FROM CLIMATE TO WEATHER RECONSTRUCTION

WITH INEXPENSIVE NEURAL NETWORKS

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WITH INEXPENSIVE NEURAL NETWORKS

Artificial intelligence achieves easy-to-adapt nonlinear global temperature reconstructions using minimal local data

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Expectation Management

1. More a proof-of-concept
2. This is about bridging ideas and communities
3. This is about cost-benefit analyses
4. This is about another tool in the toolbox

→ We keep it simple

Problem & Goal

You have point data → You want gridded / spatial data

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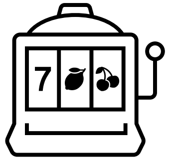
Examples:

1. Global anomalies
2. Regional absolute values

Focus is on temperature, but in theory you can reconstruct any variable in your training dataset.

→ Maybe you overfit 

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Example 1: Monthly temperature anomalies

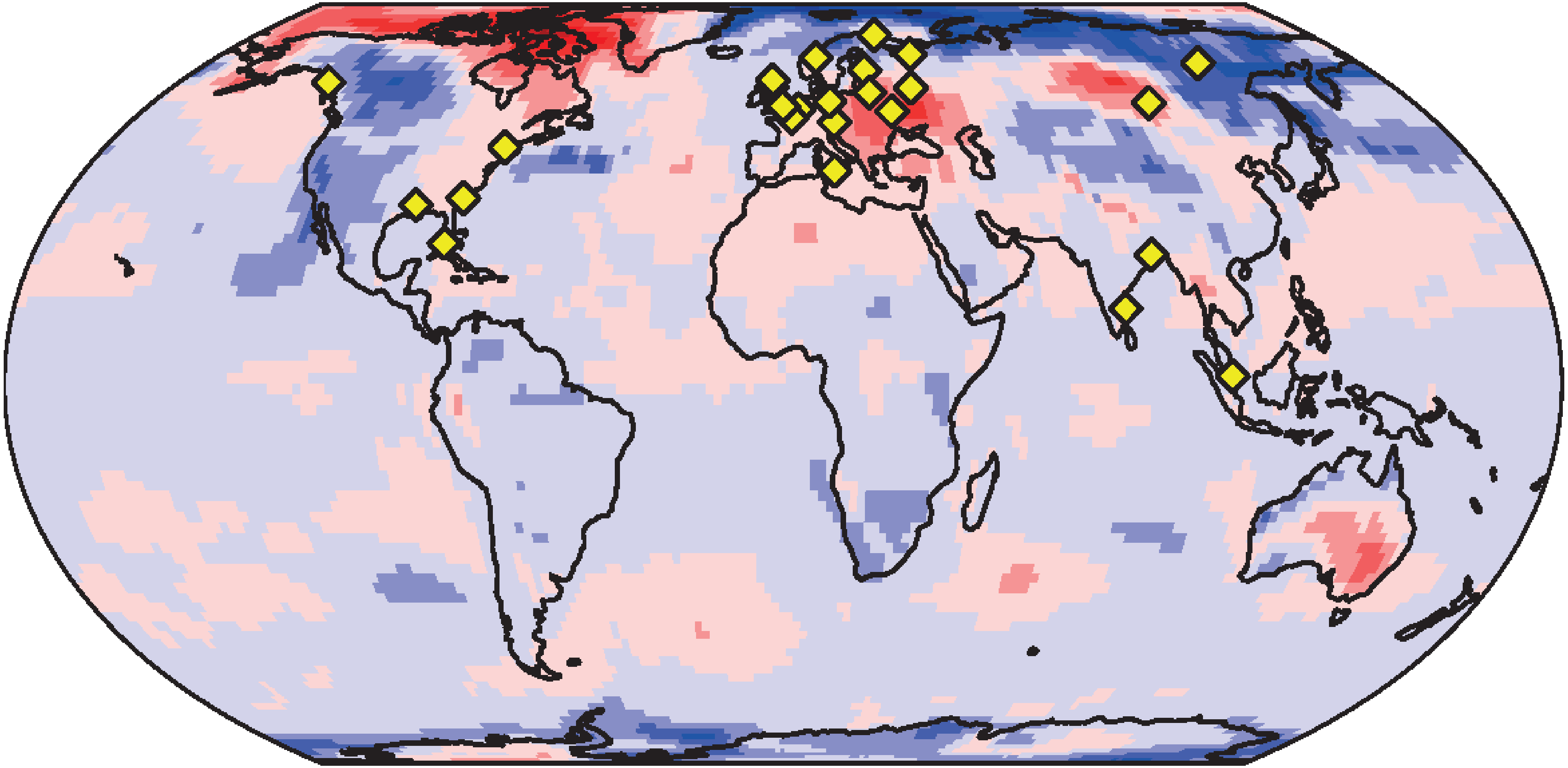
Example 1

1. Global anomalies (no help via yearly cycle)

   – Reconstruct 400 years of monthly temperature anomalies

   – We create artificial «point» data based on realistic locations → historical station locations, 25

