Improving stochastic parametrisation schemes using high-resolution model simulations

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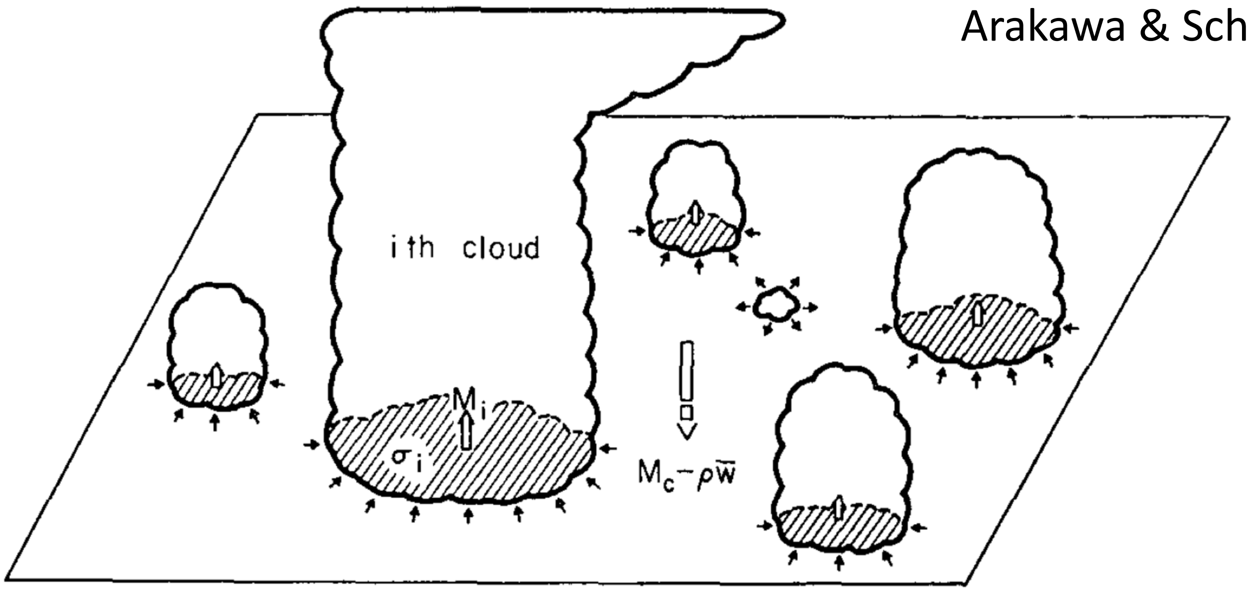
The parametrisation problem

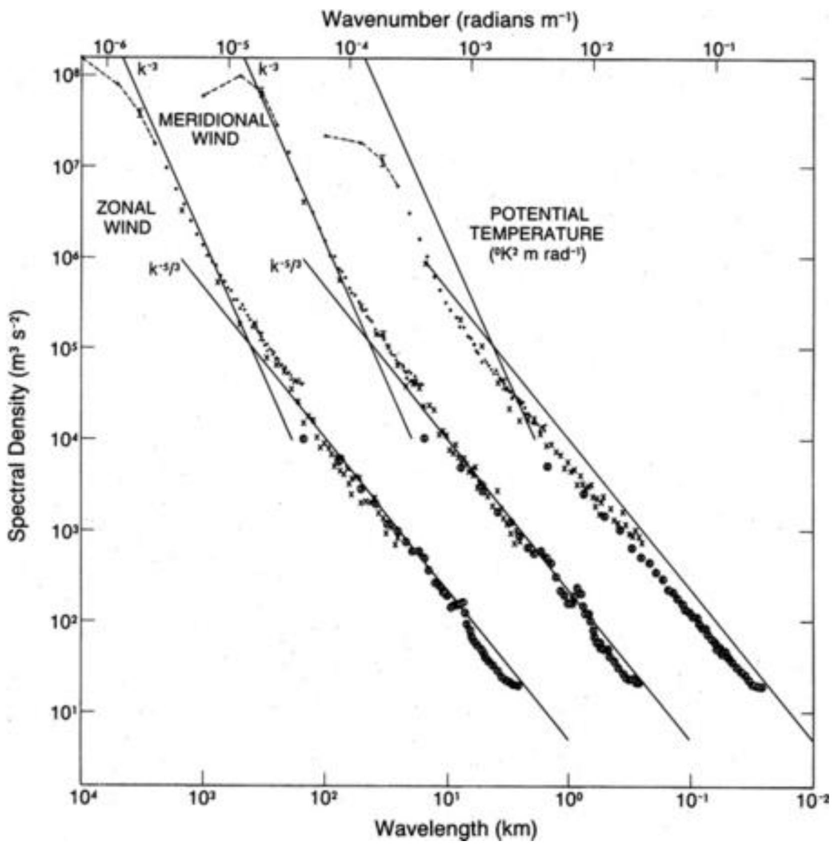
Arakawa & Schubert, 1974



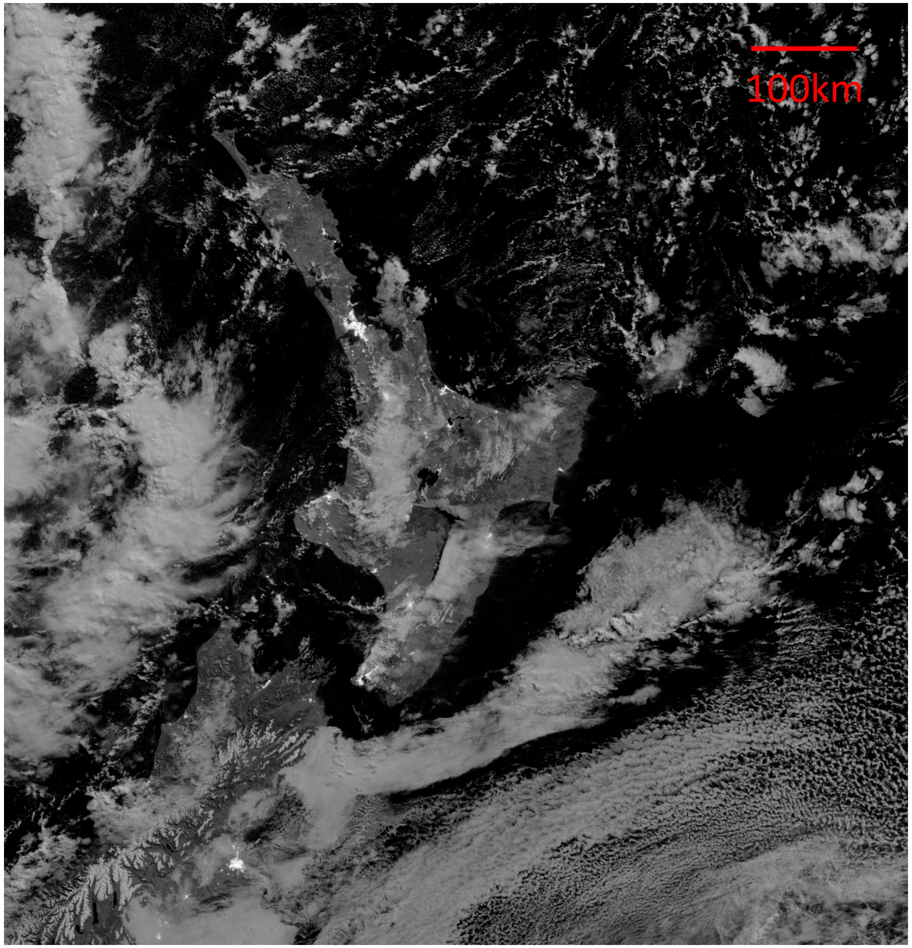
Consider a horizontal area at some level between cloud base and the highest cloud top. This horizontal area, which we designate as our unit horizontal area, is shown schematically in Fig. 1. It must be large enough to contain an ensemble of cumulus clouds but small enough to cover only a fraction of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

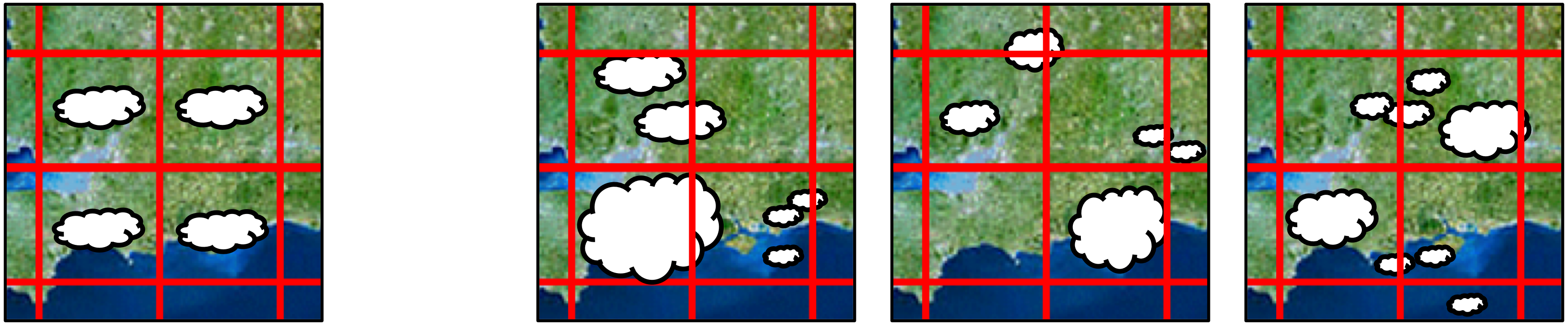


Stochastic Parametrisation

- We do not observe a clear separation of scales for many processes
- Grid-scale variables can not fully constrain sub-grid scale motions
- Stochastic parametrisation scheme: describes the sub-grid motion 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 **model uncertainty** => necessary for reliable forecasts

traditional
'best guess'

