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Response, Stochasticity and Memory Effects in Multi-level Dynamical Systems

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Goals

- Recent results of the perturbation theory for non-equilibrium statistical mechanics
 - > Deterministic & Stochastic Perturbations
- General properties
- Applications on system of geophysical fluid dynamical interest
 - > Lorenz 96 – various observables
- What is a parametrization?
 - > Mori Zwazig and Ruelle approaches
- Try to convince you this is a useful framework

Major theoretical challenges for complex, non-equilibrium systems

- Mathematics: Stability prop of time mean state say nothing on the prop of the system
 - > Cannot define a simple theory of the time-mean properties relying only on the time-mean fields.
- Physics: “no” fluctuation-dissipation theorem for a chaotic dissipative system
 - > non-equivalence of external/ internal fluctuations
 - ➔ Climate Change is hard to parameterise
- Numerics: Complex systems feature multiscale properties, they are stiff numerical problems, hard to simulate “as they are”

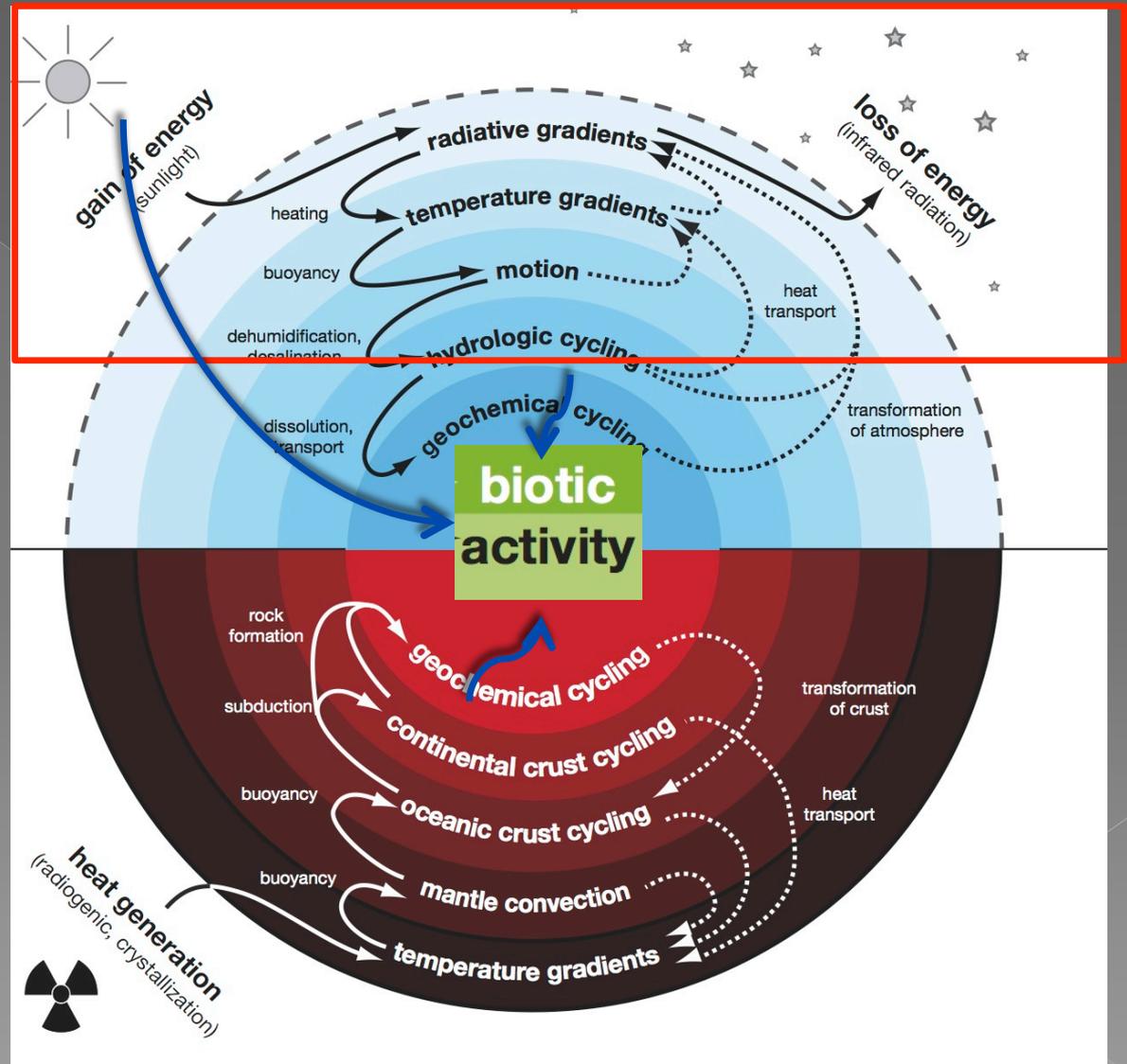
A complex system: our Earth

Nonlinearity

Irreversibility

Disequilibrium

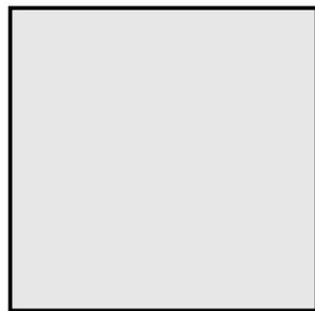
Multiscale



(Kleidon, 2011)

Looking for the big picture

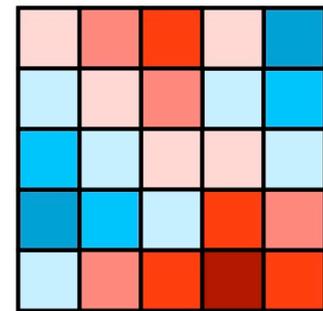
- ◉ Global structural properties (Saltzman 2002).
- ◉ Deterministic & stochastic dynamical systems
 - > Example: stability of the thermohaline circulation
 - > Stochastic forcing: ad hoc “closure theory” for noise
- ◉ Stat Mech & Thermodynamic perspective
 - > Planets are non-equilibrium thermodynamical systems
 - > Thermodynamics: large scale properties of climate system; definition of robust metrics for GCMs, data
 - > Ergodic theory and much more
 - > Stat Mech for Climate response to perturbations



EQ



*power required to
maintain disequilibrium*



NON EQ

Response theory

- The response theory formalizes a Gedankenexperiment: a system, a measuring device, a clock, and a set of turnable knobs.
- Changes of the statistical properties of a system in terms of the unperturbed system
- Divergence in the response is informative of “tipping points”, where phase transitions occur
- This seems a suitable environment for developing a climate change theory
 - “Blind” use of several CM experiments
 - We struggle with concepts and computations of climate sensitivity and climate response
- We can use the theory for deriving parametrizations!

Axiom A systems

- Axiom A dynamical systems are very special
 - > Include Anosov flows (hyperbolic, struct. stable, dense)
 - > Non-wandering set is hyperbolic
 - > Periodic points are dense
 - > SRB invariant measure: time averages converge in a Lebesgue sense to the ensemble averages for measurable observables
- When we perform numerical simulations, we more or less implicitly set ourselves in these hypotheses
 - > Not generic systems, but, following the chaotic hypothesis by Gallavotti and Cohen (1995, 1996), systems with many d.o.f. can be treated as if they were Axiom A systems when macroscopic averages are considered.
 - > Extension of ergodic hypothesis
 - > These are, in some sense, good physical models!!!

