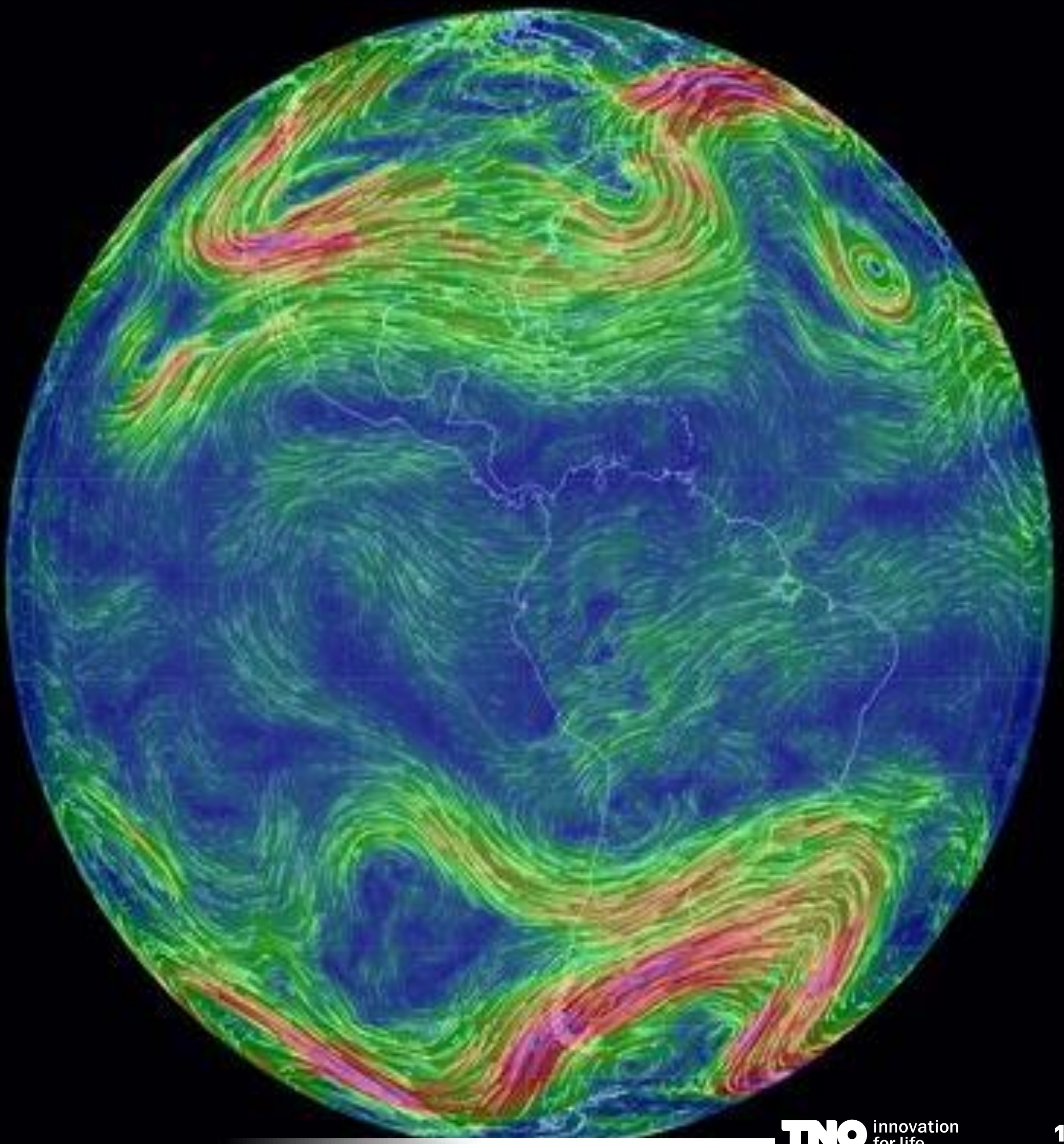
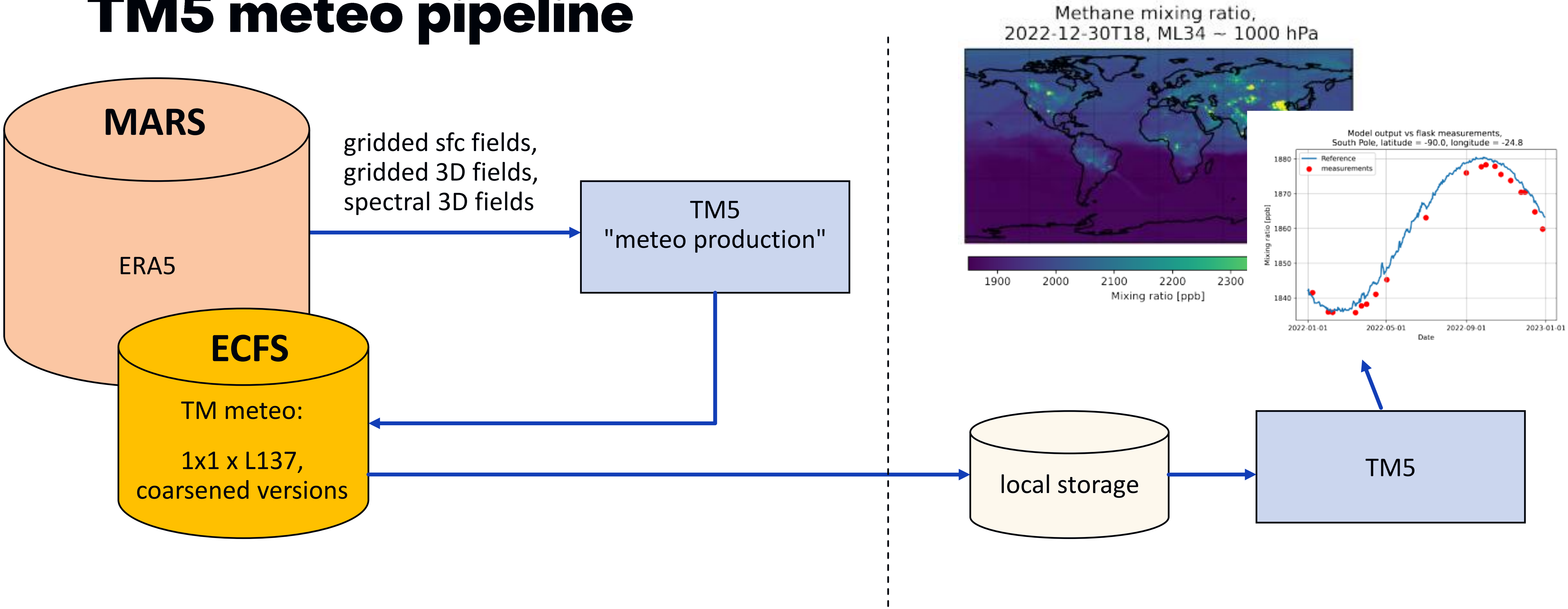
Running TM5 on AI-generated meteo

Alexander Havinga (TU Delft)

Arjo Segers (TNO)



TM5 meteo pipeline



TM5 meteo pipeline

MARS

ERA5

gridded sfc fields,
gridded 3D fields,
spectral 3D fields

TM5
"meteo production"

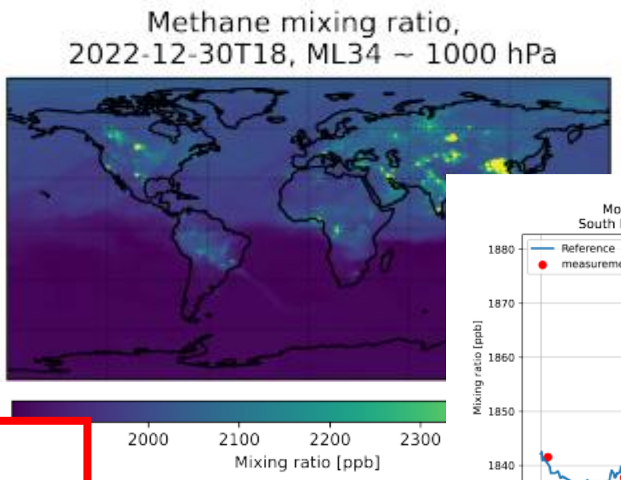
ECFS

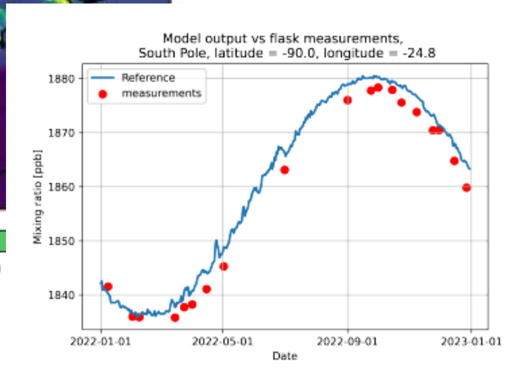
TM meteo:

1x1 x L137,
coarsened version

Could we generate the meteo for TM5 with an AI based emulator?

