# Representing deep convective organization in a high resolution NWP LAM model using cellular automata

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ECMWF, WMO/WGNE, WMO/THORPEX and WCRP WS on
Representing model uncertainty and error in numerical weather and climate prediction models

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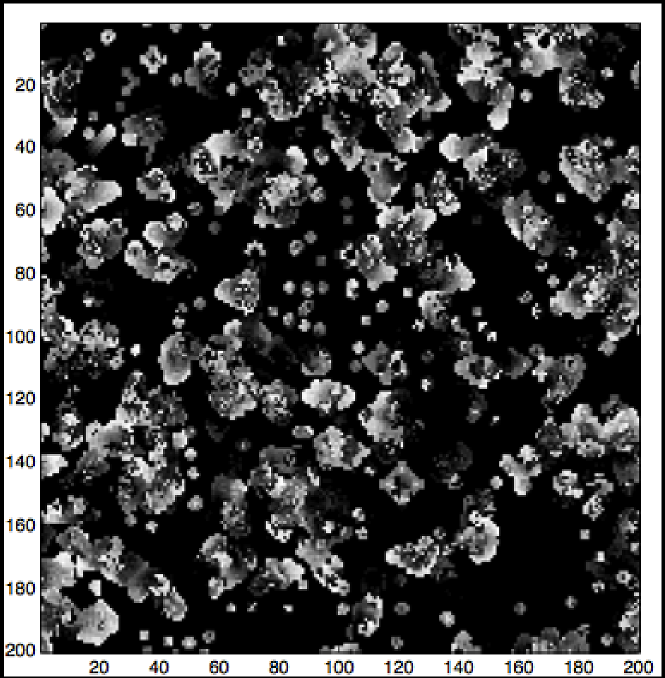
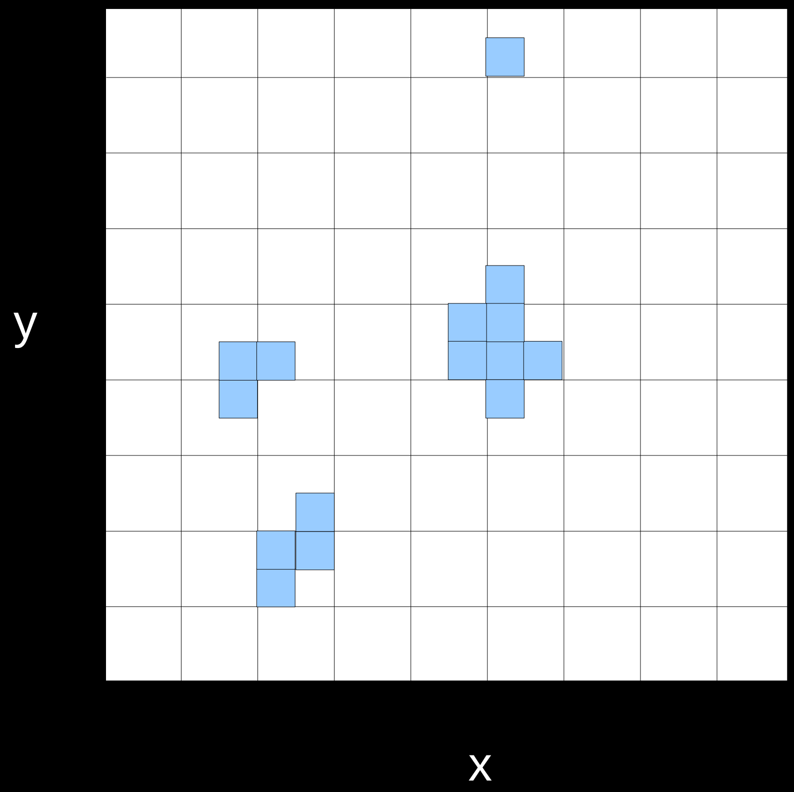
# What is cellular automata

An elementary cellular automata (Wolfram 1983) is a dynamical system with a state vector which takes on a number of discrete states determined by a given rule. This rule relates the state at one point in space and time to the state of the neighbouring CA grid-cells at the previous time-step.



# Interesting for organization of deep convection




- Auto-correlation in space and time
- Spatial and temporal scales of deep convection
- Inherent memory
- Lateral communication, organization.
- Stochastic statistical representation of sub-grid variability

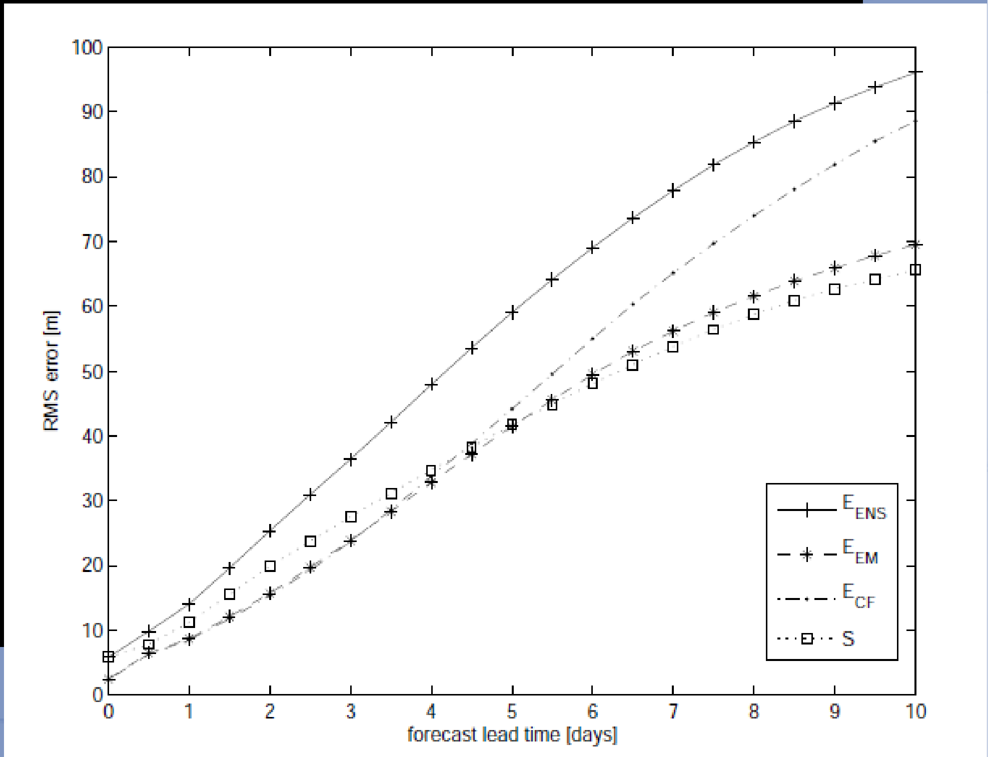
CA acting on a higher resolution than that of the model grid.

# Atmospheric Variability

- How well does a forecast model reproduce the characteristic variability of the atmosphere in the limit of deterministic predictability?
- Lorenz (1982) suggested a way to parameterize the growth of small initial errors in a perfect model:

