Department of Meteorology

University of Reading

Representing uncertainties due to modest numbers of coherent sub-grid structures

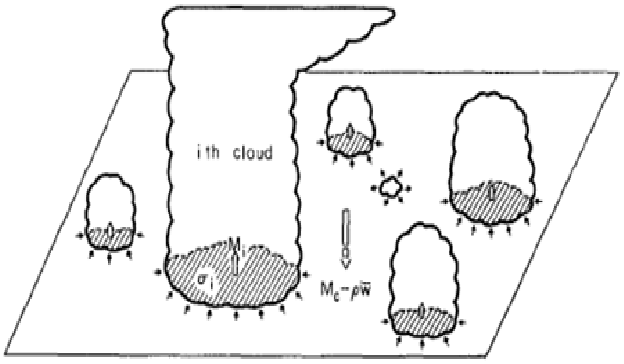
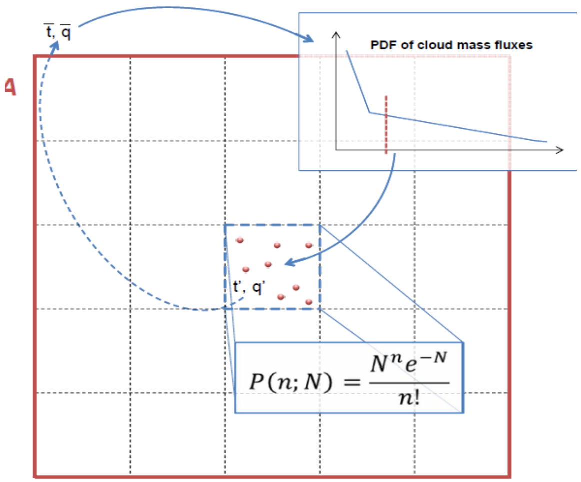
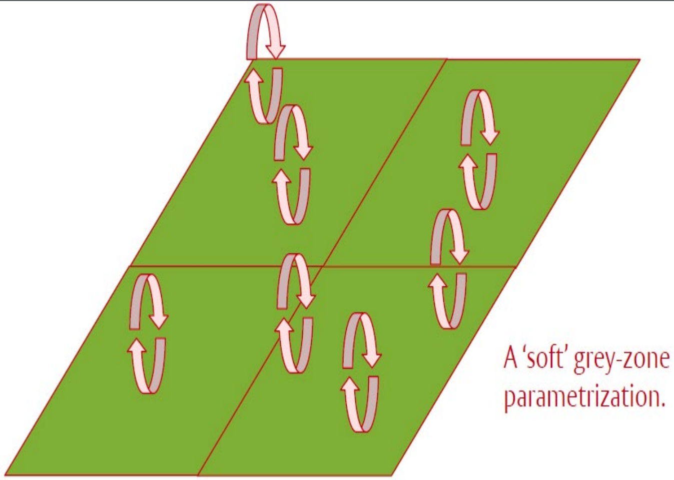


FIG. 1. A unit horizontal area at some level between cloud base and the highest cloud top. The taller clouds are shown penetrating this level and entraining environmental air. A cloud which has lost buoyancy is shown detraining cloud air into the environment.





Bob Plant and Peter Clark

ECMWF Workshop on Model Uncertainty

9-12 May 2022

Introduction

- Discuss a general class of stochastic parameterizations
- Key aspect is that the flux is dominated by finite number of coherent structures
- Exemplified by the stochastic BL method of Clark et al (2021)
- Designed for convection-permitting scales of o(1km)
- Focus on the method here, with impacts presented in poster by Clark

