Flow dependence of error-growth mechanisms:

PV diagnostics and feature framework

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Why diagnose error-growth mechanisms?

- The intrinsic limit of predictability is characterized by a distinct sequence of error-growth mechanisms (presentation by Tobias Selz on Monday).
- Representation of error-growth mechanisms in numerical (ensemble) models determines representation of forecast uncertainty.

Why diagnose flow dependence?

- may indicate flow situations, in which intrinsic limit is already reached
- enables more focused model verification and development
- aids in recognizing model error wrt. representation of uncertainty, a limitation of current ML models*

* (e.g., Selz, T., & Craig, G. C. (2023). Can artificial intelligence-based weather prediction models simulate the butterfly effect?. *GRL*, *50*(20))

Potential-vorticity diagnostic for error-growth mechanisms

Why potential vorticity (PV)?

A single scalar quantity – PV – subsumes the balanced state of the atmosphere.
 PV is a key quantity of atmospheric dynamics

Upscale error growth eventually affects the balanced state.

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$$\frac{\partial PV}{\partial t} = -\vec{u} \cdot \vec{\nabla} PV + \frac{\vec{\eta}}{\rho} \cdot \vec{\nabla} \dot{\Theta} + \text{(nonconservative momentum sinks/ sources)}$$

advective tendencies

direct diabatic modification

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piecewise PV inversion
+ Helmholtz partition

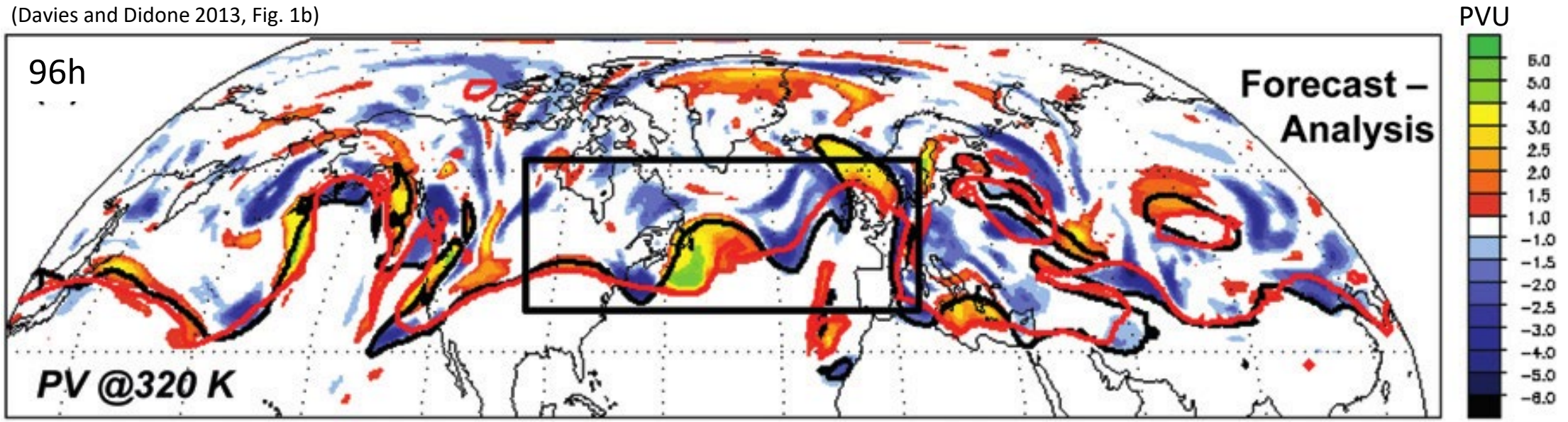
Processes A B C …. X Y Z

Piecewise PV tendency framework

 Mechanistic understanding

PV perspective on forecast errors

(Davies and Didone 2013, Fig. 1b)



2 PVU contour: forecast analysis

Davies and Didone (2013):

- PV errors maximize near the tropopause; displacement of the tropopause
- PV-error tendency equation

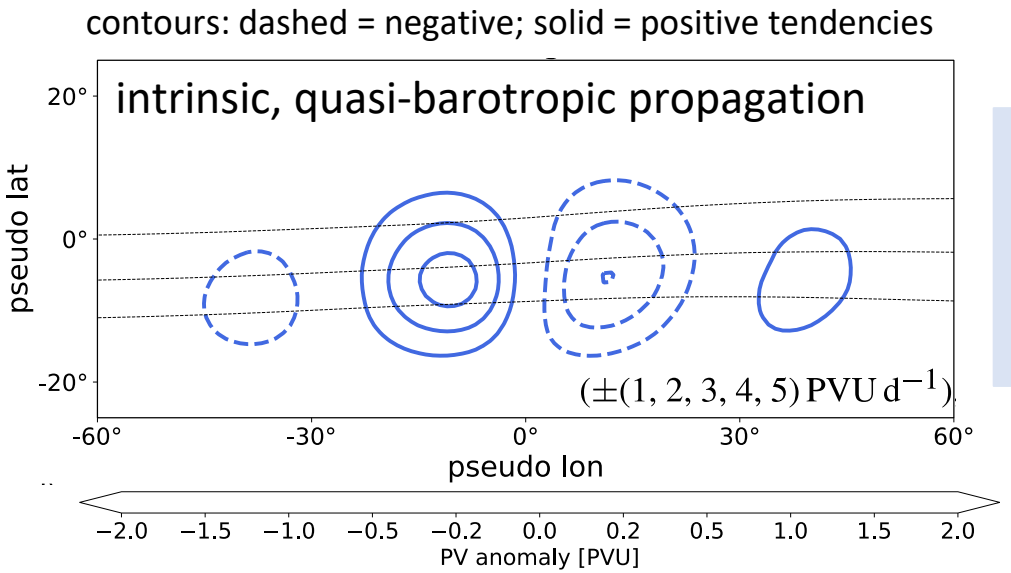
Baumgart et al. (2018, 2019); Baumgart and Riemer (2019):

Piecewise PV-error tendencies = quantification of *individual* contributions to error/ spread growth

Piecewise PV tendencies: Illustration

- Dynamics of Rossby wave packets
- Upper-level perspective on isentropes that intersect the midlatitude tropopause
- Composites over ERA-5 period

(Teubler and Riemer 2021, Fig. 3, modified)



includes *nonlinear* tropopause dynamics

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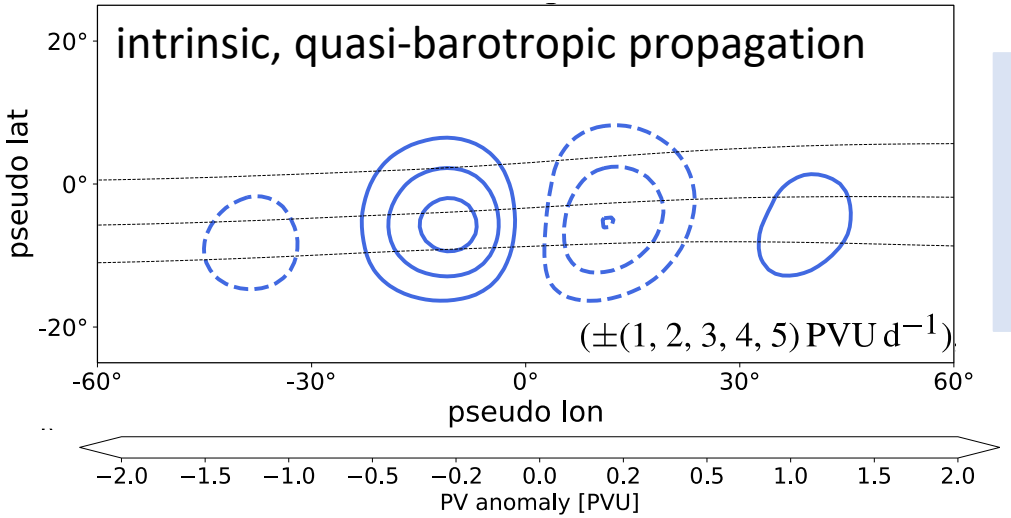
contours: dashed = negative; solid = positive tendencies



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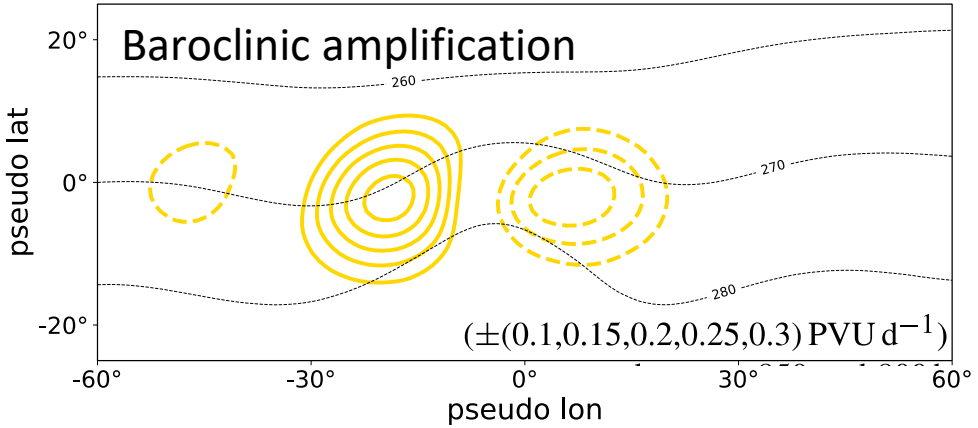

