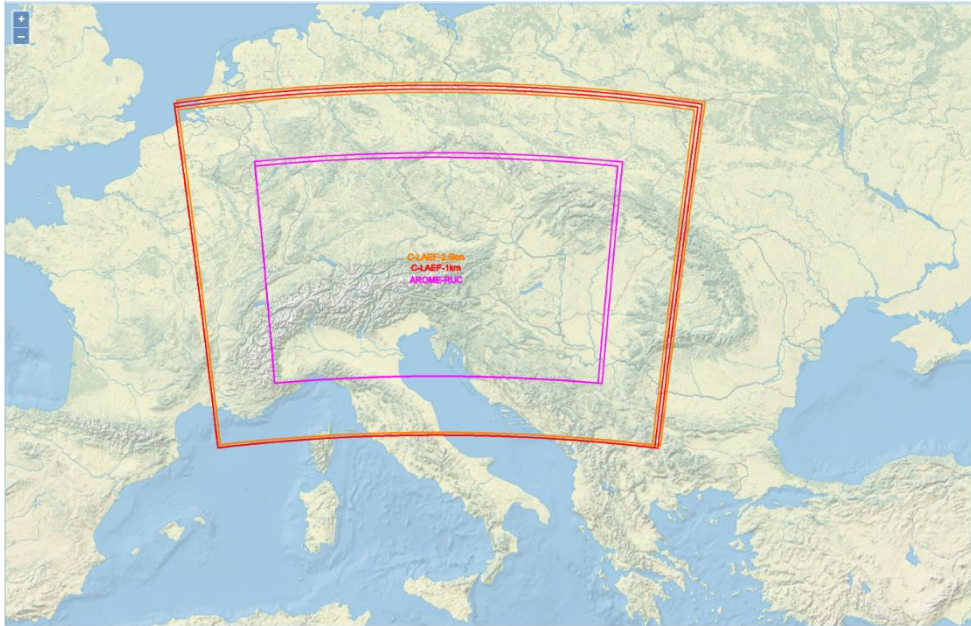
# Observation data set

- Data period from 9.9.2021 to 16.10.2021 with approx. 10 trains per day
- Raw data with 1 second time resolution, but processed data are averaged to 1 minute to reduce noise in the observations
- Trains are identified by a unique ID, trains are operating in the same area throughout the period but not necessarily every day on the exact same track
- Trains are not operating for the whole day, some have breaks or operate only for a limited time (train020)
- Some trains are circulating between two cities with remarkable height differences (train011)
- Question: How do bias behave if train operates in highly orographic terrain? How to apply bias correction?



# AROME-RUC setup and reference run

- Operational AROME-RUC setup with some limitations regarding availability of observations
  - > Radar, GPSRO, MODE-S MRAR, snow model are dismissed
- Station based GNSS observations with static bias correction
- Period 9.9. – 19.9.2021 serves as training period, for spin up and to calculate bias correction factors
- 20.9.2021 – 16.10.2021 is evaluation period



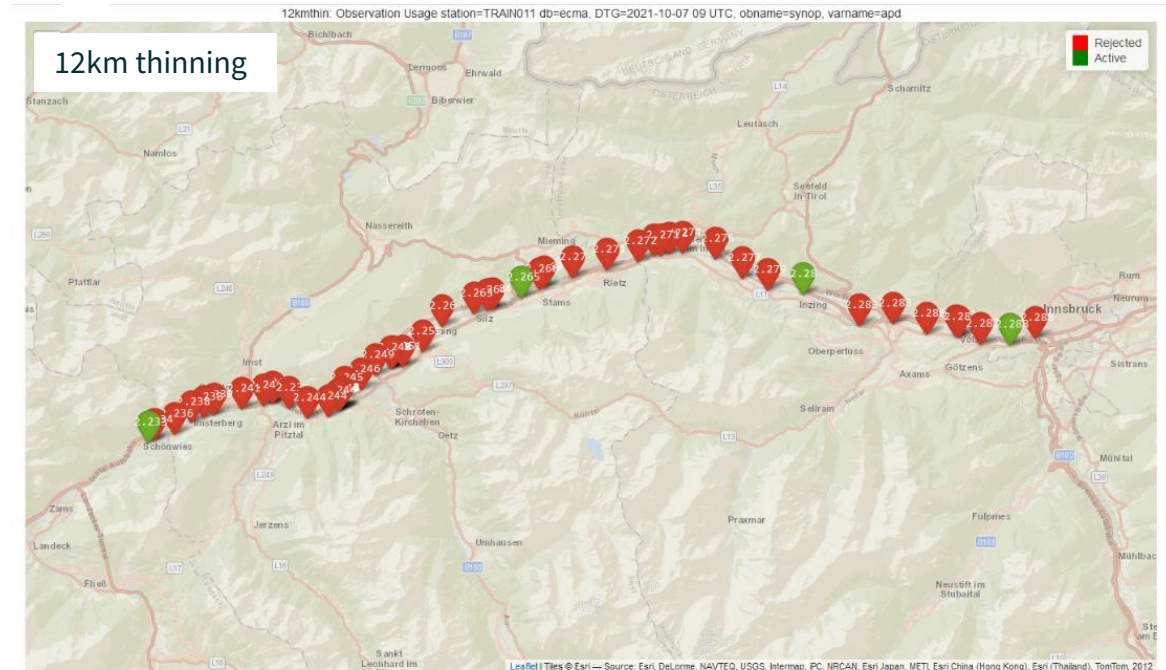
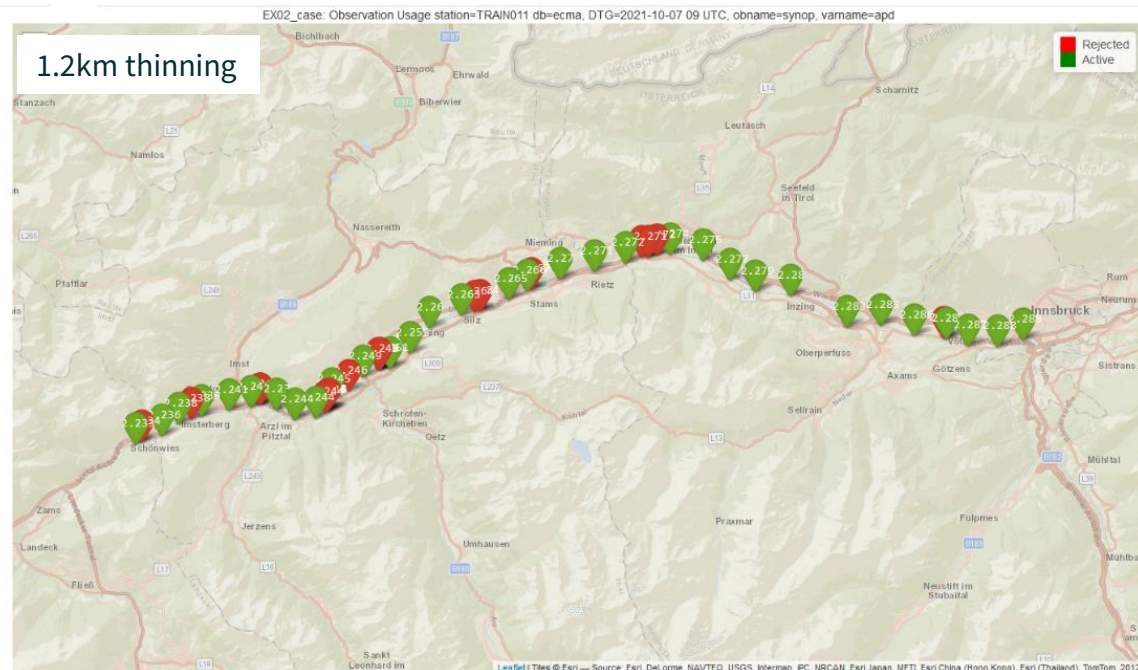
	AROME-RUC
Model version	cy43t2bf11
Resolution	1.2km
Area	Austrian area (900x576)
Members	1
Levels (lowest/highest)	90 (5m / 35km)
Starting times	00, 01,...,22,23 UTC
Forecast range	12 hours(05UTC+25h)
Time step	30s
Output Frequency	15min 2D/1h 3D
Orography / physiography	SRTM 90m ECOCLIMAP 1
LBC model	AROME-Aut
LBC update	1h
Surface scheme	SURFEX 8.0
Initial conditions (3D / Surf.)	3DVAR / OI +IAU+Nudging/LHN
Cycle interval	1 hour
Assimilation Window	-90min+30min
B-Matrix	AROME-RUC EDA climatologic
Hardware	HPE Apollo 8600 (ZAMG)

