Model Uncertainty and Stochastic Parametrisation

Tim Palmer

University of Oxford

Why are models uncertain?

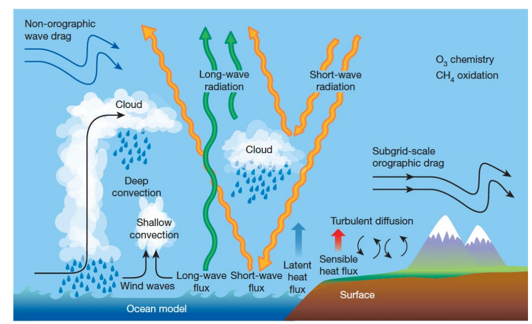
Resolved scales

Unresolved scales

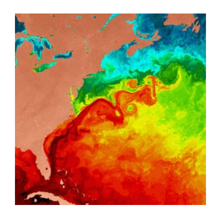
Dynamical Core

Parametrisations

$$P\left(X_{\mathrm{Tr}};\alpha\right)$$



$$D = P$$



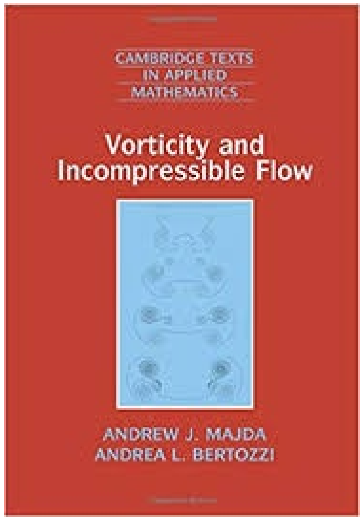
$$\rho\left(\frac{\partial}{\partial t}+\mathbf{u}.\nabla\right)\mathbf{u}=\rho\mathbf{g}-\nabla p+\mu\,\nabla^2\mathbf{u}$$

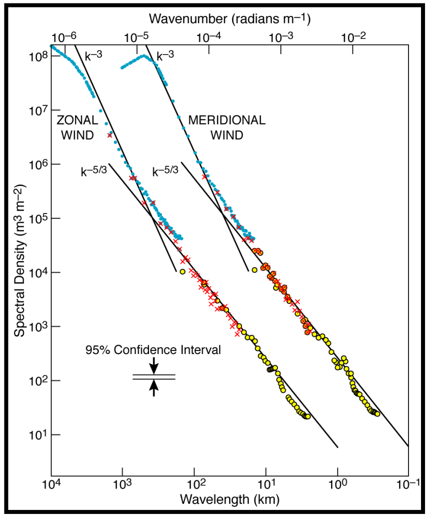
If $u(x,t)$ is the velocity field and $p(x,t)$ is the pressure field associated with a solution to the Navier-Stokes equations, then so is

$$u_\tau(x,t)=\tau^{-1/2}u(\frac{x}{\tau^{1/2}},\frac{t}{\tau}),$$

$$p_\tau(x,t)=\tau^{-1}p(\frac{x}{\tau^{1/2}},\frac{t}{\tau})$$

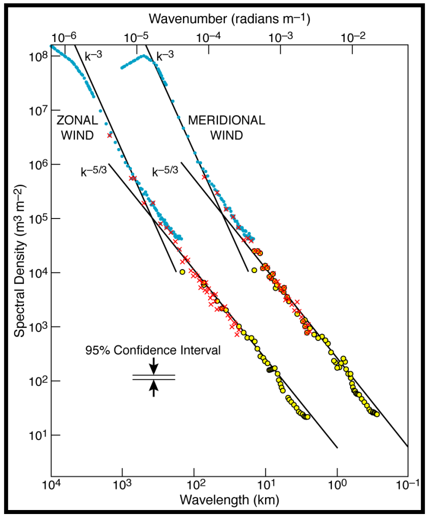
where $\tau>0$ is a dimensionless scaling parameter.





Model Uncertainty is a consequence of violating the scaling symmetries of the PDEs by introducing a finite discretisation.

Model uncertainty is fundamentally "ontological" not "epistemological".



The problem is acute because of the -5/3 spectrum: at smaller scales, in the tropics and perhaps the summer extratropics.

IOP Publishing | London Mathematical Society Nonlinearity

Nonlinearity 27 (2014) R123–R141 doi:10.1088/0951-7715/27/9/R123

Invited Article

The real butterfly effect

T N Palmer[1], A Döring[1,2] and G Seregin[3]

[1] Department of Physics, University of Oxford, Parks Rd, Oxford, OX1 3PU, UK
[2] Department of Physics, University of Erlangen-Nürnberg, Staudstrasse 7, 91058, Germany
[3] Mathematical Institute, University of Oxford, Woodstock Rd, Oxford, OX2 6GG, UK

E-mail: t.n.palmer@atm.ox.ac.uk

Received 4 February 2014, revised 13 July 2014
Accepted for publication 14 July 2014
Published 19 August 2014

