The transition from practical to intrinsic predictability

… and how to diagnose it

Tobias Selz, Michael Riemer and George Craig

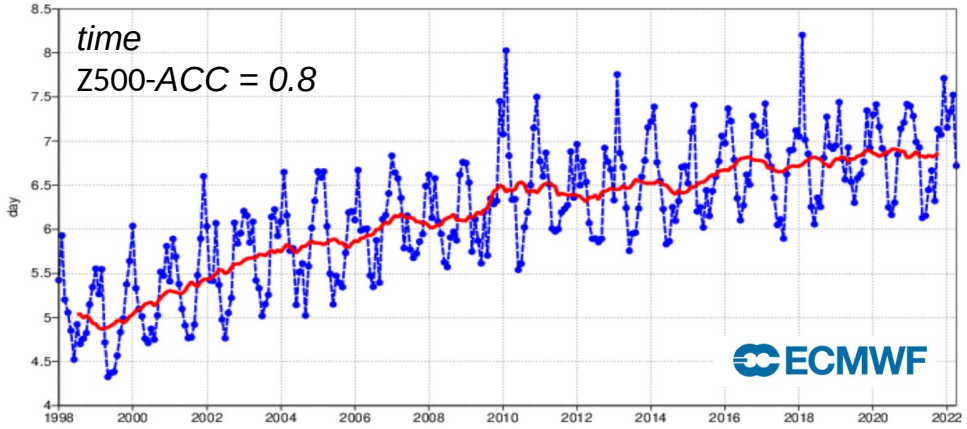
Practical vs. intrinsic predictability

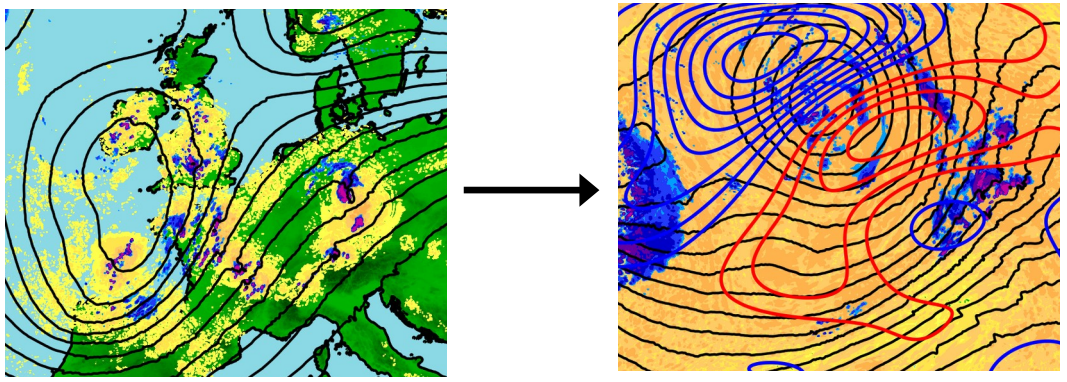
Practical predictability

- Ability to predict with **current methods**
- Continuously improving over the last decades

Intrinsic predictability

- Fundamental, physical limit
- Caused by scale interactions ("**Butterfly effect**")





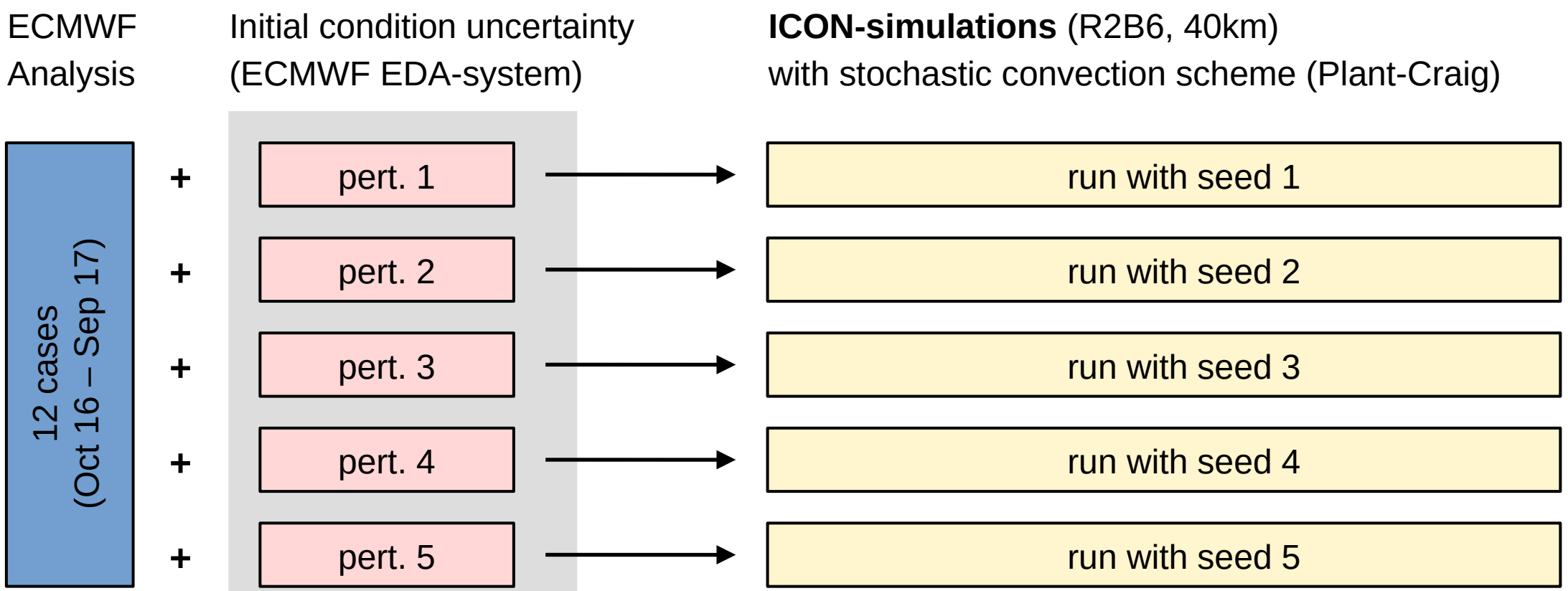
(Selz and Craig, 2015)

Where are we right now?

How much **improvement potential**?

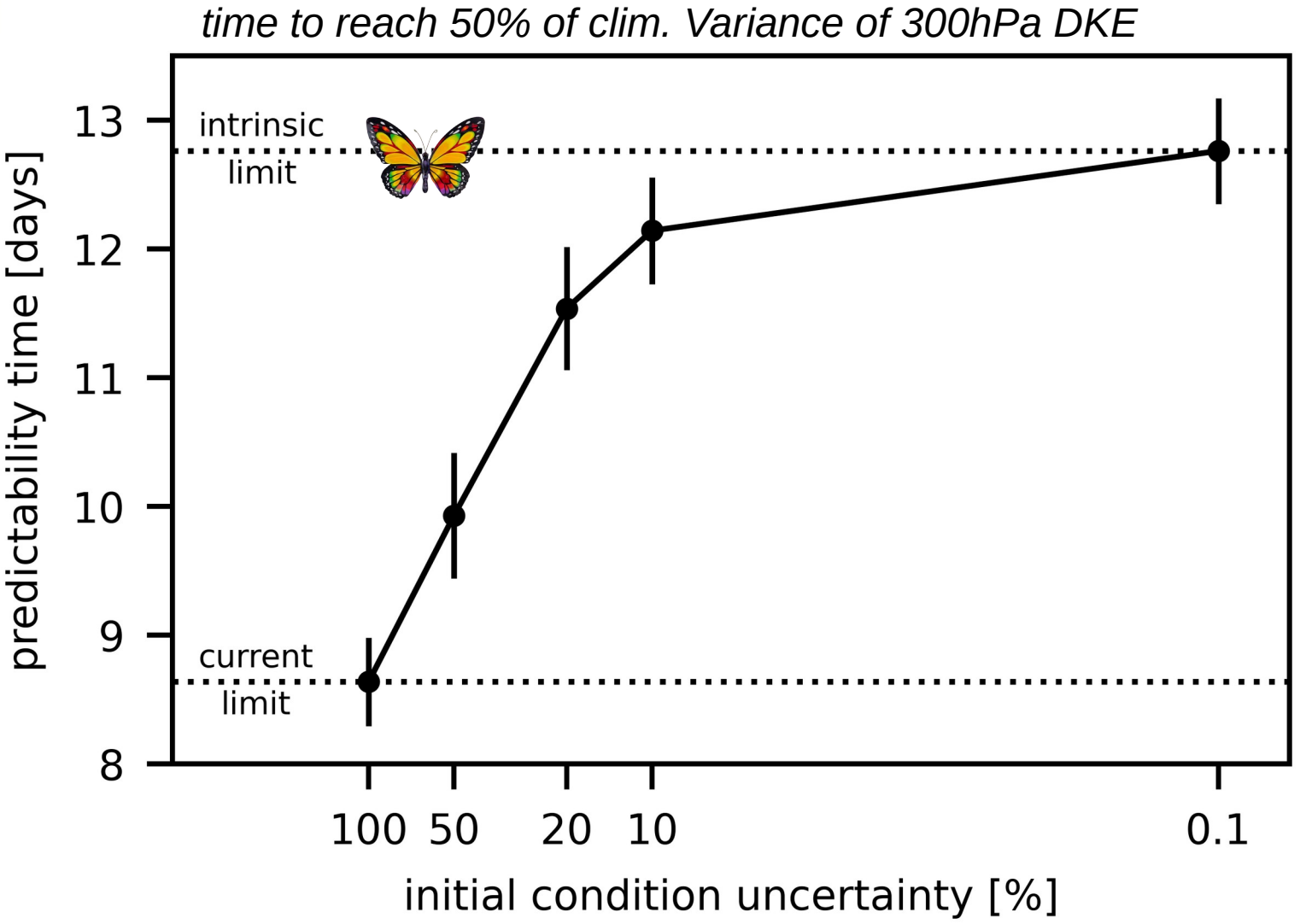
How **can we diagnose**?