stochastic
Trial #1 Trial #2 ... Trial #N



A general framework for stochastic parametrisation

Identify uncertain process in forecast model

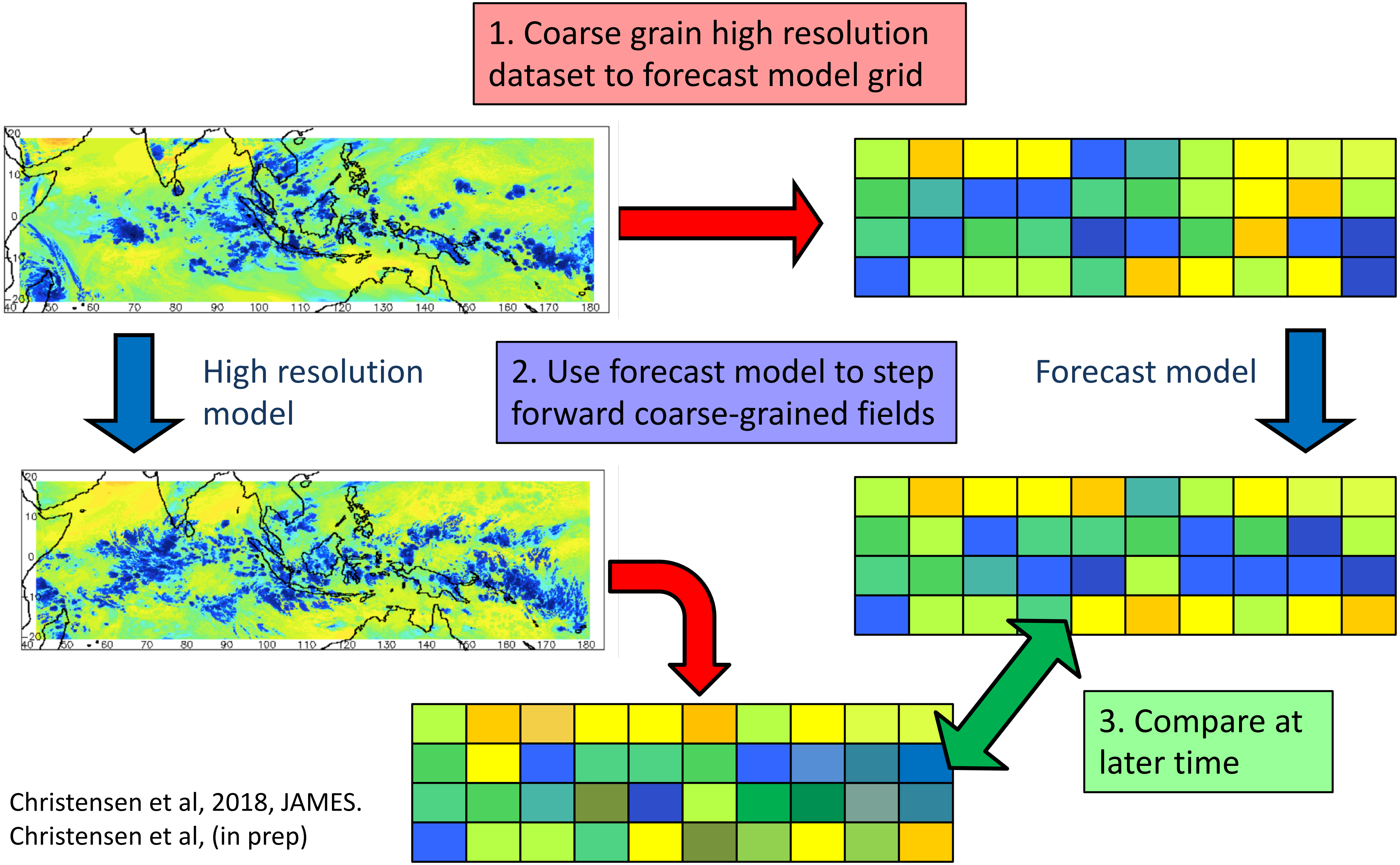
Theory

Measurements

Characterise uncertainty in that process

Design stochastic parametrisation to explore this uncertainty

Use an existing high resolution dataset as ‘truth’



Christensen et al, 2018, JAMES.
Christensen et al, (in prep)

SCM as Forecast model

- How can we use an SCM? Use high resolution simulation to prescribe:
  - Initial conditions
  - Forcing: advective tendencies, geostrophic winds, vertical velocity
  - Boundary conditions: Surface sensible and latent heat fluxes

Why use the SCM?

- Supply dynamical tendencies → target uncertainty in the parametrisation schemes
- The SCM is more portable than global models, and is cheap to run. Can run SCM on computer where high resolution data is stored
- (e.g.) The IFS is a spectral model, so cannot be run over a limited domain, but we can tile many independent SCM to cover the limited domain.

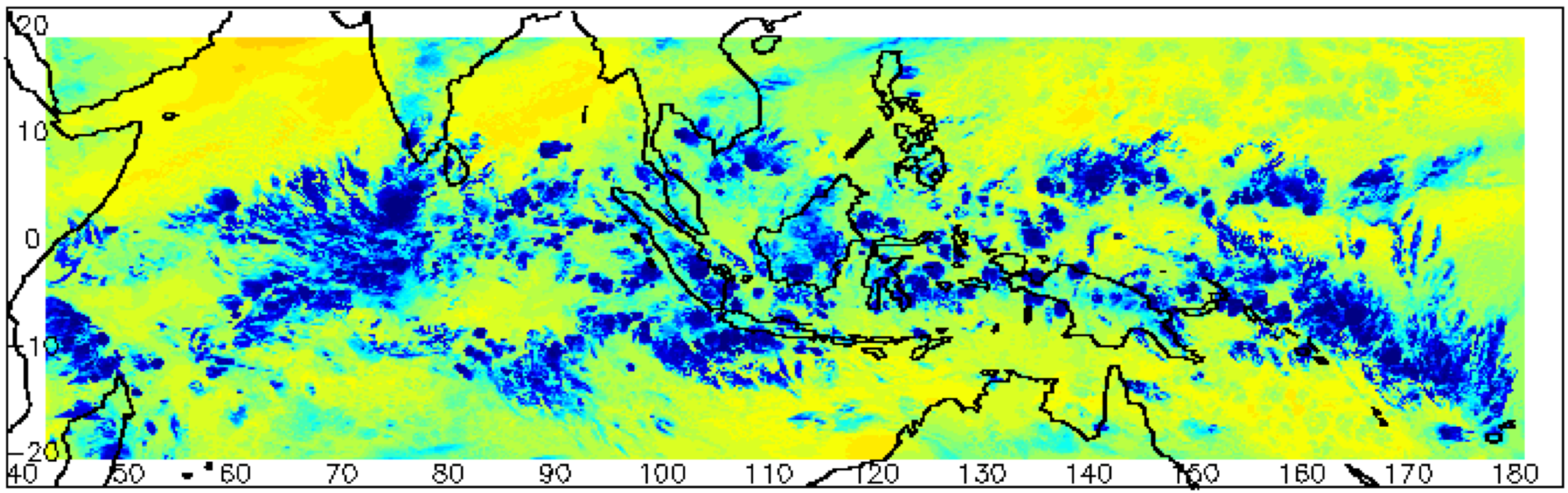
- IFS SCM CY40R1 at T639, 91 vertical levels (available through openIFS)

Christensen et al, 2018, JAMES.
Christensen et al, (in prep)

Existing High resolution dataset: Cascade

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

- UK Met Office atmospheric model setup
- Semi-Lagrangian, non-hydrostatic dynamics, <u>4km resolution</u>
- Large tropical domain (15,500 km x 4,500 km), 10 days of data. <u>Hourly dumps.</u>
- 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

Case study: is there any physical basis for SPPT?

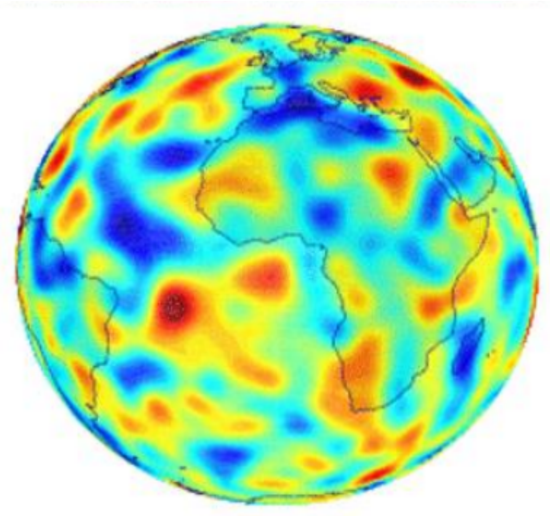
- **Stochastically Perturbed Parametrisation Tendencies (SPPT)**
  - represents random errors due to model's physical parametrisation schemes
- Implemented in models worldwide

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

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 schemes are perturbed using same pattern.
All variables perturbed using same pattern.
Pattern constant in height

Palmer et al, 2009.
ECMWF Tech Memo 598

Case study: is there any physical basis for SPPT?

- **SPPT scheme includes several assumptions**

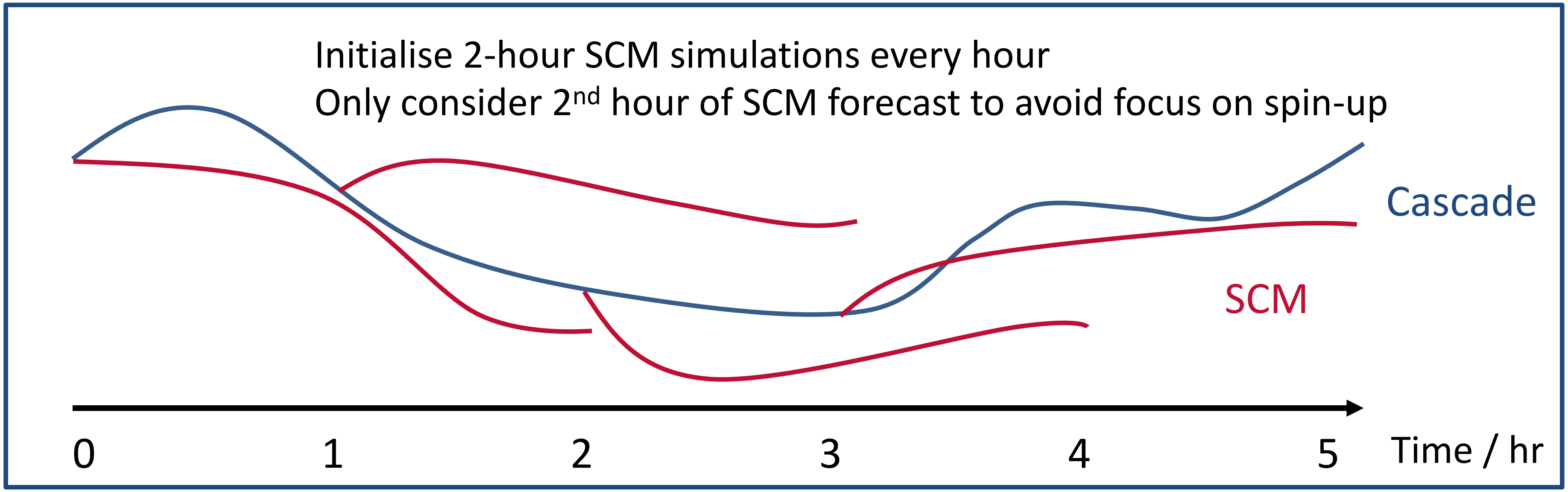
$$T = D + (1+e)\sum_{i=1} P_i$$

  - Multiplicative noise
  - All schemes treated the same: uncertainly in tendency proportional to total tendency (errors from schemes perfectly correlated)
  - Specifies standard deviations, temporal and spatial correlations with no physical reason for choices

- **Q: Can we constrain some of the characteristics of the SPPT stochastic term using high-resolution model output?**

What we do

- 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



Analysing the data: multiplicative noise?

SPPT:

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

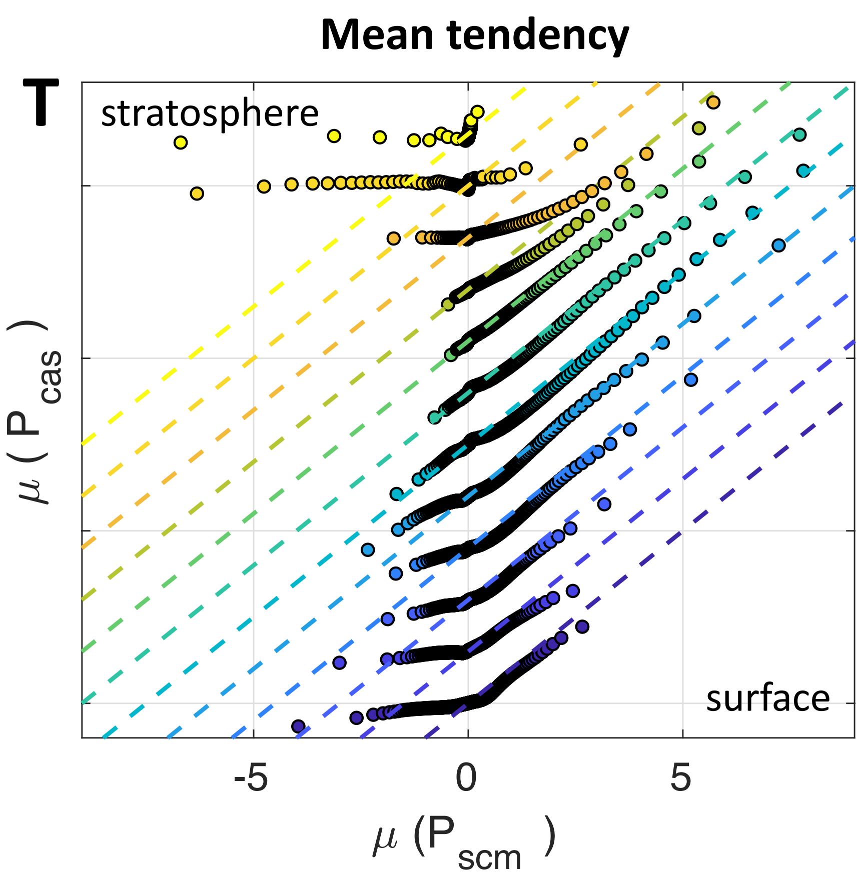
Calculate 'true' total tendency from CASCADE