Recommended by K Julien

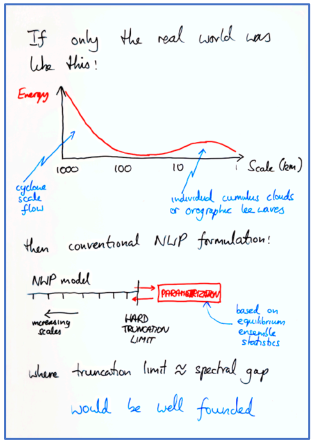
Abstract
Historical evidence is reviewed to show that what Ed Lorenz meant by the iconic phrase 'the butterfly effect' is not at all captured by the notion of sensitive dependence on initial conditions in low-order chaos. Rather, as presented in his 1969 Tellus paper, Lorenz intended the phrase to describe the existence of an absolute finite-time predicability barrier in certain multi-scale fluid systems, implying a breakdown of continuous dependence on initial conditions for large enough forecast lead times. To distinguish from 'mere' sensitive dependence, the effect discussed in Lorenz's Tellus paper is referred to as 'the real butterfly effect'. Theoretical evidence for such a predictability barrier in a fluid described by the three-dimensional Navier–Stokes equations is discussed. Whilst it is still an open question whether the Navier–Stokes equation has this property, evidence from both idealized atmospheric simulators and analysis of operational weather forecasts suggests that the real butterfly effect exists in an asymptotic sense, i.e. for initial-time atmospheric perturbations that are small in scale and amplitude compared with (weather) scales of interest, but still large in scale and amplitude compared with variability in the viscous subrange. Despite this, the real butterfly effect is an intermittent phenomenon in the atmosphere, and its presence can be signalled *a priori*, and hence mitigated, by ensemble forecast methods.

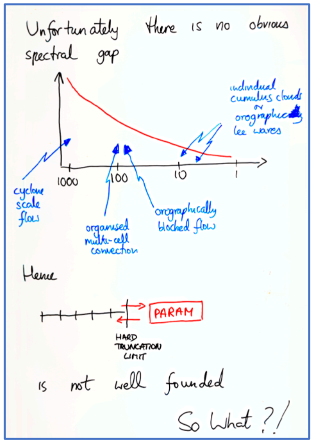
Keywords: butterfly effect, finite-time predictability, chaos, surface quasi-geostrophic equations
Mathematics Subject Classification: 37L99

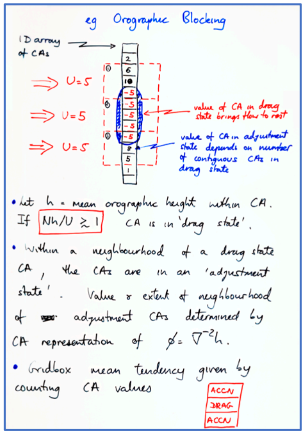
1. Introduction

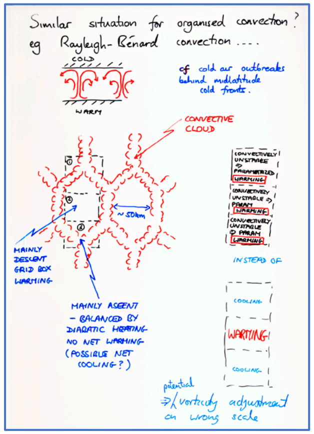
The butterfly effect is one of the most iconic phrases in 20th century science. As described in numerous textbooks and as understood by almost all those who work in nonlinear dynamics,

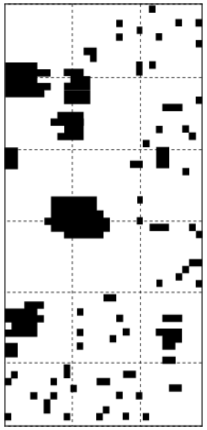
ECMWF Workshop on New Insights and Approaches to Convective Parametrization
4-7 November 1996











Eventually written up as Palmer (2001)

SPPT: Devised as an alternative to parameter perturbation.

MM: Perturbing parameter values as if they were independent of one another makes no physical sense. We should treat model uncertainty more holistically.

TP: We need to address the representation of ontological model uncertainty associated with the need to truncate the underlying PDEs and hence go beyond parameter perturbation schemes.

SPPT is easy to maintain across model cycles. By contrast, parameter perturbation schemes will have to be retuned each time new or revised parametrisations are introduced.

$$\rho\left(\frac{\partial}{\partial t}+\mathbf{u}.\nabla\right)\mathbf{u}=\rho\mathbf{g}-\nabla p+\mu\,\nabla^{2}\mathbf{u}$$

