Global deep-learning weather prediction model evaluation and error diagnostics

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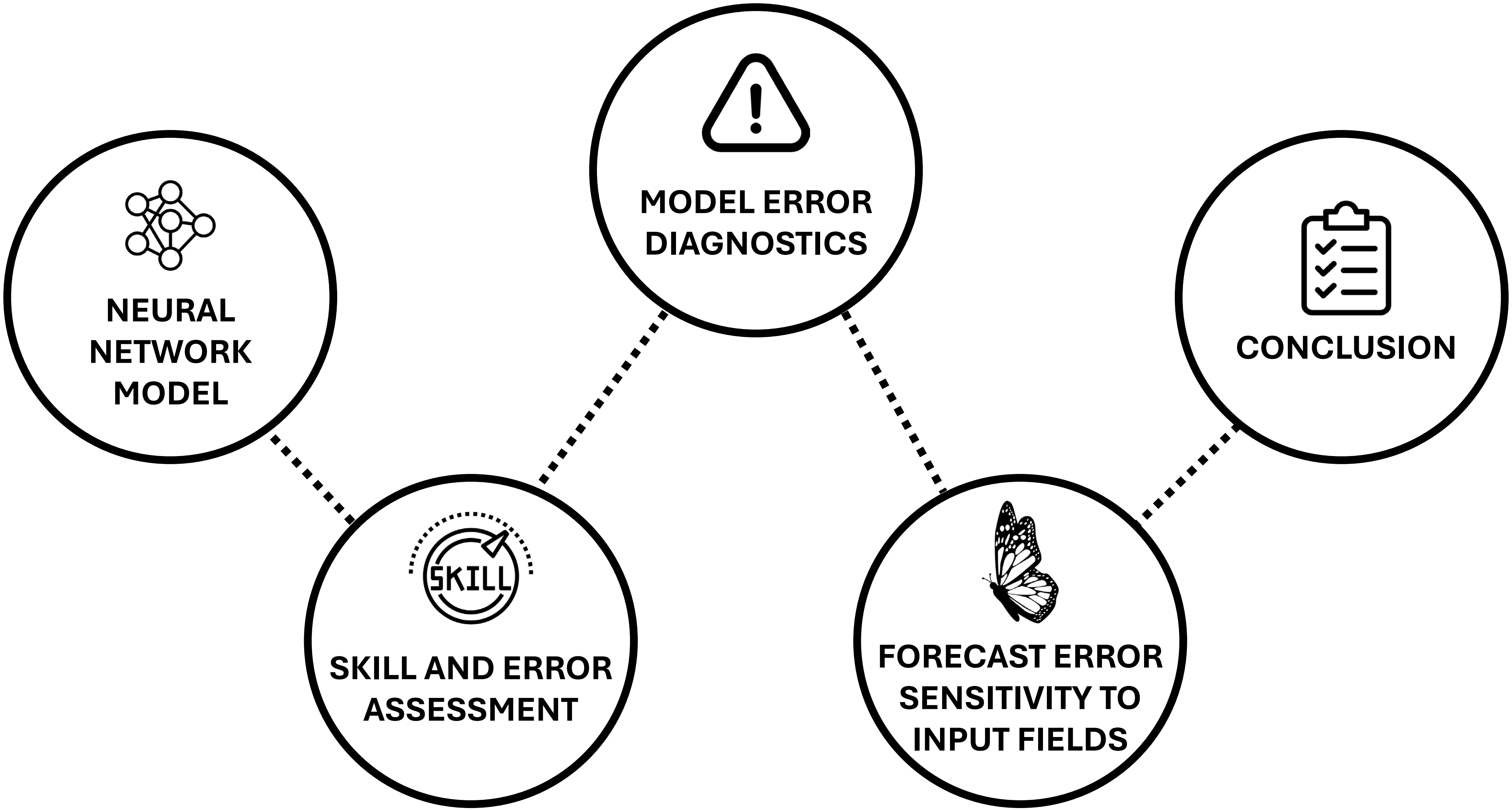
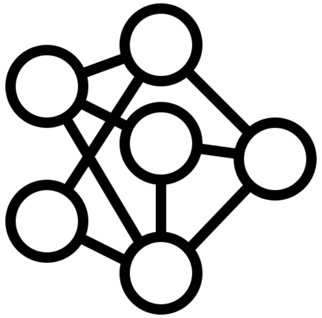


NEURAL NETWORK MODEL
SKILL
SKILL AND ERROR ASSESSMENT
MODEL ERROR DIAGNOSTICS
FORECAST ERROR SENSITIVITY TO INPUT FIELDS
CONCLUSION