- fast
- less data needed
- flexible in resolutions
- …





cal storage

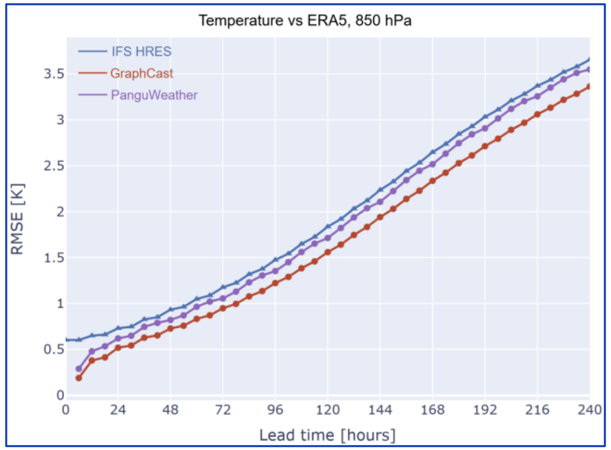
TM5

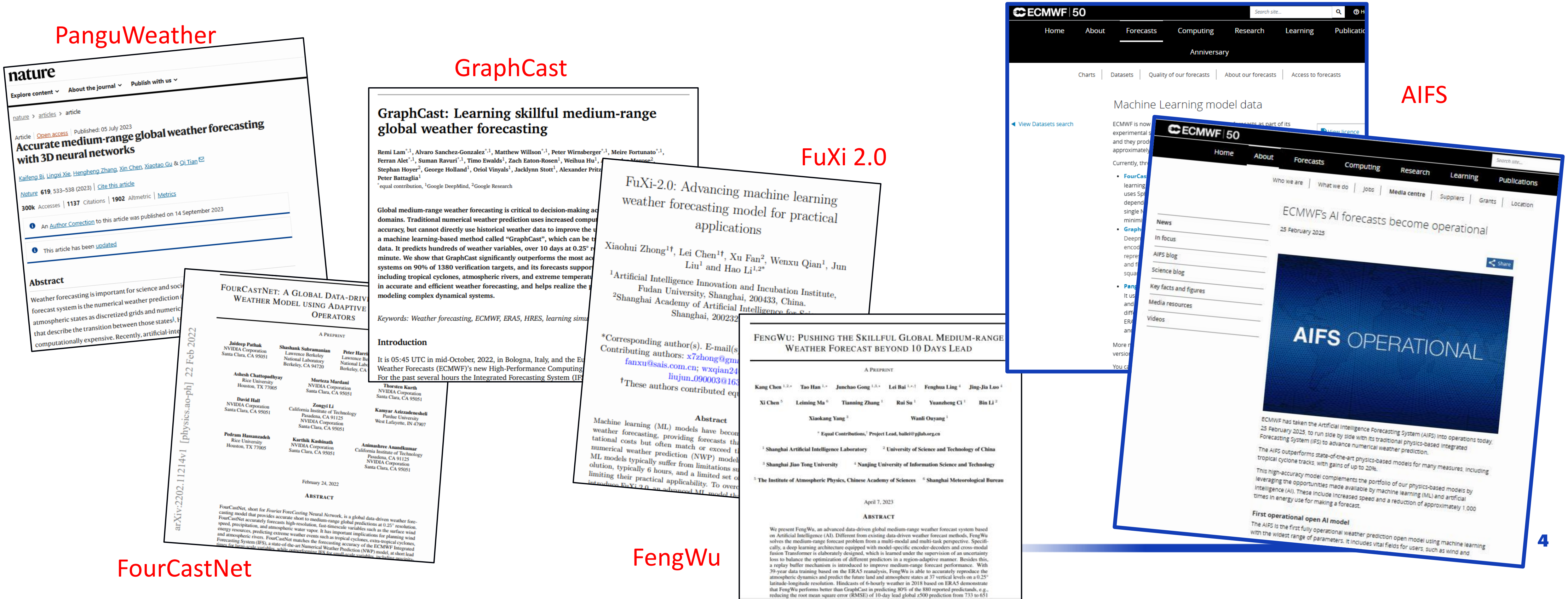
AI meteo emulator

smaller storage

AI based global weather emulators

- Not based on physics, but trained on long time series of meteorological data
- When trained, extreme fast (seconds on a GPU), and very good statistics
- ECMWF joined the arena with AIFS



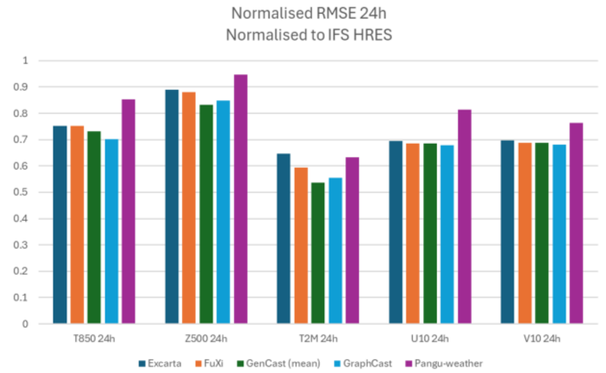


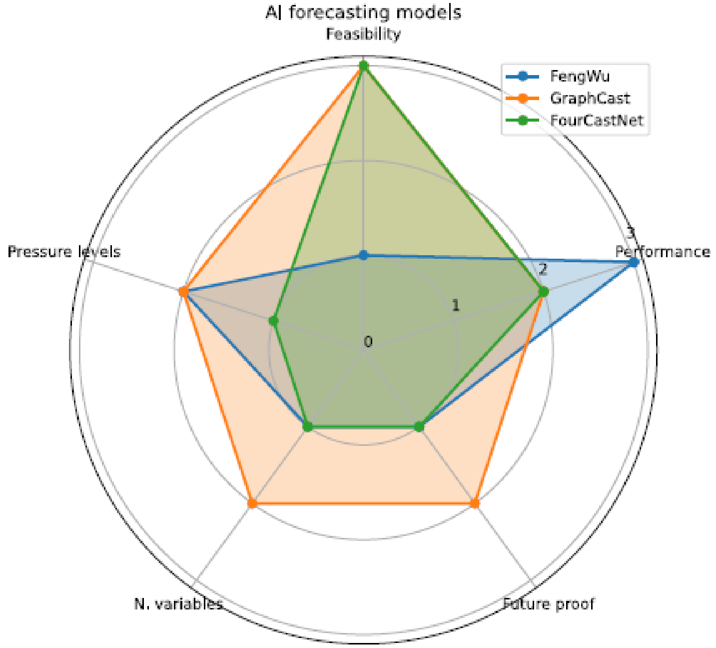
AI based global weather emulators

Criteria to select an appropriate AI-weather-model to generate input for TM5:

- **Feasibility:**
  Can we get it running on our local server?
- **Vertical resolution:**
  Most emulators have 13 or 37 (pressure) levels
- **Output parameters:**
  All have pressure, temperature, horizontal wind.
  But also vertical velocity? Or even mass fluxes as used in TM5?
- **Performance:**
  Quality when compared to ERA5?
- **Future proofing:**
  Likely we would use ECMWF's AIFS, but that is not available yet.
  Which emulators are already supported by ECMWF, or comparable to AIFS?

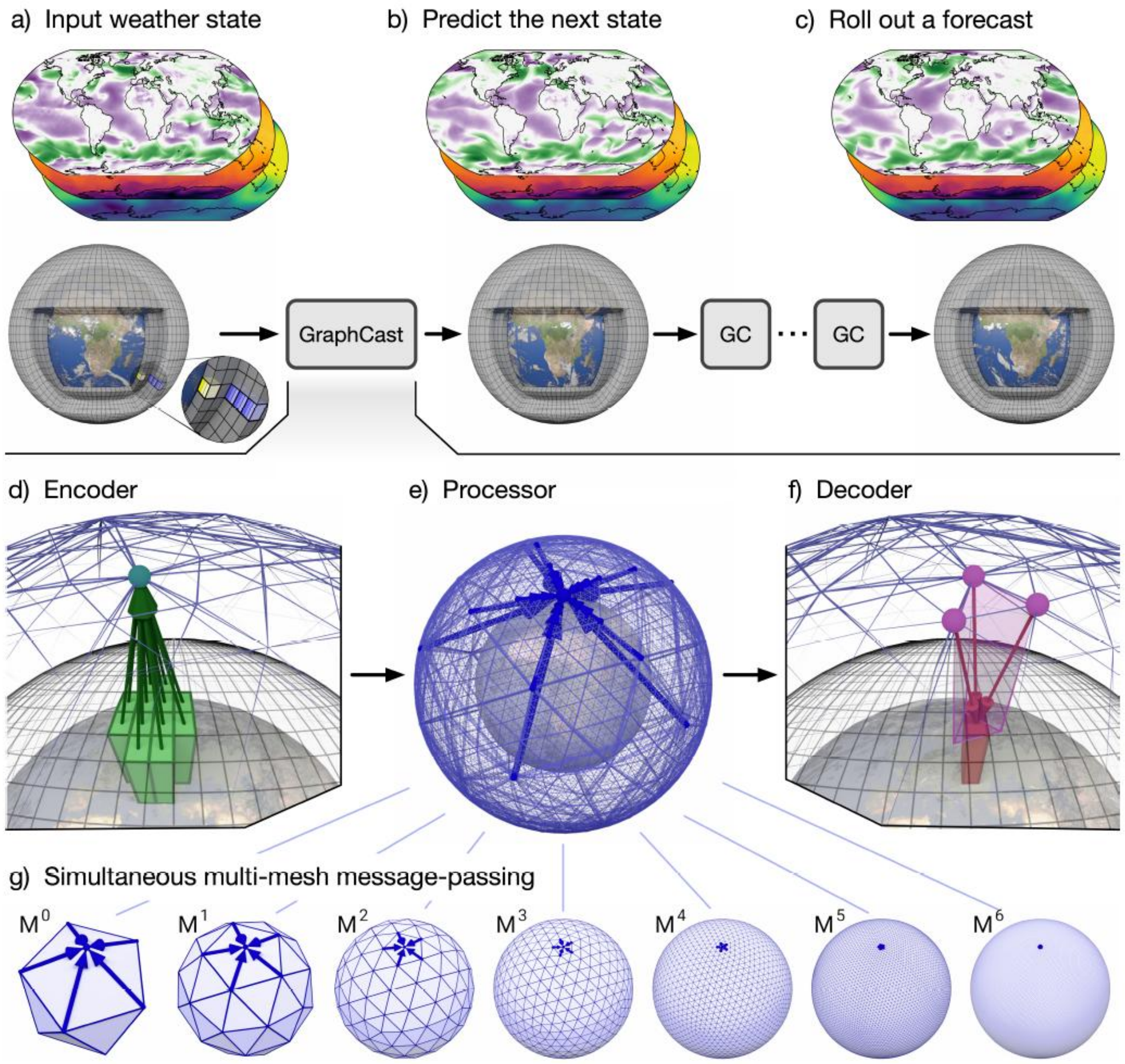
Model	Introduction	Architecture	Vertical resolution	Timesteps	N. variables
PanguWeather	2022	3D transformer	13 PL	1 hour	9
FourCastNet	2022	Adaptive Fourier Neural Operator	13 PL	6 hour	13
GraphCast	2023	Graph Neural Network	37 PL	6 hour	11
FuXi 2.0	2024	U-Transformer	13 PL	1 hour	28
FengWu	2023	Cross-modal fusion Transformer	37 PL	6 hour	9
AIFS	2024	Graph Neural Network	13 PL	6 hour	13