Experimental design



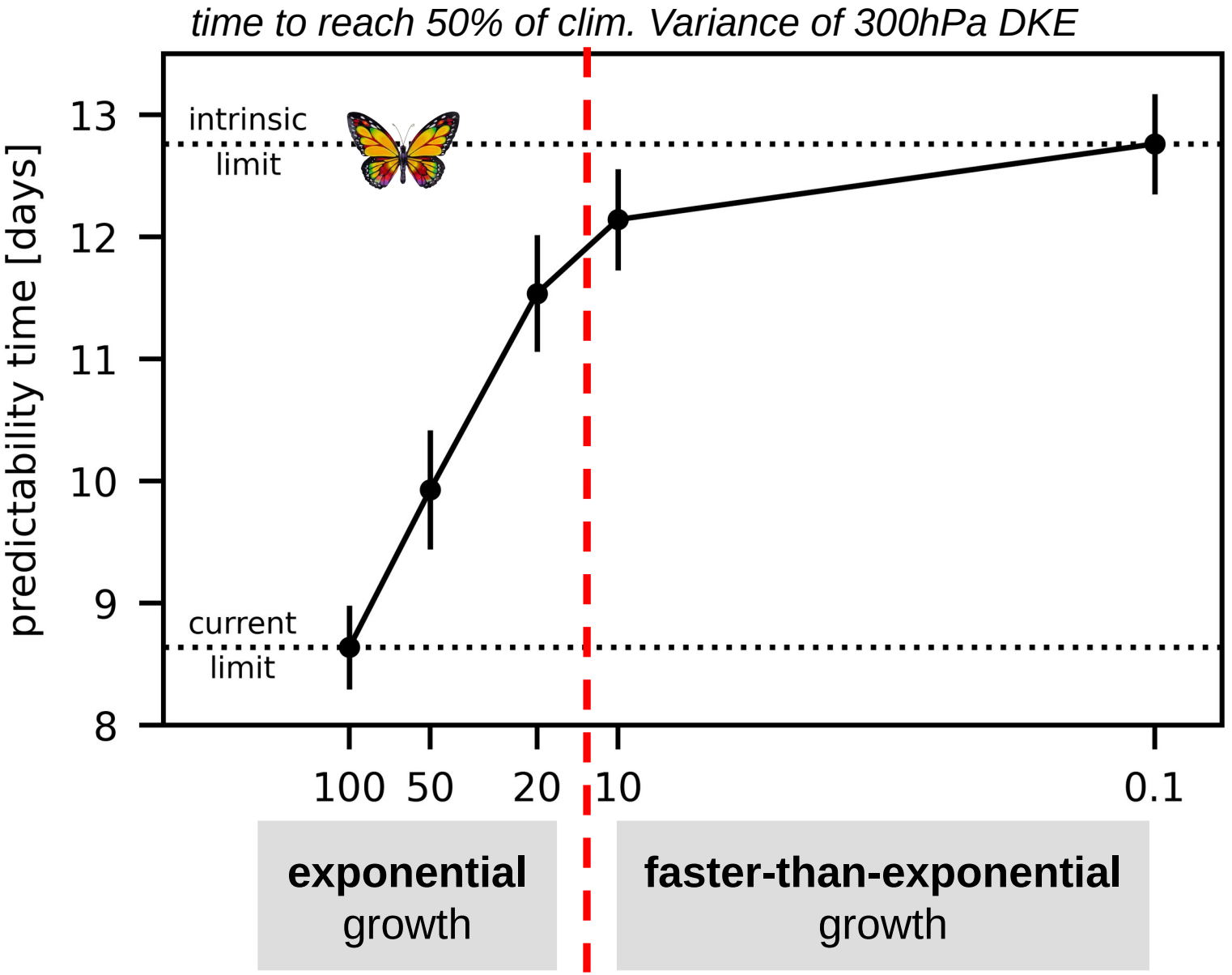
Stochastic convection scheme to better represent uncertainty growth from unresolved convective motions

Predictability time



- Possible gain through initial condition-perfection: ca. **4-5 days**
- Can be achieved with **≈ 90% reduction** of initial condition uncertainty
- Further improvement will show **little additional benefit**

Predictability time



- Possible gain through initial condition-perfection: ca. **4-5 days**
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Potential vorticity diagnostics

PV tendency equation on isentropic levels

$$\partial_t \pi = -\mathbf{v} \cdot \nabla \pi + N$$

Prognostic equation for the ensemble variance

$$\partial_t \, \mathrm{var}(\pi) = \frac{2}{n-1} \sum_{i=1}^{n} \left[-\delta\pi_i \delta\mathbf{v}_i \cdot \nabla \overline{\pi} + \frac{\delta\pi_i^2}{2} \nabla \cdot \mathbf{v}_i + \delta\pi_i \delta N_i \right]$$

Separation of processes

$$\mathbf{v} = \sum_j \mathbf{v}^{(j)}, \qquad N = \sum_j N^{(j)}$$

Here:

v → div, rot

N → convection, gridsc. prec., lw-radiation

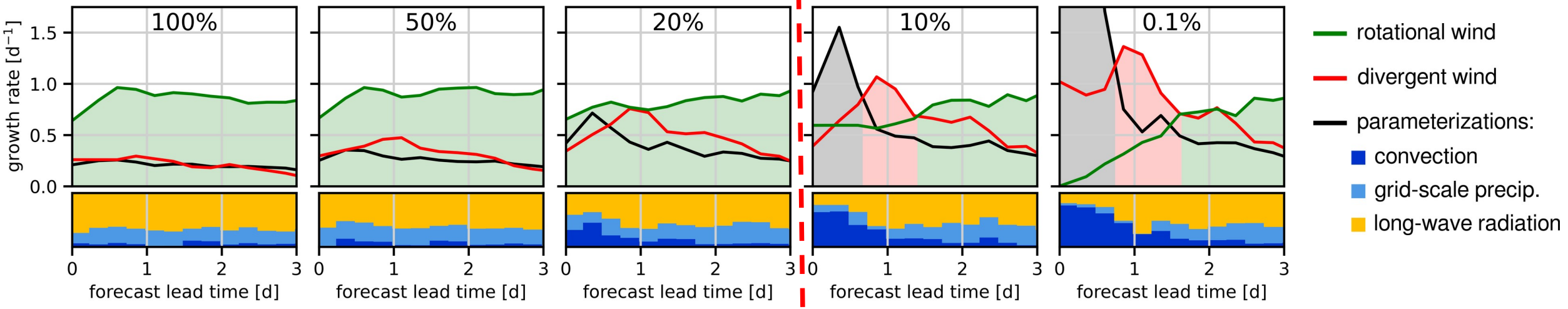
Spatial integration over midlatitudes (40°-60°) at tropopause (2PVU)