Example 1



International Surface Temperature Initiative (ISTI) data bank:
25 station locations that go back to the 19th or 18th century

Data

DATA	INPUT	MODEL	LABEL / OUTPUT

1) TRAINING

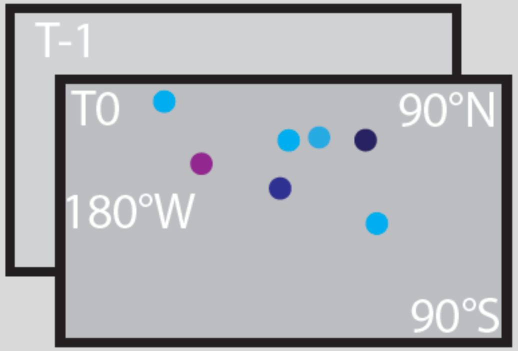
DATA

<u>20CRv3</u>
1851–2015 CE
ensemble mean and 80 members

<u>MPI-GE</u>
1850–2005 CE
100 member

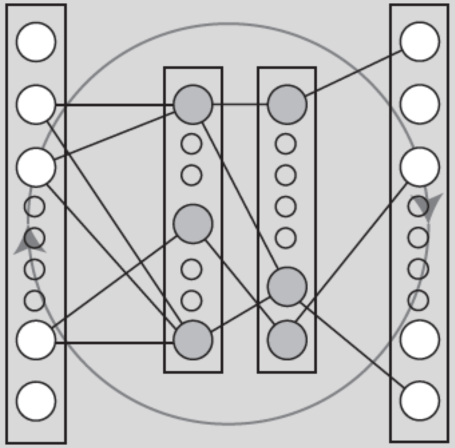
<u>CESM-LME</u>
850–2005 CE
13 member

INPUT



Monthly 2m Temperature anomalies
25 extracted lat. & lon. positions
Training Size:
N=1980 & N=20000 months

