Constraining Stochastic Parametrisation Schemes Using High-Resolution Model Simulations and the OpenIFS Single Column Model

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With thanks to Andrew Dawson (Oxford, ECMWF),
Chris Holloway (U. Reading), Tim Palmer (Oxford), Judith Berner (NCAR), Filip Vana (ECMWF)

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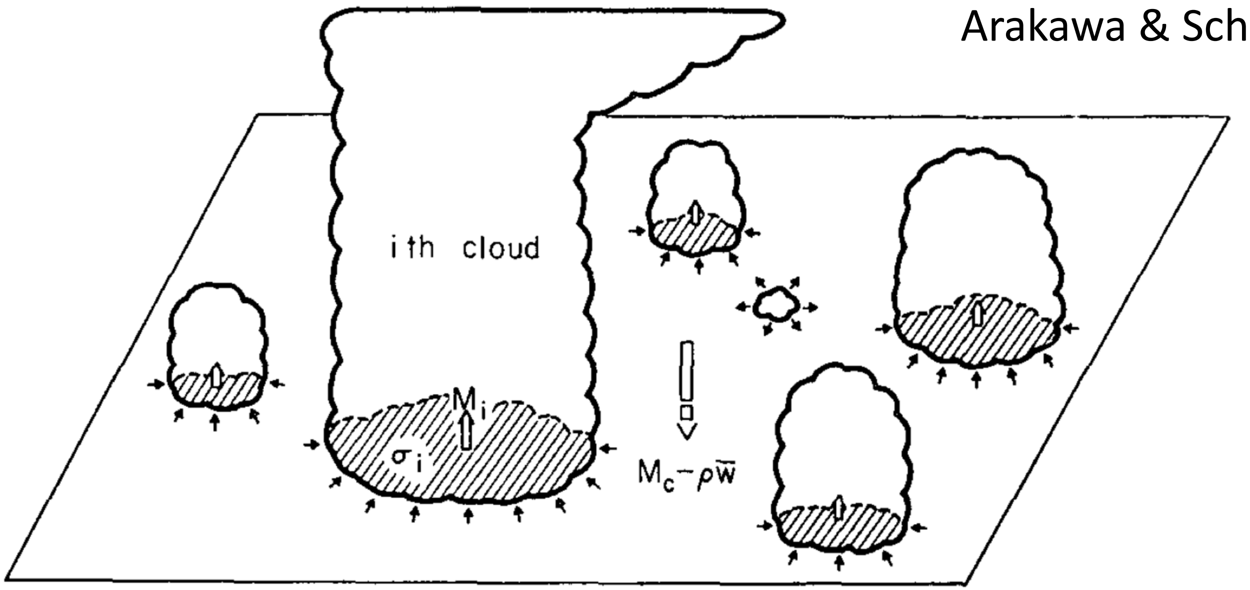
Designing a parametrisation scheme e.g. convection

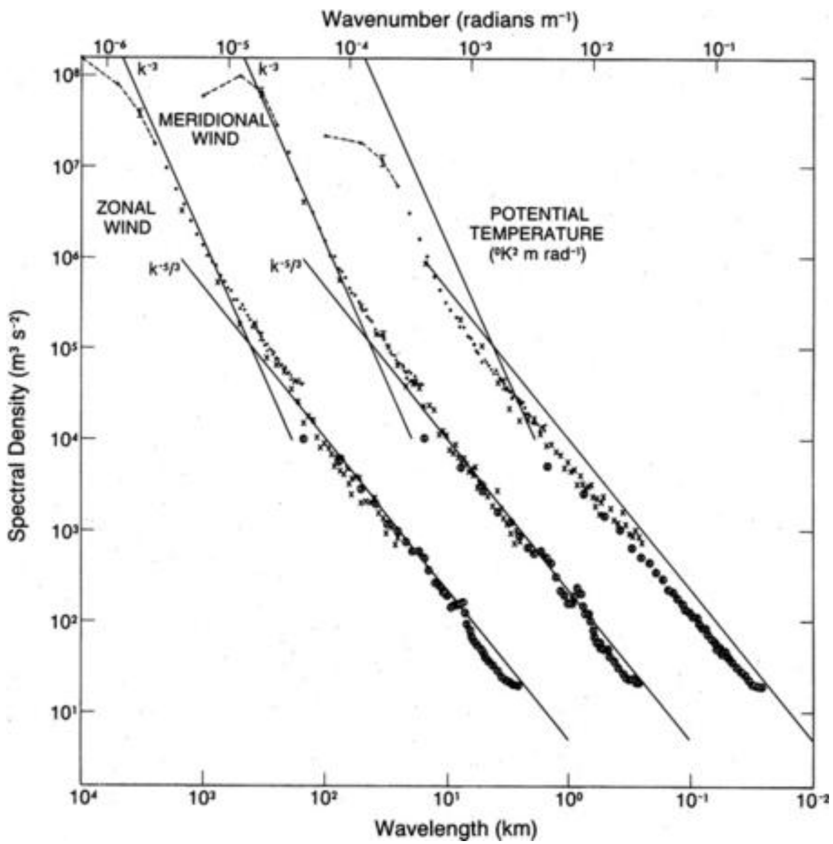
Arakawa & Schubert, 1974



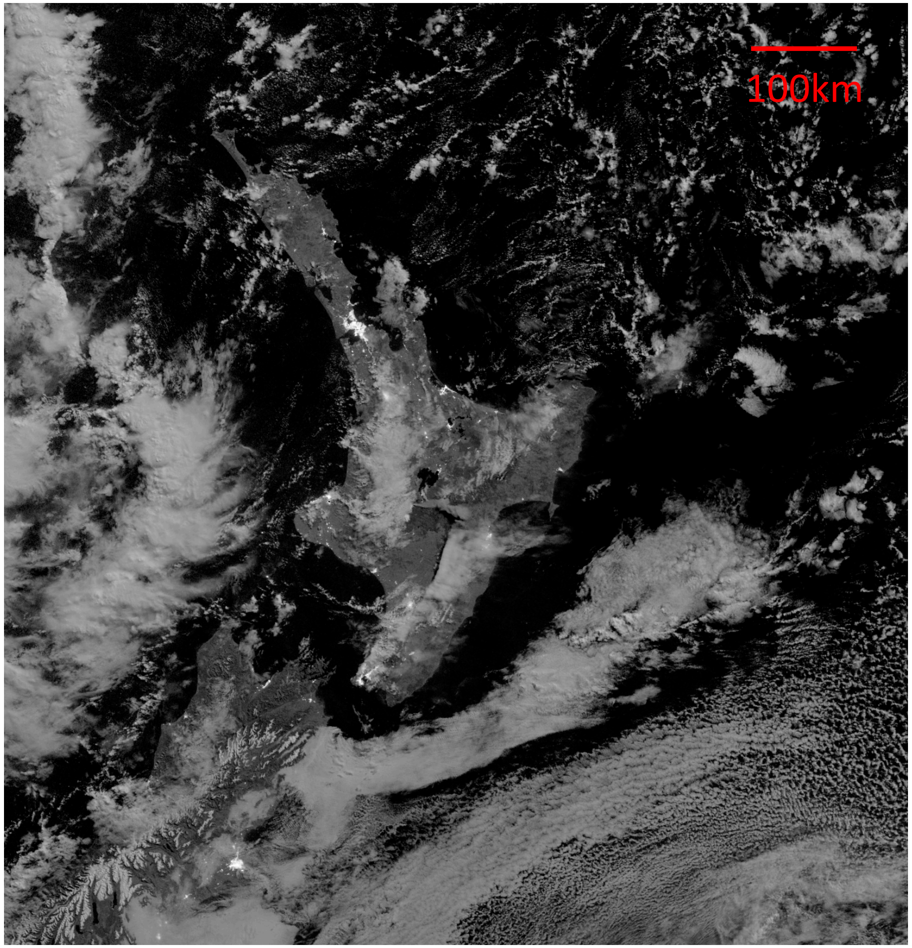
Consider a horizontal area at some level between cloud base and the highest cloud top. This horizontal area, which we designate as our unit horizontal area, is shown schematically in Fig. 1. It must be large enough to contain an ensemble of cumulus clouds but small enough to cover only a fraction of a large-scale disturbance. The existence of such an area is one of the basic assumptions of this paper.

= grid box

We observe a continuum of scales of motion



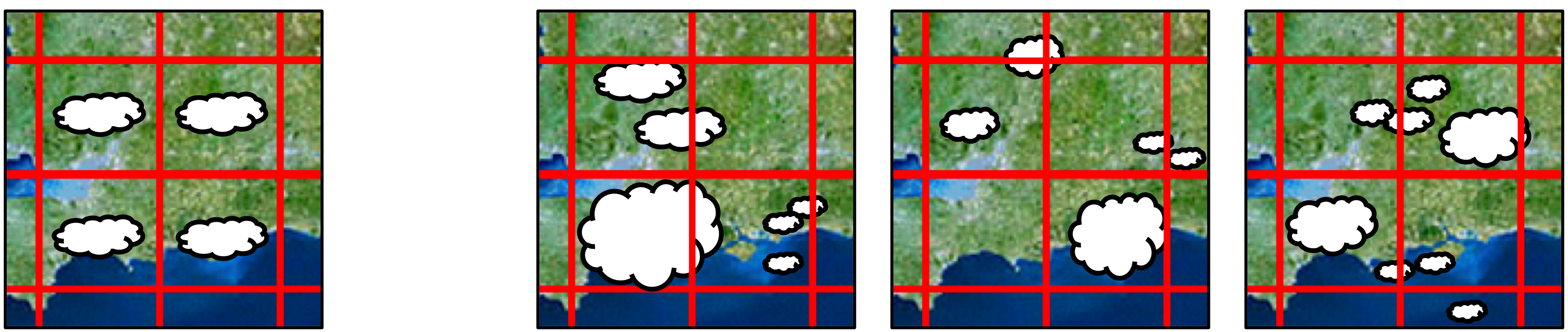
Nastrom & Gage, 1985



Stochastic Parametrisation

- We do not observe a clear separation of scales for many processes
- Grid-scale variables do not fully constrain sub-grid scale motions
- Stochastic parametrisation scheme: describes the sub-grid tendency in terms of a pdf constrained by the resolved-scale flow
- Provides stochastic realisations of the sub-grid flow, not some assumed bulk average effect.
- Represents unresolved sub-grid variability

traditional 'best guess'   stochastic Trial #1   Trial #2 ...   Trial #N

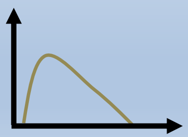


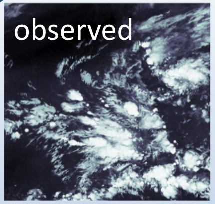
A general framework for stochastic parametrisation

Identify uncertain process in forecast model

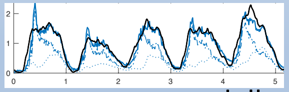
$$\rho\left(\frac{\partial \mathbf{u}}{\partial t} + (\mathbf{u}\cdot\nabla)\mathbf{u}\right) = -\nabla \mathbf{p} + \eta\nabla^2\mathbf{u}$$