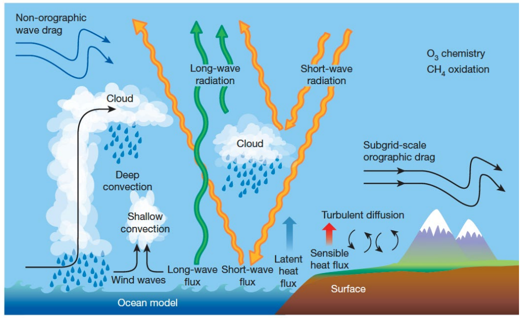
Resolved scales ←

→ Unresolved scales

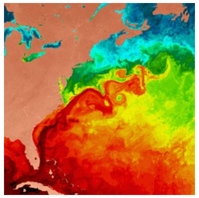
Dynamical Core

Stochastic Parametrisations

$$(1+r)P(X_{tr};\alpha)$$



$$D=P$$



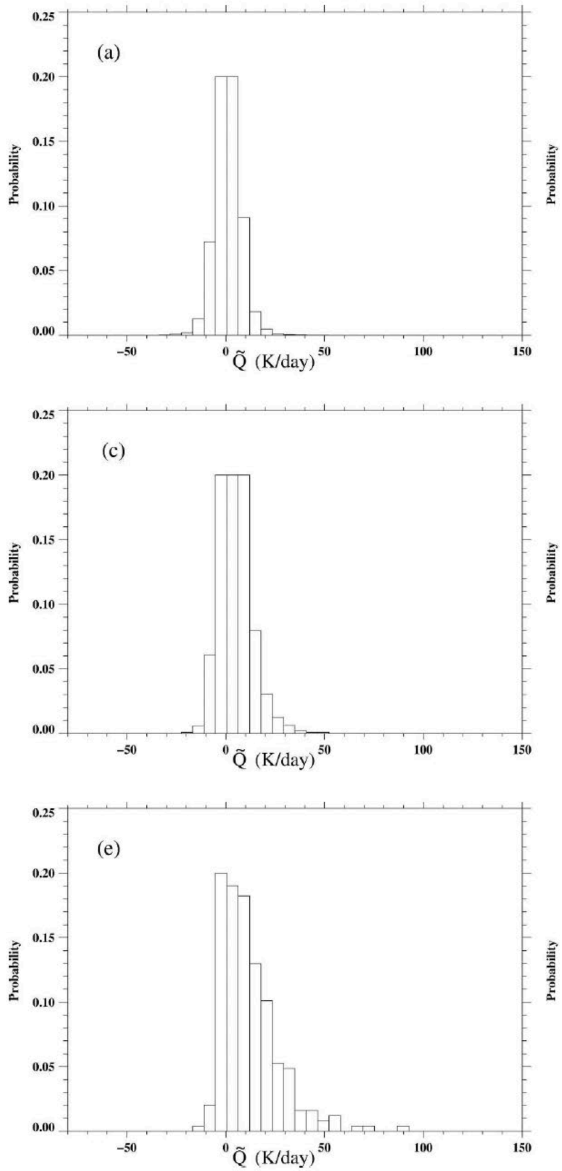


FIG. 7. Histograms of effective temperature tendencies ob
Each histogram is created from a subsample of all coarse bo
(a) −0.1 to +0.1; (b) 0.1 to 9; (c) 9 to 18; (d) 18 to 27; (e)

Shutts and Palmer (2007). Coarse-graining as a way to justify SPPT assumptions

SPPT has a dramatically positive impact on tropical skill scores at virtually no extra cost.

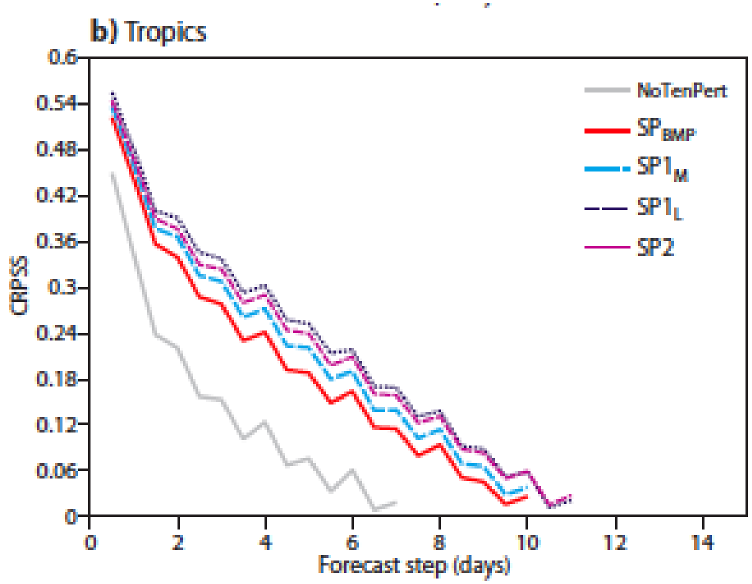
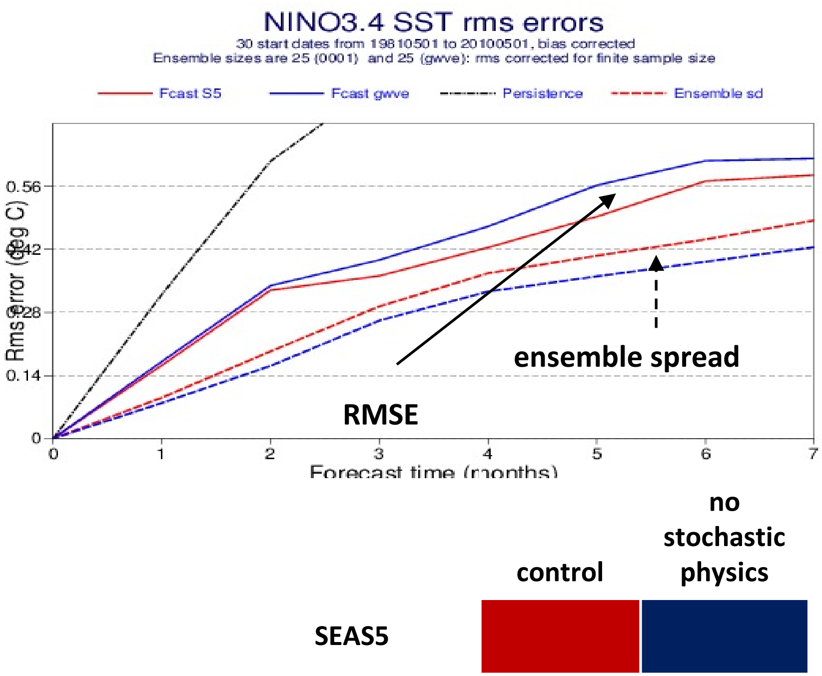


