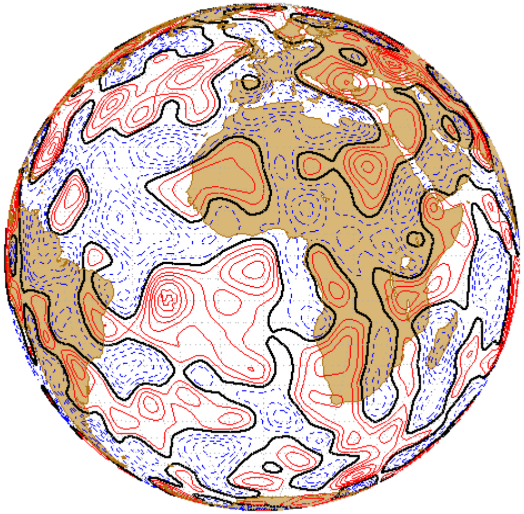
Tracking down the origin of NWP model uncertainty : coarse-graining studies and the efficacy of various stochastic parametrizations

by

Glenn Shutts (Met Office/ECMWF)



Talk outline:

- Coarse-graining and estimates of parametrization uncertainty
- Early results from re-tuning the perturbed parametrization tendency scheme (SPPT)
- Backscatter, vorticity confinement and stochastic vorticity confinement

Coarse-graining IFS fields

$$\hat{f}(\lambda,\phi,t_6) = \sum_{k=1}^{11}\sum_{m=-N}^{m=N}\sum_{n=|m|}^{N} f_{mn}^{k} W_{mn}^{k} Y_{n}^{m}(\lambda,\phi,$$

spherical harmonic

k is the hourly dump number and the weighting function W_{mn}^{k} is given by:

$$W_{mn}^{k} = \underbrace{\exp\left[-\frac{1}{2}\left(\frac{R_f}{a}\right)^2 n(n+1)\right]}_{\text{Quasi-Gaussian spatial filter}} \cdot \underbrace{\frac{1}{36}\left(1-\frac{|k-6|}{6}\right)}_{\text{Triangular time filter centred on t+ 6 hrs}}$$

R_f is the filter scale

‘a’ is the Earth’s radius

Use T1279 model forecasts to estimate the uncertainty in the parametrization tendencies of T159 forecasts

- Assumption: coarse-grained T1279 parametrization tendencies are much more realistic than their T159 counterparts

- Define 'error' to be their difference and examine how this varies with the magnitude of the tendency

Comment:
an observations-based study would obviously be desirable too

technique

Let the filter scale $R_f = 250$ km and

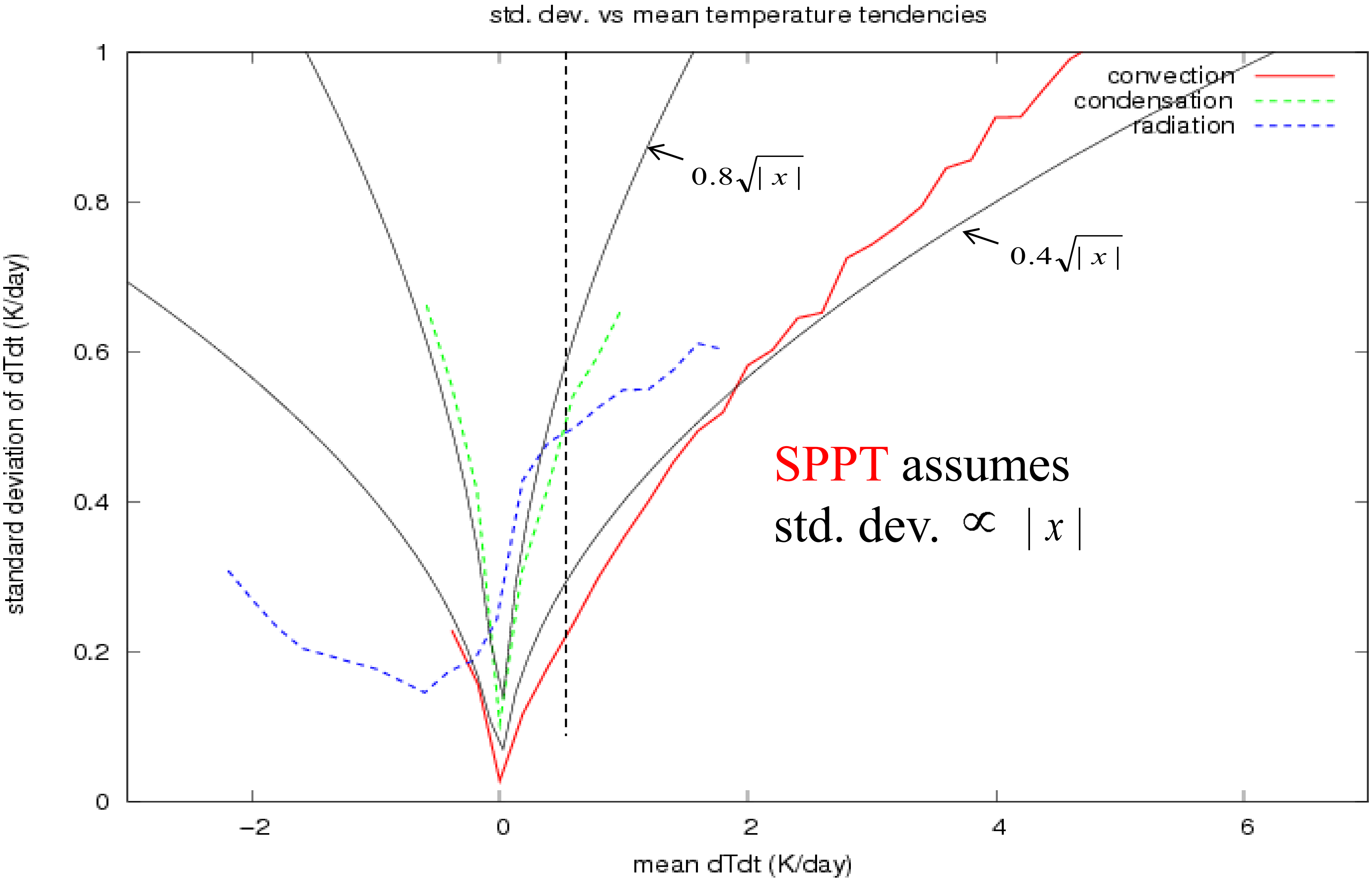
$$E(\lambda,\varphi,t_6) = \hat{f}_{159}(\lambda,\varphi,t_6) - \hat{f}_{1279}(\lambda,\varphi,t_6)$$

where $E(\lambda,\varphi,t_6)$ is the ‘error’ in the T159 forecast temperature tendency $\hat{f}_{159}(\lambda,\varphi,t_6)$

sample points with $\hat{f}_{159}(\lambda,\varphi,t_6)$ lying in different ranges