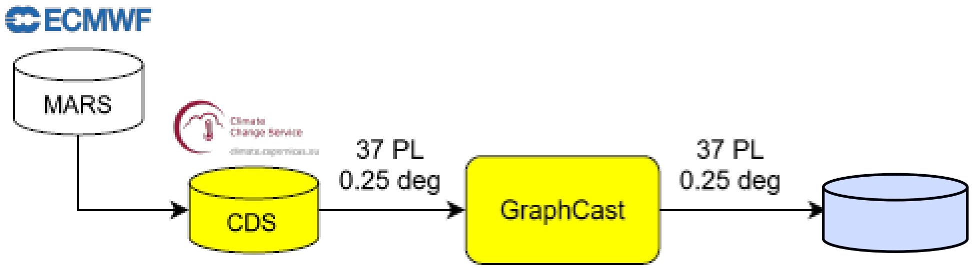
Google's "GraphCast" selected as most feasible, most all-round emulator

Google's GraphCast

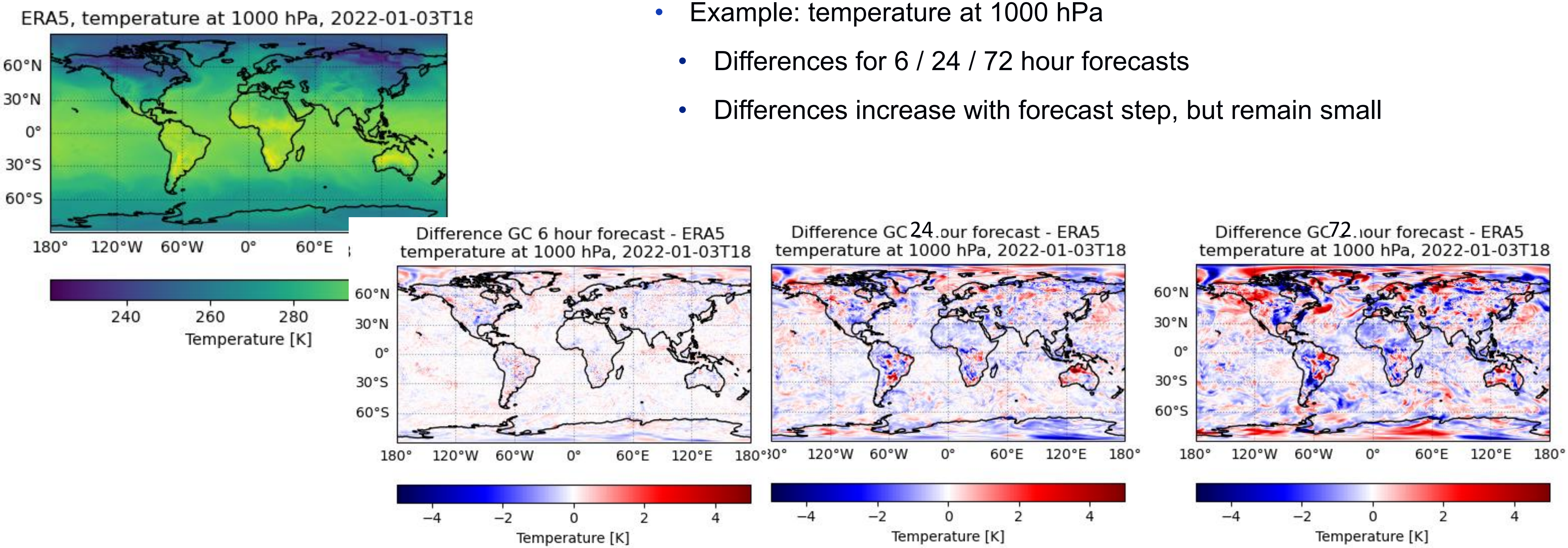


- Trained on ERA5 data:
  - publicly available data from Climate Data Store
  - horizontal resolution: 0.25°
  - vertical: 37 pressure levels
  - analysis fields (data assimilated)
- Source:
  - python package
  - configuration file (neural network weights)
- Input:
  - 2 data sets for -6 and 0 hour
    (subsets of ERA5, or GraphCast generated sets)
- Output:
  - same grid/levels as input set
  - forecast over 6 hour

How well does our GraphCast copy emulate ERA5?



- Compared GraphCast forecasts with ERA5 analysis:
  - initialized from ERA5 analysis, roll-out over 72 hours
- Example: temperature at 1000 hPa
  - Differences for 6 / 24 / 72 hour forecasts
  - Differences increase with forecast step, but remain small



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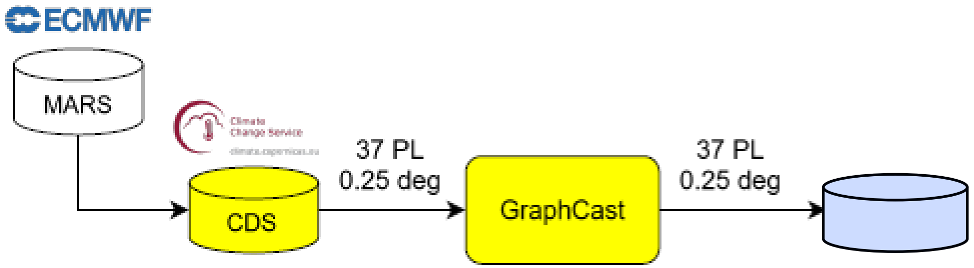
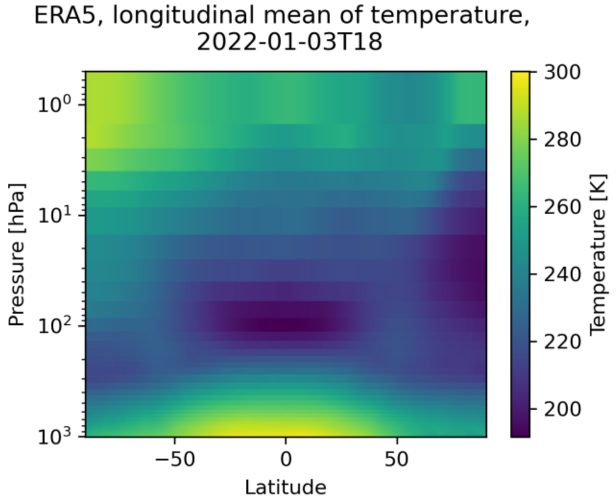
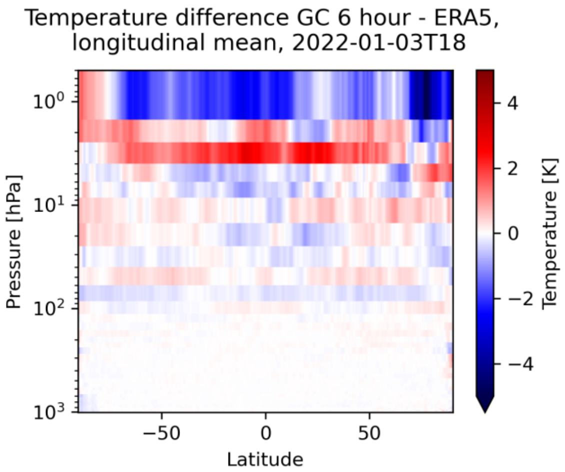


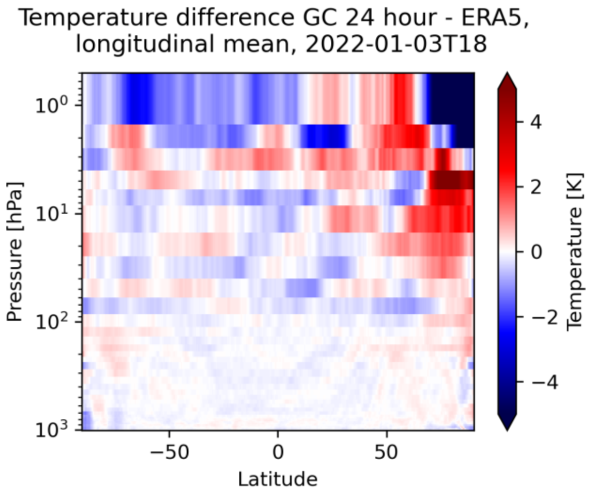
- Compared GraphCast forecasts with ERA5 analysis:
  - initialized from ERA5 analysis, roll-out over 72 hours

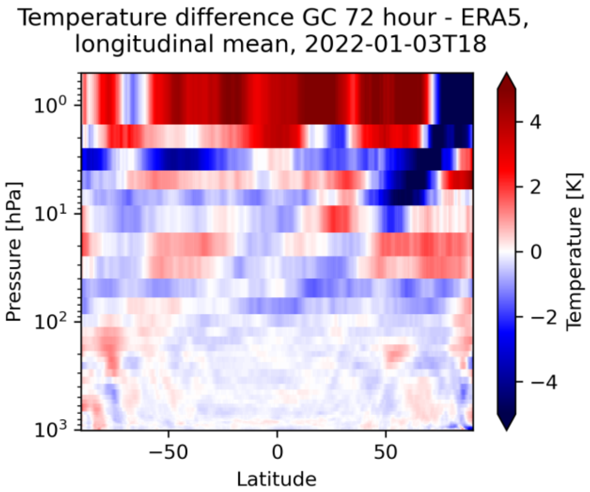
- Example: temperature zonal mean
  - Differences for 6 / 24 / 72 hour forecasts
  - Differences in stratosphere become rather large

  GraphCast training is less constrained for higher levels!