Figure 3: Continuous Ranked Probability Skill Score for 850 hPa temperature.

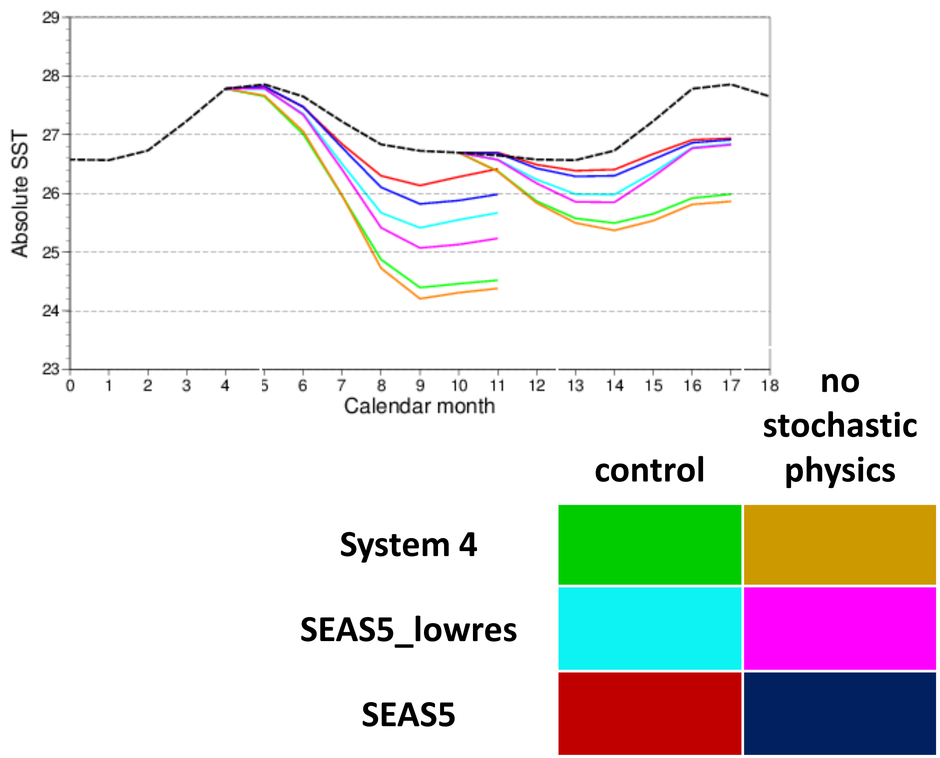
Palmer et al (2009)