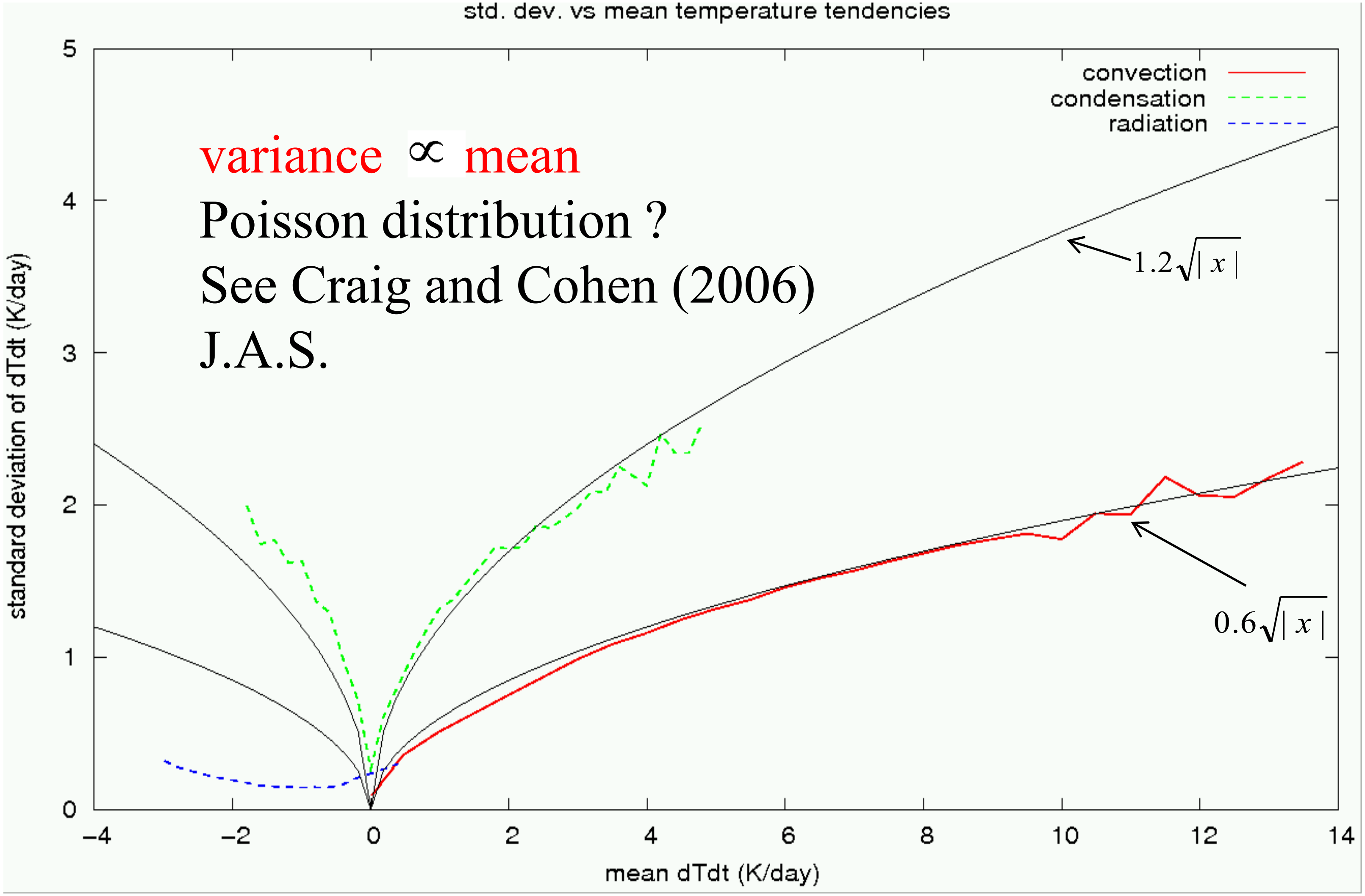
and compute standard deviation of $E(\lambda,\varphi,t_6)$ about the mean

Standard deviation of parametrized T tendency 'error' vs mean at 250 hPa



SPPT assumes std. dev. $\propto |x|$

Standard deviation of parametrized T tendency ‘error’ vs mean at 400 hPa

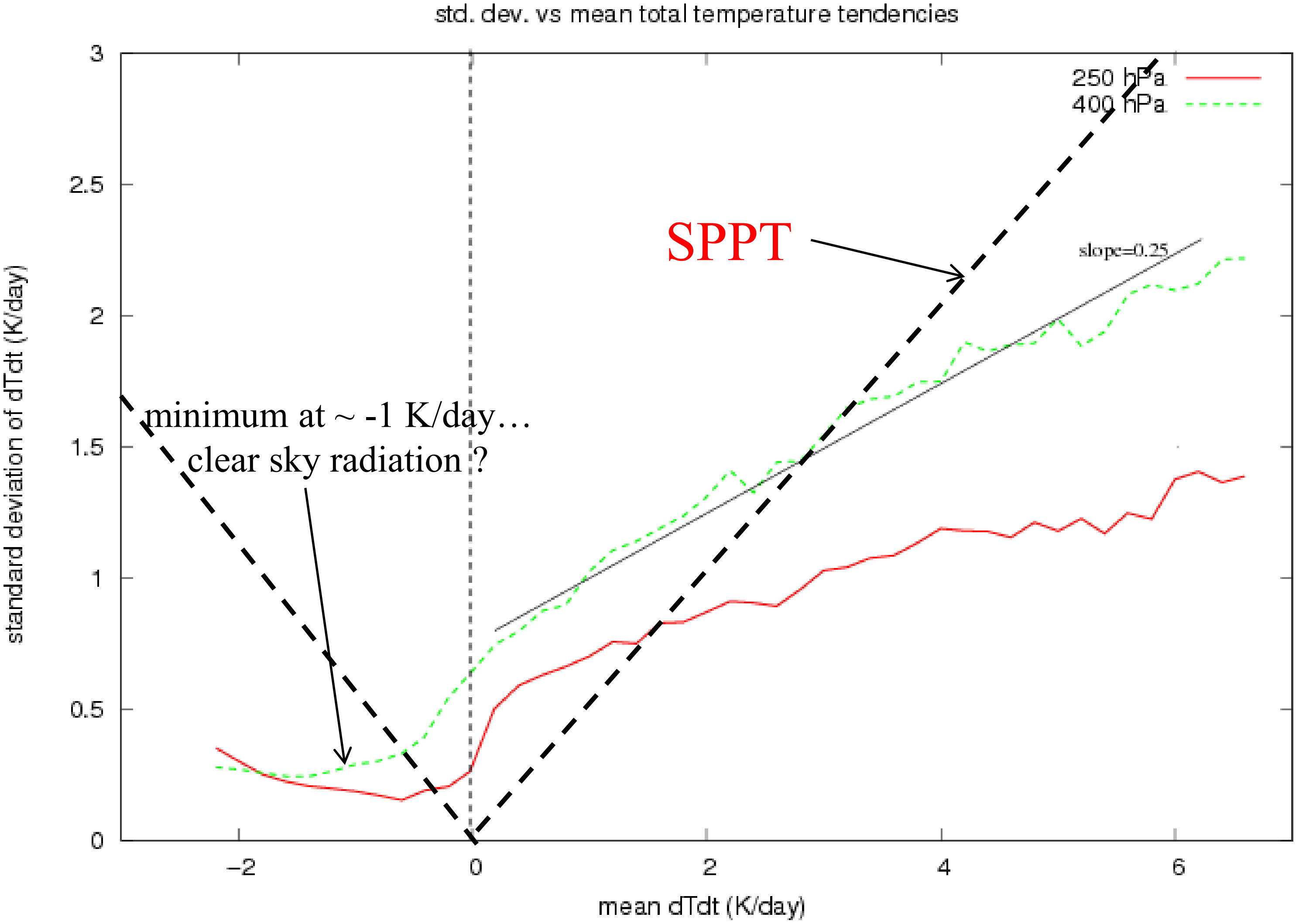


variance ∝ mean

Poisson distribution ?

See Craig and Cohen (2006) J.A.S.