SRB measure

- The invariant measure of the unperturbed system is not absolutely continuous w.r.t. Lebesgue
 - > it is so only along the unstable (and neutral) manifold
 - > it is singular in the stable directions (effect of the contraction!)
 - > Locally, "Cantor set times a smooth manifold".
 - > Kolmogorov measure...
- For deterministic, dissipative chaotic etc. systems FDT does not work
 - > It is not possible to write the response as a correlation integral, there is an additional term
 - > The system, by definition, never explores the stable directions, whereas a perturbation has components also outside the unstable manifold
- But...

Applicability of FDT

- For deterministic, dissipative chaotic etc. systems FDT does not work
 - It is not possible to write the response as a correlation integral, there is an additional term
 - The system, by definition, never explores the stable directions, whereas a perturbation has components also outside the unstable manifold
- Recent studies (Branstator et al.) suggest that, nonetheless, information can be retrieved
- What is the time needed to build up a statistics such that the FDT gives useful results?
 - Probably, numerical noise also helps
 - The choice of the observable is surely also crucial

Ruelle ('98) Response Theory

○ If the Axiom A flow is perturbed as: $\dot{x} = F(x) + e(t)X(x)$

○ We can express the expectation value of an observable Φ as:

$$\langle \Phi \rangle(t) = \langle \Phi \rangle_0 + \sum_{n=1}^{\infty} \langle \Phi \rangle^{(n)}(t)$$

○ where the n^{th} order perturbation can be expressed as:

$$\langle \Phi \rangle^{(n)}(t) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \dots \int_{-\infty}^{\infty} d\sigma_1 d\sigma_2 \dots d\sigma_n G^{(n)}(\sigma_1, \dots, \sigma_n) e(t - \sigma_1) e(t - \sigma_2) \dots e(t - \sigma_n).$$

This is a perturbative theory...

- with a causal Green function:

$$G^{(n)}(\sigma_1, \dots, \sigma_n) = \int \rho_{SRB}(dx) \Theta(\sigma_1) \Theta(\sigma_2 - \sigma_1) \dots \Theta(\sigma_n - \sigma_{n-1}) \times \\ \times \Lambda \Pi(\sigma_n - \sigma_{n-1}) \dots \Lambda \Pi(\sigma_2 - \sigma_1) \Lambda \Pi(\sigma_1) \Phi(x)$$

- > Expectation value of an operator evaluated over the invariant measure $\rho_{SRB}(dx)$ of the unperturbed flow!

- where: $\Lambda(\bullet) = X(x)\nabla(\bullet)$ and $\Pi(\tau)A(x) = A(x(\tau))$

Projection on the
perturbation flow

Unperturbed evolution operator

- Kubo theory (Equil.) is a special case... L. 2008

Linear case

○ Perturbation to Φ : $\langle \Phi \rangle^{(1)}(t) = \int d\sigma G_{\Phi}^{(1)}(\sigma) e(t-\sigma)$

○ Linear Green: $G_{\Phi}^{(1)}(t) = \int \rho_0(dx) \Theta(t) \Lambda \Pi(t) \Phi$

○ Short-term for G $G_{\Phi}^{(1)}(t) \approx \alpha \Theta(t) t^{\beta} + o(t^{\beta})$

○ Asymptotics for χ $\chi_{\Phi}^{(1)}(\omega) \approx \alpha i^{\beta+1} \beta! \omega^{-\beta-1} + o(\omega^{-\beta-1})$

○ If β is even, $\text{Im} \{ \chi \}$ dominates

○ If β is odd, $\text{Re} \{ \chi \}$ dominates

○ Short term behaviour of $G \rightarrow$ asymptotic behaviour of χ !

Kramers-Kronig relations

- The in-phase and out-of-phase responses are connected by Kramers-Kronig relations:
 - Measurements of the real (imaginary) part of the susceptibility \rightarrow K-K \rightarrow best estimate of the imaginary (real)
- Every causal linear model obeys these constraints
- K-K exist also for nonlinear susceptibilities

$$\Re \left\{ \chi^{(1)}(\omega) \right\} = \frac{2}{\pi} \mathcal{P} \int_0^{\infty} \frac{\omega' \Im \left\{ \chi^{(1)}(\omega') \right\}}{\omega'^2 - \omega^2} d\omega'$$
$$\Im \left\{ \chi^{(1)}(\omega) \right\} = -\frac{2\omega}{\pi} \mathcal{P} \int_0^{\infty} \frac{\Re \left\{ \chi^{(1)}(\omega') \right\}}{\omega'^2 - \omega^2} d\omega'$$

with $\chi^{(1)}(\omega) = [\chi^{(1)}(-\omega)]^*$

Noise in Numerical Modelling

- Deterministic numerical models are supplemented with additional stochastic forcings.
- Overall practical goals:
 - an approximate but convincing representation of the spatial and temporal scales which cannot be resolved;
 - faster exploration of the attractor of the system, due to the additional “mixing”;
 - Especially desirable when computational limitations
- Fundamental reasons:
 - A good (“physical”) invariant measure of a dynamical system is robust with respect to the introduction of noise
 - exclusion of pathological solutions;
 - Limit of zero noise → statistics of the deterministic system?
 - Noise makes the invariant measure smooth
- A very active, interdisciplinary research sector

Stochastic forcing

○ $e(t) = \varepsilon \eta(t) = \varepsilon dW(t)/dt$ where $W(t)$ is a Wiener process

○ Therefore, $\langle \eta(t) \rangle = 0$ and $\langle \eta(t) \eta(t') \rangle = \delta(t - t')$

○ We obtain:

$$\begin{aligned} \delta_{\varepsilon,t} \rho(\Phi) = & \varepsilon \int d\tau G_{\Phi}^{(1)}(\tau) \eta(t - \tau) + \\ & + \varepsilon^2 \int d\tau_1 d\tau_2 G_{\Phi}^{(2)}(\tau_1, \tau_2) \eta(t - \tau_1) \eta(t - \tau_2) + o(\varepsilon^3) \end{aligned}$$

....

$$\begin{aligned} \langle \delta_{\varepsilon} \rho(\Phi) \rangle = & \varepsilon^2 \int d\tau_1 G_{\Phi}^{(2)}(\tau_1, \tau_1) + o(\varepsilon^4) = \\ = & 1/2 \varepsilon^2 \int \rho_0(dx) \int d\tau_1 \Theta(\tau_1) X_i \partial_i X_j \partial_j \Phi(f^{\tau_1} x) + o(\varepsilon^4) \end{aligned}$$

○ The linear correction vanishes; only even orders of perturbations give a contribution

○ No time-dependence

Some observations

- The correction to the expectation value of any observable \sim variance of the noise
 - › Stochastic system \rightarrow deterministic system
 - › Convergence of the statistical properties is fast
- We have an explicit formula!

Correlations...