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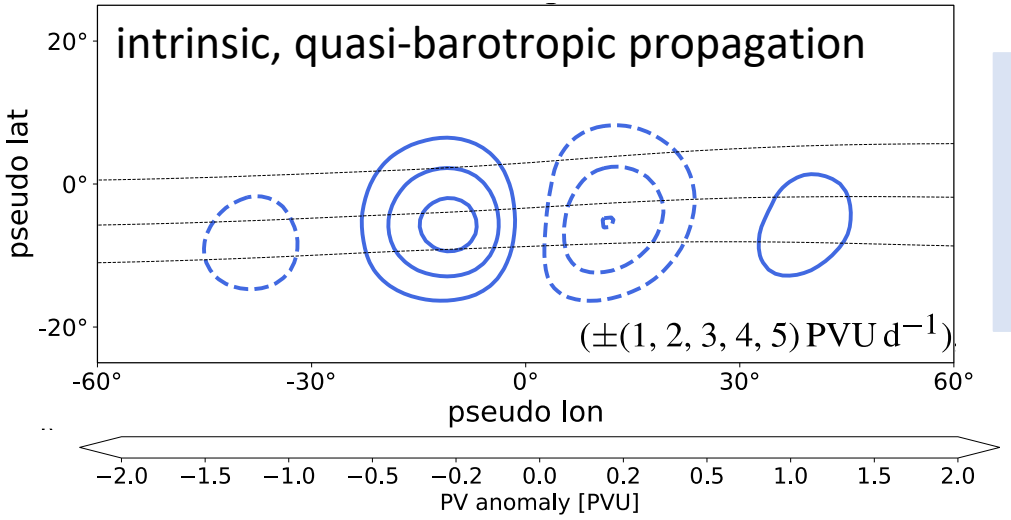

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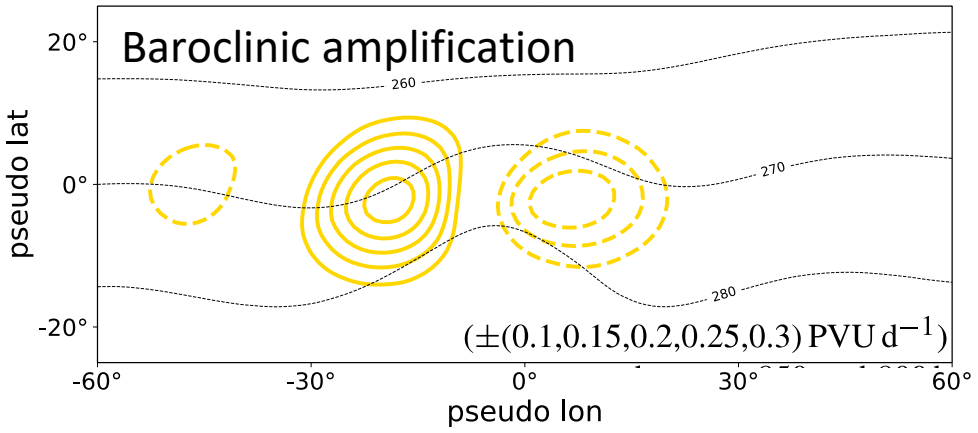
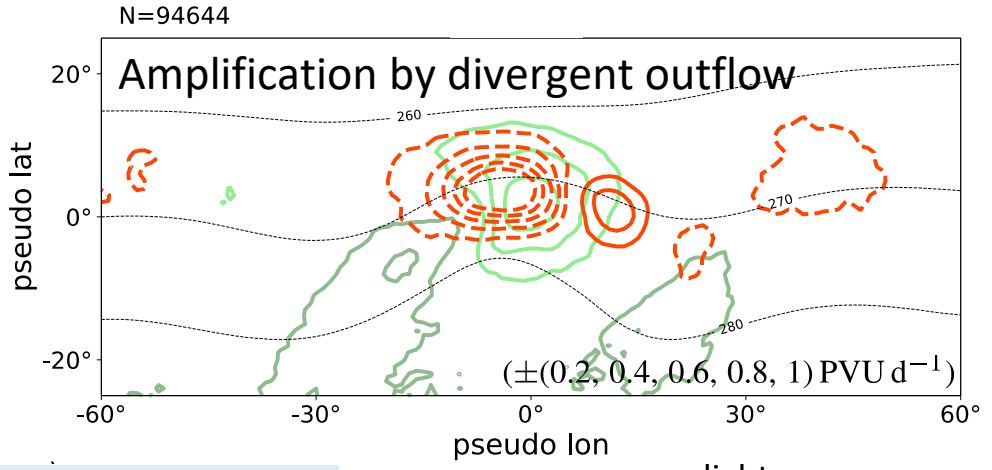


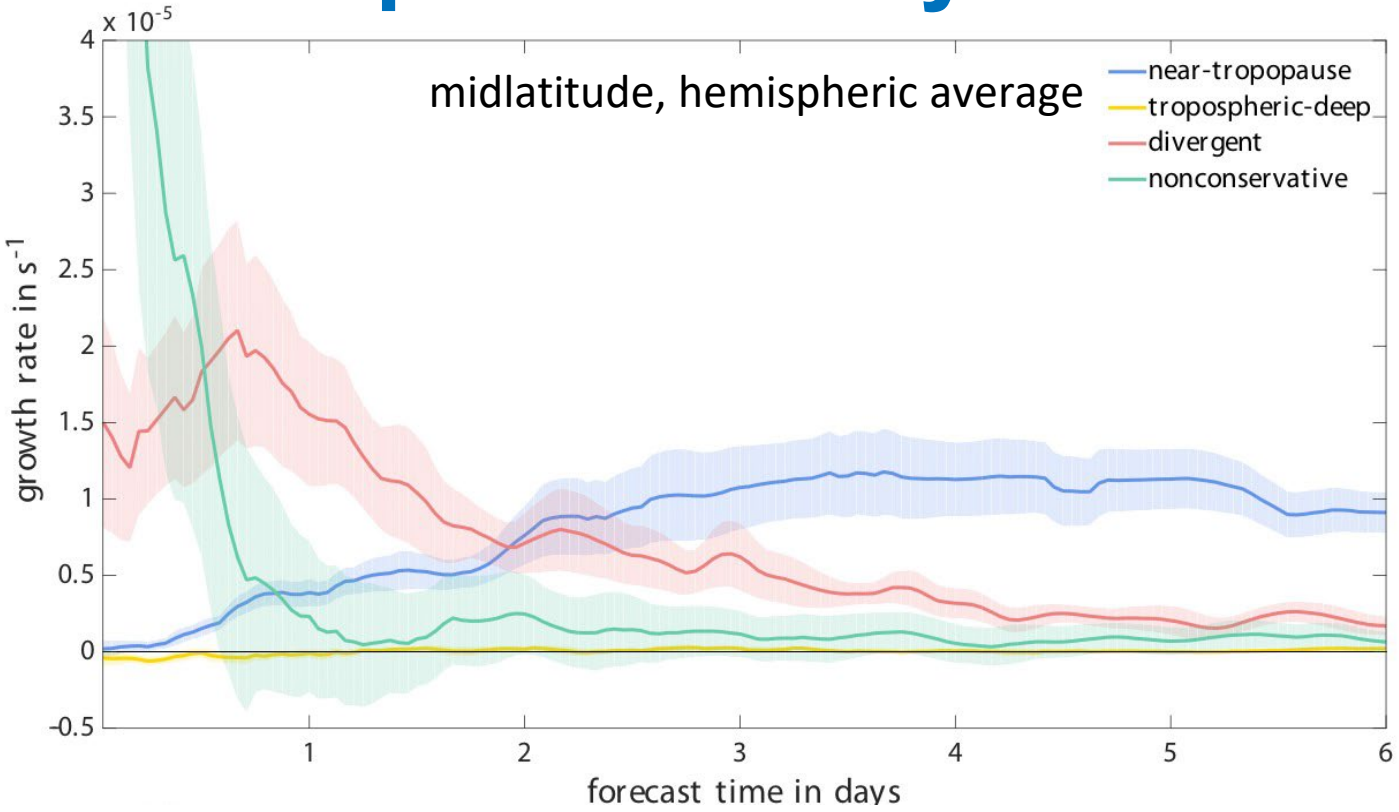


moist-baroclinic development

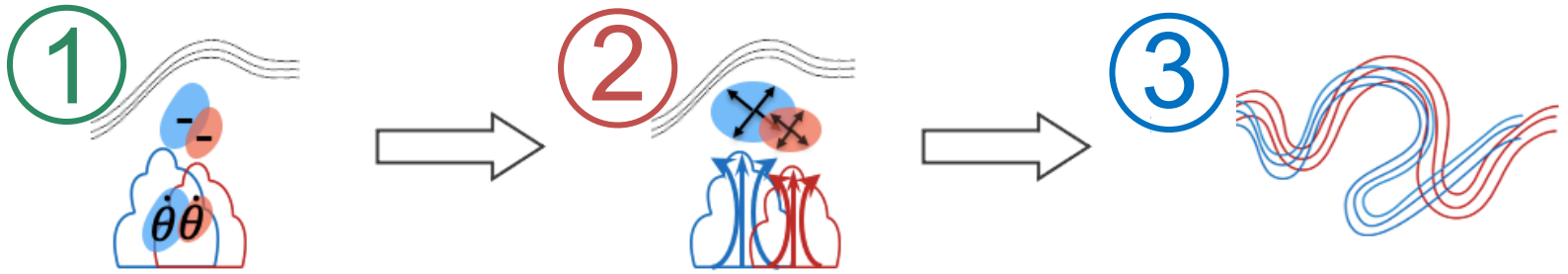
light green: proxy of latent heat release

Same result as presented by Tobias Selz

PV diagnostic applied to error-growth experiment with minimal IC uncertainty (Baumgart et al. 2019)



Sequence of dominant error-growth mechanisms (3-stage model)