Observation Type	Parameter assimilated	AROME-RUC	Experimental mode
SYNOP/TAWES	U10m, V10m, Z, T2m,RH2m	x	x
AMDAR, MODE-S (Flugzeuge)	U,V,T,Q	x	x
MODE-S MRAR (Flugzeuge)	U,V,T	x	
GEOWIND (SAT-Winde) MSG3	U,V	x	x
GEOWIND-HR (SAT-Winde) MSG3	U,V	x	x
TEMP (Radiosonde)	U,V,T,Q,Z	x (bufr)	x
PILOT	U,V	x	x
WINDPROFILER, SODAR	U,V	x	x
SCADA	U,V,T	x	x
MSG3-SEVIRI	WV-radiances	x	x
NOAA16/18/19/20/SNPP/MetOp-B-C AMSU-A, MHS, ATMS	radiances	x	x
MetOp-B-C IASI	radiances	x	x
ASCAT wind	U10m,V10m	x (12,5km)	x
RADAR	reflectivity / radial winds	x	
INCA-RR	RR 5min latent heat nudging	x	x
SNOWGRID Schneemodell	snowheight/density	x	
GNSS	ZTD ( optional STD)	x	x (static bias corr.)
Radio Occultation	GPSRO bending angles	x	
ZTD on trains	ZTD		x
T-LAKE	T Water	x	



# Include train observations in 3D-Var

- Necessary code adaptations to allow usage of ZTD observations from moving trains (pretty much hard coded at the moment):
  - Call spatial thinning method for ZTD obs from trains (reuse thinning code for ships); thinning threshold hard-coded
  - Adaptions in filter\_gpssol/write\_obsoul\_gpssol to handle multiple entries with same statid: apply static bias correction, skip location check
  - Blacklisting in case trains should be used only in passive mode

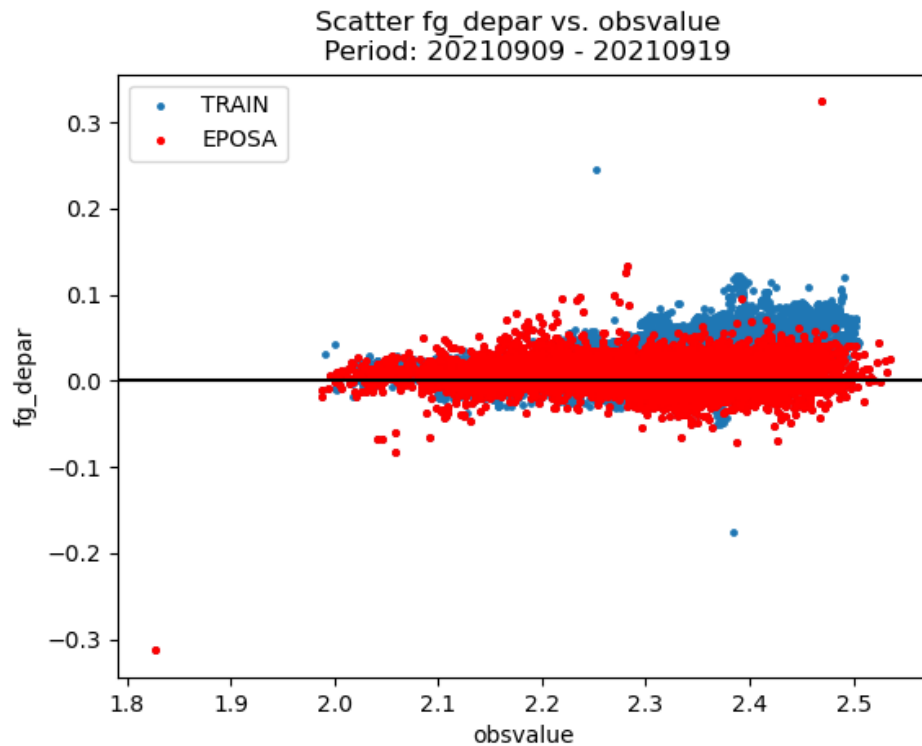


*Demonstration that it technically works*

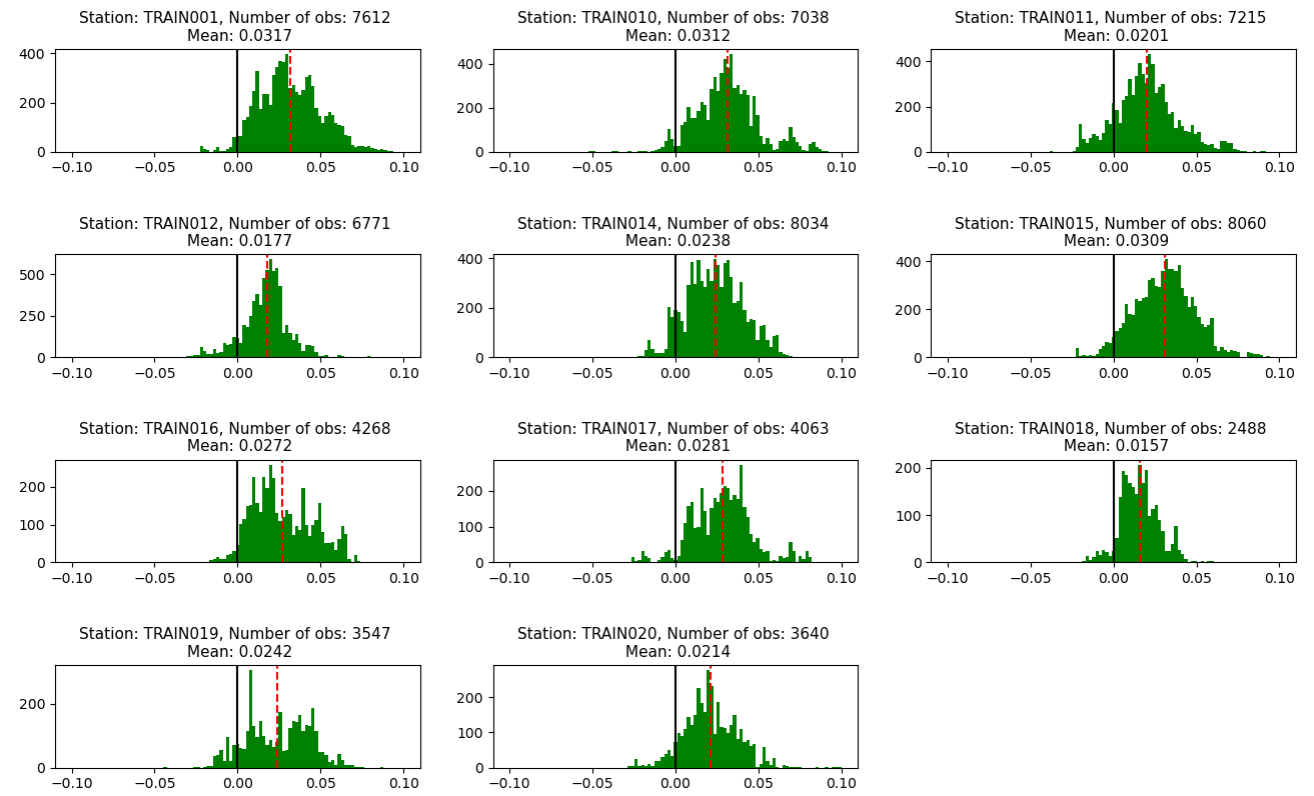
# Analyse first guess departures from trains

- Reference run with passive assimilation of train based ZTD for the first 10 days of period under study
- Spatial thinning of passive train observations 200m
- Observation error for train observations 0.02m

