DWD's vision for future NWP: A fully data-driven data assimilation approach

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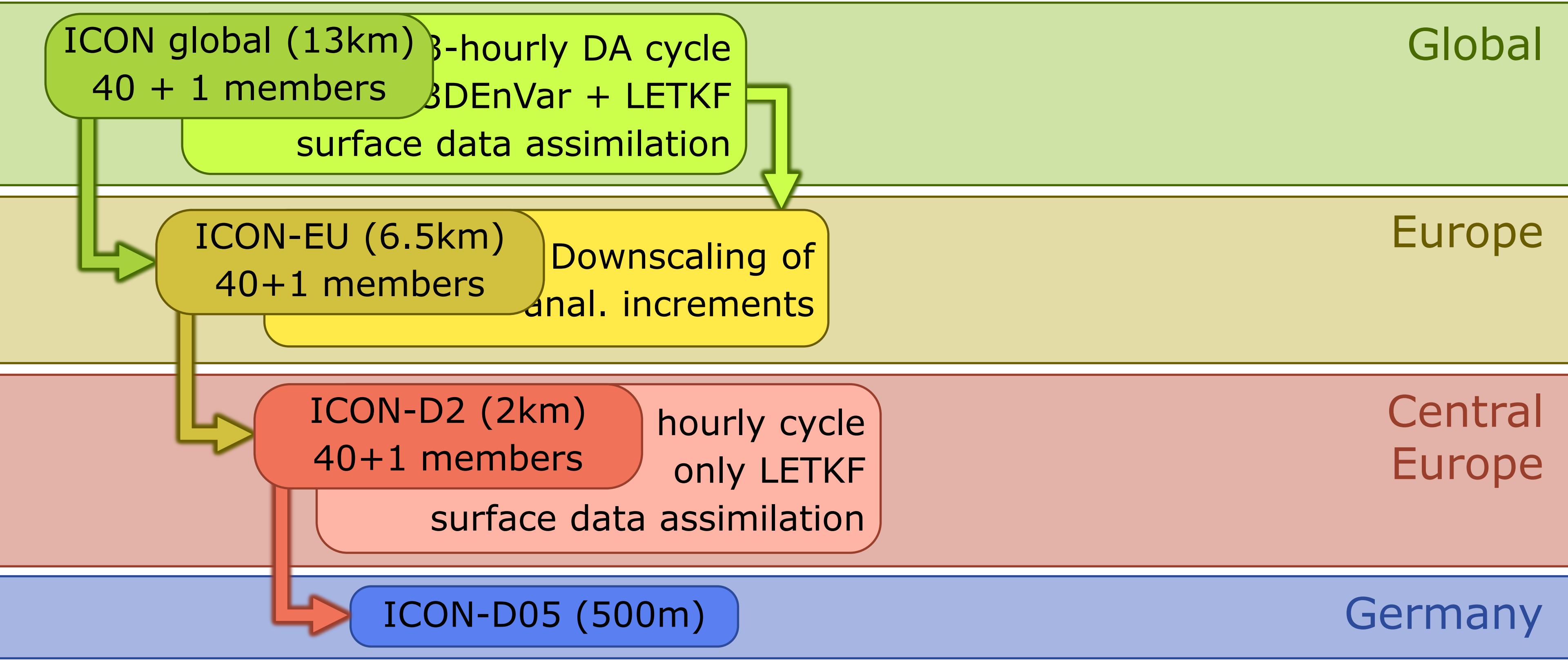
Data Assimilation at DWD – Status



Data Assimilation at DWD – Status

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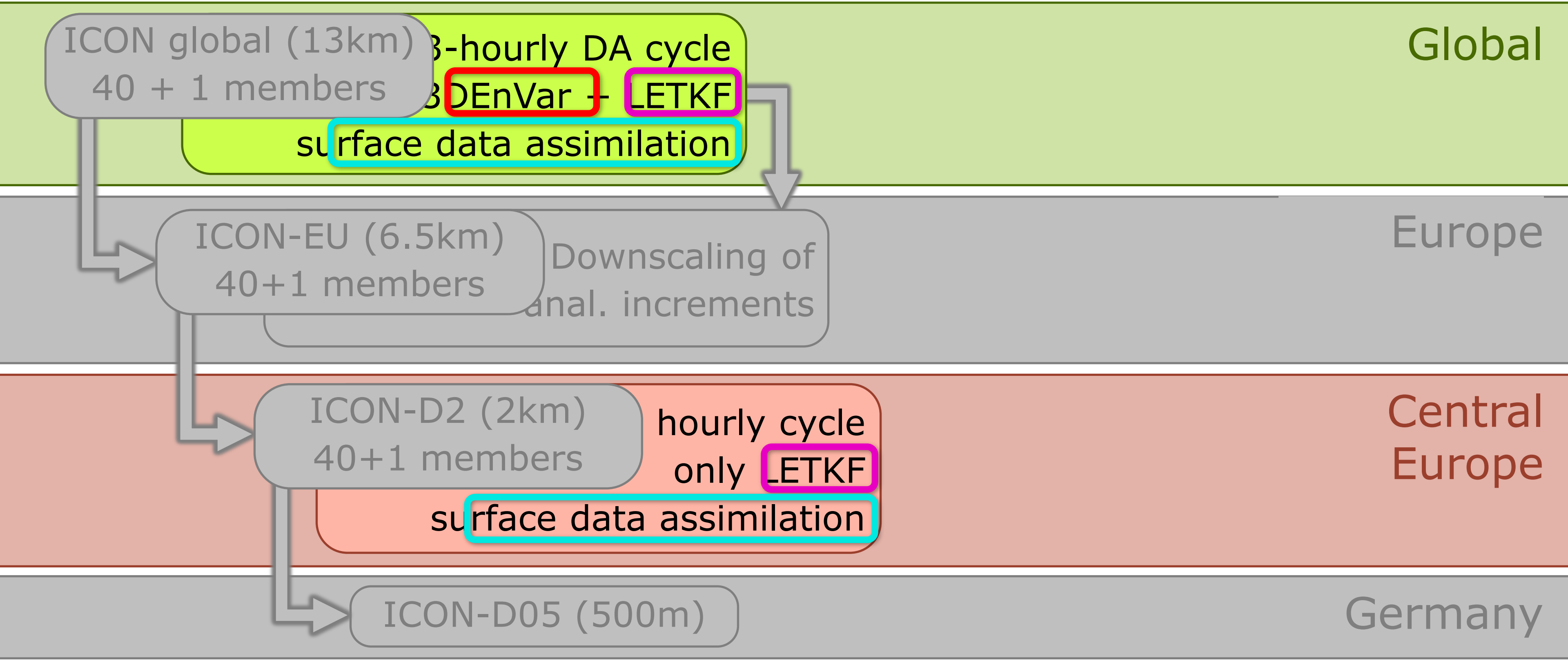
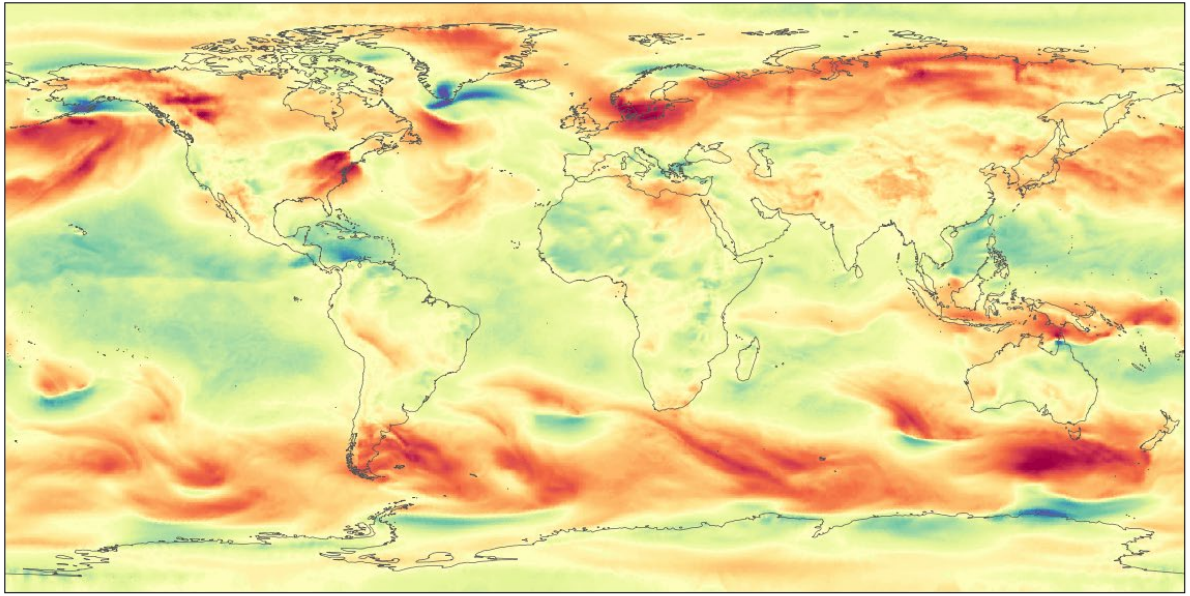


