Entrainment, Detrainment, Multiplumes & Stochastic Convection

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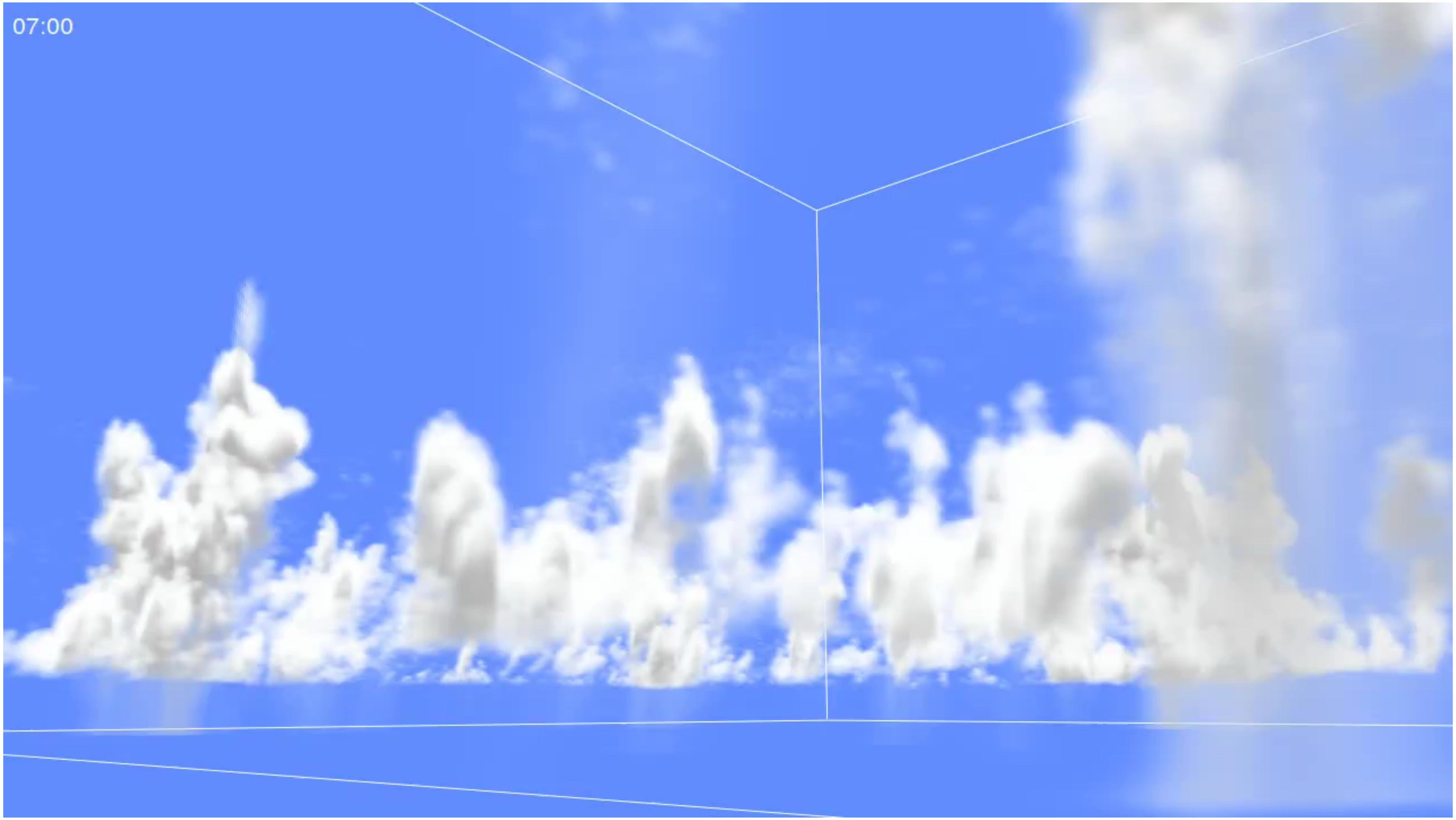
1.

Entrainment

But what about detrainment?

S.J. Boing, A.P. Siebesma, J.D. Korpershoek and Harm J.J. Jonker
GRL (2012)

Dutch Atmospheric Large Eddy Simulation Model (DALES)

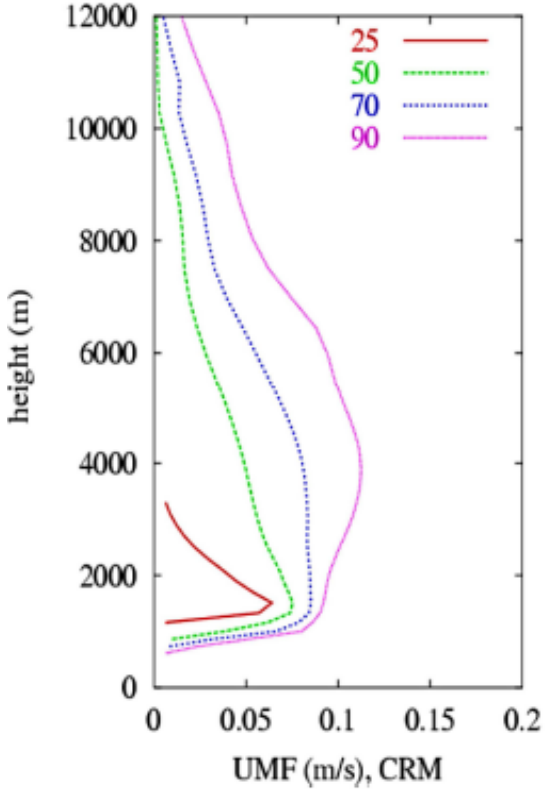


https://github.com/dalesteam/dales Heus et al. Geoscientific Model Development (2010)

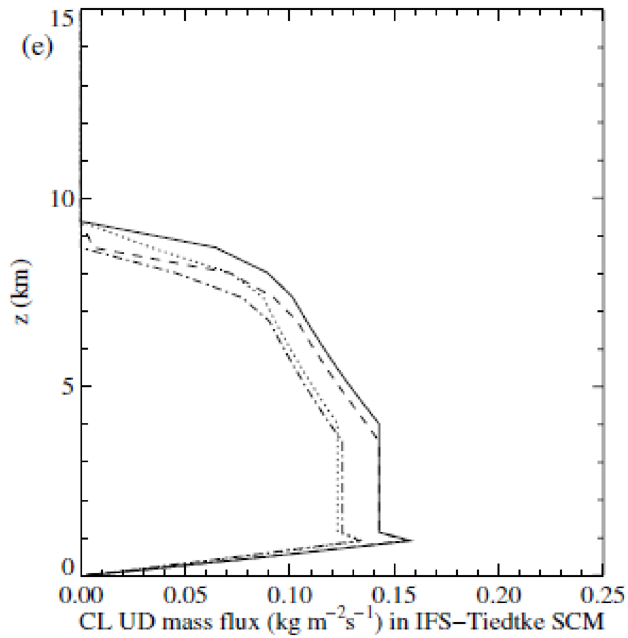
Motivation

Derbyshire et al. QJRMS (2004)

CRM



Single Column Model
(ECMWF) 2004



Mass Flux Profiles

For different environmental RH-conditions

New ECMWF entrainment parameterization (Bechtold 2008 QJRMS)

$$\varepsilon = \varepsilon_0 \left(1.3 - RH(z)\right) f_{scale}$$

Larger entrainment rates: lower cloud top height.

Is this justified?

Kain_Fritsch mixing (1) (Kain Fritsch JAS1990)

$$\frac{\partial}{\partial z}\ln M = \epsilon - \delta$$

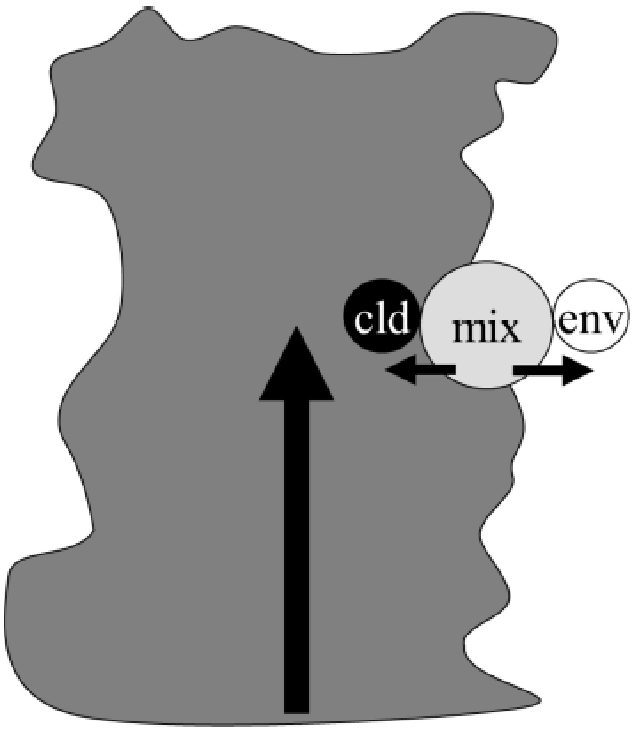
- Fractional inflow rate ε_0

- Assume uniform distribution of all possible mixtures

(Bretherton et al. MWR 2004,

Raymond & Blyth JAS 86)

- Entrainment/Detrainment rate dependent on buoyancy

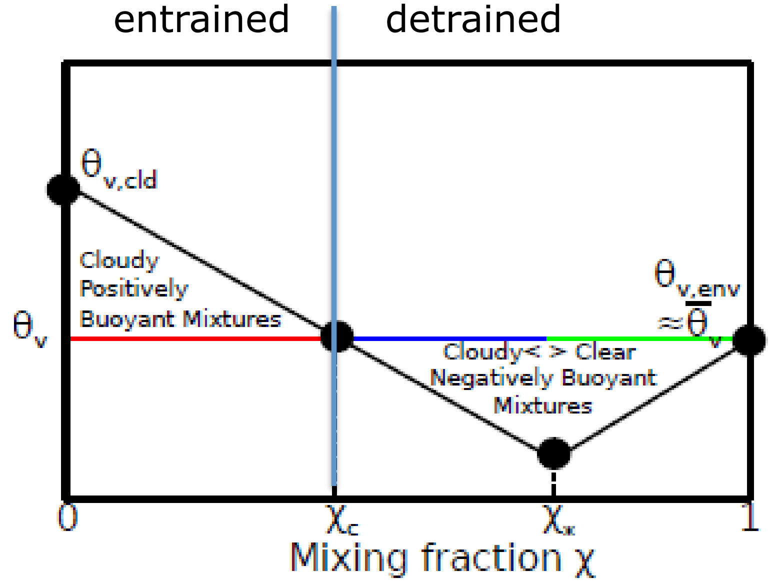


Kain_Fritsch mixing (2) (Kain Fritsch JAS1990)

$$\epsilon = 2\int_0^{\chi_c} \chi p(\chi) d\chi = \epsilon_0 \chi_c^2$$

$$\delta = 2\int_{\chi_c}^{1} (1-\chi) p(\chi) d\chi = \epsilon_0 (1-\chi_c)^2$$

$$\frac{\partial}{\partial z}\ln M = \epsilon_0 (2\chi_c - 1)$$



$$\chi_c = (c_p \pi / L) \frac{\Delta\theta_v}{q_{se}(\beta - \alpha)(1 - RH) - \alpha q_{\ell u}}$$

$\Delta\theta_v \uparrow \;\; => \;\; \chi_c \uparrow$

$RH \uparrow \;\; => \;\; \chi_c \uparrow$

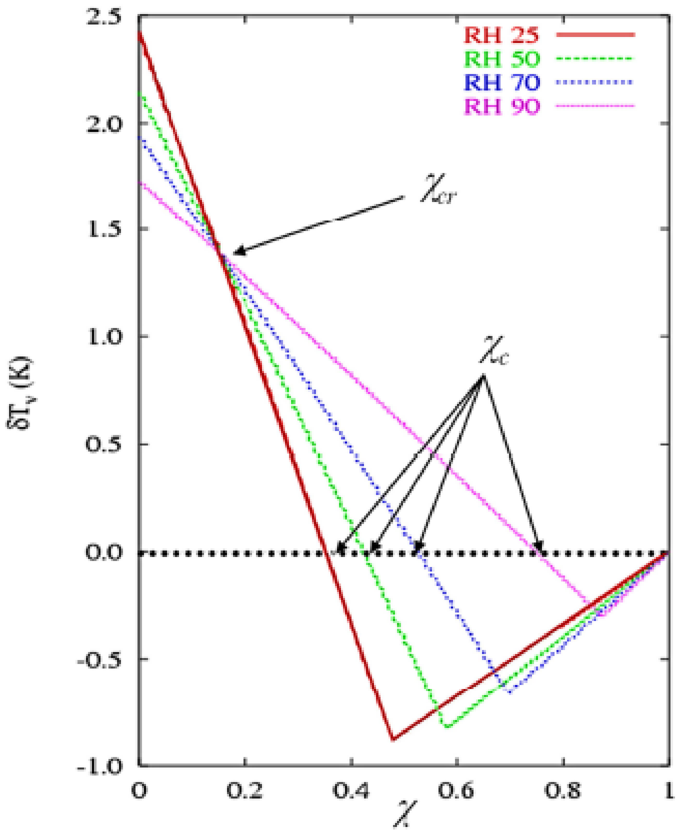
De Rooy and Siebesma MWR 2008

Opposite RH sensitivity for entrainment in plume models

- $\epsilon = \epsilon_0 \chi_c^2$

Larger RH => larger χ_c => higher entrainment => lower cloud top

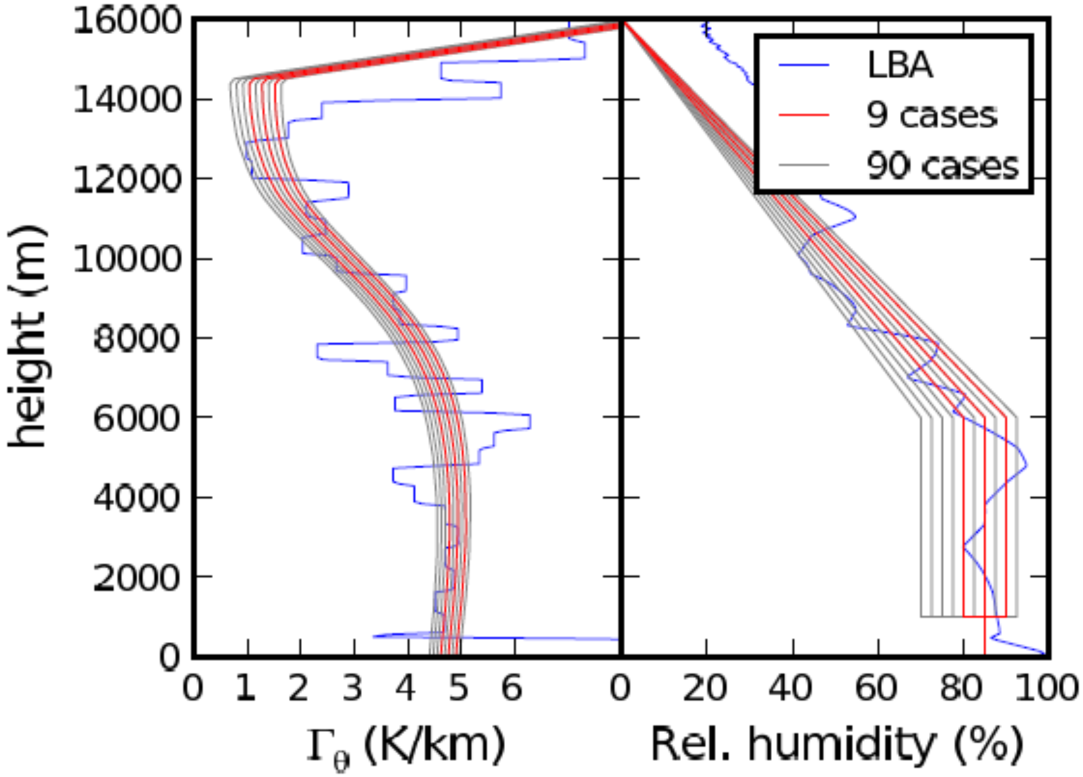
But what about detrainment…?