## Both data set without bias correction



Histogram of fg-departures by Train ID  
period: 20210909 - 20210919



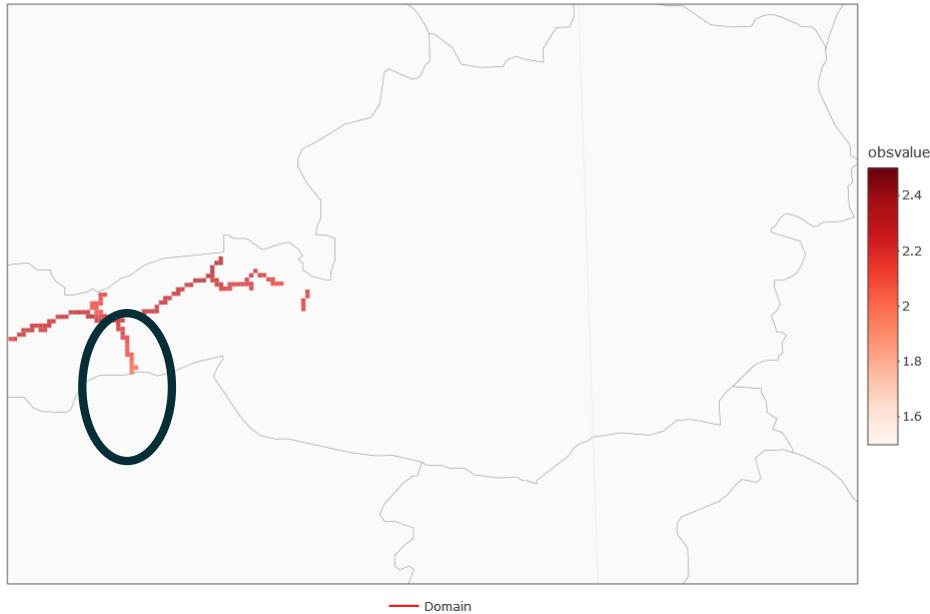
Used to populate LIST\_GPSSOL for static bias correction



# Analyse first guess departures from trains

REF: Average Observations Map  
station=TRAIN011

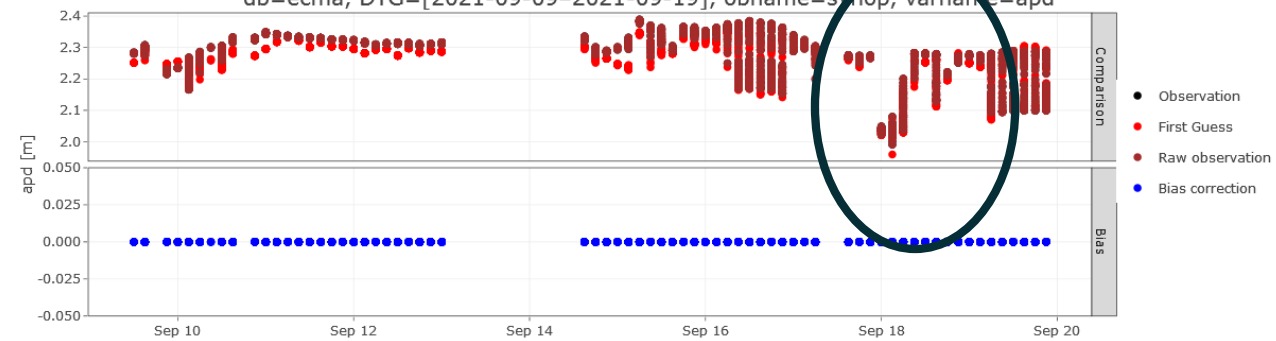
db=ccma, DTG=[2021-09-09-2021-09-19], obname=synop, varname=apd



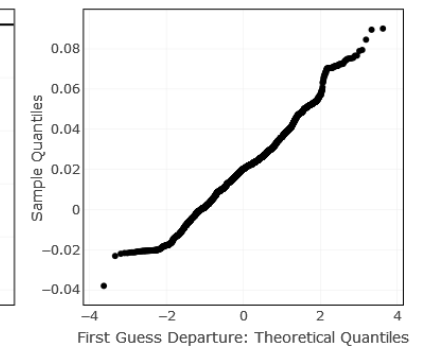
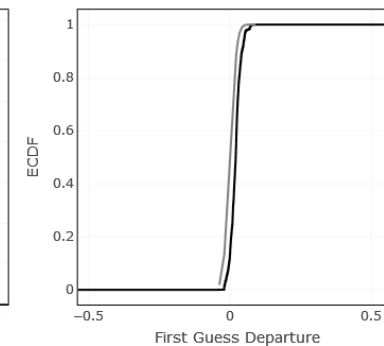
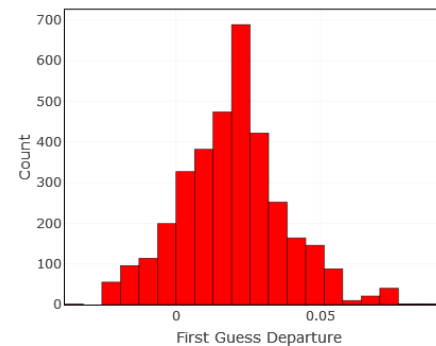
- Data extraction for obsmon only every 3 hours
- Train operates in the area of Innsbruck
- 18/9/2021 train was moving between Innsbruck (570m) and Brenner Pass (1400m) in the morning

REF: Station Diagnostics  
station=TRAIN011

db=ecma, DTG=[2021-09-09-2021-09-19], obname=synop, varname=apd



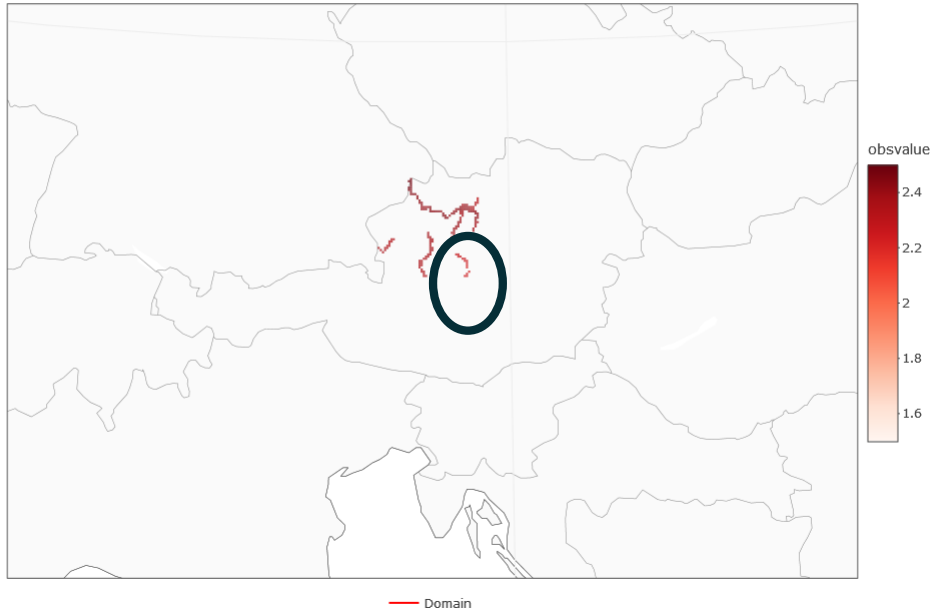
- Histogram of fg-departures indicate positive Bias
- Q-Q Plot confirms assumption of normal-distributed data set



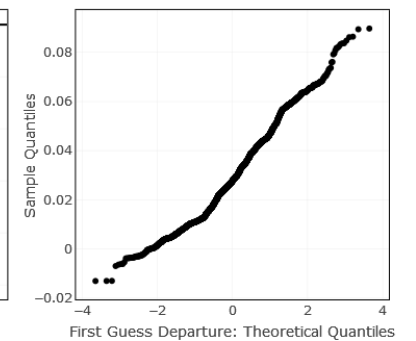
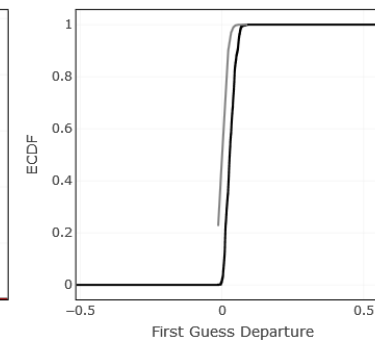
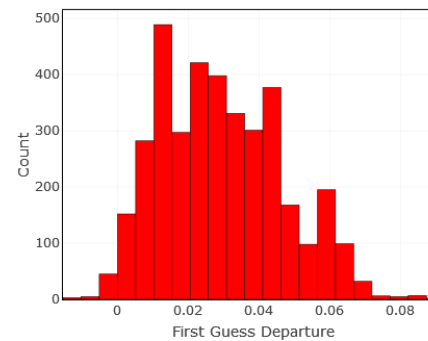
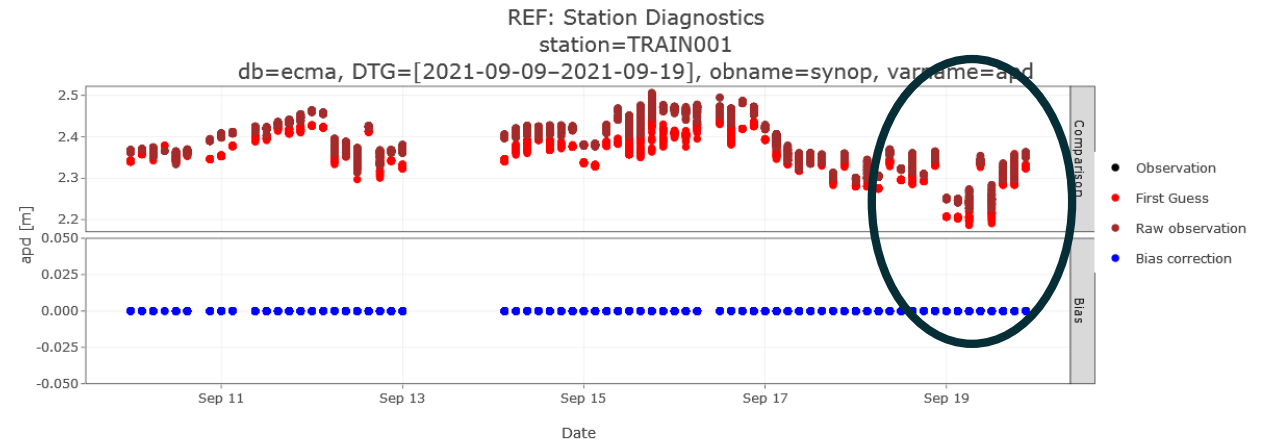
# Analyse first guess departures from trains