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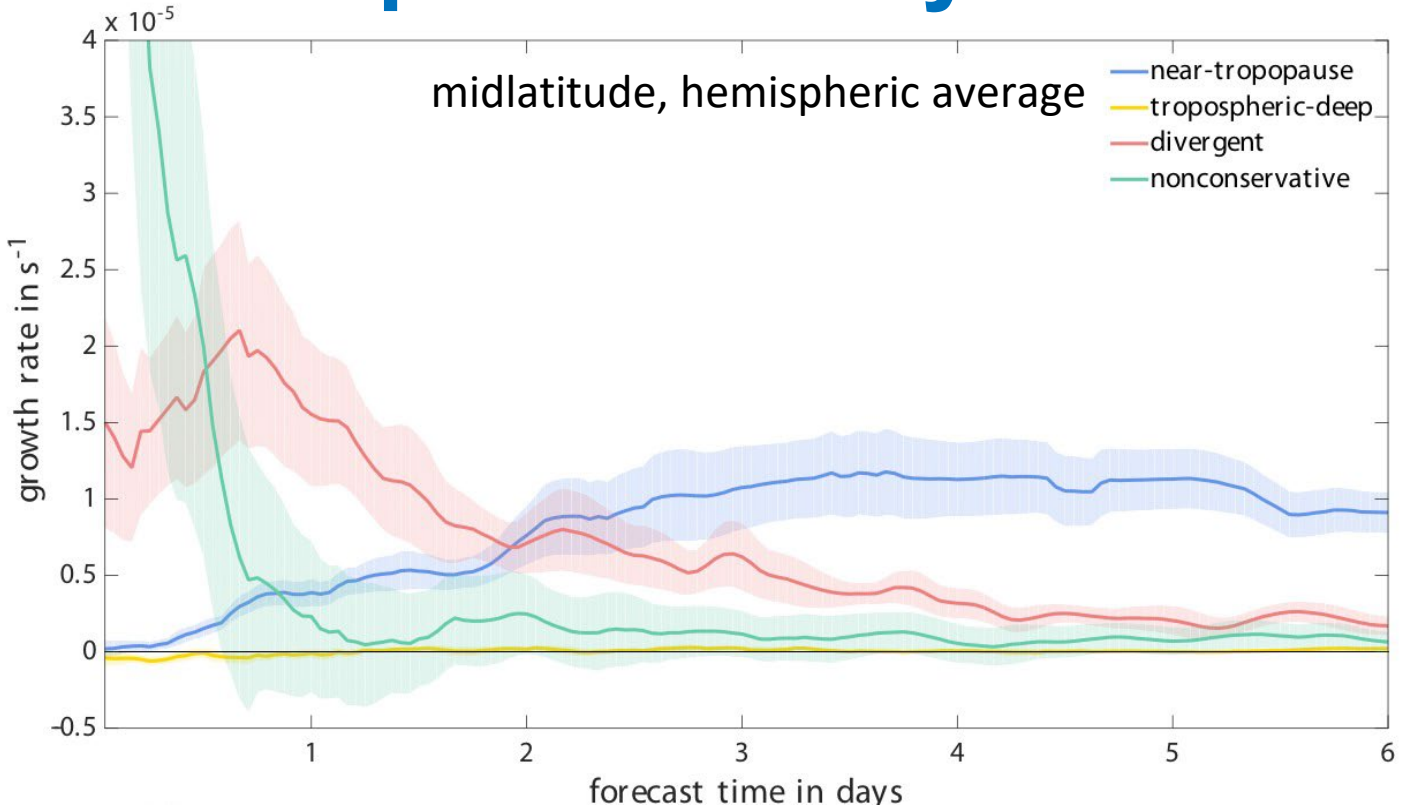

Tropospheric-deep baroclinic growth is *on average* a subordinate error-growth mechanism

(costly piecewise PV inversion for many applications not required)

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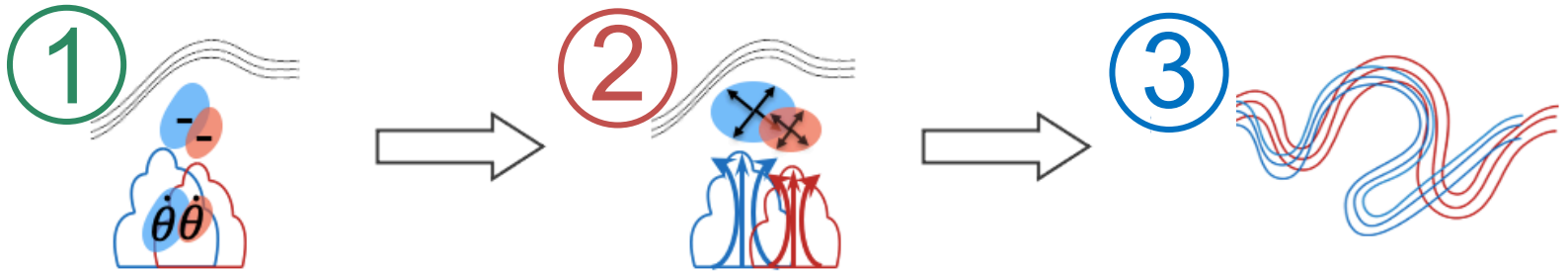
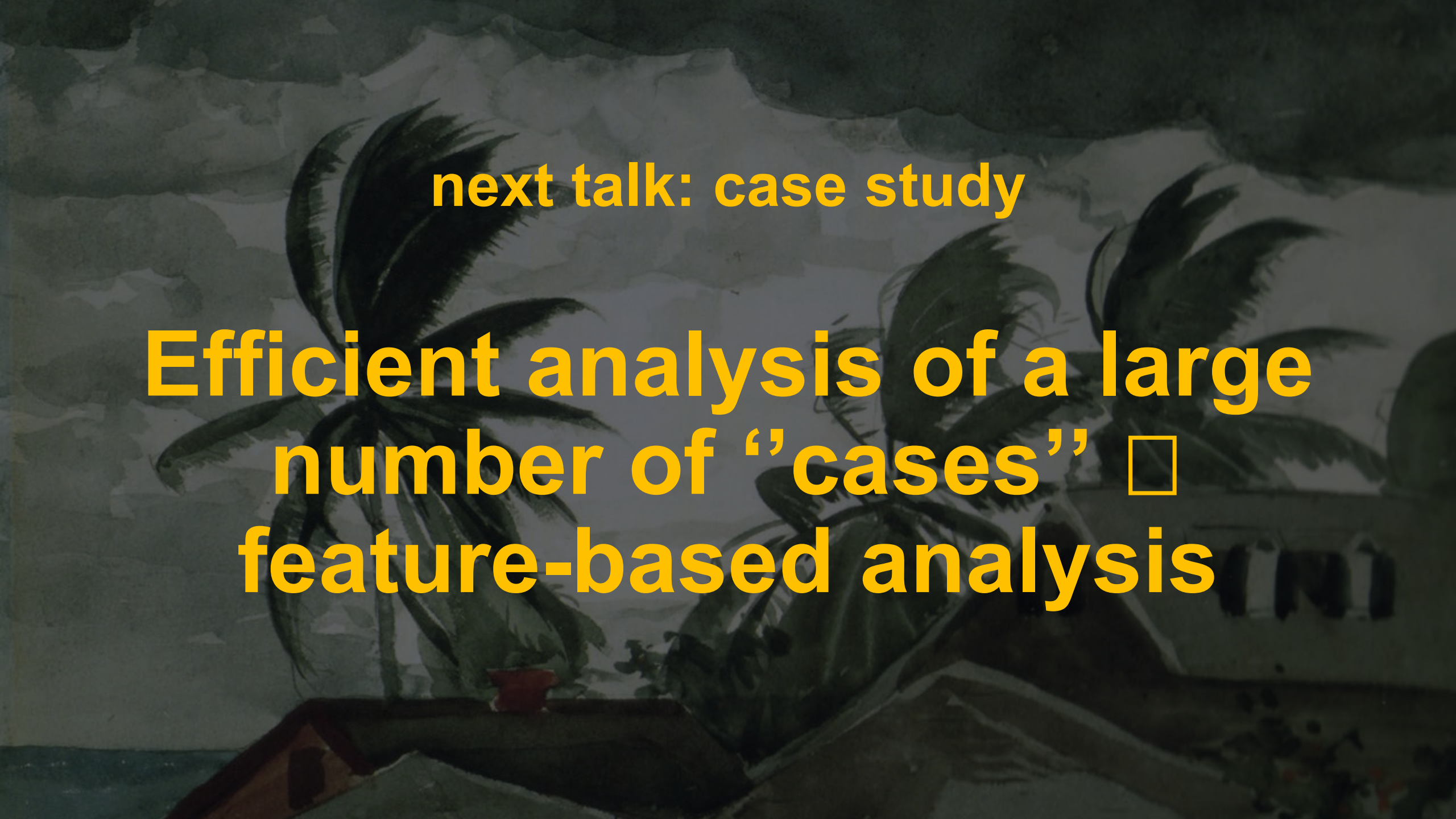
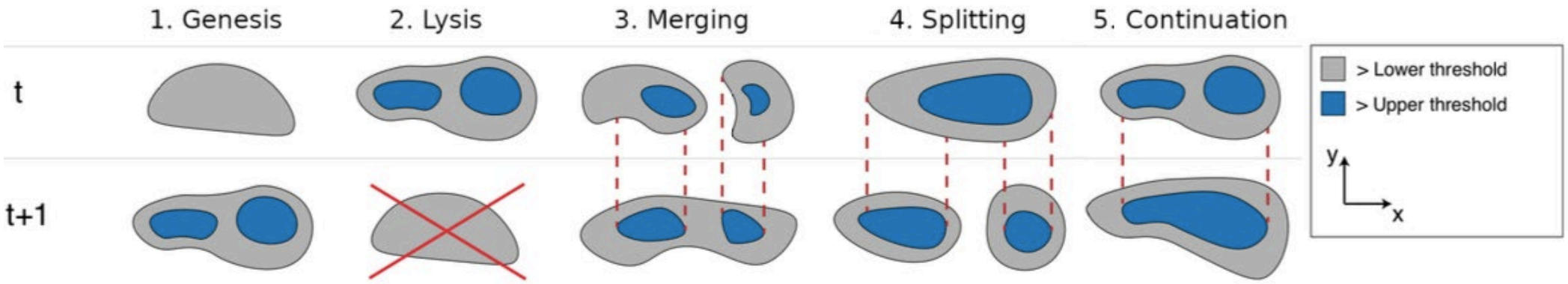



next talk: case study
Efficient analysis of a large number of ‘’cases’’ □ feature-based analysis