AICON – DWD's AI-based NWP model

- Developments show benefits of AI-based models
  - Higher performance and better forecast quality
- AICON
  - AI model for ICON
  - Global and LAM configurations in development



AICON – DWD‘s AI-based NWP model

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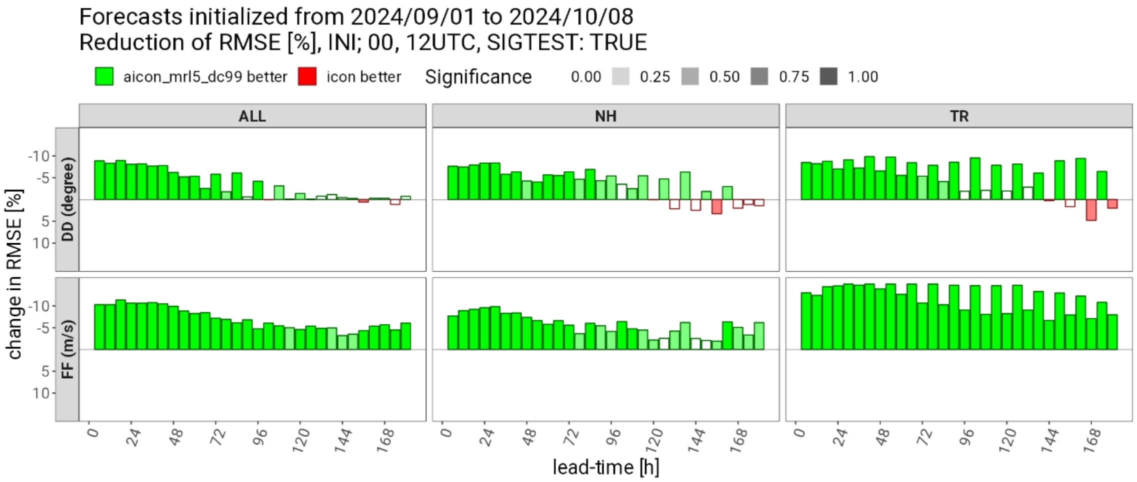
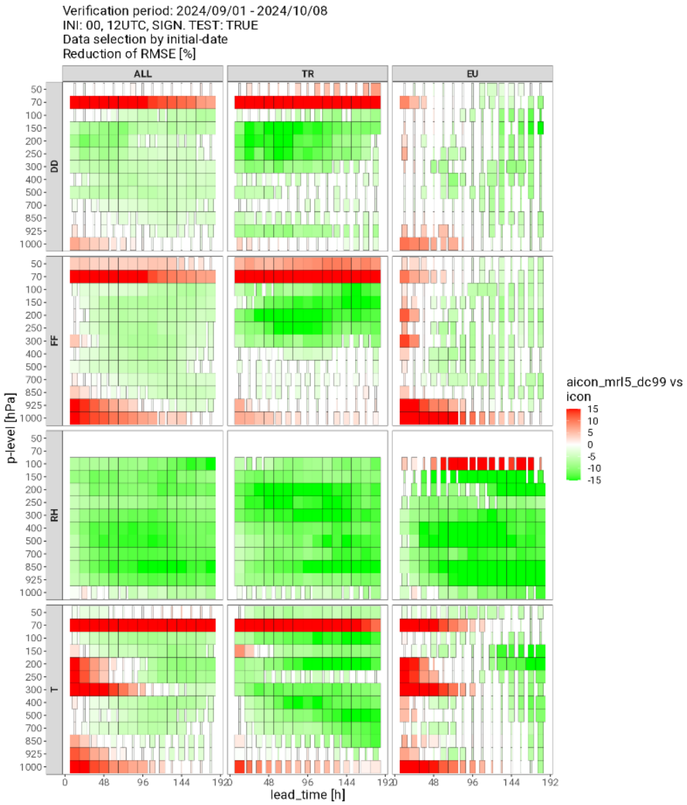
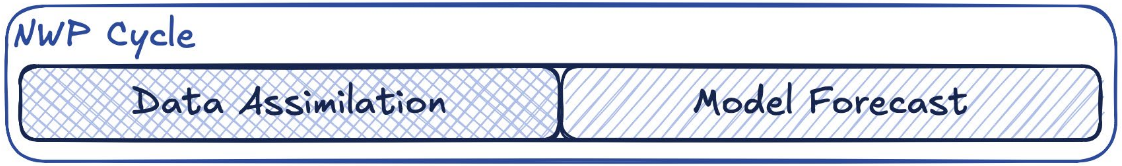
- AICON global (development version) performance against operational ICON