REF: Average Observations Map  
station=TRAIN001

db=ccma, DTG=[2021-09-09-2021-09-19], obname=synop, varname=apd

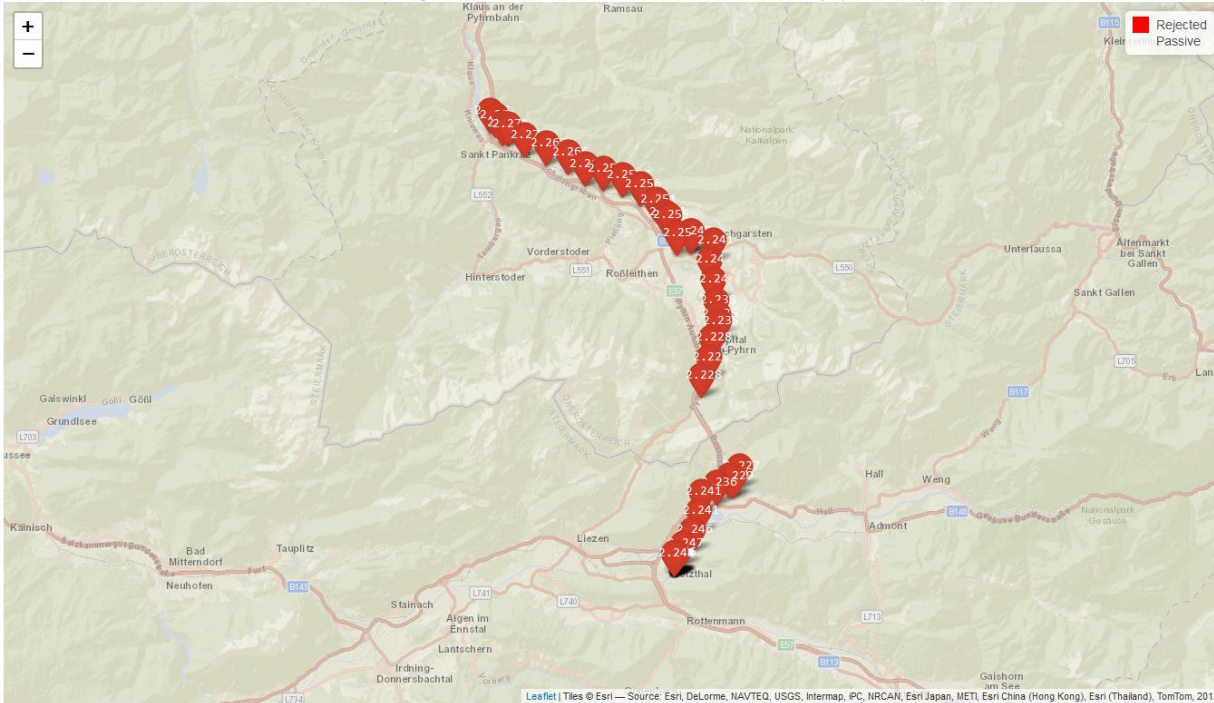


- Data extraction for obsmon only every 3 hours
- Train operates in upper Austria, both in relatively flat and orographic terrain
- 19/9/2021 moves along narrow valley



# Analyse first guess departures from trains

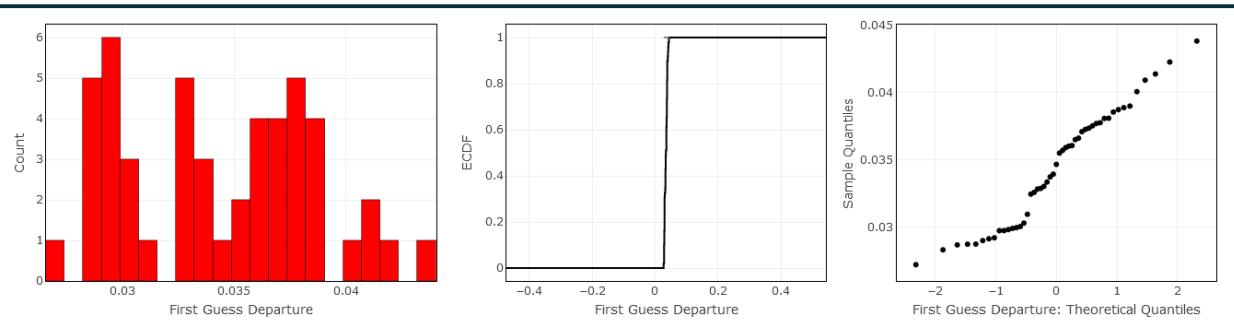
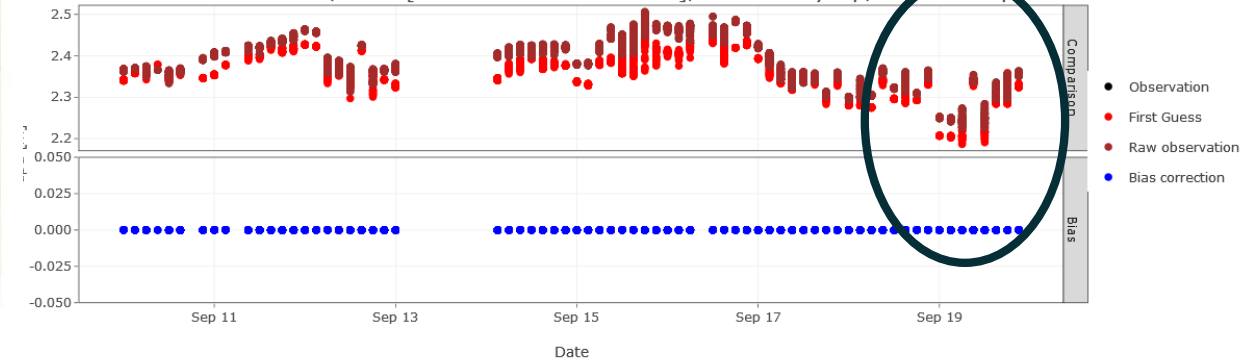
REF: Observation Usage station=TRAIN001 db=ecma, DTG=2021-09-19 06 UTC, obname=synop, varname=apd



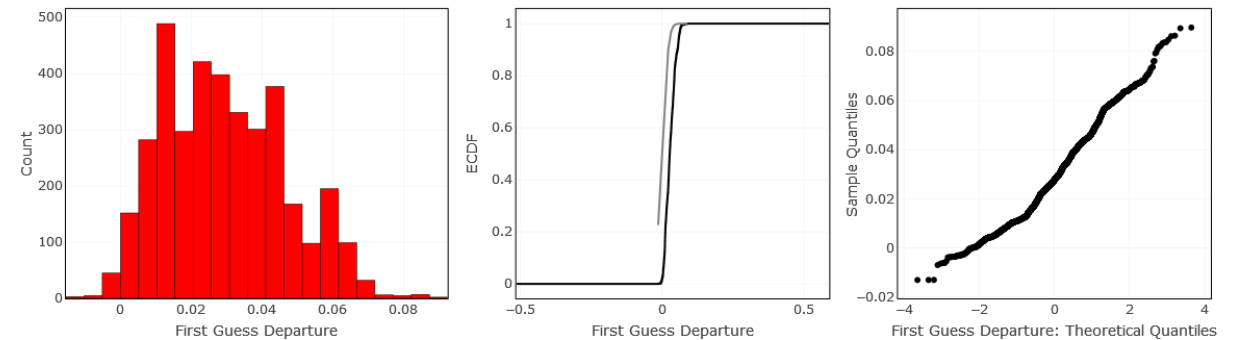
- Even in complex terrain with tunnels data quality seems to be reasonable
- FG-departure distribution for 6 UTC run on 19/09/2021 is in the middle of 10-day distribution