$$\frac{dE}{dt} = (\alpha E + s)\left(1 - \frac{E}{\beta}\right)$$

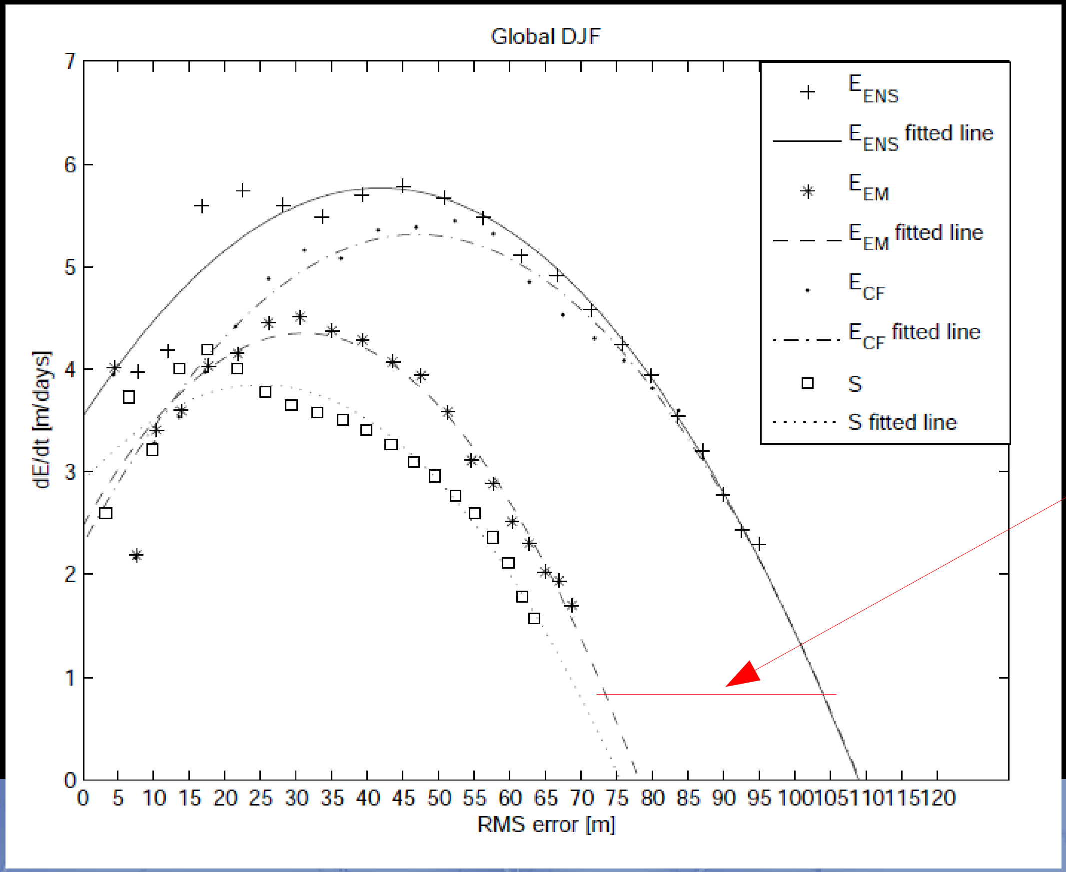
E = Error
alpha = growth rate
s = systematic (climate drift) error
beta = Asymptotic saturation value



# Atmospheric Variability

- If the error growth is governed by $\frac{dE}{dt} = (\alpha E + s)\left(1 - \frac{E}{\beta}\right)$

the relation between E and dE/dt will lie on a parabola and can be fitted with a quadratic polynomial.

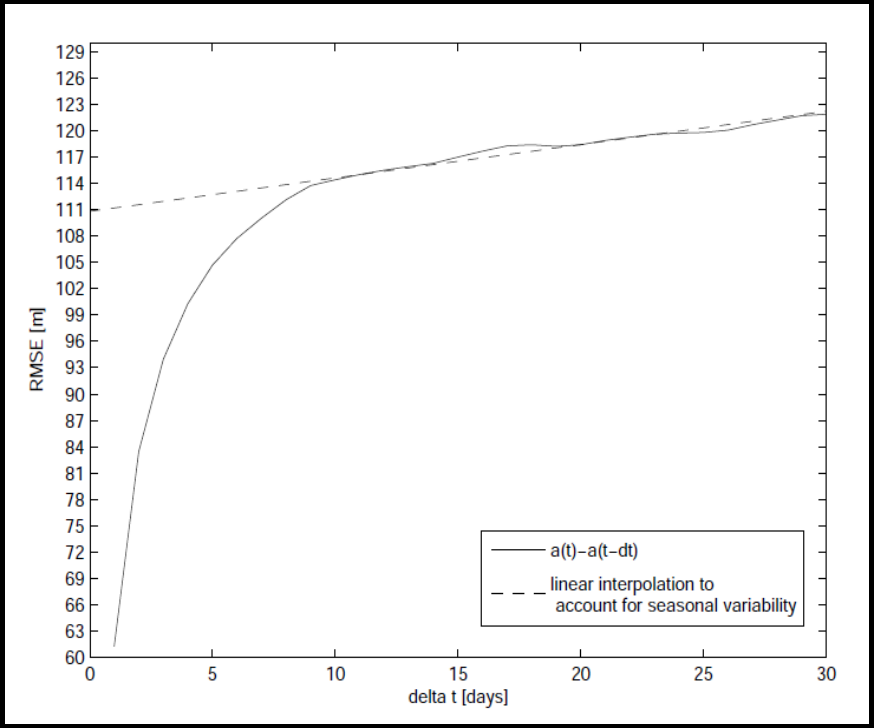


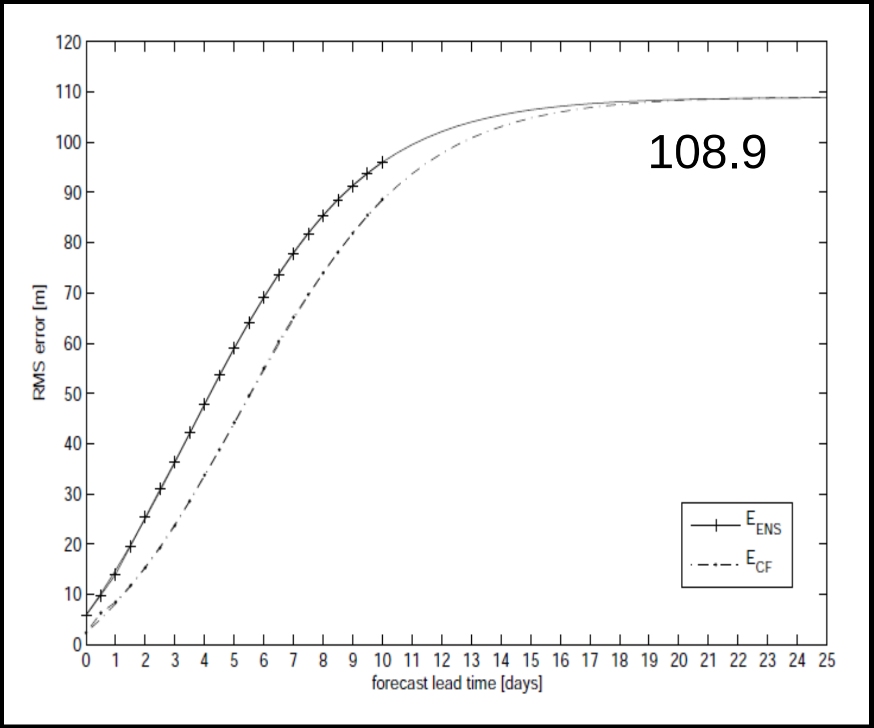

$$E_{ENS} = \sqrt{2}E_{EM}$$

= 110.5 m

Bengtsson et. al 2008

# Atmospheric Variability




= 110.8 m

$$E_{ENS} = \sqrt{2}E_{EM}$$ = 110.5 m

Bengtsson et. al
2008

# Atmospheric Variability

- The particular example shows an EPS which is under-dispersive, i.e not variable enough.
- One solution is to add stochastic physics.
- Question is, should such “noise” be added within the EPS as “multiplicative noise” (i.e Buizza, 1999), or, if the model itself is lacking in variability, should we aim to construct parameterizations in the deterministic model which have stochastic elements? i.e. Lin and Neelin (2002, 2003), Shutts (2005), Teixeira and Reynolds (2008), Plant and Craig (2008)

# Atmospheric Variability

- A typical example of sub-grid variability arises from deep convection in the atmosphere.
- Idea from Palmer, (1997, 2001), Shutts, 2005 and Berner, 2008 to use a cellular automaton as a “pattern generator” in order to introduce “multiplicative noise” on the spatial scales of convection in the ECMWF EPS
- Another approach could be to use a CA within the deep convection parameterization of the deterministic model, and let the CA be a function of the atmospheric model fields.

# Deep convection organization

- Many “organizing mechanisms” in the atmosphere.
- Examples of such processes are vertical wind shear, underlying sea surface temperature (SST) gradients, cold pool dynamics and water vapour feedbacks (Tompkins 2001).
- Also, ducted gravity waves, initiated from deep convection, act to organize convective clusters and meso-scale convective systems (Huang 1998).
- Fast moving gravity waves are either damped, or not resolved in time in most NWP models.