- Ensemble average over the realisations of the stochastic processes of the expectation value of the time correlation of the response of the system:

$$\begin{aligned}\langle \int d\sigma \delta_{\varepsilon, \sigma} \rho(\Phi) \delta_{\varepsilon, \sigma-t} \rho(\Phi) \rangle &= \varepsilon^2 \int d\sigma d\tau_1 d\tau_2 G_{\Phi}^{(1)}(\sigma - \tau_1) G_{\Phi}^{(1)}(\sigma - t - \tau_2) \langle \eta(\tau_1) \eta(\tau_2) \rangle + o(\varepsilon^4) \\ &= \varepsilon^2 \int d\sigma G_{\Phi}^{(1)}(\sigma) G_{\Phi}^{(1)}(\sigma - t) + o(\varepsilon^4)\end{aligned}$$

- Leading order is proportional to ε^2
- It is the convolution product of the linear Green function!

So what?

- Computing the Fourier Transform we obtain:

$$\langle |\delta_{\varepsilon, \omega} \rho(\Phi)|^2 \rangle \approx \varepsilon^2 |\chi_{\Phi}^{(1)}(\omega)|^2$$

- Interestingly, we end up with the linear susceptibility...

- Let's rewrite the equation:

$$\langle P_{\varepsilon, \omega}(A) \rangle - P_{\omega}(A) \approx \langle |\delta_{\varepsilon, \omega} \rho(A)|^2 \rangle \approx \varepsilon^2 |\chi_1(\omega)|^2$$

- So: **difference** between the **power spectrum** of the signal in the cases with and without noise → **linear susceptibility**
 - Stoch forcing enhances the Power Spectrum

With some complex analysis

- We know that $\chi_{\Phi}^{(1)}(\omega)$ is analytic in the upper complex plane
- So is $\log[\chi_{\Phi}^{(1)}(\omega)] = \log|\chi_{\Phi}^{(1)}(\omega)| + i \arg[\chi_{\Phi}^{(1)}(\omega)]$
 - › Apart from complex zeros...
- The real ($\log|\chi_{\Phi}^{(1)}(\omega)|$) and imag ($\arg[\chi_{\Phi}^{(1)}(\omega)]$) obey KK relations
 - › From the observation of the power spectra we obtain the real part
 - › With KK analysis we obtain the imaginary part
- We can reconstruct the linear susceptibility!
- And from it, the Green function

Extensions: $\Delta (PS) > 0$ (noise)

> If $dx_i/dt = F_i(x) \rightarrow dx_i/dt = F_i(x) + \sum_{j=1}^p \varepsilon_j X_i^j(x) \eta_j(t)$ $\langle \eta_i(t) \eta_j(t') \rangle = C_{ij} \delta(t - t')$

○ $\langle P_{\{\varepsilon\}, \omega}(A) \rangle - P_\omega(A) \approx \langle |\delta_{\{\varepsilon\}, \omega} \rho(A)|^2 \rangle \approx \sum_{k=1}^p \varepsilon_k^2 |\chi_1^k(\omega)|^2 + \sum_{l>m=1}^p \varepsilon_l \varepsilon_m C_{l,m} [\chi_1^l(\omega) (\chi_1^m(\omega))^* + (\chi_1^l(\omega))^* \chi_1^m(\omega)]$

> If $dx_i/dt = F_i(x) \rightarrow dx_i/dt = F_i(x) + X_i(x) \eta(t)$ $\langle \eta(\tau_1) \eta(\tau_2) \rangle = D(\tau_2 - \tau_1)$

○ $\langle P_{\varepsilon, \omega}(A) \rangle - P_\omega(A) \approx \langle |\delta_{\varepsilon, \omega} \rho(A)|^2 \rangle \approx |\chi_1(\omega)|^2 D(\omega)$

> If $dx_i/dt = F_i(x) \rightarrow dx_i/dt = F_i(x) + X_i(x, t)$ → Schauder Dec.

○ $\langle P_{\varepsilon, \omega}(A) \rangle - P_\omega(A) \approx \langle |\delta_{\{\varepsilon\}, \omega} \rho(A)|^2 \rangle \approx \sum_{l=1}^p |\chi_1^l(\omega)|^2 D_{l,l}(\omega) + \sum_{l>m=1}^p D_{l,m}(\omega) \chi_1^l(\omega) [\chi_1^m(\omega)]^* + D_{m,l}(\omega) [\chi_1^l(\omega)]^* \chi_1^m(\omega)$

Lorenz 96 model

- Excellent toy model of the atmosphere
 - > Advection
 - > Dissipation
 - > Forcing
- Test Bed for Data assimilation schemes
- Becoming popular in the community of statistical physicists
 - > Scaling properties of Lyapunov & Bred vectors
- Evolution Equations

$$\dot{x}_i = x_{i-1} (x_{i+1} - x_{i-2}) - x_i + F \quad i = 1, \dots, N \quad x_i = x_{i+N}$$

- Spatially extended, 2 Parameters: N & F

Some properties

○ Let

$$E = \sum_{j=1}^N \frac{x_j^2}{2} \quad M = \sum_{j=1}^N x_j$$

○ and

$$e = \frac{E}{N} \quad m = \frac{M}{N}$$

○ Stationary State:

$$2\langle e \rangle_0 = F\langle m \rangle_0$$

○ Closure: $\langle m \rangle_0 \approx \lambda F^\gamma \quad F \geq 5; \lambda \approx 1.15; \gamma \approx 0.35$

> System is extended, in chaotic regime the properties are intensive

○ We perform simulations with specific $F=8$ and $N=40$, but results are “universal”

