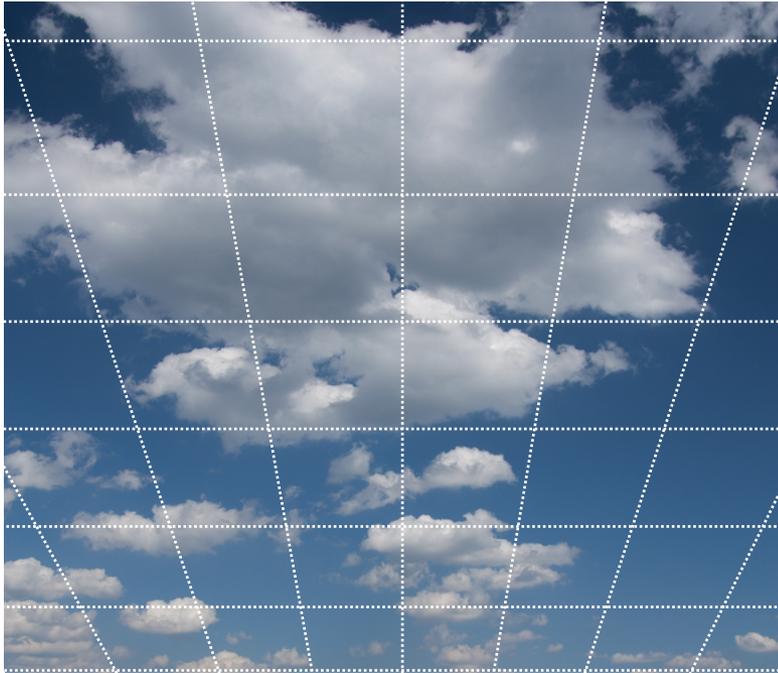


# Challenges in modelling of shallow convection on kilometre scales



Mirjana Sakradzija  
Cathy Hohenegger and Daniel Klocke  
MPI-M, HERZ DWD

Workshop on shedding light on the greyzone, ECMWF

# Overview

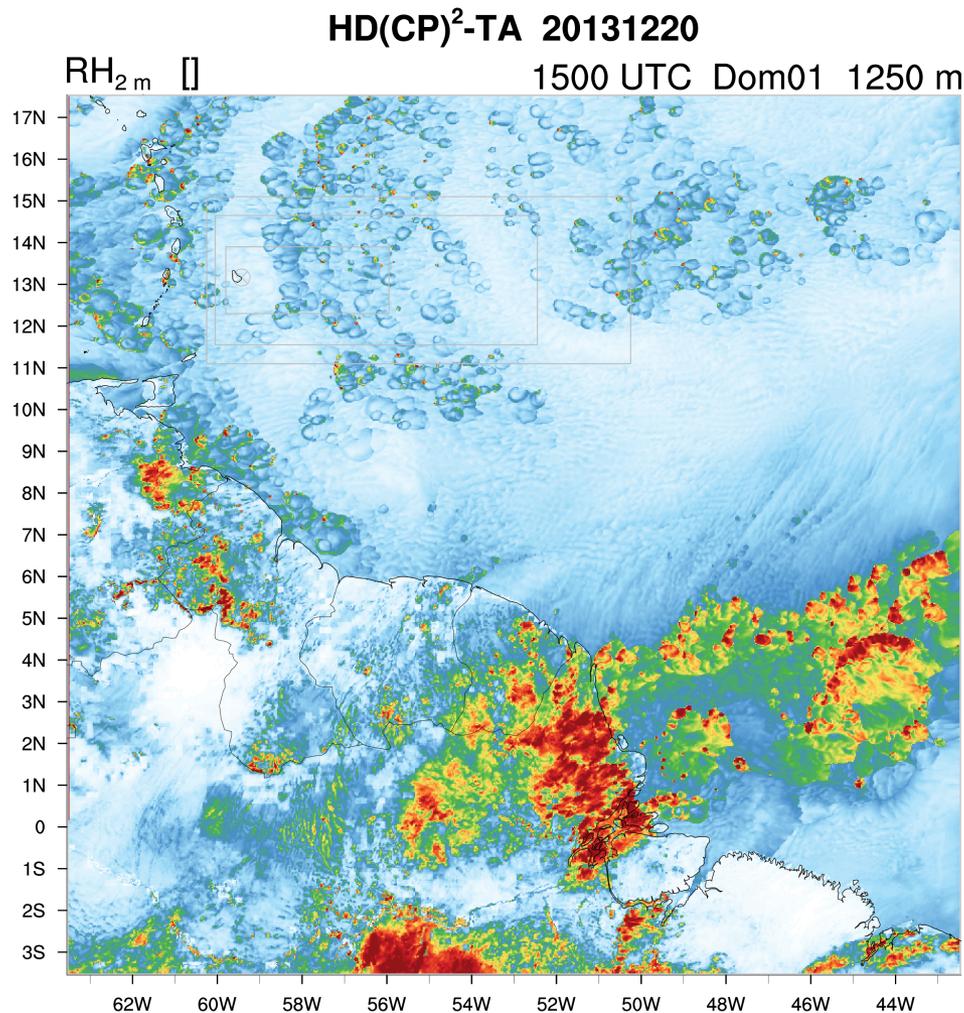


image: Matthias Brueck, MPI-M

increase the resolution - resolve more of deep convection  
investigate resolution dependency of the resolved flow and of the subgrid processes  
further the understanding of convective processes

Challenges we face come from

- 1) subgrid physics,
  - 2) resolved dynamics and
  - 3) their coupling
- (and I think it is equally important to address all three)

# The two case studies

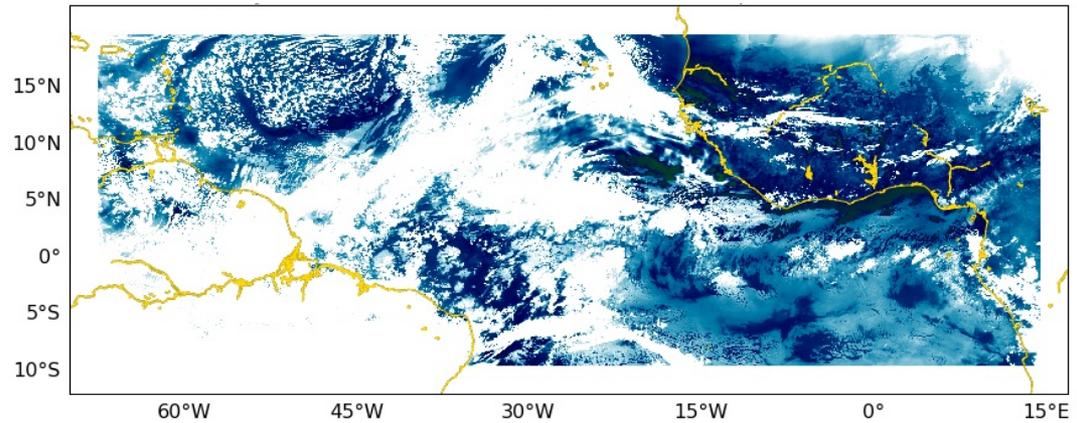
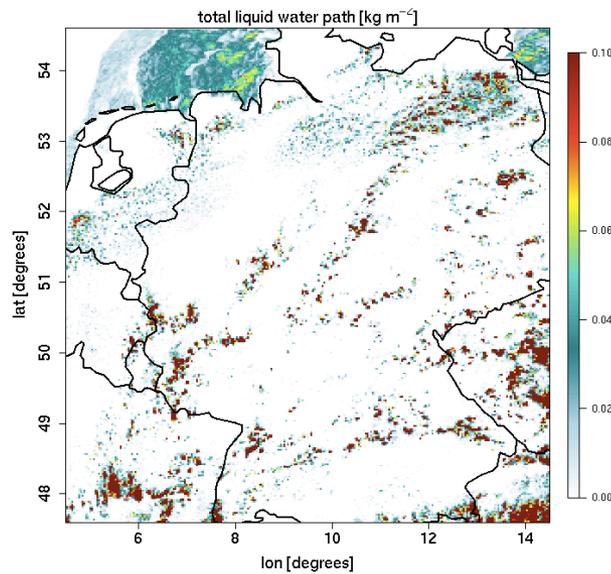
Model: ICON-NWP, ICON-LEM (Daniel's talk)

Two cases:

Germany 5.5.2013

and

Tropical Atlantic 20.12.2013



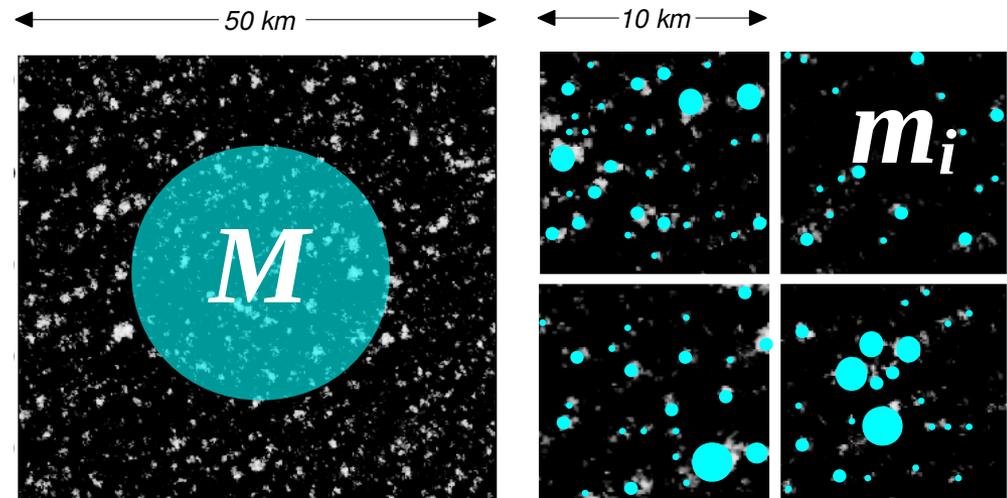
## Challenge 1: formulation of the subgrid physics

main assumption of a convection parameterization:  
a grid box is large enough to hold a cloud ensemble which is uniquely determined by the imposed forcing

however, subgrid cloud samples are not statistically robust;  
given the same conditions imposed on the grid cells, different realisations of subgrid convection are possible

fluctuations increase with increasing resolution

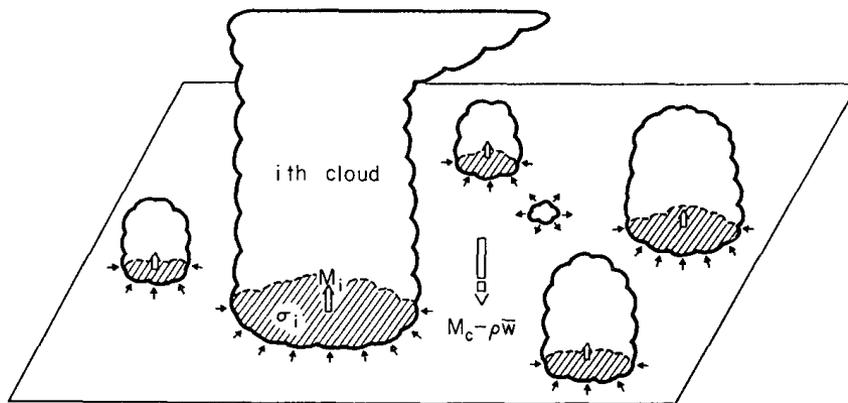
a **stochastic** cloud ensemble to achieve a **scale-aware** representation of fluctuations of subgrid convection around the ensemble average state



# Challenge 1: formulation of the subgrid physics

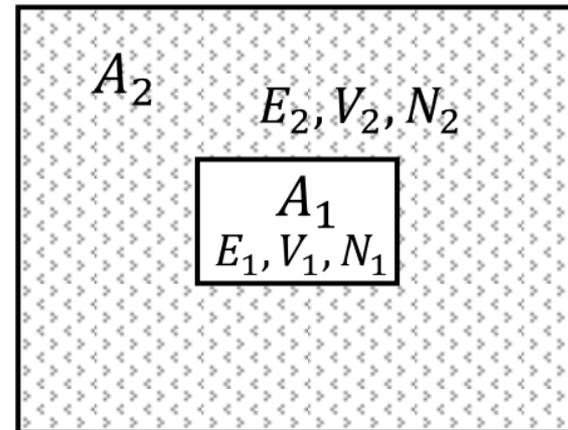
cloud ensemble in analogy to statistical ensembles  
(Craig and Cohen, 2006; Plant and Craig 2008,...)

A cumulus cloud ensemble



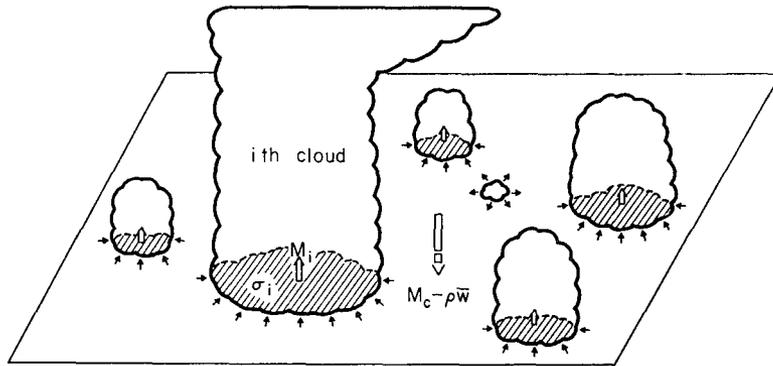
Arakawa and Schubert (1974)

A statistical ensemble



Find a set of variables to describe the cloud ensemble...

# Cloud population distribution



we define the mass flux of each cloud as

$$m_i = \rho a_i w_i$$

*Arakawa and Schubert (1974):*

Due to our lack of theoretical understanding and empirical knowledge, we do not attempt in this paper to determine  $\mathfrak{N}(\lambda)$ ,  $\tau(\lambda)$  and  $\mathfrak{M}_B(\lambda)$  separately, although that should be an eventual goal of statistical cumulus dynamics.

$$m, \tau, N, \quad M = \sum_i^N m$$

Our final problem is to find the mass flux distribution function,  $\mathfrak{M}_B(\lambda)$ .

This is the essence of the parameterization problem.

We are interested in the cloud population distribution of cloud-base mass flux  $p(m)$ .

(Craig and Cohen, 2006; Plant and Craig 2008; Sakradzija et al. 2015, 2016)

# Stochastic cloud ensemble

Two sampling processes:

$n$  random number of clouds is drawn from the Poisson distribution:

$$p(n) = \frac{\langle N \rangle^n e^{-\langle N \rangle}}{n!}$$

$m$  is sampled from the Weibull distribution:

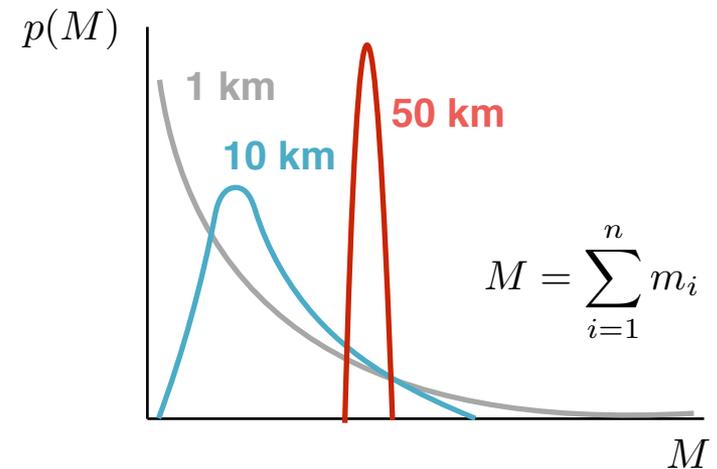
$$p(m) = \frac{k}{\lambda^k} m^{k-1} e^{-\left(\frac{m}{\lambda}\right)^k}$$

A grid box then contains a random number of clouds that have different areas and mass flux values.