Theoretical ideas





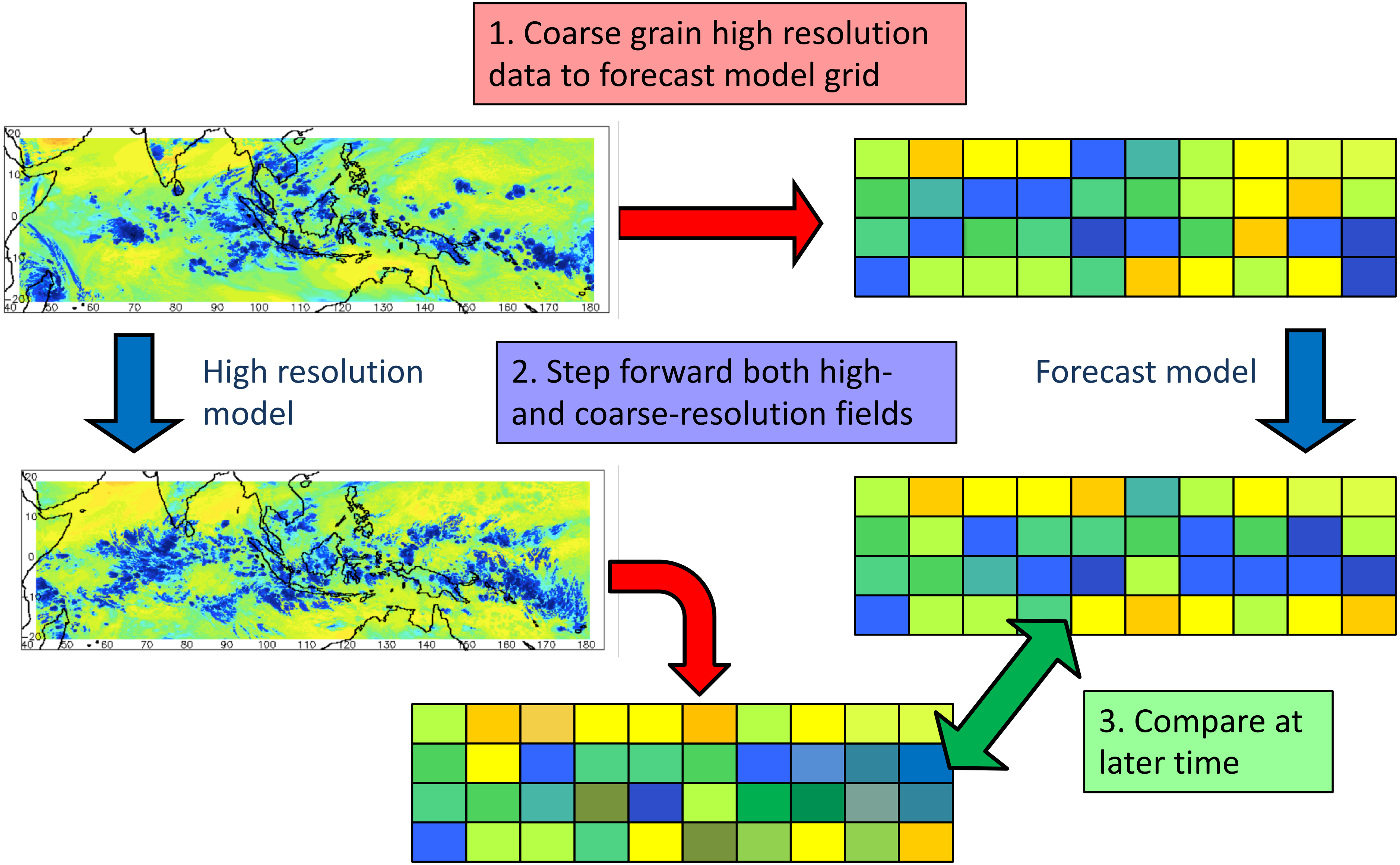
Measurements



Characterise uncertainty in that process

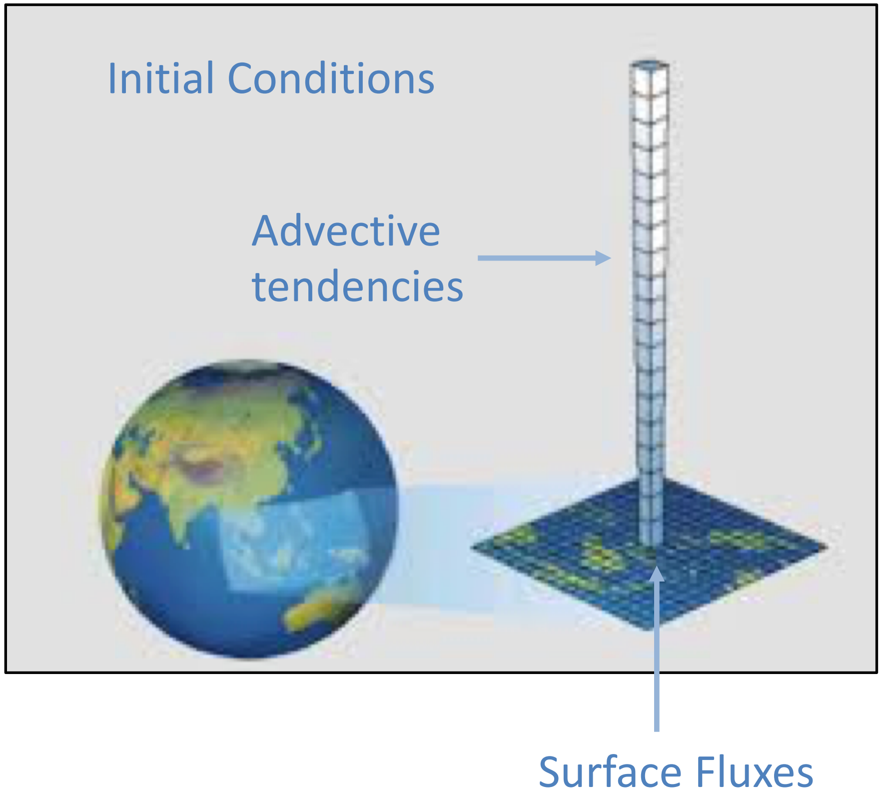
Design stochastic parametrisation to explore this uncertainty

Use a high resolution simulation as 'truth'



OpenIFS SCM as Forecast Model

- How do we use an SCM?
  - Use coarsened high-res simulation to prescribe Initial conditions, Advective tendencies (dynamical forcing) and Boundary conditions
- Benefits of using SCM?
  - Supply dynamical tendencies targets uncertainty in the parametrisation schemes
  - SCM portable and cheap
  - Tile many SCM to cover domain
- OpenIFS SCM CY40R1 at T_L639, 91 vertical levels

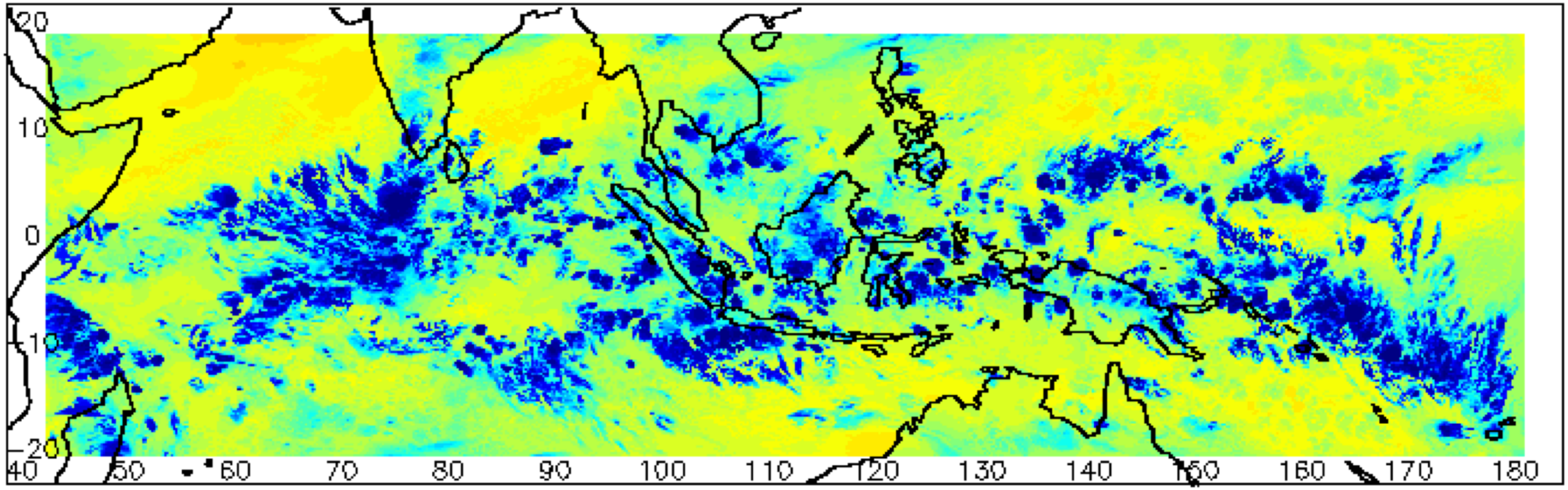


Christensen, Dawson and Holloway, 2018, JAMES

Existing high resolution dataset: Cascade

thanks to **Chris Holloway, U. Reading**

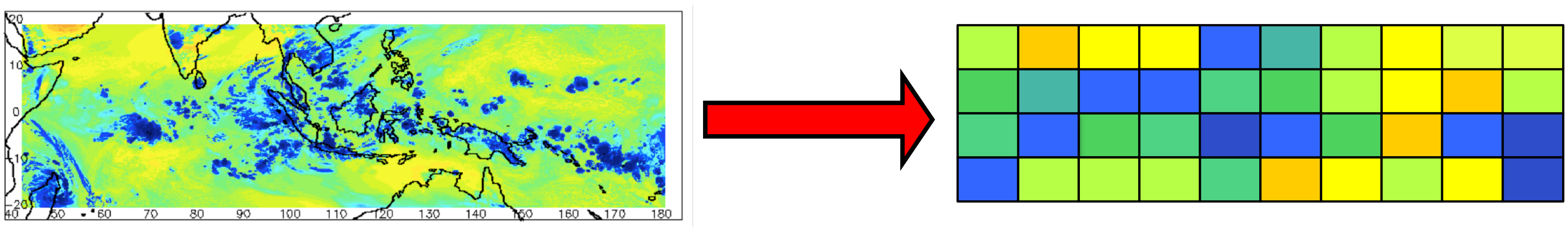
- UK Met Office atmospheric model setup
- Semi-Lagrangian, non-hydrostatic dynamics, 4km resolution
- Large tropical domain (15,500 km x 4,500 km), 9 days of data. Hourly dumps.
- Prescribe observed SST; boundary conditions from ECMWF 25 km analysis
- Convection scheme switched on but only active in low CAPE environments



Holloway et al, 2012; 2013

What we do

- Coarse-grain Cascade to T_L639
- Run an independent SCM simulation, initialised every hour, from every lat-lon point in the coarse-grained domain (>68,000)
- Compare evolution of SCM over **one hour** with Cascade
- Repeat for entire 9-day Cascade simulation



Case study: is there any physical basis for SPPT?

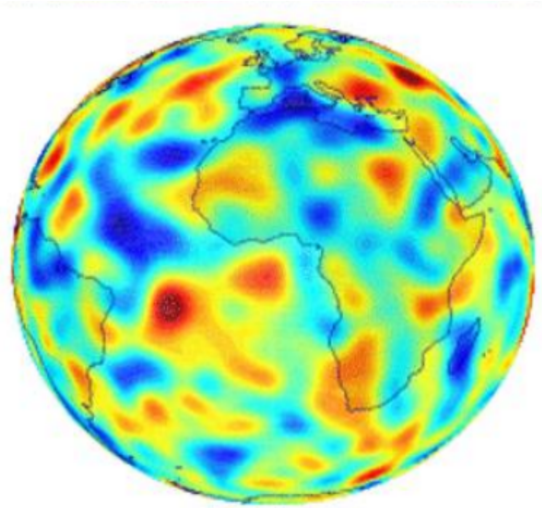
- **Stochastically Perturbed Parametrisation Tendencies (SPPT)**
  - represents random errors due to model's physical parametrisation schemes
  - Developed at ECMWF. Implemented in models worldwide

$$T = D + (1+e)\sum_{i=1} P_i$$

T – Total tendency
D – Dynamics tendency
P – Physics tendency

Pattern correlated in space & AR(1) in time:

σ	L (km)	τ (days)
0.52	500	0.25
0.18	1000	3
0.06	2000	30



All variables see same perturbation
Perturbation constant in height

Palmer et al, 2009.
ECMWF Tech Memo 598

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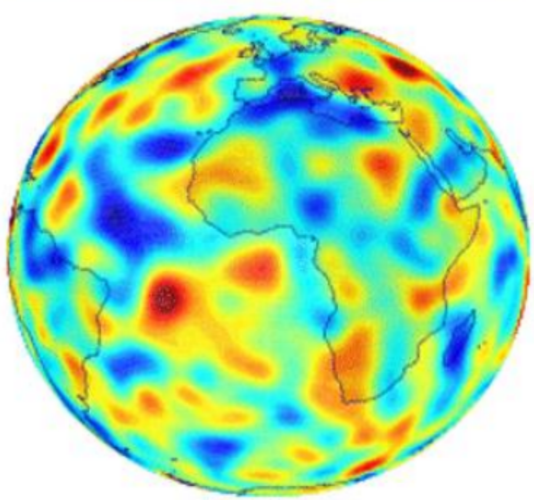


Palmer et al, 2009.
ECMWF Tech Memo 598

Analysing the data: multiplicative noise?