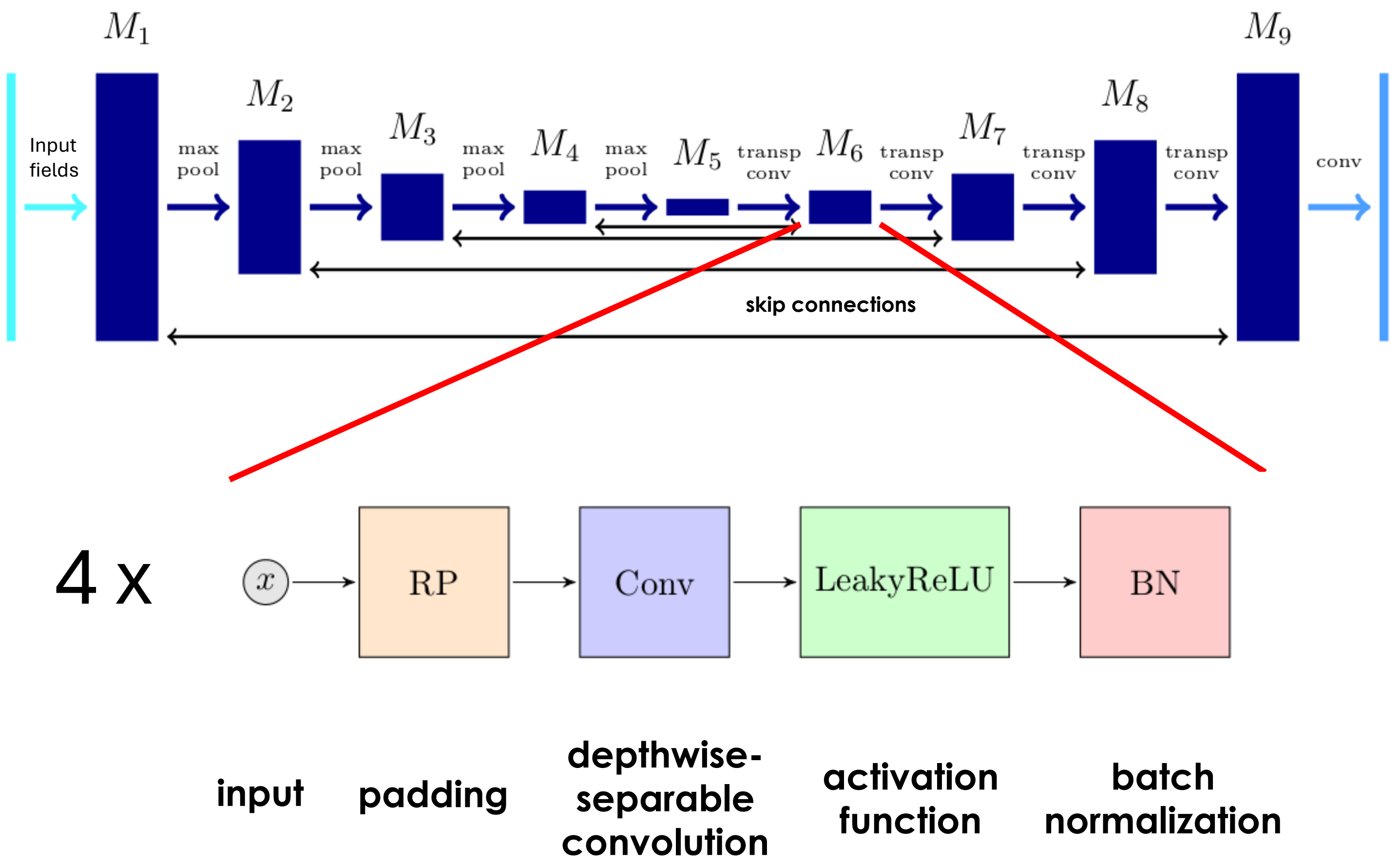
NEURAL NETWORK MODEL



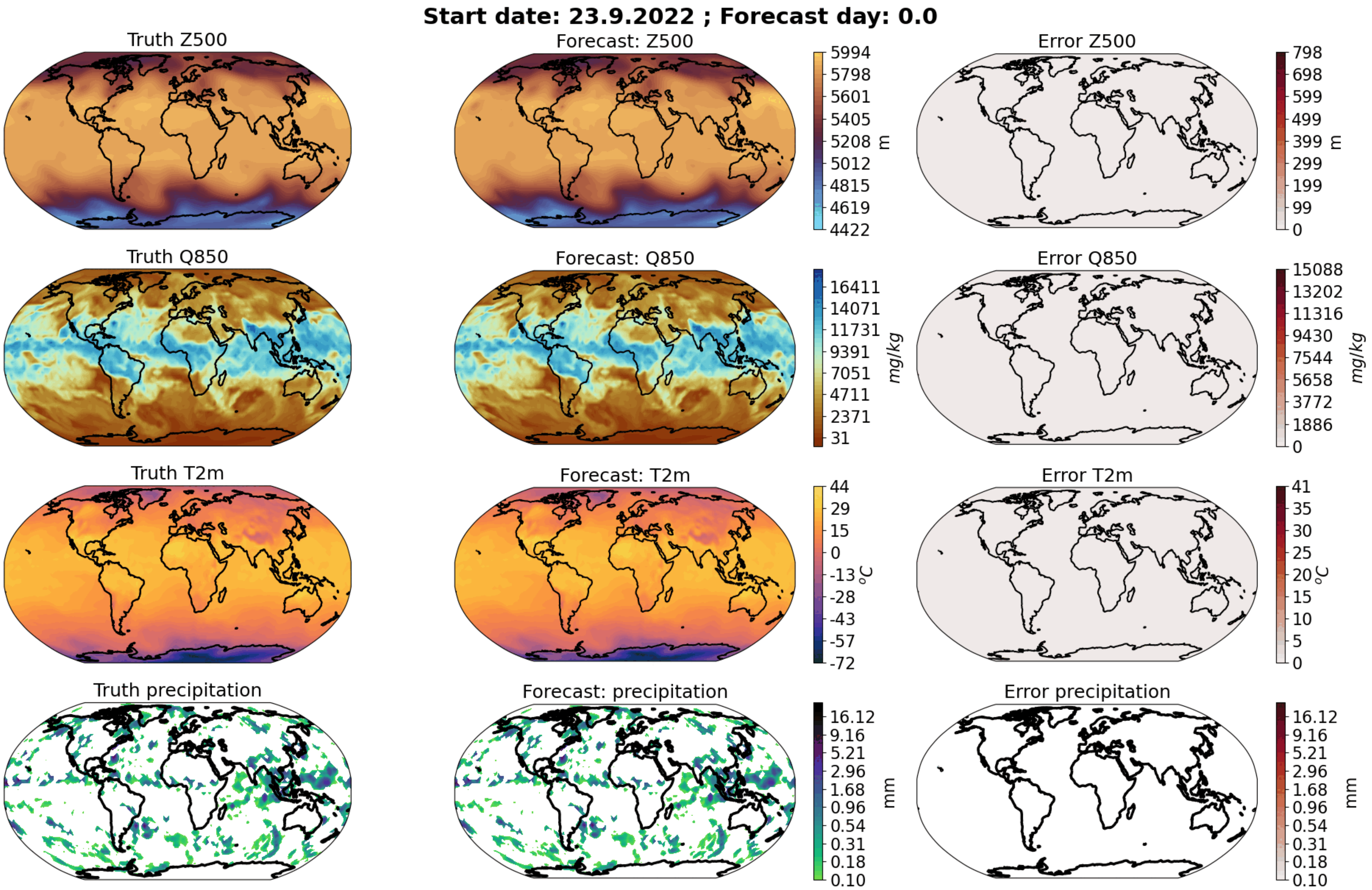
NEURAL NETWORK MODEL

ConvCastNet: convolutional weather forecasting neural network

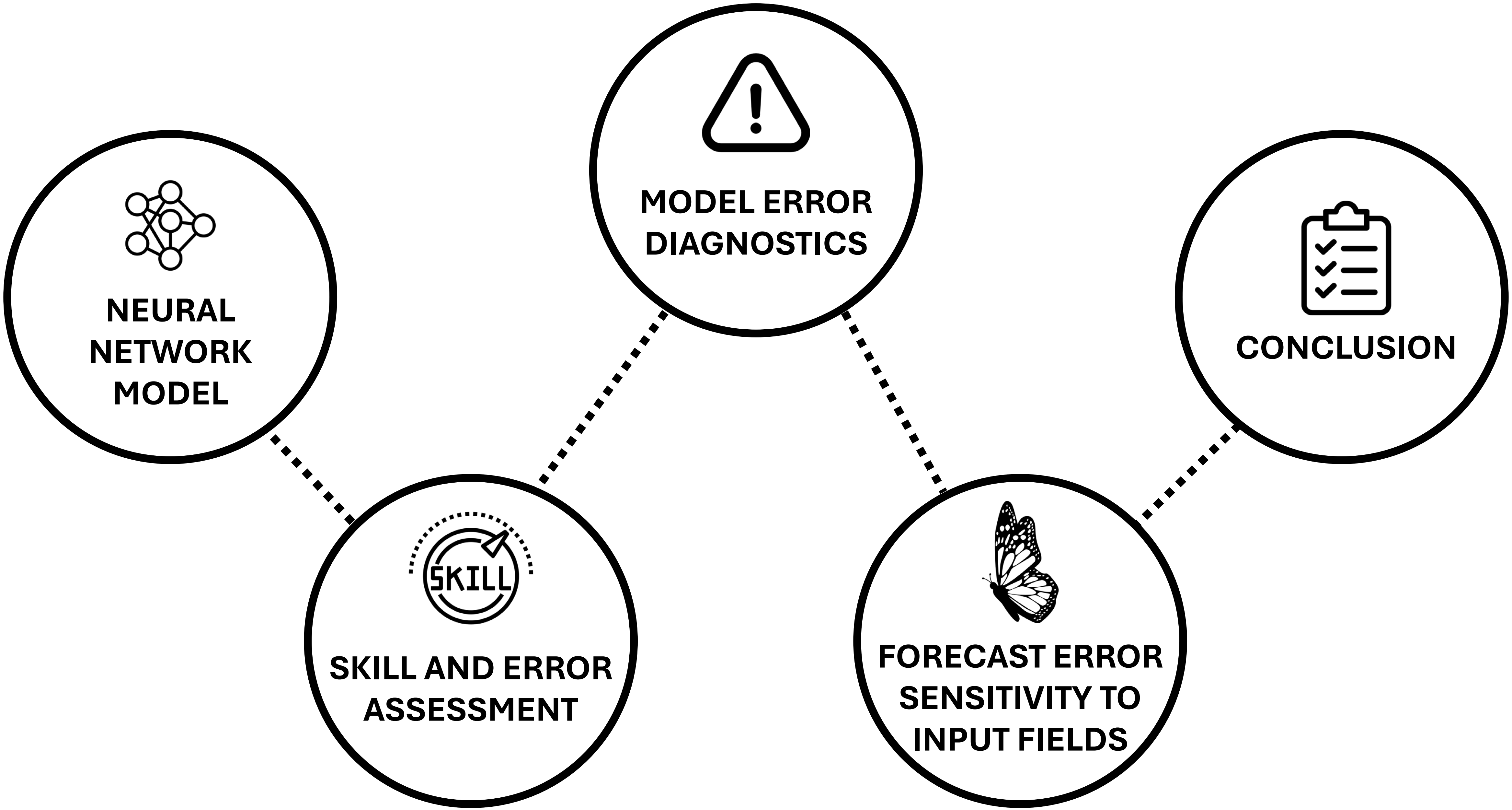
MODEL ARCHITECTURE



- Training data ERA5 reanalysis:
  - Train: 1970 – 2014
  - Validation: 2015 – 2019
  - Test: 2020 - 2022
- Model resolution: 3º
- Variables
  - Z, u, v, ω, T, q at 13 pressure levels
  - T2m, u10, v10, land and ice surface temperature, SST, mslp, tp
  - Sea ice, snow depth, soil moisture, top-of-atmosphere solar radiation, …
- Training: 4 autoregressive steps
- Time step: 12 hr



Start date: 23.9.2022 ; Forecast day: 0.0
Truth Z500
Forecast: Z500
Error Z500
5994
5798
5601
5405
5208
5012
4815
4619
4422
m
798
698
599
499
399
299
199
99
0
m
Truth Q850
Forecast: Q850
Error Q850
16411
14071
11731
9391
7051
4711
2371
31
mg/kg
15088
13202
11316
9430
7544
5658
3772
1886
0
mg/kg
Truth T2m
Forecast: T2m
Error T2m
44
29
15
0
-13
-28
-43
-57
-72
°C
41
35
30
25
20
15
10
5
0
°C
Truth precipitation
Forecast: precipitation
Error precipitation
16.12
9.16
5.21
2.96
1.68
0.96
0.54
0.31
0.18
0.10
mm
16.12
9.16
5.21
2.96
1.68
0.96
0.54
0.31
0.18
0.10
mm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SKILL AND ERROR ASSESSMENT

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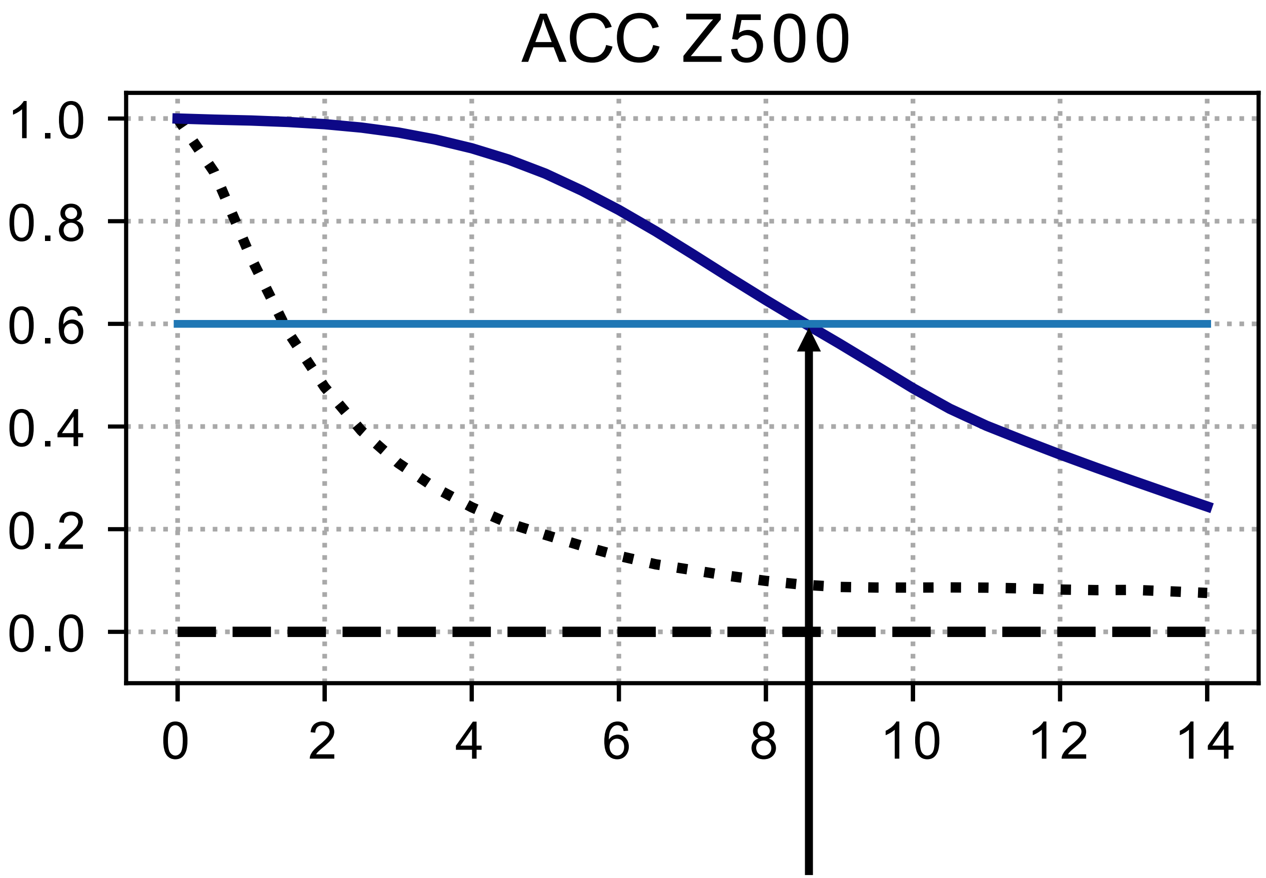
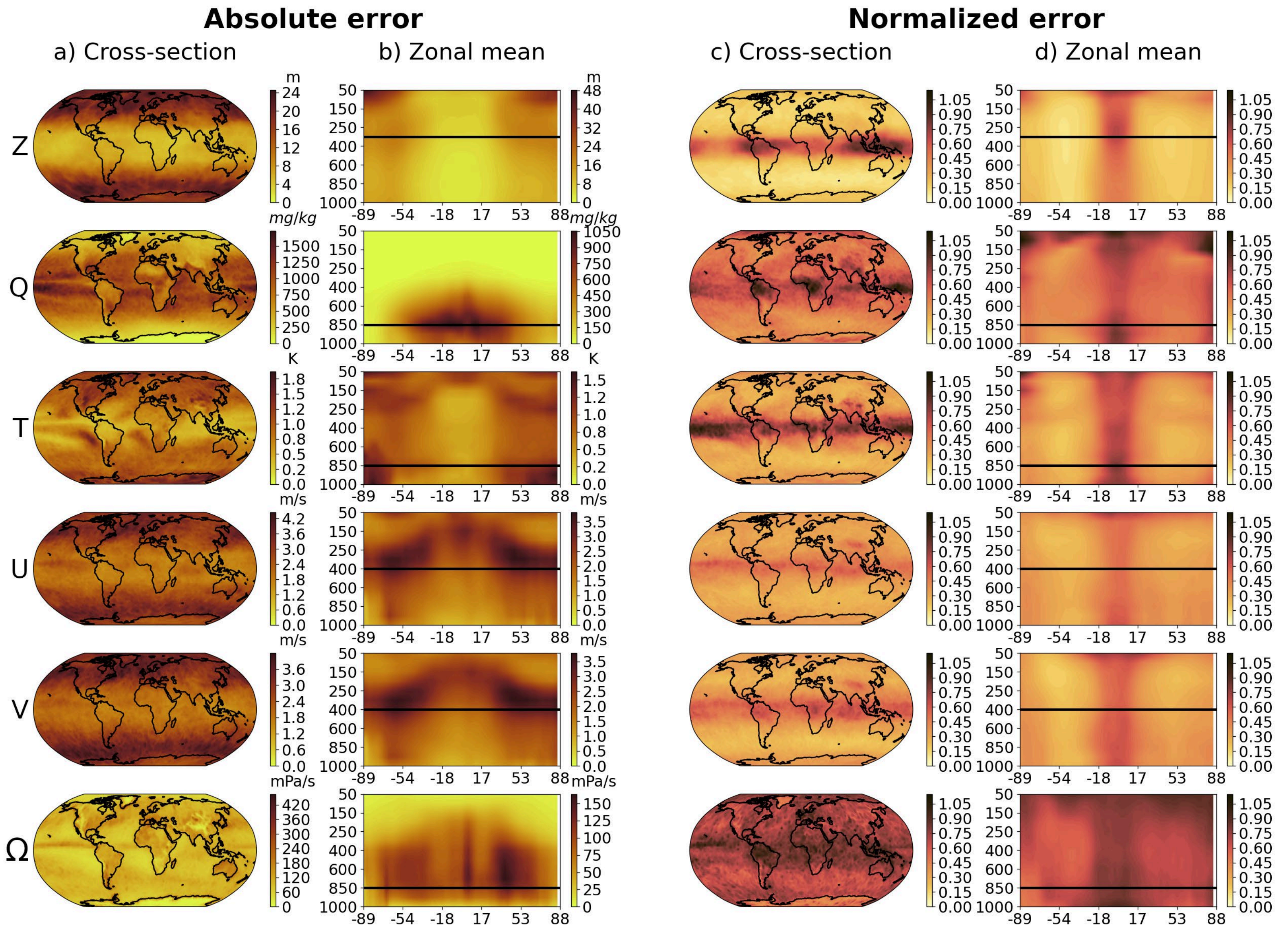
GLOBAL SKILL