$n$  - number of clouds in a grid box

$\langle N \rangle$  - ensemble average number of clouds

$m$  - mass flux of a single cloud



scale-aware distribution  
of the total mass flux

(Craig and Cohen 2006; Plant and Craig 2008; Sakradzija et al. 2015, 2016)

# Physical constraints on the ensemble distribution

Why Weibull distribution? - memory

$$p(m) = \frac{k}{\lambda^k} m^{k-1} e^{-\left(\frac{m}{\lambda}\right)^k}$$

$$\frac{\tau_i}{\langle \tau \rangle} = \left( \frac{m_i}{\langle m \rangle} \right)^\gamma \quad \gamma = k = 0.8$$

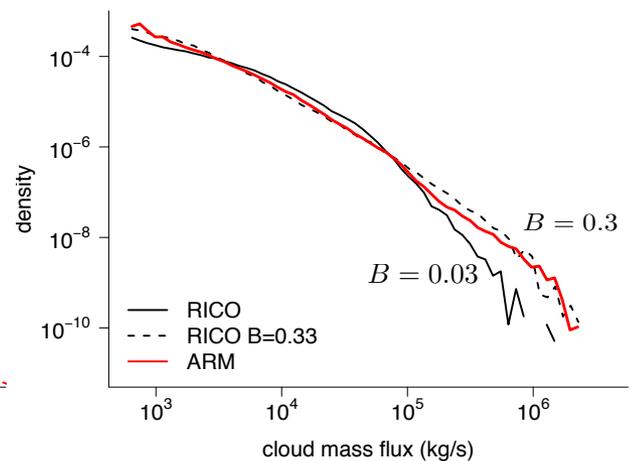
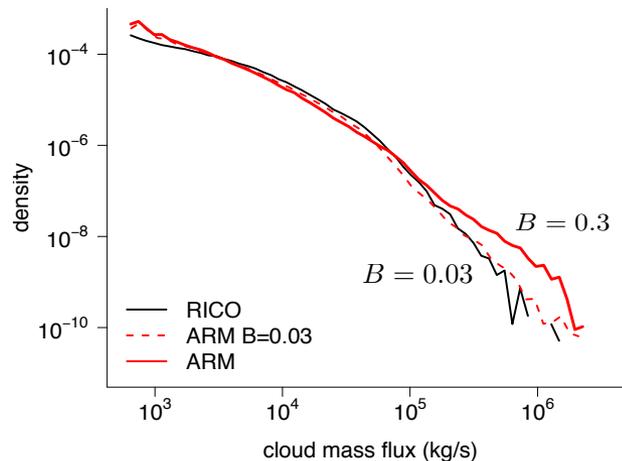
correlation of mass flux with lifetime sets k (universal constant)

Bowen ratio *is the only* parameter that has a power to alter the overall shape of  $p(m)$  by controlling the efficiency of the convective heat cycle.

$$B = \frac{F_{SH}}{F_{LH}}$$

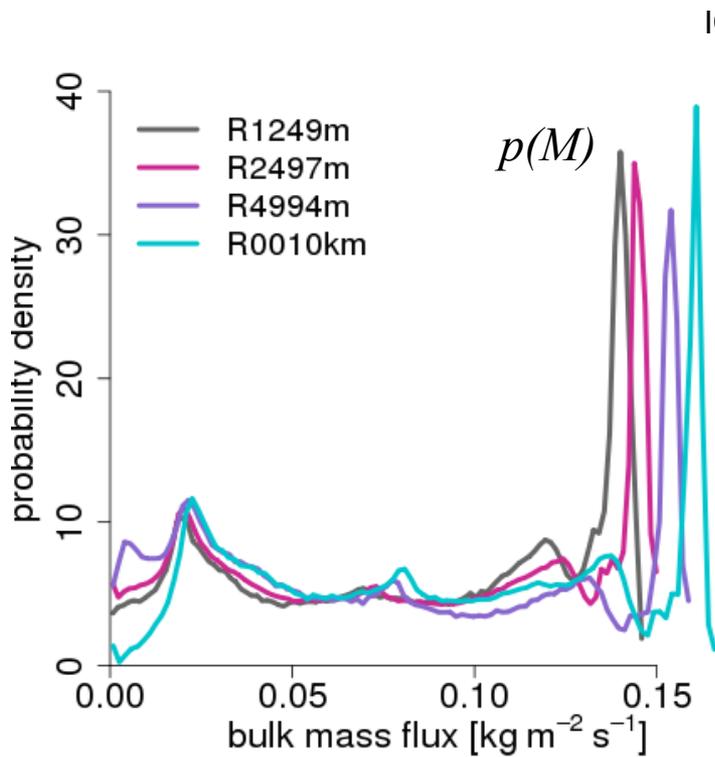
Sakradzija, M., and C. Hohenegger,  
What determines the distribution of  
shallow convective mass flux through  
cloud base?

J. Atmos. Sci., 2017

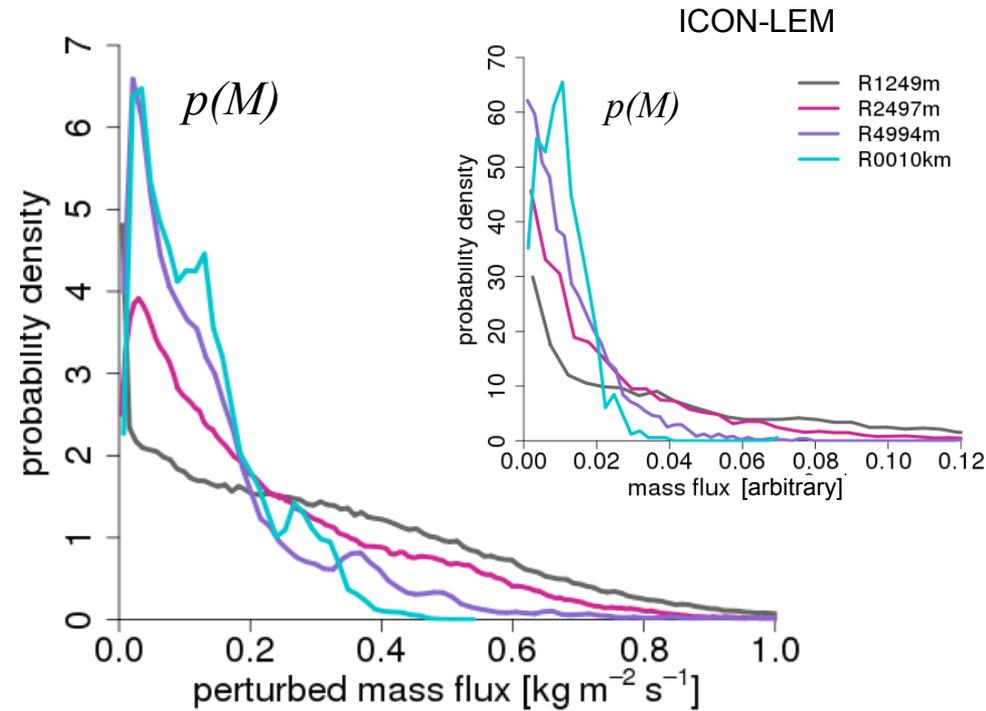


# The scale-aware mass flux distribution in ICON-NWP

as a result of subsampling, we get the resolution-dependent  $p(M)$



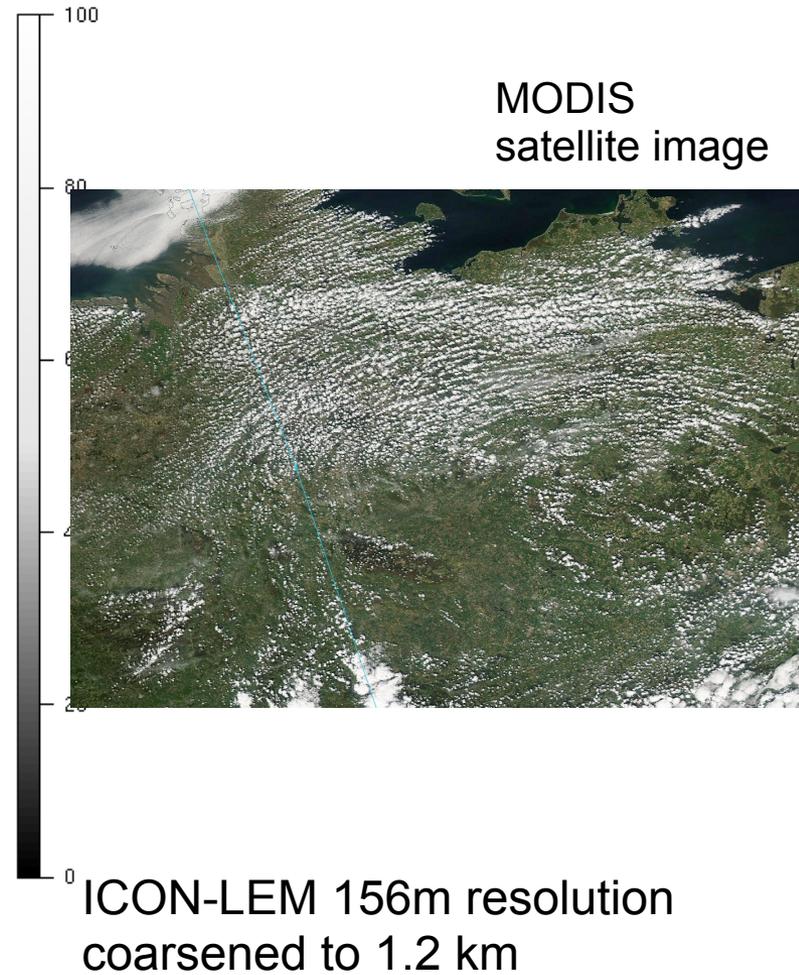
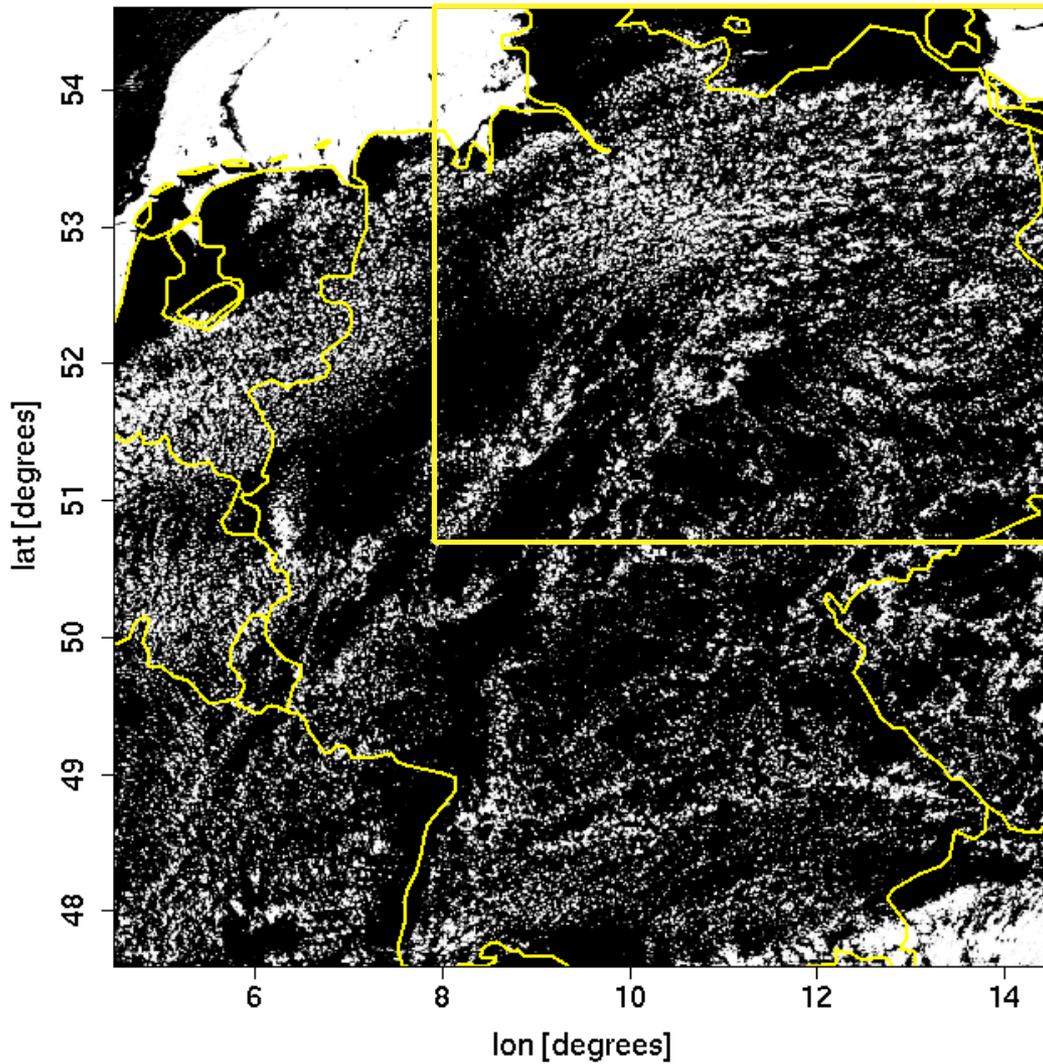
*Resolution independence of the bulk mass flux*



*Resolution-dependent distribution of the perturbed cloud-base mass flux*

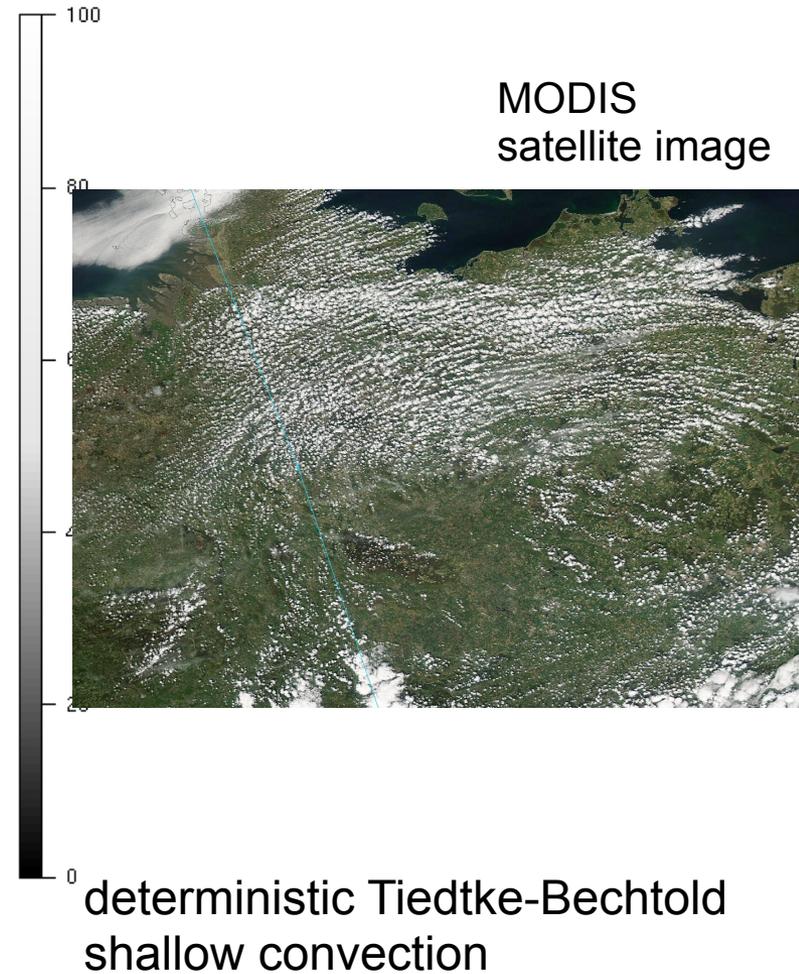
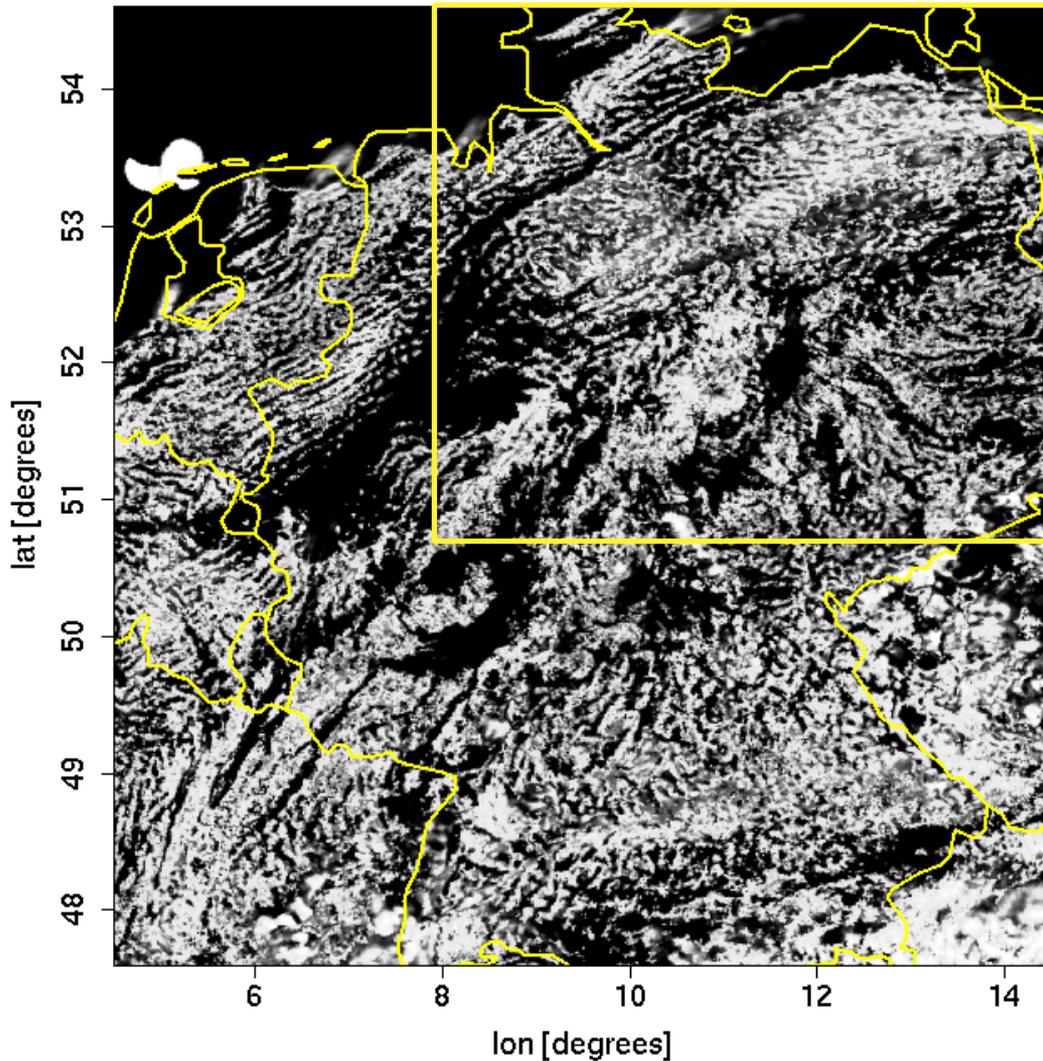
# A shallow convective day in Germany, 5.5.2013

low-level cloud fraction [%]