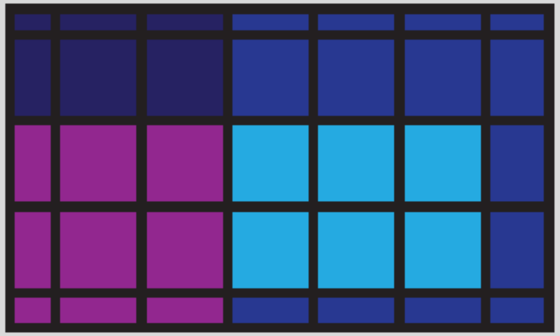
MODEL



- Simple RNN
- GRU
- LSTM
- Conv1D

different layer sizes, neuron counts & dropout values

LABEL / OUTPUT



Monthly 2m Temperature anomalies
2° global grid

Data

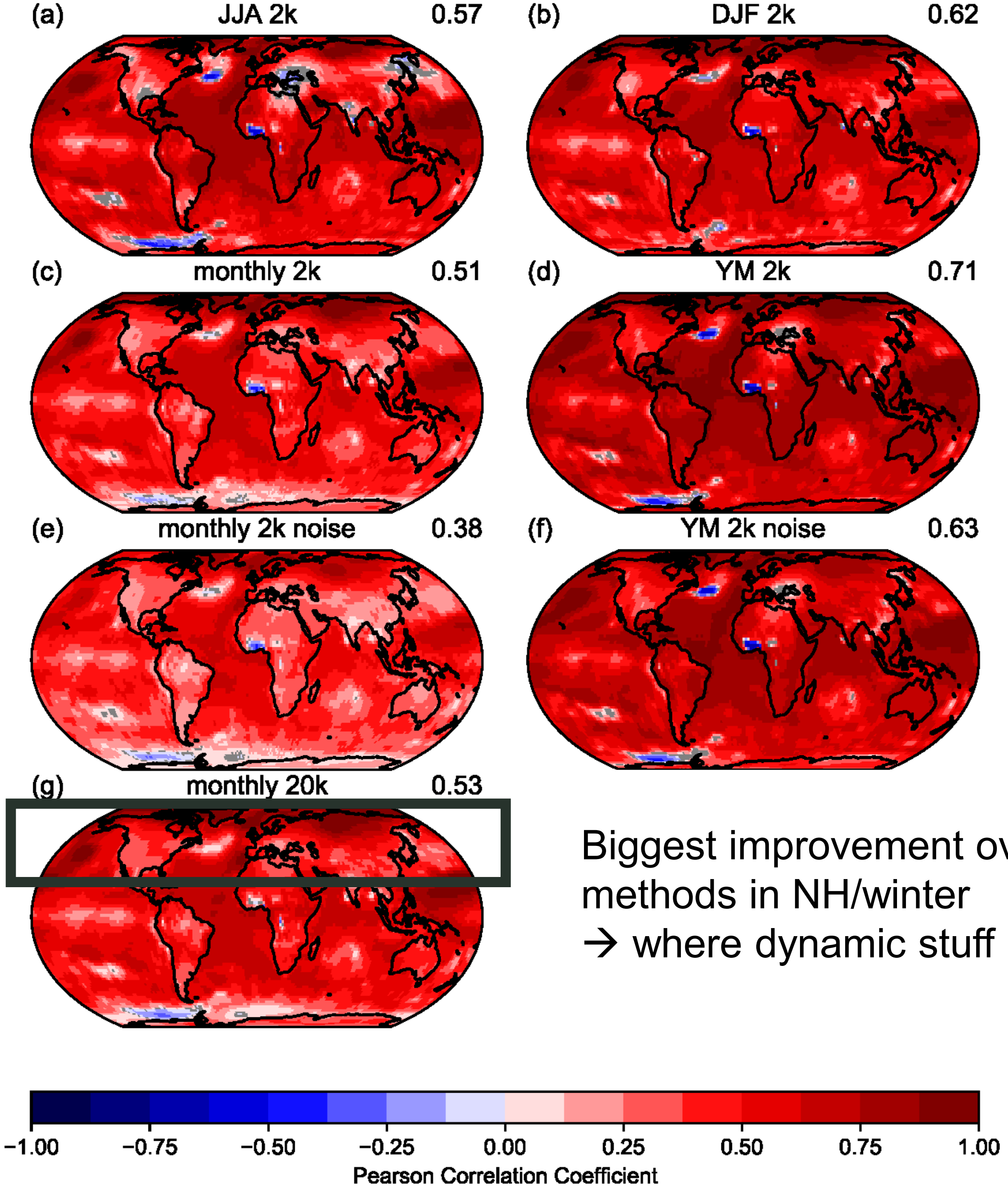
- **Train / Validate Data (2000 vs 20000 data points)**
  - MPI-GE 1850-2005 (Maher et al. 2019)
  - CESM-LME 850-2005 (Otto-Bliesner et al. 2016)
  - 20CRv3 ensemble 1851-2015 (Slivinski et al. 2019)
- **Test Data**
  - EKF400v2 1602-2005 (Valler et al. 2022)
  - 20CRv3 1836-1850 (Slivinski et al. 2019)
  - LRMv2 (Hakim et al. 2016)
- **Features:**
  - XYTemp data

Results

Reconstruction using MPI-GE training data…

…compared to…

…EKF400v2



Biggest improvement over linear methods in NH/winter
→ where dynamic stuff is happening

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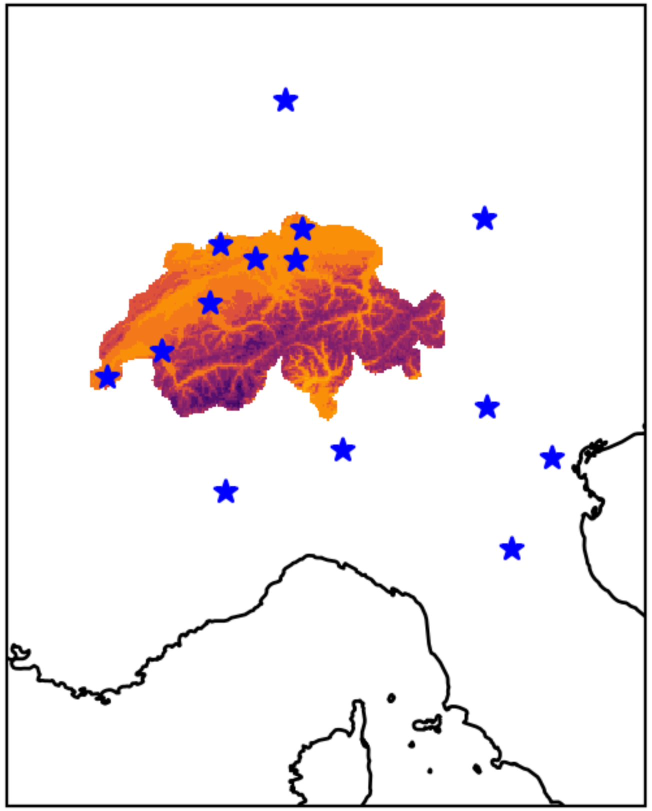
Example 2: Daily absolute temperature