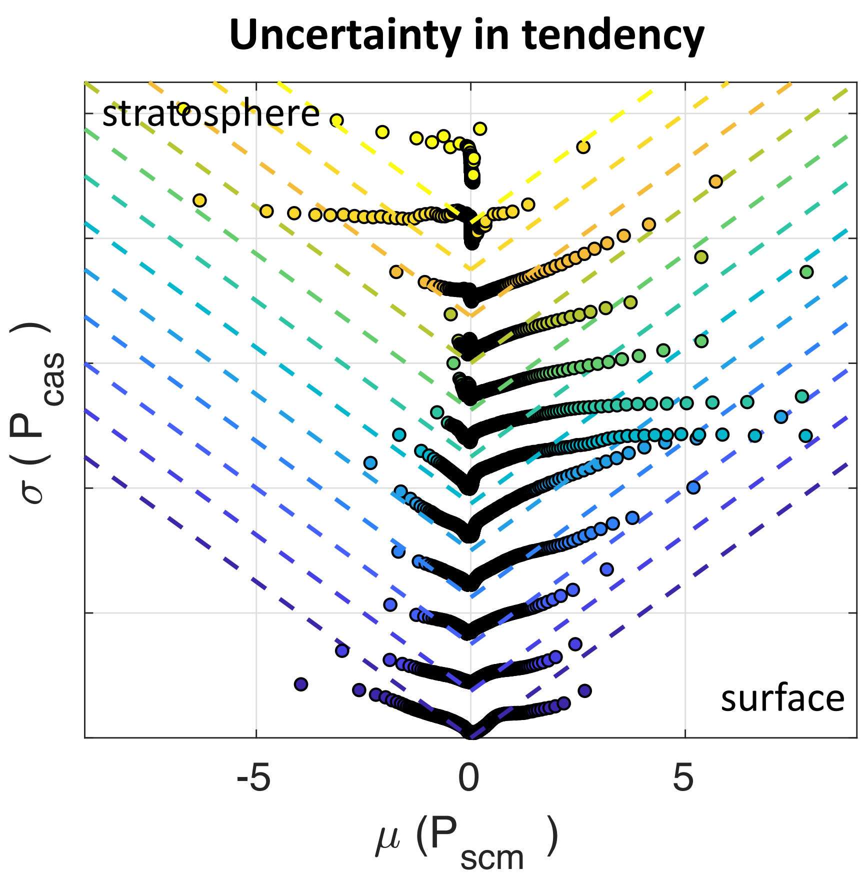
Assume SCM dynamics tendency is 'correct'

Consider error in SCM physics tendencies

$$\underbrace{T - D}_{\text{Compare 'true' physics tendency ...}} = \underbrace{(1+e)\sum_{i=1} P_i}_{\text{... to parametrised physics tendency}}$$

Consider T tendency





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

Analysing the data: characteristics of *e*

SPPT:

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

Systematic bias

Calculate 'true' total tendency from CASCADE

Assume SCM dynamics tendency is 'correct'

Consider error in SCM physics tendencies

SOLVE

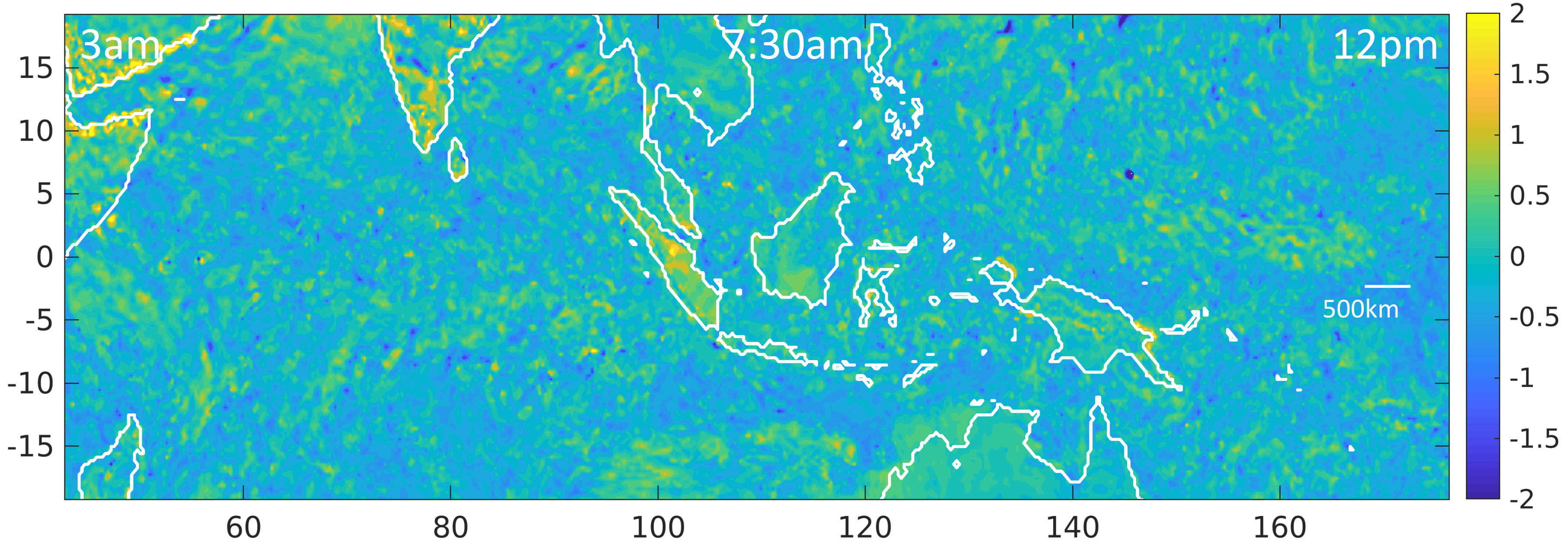
$$T - D - \sum_i P_i - b(P) = e\sum_i P_i$$

T
q
U
V

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

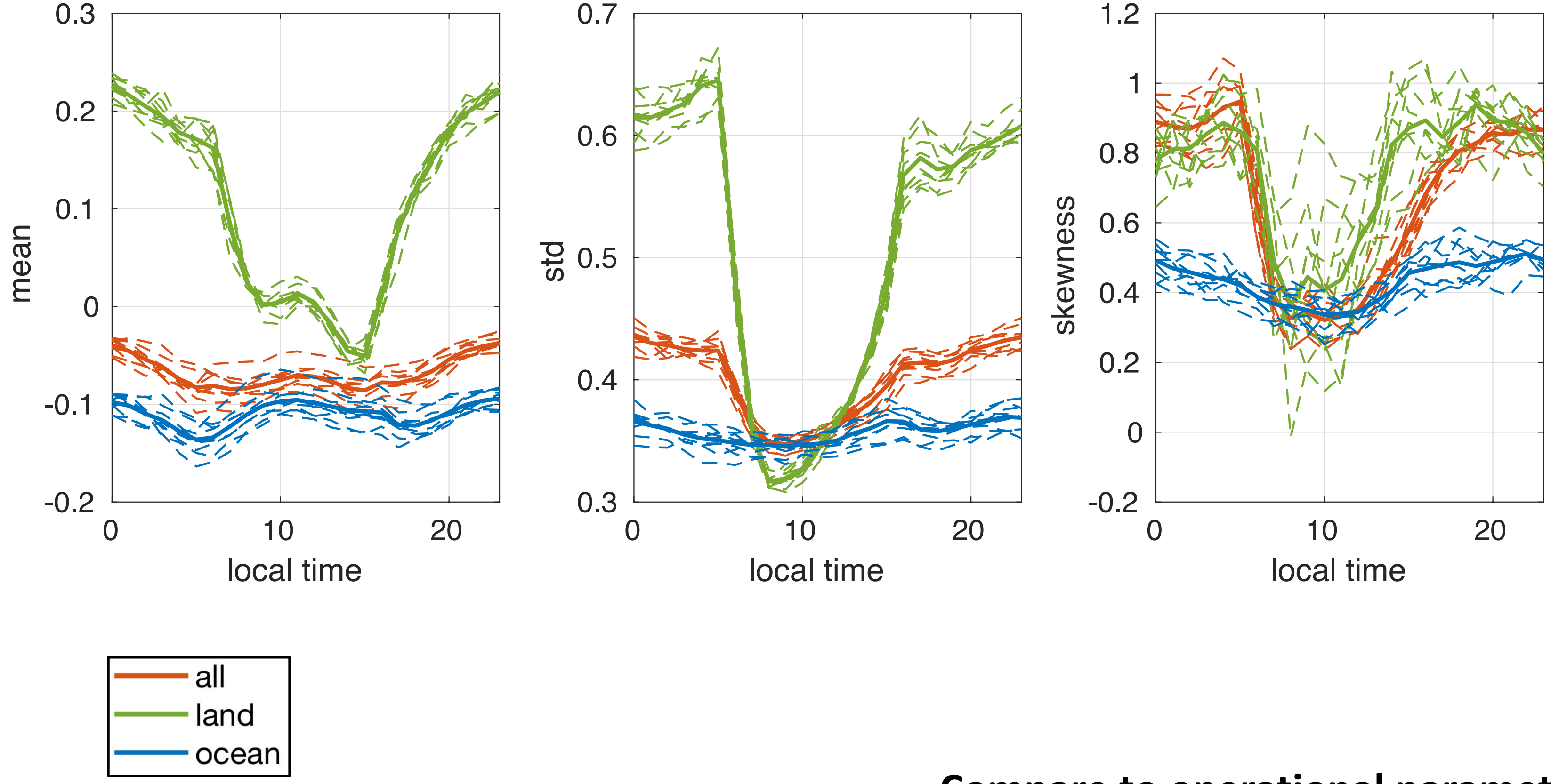


$$T - D - \sum_i P_i - b(P) = e \sum_i P_i$$

Calculate best fit ***e*** as a function of position for a single time step

$\Rightarrow$ Snapshot of optimal stochastic perturbation at a given time

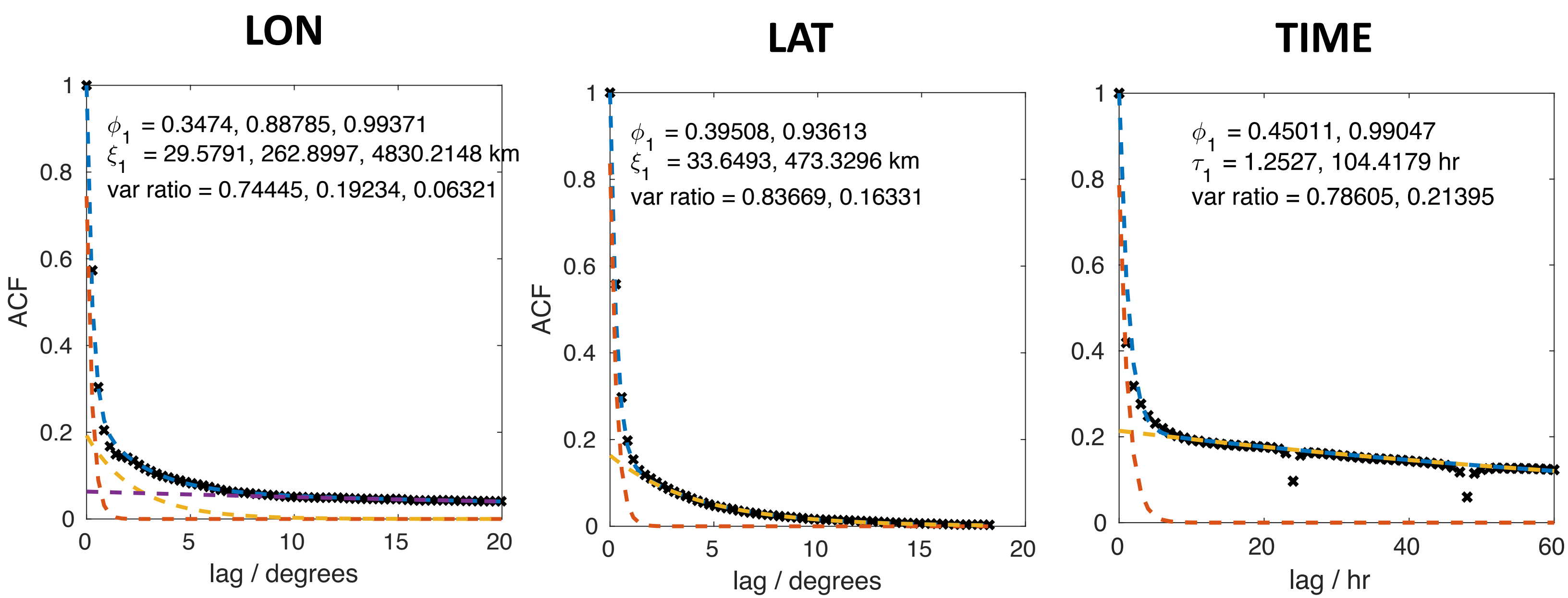
Characteristics of 'e'



