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# A framework to analyze regime behaviors and metastability in the climate system

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# Regimes in Climate - examples

Weather pattern over central Europe (Baur, 1951), North Atlantic Oscillation (NAO), Arctic Oscillation (AO), Pacific-North American (PNA) pattern, etc.

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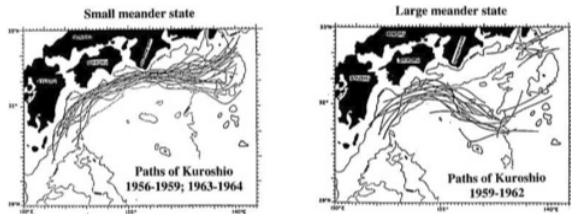
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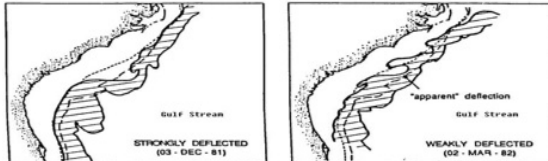
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Kuroshio current (Taft, 1972)



Gulf stream (Bane and Dewar, 1988)





# Regimes in Climate

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- Regimes as multiple equilibrium states of barotropic models (Charney–Devore 79, Legras–Ghil 85, Tung–Tosenthal 85, ...).
- Regimes as most likely states of equilibrium distribution from statistical mechanics (Miller 90, Robert–Sommeria 91, Majda *et al.* 05, 06, ...).
- Data-driven approaches (Majda *et al.* 10, 11, ...).

## Dynamics of transitions between regimes?

- Transitions caused by effect of noise - typically analyzed in small dimensional idealized models (Hasselmann 76, Egger 81, Saravanan *et al.*, Sura 02, ...).
- Transition as heteroclinic orbits (Crommelin *et al.* 03, Selten–Branstator 04, Ide–Ghil 04, ...).

No dynamical information from standard equilibrium statistical mechanics approaches!



# Our strategy

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- Use equilibrium statistical mechanics framework (information theory) to determine invariant measure (IM) of the climate system;
- Establish conditions under which this IM is multimodal, i.e. may displays several regimes;
- *Re-install dynamics* - add appropriate forcing and damping terms in the bare equations to guarantee that the resulting stochastic partial differential equations (SPDEs) have the correct IM;
- Analyze these SPDEs in the small noise limit using large deviation theory and the string method to find most likely pathways between the different regimes.



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# Two-dimensional barotropic QG equations

$$\frac{\partial q}{\partial t} + \nabla^\perp \psi \cdot \nabla q + U(t) \frac{\partial q}{\partial x} + \beta \frac{\partial \psi}{\partial x} = \mathcal{D}_q(\Delta)q + F_q,$$

$$q = \Delta \psi + h,$$

$$\frac{dU}{dt} = \int h \frac{\partial \psi}{\partial x} dx dy + \mathcal{D}_U(U) + F_U,$$

Here  $\psi(t, x, y)$  is the stream function,  $q(t, x, y)$  the vorticity,  $h(x, y)$  the bottom topography,  $U(t)$  the zonal base flow and  $\beta$  the beta-plane parameter (Pedlosky 79, Vallis 05).

Inviscid equations with  $\mathcal{D} = F = 0$  preserve

**Energy**  $E = \frac{1}{2}U^2 + \frac{1}{2} \int |\nabla \psi|^2 dx dy,$

**Enstrophy**  $Q = \beta U + \frac{1}{2} \int |q|^2 dx dy.$



# Predictions of equilibrium statistical mechanics

IM maximizes the entropy  $-\int \mu \log \mu$  under the constraints:

Canonical:  $\int Q d\mu = Q_0$ ,    Microcanonical:  $E = E_0$ .

$$d\mu = Z^{-1} \exp(-\varepsilon^{-1} Q) \delta(E - E_0) dU d\psi,$$

- Most likely states = selective decay states – in QG flow, enstrophy varies faster than energy.
- Only choice leading to multimodal distribution.