Msc thesis Sander Jonker (2004)

Deep Convection: the case

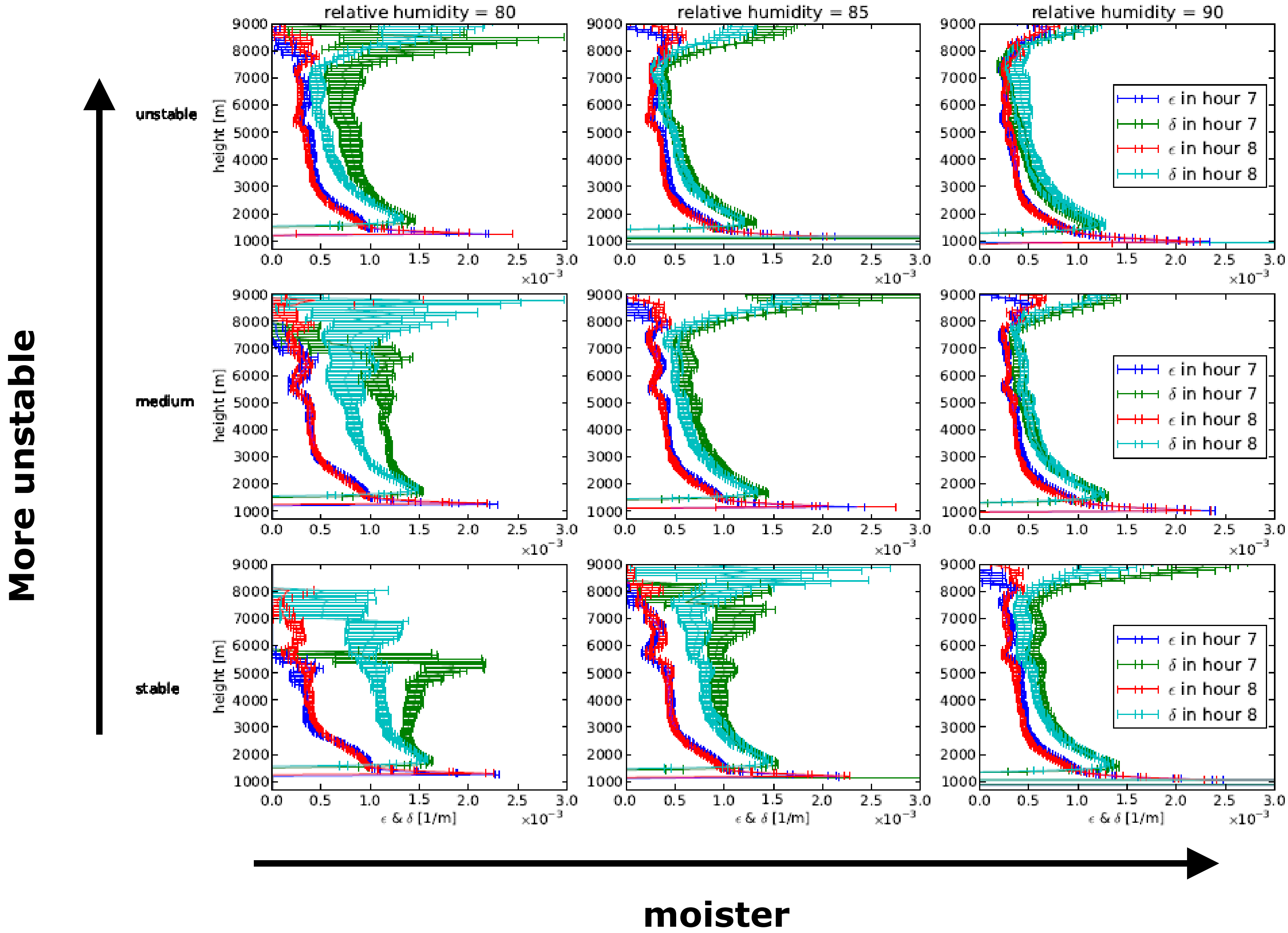
Similar set up as in: Wu, Stevens, Arakawa JAS 2009



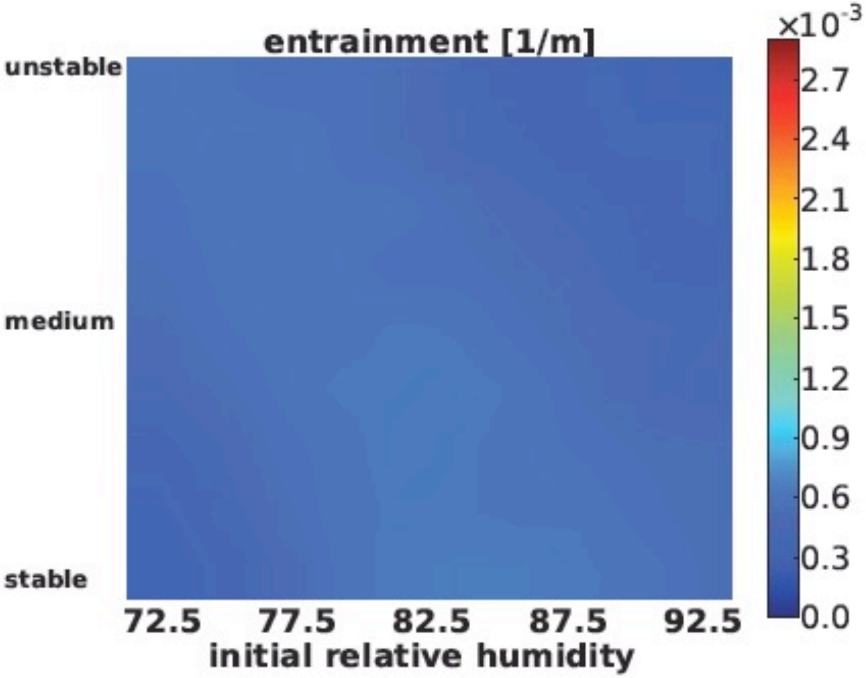
- Domain Size 75X75X25km
- $\Delta x = \Delta y = 150$m $\Delta z = 40\sim190$m
- Fixed surface fluxes:
  - LHF ~350W/m2
  - SHF ~150W/m2
- No windshear
- No radiation

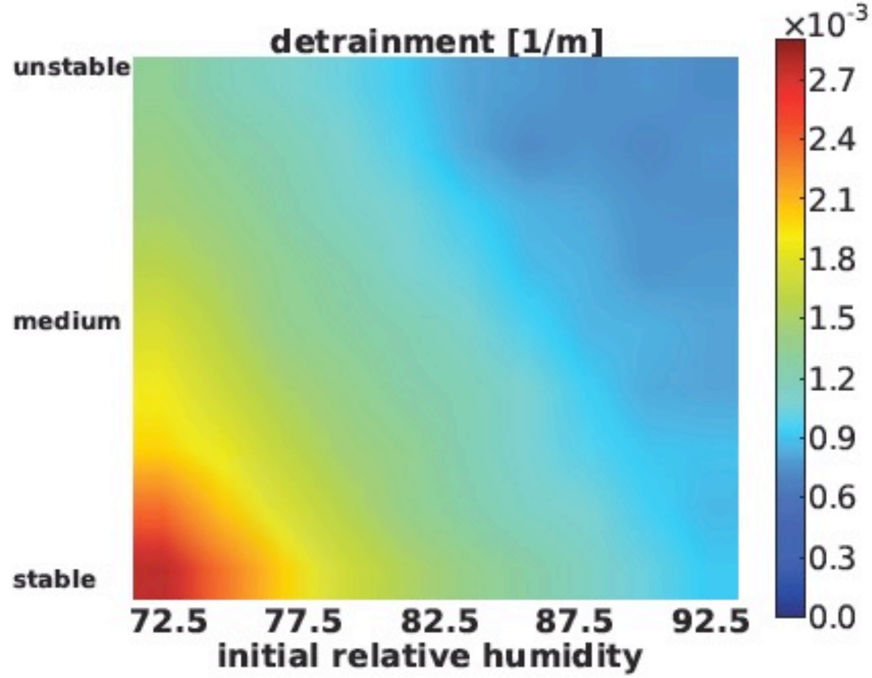
Most cases repeated 5 times with different random initialisation (200 similations)

entrainment and detrainment (hour 7 & 8)



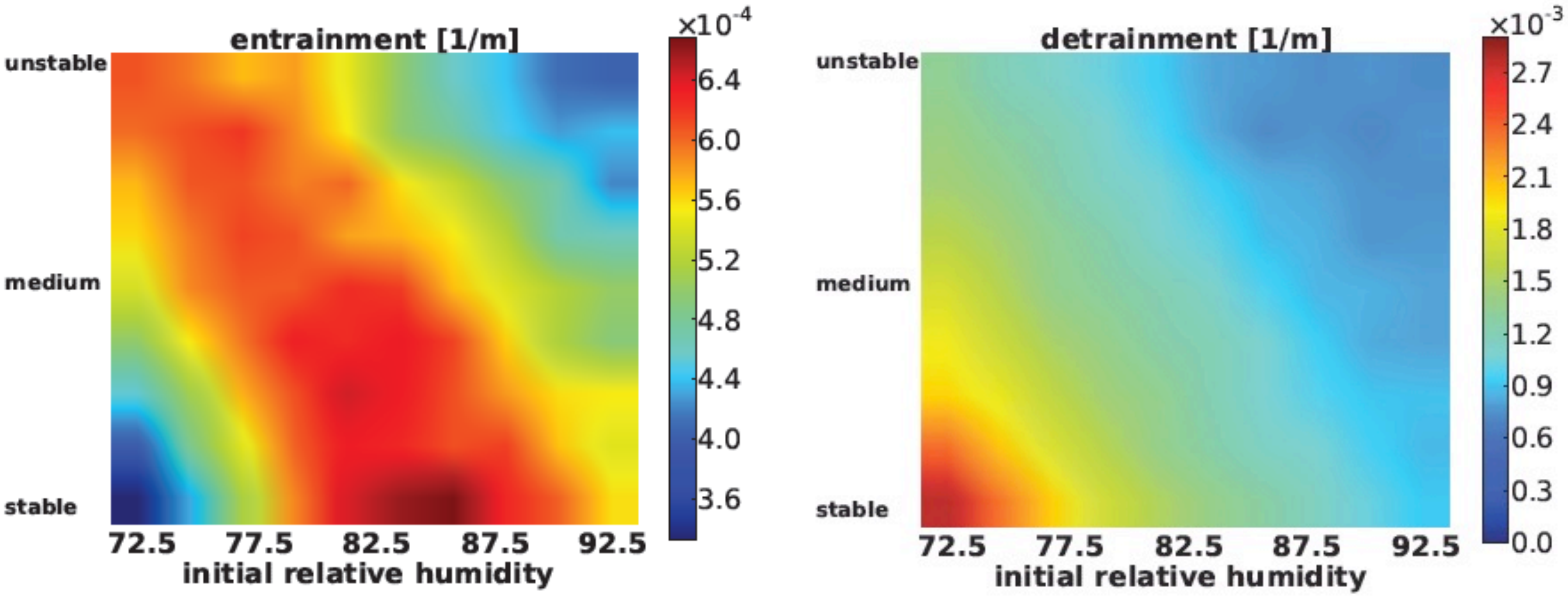
entrainment and detrainment (2000~3000m)





- Detrainment decreases with increasing humidity
- Detrainment decreases with increasing instability
- Variations of Entrainment small……..compared with the variations of detrainment

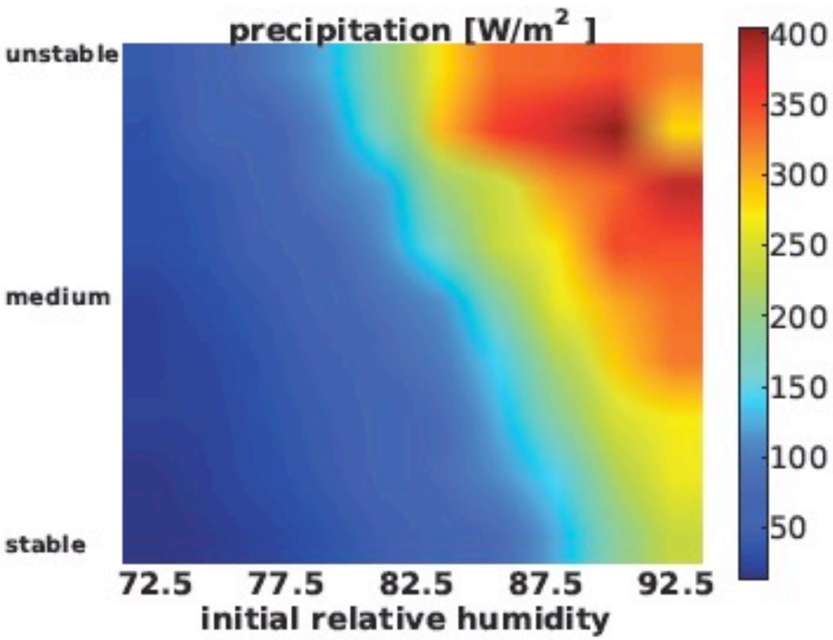
entrainment and detrainment (2000~3000m)