Example studies related to this approach

University of Reading

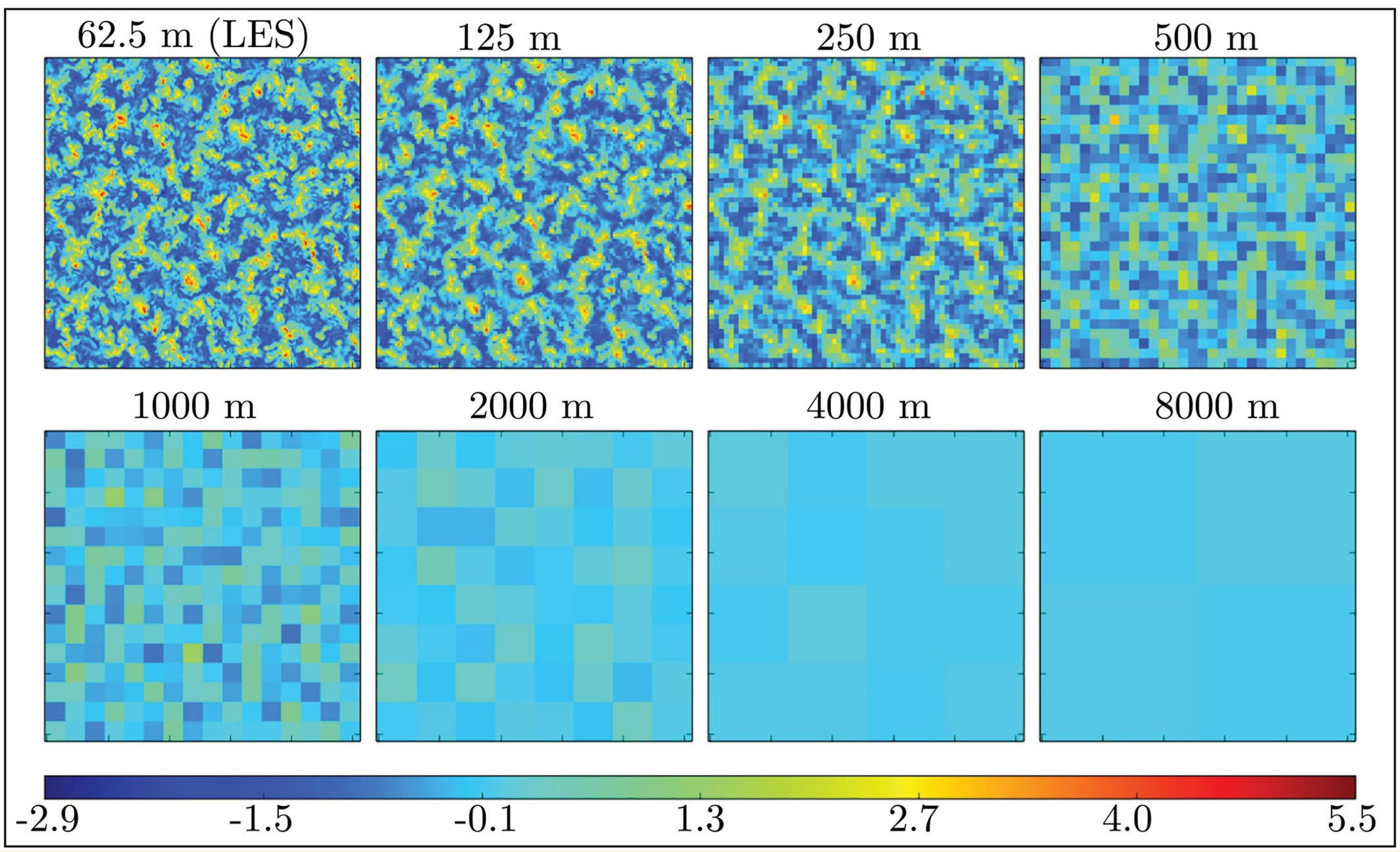
- Applications to deep convection: Pant and Craig (2008), Keane et al (2014, 2016), Selz and Craig (2015), Wang et al (2016, 2021),
- Applications to shallow convection: Sakradzija et al (2015), Sakradzija and Klocke (2018)
- Less-demanding approximation of these methods: Machulskaya and Seifert (2019)
- Applications to CBL eddies used as basis for stochastic perturbations for deep convective triggering: Rochetin et al (2014), d'Andrea (2014), Chui (2021)
- Earlier convective-scale predictability studies showing that such BL perturbations can be important source of uncertainty: Done et al (2012), Leoncini et al (2013), Flack et al (2018)
- Application to convective boundary layers: Clark et al (2021), Beare et al (2019), Kober and Craig (2016) and Hirt et al (2019)

Filtering in Convection-Permitting Models

- Parameterizations estimate fluxes, $\overline{w'\chi'}$
- The estimation depends on the nature of the filtering
- If the overbar is an ensemble average of sub-filter flow:
  - The parameterization is deterministic
  - Model fields near the filter scale are smooth
- If the overbar is a space-time filter:
  - Model represents one possible state
  - Parameterization is **naturally stochastic** and samples possible realization of sub-filter flow condition on filtered state
  - Model fields look turbulent, including partially-resolved structures near the filter scale

- If averaging scale is large enough to sample many eddies, then there is no practical difference

Filtering in Convection-Permitting Models



Successive coarse-graining of w data from an LES of the convective boundary layer

Honnert et al, 2020

Filtering in Convection-Permitting Models

- In CPMs, we want to use a space-time filter not an ensemble filtering
- i.e. we want to see (permit!) individual convective storms in the model output, not some large area of light ensemble-mean rain
- BUT: BL schemes (including shallow convection) are designed to predict the ensemble mean of realizations of a turbulent BL in quasi-equilibrium
- Distinction is most important when convection is initiated by the largest CBL eddies with size L ~ h ~ cloud size

Assume coherent structures dominate

- Partition turbulent flux into contributions from a discrete set of coherent structures

$$\overline{w'\chi'} = \sum_{i=1}^{N} \left(\overline{w'\chi'}\right)_i + non - coherent\ contributions$$

