The fluctuation-dissipation theorem: from statistical physics to climate dynamics?

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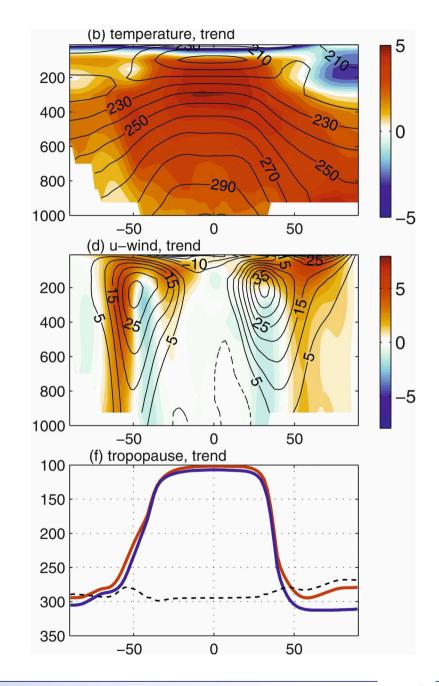




The climate response problem

Lu et al 2008: simulations with GFDL CM2.1 model, 2081-2100 compared with 2001-2020 in A2 scenario.

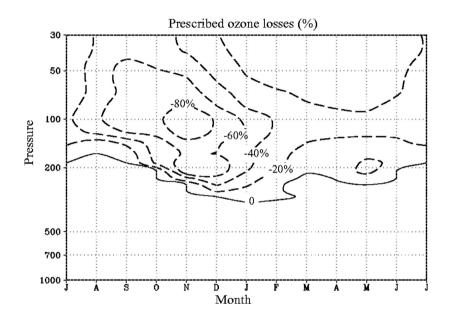
Longitudinal/time average change depends on physical processes which fluctuate in longitude and time.





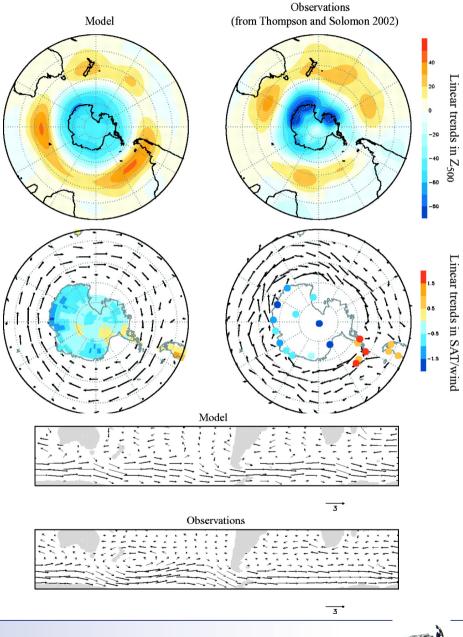


Changes in the SH troposphere as a dynamical response to stratospheric ozone depletion



Ozone perturbation applied to AGCM

(Thompson and Solomon 2002, Gillett and Thompson, 2003)



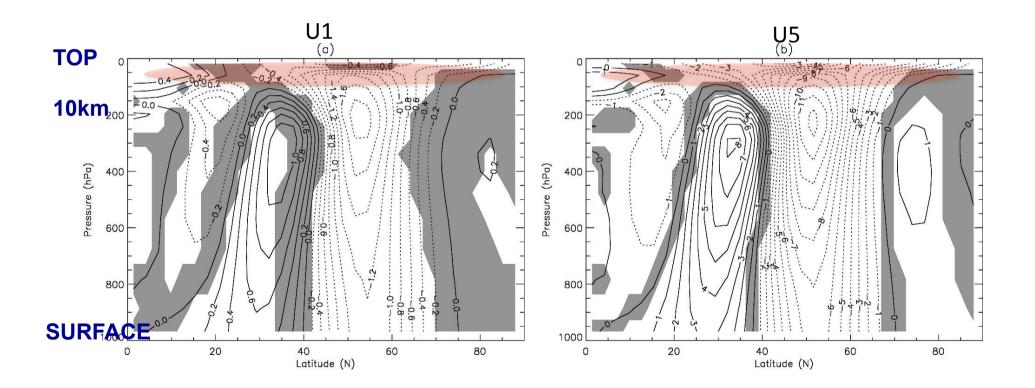


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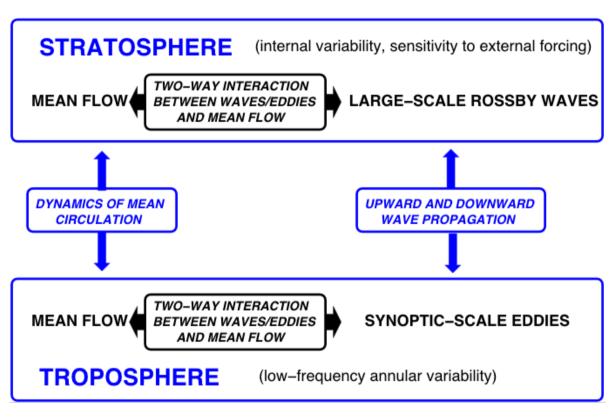
Simple model of solar cycle effects

