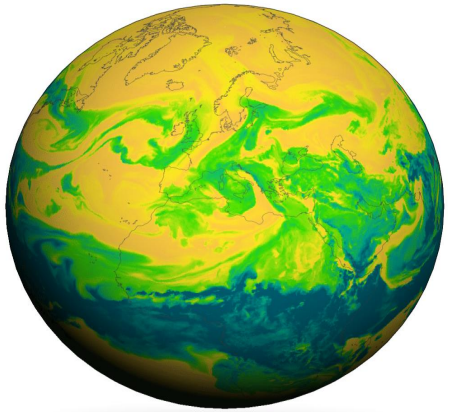
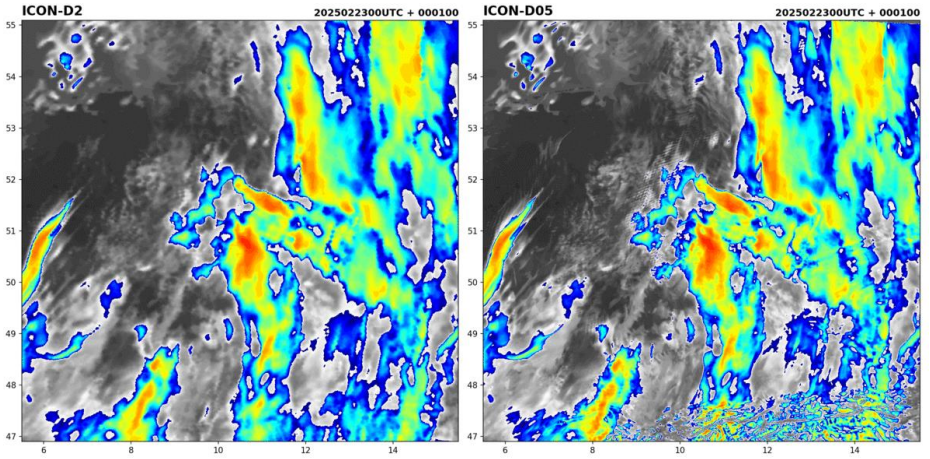
Deutscher Wetterdienst
Wetter und Klima aus einer Hand

Observations for AI forecasts – what do we need?



Roland Potthast, Jan Keller, Stefanie Hollborn, Nora Schenk, Thomas Deppisch, Nastaran Najari, Florian Prill, Tobias Göcke, Marek Jacob, Hendrik Reich, Sabrina Wahl, Sven Ulbrich



Developments Since 2022 in Forecasting Systems

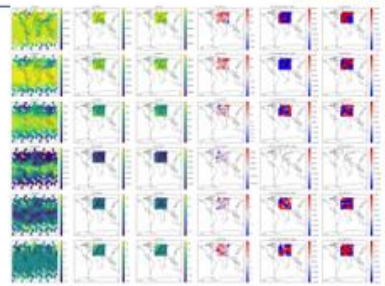
Compare RP Talk at EUMETSAT Lyon 2025

AI Weather Forecasting – ongoing Developments

AICON-LAM

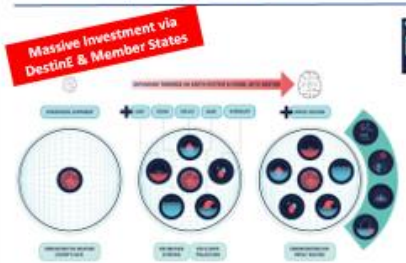
Regionalization with particular applications on a km scale

ICON-EU application

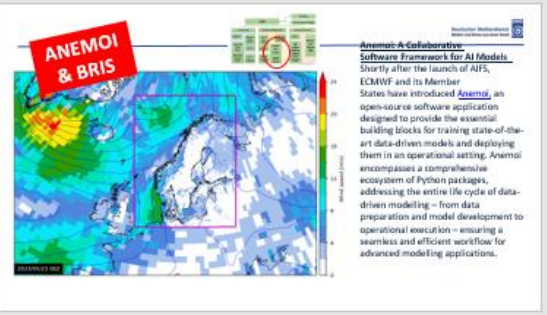


ECMWF Perspective / DestinE

Massive investment via DestinE & Member States



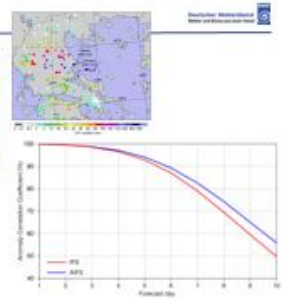
ANEMOI & BRIS



Anemoi: A Collaborative Software Framework for AI Models

Shortly after the launch of AIFS, ECMWF and its Member States have introduced Anemoi, an open-source software application designed to provide the essential building blocks for training state-of-the-art data-driven models and deploying them in an operational setting. Anemoi encompasses a comprehensive ecosystem of Python packages, addressing the entire life cycle of data-driven modelling – from data preparation and model development to operational execution – ensuring a seamless and efficient workflow for advanced modelling applications.

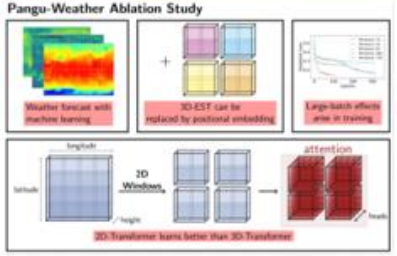
AIFS (ECMWF)



ECMWF took the challenge

KANGU Weather: Transformer for NWP

Pangu-Weather Ablation Study



Architectural insights into and training methodology optimization of Pangu-Weather

Dellis To, Julian Quinting, Gholam Ali Hoshyaripour, Markus Götz, Achim Streit, and Charlotte Debus

Kangu Container Running in Operational Framework

Weather Generator

RainA Cooperation Project Jülich

ECMWF is coordinating a project called WeatherGenerator which aims to use machine learning in novel ways for weather forecasting and to model related Earth system processes. The developments in the WeatherGenerator will feed into the digital twins implemented by ECMWF in the EU's Destination Earth (DestinE) initiative, in which we are one of three entrusted entities alongside ESA and EUMETSAT. It is anticipated that it can also be used to supplement the Centre's standard weather forecasts.

The WeatherGenerator is being developed by 16 European organisations, in a four-year EU-funded initiative which is to start in February 2025.

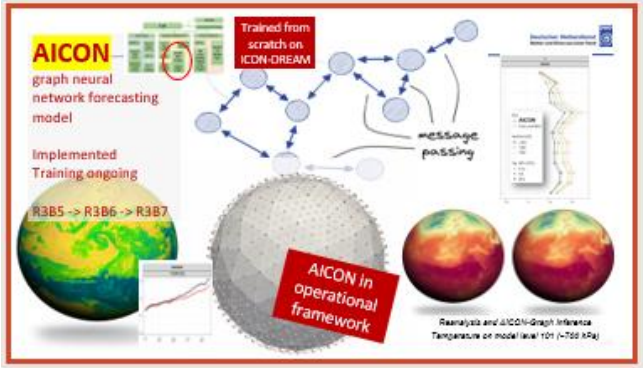
AICON

graph neural network forecasting model

Implemented

Training ongoing

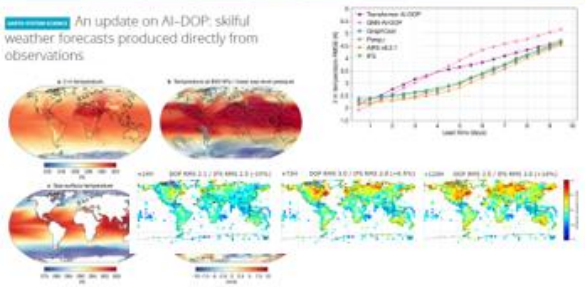
Trained from scratch on ICON-DREAM



Neural LAM

Direct Observation Prediction DOP (ECMWF)

An update on AI-DOP: skilful weather forecasts produced directly from observations