Example 2

2. Regional absolute values

– Reconstruct the year 1807 in daily temperatures over Switzerland

– We have 14 «weather station» locations



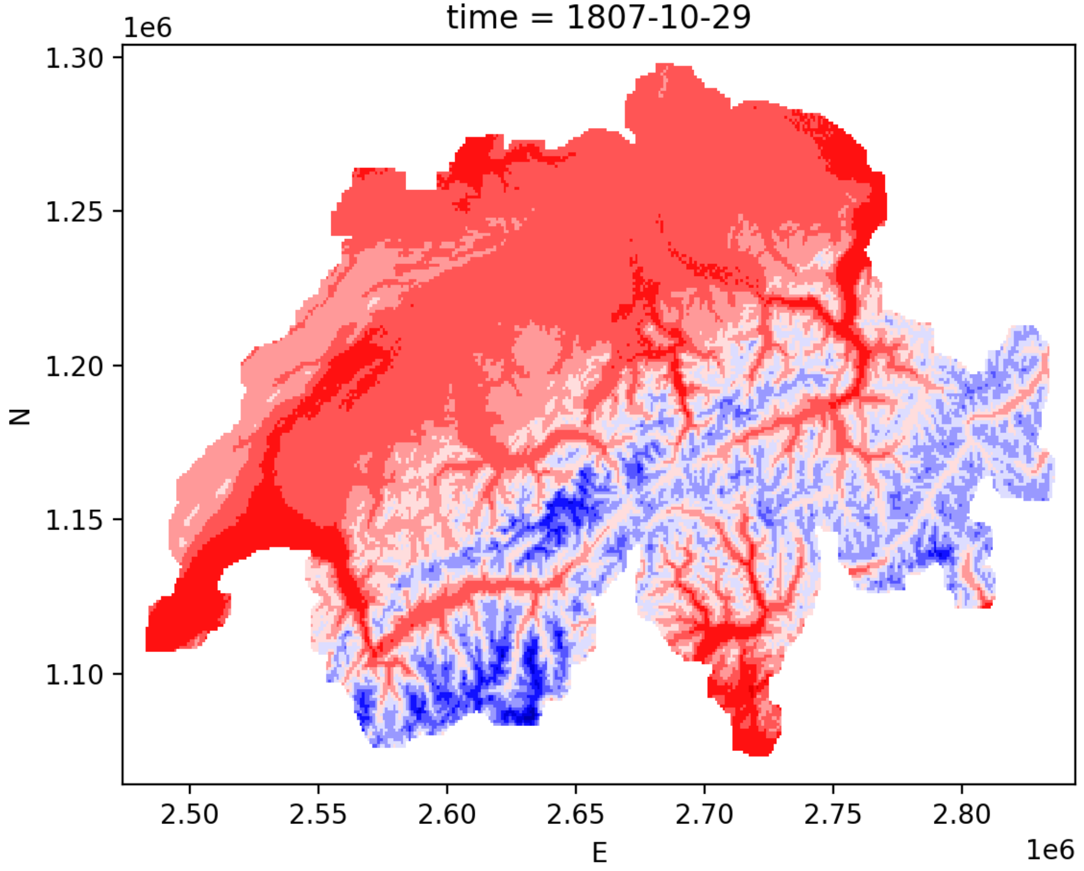
Data

- **Train / Validate Data (21900 data points)**
  - MeteoSwiss Daily Grid 1961-2020 (MeteoSwiss 2021)
  - Synthetic (e-obs) or real station data (Imfeld et al. 2023)
- **Test Data**
  - Analogue sampling + data assimilation 1763-2020 (Imfeld et al. 2023)
- **Features**
  - XYZ Pres. PresTend. Temperature WeatherType WetDay