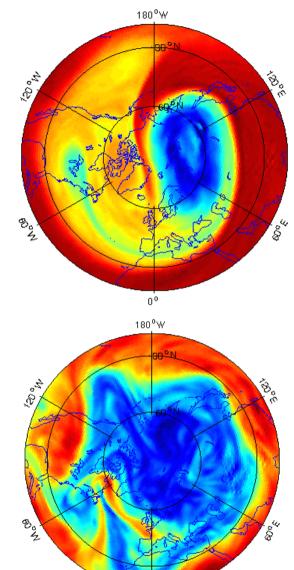
Haigh et al (2005): response of simple troposphere to imposed changes, e.g. uniform increase in radiative equilibrium temperature in stratosphere







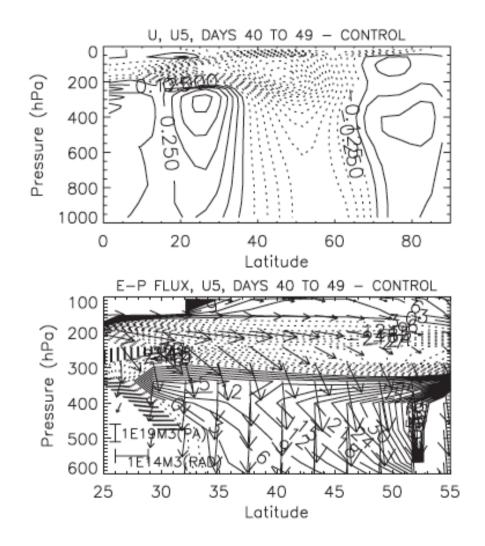








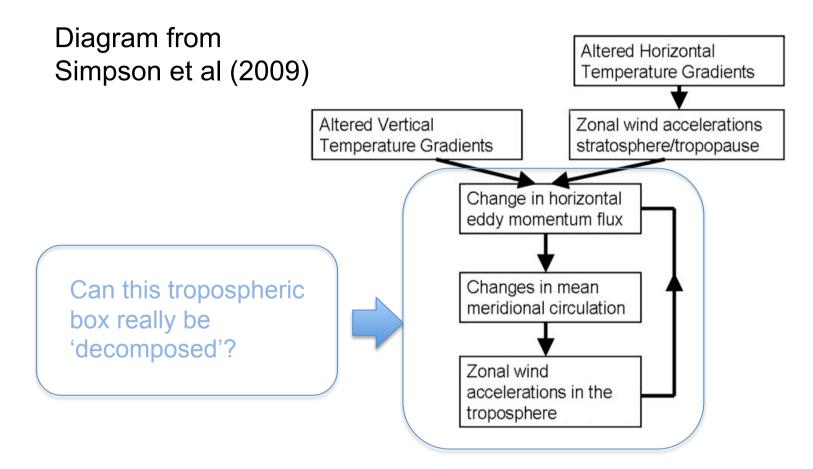
Changes in eddy fluxes are a vital part of the tropospheric dynamical response (possibility of 'amplification')







Can we make *predictions* about the response of the tropospheric circulation?



Analogous tropospheric response problems: ozone hole (Gillett and Thompson 2003), stratospheric perturbation (Polvani and Kushner 2002, Song and Robinson 2004), surface friction (Chen et al 2007), tropospheric heating (Butler et al 2010)





(b) U (m/s), σ= 0.875 90 (a) U (m/s), $\sigma = 0.275$ I'VII MVV Latitude (deg) 6 7 9 9 2 09 Latitude (deg) o . a born -50 -50 (c) energy (d) $-\partial(vu)/\partial y$ (m/s/day), $\sigma = 0.275$, (6 day mean) _K_F __K_ Latitude (deg) 10⁵ J/m² F -50 200 250 -50 100 150 200 250 300 Time(day) Time(day)

Reduction in surface friction in simple circulation model

Chen et al (2007): two-stage adjustment (short-time in jet strength followed by longer term change in jet position)





Chen et al (2007)

- 1) As the surface drag is reduced, the zonal wind acceleration is barotropic and proportional to the surface wind in the extratropics. Meanwhile, the baroclinic eodies are weakened by the incressifiace tropic motional shears are directly implicated in the poleward shift.
- 2) The increase in the strength of the westerlies in the extratropics ands to faster eddy phase speeds, while the subtropical zonal winds barely shange. Hence, the critical latitude for these eddies is displaced poleward.
- 3) The dynamics of the wave breaking in the upper troposphere, in the presence of this poleward shift in critical latitude, shifts the eddy momentum flucts poleward, driving a poleward shift in the surface zonal winds and the eddy-driven is. This is particularly supported by the shallow water model results.
 Eddy
 - 4) Eddy heat fluxes, and the associated upward Eliasser Momentum effuxed to follow this upper-level eddy activity. This shift in the baroclinic eddy production provides some positive feedback on the upper-level shift.





Questions

- What is relation between spatial pattern of forcing and the amplitude and spatial pattern of response? ('preferred response', 'most effective forcing')
- Will different models overpredict or underpredict response (and correct pattern of response) relative to real atmosphere?