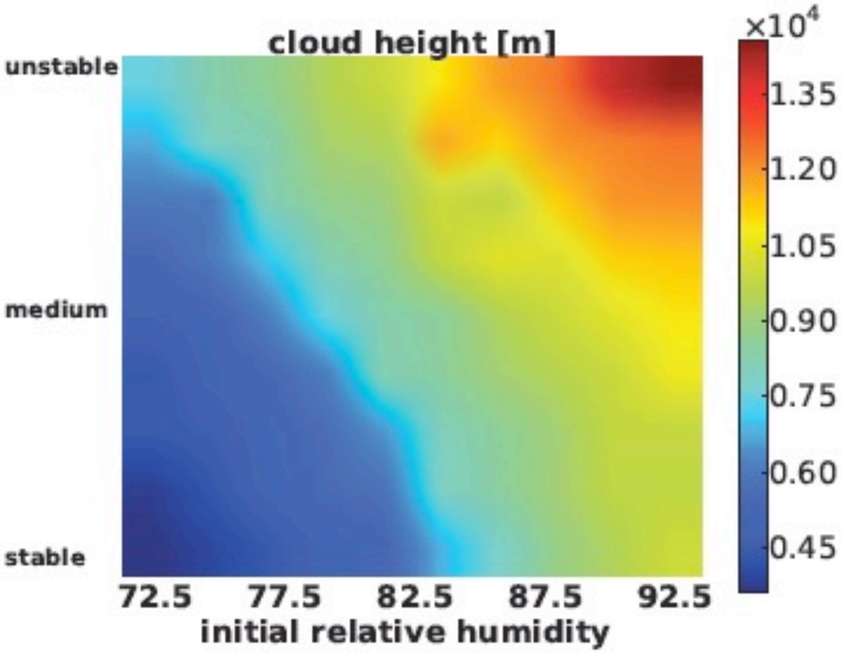


- Entrainment decreases with increasing RH, instability …. But differences are much smaller

precipitation and cloud top height

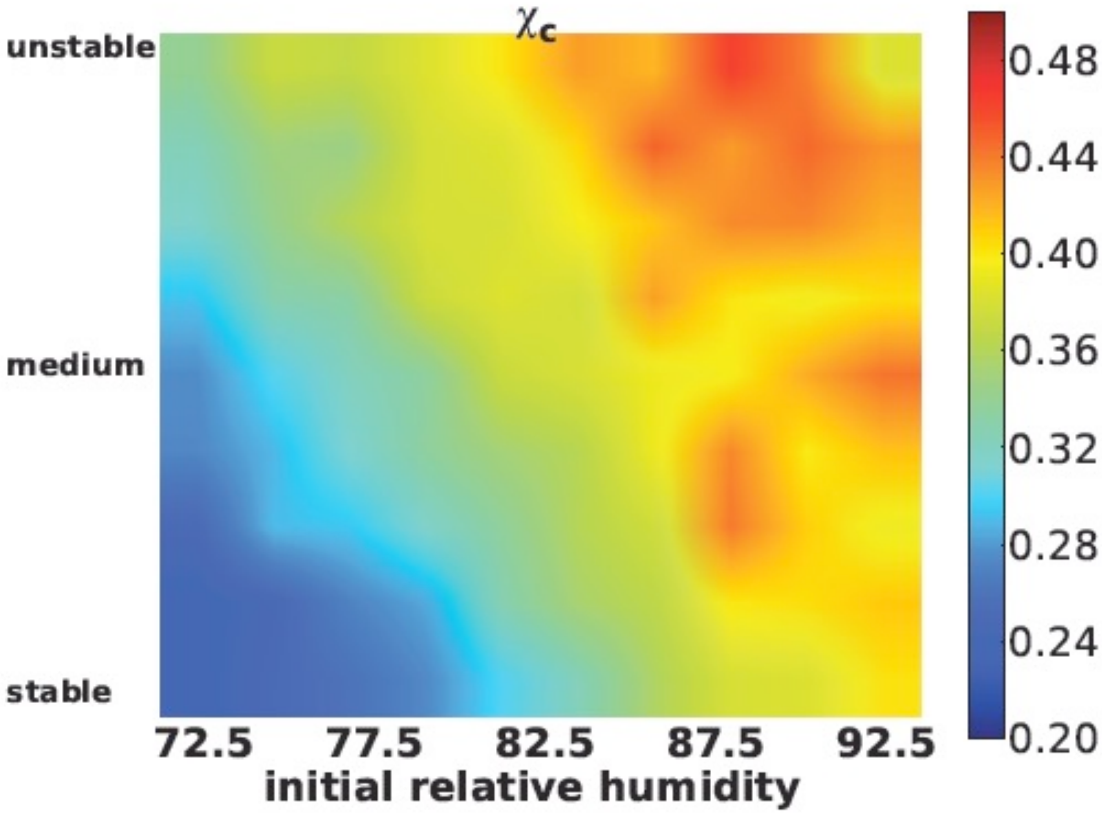
Cloud height ~ 0.01 M_{max}





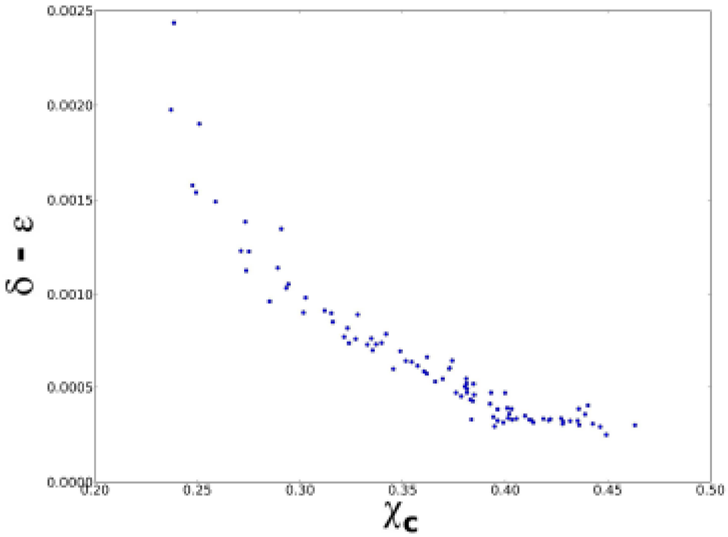
Precip , cloud top height increase with increasing RH, instability

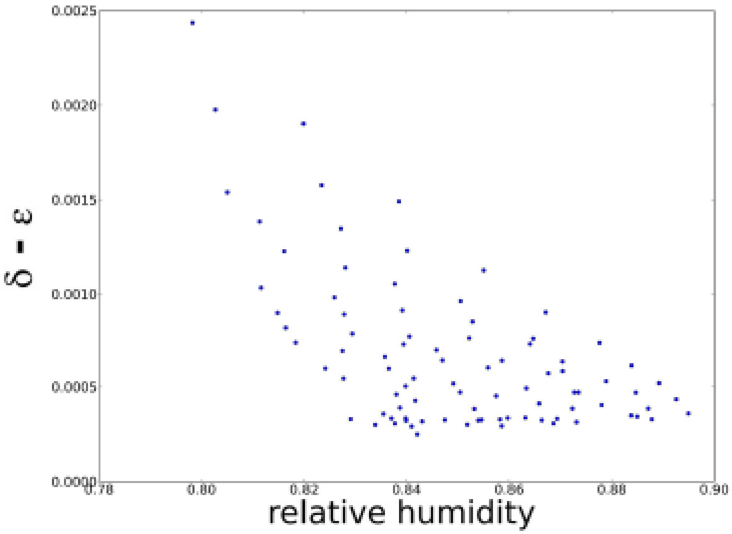
How about χ_{crit} (2~3km)?



χ_{crit} as the key parameter (2~3km)

$$\frac{\partial}{\partial z}\ln M = \epsilon - \delta$$



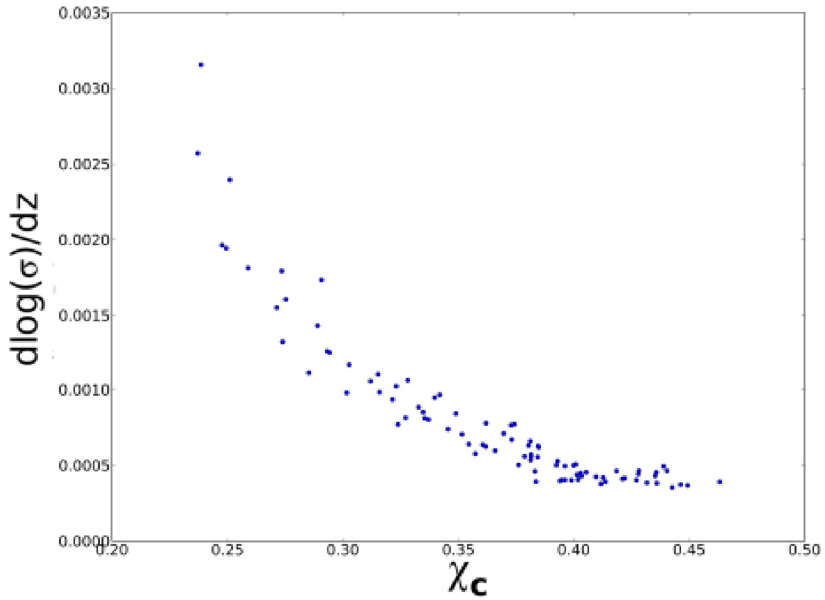


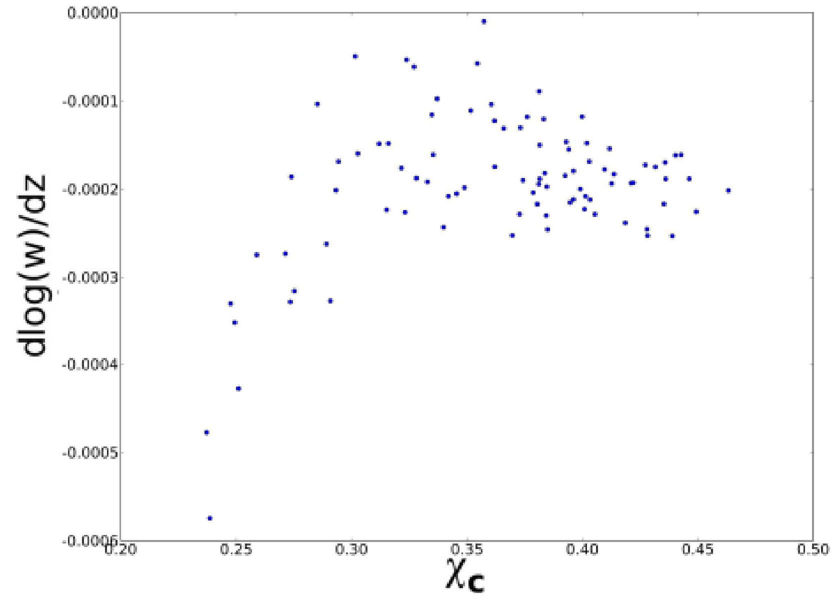
$$M \equiv \rho_0 \sigma w_c$$

Variation due to cloud core fraction or due to incore vertical velocity?

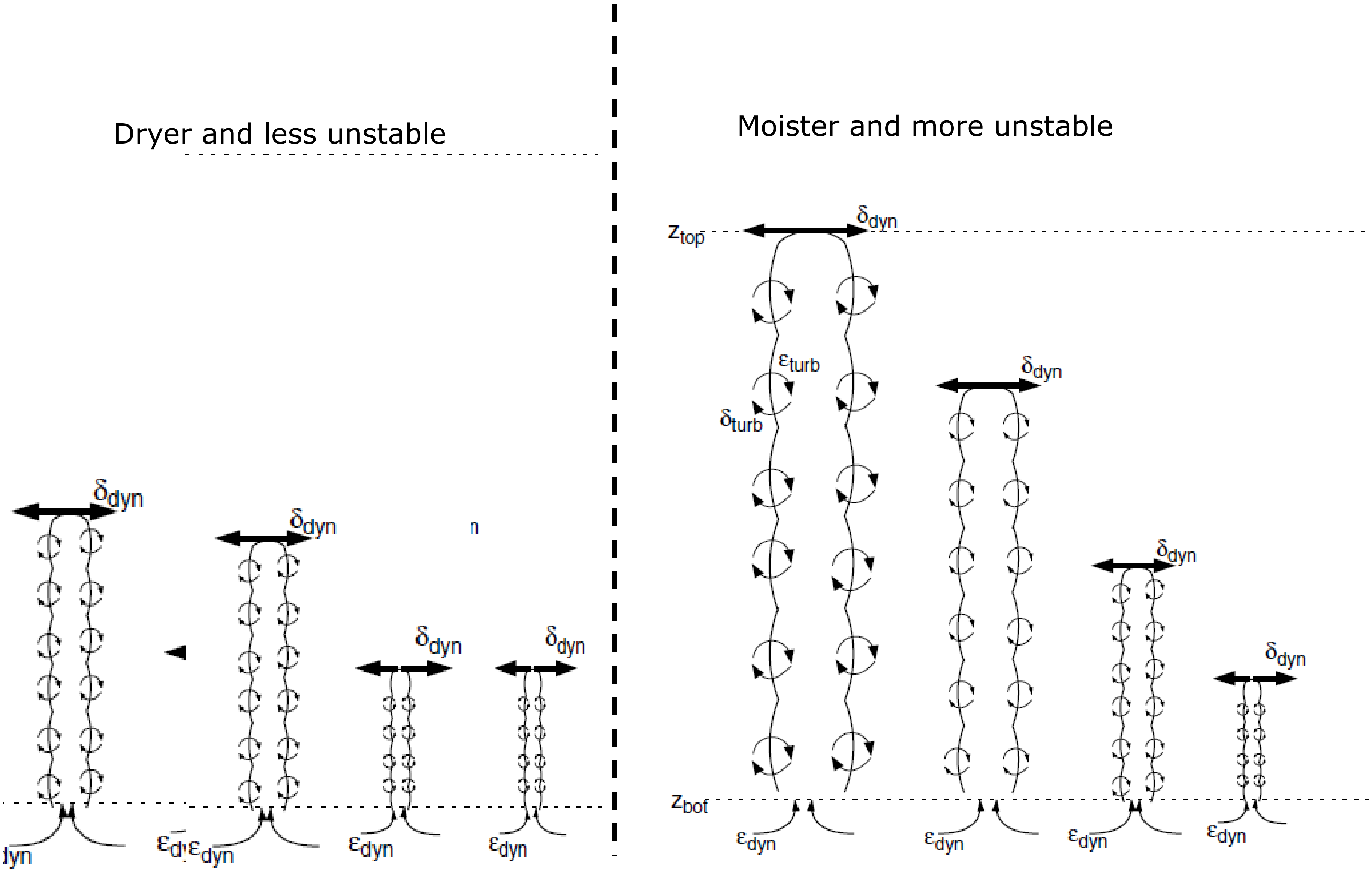
Cloud fraction and vertical velocity

$$\frac{\partial}{\partial z}\ln M = \frac{\partial}{\partial z}\ln\sigma + \frac{\partial}{\partial z}\ln\rho_0 + \frac{\partial}{\partial z}\ln w_c$$