Compare to operational parameters

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

Spatial and temporal correlation



- Model temporal and spatial correlation scales as arising from a sum over several scales
- Iteratively fit each scale, long to short

First scale: ~ grid scale
Second scale: ~ 200–400 km
Ocean provides spatial correlations

New optimal parameters for SPPT in IFS?

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

NEW:

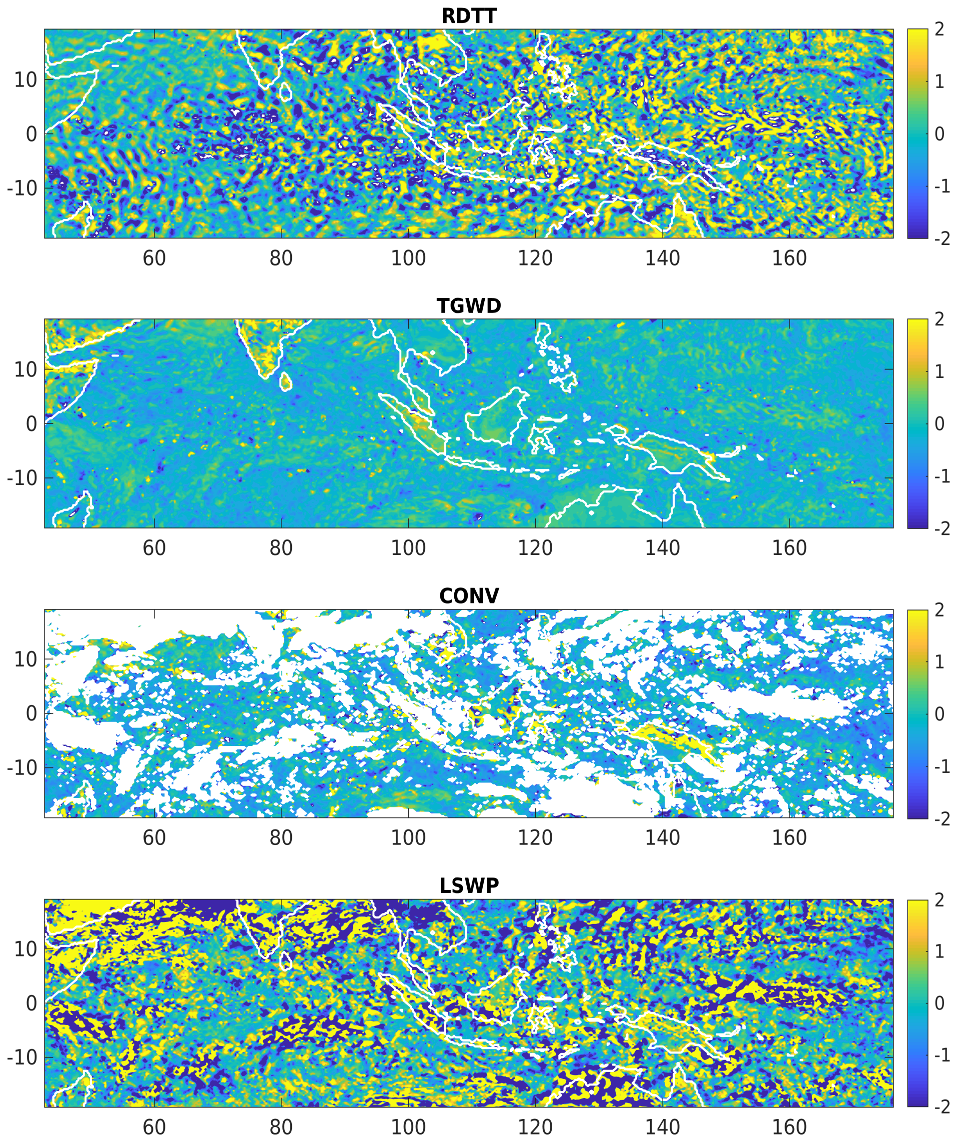
σ	L (km)	τ
0.35	32	1 hr
0.17	370	4.5 d
0.10	(2000)	(30 d)

ORIGINAL:

σ	L (km)	τ
0.52	500	6 hr
0.18	1000	3 d
0.06	2000	30 d

- + **skewness**?

Relax SPPT assumptions: e.g. independent SPPT



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

iSPPT $$T = D + \sum_i (1+e_i)\, P_i + b(P)$$

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

Little correlation between e_i for different schemes: $r < 0.2$

iSPPT significantly improves reliability in ensemble forecasts

- Especially in convecting areas
- Improves forecast busts
- Christensen et al, 2017, QJRMetS

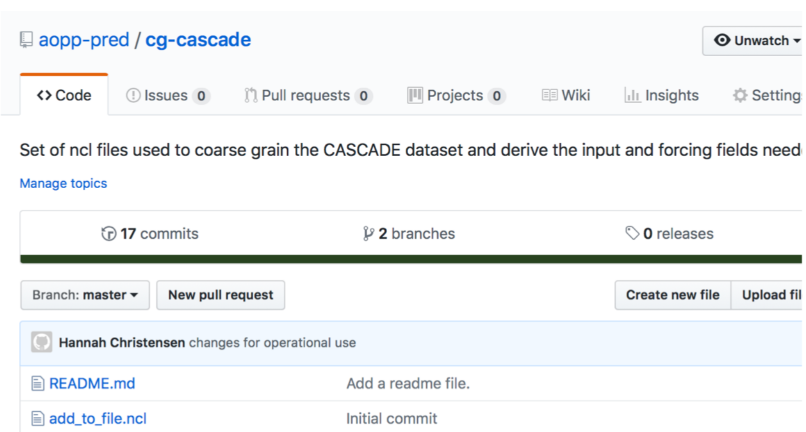
Conclusions

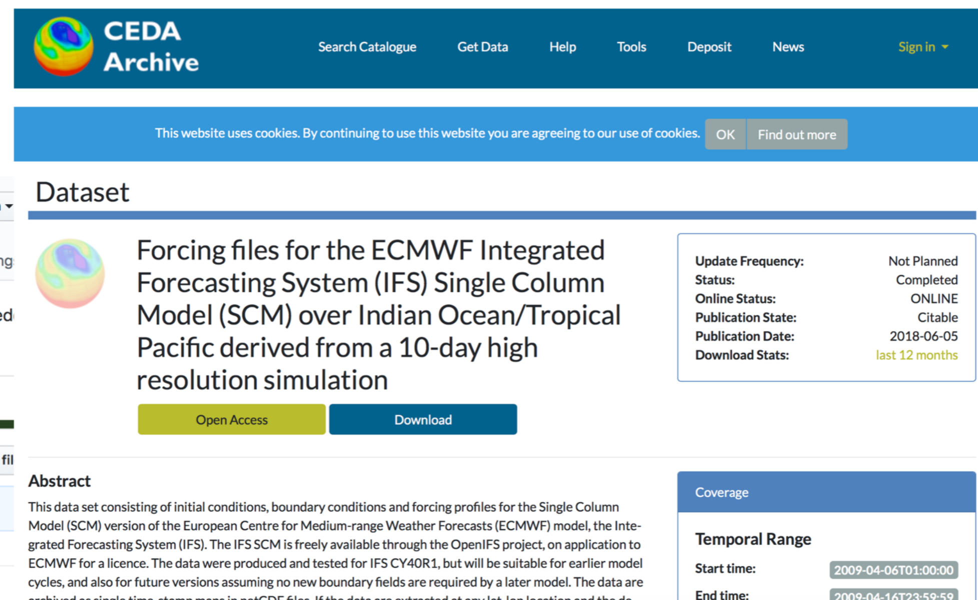
- Proposed a powerful & general technique for assessing model error
  - Low entry bar: uses existing high-resolution simulations
  - Estimates 3D physics and dynamics tendencies, and error fields
  - Can be used to constrain existing stochastic parametrisation schemes and potentially motivate new approaches
- Take SPPT as a case study
  - Some indication that multiplicative noise is a good model
  - Differences in error characteristics over land vs. ocean
  - Optimal perturbations are indeed correlated in space/time
  - Able to ‘measure’ the temporal and spatial correlation scales.
  - Also highlights limitations of SPPT approach

References

- Christensen, Dawson and Holloway, 2018, JAMES, 'Forcing Single-Column Models Using High-Resolution Model Simulations' 10(8) 1833-1857
- Christensen et al, in prep, 'Improving Stochastic Parametrisation Schemes using High-resolution Model Simulations' for submission to QJRMetS