SPPT:

$$T = D + (1+e)\sum_{i=1} P_i$$

Calculate 'true' total tendency from Cascade

Dynamics tendency from Cascade, processed by SCM

Consider error in SCM physics tendencies

$$T - D = (1+e)\sum_{i=1} P_i$$

'true' physics tendency

parametrised physics tendency

P_{CAS}

P_{SCM}

SPPT: standard deviation proportional to mean

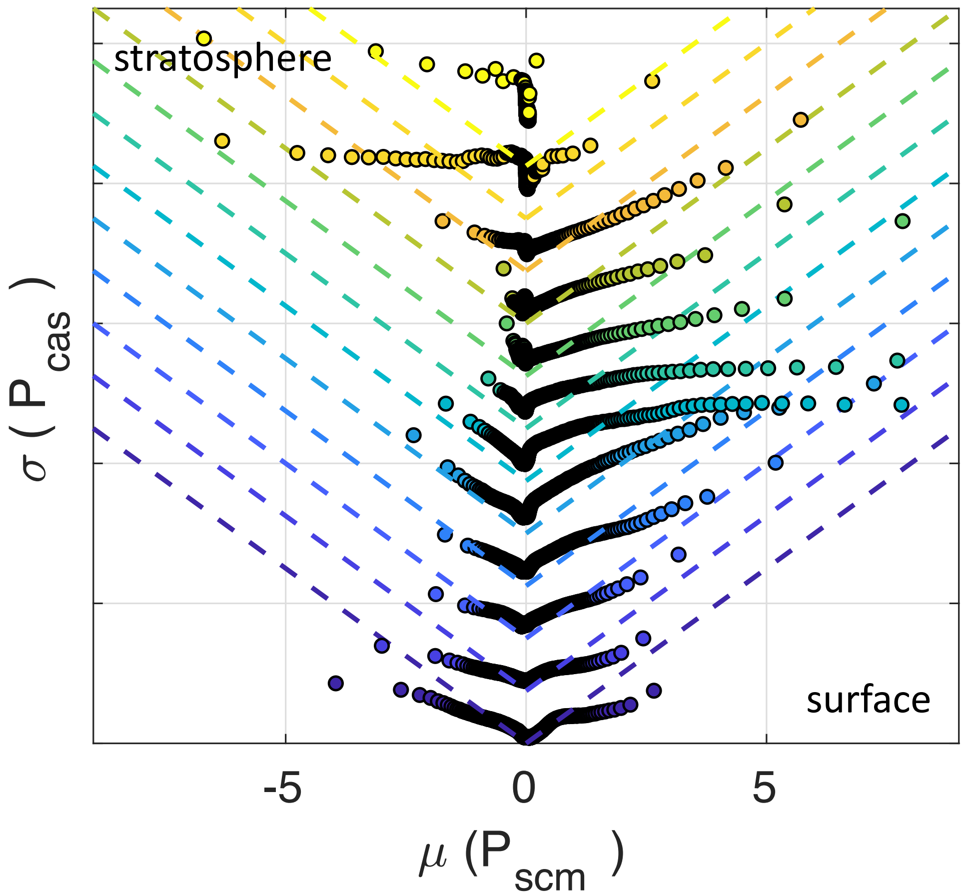
Hypothesis:

$$\underbrace{T - D}_{\mathbf{P_{CAS}}} = (1+e)\underbrace{\sum_{i=1} P_i}_{\mathbf{P_{SCM}}}$$

If this is true:

$$\sigma(P_{CAS} \mid P_{SCM}) = \sigma_e P_{SCM}$$

Uncertainty in T tendency



Data grouped by level.
Dark blue: levels 91—87 (ground—995 hPa)
Yellow: levels 32—36 (86—60 hPa)

SPPT: standard deviation proportional to mean

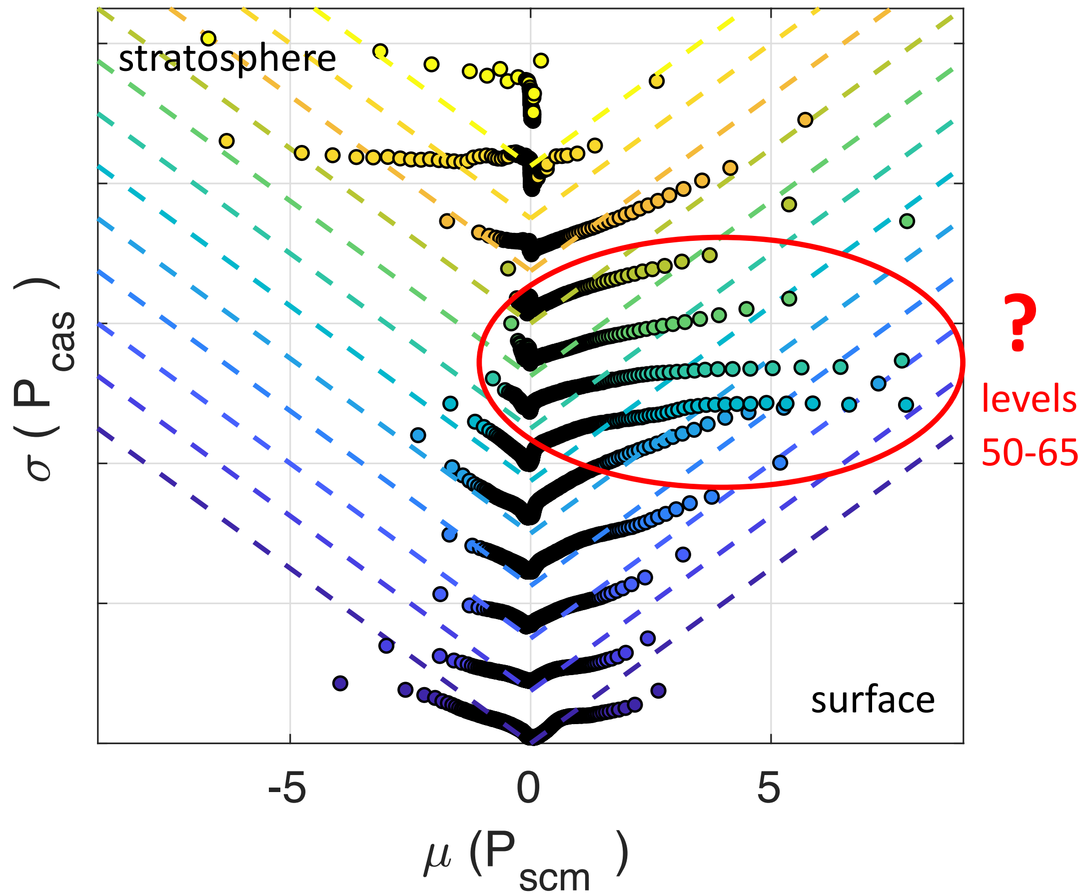
Hypothesis:

$$\underbrace{T - D}_{P_{CAS}} = (1+e)\underbrace{\sum_{i=1} P_i}_{P_{SCM}}$$

If this is true:

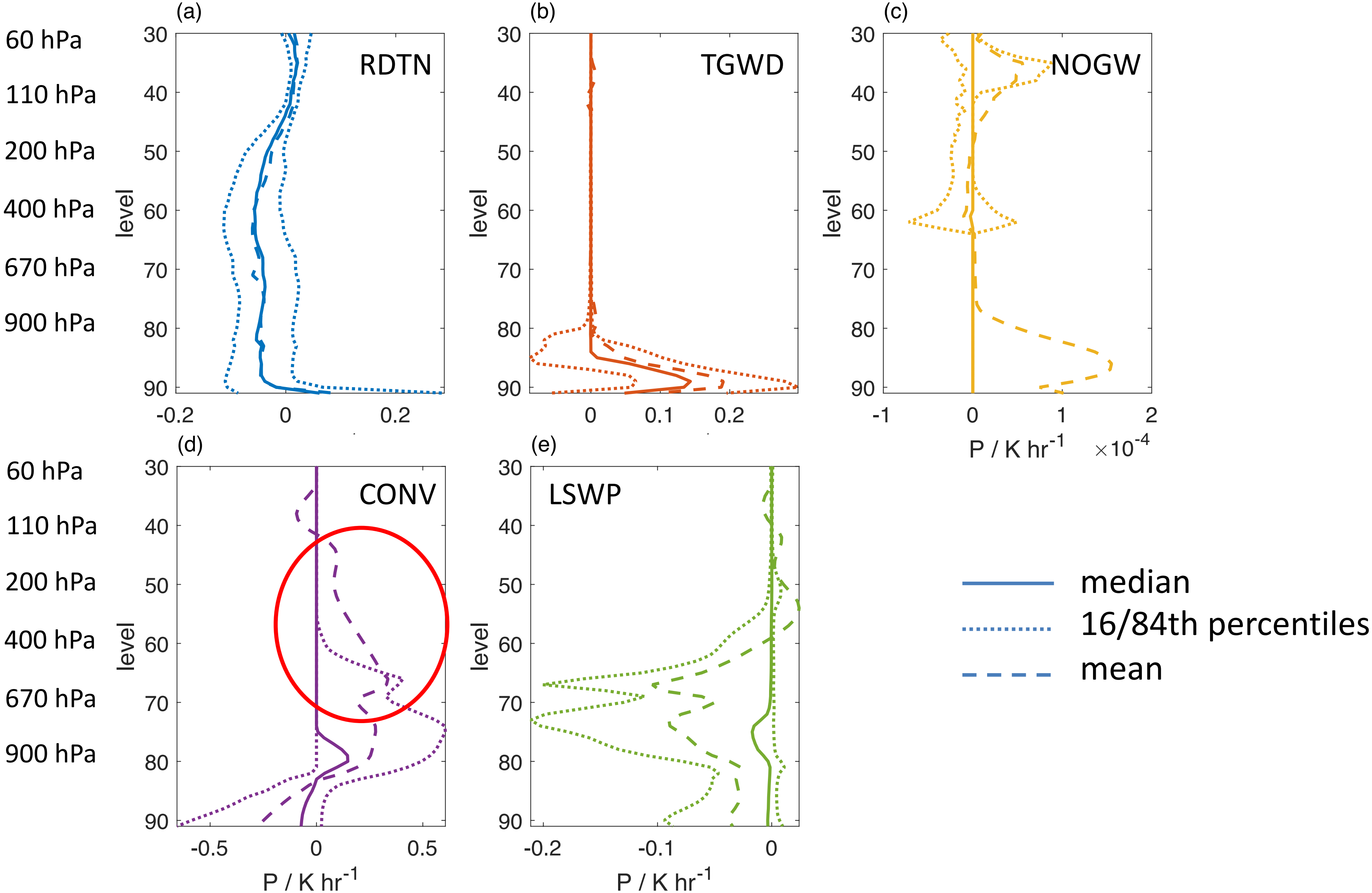
$$\sigma(P_{CAS} \mid P_{SCM}) = \sigma_e \, P_{SCM}$$

Uncertainty in T tendency



Data grouped by level.
Dark blue: levels 91—87 (ground—995 hPa)
Yellow: levels 32—36 (86—60 hPa)

Where are the different schemes active?



Can we use the Cascade simulation to 'tune' SPPT?