# Idealized study of CA parameters

- Design neighbourhood rules that govern the CA to achieve a statistical representation of the sub-grid scale motions.
- In particular the horizontally propagating gravity waves.
- Study impact of CA parameters in an idealized setup.

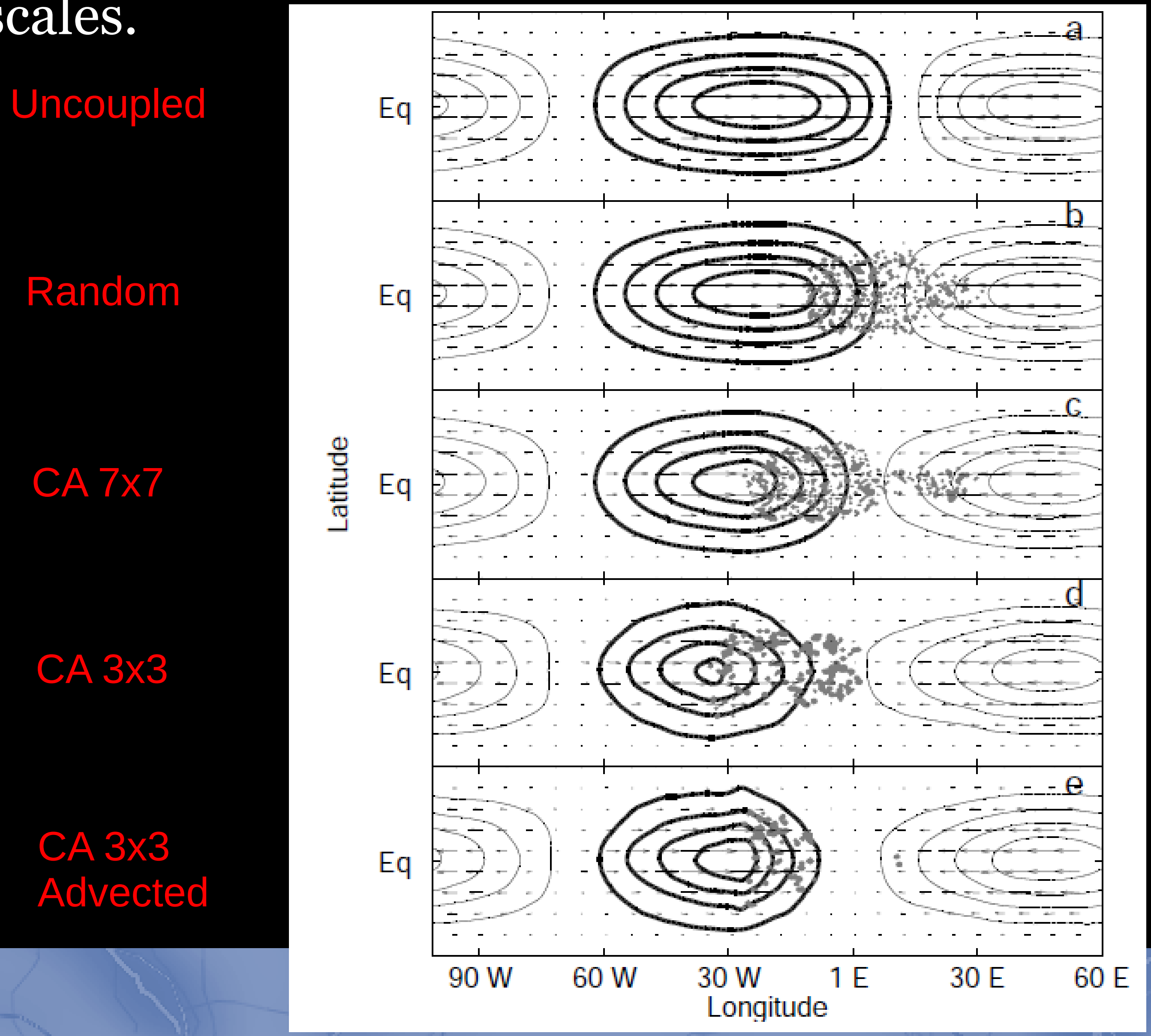
$$\frac{du}{dt} + \mathbf{V}\cdot\nabla u - fv = -g\frac{\partial h}{\partial x} + K_u$$

$$\frac{dv}{dt} + \mathbf{V}\cdot\nabla v + fu = -g\frac{\partial h}{\partial y} + K_v$$

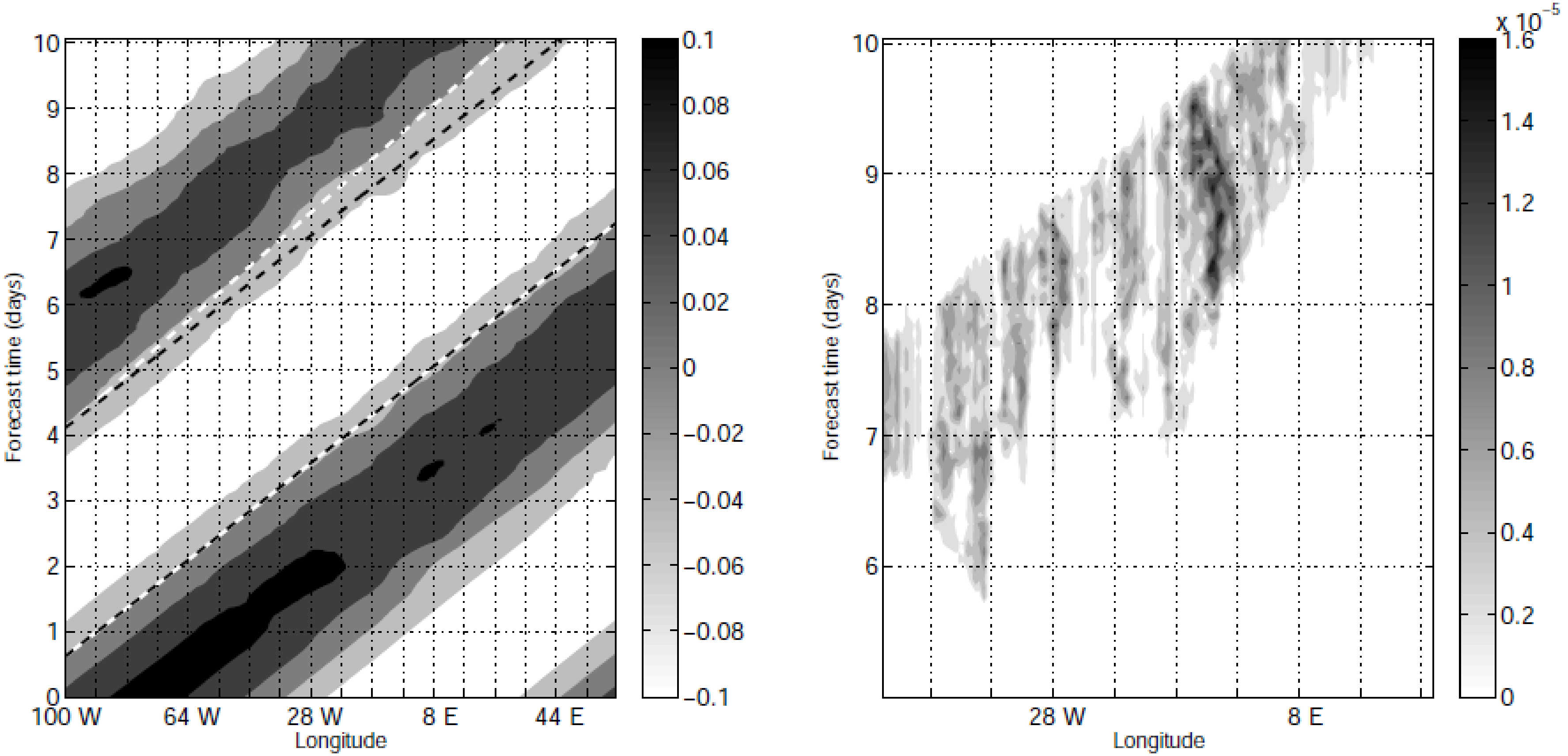
$$\frac{dh}{dt} + \mathbf{V}\cdot\nabla h + h\nabla\cdot\mathbf{V} = Q + K_h$$