Feature framework

identification

tracking with time



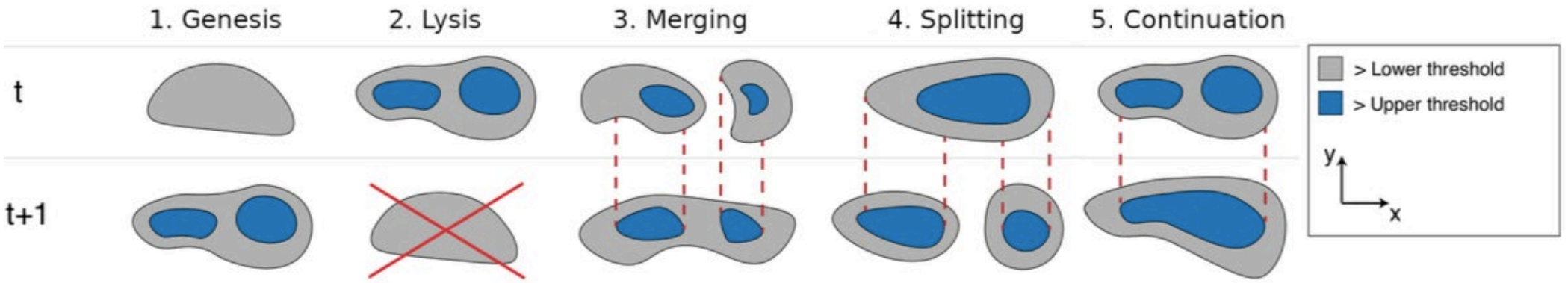
Goal: identify evolution that is coherent in space and *time*

Weather systems (MSC, cyclones, …)

Feature framework difficult for errors/ spread

identification

tracking with time



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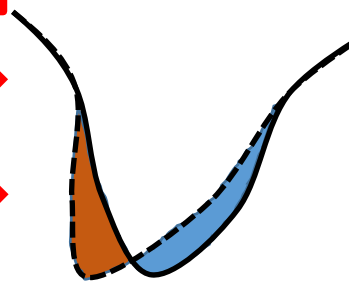

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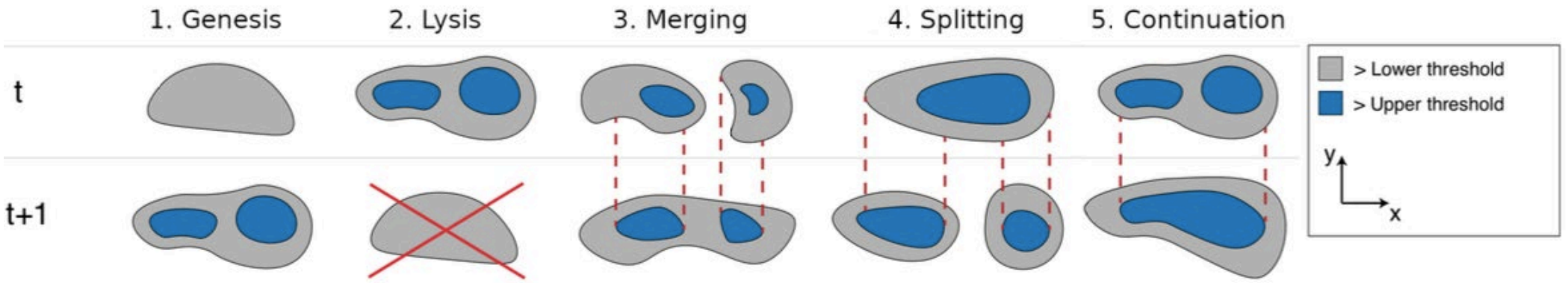

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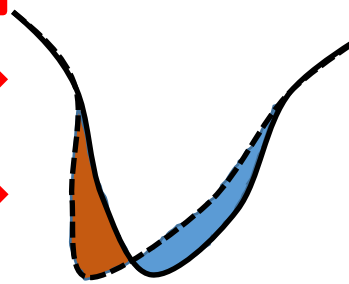
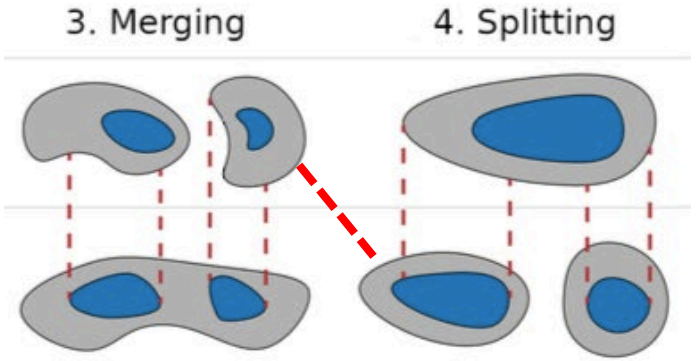


Splitting and merging is ubiquitous for error features.

Feature framework difficult for errors/ spread

identification t

tracking with time t+1



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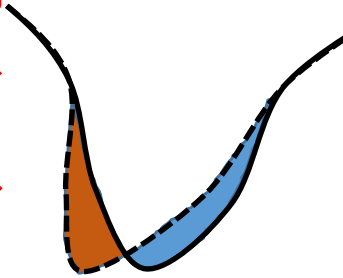
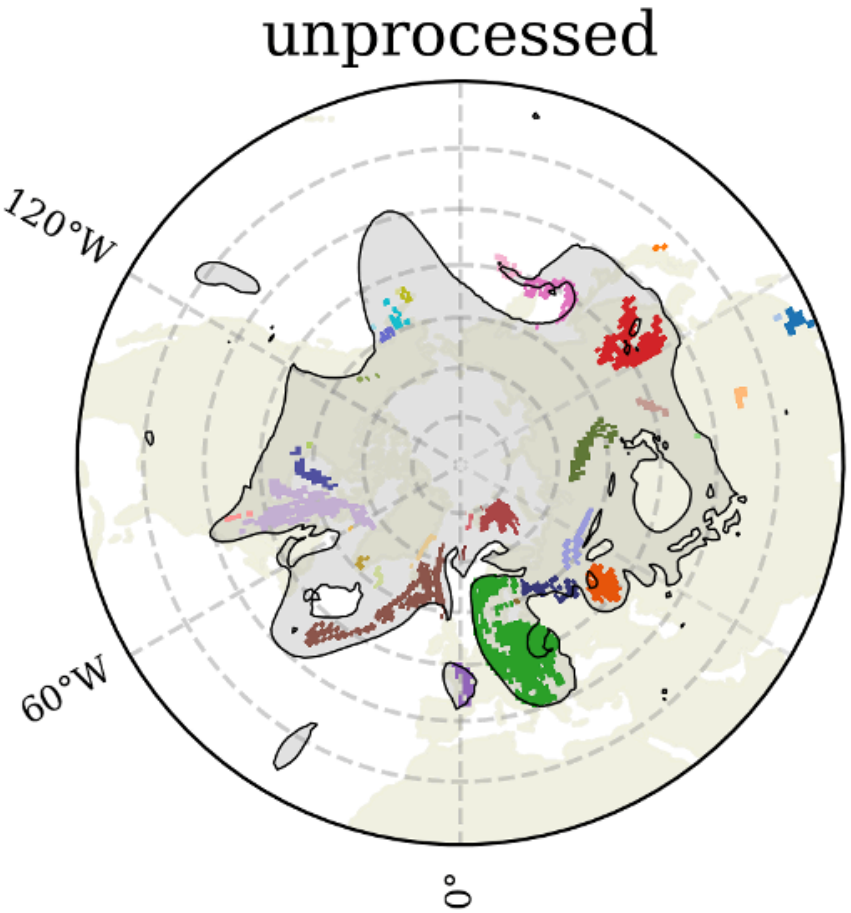
Forecasts errors/ spread ✗



Splitting and merging is ubiquitous for error features.
→ non-uniqueness in the temporal evolution of features *or*
→ severe limitation to track features back in time

Illustration of problem (grey features)

lead time 72h



Colors: Features identified at 72h lead time

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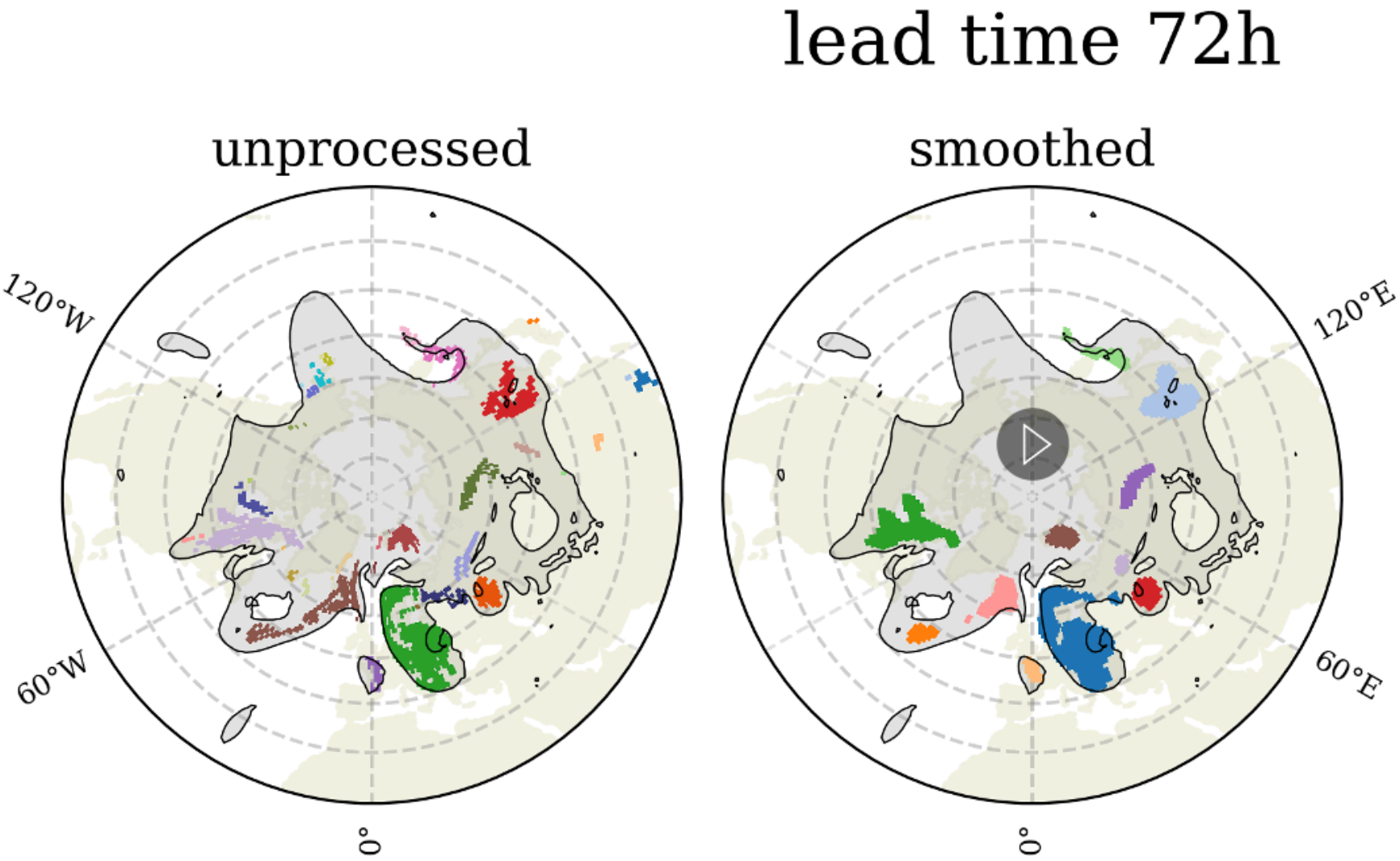

