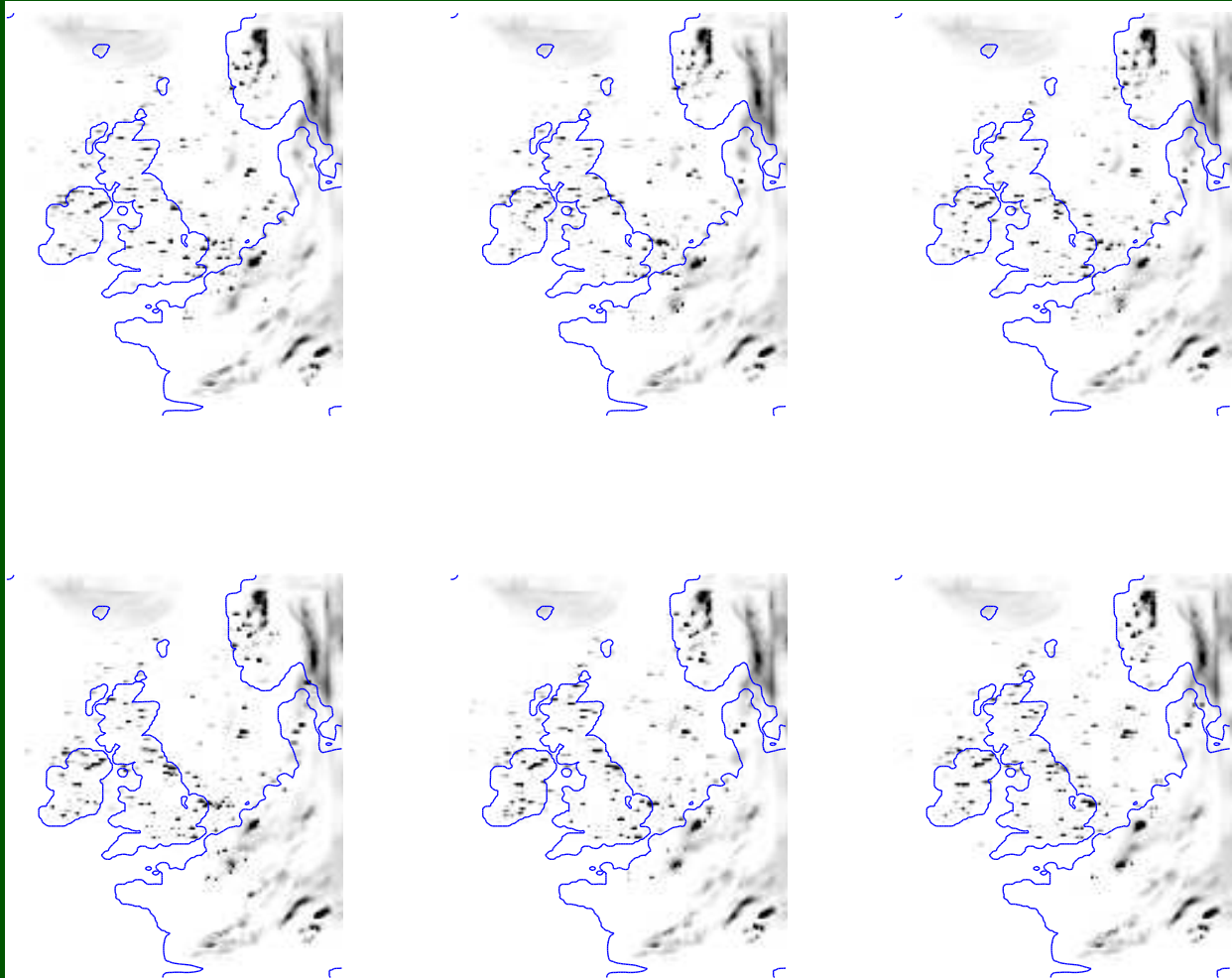




Development of a stochastic convection scheme

R. J. Keane, R. S. Plant, N. E. Bowler, W. J. Tennant

Mini-ensemble of rainfall forecasts





Outline

- Overview of stochastic parameterisation.
- How the Plant Craig stochastic convective parameterisation scheme works and the 3D idealised setup.
- Results: rainfall statistics.
- A look at the Plant Craig scheme in a mesoscale run.
- Conclusions and future work.

Ensemble Forecasting & Stochastic Parameterisation

- Single Deterministic Forecast:

$$\dot{\mathbf{E}}_0(\mathbf{X}, t) = \mathbf{A}(\mathbf{E}_0, \mathbf{X}, t) + \mathbf{P}(\mathbf{E}_0);$$

$$\mathbf{E}_0(\mathbf{X}, 0) = \mathbf{I}(\mathbf{X})$$

- Ensemble of Deterministic Forecasts:

$$\dot{\mathbf{E}}_j(\mathbf{X}, t) = \mathbf{A}(\mathbf{E}_j, \mathbf{X}, t) + \mathbf{P}(\mathbf{E}_j);$$

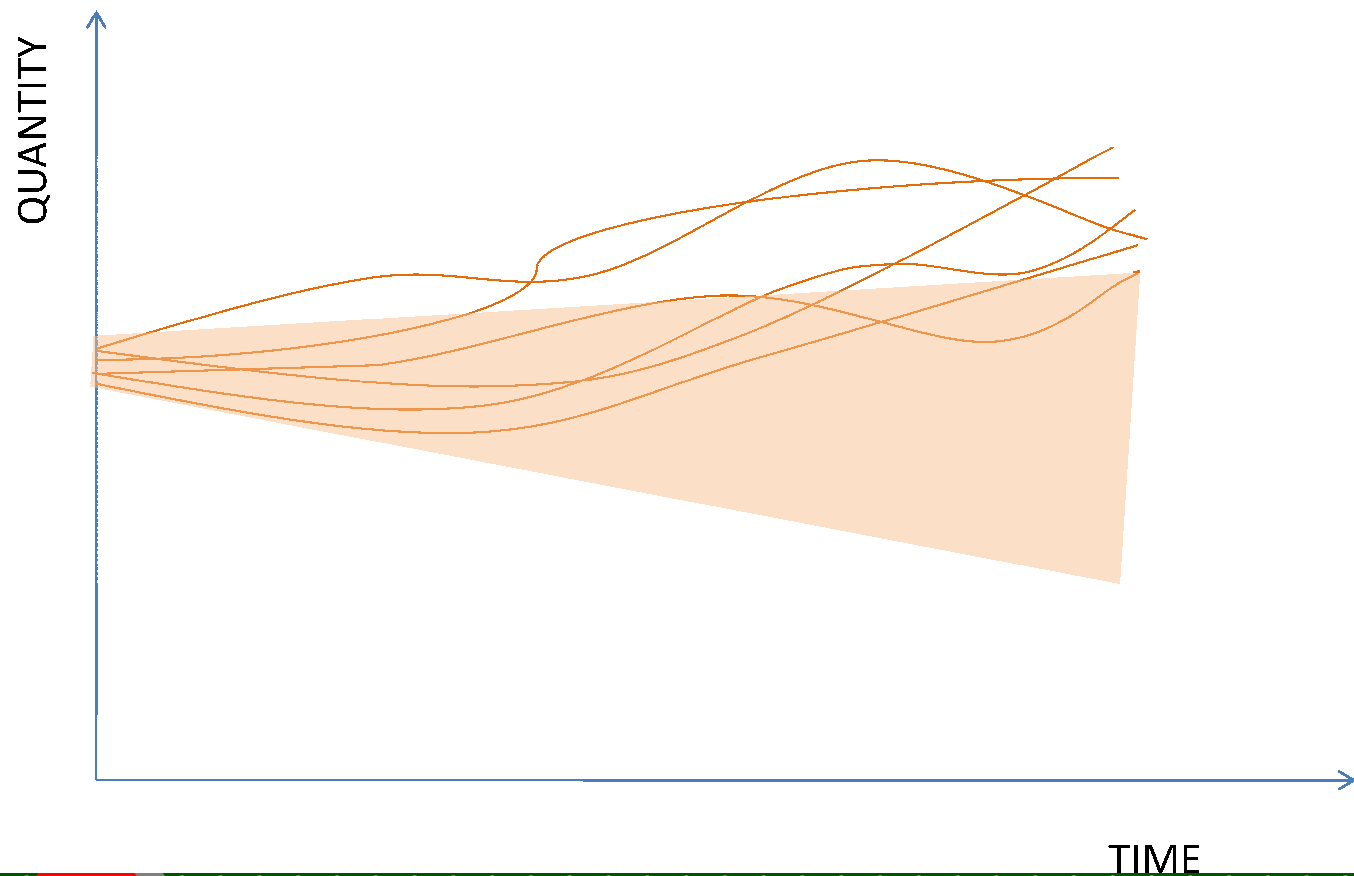
$$\mathbf{E}_j(\mathbf{X}, 0) = \mathbf{I}(\mathbf{X}) + \mathbf{D}_j(\mathbf{X})$$

- Ensemble of Stochastic Forecasts:

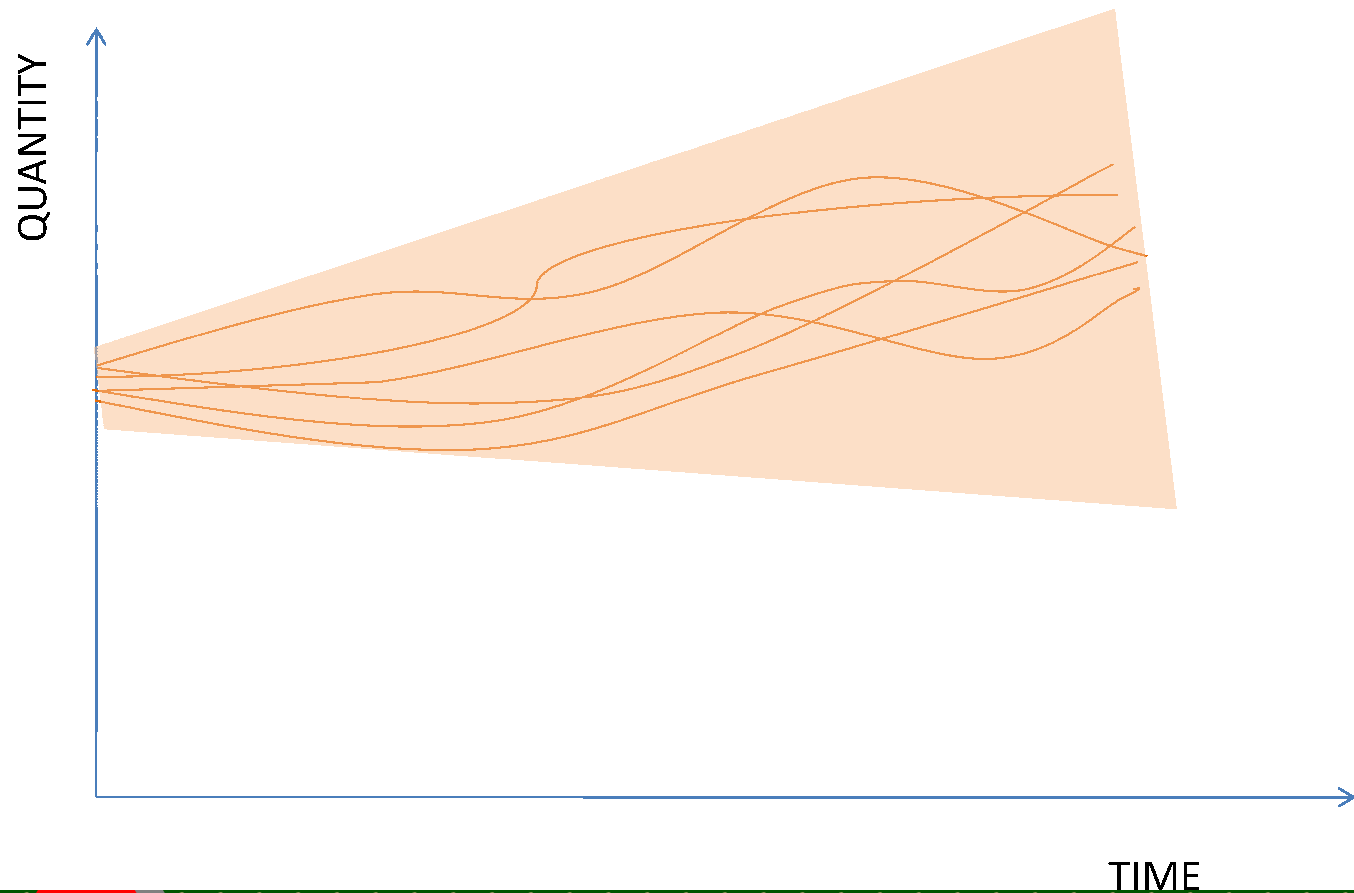
$$\dot{\mathbf{E}}_j(\mathbf{X}, t) = \mathbf{A}(\mathbf{E}_j, \mathbf{X}, t) + \mathbf{P}_j(\mathbf{E}_j, t);$$

$$\mathbf{E}_j(\mathbf{X}, 0) = \mathbf{I}(\mathbf{X}) + \mathbf{D}_j(\mathbf{X})$$

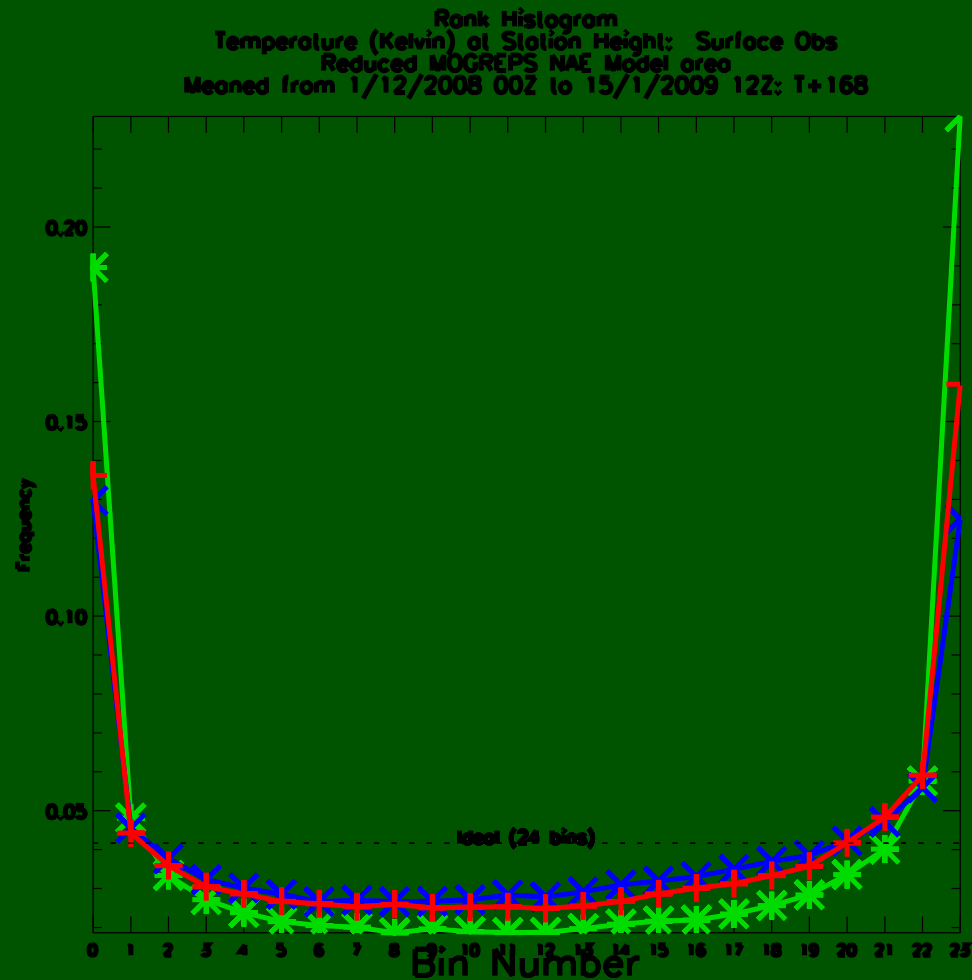
How stochastic parameterisations may improve ensemble forecasts: noise-induced drift