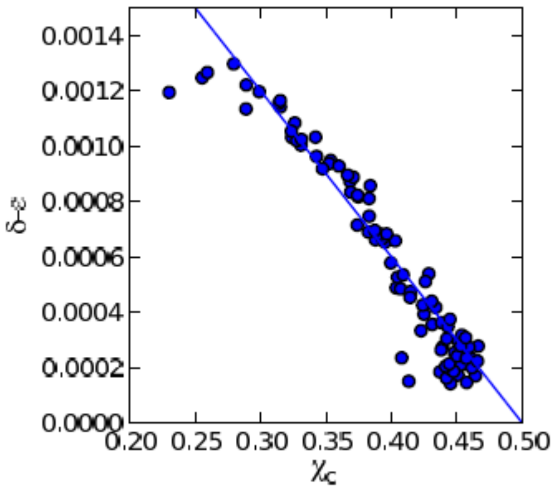


Simplified Physical Picture

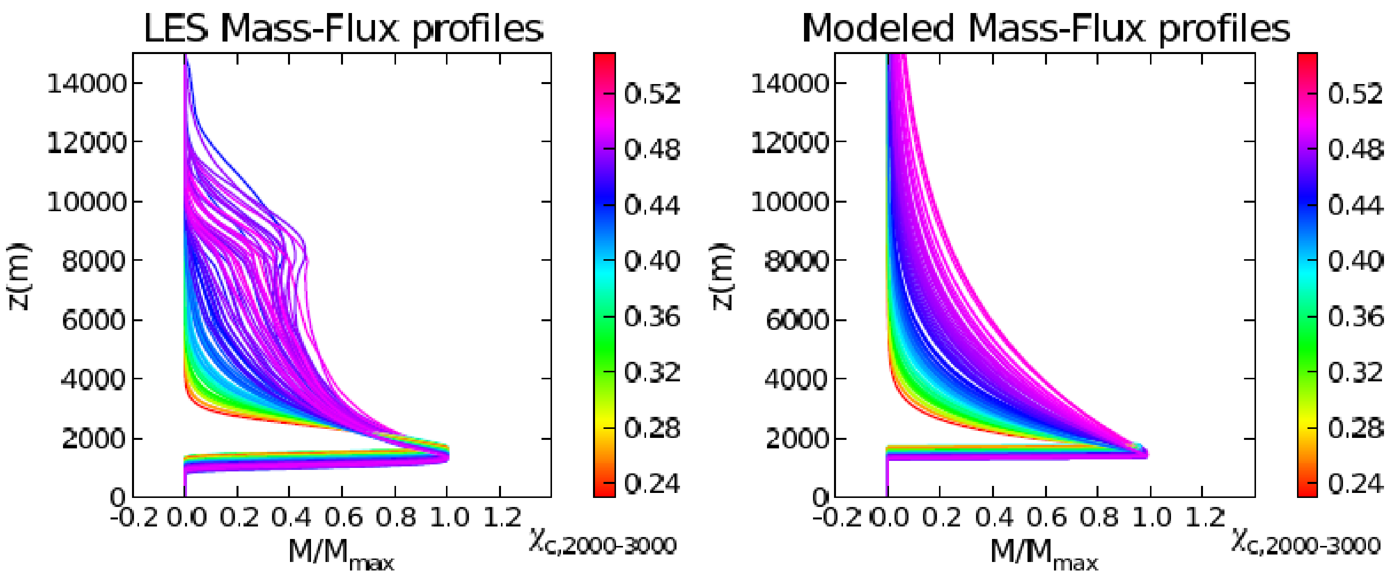


The simplest mass flux parameterization

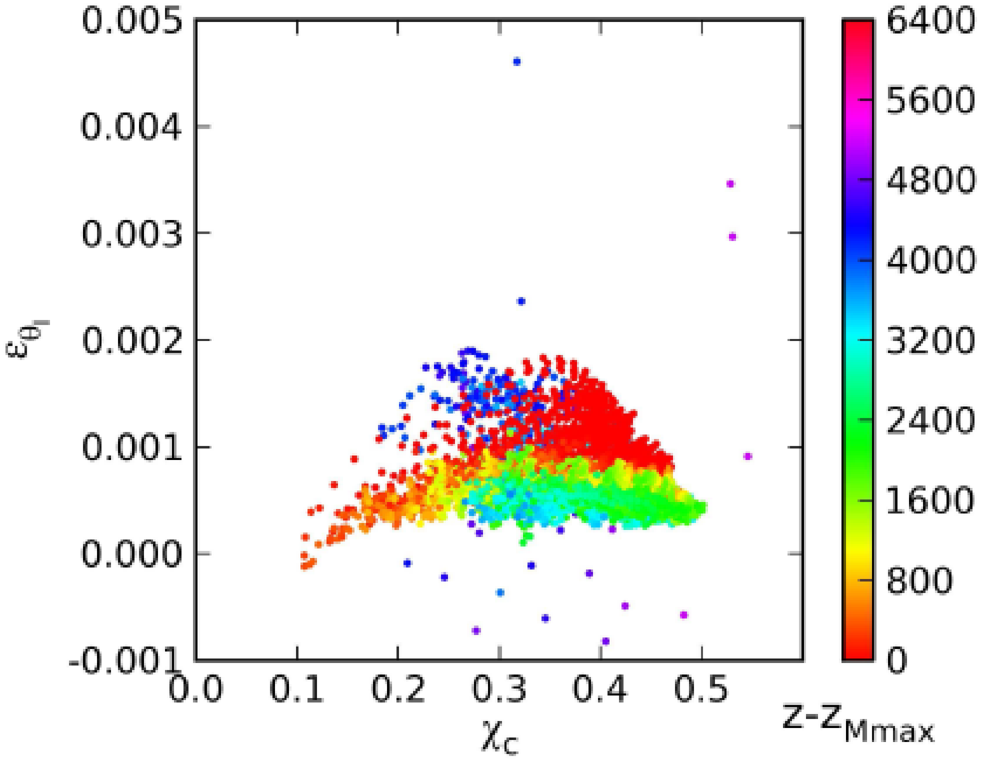
- Directly parameterize $\frac{\partial}{\partial z} \ln M = \epsilon - \delta$ as a function of χ_c
- Use χ_c between 2 and 3 kilometers
- Fit: using relation between χ_c and $\epsilon - \delta$ below $z/z_{top} = 0.5$
- Cloud top requires separate parameterization



- Fit: $\delta - \epsilon = 0.003 - 0.006\chi_c$



What about entrainment?



Use a simple $\epsilon \simeq z^{-1}$ instead.

Conclusions and outlook

- Strong dependency of moist convection on tropospheric relative humidity and stability
- Mostly related to detrainment and hence due to the cloud height distribution
- Allows for simpler and more realistic bulk mass flux convection parameterization (get around detrainment)
- No need to seperate shallow and deep convection
- Can this behaviour also be captured by a multi-plume approach??

2.

Multi-Plume Approach

Neggers JAMES (2017)

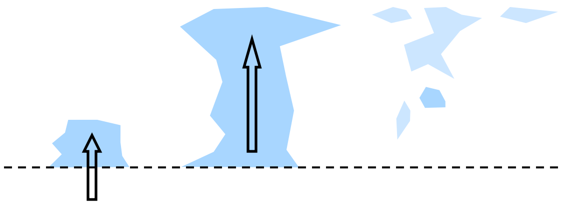
Cloud Ensemble as a Predator-Prey System

Idea: Application of LV to cloud populations

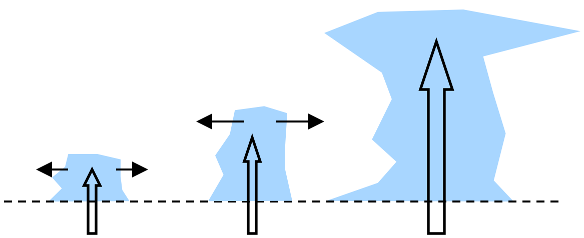
See each size as a different species

Interactions between clouds of different size:

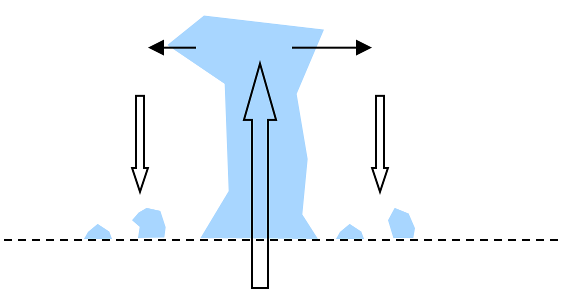
* Big clouds die and break apart into smaller ones (downscale energy cascade)



* Smaller clouds feed bigger ones by ‘preparing the ground’ for their existence (pulsating growth)

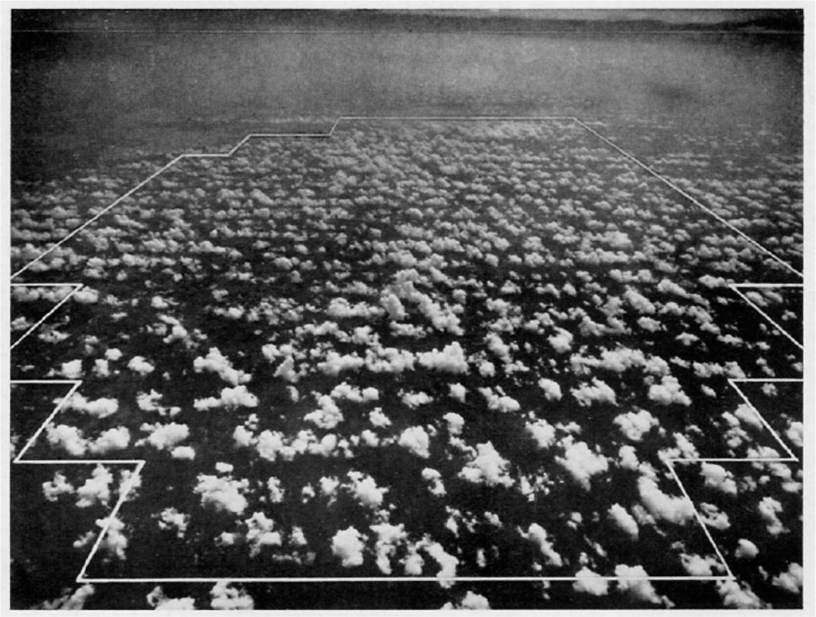


* Bigger clouds prey on smaller clouds, by suppressing them through compensating subsidence & the effect of gravity waves

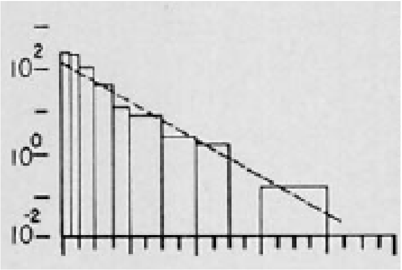


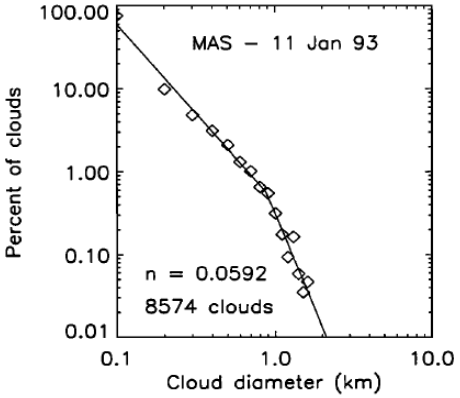
Cloud size densities

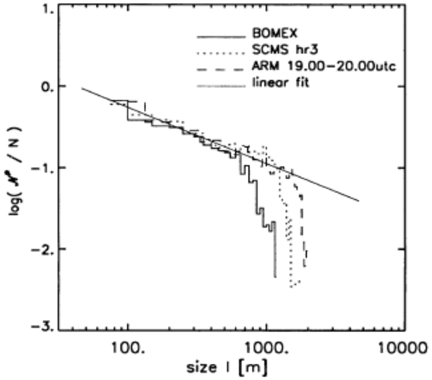
Pretty well known from observations and LES

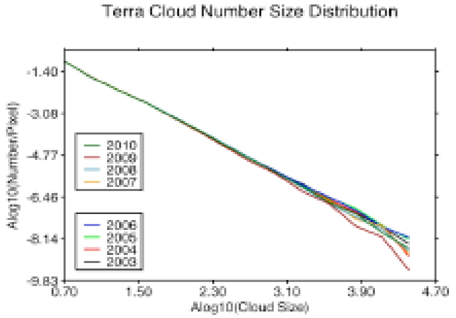


Plank, J App Met, 1969







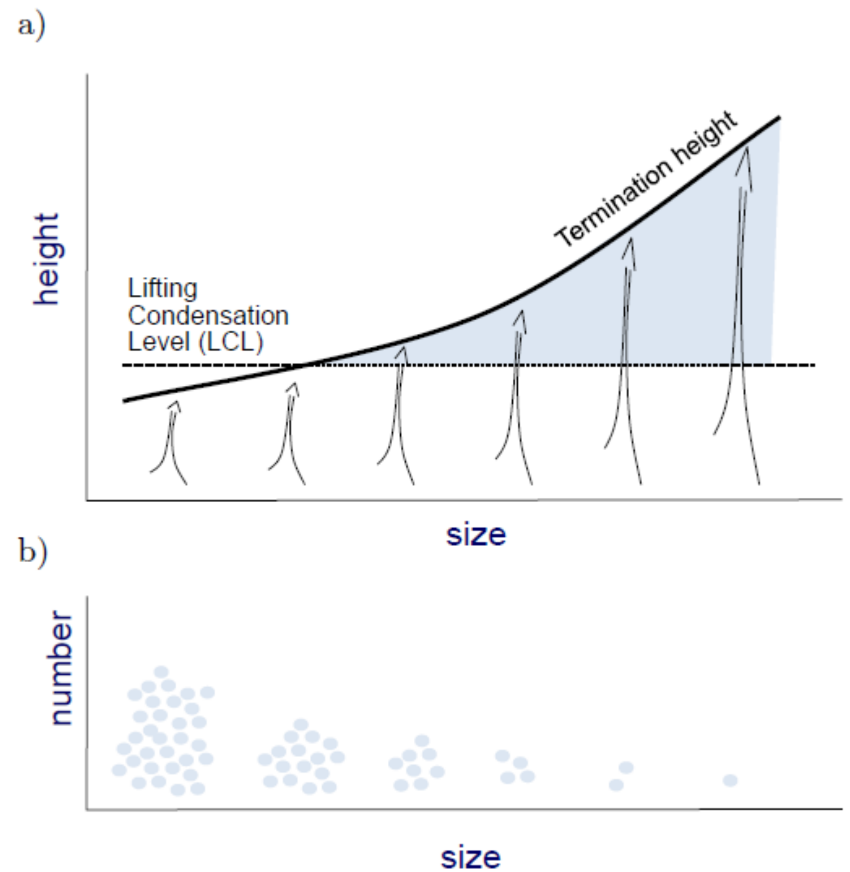


Model development : ED(MF)^n "Bin-Macrophysics"