- Index *i* labels individual BL thermals, or shallow or deep convection

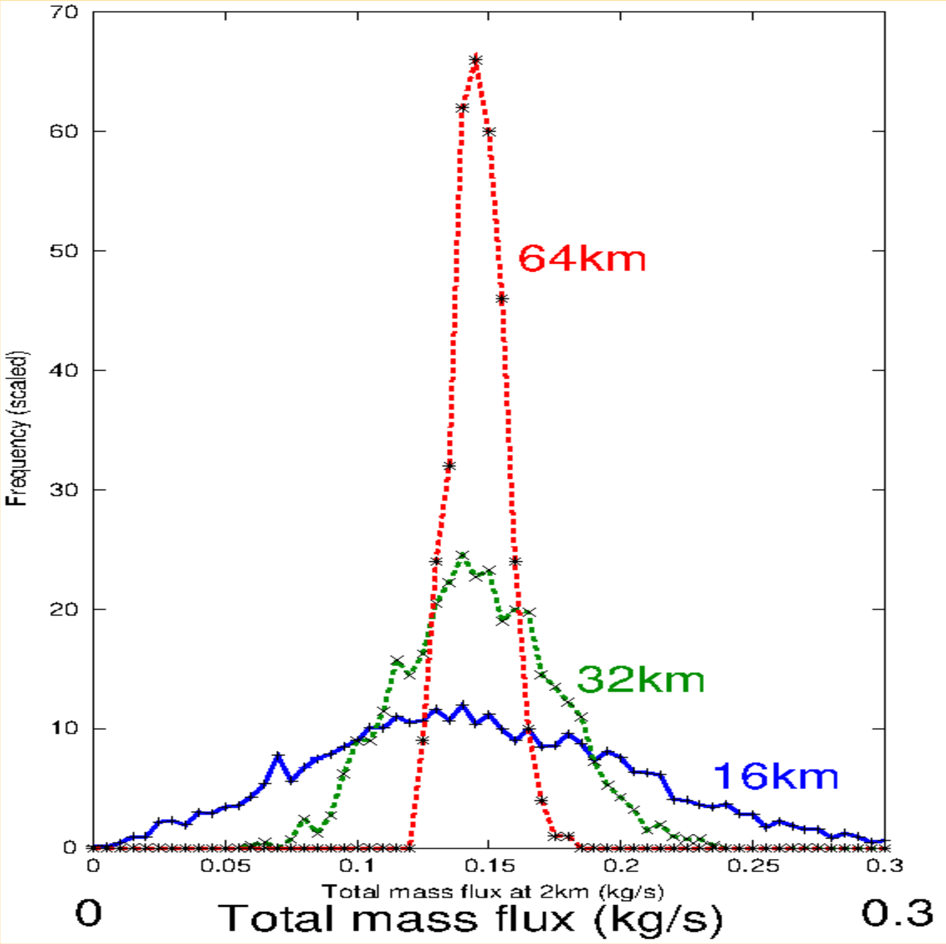
- We distinguish:
  - *<N>* the expected number of elements, which we need to estimate to quantize the process
  - *N* the actual number of elements, which we sample

- The elements could have a spectrum of properties based on size or mass flux or…

Example for deep convection

- Mass flux pdf over varying averaging areas in RCE
- Attempt to capture the variability by model random sample of N clouds
- With spectrum of clouds having an exponential pdf of mass flux

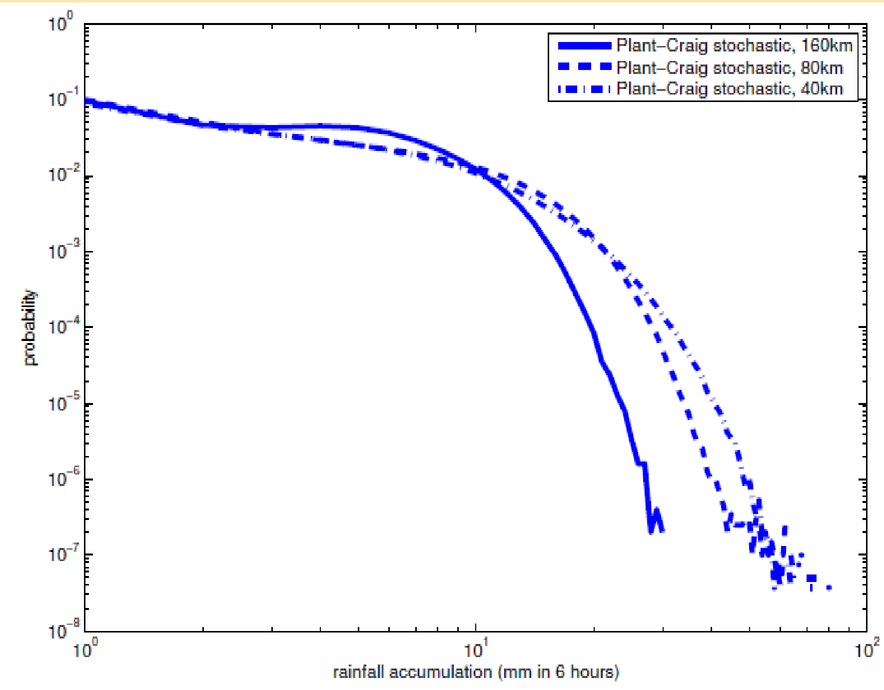
- Method captures dependence on averaging scale and convective forcing