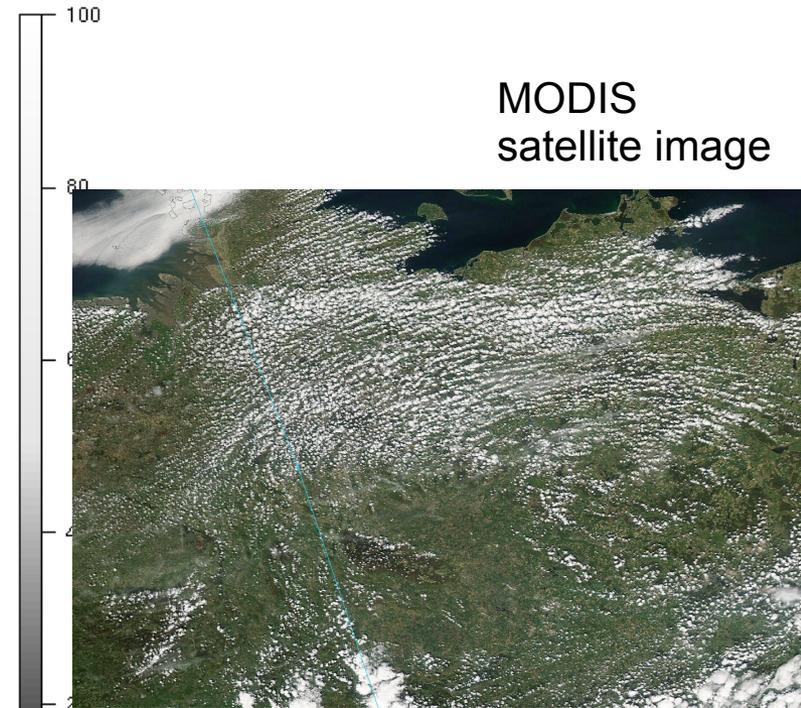
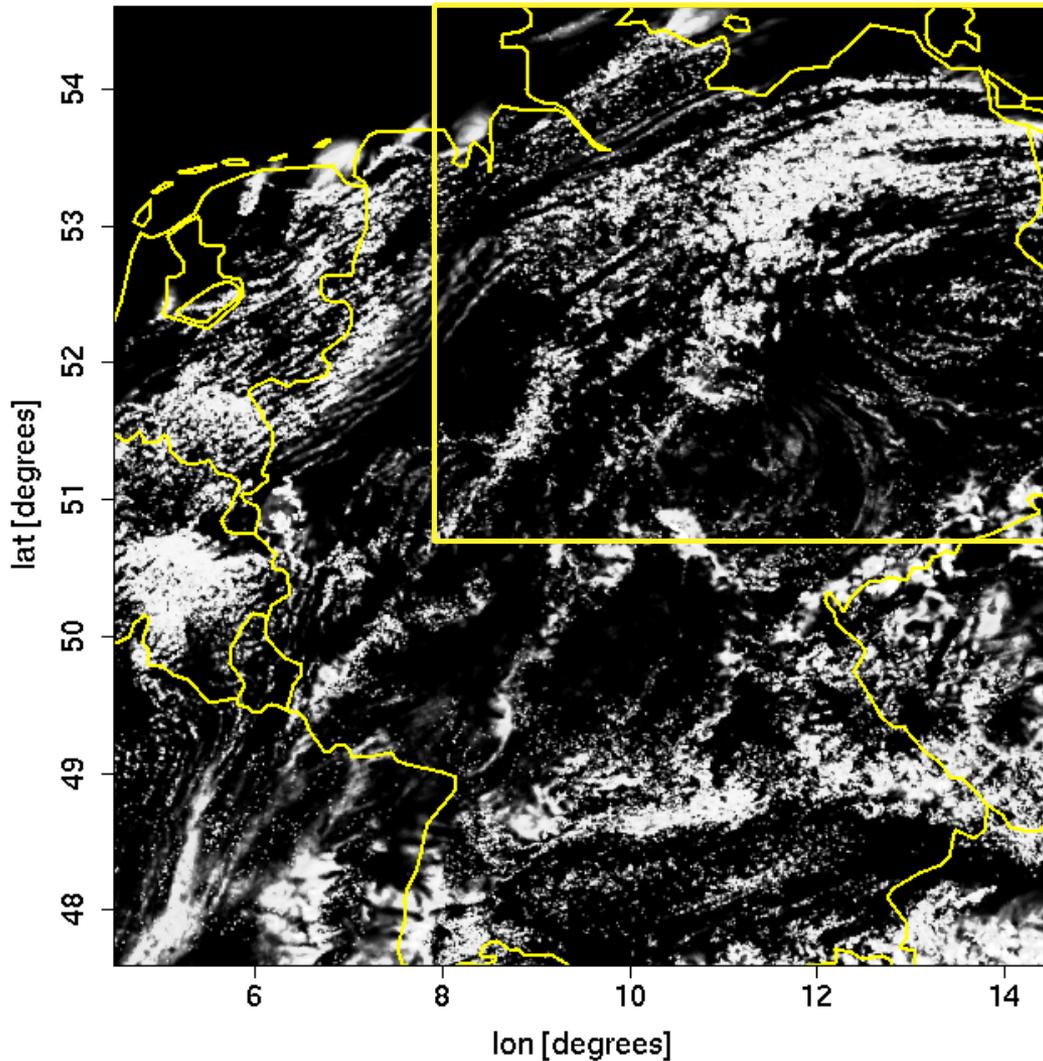
# A shallow convective day in Germany, 5.5.2013

low-level cloud fraction [%]



# A shallow convective day in Germany, 5.5.2013

low-level cloud fraction [%]



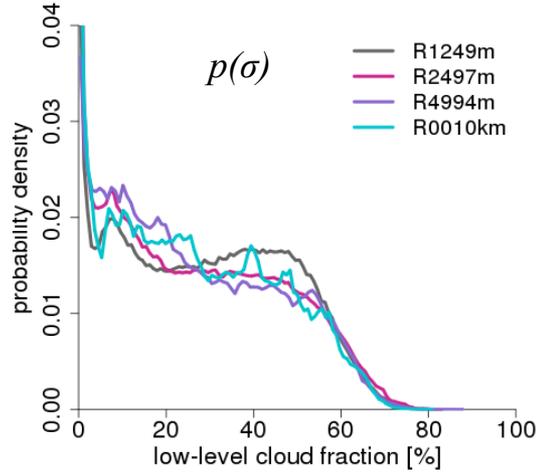
MODIS  
satellite image

stochastic Tiedtke-Bechtold  
shallow convection

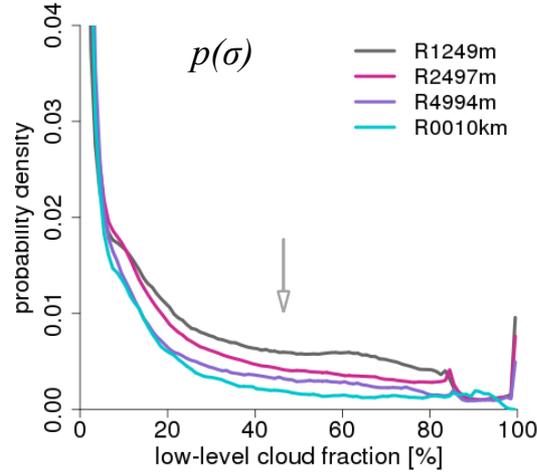
# Scale-adaptivity

ICON-NWP

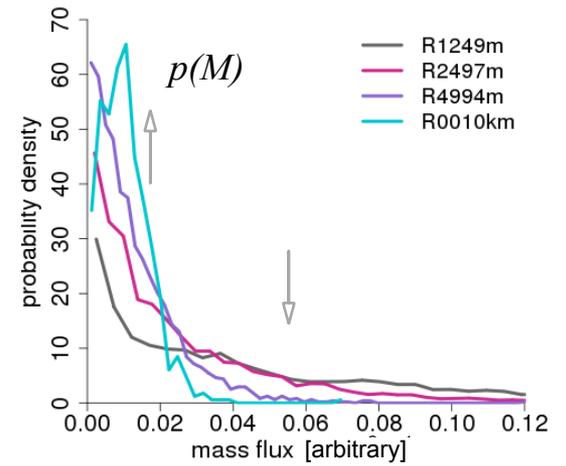
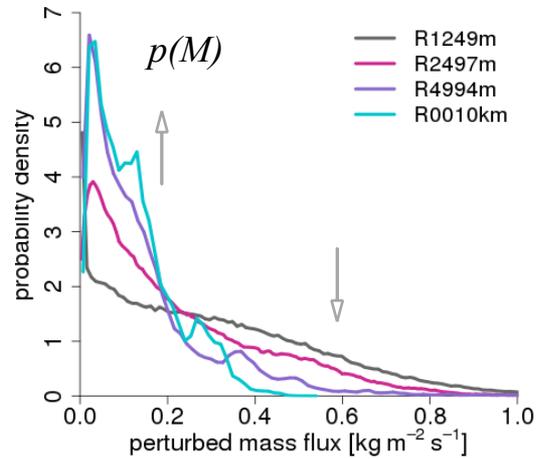
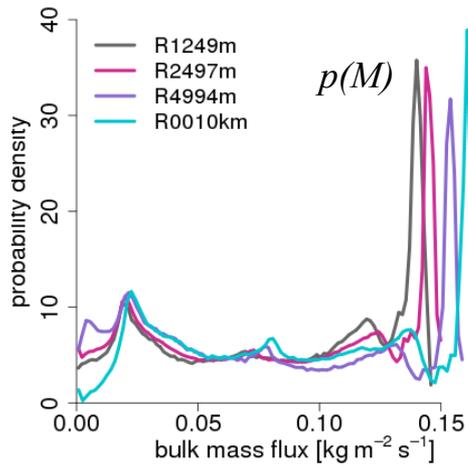
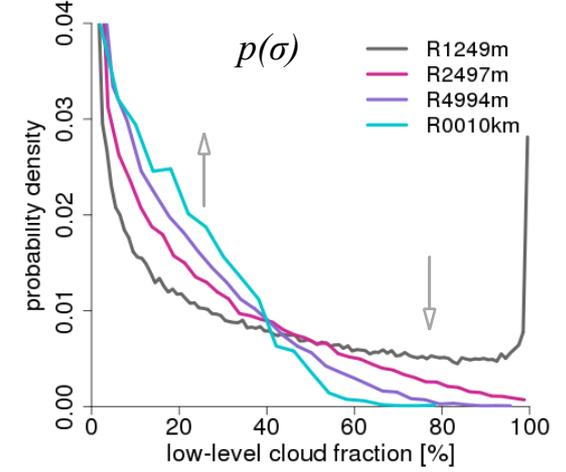
det



stoch



reference: ICON-LEM



## Challenge 2: correcting the under-resolved model dynamics

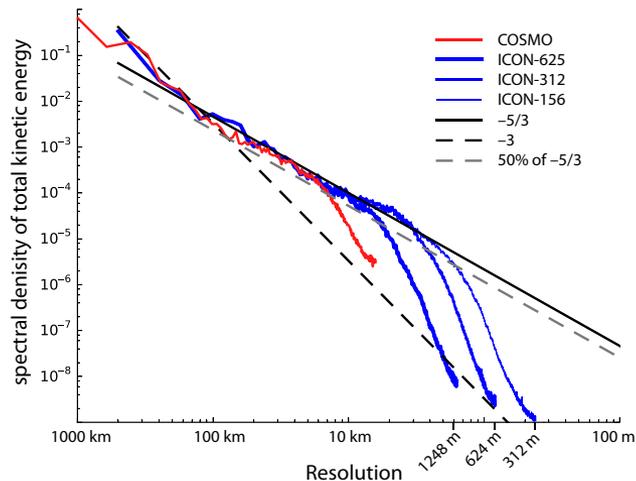
convective circulations depend on the grid resolution in the gray zone

explicit shallow convection is under-resolved

artificial organization modes

model effective resolution

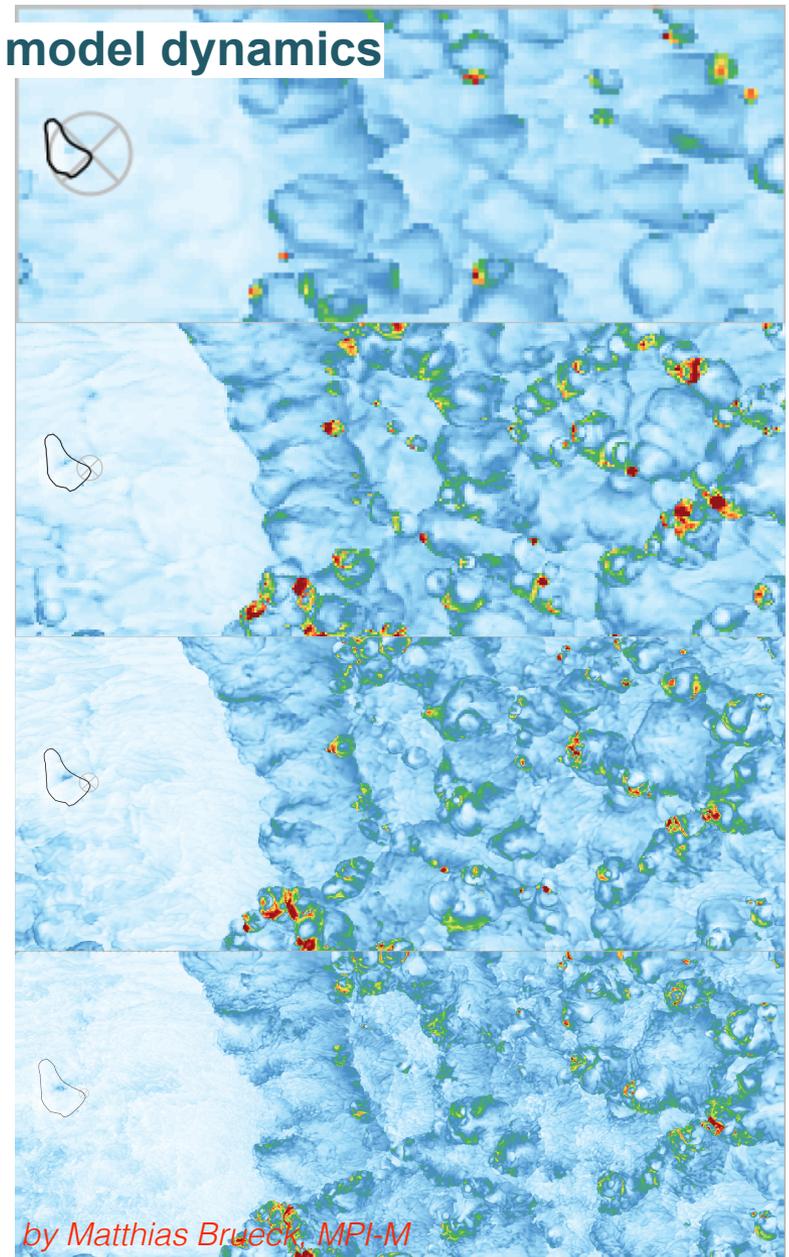
(Skamarock, 2004)