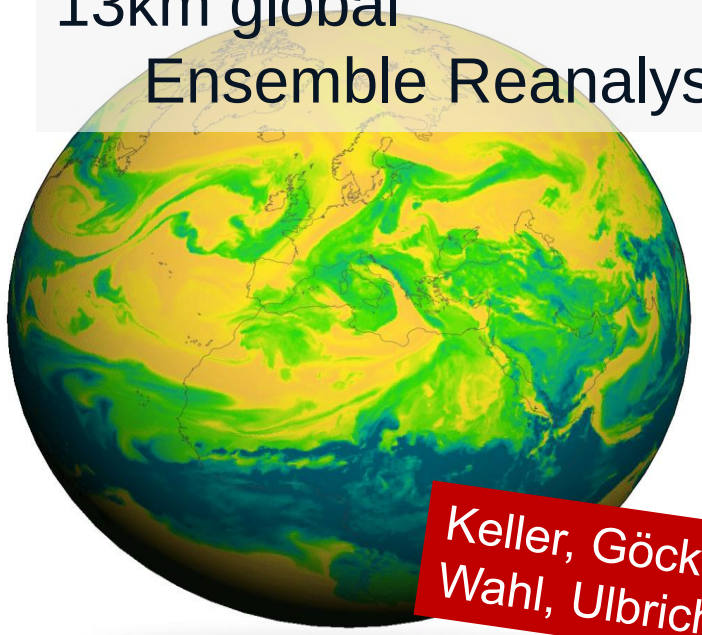
EUMETNET

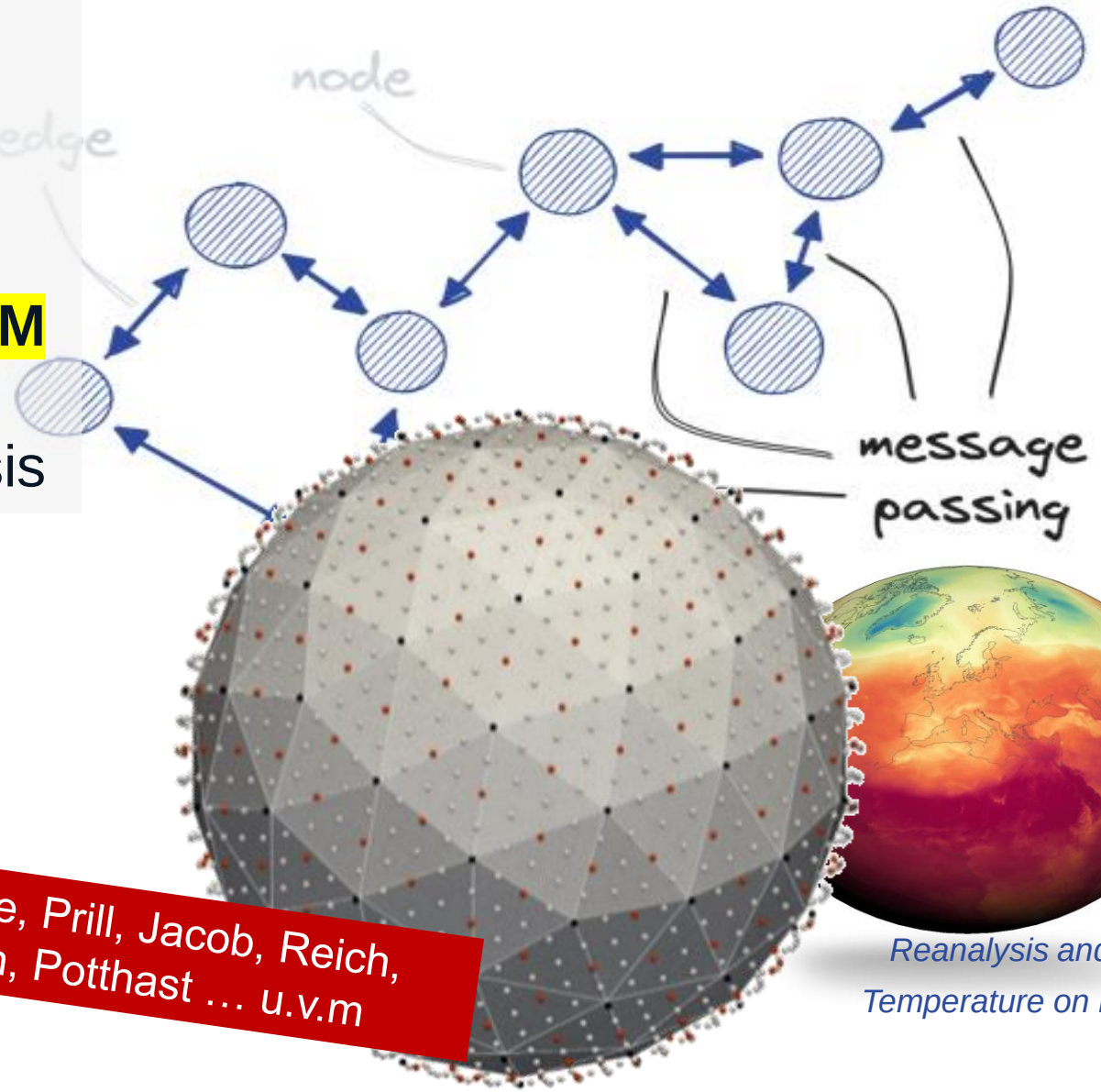
AICON in operational production

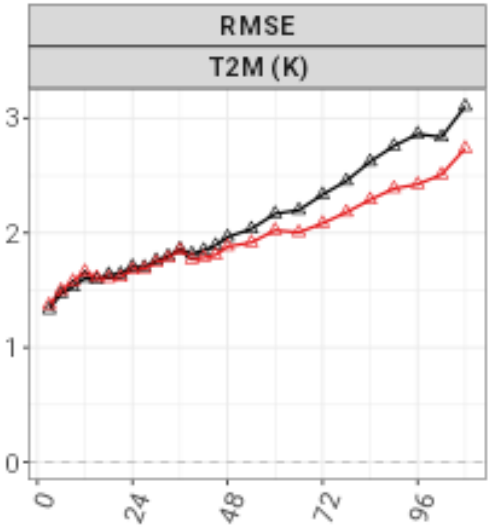
Deutscher Wetterdienst
Wetter und Klima aus einer Hand

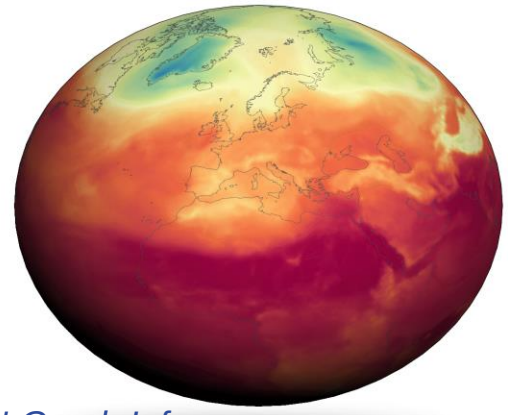
AICON
graph neural network
forecasting model

Based on **ICON-DREAM**
13km global
Ensemble Reanalysis









Reanalysis and AICON-Graph Inference

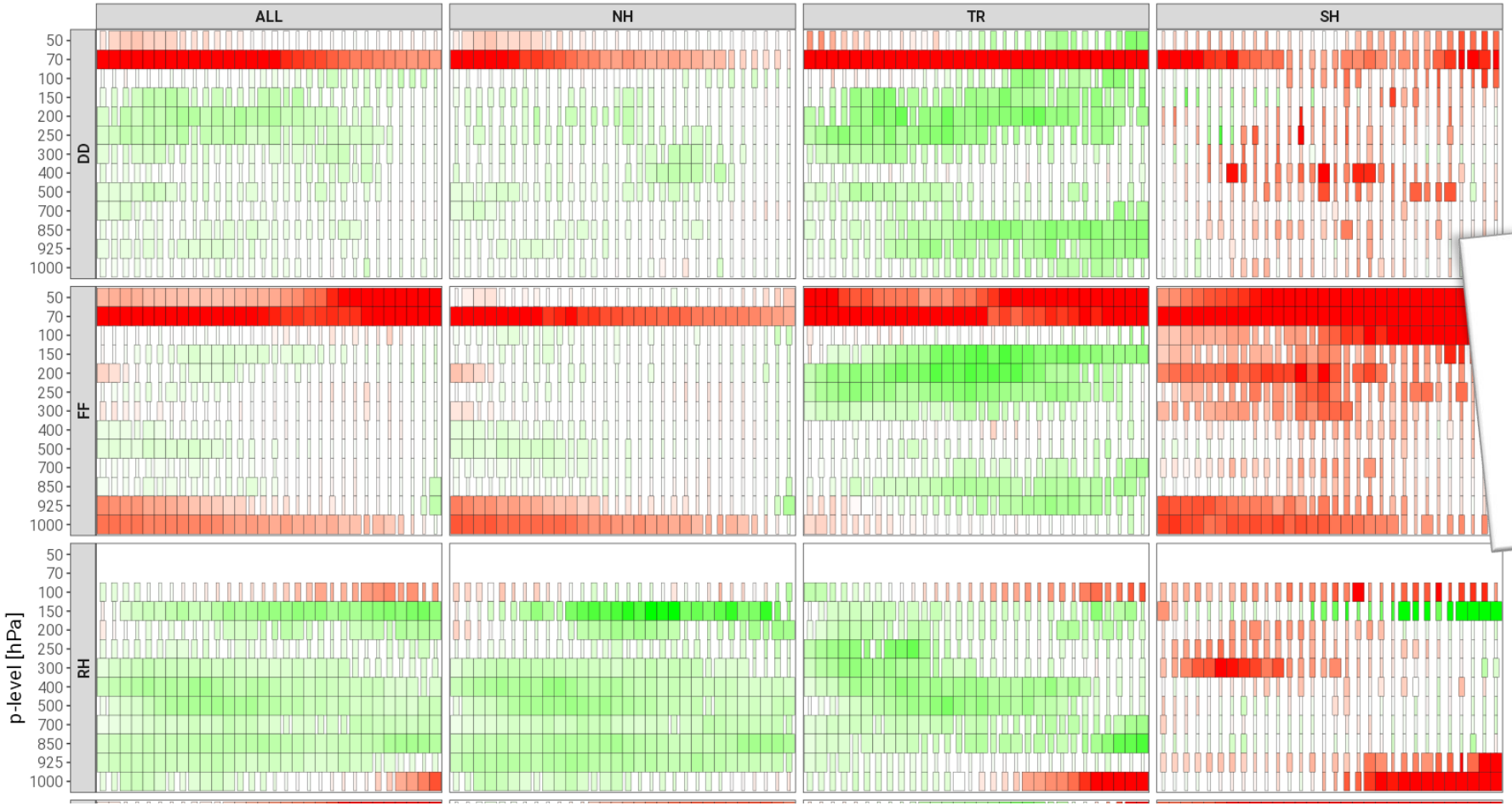
Temperature on model level 101 (~700 hPa)

Keller, Göcke, Prill, Jacob, Reich, Wahl, Ulbrich, Potthast … u.v.m

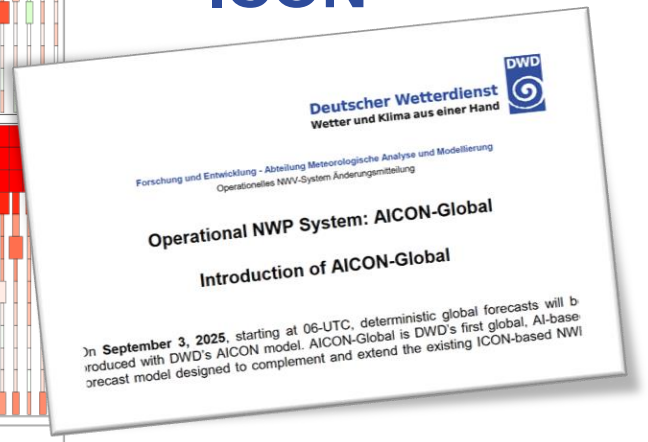
AICON Operational Scores

Deutscher Wetterdienst
Wetter und Klima aus einer Hand

Upper Air Scores



AICON vs. ICON

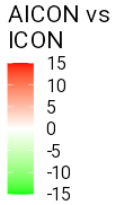

Deutscher Wetterdienst
Wetter und Klima aus einer Hand

Forschung und Entwicklung - Abteilung Meteorologische Analyse und Modellierung
Operationelles NWV-System Änderungsmitteilung