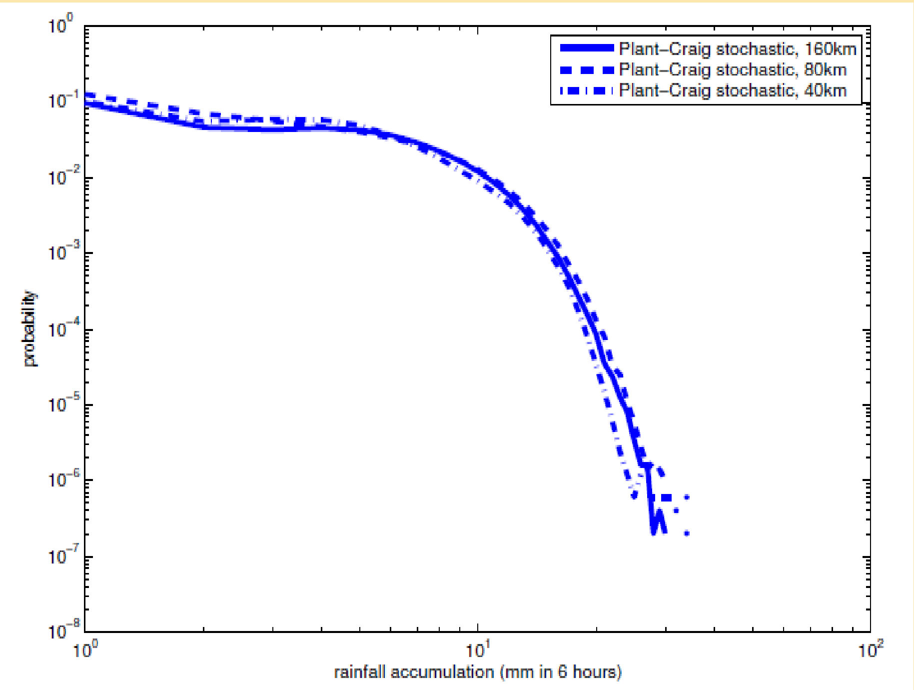


Plant and Craig, 2008

Scale awareness

- Variability should scale appropriately with the filter scale, and so scheme has in-built scale awareness





pdf on native grid

pdf on 160km grid

- Aqua-planet 6 h rainfall pdf for a given spatial scale is resolution independent with scale-aware stochastic convection

Keane et al, 2014

Perturbing Convection-Permitting Models

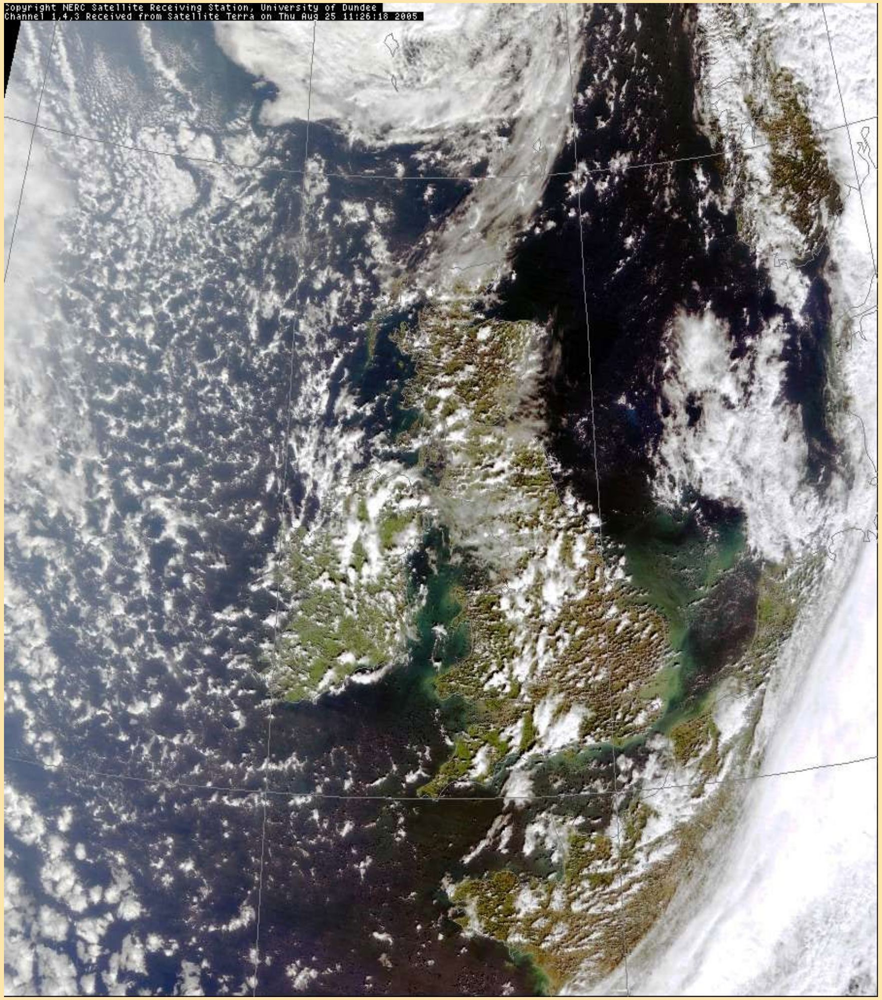
University of Reading

- Predictability studies show that errors grow primarily through processes that impact moist convection
- Especially perturbations within the BL during the initiation and early development of convection
- These can lead to improvements to the spin-up of explicit convection and e.g. help with diurnal cycle