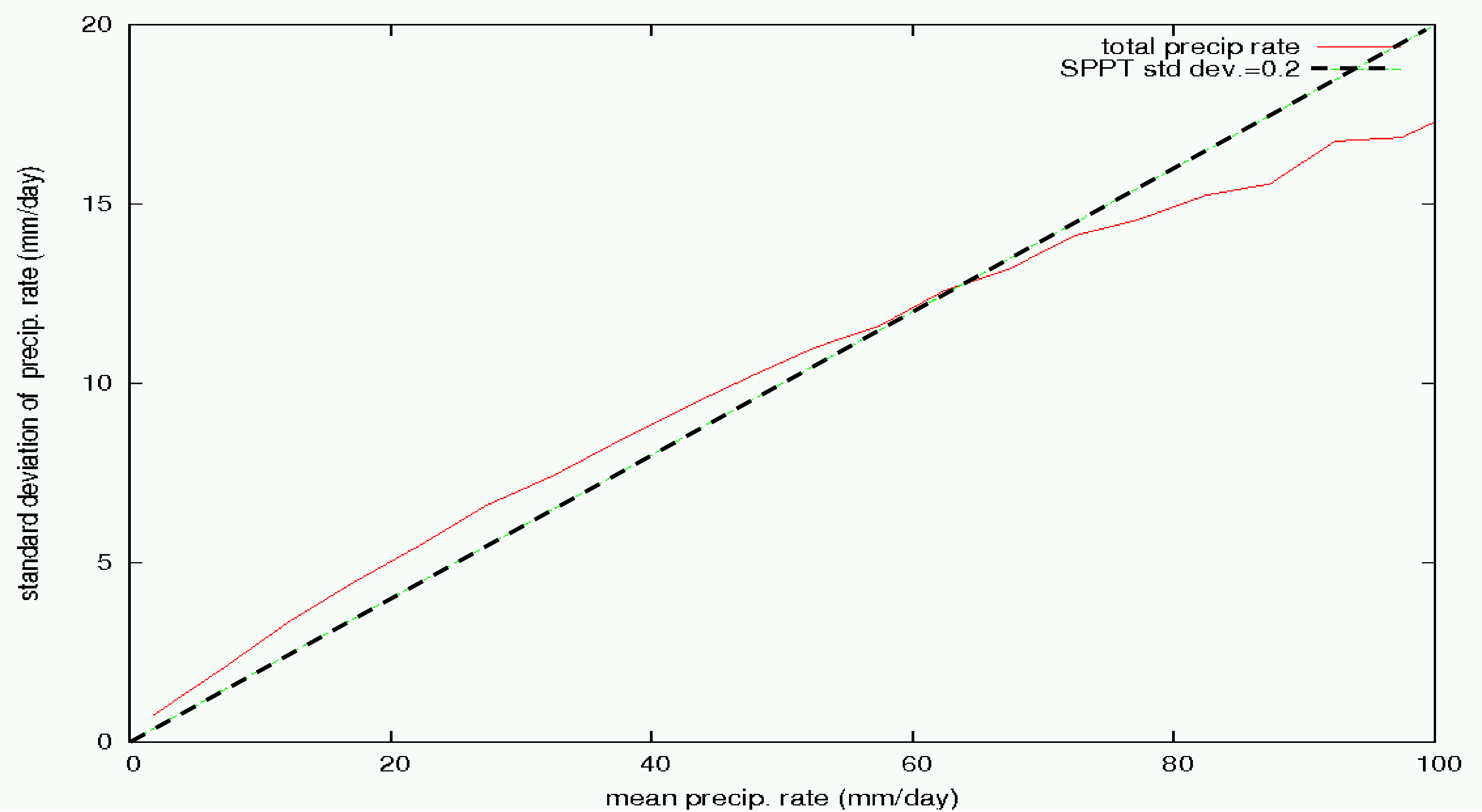
Standard deviation of total parametrized T tendency 'error' vs mean



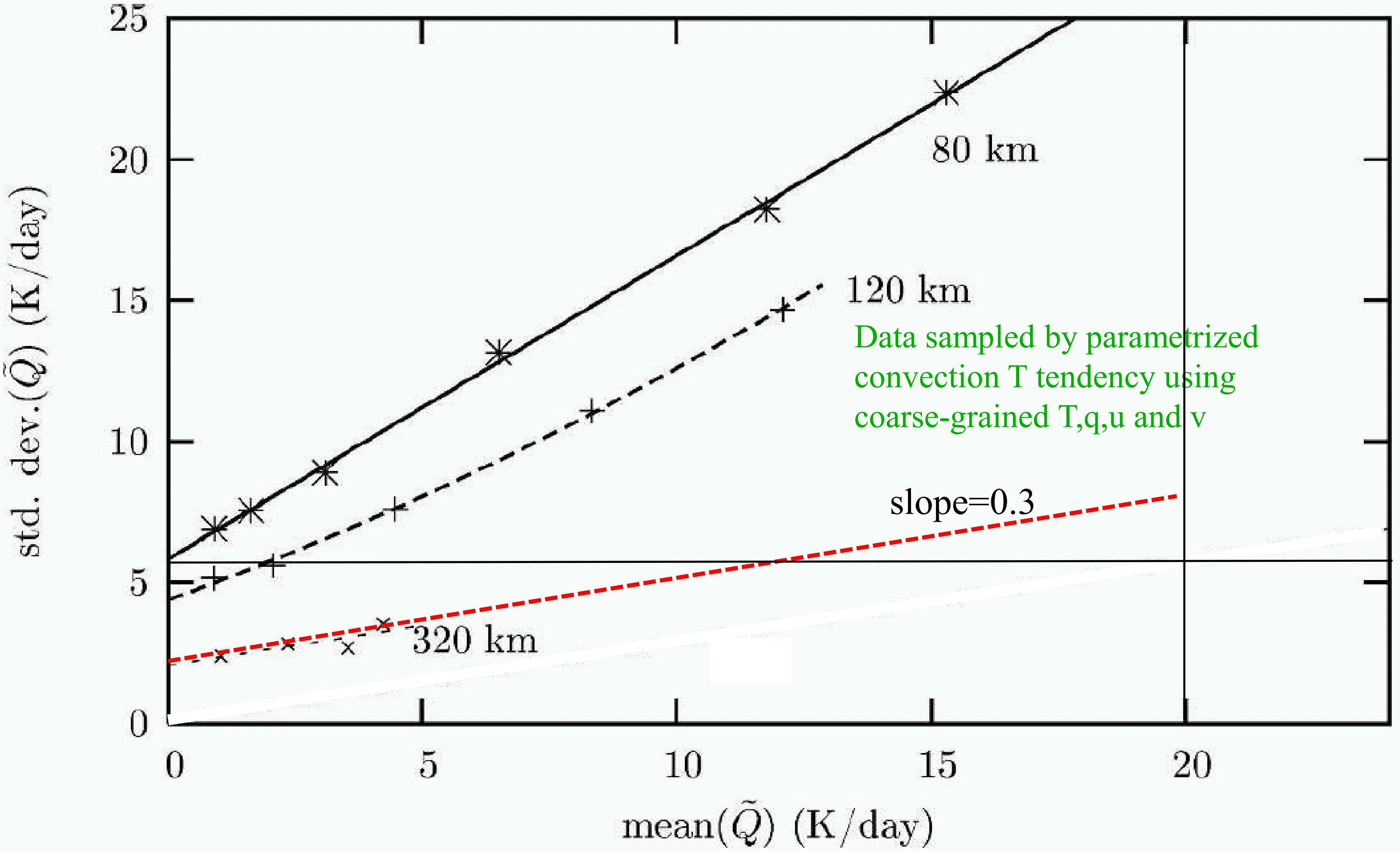
SPPT

minimum at ~ -1 K/day…
clear sky radiation ?

Standard deviation of convective precipitation rate ‘error’ vs mean



Cloud-resolving model coarse-graining study (Shutts and Palmer, 2008; Fig. 12)



Data sampled by parametrized convection T tendency using coarse-grained T,q,u and v

Simple model to understand std. dev. versus mean plots

define 3 parametrized tendency time series:

$$\text{CONTROL}\begin{cases} f_1^n = a_1 \sin(\beta \quad) \\ f_2^n = a_2 \sin(\beta \quad + \varepsilon \\ f_3^n = a_3 \end{cases}$$

where a_i, β and ε are constants

and perturbed tendencies:

$$\text{PERTURBED}\begin{cases} F_1^n = f_1^n (1 + b_1^n) \\ F_2^n = f_2^n (1 + b_2^n) \\ F_3^n = f_3^n \end{cases}$$

where b_i are independent first-order autoregressive processes

$$b_i^{n+} = (1-\alpha)\, b_i^n + r_i^n$$

where r_i^n are random number sequences with zero mean

Now define the total unperturbed tendency by:

$$f^n = f_1^n + f_2^n + f_3^n$$

and the total perturbed tendency by:

$$F^n = F_1^n + F_2^n + F_3^n$$

Compute the root mean square of $F^n - f^n$

for bins based on ranges of f^n

Example

$$a_1 = .0$$

$$a_2 = - \; .5$$

$$a_3 = - \; .1$$

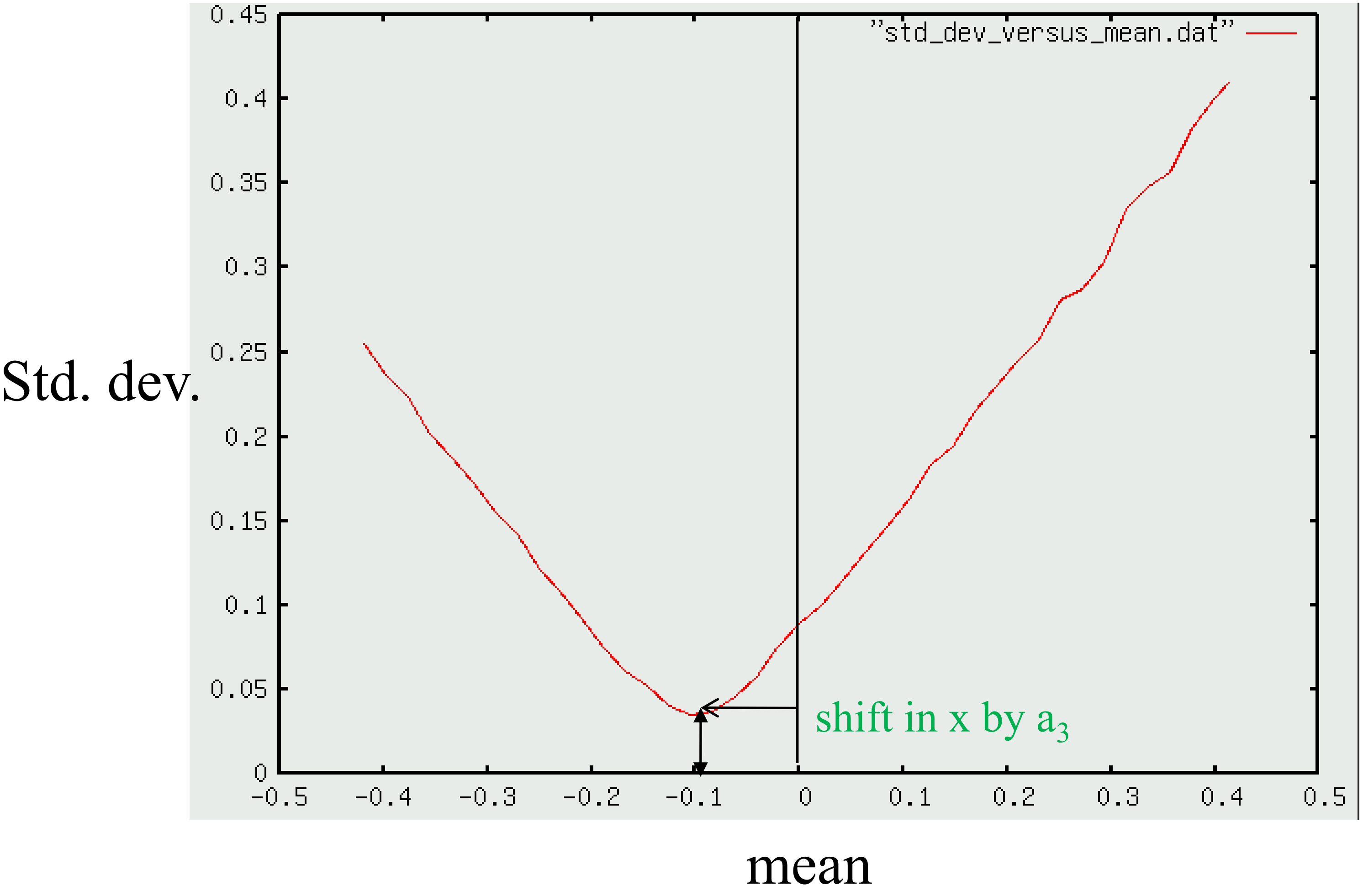
$$\varepsilon = \tau \quad 8$$

$$\alpha =).1$$

$$\beta = \frac{20\pi}{N}$$

$$N = 000000$$

Plot of standard deviation of the net perturbation tendency versus the unperturbed mean tendency

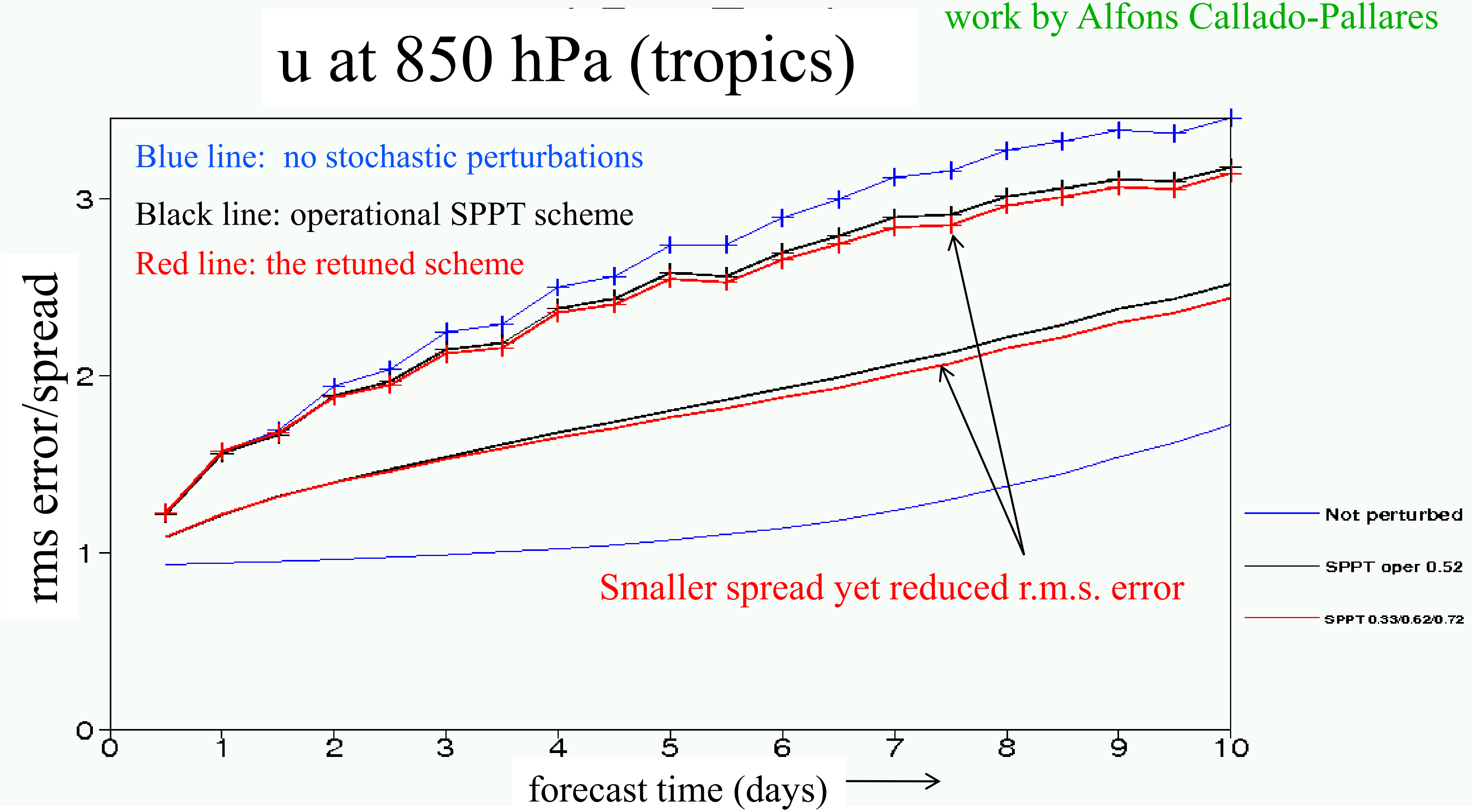


Use of coarse-graining results to retune the strength of the SPPT perturbations

- 3-pattern operational version of SPPT but with the small-scale pattern std. dev. reset to:
  - 0.33 for radiation
  - 0.52 for convection
  - 0.72 for resolved condensation
- 16 start-dates in Aug 2008, 51 member ensemble
- 10 day forecasts made at T159 resolution

The effect of using standard deviations of 0.33, 0.52 and 0.72 to the radiation, convection and condensation respectively in T159 eps forecasts (16 cases) : member spread versus r.m.s. error

work by Alfons Callado-Pallares


u at 850 hPa (tropics)