Heinze et al., 2017

1 km

100 m



by Matthias Brueck, MPI-M

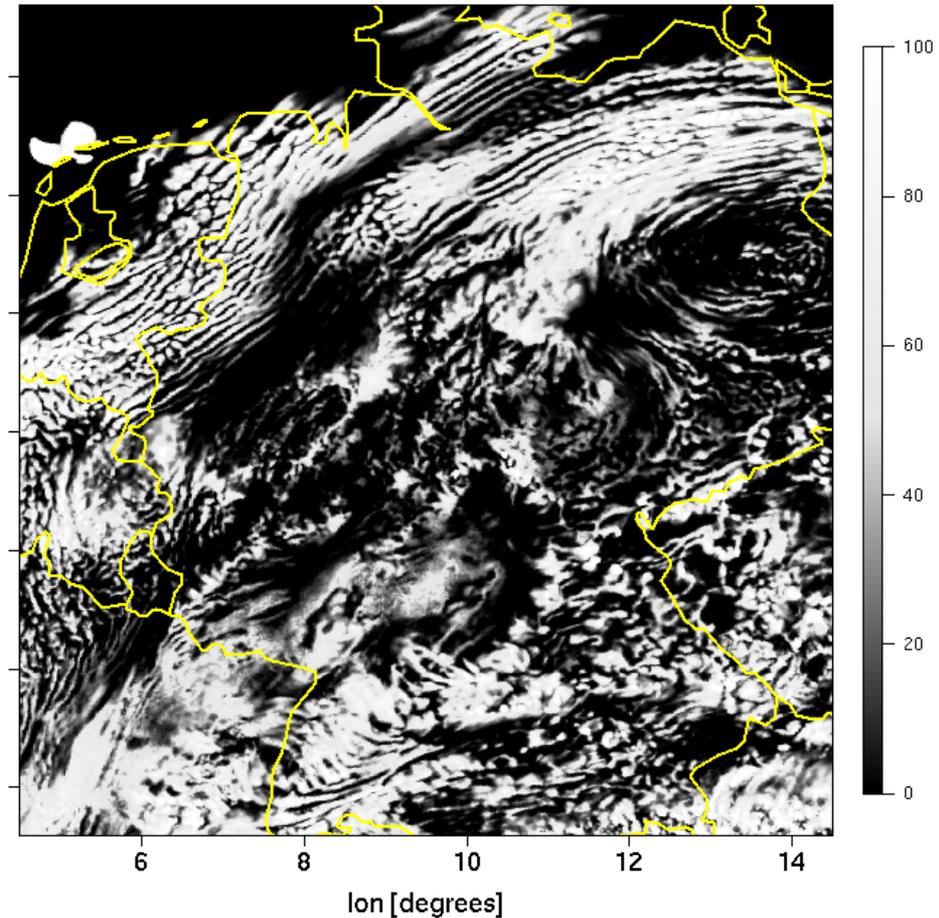
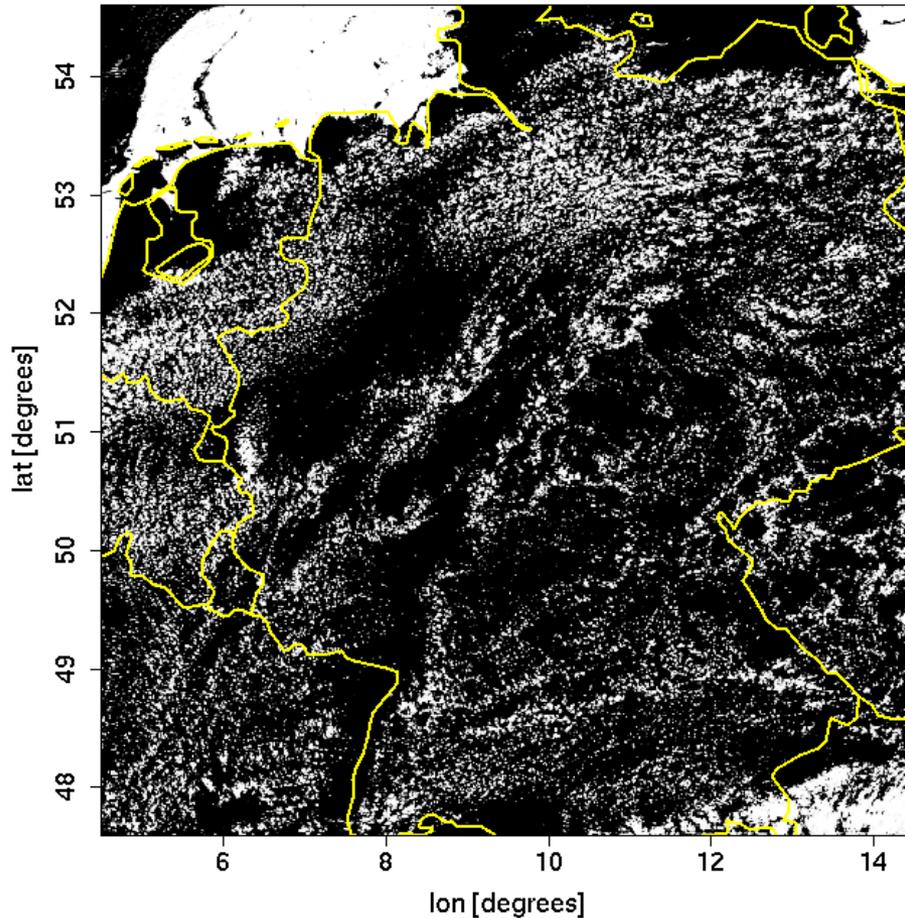
# A shallow convective day in Germany, 5.5.2013

LEM to 1.2 km

no convection

low-level cloud fraction [%]

low-level cloud fraction [%]



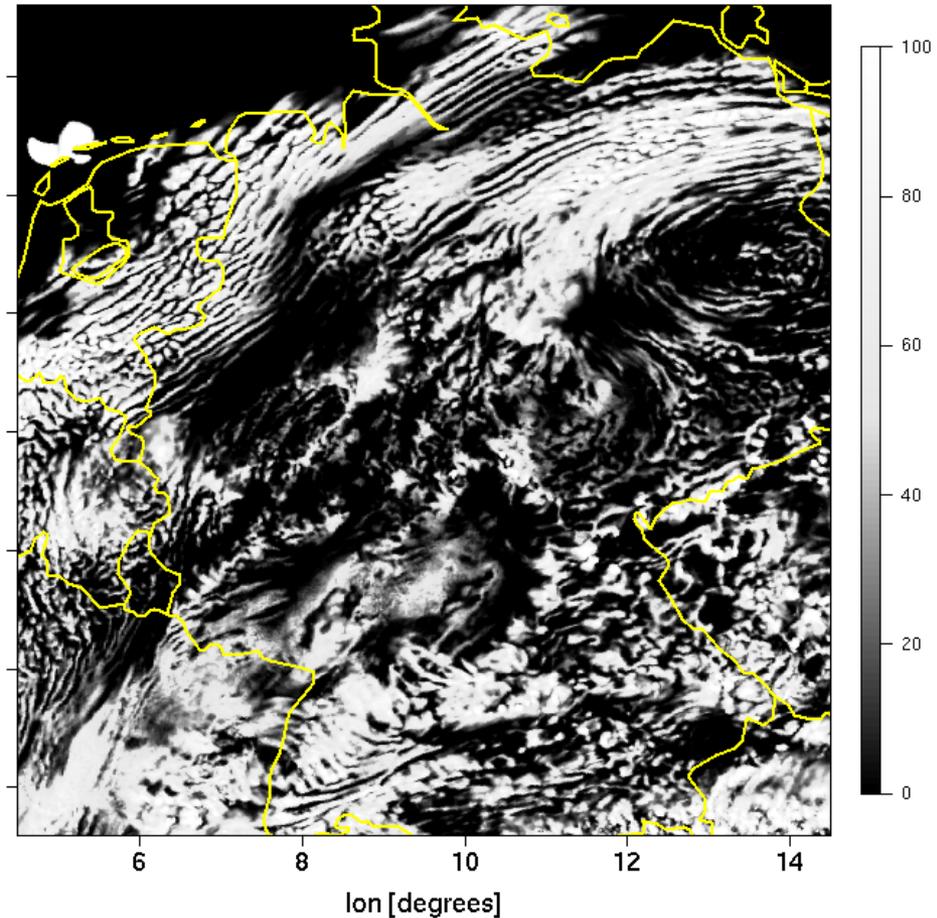
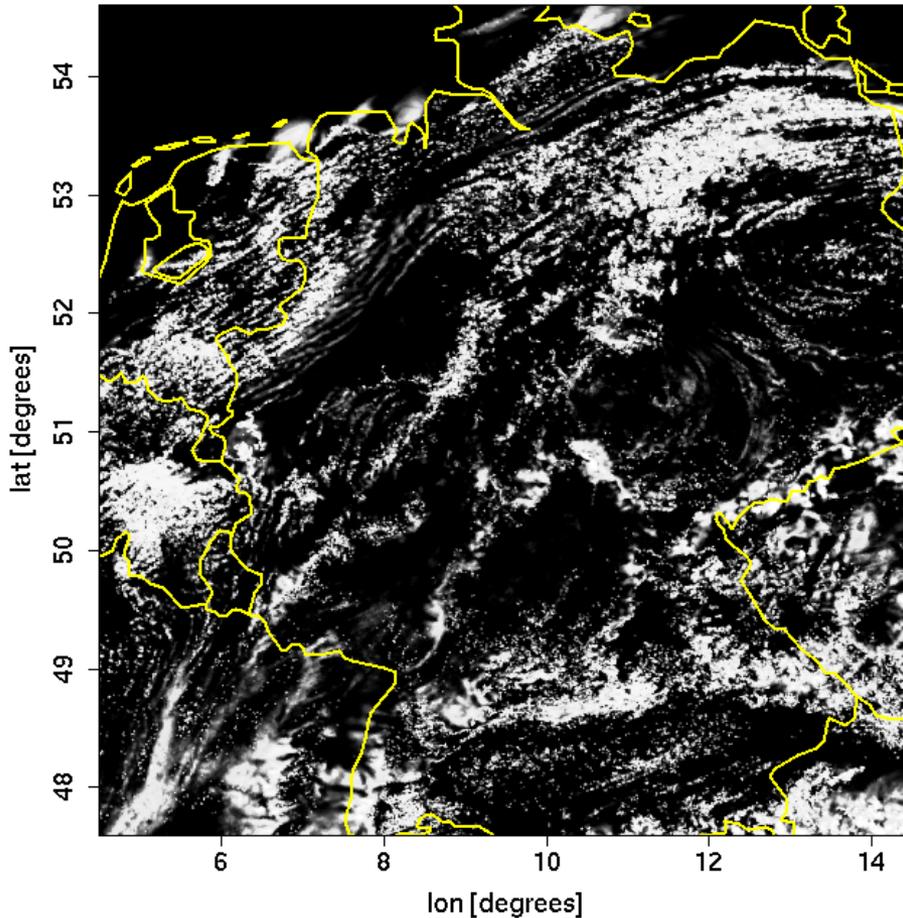
# A shallow convective day in Germany, 5.5.2013

stochastic

no convection

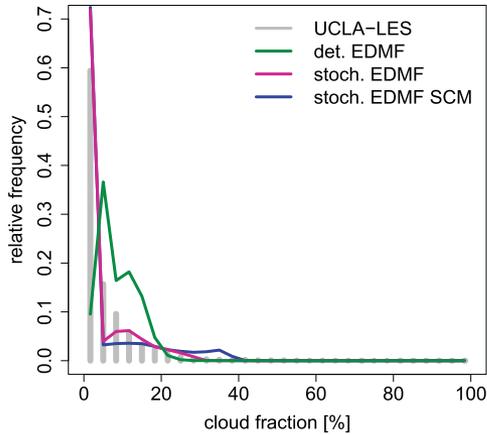
low-level cloud fraction [%]

low-level cloud fraction [%]

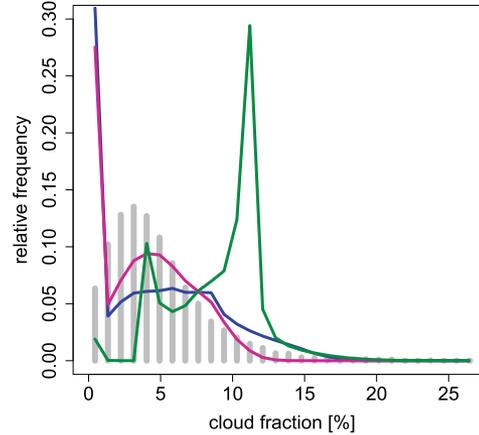


# Idealized case - RICO in ICON

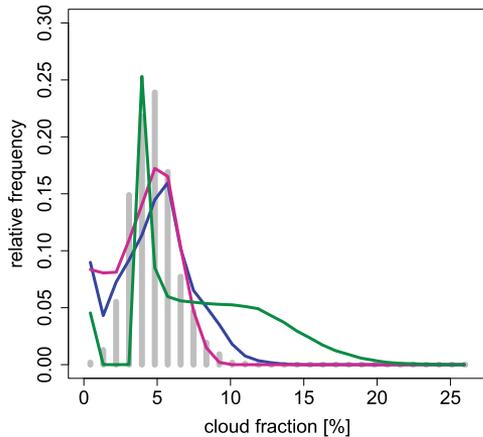
a) 1.6 km



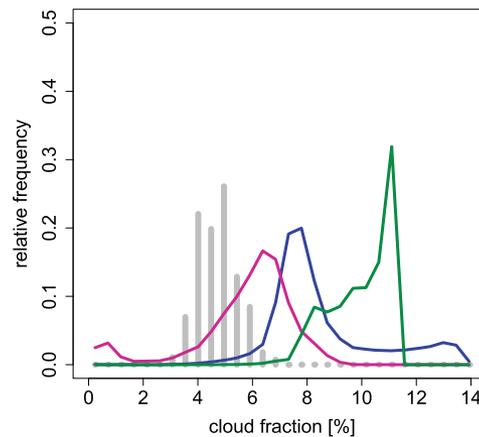
b) 3.2 km



c) 6.4 km



d) 12.8 km



ICON setup with doubly-periodic boundary conditions over a large domain of about 400x400 km<sup>2</sup>

Who is in control?

dynamics is driving the deterministic parameterization

stochastic parameterisation takes over the control as the scale-dependent fluctuations alter convective flow dynamics

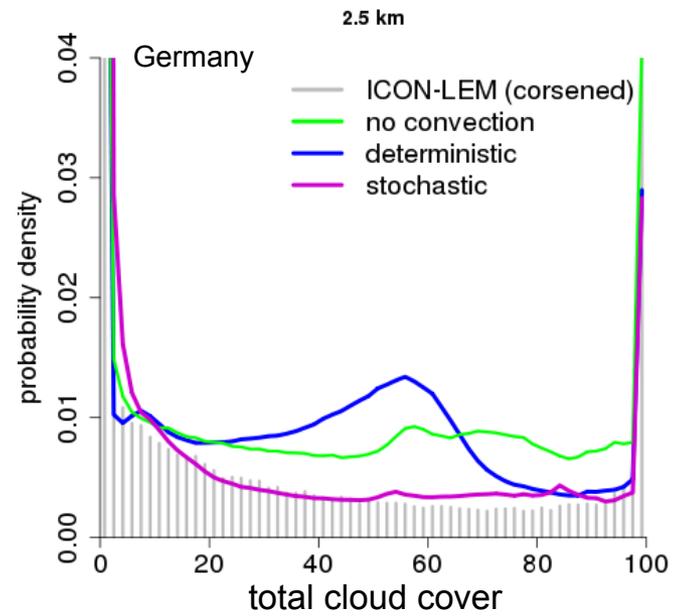
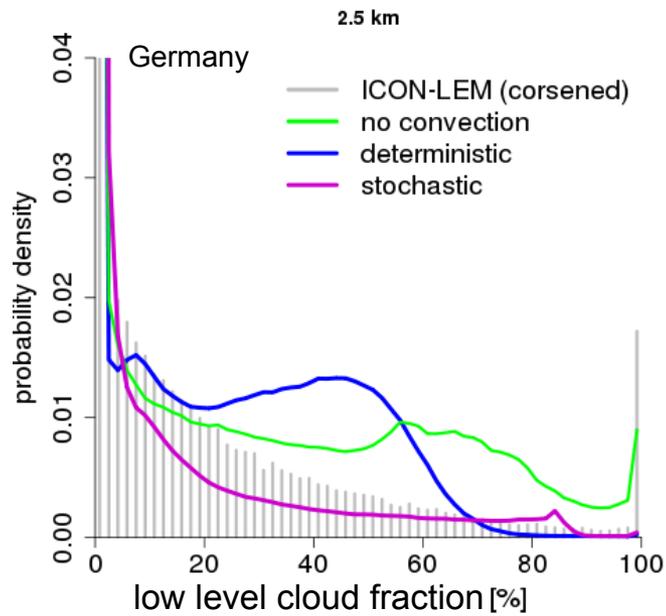
so,