SPPT seems like good first-order representation of uncertainty in IFS

- Measure optimal parameters for SPPT to improve scheme

Analysing the data: characteristics of *e*

SPPT:

$$T = D + (1 + e)\sum_i P_i$$

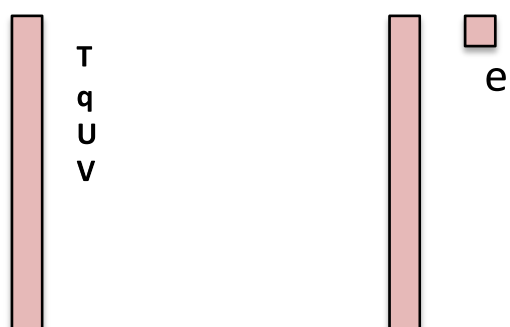
Calculate 'true' total tendency from CASCADE

Assume SCM dynamics tendency is 'correct'

Consider error in SCM physics tendencies

SOLVE

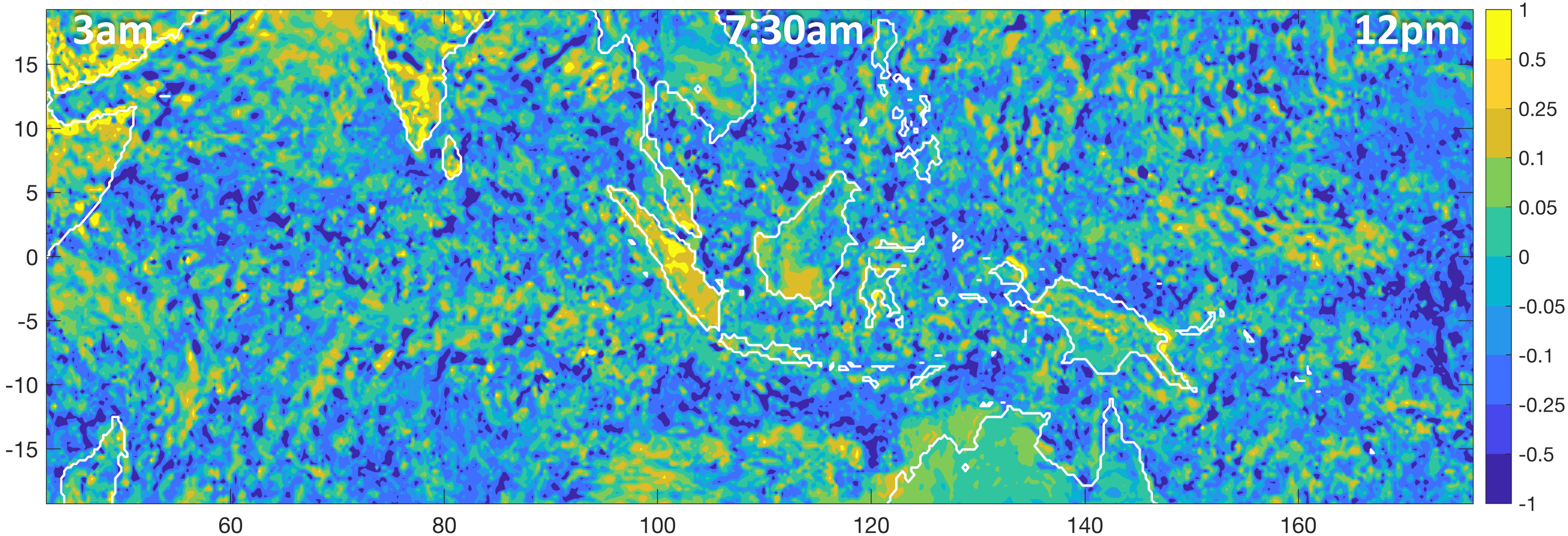
$$T - D - \sum_i P_i = e\sum_i P_i$$



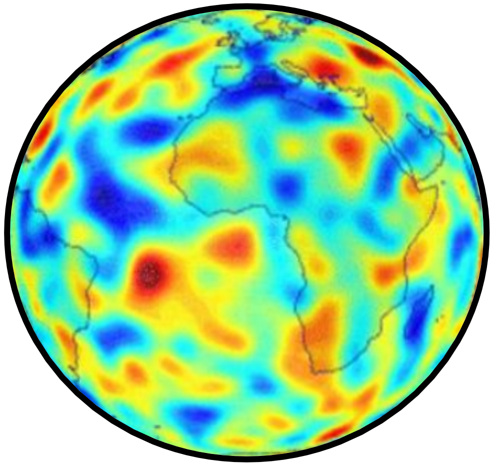
Do not use data from BL or stratosphere (tapered)

i.e. Following the assumptions of SPPT, can we measure the statistical characteristics of the perturbation ***e***

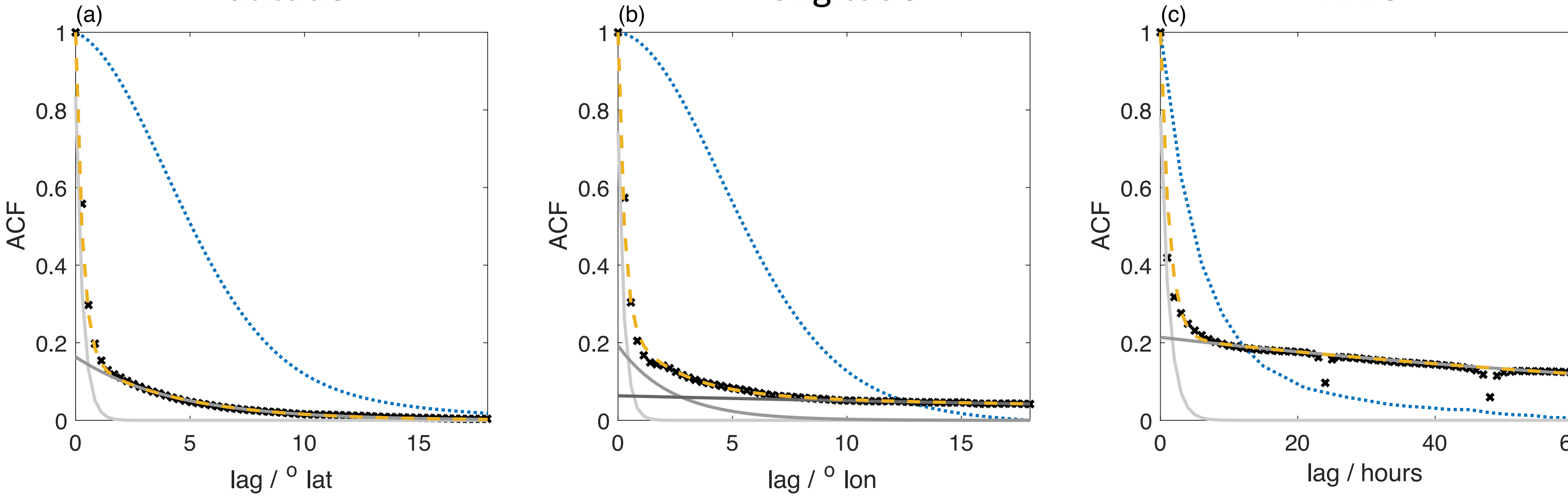
Snapshot of optimal SPPT '*e*' perturbation



	Operational SPPT	Fitted SPPT
μ(e)	0.0	-0.07
σ(e)	0.55	0.40
skew(e)	0.0	0.6

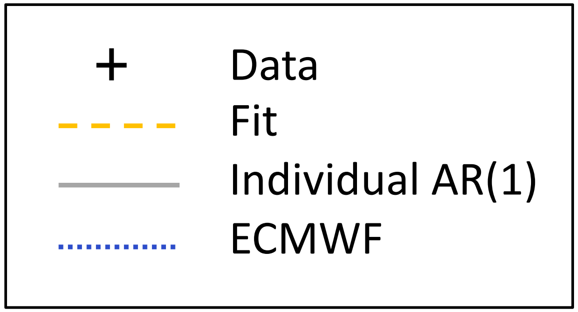


Spatio-temporal correlations



- Model spatio-temporal correlations as a sum over *n* AR(1) processes with different scales

	Operational SPPT			Fitted SPPT		
σ_i	0.52	0.18	0.06	0.35	0.17	0.10
L_i (km)	500	1000	2000	32	370	-
τ_i	6 h	3 d	30 d	1.2 h	4.3 d	-



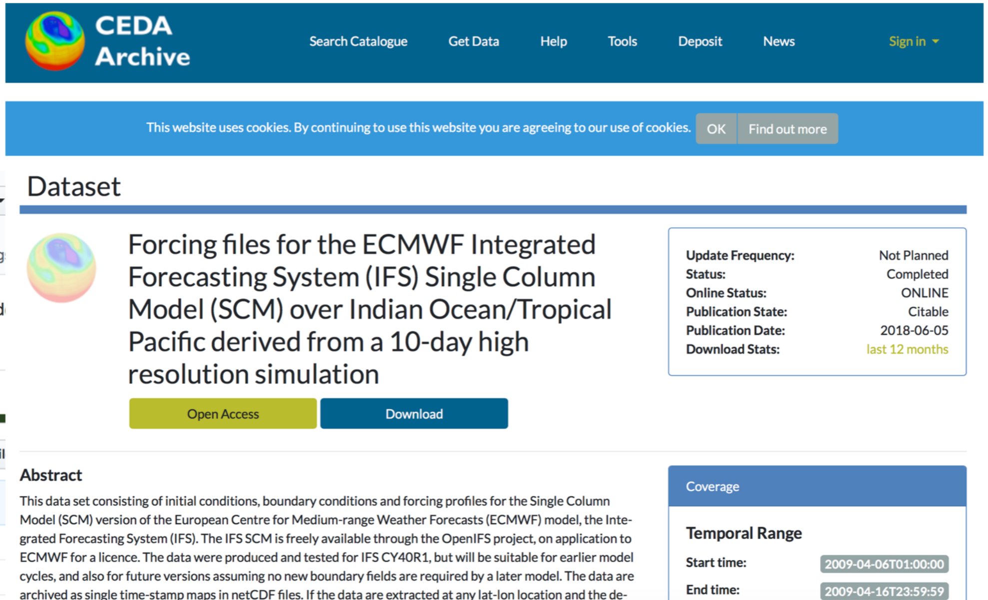
Conclusions and relevance for SPPT

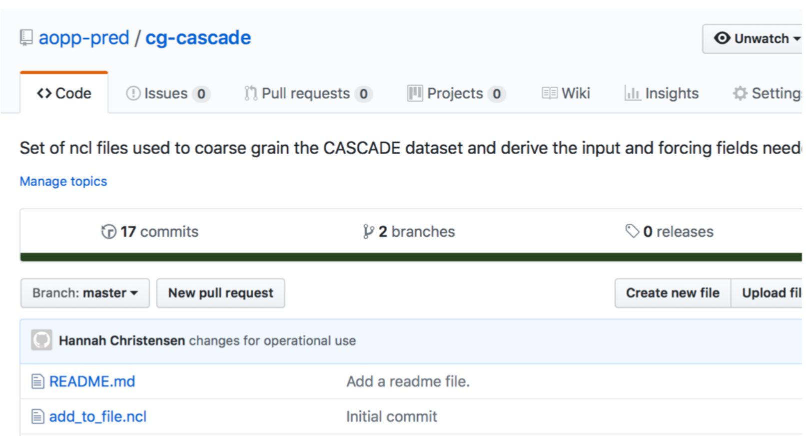
- Defined a framework to derive SCM forcing files from high-resolution model data
- Proposed a general technique for assessing model error
  - Can be used to constrain existing stochastic parametrization schemes and potentially motivate new approaches
- Multiplicative noise reasonable first-order approach
  - Convection in particular could benefit from a separate stochastic scheme
- Spatio-temporal correlation scales used in stochastic parametrisations have a physical basis
  - Not just pragmatic solution to get decent ensemble spread
- To tune SPPT, reduce standard deviation but include skewness

References

- Christensen, Dawson and Holloway, 2018, JAMES, ‘Forcing Single-Column Models Using High-Resolution Model Simulations’ 10(8) 1833-1857
- Christensen, ‘Improving Stochastic Parametrisation Schemes using High-resolution Model Simulations’. submitted to QJRMetS