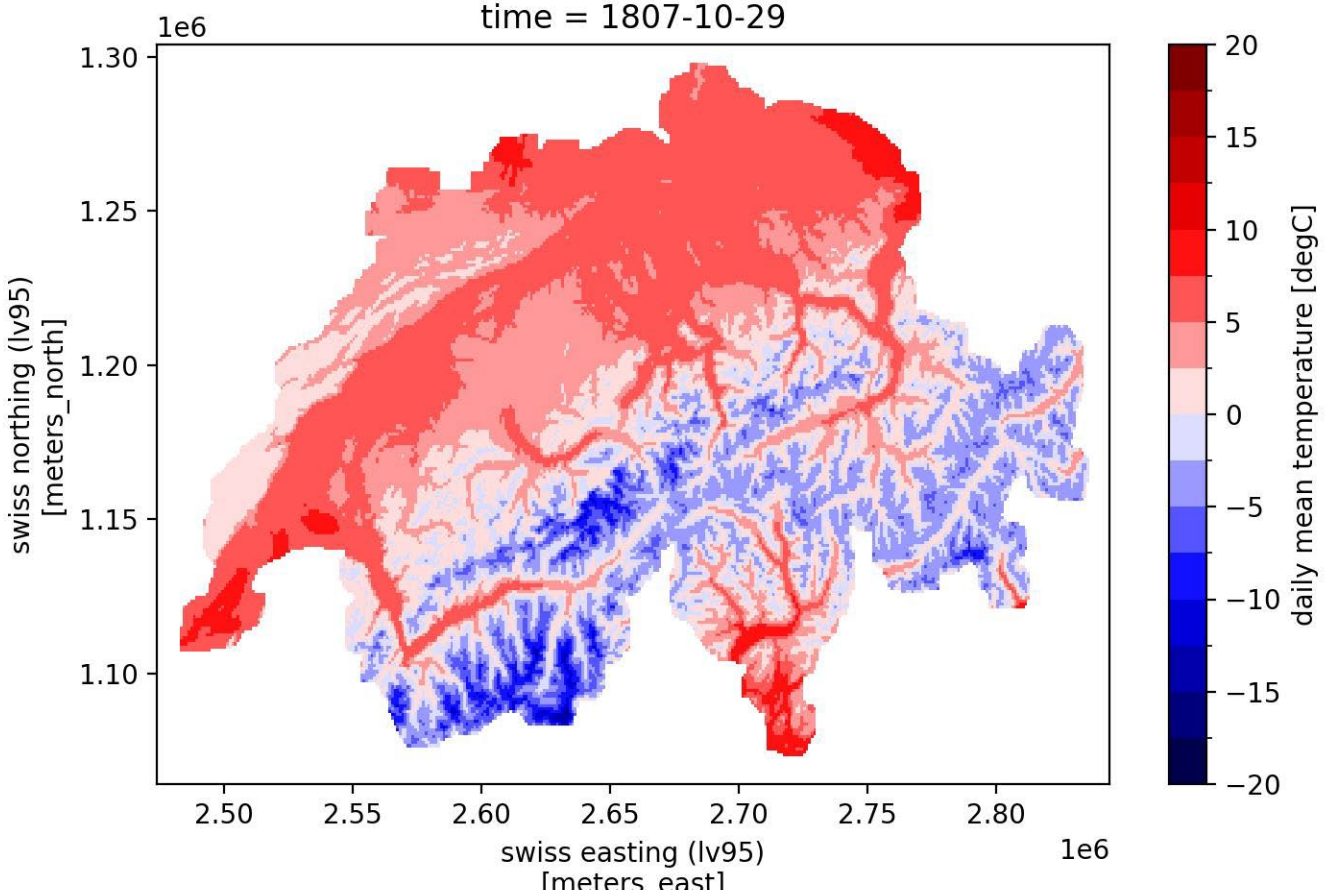
(A LOT OF MISSING DATA)