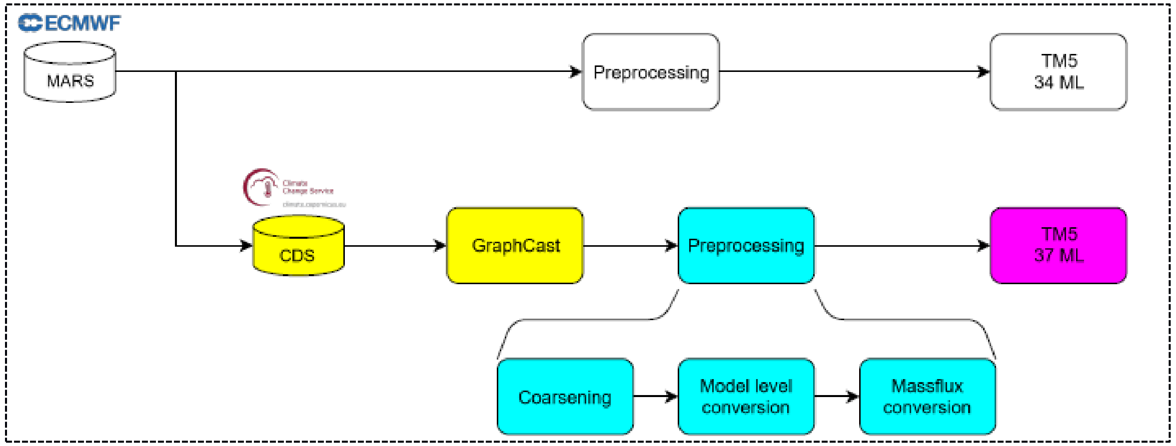




How well could GraphCast output be converted into TM5 input?

TM5 meteo input *(for CAMS CH4 inversions)*:

- horizontal resolution 1ºx1º
- 34 hybride model layers
- 3D fields: temperature, humidity,
  horizontal mass fluxes, vertical mass fluxes
- *mass fluxes computed from spectral vorticity/divergence*



Preprocessing of GraphCast output needed for TM5:

- horizontal averaging [easy]
- vertical mapping: from 37 pressure levels,
  to 37 hybride model layers (newly defined!) [less easy]
- variable conversion:
  - horizontal mass fluxes [rather easy]
  - vertical mass fluxes [complicated]

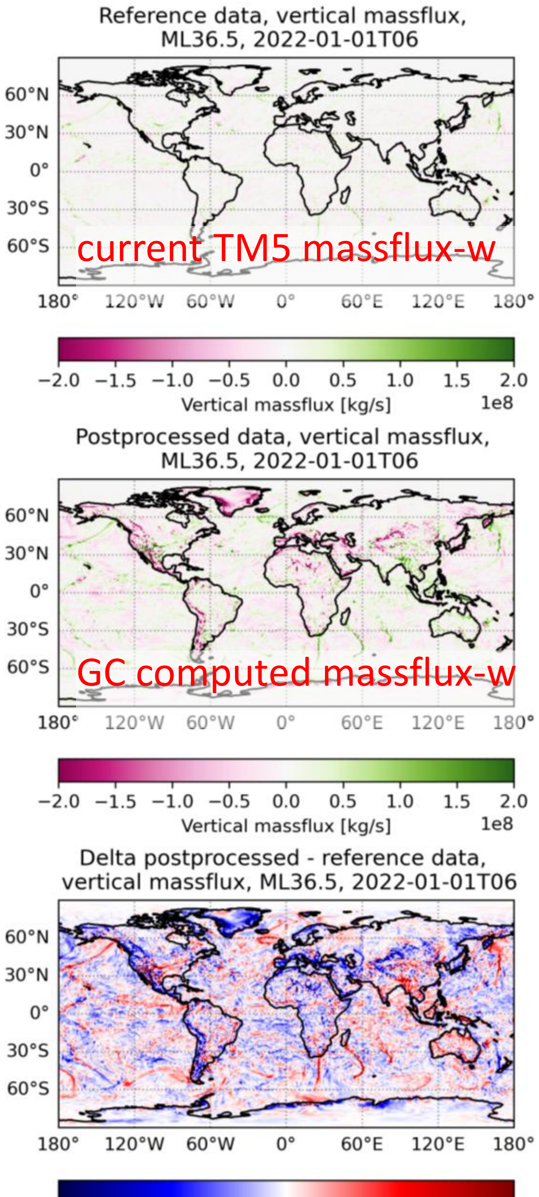
How well could GraphCast output be converted into TM5 input?

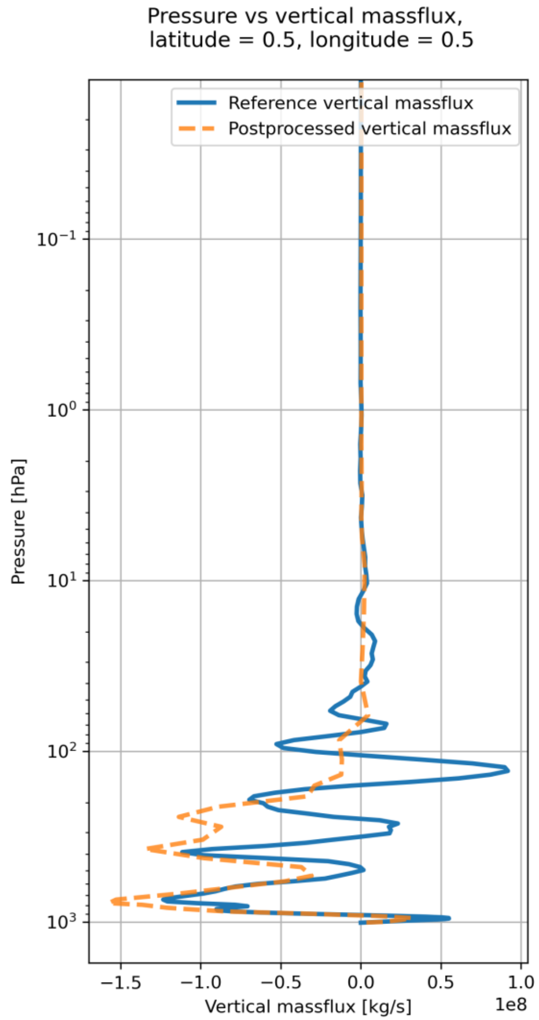
- Temperature, humidity, and horizontal mass fluxes for TM5 could be represented rather well:
- At some locations, mapping from pressure levels to model layers is inaccurate
  → for 3D temperature, fixed using 2m-temperature

- Vertical flux has rather large errors:
  - Derived from pressure tendency, vertical velocity, horizontal velocities, and pressure gradient:

$$\Phi^w = \frac{R^2}{g} \iint_{A_{ij}} \left(-\frac{\partial p}{\partial t} + \omega - \mathbf{v}_H \cdot \nabla P \right) d\phi \, d\lambda \cos\phi$$

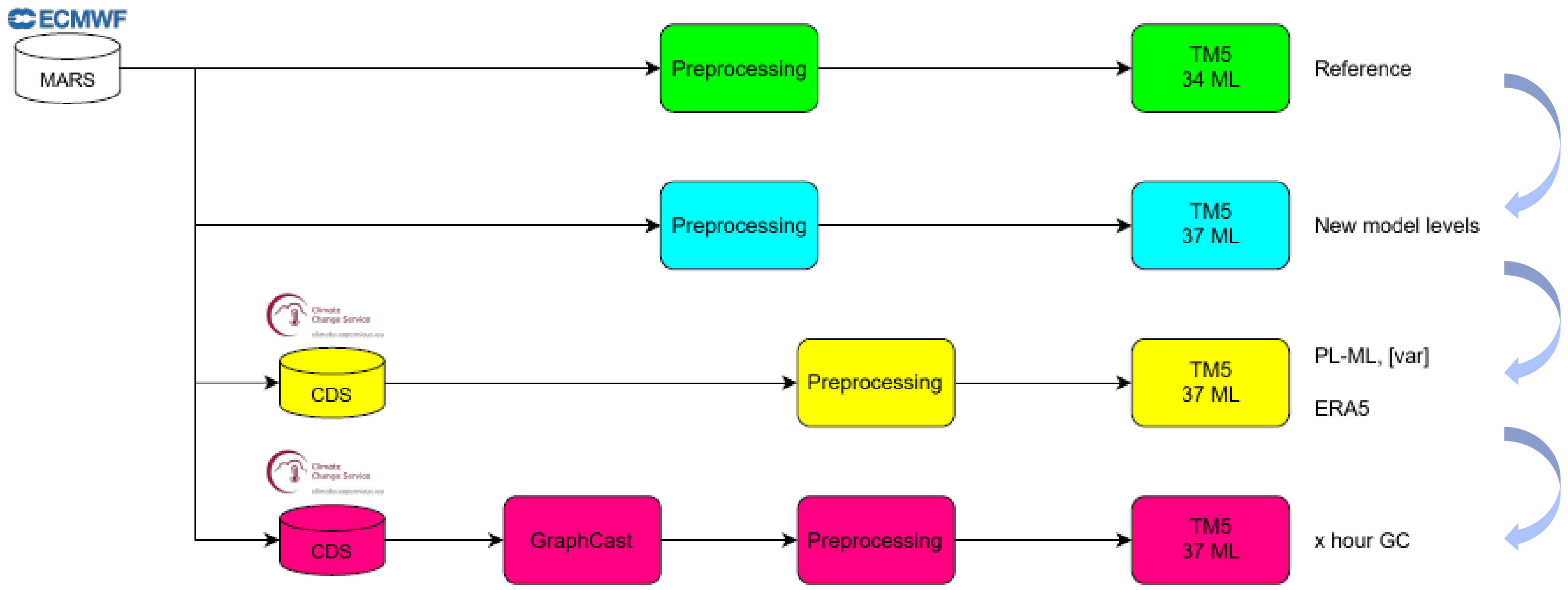
  - Result is noisy …





TM5 simulations of CH_4

Four different pipelines for TM5 simulations:



Impact of change from 34 to 37 model layers
→ neglecatble

Impact of using GraphCast-like variables ?

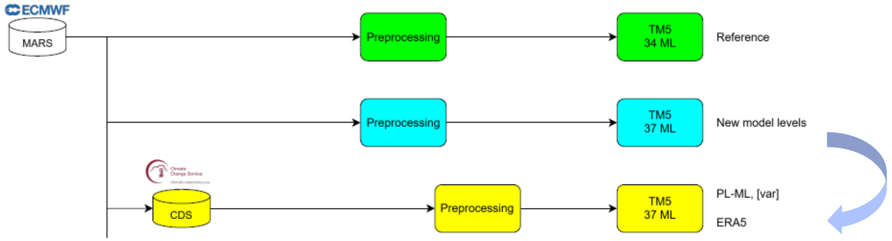
Impact of using GraphCast forecasts?