- Coarse-grained Cascade data published on UK CEDA archive
- NCL coarse graining scripts, and python SCM deployment scripts available on github





Thanks for listening

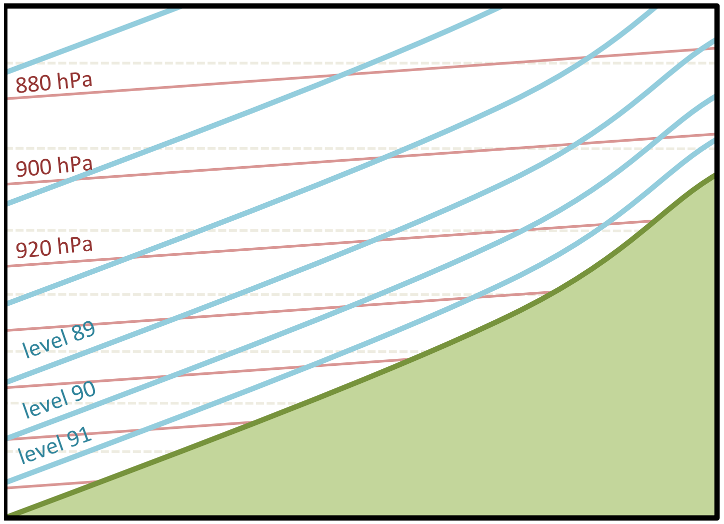
Extra Slides

Coarse graining details

1. Local area averaging for coarse graining

$$\overline{\psi}_{n,k} = \sum_{i}^{I} W_{n,i}\psi_{i,k}$$

2. Linearly interpolate in time
3. Vertical interpolation
   - Evaluate coarse-scale grid box mean p_{sfc}
   - Coarse-grain other fields along model levels
   - Interpolate from native model levels to target model levels



4. Above high-resolution model top, pad data using ECMWF analysis
5. Advective tendencies estimated from the coarsened fields

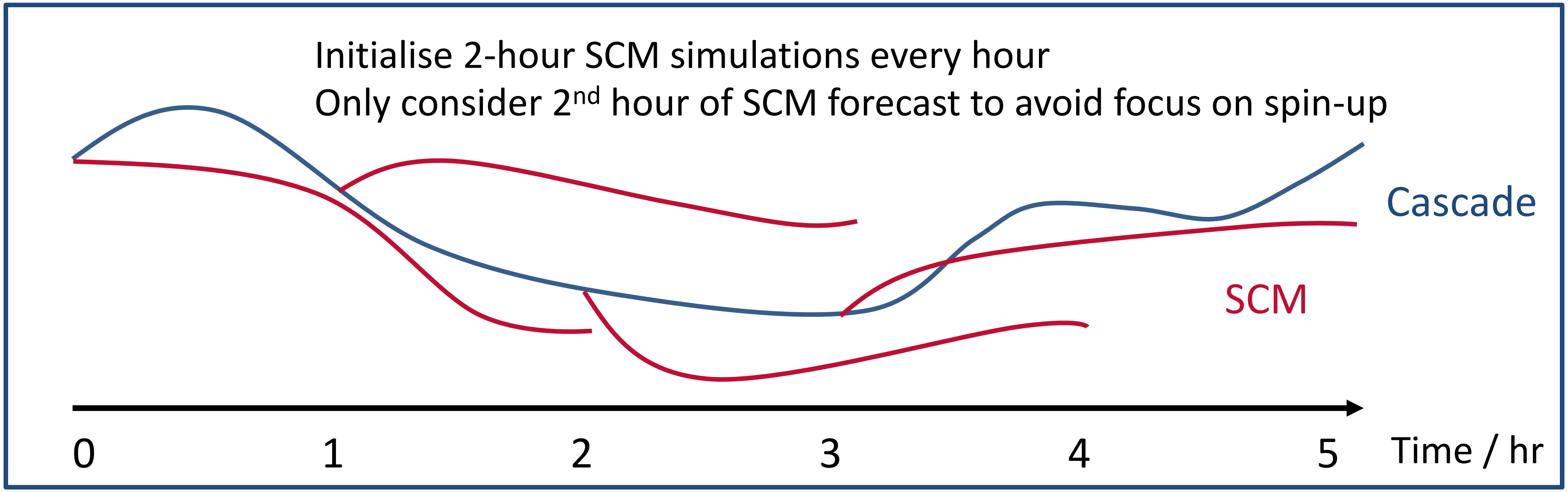
$$\mathrm{adv}(\psi)|_{n,k} = -\overline{\mathbf{u}}_{n,k} \cdot \overline{\nabla}_k(\overline{\psi_{n,k}})$$

6. Specify sensible and latent heat fluxes from high-resolution dataset, but take static boundary conditions from operational ECMWF model at T639

Christensen et al, 2018, JAMES.

What we do

- Coarse-grain Cascade to T_L639
- Run an independent SCM simulation, initialised every hour, from every lat-lon point (>68,000) in the coarse-grained domain
- Run each SCM simulation for two hours, discard the first hour to avoid focus on spin up
- Repeat for entire 9-day Cascade simulation



What information do we have?

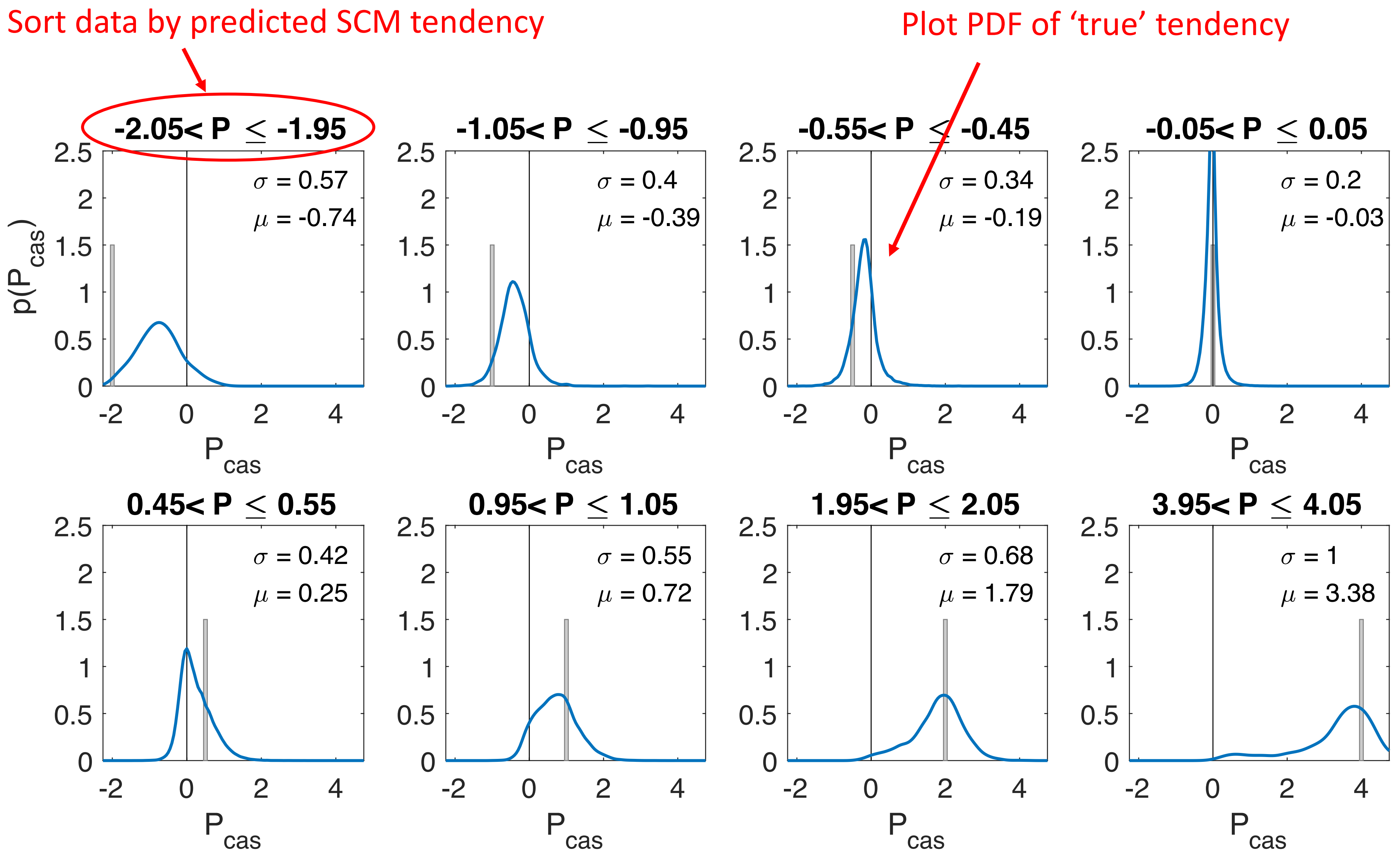
- ✓ **Total change in (T, q, U, V) in high-resolution Cascade** over 1hr time interval as a function of model level, location and forecast start time
- ✓ **Change in (T, q, U, V) in IFS SCM** over 1 hr, **decomposed into dynamics and individual parametrized tendencies**, as a function of model level, location and forecast start time

Cf. existing approaches to identify model error

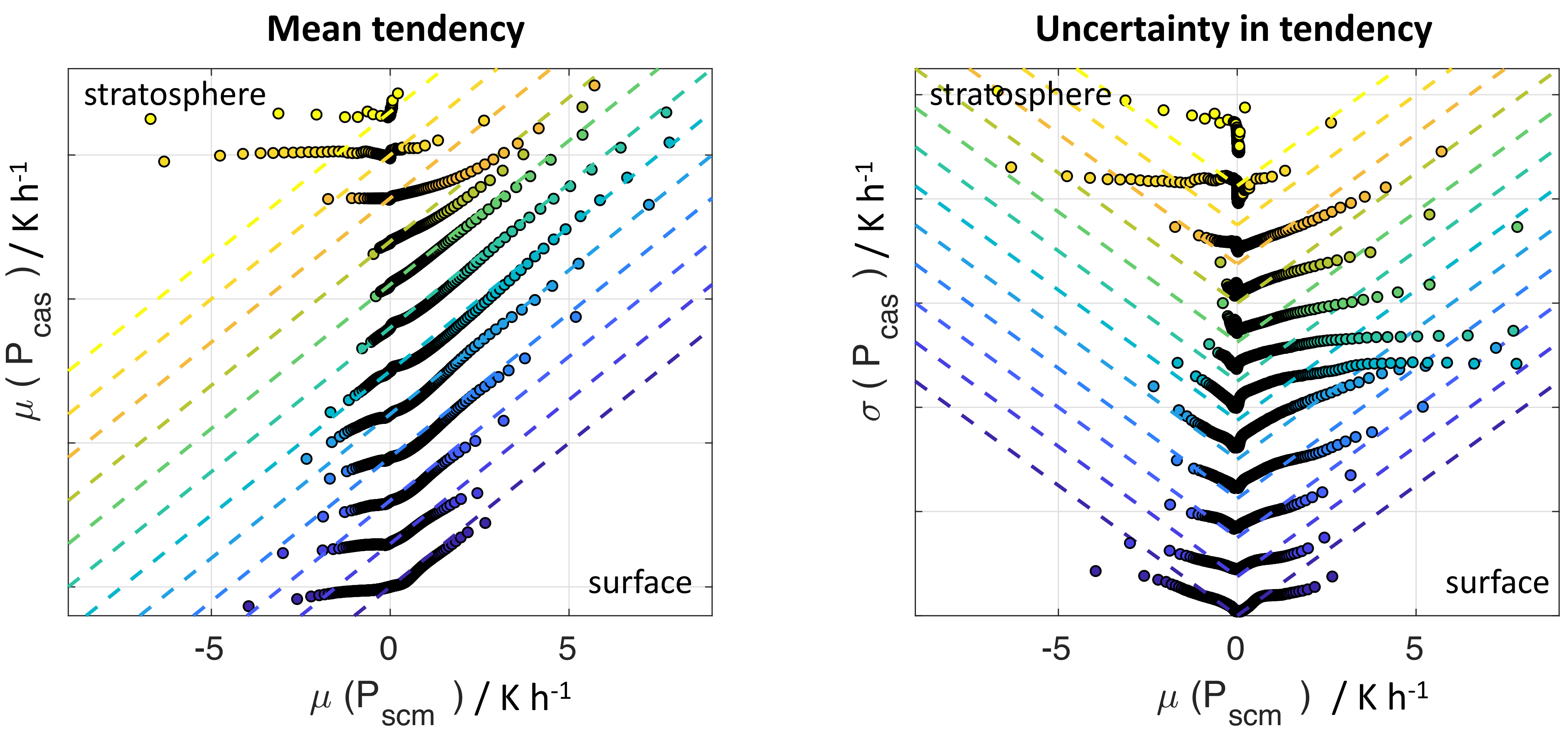
- **E.g. Initial tendency approach** in which physics tendencies in data assimilation cycle are compared to the analysis
- **E.g. Transpose AMIP** in which climate models are run in weather forecasting mode from common initial conditions

	Initial tendency	Transpose AMIP	My SCM approach
Decompose model evolution (& error) into single processes	☺		☺
No data assimilation capabilities needed to evaluate forecast model		☺	☺
Comparison of model with its native analysis may mask errors	☹		
Inconsistencies in IC can lead to systematic drifts		☹	☹

Consider T850 tendency (/ K h^{-1})



Consider T tendency



Data grouped by level.