Perturbing Convection-Permitting Models

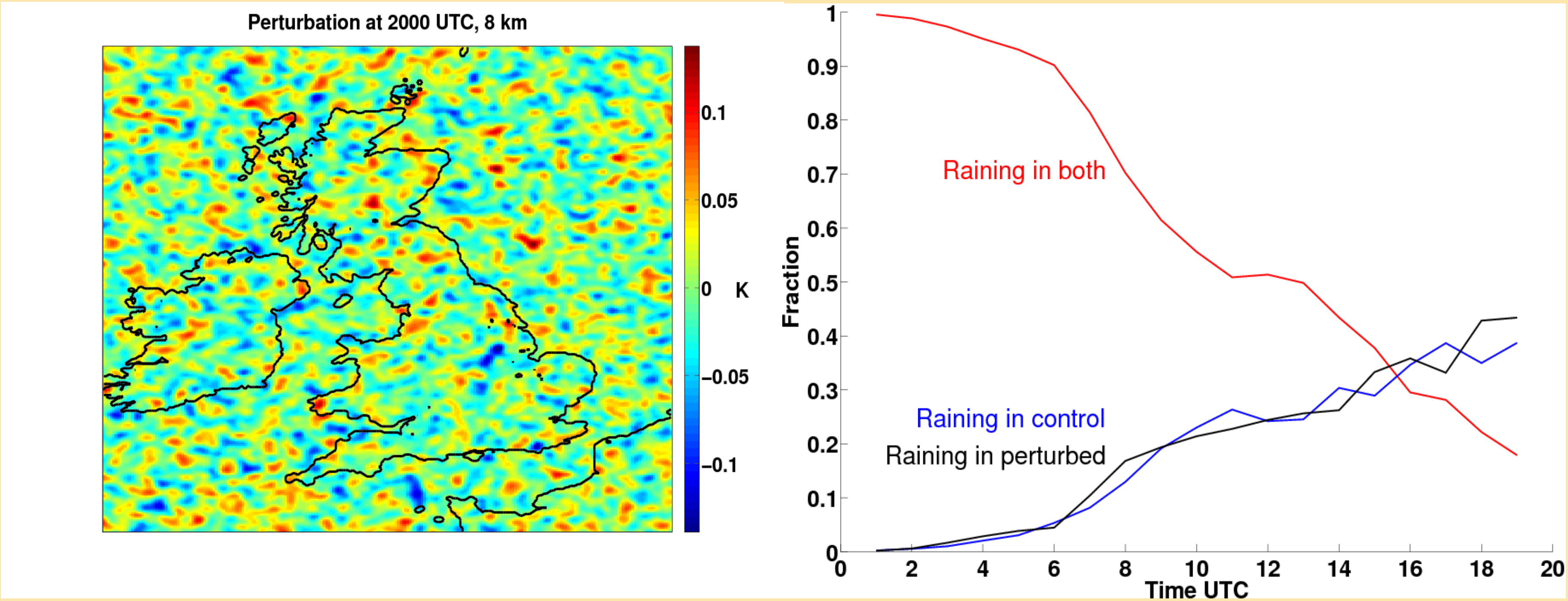
University of Reading

- Predictability study based on CSIP IOP18
- Scattered convection over England, 4km MetUM simulation
- Model produces scattered storms ok
- Many of them could easily be scattered in many different ways by applying small perturbations to boundary-layer θ



Leoncini et al, 2010

Perturbing Convection-Permitting Models



- ~ 0.1K perturbations at one model level in BL, applied every 30min, correlated over a few grid points
- Amplitude of buoyancy perturbations is the most important sensitivity

Clark et al (2021) scheme

- Stochastic BL perturbations to account for variation in sampling the largest BL eddies
- Perturbations are thus physically based and explicitly depend on resolution, increasing as resolution decreases
- Take the sampled eddies to be identical and independent, so

$$\left.\frac{\partial \chi}{\partial t}\right|_{BL} = \frac{N}{\langle N \rangle}\left\langle \left.\frac{\partial \chi}{\partial t}\right|_{BL} \right\rangle$$

- Thus *N* is sampled from a Poisson distribution, which has the single parameter <*N*>

What is <*N*>?

- Full scheme is not specific to CBL but perturbations are largest and most impactful there
- Use standard BL scalings for velocity and temperature fluctuations

$$w^* = \left(\frac{gHh}{\rho C_p \bar{\theta}}\right)^{1/3} \qquad \theta^* = \frac{H}{\rho C_p w^*}$$

- Which lead to an eddy turnover timescale

$$\tau = \frac{h}{w^*}$$

- In a well-mixed BL, *H* decays linearly with height, so we also estimate

$$\left\langle \left.\frac{\partial \theta}{\partial t}\right|_{BL} \right\rangle \approx \frac{H}{\rho C_p h} = \frac{\theta^*}{\tau}$$

What is <N>?