it is a good idea to constrain fluctuations by some physical principle

*Sakradzija et al., 2016*

# A shallow convective day in Germany, 5.5.2013

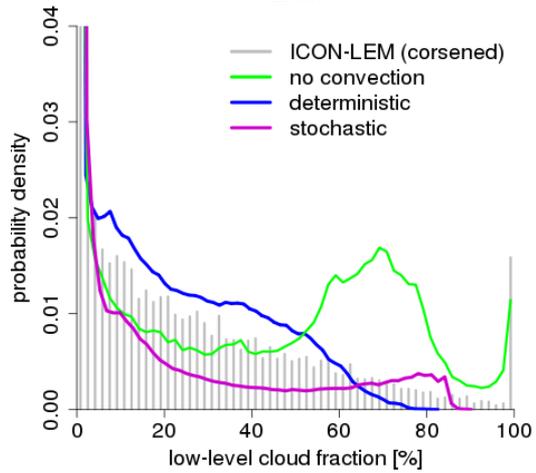
## Cloud cover histograms



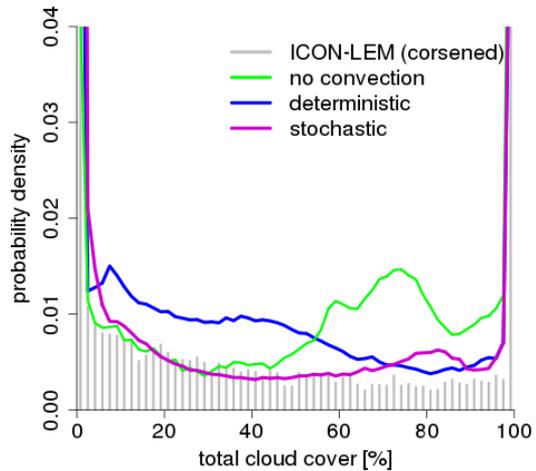
# Cloud cover histograms - regions

north

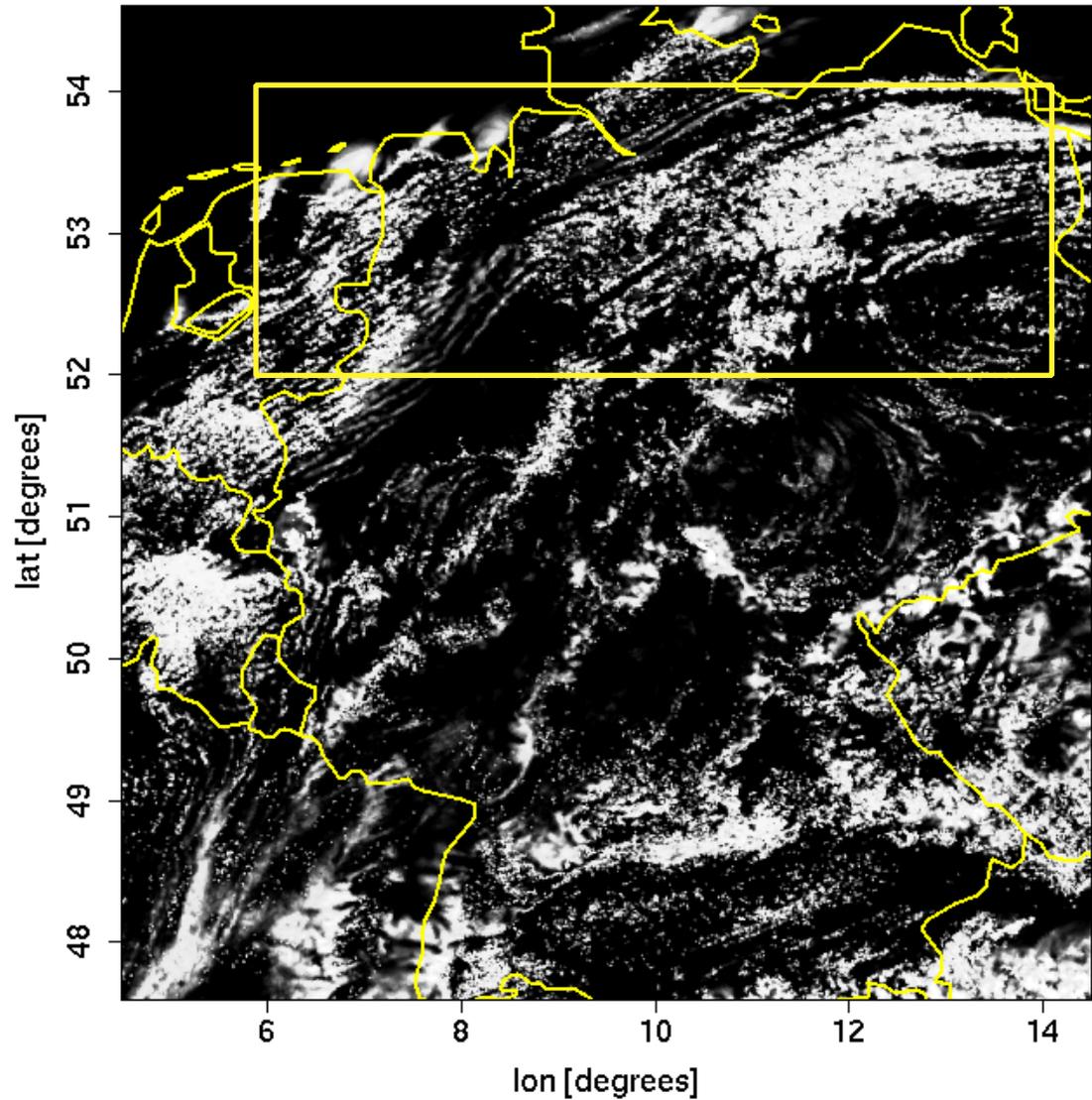
2.5 km



total



low-level cloud fraction [%]

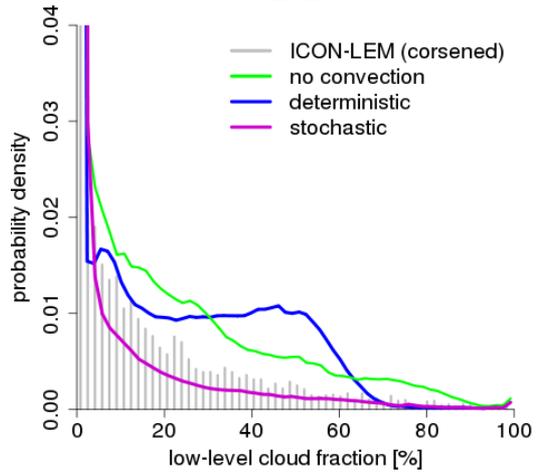


# Cloud cover histograms - regions

mid

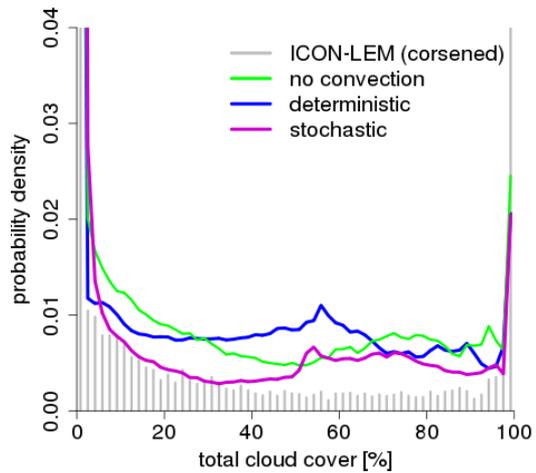
2.5 km

- ICON-LEM (coarsened)
- no convection
- deterministic
- stochastic

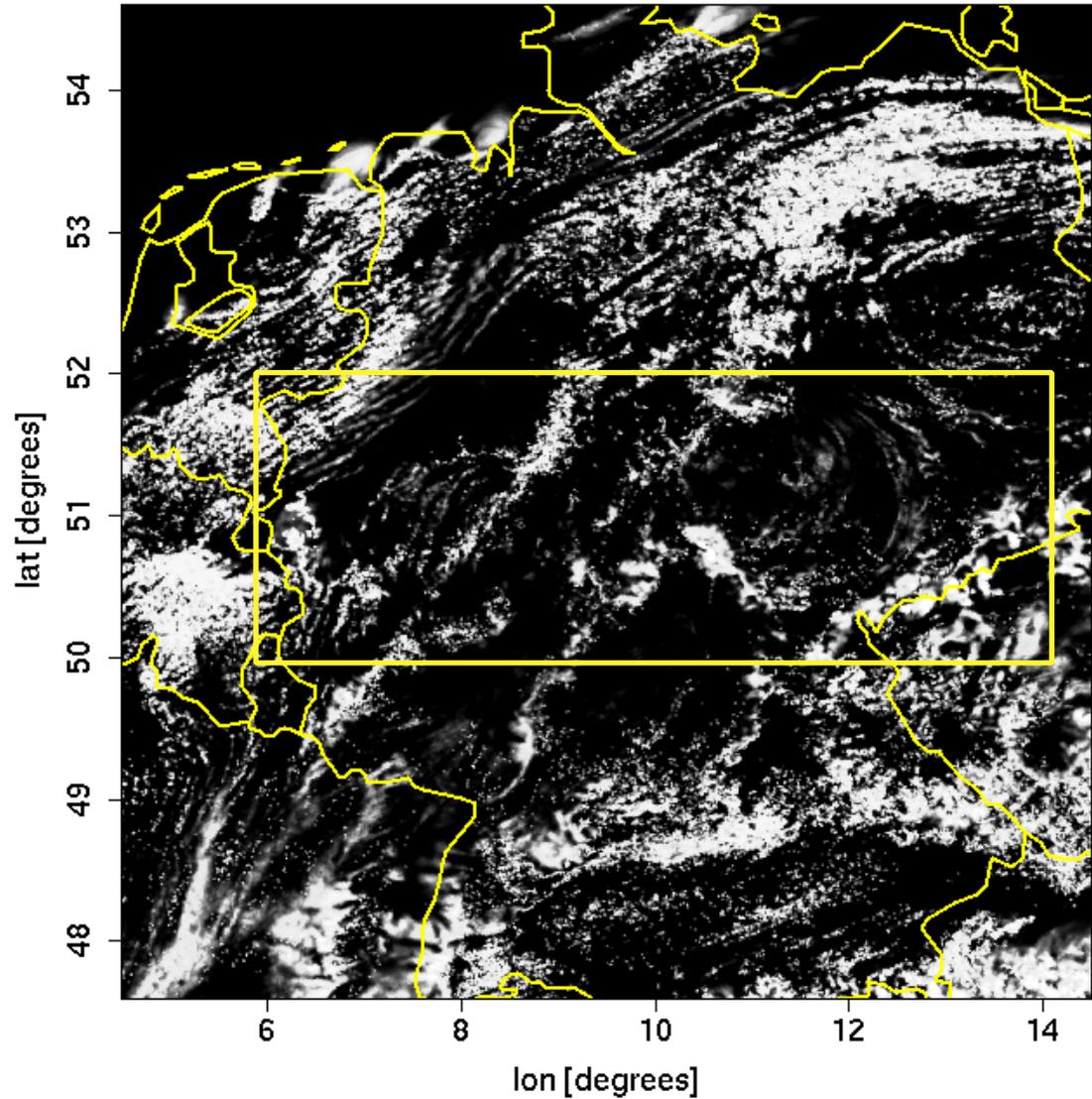


low

total



low-level cloud fraction [%]

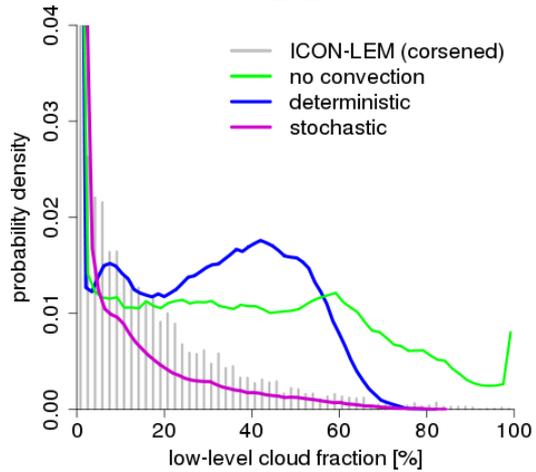


# Cloud cover histograms - regions

south

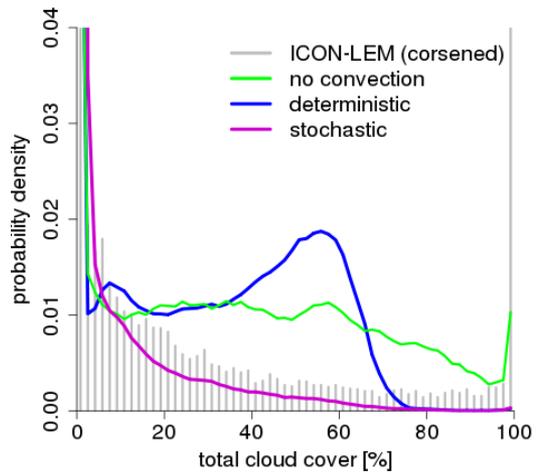
2.5 km

- ICON-LEM (coarsened)
- no convection
- deterministic
- stochastic

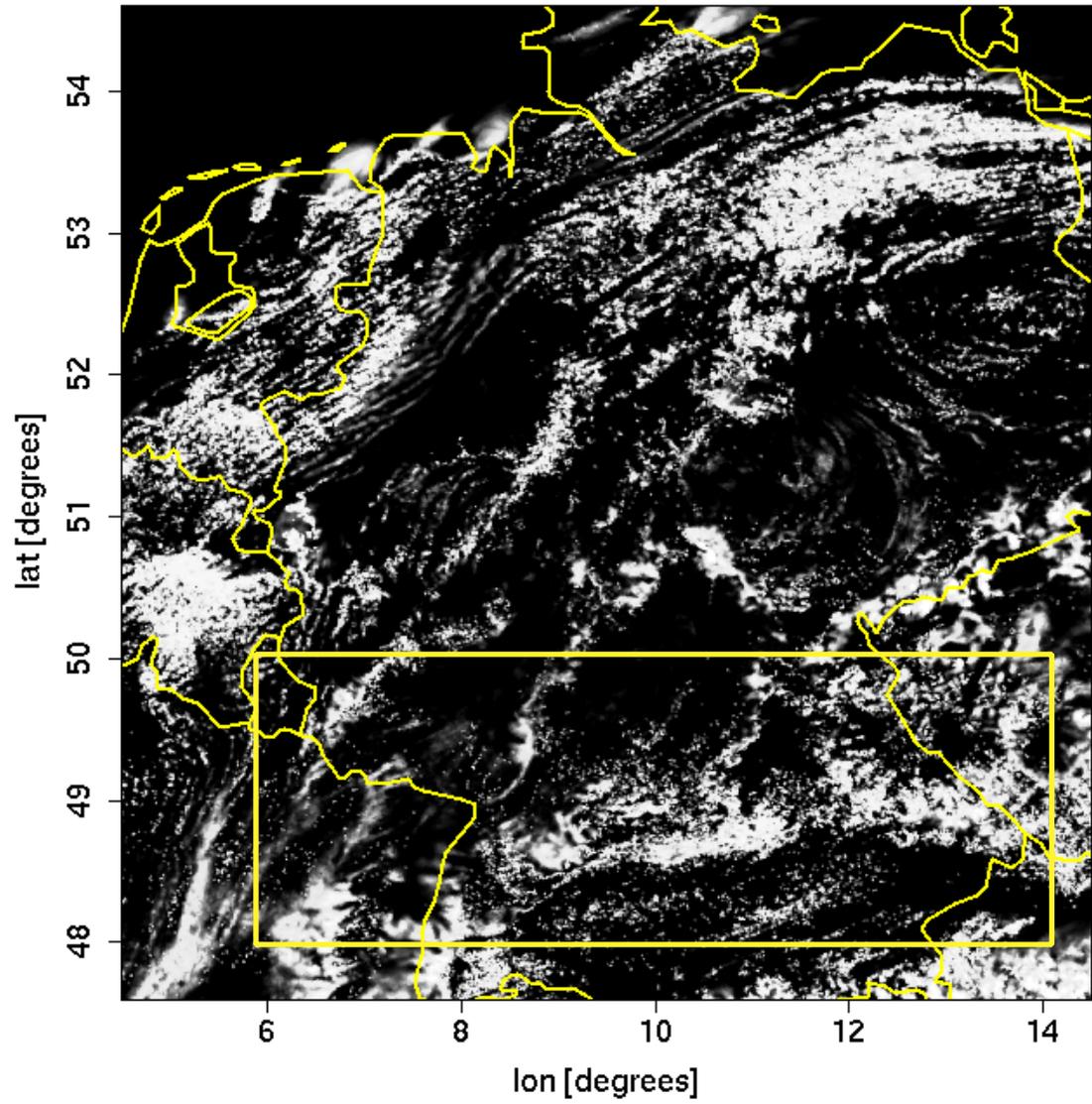


low

total



low-level cloud fraction [%]



### Challenge 3: physics-dynamics coupling and the artificial noise

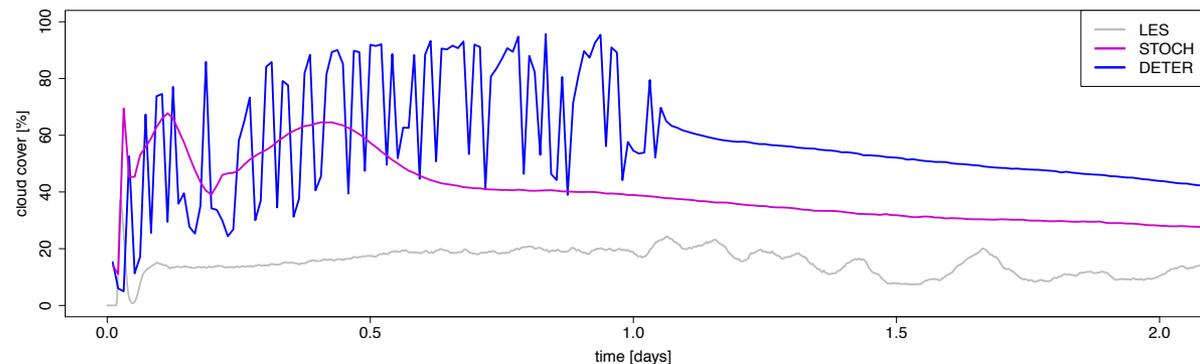
Parameterizations should be applied at those scales where the processes are well resolved (model effective resolution) - “believable scales”.