How stochastic parameterisations may improve ensemble forecasts: better forecast of variability

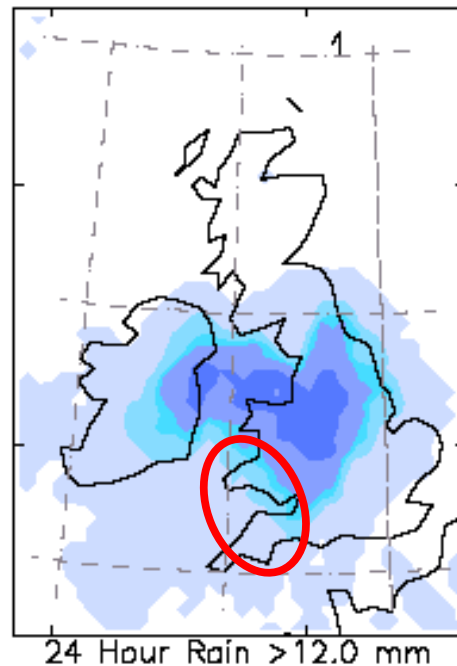
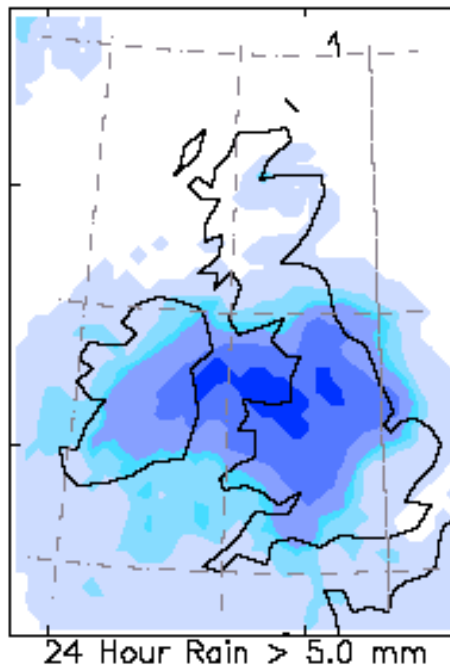
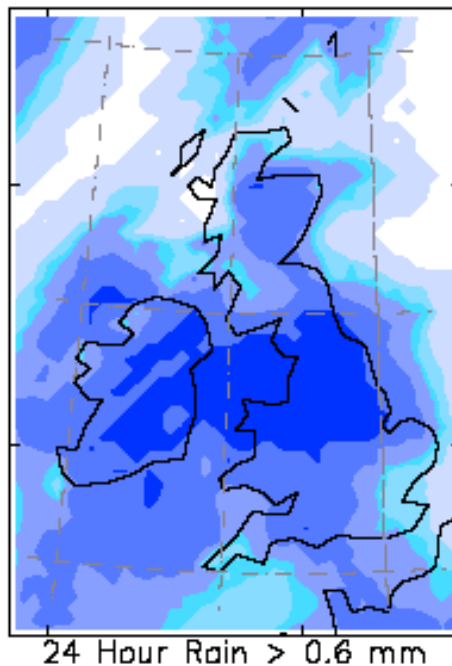


Rank Histograms of surface temperature



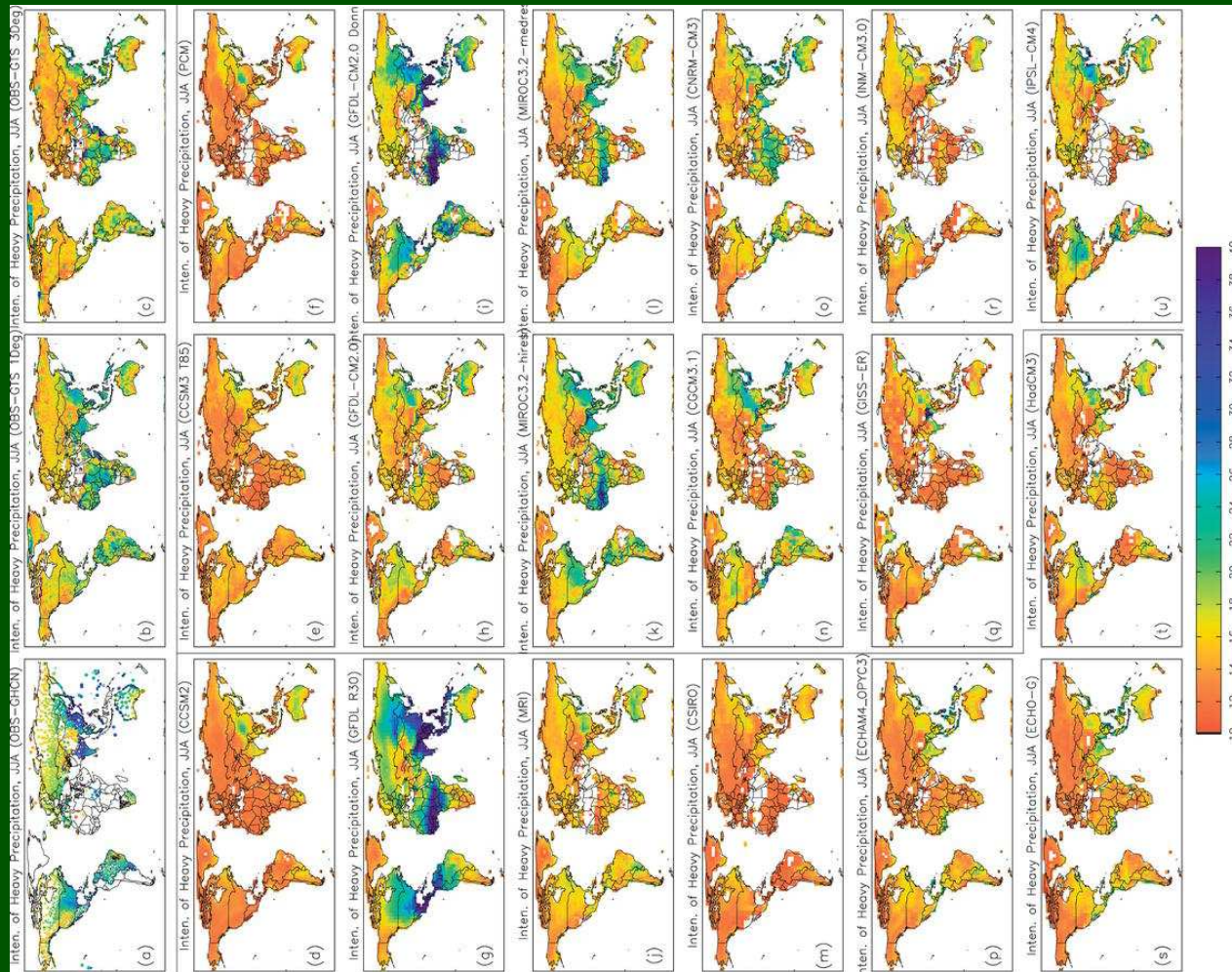
Heavy Rain Devon and South Wales 6th June 2009

Ken Mylne, 4th SRNWP workshop on Short Range Ensemble Prediction Systems, 2009.



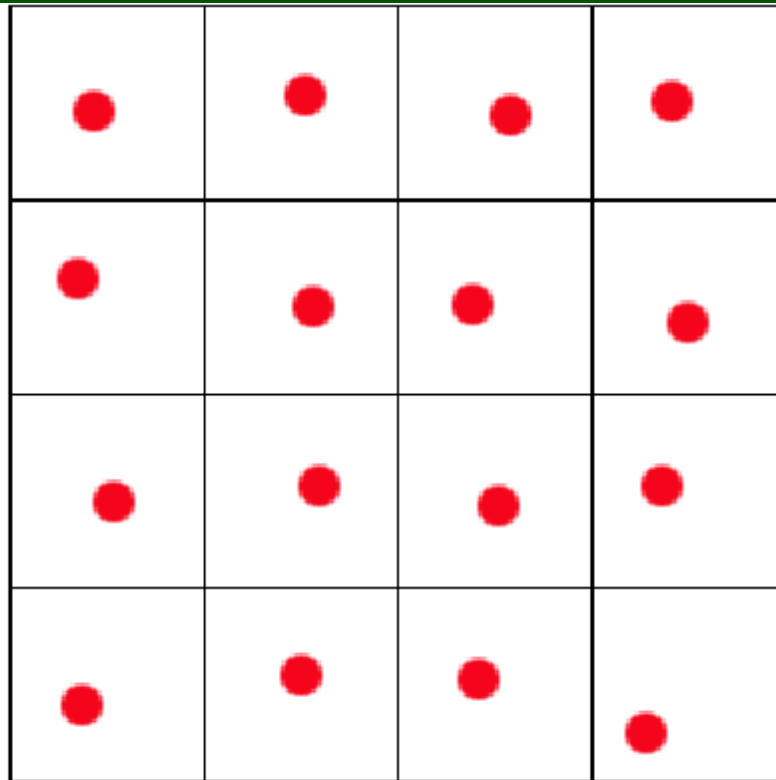
Climate modelling of heavy precipitation

Sun et. al. J. Clim. 2006



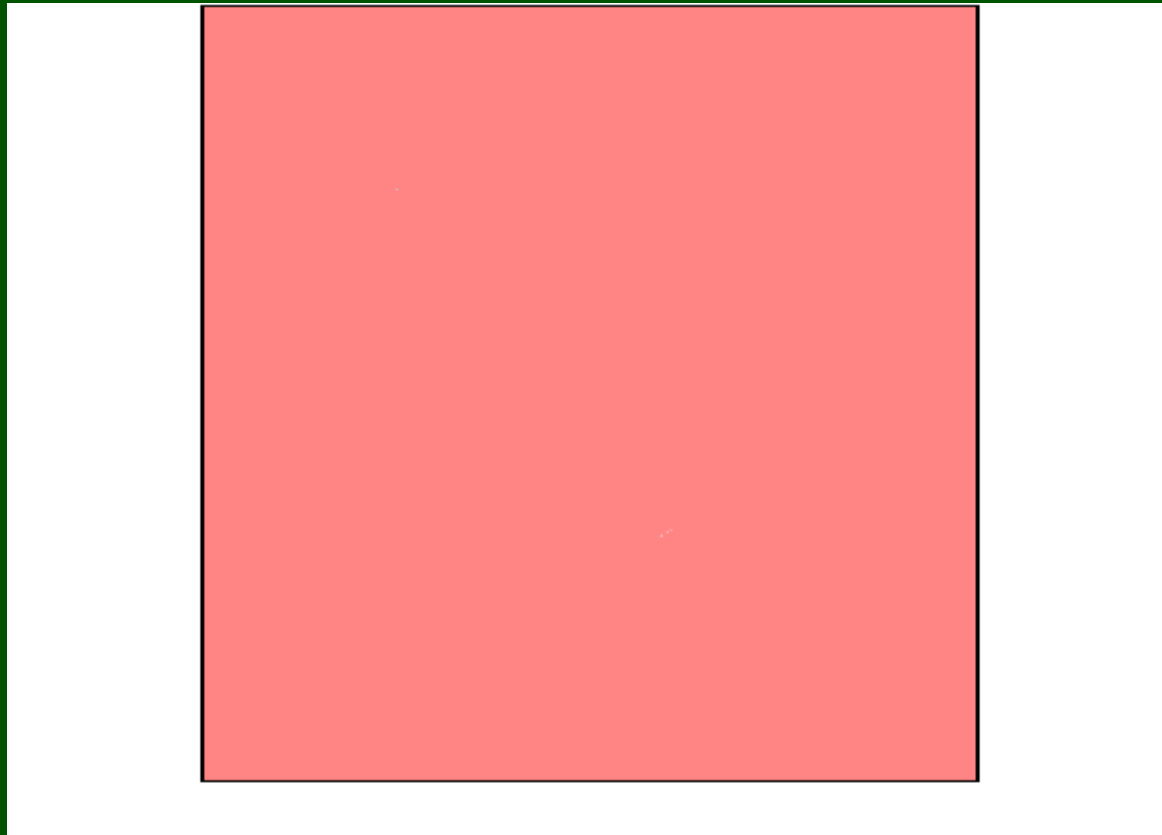
Conventional convective parameterisation

For a constant large-scale situation, a conventional parameterisation models the convection independently of space:



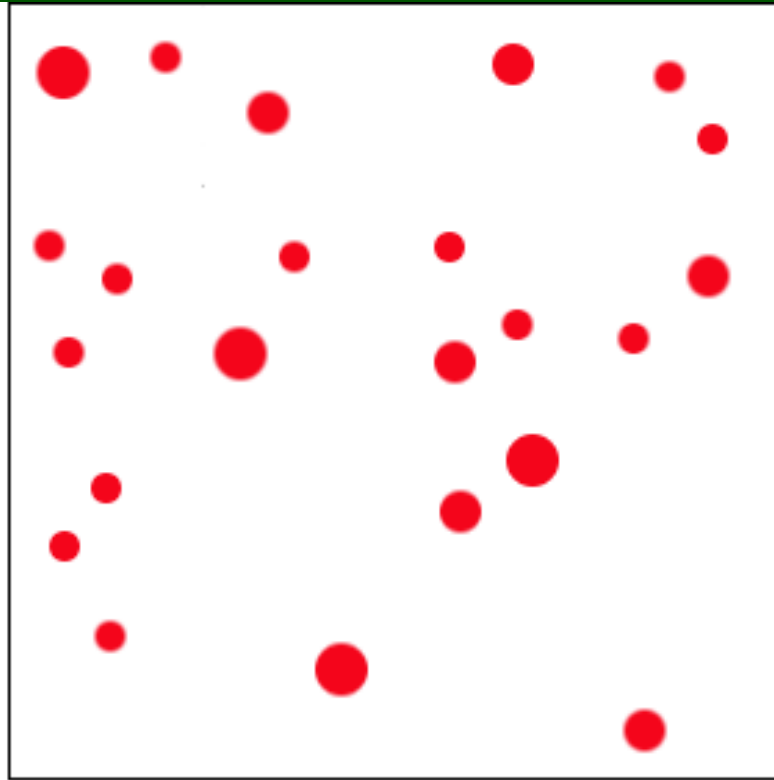
Conventional convective parameterisation

This leads to a uniform, mean value of convection whatever the grid box size:



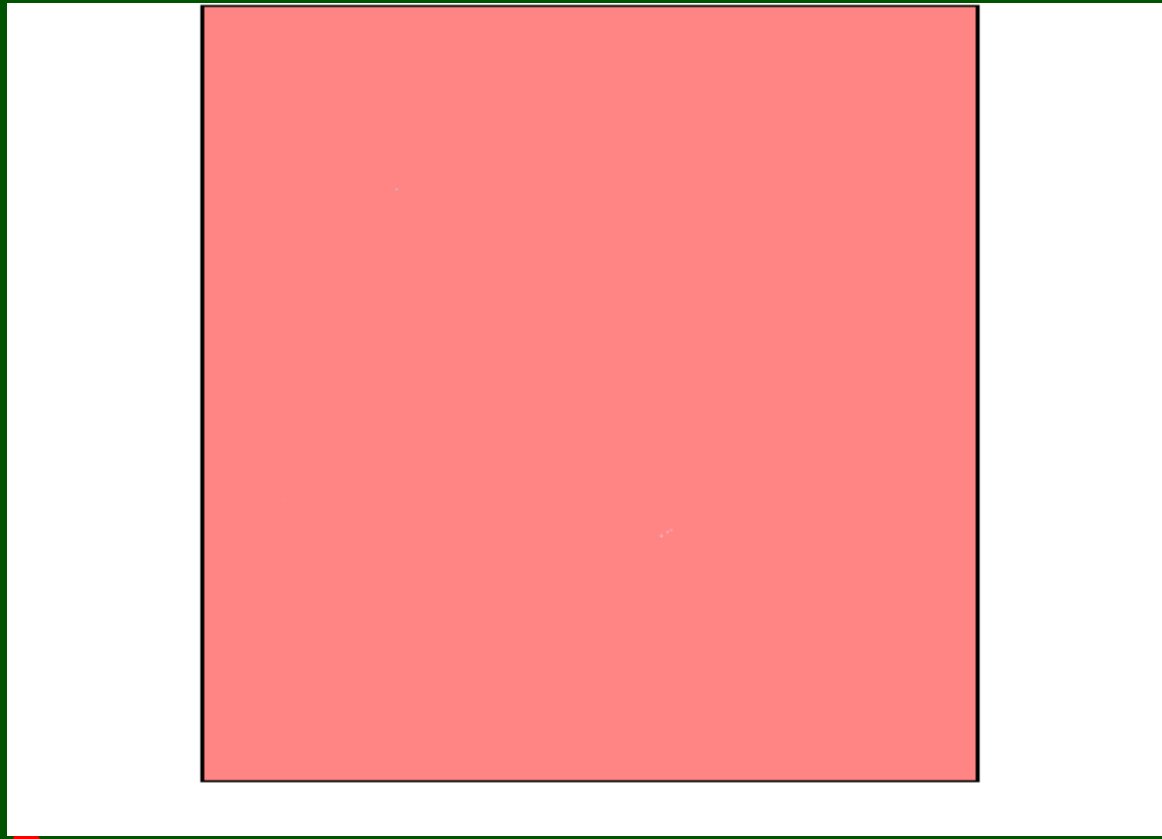
Stochastic parameterisation

A stochastic scheme allows the number and strength of clouds to vary consistent with the large-scale situation:



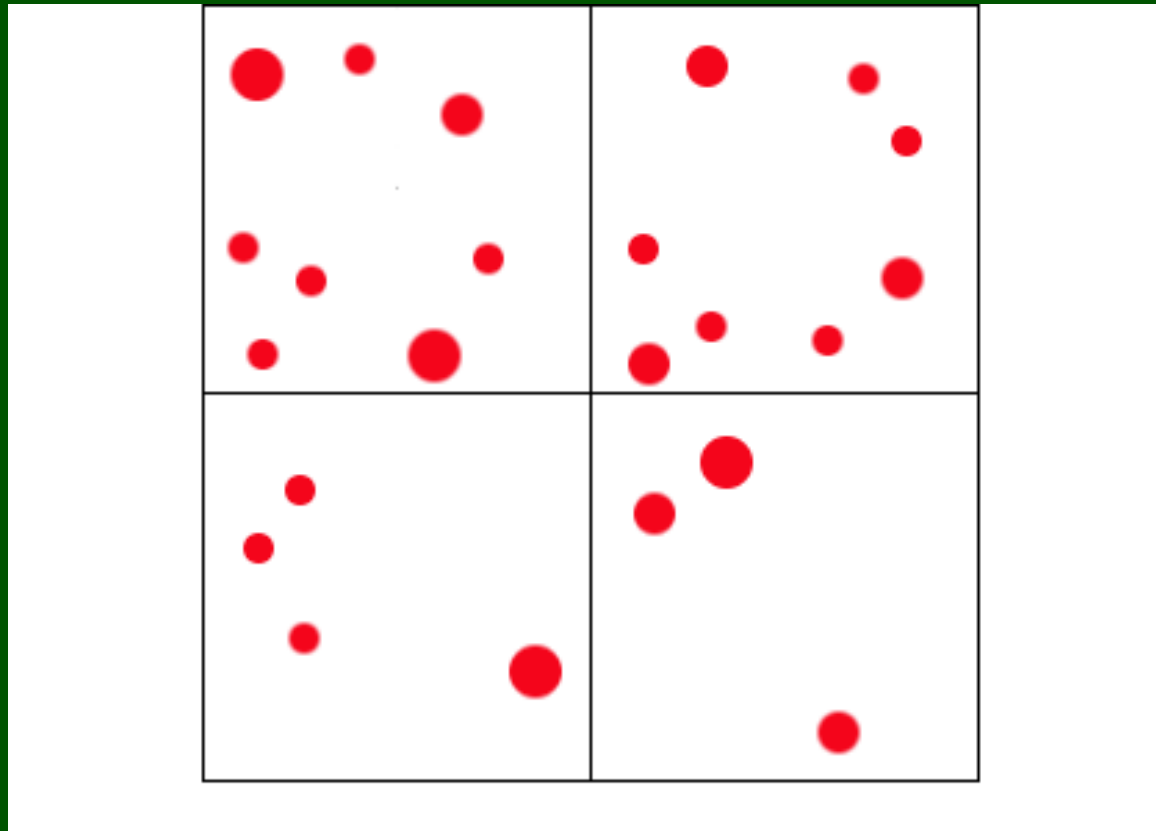
Effect of Paramterisation

Of course, this has no effect if the grid box is large enough:



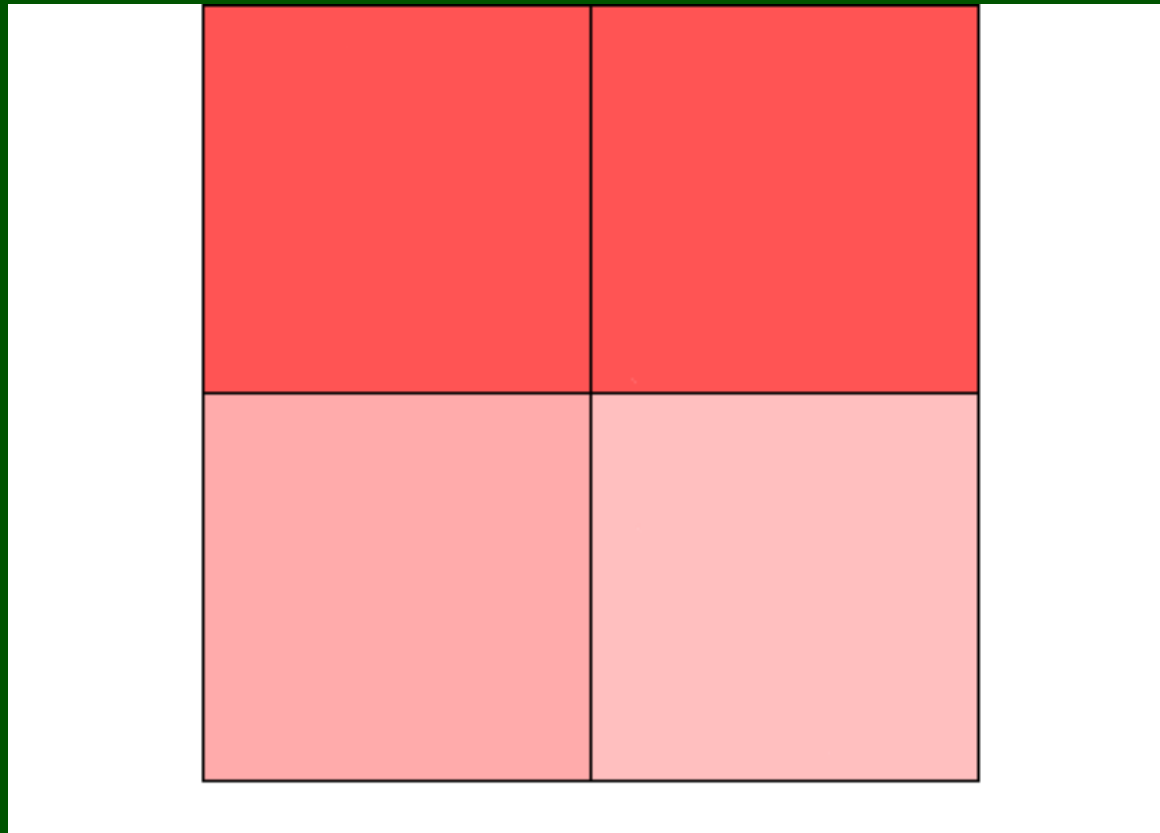
Stochastic Parameterisation

But for a smaller gridbox ...

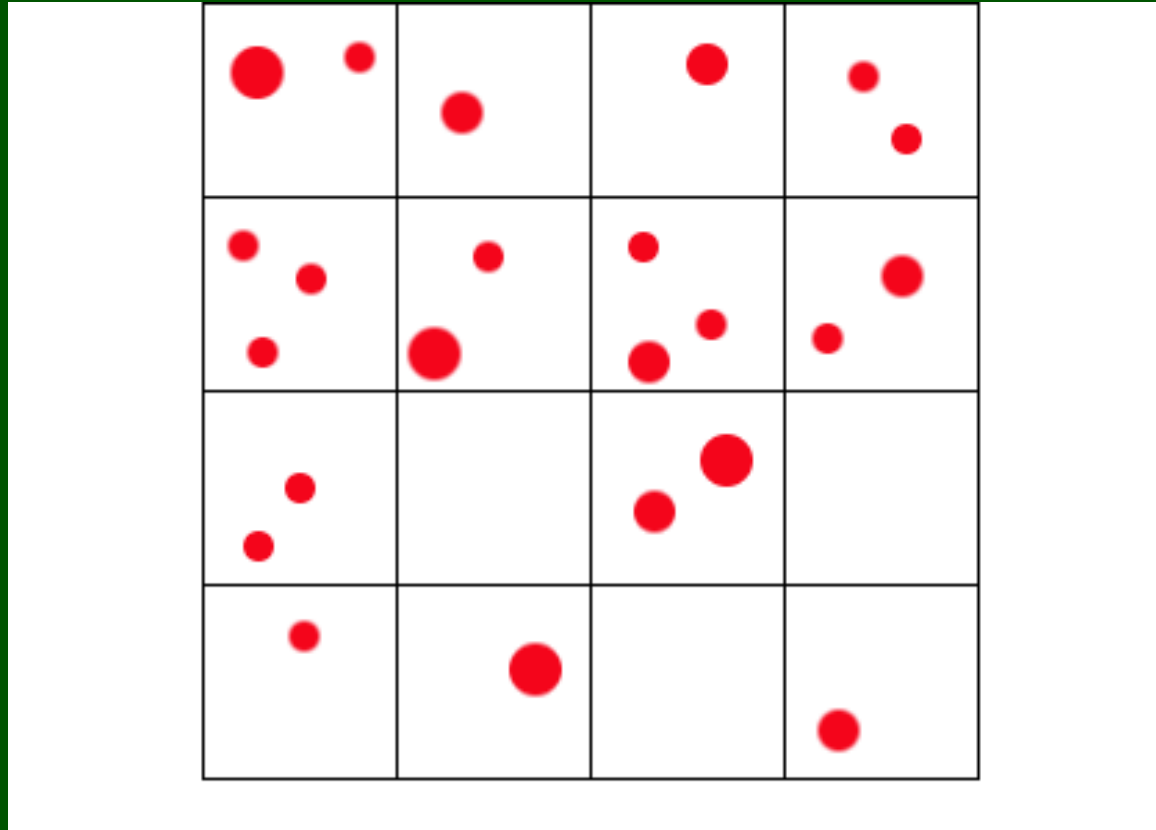


Effect of Paramterisation

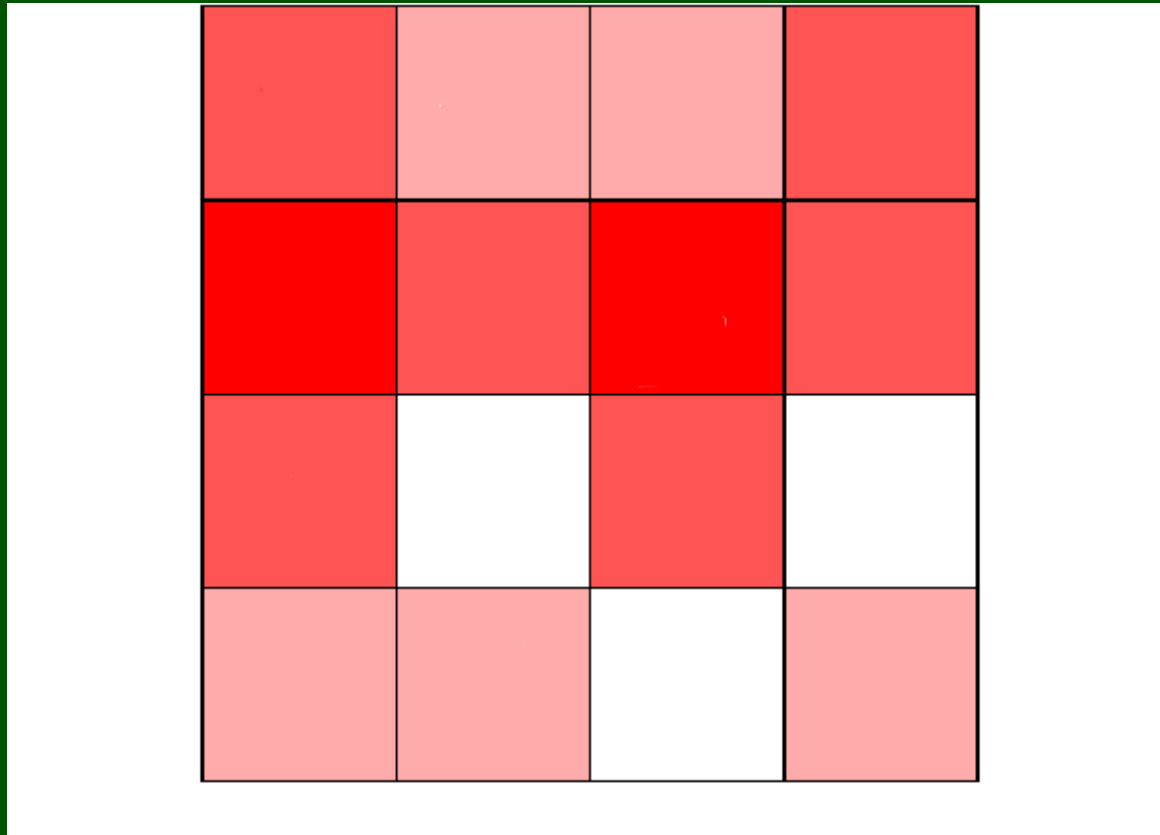
The scheme allows some convective variability:



Stochastic Parameterisation

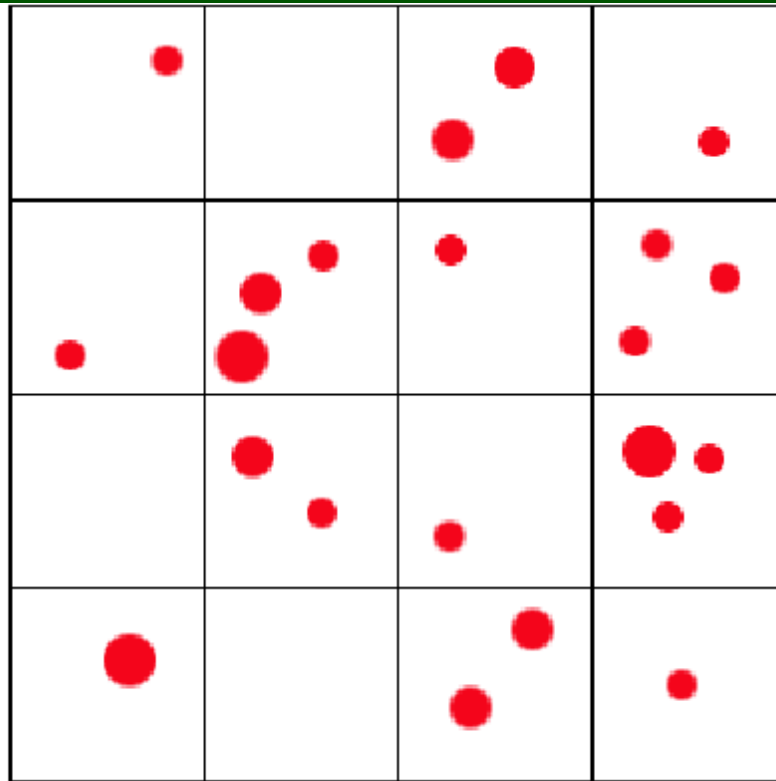


Effect of Paramterisation



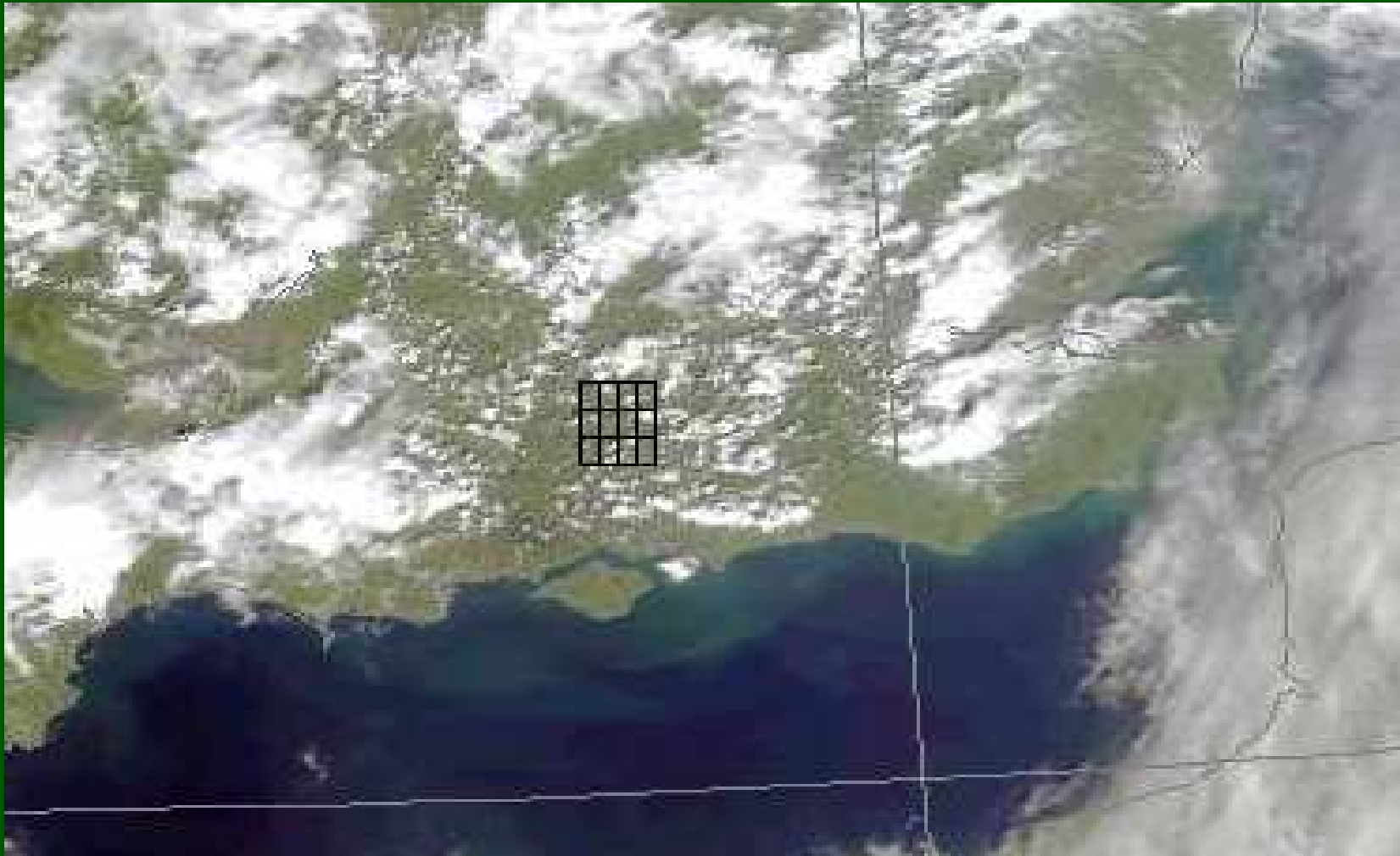
The real world

The distribution will be different in reality, but the *variability* will be similar.

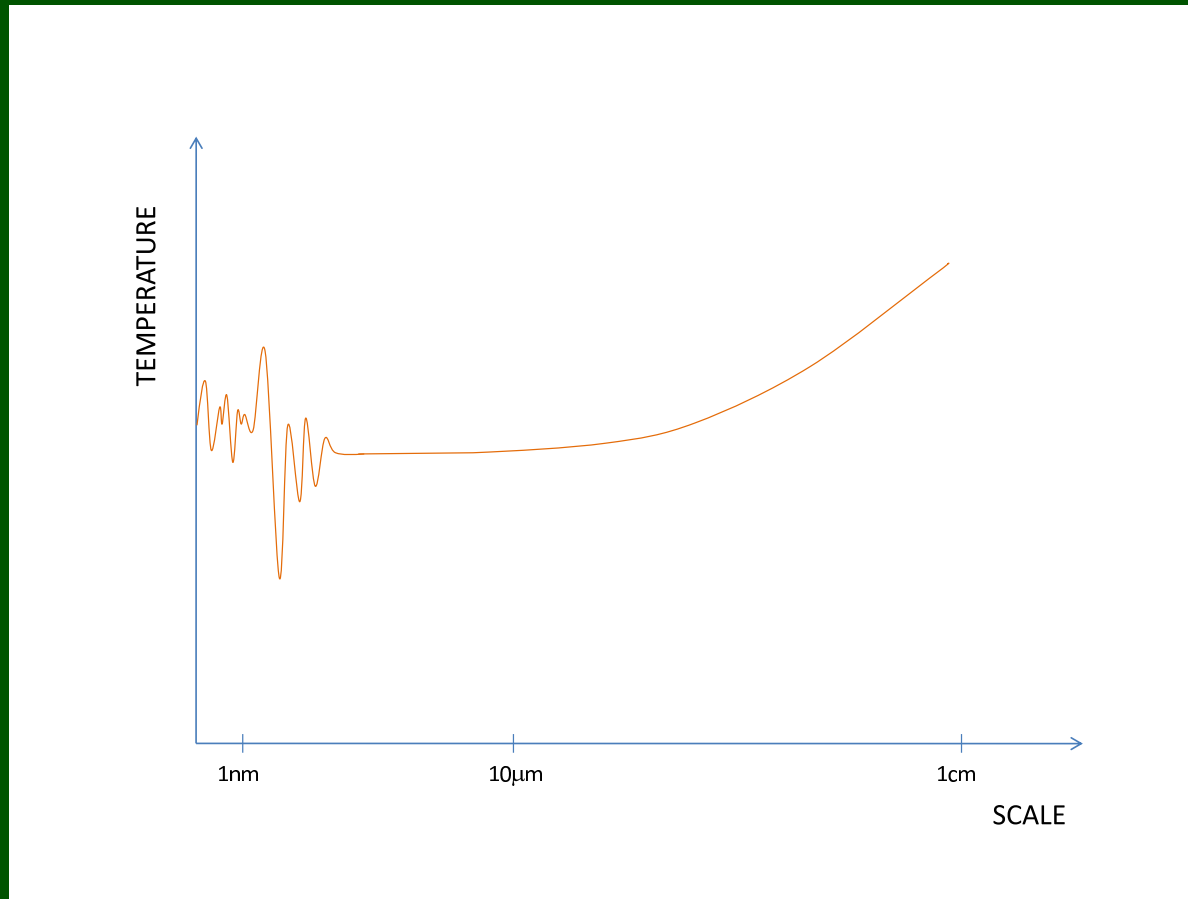


Satellite image example

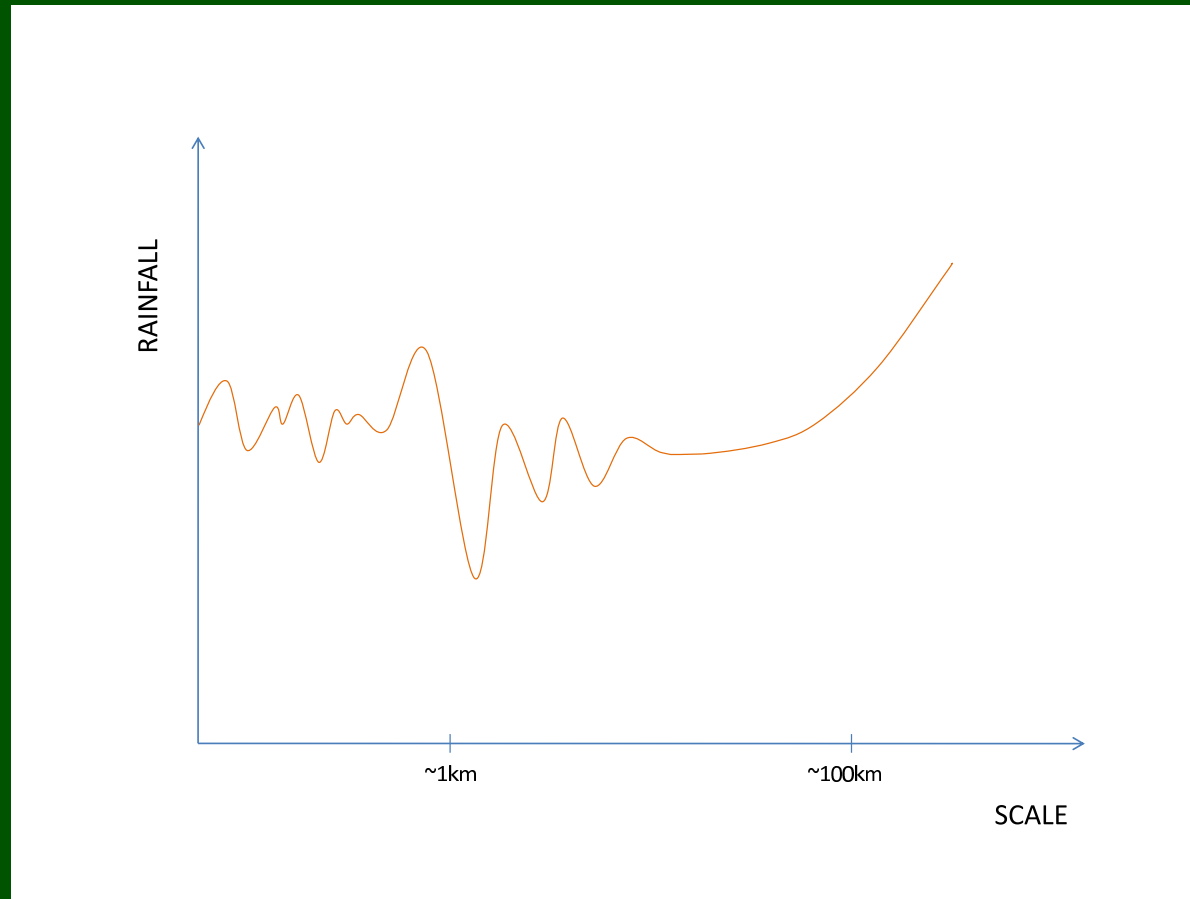
NERC SRS, Dundee, 15/06/09 13:32.



Scale separation: thermodynamics



Scale separation: rainfall



Convection schemes *parameterisation*

- Trigger function
- Mass-flux plume model
- Closure
- Examples
 - Gregory Rowntree (UM standard)
 - Kain Fritsch
 - Plant Craig (based on Kain Fritsch)

Plant Craig scheme: Analogies

Statistical Mechanics

Particle

Energy per particle

Number of particles

Ensemble average energy

Temperature

Entropy

Convection

Cloud

Mass flux per cloud m

Number of clouds N

Ensemble average mass flux $\langle M \rangle$

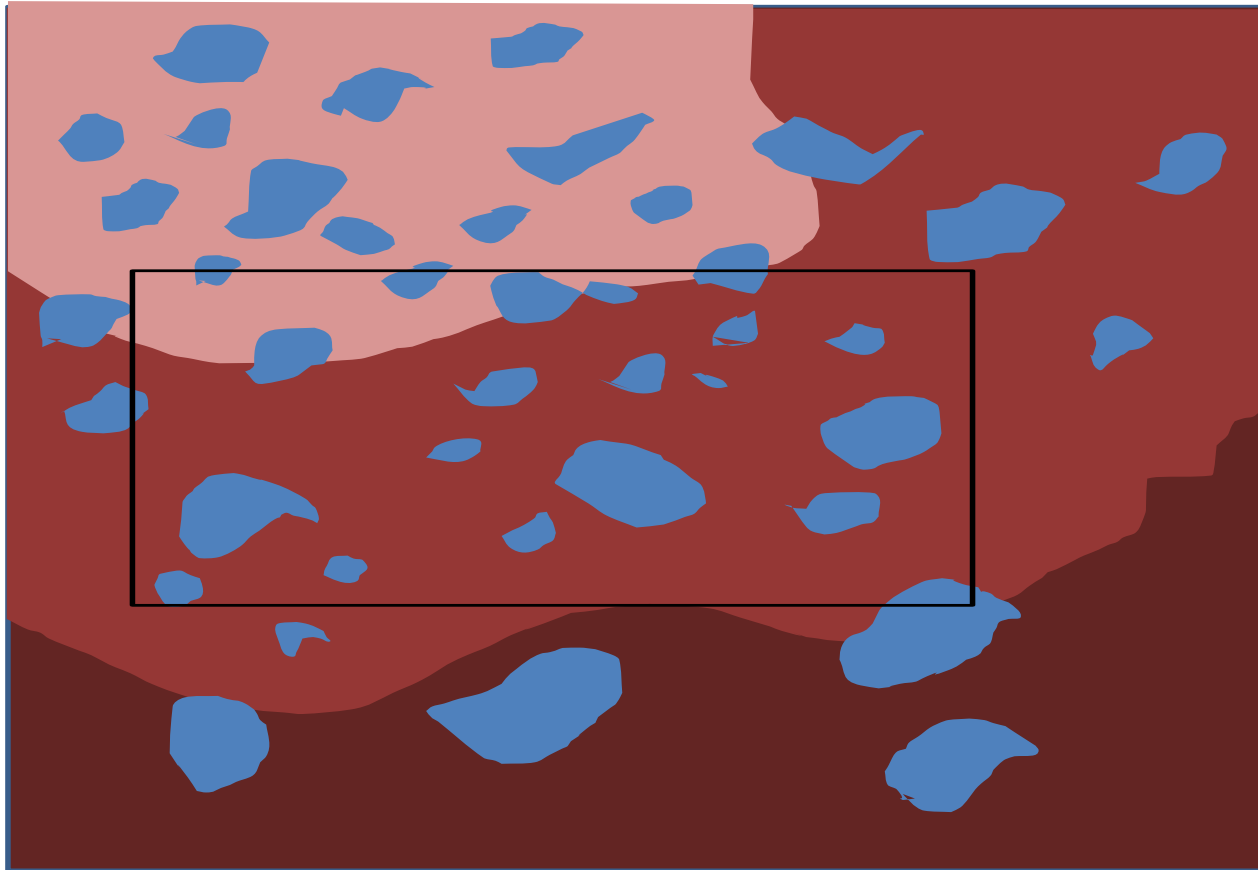
Ensemble mean mass flux per cloud $\langle m \rangle$

Ensemble mean number of clouds $\langle N \rangle$

Plant Craig scheme: Methodology

- Obtain the large-scale state by averaging resolved flow variables over both space and time.
- Obtain $\langle M \rangle$ from CAPE closure and define the equilibrium distribution of m (Cohen-Craig theory).
- Draw randomly from this distribution to obtain cumulus properties in each grid box.
- Compute tendencies of grid-scale variables from the cumulus properties.