Global Perturbation

- $F \rightarrow F + \varepsilon e(t)$

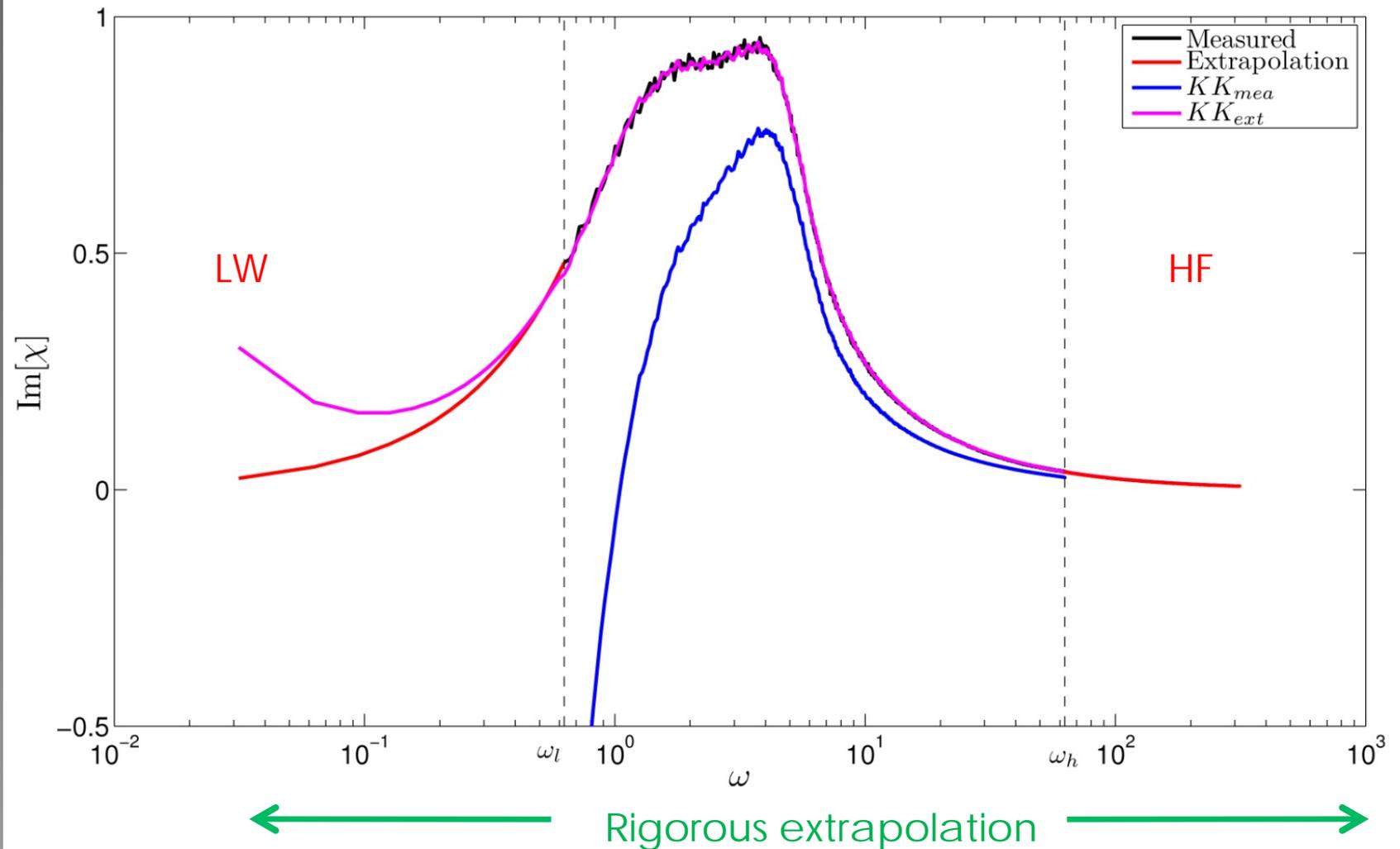
- Observable: $e = E/N$

$$G_e^{(1)}(t) \approx \Theta(t) \langle m \rangle_0 + \Theta(t) t (F - 2 \langle m \rangle_0) + \dots$$

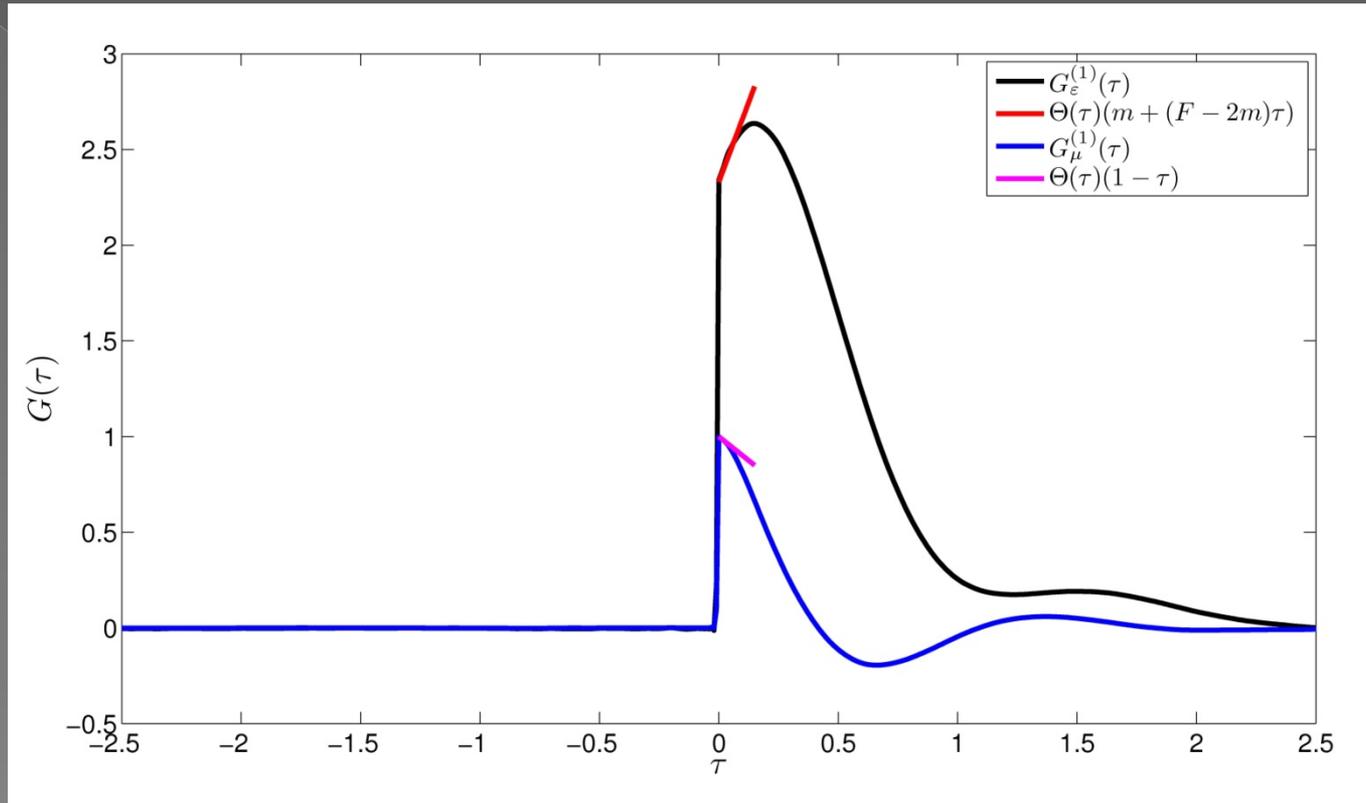
$$\chi_e^{(1)}(\omega) \approx i \frac{\langle m \rangle_0}{\omega} - \frac{(F - 2 \langle m \rangle_0)}{\omega^2} + \dots$$