REF: Station Diagnostics  
station=TRAIN001

db=ecma, DTG=[2021-09-09-2021-09-19], obname=synop, varname=apd



06 UTC run on 19/09/2021



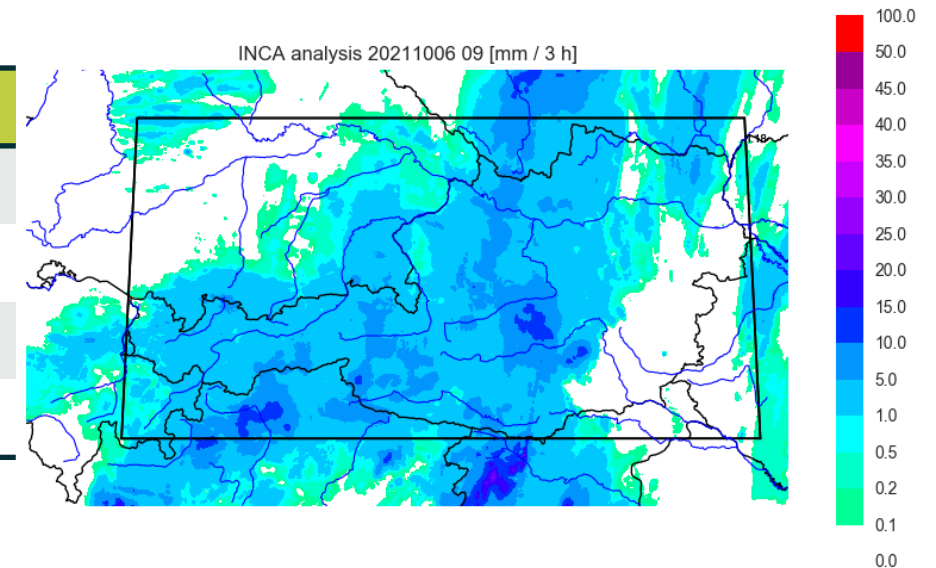


# Case study 6.10.2021

Finding optimal setup for assimilation of train based ZTD observations:

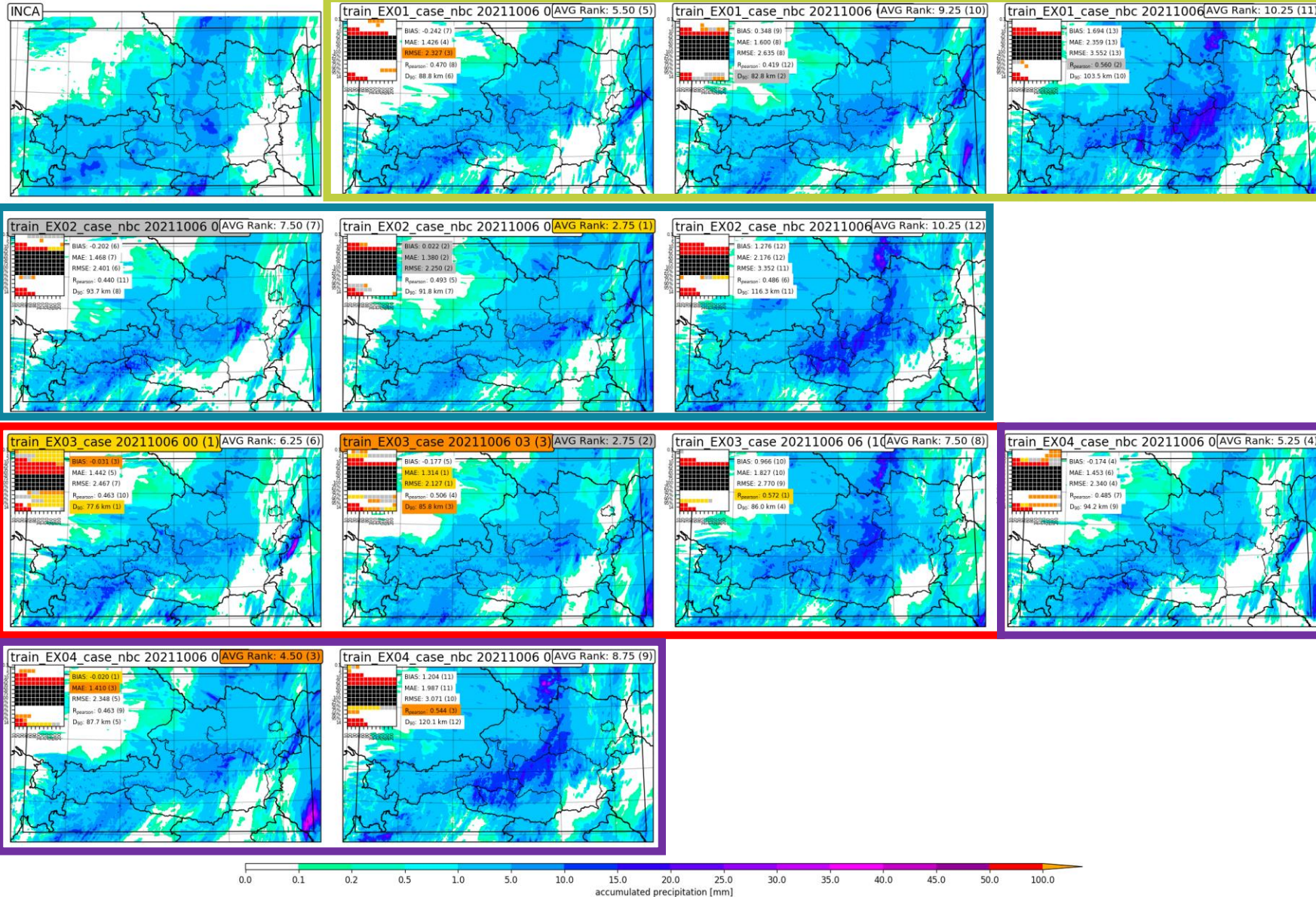
- Running case studies to evaluate impact of train observations
- Reference run (less observations than operational AROME-RUC) with static bias correction for stationary GNSS receivers
- Case selected as station based point verification revealed strong positive bias for 6 UTC precipitation forecast
- Experiments initialized on 5.10.2021 00 UTC with identical initial conditions
- Evaluation based on precipitation up to now

Experiment	Static GNSS	Train GNSS	thinning
<b>REF</b>	<b>X</b>		
incl_trains	<b>X</b>	<b>X</b>	1200m
Only_trains		<b>X</b>	1200m
12km_thin	<b>X</b>	<b>X</b>	12000m