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





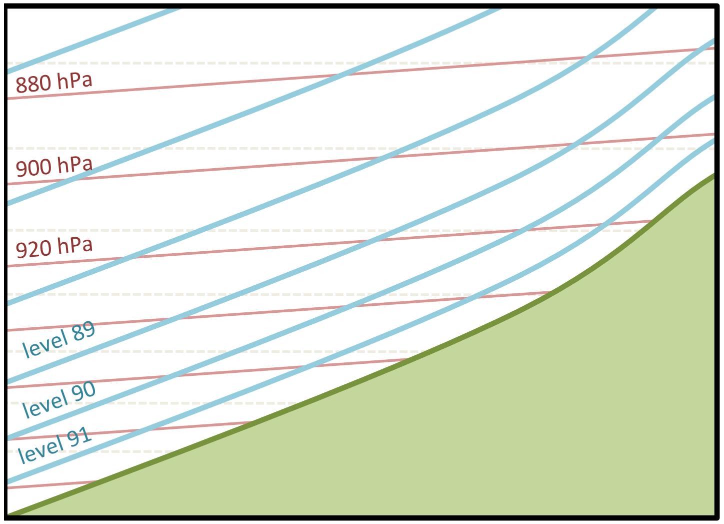
Thanks for listening

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



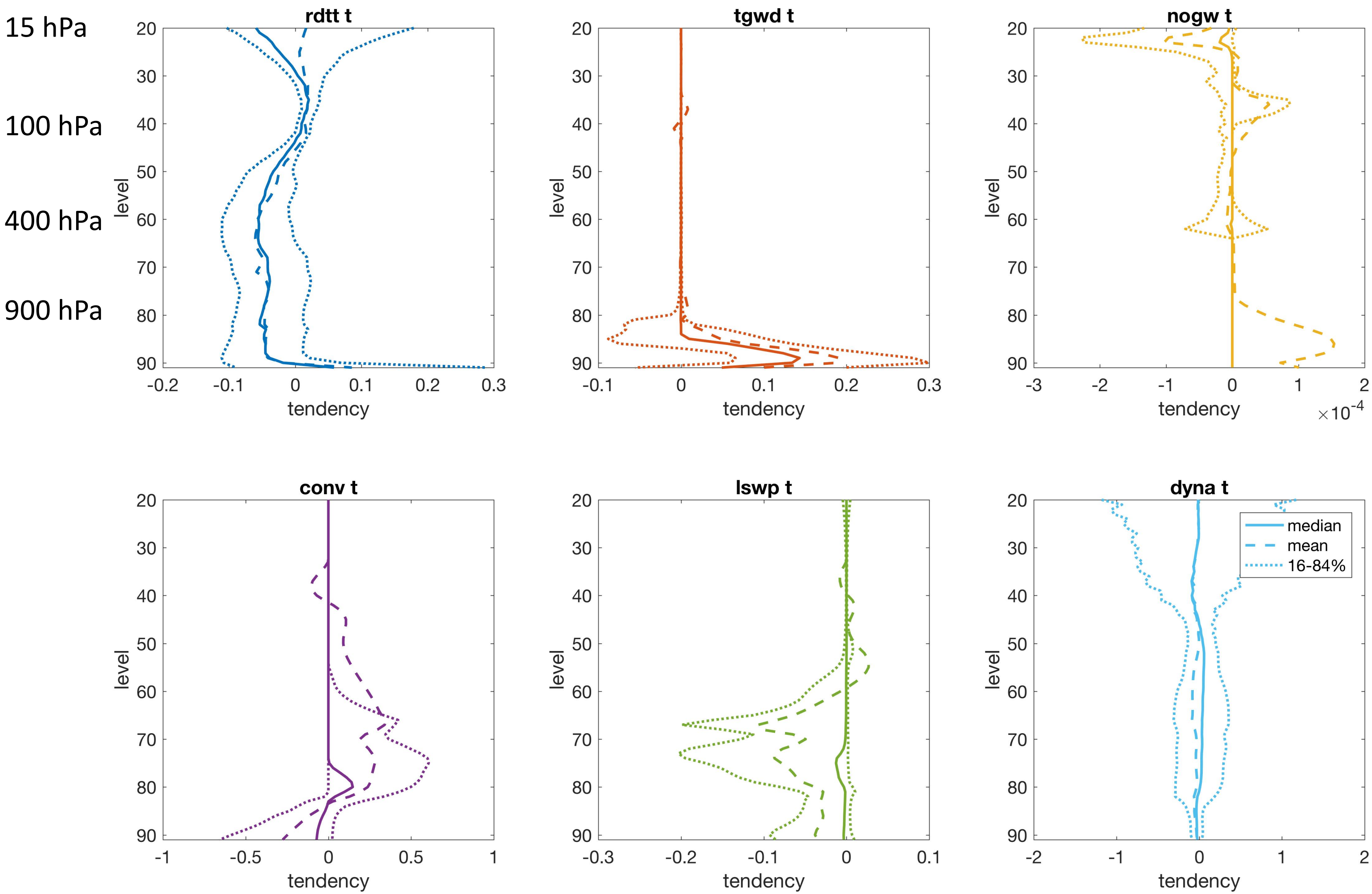
4. Above high-resolution model top, pad data using ECMWF analysis
5. Advective tendencies estimated from the coarsened fields

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

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.

Where are the different schemes active?



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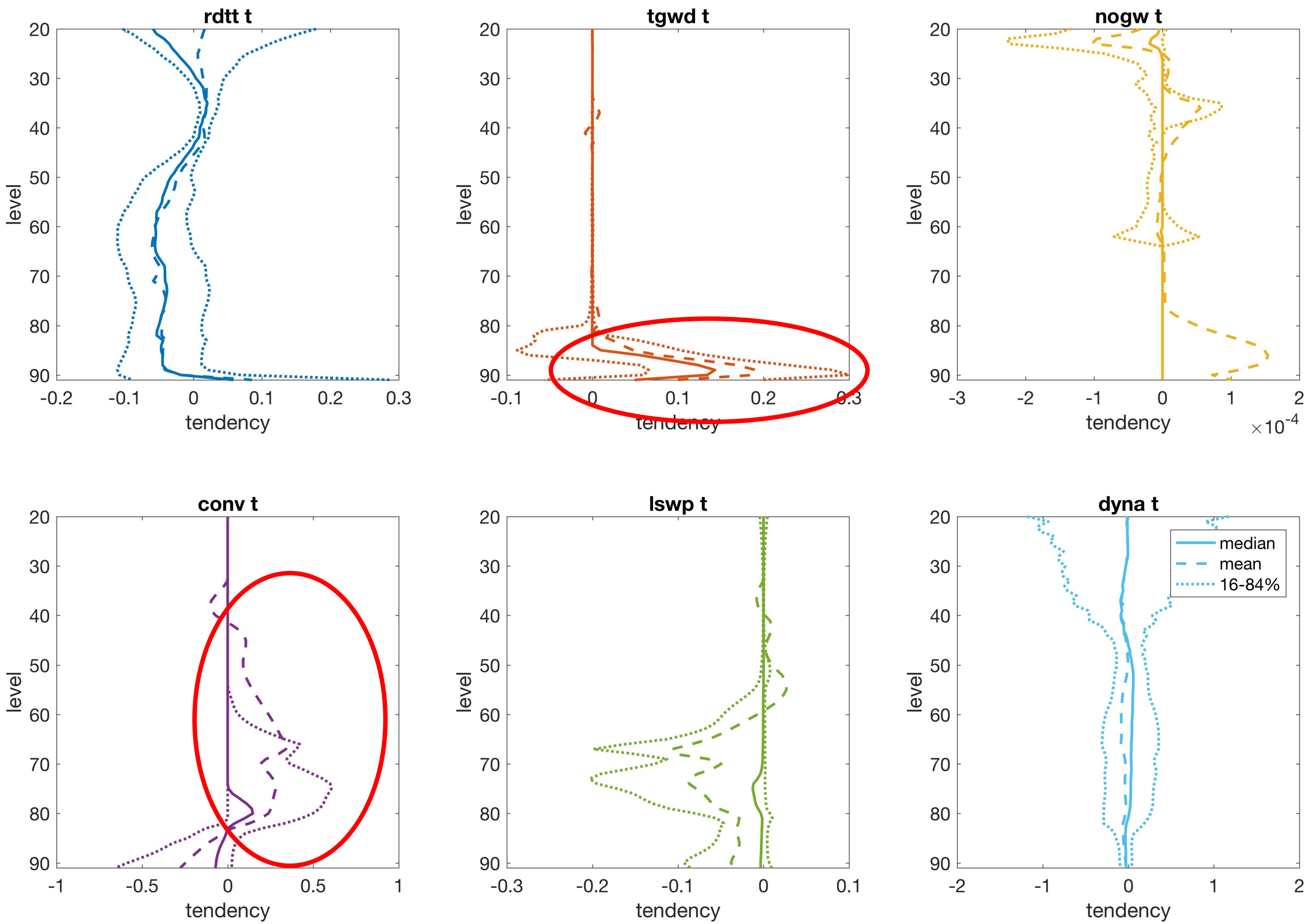
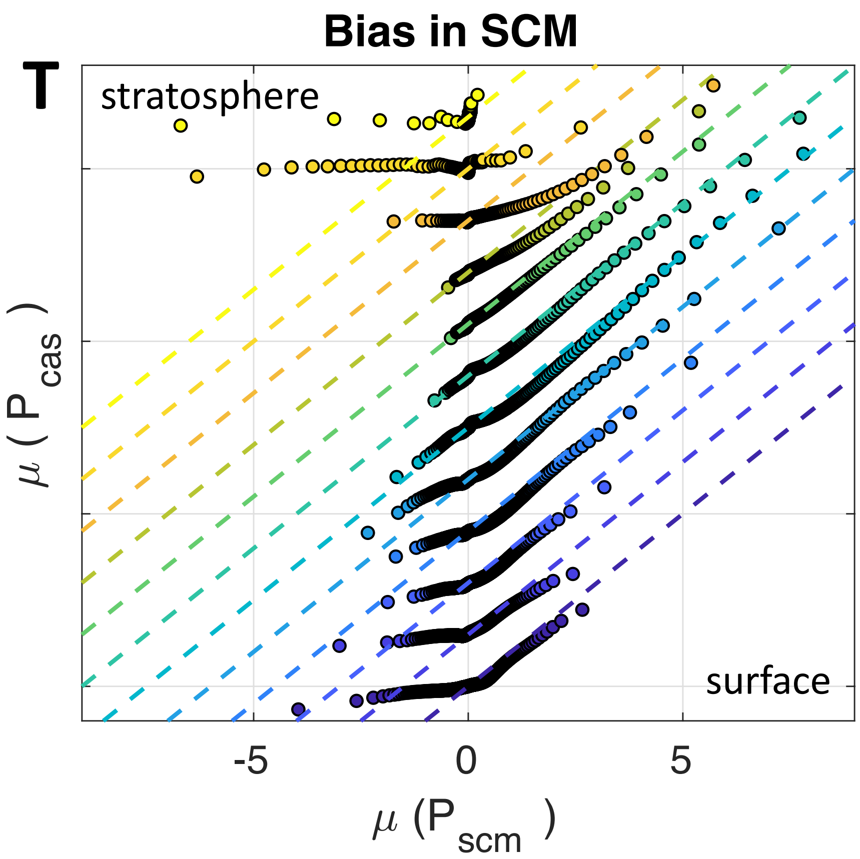
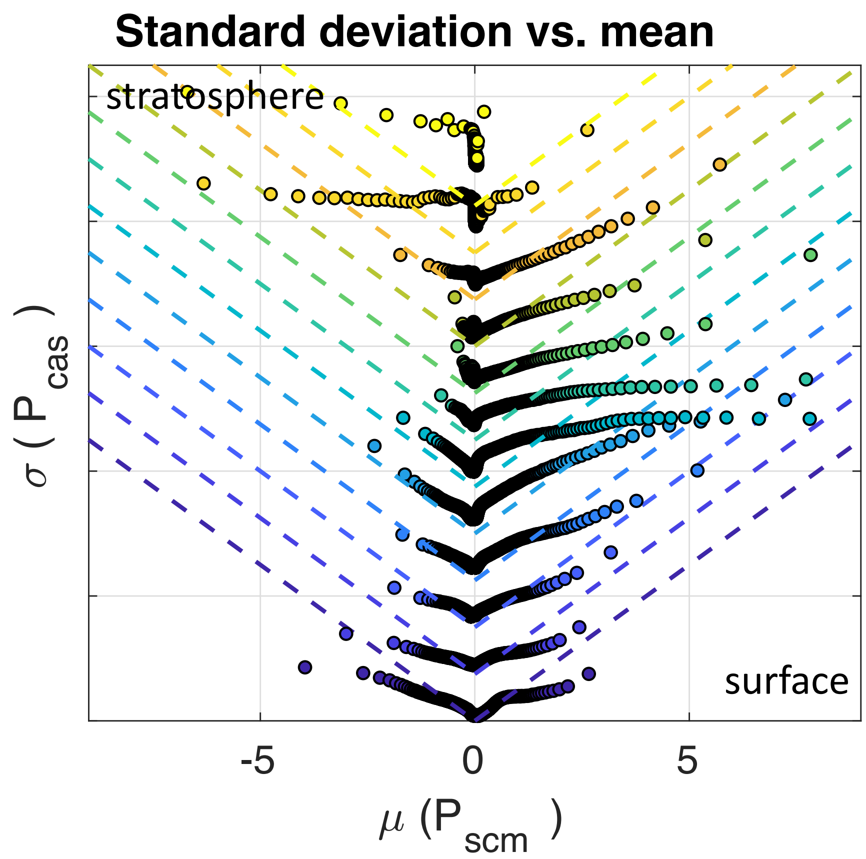