Q(x,y,t)=fraction of CA

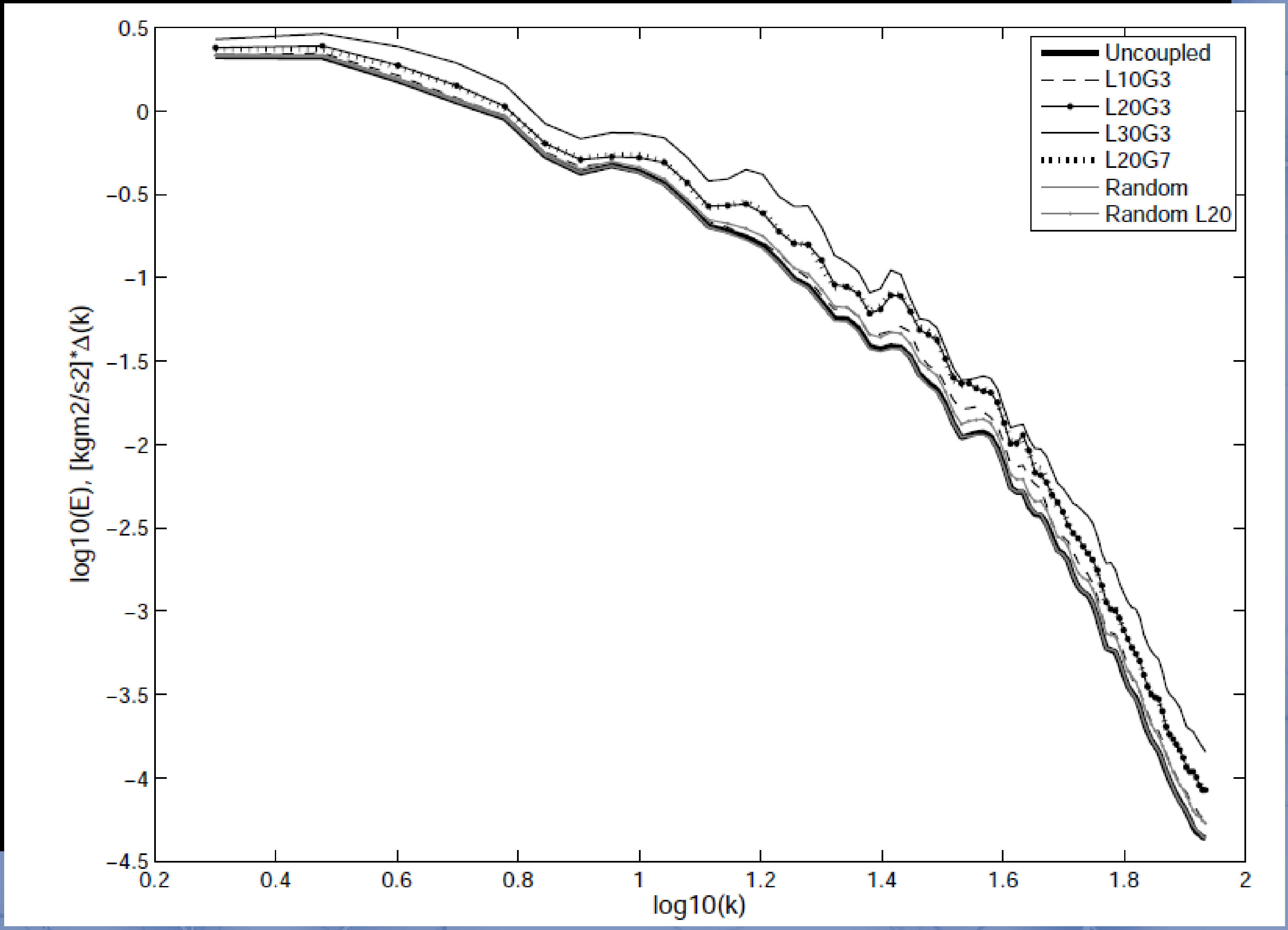
Forget about physical processes of deep convection for a moment, and look only at scale interaction between different atmospheric scales. i.e. how large-scale waves interact with the convective scales.



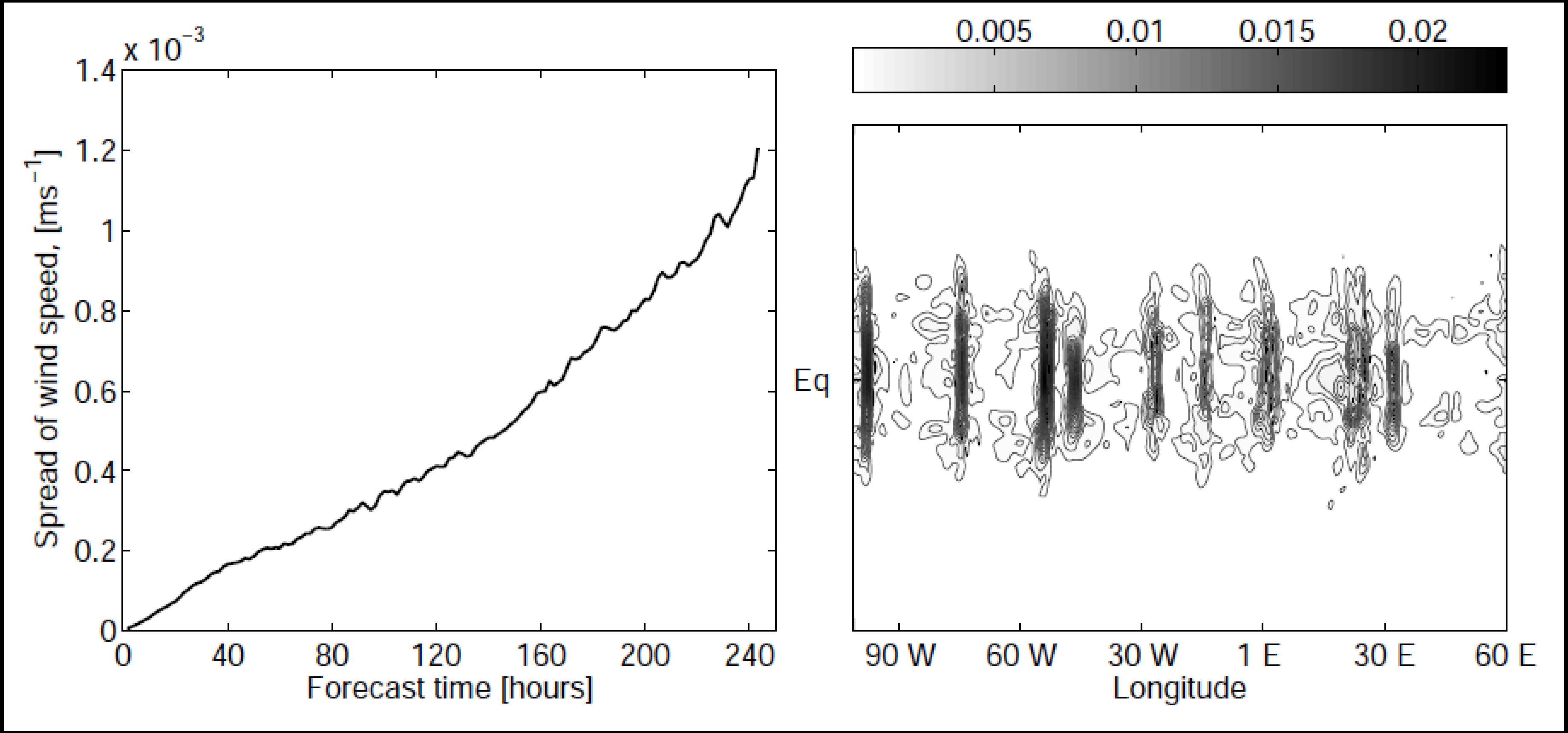
# Hovmöller diagram



Even if different horizontal resolutions generate different sizes of convective structures, the time-scale is the most important for how much energy is back-scattered to the larger scales



# Ensemble Spread



# Using a CA in a 3D model with full physics.

- Thus far, we've studied scale interaction using a CA to generate “clusters” mimicking organization through atmospheric gravity waves.
- The structures generated by the CA yields a greater back-scatter to the larger scales than that of pure random noise.
- The amount of energy back-scattered to the larger atmospheric scales depends on the parameters of the CA scheme, and the memory is the most important.
- We've seen that a CA encompasses several components which are of interest for deep convection organization, such as lateral communication, memory and stochasticity.
- Want to explore in a state-of-the-art NWP model.