Plant Craig scheme: Averaging area



Plant Craig scheme: Probability distribution

Assuming a statistical equilibrium leads to an exponential distribution of mass fluxes per cloud:

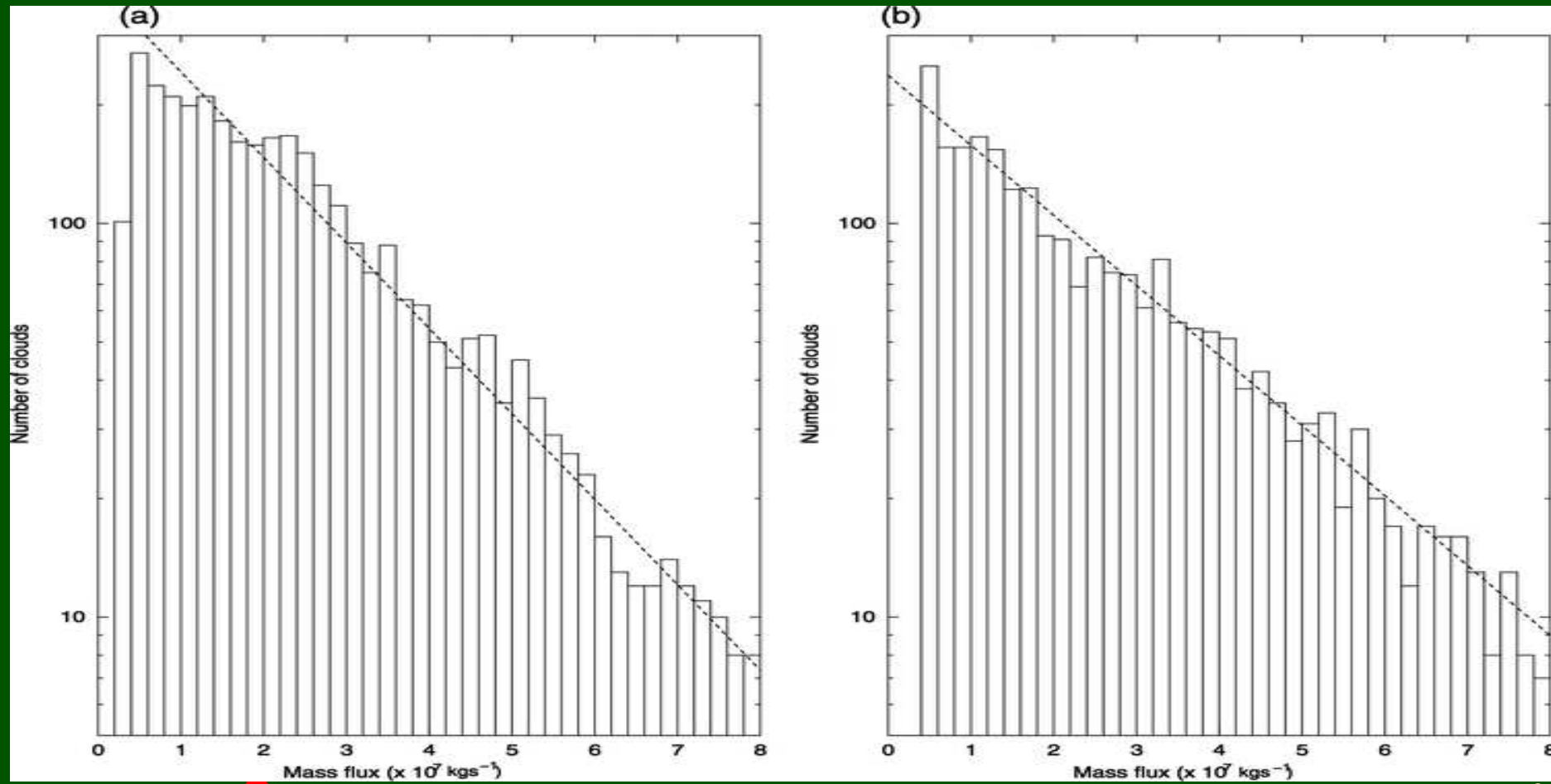
$$p(m)dm = \frac{1}{\langle m \rangle} \exp \left(\frac{-m}{\langle m \rangle} \right) dm.$$

So if $m \sim r^2$ then the probability of initiating a plume of radius r in a timestep dt is

$$\frac{\langle M \rangle 2r}{\langle m \rangle \langle r^2 \rangle} \exp \left(\frac{-r^2}{\langle r^2 \rangle} \right) dr \frac{dt}{T}.$$

Exponential distribution in a CRM

Cohen, PhD thesis (2001)



Ensemble Forecasting & Stochastic Parameterisation

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$$\mathbf{E}_0(\mathbf{X}, 0) = \mathbf{I}(\mathbf{X})$$

- Ensemble of Deterministic Forecasts:

$$\dot{\mathbf{E}}_j(\mathbf{X}, t) = \mathbf{A}(\mathbf{E}_j, \mathbf{X}, t) + \mathbf{P}(\mathbf{E}_j);$$

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$$\mathbf{E}_j(\mathbf{X}, 0) = \mathbf{I}(\mathbf{X}) + \mathbf{D}_j(\mathbf{X})$$

PDF of total mass flux

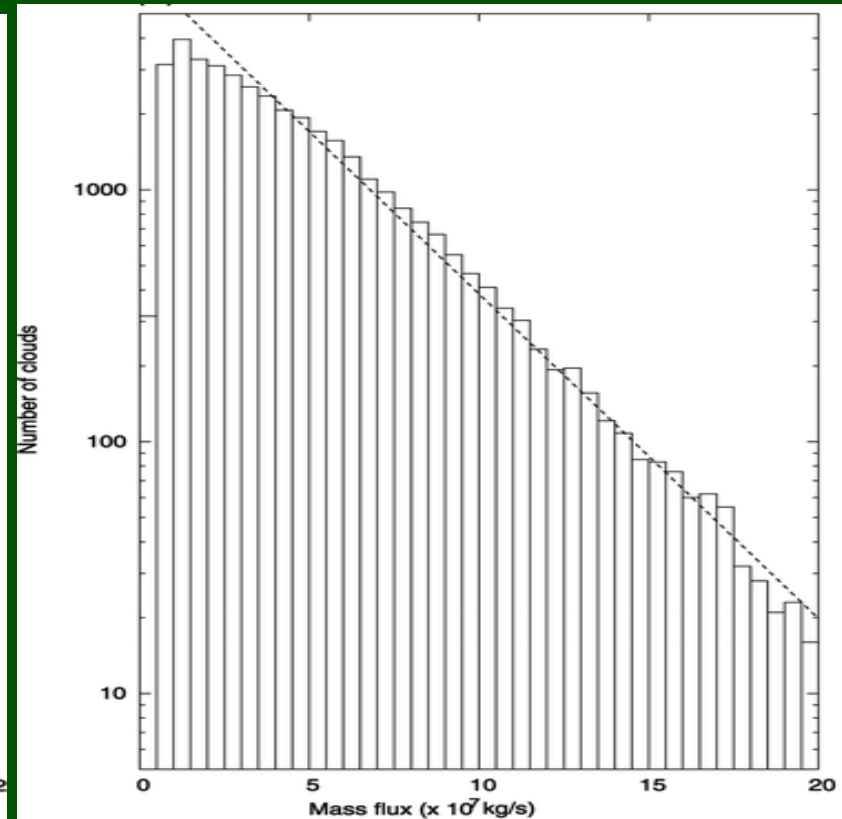
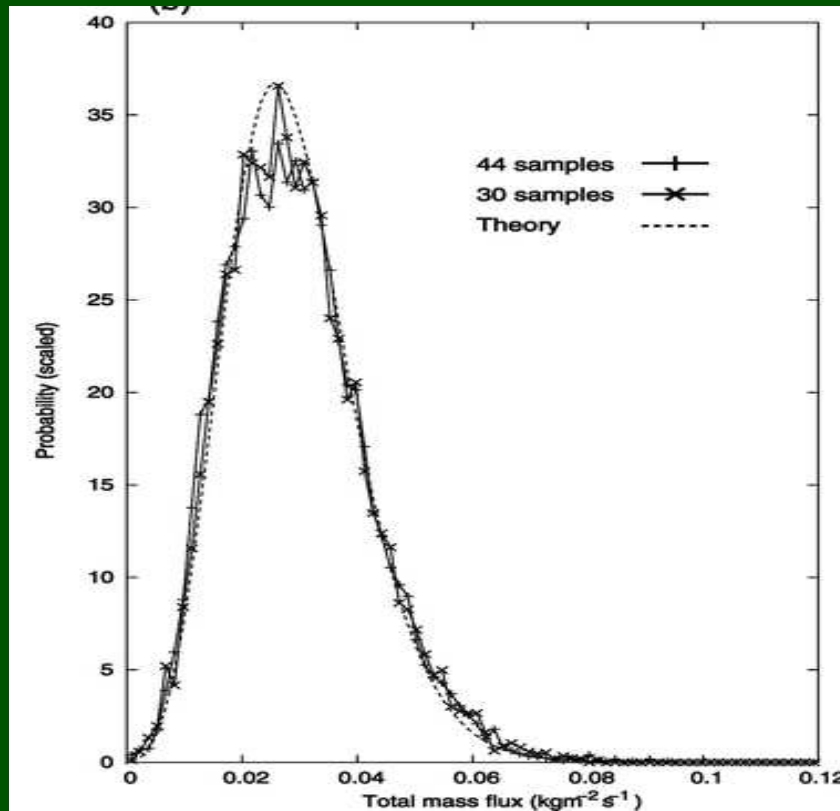
Assuming that clouds are non-interacting, $p(m)$ can be combined with a Poisson distribution for cloud number,

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

leading to the following distribution for total mass flux:

$$p(M) = \left(\frac{\langle N \rangle}{\langle m \rangle} \right)^{1/2} e^{-(\langle N \rangle + M/\langle m \rangle)} M^{-1/2} I_1 \left(2 \sqrt{\frac{\langle N \rangle}{\langle m \rangle} M} \right)$$

PDFs of mass flux in an SCM



- Plant & Craig, JAS, 2008

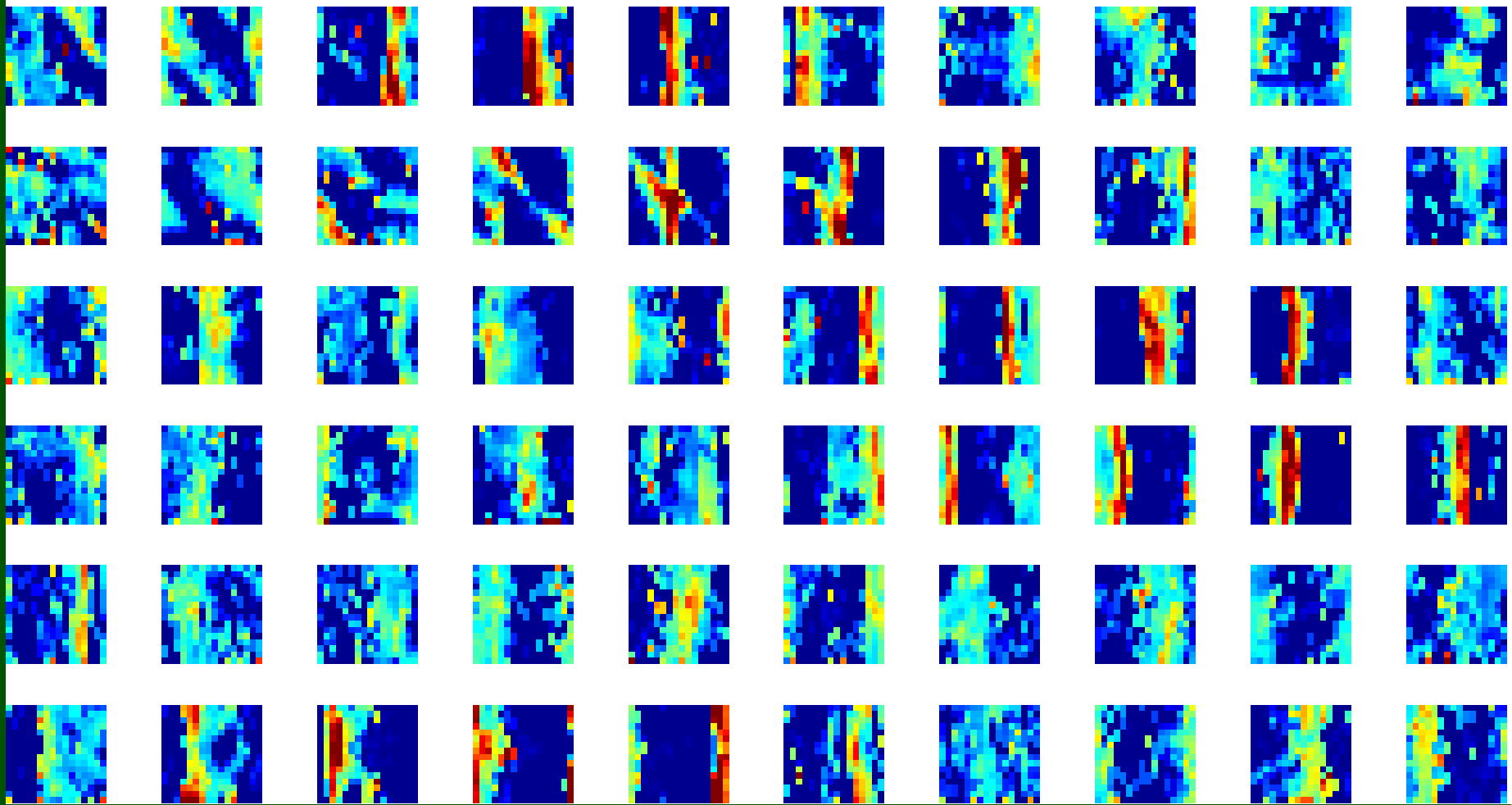


3D Idealised UM setup

- Radiation is represented by a uniform cooling.
- Convection, large scale precipitation and the boundary layer are parameterised.
- The domain is square, with bicyclic boundary conditions.
- The surface is flat and entirely ocean, with a constant surface temperature imposed.
- Targeted diffusion of moisture is applied.
- The grid size is 32 km.