Impact of SPPT on ENSO forecasts

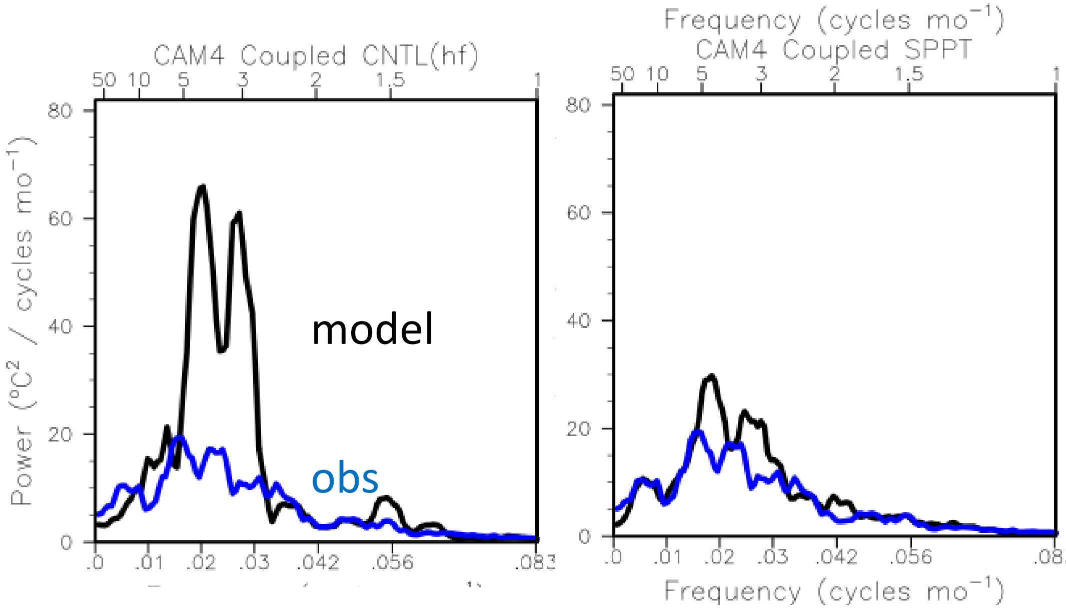
- SPPT helps reduce the RMS error
- It also increases the ensemble spread
  → More reliable forecasts
- SPPT reduces cold bias



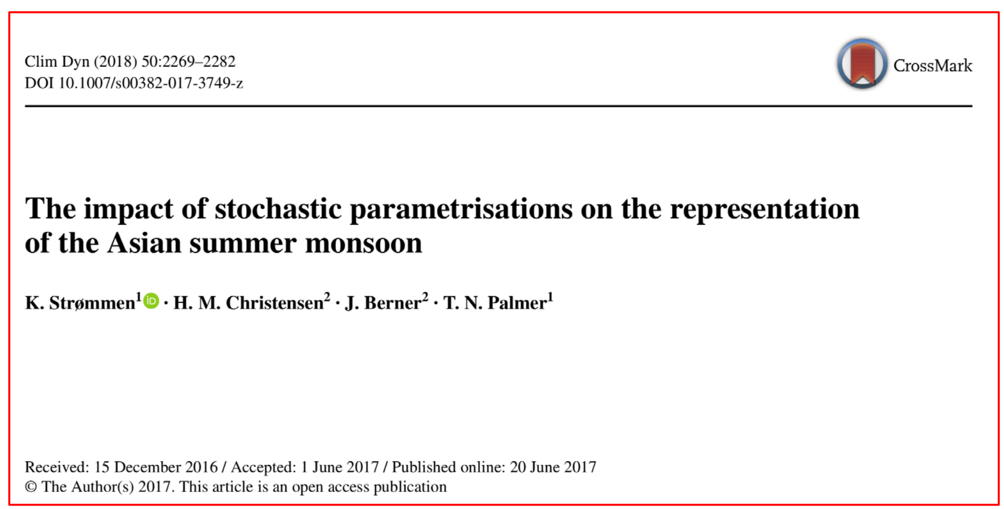
Systematic Error Nino 3.4



Antje Weisheimer, 2019



NCAR, CAM4 ENSO without and with stochastic parametrization.
Christensen et al, 2017



Clim Dyn (2018) 50:2269–2282
DOI 10.1007/s00382-017-3749-z

CrossMark

The impact of stochastic parametrisations on the representation of the Asian summer monsoon

