CRC 1114
Scaling Cascades in Complex Systems

# A01 Reduced stochastic aggregation of convection conditioned by large scale dynamics in the atmosphere

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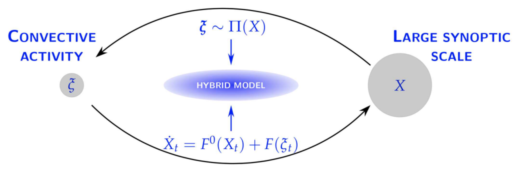
## Project background

**Research objective:**

Efficient and scalable coupling of a hierarchical precipitation model driven by stochastic convective activity on small scale $\xi_t$ to large scale atmospheric flow dynamics $X_t$

$\mathrm{Prob}(\ldots) = \Pi_{\mathrm{Hierarch}}(\mathrm{DSI}_{\mathrm{QG}}, \mathrm{CAPE}, \langle \mathrm{Temp} \rangle, \ldots)$

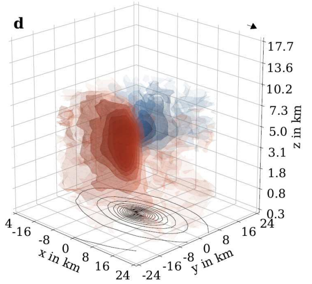



**Aims:**

- a conceptual model for convection structure is developed using the extended theory of coherent sets (defining $\xi_t$);
- a stochastic model for convection is computed, depending on the large scale variables ($\xi \sim \Pi(X)$, [10]); and
- the effect of the small on the large scales is computed in form of a deterministic feedback ($\dot{X}_t = F^0(X_t) + F(X_t, \xi_t) \approx F^0(X_t) + F(\xi_t)$, [8]).

**Characteristic variables of convection:**

- Evaluation of 3D structures of variables
- evaluation of 15.222 cases of 22x22 km domains, 2x2 km grid boxes, with strong precipitation
- 3785 events with precipitation $\geq 29mm/h$, COSMO-REA2 data



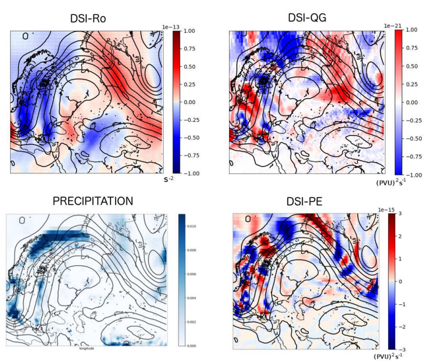

[1]

- The **Potential Vorticity (PV)**

$$\Pi = \frac{1}{\rho} \xi \cdot \nabla \Theta$$

- $\rho$: density, $\mathbf{v}$: velocitiy
  $\xi = \nabla \times \mathbf{v}$ vortex vector
  $\Theta = T \cdot \left(\frac{p}{p_0}\right)^{\frac{R}{c_p}}$ pot. Temp.
- black isolines: mean precipitation within the next hour (3-39 mm/h)
- red (blue) isosurfaces: positive (neg.) PV (0.2 - 3.2 PVU)

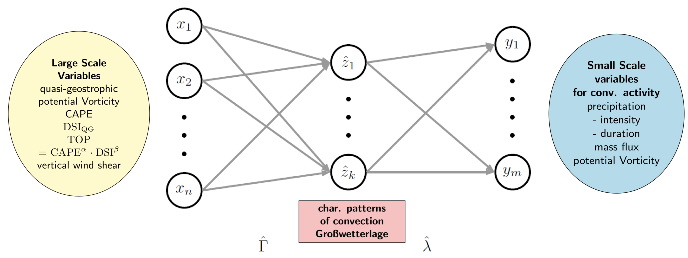
- **Dynamic State Index (DSI)** variants can be applied to atmospheric processes, or phenomena on different scales
- enabling a model-dependent comparison and scale-dependent analysis of these processes
- **Atmospheric Blocking**: steady high pressure area, the back side is related to convective activity




## Downward coupling method (DBMR)

Aim: efficient and scalable estimation of $\Lambda = \mathbb{P}[Y \mid X]$, given samples $(X_i, Y_i)$

- Idea: introduce intermediate latent states, s.t. $\Lambda = \hat{\lambda}\hat{\Gamma}$
- Number of latent states $\ll$ number of input/output states
- Alternating maximum likelihood estimation $\rightsquigarrow$ scalable computation



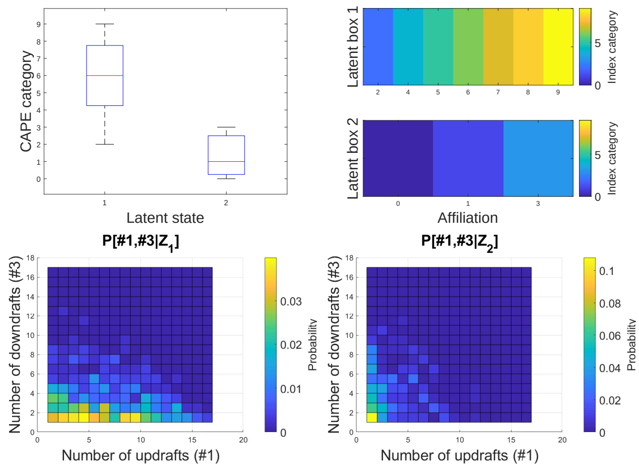

$\hat{\Gamma}_{i\ell} = \mathbb{P}[\hat{Z} = \hat{z}_\ell \mid X = x_i]$ $\quad \hat{\lambda}_{\ell j} = \mathbb{P}[Y = y_j \mid \hat{Z} = \hat{z}_\ell]$

## DBMR applied to meteorological data

**Setting:**

- Data: COSMO-REA6 data
- large scale parameter: CAPE, horizontal resolution ca. 250x250 km
- small scale parameter: vertical velocity, horizontal resolution ca. 62x62 km, 600 hPa
- time resolution: daily mean, July and August 2005-2015

**Collective causality for 2 latent states:**




## Summary and results

- Goal: show that small scale convective processes are related to larger scale dynamics
- Using DBMR to describe a relation of the mass flux on the smaller scale to CAPE on the larger scale. DBMR gives the probabilistic relation of both variables via model reduction
- Key step: Reducing the information on the large scale to two latent states and calculate the conditioned probabilites $\Lambda = \hat{\lambda}\hat{\Gamma}$
- We confirm that large CAPE values are related to updrafts, and small CAPE values are more related to downdrafts
- Next steps: Applying DBMR to further variables such as DSI and PV and investigating, how many latent states provide the best model to describe the relations between the variables on different scales

## References

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