Blue line: no stochastic perturbations

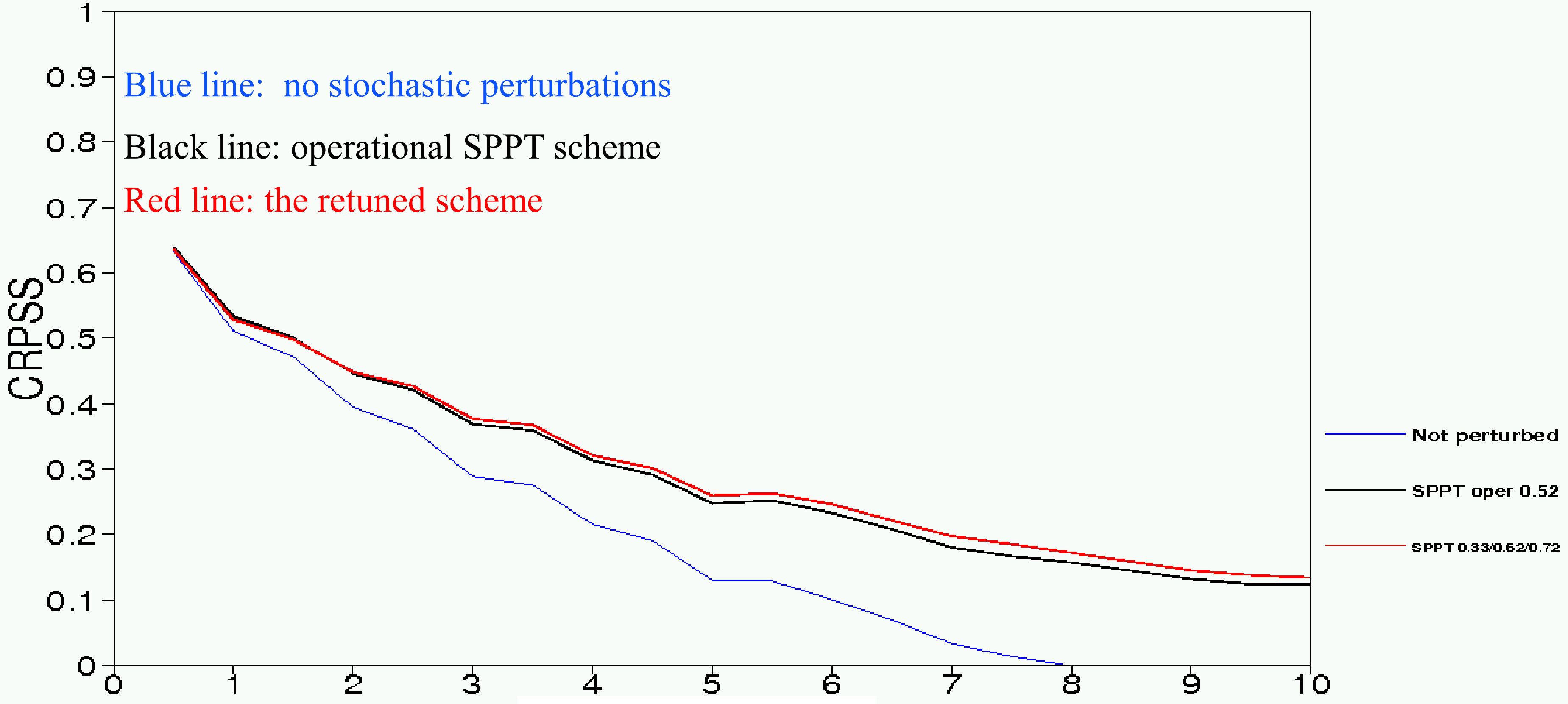
Black line: operational SPPT scheme

Red line: the retuned scheme

Smaller spread yet reduced r.m.s. error

The effect of using standard deviations of 0.33, 0.52 and 0.72 to the radiation, convection and condensation respectively in T159 eps forecasts (16 cases) : continuous ranked probability skill score

u at 850 hPa (tropics)



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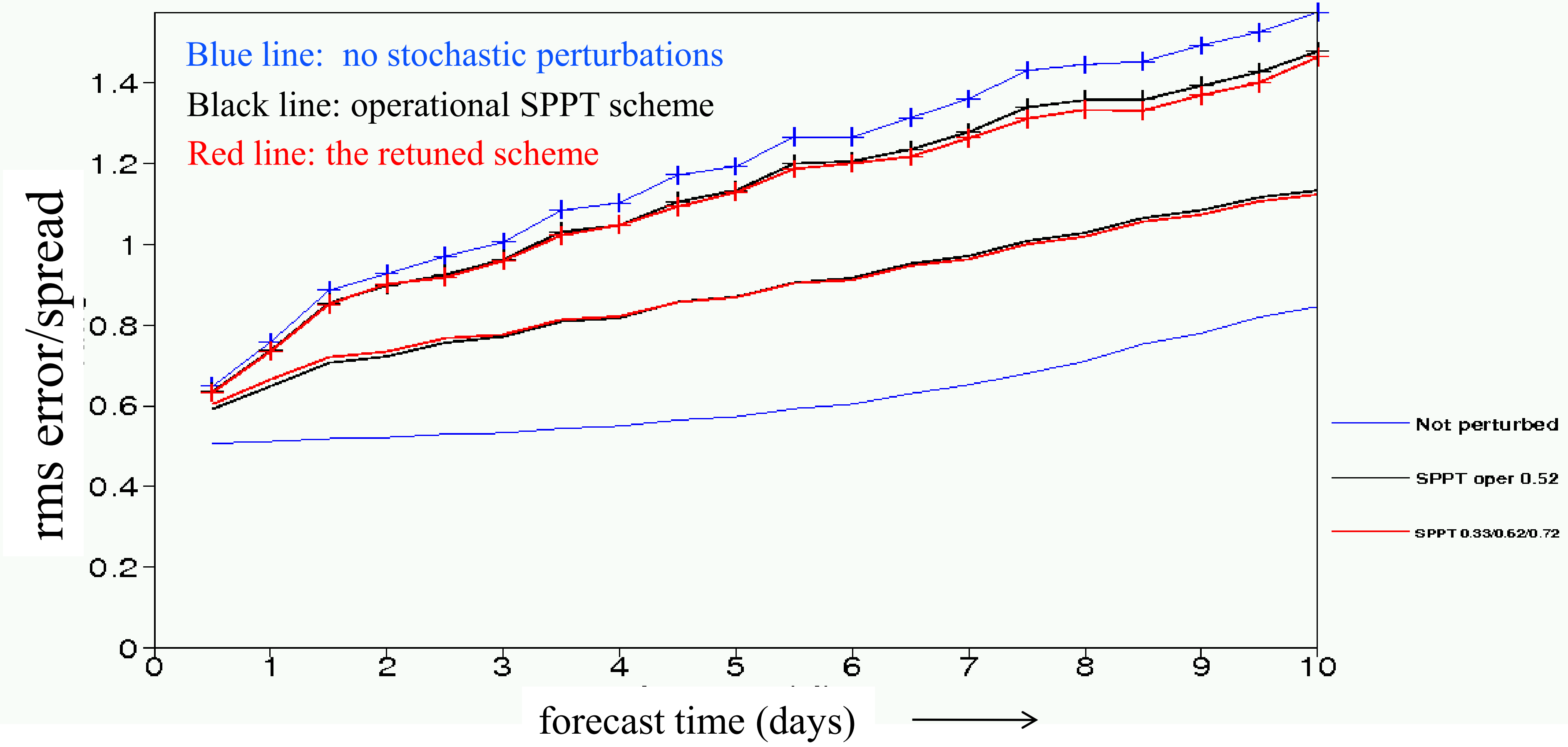
Red line: the retuned scheme

forecast time (days) →

The effect of using standard deviations of 0.33, 0.52 and 0.72 to the radiation, convection and condensation respectively in T159 eps forecasts (16 cases) : member spread versus r.m.s. error

T at 850 hPa (tropics)