ACC > 0.6 for 8.5 days

Large-scale forecast skill close to state-of-the-art ML models

SPATIAL DISTRIBUTION OF ERRORS

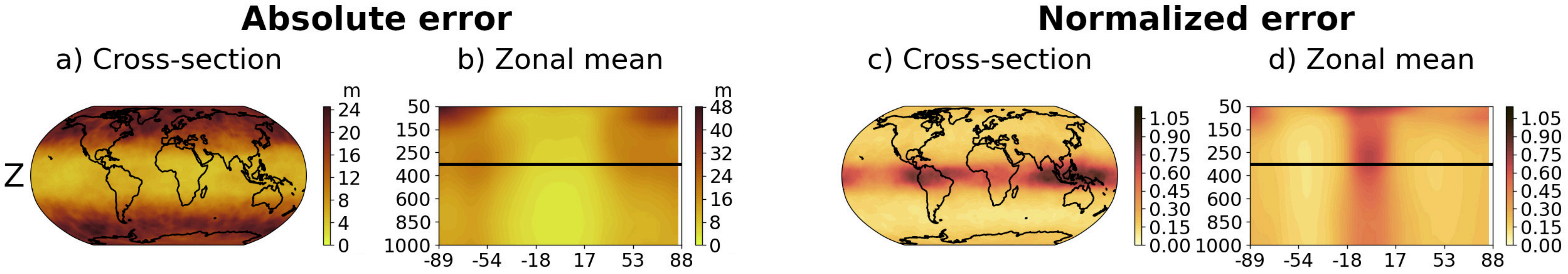


Lead time: 2 days

Absolute error:
absolute difference between forecast and ERA5 „truth“

Normailzed error:
absolute error divided by natural variability

GEOPOTENTIAL



Large absolute errors:

- Mid-to-high latitudes
- Polar stratosphere

Correspond to large natural variability

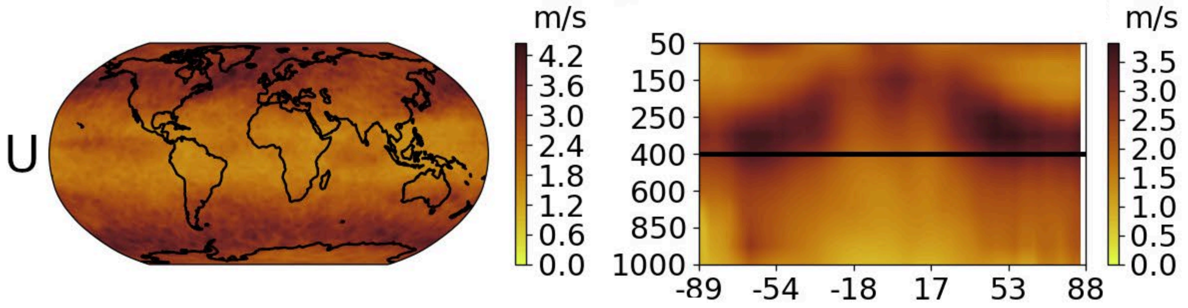
Large normalized errors:

- Tropics
- Polar and tropical stratosphere

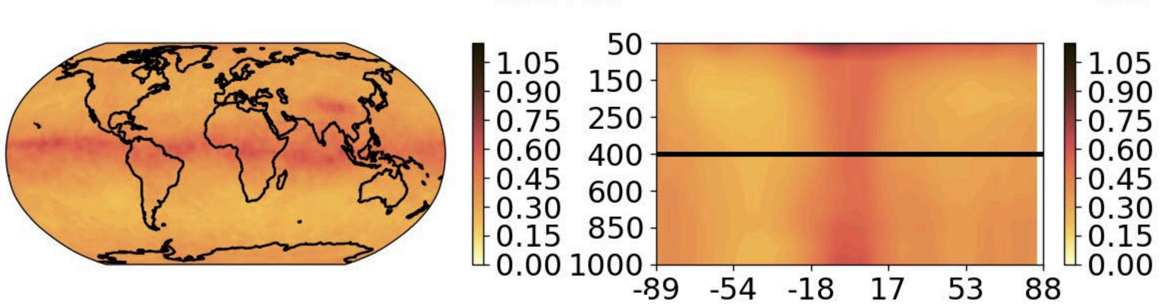
Better describes error relative to expected natural weather variability

ZONAL WIND

Absolute error



Normalized error



Large absolute errors:

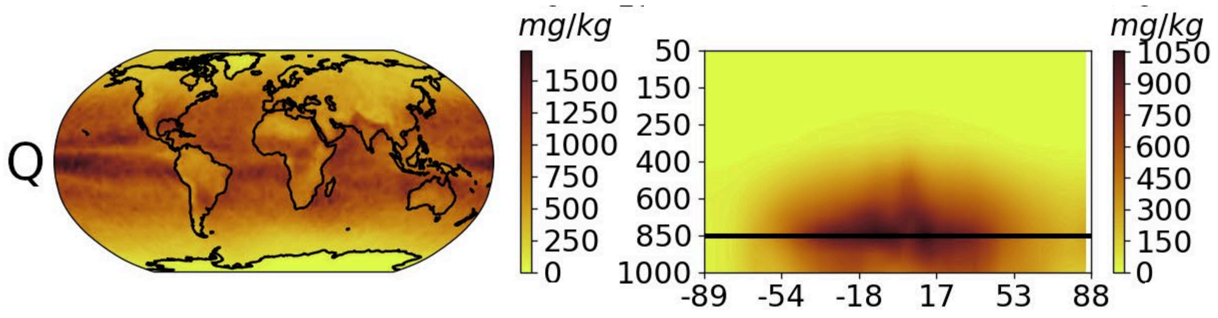
- Region of strong mid-latitude westerly jet
- Stratosphere

Large normalized errors:

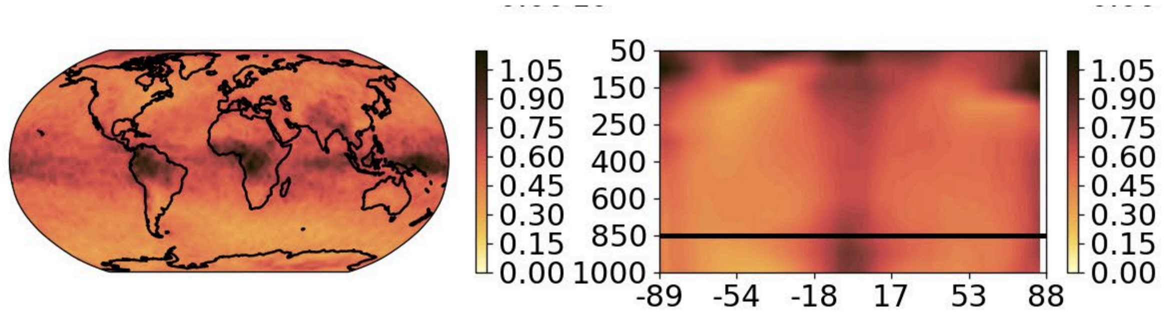
- Tropical atmosphere
- Tibetan Plateau

SPECIFIC HUMIDITY

Absolute error



Normalized error

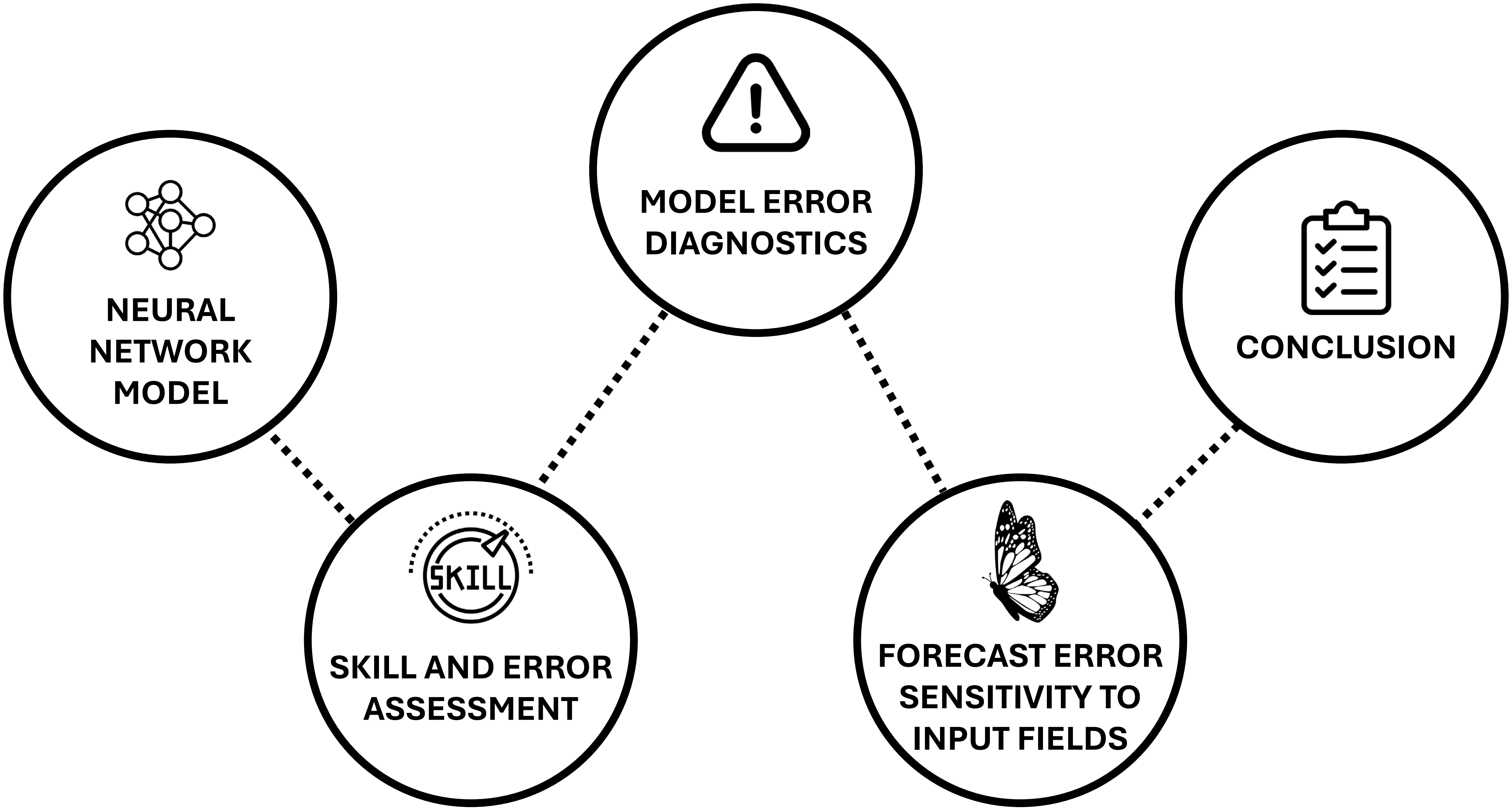


Large absolute errors:

- Above oceans
- Lower tropospere

Large normalised errors:

- Congo and Amazon basin
- Maritime continent
- Tropical oceans
- Stratosphere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MODEL ERROR DIAGNOSTICS

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- How does the forecast skill improve if we continuously replace forecasted fields with ERA5 „truth“ in:
  1. Tropics?
  2. Stratosphere?
- We perform the analysis by replacing forecasted fields in the tropics/stratosphere with ERA5 „truth“:

autoregressive input field

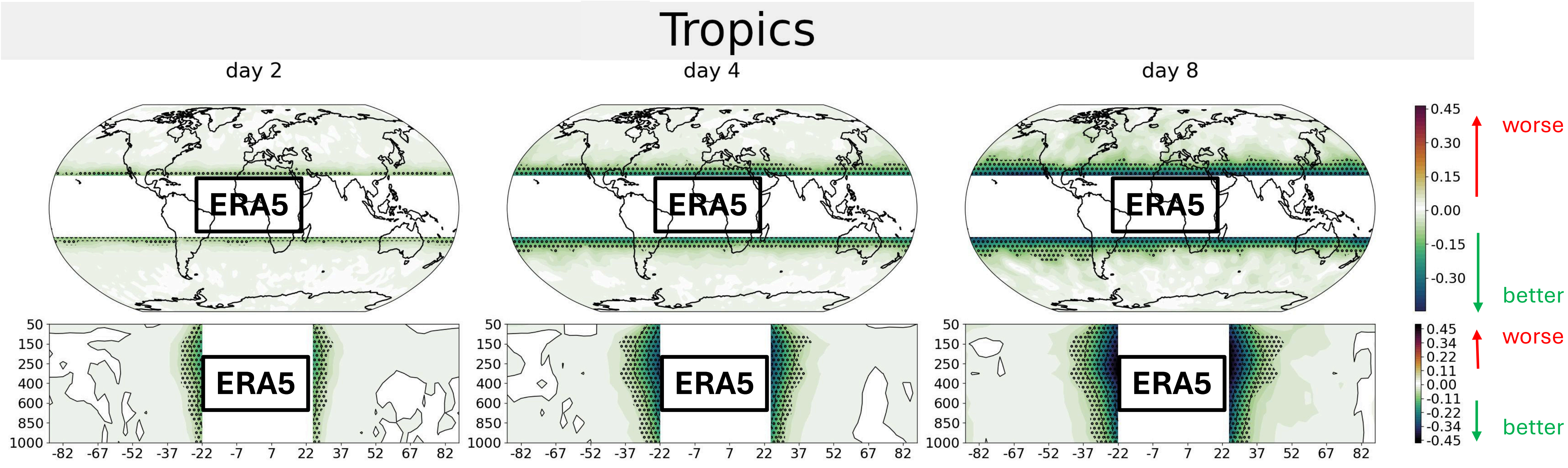
ERA5 „truth“ term

Model forecast term

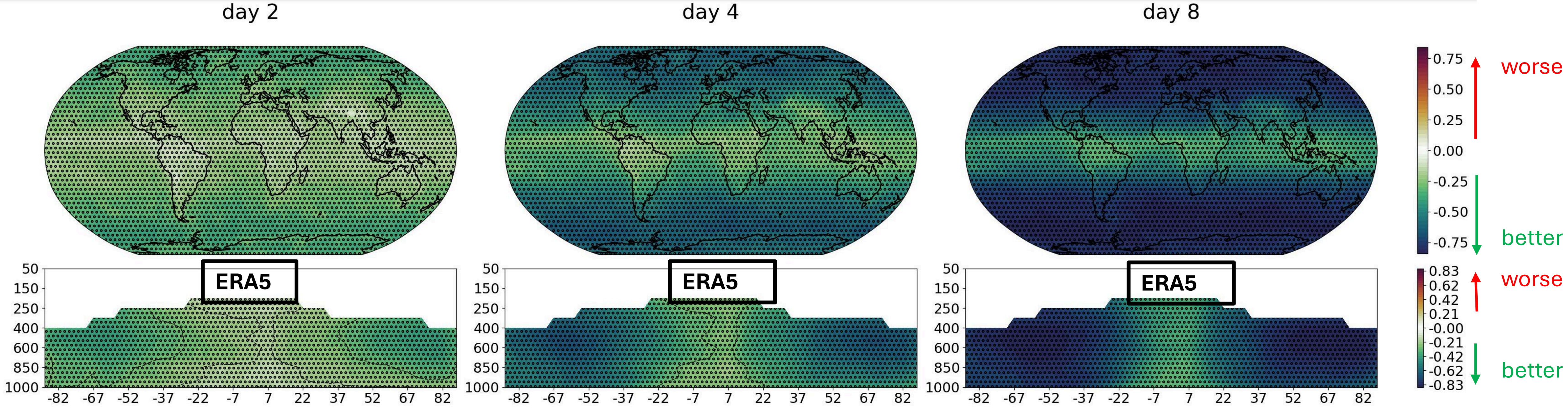
$$x(\lambda, \varphi, p, t + \Delta t) = \text{weight}_\tau(\lambda, \varphi, p) \cdot \text{ERA5}(\lambda, \varphi, p, t + \Delta t) + (1 - \text{weight}_\tau(\lambda, \varphi, p)) \cdot \mathcal{M}_{t \to t+\Delta t}(s(t))(\lambda, \varphi, p)$$

- We measure skill gain with the following metric: $1 - \dfrac{error(M(x))}{error(M(x_{forced}))}$