Baumgart and Riemer, 2019

Potential vorticity diagnostics

initial condition uncertainty:

current estimates → “butterflies“



Large-scale uncertainty growth in **dry, balanced** flow

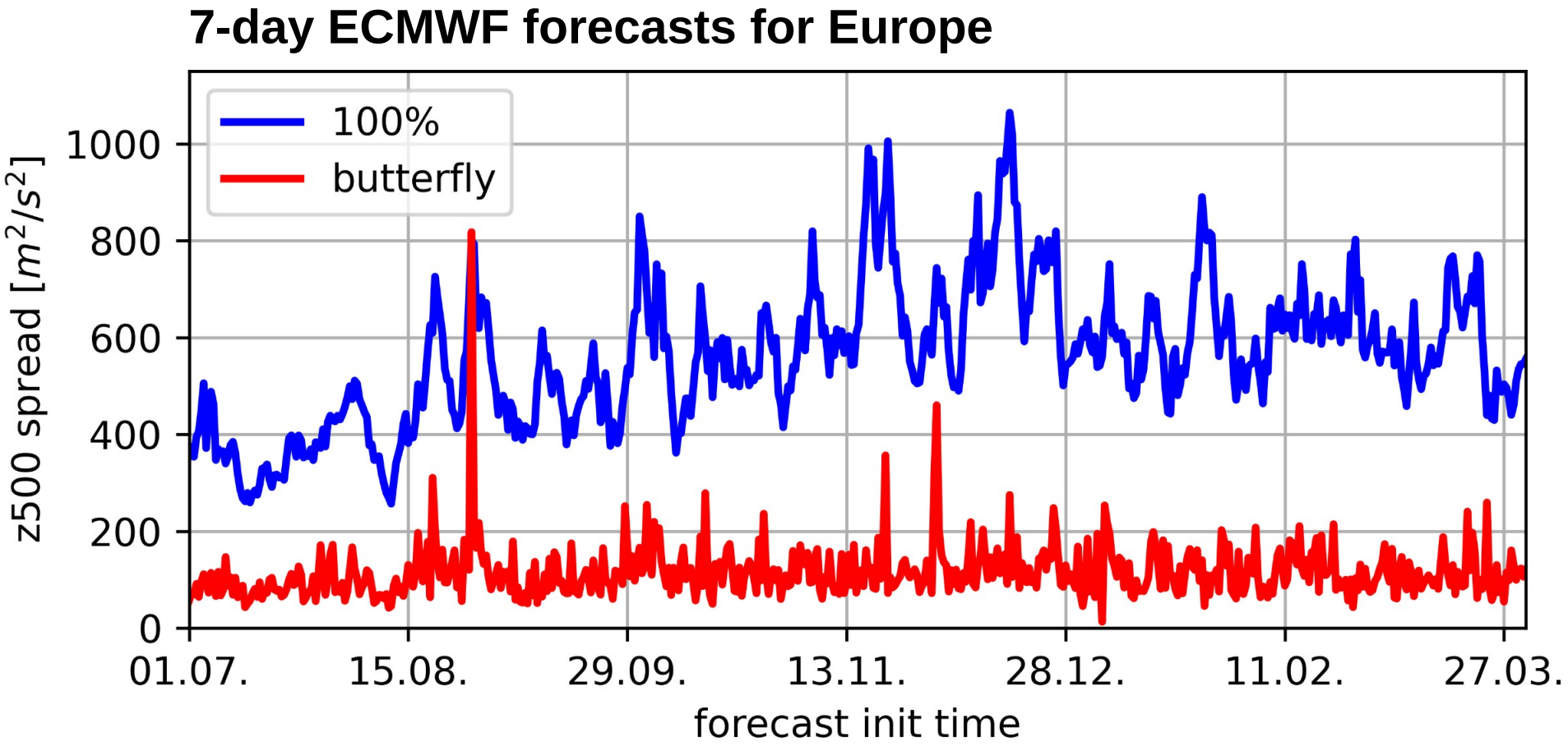
Upscale uncertainty growth from **moist convection**

Summary and conclusions I

- Possible gain through initial condition-perfection: **4-5 days** (model improvement excluded)
- **Reduction** of current initial condition uncertainty **by 90%** is required
- **Practically predictability** is mostly limited by uncertainty growth in **balanced 2D dry** motions
- **Intrinsic predictability** is limited by **diabatically-driven** uncertainty growth on **convective scales** and subsequent upscale interactions
- The predictability “regime” can be identified with the **PV-diagonsics**

These results hold on average

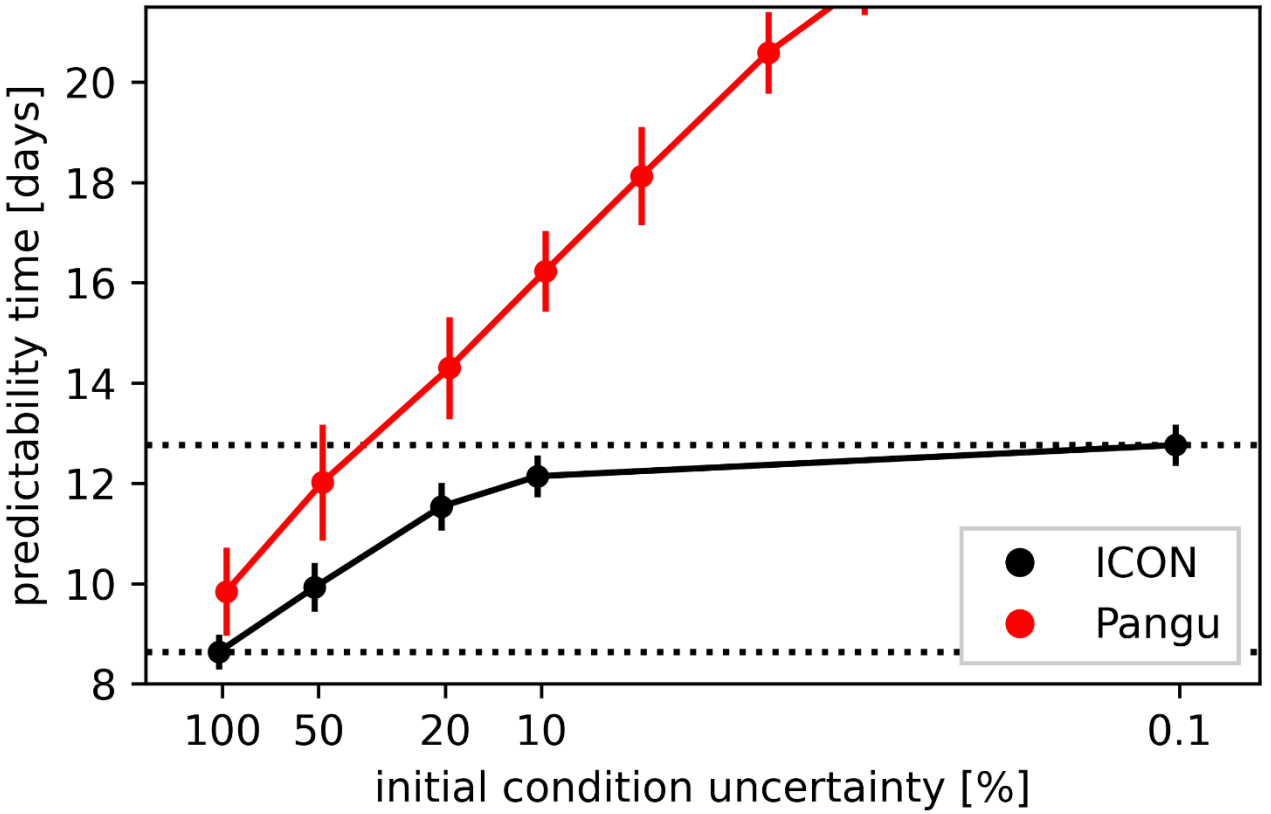
There may be exceptions …



localized PV-diagnostics required

→ Talk by Michael Riemer on Thursday, 10:00

Can AI models simulate the “butterfly effect”?

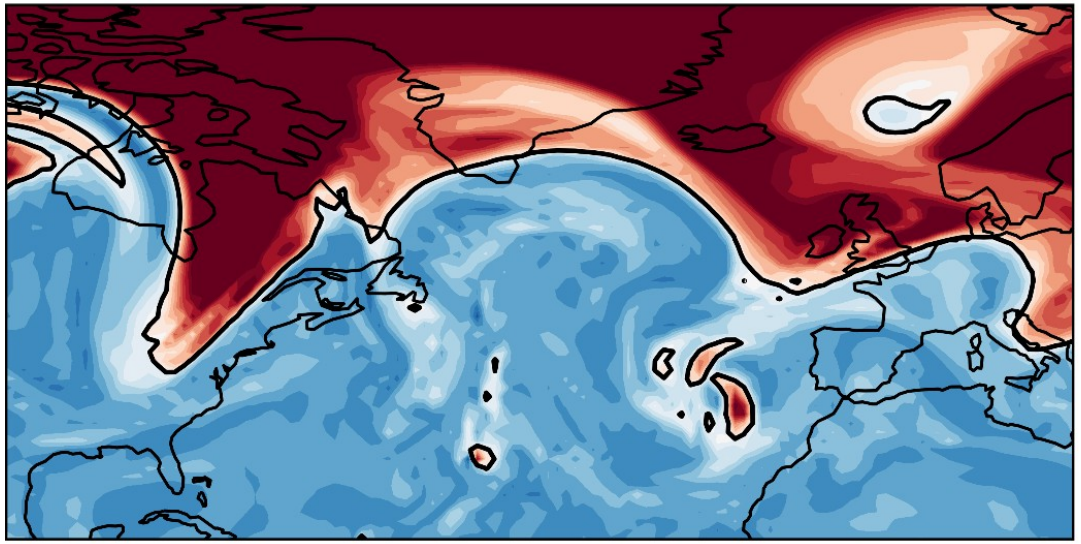


- **AI models**
  [Pangu, GraphCast, FourCastNet, NeuralGCM]
  incorrectly suggest **infinite predictability**