- Each thermal event is associated with an area $A_e \sim h^2$ and a duration $\tau_e \sim \tau$ and delivers a potential temperature increment of $\Delta\theta \sim \theta^*$
- Based on these assumptions

$$\left\langle \left. \frac{\partial\theta}{\partial t} \right|_{BL} \right\rangle = \langle N \rangle \frac{\Delta\theta}{\Delta t} \frac{A_e}{\Delta A} \sim \langle N \rangle \frac{\theta^* h^2}{\Delta t \Delta A}$$

where <*N*> is the expected number of eddies within the interval Δt over an area *ΔA*

- This expression gives us <N>, to within a scaling factor of o(1), which we absorb into our choice for *ΔA*

- For the well mixed BL it is simply $\langle N \rangle = \dfrac{\Delta t \, \Delta A}{\tau \, h^2}$

Application: Spatial Correlation

- Spatial scales represented well by the model are several grid lengths
- Perturbations applied on a tiled grid with $\Delta A = (m\,\Delta x)^2$ and m = 5 or 6
- This reduces the magnitude of the perturbations
- But they are applied over a model-resolved area, so will couple more strongly to the model dynamics

Application: Time Correlation

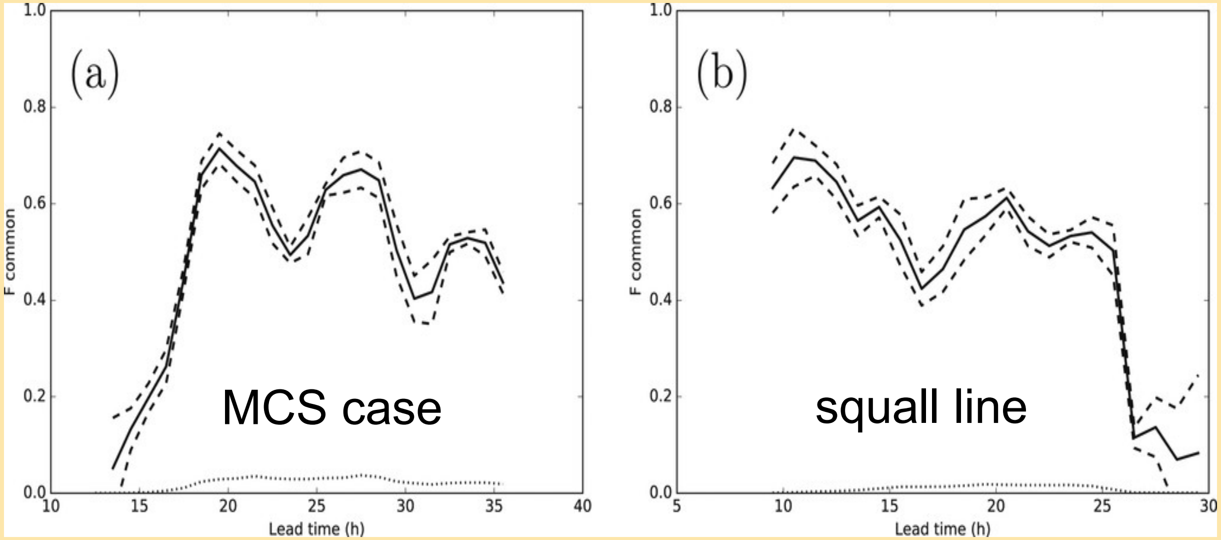
- Time correlations arise from thermal lifetime
- We wish to apply each θ^* increment over the course of a turnover time τ
- τ ~10min but CPM timestep, $\delta t \sim$ 1min
- Brute force approach would remember initiation for each thermal sampled, use factor $\delta t/\tau$ for heating per thermal at each timestep, and apply heating for $\tau/\delta t$ timesteps
- Instead, time correlation is imposed via an AR1 process with autocorrelation time scale τ

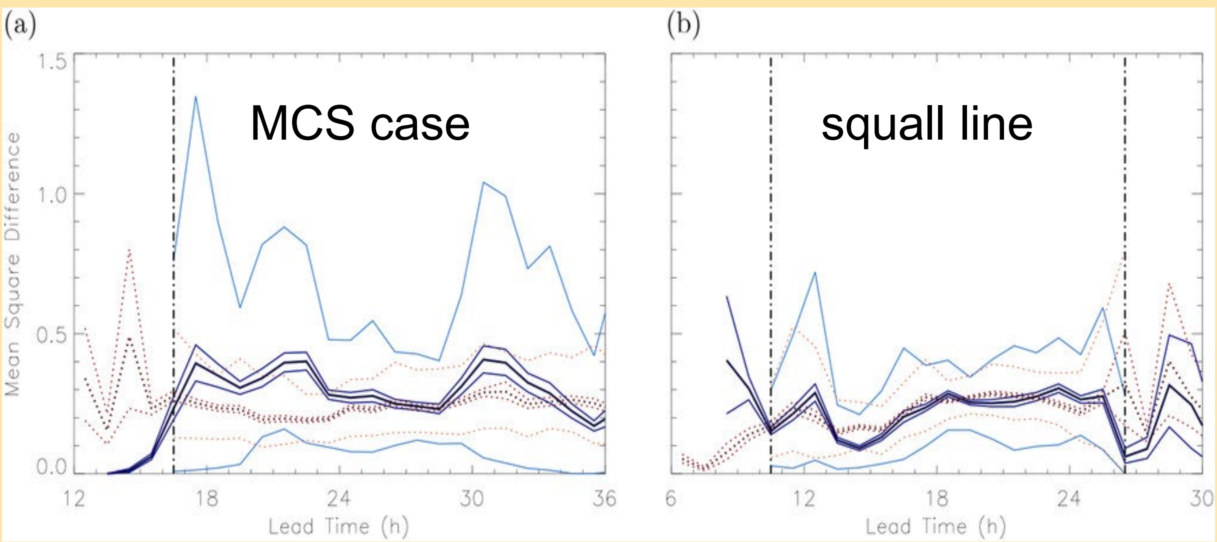
Application: Other details

$$\left.\frac{\partial \chi}{\partial t}\right|_{BL} = \frac{N}{\langle N \rangle}\left\langle \left.\frac{\partial \chi}{\partial t}\right|_{BL} \right\rangle$$