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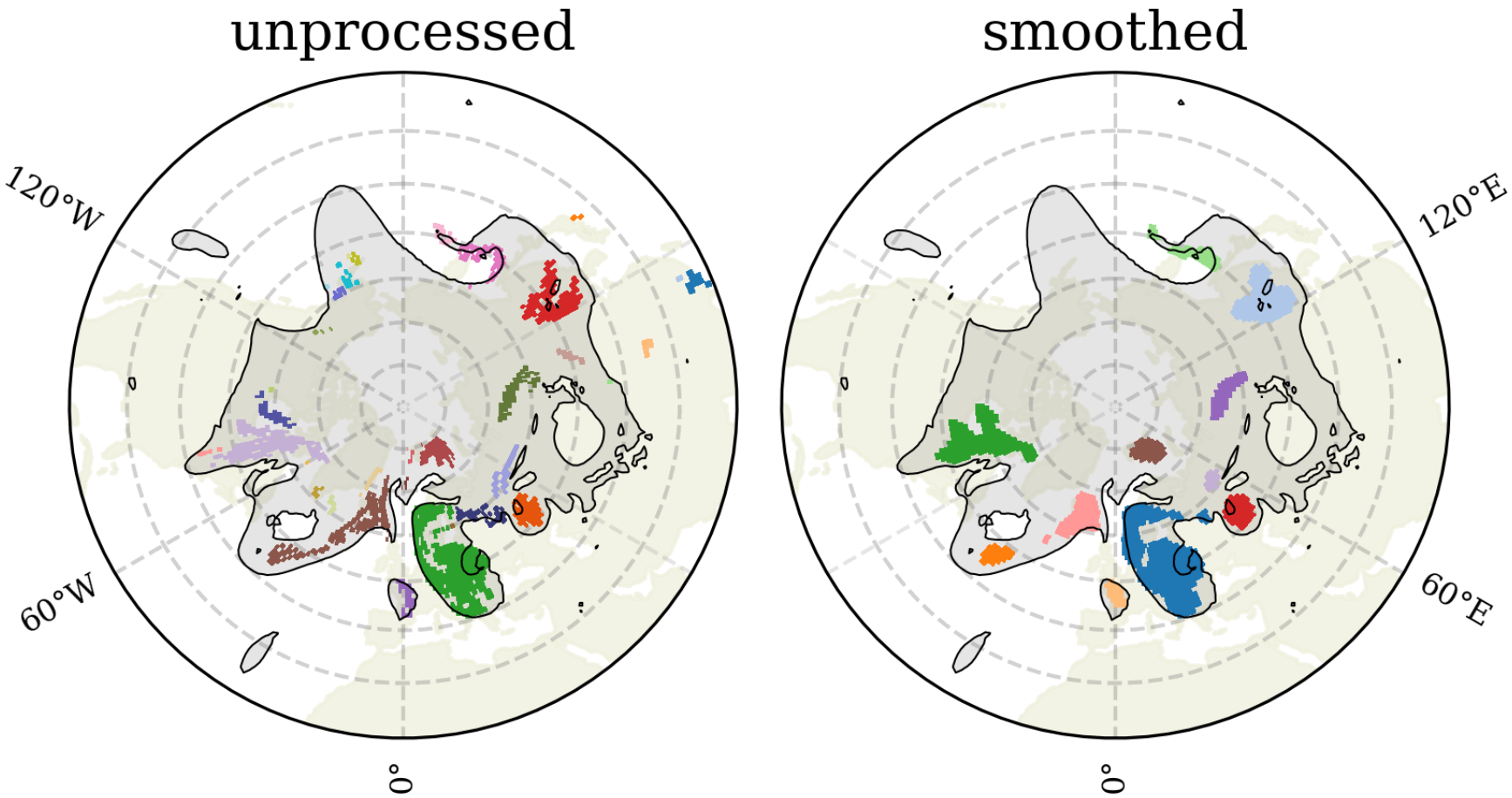

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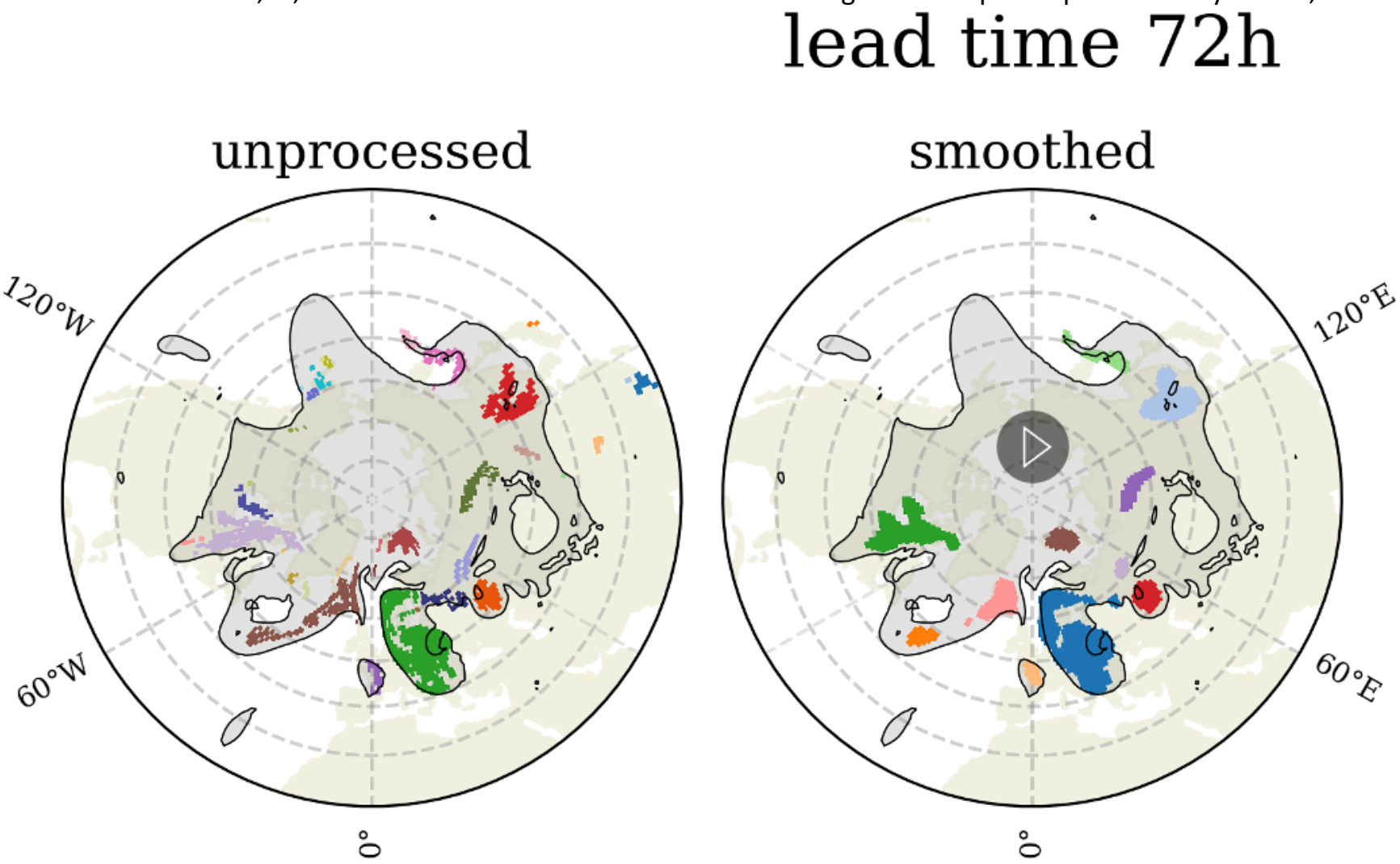
Smoothing of underlying data and size-filtering of features improves the situation, but

- … does *not* solve the fundamental problem.
- … implies loss of information.