- We can compute the leading order for both the real and imaginary part

Imag part of the susceptibility



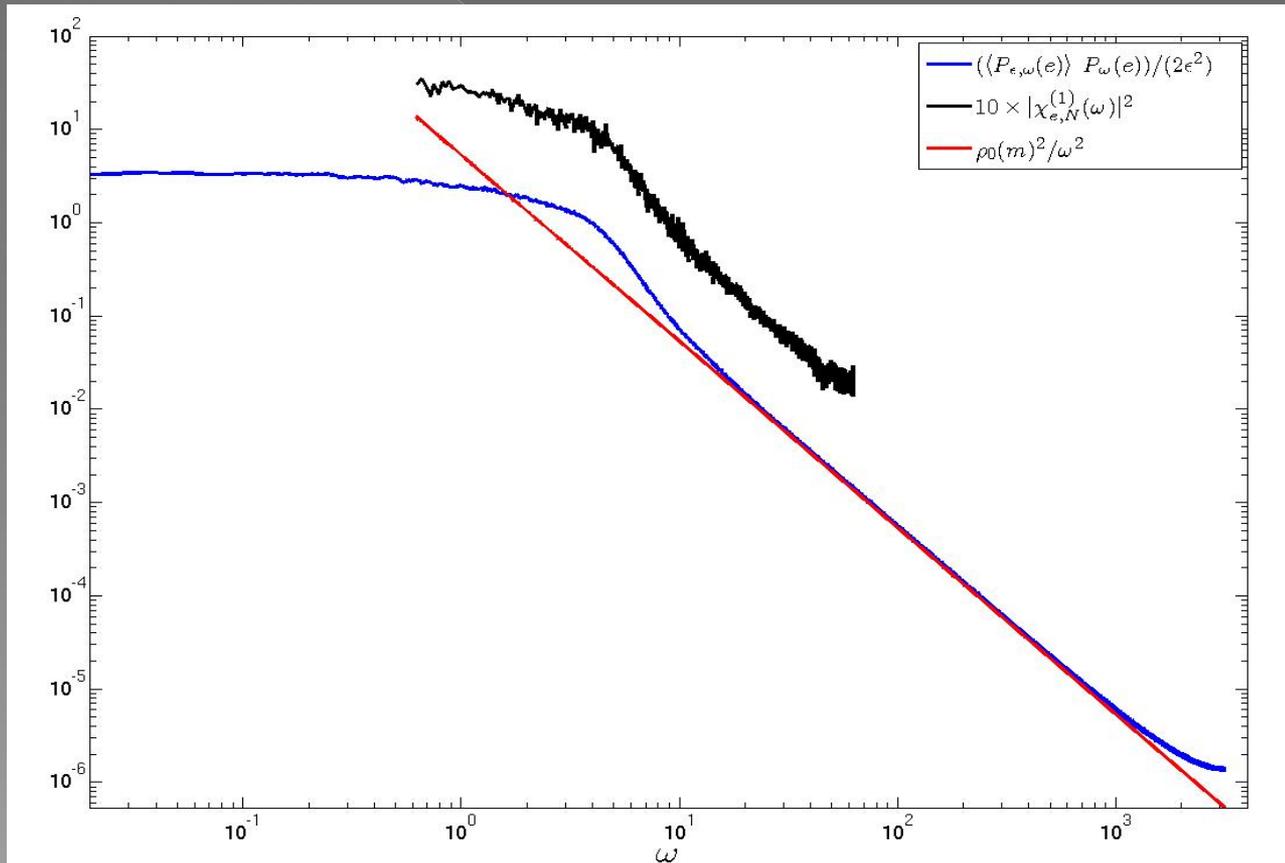
Green Function!



- Inverse FT of the susceptibility
- Response to any forcing with the same spatial pattern but with general time pattern

Using stochastic forcing...

- Squared modulus of $\chi_e^{(1)}(\omega)$
- Blue: Using stoch pert; Black: deter forcing
- ... And many many many less integrations



A Climate Change experiment

- ▶ Observable: globally averaged T_S
- ▶ Forcing: increase of CO_2 concentration
- ▶ Linear response: $\langle T_S \rangle^{(1)}(t) = \int d\sigma G_{T_S}^{(1)}(\sigma) e(t - \sigma)$
- ▶ Let's perform an ensemble of experiments
 - ▶ Concentration is increased at $t=0$ and brought back to initial value at $t = \tau$ $e(t) = \varepsilon [\Theta(t) - \Theta(t - \tau)]$
- ▶ Fantastic, we estimate $\langle T_S \rangle^{(1)}(\omega)$
- ▶ ...and we obtain: $\chi^{(1)}(\omega) = \frac{\langle T_S \rangle^{(1)}(\omega)}{\varepsilon (\sin(\omega\tau) + i(1 - \cos(\omega\tau)))}$
- ▶ ... Now we can predict future T_S

What is a Parametrization?

Consider a two-level system

$$\begin{cases} \dot{X} = F_X(X) + \Psi_X(X, Y) \\ \dot{Y} = F_Y(Y) + \Psi_Y(X, Y) \end{cases}$$

- **unperturbed** = uncoupled
- **perturbation** = coupling Ψ
- modelling = a perturbation of X that mimics this response

- Surrogating the coupling: Fast \rightarrow Slow Variables
- Optimising Computer Resources
- Underlining Mechanisms of Interaction

How to Construct a Parametrization?

- We try to match the evolution of the single trajectory of the X variables
 - Mori-Zwanzig Projector Operator technique: needs to be made explicit
 - Accurate "Forecast"
- We try to match the statistical properties of a general observable $A=A(X)$
 - Ruelle Response theory
 - Accurate "Climate"
- Match between these two approaches?

That's the result!

- This system has the same expectation values as the original system (up to 2nd order)
- We have explicit expression for the three terms a (deterministic), b (stochastic), c (memory)- 2nd order expansion

$$\frac{dX(t)}{dt} = F_X(X(t)) + M_X(X(t)) + \sigma(t)$$

Deterministic ✓

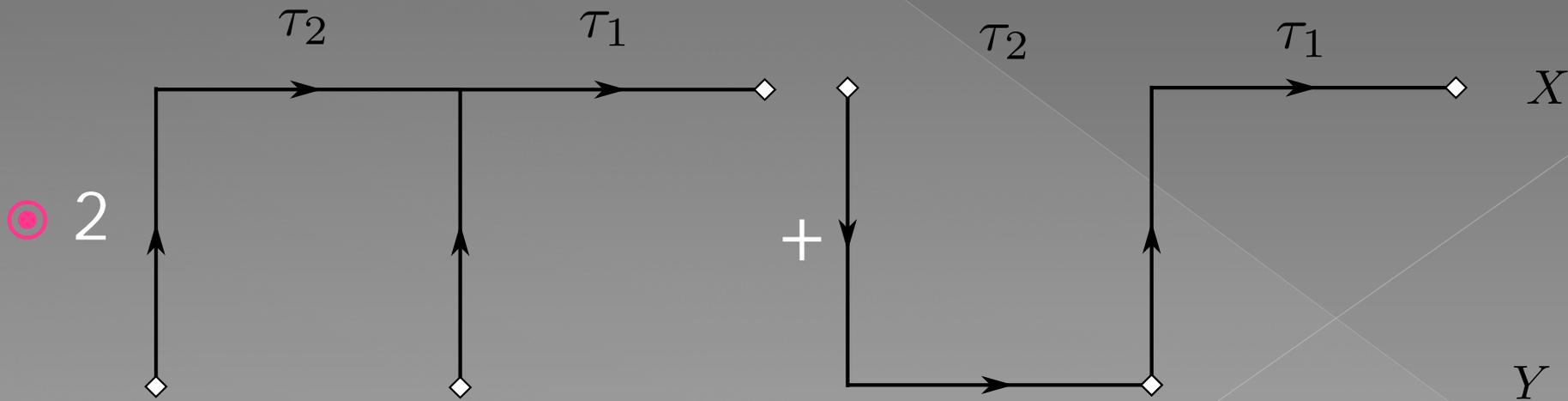
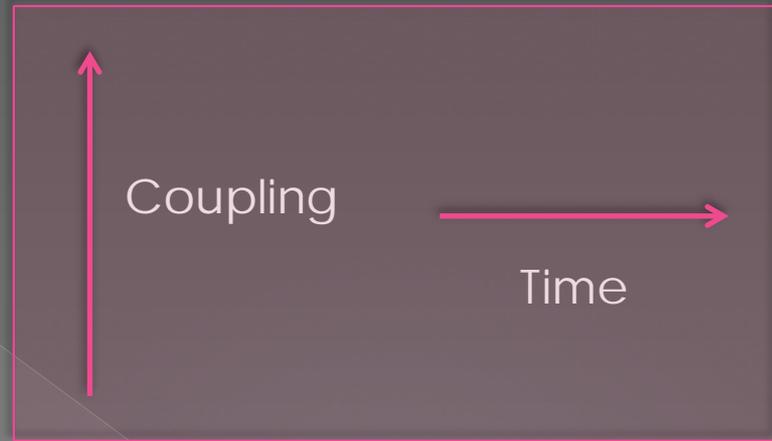
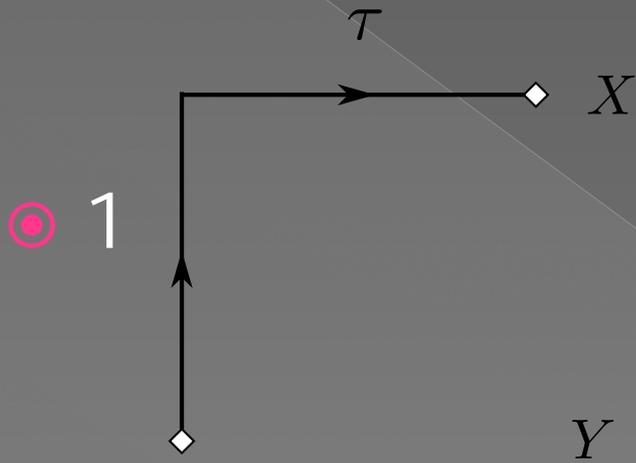
Stochastic ✓