# NWP model implementation

- Branch of ALADIN model for the gray-zone scale (~5 km) “ALARO”
- Link CA to the closure assumption based on the prognostic equation of updraft mesh fraction.
- Use CAPE and moisture convergence as input to CA
- CA in “IFS” used from Martin Steinheimer, Peter Bechtold, Judith Berner

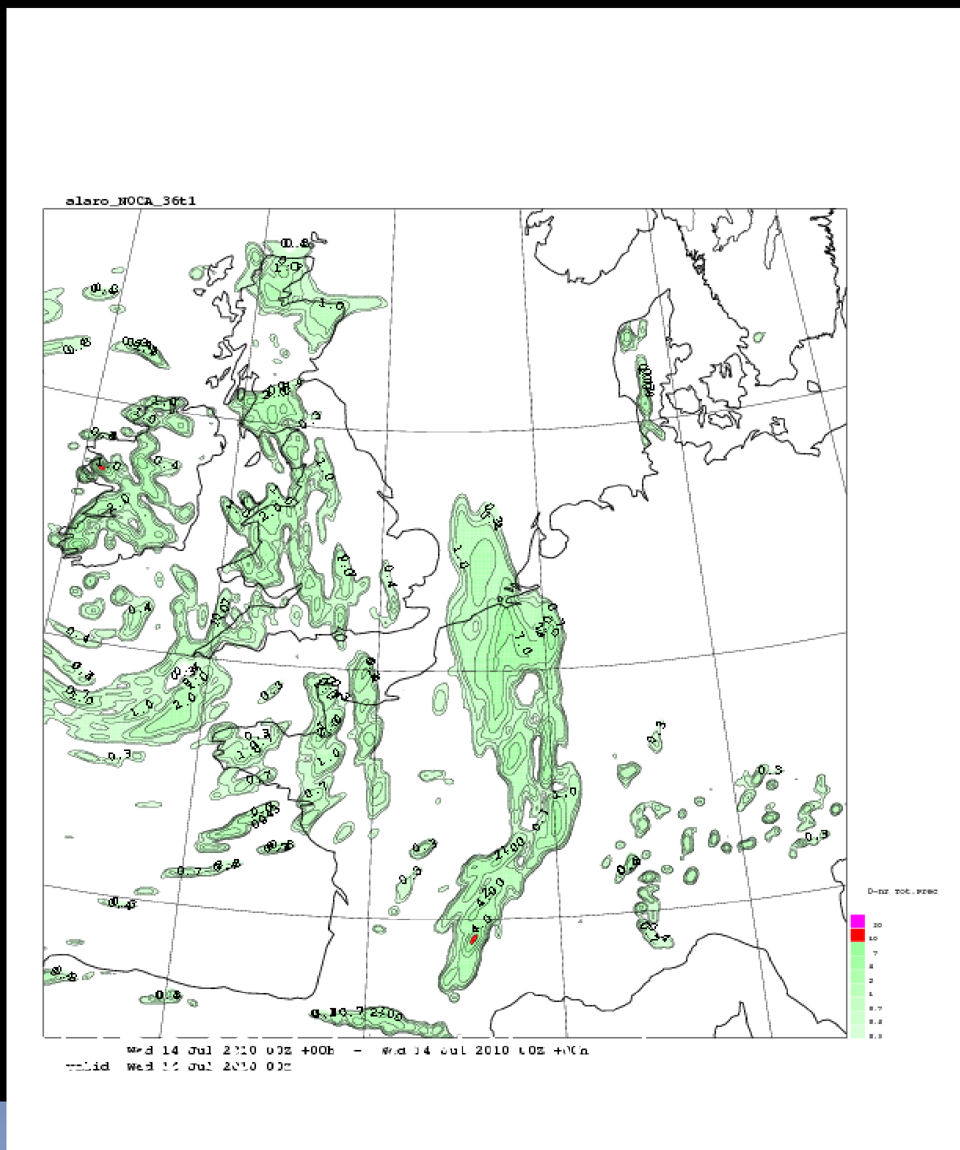
# Updraught mesh-fraction

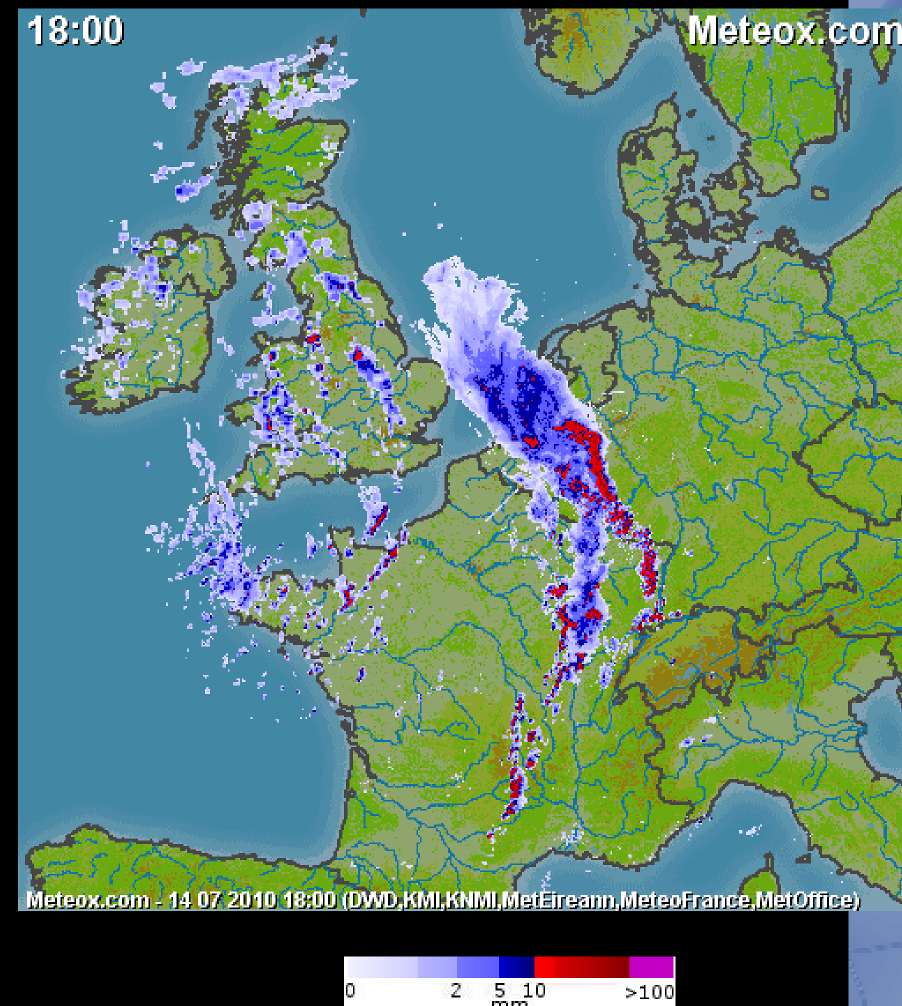
$$\frac{\partial \sigma_u}{\partial t} \int (h_u - \overline{h}) \frac{dp}{g} = L \int \sigma_u \omega_u^* \frac{\delta q_{ca}}{g} + \alpha_{cvg} L \int CVGQ \frac{dp}{g} + \frac{\sigma_{CA} - \sigma_u}{\tau} * (\int (h_u - \overline{h}) \frac{dp}{g})$$

| I | II | III | IV |
| --- | --- | --- | --- |
| Storage = Increase of mesh fraction | Sink = Gross condensation (consumption by updraft) | Source = resolved moisture convergence | Source/(sink) organization by CA |
| | | | Function of CAPE or/and Low level moisture convergence |

$$\frac{\sigma_u^+ - \overline{\sigma_u}}{\Delta t} = \frac{\sigma_{CA} - \sigma_u^+}{\tau}$$