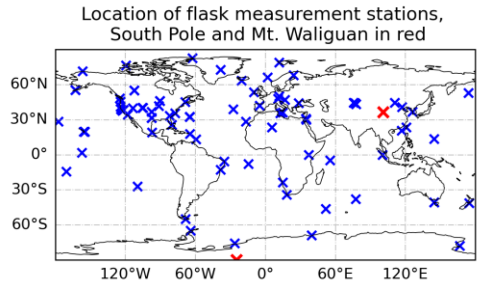
Test configuration:

- 1ºx1º grid, 37 model layers,
- simulation over 2022, initialized from CAMS emission optimized mixing ratios

TM5 simulations of CH_4

What is the impact of using meteo variables like GraphCast produces?

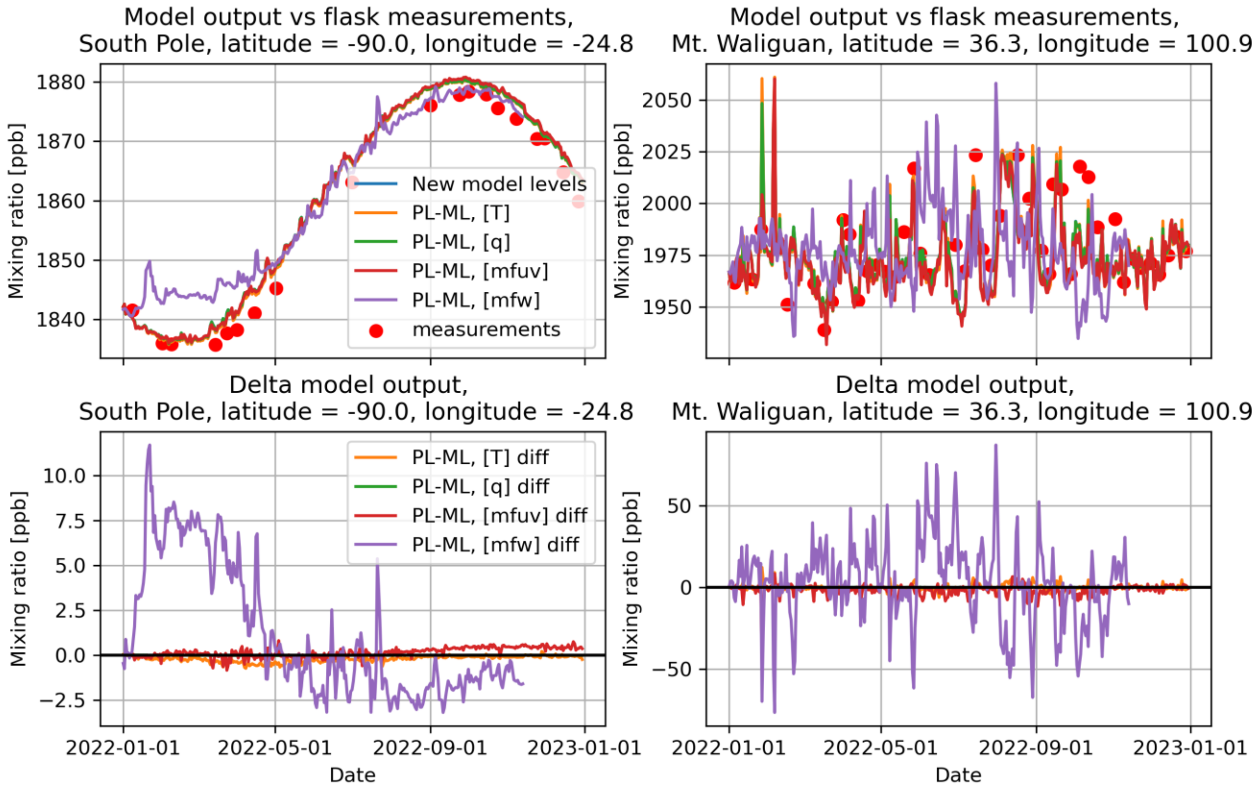




4 simulations, each with one new variable:

→ Neglectable impact of T, Q, massflux-uv

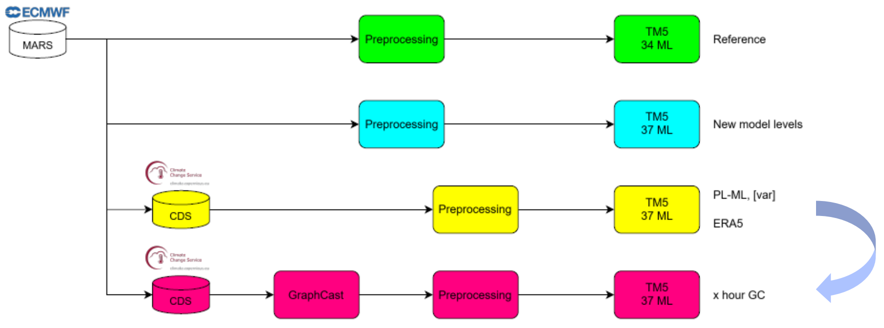
→ Strong impact of using massflux-w



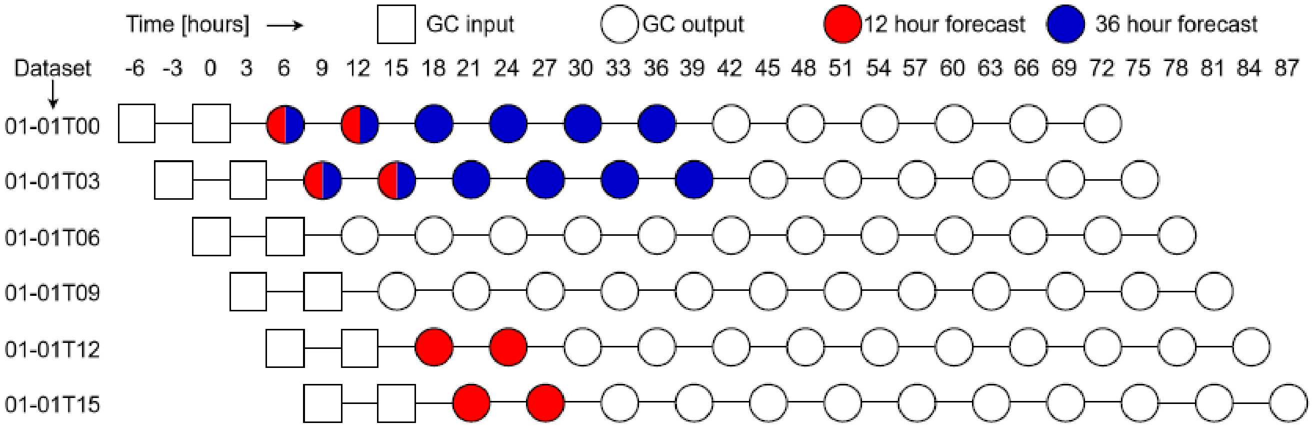
→Do not use the new computed **vertical** massfluxes yet!

TM5 simulations of CH_4

What is the impact of using GraphCast produced forecasts?



Simulations using GraphCast forecasts with different max. steps; many configurations possible …



TM5 simulations of CH_4

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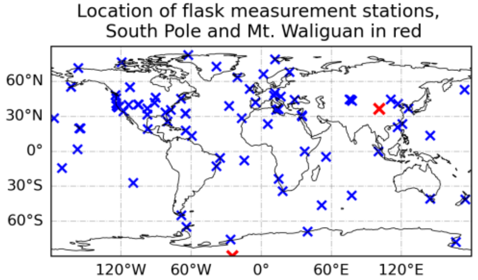
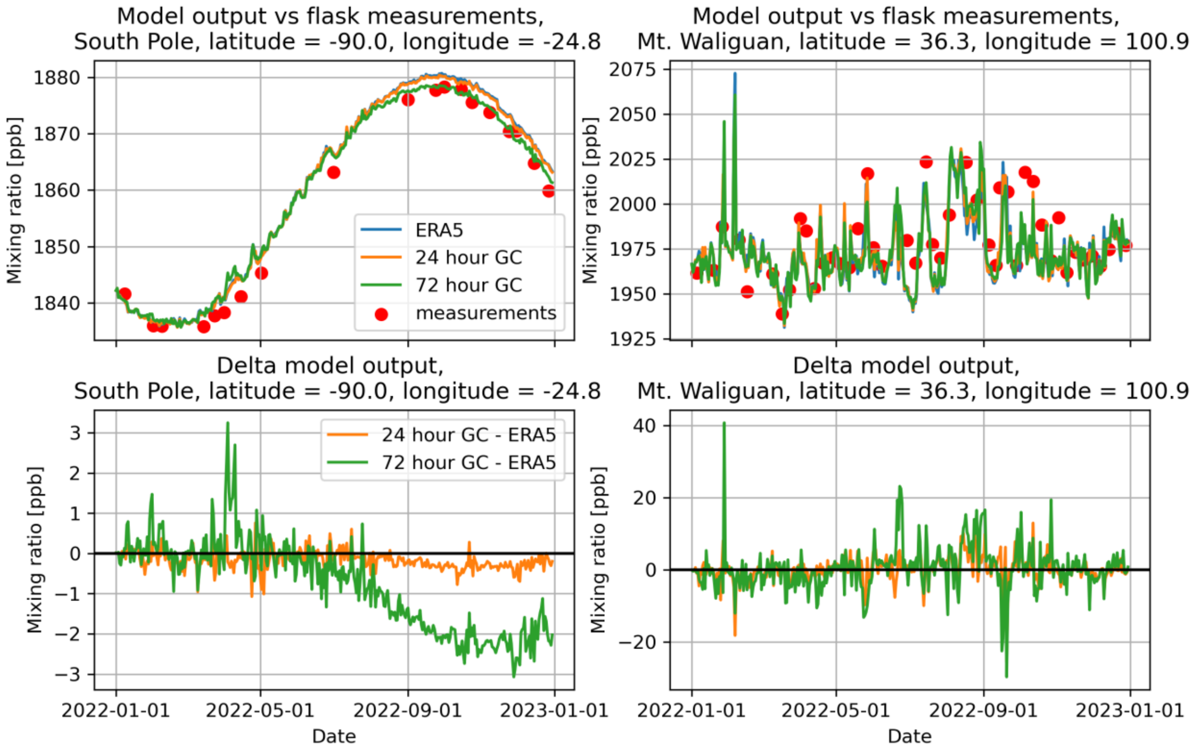
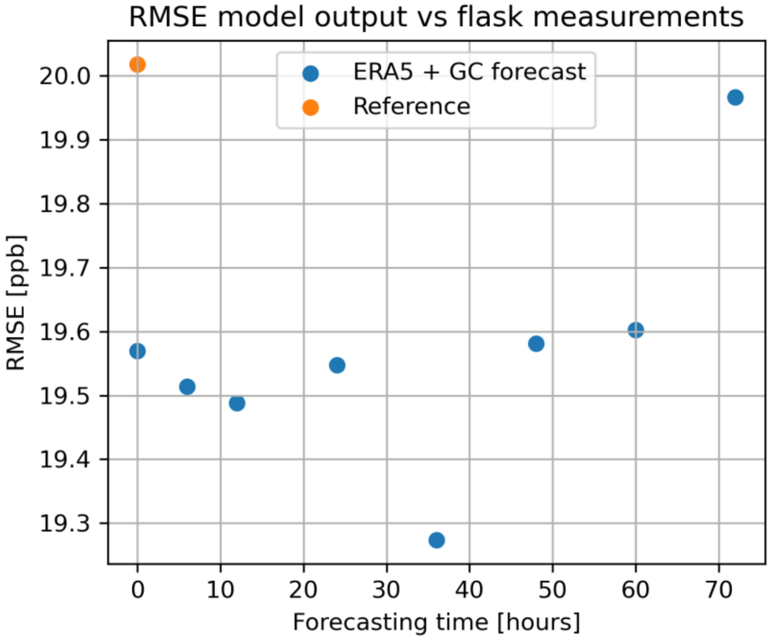