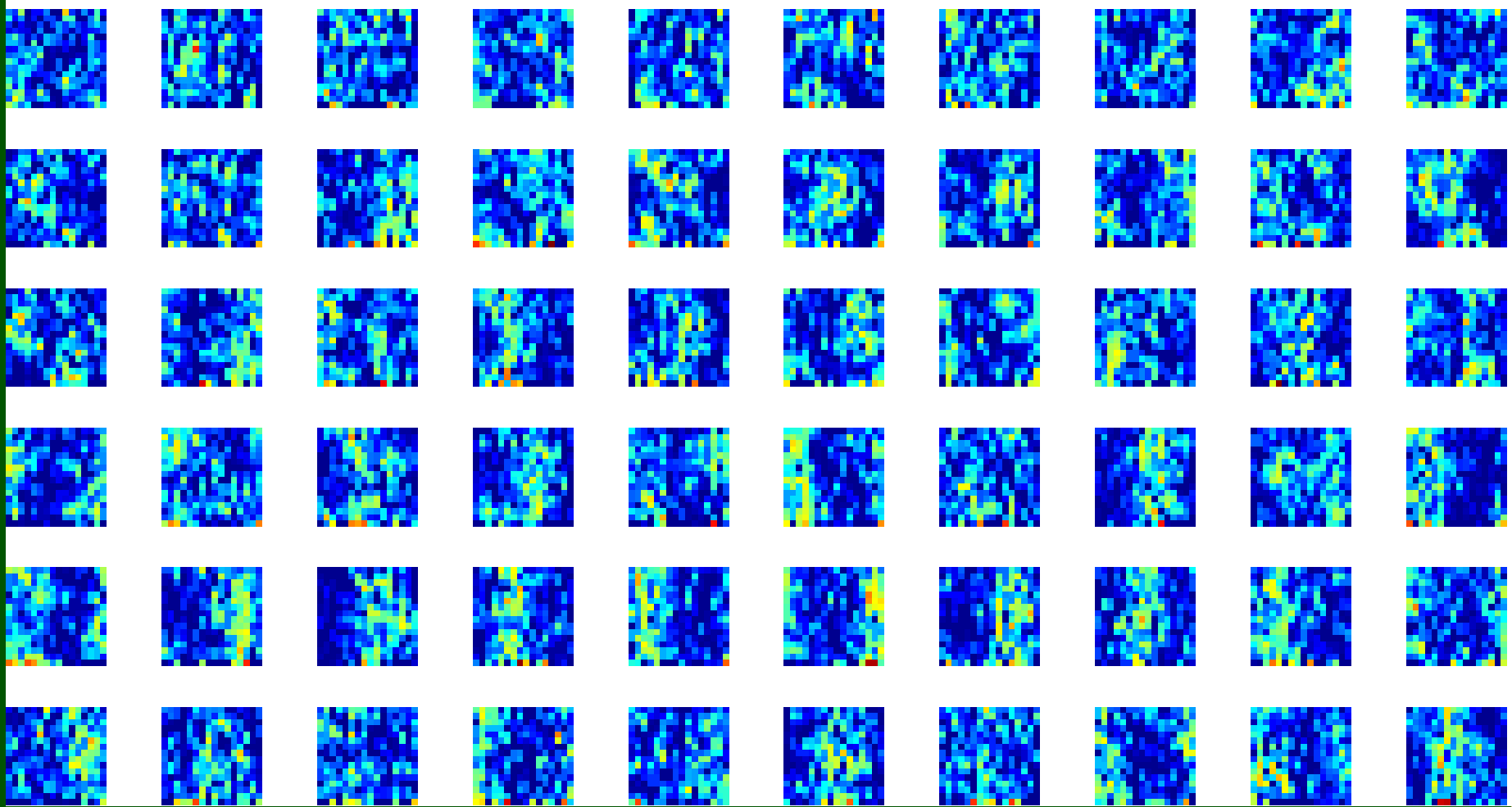
Rainfall snapshots: Rowntree scheme

Gregory



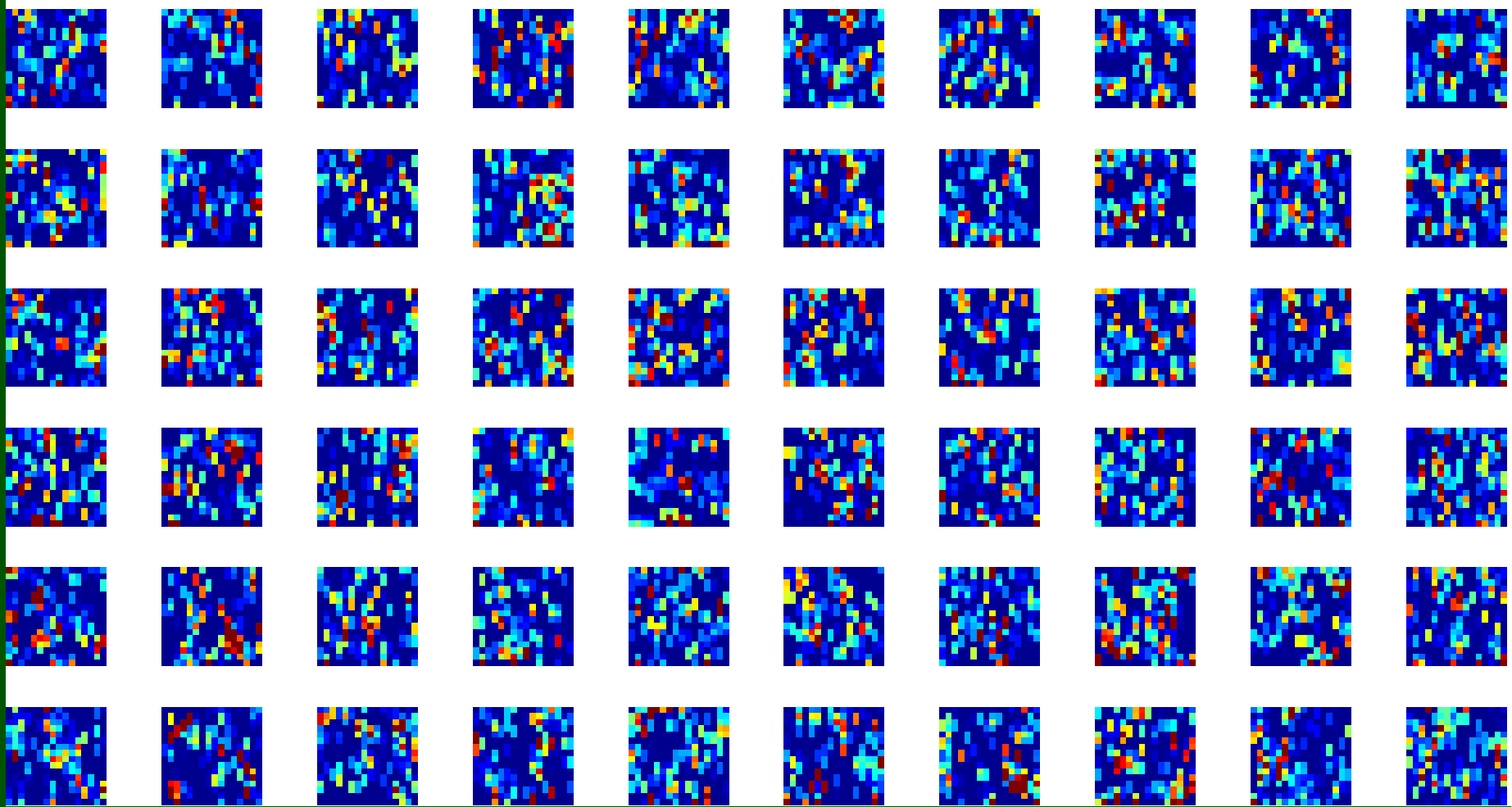
animation

Rainfall snapshots: Kain Fritsch scheme



animation

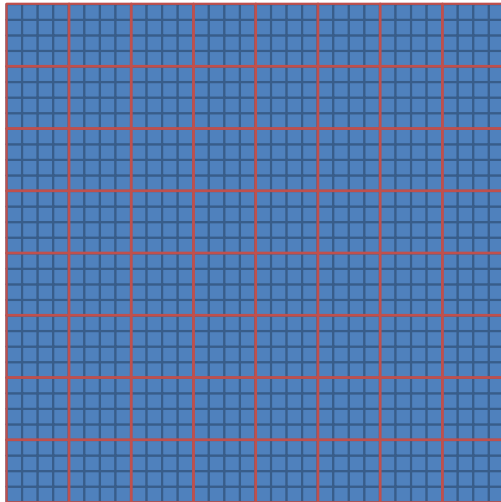
Rainfall snapshots: Plant Craig scheme



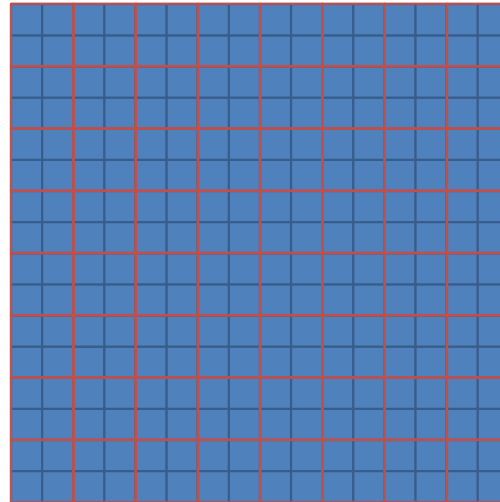
animation

Model grid division

16km



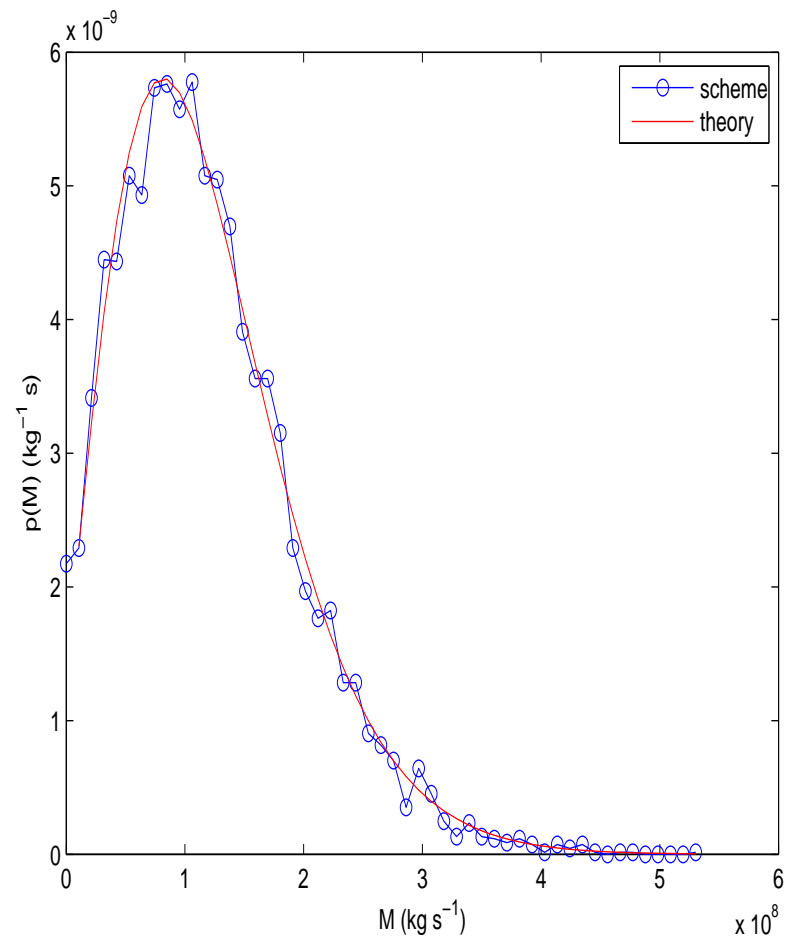
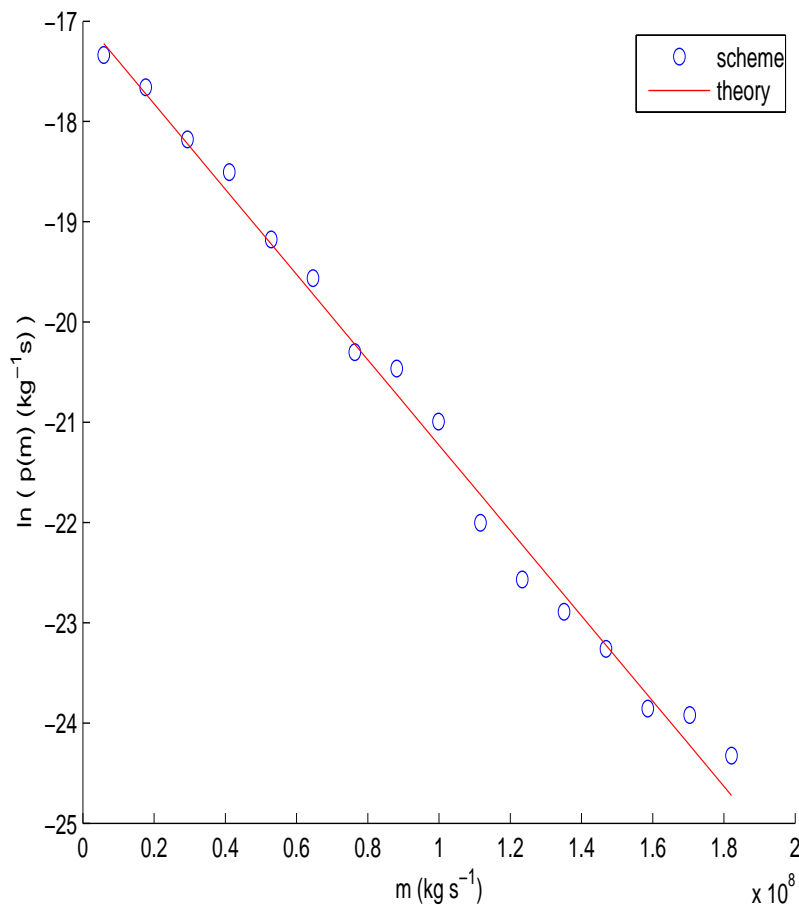
32km