Seek a 'unified' approach to quantitative prediction of tropospheric response, rather than post-hoc explanation of each special case



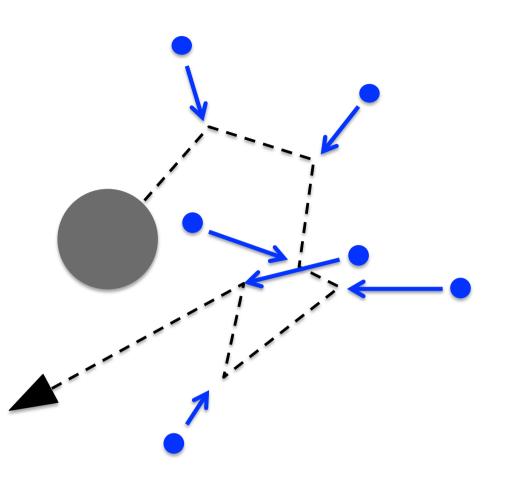


Brownian motion

Einstein (1905,1906) Smoluchowksi (1906)

'Observable' Diffusivity of Particle:

 $D_x = \langle V_x^2 \rangle \tau_{corr}$



Equipartition of kinetic energy:
$$\frac{1}{2}m\langle V_x^2\rangle = \frac{1}{2}\frac{RT}{N_A}$$

Stokes law for viscous drag force: $F_S = -k_S V = -6\pi \mu a V$





$$m\frac{dV_x}{dt} = -k_S V_x + f_R(t)$$

$$\langle f_R(t_1) f_R(t_2) \rangle = C\delta(t_1 - t_2)$$

$$\langle V_x(t_1) V_x(t_2) \rangle = \langle V_x^2 \rangle \exp(-k_S |t_1 - t_2|/m) \qquad \tau_{corr} = m/k_S$$

$$D = \frac{RT}{6N_A\pi\mu a} \qquad \text{EINSTEIN RELATION}$$

Velocity response to applied force

Applied force

FLUCTUATION -- DISSIPATION

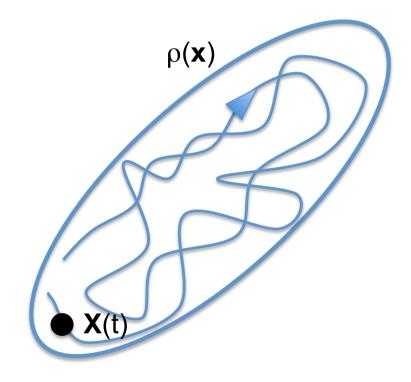
Time scale of fluctuations $\tau_{corr} = m/k_S$

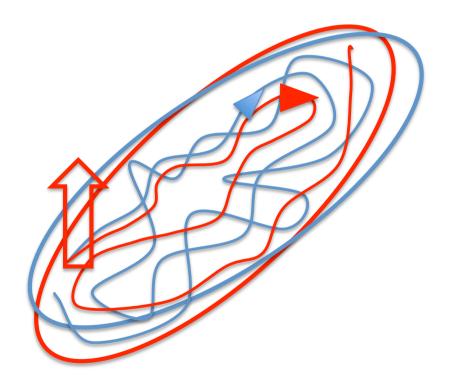




"Dynamical systems" approach

Calculation of change in statistical measure of chaotic/random system due to applied perturbation





UNDISTURBED SYSTEM

DISTURBED SYSTEM





Evolution equation
$$\frac{d\mathbf{X}}{dt} = \mathbf{U}(\mathbf{X}, t)$$

 $\mathbf{U}(\mathbf{X},t)$ is usually nonlinear and could contain explicit randomness

Equilibrium statistical properties described by probability density function $\rho(\mathbf{X})$

Perturb evolution equation
$$\ rac{d{f X}}{dt}={f U}({f X},t)+\Delta{f F}({f X},t)$$
 What is new $\
ho({f x})$?

[Perturbations to individual trajectories are large – perturbations to overall statistics are small.]





Consider small applied forcing $\, \Delta {f F} = {f f}({f x}) \delta(t) \,$

At
$$t=0: \rho(\mathbf{x}) \to \rho_+(\mathbf{x}) \simeq \rho(\mathbf{x}) - \nabla_{\mathbf{x}} \cdot (\mathbf{f}(\mathbf{x})\rho(\mathbf{x}))$$

 $\langle \phi(\mathbf{X}(\tau)) \rangle_{\mathbf{f}} = \int d\mathbf{x} \int d\mathbf{y} \phi(\mathbf{y}) \mathcal{P}(\mathbf{X}(\tau) = \mathbf{y} | \mathbf{X}(0) = \mathbf{x}) \rho_+(\mathbf{x})$

Compare identity

$$\langle \phi(\mathbf{X}(\tau))\psi(\mathbf{X}(0))\rangle =$$

$$\int d\mathbf{x} \int d\mathbf{y}\phi(\mathbf{y})\mathcal{P}(\mathbf{X}(\tau) = \mathbf{y}|\mathbf{X}(0) = \mathbf{x})\psi(\mathbf{x})\rho(\mathbf{x})$$
Hence $\langle \phi(\mathbf{X}(\tau))\rangle_{\mathbf{f}} \simeq \langle \phi(\mathbf{X}(\tau))\frac{\rho_{+}(\mathbf{x})}{\rho(\mathbf{x})}|_{\mathbf{x}=\mathbf{X}(0)}\rangle$ and
 $\Delta \langle \phi(\mathbf{X}(\tau))\rangle = -\langle \phi(\mathbf{X}(\tau))\frac{\nabla_{\mathbf{x}} \cdot (\mathbf{f}(\mathbf{x})\rho(\mathbf{x}))}{\rho(\mathbf{x})}|_{\mathbf{x}=\mathbf{X}(0)}\rangle$





