Predicting Extreme Events for Passive Scalar Turbulence through Reduced-Order Models

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Long tails of natural tracers from observation

Intermittency is a key feature of turbulent flows and correctly taking it into account in turbulence models is of critical importance.

- Passive tracer distributions exhibit approximately exponential tails.
- Such tails are indeed ubiquitous in observation, model, and reanalysis data sets for a variety of tracers.¹



¹Neelin et al, Geophys. Res. Lett., 2010

Simplified passive scalar models

• Simplified models in tracer turbulence:

- Understanding the fundamental mechanisms that can potentially lead to such behavior is a question of great theoretical interest.
- The analysis of simple systems with a Gaussian core can shed some light on similar behaviors observed in more complex models.

Major Questions:

- What structure is needed for a velocity field so that the PDF for a passive scalar exhibits a transition from a Gaussian PDF to a broader than Gaussian shape.
- How to develop explicit reduced-order models with unambiguous behavior for intermittency of scalar PDFs.

Turbulent diffusion models with mean gradient formulation

- Elementary models with intermittency for passive scalars
- Rigorous intermittency in a random resonance regime

Two-layer baroclinic turbulence as advection flow

- Two-layer baroclinic turbulence in ocean and atmosphere regimes
- A reduced-order stochastic model with consistency and sensitivity

- Model calibration in Gaussian velocity field
- Prediction skill of low-order stochastic models

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Passive tracer with a mean gradient

Passive tracer of turbulent advection, diffusion, and damping

$$\frac{\partial T}{\partial t} + \mathbf{v} \cdot \nabla T = -d_T T + \kappa \Delta T.$$

The tracer field is assumed to have a background mean gradient

$$T(\mathbf{x},t) = \alpha_1 x + \alpha_2 y + T'(x,y,t).$$

The model for the velocity field is two dimensional and periodic in space

$$\mathbf{v}(\mathbf{x},t) = (U(t),v(x,t)),$$

with the *cross-sweep*, U(t), and the *shear flow*, v(x,t).

• T'(x,t) denotes fluctuations around the mean gradient

$$\frac{\partial T'}{\partial t} + U(t)\frac{\partial T'}{\partial x} = -\alpha v(x,t) - d_T T' + \kappa \Delta T'.$$

Elementary model with intermittency²

It is the time modulation in the transverse sweep, more precisely the fact that *the sweep crosses zero periodically*, that leads to the intermittency.

$$\frac{\partial T'}{\partial t} + \operatorname{Pe} U(t) \frac{\partial T'}{\partial x} - \frac{\partial^2 T'}{\partial x^2} = -\alpha \operatorname{Pe} v(x,t), \quad \boxed{\operatorname{Pe} = VL/\kappa}$$
$$T = \alpha y + T', \quad U(t) = \sin \omega t, \quad v(x,t) = \sin 2\pi x.$$



²Bourlioux & Majda, Physics of Fluids, 2002

- when U = 0, the open streamlines in the horizontal direction, along the mean gradient αy, promote strong mixing by diffusion.
- when U ≠ 0, the transverse sweep corresponds to blocked streamlines, little transport along the gradient, little opportunity for mixing by diffusion.

Elementary model with intermittency



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The two-layer flow as advection flow

The **two-layer quasi-geostrophic model** is one simple but fully nonlinear fluid model capable in capturing the essential physics.

Two-layer model

$$\frac{\partial q_{\psi}}{\partial t} + J(\psi, q_{\psi}) + J(\tau, q_{\tau}) + \beta \frac{\partial \psi}{\partial x} + U \frac{\partial \Delta \tau}{\partial x} = -\frac{\kappa}{2} \Delta(\psi - \tau) - v \Delta^{s} q_{\psi},$$

$$\frac{\partial q_{\tau}}{\partial t} + J(\psi, q_{\tau}) + J(\tau, q_{\psi}) + \beta \frac{\partial \tau}{\partial x} + U \frac{\partial}{\partial x} (\Delta \psi + k_{d}^{2} \psi) = -\frac{\kappa}{2} \Delta(\tau - \psi) - v \Delta^{s} q_{\tau}.$$

barotropic and baroclinic modes:

energy and heat flux:

$$egin{aligned} q_{\psi} &= \Delta \psi, \, \psi = rac{1}{2} \left(\psi_1 + \psi_2
ight), \ q_{ au} &= \Delta au - k_d^2 au, \, au = rac{1}{2} \left(\psi_1 - \psi_2
ight). \end{aligned}$$

$$E = \frac{1}{2} \int |\nabla \psi|^2 + |\nabla \tau|^2 + k_d^2 \tau^2,$$

$$H_f = k_d^2 U \int v\tau.$$

Illustration about tracer intermittency with heat flux



(c) time-series of heat flux and scalar tracer

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Stochastic formulations for the passive tracer and turbulent flow field

• reduced-order advection flow equations $\vec{q}_{\mathbf{k}} = \left(\hat{q}_{1,\mathbf{k}},\hat{q}_{2,\mathbf{k}}\right)^{T}$

$$\begin{aligned} d\vec{q}_{M,\mathbf{k}} &= -\left(\gamma_{q,\mathbf{k}} + i\omega_{q,\mathbf{k}}\right)\vec{q}_{M,\mathbf{k}}dt - D^{M}_{q,\mathbf{k}}\vec{q}_{M,\mathbf{k}}dt + \sum^{M}_{q,\mathbf{k}}d\vec{W}_{q,\mathbf{k}}, \quad 1 \le |\mathbf{k}| \le M. \\ \mathbf{v}_{M} &= \nabla^{\perp}\vec{\psi}_{M}, \quad \vec{q}_{M,\mathbf{k}} = H_{\mathbf{k}}\vec{\psi}_{M,\mathbf{k}}, \\ \hline -\frac{1}{2}\sum_{\mathbf{m}+\mathbf{n}=\mathbf{k}}(A_{\mathbf{km}}\vec{q}_{\mathbf{m}}\circ\vec{q}_{\mathbf{n}} + A_{\mathbf{kn}}\vec{q}_{\mathbf{n}}\circ\vec{q}_{\mathbf{m}}) \rightarrow -D^{M}_{q,\mathbf{k}}\vec{q}_{M,\mathbf{k}}dt + \sum^{M}_{q,\mathbf{k}}d\vec{W}_{q,\mathbf{k}}. \end{aligned}$$

• reduced-order passive tracer equations $\vec{\tau}_{\mathbf{k}} = (\hat{\tau}_{1,\mathbf{k}},\hat{\tau}_{2,\mathbf{k}})^T$

$$\begin{aligned} d\vec{\tau}_{M,\mathbf{k}} + \left(\mathbf{v}_{M} \cdot \nabla \vec{\tau}_{M}\right)_{\mathbf{k}} d\tilde{t} &= \alpha \Gamma_{\mathbf{k}} \vec{\psi}_{M,\mathbf{k}} d\tilde{t} - \left(\gamma_{T,\mathbf{k}} + i\omega_{T,\mathbf{k}}\right) \vec{\tau}_{M,\mathbf{k}} d\tilde{t}, \quad 1 \leq |\mathbf{k}| \leq M. \\ \mathbf{v}_{M} &= \sum_{|\mathbf{k}| \leq M_{1}} i \mathbf{k}^{\perp} \vec{\psi}_{M,\mathbf{k}} e^{i\mathbf{k} \cdot \mathbf{x}}. \end{aligned}$$

Model calibration in the advection flow field

- The imperfect model calibration parameters (D_q^M, Σ_q^M) need properly reflect the true nonlinear energy mechanism.
- The statistical equations for the fluctuation covariance matrix $R^q_{\bf k} = \langle \vec{q}_{\bf k} \vec{q}^*_{\bf k} \rangle$ become⁴

$$\begin{aligned} \frac{dR_{\mathbf{k}}^{q}}{dt} + Q_{F}^{q} &= \left(\mathscr{L}_{\mathbf{k}}^{q} + \mathscr{D}_{\mathbf{k}}^{q}\right)R_{\mathbf{k}}^{q} + R_{\mathbf{k}}^{q}\left(\mathscr{L}_{\mathbf{k}}^{q} + \mathscr{D}_{\mathbf{k}}^{q}\right)^{*}, \quad |\mathbf{k}| \leq N, \\ Q_{F}^{q}(\vec{q}_{\mathbf{k}}) &= \frac{1}{2}\sum_{\mathbf{m}+\mathbf{n}=\mathbf{k}}\left\langle \left(A_{\mathbf{km}}\vec{q}_{\mathbf{m}}\circ\vec{q}_{\mathbf{n}} + A_{\mathbf{kn}}\vec{q}_{\mathbf{n}}\circ\vec{q}_{\mathbf{m}}\right)\vec{q}_{\mathbf{k}}^{*}\right\rangle. \end{aligned}$$

• In the statistical steady state, $dR^q_{\bf k}/dt = 0$, then the nonlinear fluxes can be calculated at equilibrium as $t \to \infty$

$$Q_{F,\mathrm{eq}}^{q} = \left(\mathscr{L}_{\mathbf{k}}^{q} + \mathscr{D}_{\mathbf{k}}^{q}\right) R_{\mathbf{k},\mathrm{eq}}^{q} + R_{\mathbf{k},\mathrm{eq}}^{q} \left(\mathscr{L}_{\mathbf{k}}^{q} + \mathscr{D}_{\mathbf{k}}^{q}\right)^{*}.$$

⁴Sapsis & Majda, Physica D, 2013

Di Qi (CIMS)

Imperfect model correction from equilibrium statistics and additional terms

• the first proposal for the linear damping and Gaussian random noise correction can be introduced as

$$D_{q,\mathbf{k}}^{\rm eq} = -\frac{1}{2} Q_{F,{\rm eq},\mathbf{k}}^{q,-} \left(R_{\mathbf{k},{\rm eq}}^{q} \right)^{-1}, \quad \Sigma_{q,\mathbf{k}}^{\rm eq} = \left(Q_{F,{\rm eq},\mathbf{k}}^{q,+} \right)^{1/2};$$

 a further correction for the noise and damping with a simple constant damping and noise

$$Q_{M,\mathbf{k}}^{\mathrm{add}} = -D_{M}^{\mathrm{add}}R_{M,\mathbf{k}} + \left(\Sigma_{M,\mathbf{k}}^{\mathrm{add}}\right)^{2}, \quad D_{M}^{\mathrm{add}} = \begin{bmatrix} d_{M} + i\omega_{M} & \\ & d_{M} - i\omega_{M} \end{bmatrix}.$$

• Combining the ideas, we propose the additional damping and noise corrections for the reduced-order flow vorticity mode

$$D_{q,\mathbf{k}}^{M} = -\frac{1}{2} Q_{F,\mathrm{eq},\mathbf{k}}^{q,-} \left(R_{\mathbf{k},\mathrm{eq}}^{q} \right)^{-1} - D_{M}^{\mathrm{add}}, \quad \Sigma_{q,\mathbf{k}}^{M} = \left(Q_{F,\mathrm{eq},\mathbf{k}}^{q,+} + \left(\Sigma_{M,\mathbf{k}}^{\mathrm{add}} \right)^{2} \right)^{1/2}$$

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Gaussian velocity stochastic models for passive tracer statistics

 Apply the Galerkin truncation strategy by resolving only the first M leading modes in spectral space

$$\frac{d\hat{u}_{k}^{M}}{dt} = \left(-\gamma_{u_{k}} + i\omega_{u_{k}}\right)\hat{u}_{k}^{M} + \sigma_{u_{k}}\dot{W}_{k}, \quad |k| \leq M.$$

• One of the simplest and most direction way to estimate the undetermined coefficients $\gamma_{u_k}, \omega_{u_k}, \sigma_{u_k}$ is through the mean stochastic model (MSM):

$$\begin{split} E_{k} &\equiv \operatorname{var}(\hat{u}_{k}(t)) = \left\langle |\hat{u}_{k}(t) - \langle \hat{u}_{k} \rangle|^{2} \right\rangle, \\ R_{k} &= \int \mathscr{R}_{k}(t) \equiv \int \frac{\left\langle (\hat{u}_{k}(\tau) - \langle \hat{u}_{k} \rangle) (\hat{u}_{k}(\tau+t) - \langle \hat{u}_{k} \rangle)^{*} \right\rangle}{\operatorname{var}(\hat{u}_{k}(\tau))} \end{split}$$

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Spectral Information criterion for improving imperfect model prediction skill

A natural way of measuring the lack of information is the relative entropy

$$\mathscr{P}\left(\pi,\pi^{\mathsf{M}}\right) = \int \pi \log \frac{\pi}{\pi^{\mathsf{M}}}.$$

Khinchin's formula: if the autocorrelation function $\mathscr{R}(t)$ is smooth and rapid-decay,

$$u(t) = \int_{-\infty}^{\infty} e^{i\lambda t} \hat{Z}(d\lambda), \quad \mathscr{R}(t) = \int_{-\infty}^{\infty} e^{i\lambda t} dF(\lambda) = \int_{-\infty}^{\infty} e^{i\lambda t} E(\lambda) d\lambda,$$

Energy spectrum can be represented by $E(\lambda)$ or $dF(\lambda)$

$$dF(\lambda) = E(\lambda) d\lambda = \mathbb{E} |\hat{Z}(d\lambda)|^2.$$

Spectral information criterion

A)
$$\max |\mathscr{R}(t) - \mathscr{R}^{M}(t)| \leq 2\sqrt{3} \left(\int (E^{2}(\lambda) + E_{M}^{2}(\lambda)) d\lambda \right)^{1/2} \mathscr{P}(E(\lambda), E^{M}(\lambda))^{1/2};$$

B) $\int |\mathscr{R}(t) - \mathscr{R}^{M}(t)|^{2} dt \leq 12 \max |E^{2}(\lambda) + E_{M}^{2}(\lambda)| \mathscr{P}(E(\lambda), E^{M}(\lambda)).$

PDFs in stream functions of the advection flow

regime	Ν	β	k _d	U	r	d _T	κ	α
ocean, high lat.	128	2	40	0.1	0.1	0.5	0.001	1
atmosphere, high lat.	128	2	4	0.2	0.2	0.1	0.001	1
atmosphere, mid lat.	128	1	4	0.2	0.1	0.1	0.001	1



Autocorrelation functions for representative modes

$$\mathscr{R}_{k}(t) = rac{\left\langle (\hat{u}_{k}(\tau) - \langle \hat{u}_{k} \rangle) (\hat{u}_{k}(\tau+t) - \langle \hat{u}_{k} \rangle)^{*} \right\rangle}{\operatorname{var}(\hat{u}_{k}(\tau))}$$



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Summary

- The single-point probability distribution function of a passive scalar has been the focus of much interest and requires better understanding.
- The generation of tracer intermittency is related with the competition between the blocked and unblocked modes in advection flow.
- The complex strongly turbulent dynamical system requires proper reduced-order modeling strategy of adopting simple advection flow models.
- Reduced-order stochastic models in passive scalar turbulence are useful in predicting extreme events and intermittency.
- D. Qi and A. Majda, Predicting fat-tailed Intermittent probability distributions in passive scalar turbulence with imperfect models through empirical information theory, CMS, 2015.
- D. Qi and A. Majda, *Predicting extreme events for passive scalar turbulence in two-layer baroclinic flows through reduced-order stochastic models*, submitted, 2017.

Thank you for your attention!