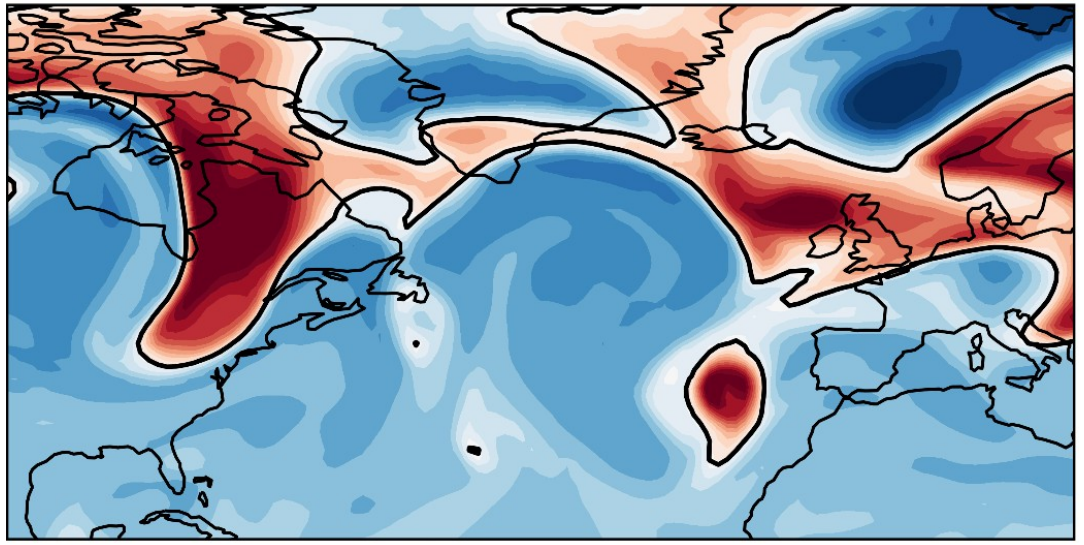
Can we apply the PV diagnostics to AI models?

PV field from an AI model

ICON PV (320K)



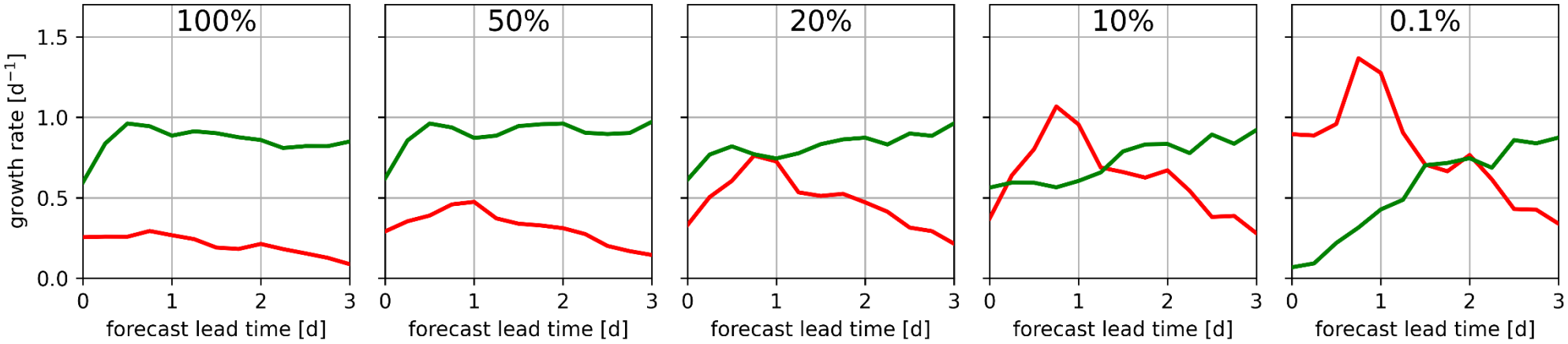
Pangu PV (320K)



- Effective resolution is low
- Troposphere and tropopause look realistic
- Stratospheric stratification is incorrect

Simplified PV diagnostic from AI model

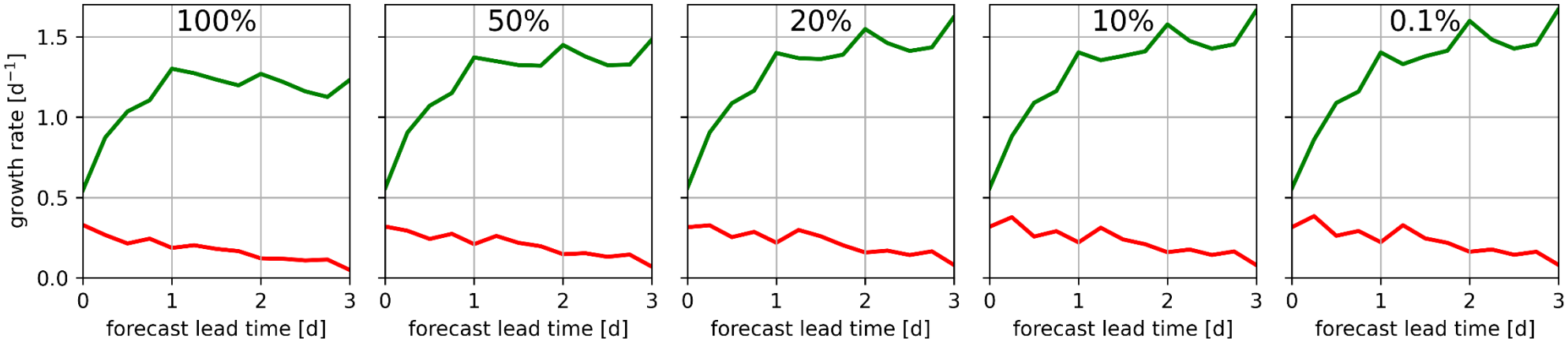
ICON simulations



rotational wind

divergent wind

Pangu simulations



Summary and conclusions II

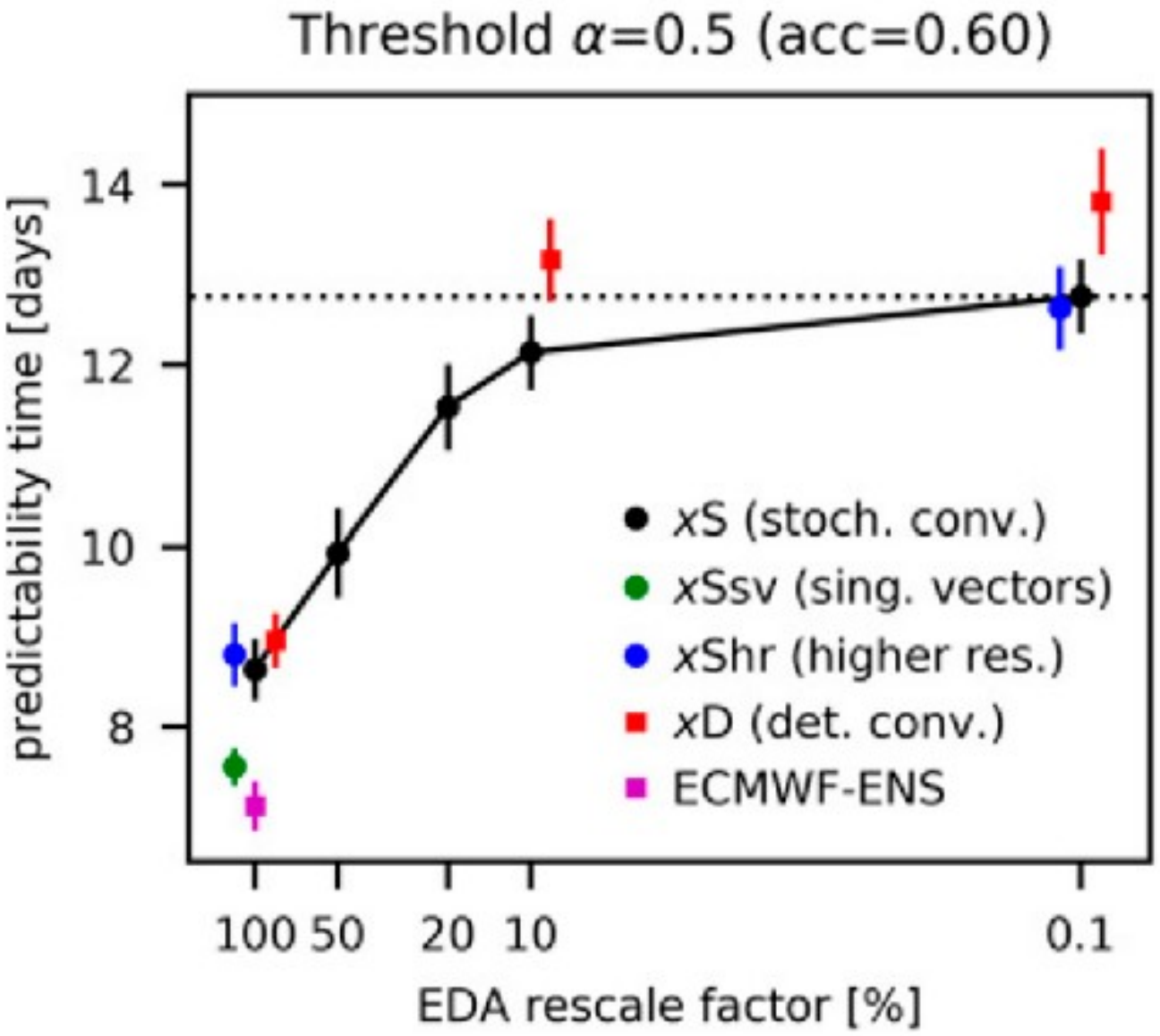
- Current **AI models cannot** simulate the **“butterfly effect”** *[Pangu, GraphCast, FourCastNet, NeuralGCM]*
- They **incorrectly** suggest **infinite** predictability
- Yet to **test**: **Generative AI** models
- A **simplified PV diagnostic** could be applied
- **No transition** to the **divergent** component of the flow