Fluctuation-Dissipation Theorem

For steady **x**-independent $\Delta \mathbf{F}$

$$\Delta \langle \mathbf{X} \rangle = -\int_0^\infty d\tau \langle \mathbf{X}(\tau) \frac{\nabla_{\mathbf{x}} \rho(\mathbf{x})}{\rho(\mathbf{x})} |_{\mathbf{x} = \mathbf{X}(0)} \rangle . \Delta \mathbf{F} = \mathbf{L} \Delta \mathbf{F} \qquad \begin{array}{l} \mathbf{A}:\\ \text{General} \end{array}$$

f **X** is Gaussian then
$$\Delta \langle \mathbf{X} \rangle = \int_0^\infty d\tau \mathbf{C}(\tau) \mathbf{C}(0)^{-1} \cdot \Delta \mathbf{F} = \mathbf{L} \Delta \mathbf{F}$$
 B:
Gaussian

where
$$\mathbf{C}(au) = \langle \mathbf{X}(au) \mathbf{X}(0)
angle$$

Linear operator L given in terms of properties of undisturbed system

Crude approximation $\Delta \langle \mathbf{X} \rangle \sim \tau_{\text{correlation}} \times \Delta \mathbf{F}$





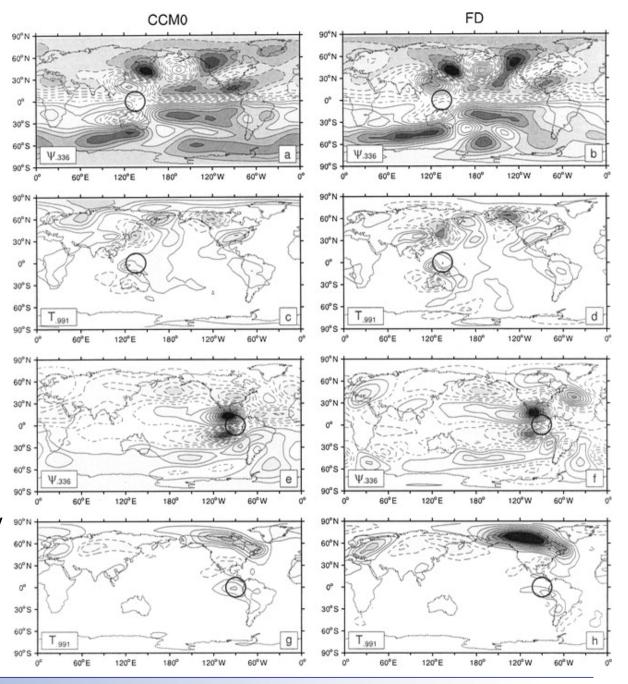
B:

Gritsun and Branstator (2007)

Application of Gaussian FDT to predict response to localised tropical heating in GCM

Individual AGCM integrations 40000 days

FDT estimate constructed from 4M day integration

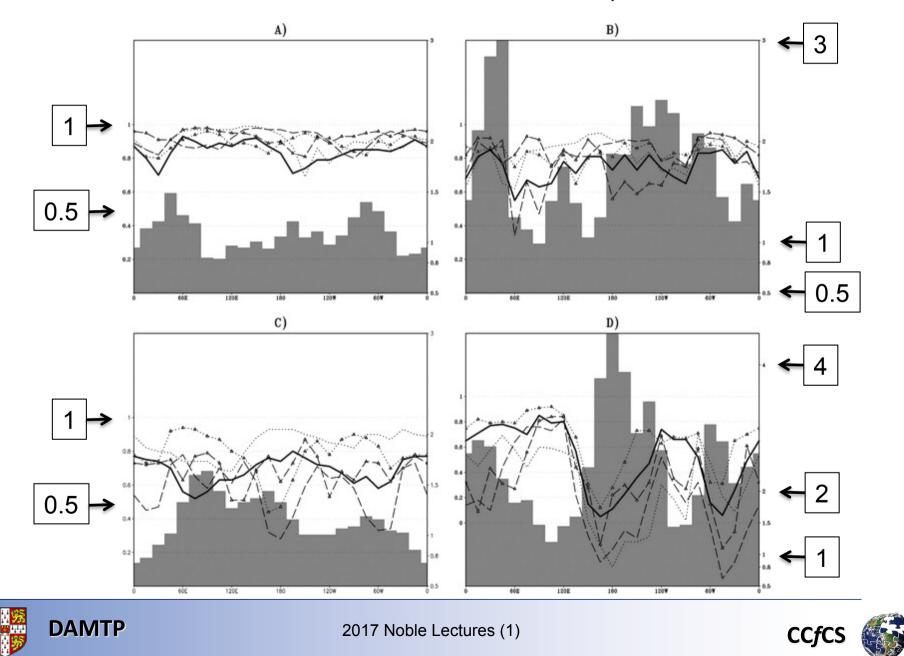


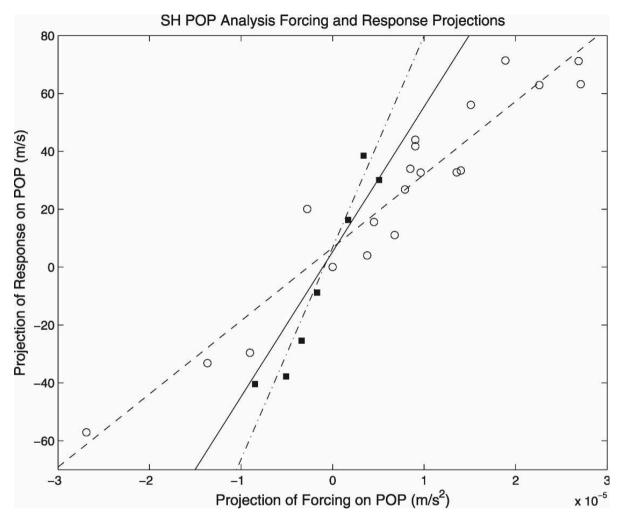




Gritsun and Branstator (2007)

Success of FDT measured by pattern correlation and amplitude ratio.