What is **ED(MF)^n** ? The Eddy-Diffusivity **(ED)** multiple Mass Flux **(MF)^n** scheme

Novelties:

- Spectral formulation in terms of size densities - back to the ideas of Arakawa & Schubert (1974)
- Discretized into histograms with a limited number of bins
- Each bin represents the average properties of all plumes of a certain size
- The discretized size densities are "resolved" using a rising plume model for each bin



Model formulation – Step I

Foundation: the number density as a function of size

$$N = \int_l \mathcal{N}(l)\, dl$$

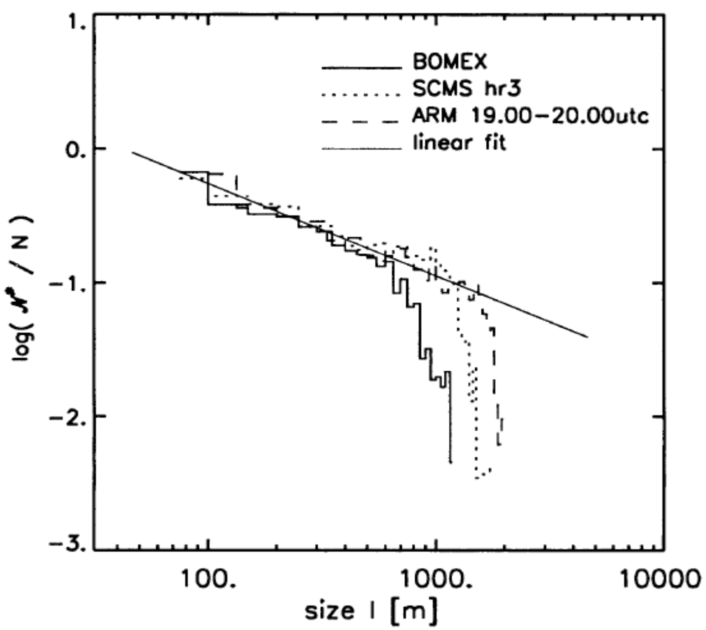
l : size
N : total nr

Adopted shape: power-law, potentially including scale-break

$$\mathcal{N}(l) = a\, l^{\,b}$$

Observations suggest:

$$b \approx \begin{cases} -1.7 & \text{for} \quad l < l_{break} \\ -3 & \text{for} \quad l \geq l_{break} \end{cases}$$

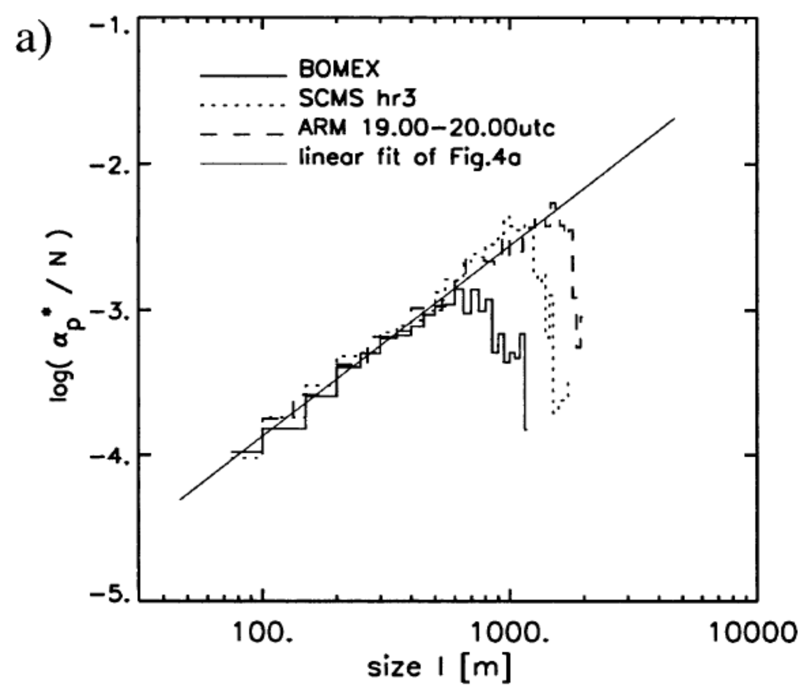


Model formulation – Step II

Related: the size density of area fraction

$$a_{MF} = \int_l \mathcal{A}(l)\, dl$$

$$= \int_l \frac{\mathcal{N}(l)\, l^2}{A}\, dl$$



Basic EDMF:

$$a_{MF} = 10\%$$ For the moment

Model formulation – Step III

Expand to fluxes, introduce dependence on height (z):

$$\overline{w'\phi'}\ (z) = \int_l \underbrace{\mathcal{A}(l,z)\, w(l,z)}_{\mathcal{M}(l,z)} \left[\phi(l,z) - \bar{\phi}(z) \right] dl$$

Mass flux

A spectral mass flux scheme (e.g. Arakawa & Schubert,1974)

To do: come up with a method to produce (l, z) fields

Model formulation – Step IV

n Plume Equations with different sizez l_i:

$$\frac{\partial \varphi_l}{\partial z} = -\varepsilon(\varphi_l - \overline{\varphi}) \text{ for } \varphi \in \{\theta_1, q_t\}$$

$$\frac{1}{2}\frac{\partial w_l^2}{\partial z} = -\varepsilon\, w_l^2 + \alpha B$$

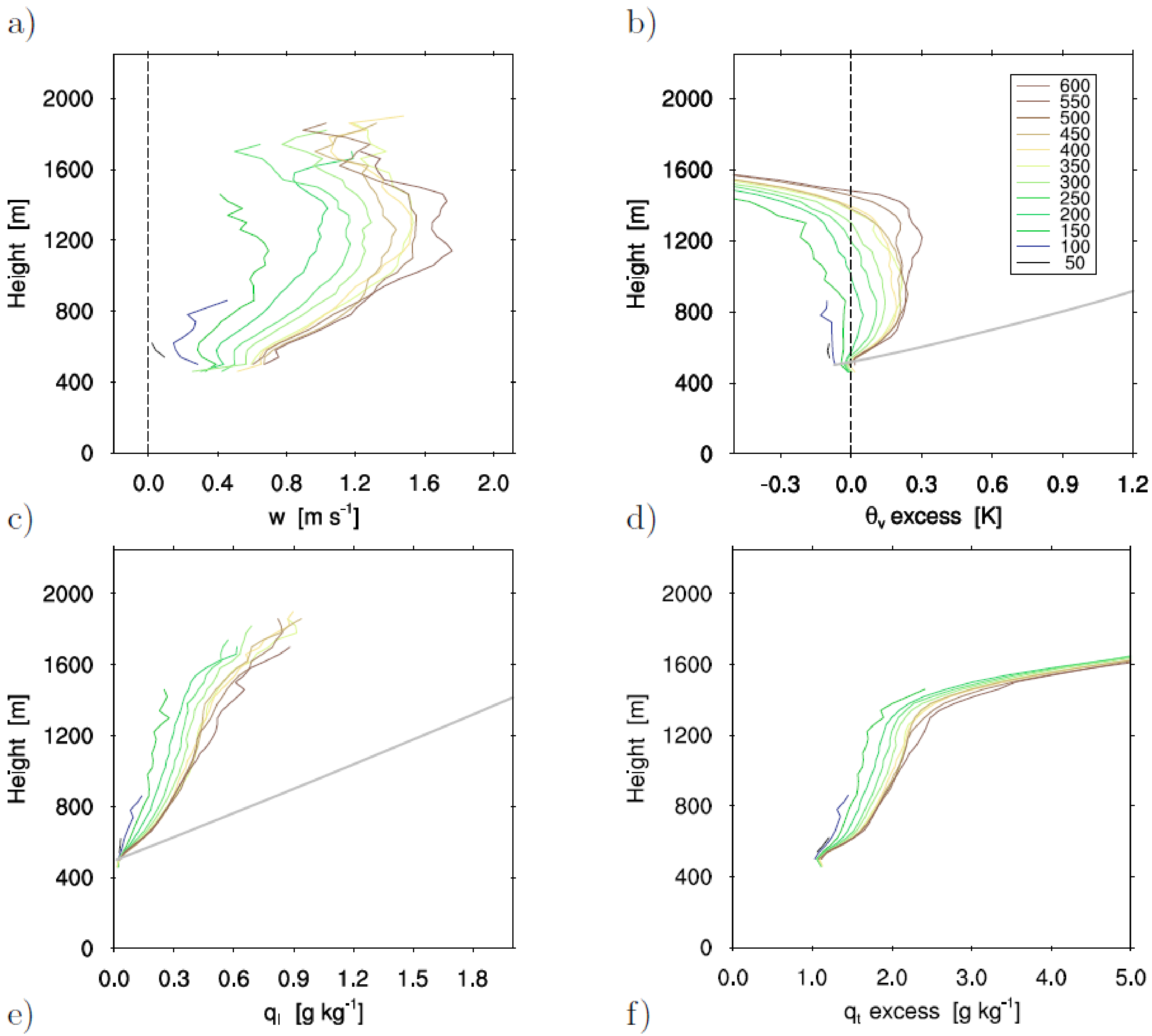
$$\varepsilon_l \propto l^{-1}$$

Remark 1 : No detrainment necessary (determined by multiplume ensemble)

Remark 2: More equations but less parameteric freedom

Justification from LES

Clouds sampled using 180 snapshots from GCSS BOMEX case



Preliminary results with ED(MF)^n

Single-column model experiments for the RICO shallow cumulus case, using a prescribed number density