Memory ✗

T
O
D
A
Y

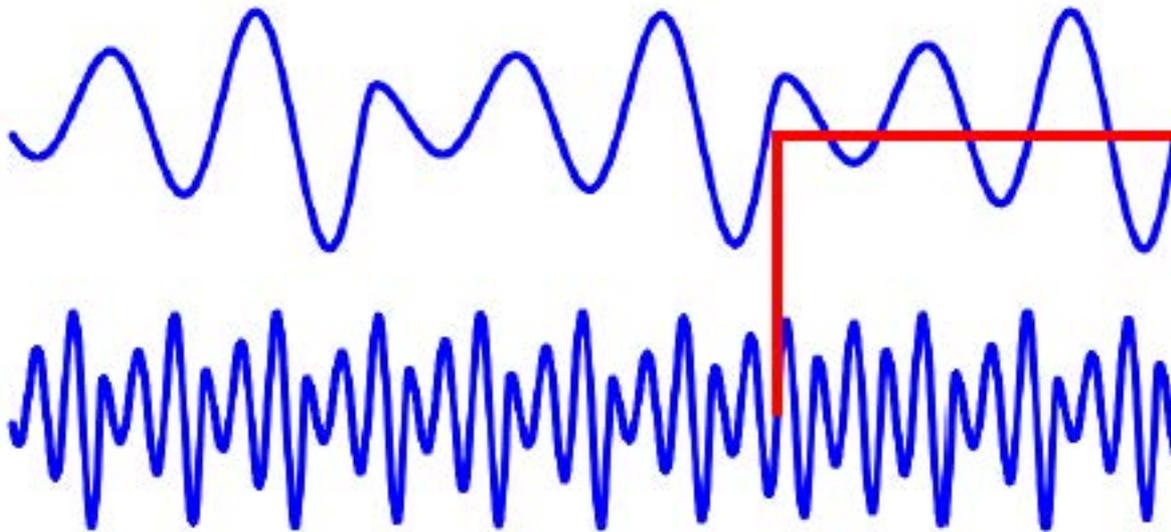
$$+ \int_0^{\infty} d\tau h(\tau, X(t - \tau))$$

Diagrams: 1st and 2nd order



Mean Field

First order term: averaged coupling $\langle \Psi_X(X, Y) \rangle_{\rho_Y}$



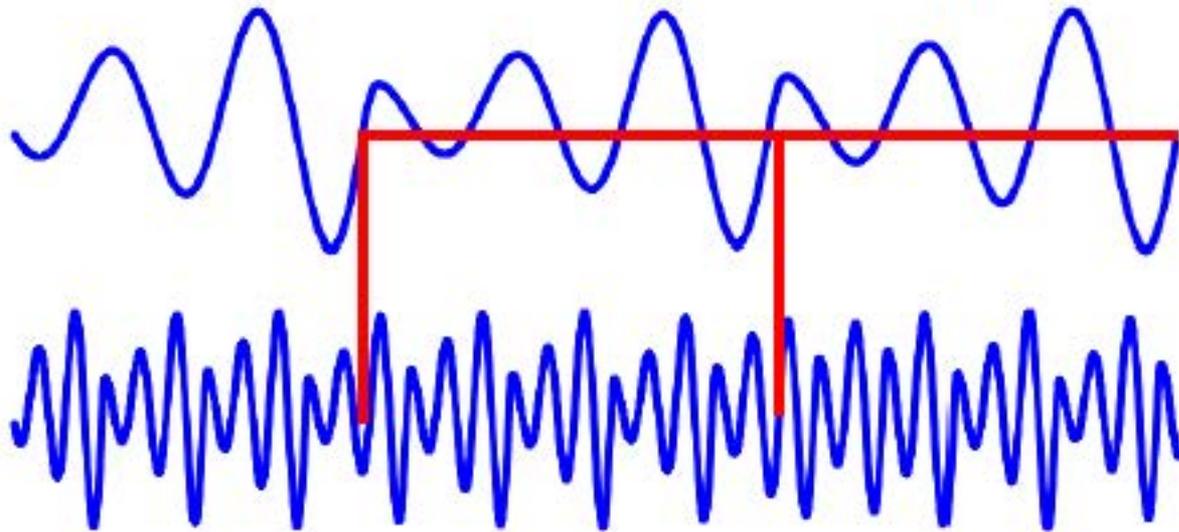
- ◉ Deterministic Parametrization
 - > This is the "average" coupling

$$M_X(X(t))$$

Fluctuations

Second order term (1/2): fluctuations around the mean

$$\langle \delta\Psi_X(X, Y) \delta\Psi_X(f^\tau(X), f^\tau(Y)) \rangle_{\rho_Y}$$

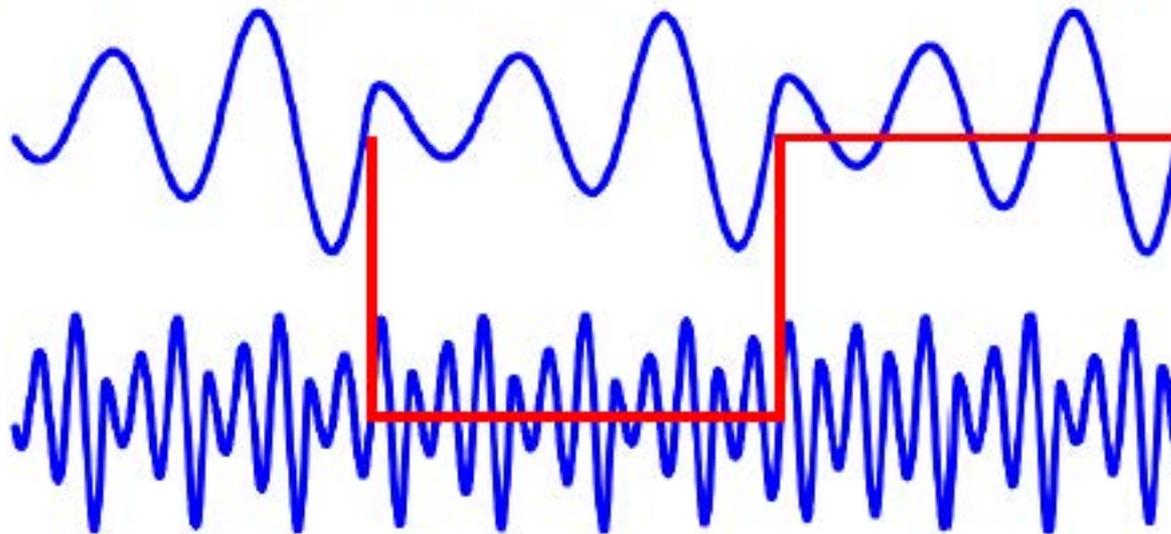


- Stochastic Parametrization
 - Expression for correlation properties

 $\sigma(t)$

Memory

Second order term (2/2): memory effect
 $\langle \Psi_{Y,i}(X, Y) \partial_{Y,i} \Psi_{X,j}(f^s(X), f^s(Y)) \rangle_{\rho_{0,Y}}$