Publications

Selz, T., Riemer, M., & Craig, G. C. (2022). The Transition from Practical to Intrinsic Predictability of Midlatitude Weather. *Journal of the Atmospheric Sciences*, *79*(8), 2013-2030. https://doi.org/10.1175/JAS-D-21-0271.1

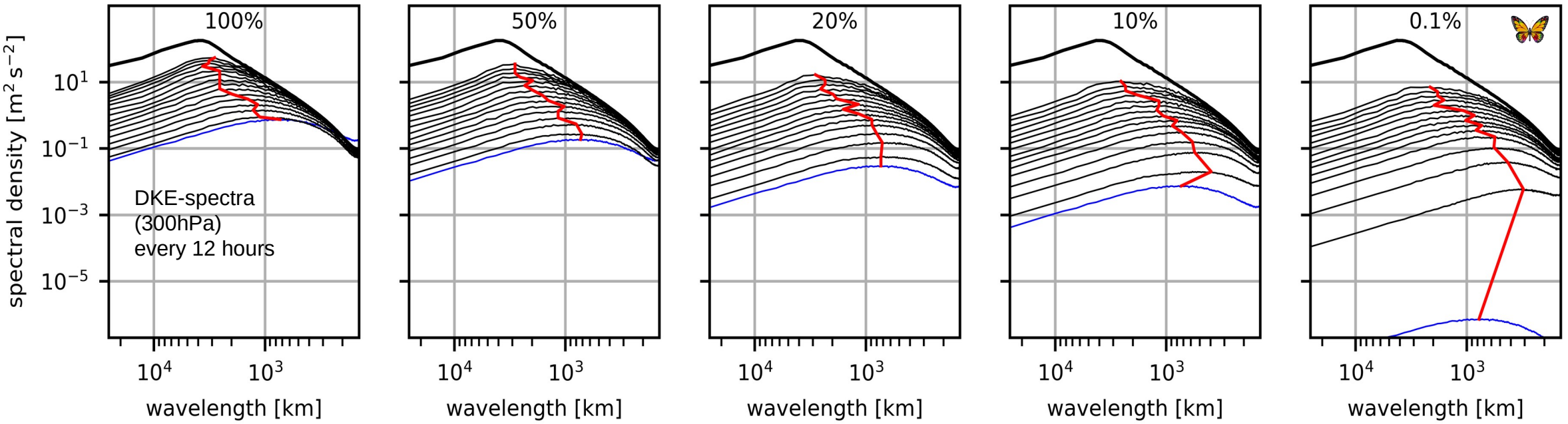
Selz, T., & Craig, G. C. (2023). Can artificial intelligence-based weather prediction models simulate the butterfly effect? *Geophysical Research Letters*, 50, e2023GL105747. https://doi.org/10.1029/2023GL105747

Extra Slides


Threshold α=0.5 (acc=0.60)
predictability time [days]
14
12
10
8
xS (stoch. conv.)
xSsv (sing. vectors)
xShr (higher res.)
xD (det. conv.)
ECMWF-ENS
100 50 20 10 0.1
EDA rescale factor [%]

initial condition uncertainty:

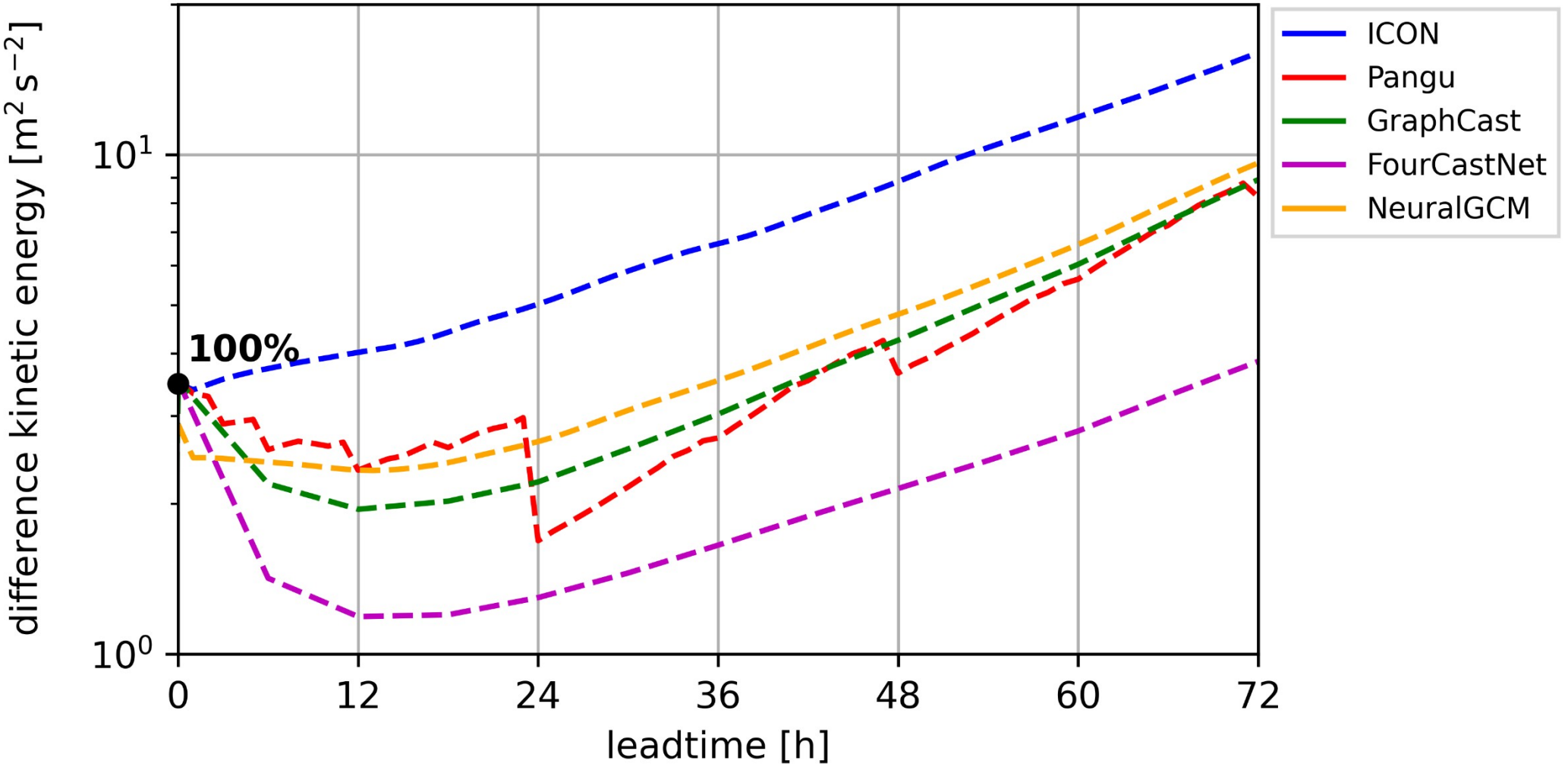
current estimates ⟶ “butterflies“



Basically **constant** error growth

Initial **fast** and **downscale** growth, upscale from there

Uncertainty growth rates
(global DKE 300hPa)