Differences between 24h or 72h forecast seen mainly at South Pole station:
(impact of stratosphere ?)

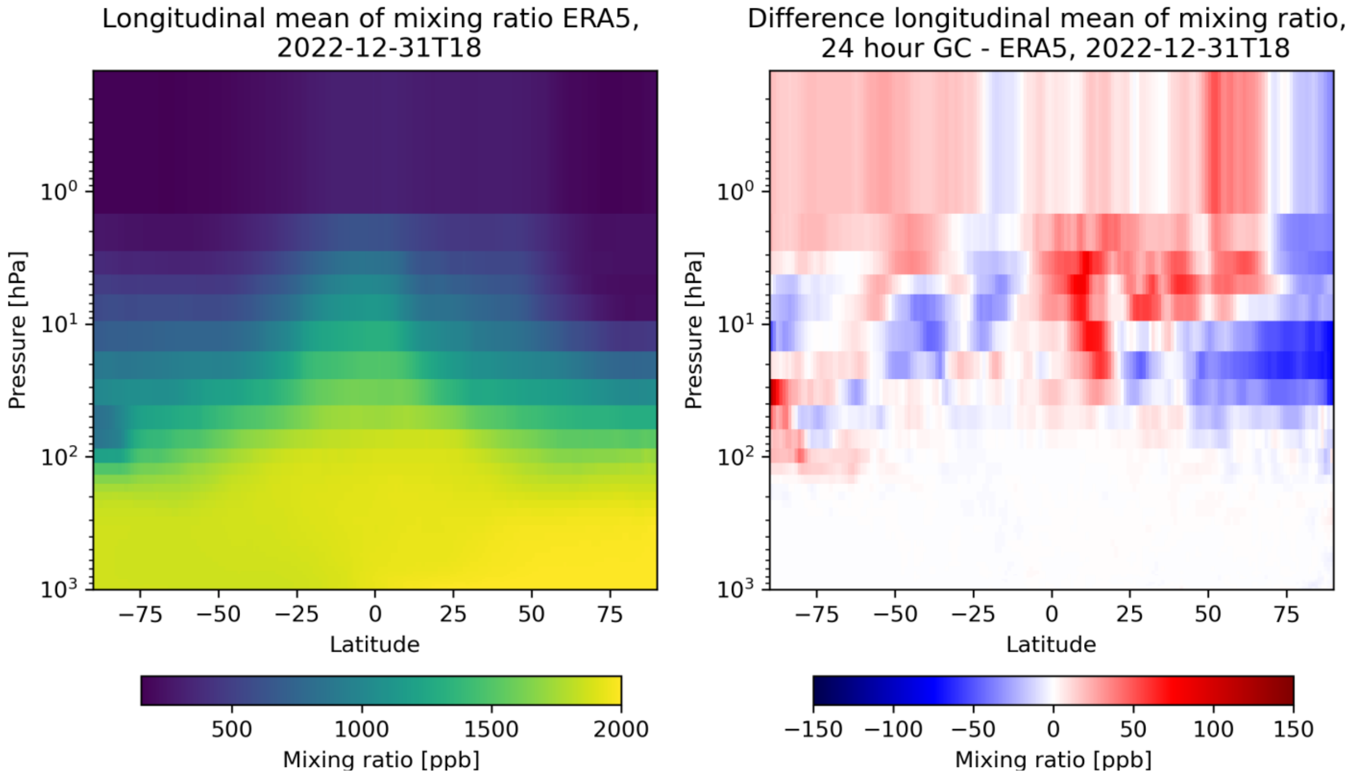


RMSE over all flasks is rather similar for the various max. forecast steps:



TM5 simulations of CH_4

What is the impact of using GraphCast produced forecasts?

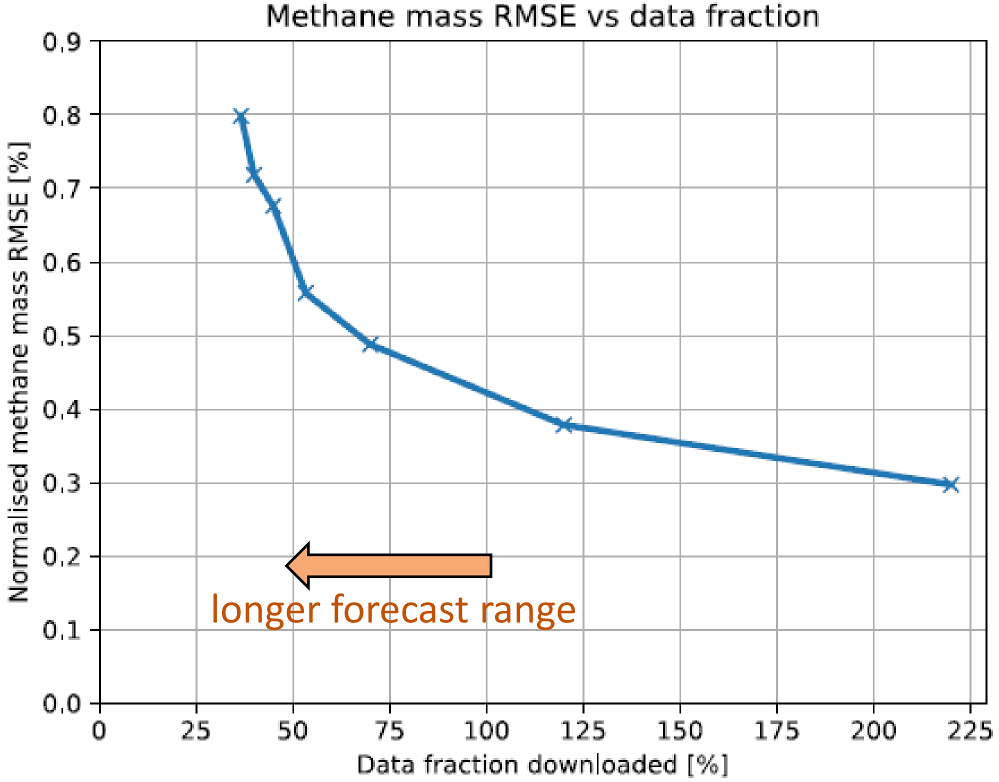


Large differences in CH4 mixing ratio's in stratosphere …

.. but only small differences near surface.

TM5 simulations of CH_4

What is the impact of using GraphCast produced forecasts?



Relative error in global total CH_4 mass is higher for longer forecast range …
But this requires less data to be downloaded!

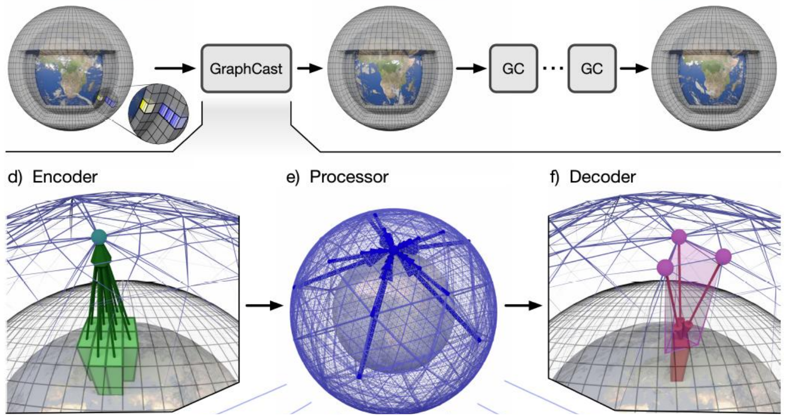
→ Trade-off between efficiency and accuracy

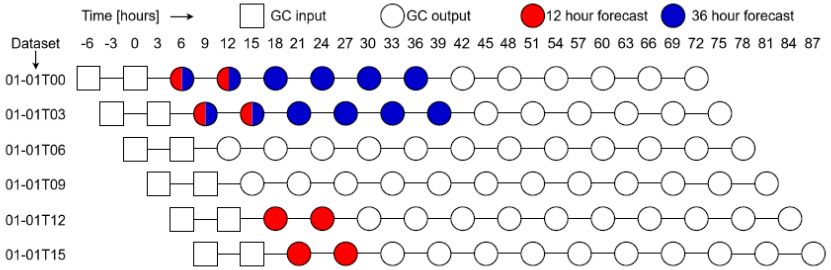
NOTE: >100% since GraphCast requires 2 previous time records for a forecast ..
To be optimized in future!