Dark blue: levels 91—87 (ground—995 hPa)

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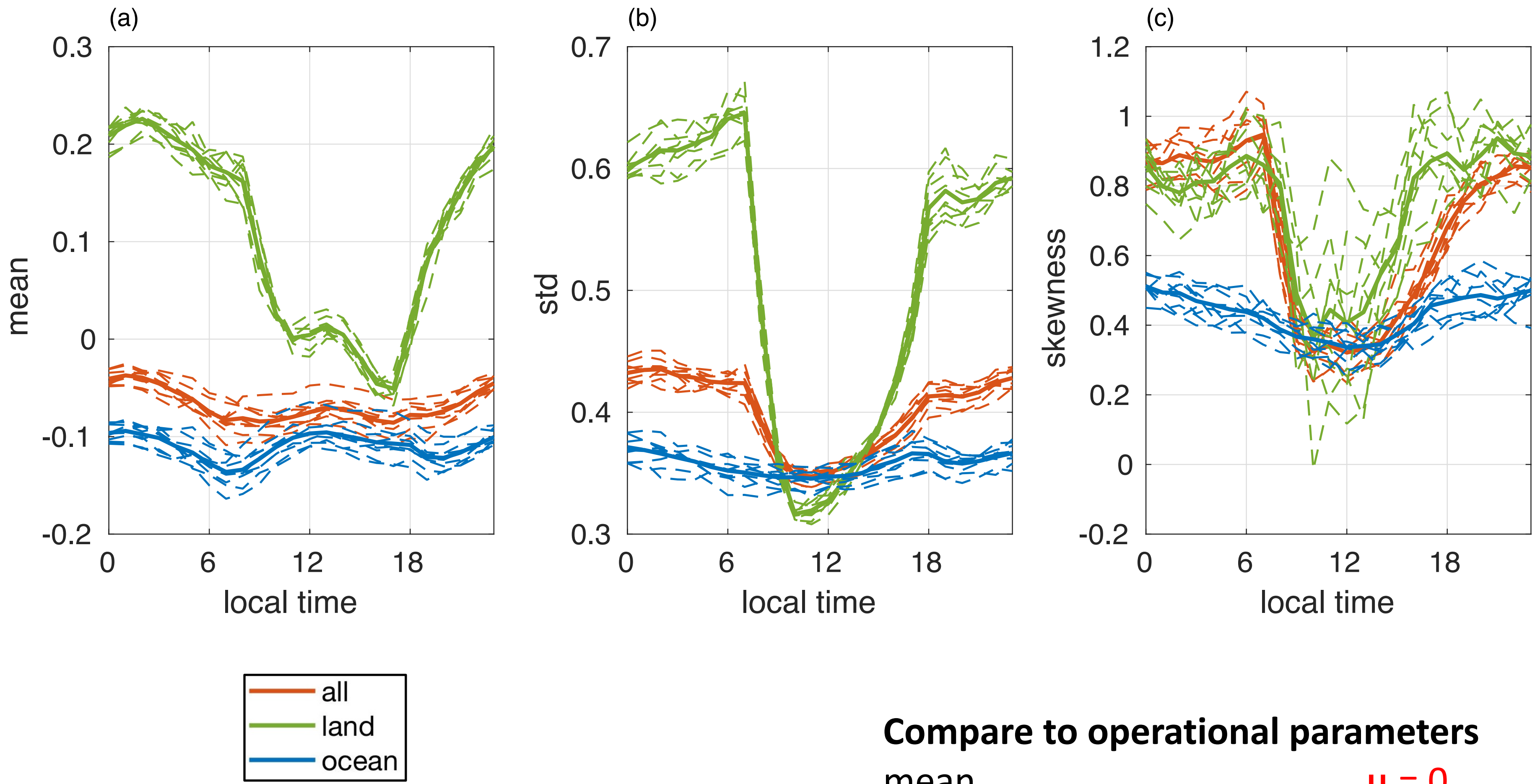
Characteristics of ‘e’



Compare to operational parameters

mean	$\mu = 0$
standard deviation	$\sigma = 0.55$
skewness	$\gamma = 0$

Correlation scales of ‘e’

- Model temporal and spatial correlation scales as arising from a sum over several scales

$$e(t) = \sum_{i=1}^{n} X_i(t),$$

<= e.g., in time

$$X_i(t) = \phi_i X_i(t-1) + \sigma_i (1 - \phi_i^2)^{\frac{1}{2}} \xi$$

- Iteratively fit each scale, long to short

$$\sigma_e^2 = \sum_{i=1}^{n} \sigma_i^2$$

$$\rho_e = \frac{\sum_{i=1}^{n} \sigma_i^2 \phi_i^{\tau}}{\sum_{i=1}^{n} \sigma_i^2}$$

<= plot log(autocorrelation) and perform linear fit

New optimal parameters for SPPT in IFS?

- Averaging over the variance ratios for the latitude, longitude and temporal correlations

	Operational SPPT			Fitted SPPT		
μ(e)	0.0			-0.07		
σ(e)	0.55			0.40		
skew(e)	0.0			0.6		
σ_i	0.52	0.18	0.06	0.35	0.17	0.10
L_i (km)	500	1000	2000	32	370	-
τ_i	6 h	3 d	30 d	1.2 h	4.3 d	-

2. Beyond SPPT?

- SPPT is not a perfect representation of uncertainty in the IFS – can we improve on it?
- Have not yet assessed other assumptions made in SPPT – are these valid?
- Simple approach:
  - Relax each assumption in turn and fit new 'optimal e'
  - If the fitted 'e' is constant in dimension of interest then we should indeed hold the perturbation constant for that dimension

e.g. height,
e.g. variable,
e.g. parametrisation

2. Beyond SPPT?

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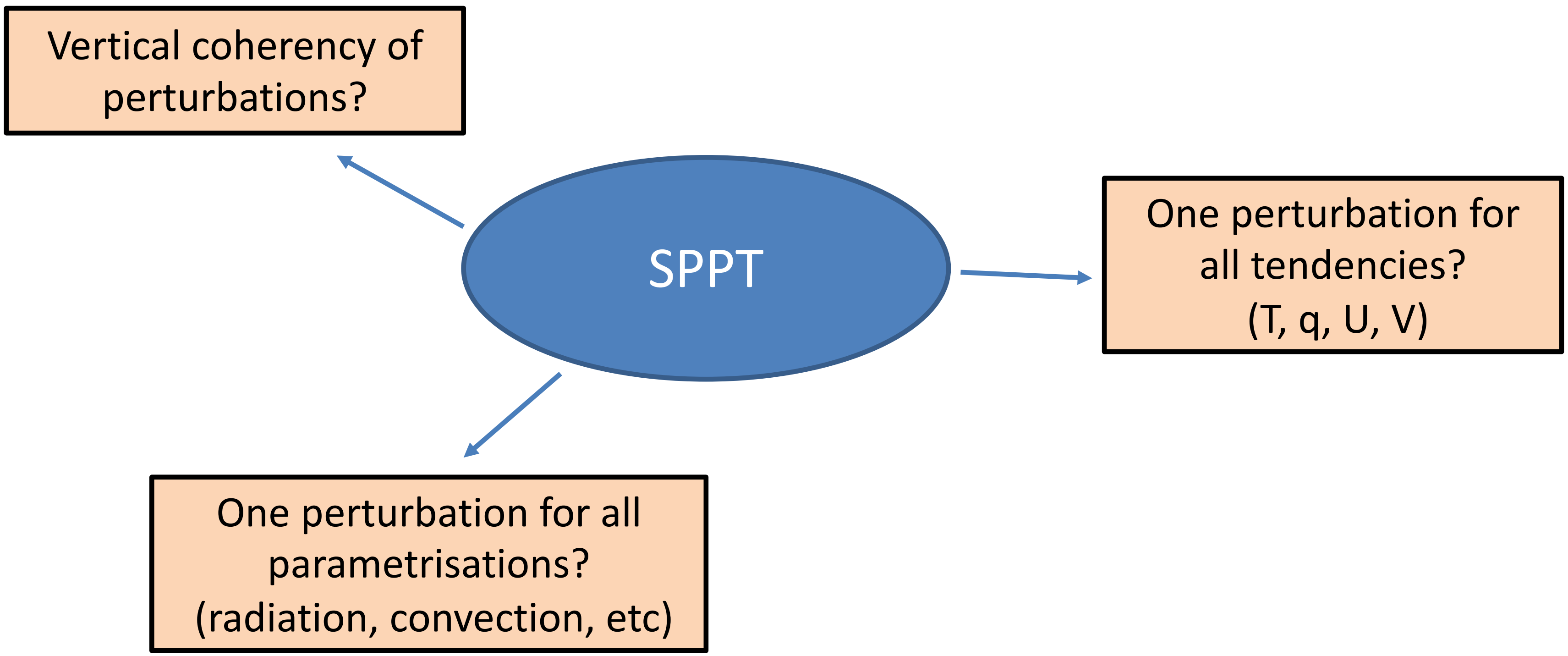


2. Beyond SPPT?

- SPPT is not a perfect representation of uncertainty in the IFS – can we improve on it?
- Have not yet assessed other assumptions made in SPPT – are these valid?

Vertical coherency of perturbations?