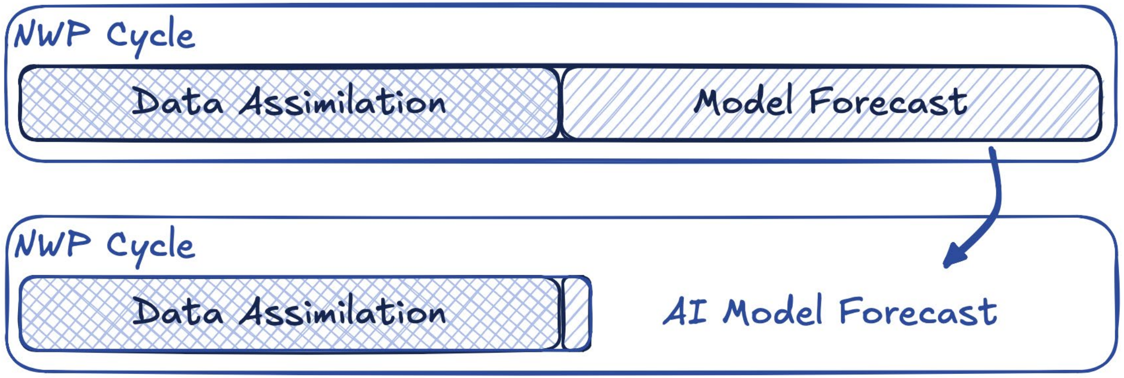




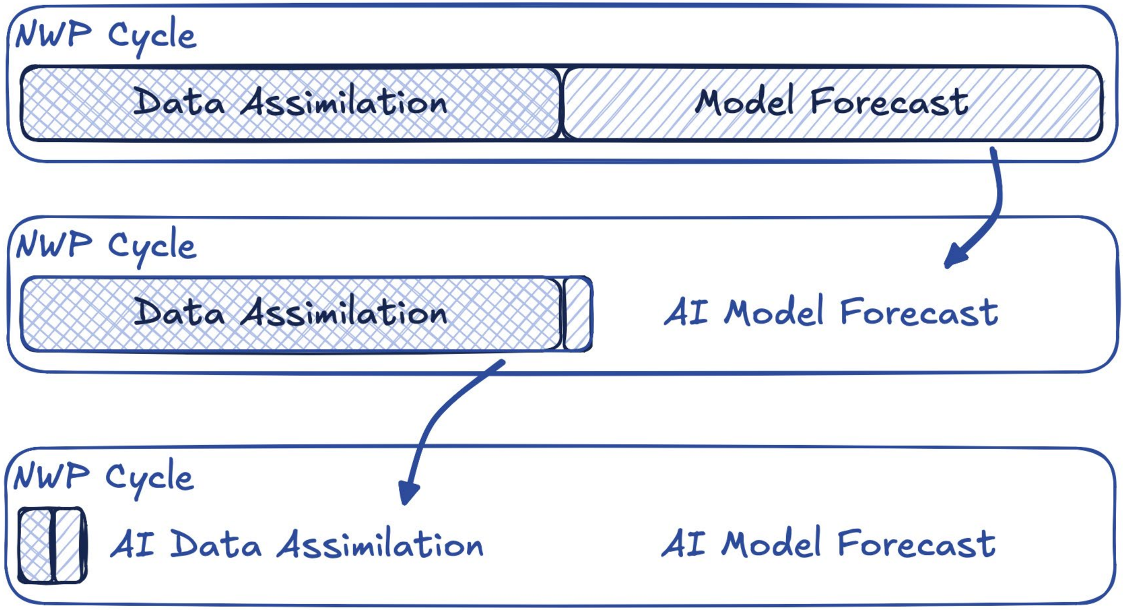
AI in the NWP cycle



AI in the NWP cycle



AI in the NWP cycle



AI in Data Assimilation

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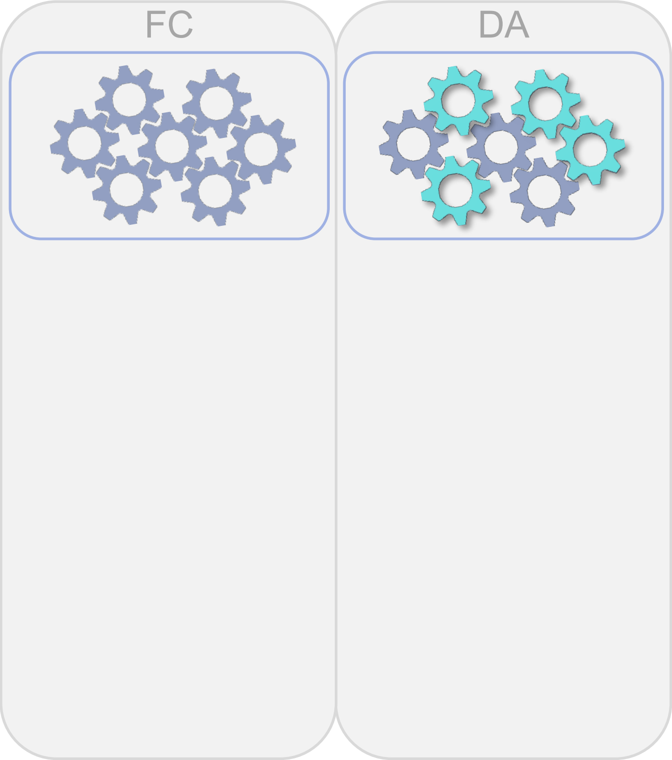
- Approaches in AI-based data assimilation
  - Substituting / adding modules in the DA system
    - bias correction
    - observation operators



AI in Data Assimilation

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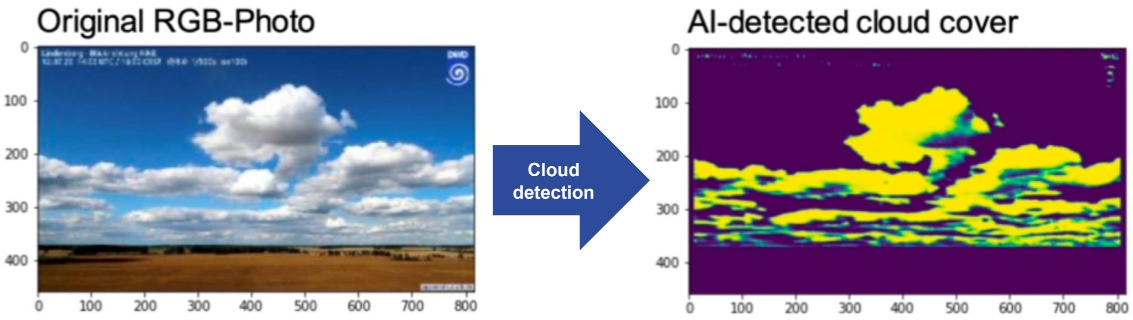
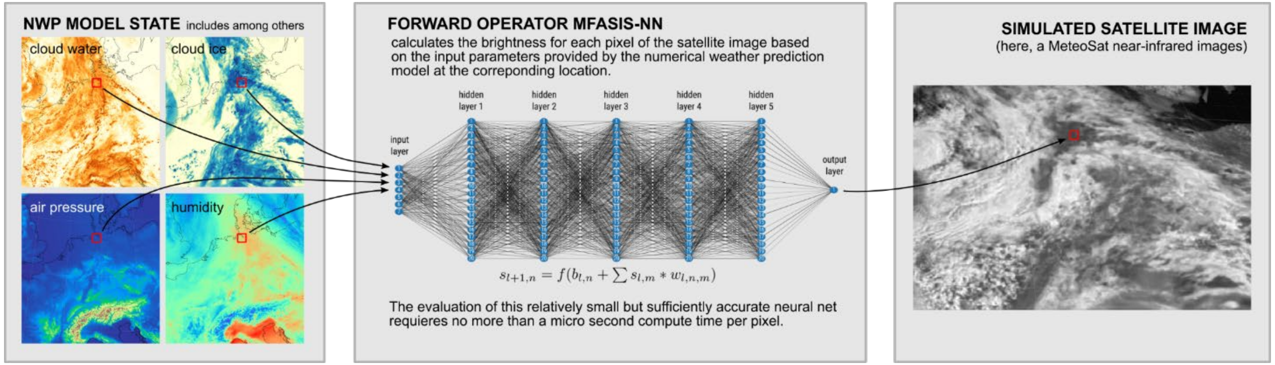
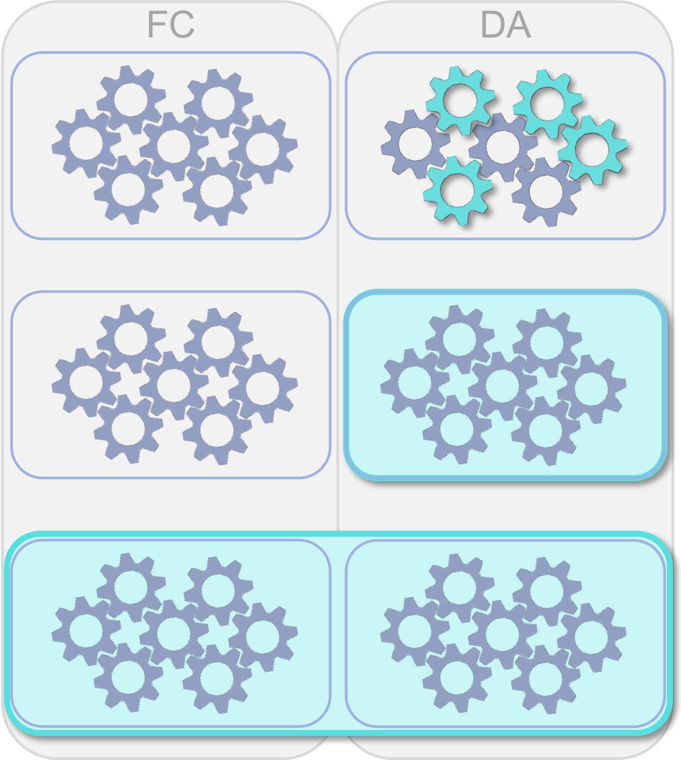
- AI components implemented and tested in DA at DWD
  - Forward operators for cloud cameras
  - Radiative transfer accelerator MFASIS
    - integrated into RTTOV