Addressing the fundamental problem

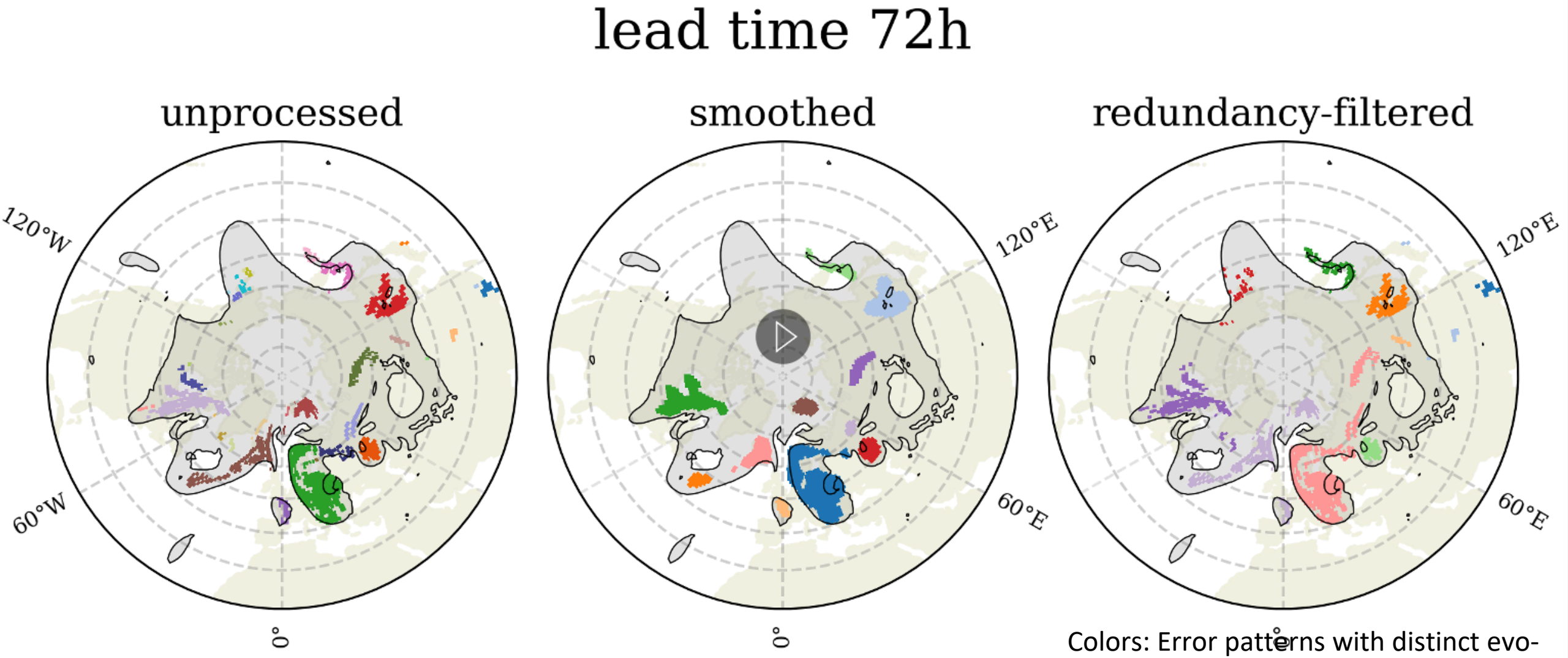
Schmidt, S., et al.: A feature-based framework to investigate atmospheric predictability. *MWR*, in revision



Colors: Features identified at 72h lead time

Basic idea:
- Group together features, for which the temporal evolution over a specified period is *not* sufficiently distinct.
- The groups of features define spatio-temporally coherent error patterns with *sufficiently distinct* evolution.

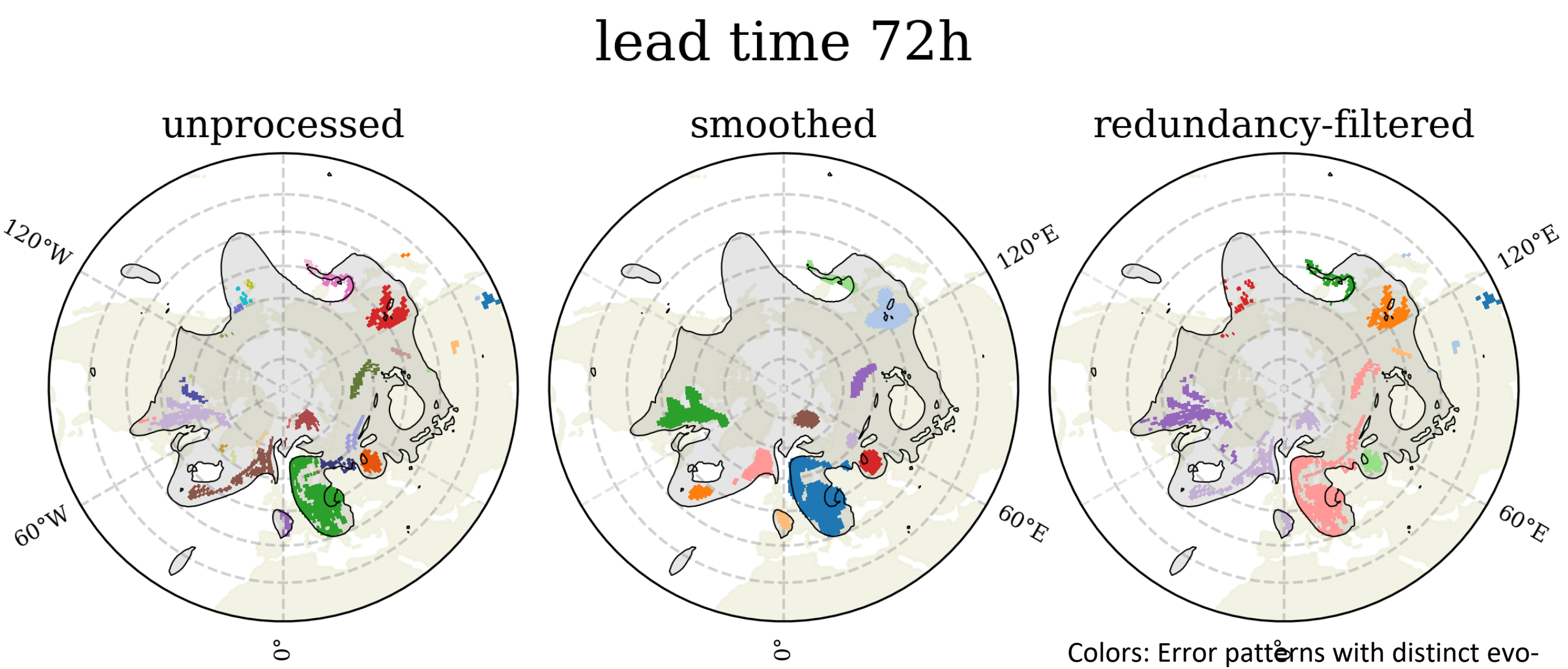
Error patterns with distinct evolution



Colors: Features identified at 72h lead time

Colors: Error patterns with distinct evolution over specified period (here 48h).

Error patterns with distinct evolution



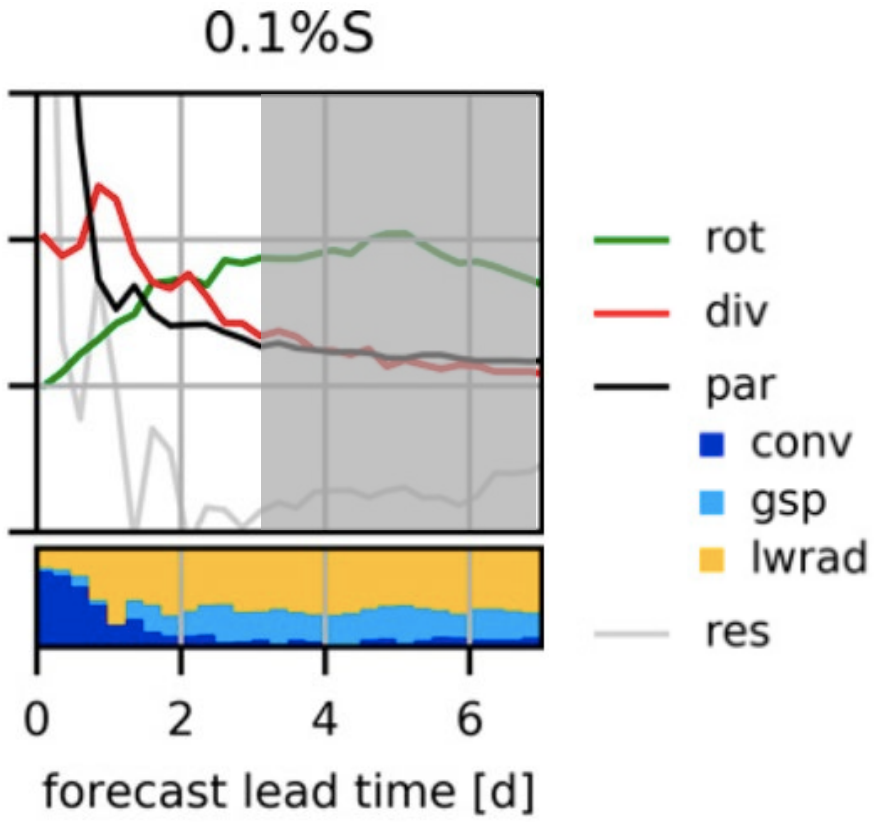
Colors: Features identified at 72h lead time

Colors: Error patterns with distinct evolution over specified period (here 48h).

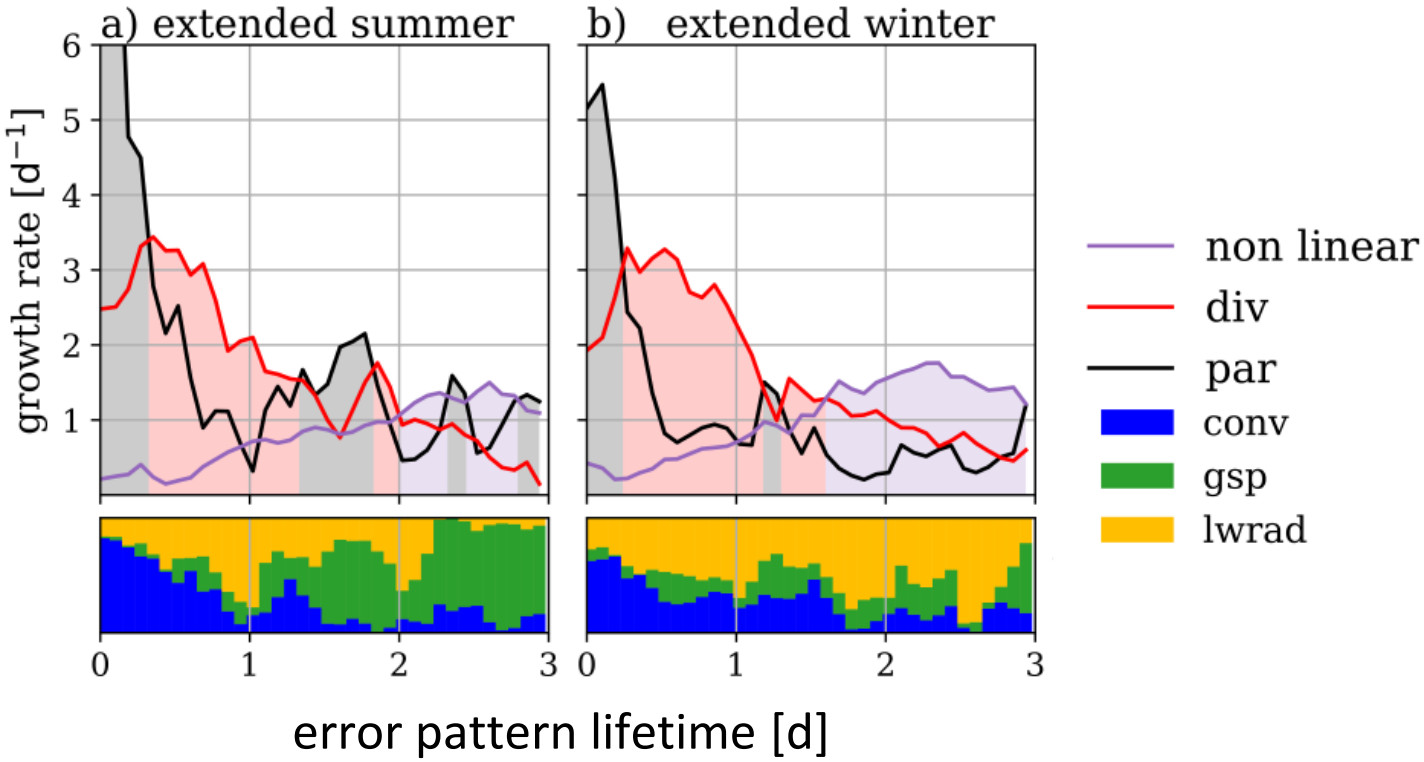
Identify flow configurations that will first reach the intrinsic limit