Parameterization and dynamical truncation scales should be separated (Lander and Hoskins, 1997)

*“If these low-amplitude small-scale features are fed into the parameterization, a parameterization can produce the tendencies of high-amplitudes but on the same small scales. These high-amplitude small-scale features can not be considered as believable phenomena, but can only be classified as noise.” (Lander and Hoskins, 1997)*

on-off behaviour: convection  
removes instability too quickly/  
strongly, and switches off at  
the next time step

idealised RICO case in ICON-NWP



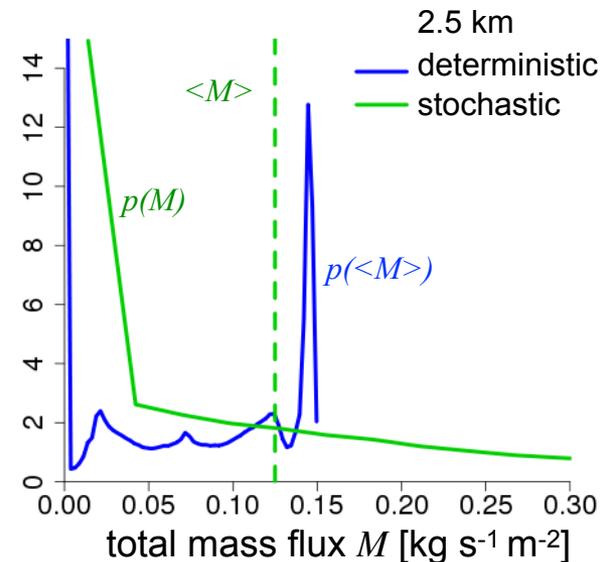
# How to deal with the artificial noise?

Artificial noise could be reduced/removed by using **dual grids** (Williamson 1999) or by **averaging** the input into the parameterization to filter out the unbelievable scales (Plant and Craig, 2008, Sakradzija et al., 2016).

Introducing  $p(m)$  instead of a bulk value  $\langle M \rangle$  (bulk) reduces the on-off behaviour!

We will:

- average (filter) the input to the parameterisation
- remove the limiters for the convective activity, mass flux values,... pass the decision to the stochastic scheme instead

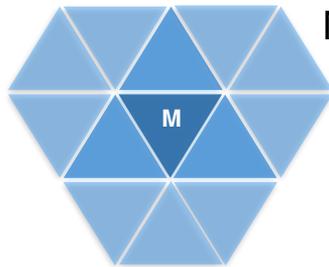


*Deterministic  $p(\langle M \rangle)$  versus stochastically sampled  $p(M)$ .*

# Coupling of the stochastic scheme in ICON

1. The Tiedtke-Bechtold shallow convection closure provides the bulk mass flux  $M$
2.  $M$  is used to constrain the mass flux distribution  $p(m)$
3.  $p(m)$  is randomly subsampled in each grid cell
4. as a result of subsampling, we get the scale-aware  $p(M)$

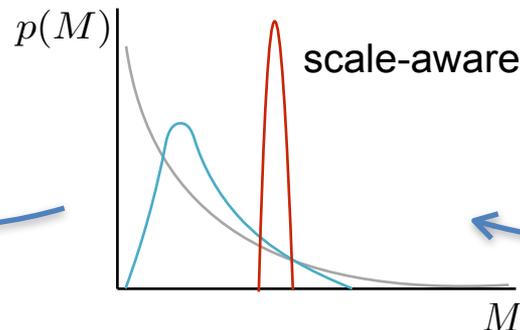
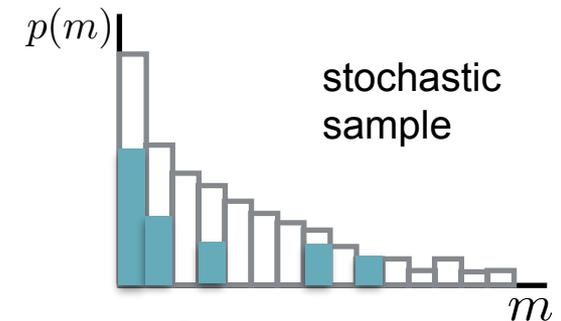
average the input



M bulk

use  $M, B, k=0.8$   
to constrain  $p(m)$

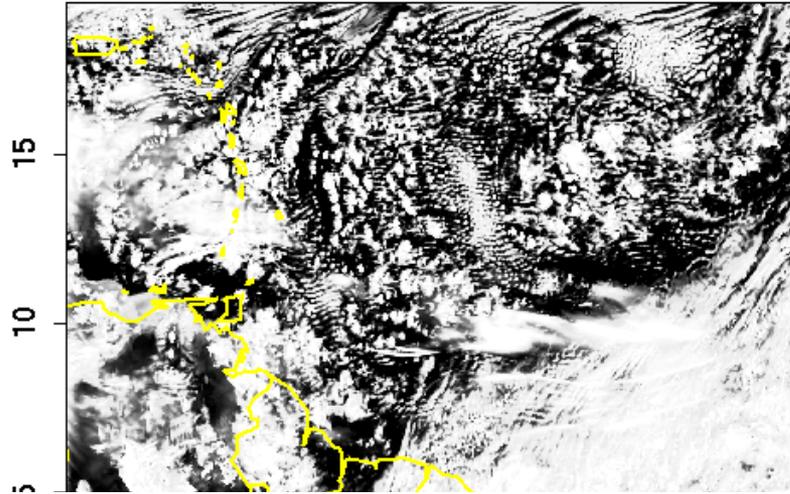
$$p(m) = \frac{k}{\lambda^k} m^{k-1} e^{-\left(\frac{m}{\lambda}\right)^k}$$



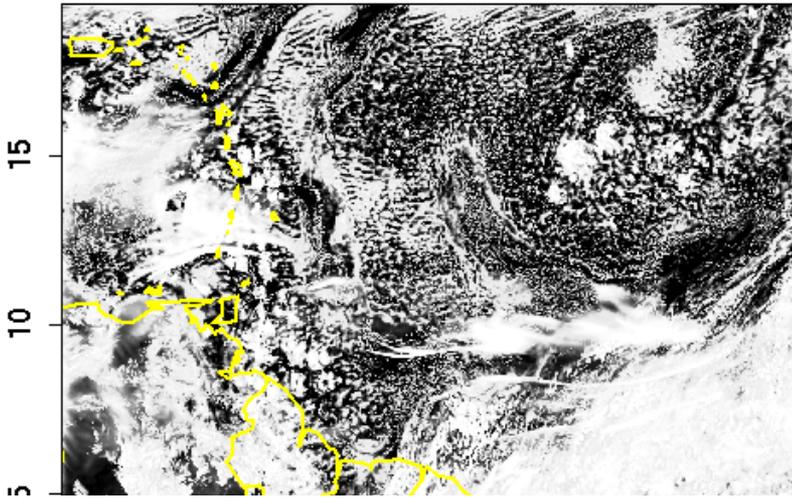
call the plume equations...

# The artificial noise is reduced by the stochastic version of convection

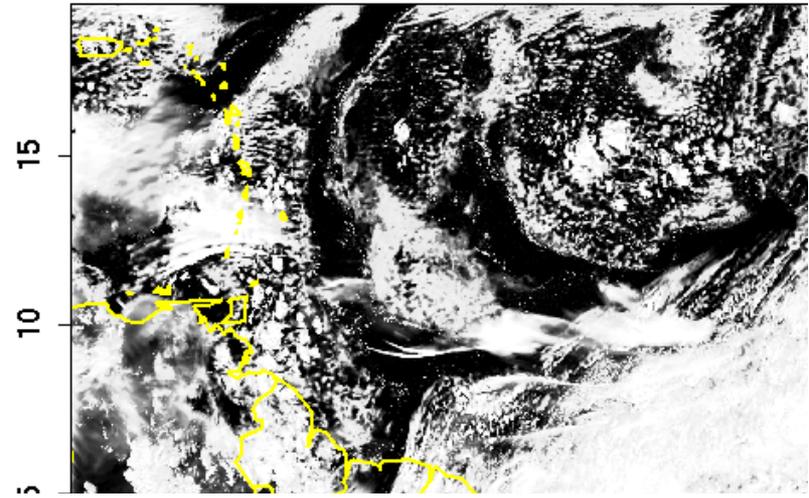
no convection



deterministic



stochastic



# Let's compare the Tropical Atlantic case to observations Meteosat SEVIRI

The Spinning Enhanced Visible and InfraRed Imager (SEVIRI) has the capacity to observe the Earth in 12 spectral channels.

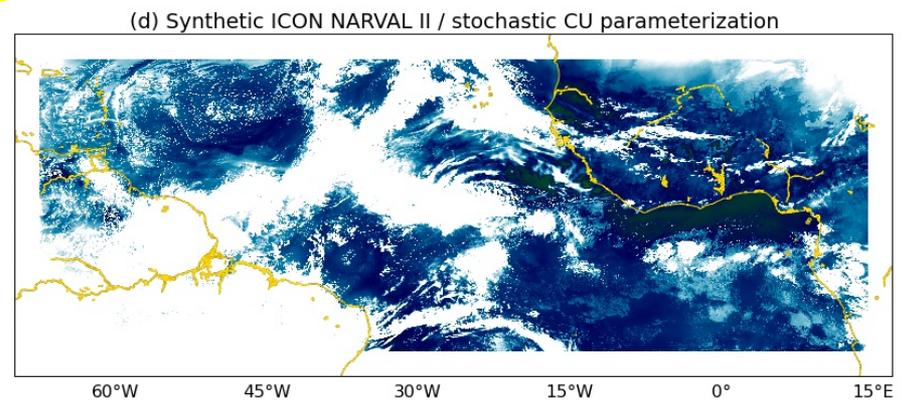
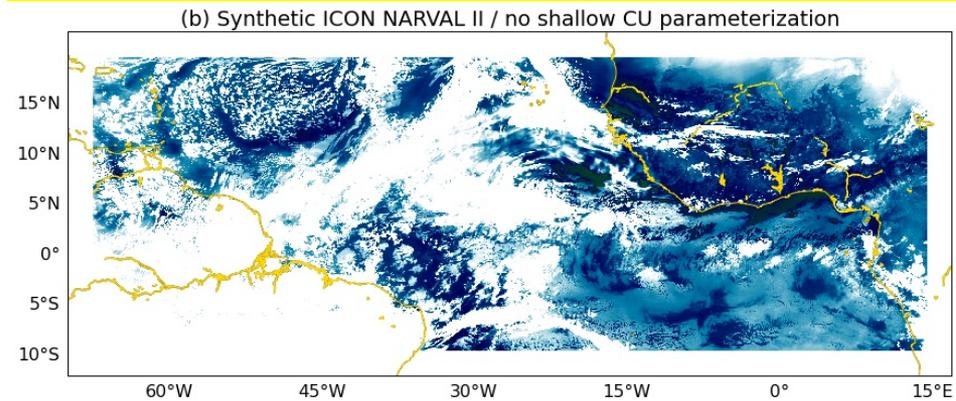
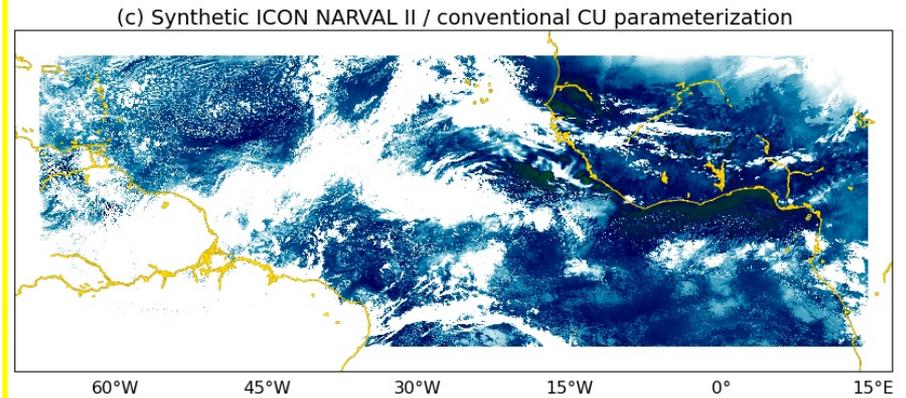
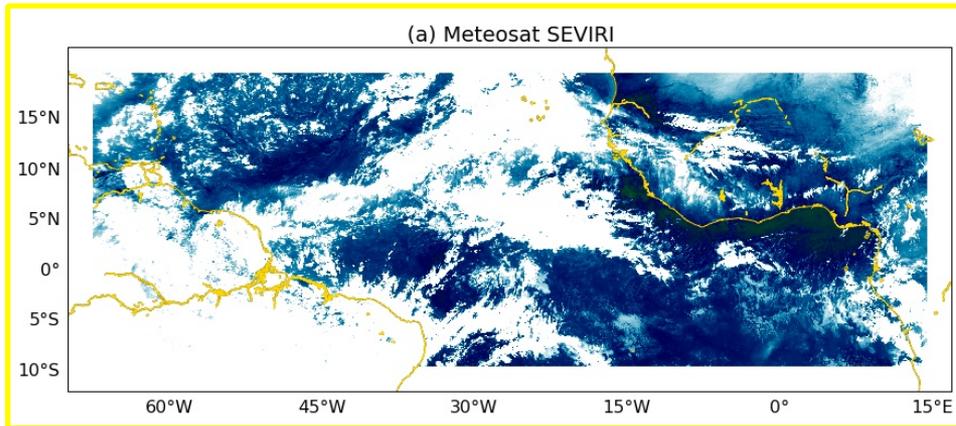
We use the channel at  $10.8 \mu\text{m}$  where the signal comes from the land or ocean surfaces or the top-layers within clouds or a combination of the two.

A radiative transfer scheme, the satellite forward operator, translates the simulation output into synthetic satellite radiances that can be directly compared to observations.

*F. Senf, D. Klocke and M. Brueck, Size-resolved evaluation of simulated deep tropical convection 2017, to be submitted soon*

1. Meteosat SEVIRI (msevi)
2. synthetic satellite radiances no convection (synsat)
3. -||- deterministic version (conv)
4. -||- stochastic version (stoch)

# Synthetic satellite radiances



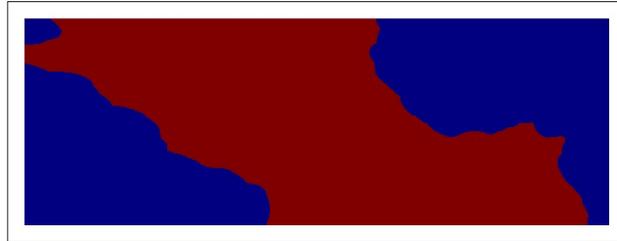
Visualization by Fabian Senf



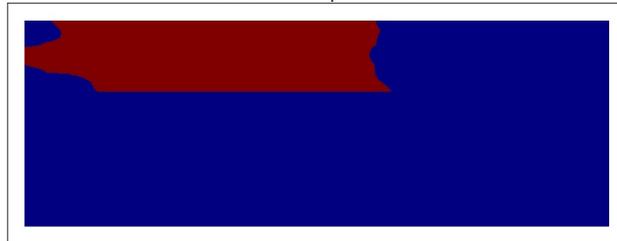
10.8 Brightness temperature (K)