SPPT

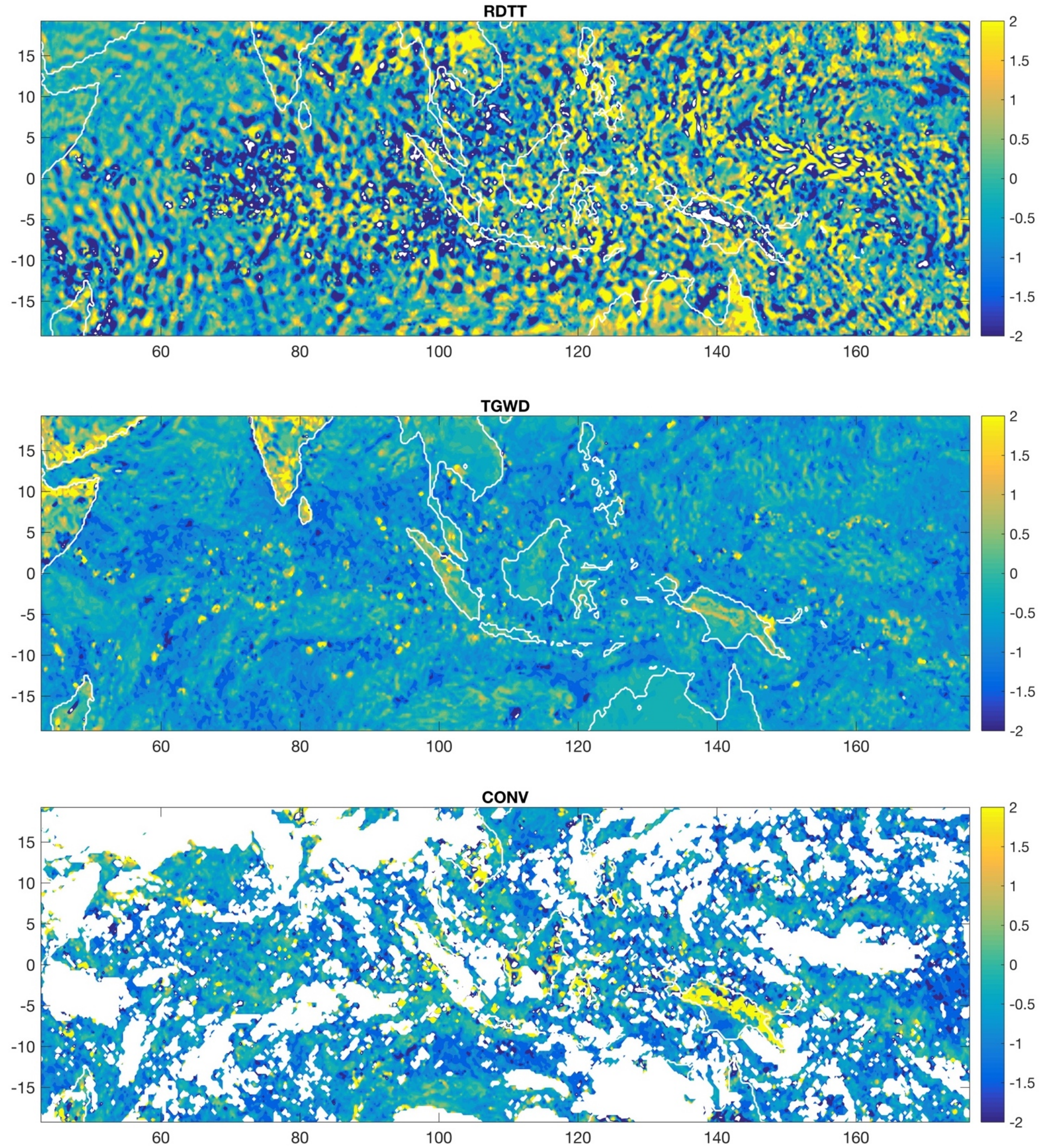
One perturbation for all tendencies? (T, q, U, V)

One perturbation for all parametrisations? (radiation, convection, etc)

"independent SPPT" (iSPPT)

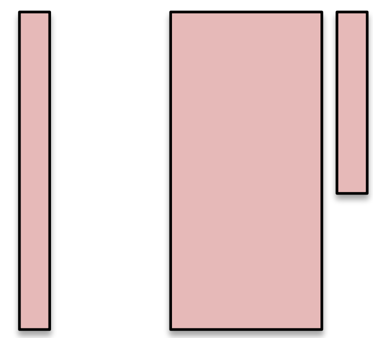
$$T = D + \sum_{i=1} (1 + e_i) P_i$$

iSPPT: Consider different schemes



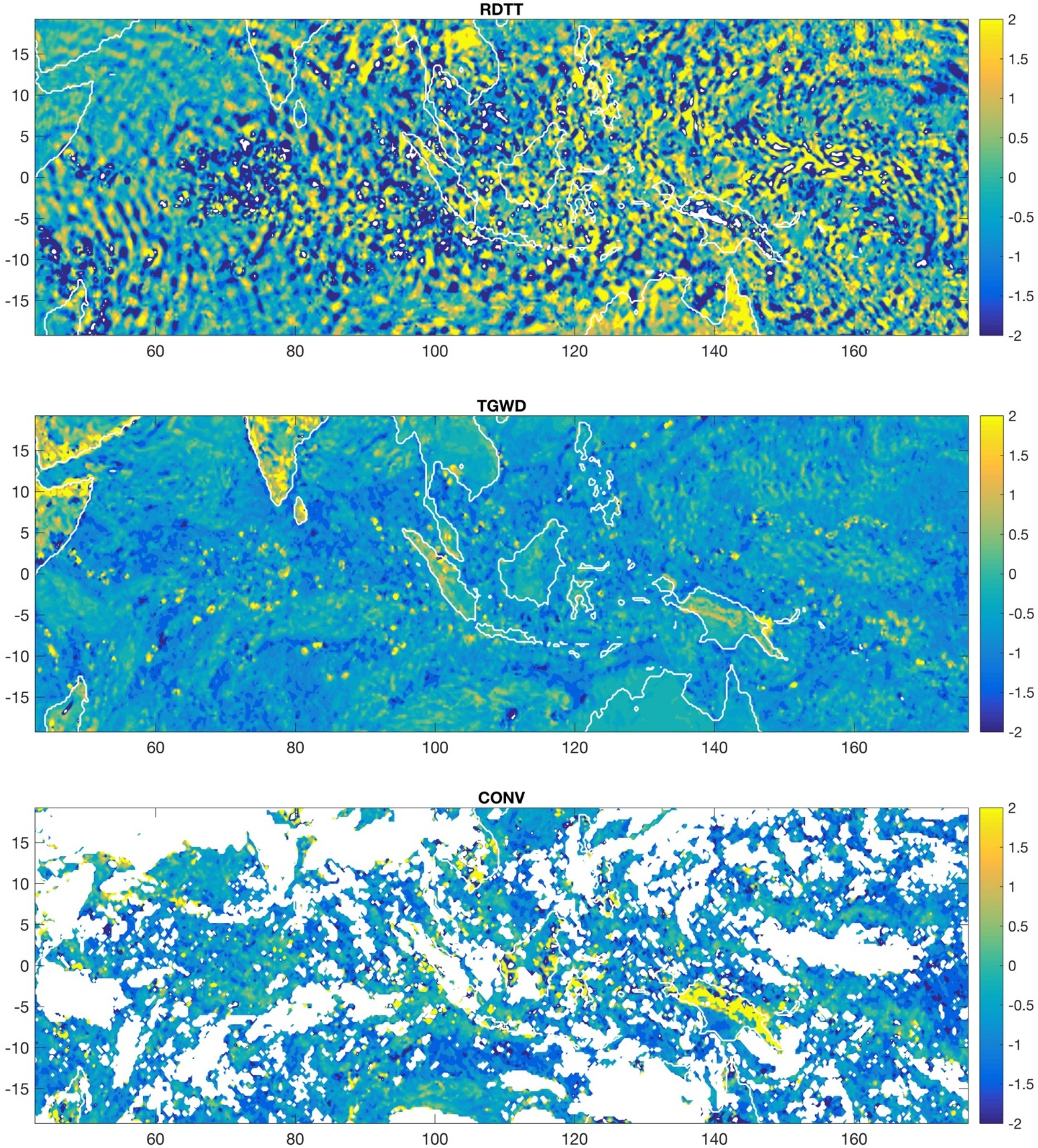
0100 UTC: image spans 3am-12pm
7:30am in centre image

$$T - D - \sum_{i=1} P_i = \sum_{i=1} e_i P_i$$



⇒ Snapshot of optimal stochastic perturbation, if different schemes can have different perturbations

iSPPT: Consider different schemes



0100 UTC: image spans 3am-12pm
7:30am in centre image

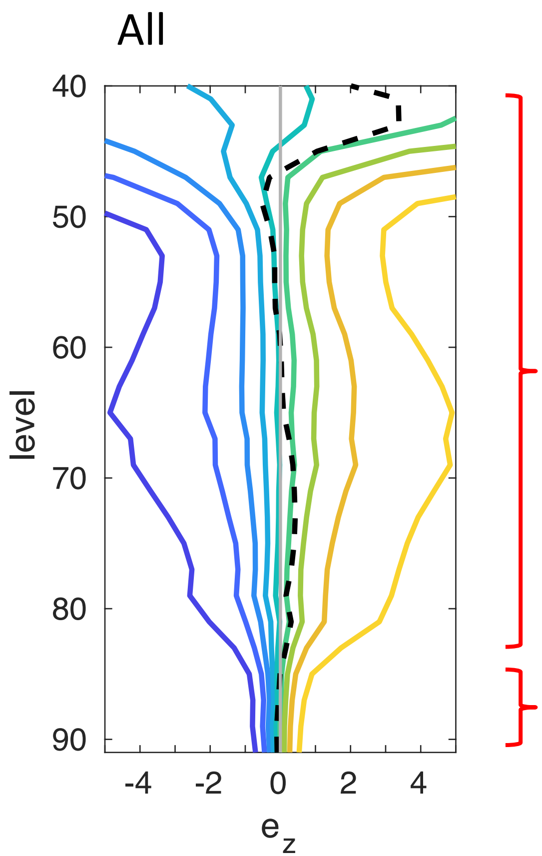
Measure standard deviations, temporal correlations and spatial correlations for each process

Generally little correlation between e_i for different schemes

Q. Vertical coherency of perturbations?

$$T_z = D_z + (1 + e_z) \sum_i P_{i,z}$$

- Fit separate e_z at each vertical level
- Consider pdf as a function of height summarised by deciles