Uncertainty growth rates
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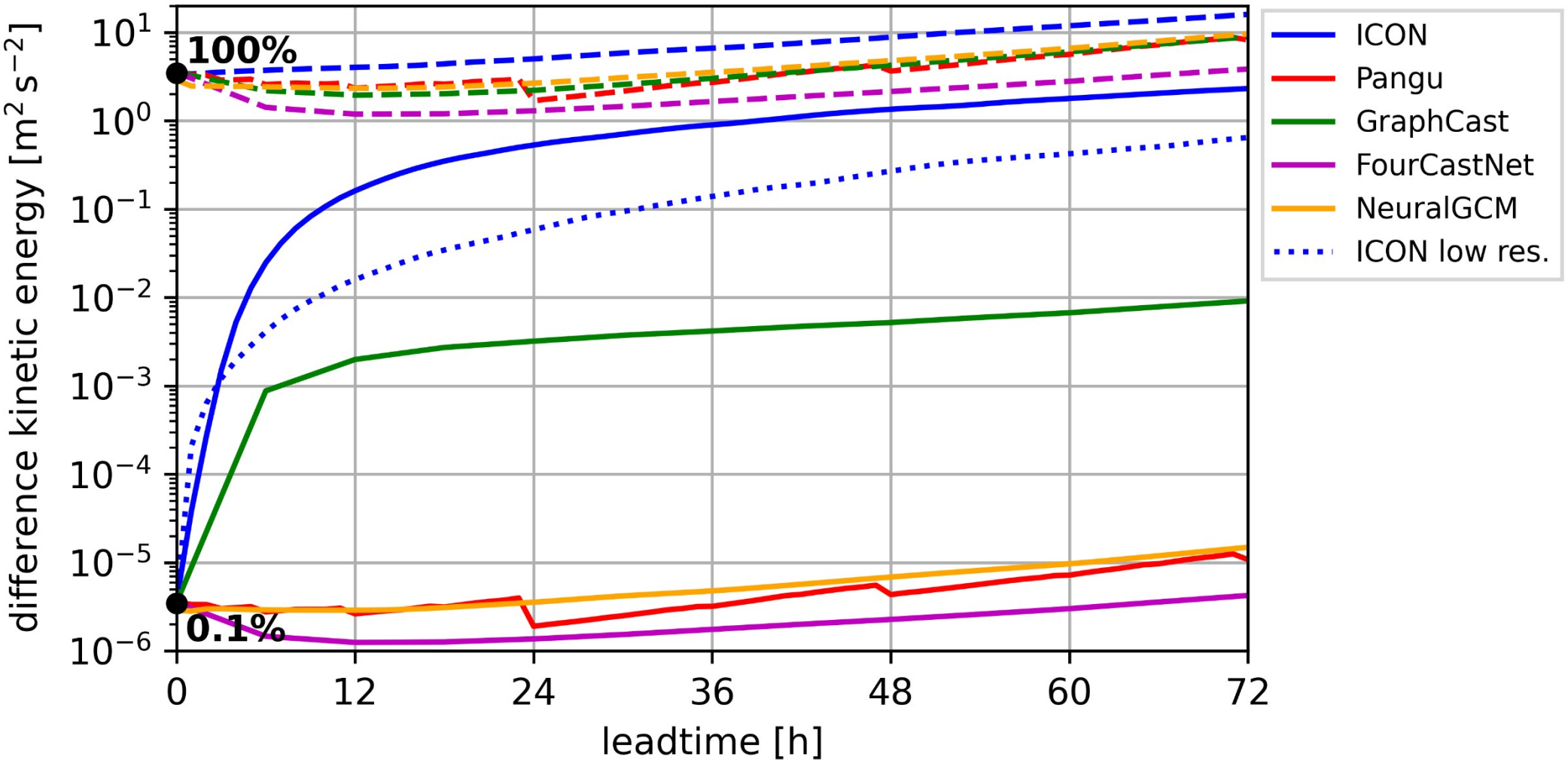
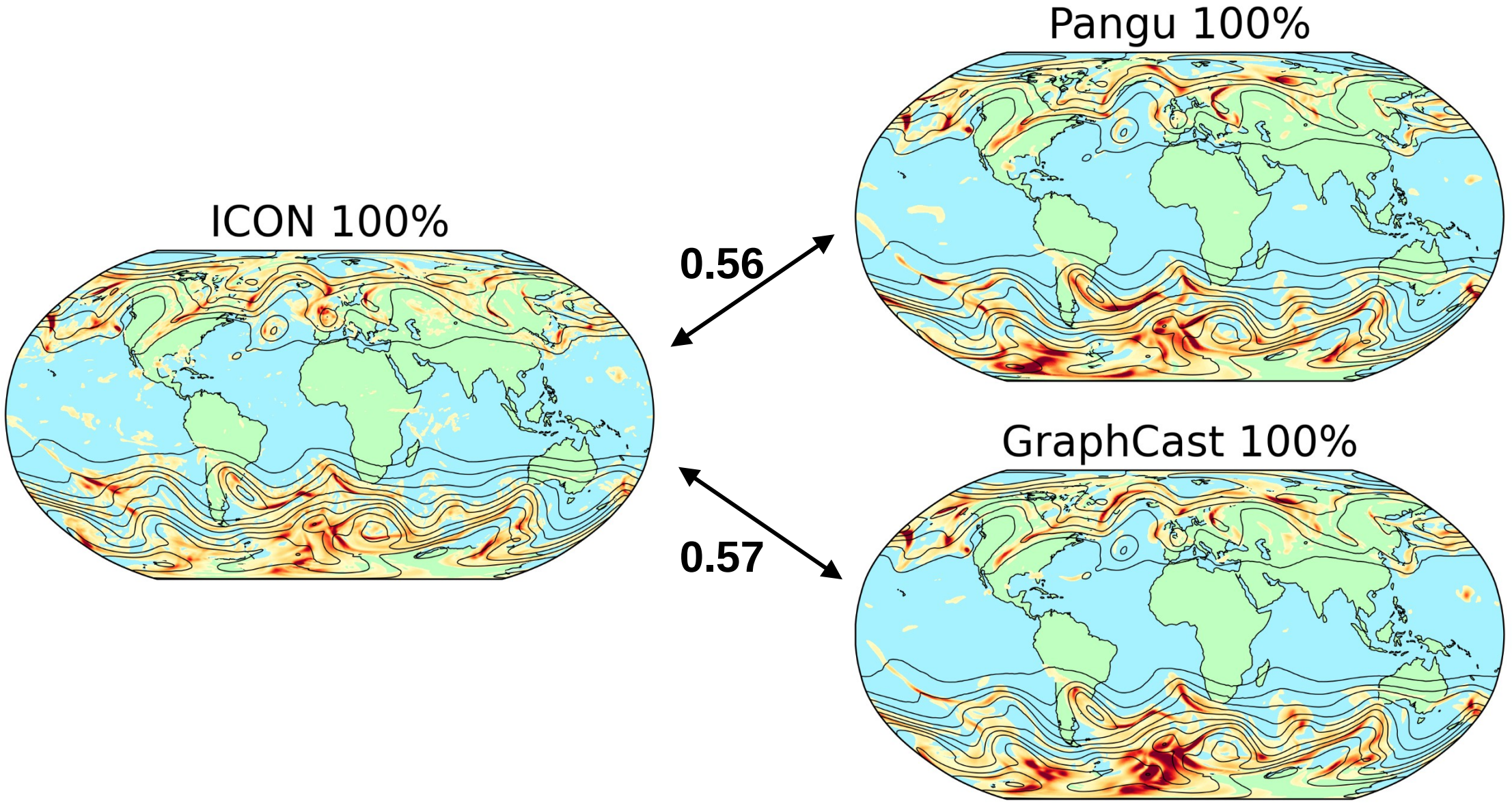
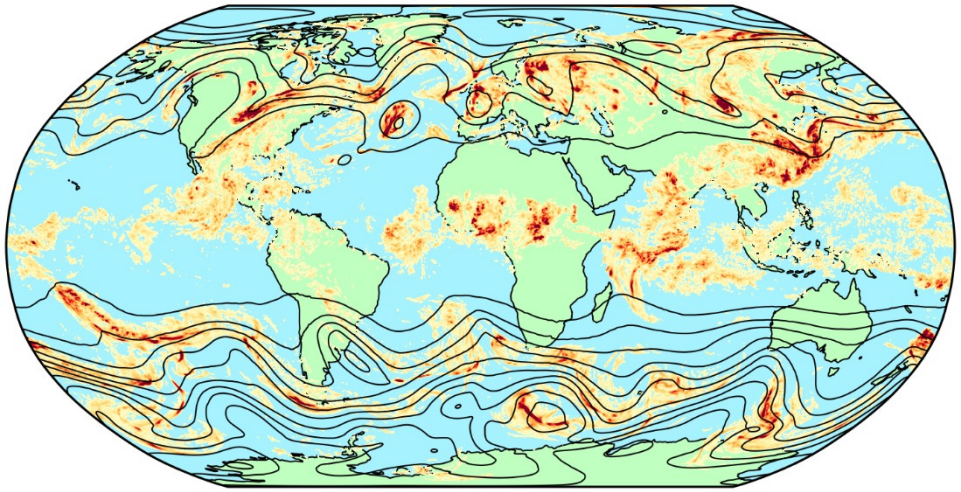