**Dynamics?** choose  $\mathcal{D}$  and  $F$  so that we formally have the invariant measure (cf strategy of Landau-Lifshitz for NS equations)





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# Single-mode truncation

$$\begin{aligned}\psi(t, x, y) &= a(t) \sin(kx) + b(t) \cos(kx), \\ h(x, y) &= H \sin(kx), \quad (k \neq 0).\end{aligned}$$

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Inviscid equations reduce to:

$$\begin{aligned}\dot{a} &= kb(t) \left( U(t) - \frac{\beta}{k^2} \right), \\ \dot{b} &= -ka(t) \left( U(t) - \frac{\beta}{k^2} \right) + \frac{U(t)H}{k}, \\ \dot{U} &= -\frac{b(t)Hk}{2}.\end{aligned}$$

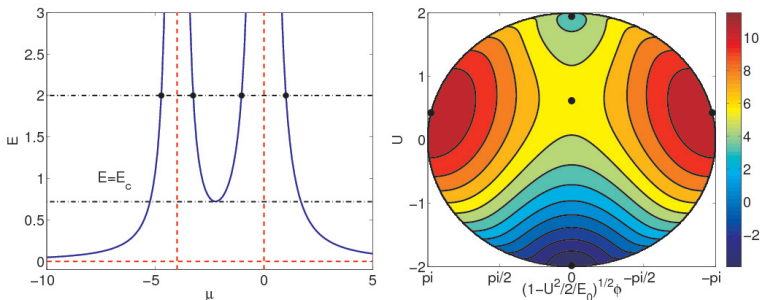
The energy and enstrophy now read:

$$\begin{aligned}E &= \frac{1}{2}U^2 + \frac{k^2}{4}(a^2 + b^2), \\ Q &= \beta U + \frac{1}{4}((H - k^2a)^2 + k^4b^2).\end{aligned}$$



Invariant measure  $\sim \exp(-\varepsilon^{-1} Q) \delta(E - E_0)$

Enstrophy landscape on energy surface  $E_0 = 2$ :



Most likely states are given by the minimizers of  $Q$  subject to the constraint  $E = E_0$ .

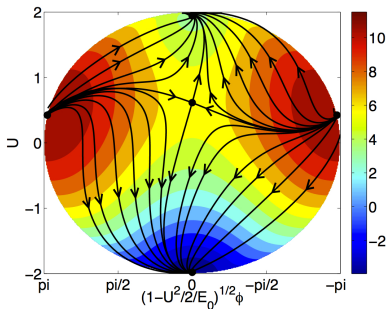


# Reinstall dynamics

$$\dot{\mathbf{X}} = \mathbf{B}(\mathbf{X}) - \mathcal{P}(\mathbf{X}) M_\gamma \nabla_{\mathbf{X}} Q(\mathbf{X}) + \sqrt{2\varepsilon} \mathcal{P}(\mathbf{X}) M_\gamma^{1/2} \circ \eta,$$

with the projection operator

$$\mathcal{P} = \text{Id} - \frac{M_\gamma \nabla_{\mathbf{X}} E \otimes \nabla_{\mathbf{X}} E}{\langle \nabla_{\mathbf{X}} E, M_\gamma \nabla_{\mathbf{X}} E \rangle}.$$



Deterministic flow

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# Maximum likelihood path

In the small noise limit, transition occurs via maximum likelihood path (MLP) of large deviation theory.

MLP is minimizer in

$$\inf_{\mathcal{M}} \frac{1}{2} \int_{-T}^T \left| \left( \mathcal{P}(\varphi) M_\gamma \right)^{-1/2} \left( \dot{\varphi} - \mathcal{P}(\varphi) (\mathbf{B}(\varphi) - M_\gamma \nabla_x Q(\varphi)) \right) \right|^2 dt,$$

where

$$\mathcal{M} = \left\{ \varphi \mid \varphi(t) \in C([-T, T], \mathbb{R}^3), \dot{\varphi} \perp \nabla_x E, \varphi(-T) = \mathbf{x}_0, \varphi(T) = \mathbf{x}_1 \right\}$$

**Nongradient system** with **conservative** nongradient force

$$\nabla_x E \perp \mathbf{B}, \quad \nabla_x Q \perp \mathbf{B}, \quad \mathcal{P}\mathbf{B} = \mathbf{B}.$$

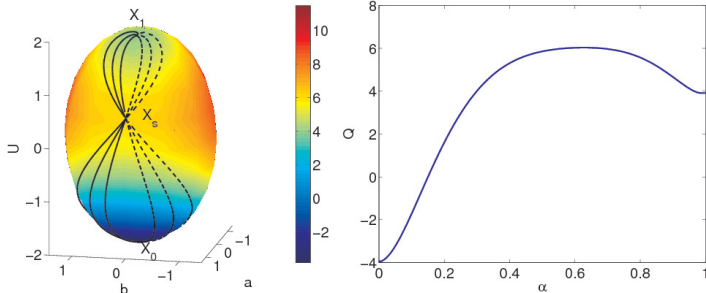


MLP solves

$$\begin{cases} 0 = [\mathbf{B} + \mathcal{P}(M_\gamma \nabla_{\mathbf{x}} Q(\varphi))]^\perp & \text{(uphill)} \\ 0 = [\mathbf{B} - \mathcal{P}(M_\gamma \nabla_{\mathbf{x}} Q(\varphi))]^\perp & \text{(downhill)} \end{cases}$$

where  $[\cdot]^\perp$  denotes projection perpendicular to the path.

Computed by string method



Here  $\beta = k = 2$ ,  $H = 1$ ,  $E_0 = 2$  and  $M_\gamma = 0.5, 1, 2$ .



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# Metastable states of invariant measure

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Minimize the enstrophy  $Q$  subject to the constraint  $E = E_0$ :

$$\begin{aligned} \min_{U, \psi} \quad & Q = \beta U + \frac{1}{2} \int q^2 \, dx \, dy, \\ \text{s.t.} \quad & \frac{1}{2} U^2 + \frac{1}{2} \int |\nabla \psi|^2 \, dx \, dy = E_0. \end{aligned}$$

Using Lagrange multiplier,

$$\mu U_c = -\beta, \quad \mu \Delta \psi_c = \Delta(\Delta \psi_c + h).$$

**N.B.** These are the stationary solutions of the original system without dissipation and forcing.





Number of critical points  $\Rightarrow$  roots of  $\mu$ :

$$E_0 = \frac{\beta^2}{2\mu^2} + \frac{1}{2} \sum_{\mathbf{k}} \frac{|\mathbf{k}|^2 |\hat{h}_{\mathbf{k}}|^2}{(\mu + |\mathbf{k}|^2)^2},$$

Stability  $\Rightarrow$  signs of eigenvalues of Hessian matrix:

$$(M_Q)_{\mathbf{k}\mathbf{k}'} = \begin{cases} \frac{\mu^3 |\mathbf{k}|^4 |\hat{h}_{\mathbf{k}}|^2}{\beta^2 (\mu + |\mathbf{k}|^2)^2} - |\mu| |\mathbf{k}|^2 + |\mathbf{k}|^4, & \text{if } \mathbf{k} = \mathbf{k}', \\ \frac{\mu^3 |\mathbf{k}|^2 |\mathbf{k}'|^2 \hat{h}_{\mathbf{k}} \hat{h}_{\mathbf{k}'}^*}{\beta^2 (\mu + |\mathbf{k}|^2) (\mu + |\mathbf{k}'|^2)}, & \text{if } \mathbf{k} \neq \mathbf{k}'. \end{cases}$$



# Stochastic partial differential equations

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$$\begin{aligned}\frac{\partial \psi}{\partial t} &= -\Delta^{-1} \left( \nabla^\perp \psi \cdot \nabla q + U(t) \frac{\partial q}{\partial x} + \beta \frac{\partial \psi}{\partial x} \right) \\ &\quad - \gamma_1 \Delta (\Delta \psi + h) + \sqrt{2\varepsilon \gamma_1} \eta(t, x, y) + \gamma_1 \frac{\delta E}{\delta \psi} \lambda(t), \\ \frac{dU}{dt} &= \int h \frac{\partial \psi}{\partial x} d\mathbf{x} - \gamma_2 \beta + \sqrt{2\varepsilon \gamma_2} \xi(t) + \gamma_2 \frac{\delta E}{\delta U} \lambda(t),\end{aligned}$$

where  $q = \Delta \psi + h$  and the Lagrange multiplier  $\lambda(t)$  is

$$\lambda(t) = \frac{\int (q - h) (-\gamma_1 \Delta q + \sqrt{2\varepsilon \gamma_1} \circ \eta) d\mathbf{x} + U(\gamma_2 \beta - \sqrt{2\varepsilon \gamma_2} \circ \xi)}{\int (q - h) \gamma_1 (q - h) d\mathbf{x} + \gamma_2 U^2}.$$

**N.B.**  $\gamma_1$  and  $\gamma_2$  can be pseudo-differential operators.



# Dissipation via Ekman drag: $\gamma_1 = \gamma \Delta^{-2}$ , $\gamma_2 = \tilde{\gamma}$

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$$\frac{\partial \mathbf{q}}{\partial t} + \nabla^\perp \psi \cdot \nabla \mathbf{q} + U(t) \frac{\partial \mathbf{q}}{\partial x} + \beta \frac{\partial \psi}{\partial x} = -\gamma \mathbf{q} + \sqrt{2\varepsilon\gamma} \eta(t, x, y) - \gamma \psi \lambda(t),$$

$$\mathbf{q} = \Delta \psi + h,$$

$$\frac{dU}{dt} = \int h \frac{\partial \psi}{\partial x} d\mathbf{x} - \tilde{\gamma} \beta + \sqrt{2\varepsilon\tilde{\gamma}} \xi(t) + \tilde{\gamma} U \lambda(t),$$

where

$$\lambda(t) = \frac{\int \psi (-\gamma \mathbf{q} + \sqrt{2\varepsilon\gamma} \circ \eta) d\mathbf{x} + U(\tilde{\gamma} \beta - \sqrt{2\varepsilon\tilde{\gamma}} \circ \xi)}{\gamma \int |\psi|^2 d\mathbf{x} + \tilde{\gamma} U^2}.$$

**N.B.** fixing the damping fixes the forcing by fluctuation-dissipation theorem (FDT).



# String method to compute MLP

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- 1 Evolve the string according to

$$\tilde{\varphi} = \varphi^n + \delta t(\pm \mathbf{B}^n + \mathbf{G}^n),$$

where  $\varphi = (q, U)^T$ , and

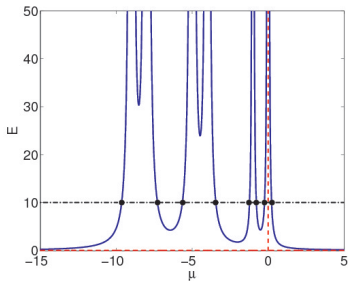
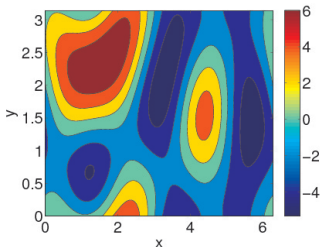
$$\mathbf{B} = \begin{pmatrix} -\nabla^\perp \psi \cdot \nabla q - U \frac{\partial q}{\partial x} - \beta \frac{\partial \psi}{\partial x} \\ \int h \frac{\partial \psi}{\partial x} d\mathbf{x} \end{pmatrix}, \quad \mathbf{G} = - \begin{pmatrix} \gamma q \\ \tilde{\gamma} \beta \end{pmatrix}.$$

- 2 Reparametrize  $\tilde{\varphi}$  via arc-length, to obtain  $\bar{\varphi}$ .
- 3 Project  $\bar{\varphi}$  on the energy surface  $E = E_0$ , to obtain  $\varphi^{n+1}$ .



## Example (16-mode topography)

We take the domain size as  $L_x = 2\pi$ ,  $L_y = \pi$ . The parameters are chosen as  $\beta = 1$ ,  $E_0 = 10$ . The friction coefficients are taken as  $\gamma = \tilde{\gamma} = 4$ .





# Metastable vorticity patterns and the pathways

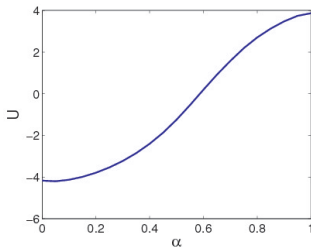
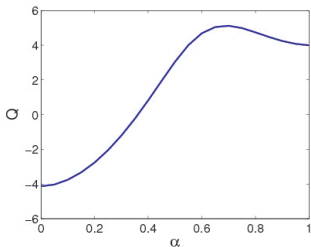
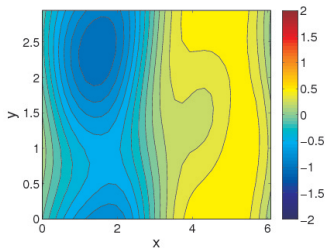
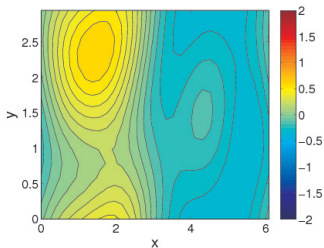
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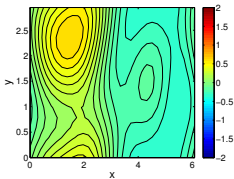
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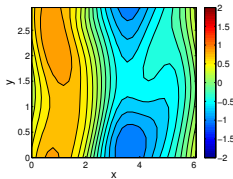


# Dynamics of streamlines and vorticity

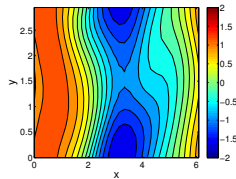
(a)



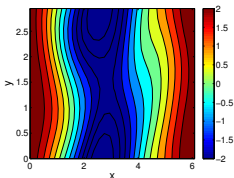
(b)



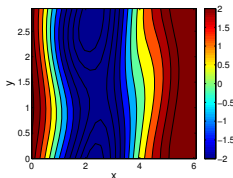
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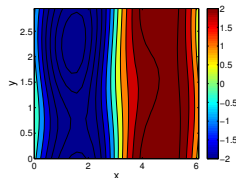
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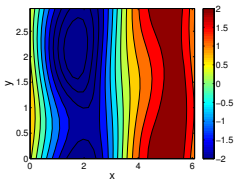
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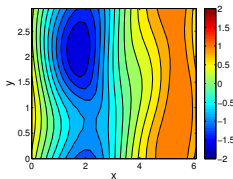
(f)



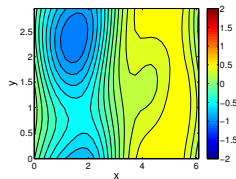
(g)



(h)



(i)



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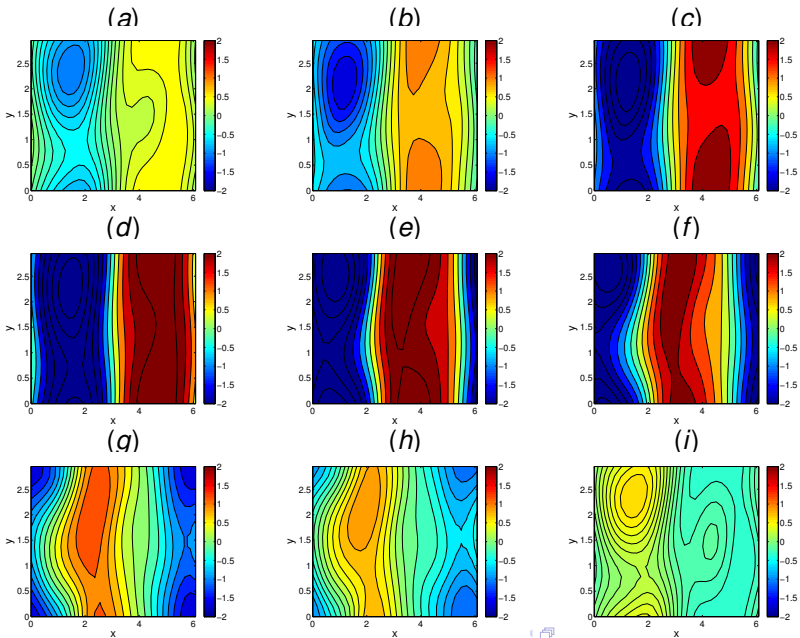
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## Conclusion:

- Design SPDE models that are consistent with predictions of equilibrium statistical mechanics and can capture the noise-induced transition between different selective decay states (representing different climate regimes).
- Calculate the maximum likelihood path of large deviation theory by the string method to describe the transitions between different regimes in the small noise limit.
- Can be generalized to other models with different forcing and dissipation, including cases where statistical mechanics framework breaks down (nonequilibrium statistical steady states).
- Can be generalized to situations with weak damping and forcing (different order of limits than weak noise).

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