Operational NWP System: AICON-Global

Introduction of AICON-Global

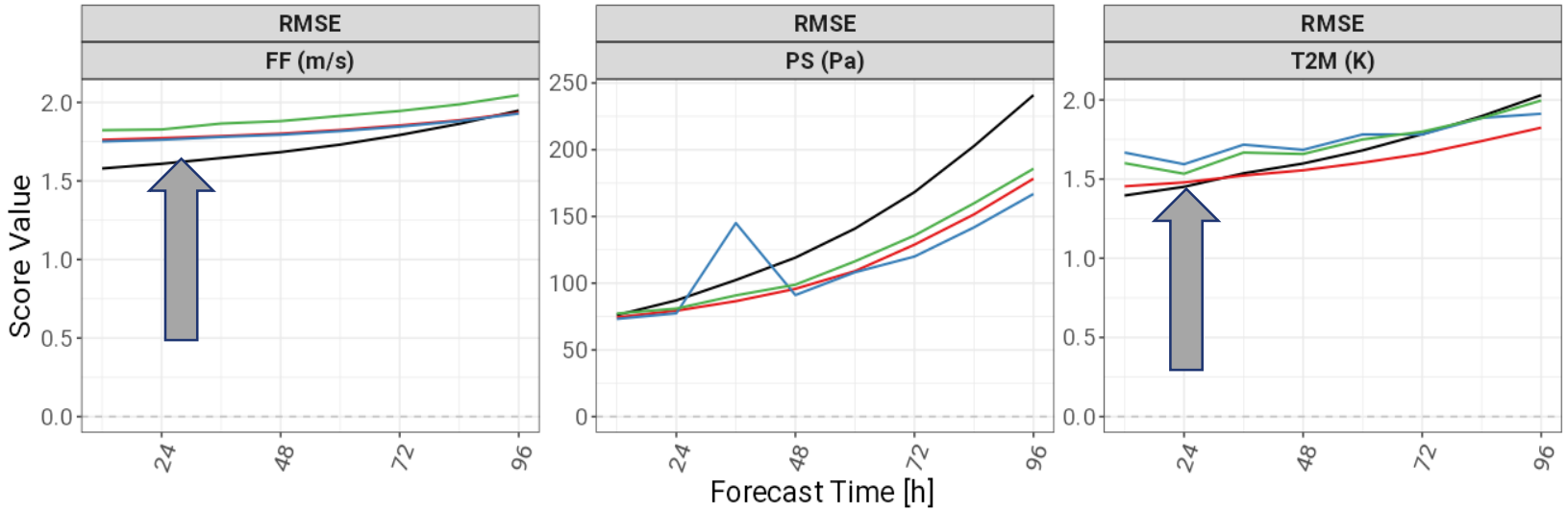
On **September 3, 2025**, starting at 06-UTC, deterministic global forecasts will b
roduced with DWD's AICON model. AICON-Global is DWD's first global, AI-base
orecast model designed to complement and extend the existing ICON-based NWI



AICON Operational Scores

Deutscher Wetterdienst
Wetter und Klima aus einer Hand

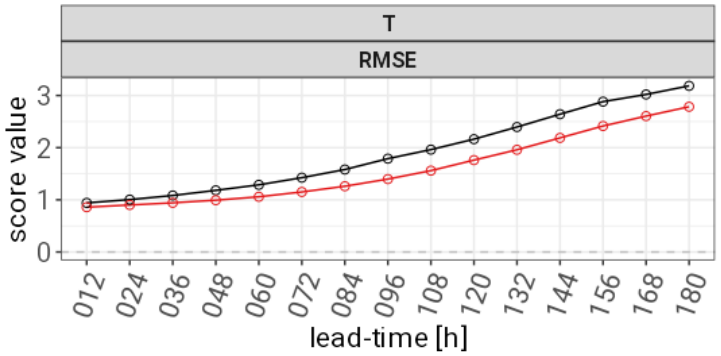
2025/09/03-00UTC - 2025/09/27-12UTC
INI: ALL UTC, DOM: ALL , STAT: ALL



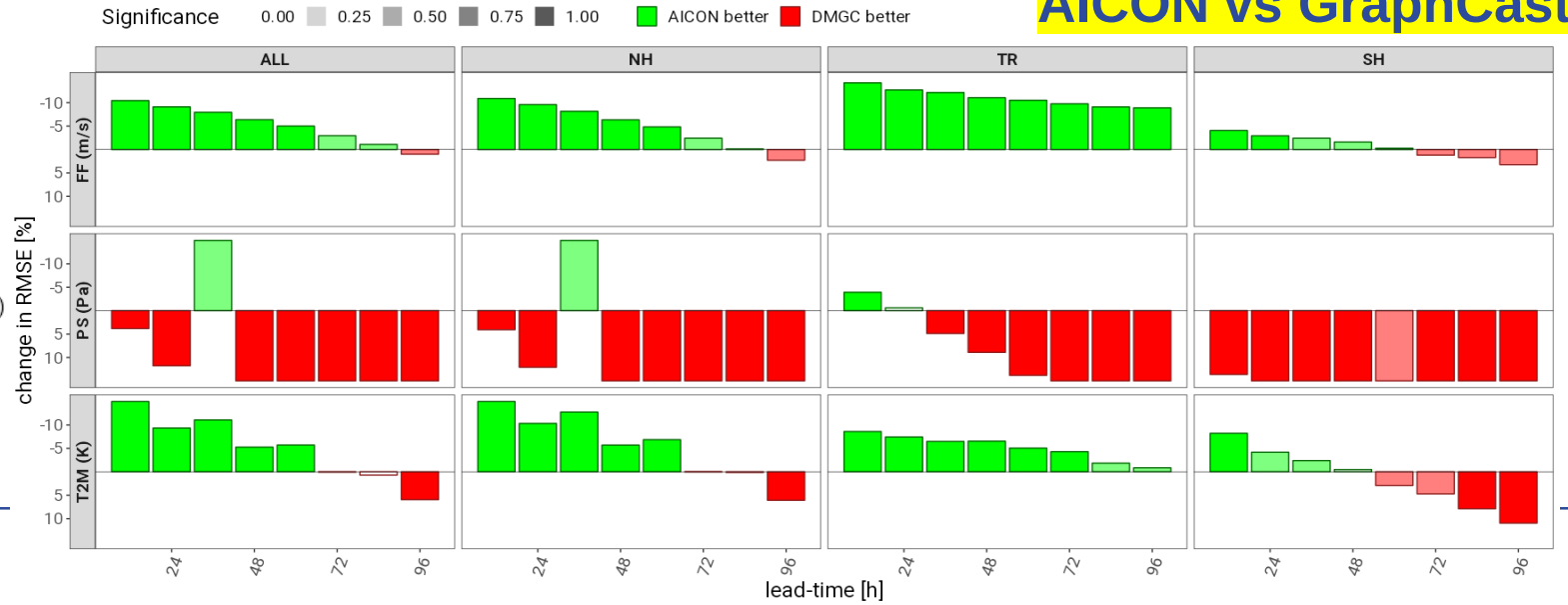
Wind, PS, T2M Surface Scores

2025/09/03 - 2025/09/29
INI: ALL UTC, DOM: ALL
LEV: 850 p-level [hPa]