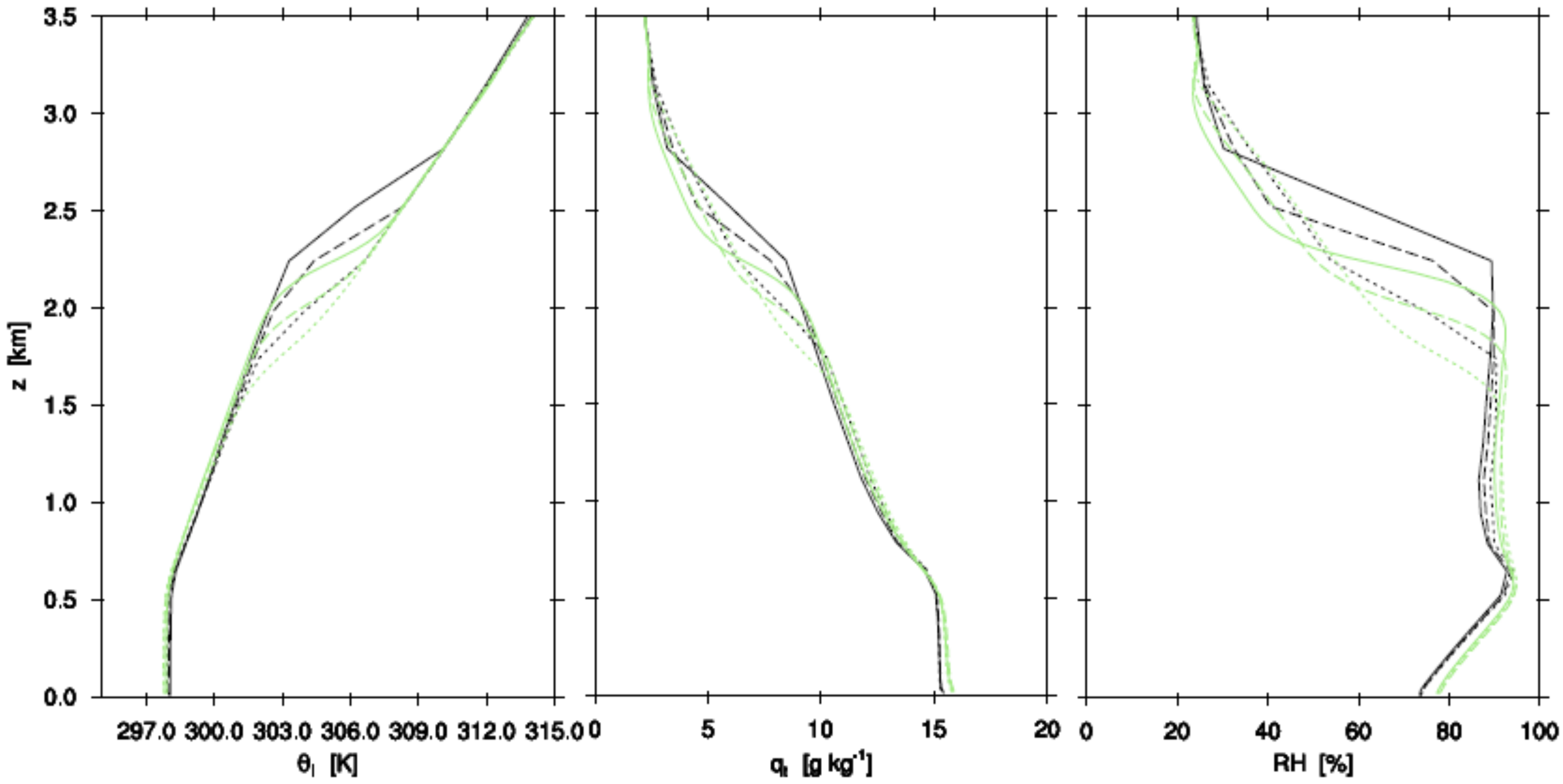
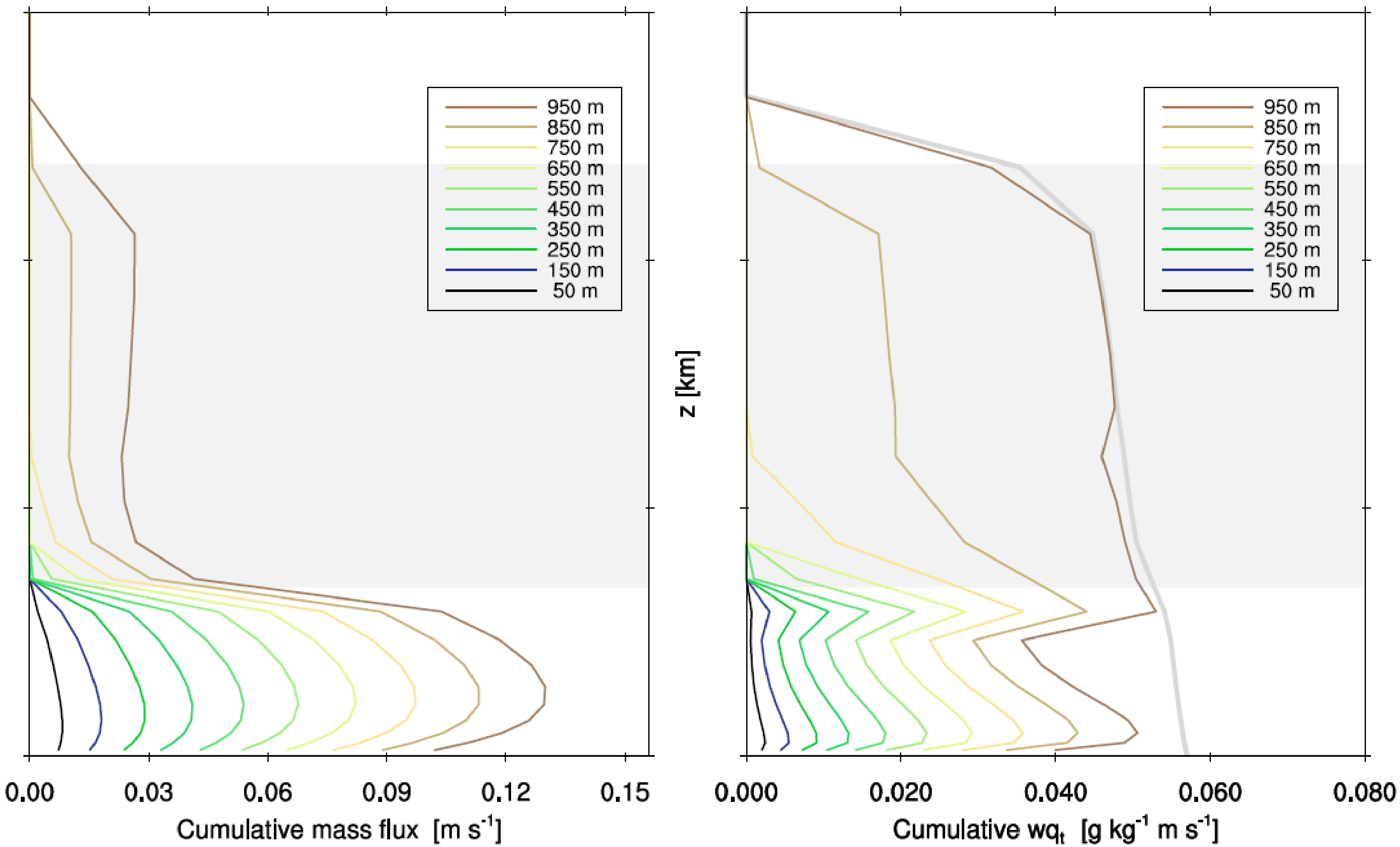


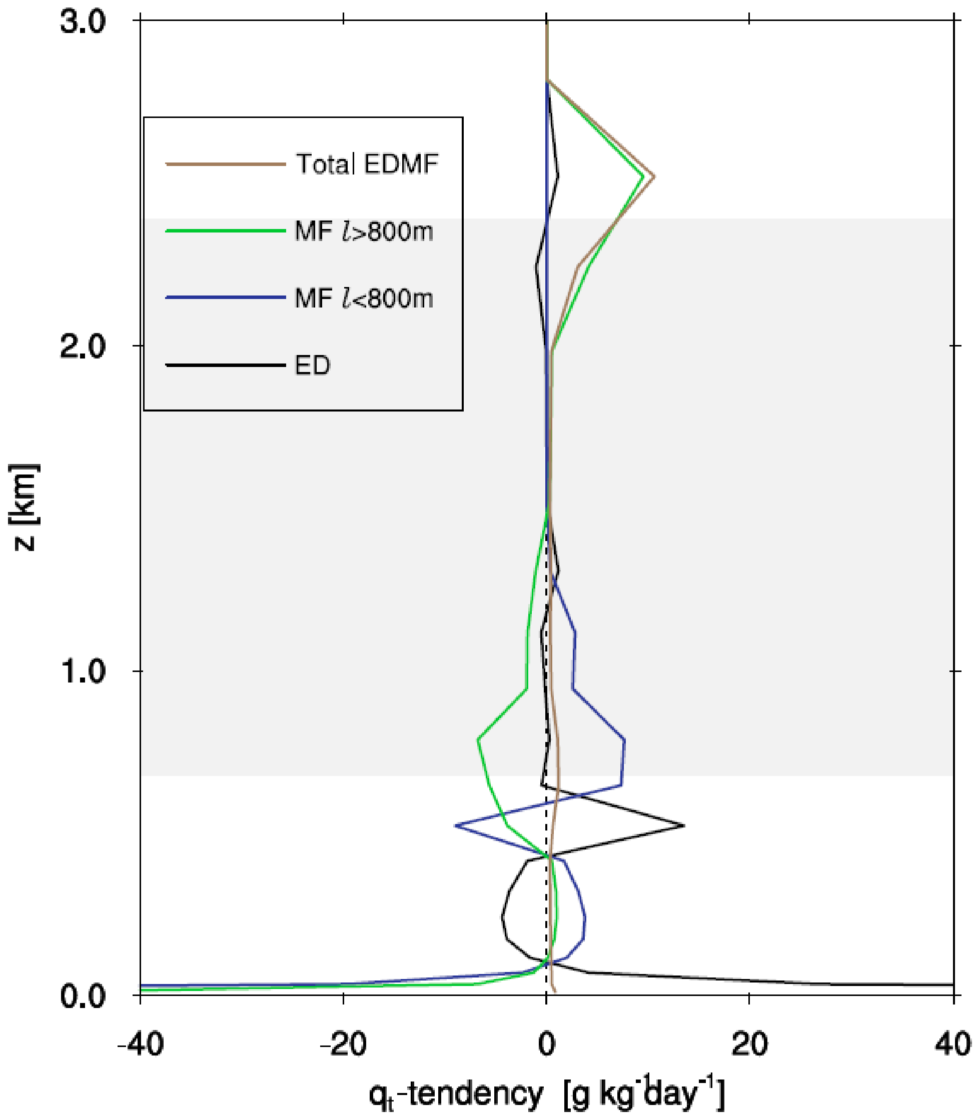
Figure 4. ED(MF)^n results for the RICO case, showing profiles of a) liquid water potential temperature θ_l, b) total water specific humidity q_t, and c) relative humidity RH. LES results (green) are included for reference. Three timepoints are shown, including t=8 hours (dotted), t=16 hours (dashed) and t=24 hours (solid).

Preliminary results with ED(MF)^n

Decomposition of the humidity flux as a function of size:
Indirect interactions between plumes of different sizes



Different sizes play a different role in equilibration



Humidity budget

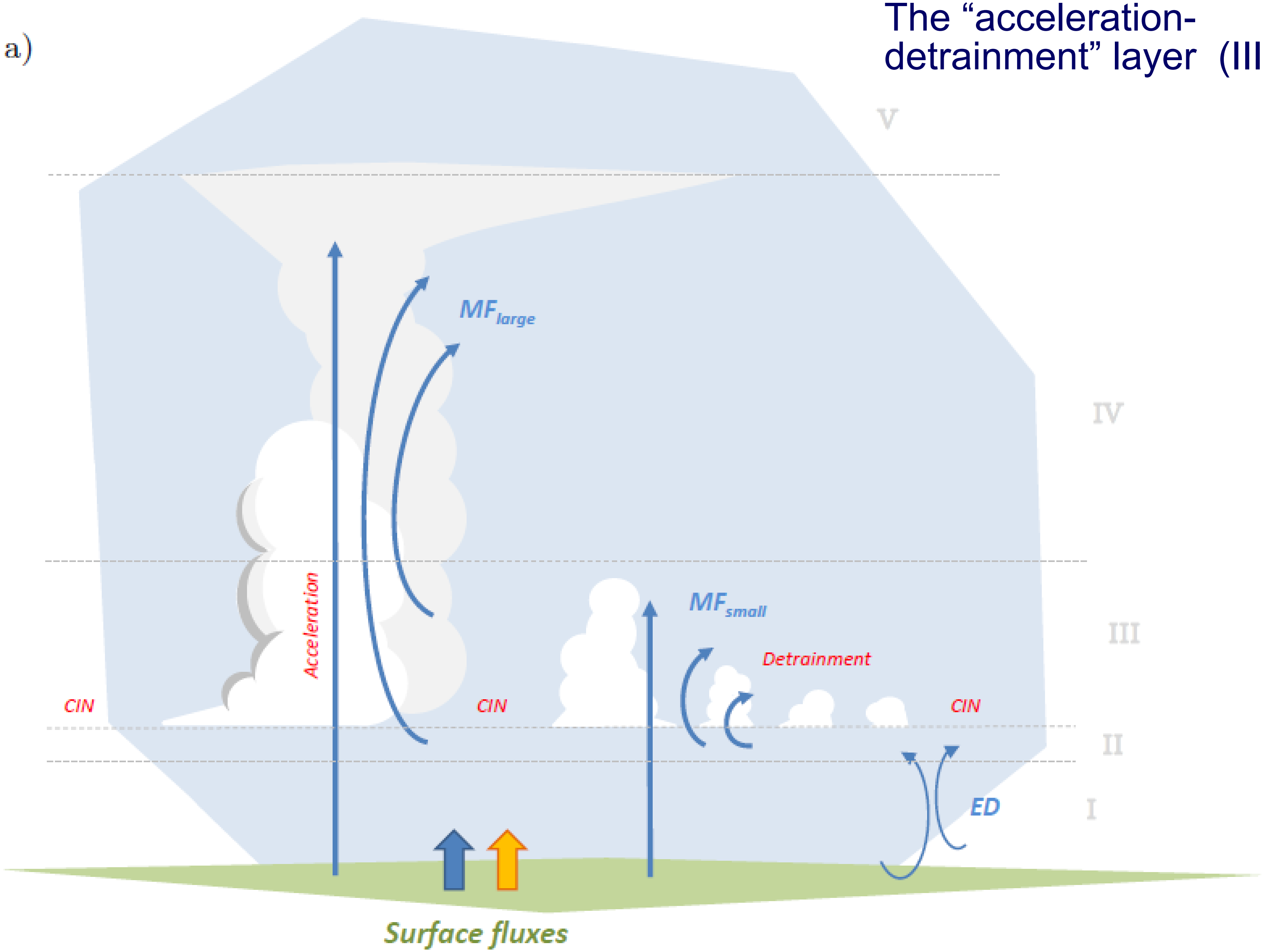
$$\frac{\partial \overline{q_t}}{\partial t} = -\frac{\partial \overline{w' q_t'}}{\partial z}$$

Smaller convective plumes pickup humidity below cloud base, and detrain this above

In turn, the largest convective plumes pickup flux above cloud base, and transport this up to the inversion

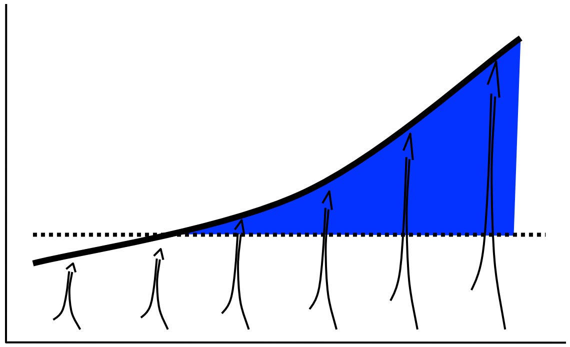
The “acceleration-detrainment” layer (III)

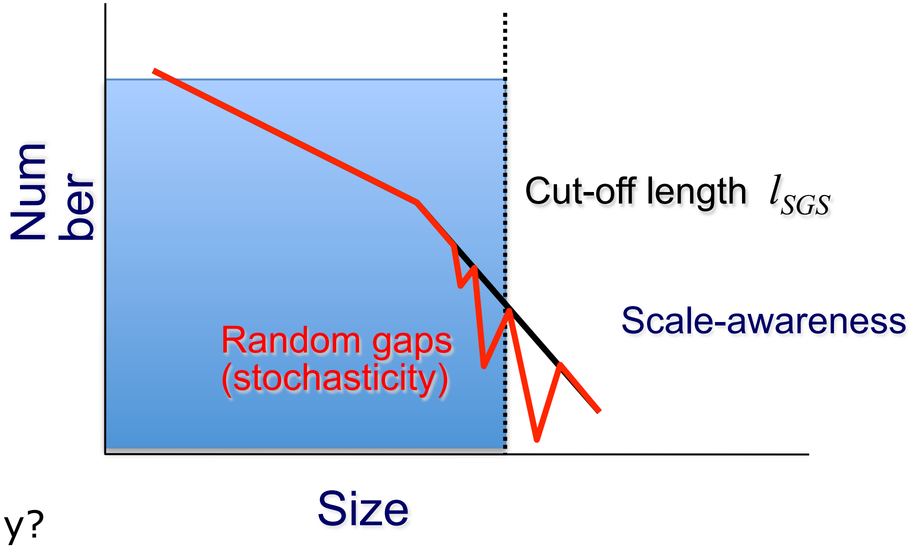
a)



Conclusions and outlook

- No need for specification of mass flux (or detrainment)
- No specific assumptions needed for entrainment
- Self-regulating physical mechanism
- All closure assumptions are condensed in the cloud base area fraction (and the cloud base size distribution)
- Microphysics, stochasticity and scale awareness can be build in naturally





But how exactly?