AI in Data Assimilation

- Approaches in AI-based data assimilation
  - Substituting / adding modules in the DA system
    - bias correction
    - observation operators
  - Learning the data assimilation step
    - Learn the mapping from forecast / observations to analysis (increments)
  - End-to-End approach
    - Integration of DA and forecasting into one model using observations for initialization



The AI-Var approach

- AI-Var as a basis for DWD‘s AIDA framework
- How does it work?
  - Common AI approach would train on
    input: forecast (background x_ξ^b) and observations (y_ξ)
    target: analysis (x_ξ^a)
  - Training data would be sampled from

$$\mathcal{S}_1 := \{s_\xi = (y_\xi, x_\xi^b, x_\xi^a), \quad \xi = 1, \ldots, n_t\}$$

and the model would train using the loss function

$$l = (\hat{\mathbf{x}} - \mathbf{x}^a)^2$$

The AI-Var approach

- However, in AI-Var, we learn the DA functional itself $f(x^b, y) \mapsto x^a$
- Training data now samples only from

$$\mathcal{S}_2 := \left\{ s_\xi = (y_\xi, x^b_\xi), \quad \xi = 1, ..., n_t \right\}$$

- Data assimilation cost function is injected into the training as loss function

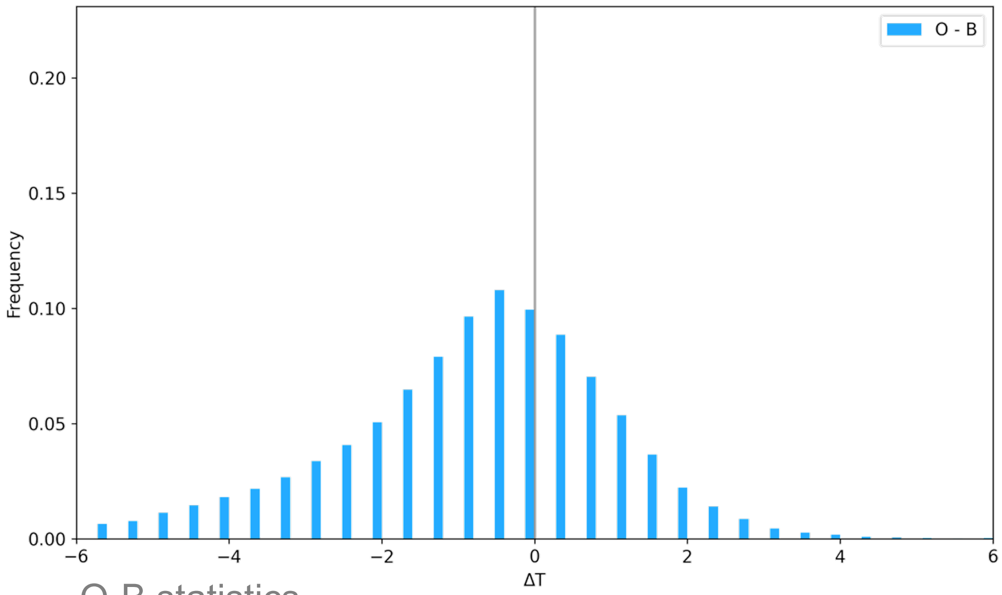
$$l = (\hat{\mathbf{x}} - \mathbf{x}^b)^T \mathbf{B}^{-1} (\hat{\mathbf{x}} - \mathbf{x}^b) + (\hat{\mathbf{y}} - \mathbf{y})^T \mathbf{R}^{-1} (\hat{\mathbf{y}} - \mathbf{y})$$

→ Loss penalizes deviations from first guess as well as observed data

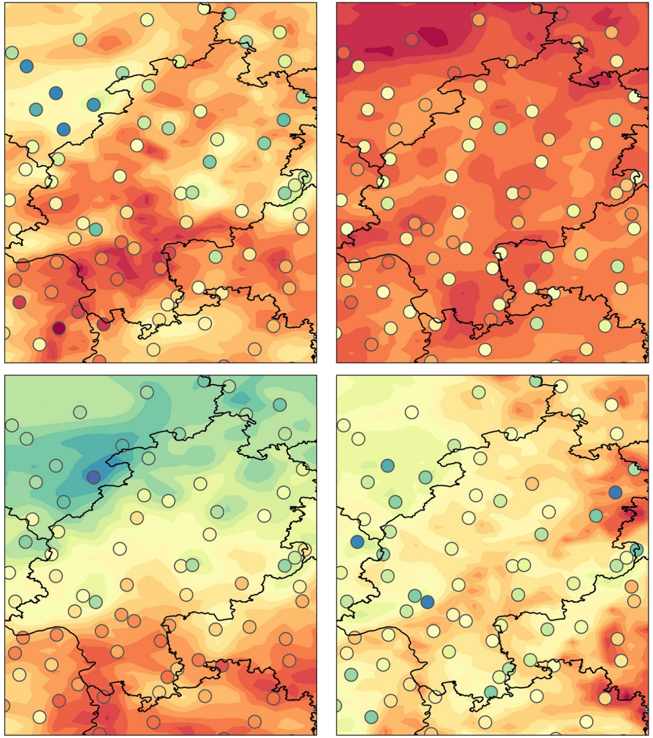
- Further details and results can be found in
  Keller and Potthast (2024, https://arxiv.org/abs/2406.00390)