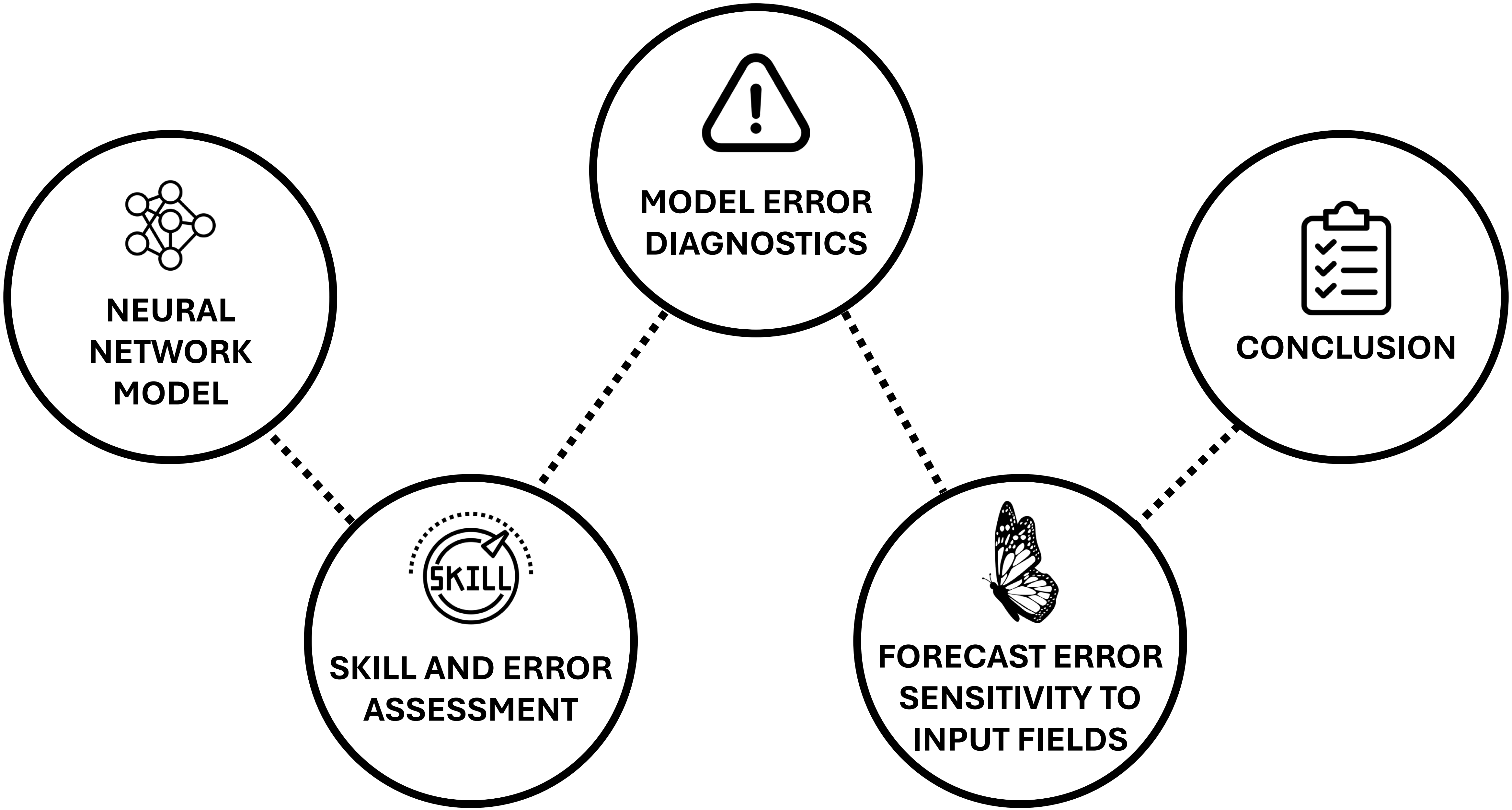
FORECAST SKILL IMPROVEMENT



Stratosphere



- This method easily diagnoses problematic regions in ML models
  - Very few issues regarding the boundary between ERA5 „truth“ and the model forecast
- We identify the stratosphere to be the key region needing better representation to improve model skill
- We could investigate other regions e.g. mountains or oceans as well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FORECAST ERROR SENSITIVITY TO INPUT FIELDS

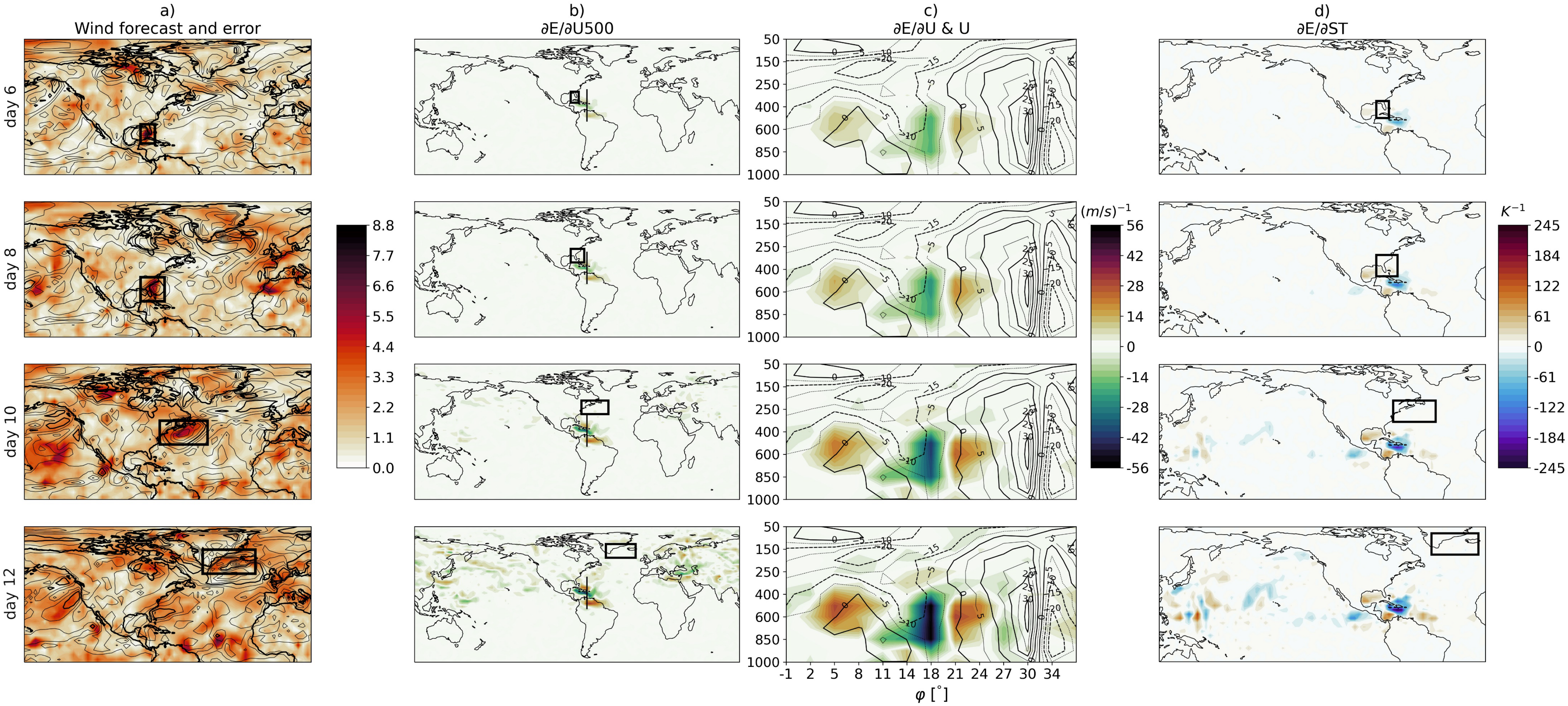
- Calculate the sensitivity of the forecast errors to the input fields:

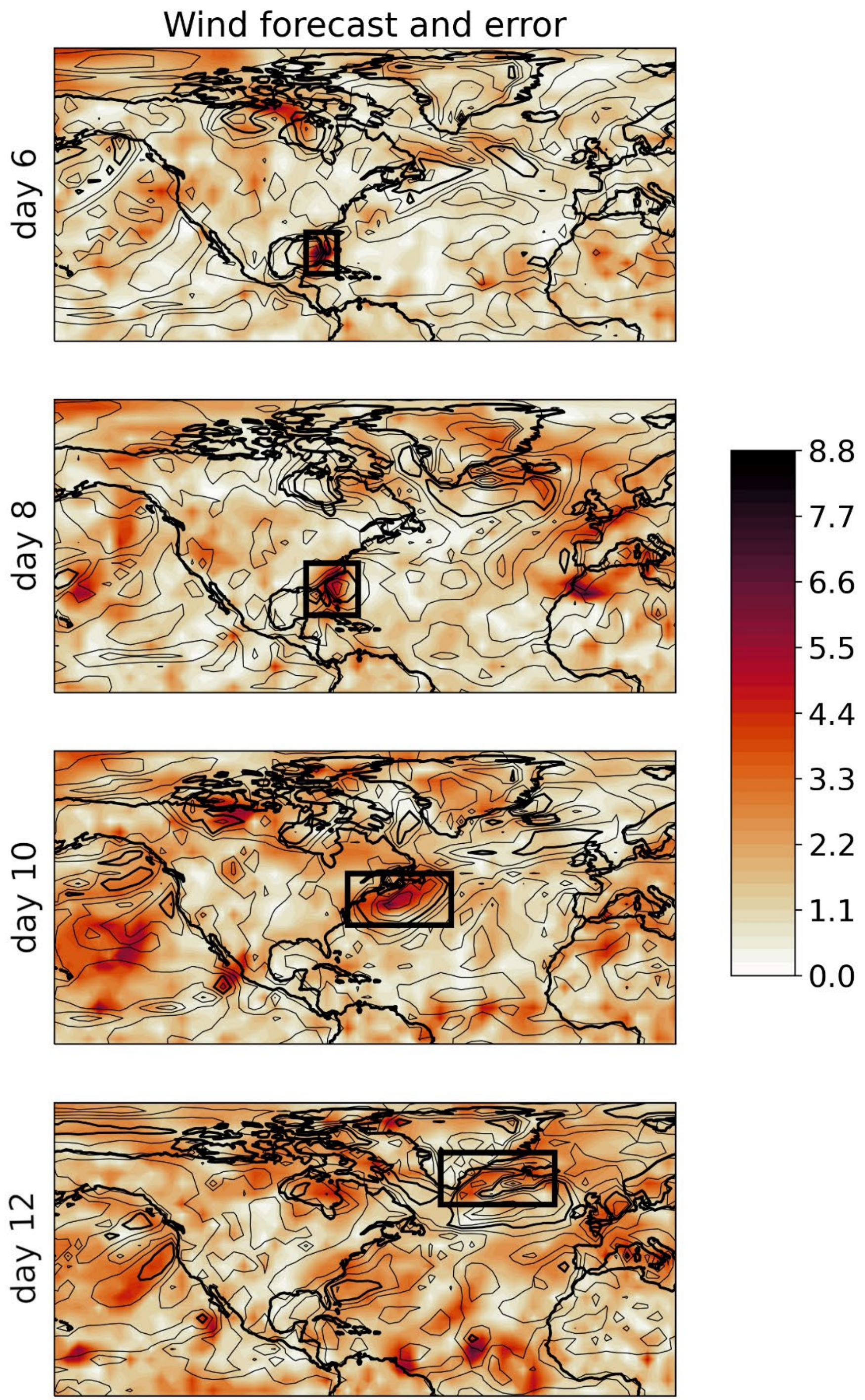
  => derivative of forecast error with respect to input fields: $\frac{\partial E}{\partial (IC)}$

  - ML models are auto-differentiable → error backpropagation

- Can it be used to improve weather forecasts?