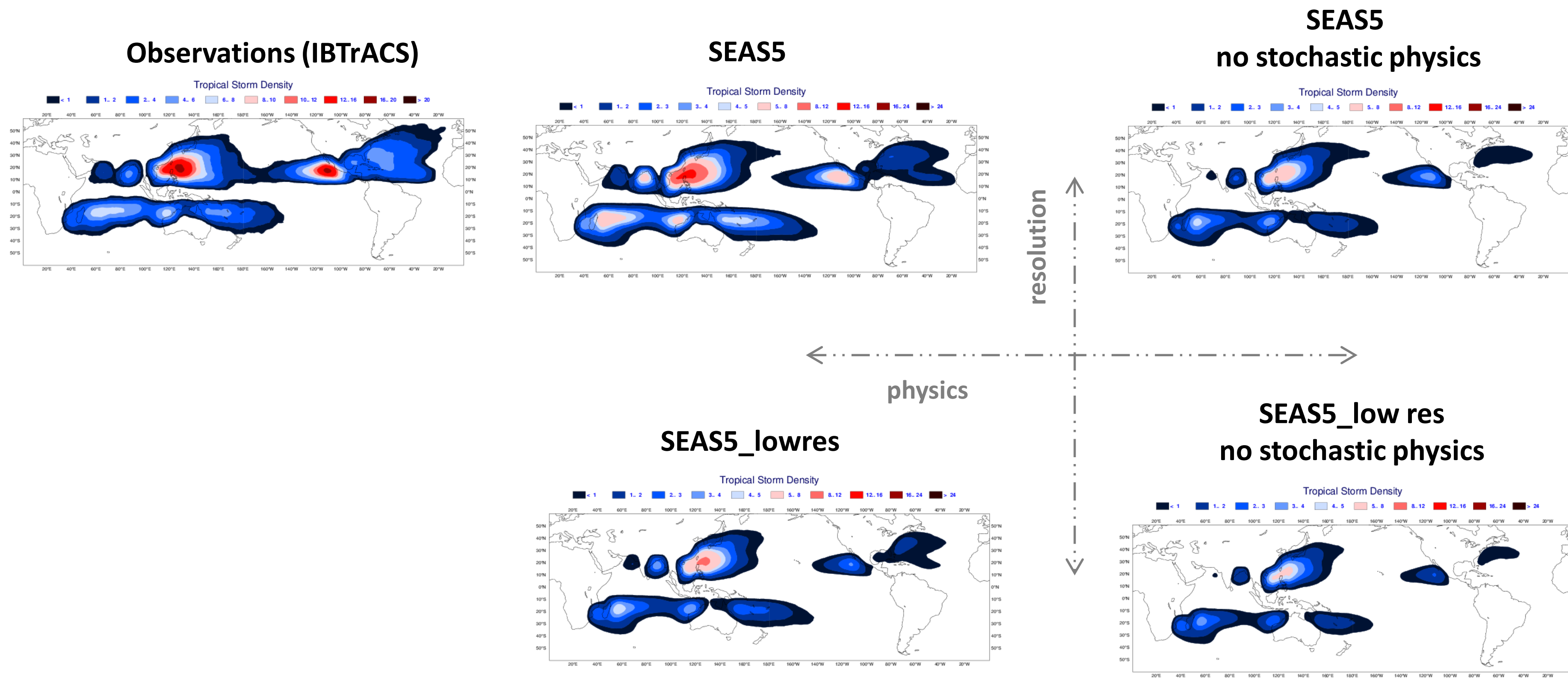
K. Strømmen[1] · H. M. Christensen[2] · J. Berner[2] · T. N. Palmer[1]

Received: 15 December 2016 / Accepted: 1 June 2017 / Published online: 20 June 2017

SPPT + SKEB

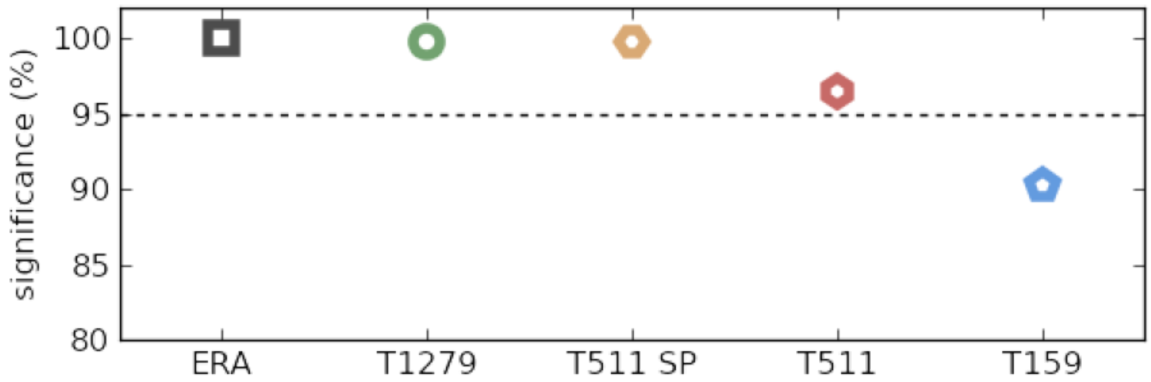
Number of tropical cyclones: Impact of resolution vs stochastic physics