- New term, small for vast scale separation
 - This is required to match local vs global

$$\int_0^{\infty} d\tau h(\tau, X(t - \tau))$$

Two words on Mori-Zwanzig

- Answers the following question
 - > what is the effective X dynamics for an ensemble of initial conditions $Y(0)$, when ρ_Y is known?
 - > We split the evolution operator using a projection operator P on the relevant variables
- Effective dynamics has a deterministic correction to the autonomous equation, a term giving a stochastic forcings (due to uncertainty in the the initial conditions $Y(0)$), a term describing a memory effect.
- One can perform an approximate calculation, expanding around the uncoupled solution...

Same result!

- Optimal forecast in a probabilistic sense
- 2nd order expansion
- Same as obtained with Ruelle
 - Parametrizations are “well defined” for CM & NWP

$$\frac{dX(t)}{dt} = F_X(X(t)) + M_X(X(t)) + \sigma(t)$$

- Memory required to match local vs global

$$+ \int_0^{\infty} d\tau h(\tau, X(t - \tau))$$

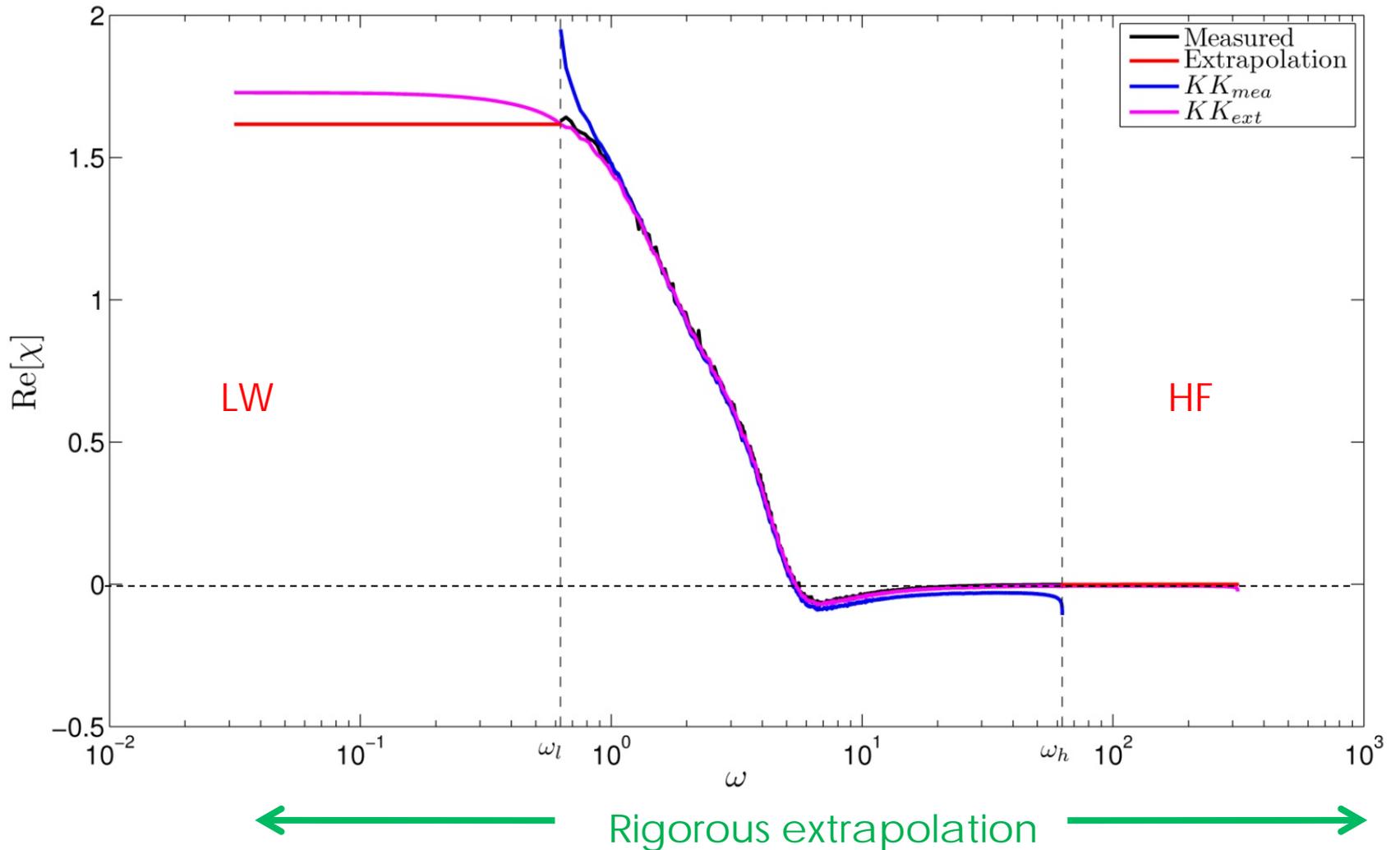
Conclusions

- We have used Ruelle response theory to study the impact of deterministic and stochastic forcings to non-equilibrium statistical mechanical systems
- Frequency-dependent response obeys strong constraints
 - > We can reconstruct the Green function!
- Δ expectation value of observable \approx variance of the noise
 - > SRB measure is robust with respect to noise
- Δ power spectral density \approx to the squared modulus of the linear susceptibility
 - > More general case: Δ power spectral density > 0
 - > The method is VERY parsimonious
- What is a parametrization? I hope I gave a useful answer
 - > We have ground for developing new and robust schemes
- Application to more interesting models
- OPENING A POST-DOC POSITION SOON

References

- D. Ruelle, Phys. Lett. 245, 220 (1997)
- D. Ruelle, Nonlinearity 11, 5-18 (1998)
- C. H. Reich, Phys. Rev. E 66, 036103 (2002)
- R. Abramov and A. Majda, Nonlinearity 20, 2793 (2007)
- U. Marini Bettolo Marconi, A. Puglisi, L. Rondoni, and A. Vulpiani, Phys. Rep. 461, 111 (2008)
- D. Ruelle, Nonlinearity 22 855 (2009)
- V. Lucarini, J.J. Saarinen, K.-E. Peiponen, E. Vartiainen: *Kramers-Kronig Relations in Optical Materials Research*, Springer, Heidelberg, 2005
- V. Lucarini, J. Stat. Phys. 131, 543-558 (2008)
- V. Lucarini, J. Stat. Phys. 134, 381-400 (2009)
- V. Lucarini and S. Sarno, Nonlin. Proc. Geophys. 18, 7-27 (2011)
- V. Lucarini, T. Kuna, J. Wouters, D. Faranda, Nonlinearity (2012)
- V. Lucarini, J. Stat. Phys. 146, 774 (2012)
- J. Wouters and V. Lucarini, J. Stat. Mech. (2012)
- J. Wouters and V. Lucarini, ArXiv (2012)