Ring and Plumb (2008): Gaussian FDT makes incorrect prediction for response to zonally symmetric thermal (■) and mechanical (**O**) forcings



Practical issues in applying the FDT

$$\mathbf{L} = \int_0^\infty \, d\tau \, \mathbf{C}(\tau) \, \mathbf{C}(0)^{-1}$$

- EOFs (which diagonalise C(0)) are a natural choice of variable (but not the only possible choice)
- < $C(\tau) C(0)^{-1}$ > must be estimated from available data.
- C(0)⁻¹ potentially ill-conditioned number of useful EOFs may be restricted by length of data series
- integration from $\tau = 0$ to $\tau = \infty$ must be approximated by finite sum





Statistical requirements on application of Gaussian FDT Cooper and H 2012

60 0.8 40 9.0 Correlation Response 20 0 0.2 -20 0 20 Lag 10 30 40 500 1000 1500 2000 Run length FDT prediction of response





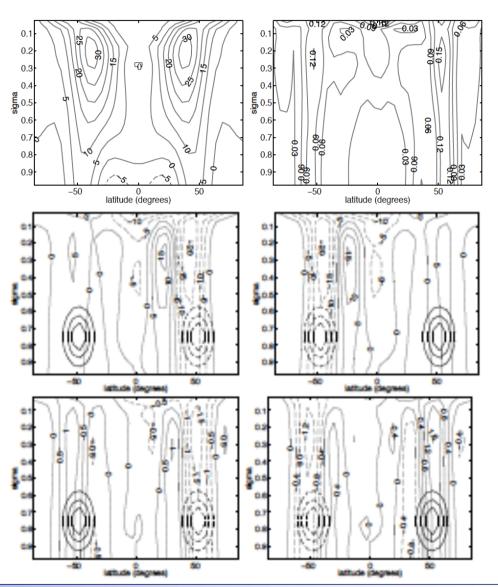


Study based on simple T21L20 general circulation model (Cooper and H 2012)

10000 day simulations, mean and variance

Forced response +/- 1 m/s/day

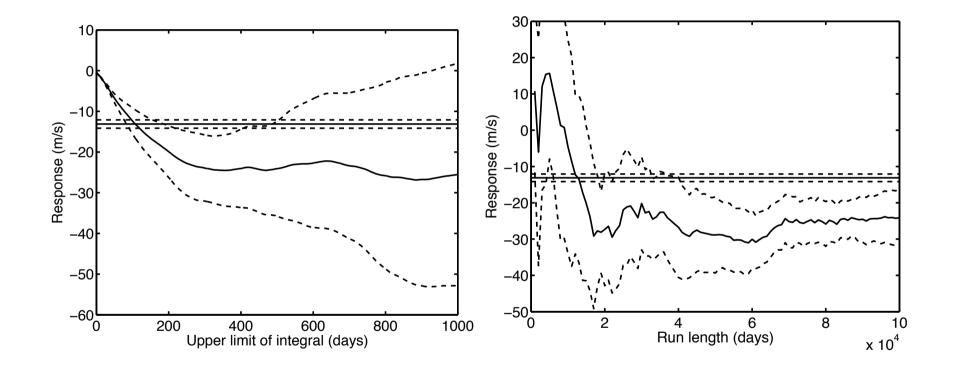
Forced response +/- 0.1 m/s/day







Application of the FDT to predict the response to forcing of a simple T21L20 general circulation model

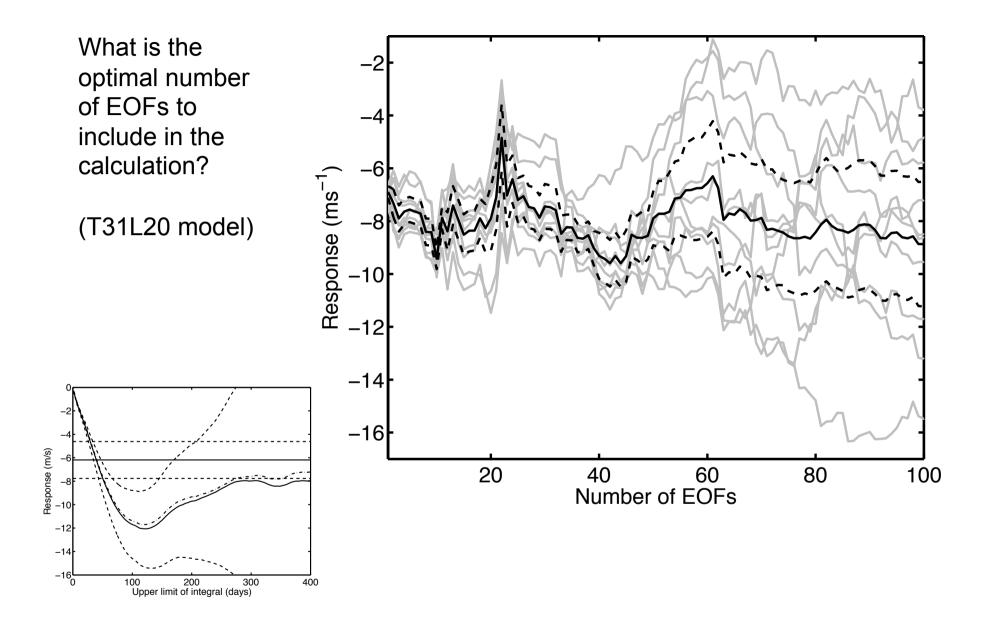


(10 x 10⁵ day integrations)