- Stochastic physics and resolution have similar impact



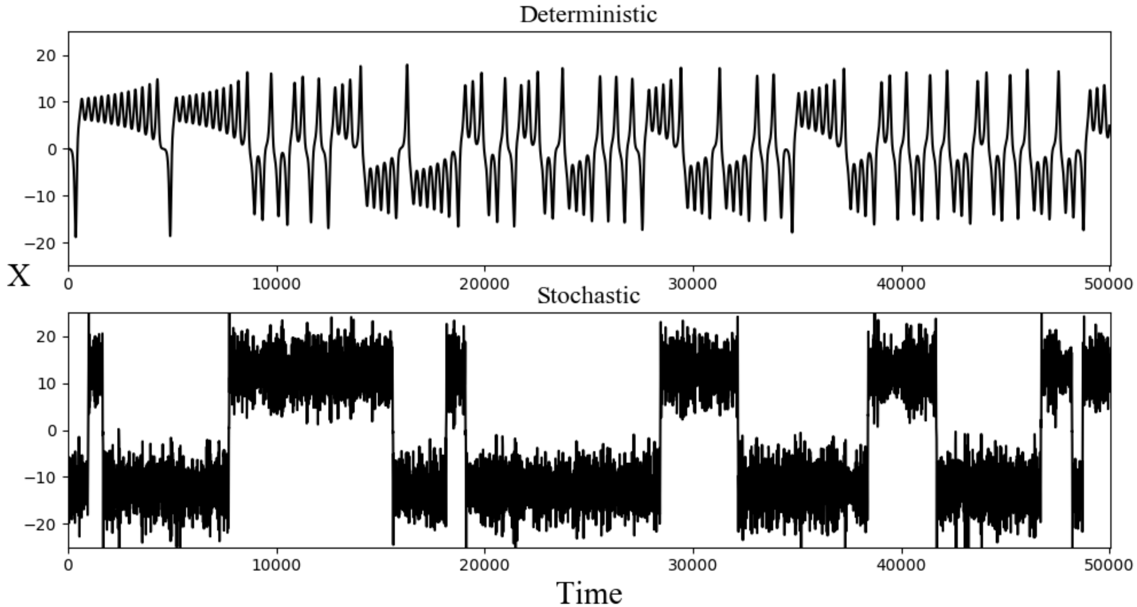
Weisheimer, Vidale 2022

Climate models simulate circulation regimes poorly



Regime significance

Dawson et al, 2012



L63

L63 + noise

Results: Ensemble TCWV and P-E with and without SPPT

Aneesh Subramanian, Milan Kloewer and Kristian Strommen.

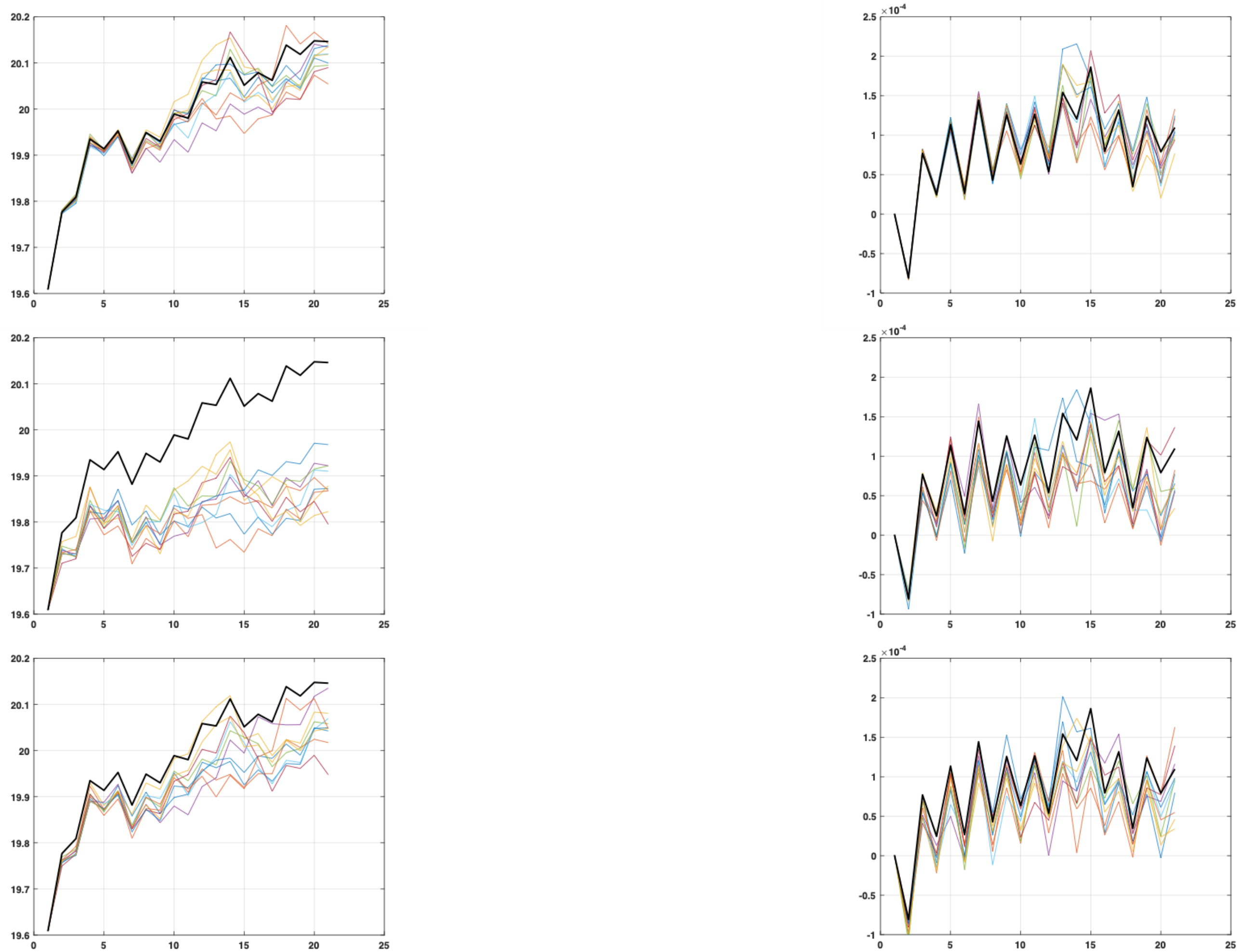
TCWV

P - E

No SPPT

SPPT

SPPT_sfc



Water closer to conservation in the ensemble members when SPPT perturbations are added to surface P-E.

