



Improving stochastic parametrisation schemes using high-resolution model simulations

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Why stochastic parametrisation?

- Stochastic parametrisation seeks to represent unresolved sub-grid variability
 - Grid-scale variables do not fully constrain sub-grid motions
 - Describe sub-grid tendency in terms of a probability distribution constrained by the resolved-scale flow
 - Include random numbers in our equations of motion
- Necessary in NWP to achieve reliable ensemble forecasts, in which the probability distribution accounts for all uncertainty in the forecast



A general framework for stochastic parametrisation



Use a high resolution simulation as 'truth'

1. Coarse grain high resolution data to forecast model grid



SCM as Forecast Model

- How do we use an SCM?
 - Use coarsened high-res simulation to prescribe Initial conditions, 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
- IFS SCM CY40R1 at T_L639, 91 vertical levels (available through openIFS)



Surface Fluxes

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, <u>4km resolution</u>
- 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
 - Implemented in models worldwide

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

- T Total tendency
- D Dynamics tendency
- P Physics tendency

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

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



All parametrisation schemes see same perturbation All variables see same perturbation Perturbation constant in height

Palmer et al, 2009. ECMWF Tech Memo 598

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Analysing the data: multiplicative noise?

SPPT:

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

i=1

Calculate 'true' total tendency from CASCADE

Assume SCM dynamics tendency is 'correct'

Consider error in SCM physics tendencies



SPPT: standard deviation proportional to mean

Hypothesis:



If this is true:

$$\sigma(\mathbf{P}_{\mathsf{CAS}} \mid \mathbf{P}_{\mathsf{SCM}}) = \sigma_e \, \mathbf{P}_{\mathsf{SCM}}$$

Uncertainty in T tendency



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

(ground—995 hPa) (86—60 hPa)

Two analysis approaches

- 1. SPPT seems like good first-order representation of uncertainty in IFS
 - Measure optimal parameters for SPPT to improve scheme
- 2. Can we move beyond/generalise SPPT to find a better representation for the IFS?
 - Relax each SPPT assumption in turn and assess whether we have found a better noise model

1. 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'

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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	-
$ au_{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?



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Improving stochastic parametrisation schemes







iSPPT: Consider different schemes

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





 ⇒ 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





- correlations for each process
- Generally little correlation between *e*_i for different schemes



Conclusions and relevance for SPPT

- 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
- The simple generalisation iSPPT looks promising
 - Different schemes show very different noise characteristics

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 Highresolution 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

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Thanks for listening