Consider T tendency





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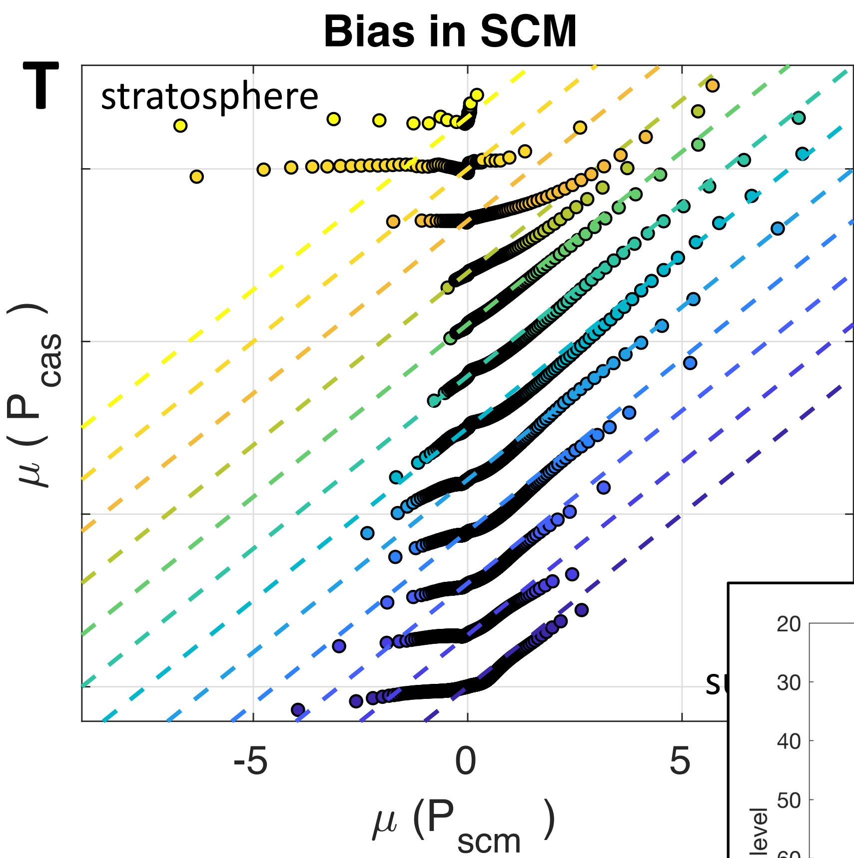
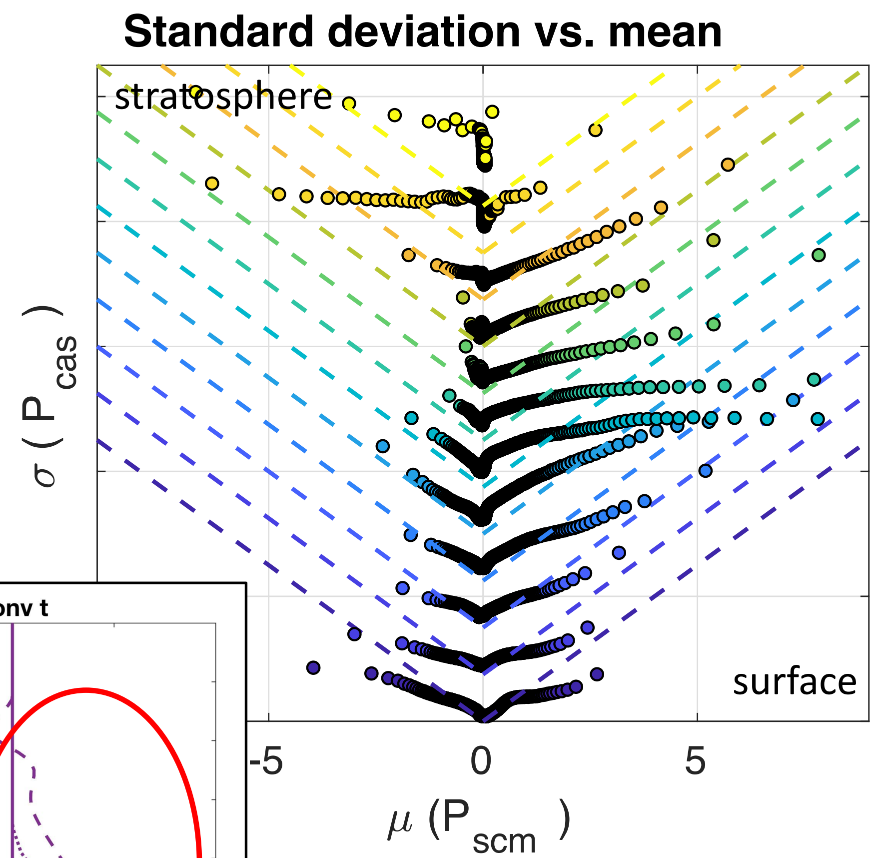
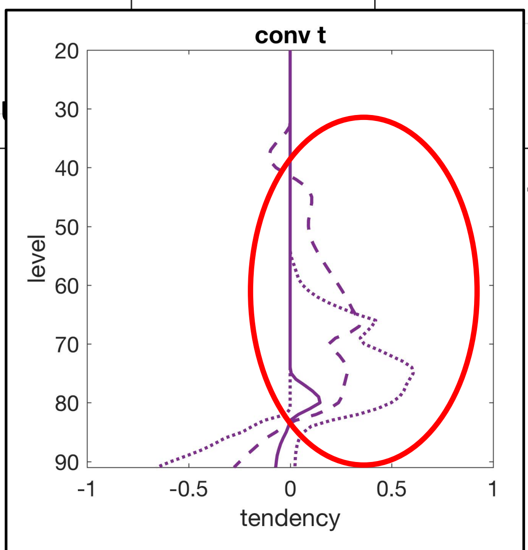
Yellow: levels 32—36 (86—60 hPa)

Consider T tendency







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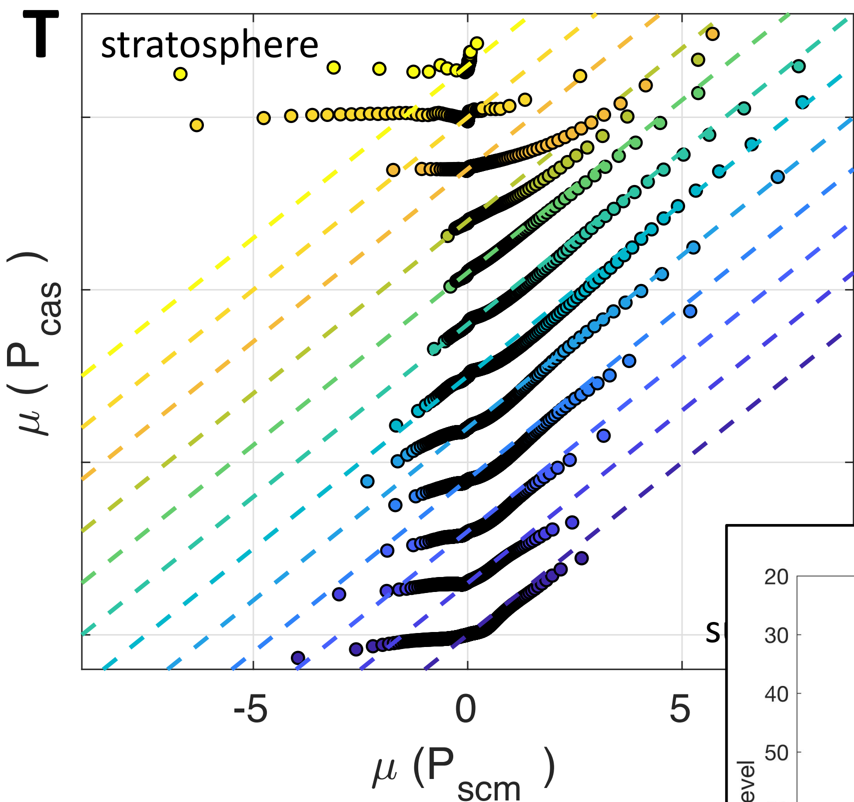
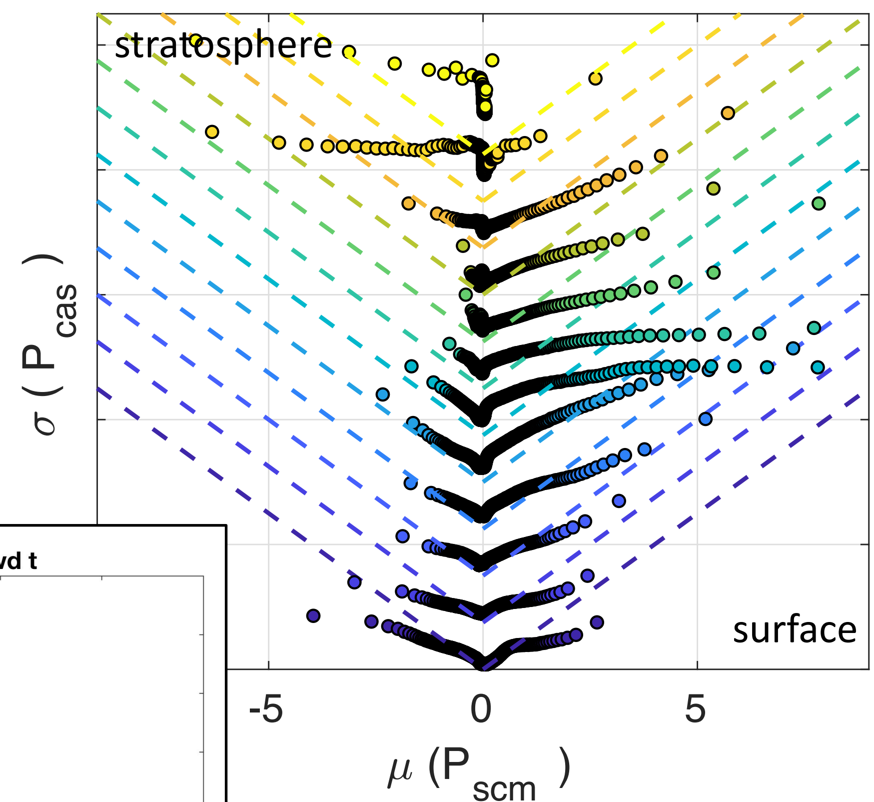
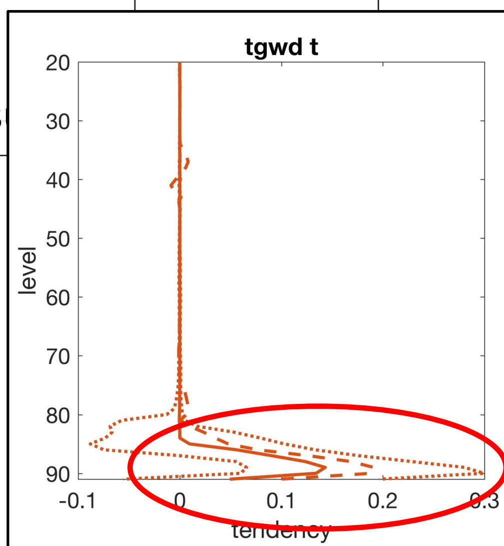
Consider T tendency