(one application; preliminary results)

Average picture reproduced



Selz et al. (2022)

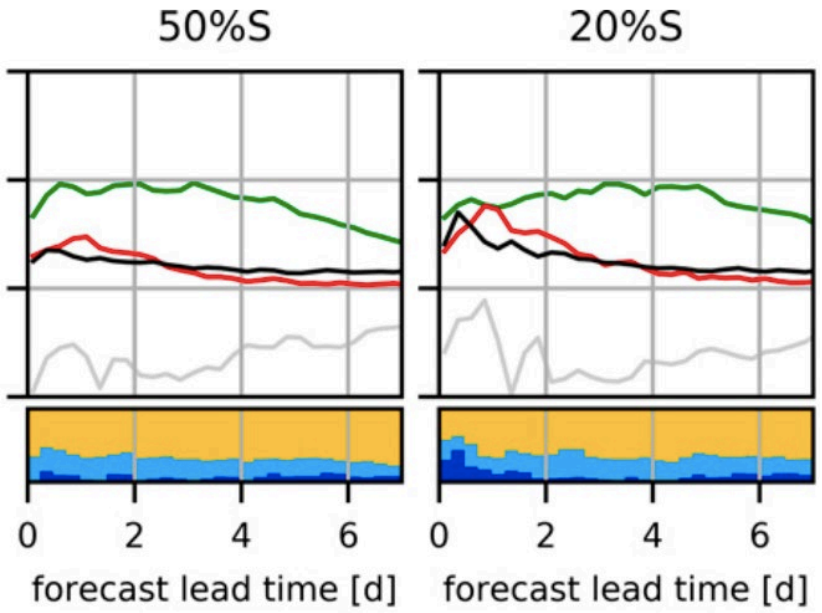


Schmidt et al. (2024)

Contrasting error-growth regimes

Most error patterns exhibit ‘operational’ characteristics.

hemispheric mean (from Selz et al. 2022)



Most error patterns exhibit ‘upscale’ characteristics.

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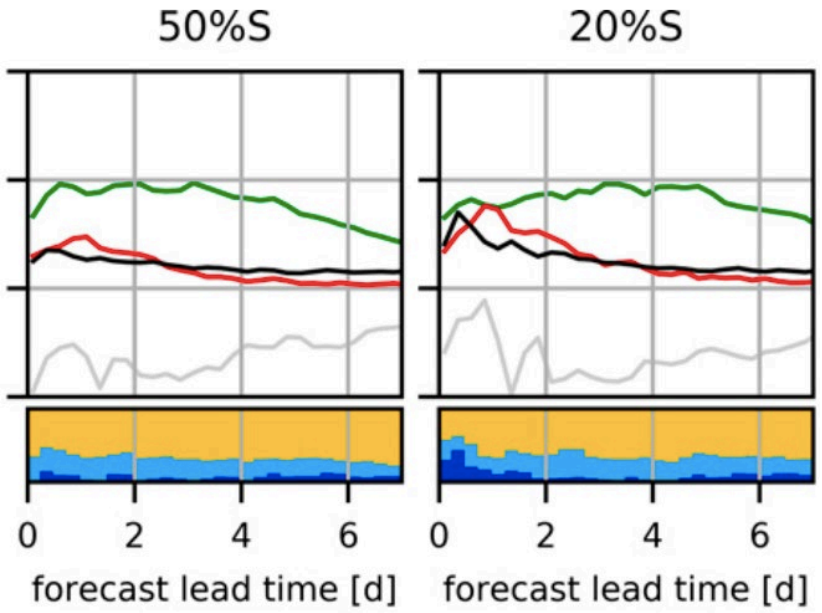

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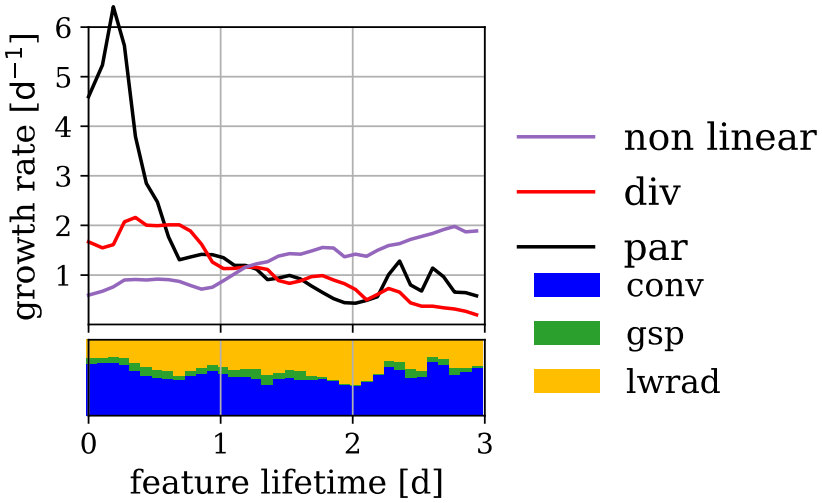

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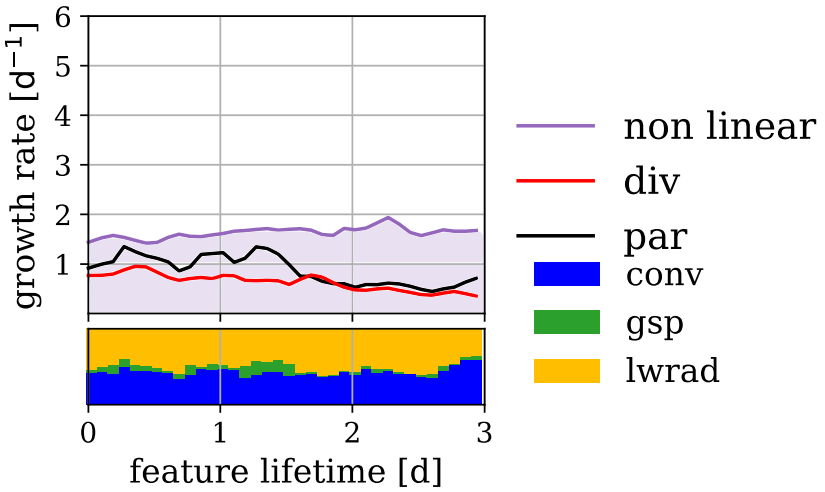

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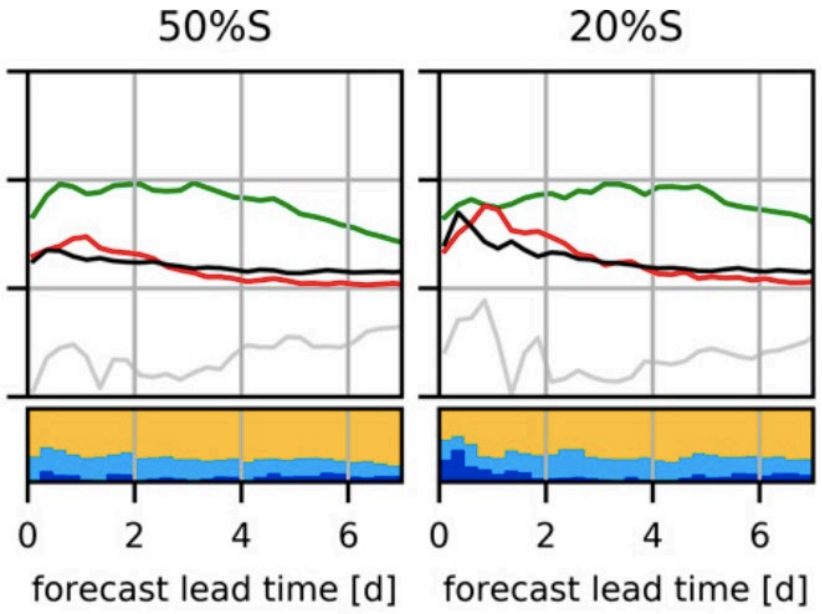