HURRICANE IAN: forecast initialisation – September 23, 2022

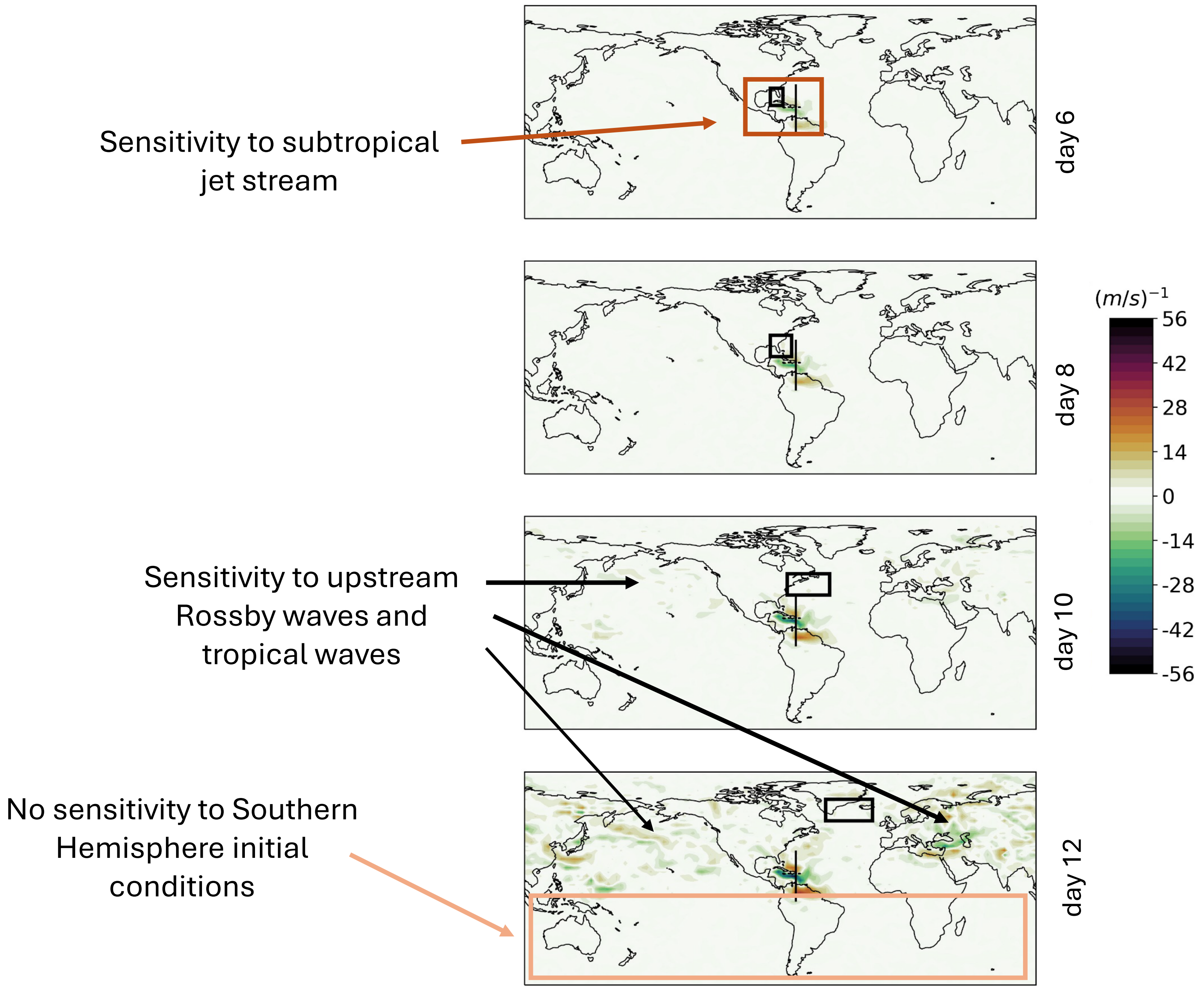




- Contours: 10 m horizontal wind speed forecast
- Colour: 10 m normalised wind forecast error
- Black box: domain for error calculation

Aim of case study: estimate the sensitivity of Hurricane Ian‘s forecast error to the initial conditions.

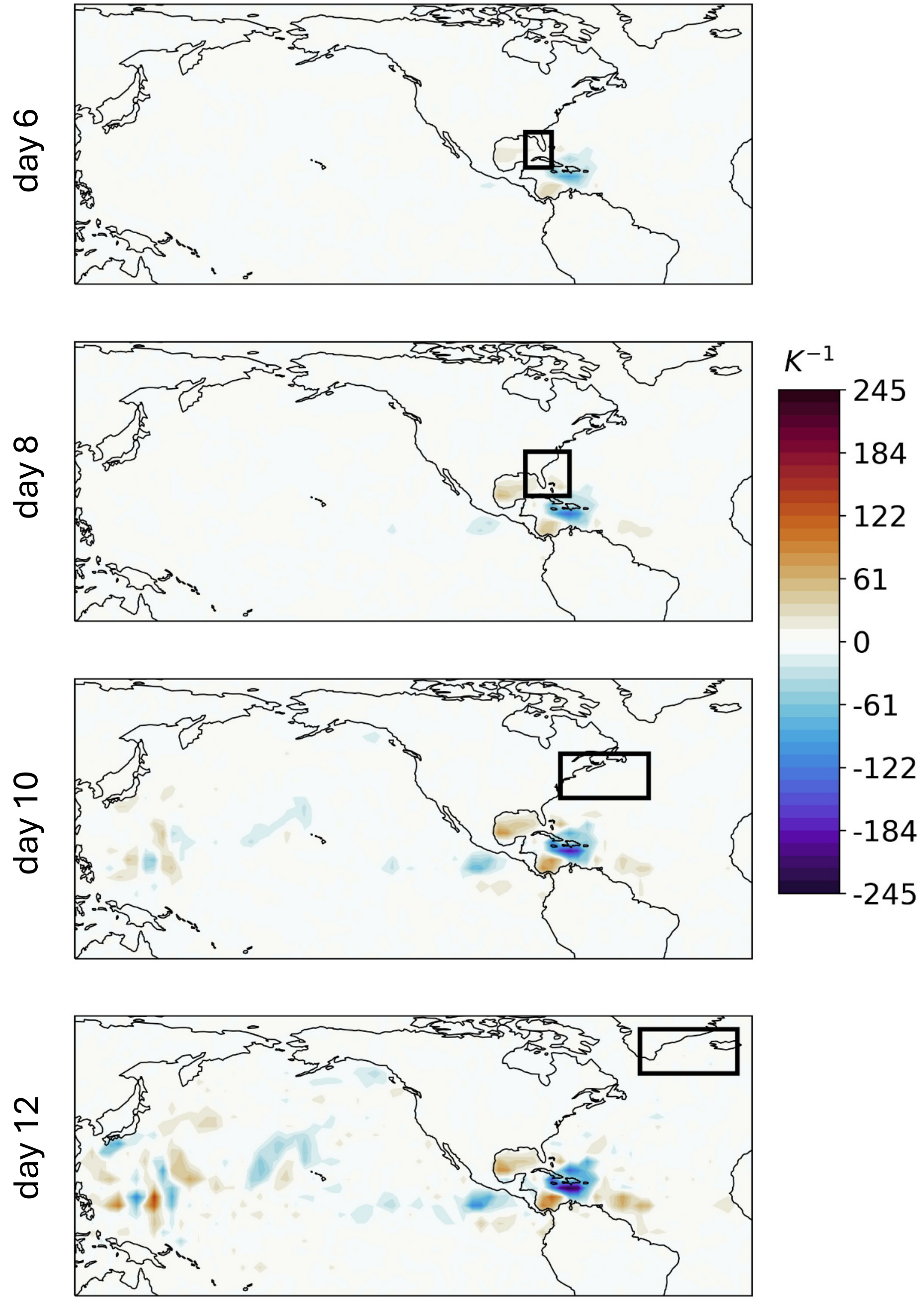
SENSITIVITY TO ZONAL WINDS



Plot: $\frac{\partial E}{\partial U500}(t=0)$

SENSITIVITY TO SURFACE TEMPERATURES

- In order to improve the forecast of hurricane Ian‘s tropical-to-extratropical transition we should improve initial condition at sensitive regions – especially at the Caribian and the Bay of Mexico.

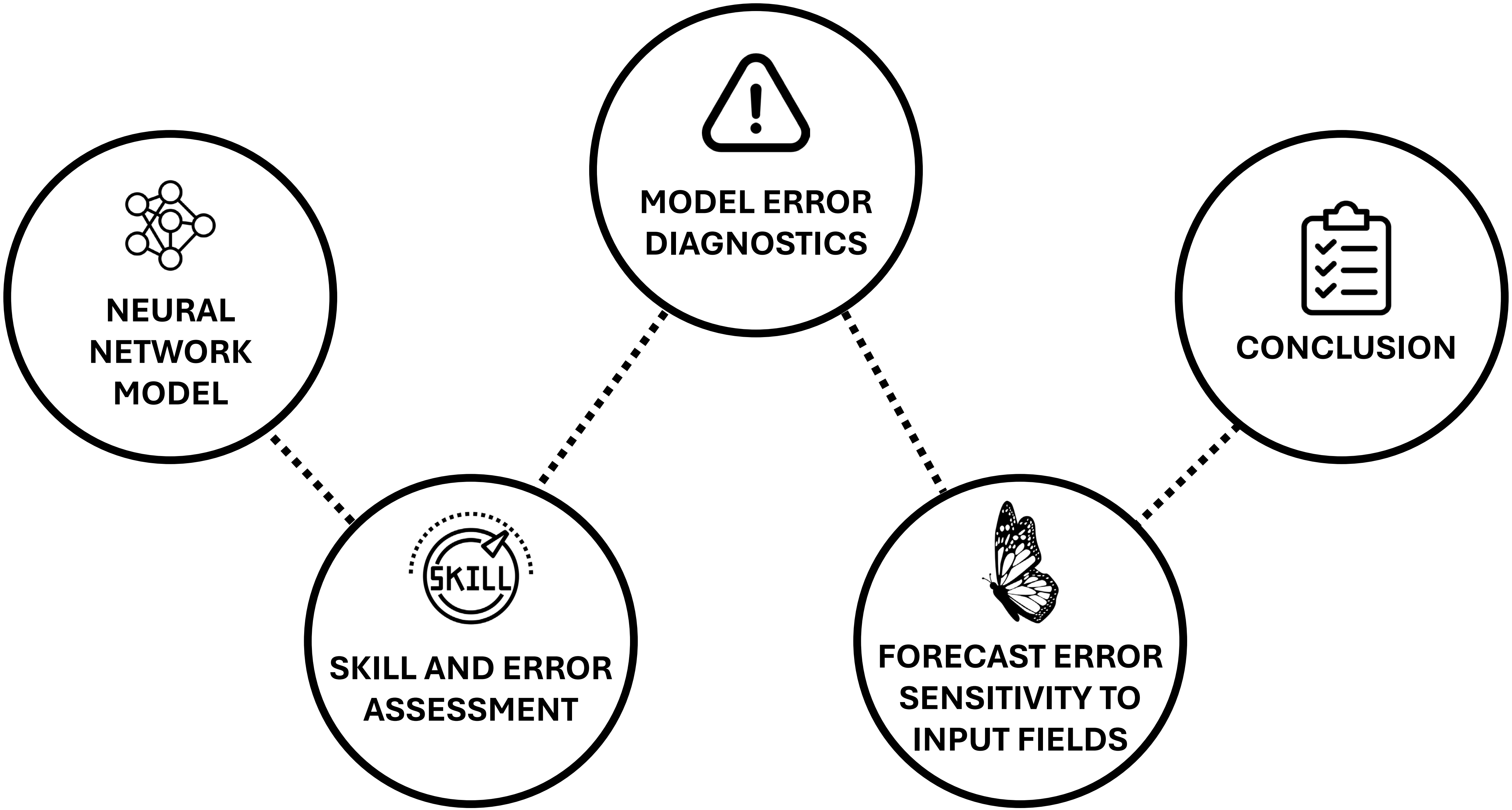


Plot: $\dfrac{\partial E}{\partial ST}(t = 0)$

POSSIBLE USE IN WEATHER PREDICTION

- Determine regions where more measurements are needed to decrease forecast uncertainty at later times
- Error calculation: use ensemble model spread as a proxy for model error