Results

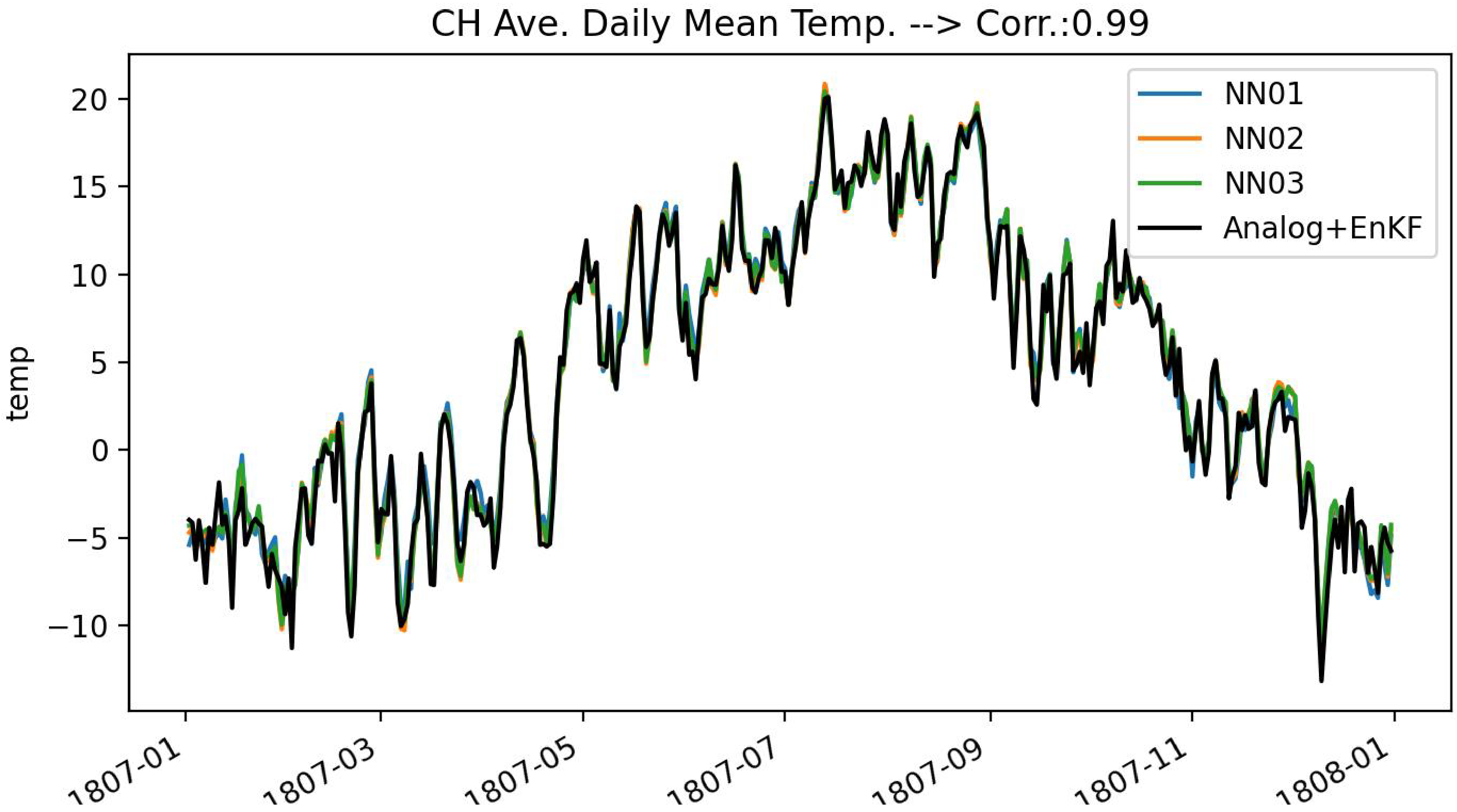
NN



AS+Assimilation

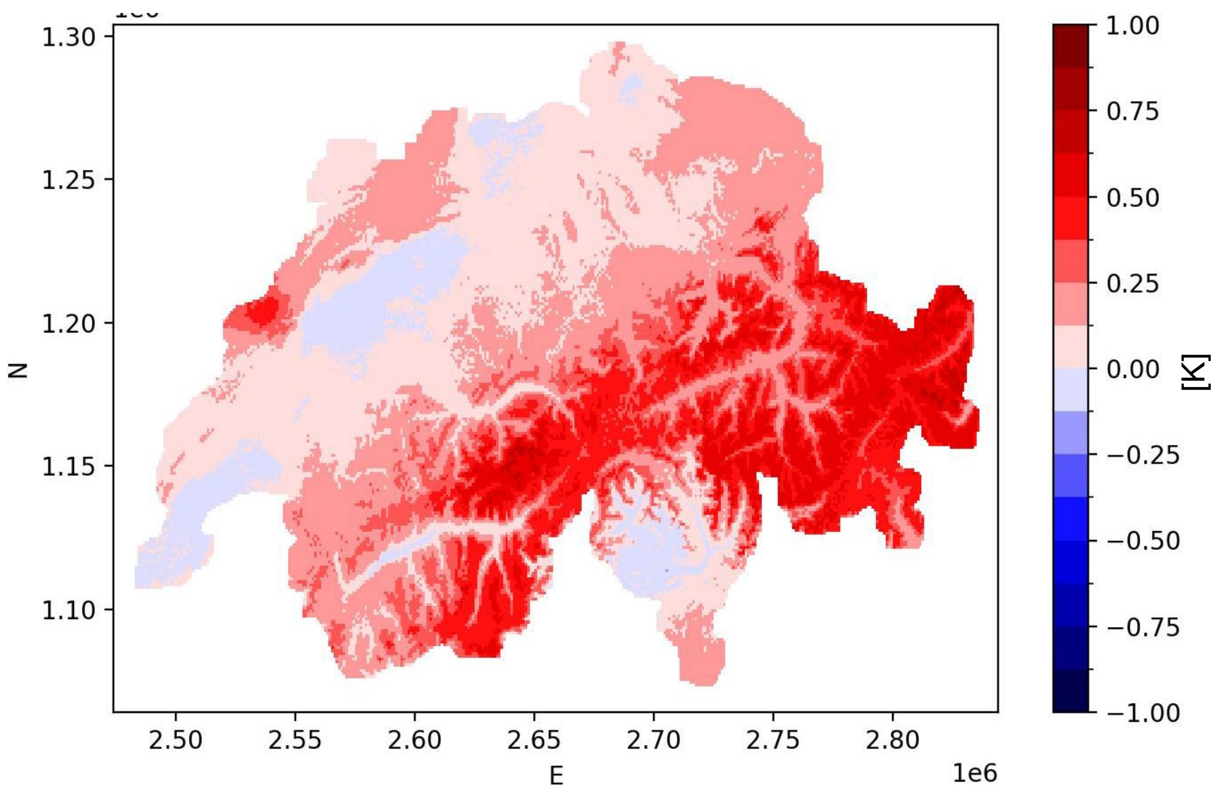


Results

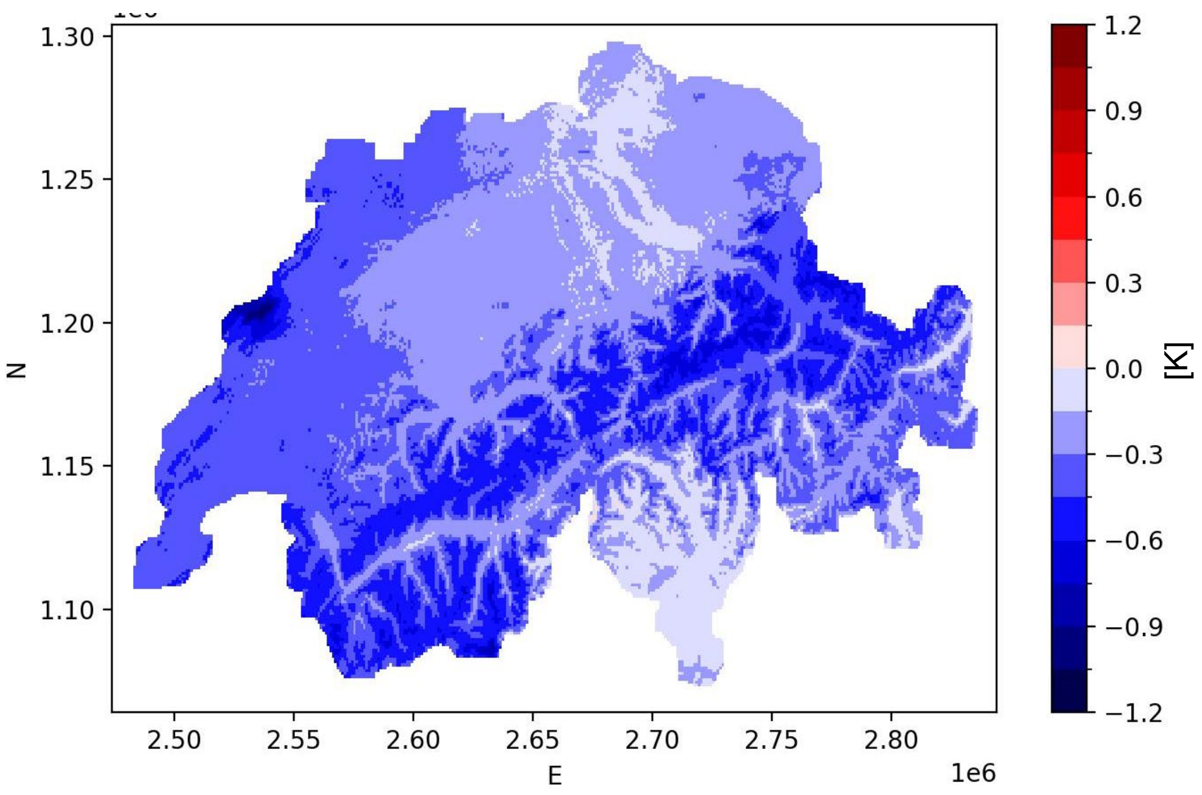

CH Ave. Daily Mean Temp. --> Corr.:0.99
temp
20
15
10
5
0
−5
−10
1807-01
1807-03
1807-05
1807-07
1807-09
1807-11
1808-01
NN01
NN02
NN03
Analog+EnKF