(300 day upper limit to integral)









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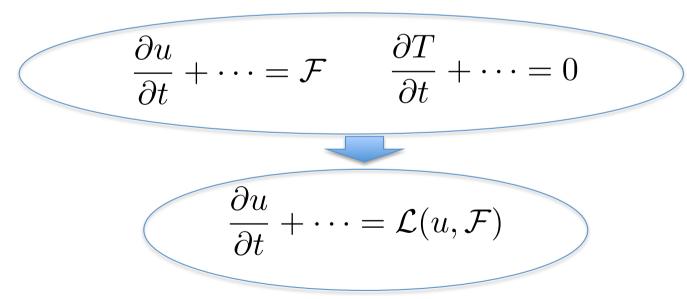


Specification of forcing

$$\mathbf{L}_{\mathrm{Gaussian}} = \int_0^\infty d\tau \mathbf{C}(\tau) \mathbf{C}(0)^{-1}$$
 Where did the equations go?

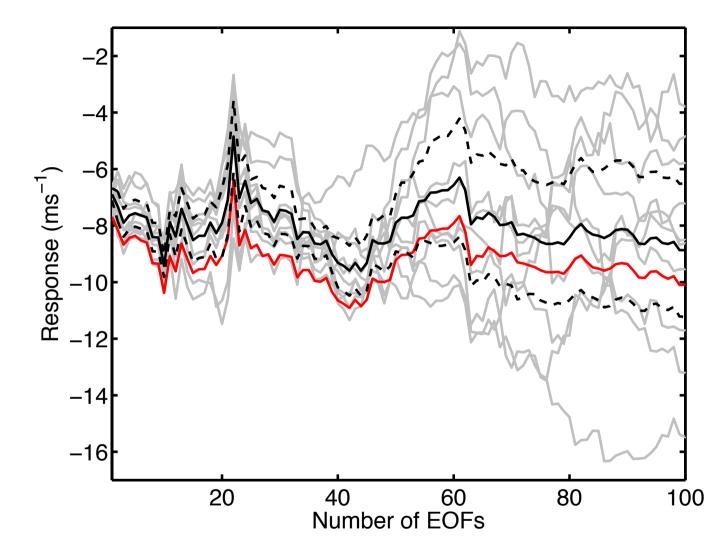
Implications of truncation

e.g. Ring and Plumb (2007)







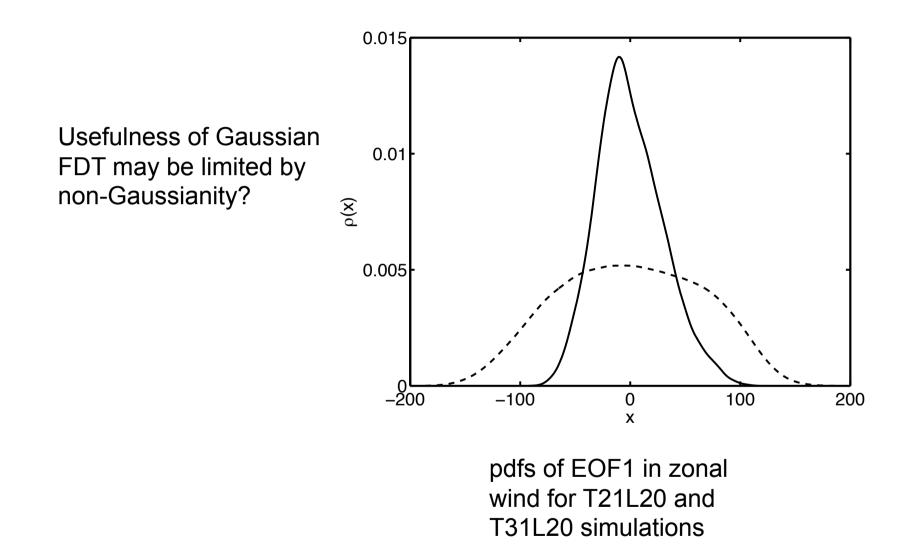


Effect of using climatological u versus u=0 in

$$\mathcal{L}(u,\mathcal{F})$$











The non-Gaussian case – a 'non-parametric FDT'

Cooper and H 2011

$$\Delta \langle \mathbf{X} \rangle = -\int_0^\infty d\tau \langle \mathbf{X}(\tau) \frac{\nabla_{\mathbf{x}} \rho(\mathbf{x})}{\rho(\mathbf{x})} |_{\mathbf{x} = \mathbf{X}(0)} \rangle. \Delta \mathbf{F}$$

Estimate using kernel density estimator method of non-parametric statistics

$$\hat{\rho}(\mathbf{x}; h, N) = \frac{1}{Nh^d} \sum_{i=1}^N K(\frac{\mathbf{x} - \mathbf{X}_i}{h})$$
$$\nabla_{\mathbf{x}} \hat{\rho}(\mathbf{x}; h, N) = \dots$$
Simplest