Uncertainty patterns 100% (DKE, 3 days)



Uncertainty patterns 0.1% (DKE, 3 days)

ICON 0.1%

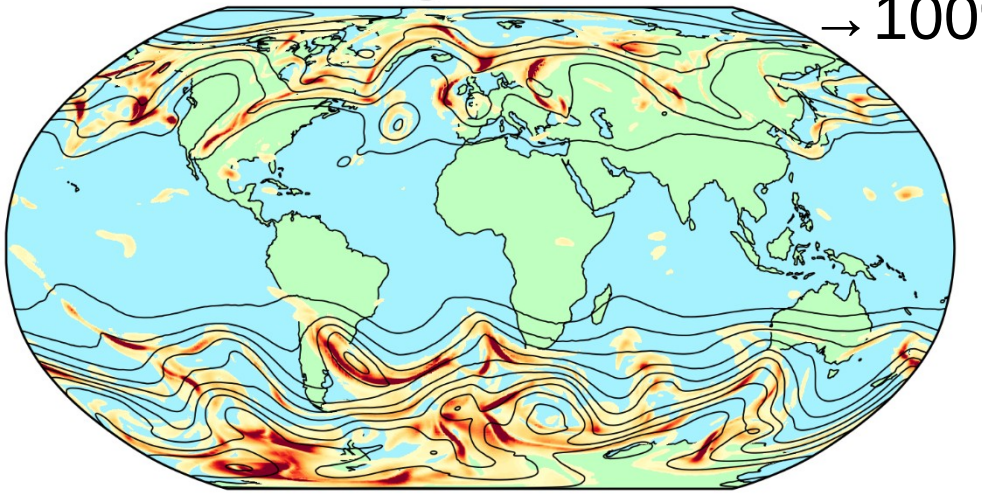


→ 100%: **0.14**

0.05

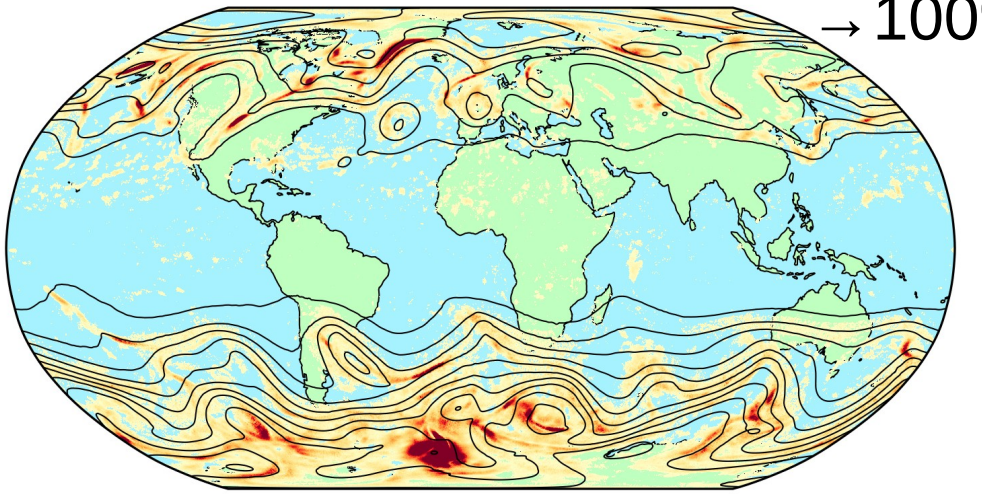
0.04

Pangu 0.1%



→ 100%: **0.74**

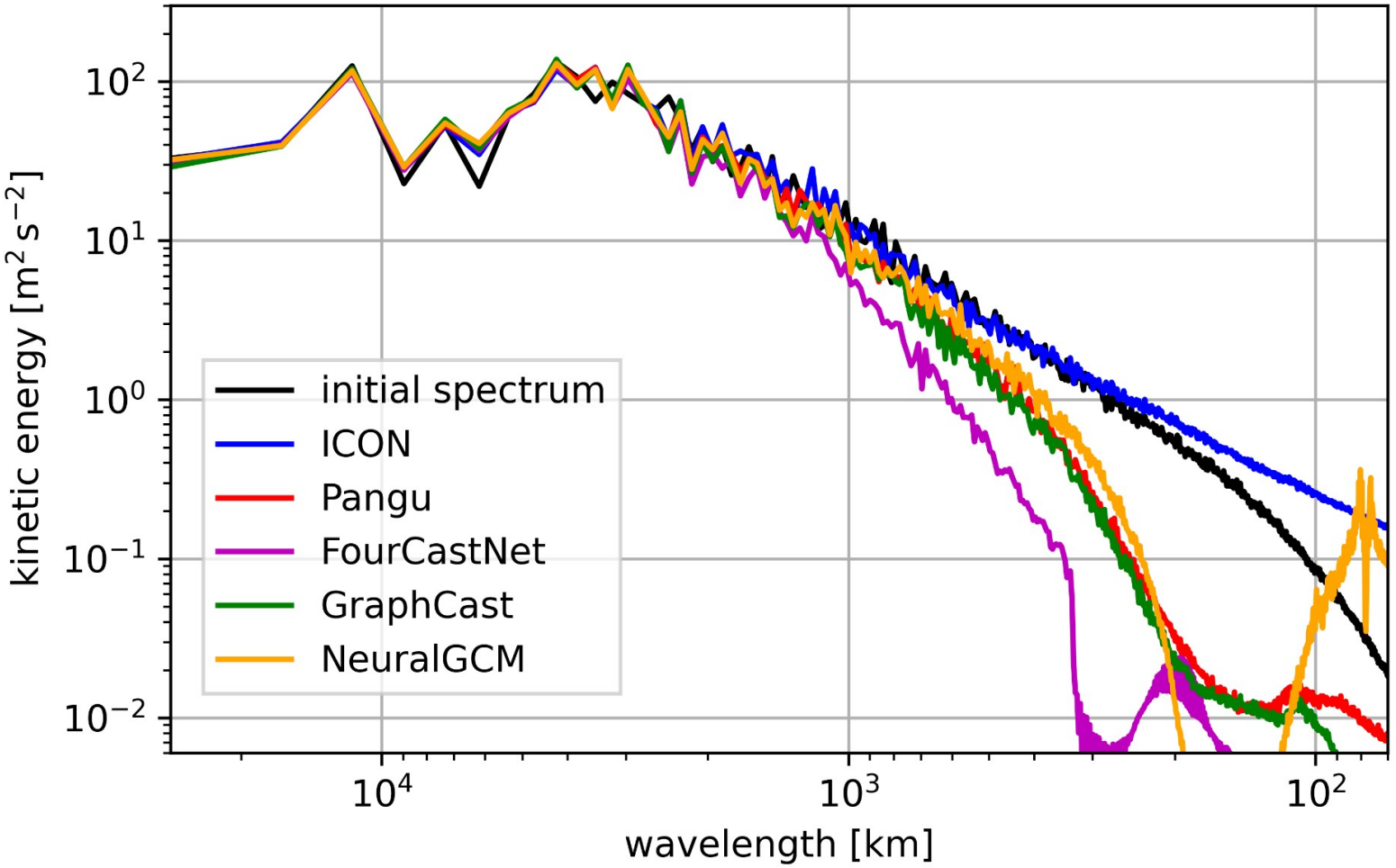
GraphCast 0.1%



→ 100%: **0.54**

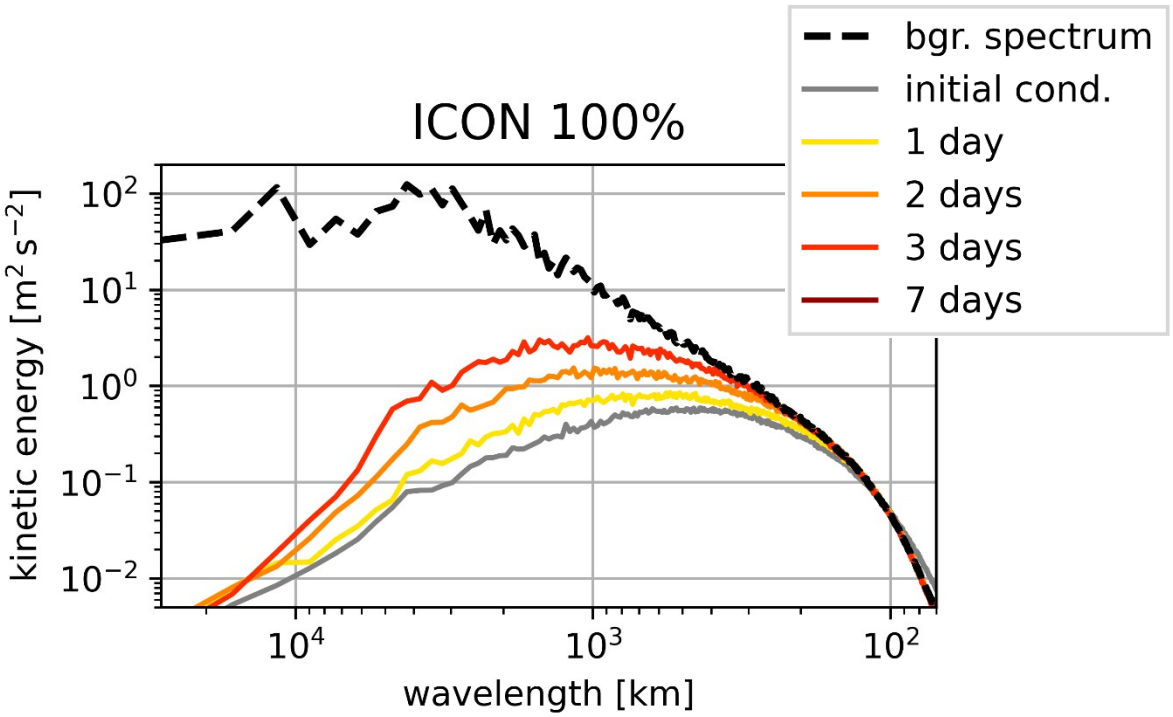
FourCastNet and **NeuralGCM** similar