- Pros ☺:
  - Sensitivity is calculated using a fully nonlinear model (instead of an adjoint model – which is valid for a limited amount of time)
- Cons ☹:
  - We assume the perfect model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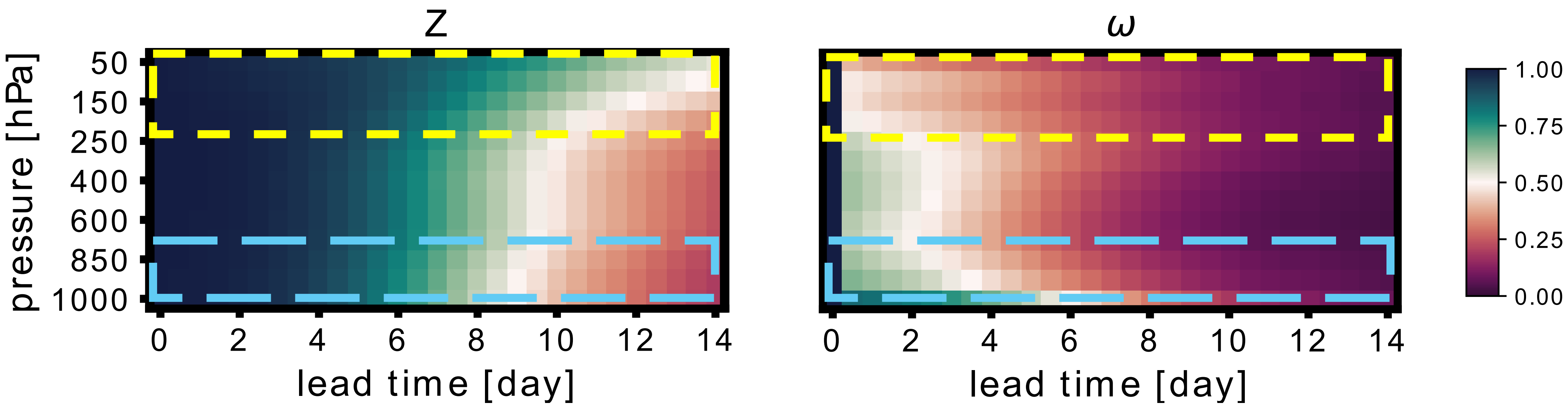
1. Regional overwriting of model forecast with the „truth“ is a simple yet efficient way for ML model error diagnostics
2. Error backpropagation could be a useful tool for:
    - Physical consistency evaluation
    - Improving initial conditions

The full analysis will be published soon.

ACC at different lead times and pressure levels

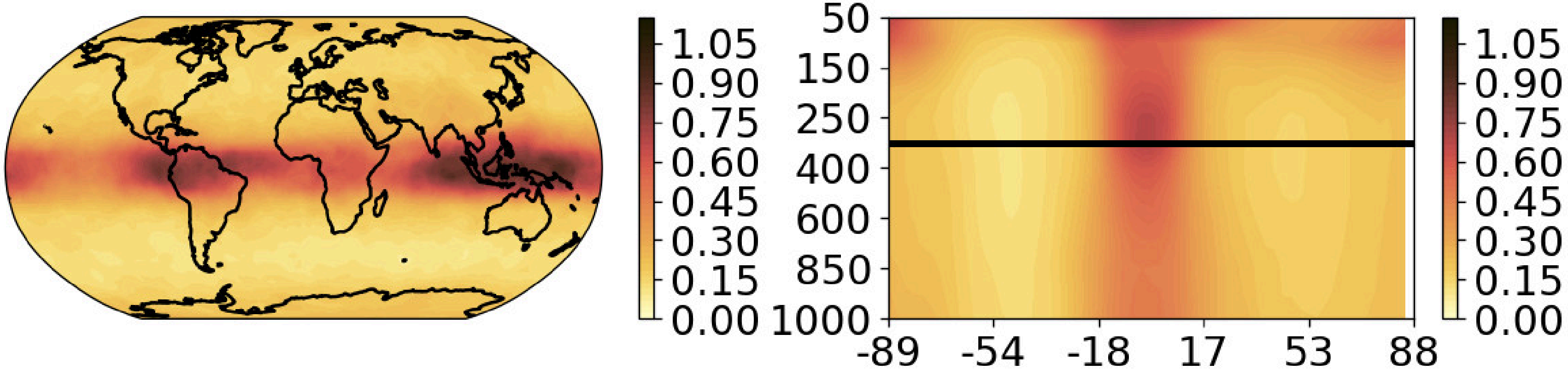


3 distinct predictability regimes:

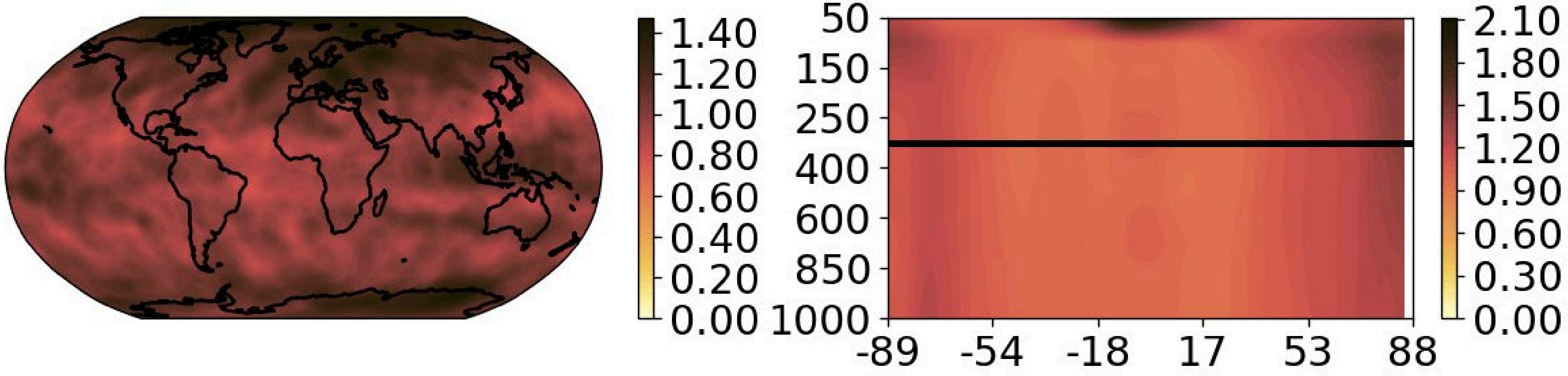
- Stratosphere
- Free troposphere
- „Planetary boundary layer“

LEAD TIME DIFFERENCE

Z: lead day 2

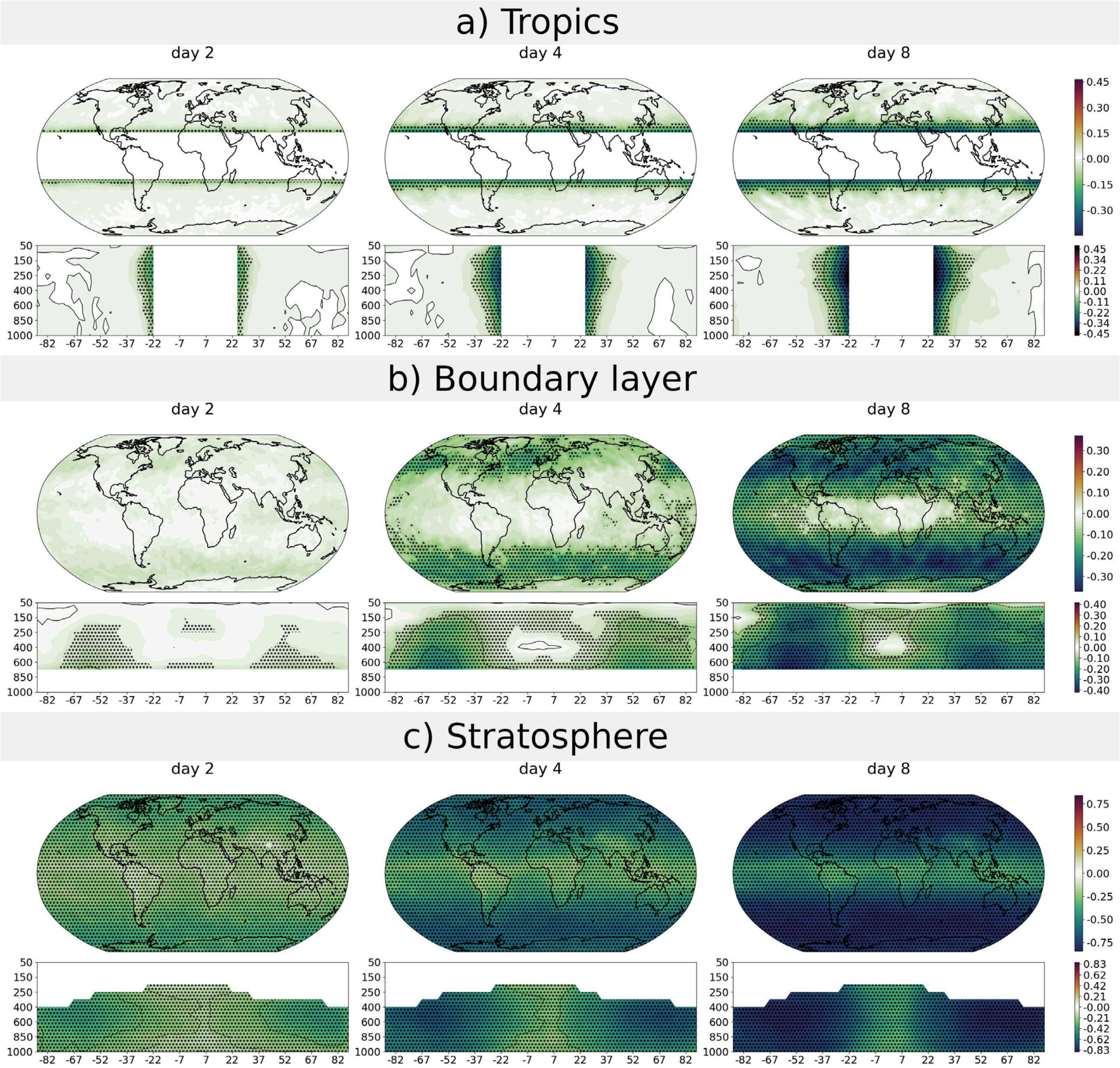


Z: lead day 10



Lead day 10 normalised error difference:

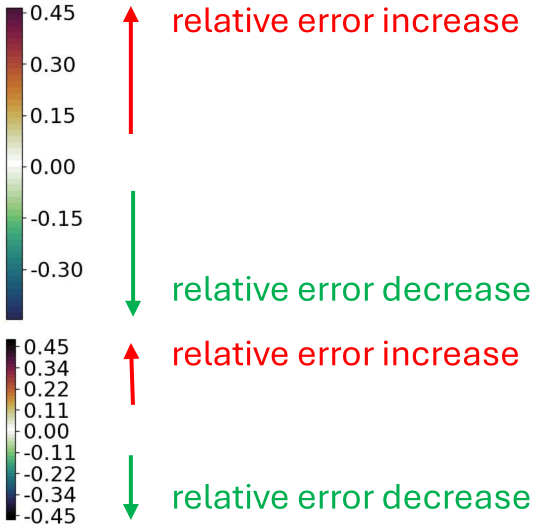
- Mid-to-high latitude errors become prevailing
- Stratospheric errors become more prominent