- Use expression for <*N*> and draw a random integer *N* from Poisson distribution
- Use it to update *N*/<*N*> following the AR1 process
- Assume thermals are fully correlated in the vertical, so this factor applies to all heights
- Apply same factor to tendencies of potential temperature, moisture and wind fields

Illustration of use, UKV model Δx=1.5km

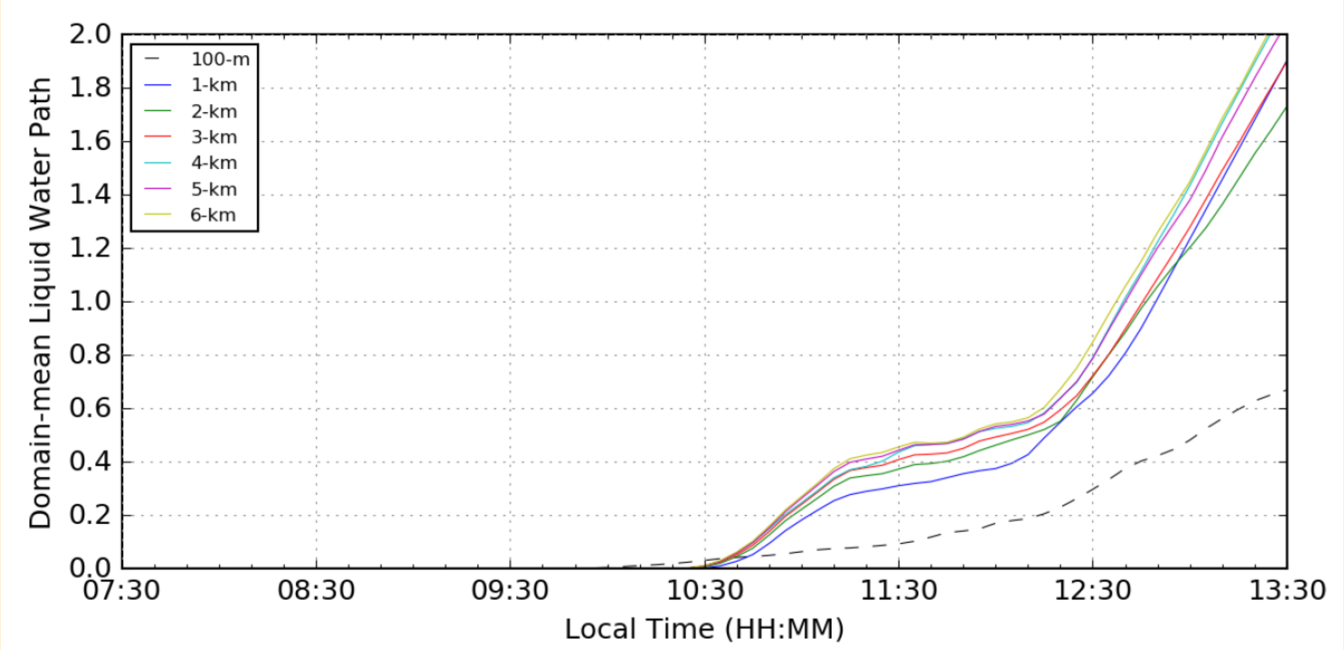




- Shifts locations of the rain, even in organized cases driven by the large scales
- Changes rain rates at the common locations by less than (but of similar magnitude) to such changes due to ic's

Triggering of grey-zone convection

- # BL thermals from Poisson pdf for with scale-dependence as per Clark et al. Each thermal has initial *w* from $\mathcal{N}(0, 0.2w^*)$ and triggering occurs for ½ w^2 > CIN
- Evolution of LWP using grey-zone convection scheme at Δx=1-6 km in LBA test case



Chui, 2021

Comparison with related schemes

	Plant-Craig	Sakradzija et al	Clark et al
Coherent structures	Deep clouds	Shallow clouds	Largest BL eddies
Multiple types?	Yes, by mass flux	Yes, by mass flux	No
Sampling distributions	Poisson + exponential	Poisson + Weibull	Poisson
Estimation of <*N*>	Mass flux per cloud assumed fixed	Mass flux per cloud depends on Bowen ratio	BL scaling argument
Spatial correlation	Averaged input to closure	Averaged input to closure	Tiled on scale of 5-6 Δx
Time correlation	Lifetime = 45min	Lifetime is f(mass flux)	AR1 with turnover timescale

Summary

- Spatial averaging ≠ ensemble averaging and this matters for CPMs
- The spatial average is what we want
- But our BL schemes are designed with ensemble-average perspective
- An important source of variability arises if the parameterized phenomenon has important dynamical modes not much below the filter scale
- We can account for this and make our schemes consistent with a spatial filtering perspective if we can estimate <*N*>
- The argument here is that such a scheme for CPMs is better physics and is a very cheap and simple add-on to existing BL methods
- So why would we not want to include it?