The AI-Var approach

- Example of T2M assimilation with the old COSMO-REA6 reanalysis as first guess



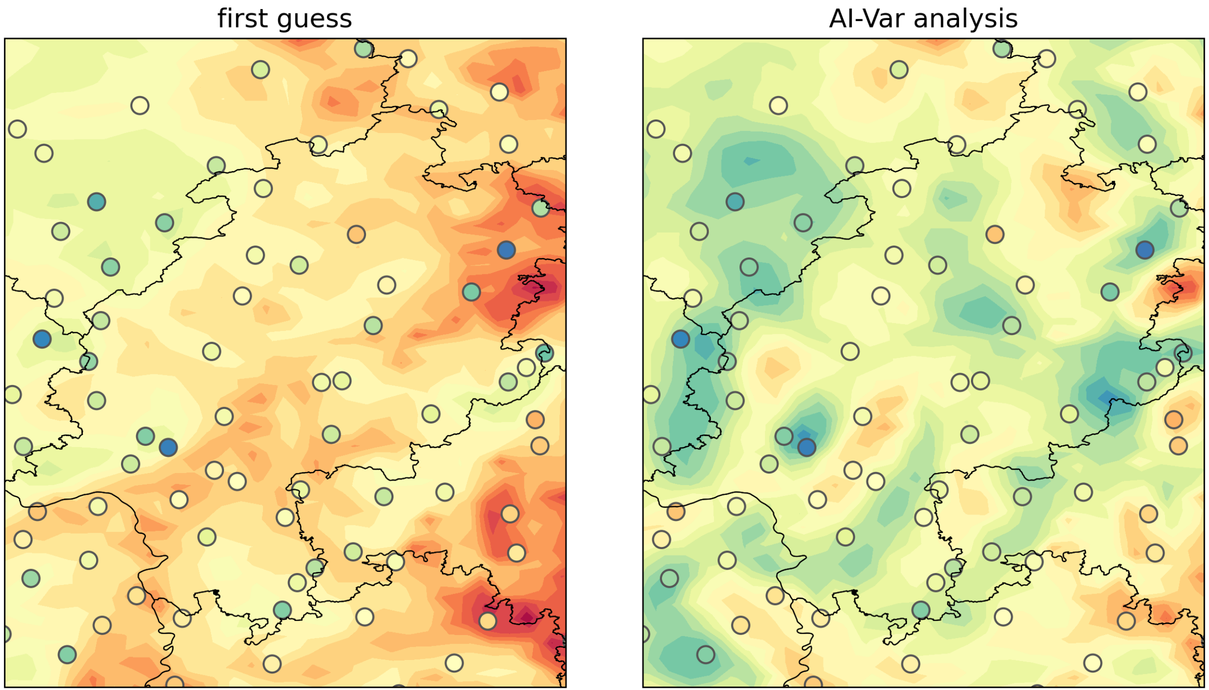
O-B statistics



Example T2M fields with corresponding observations

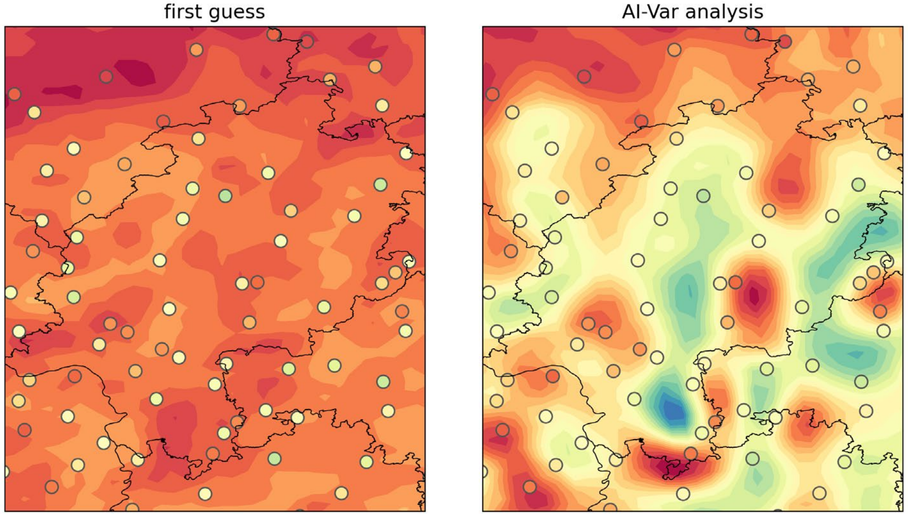
The AI-Var approach

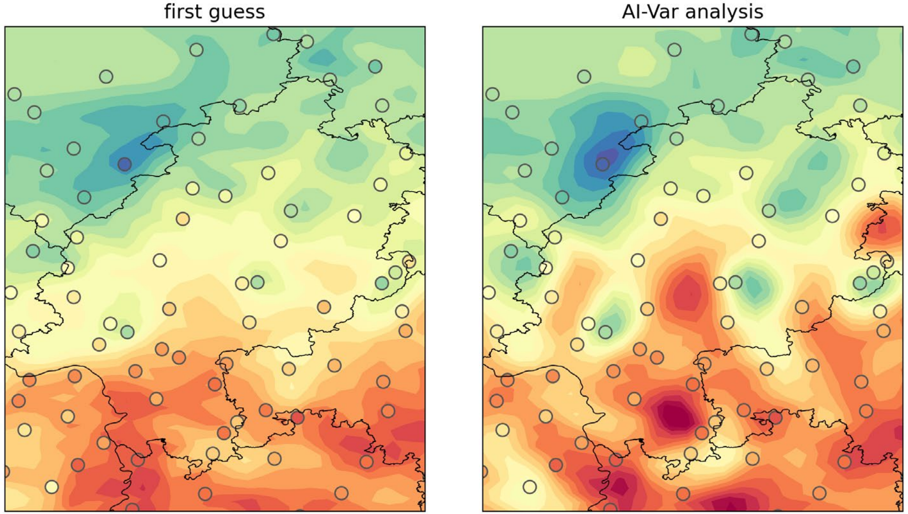
- Input for AI training
  - Observations: SYNOP T2M
  - First guess: T2M from COSMO-REA6