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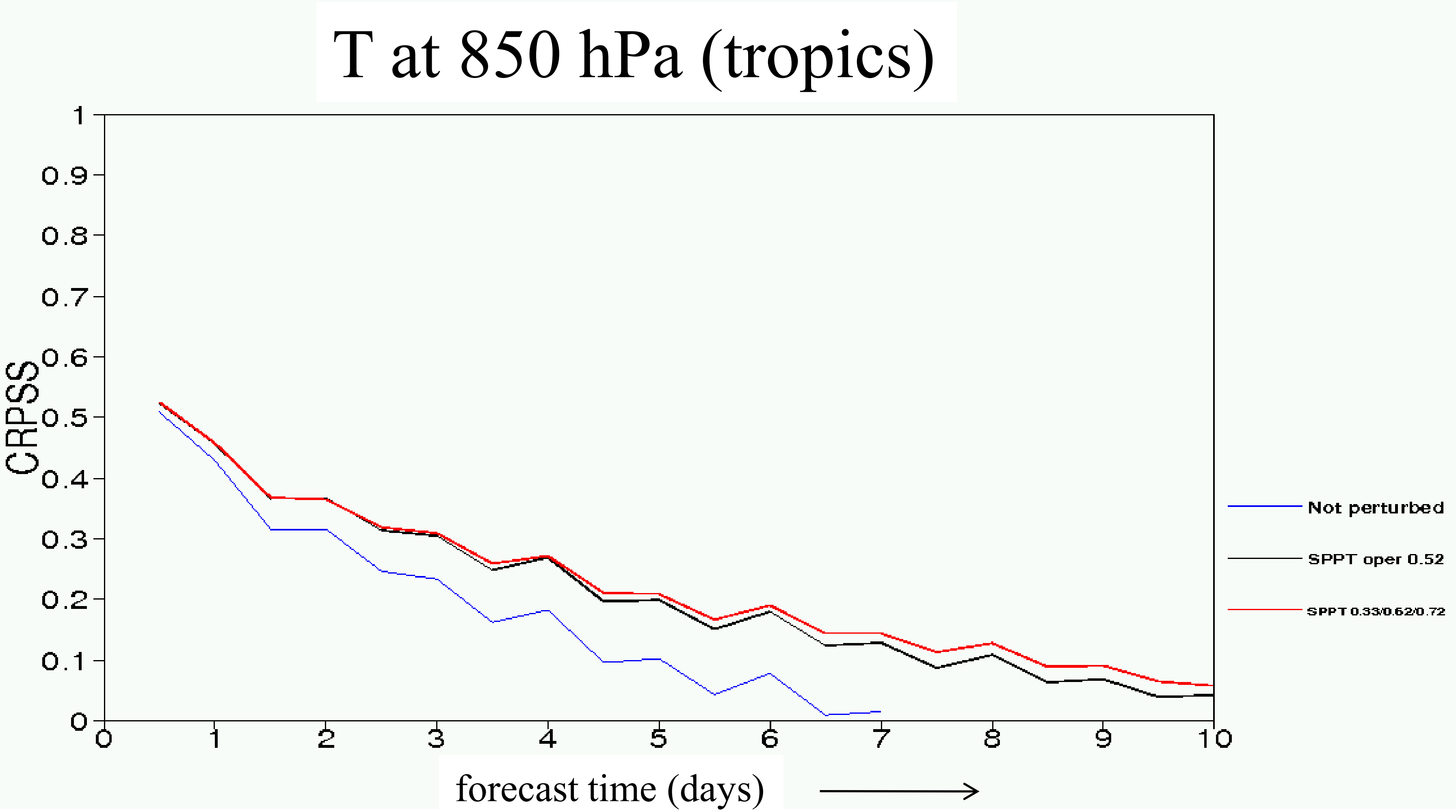


Stochastic Backscatter – the problems

- Dependence on model state is only through a smoothed dissipation rate function
- Global KE input rate by backscatter is very noisy
- Benefits to EPS skill decline with increasing resolution relative to SPPT
- optimal impact when tuned to give same energy input rate – irrespective of resolution. Why ?
- Too complex and with too many unknown or arbitrary parameters e.g. smoothing scale for the dissipation rate
- Costly numerically
- Very little benefit in seasonal and climate forecasting

Stochastic Vorticity Confinement (SVC)

- Vorticity Confinement (VC) is a type of anti-diffusion scheme proposed by John Steinhoff (Steinhoff and Underhill,1994)
- Implemented as a force in the momentum equation

- Acts as an upgradient vorticity transport term that counteracts the downgradient diffusive transport

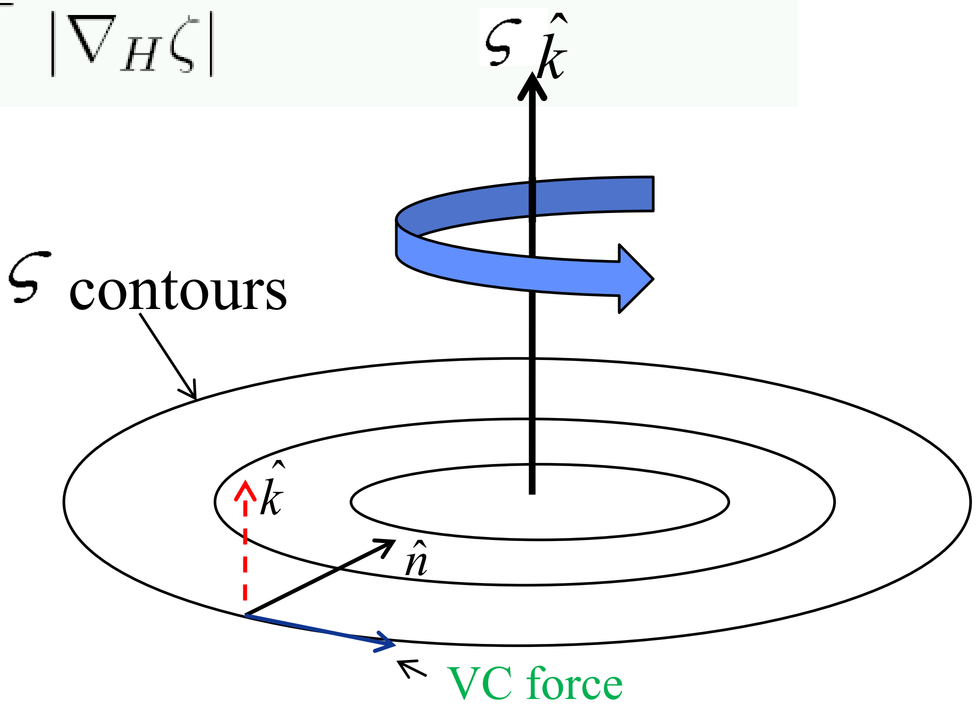
- SVC uses a pattern generator (e.g. from SPPT) to modulate the strength of this upgradient vorticity flux

Formulation:

$$\frac{D\mathbf{V_H}}{Dt} + f\mathbf{k} \times \mathbf{V}_H + \nabla\phi = \mu\nabla^2\mathbf{V}_H + \epsilon\hat{\mathbf{n}} \times |\zeta|\,\widehat{\mathbf{k}}$$