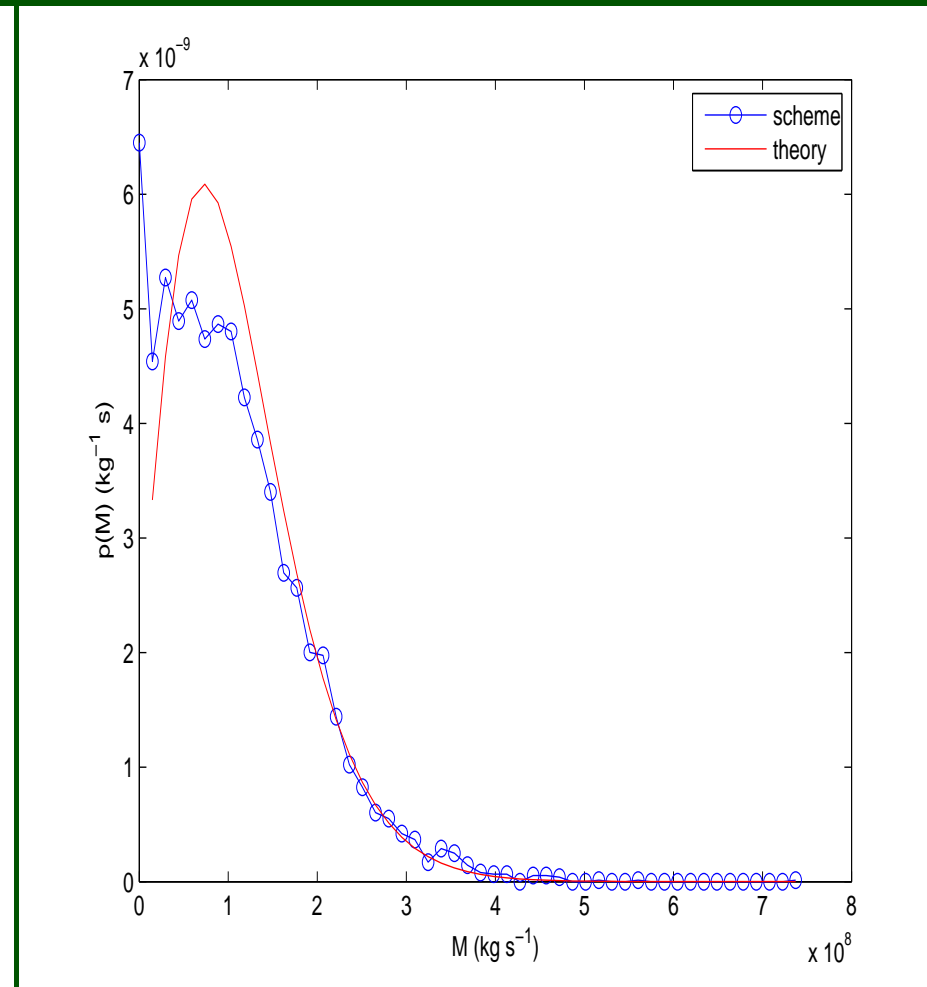
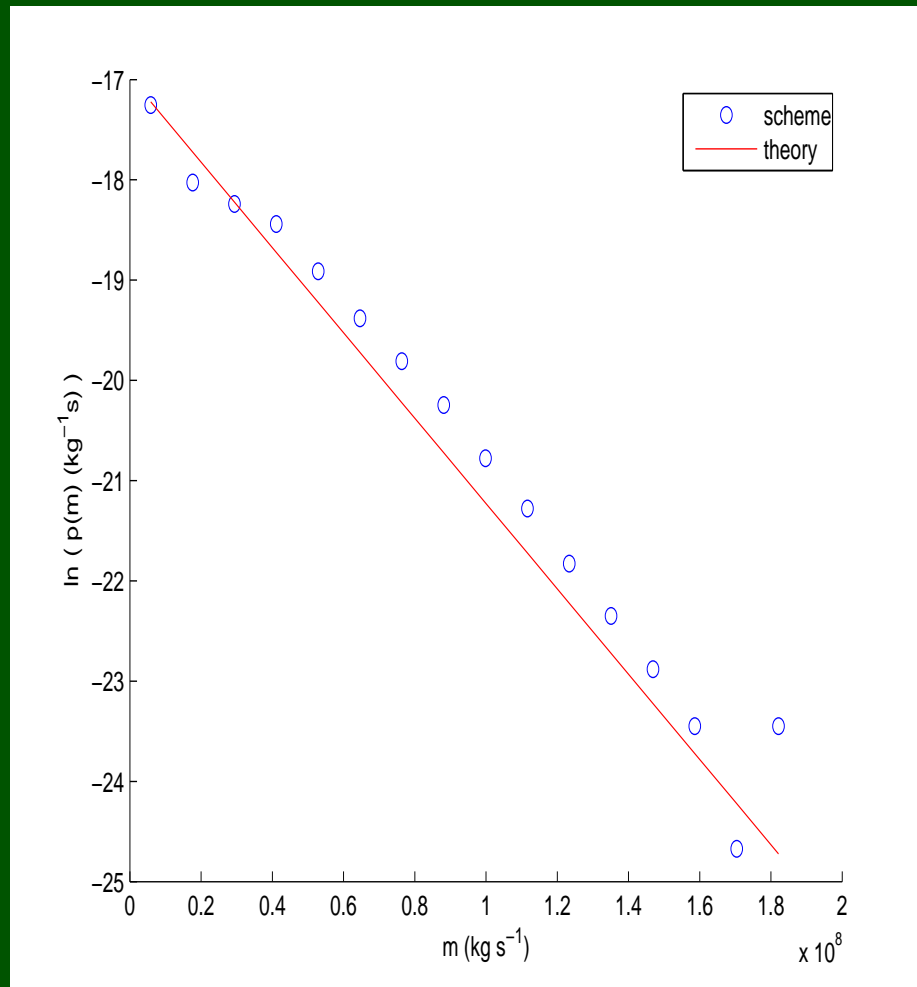
PDFs of m and M for maximum averaging

Averaging area: 480 km square.

Averaging time: 1 hour.



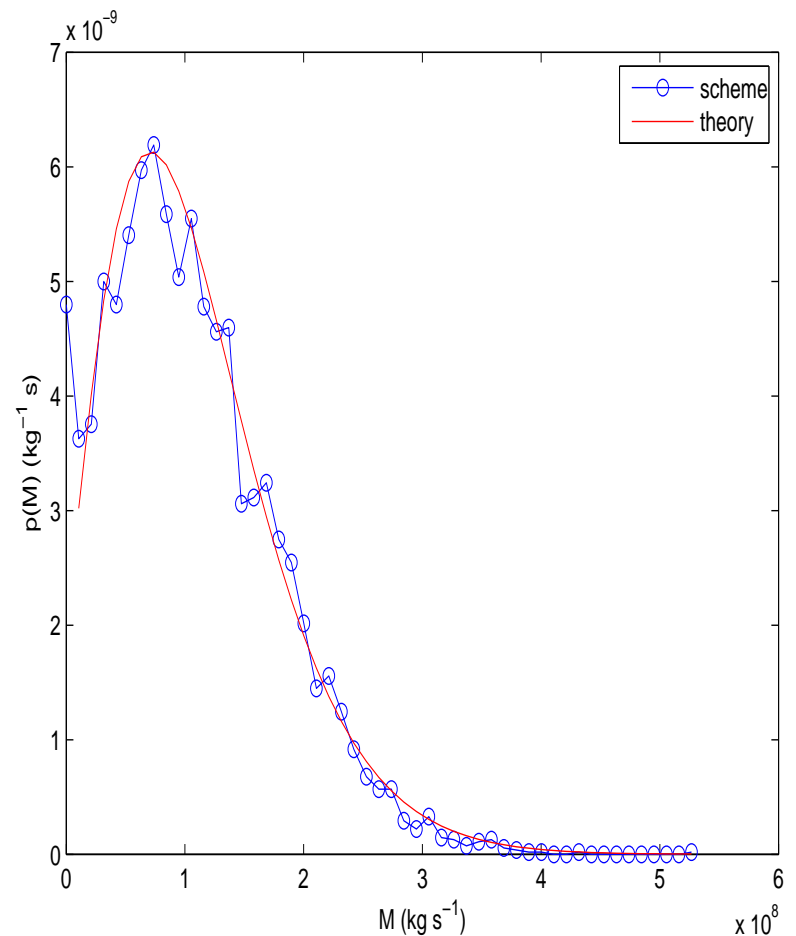
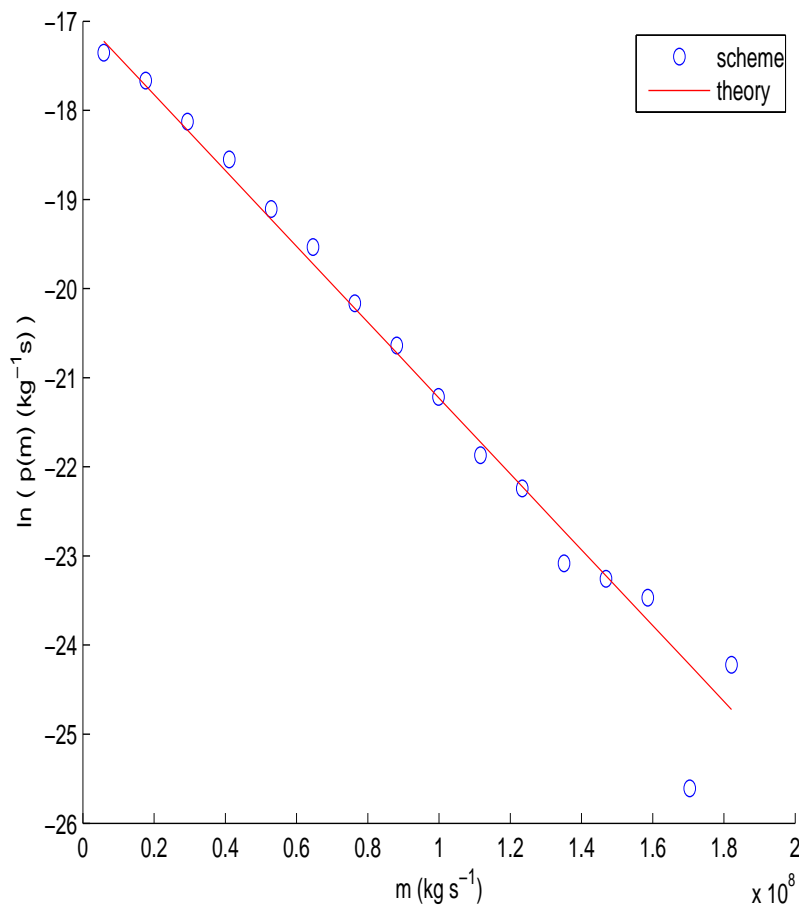
PDFs of m and M for no averaging



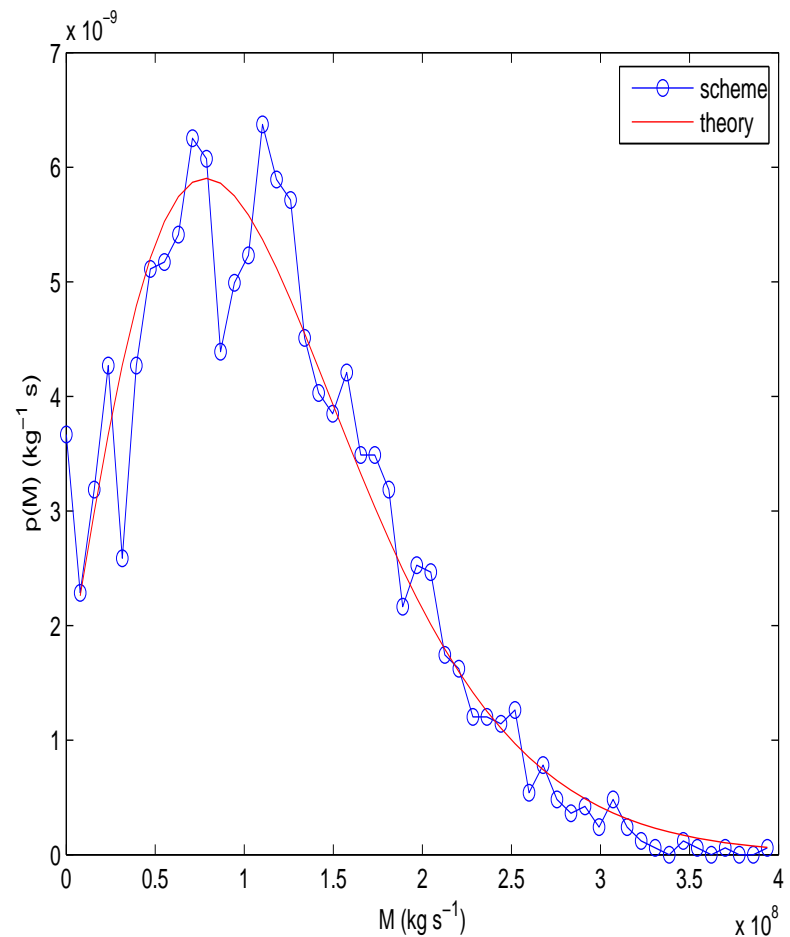
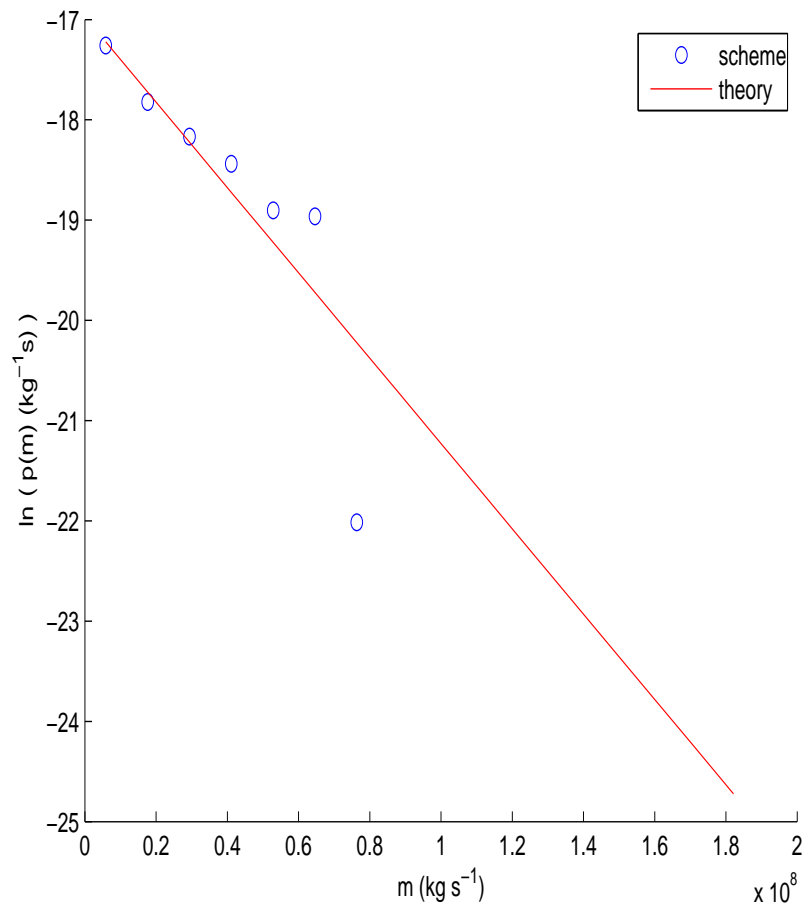
PDFs of m and M for intermediate averaging

Averaging area: 160 km square.