Statistics vary with height

Statistics constant with height in turbulent BL

Q. Vertical coherency of perturbations?

$$T_z = D_z + (1 + e_z) \sum_i P_{i,z}$$

- Fit separate e_z at each vertical level
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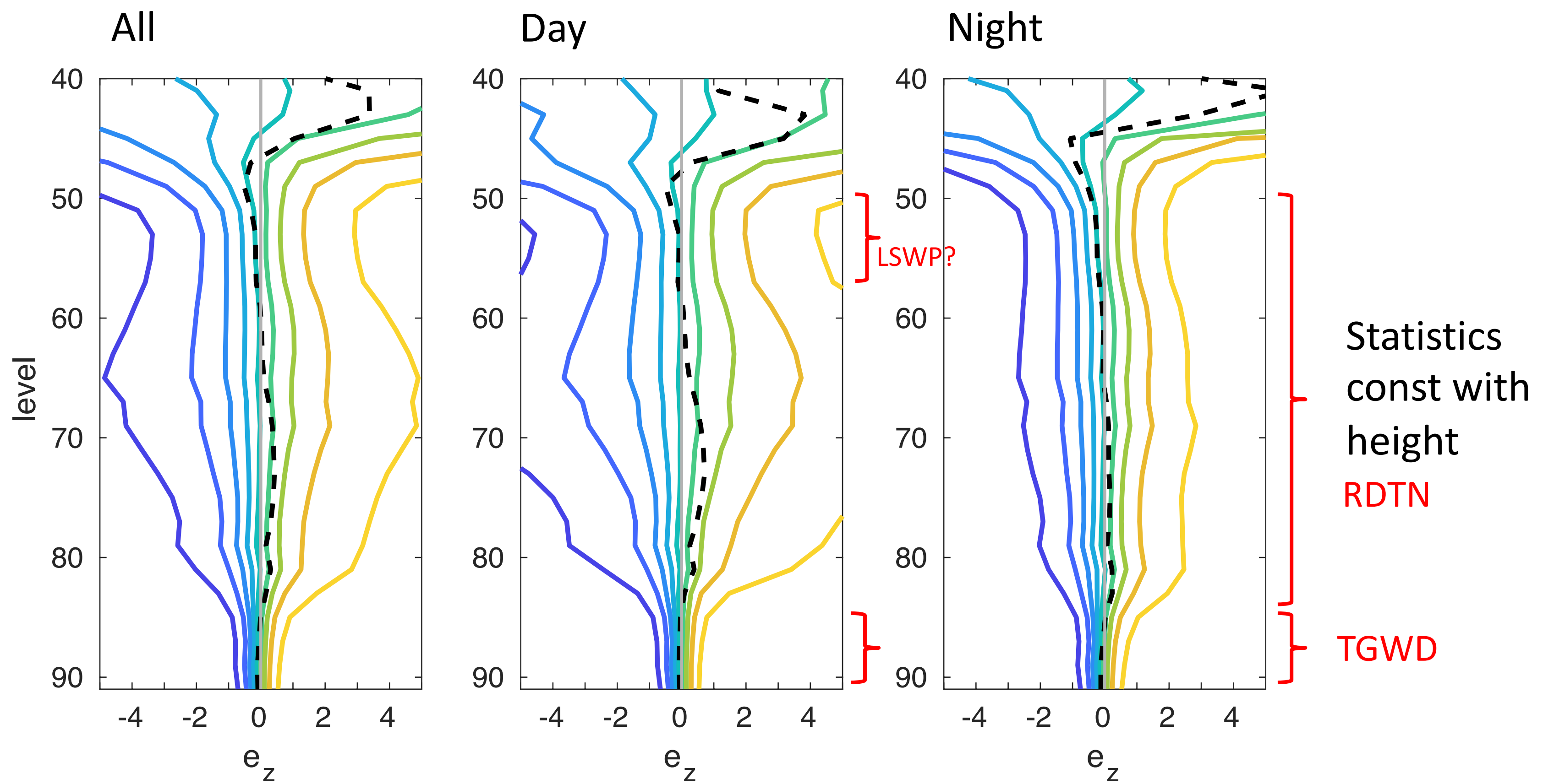
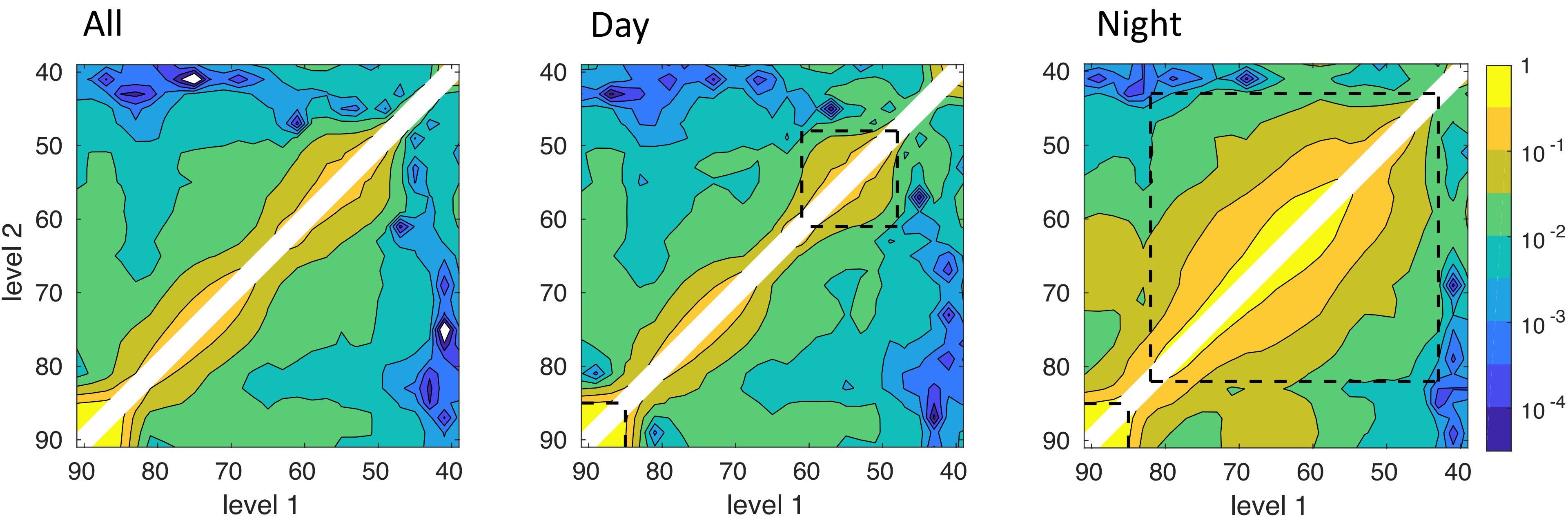


Q. Vertical coherency of perturbations?

$$T_z = D_z + (1 + e_z) \sum_i P_{i,z}$$

- Fit separate e_z at each vertical level
- Correlation between e_z fitted to different model levels



Enhanced correlations correspond to levels where one scheme dominates
High in BL.
Some evidence of enhanced correlations aloft at night.

Q. One perturbation for all tendencies? (T, q, U, V)

$$T_X = D_X + (1 + e_X) \sum_i P_{i,X}$$

- Fit separate e_X for each prognostic variable
- Assess statistics of e_X and correlation between different variables

	T			q			U			V		
μ(e)	-0.06			-0.02			-0.37			-0.52		
σ(e)	0.70			0.65			1.7			1.9		
σ_i	0.66	0.17	0.13	0.6	0.22	0.1	1.6	0.47	0.18	1.8	0.54	0.18
L_i (km)	39	400	-	33	430	-	38	270	-	26	290	-
τ_i	0.6 h	3.5 d	-	1.2 h	4.3 d	-	1.2 h	3.8 d	-	1.2 h	4.2 d	-

T, q statistics similar
Correlation = 0.35

U, V statistics similar
But low correlation = 0.08

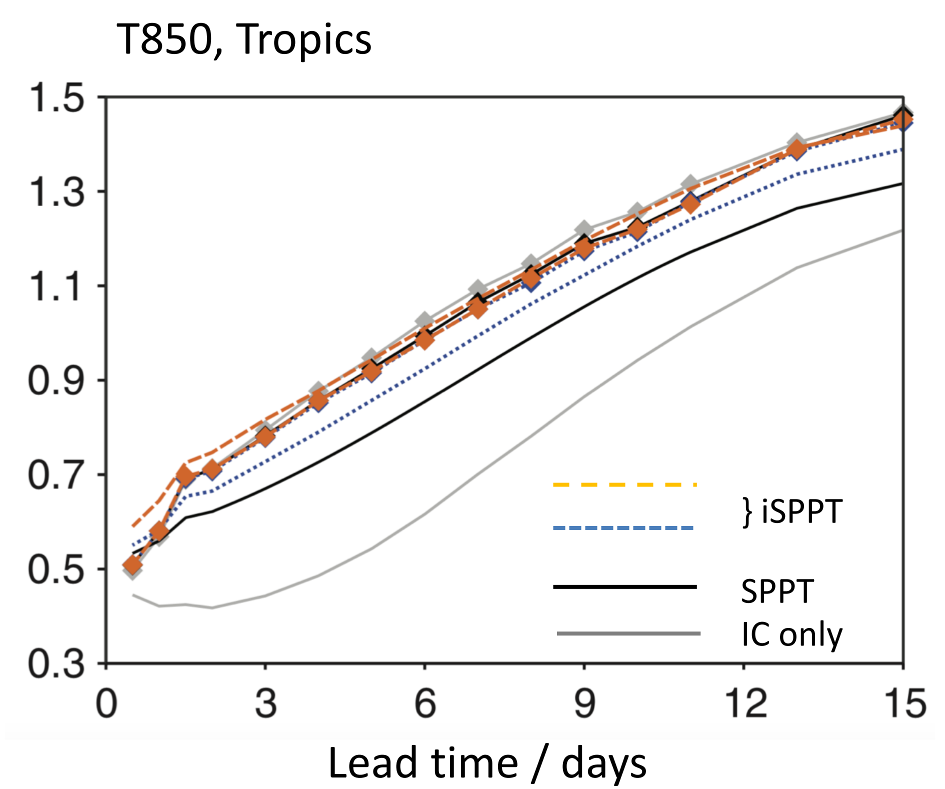
All other correlation pairs < 0.1

Q. One perturbation for all parametrisations?

- ‘independent SPPT’

SPPT $$T = D + (1+e)\sum_{i=1} P_i$$

iSPPT $$T = D + \sum_{i=1} (1+e_i) P_i$$



- Tested in IFS and found to benefit forecast reliability in the tropics

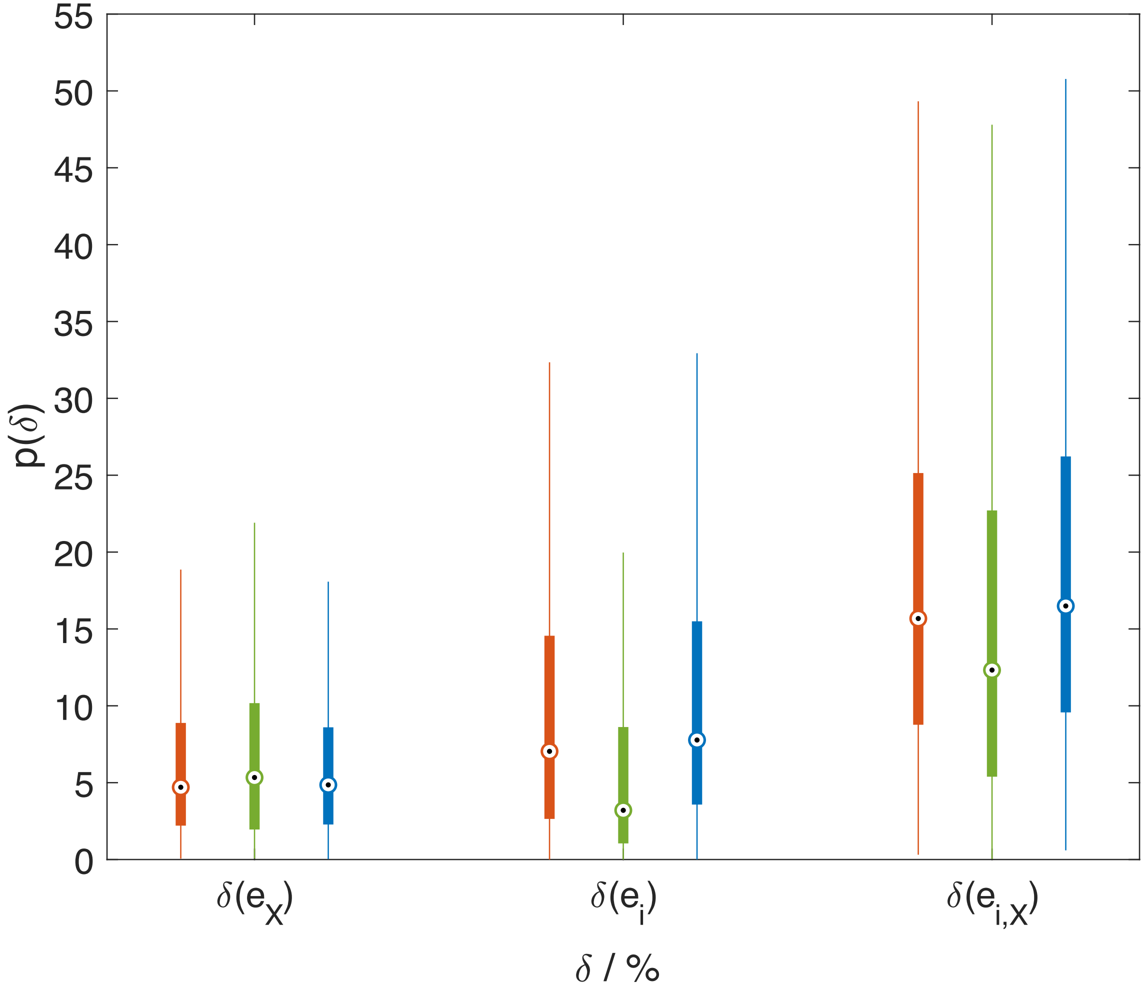
Christensen, Lock, Moroz and Palmer, 2017, QJRMetS

Q. One perturbation for all parametrisations?

- ‘independent SPPT’ seems to account for many results shown
  - Low correlation measured between perturbations fitted to different schemes
  - Perturbations to different schemes show very different noise characteristics
  - Measured correlation in the vertical is limited to within parametrisations
  - Measured correlations between perturbations applied to different variables are due to the physical relationship between those variables, as represented by the parametrisation schemes
  - Approach would enable multiplicative noise to be easily replaced by an alternative approach if desired, e.g. for convection

$$T = D + \sum_{i=1} (1 + e_i) P_i$$

Fractional variance explained



$$\delta = 100 \cdot \frac{MSD_{SPPT} - MSD_{new\ SPPT}}{MSD_{SPPT}}$$

For Mean Square Difference (MSD) between measured and modelled error