References

- F. d’Andrea, P. Gentine, A. K. Betts and B. R. Linter, 2014. Triggering deep convection with a probabilistic. plume model. *J. Atmos. Sci*., **71**, 3881-3901.
- S. Beare, W. Tennant and C. Sanchez, 2019. Stochastic physics code in the UM. Met Office Documentation Paper 81, 22pp
- C. C. Chui, 2021. On the Parameterisation of Convection in the ‘Grey-Zone’. PhD Thesis, University of Reading.
- P. A. Clark, C. E. Halliwell and D. L. A. Flack, 2021. A Physically Based Stochastic Boundary Layer Perturbation Scheme. Part I: Formulation and Evaluation in a Convection-Permitting Model, *J. Atmos. Sci*., **78**, 727-746.
- J. Done, G. C. Craig, S. L. Gray, and P. A. Clark, 2012. Case-to-case variability of predictability of deep convection in a mesoscale model. *Q. J. R. Meteorol. Soc*., **138**, 638–648.
- D. L. A. Flack, S. L. Gray, R. S. Plant, H. W. Lean, C. Keil and G. C. Craig, 2018. Convective-scale perturbation growth across the spectrum of convective regimes. *Mon. Weather Rev*., **146**, 387-405.
- D. L. A. Flack, P. A. Clark, C. E. Halliwell, N. M. Roberts, S. L. Gray, R. S. Plant, and H. W. Lean, 2021. A Physically Based Stochastic Boundary Layer Perturbation Scheme. Part II: Perturbation Growth within a Superensemble Framework, *J. Atmos. Sci*., **78**, 747–761.
- M. Hirt, S. Rasp, U. Blahak and G. C. Craig, 2019. Stochastic parameterization of processes leading to convective initiation in kilometer-scale models. *Mon. Wea. Rev.,* **147**, 3917–3934.

References

- R. Honnert, G. A. Efstathiou, R. J. Beare, J. Ito, A. Lock, R. Neggers, R. S. Plant, H. H. Shin, L. Tomassini, and B. Zhou, 2020. The Atmospheric Boundary Layer and the "Gray Zone" of Turbulence: A Critical Review. *J. Geophys. Res.*, **125**, e2019JD030317.
- R. J. Keane, G. C. Craig, G. Zängl and C. Keil, C, 2014. The Plant-Craig stochastic convection scheme in ICON and its scale adaptivity, *J. Atmos. Sci.*, **71**, 3404–3415.
- R. J. Keane, R. S. Plant, and W. J. Tennant, 2016. Evaluation of the Plant-Craig stochastic convection scheme (v2.0) in the ensemble forecasting system MOGREPS-R (24km) based on the Unifed Model (v7.3). *Geosci. Model Dev.*, **9**, 1921-1935.
- K. Kober and G. C. Craig, 2016: Physically-based stochastic perturbations (PSP) in the boundary layer to represent uncertainty in convective initiation. *J. Atmos. Sci.*, **73**, 2893–2911
- G. Leoncini, R. S. Plant, S. L. Gray, and P. A. Clark, 2013. Ensemble forecasts of a flood producing storm: comparison of the influence of model-state perturbations and parameter modifications. *Q. J. R. Meteorol. Soc.*, **139**, 198-211.
- E. Machulskaya and A. Seifert, 2019. Stochastic differential equations for the variability of atmospheric convection fluctuating around the equilibrium. J. Adv. Model. Earth Syst., **11**, 2708–272.
- R. S. Plant and G. C. Craig, 2008. A stochastic parameterization for deep convection based on equilibrium statistics. *J. Atmos. Sci.*, **65**, 87-105.
- N. Rochetin, J. Grandpeix, C. Rio and F. Couvreux, 2014. Deep Convection Triggering by Boundary Layer Thermals. Part II: Stochastic Triggering Parameterization for the LMDZ GCM, *J. Atmos. Sci.*, **71**, 515-538.

References

- M. Sakradzija, A. Seifert and T. Heus, 2015. Fluctuations in a quasi-stationary shallow cumulus cloud ensemble. *Nonlin. Proc. Geophys*., **22**, 65–85.
- M. Sakradzija and D. Klocke, 2018. Physically constrained stochastic shallow convection in realistic kilometer-scale simulations. J. Adv. Model. Earth Syst., **10**, 2755– 2776.
- T. Selz and G. C. Craig, 2015. Simulation of upscale error growth with a stochastic convection scheme, *Geophys. Res. Lett*., **42**, 3056–3062.
- Y. Wang, G. J. Zhang and G. C. Craig, 2016. Stochastic convective parameterization improving the simulation of tropical precipitation variability in the NCAR CAM5, *Geophys. Res. Lett*., **43**, 6612–6619.
- Y. Wang, G. J. Zhang, S. Xie, W. Lin, G. C. Craig, Q. Tang and H.-Y. Ma, 2021. Effects of coupling a stochastic convective parameterization with the Zhang–McFarlane scheme on precipitation simulation in the DOE E3SMv1.0 atmosphere model. *Geosci. Model Dev*., **14**, 1575–1593.