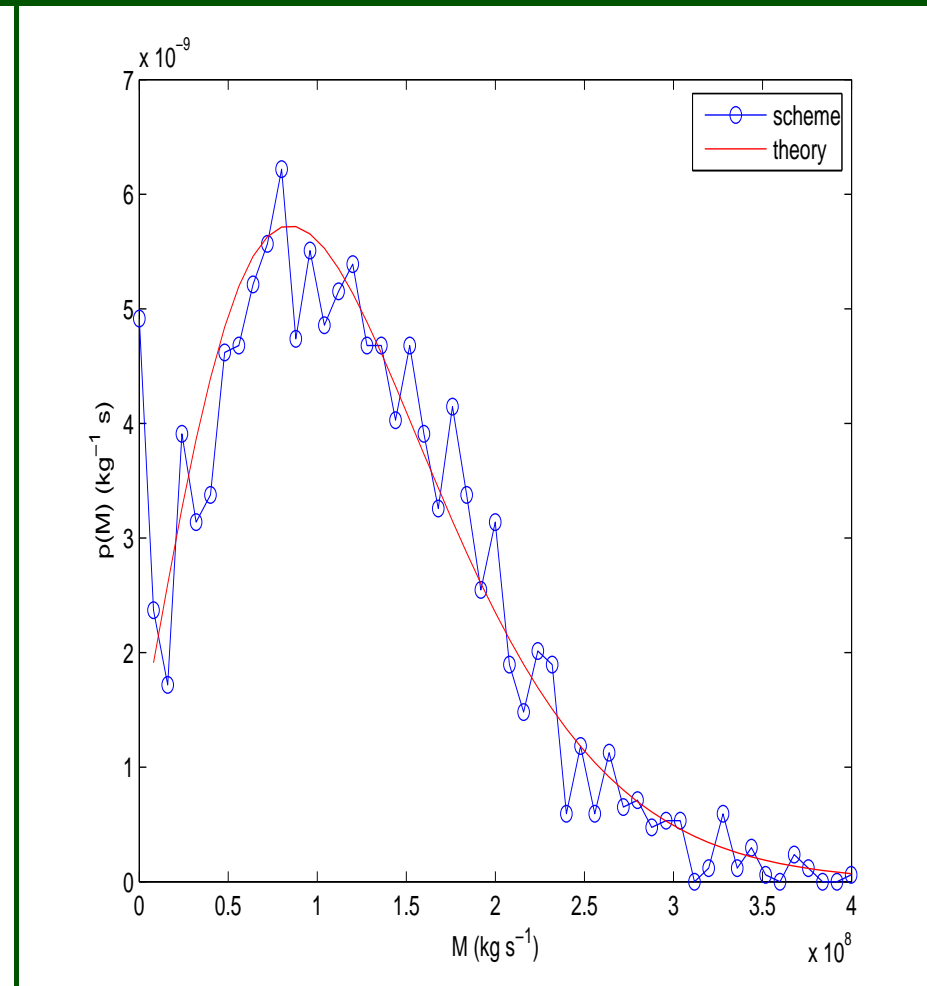
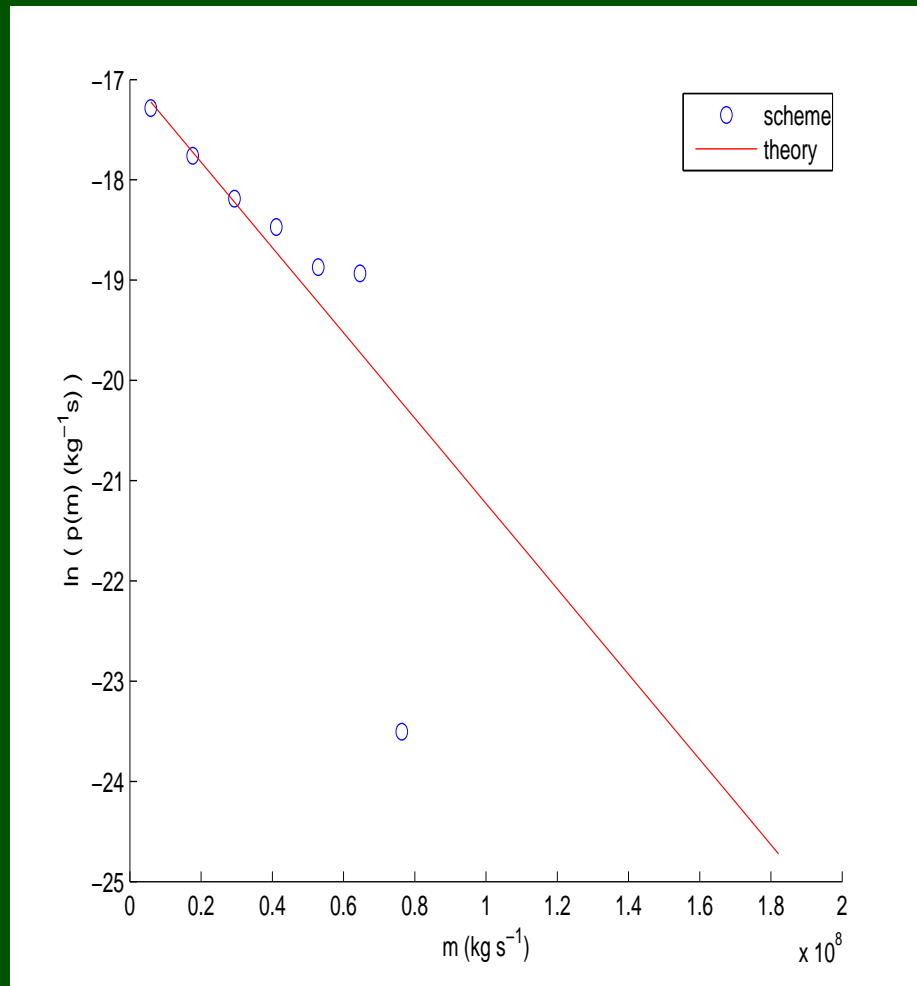
Averaging time: 1 hour.



PDFs of m and M for 16 km (no averaging)

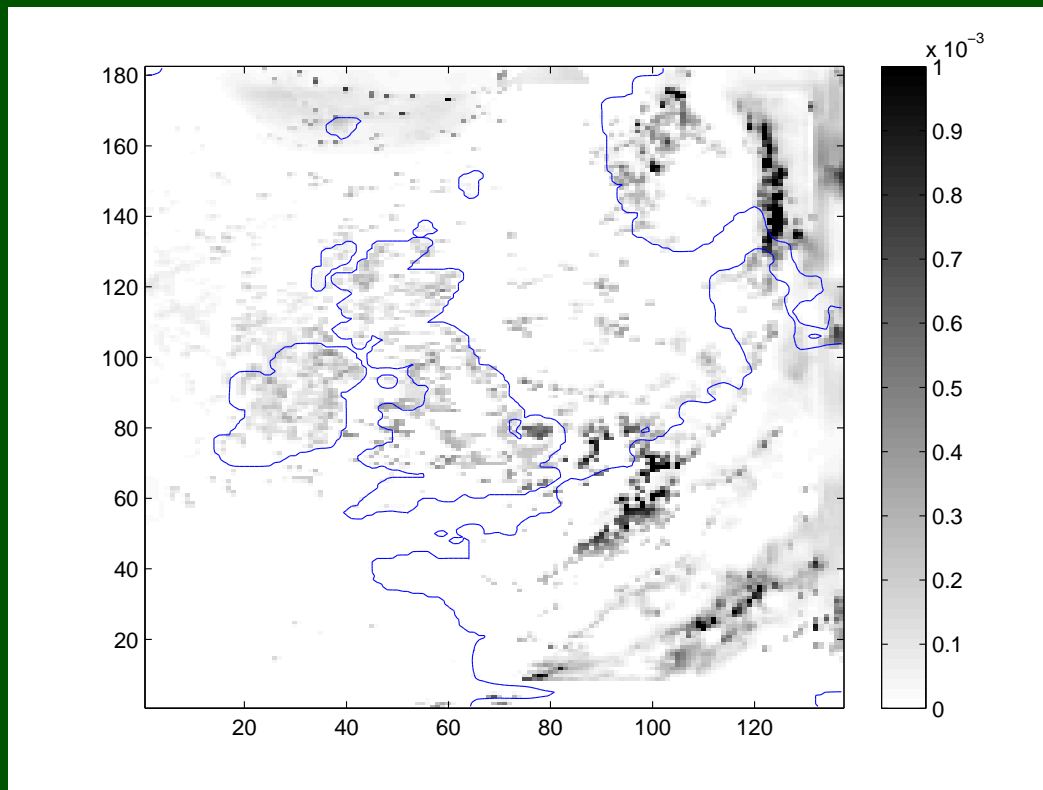


PDFs of m and M for 16 km (intermediate averaging)

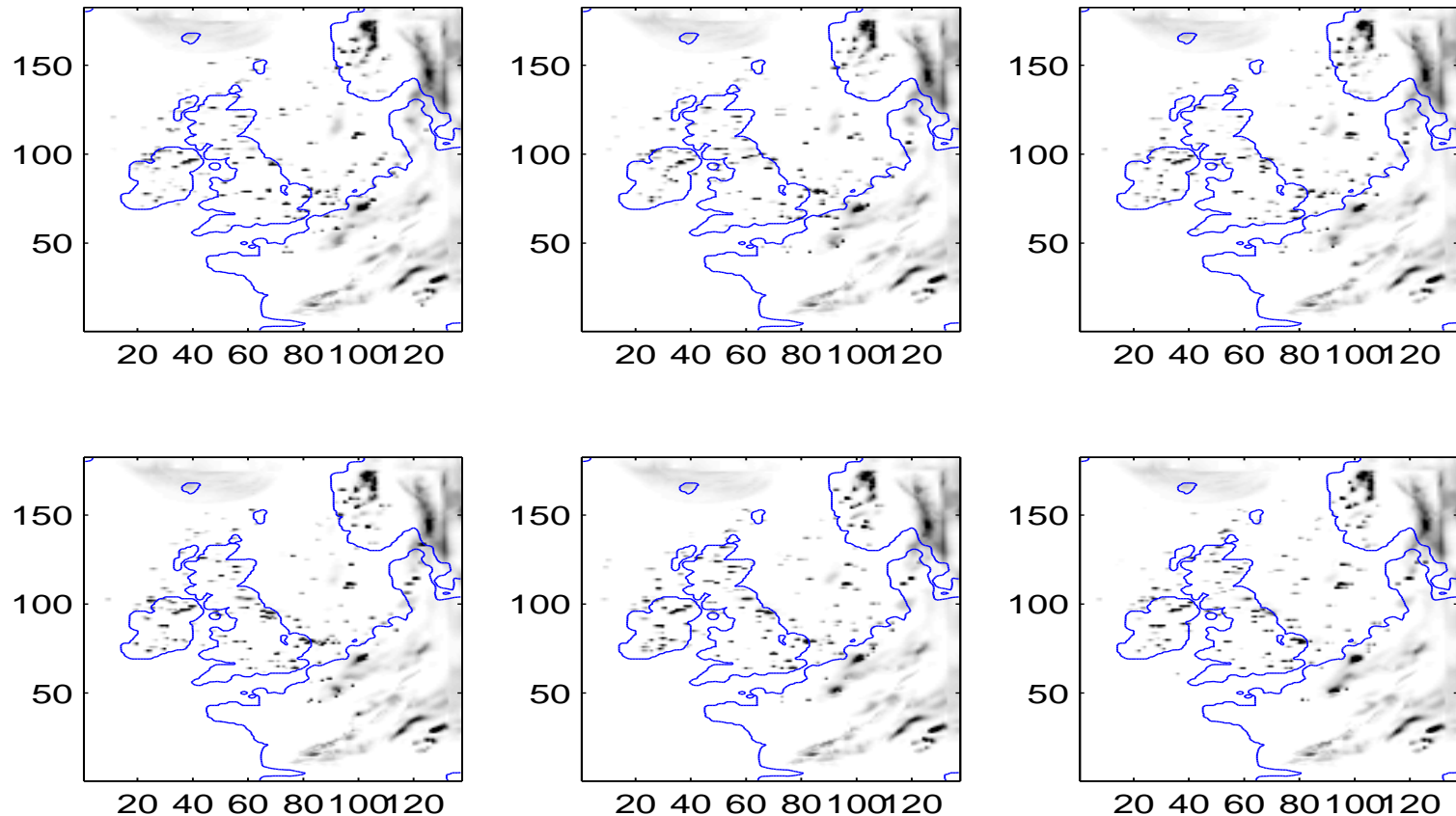


Case study: CSIP IOP18

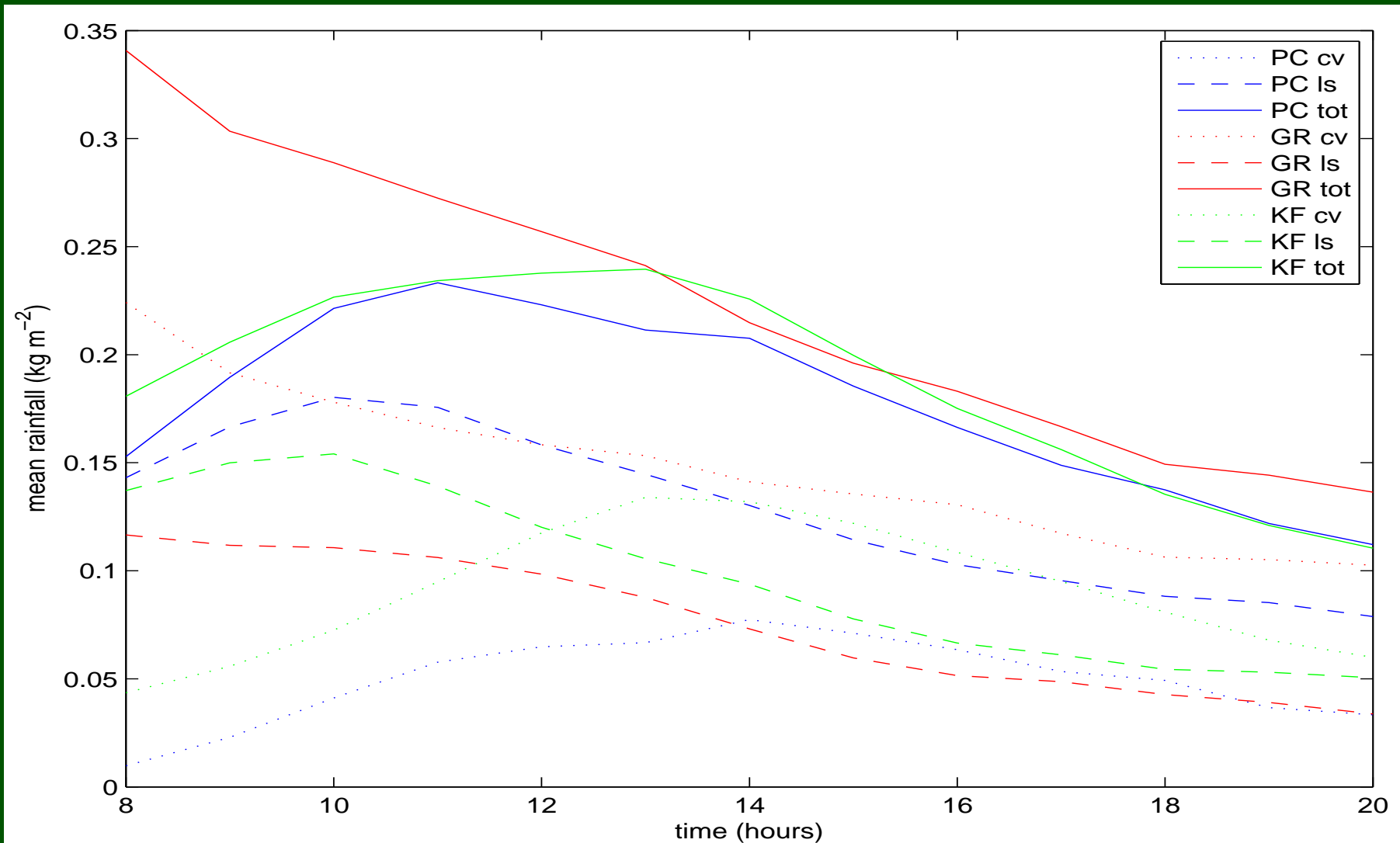
- Starts at 25th August 2005, 07:00.
- 12 km grid with 146×182 grid points.



Ensemble of 6 runs using PC scheme



Rainfall against time for each of three schemes





Future work

- Implement the PC scheme in MOGREPS, to determine its impact on variability.
- Run on NAE domain (~ 20 km), for one Summer month.
- Compare with existing GR run and deterministic version of PC.
- Look at the effect of the scheme, and its stochastic nature, on the variability of the ensemble and the spread-error relationship.



Conclusions

- The convective variability in the scheme is according to the Cohen Craig theory, and is not due to spurious noise from the large-scale.
- An averaging area of roughly 160 km is required to effect this.
- The statistical behaviour of the scheme is correct at different resolutions, although the amount of averaging required may vary.
- The scheme behaves sensibly in a mesoscale setup, and is ready to be implemented in an ensemble prediction system.