Simplest choice for K(.) is isotropic Gaussian

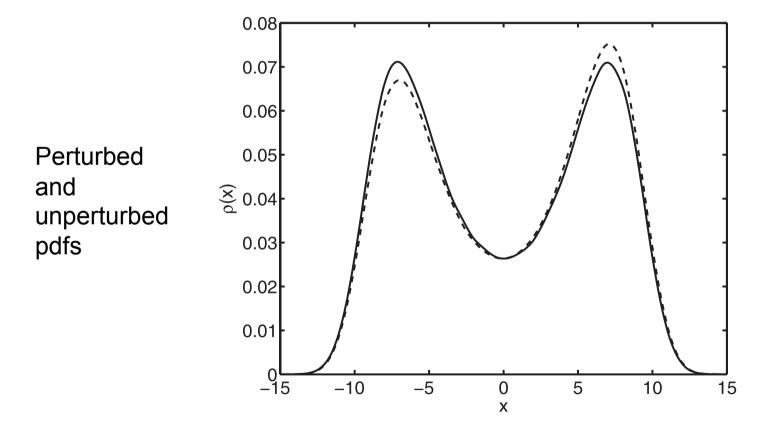
Bias and Uncertainty depend on h and N.





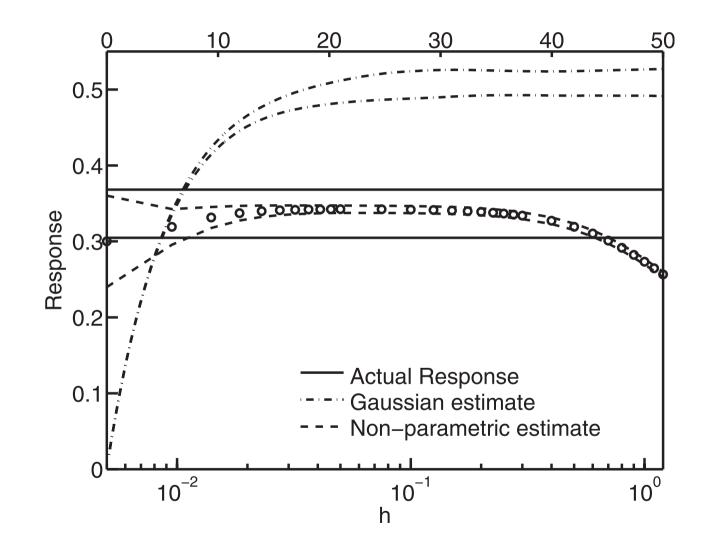
strongly non-Gaussian test case

$$\frac{dX}{dt} = b_1 X - b_2 X^3 + \xi$$





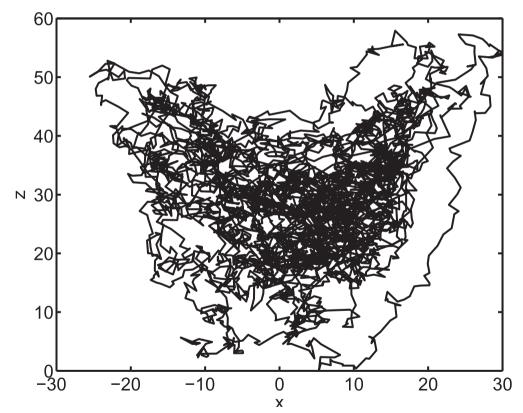






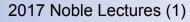


Application to stochastic Lorenz 1963 model

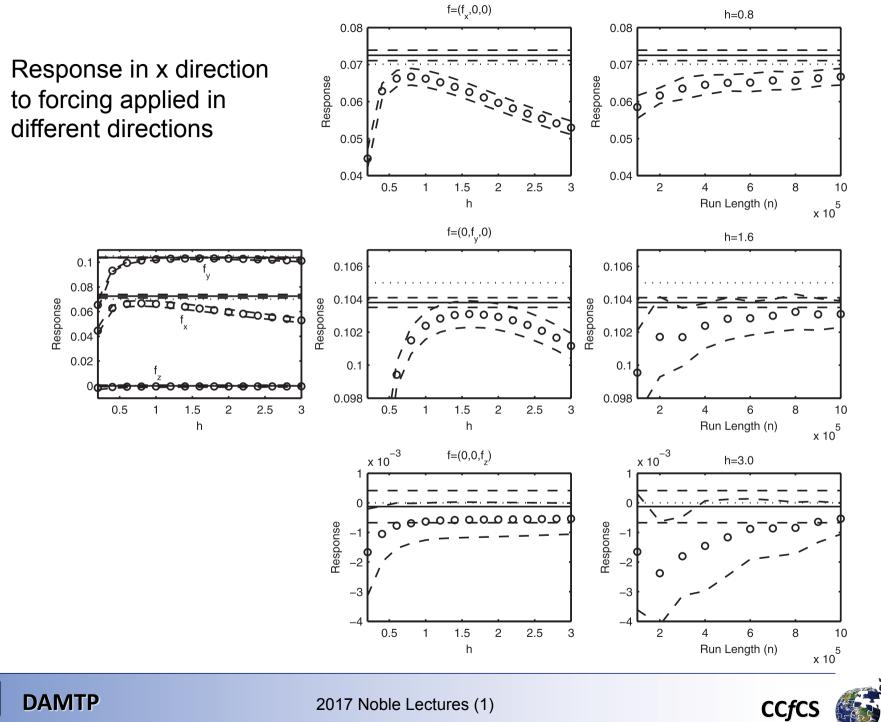


Compare with Thuburn (2005) approach of solving Fokker-Planck equation



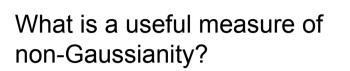


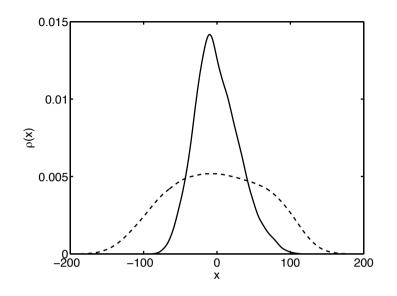




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DAMTP





$$\mathbf{L} - \mathbf{L}_{\text{Gaussian}} = \int_0^\infty d\tau \langle \{ \langle \mathbf{X}(\tau) | \mathbf{X}(0) \rangle \{ -\rho(\mathbf{x})^{-1} \nabla_{\mathbf{x}} \rho(\mathbf{x}) |_{\mathbf{x} = \mathbf{X}(0)} - \mathbf{X}(0) \cdot \mathbf{C}(0)^{-1} \} \rangle$$

Depends on structure of time correlations as well as form of pdf





Summary

•FDT potentially provides a quantitative description of tropospheric response to forcing (e.g. ozone hole, solar cycle, greenhouse gas increase) given information on statistics of unforced circulation

•If model low-frequency variability (timescales and patterns) is wrong then response to forcing will be wrong

•Typical response to forcing will be leading singular vector of response operator (providing forcing has significant projection onto leading singular vector), not necessarily the leading EOF.

•In practice can FDT do better than simple estimation of timescale of leading EOF?

•Applications? Model assessment/intercomparison?