# Synthetic satellite radiances - regions

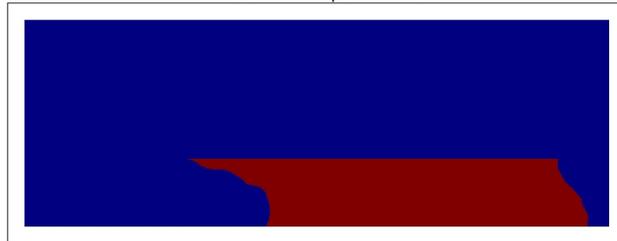
Full Atlantic Ocean

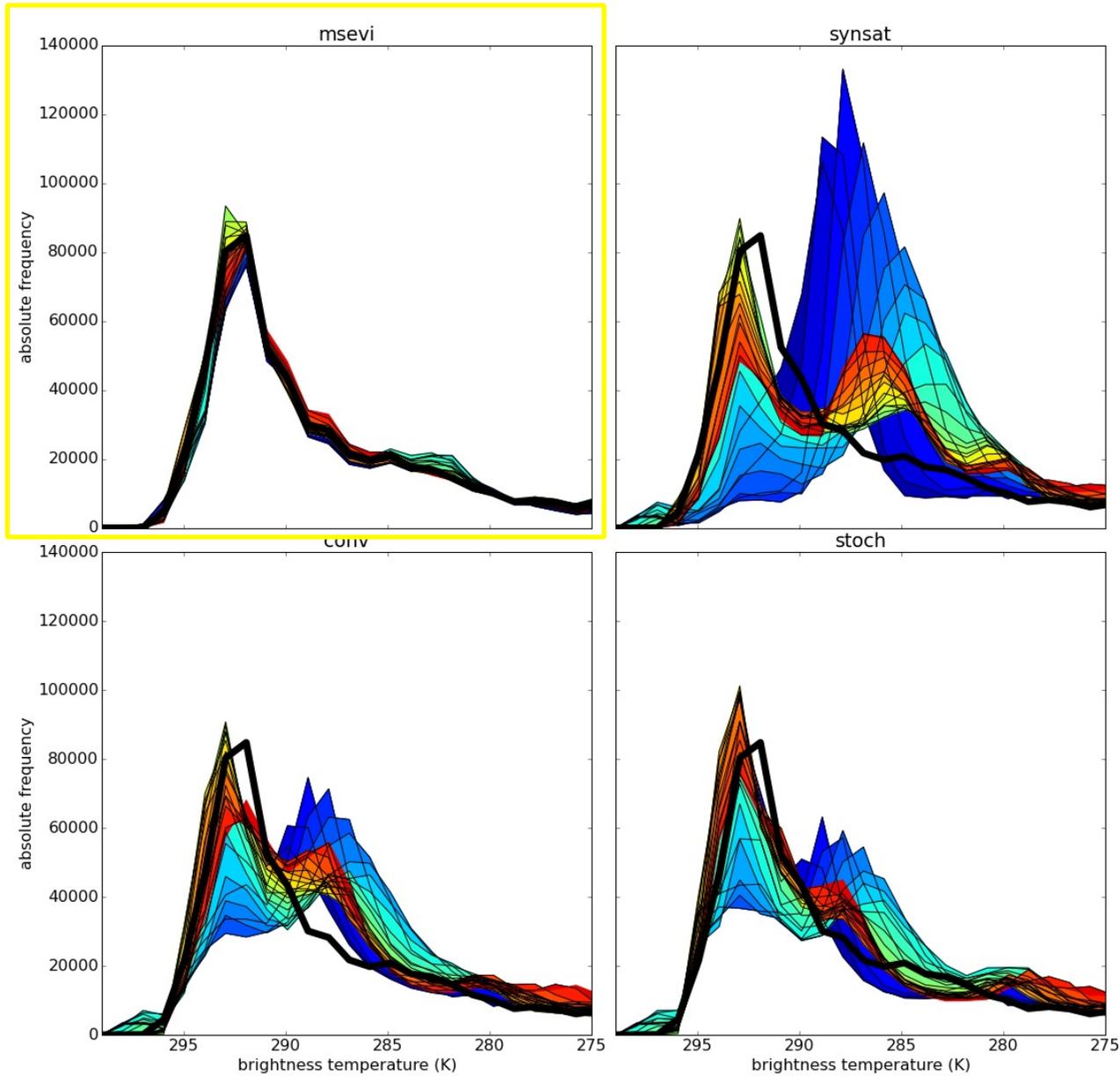


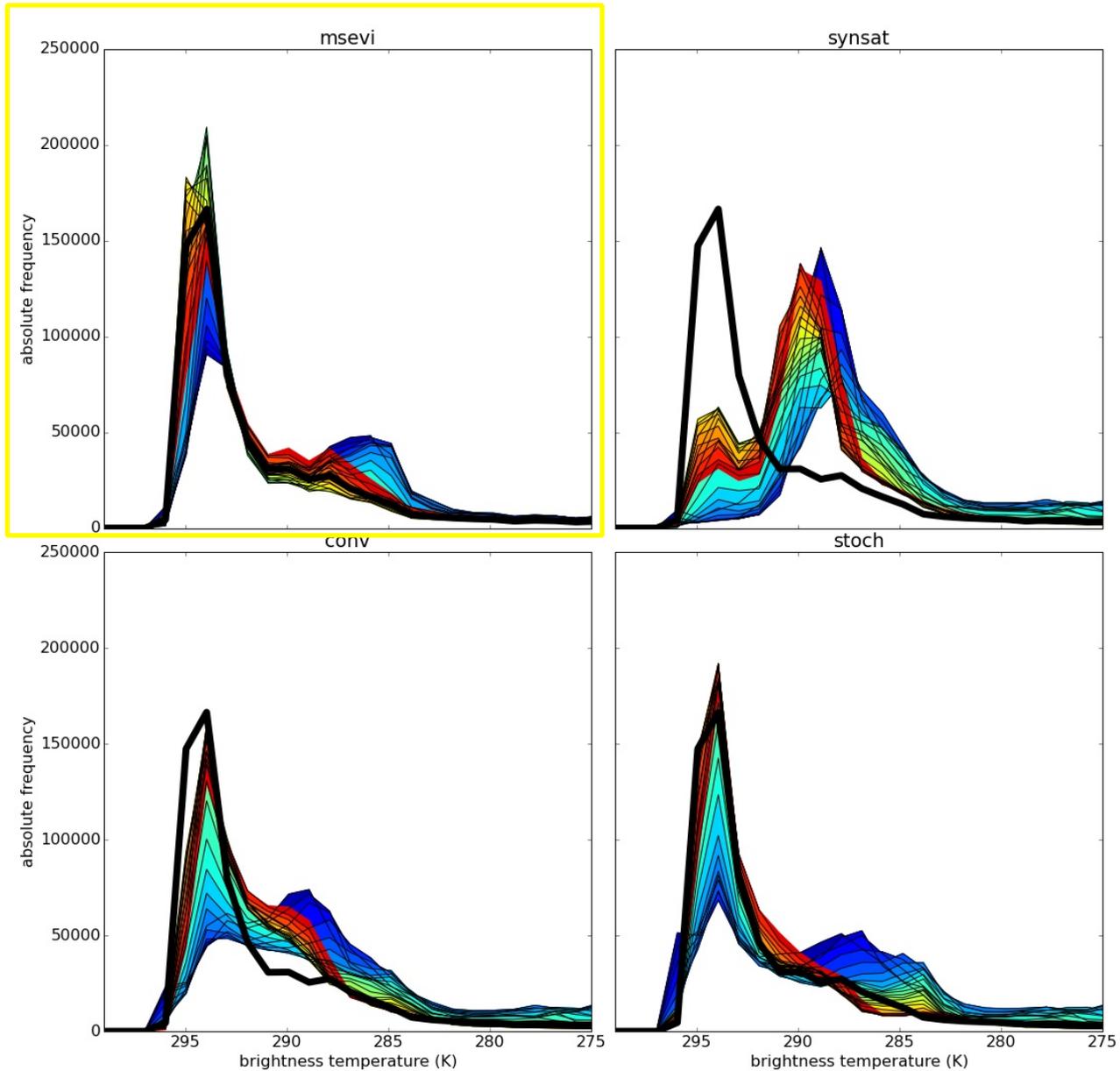
Northern Subtropical Atlantic



Southern Subtropical Atlantic







## Summary

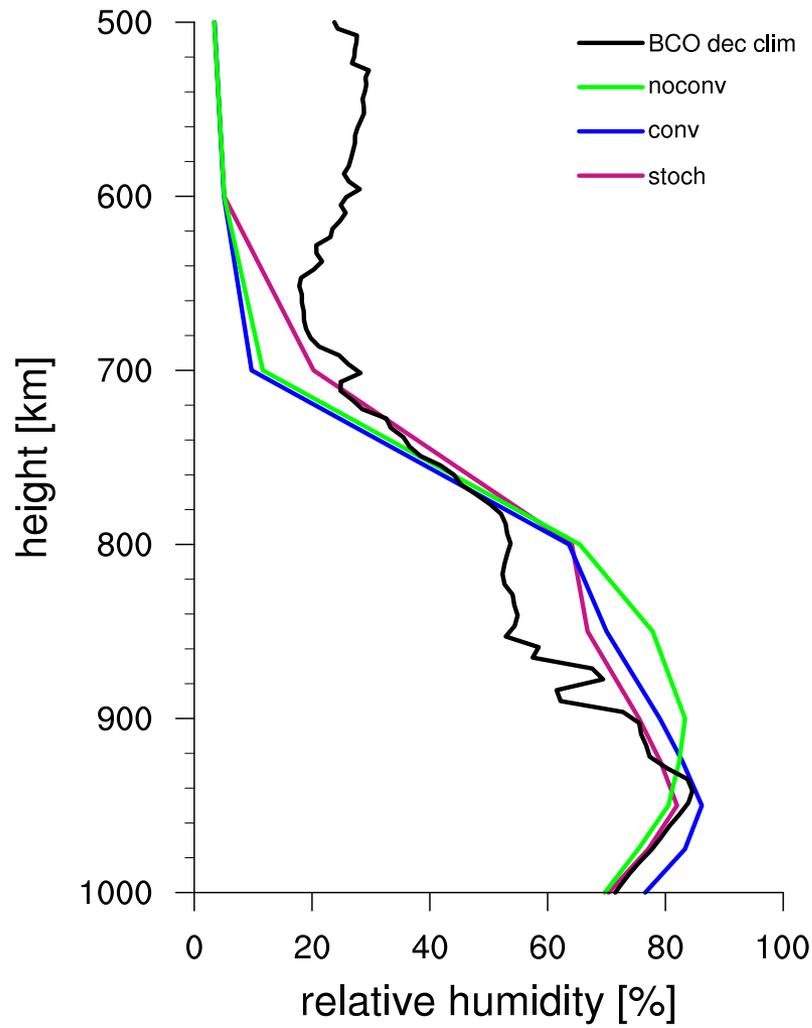
A holistic approach to modelling of convection is needed in the gray zone. Challenges stem from all components: subgrid physics, dynamics and their coupling.

Subgrid convection has to be parameterized using a stochastic scale-aware approach.

Stochastic perturbations (physically constrained) have a power to correct model dynamics.

A stochastic version of shallow convection reduces the noise by different truncation scales in physics and dynamics and by random sampling of  $p(m)$ .

A stochastic parameterization based on could ensembles is a promising method for convection-permitting models - it can address all three main challenges.



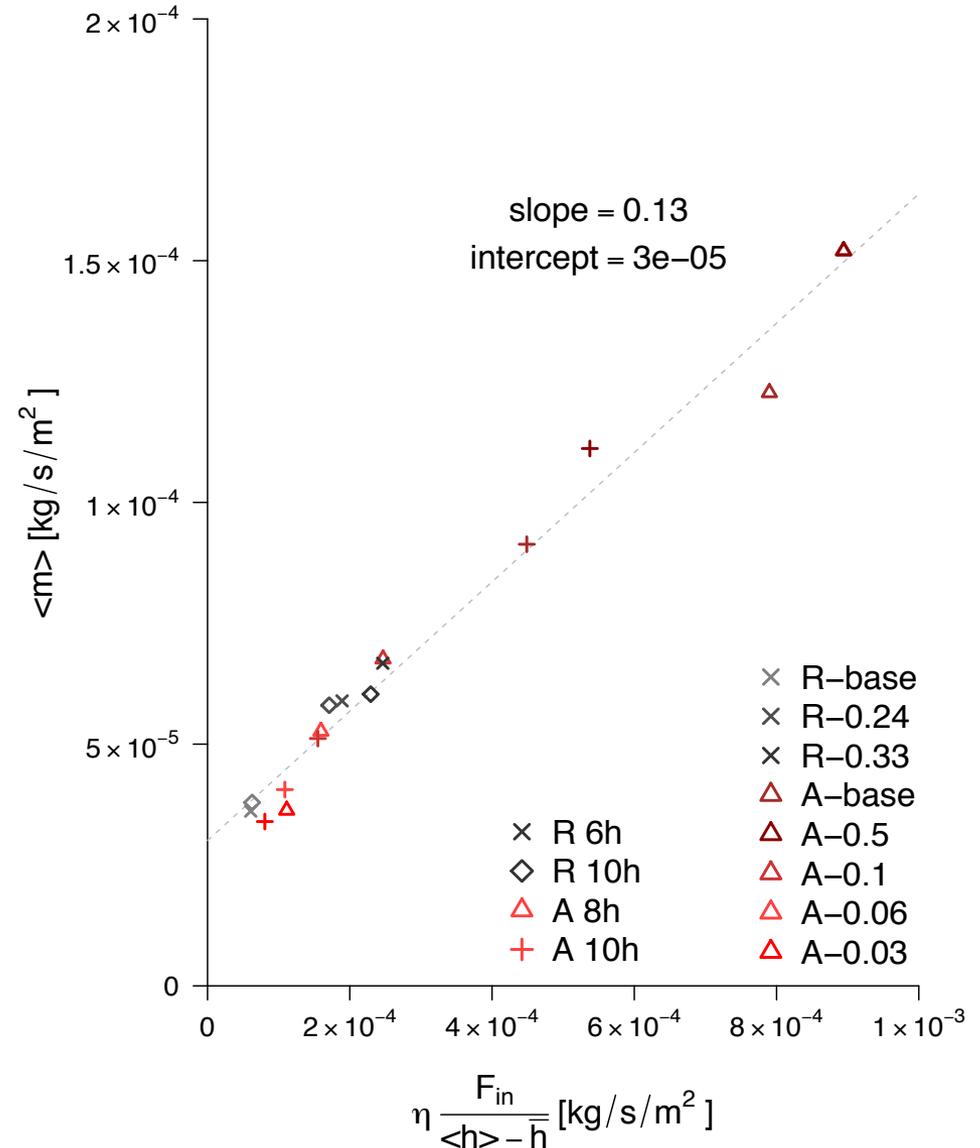
# Why is B important?

$$\langle m \rangle = m_0 + C_1 \frac{\eta F_{in}}{\langle h \rangle - \bar{h}}$$

what controls the distribution? - heat cycle and the Bowen ratio!

*Sakradzija, M., and C. Hohenegger, What determines the distribution of shallow convective mass flux through cloud base?*

J. Atmos. Sci., 2017



We have a physically constrained probability distribution of cloud base mass fluxes.

sampling distribution:

$$p(m) = \frac{k}{\lambda} \left(\frac{m}{\lambda}\right)^{k-1} e^{-(m/\lambda)^k}$$

physical constraints:

$$\sum p_i = 1$$

$$\frac{\tau_i}{\langle \tau \rangle} = \left(\frac{m_i}{\langle m \rangle}\right)^\gamma \quad \gamma = k = 0.8$$

$$\langle m \rangle = m_0 + C_1 \frac{\eta F_{in}}{\langle h \rangle - \bar{h}}$$

No need for a statistical distribution fitting under different meteorological conditions, different regions, warmer climate, etc...

This also means that the parameterisation will not be "tunable".

# Deviations from exponential due to cloud lifecycles

Theory of extreme events:

Long-term correlations with a **power-law** decay of the autocorrelation function lead to **Weibull** distributions of return intervals between rare events.