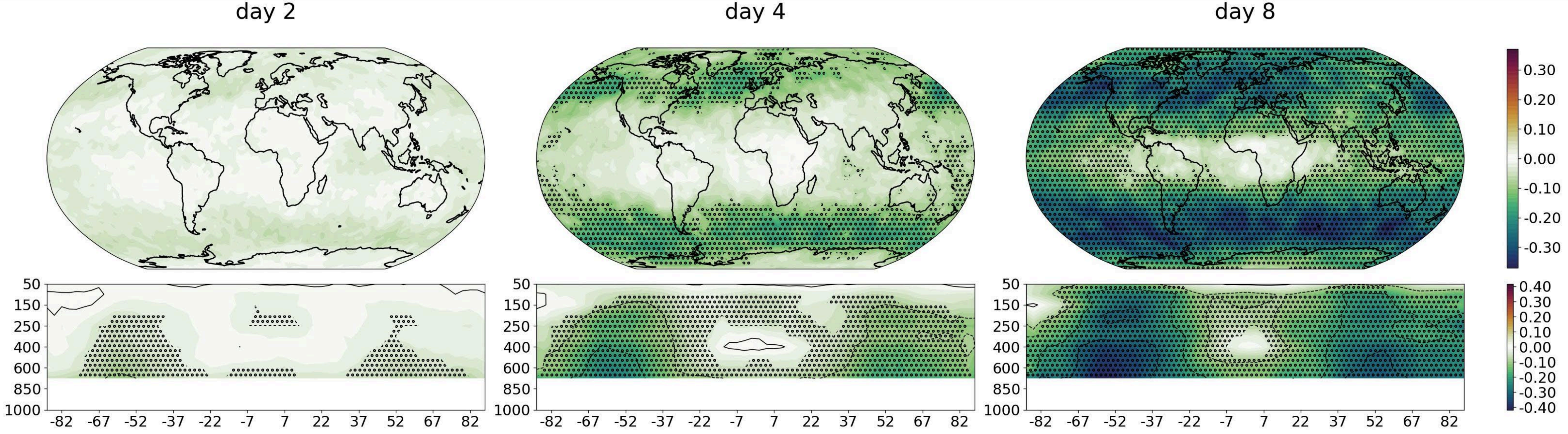
Plot:

- Verticaly and zonally averaged relative temperature error comparison

$$1 - \frac{error(M(x))}{error(M(x_{forced}))}$$



b) Boundary layer



- Statistically significant improvements spread with time:
  - Starting from mid-latitude 850 hPa ERA5 boundary
  - Surrounding tropical mid-troposphere
  - Reaching stratosphere after lead day 4
- Big improvements in mid-latitudes

MODEL FORCING METHODOLOGY

autoregressive input field

ERA5 „truth“ term

Model forecast term

$$x(\lambda, \varphi, p, t + \Delta t) = \text{weight}_\tau(\lambda, \varphi, p) \cdot \text{ERA5}(\lambda, \varphi, p, t + \Delta t) + (1 - \text{weight}_\tau(\lambda, \varphi, p)) \cdot \mathcal{M}_{t \to t+\Delta t}(s(t))(\lambda, \varphi, p)$$

Vertical weights equation: $\text{weight}_p = \frac{1}{2} \tanh \frac{p - p_0}{\Delta p} + \frac{1}{2}$

Latitude weihts equation: $\text{weight}_\varphi = \frac{1}{2} \tanh \frac{\varphi - \varphi_{\min}}{\Delta \varphi} - \frac{1}{2} \tanh \frac{\varphi - \varphi_{\max}}{\Delta \varphi} + 1$

FORECAST ERROR

Sum over predetermined domain

Standardized ERA5 fields

Standardized input fields

$$\text{error} = \sum_{\lambda,\varphi,p\in\mathcal{D}} \mid \mathcal{S}(\mathbf{ERA5}(\lambda,\varphi,p,t+\Delta t)) - \mathcal{M}_{t\to t+\Delta t}(\mathbf{s}(t))(\lambda,\varphi,p) \mid$$

$$\frac{\partial \text{error}}{\partial \mathbf{s}(t)} = \sum_{\lambda,\varphi,p\in\mathcal{D}} \operatorname{sgn}\left[\mathcal{S}(\mathbf{ERA5}(\lambda,\varphi,p,t+\Delta t)) - \mathcal{M}_{t\to t+\Delta t}(\mathbf{s}(t))(\lambda,\varphi,p)\right] \frac{\partial \mathcal{M}_{t\to t+\Delta t}(\mathbf{s}(t))(\lambda,\varphi,p)}{\partial \mathbf{s}(t)}$$

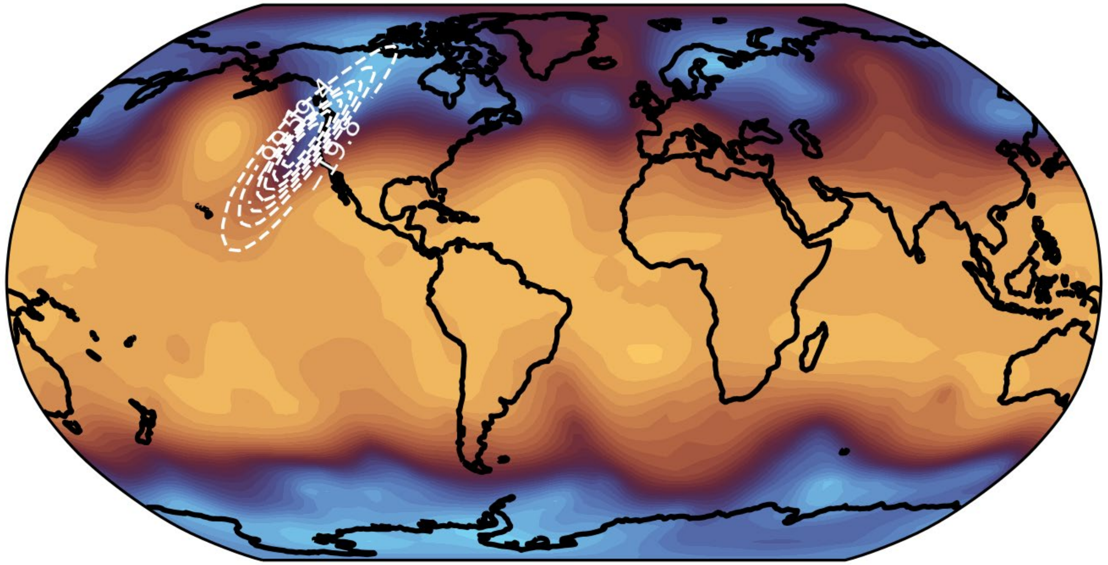
Error derivative with respect to standardized input fields

Sign function

Diferentiation of the model with respect to standardized input fields

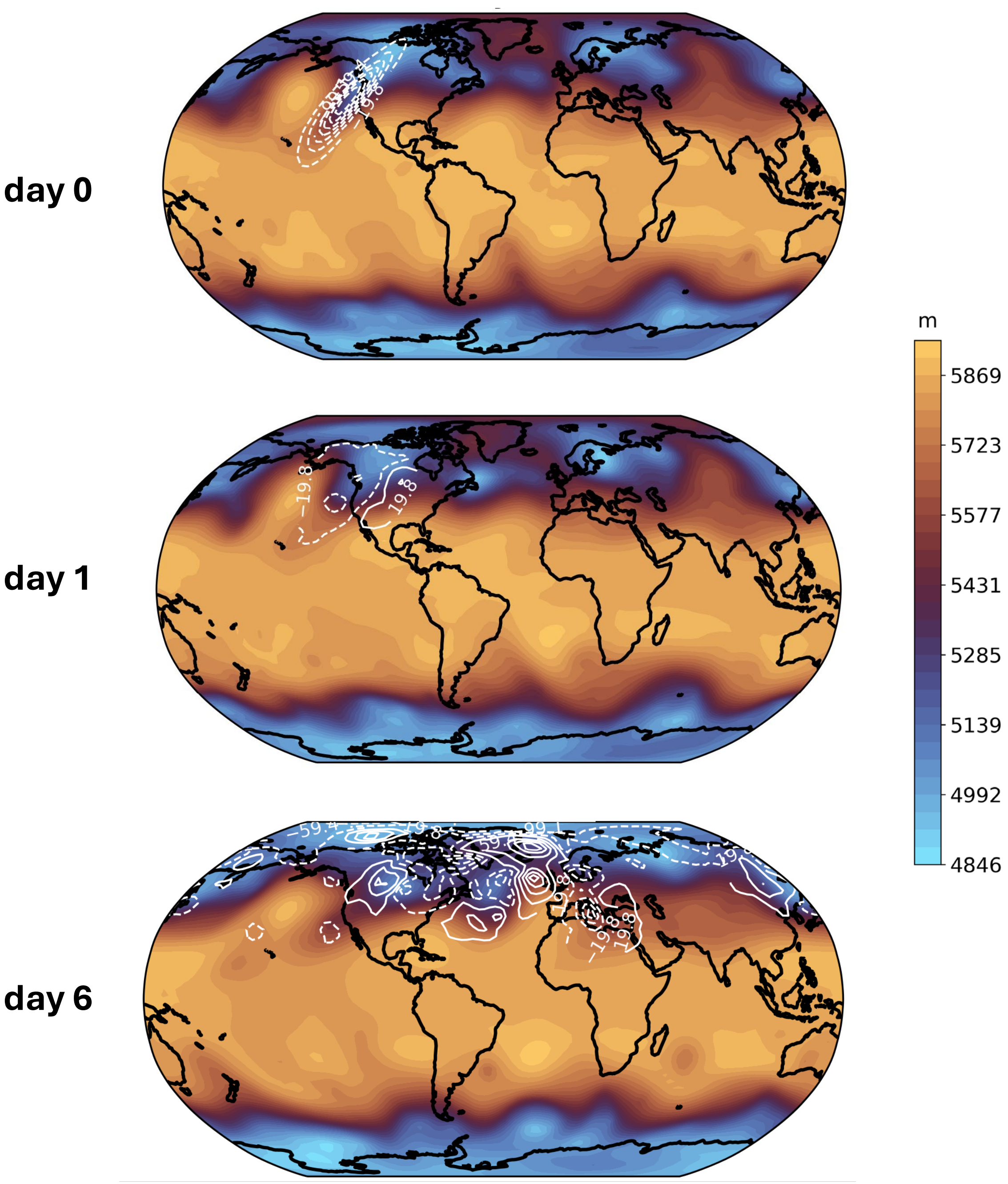
ADJUSTMENT EXPERIMENTS

Z500 initial condition perturbation



Goal:

- Compare model response with dynamics expectations
- ML models not so sensitive to instability => easy to initialize forecast



Propagation features:

- Propagates downstream
- Faster than Rossby wave phase speed
- Confined to Northern Hemisphere for first 6 forecast days