T 850 hPa



AICON vs GraphCast

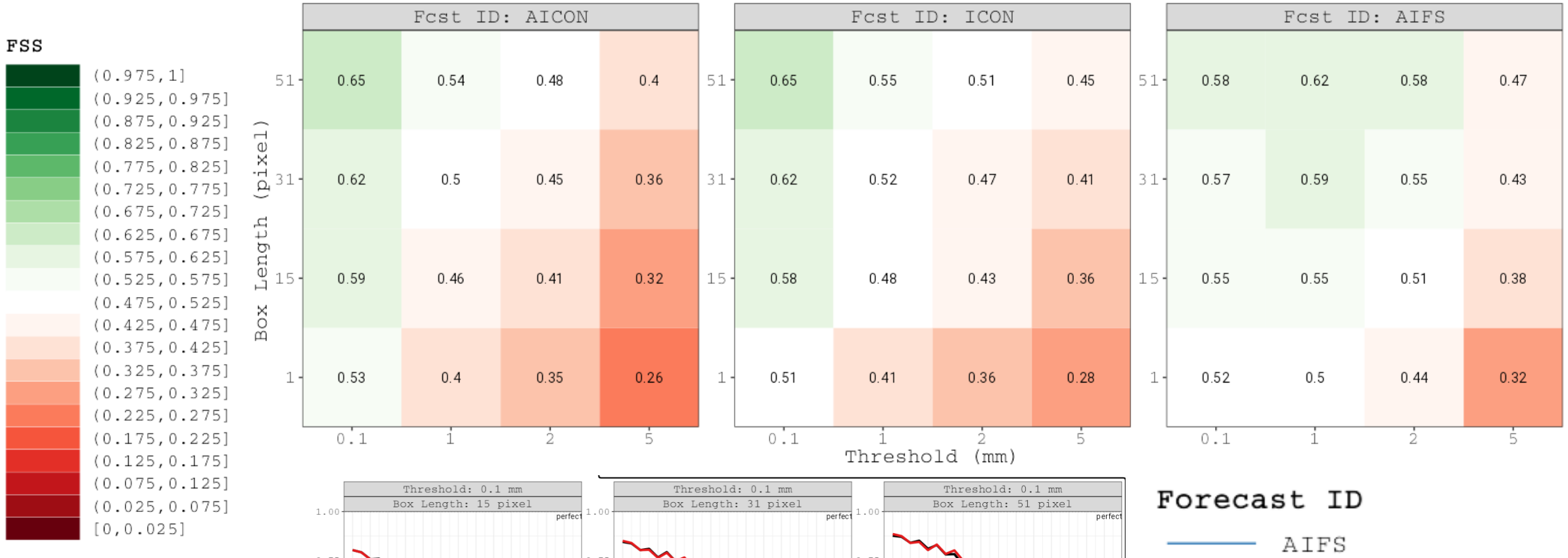


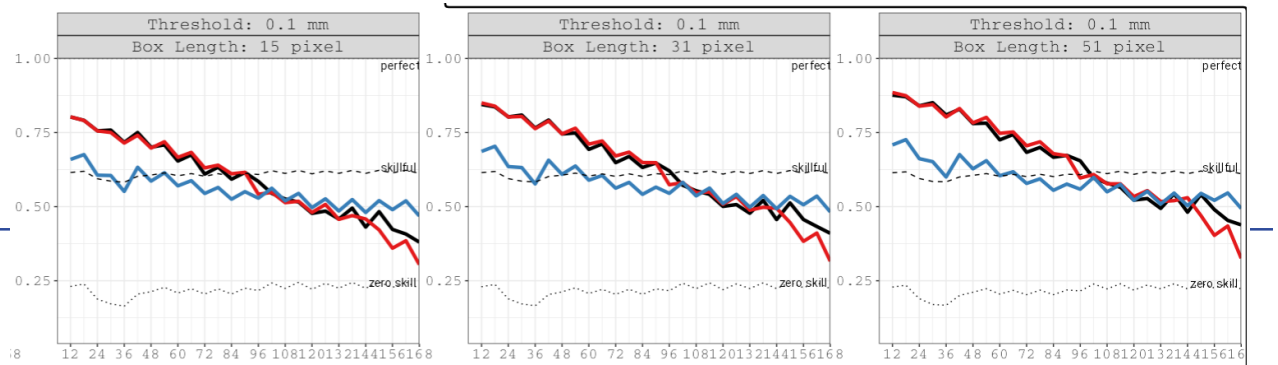
AICON Operational Scores

Deutscher Wetterdienst
Wetter und Klima aus einer Hand

Fractional Skill Scores for **Precipitation**
Sept 2025

AICON, ICON, AIFS





AICON – ML-based Weather Prediction

Deutscher Wetterdienst
Wetter und Klima aus einer Hand

Example for

Hurricane Melissa

Film by
Jan Keller

CTH Image Interpretation

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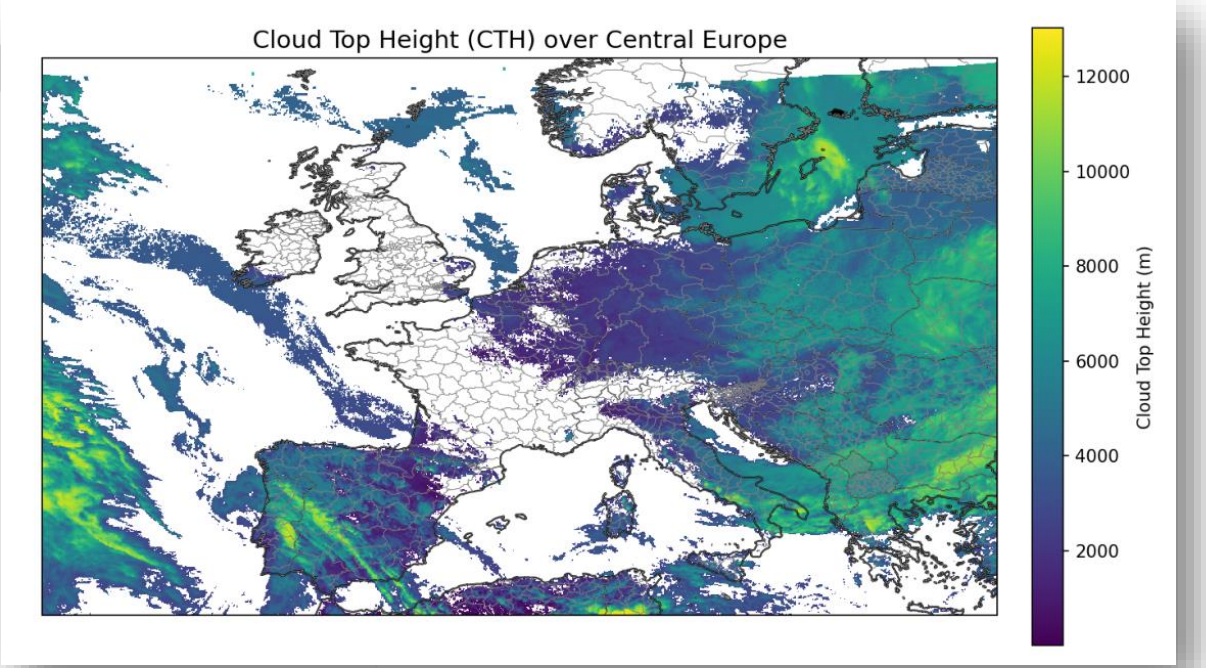
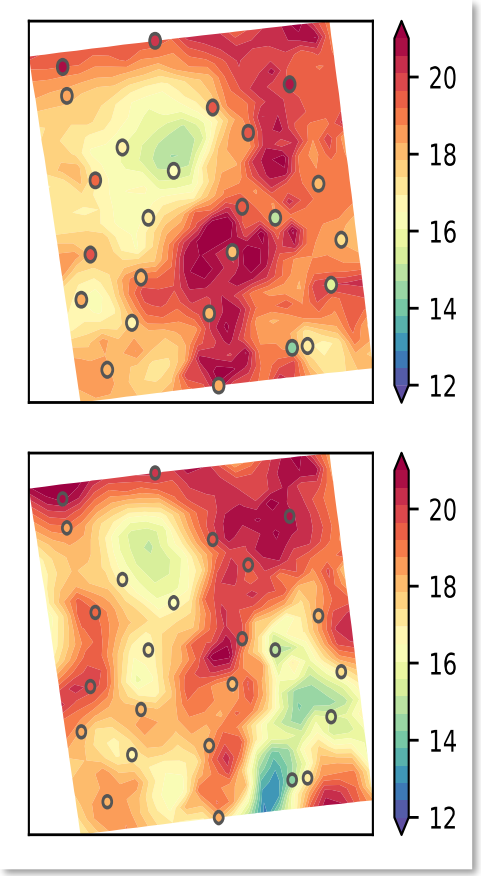
Wetter und Klima aus einer Hand

python

```python
from openai import OpenAI
from dotenv import load_dotenv
import os
import base64
from IPython.display import Markdown, display

load_dotenv()
client = OpenAI(api_key=os.getenv("OPENAI_API_KEY"))

with open("cth_map.png", "rb") as image_file:
    base64_image = base64.b64encode(image_file.read()).decode("utf-8")

response = client.chat.completions.create(
    model="gpt-4-turbo",
    messages=[
        {
            "role": "user",
            "content": [
                {
                    "type": "text",
                    "text": (
                     "This is a satellite-derived Cloud Top Height (CTH) image over Europe."
                        "Please interpret the structure shown in the image: \n"
                        "- Identify regions of high or low cloud tops.\n"
                        "- Estimate where deep convection may be present.\n"
                        "- Describe what synoptic or convective features are visible.\n"
                        "- Provide a summary of the possible weather situation."
                    )
                },
                {
```



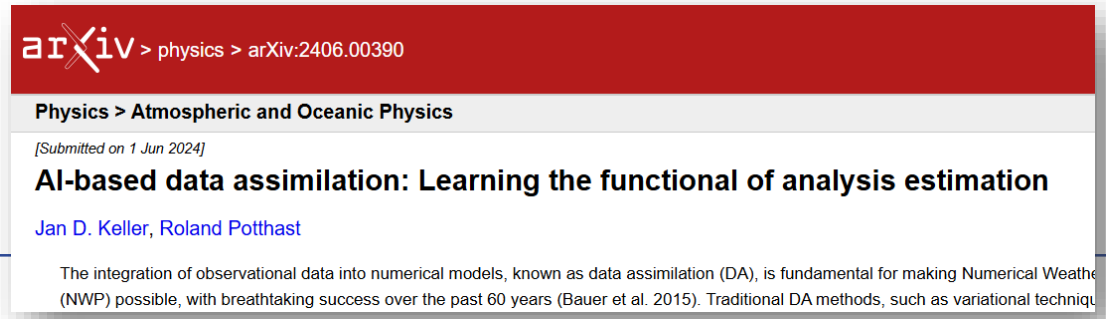
AI-VAR: Learning Analysis from Obs



$$l = (\hat{\mathbf{x}} - \mathbf{x}^b)^T \mathbf{B}^{-1} (\hat{\mathbf{x}} - \mathbf{x}^b) + (\hat{\mathbf{y}} - \mathbf{y})^T \mathbf{R}^{-1} (\hat{\mathbf{y}} - \mathbf{y})$$

ML methods are
minimizing some functional

Train with
Data Assimilation
Loss Function!


arXiv > physics > arXiv:2406.00390

Physics > Atmospheric and Oceanic Physics

[Submitted on 1 Jun 2024]

AI-based data assimilation: Learning the functional of analysis estimation

Jan D. Keller, Roland Potthast

The integration of observational data into numerical models, known as data assimilation (DA), is fundamental for making Numerical Weathe
(NWP) possible, with breathtaking success over the past 60 years (Bauer et al. 2015). Traditional DA methods, such as variational techniqu

AI-VAR / SynCast
neural network based
data assimilation

Implementation & Testing

AI PF

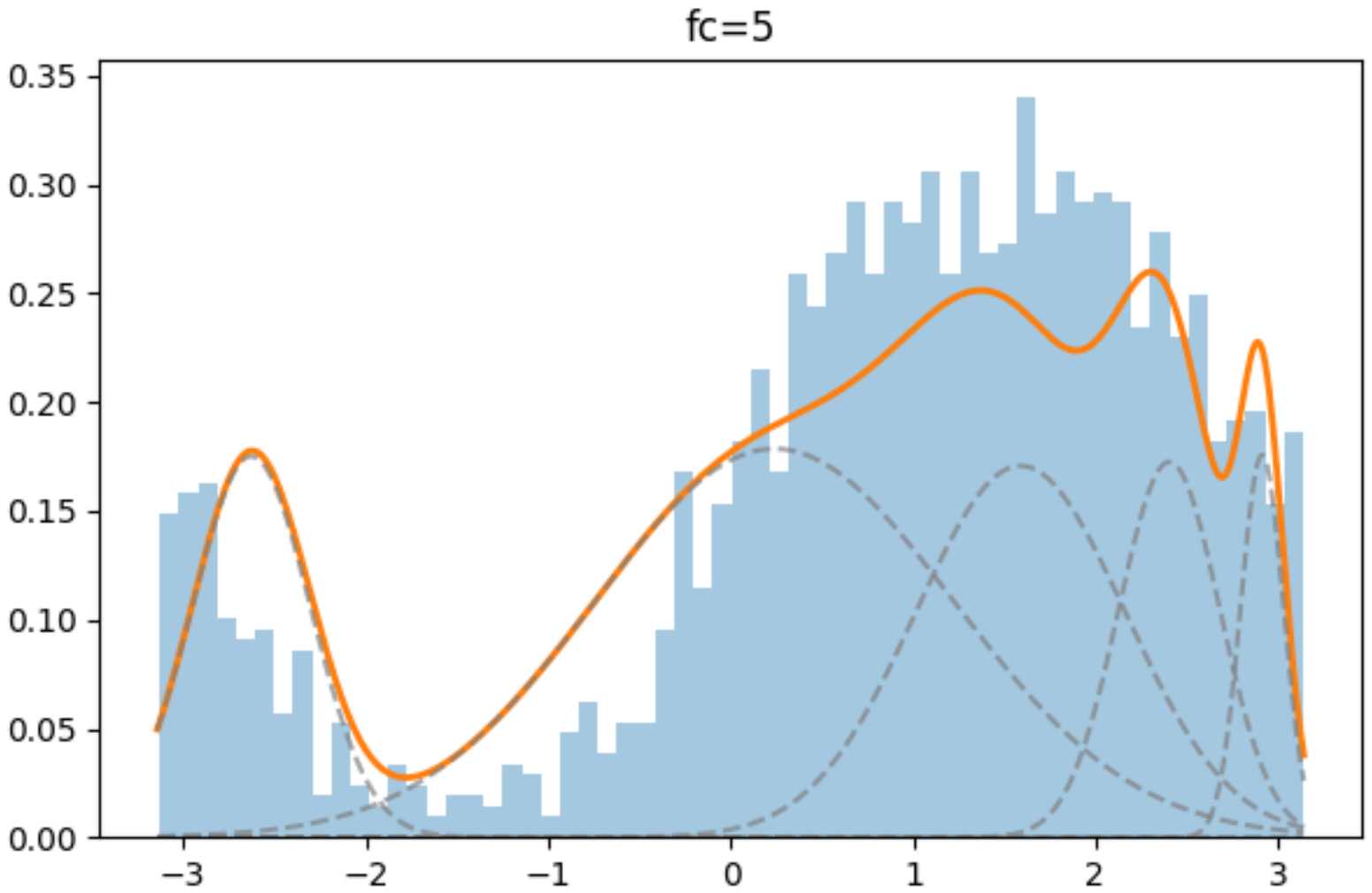
Learn to place particles

to fit the **posterior distribution**

Based on the first guess ensemble and

the observation

just from Observations!