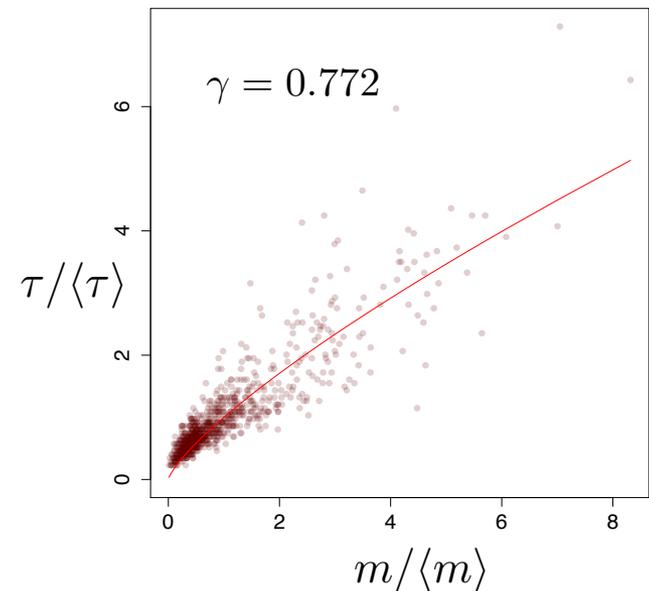
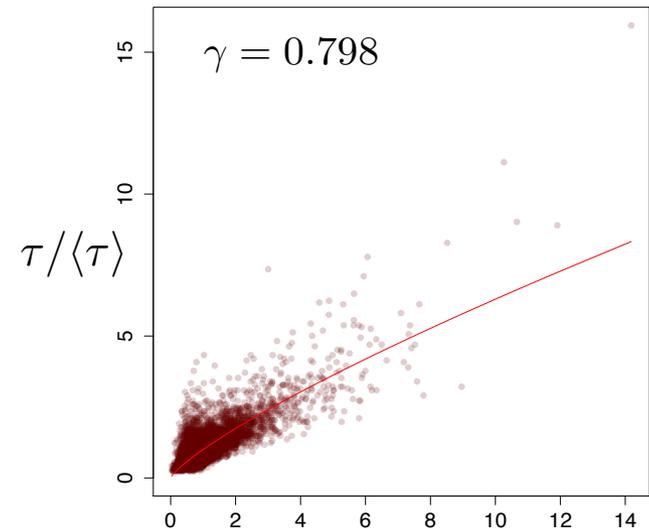
In that case the power-law exponent of the autocorrelation function,  $t^{-\gamma}$  can be assumed equal to the shape parameter of the Weibull distribution,  $k$  (e.g. Bunde et al. 2003; Blender et al. 2015).

$$\tau / \langle \tau \rangle = (m / \langle m \rangle)^\gamma$$

$$k \approx \gamma \approx 0.8$$

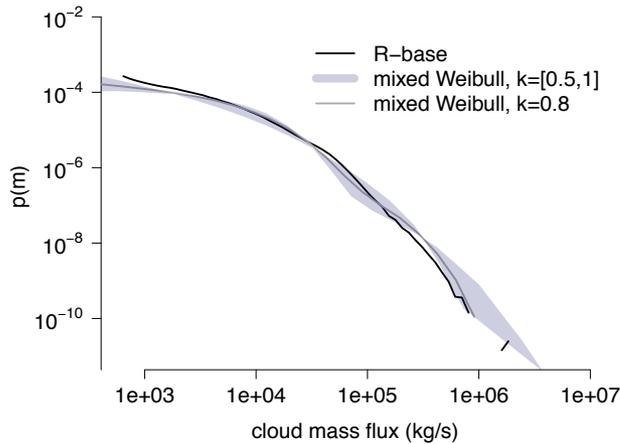
$k$  - shape parameter  
of the Weibull distribution

$$p(m) = \frac{k}{\lambda} \left( \frac{m}{\lambda} \right)^{k-1} e^{-(m/\lambda)^k}$$

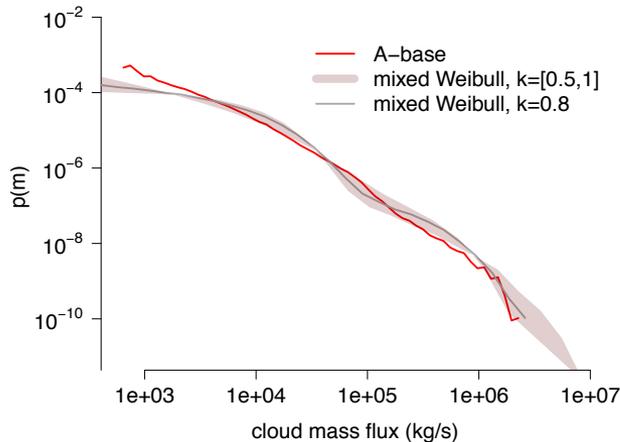


# Deviations from exponential due to cloud lifecycles

a) RICO

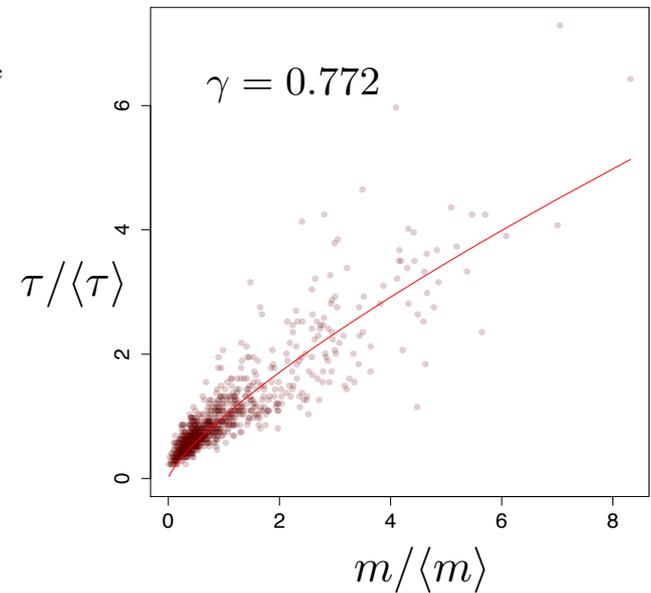
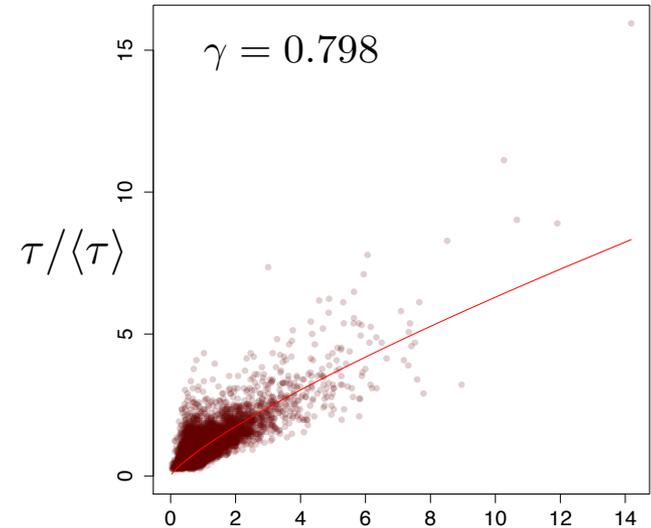


b) ARM

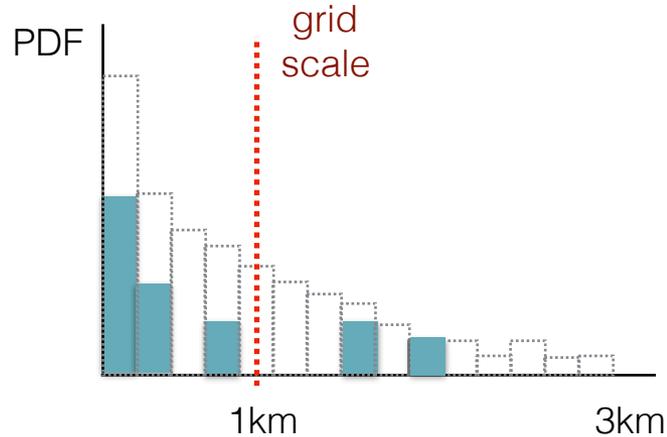


$$k \approx \gamma \approx 0.8$$

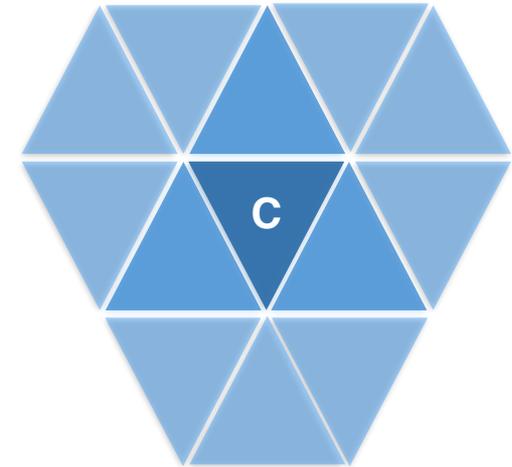
$$p(m) = \frac{k}{\lambda} \left(\frac{m}{\lambda}\right)^{k-1} e^{-(m/\lambda)^k}$$



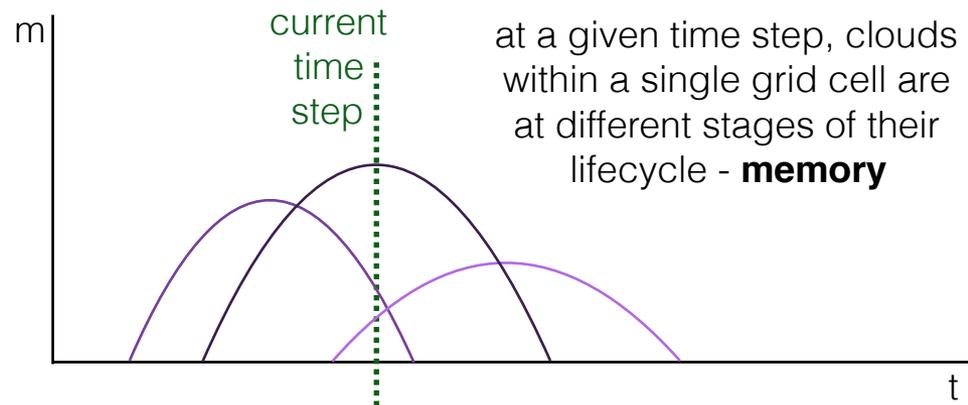
# Spatial and temporal non-locality



if a cloud does not fit into a single cell, it is allowed to spread over neighbouring cells



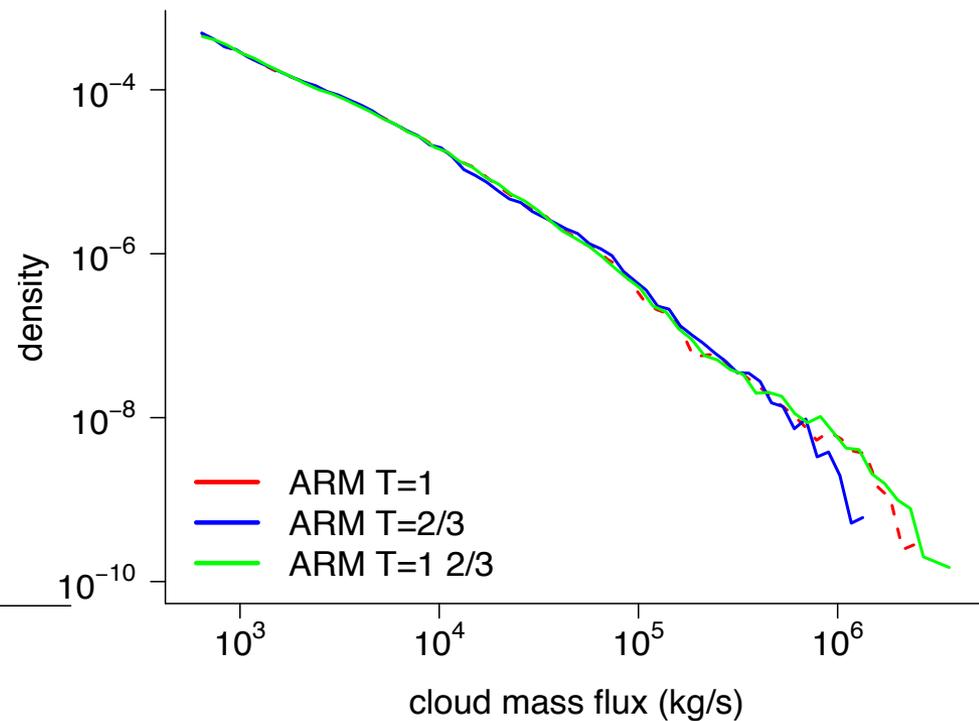
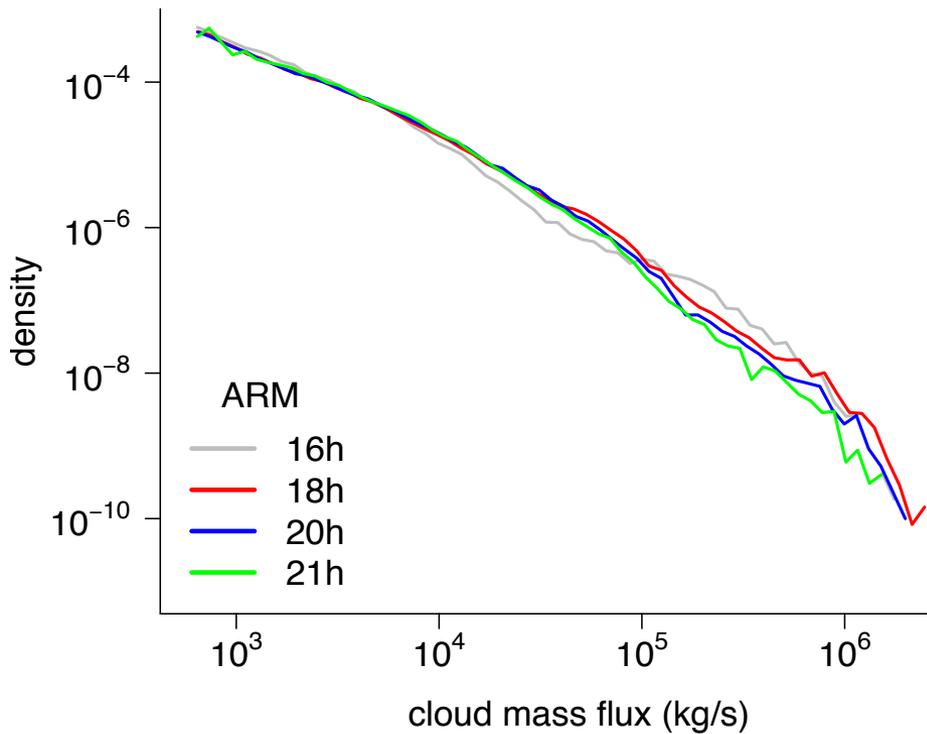
clouds live longer than a single model time step



# 1) Memory: diurnal cycle

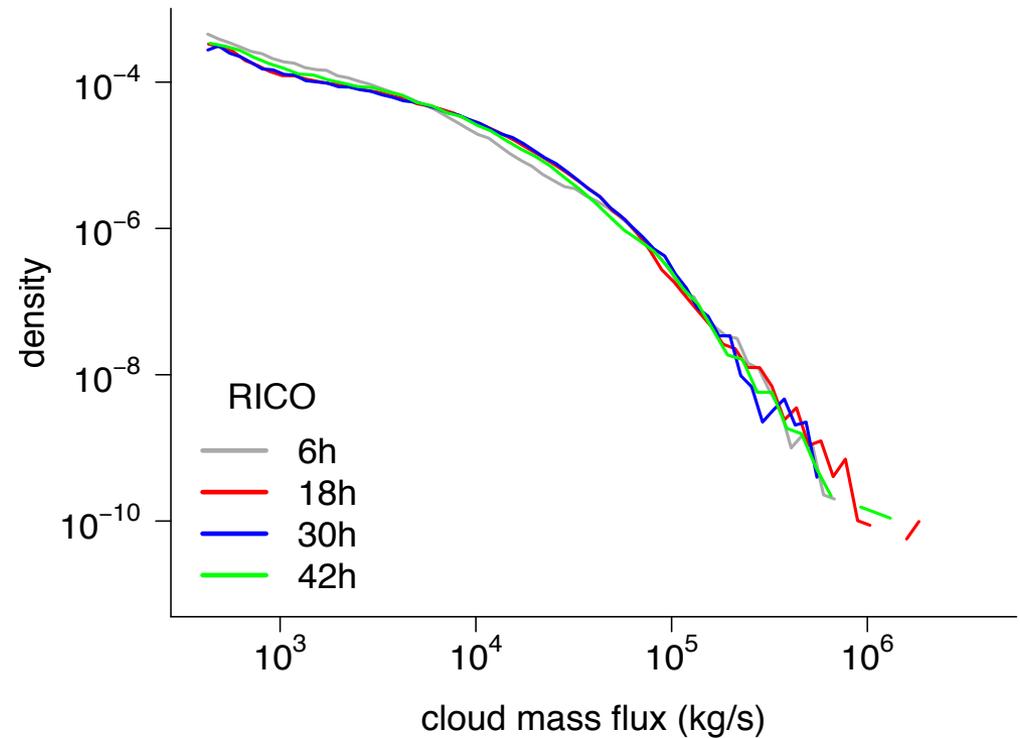
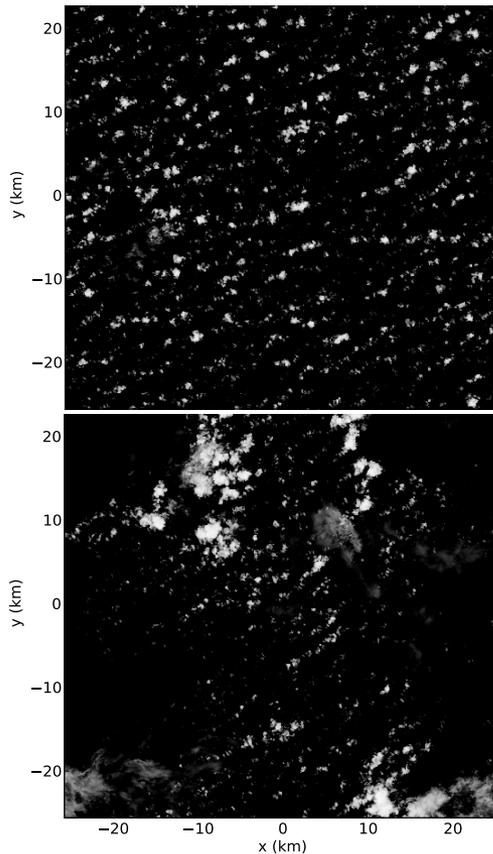
Diurnal cycle of convection is not responsible for the overall distribution shape.

no strong self-organization,  
but still a power-law-like shape!



## 2) Self-organization

Different degrees of organization between RICO and ARM cannot explain the differences in  $p(m)$



### 3) Surface flux magnitude

- strength of the surface fluxes or
- their ratio  $B$