# Case study 6.10.2021

Acc. Precip. 1mm1 from 20211006 06 to 20211006 09 UTC



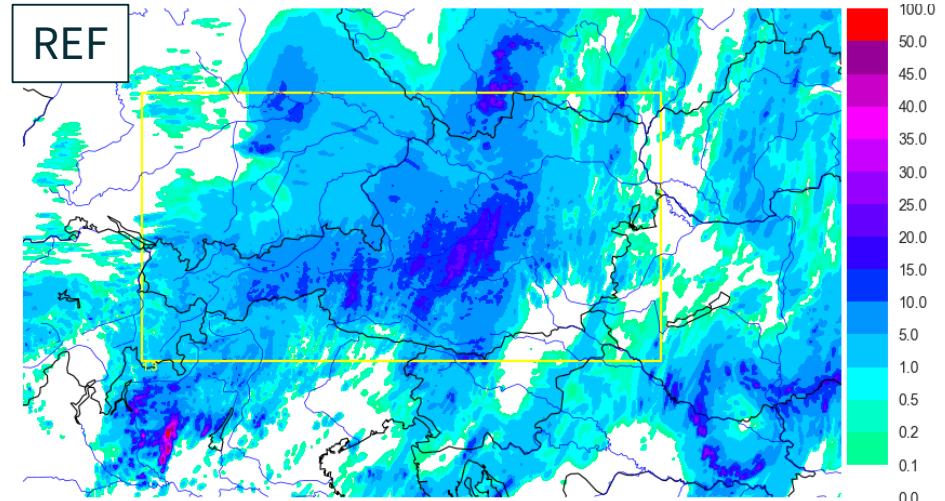
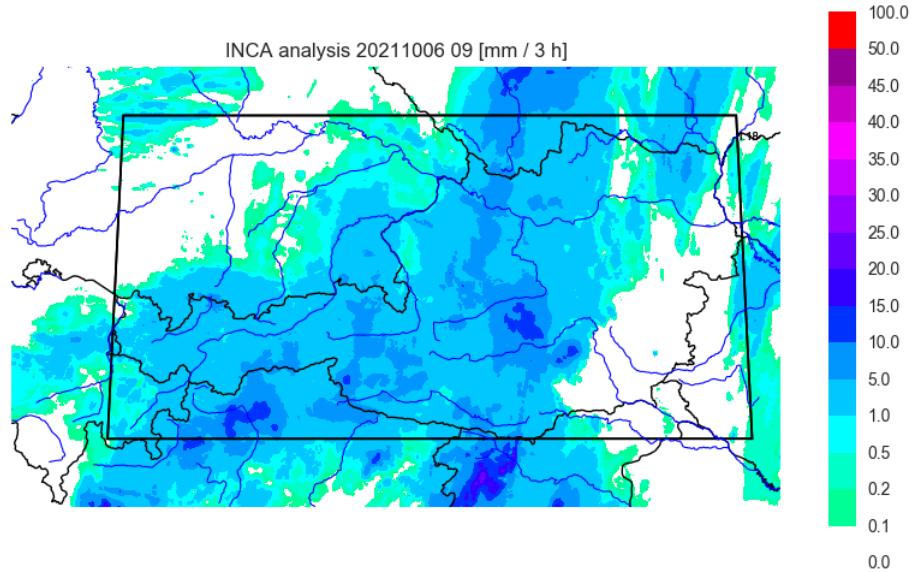
**REFERENCE**  
Trains included  
**Only trains**  
12km tinning

**Nice:** Including train data is beneficial for that case study

**Not so nice:** Runs with longer lead times perform better than short lead times

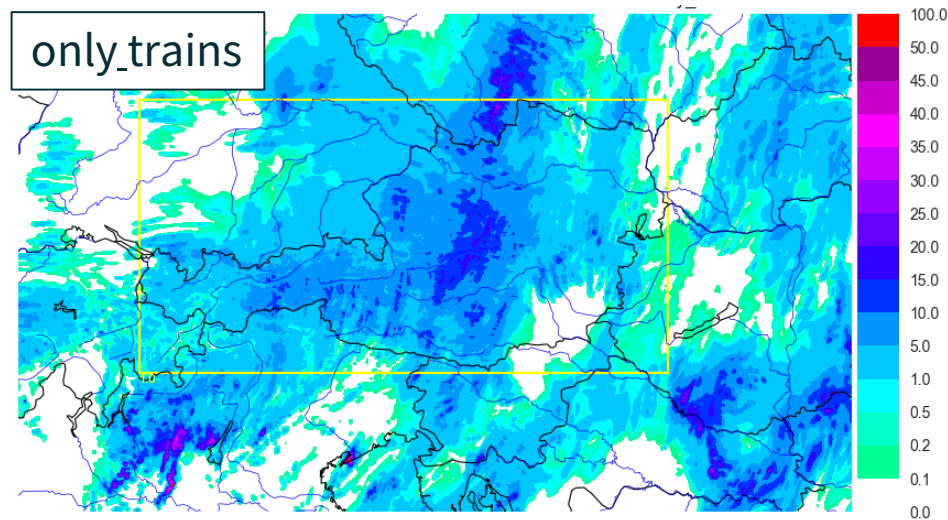
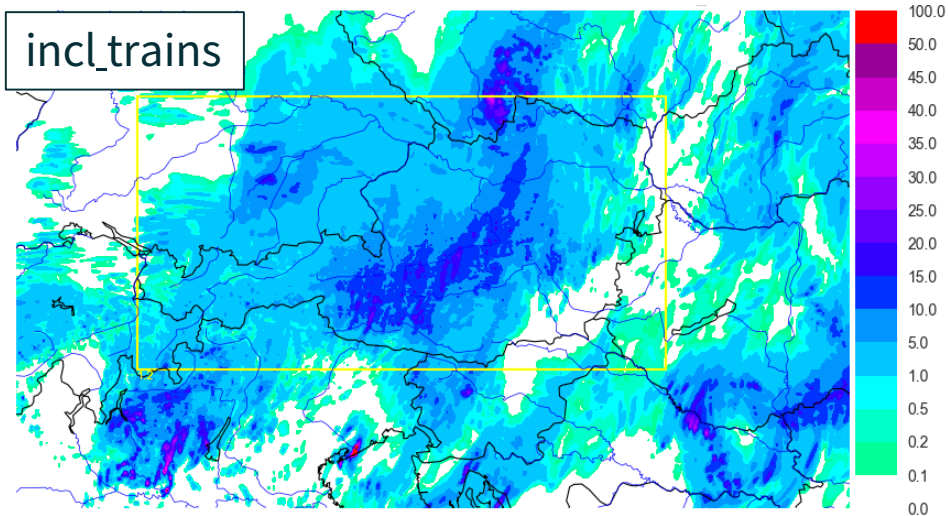


# Case study 6.10.2021, initialized at 06 UTC



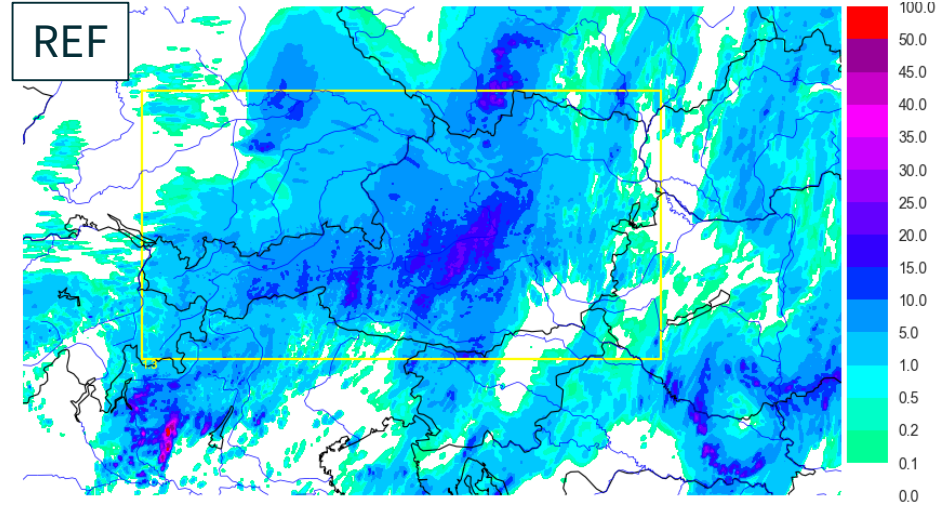
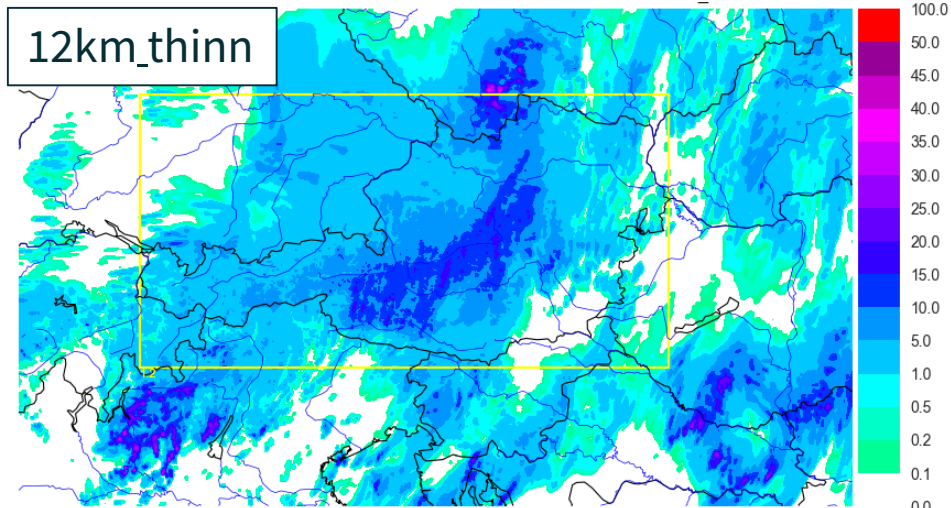
**REF:** overestimates prec amount