Learning the PF from Obs: AI PF

Total Loss

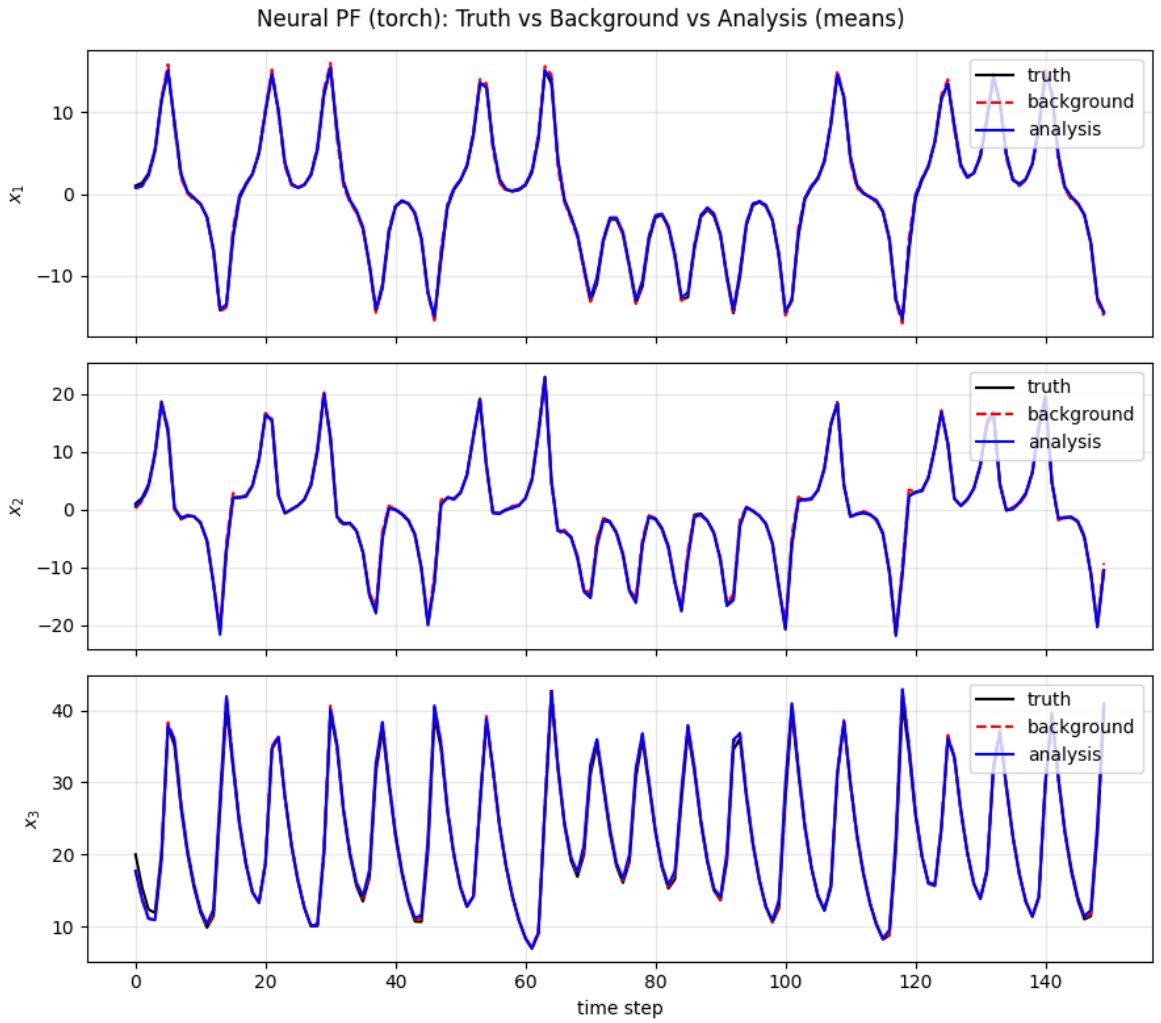
$$\mathcal{L}(\theta) = \mathcal{L}_{\text{obs}} + \lambda_{\text{bg}} \mathcal{L}_{\text{bg}}$$

$$\mathcal{L}_{\text{obs}} = -\log\left(\frac{1}{N}\sum_{i=1}^{N}\exp\left(\log p(y_t \mid x_{t,i}^{a})\right)\right)$$

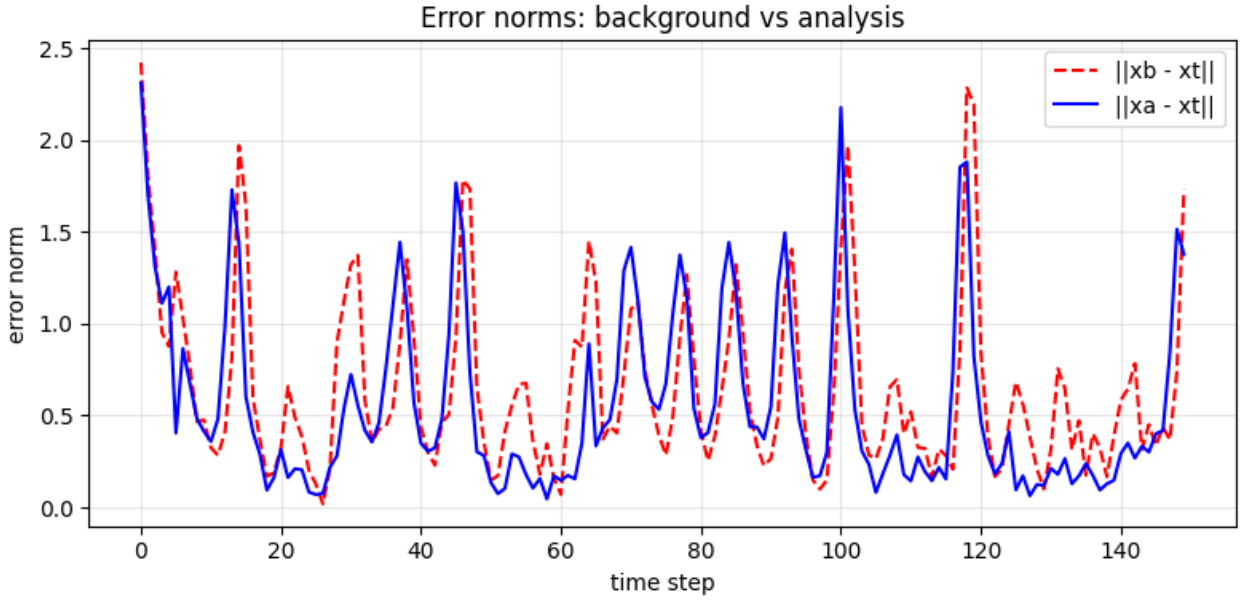
$$\mathcal{L}_{\text{bg}} = \mathrm{KL}\left(p^{\text{post}}(Z) \,\|\, q_a(Z)\right) = \sum_k w^{\text{post}}(Z_k)\left(\log w^{\text{post}}(Z_k) - \log w_\theta(Z_k)\right)$$

Combined loss function, matching the non-Gaussian posterior distribution!