The AI-Var approach

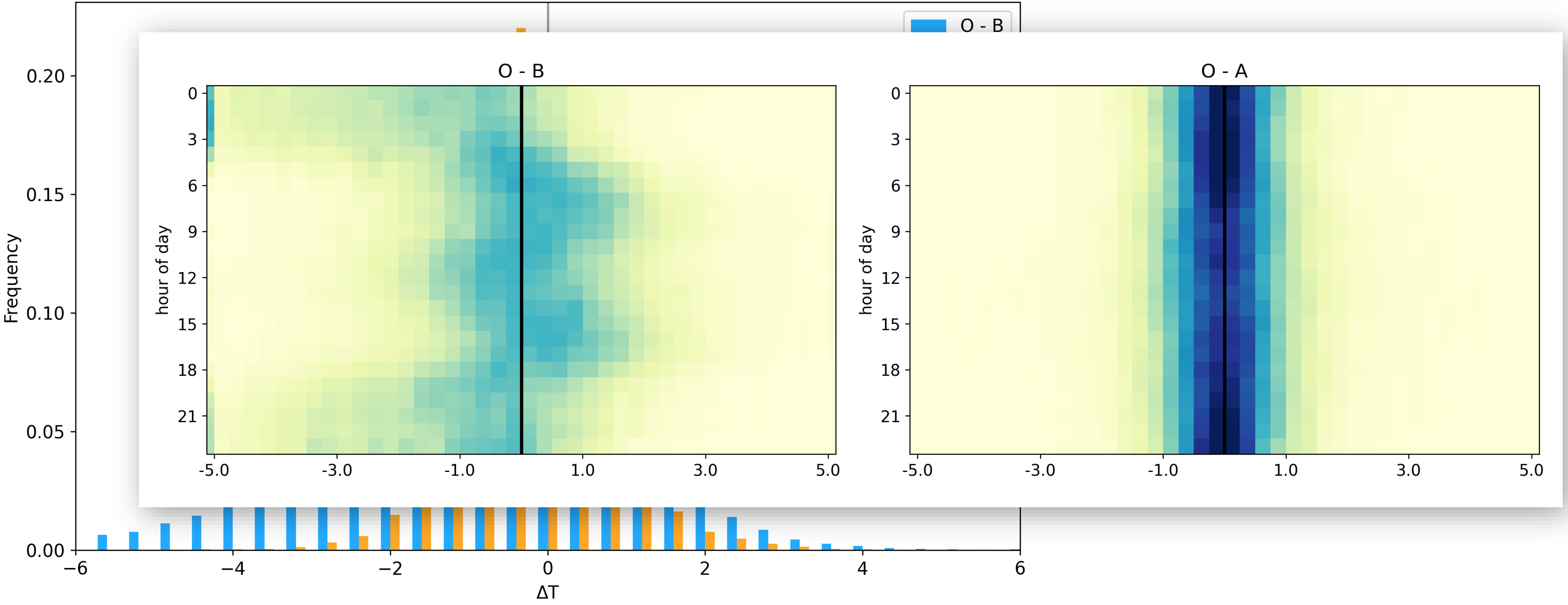
- Further examples





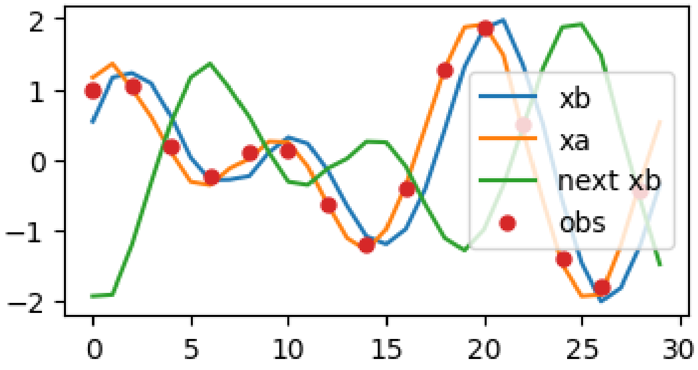
The AI-Var approach

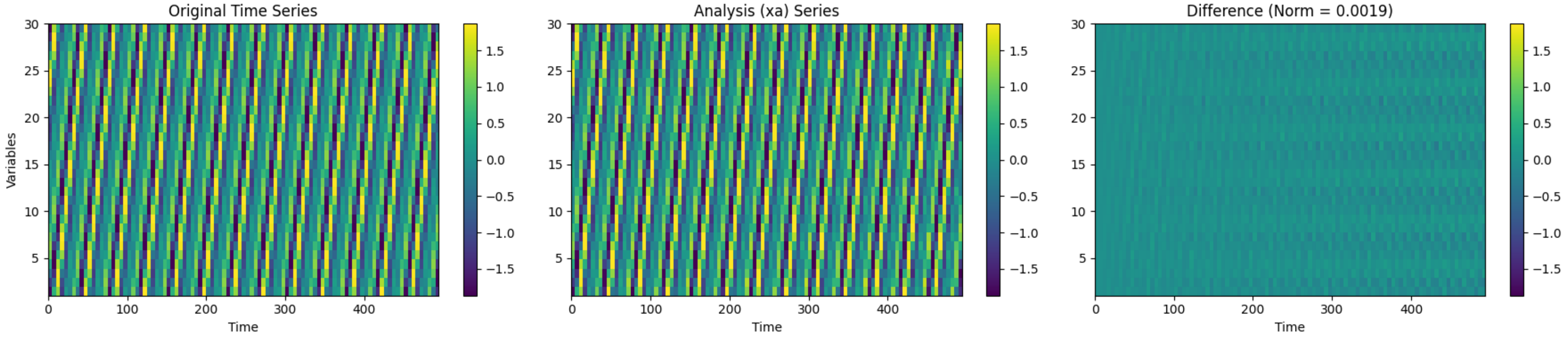
- Evaluation



The AI-Var approach

- Cycling with AI-Var
  - DA cylce was implemented and tested with Lorenz96





From AI-Var to AIDA

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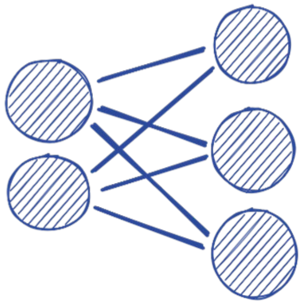
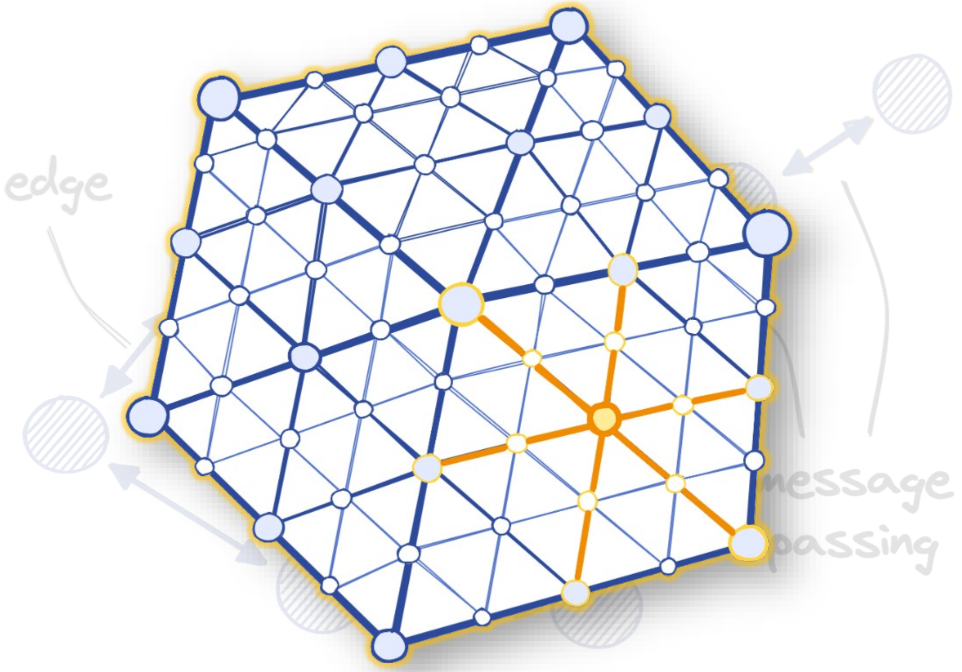
- Building a general framework for AI-based data assimilation → AIDA
  - Flexibility of
    - first guess structure (horizontal or vertical grid)
    - observation types
  - Built on a Graph Neural Network (GNN) architecture
  - First guess:
    T2M reanalysis