For this case, trains reduce humidity in the analysis, while some stations especially in central Alps depict negative fg-departures -> introduce moisture



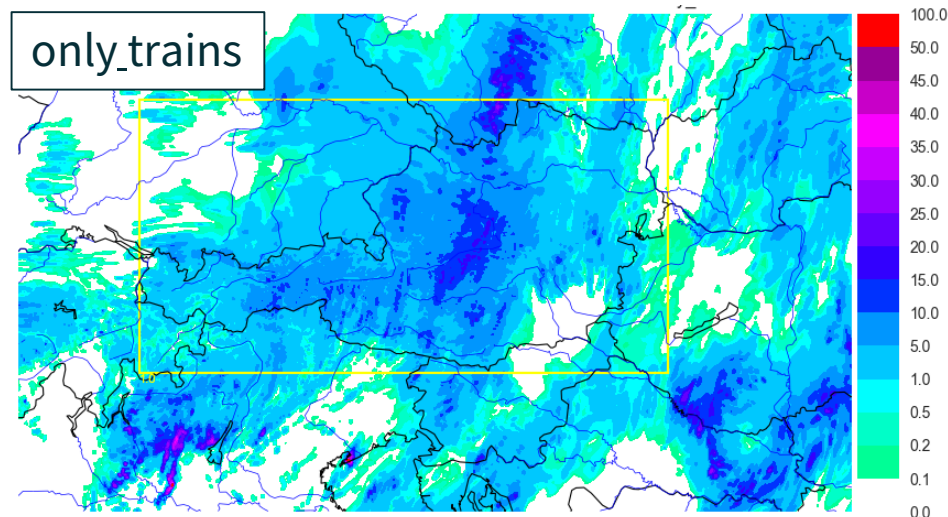
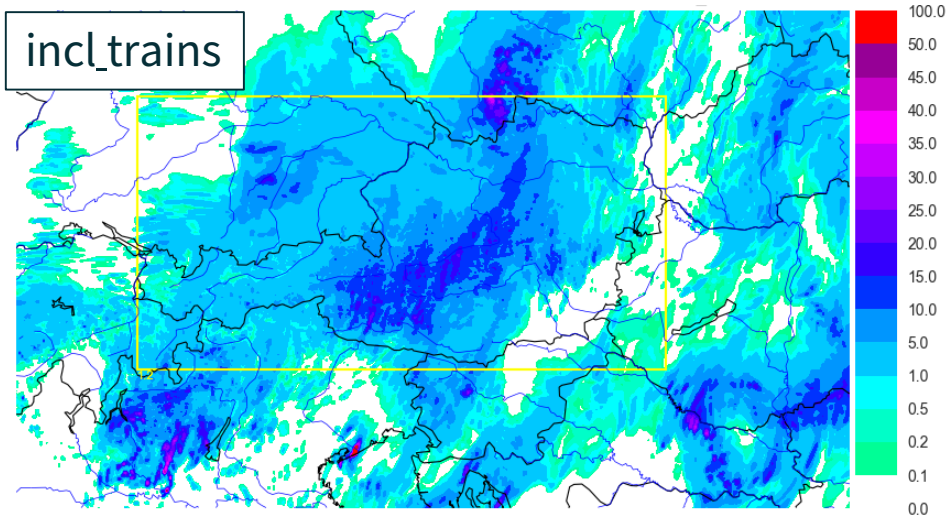


# Case study 6.10.2021, initialized at 06 UTC



**REF:** overestimates prec amount

With stricter thinning impact of trains is reduced -> precipitation forecast is in the middle between REF and incl trains



# Summary and outlook

## Summary:

- Approx. one month of data are available
- Train based ZTD observations look surprisingly good even in very complex terrain
- Simple bias correction by train-ID seems to do its job reasonably well
- Further testing of best setup required

## Outlook for the project:

- Can we apply VARBC? Height dependent predictors might require to treat observations separated by trainID and terrain height.
- Further case studies planned as well as the usage in a sub-hourly AROME-RUC cycle
- At least one experiment over whole period planned

## Can we go operational in a foreseeable future?

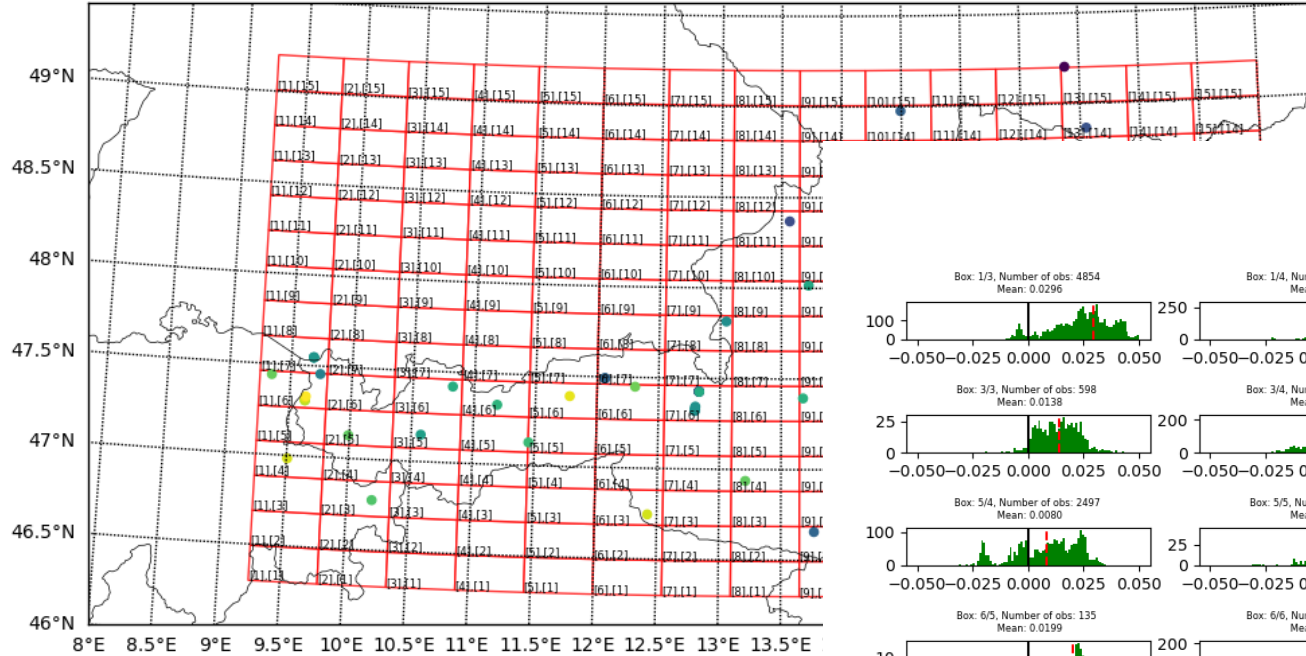
- Currently data retrieve is technically not possible on the fly, data have to be downloaded from on-board hard-disc manually
- Investigations at OEBA are on-going how to retrieve data on-the-fly, one possible solution would be a data transfer at larger train stations, or possibly with the usage of 5G
- Timely processing of large amount of data by TU-Wien is under investigation