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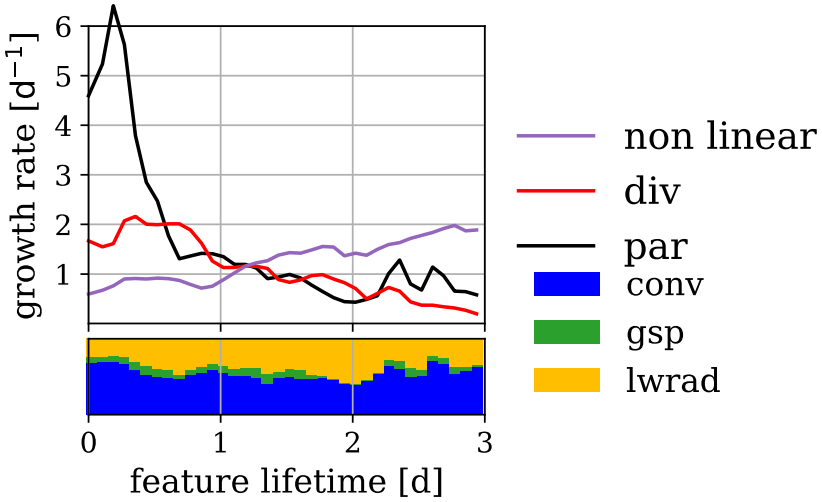
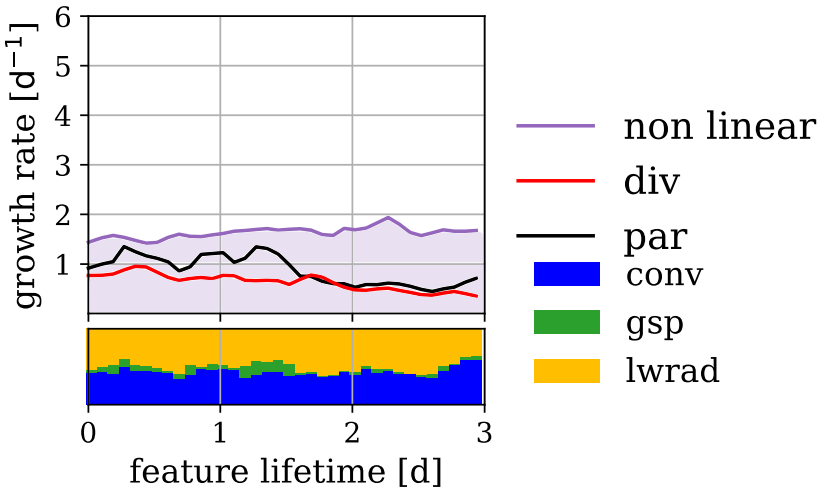


50 error patterns each

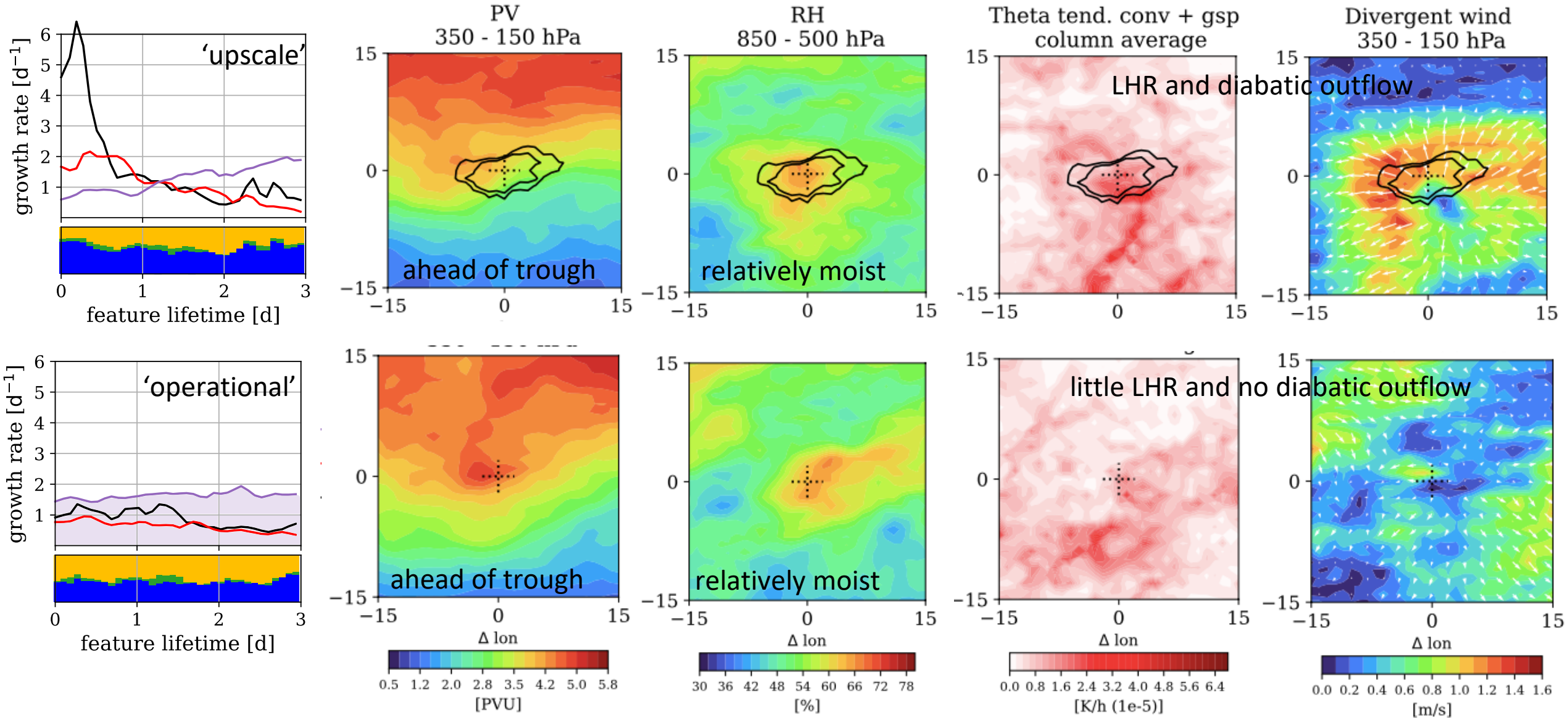
2 years of experiments,
Initialized every 4 days,
extended summer

Select cases that exhibit ‘operational’ characteristics.



preliminary – preliminary – preliminary

Contrasting regimes: environmental conditions



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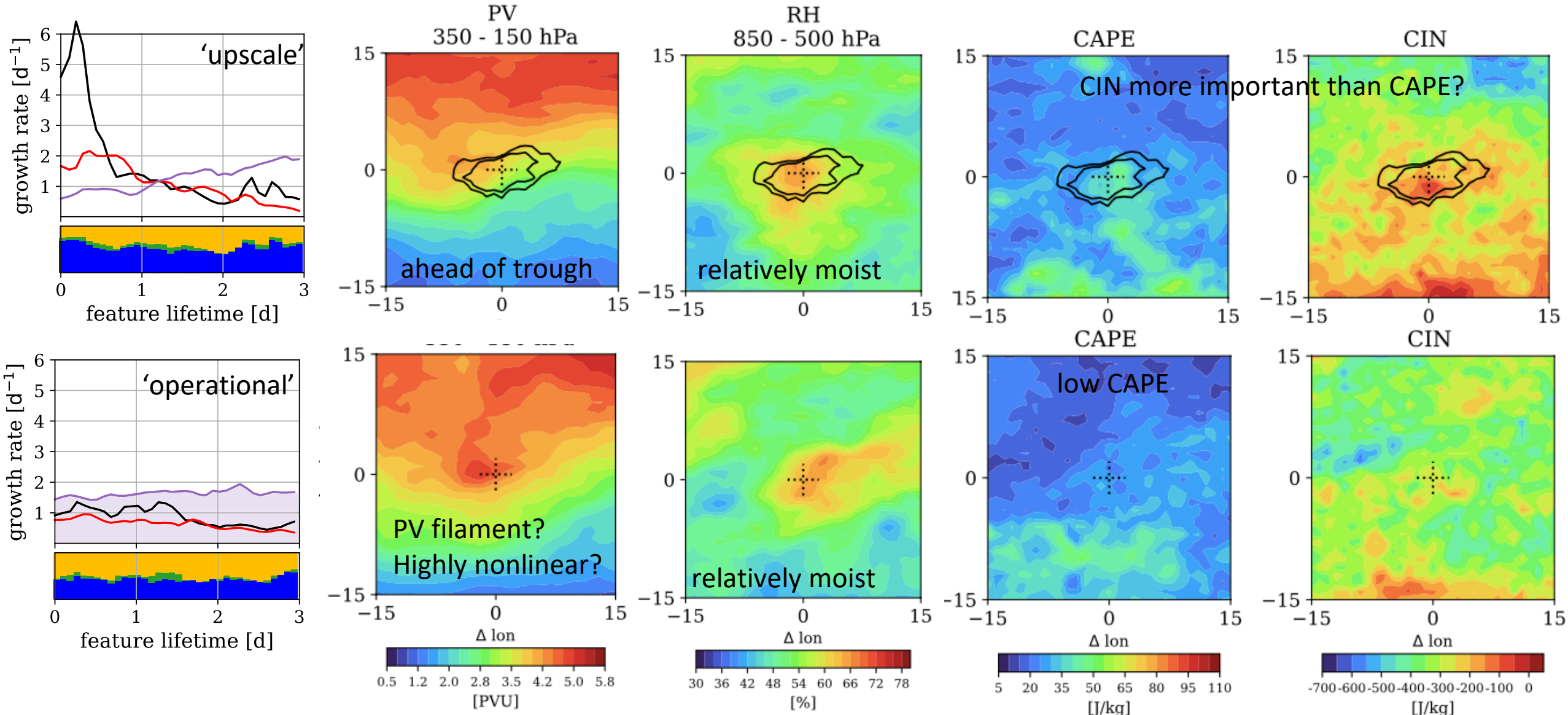

Summary

- Piecewise PV-tendency framework quantifies (upscale) error growth mechanisms (midlatitude tropopause region).
- Error-feature framework enables efficient analysis of many ‘cases’.

preliminary:

- Intrinsic limit of predictability may first be reached in high-CIN convective situation ahead of a trough.
- Highly nonlinear tropopause evolution with little LHR may benefit most from reduction in initial condition uncertainty.

References:
Baumgart et al. 2018: Potential vorticity dynamics of forecast errors: A quantitative case study. *MWR*, *146,* 1405-1425.
Baumgart et al. 2019: Quantitative view on the processes governing the upscale error growth ... using a stochastic convection scheme. *MWR*, *147*, 1713-1731.
Baumgart and Riemer 2019: Processes governing the amplification of ensemble spread in a medium-range forecast … . *QJRMS*, *145*, 3252-3270.
Schmidt et al. 2024: A feature-based framework to investigate atmospheric predictability. *MWR*, in revision
Selz et al. 2022: The transition from practical to intrinsic predictability of midlatitude weather. *JAS*, *79*, 2013-2030.