However, there may be a much simpler way to enforce conservation

that shown in Fig. 7. The problem of energetic consistency could be addressed straightforwardly if, instead of the parametrization tendency, the parametrization input fields were stochastically perturbed, i.e.

$$\dot{X}_j = F_j[X] + P[X_j + \beta; \alpha]. \qquad (20)$$

Experimentation with such a scheme is in preparation.

From Palmer (2001)

Milan Klöwer has suggested a way of implementing (20) whilst retaining the rationale behind SPPT:

1) Integrate model-with-SPPT over a partial timestep. Estimate perturbations to dynamical variables.
2) Using these perturbations, run model-with-(20) rather than SPPT.
3) These define the stochastic tendencies for arriving at the next timestep.
4) Nb (1) could be performed at low numerical precision to minimize cost implications.

A strength of ECMWF

Test different representations of model uncertainty in data assimilation mode – c.f. Rodwell and Palmer (2007).

Other Model Components

We need representation of model uncertainty for the oceans and land surface, otherwise we might be overdoing atmospheric schemes to compensate for an overly deterministic ocean/land-surface scheme.

We have done this for EC-Earth.

Conclusions

At a fundamental level, model uncertainty arises because we violate the scaling symmetries of Navier-Stokes when we truncate the equations numerically. Model uncertainty is ontological not epistemic.

SPPT attempts to represent such ontological uncertainty. By design it goes beyond parameter uncertainty. It is holistic but not ad hoc. It is supported (and could be improved) by coarse-grain statistics from high-res data sets. It improves not only NWP scores, but systematic errors on climate timescales.

Non-conservation issues e.g. for water can be addressed by perturbing surface fluxes consistently or by a hybrid SPPT/SPPI scheme.

SPPT is easy to maintain across new model cycles. By contrast, parameter perturbation schemes will have to be retuned each time new or revised parametrisations are introduced.

Schemes to represent model uncertainty should be tested in data assimilation mode.

We need to introduce representations of model uncertainty for the ocean and land surface too to avoid ”compensating errors”.

JAMES | Journal of Advances in Modeling Earth Systems®

RESEARCH ARTICLE

10.1029/2021MS002794

Special Section:
Machine learning application to Earth system modeling

Correcting Coarse-Grid Weather and Climate Models by Machine Learning From Global Storm-Resolving Simulations

Christopher S. Bretherton[1], Brian Henn[1], Anna Kwa[1], Noah D. Brenowitz[1], Oliver Watt-Meyer[1], Jeremy McGibbon[1], W. Andre Perkins[1], Spencer K. Clark[1,2], and Lucas Harris[2]

[1]Vulcan Inc. and Allen Institute for Artificial Intelligence, Seattle, WA, USA, [2]Geophysical Fluid Dynamics Laboratory, NOAA, Princeton, NJ, USA

Key Points:

- With a state-dependent machine learning correction, a coarse-grid global atmospheric model evolves more like a fine-grid model version
- The skill of coarse-grid weather forecasts and time-mean rainfall are improved compared to the fine-grid storm-resolving reference model
- Accounting for cloud biases by correcting surface downwelling radiation improves surface turbulent fluxes and precipitation over land

Correspondence to:

C. S. Bretherton,
christopherb@allenai.org

Citation:

Bretherton, C. S., Henn, B., Kwa, A., Brenowitz, N. D., Watt-Meyer, O., McGibbon, J., et al. (2022). Correcting coarse-grid weather and climate models by machine learning from global

Abstract

Global atmospheric "storm-resolving" models with horizontal grid spacing of less than 5 km resolve deep cumulus convection and flow in complex terrain. They promise to be reference models that could be used to improve computationally affordable coarse-grid global climate models across a range of climates, reducing uncertainties in regional precipitation and temperature trends. Here, machine learning of nudging tendencies as functions of column state is used to correct the physical parameterization tendencies of temperature, humidity, and optionally winds, in a real-geography coarse-grid model (FV3GFS with a 200 km grid) to be closer to those of a 40-day reference simulation using X-SHiELD, a modified version of FV3GFS with a 3 km grid. Both simulations specify the same historical sea-surface temperature fields. This methodology builds on a prior study using a global observational analysis as the reference. The coarse-grid model without machine learning corrections has too few clouds, causing too much daytime heating of land surfaces that creates excessive surface latent heat flux and rainfall. This bias is avoided by learning downwelling radiative flux from the fine-grid model. The best configuration uses learned nudging tendencies for temperature and humidity but not winds. Neural nets slightly outperform random forests. Forecasts of 850 hPa temperature gain 18 hr of skill at 3–7 days leads and time-mean precipitation patterns are improved 30% by applying the ML correction. Adding machine-learned wind tendencies improves 500 hPa height skill for the first five days of forecasts but degrades time-mean upper tropospheric temperature and zonal wind patterns thereafter.