$$\hat{\mathbf{n}} = \frac{\nabla_H\zeta}{|\nabla_H\zeta|}$$

ε ì acts as an advective velocity



Stochastic vorticity confinement

- Use the pattern generator for SPPT to modulate ε

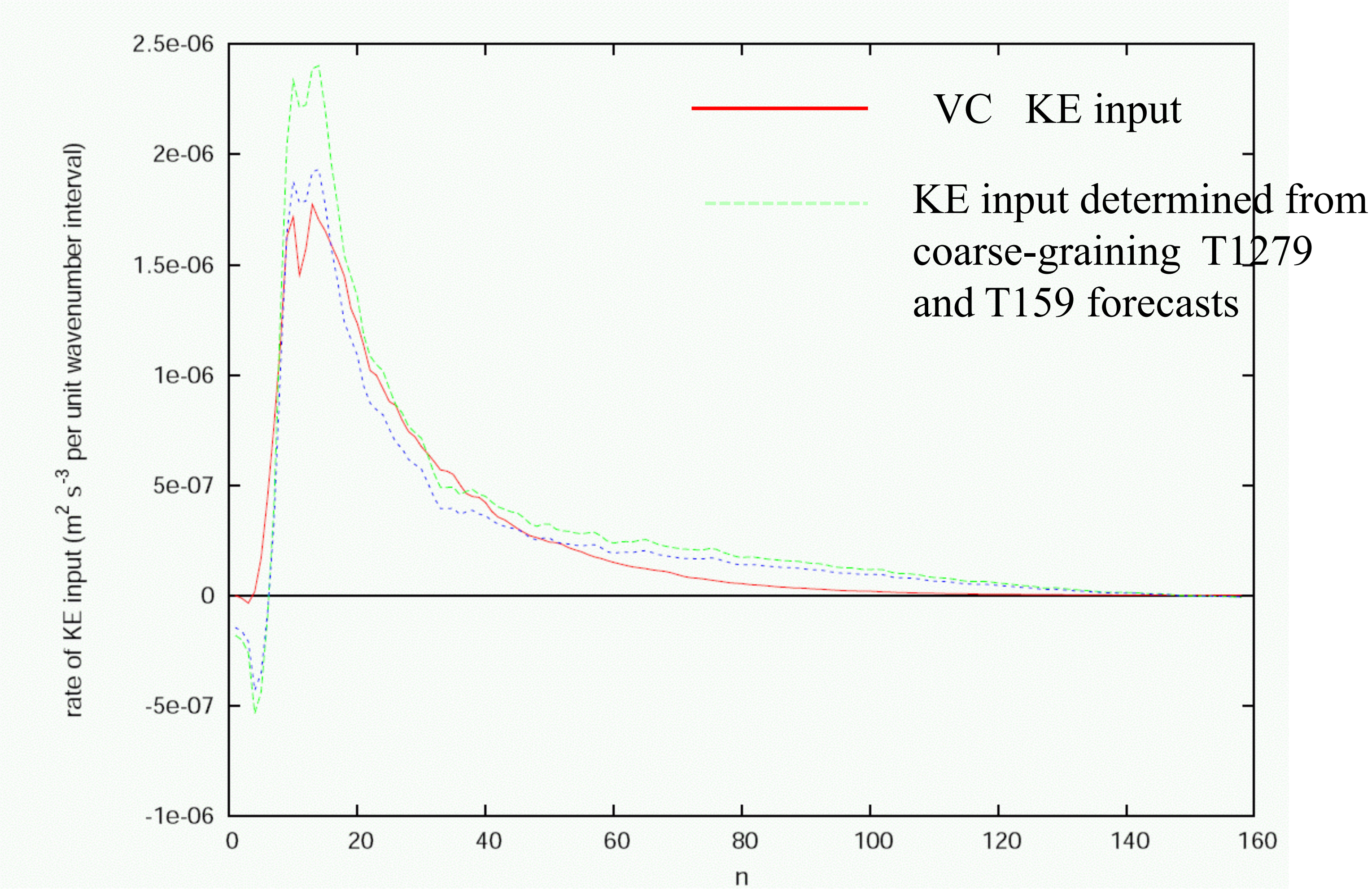
- Vorticity gradient field computed efficiently in

  spectral->grid transform

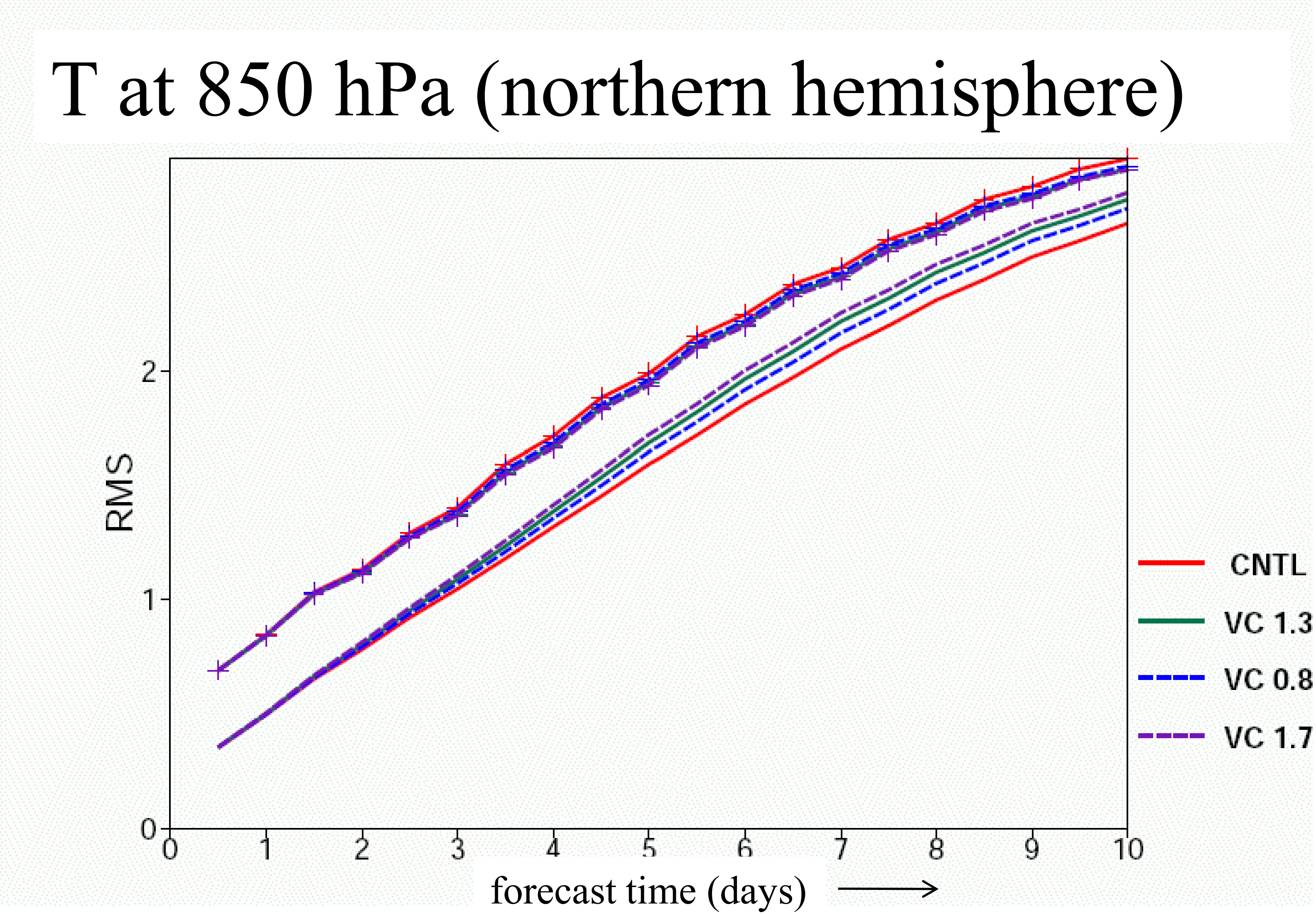
- Pre-filter the vorticity field to remove spherical harmonic modes with $n < 10$

- alternative implementation at the Met Office allows ε to be a proportional to the square root of the dissipation rate (Claudio Sanchez)