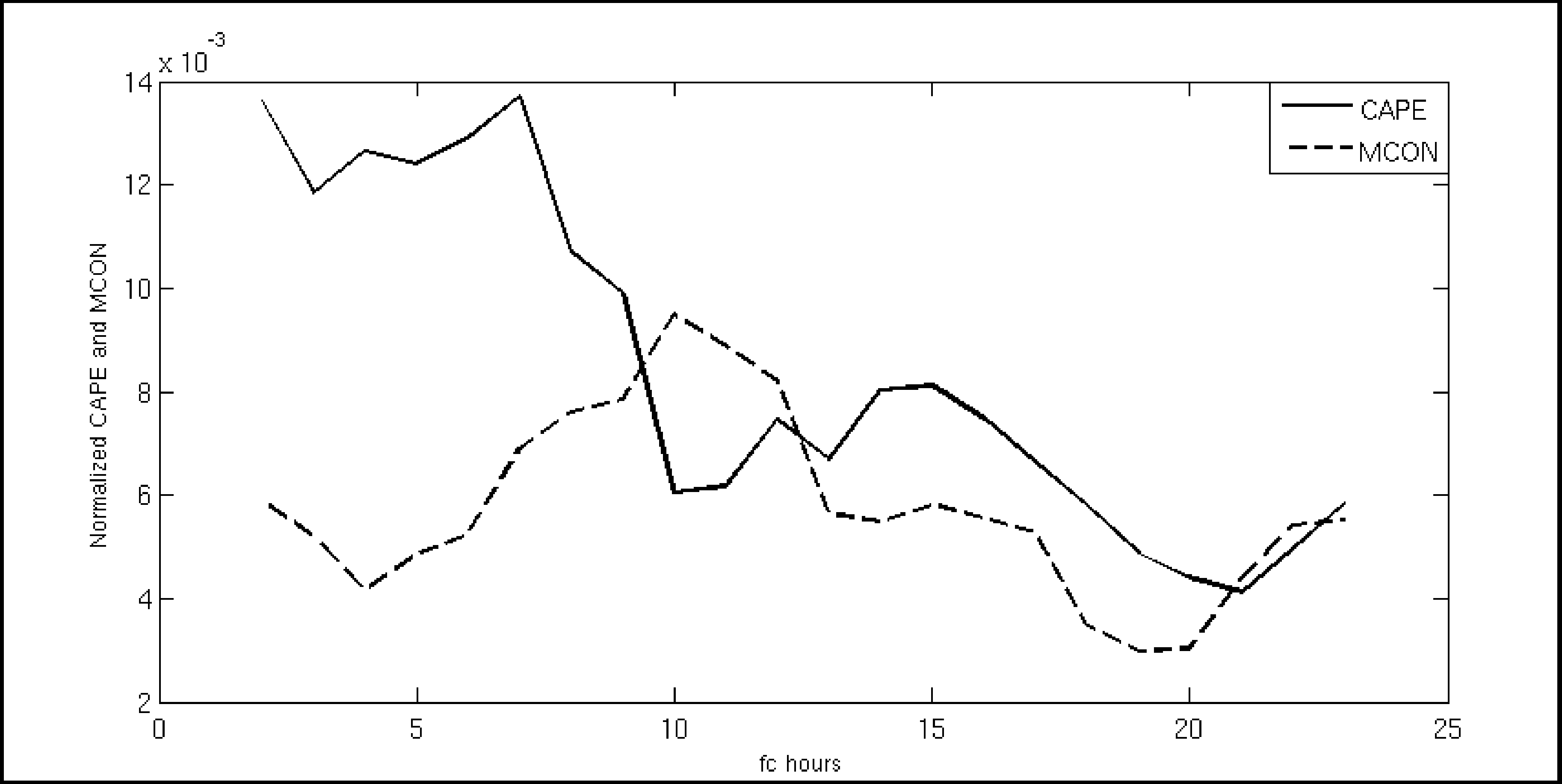
# Radar image, squalline 14/7-10
# 16 UTC (or 18 CET)




1 hour precip from radar image.

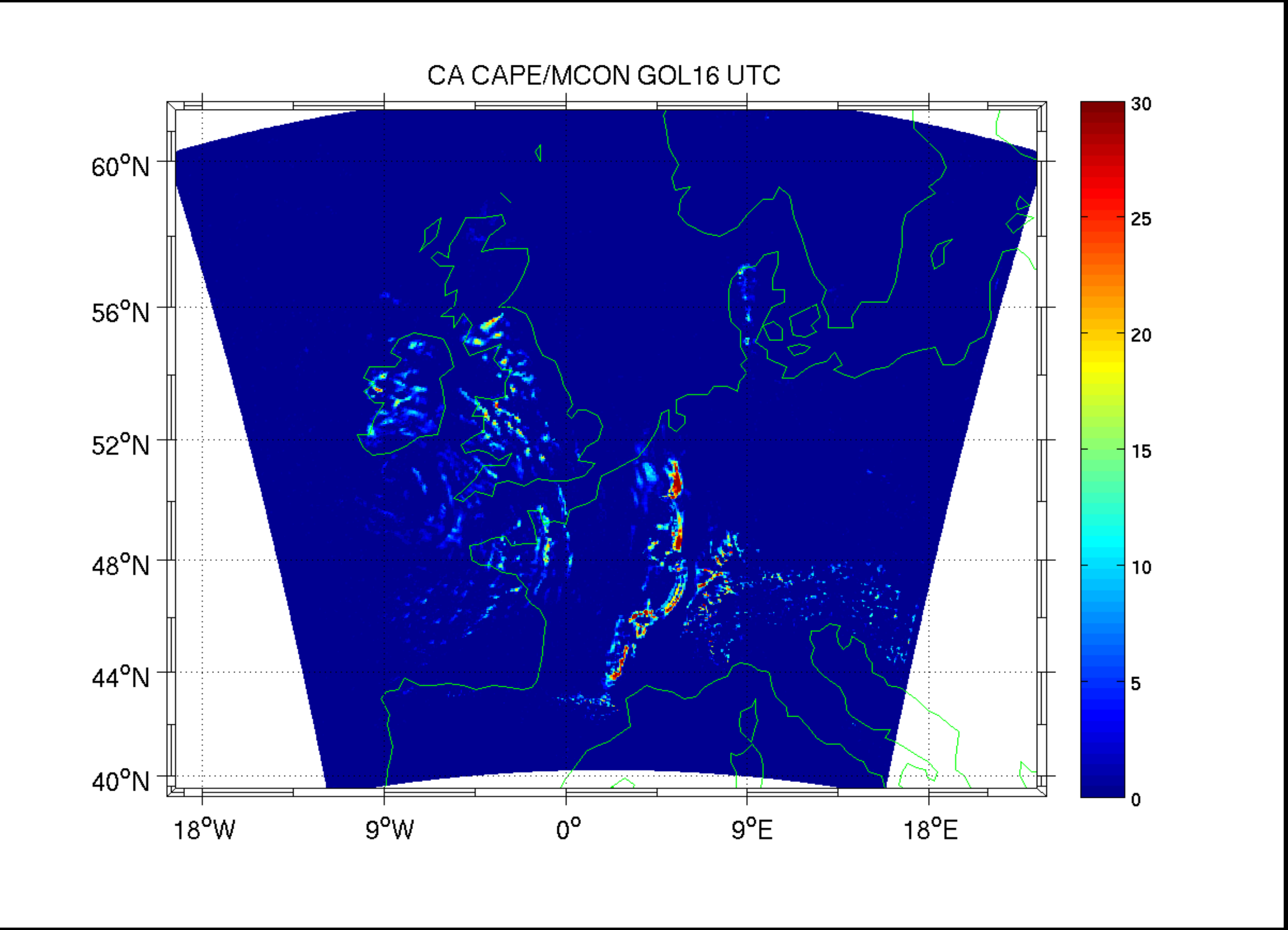
# Time evolution of normalized CAPE and moisture convergence (term III).