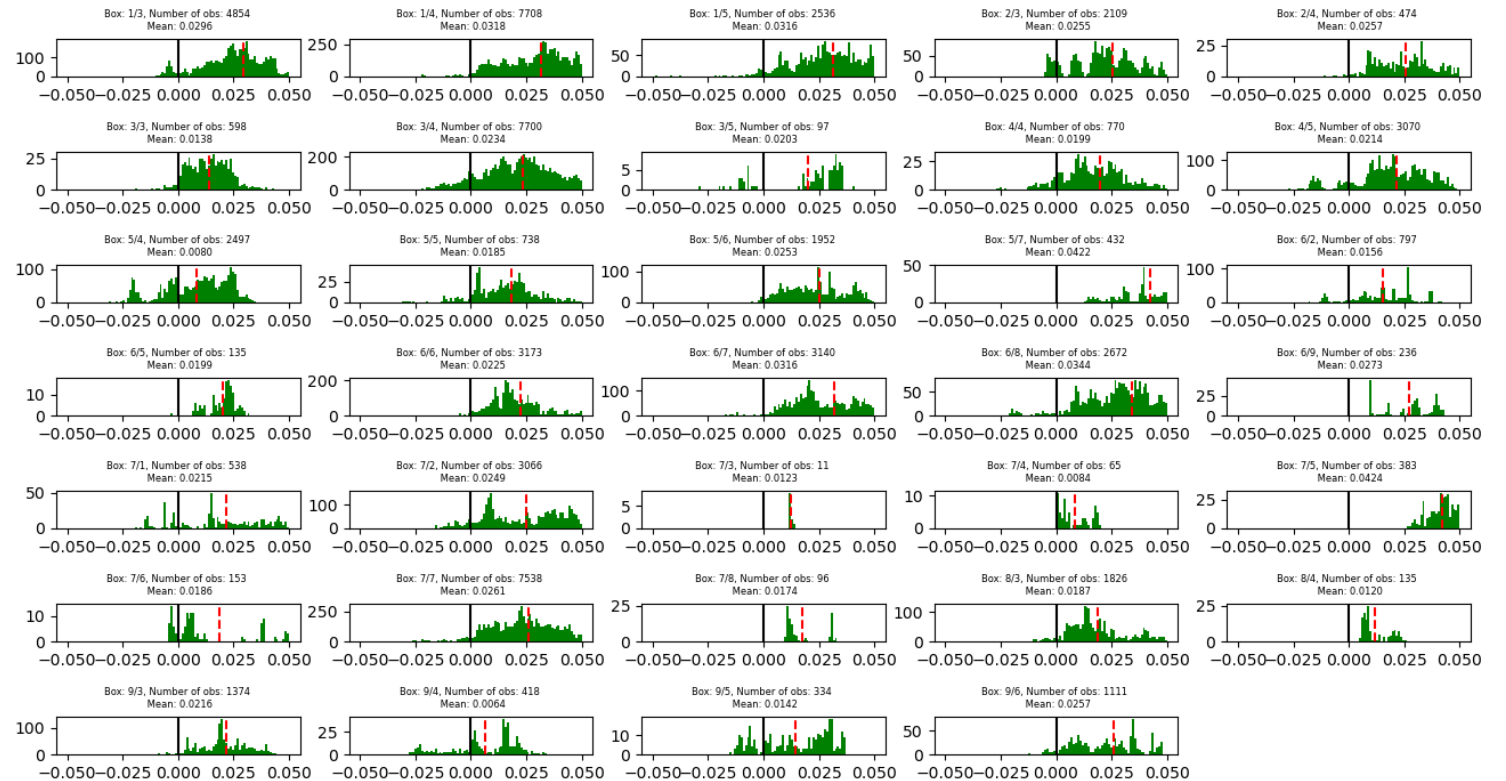
# Analyse first guess departures from trains

Mean fg\_departures for period 20210909 - 20210909  
number of lonboxes: 15, latboxes:15



For completeness

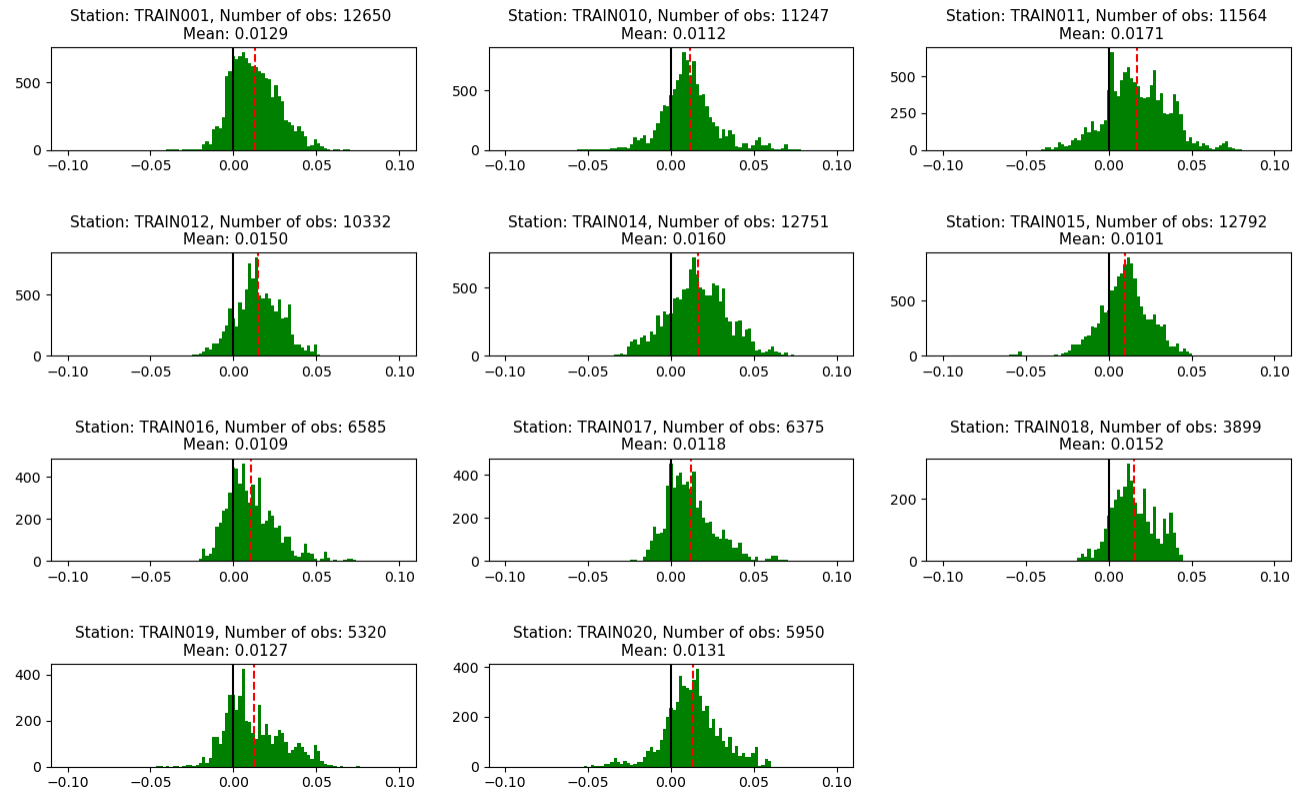
Histogram of fg-departures by Gridbox  
period: 20210909 - 20210919



# Apply static bias correction and rerun trainingsperiod

Bias reduced ....

Histogram of fg-departures by Train ID  
period: 20210909 - 20210919

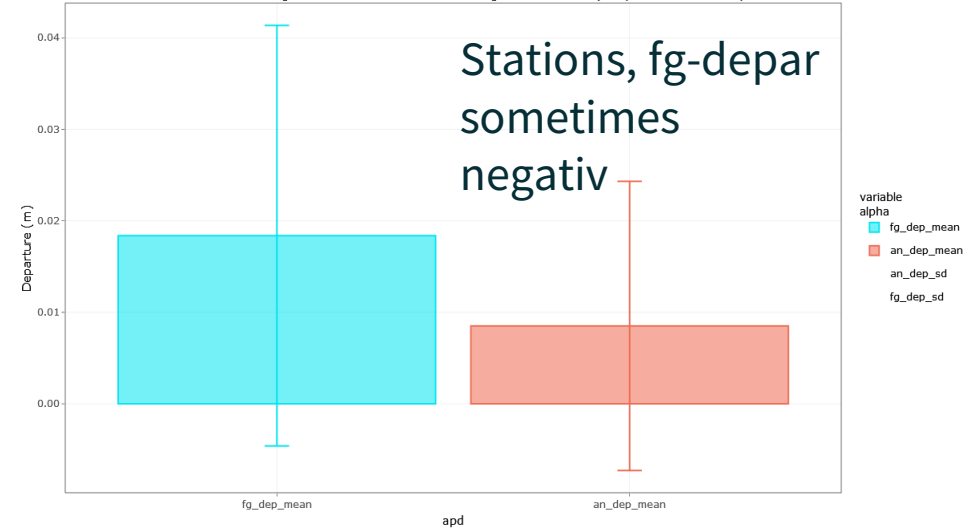


# Analysis fg-departures case1

EX02\_case: Station Average First Guess and Analysis Departure  
station=[TRAIN001, TRAIN010, ..., TRAIN019, TRAIN020]  
db=ccma, DTG=[2021-10-05-2021-10-06], obname=synop, varname=apd



EX02\_case: Station Average First Guess and Analysis Departure  
station=[ALSTTUAT, AMS1TUAT, ..., ZIDFTUAT, ZNAITUAT]  
db=ccma, DTG=[2021-10-05-2021-10-06], obname=synop, varname=apd



EX02\_case: Station Average First Guess and Analysis Departure  
station=LIEZTUAT  
db=ccma, DTG=[2021-10-05-2021-10-06], obname=synop, varname=apd