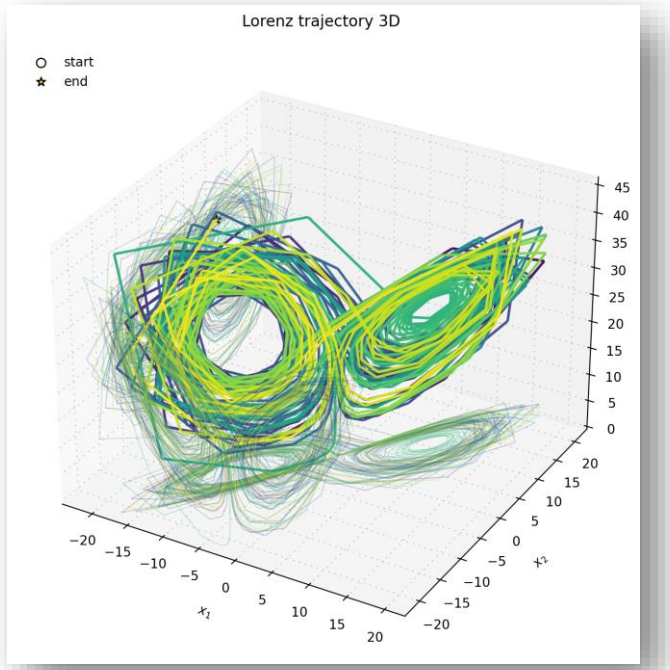
Learning the PF from Obs: AI PF



Running Cycling with AI PF



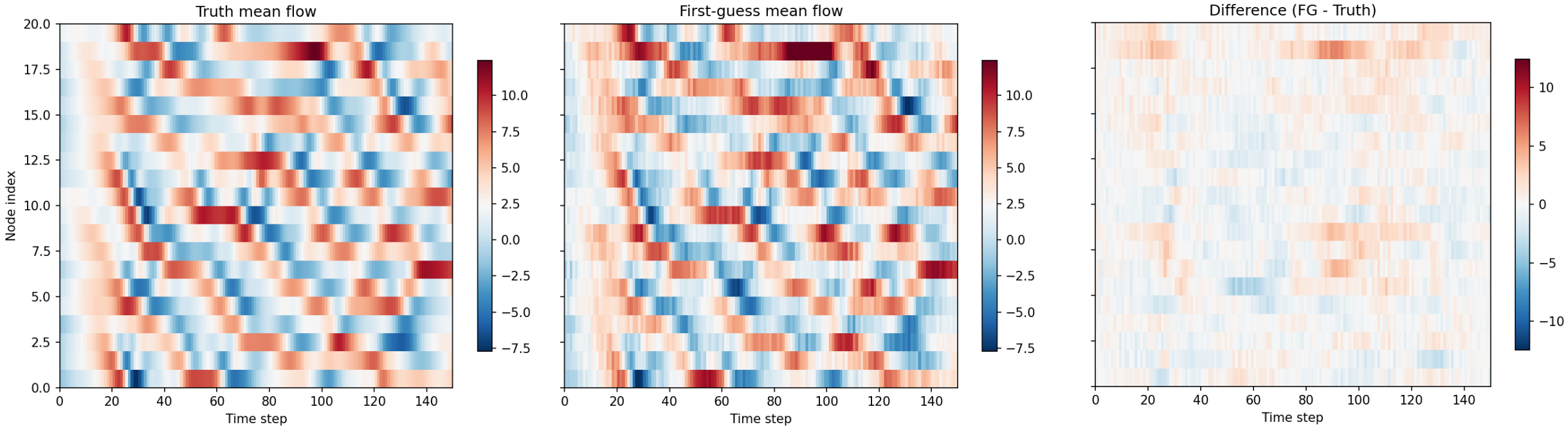
Learning the PF from Obs: AI PF



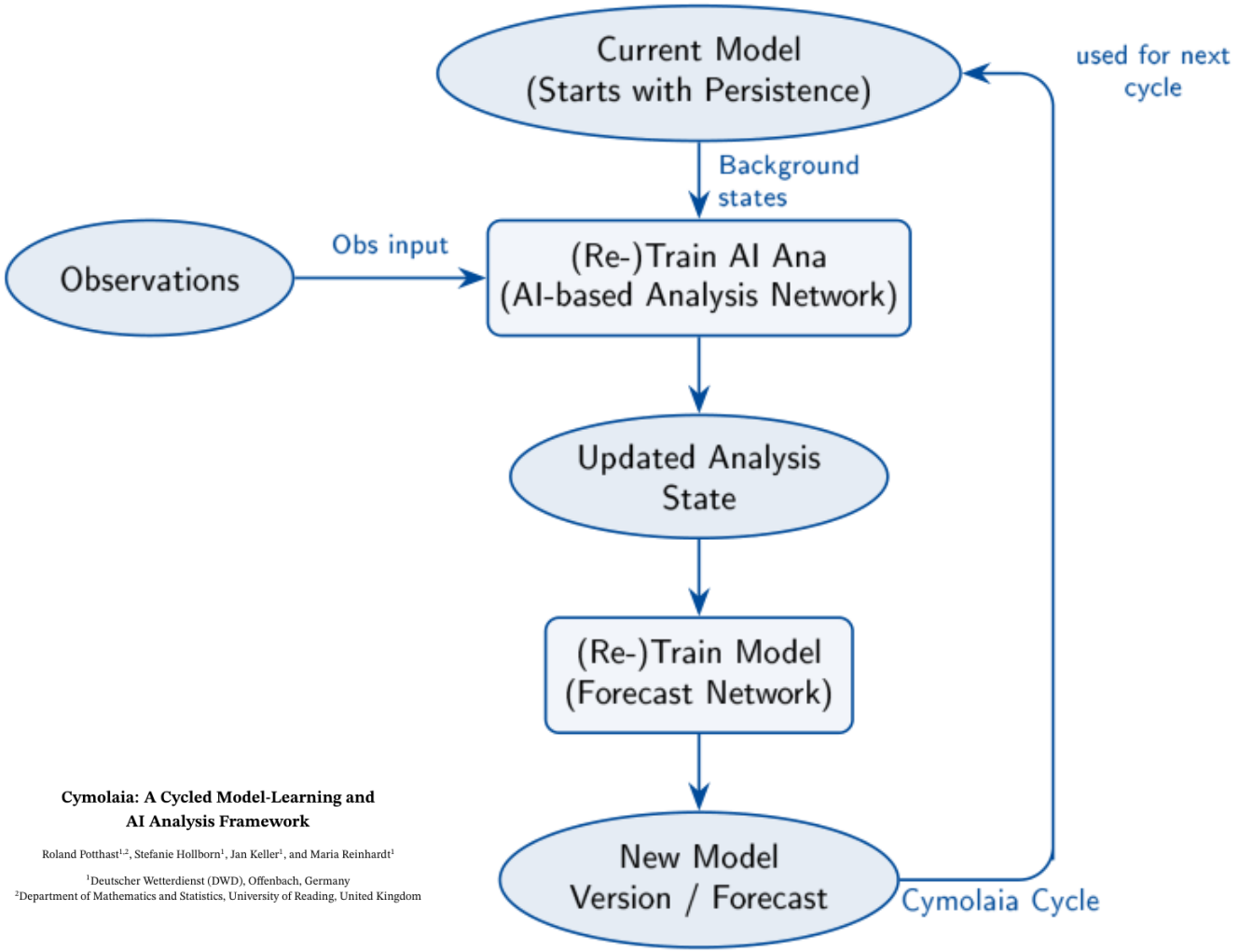
Learning the PF from Obs: AI PF

Deutscher Wetterdienst
Wetter und Klima aus einer Hand

Lorenz 96 Conceptual Tests with **AIPF**



ORIGEN: Observation based Reconstruction and Inference for Generative Emulation of Nonlinear Systems



Cymolaia: A Cycled Model-Learning and AI Analysis Framework

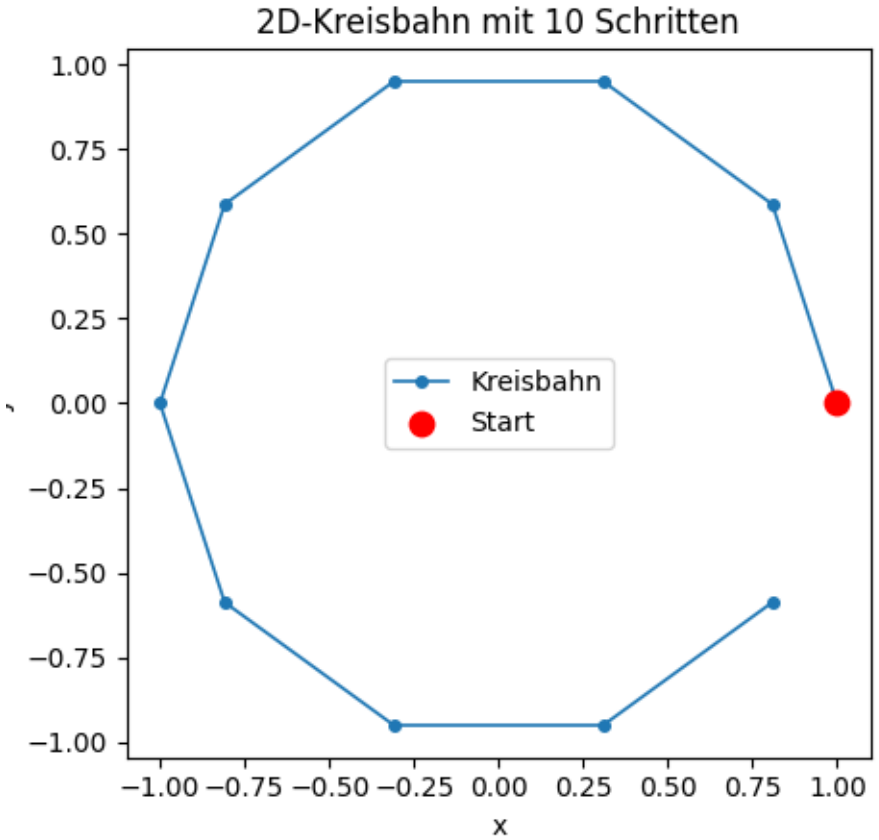
Roland Potthast[1,2], Stefanie Hollborn[1], Jan Keller[1], and Maria Reinhardt[1]

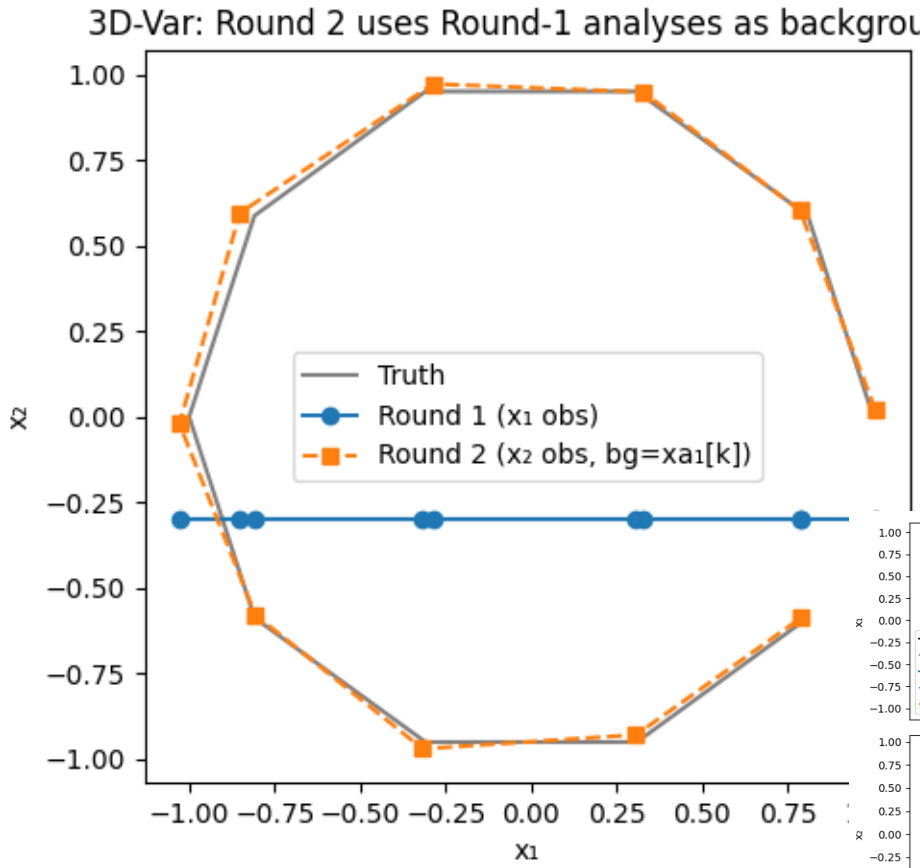
[1]Deutscher Wetterdienst (DWD), Offenbach, Germany
[2]Department of Mathematics and Statistics, University of Reading, United Kingdom

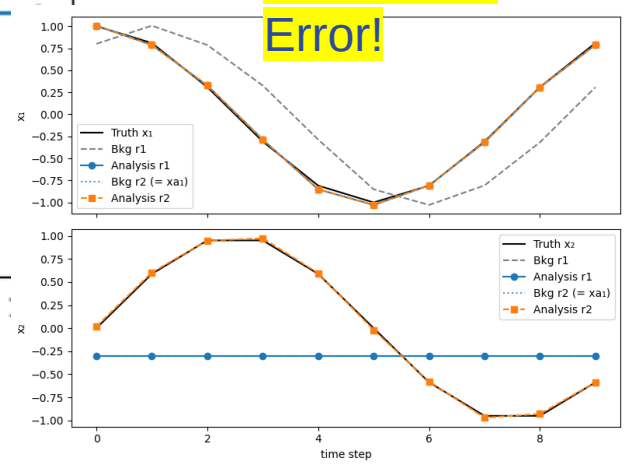
1. Carry out Assimilation with Persistence
2. Lean a simple model
3. Use the model to carry out Assimilation with it
4. Learn a better model
5. Continue the cycled iteration!