From AI-Var to AIDA

- The GNN approach



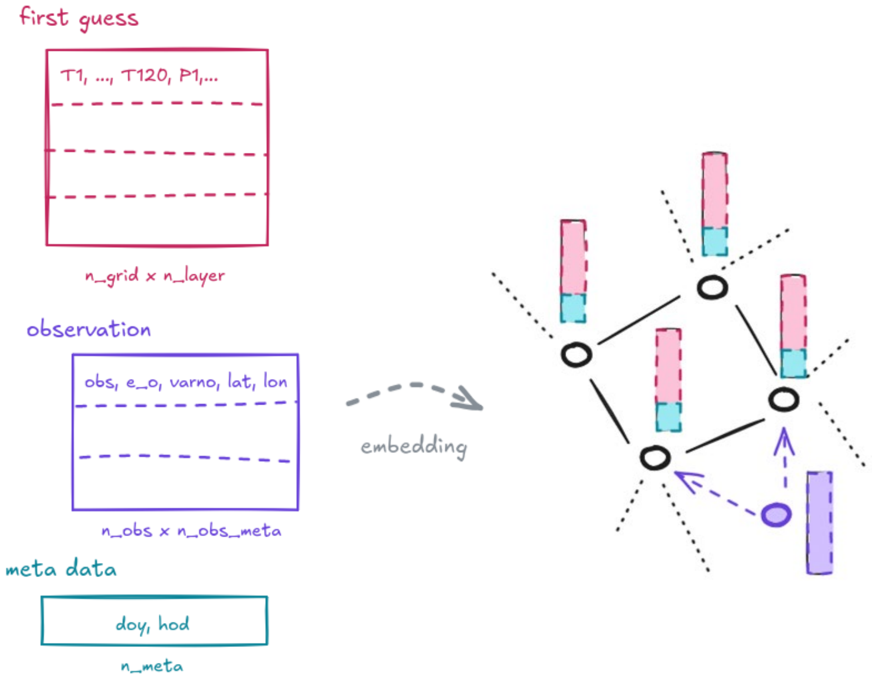
Fully connected
Neural Network



Graph Neural Network

From AI-Var to AIDA

- Observations in the GNN
  - Information on the nodes through vector of data
    - model data
    - meta data
  - Observations
    - can be added to vector, e.g., nearest neighbor
    - can be added as separate nodes in graph



From AI-Var to AIDA

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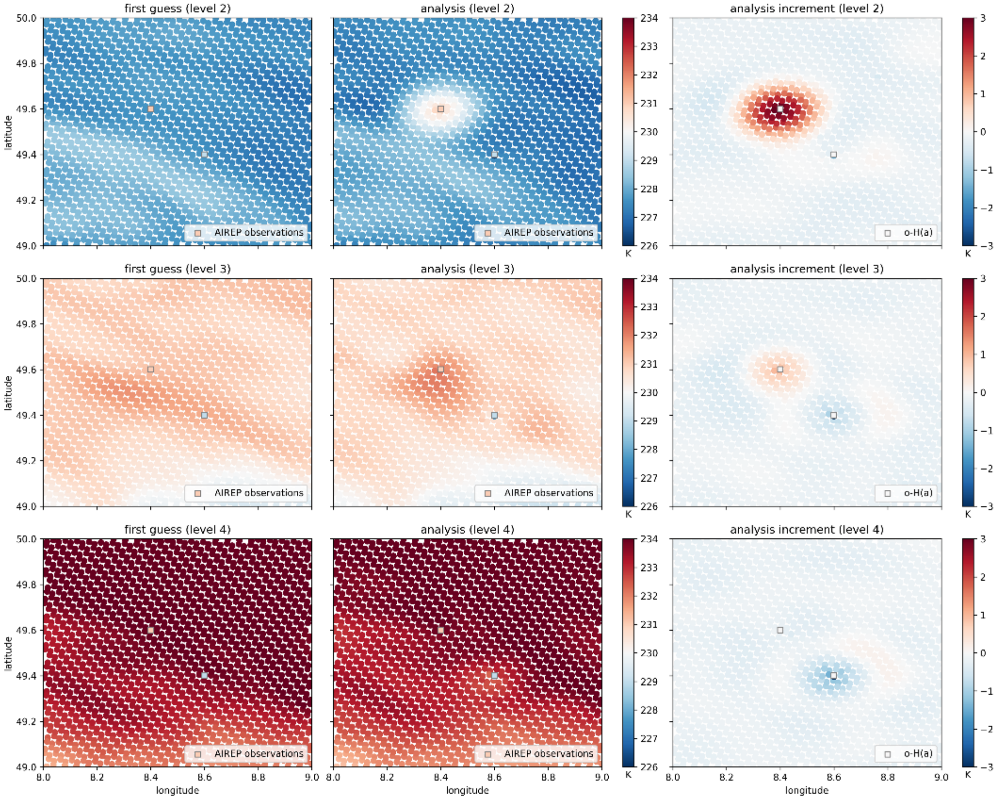
- Test case AIREP assimilation



From AI-Var to AIDA

- Code has to be reimplemented - not an easy task
- Methods have to be reviewed and adapted
  - Observation operators
    - Conventional implemented
    - RTTOV also works for specific cases
  - Error covariances
  - Bias correction
  - Quality control
  - Localization

From AI-Var to AIDA

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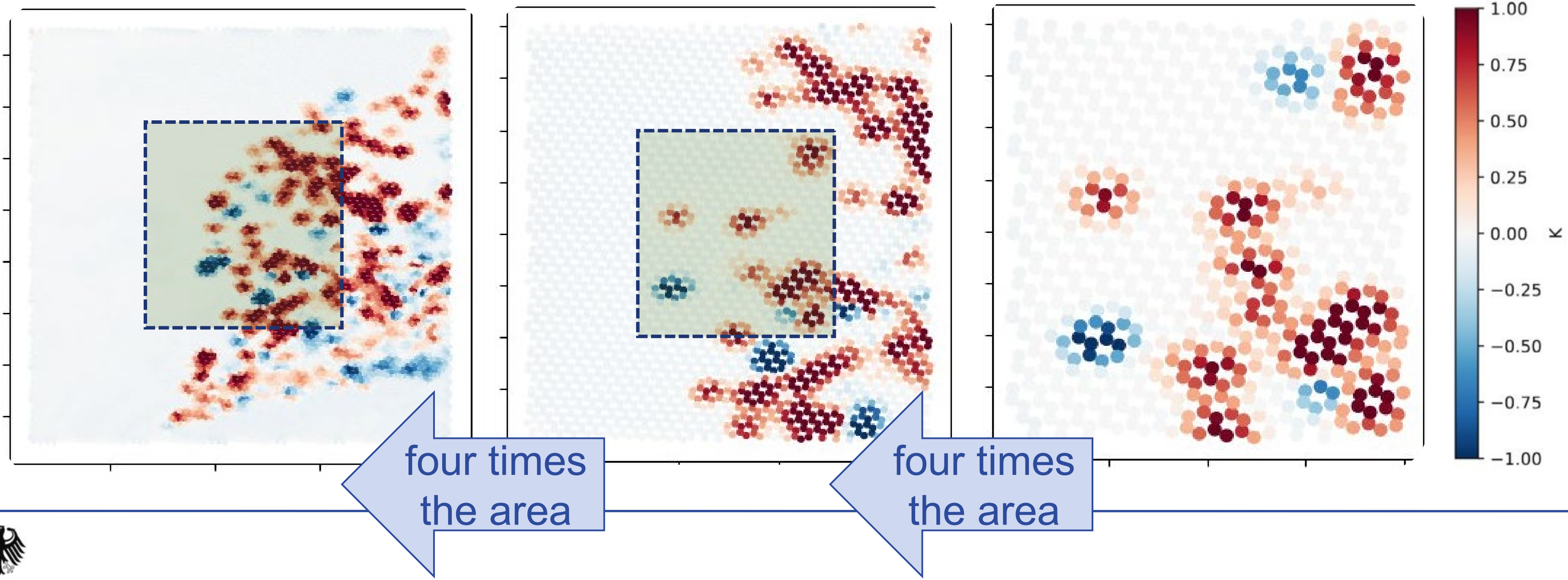
- Currently the main challenge: Scalability
  - At the moment the setup has a maximum number of grid points of 70.000 on 8xA100 GPUs