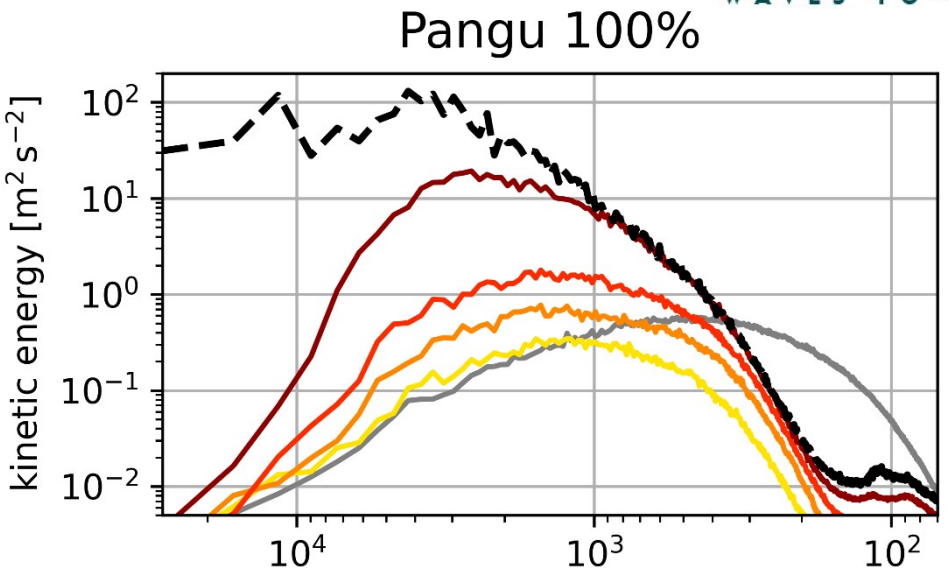
Kinetic energy spectra (300hPa, 3days)

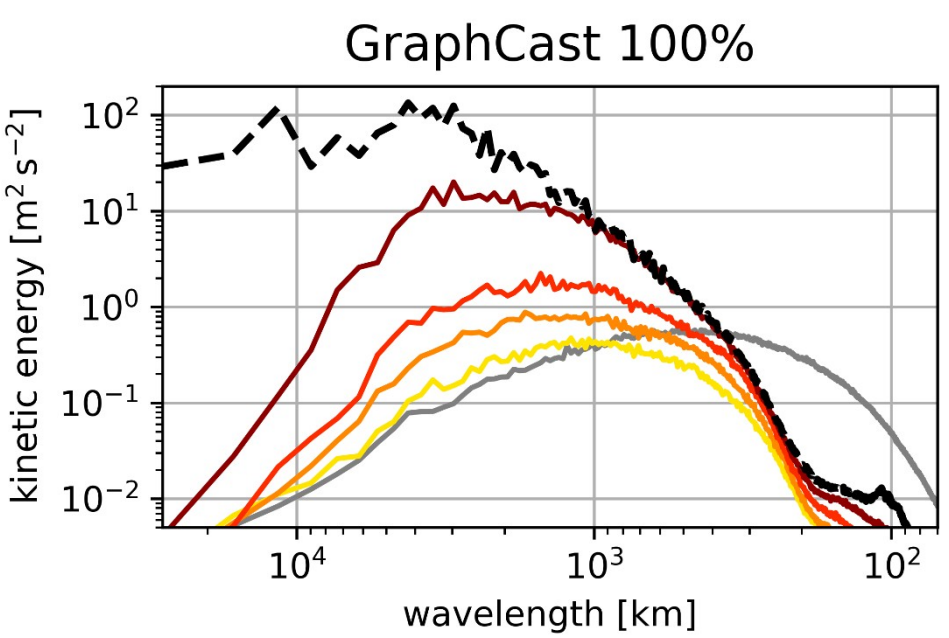


AI models have a pretty **low effective resolution** (ca. 40 Δx; 1000km)

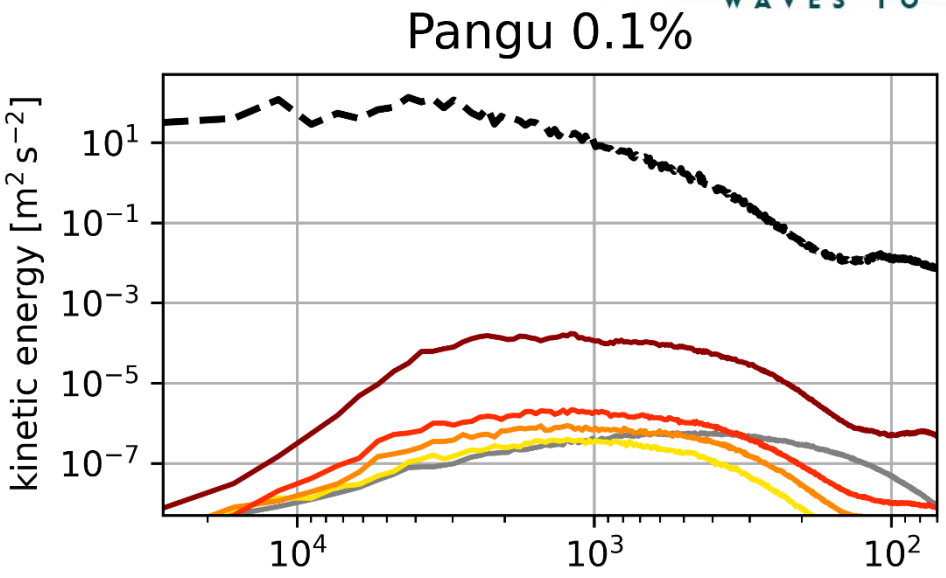
Uncertainty spectra 100% (DKE 300hPa)

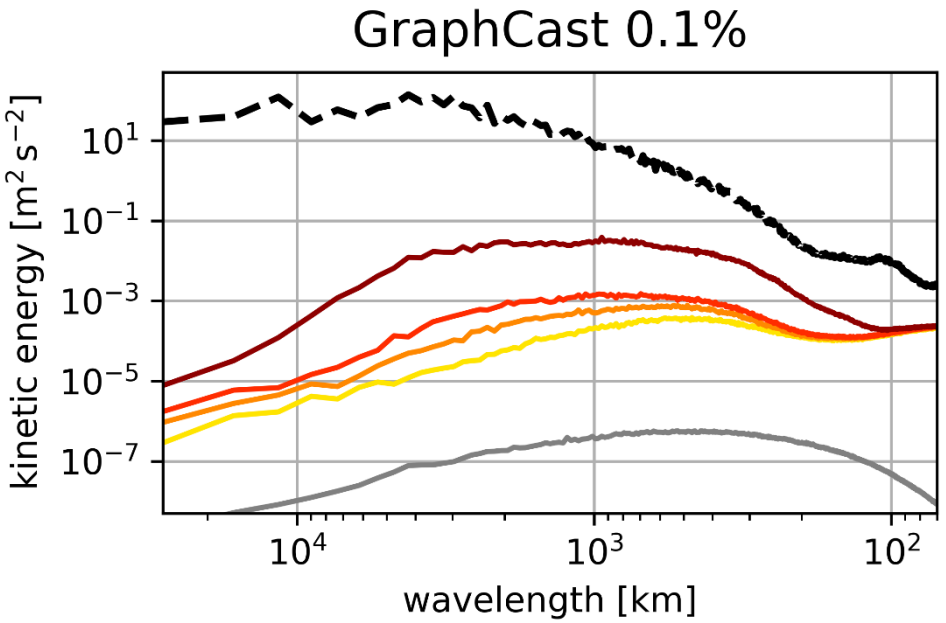






Uncertainty spectra 0.1% (DKE, 300hPa)





FourCastNet and **NeuralGCM** similar to Pangu