ORIGEN: Oscillator Example

Deutscher Wetterdienst
Wetter und Klima aus einer Hand







Learn from **only x1** observations for one cycle, then **only x2** observations for a second cycle.

Small Obs Error!

Cymolaia: A Cycled Model-Learning and AI Analysis Framework

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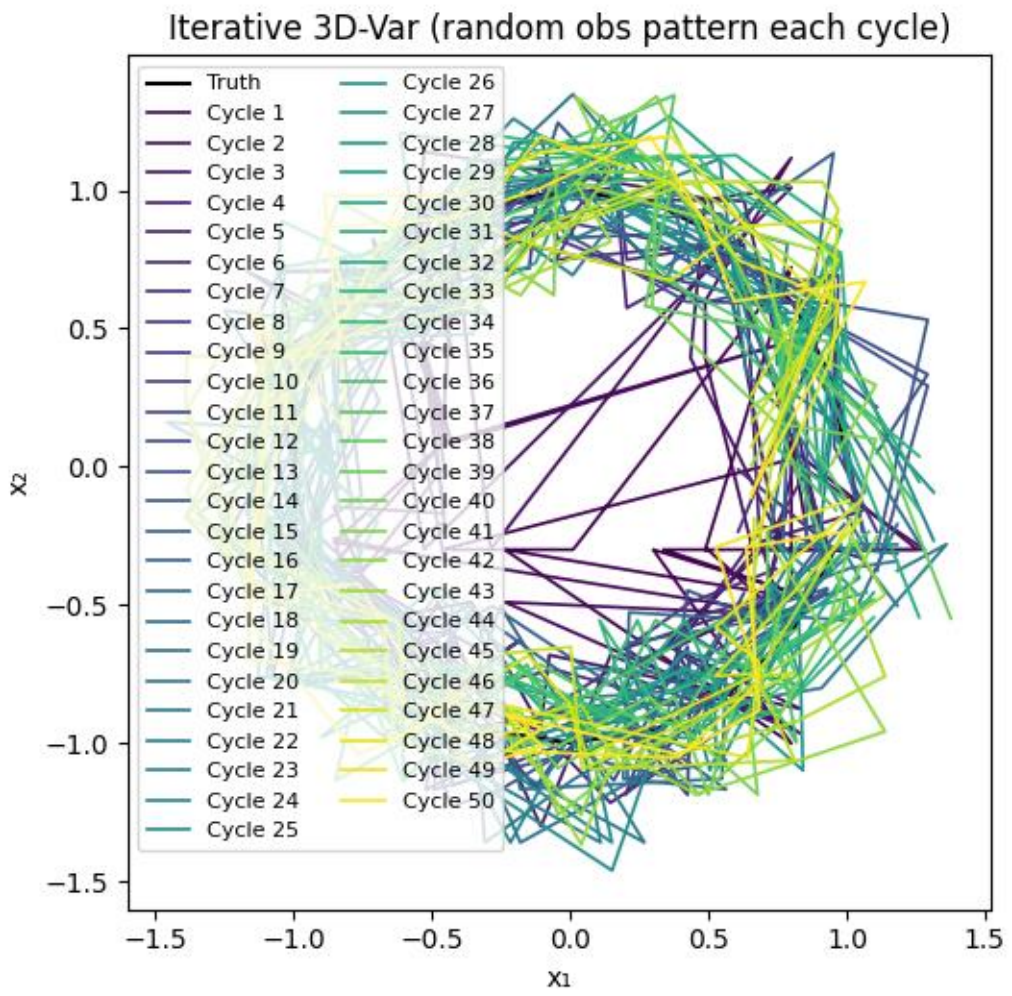
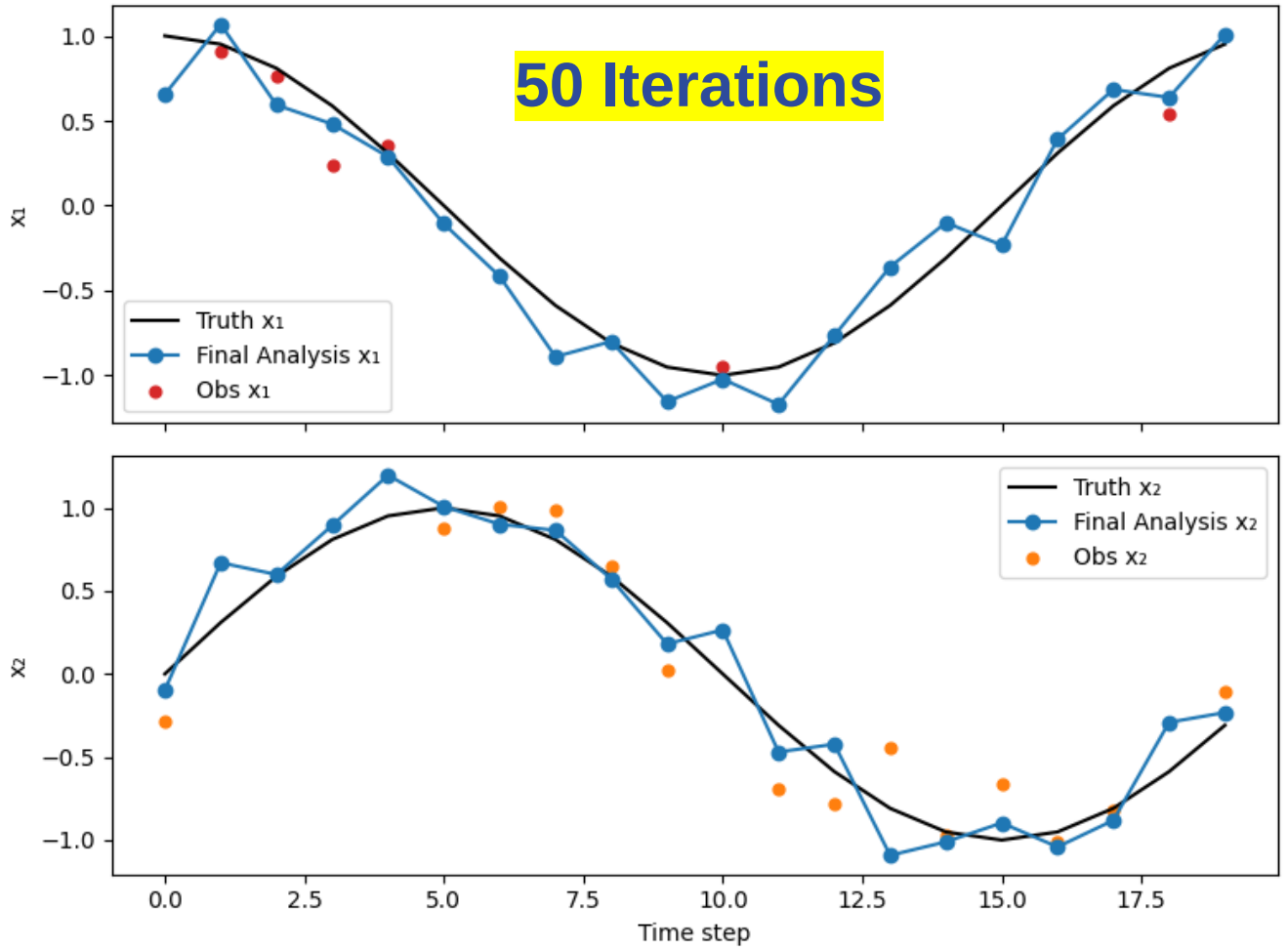
ORIGEN: Oscillator Example