Bias in SCM



Standard deviation vs. mean

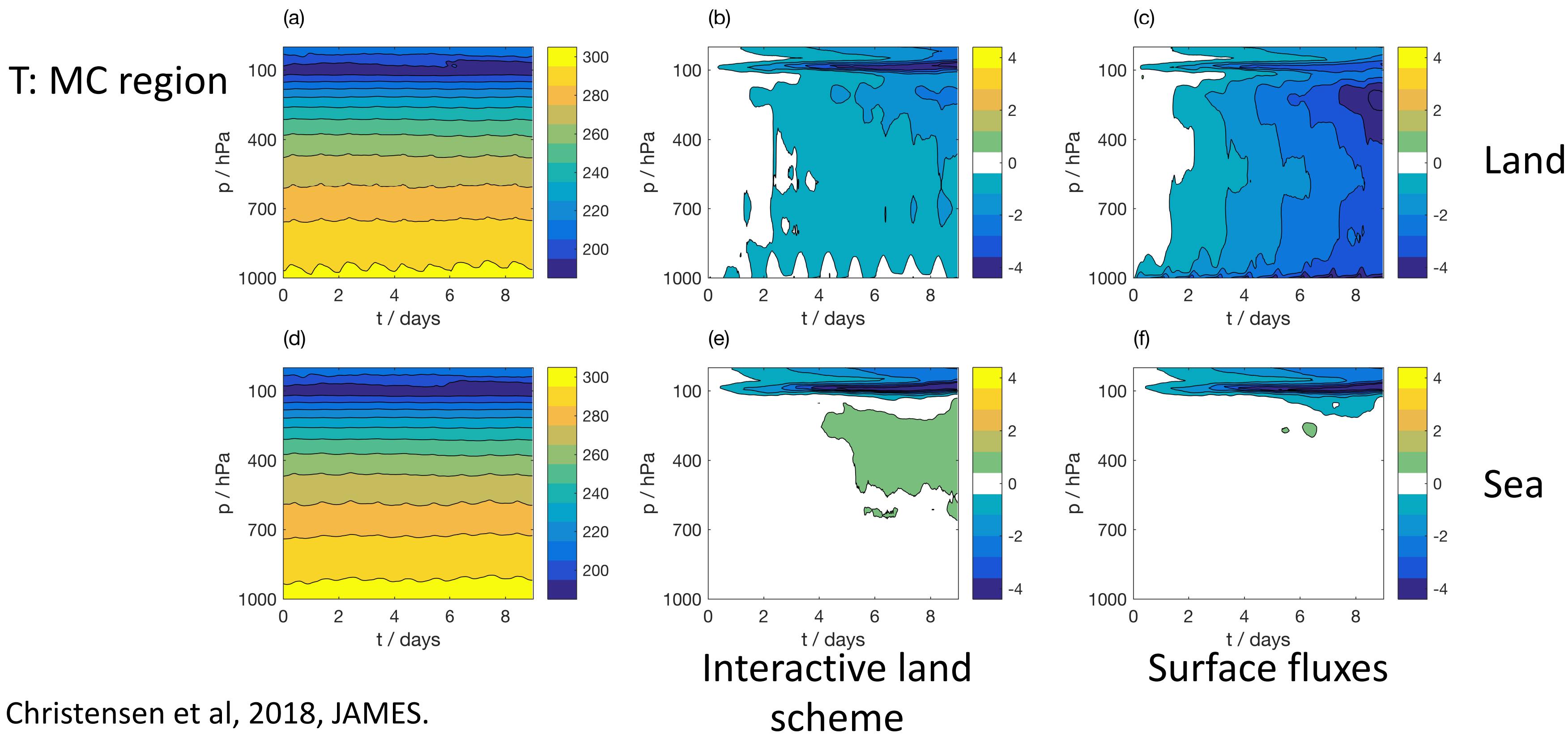




Data grouped by level.
Dark blue: levels 91—87
Yellow: levels 32—36

Implementation details

1. Verify coarse-graining procedure by taking IFS forecast data at T639
   - Linearly interpolate 1hr -> 15 mins
   - Estimate advective fluxes from gridpoint fields
   - Supply sensible and latent fluxes instead of interactive land scheme
   - Interpolate from native model levels to target model levels



Christensen et al, 2018, JAMES.

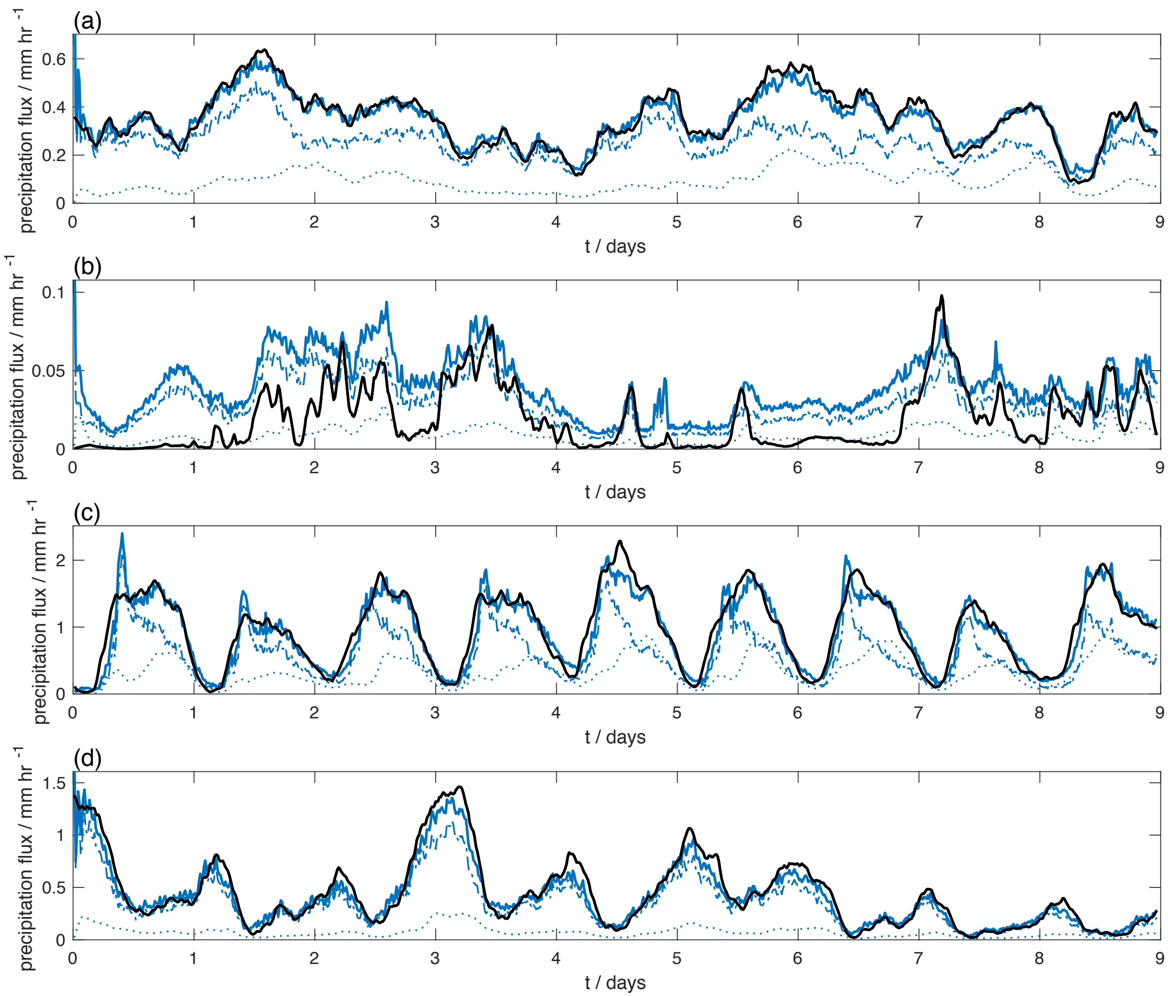
How does the SCM compare to Cascade?

W. Pacific Ocean

Ocean West of Australia

Maritime Continent Land

Maritime Continent Ocean



Precipitation

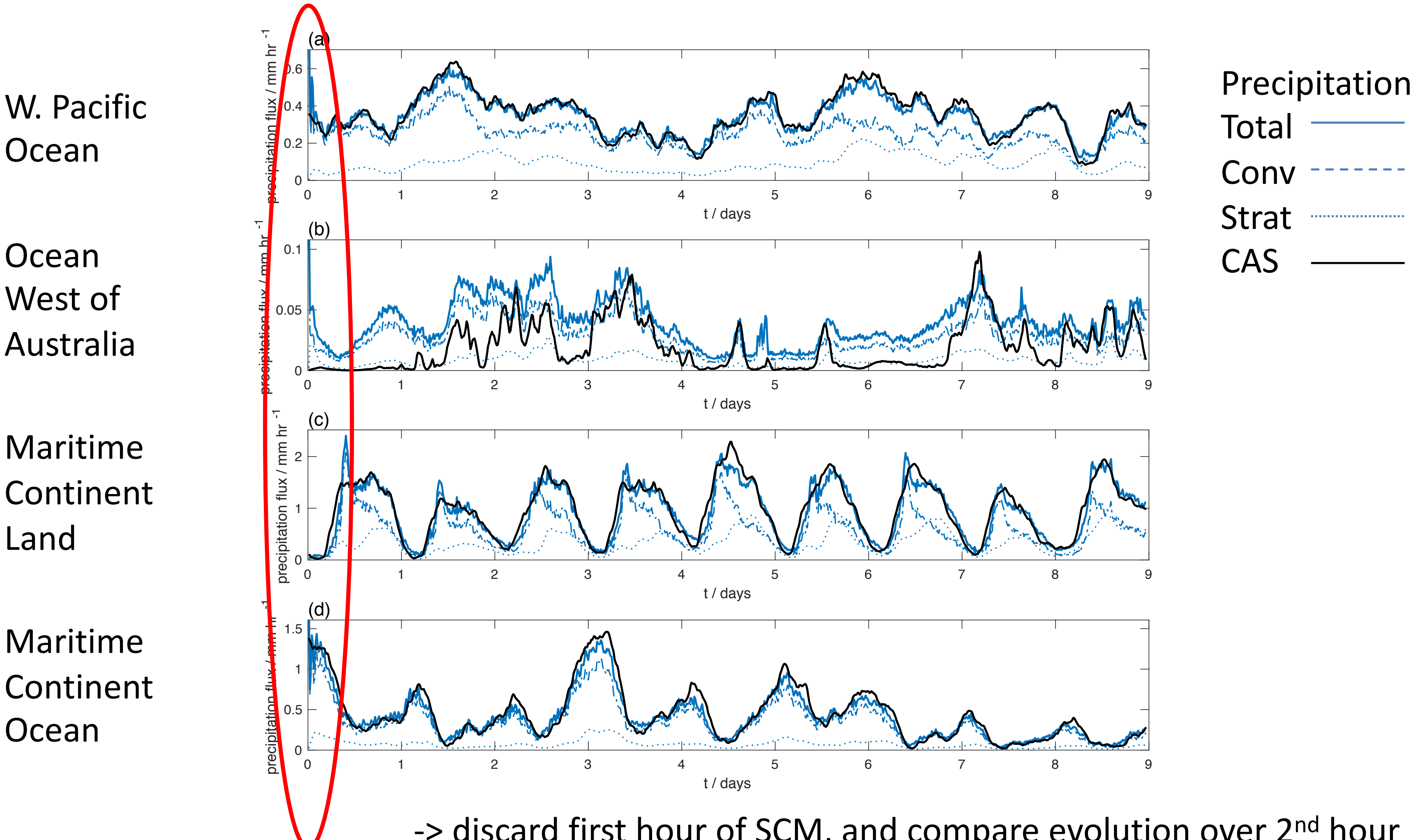
Total

Conv

Strat

CAS

How does the SCM compare to Cascade?