Spectral energy input

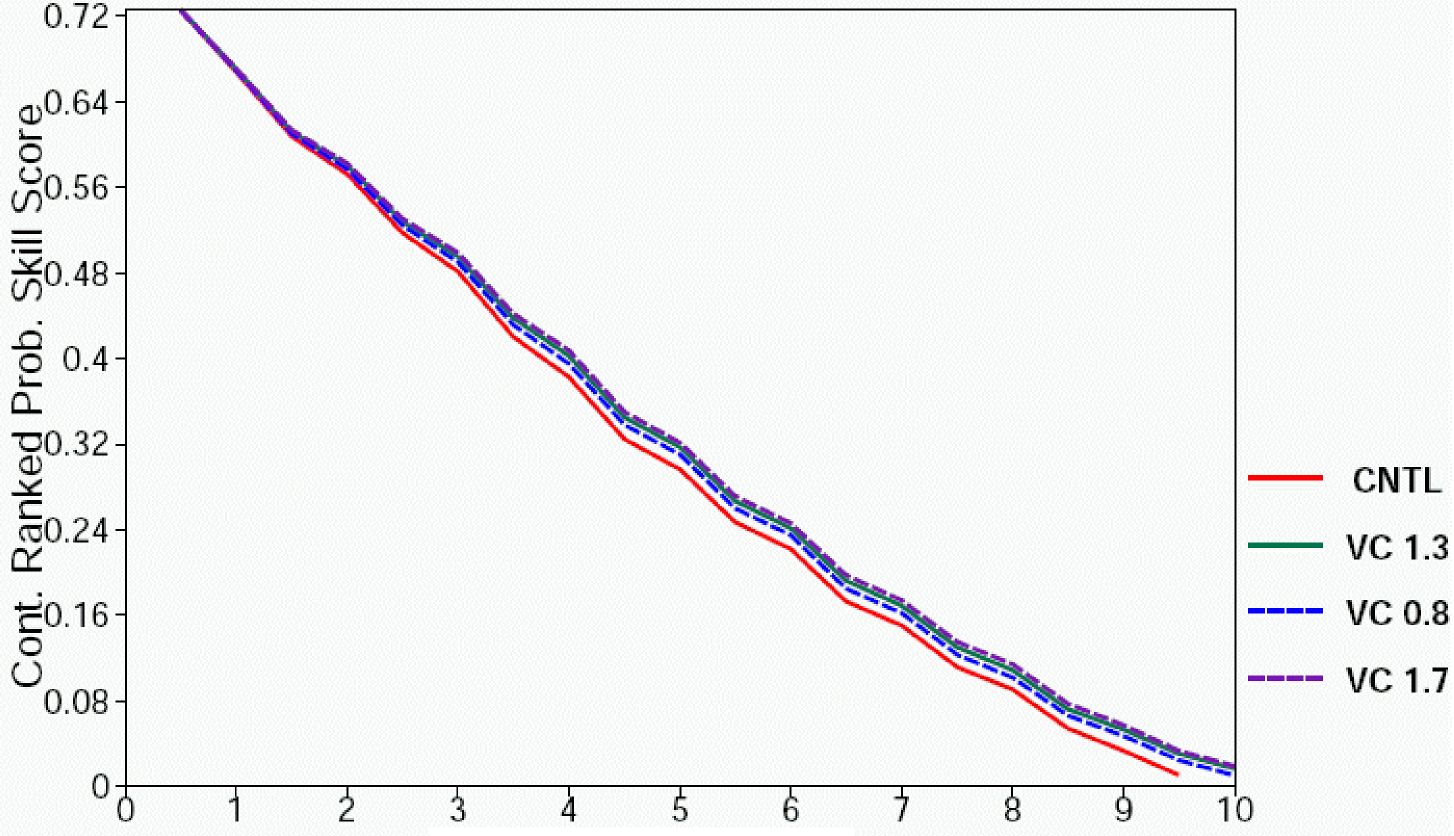


Impact of different strengths of SVC: spread and error



Impact of different strengths of SVC: CRPSS

T at 850 hPa (northern hemisphere)



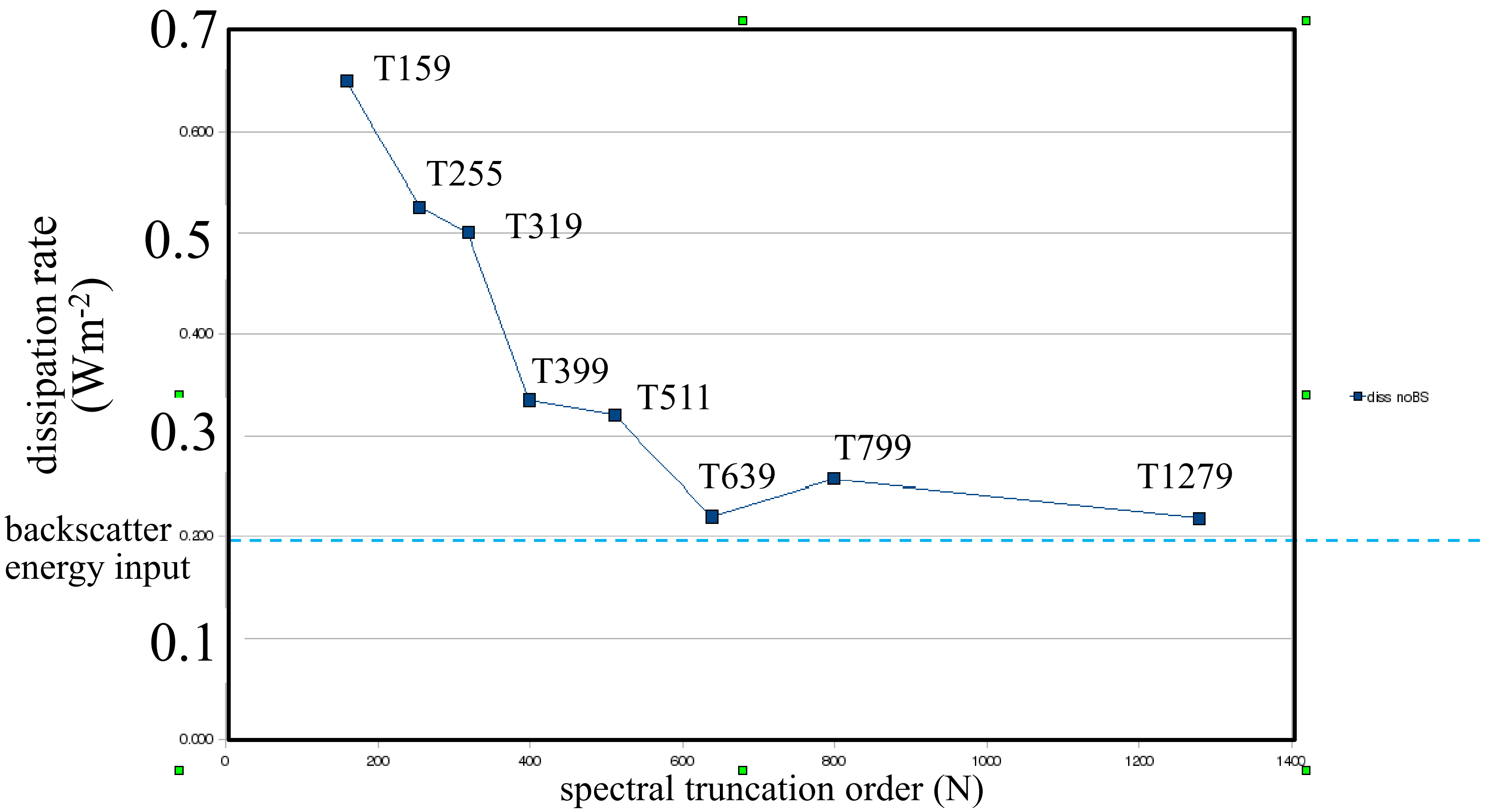
forecast time (days) →

vorticity confinement findings

- in deterministic T95 forecasts VC reduces r.m.s. error in first 4 days (by up to 2 % in Z500)
- Stochastic VC potentially could replace stochastic backscatter
- Positive impact on low-resolution (e.g. N48) climate forecasts (Claudio Sanchez poster)
- Far simpler formulation than stochastic backscatter
- Deterministic VC spectral energy transfers supported by coarse-graining and the work of Kent and Thuburn

Resolution dependence of the numerical dissipation rate

work by Martin Steinheimer



Subjective assessment of the efficacy of stochastic parametrizations

ECMWF perspective

- The perturbed parametrization tendency approach is the simplest and most effective technique
- Stochastic backscatter is most effective when the horizontal resolution is T255 or less (gridlengths > 80 km).
- EPS skill improved by increasing spread but some spread is better than others (backscatter cannot replace SPPT at T639)
- Mesoscale pattern of SPPT is ineffective on its own in providing spread in the seasonal forecast ensemble

Summary

- Coarse-graining can provide the statistical information required to calibrate stochastic parametrization
- At current operational EPS resolution, perturbed parametrization tendency method best targets model uncertainty
- Stochastic vorticity confinement may be a simple, cheap replacement for stochastic backscatter

Recommendations

- generalize SPPT to perturb physical processes independently (calibrated by coarse-graining)
- Use observational datasets to quantify uncertainty, particularly w.r.t. cloud