Deutscher Wetterdienst
Wetter und Klima aus einer Hand





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ORIGEN: Oscillator Example

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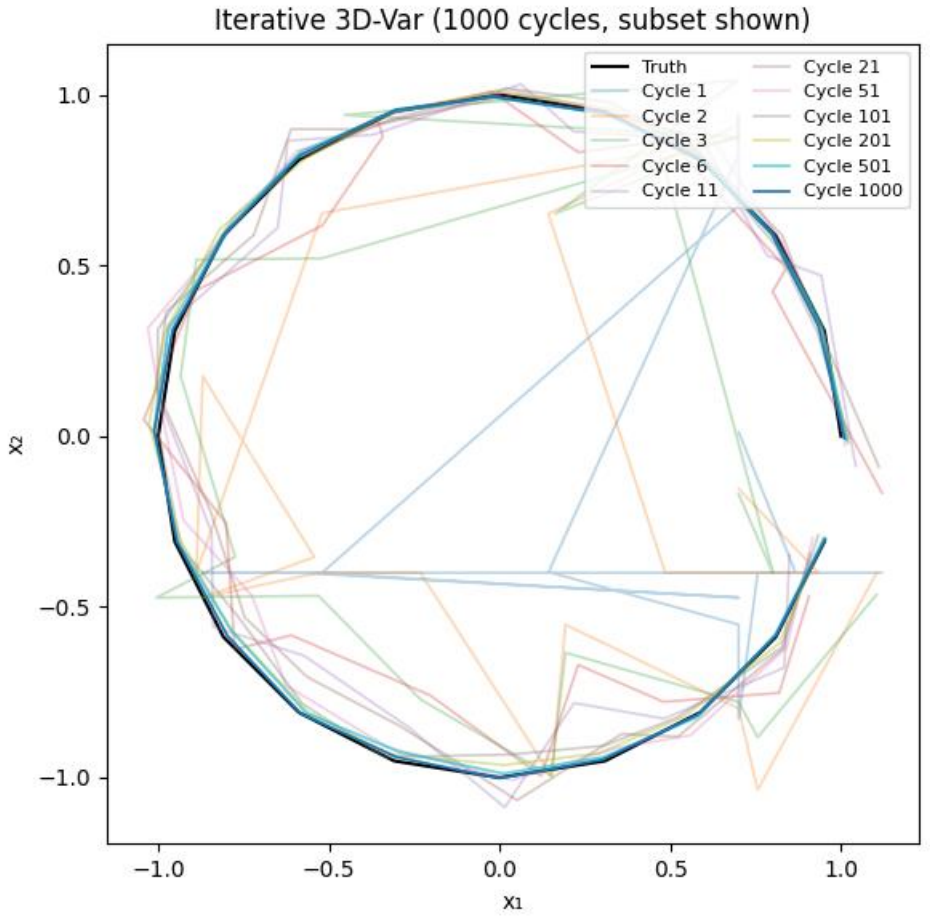
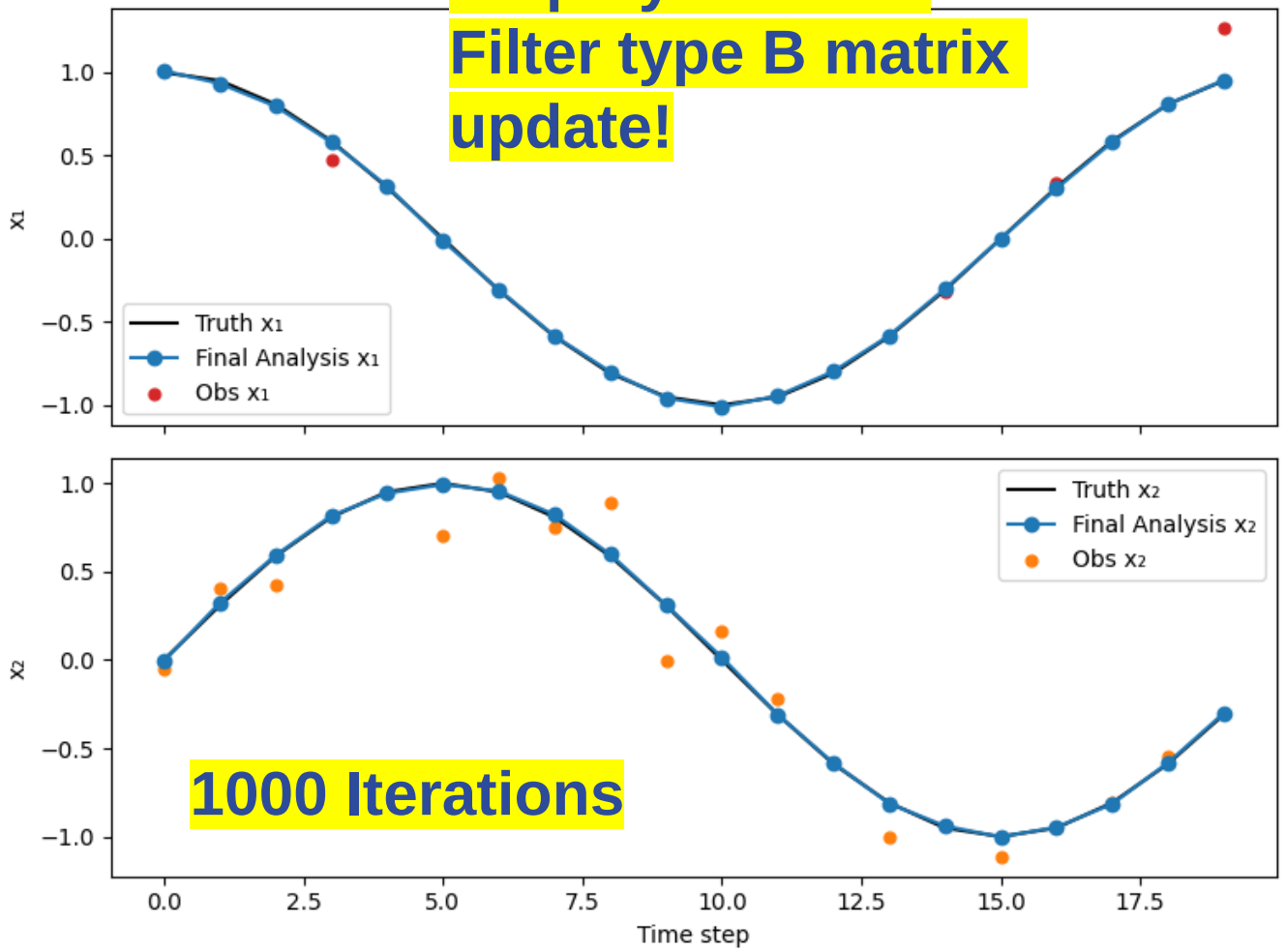
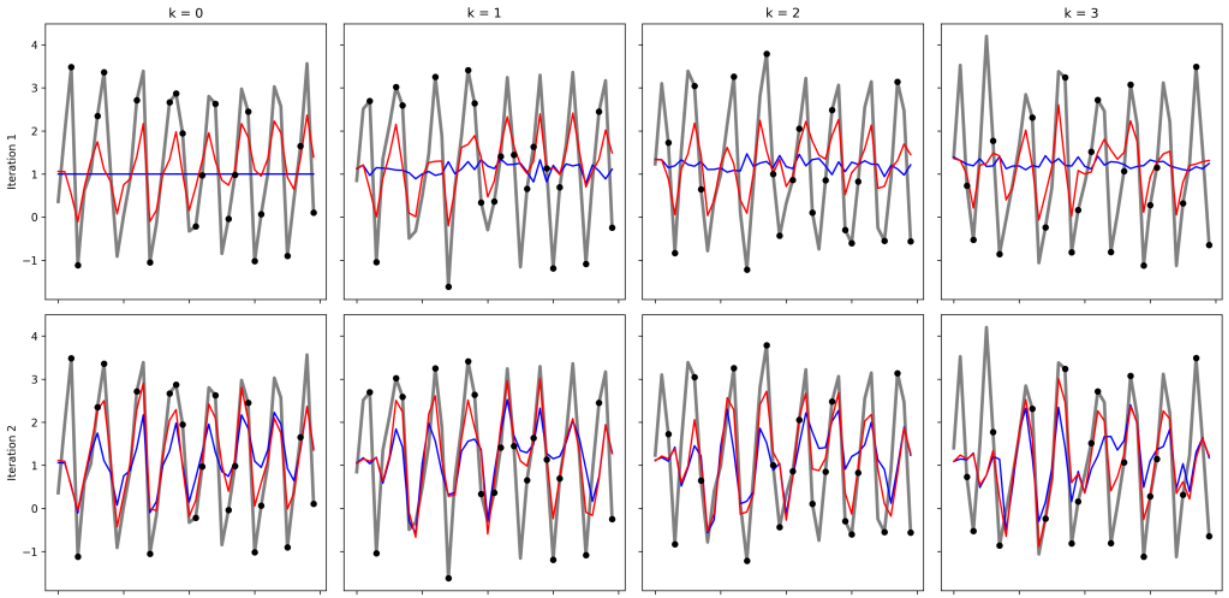


Employ Kalman Filter type B matrix update!



1000 Iterations

ORIGEN: Lorenz 96

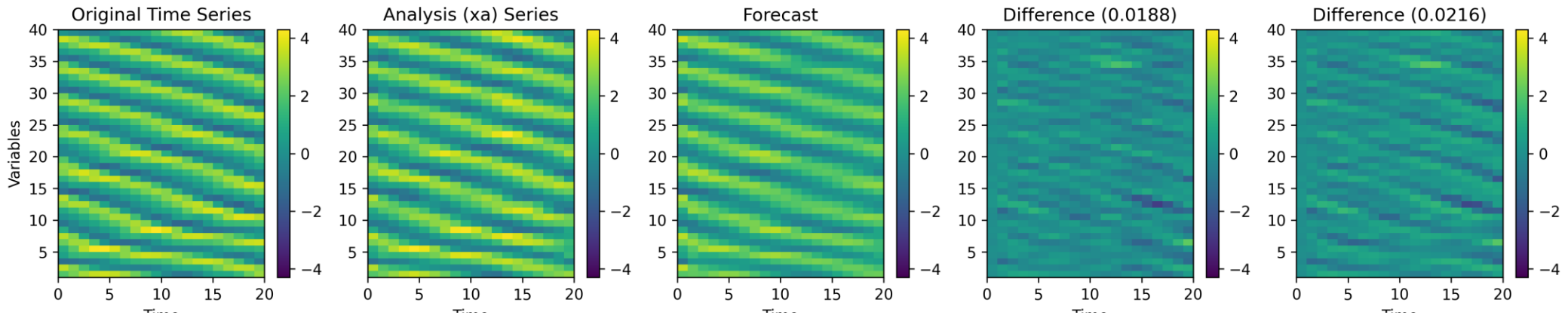


Learning Lorenz 96 from observations of a random selection of observed points

Cymolaia: A Cycled Model-Learning and AI Analysis Framework

Roland Potthast[1,2], Stefanie Hollborn[1], Jan Keller[1], and Maria Reinhardt[1]

[1]Deutscher Wetterdienst (DWD), Offenbach, Germany
[2]Department of Mathematics and Statistics, University of Reading, United Kingdom



Observations and **Artificial Intelligence**

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Consequences of current developments, main lines

- Users get **new access** to information through large language models
- There are new techniques for fast **analysis** and modelling, **nowcasting** and **forecasting**, and **monitoring**
- Characterization and detection of phenomena, processes, **features** and their relevance can be automatized in a new way
- **Conceptual Interpretation** of observations becomes possible in an new way, with **insight**, **understanding** and **impact**

Summary: back to physics and processes

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- AI helps us to find and emulate **physical processes** from observations
- AI is a tool which helps us to identify and interpret
  - **phenomena**,
  - **characteristics,**
  - **Processes**
- AI can learn to observe (identify) and characterize phenomena and temporal changes or evolution of phenomena

We need to **think in processes** and what information we observe on what temporal scale needed for application areas and tasks

Global to Regional ICON

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Global	EU	D2 + D05	RUC	ART	K	AICON	
ICON Global Non-Hydrostatic	**ICON-EU 2-way-nest**	**ICON D2 LAM Convective Scale**	**ICON-D2 RUC Convective Scale**	**ICON ART Ensemble**	**Kangu**	**AICON**	AICON-LAM
Det **13 km** Resolution EPS 26 km Resolution 120 level 40 member Analysis every **3h** EnVAR + LETKF **Forecasts** **180h: 00,12 UTC, 120h: 06, 18 UTC, 51h: 03, 09, 15, 21UTC**	Det **6.5 km** Resolution EPS 13 km Resolution 74 level 40 member Analysis every 3h EnVAR + LETKF **Forecasts** **120 h: 00, 06, 12, 18 UTC, 51 h: 03, 09, 15, 21 UTC**	Det **2 km + 500m** Resolution EPS **2 km** Resolution 65 level 40/20 member **Analysis every 1h** KENDA: 4D-LETKF **Forecasts** **48h: 00, 03, 06, 09, 12, 15, 21 UTC**	Det **2 km** Resolution EPS 2 km Resolution 65 level 40/20 member **Analysis every 1h** KENDA: 4D-LETKF **Forecasts** **8h: 06, 07, 08, … 17, 18 UTC**	26 km resolution **10 member** Analysis every 3h EnVAR + LETKF **Forecasts 120h**	**AI Forecast** **Forecasts Every 3h** **7 days**	**AI Forecast** **Forecasts Every 3h** **7 days**	**AI Forecast** **Forecast Every 1h** **3 days**

Operational Chain

GLORI = Global-to-Regional ICON Digital Twin