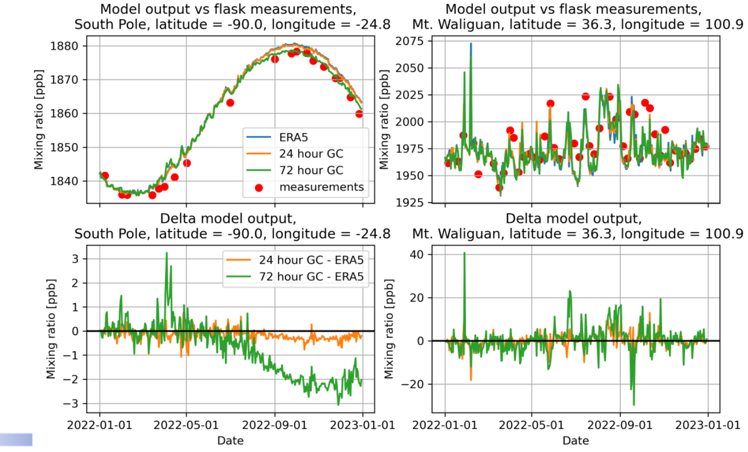
Conclusions

Using AI-based meteo emulators to generate TM5 input?

- Promising! This could save a lot of preprocessing/storage/slow-down ….
- First tests using GraphCast to generage "ERA5"-like meteo:
  - Accurate at surface
  - Less accurate in stratosphere
    - need more layers?
    - AI-model should be constrained on stratosphere
  - Vertical velocity seems most problematic, and thus vertical fluxes in TM5
    - Requires dedicated training of models?
- Not tested yet: convective fluxes, diffusion coefficients
  - Preferably these are also put out by emulators
- Run time of few seconds on GPU?
  To be solved: `segmentation fault`



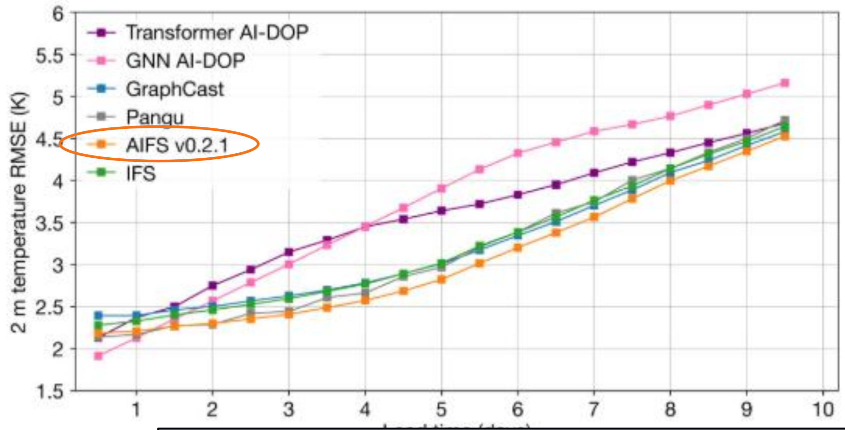




Outlook

Next: tests using ECMWF's AIFS ?

- Possibly more focus on all layers of the atmoshere
- … and on (vertical,convective) mass fluxes



GRAPHDOP: TOWARDS SKILFUL DATA-DRIVEN MEDIUM-RANGE WEATHER FORECASTS LEARNT AND INITIALISED DIRECTLY FROM OBSERVATIONS

A PREPRINT

Mihai Alexe, Eulalie Boucher, Peter Lean, Ewan Pinnington, Patrick Laloyaux
Anthony McNally, Simon Lang, Matthew Chantry, Chris Burrows, Marcin Chrust
Ethel Villeneuve, Niels Bormann, Sean Healy
Medium-Range Weather Forecasts (ECMWF)

December 23, 2024

ABSTRACT

…data-driven, end-to-end forecast system developed at the European …her Forecasts (ECMWF) that is trained and initialised exclusively … with no physics-based (re)analysis inputs or feedbacks. GraphDOP … observed quantities - such as brightness temperatures from polar …lites - and geophysical quantities of interest (that are measured by …orm a coherent latent representation of Earth System state dynamics …pable of producing skilful predictions of relevant weather parameters

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doi:10.5194/acp-15-113-2015

Atmospheric Chemistry and Physics
Open Access

Inverse modelling of CH_4 emissions for 2010–2011 using different satellite retrieval products from GOSAT and SCIAMACHY

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[4]Earth Observation Science Group, Space Research Centre, University of Leicester, Leicester, UK
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Data-driven ensemble forecasting with the AIFS

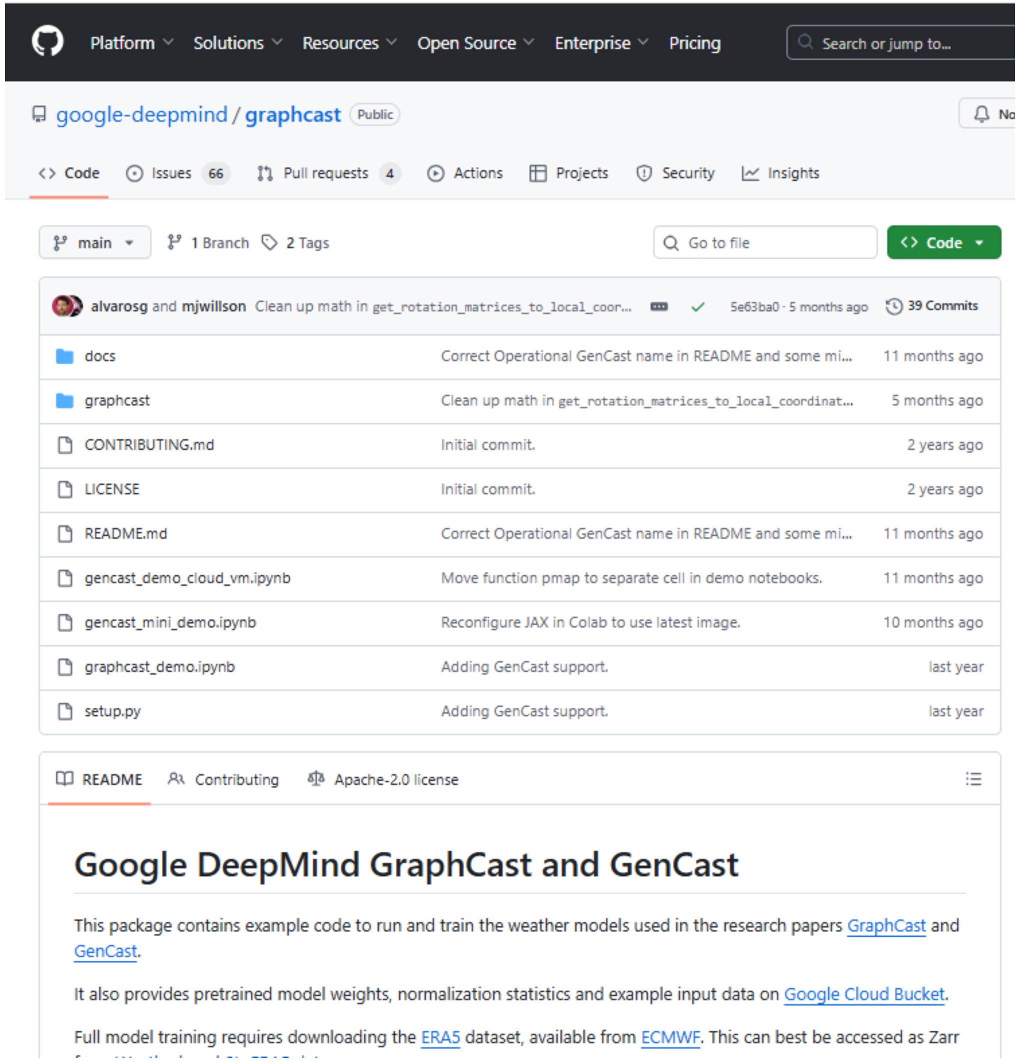
Mihai Alexe, Simon Lang, Mariana Clare, Martin Leutbecher, Christopher Roberts, Linus Magnusson, Matthew Chantry, Rilwan Adewoyin, Ana Prieto-Nemesio, Jesper Dramsch, Florian Pinault, Baudouin Raoult

Data-driven weather forecast models are a promising addition to physics-based numerical weather prediction (NWP) models. ECMWF now runs the Artificial Intelligence Forecasting System (AIFS) in an experimental real-time mode. It is run four times daily and is open to the public under ECMWF's open data policy. This AIFS version (henceforth referred to as 'deterministic AIFS') is trained to produce forecasts that minimise mean squared error (MSE) up to 72 h into the forecast. The MSE optimisation leads to excessive smoothing and reduced forecast activity (Lang et al., 2024(a)). This is detrimental to ensemble forecasts, which rely on a realistic representation of the intrinsic variability of the atmosphere.