Results

Difference
NN minus AS



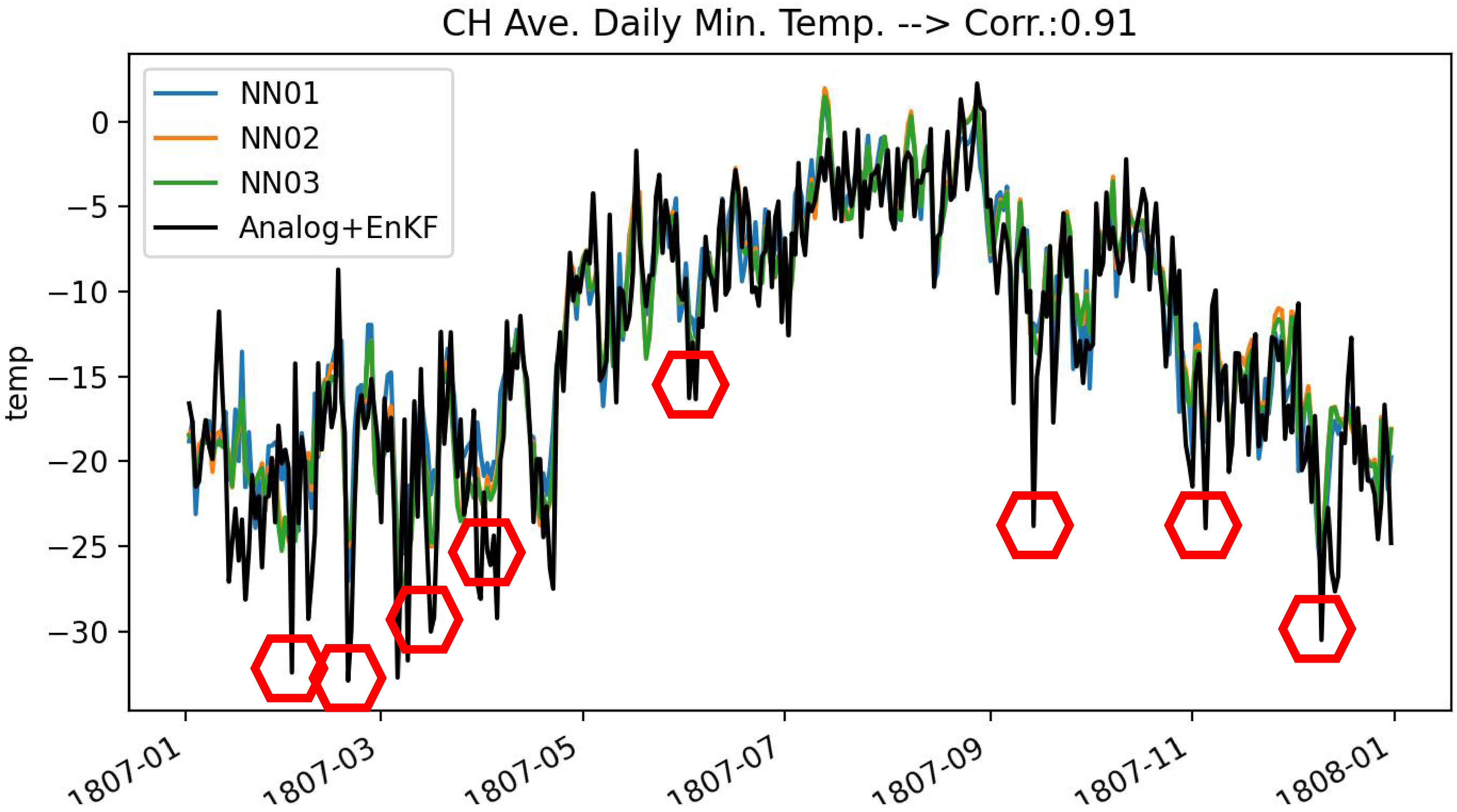
Difference in Standard Deviation
NN minus AS



☹ NNs too warm
→ Especially true for peaks

☹ Variability not preserved
→Especially true for peaks/minima

Results



CH Ave. Daily Min. Temp. --> Corr.:0.91
NN01
NN02
NN03
Analog+EnKF
temp
0
−5
−10
−15
−20
−25
−30
1807-01
1807-03
1807-05
1807-07
1807-09
1807-11
1808-01

Summary

PART1

- Training with reanalysis shows an edge for summer skill and variability preservation
- Yes, noise makes the prediction worse
- Improvements over linear where stuff gets dynamic (NH, Winter)

PART2

- If you go back in time, your test / reference data is also not reality
- Analog method keeps the variability and does not smear/smooth out
- Uncertainty communication with analog method tricky
- Historical data has missing values (do you want to fill the gaps first?)

- A lot of ways to improve it (loss function, architecture), who wants to collaborate?