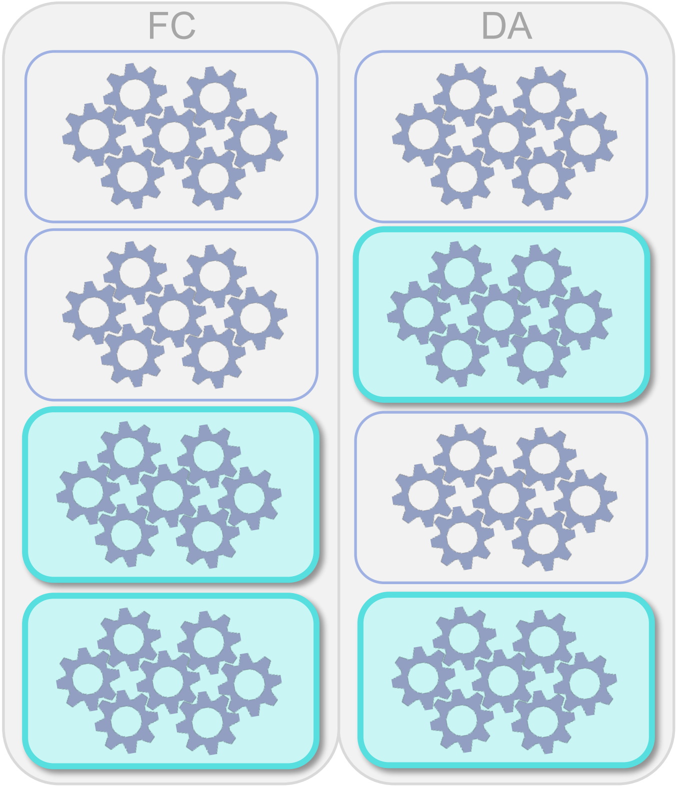


From AI-Var to AIDA

- Possible applications
  - AI-based NWP
  - Ultra rapid data assimilation
  - Reanalysis
  - Post-processing
- Framework is also intended as the backbone for tempo-spatial AI applications in DWD‘s AI development unit

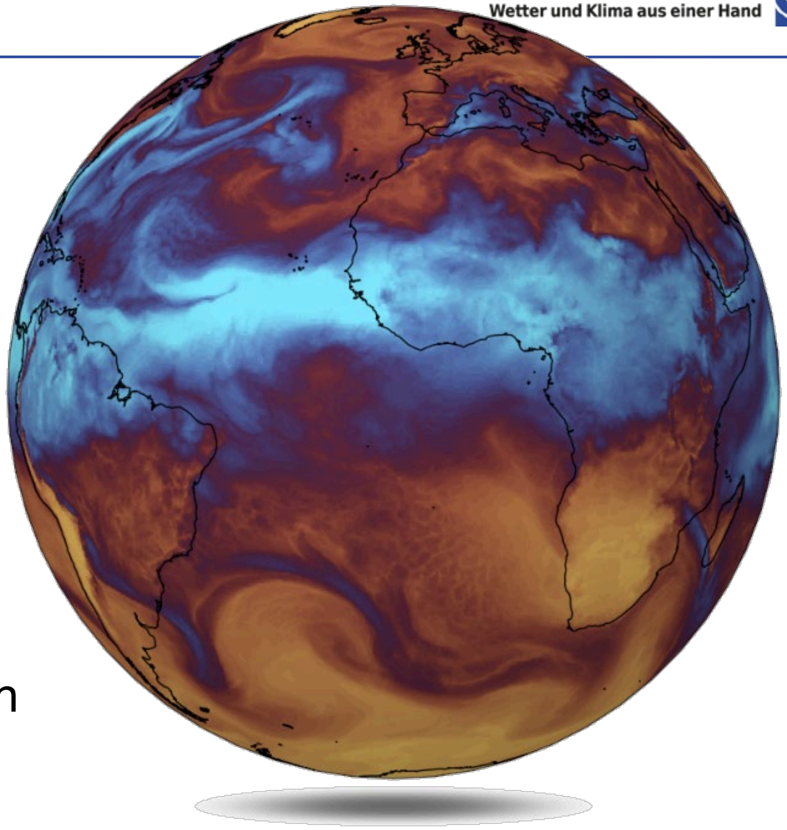
Plans for DWD's future DA

- Modular approach to allow for various combinations
  - Physics-based model - classical DA
  - Physics-based model – AI-based DA
  - AI-based model - classical DA
  - AI-based model - AI-based DA



Reanalysis data for training

- ICON-DREAM
  - Global reanalysis (13km) with additional refinement over Europe (6.5km)
  - 20 member ensemble
  - 15 years produced (2010-2024) with back-extension to 1978 in progress
- ICON-FORCE
  - Reanalysis for Central Europe (2km) with 20 member ensemble
  - Aimed at a 10 year period (2016-2025)



Vertically integrated water vapor

Plans for DWD‘s future DA - Reanalysis

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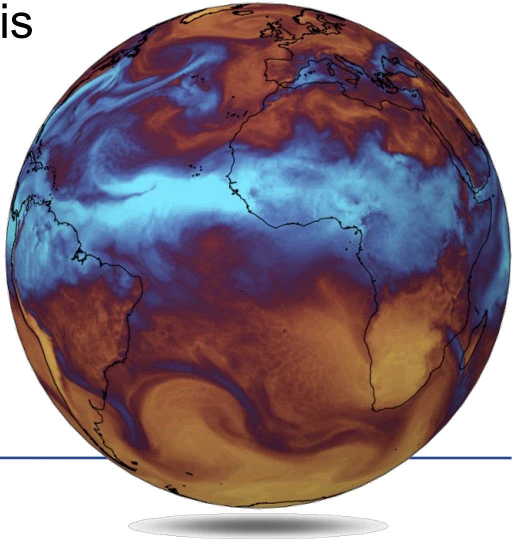
- How will we produce new reanalysis data?
    1. Model resolution can be „easily“ increased for physical models
       → Downscaling
    2. AI-based model will be trained on downscaled data (emulator for the model)
    3. AI model and AI data assimilation to create a reanalysis
    4. AI-based model will be trained on reanalysis data
    5. …

    → Iterative approach



Plans for DWD‘s future DA - Summary

- Building an AI-based data assimilation framework together with an AI NWP model
  - Based on the AI-Var approach
- Enabling a fast data assimilation cycle and quick production of forecasts
  - Preferrably with a higher forecats quality
- Higher frequency allows for an ultra rapid data assimilation (URDA)
  - New forecasts possible every 15, 10 or even 5 minutes?
  - Important in severe weather situations
  - Blending of NWP and nowcasting through AIDA
- SynCast – AIDA-based platform for merging various data sets into one

Plans for DWD‘s future DA - Questions

- What about estimating background error covariances?
  - Will we use huge ensemble?
  - Will we use ensembles at all?
- How to generate ensembles?
  - Initial condition uncertainty, model uncertainty
- Which parts of the NWP chain will be replaced?
- Is there still the need for classical modelling / DA?

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DWD's vision for future NWP: A fully data-driven data assimilation approach

A fully data-driven data assimilation approach

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