Future lines of work? (Is the FDT a practical quantitative tool?)

•Statistical nature of FDT requires explicit information on/ estimates for bias and uncertainty

•Non-gaussian extension of FDT potentially extends validity (but there are challenges in implementation – can we escape the 'curse of dimensionality' or avoid it by working in a truncated system?)

•FDT for truncated system is non-trivial – need to consider proper 'effective forcing' on truncated system.

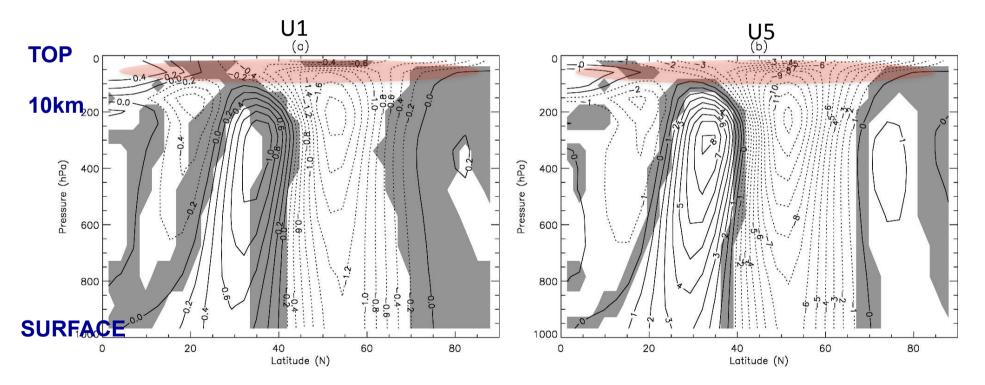
•Clearer practical guide to implementation of FDT (How long a data record is needed for required precision? How many degrees of freedom to include?)





Usefulness of linear theory?

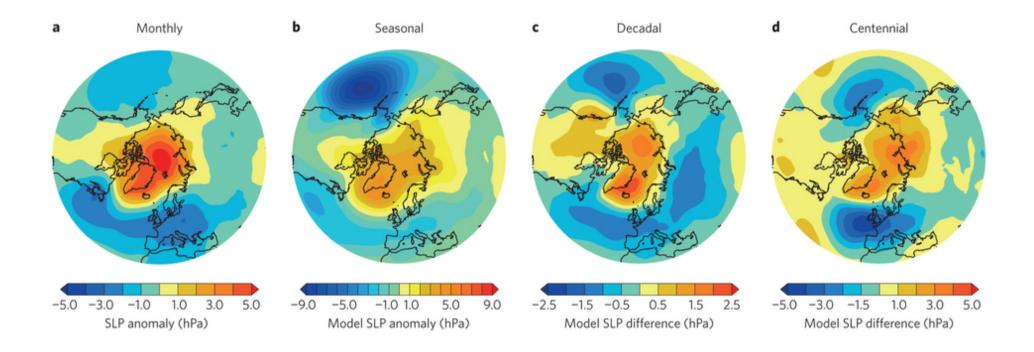
depends on problem being considered – but recall Haigh et al (2005)







Kidston et al (2015): tropospheric response to stratosphere on different timescales







FDT – cultural differences

20th century physics: large systems, small fluctuations, FDT has been discussed/applied/interpreted in terms of macroscopic variables.

21st century physics: extension to non-equilibrium small systems with large fluctuations?

Dynamical systems: Formal derivation/justification of 'fluctuation-response' operators, conditions for applicability, can problems of non-smoothness/non-differentiability be overcome?

Climate/circulation: Evaluation of 'fluctuation-response' operator from model simulation (or from data?) is a problem in statistics of large-degree-of-freedom systems. How much data is needed for required accuracy? How can effective dimensionality be most effectively reduced?