Real part of the susceptibility



Applicability of FDT

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 - It is not possible to write the response as a correlation integral, there is an additional term
 - The system, by definition, never explores the stable directions, whereas a perturbations has components also outside the unstable manifold
- Recent studies (Branstator et al.) suggest that, nonetheless, information can be retrieved
- What is the time needed to build up a statistics such that the FDT gives useful results?
 - Probably, numerical noise also helps
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Some observations

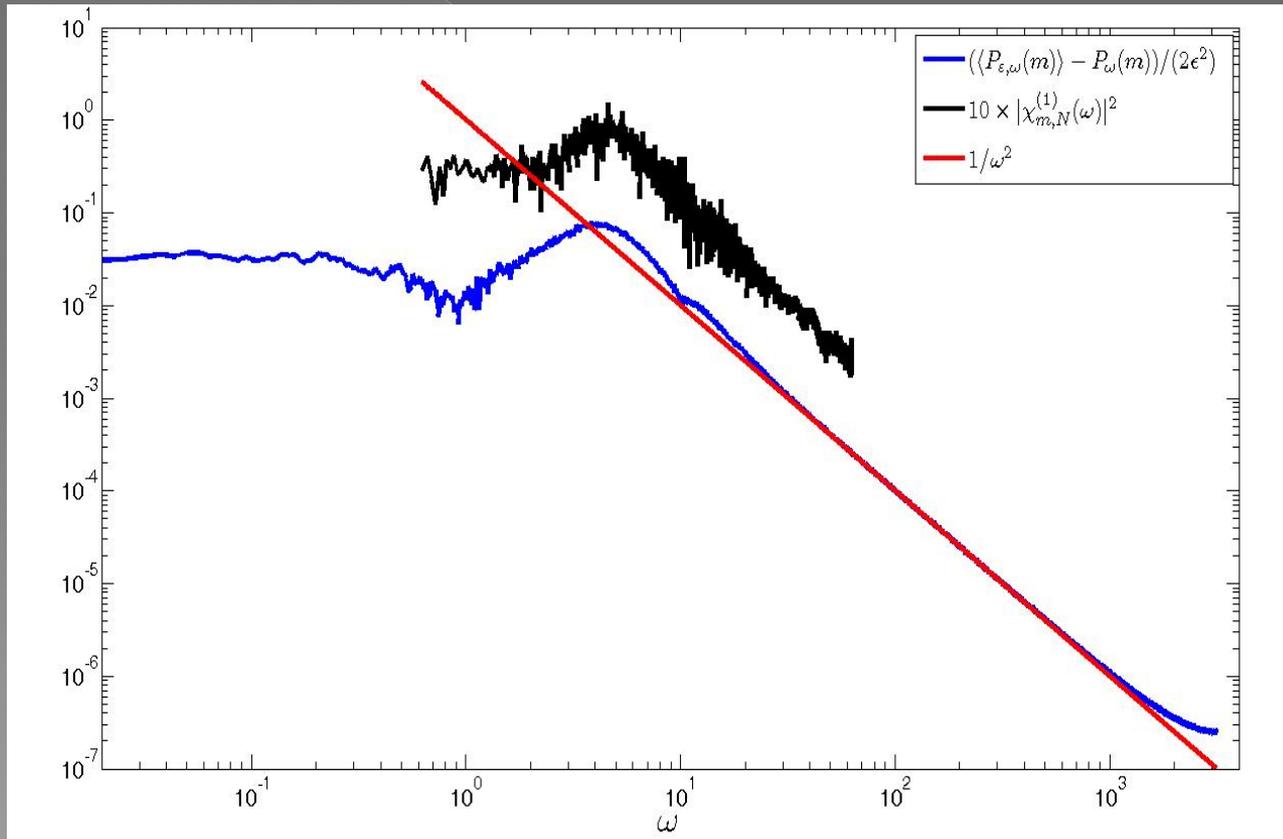
- The correction to the expectation value of any observable ~ variance of the noise
 - > Stochastic system → deterministic system
 - > Convergence of the statistical properties is fast
 - We have an explicit formula!
 - If the unperturbed system has an acim:
- We have a correlation integral, like in a FDT:

$$\langle \delta_\varepsilon \rho(\Phi) \rangle \approx -\varepsilon^2 \int d\tau \Theta(\tau_1) \int \rho_0(x) dx (\partial_i X_i) X_j \partial_j \Phi(f^{\tau_1} x)$$

$$\langle \delta_\varepsilon \rho(\Phi) \rangle \approx -\varepsilon^2 \int d\tau \int \rho_0(dx) B(x) C(f^{\tau_1} x)$$

Another observable

- Squared modulus of $\chi_m^{(1)}(\omega)$
- Blue: Using stoch pert; Black: deter forcing
- ... And many many many less integrations



Three major experimental challenges in analysing the CS

- Synchronic coherence of data
 - › Data feature hugely varying degree of precision
- Diachronic coherence of data
 - › Technology and prescriptions for data collection have changed with time
- Space-time coverage
 - › Data density (Antarctica vs Germany)
 - › We have “direct” data only since Galileo time
 - › Before, we have to rely on indirect (proxy) data
- Merging of Data and Models

A rigorous view on Climate Change

- The analysis of how systems respond to external perturbations to their steady state constitutes one of the crucial subjects in physics and mathematics
- Sometimes, we use “blindly” several CM experiments in order to understand the response
- The natural variability blurs the signal, in order to be rigorous we should repeat many times the same experiment (and with various CMs)
- In climate science, we struggle considerably with concepts and computations of climate sensitivity and climate response
- We would like to be able to define more rigorously Climate Change!

Linear case

- ◉ The input $I(t)=e(t)$ and the output $O(t)=\langle\Phi^{(1)}(t)\rangle$ are connected by the following linear relationship involving $a(t)=G^{(1)}(t)$:

$$O(t) = \int_{-\infty}^{\infty} a(t-t')I(t')dt'$$

- ◉ By applying Fourier Transform to both members we obtain:

$$O(\omega) = a(\omega)I(\omega)$$

- ◉ Is there a connection between the properties of $a(t)=G^{(1)}(t)$ and those of $a(\omega)=\chi^{(1)}(\omega)$?

Background

- In quasi-equilibrium statistical mechanics, the Kubo theory ('50s) allows for an accurate treatment of perturbations to the canonical equilibrium state
 - > In the linear case, the FDT bridges the properties of the forced and free fluctuations of the system
- When considering general dynamical systems (e.g. forced and dissipative), the situation is more complicated (no FDT, in general)
- Recent advances (Ruelle, mostly): for a class of dynamical systems it is possible to define a perturbative theory of the response to small perturbations
 - > We follow this direction...
- We apply the theory also for stochastic forcings