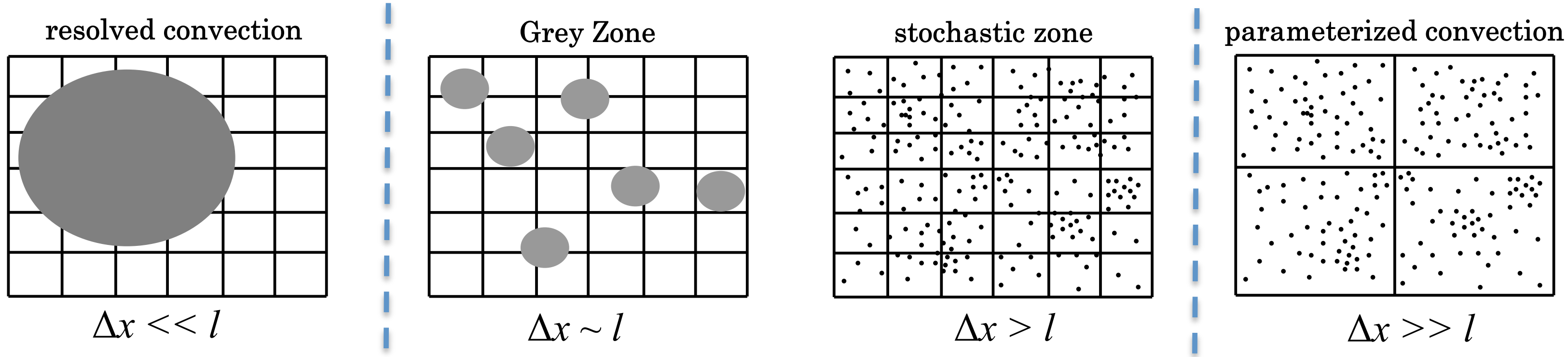
3.

Stochastic Closure

Dorrestijn, J., D. Crommelin, P. Siebesma, H. Jonker, and C. Jakob, JAS (2015)

J. Dorrestijn; Daan T. Crommelin, A.P. Siebesma, H.J.J. Jonker and F. Selten JAS (2016)

Breakdown of statistical quasi-equilibrium



LES

100 m

Mesoscale GCM

1~10 km

High res GCM

100km

Traditional GCM

250 km

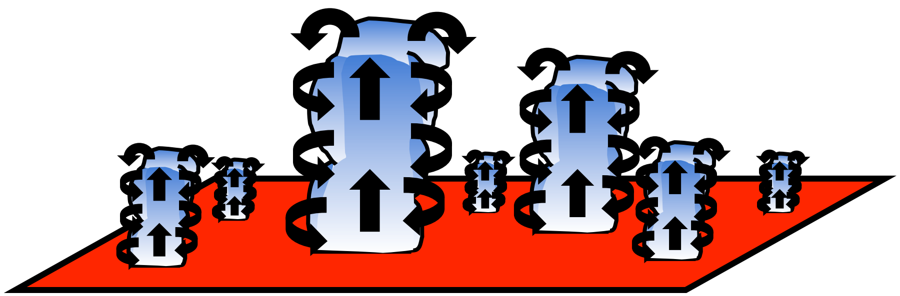
Resolved

Stochastic

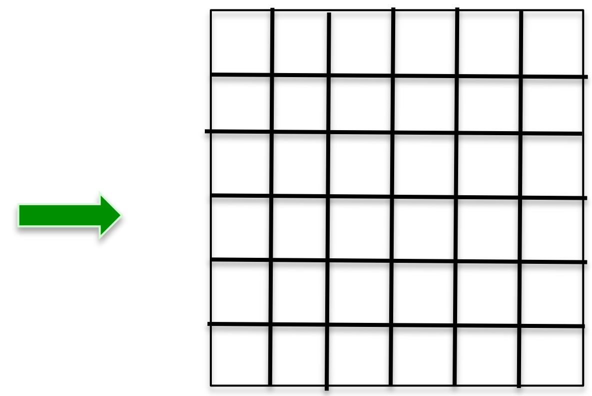
Deterministic

Dorrestijn & Siebesma 2014

2. Stochastic Multicloud Approach

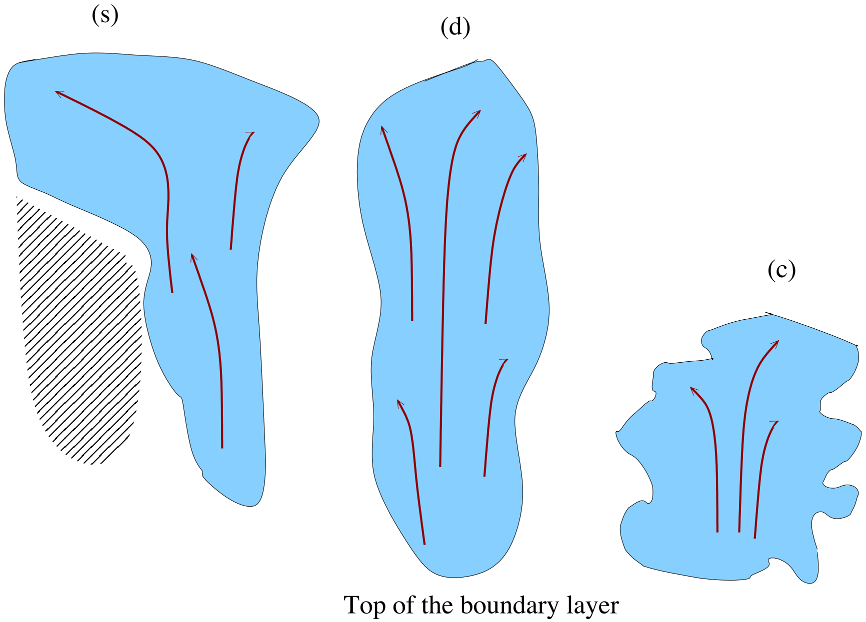


GCM grid box



a micro-grid (N micro-grid nodes)

Each micro-grid node can be in one of the M (=4) states:



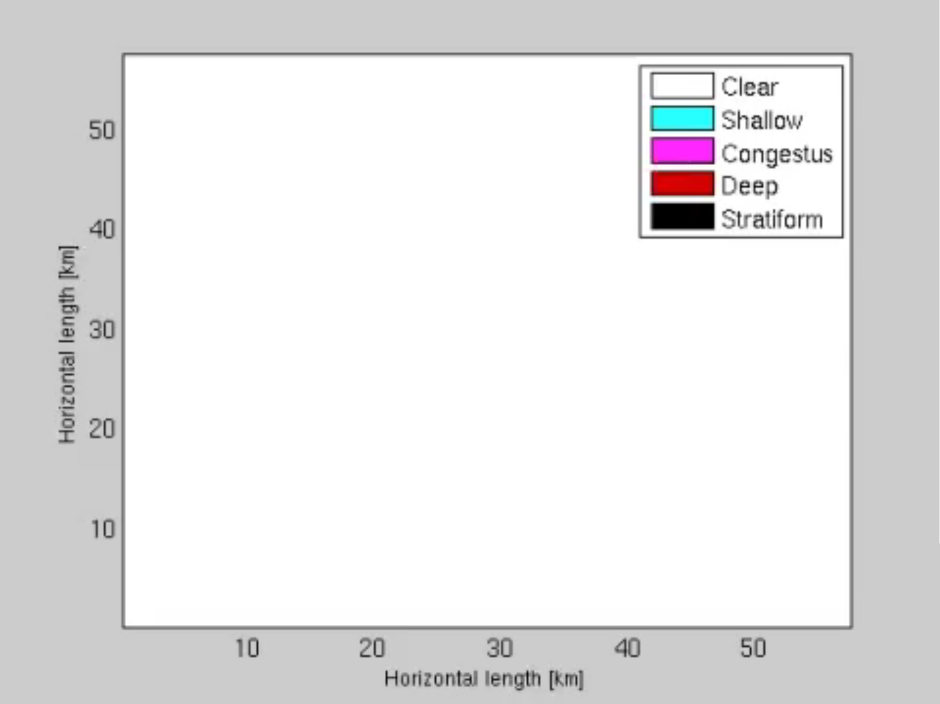
(Khouider et al 2010)

Stratus deep convective congestus clear

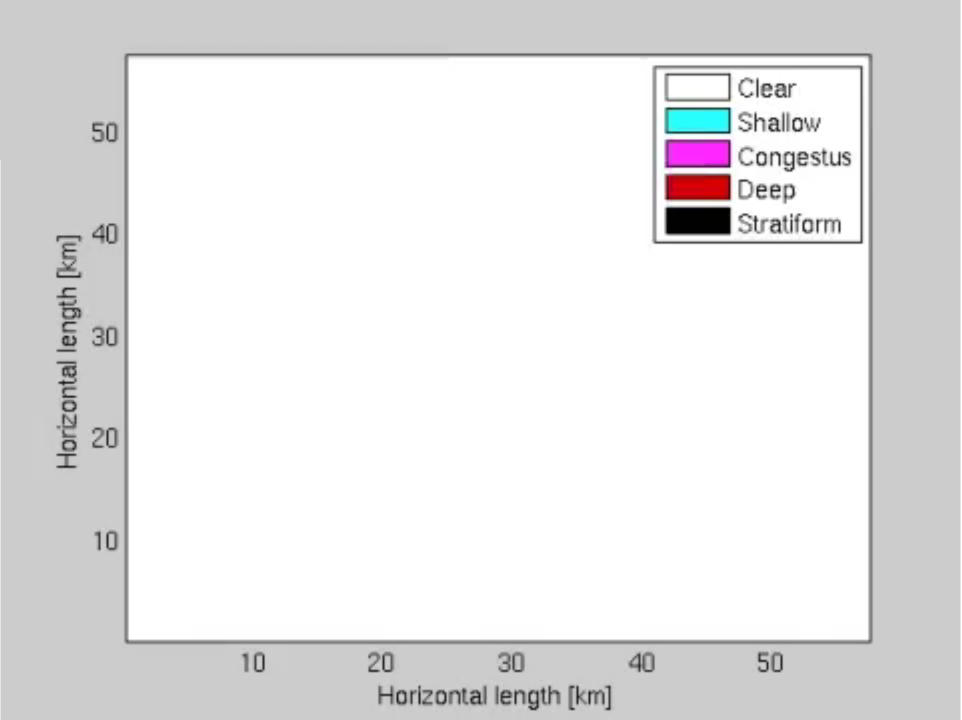
- Each type has a area fraction defined by: $$\sigma_m(t) = \frac{1}{N}\sum_{n=1}^{N} \mathbf{1}[Y_n(t) = m],$$

- Probability to switch from state α to β : $$P_{\alpha\to\beta} = \frac{T(\alpha,\beta)}{\sum_{\beta} T(\alpha,\beta)}$$

Transition Probabilities can be found through: Obs data, LES data, Theory



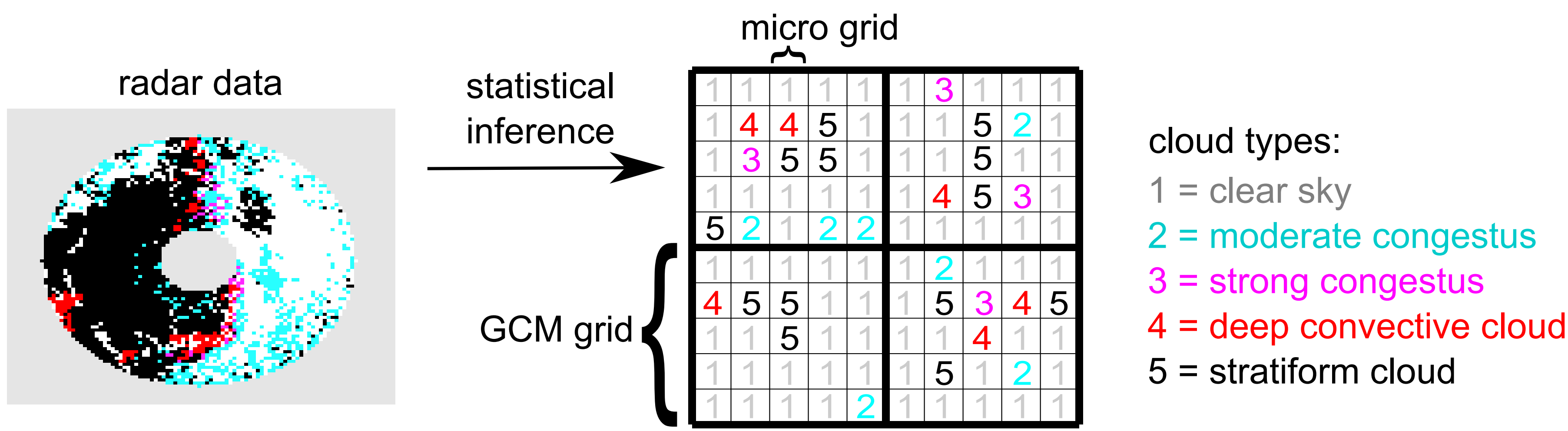
LES data labeled with 4 cloud types



Trained Cellular Automata
(i.e. CMC with neighbour interaction)

Dorrestijn et al: Phil Trans R Soc A (2013)

Training the system with obs



- Finding the transition probabilities
- Condition them on the present state in order to get conditional probabilities (w, CAPE, state of the neighbour))
- Leading to a conditional Markov Chain (CMC)