# Probabilistic/Deterministic rules

- Probabilistic
  - (+): Can update the CA on a more physical basis
  - (+): Can introduce stochastisity within the parameterization
  - (-) : Does not necessarily remain active (i.e all cells can "die"). Needs to be seeded more frequent, strong dependence on the "convective input fields"
- Deterministic (GOL)
  - (+): Designed with rules such that the CA remains active throughout the forecast period (without seeding new cells). Inherent autocorrelation in space and time, through self-organization, allowing for communication between grid-boxes -> larger spatial scales.
  - (-) : No physical basis for the rules. (However, accurate space/time scales (through clustering) can be achieved, depending on tuning parameters of the scheme).

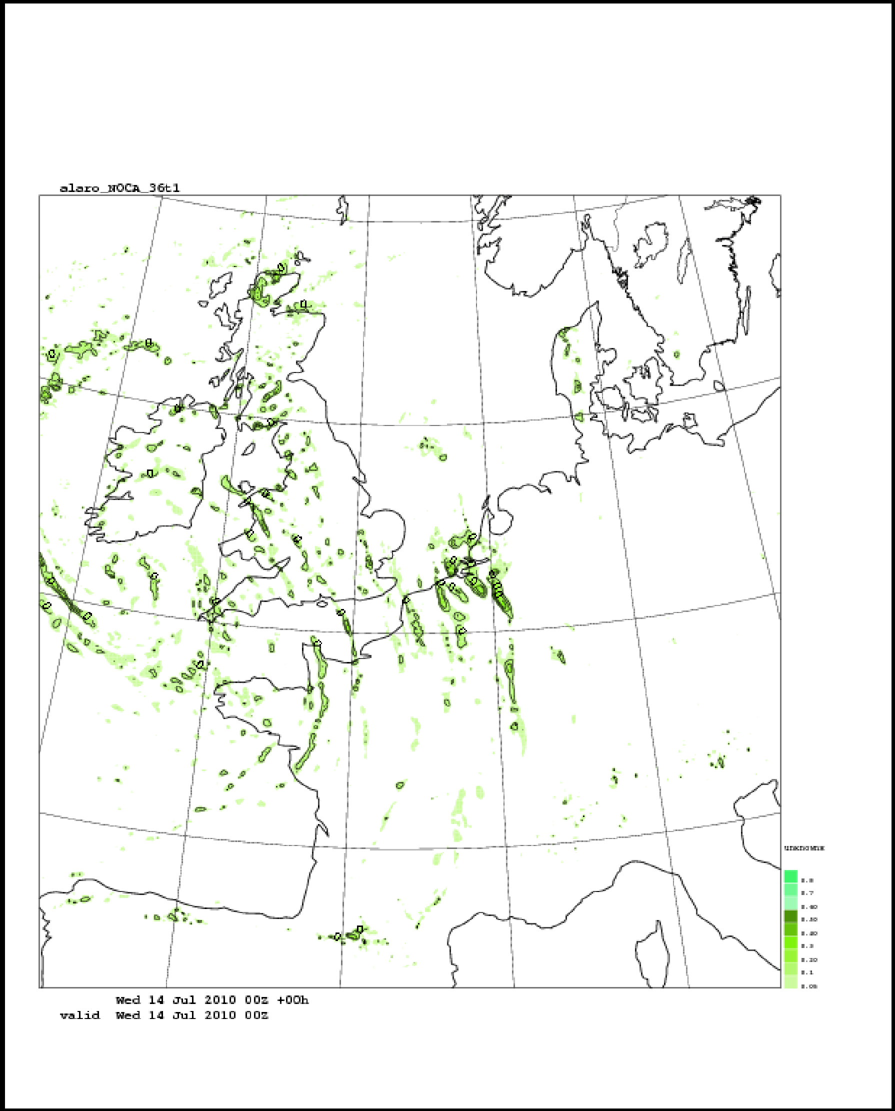
# CA field


CA CAPE/MCON GOL16 UTC
60°N
56°N
52°N
48°N
44°N
40°N
18°W
9°W
0°
9°E
18°E
30
25
20
15
10
5
0

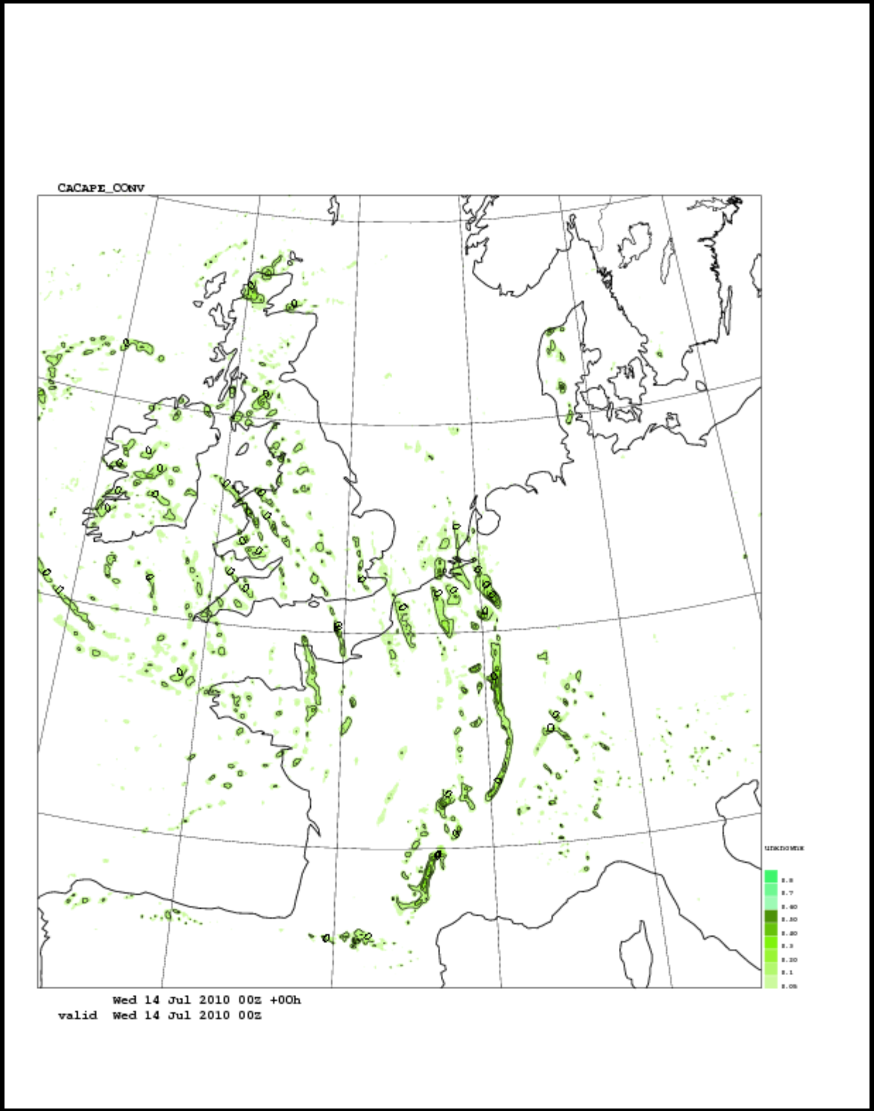
# Updraught mesh fraction, 2010-07-14, 16 UTC