-> discard first hour of SCM, and compare evolution over 2nd hour

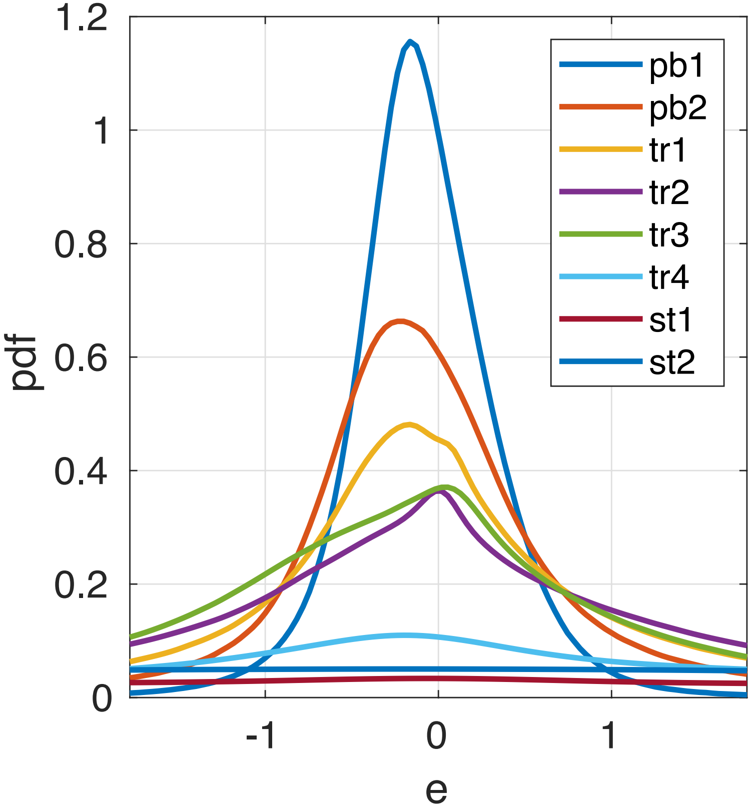
Cf. existing approaches to identify model error

- **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		☹	☹

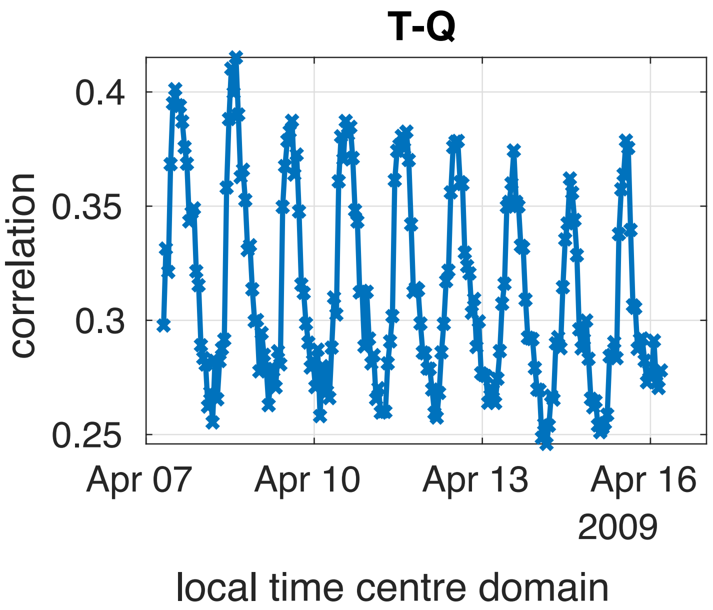
Relax SPPT assumptions: 1. constant in z

- Split atmosphere up into vertical chunks
- Calculate e independently for each chunk
  - Different statistics at different levels
  - Low correlation between e fitted at different levels



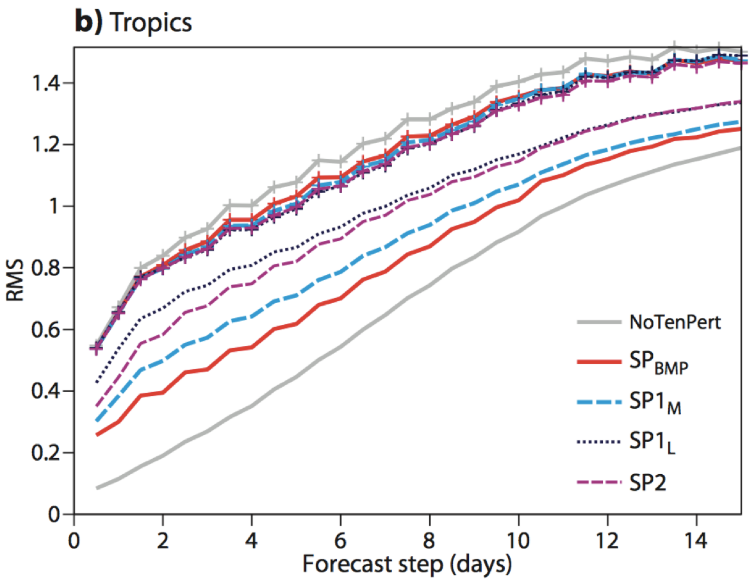
Relax SPPT assumptions: 2. variables

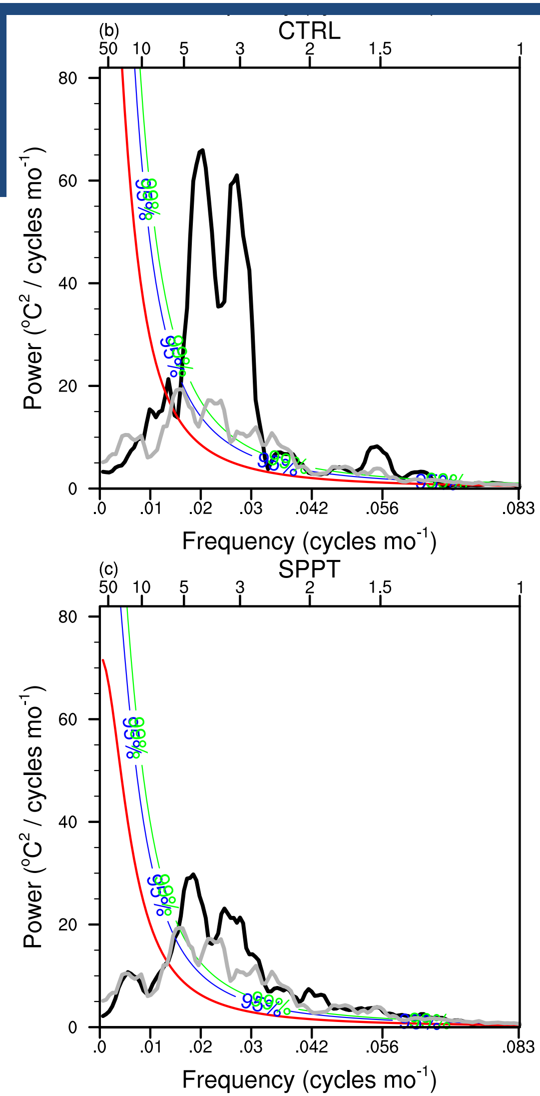
- Calculate separate perturbation for each prognostic variable (T, q, U, V)
- Find e_T and e_q have similar statistics
- Find e_U and e_V have similar statistics
- Find correlations of 0.3-0.4 for (e_T, e_q)
- Low correlations for all other pairs



Impact of SPPT

Palmer et al, 2009. ECMWF Tech Memo 598

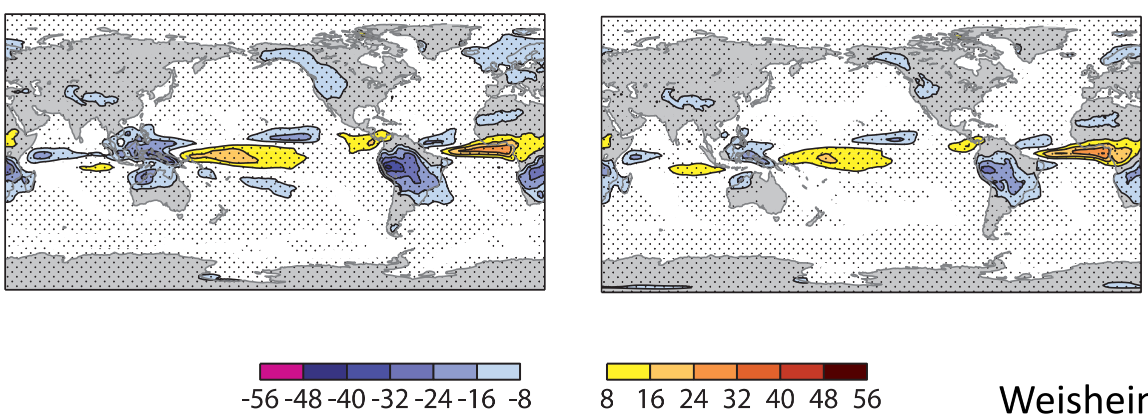




Christensen et al, 2017, J. Climate

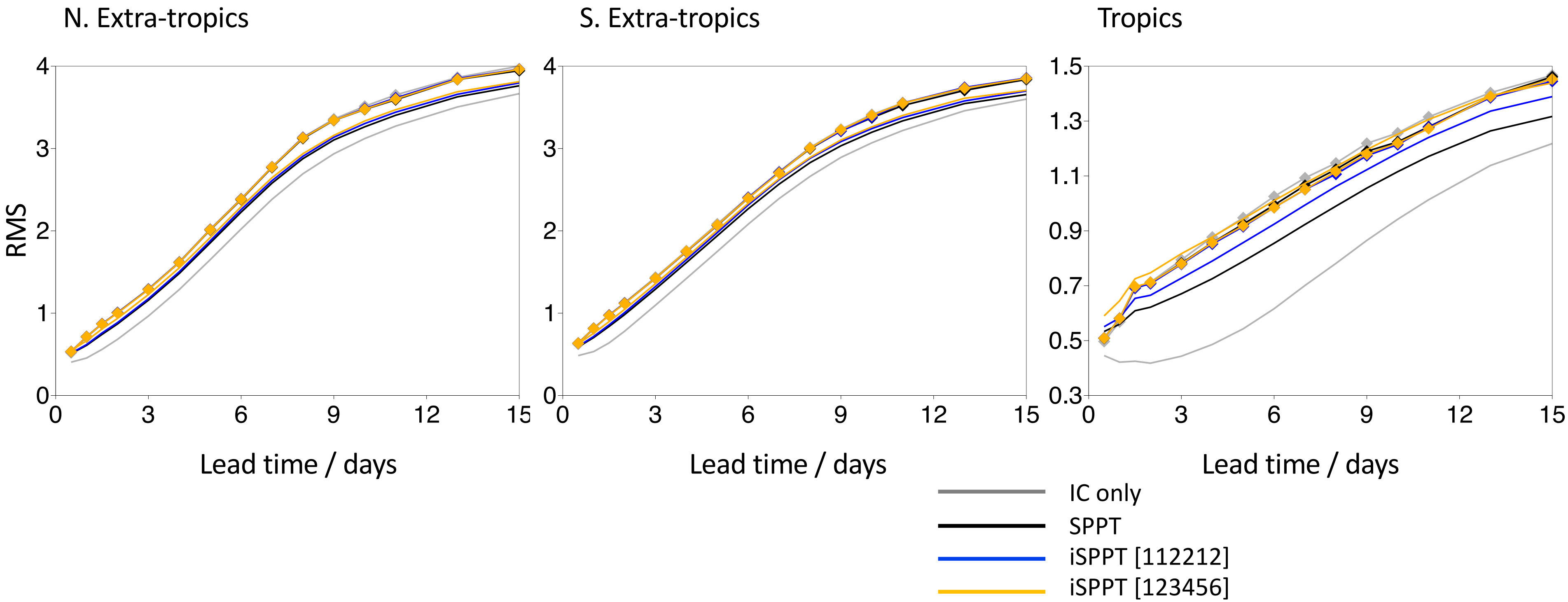
stochphysOFF – reanalysis

S4 – reanalysis



Weisheimer et al 2014, Phil Trans R Soc A.

iSPPT Results: medium range



Christensen, Lock, Moroz, Palmer, 2017, QJ.

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 parametrised tendencies**, as a function of model level, location and forecast start time