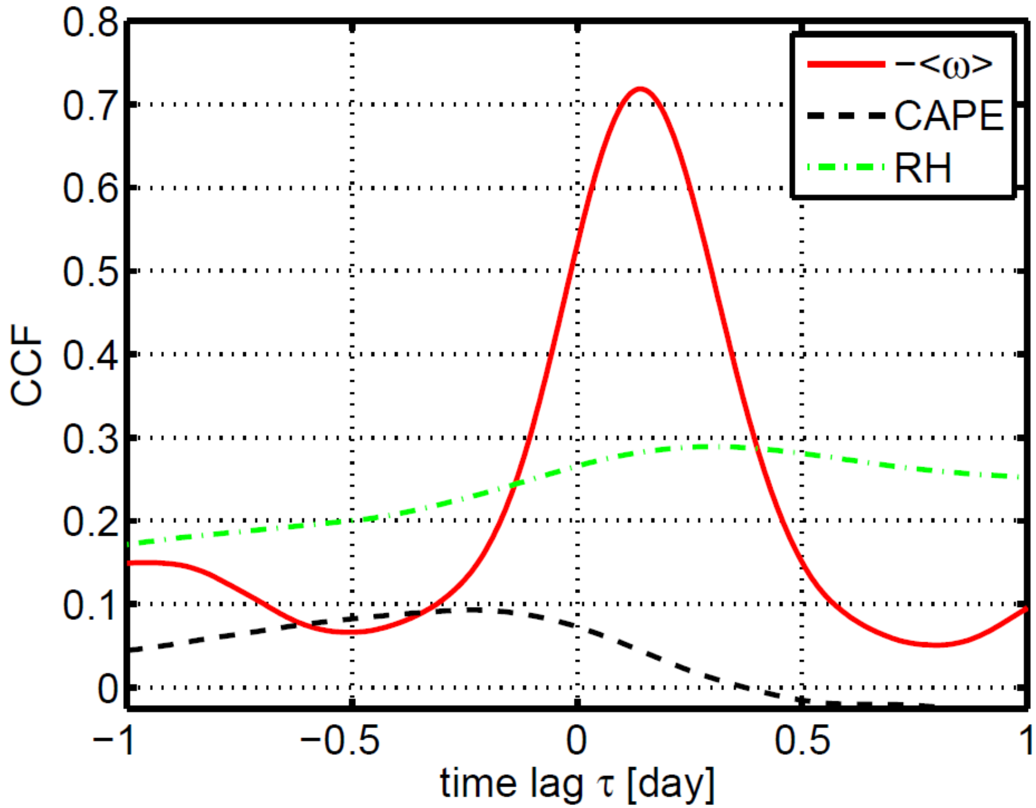
Unconditional Markov Chain

$$\hat{\mathbf{M}} = \begin{pmatrix} 0.8987 & 0.0668 & 0.0006 & 0.0011 & 0.0329 \\ 0.4147 & 0.4707 & 0.0033 & 0.0026 & 0.1086 \\ 0.2563 & 0.2686 & 0.2177 & 0.0545 & 0.2029 \\ 0.1757 & 0.0284 & 0.0124 & 0.4295 & \mathbf{0.3540} \\ 0.1185 & 0.0779 & 0.0010 & 0.0091 & 0.7935 \end{pmatrix}$$

1 Clear Sky
2 Moderate Congestus
3 Strong Congestus
4 Deep Convection
5 Stratiform

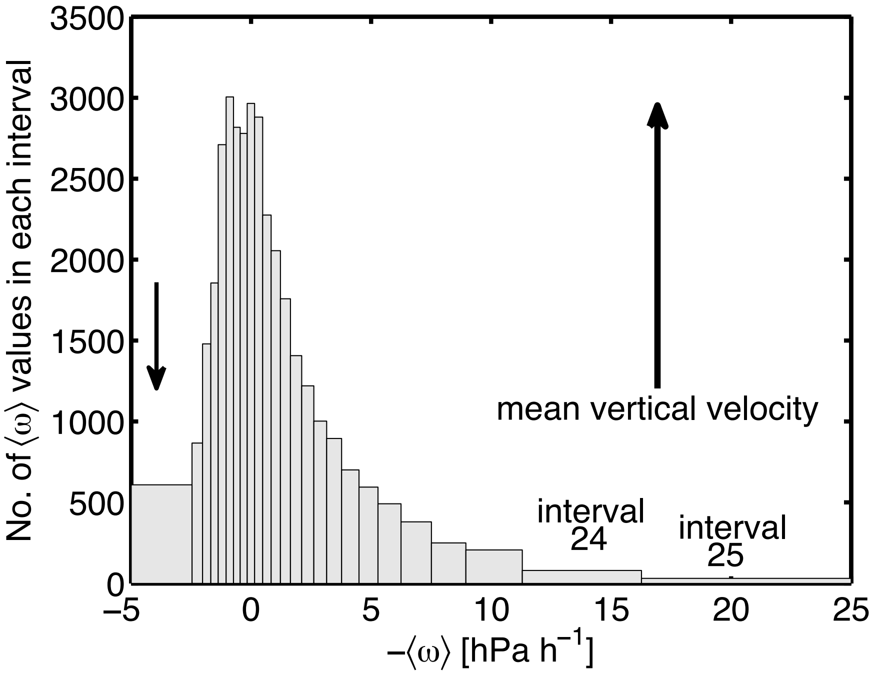
Next step: Condition the transition probabilities on the large scale state

Lagged Correlation Analysis



$$\mathrm{CCF}(\tau) = \int_{-\infty}^{\infty} \tilde{X}(t+\tau)\tilde{\sigma}_4(t)dt$$

Conditioning on ω-intervals

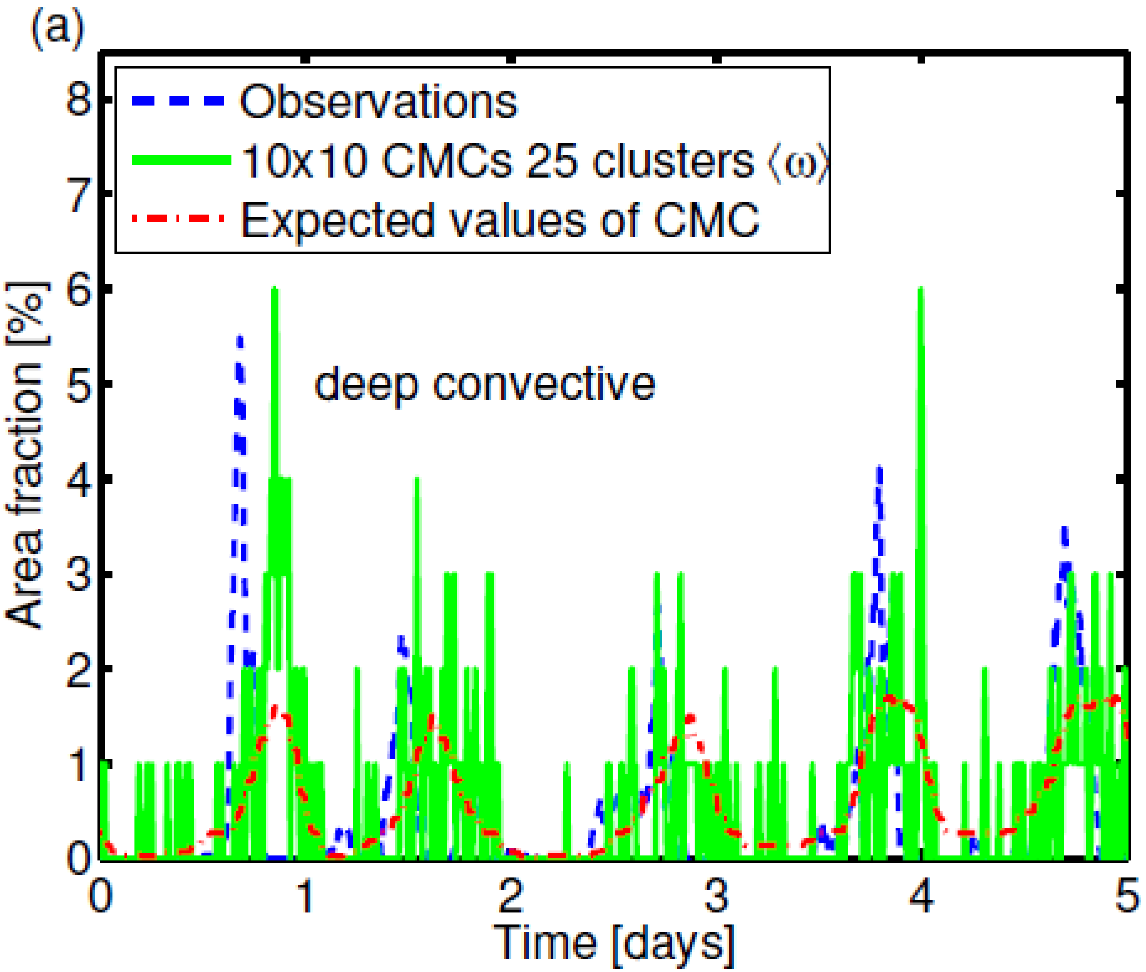


- For each state γ (i.e. w-interval a transition matrix is constructed from the data set

- So in total we have now Γ=25 5x5 transition matrices describing the transition probabilities (γ = 1….Γ)

- $$P_{\gamma,\alpha\to\beta} = \frac{T_\gamma(\alpha,\beta)}{\sum_\beta T_\gamma(\alpha,\beta)}$$ Conditional Markov Chain (CMC)

Deep convective fractions in more details



Adds more realistic variability to the convection scheme

Dorrestijn, Siebesma & Crommelin (2015)

SPEEDY

- SPEEDY : Simplified Parameterizations, primitivE-Equations Dynamics (Molteni)
- GCM of intermediate complexity
- 98x48 grid columns (T30) and 8 vertical levels
- Simplified Mass Flux Scheme (Tiedtke 1988)
- The Markov chain fractions are used as a closure for the mass flux at cloud base M_b.

$$M_b = \rho \sigma_b w_{b,c}$$

σ_b: cloud core fraction at cloud base

$W_{c,b}$: vertical velocity of cloud core at base

Closure

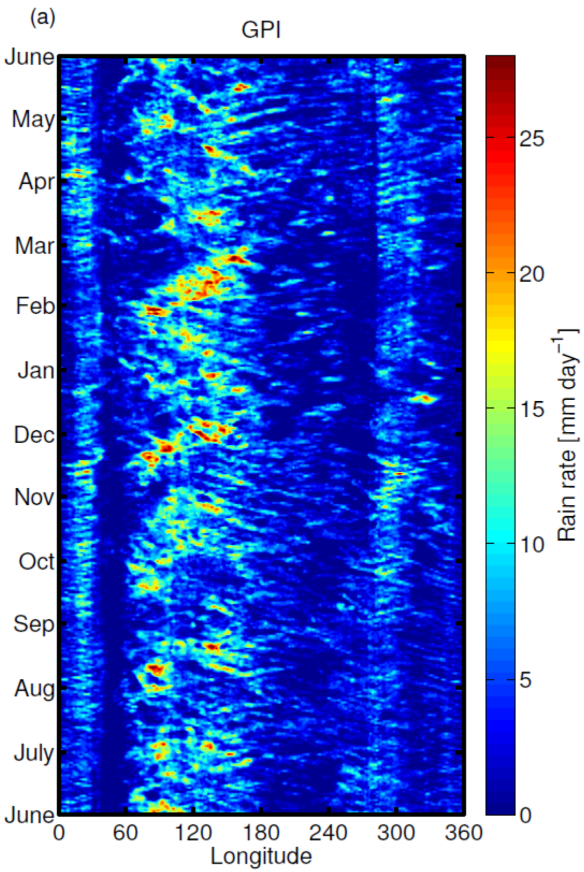
$$\sigma_b = \sigma_3 + \sigma_4$$

$$\rho w_{c,b} = 1$$

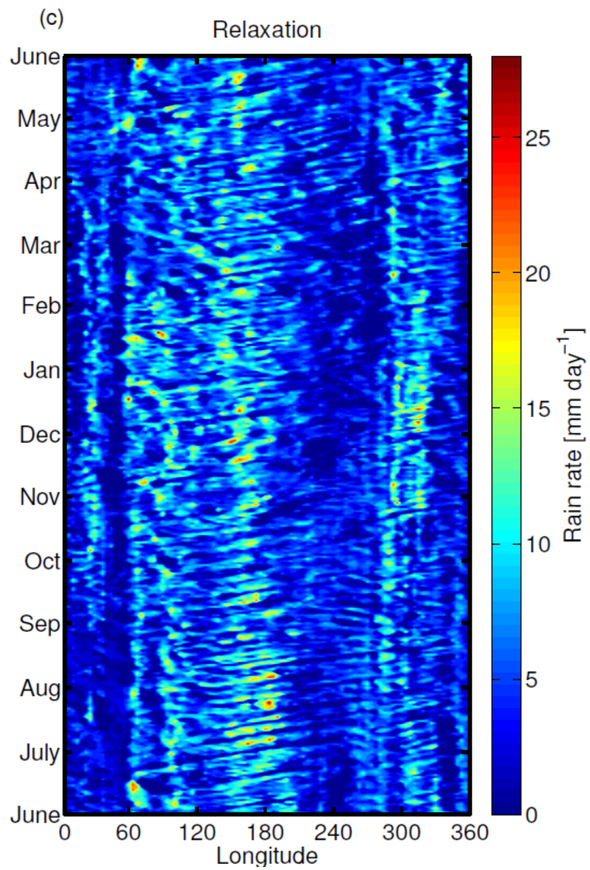
Histograms Hovmoller Diagrams

(Tropics: -15^0 - $+15^0$)

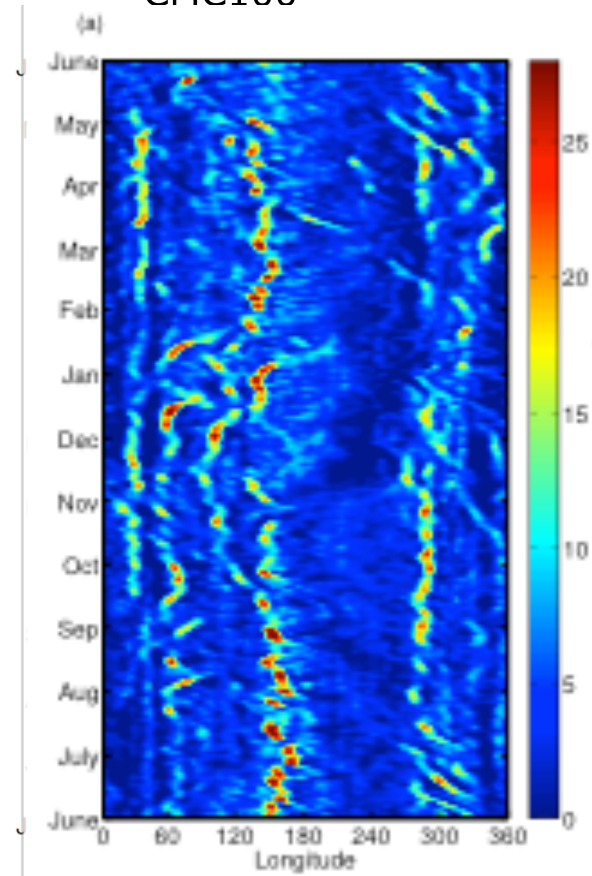
OBS



CTRL



CMC100



Conclusions and outlook

- Conditional Markov Chains (CMC's) have been used to describe the transitions between the states of the multicloud model.

- Conditional transition rates have been trained with observational data and work best when conditioned on ω

- Increased and more realistic variability of the convective mass flux

- Model can be coupled to convection scheme of (any) GCM (such as the multiplume) via the convective area fraction in the cloud base mass flux.