ALARO reference, 36h1.1

ALARO CA-CAPECONV, 36h1.1



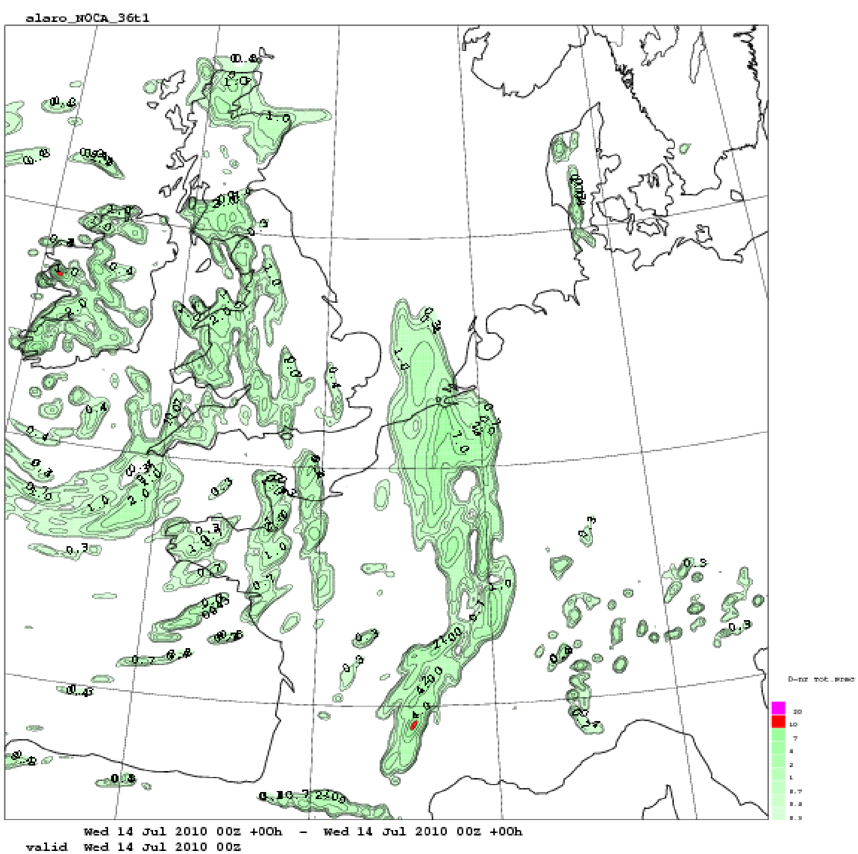

16 UTC




16 UTC

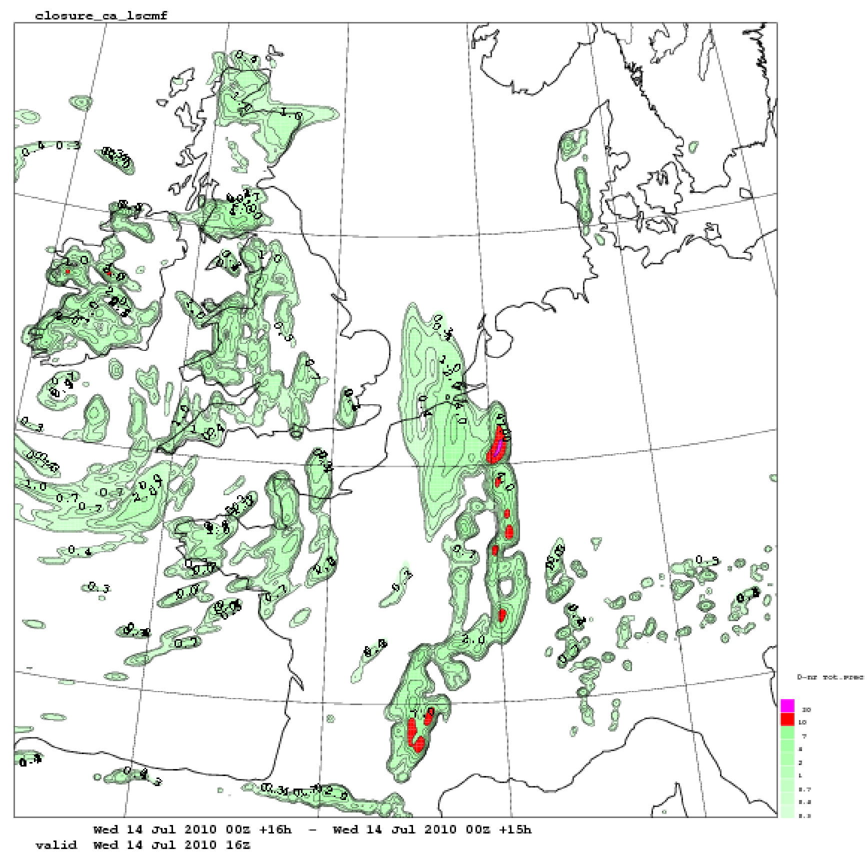
# Total precipitation, 2010-07-14, 16 UTC

ALARO reference, 36h1.1



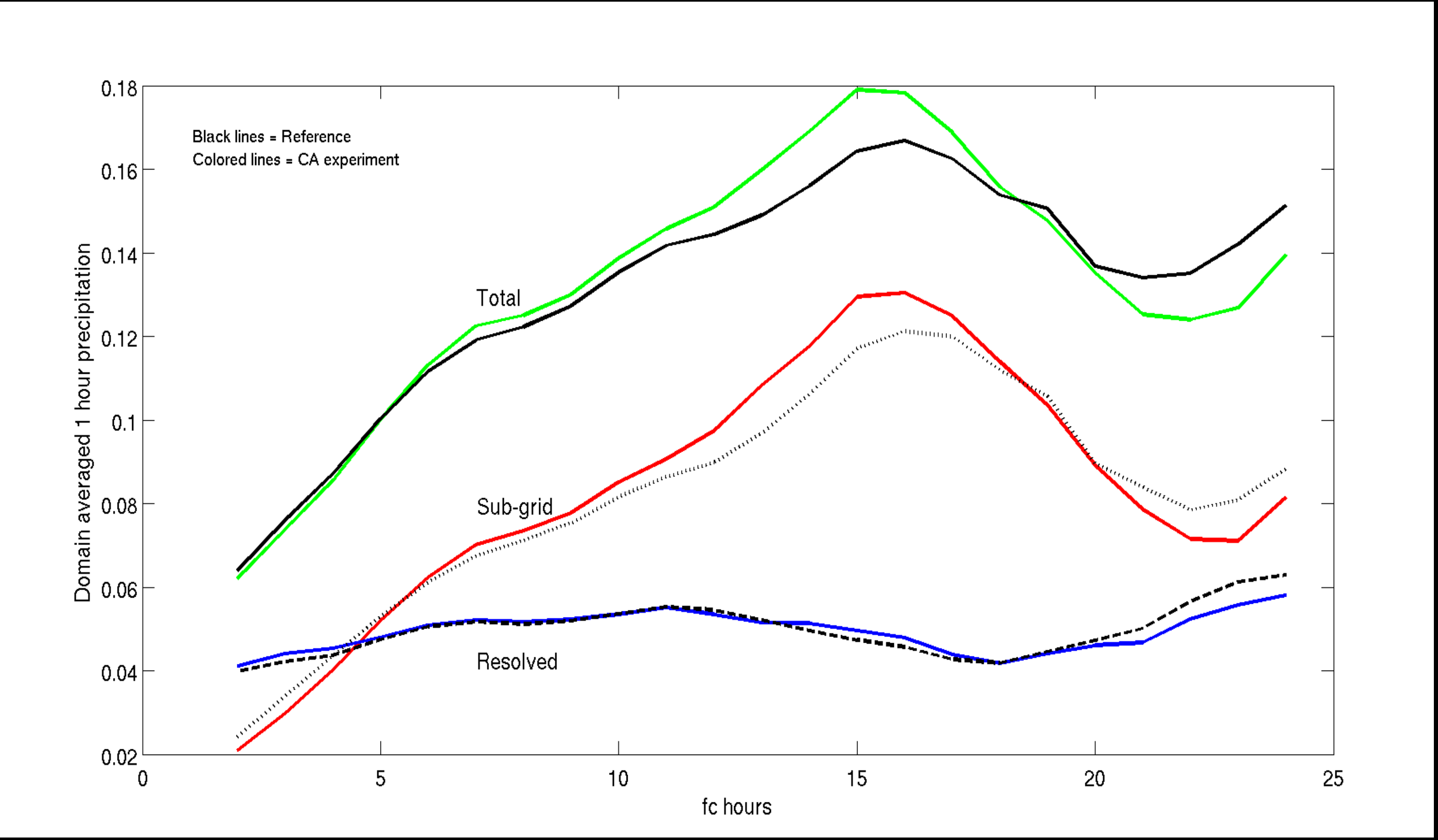

16 UTC

ALARO CA-CAPECONV, 36h1.1




16 UTC

# Time evolution of precipitation




Seems to be an increase in total amount, as a result of an increase of the sub-grid

# Future direction and key research questions

- Should stochastic physics be introduced to the deterministic model? Increased model variability -> saturate at the limit of deterministic predictability.
- Can enhanced organization by CA yield a more variable deterministic model?
- Can enhanced organization by CA help improve forecast of MJO?
- How to measure “organization”?