In this article, we describe two training approaches for data-driven forecast models to produce skilful ensemble forecasts: *diffusion training* (Karras et al., 2022, and Price et al., 2024), where the forecast is the

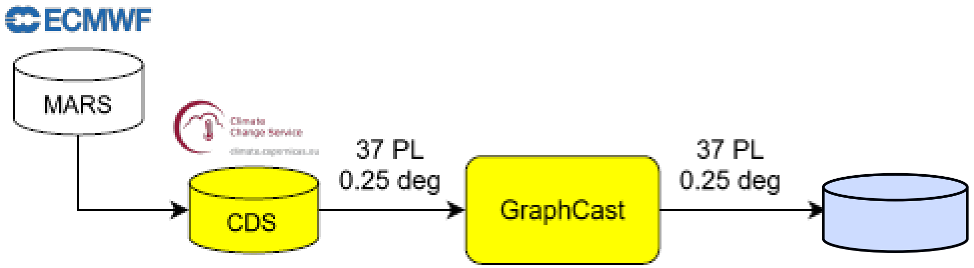
Thursday: online meeting with Mihai.Alexe@ECMWF about our whishlist …

Google's GraphCast

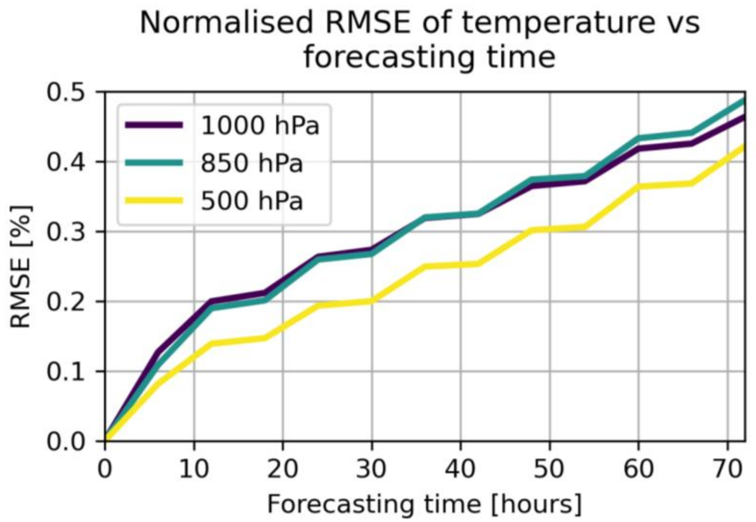


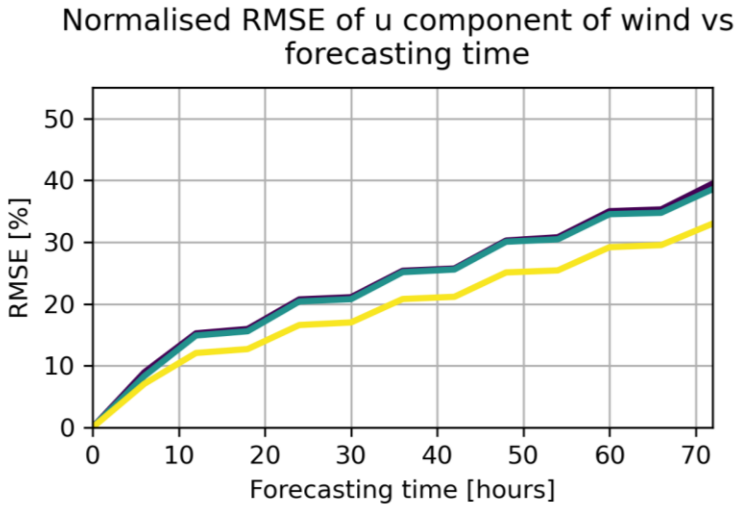
- Installation:
  - Download Python source package
  - Download model configuration data (*weights for neural network)*
  - Download input data (from CDS)
- Run …

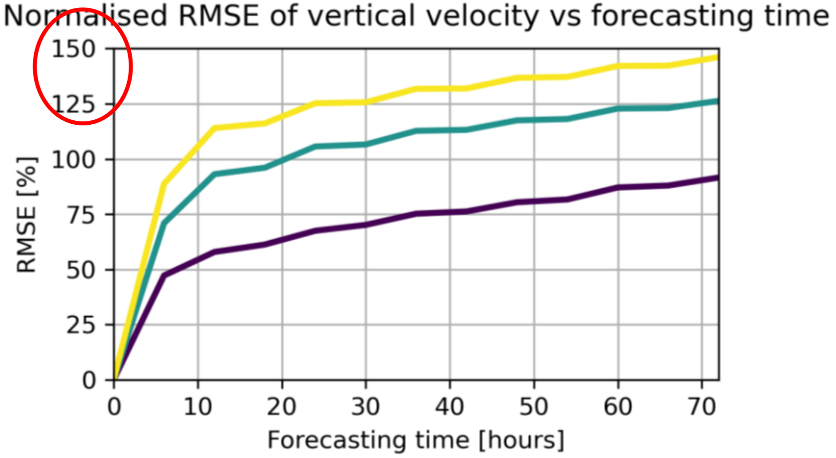
How well does our GraphCast copy emulate ERA5?



- Compared GraphCast forecasts with ERA5 analysis:
  - initialized from ERA5 analysis, roll-out over 72 hours
- normalized RMSE (divided by mean) of T/U/W for different levels
  - error increases with forecast time
  - error increases with altitude
  - vertical velocity has rather high errors







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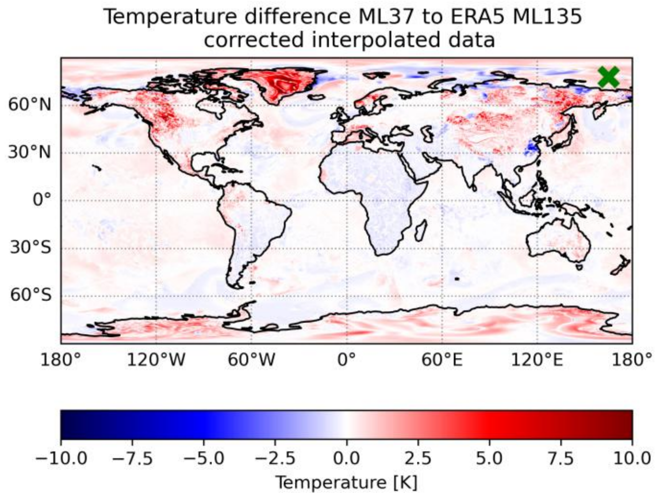
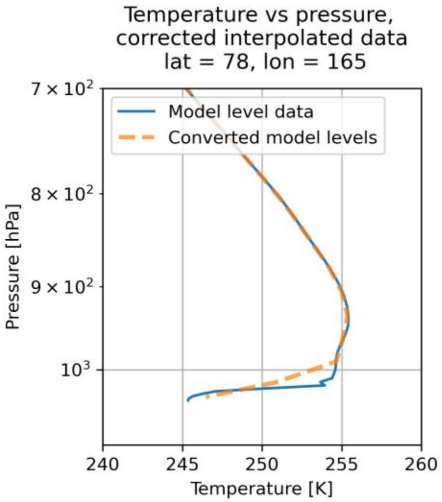
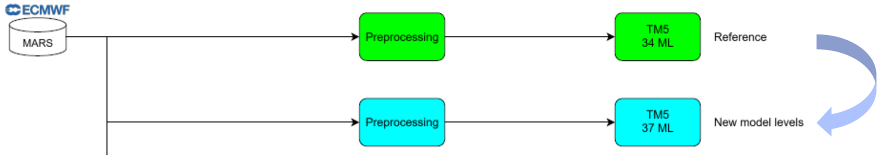


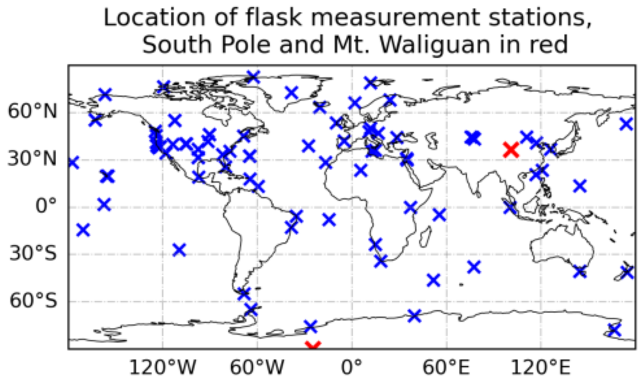


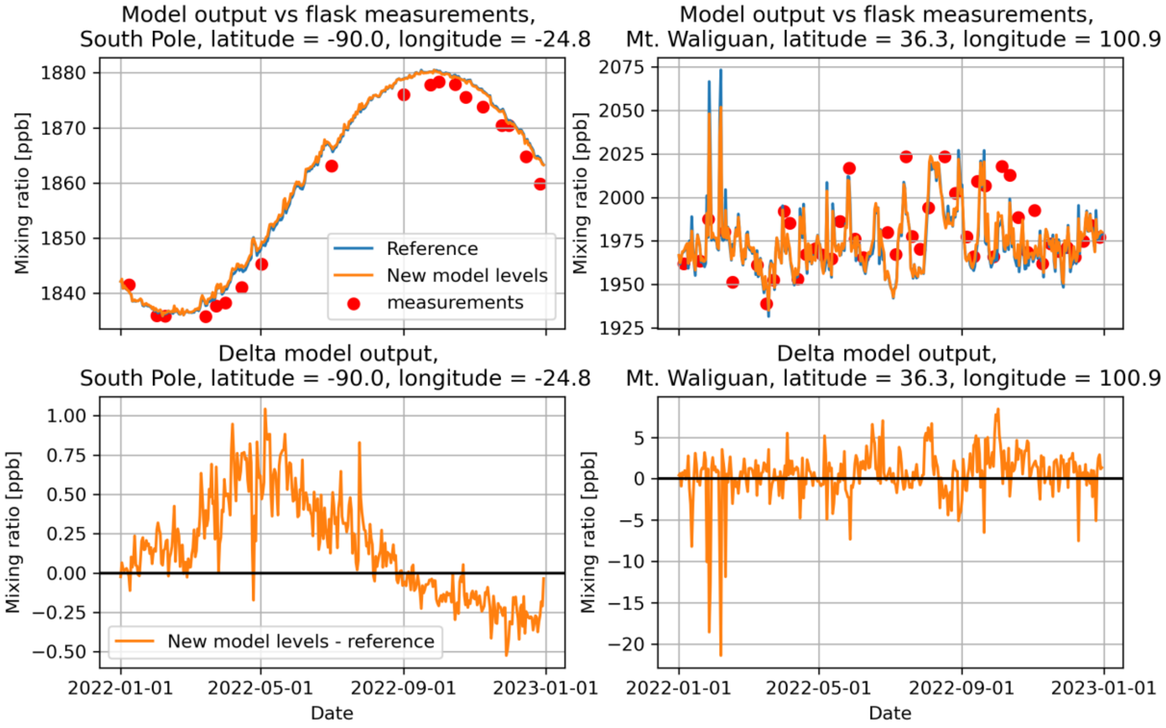
TM5 simulations of CH_4

What is the impact of changing to 37 layers?



→ Neglectable impact of changing layers





GraphCast training

- Weights in loss-function used for training of GraphCast: