
Rare events in turbulence and **applications**

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My background is wind energy and turbulence





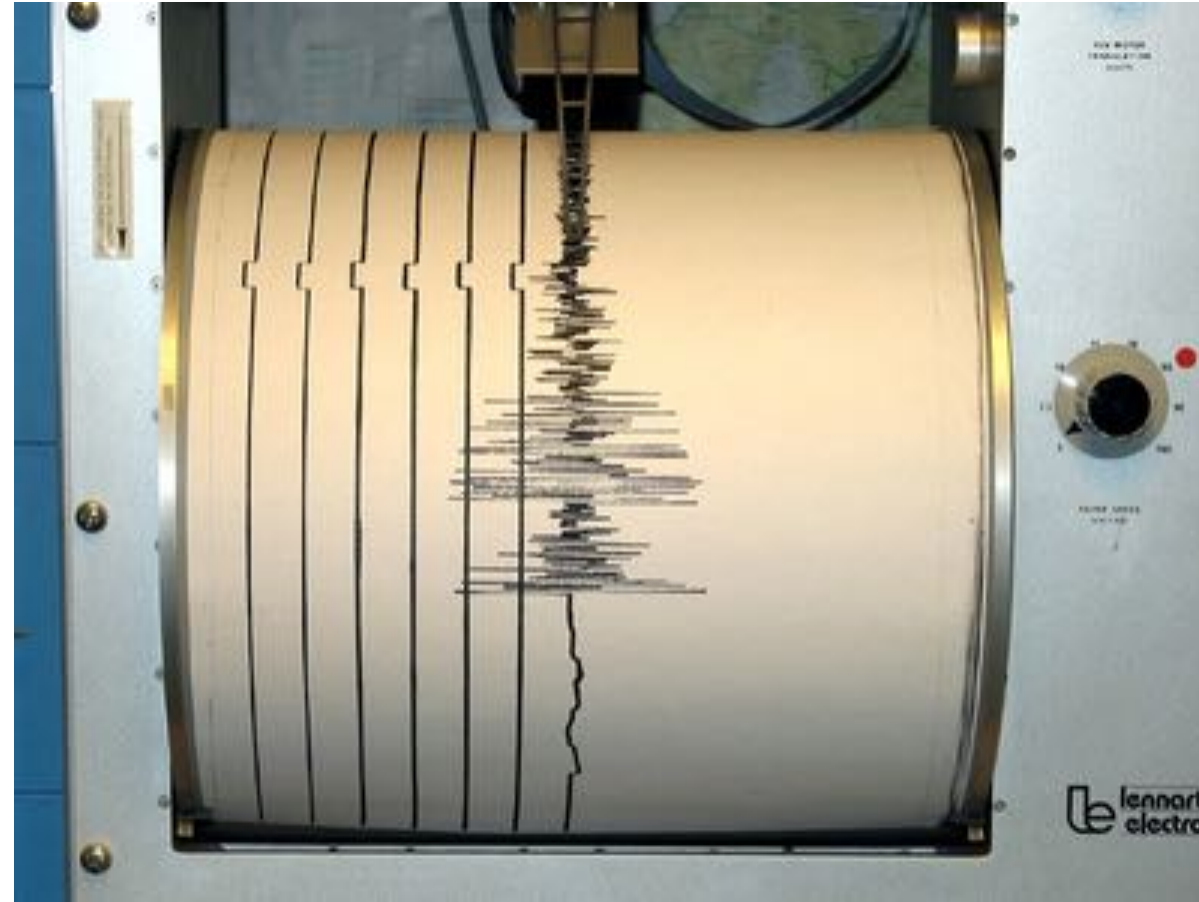
what is an extreme event?



Snow avalanches



earthquakes



06.04.2009 - Erdbeben in Italien: Helfer transportieren einen Verletzten nach dem schweren Erdbeben in der italienischen

epilepsy

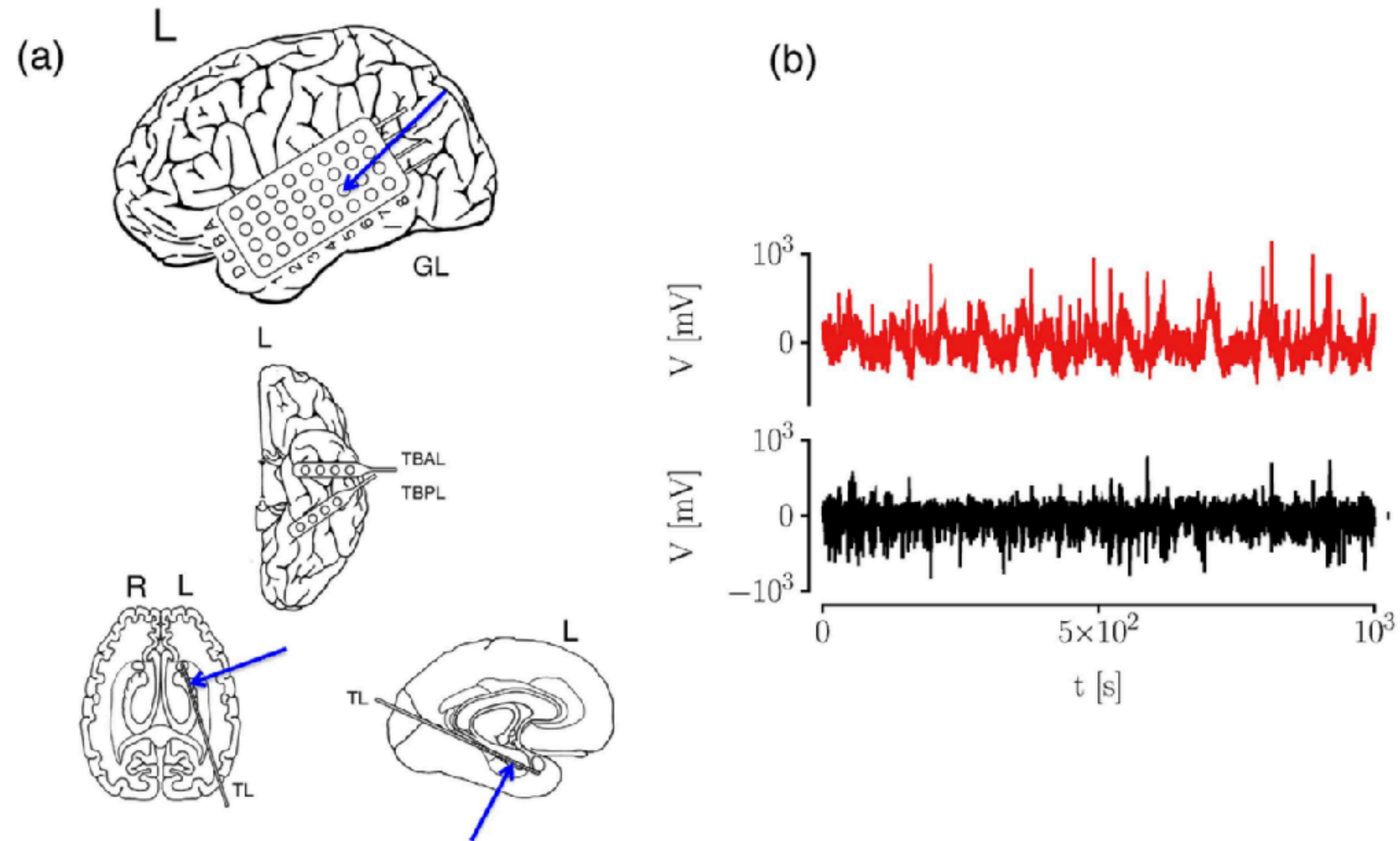


Figure 2. Exemplary recording scheme and intracranial electroencephalographic (iEEG) time series.

market crash

the economist March 1st 2007
stock decline on Febr. 27th

grey tuesday

- extreme event
- „According to Goldman and Sachs, the latest jump in VIX (a measure of stock-market volatility) took it **eight standard deviations** from its average. If conventional models are correct, such an event should not have happened in the history of the known **universe**.“



“extreme events are generally easy to recognize but difficult to define.”

Stephenson, D. B. (2008). In H. F. Diaz & R. J. Murnane (Eds.), *Climate Extremes and Society*. Cambridge,

rare or extreme events categories:

rare or extreme events **categories:**

1) **Extreme events :**

- based on statistics
- based on effect - outcome
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 - coupled to a system - same event may be extrem or not



Rare big events

Events $x_i, i = 1, \dots, N$

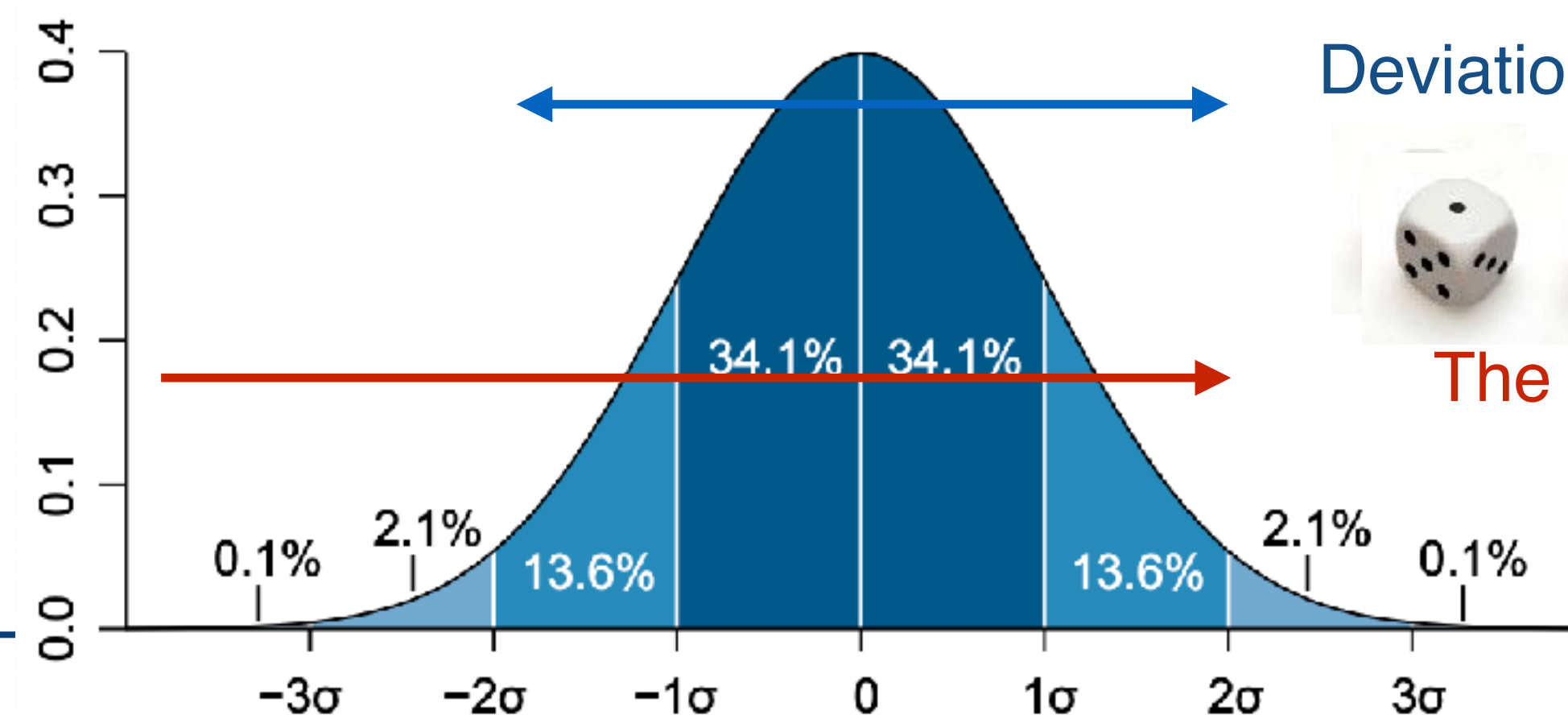


8σ event

What is the probability of $x_i > B$,

Gauß-distribution $\rightarrow$ extreme value statistics

$$P(x_i | x_i > B)$$



Deviation from mean value



The magnitude of the events is asked - $xx \sigma$



Rare big events

Events $x_i, i = 1, \dots, N$



$$P(x_i | x_i > B)$$

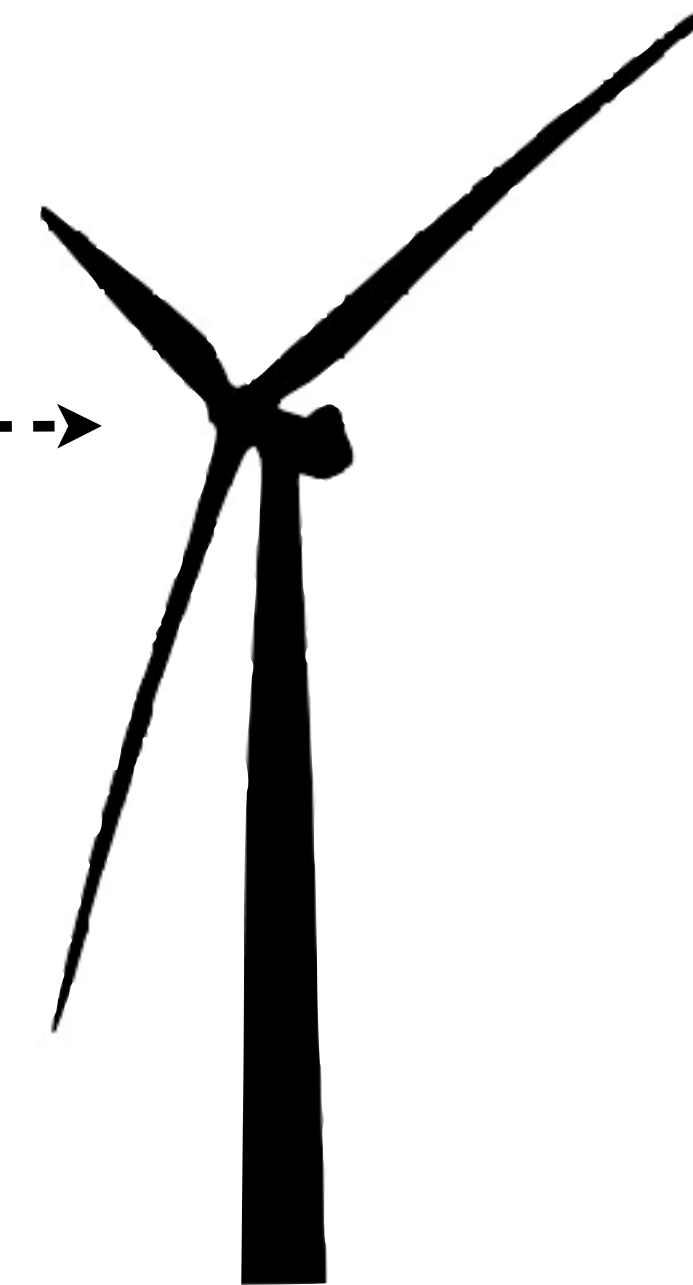
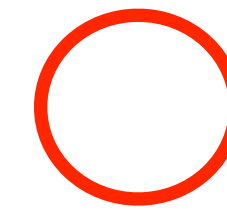
What happen if p is not Gaussian

energy resource: wind gusts

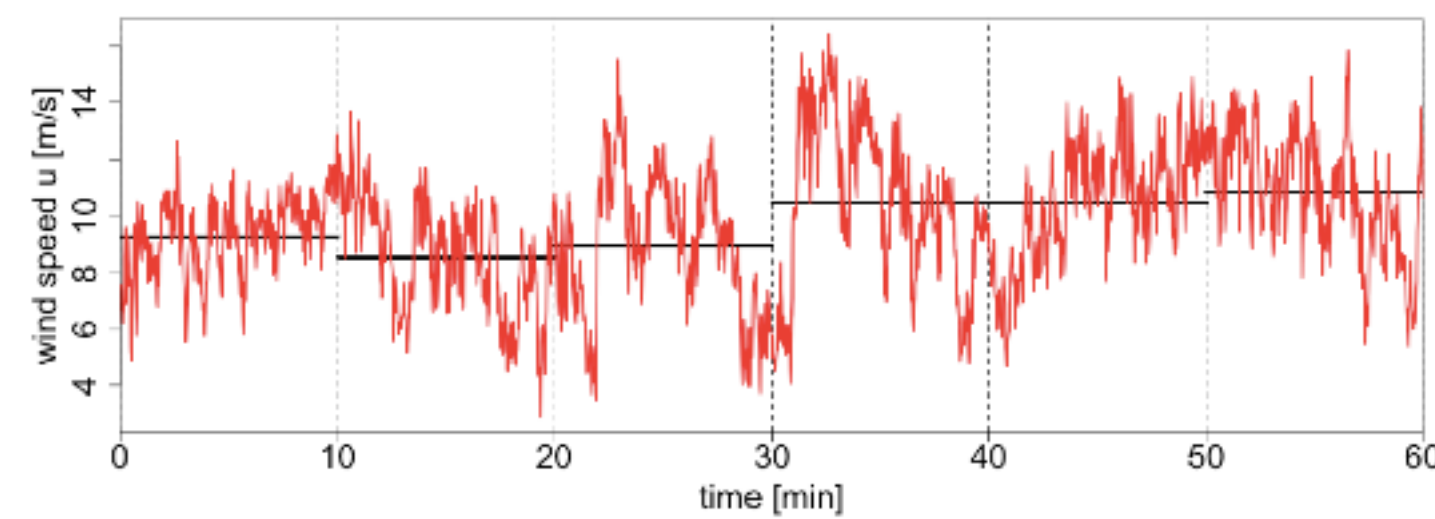
INTERNATIONAL
STANDARD

IEC
61400-1

Third edition
2005-08

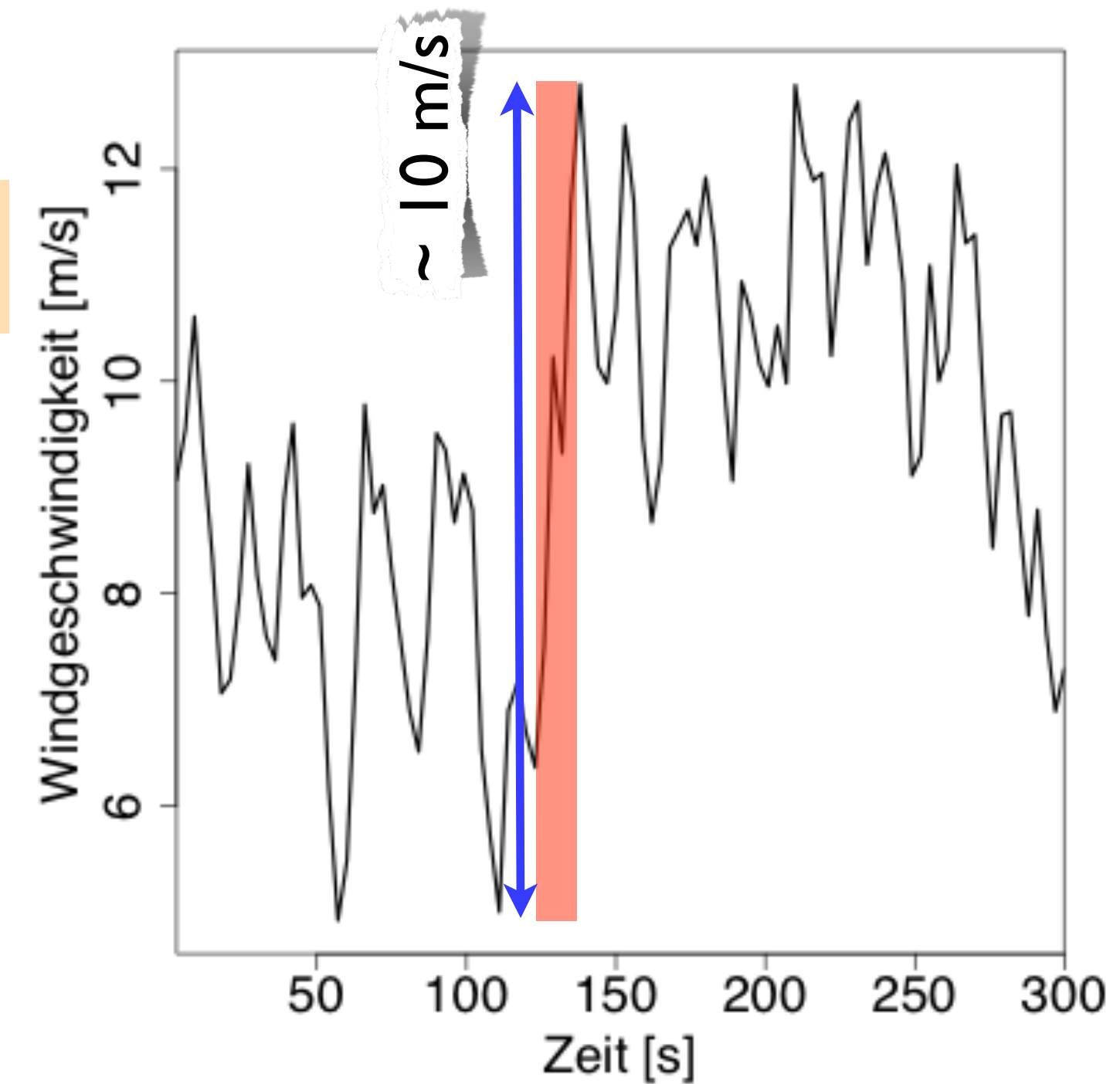
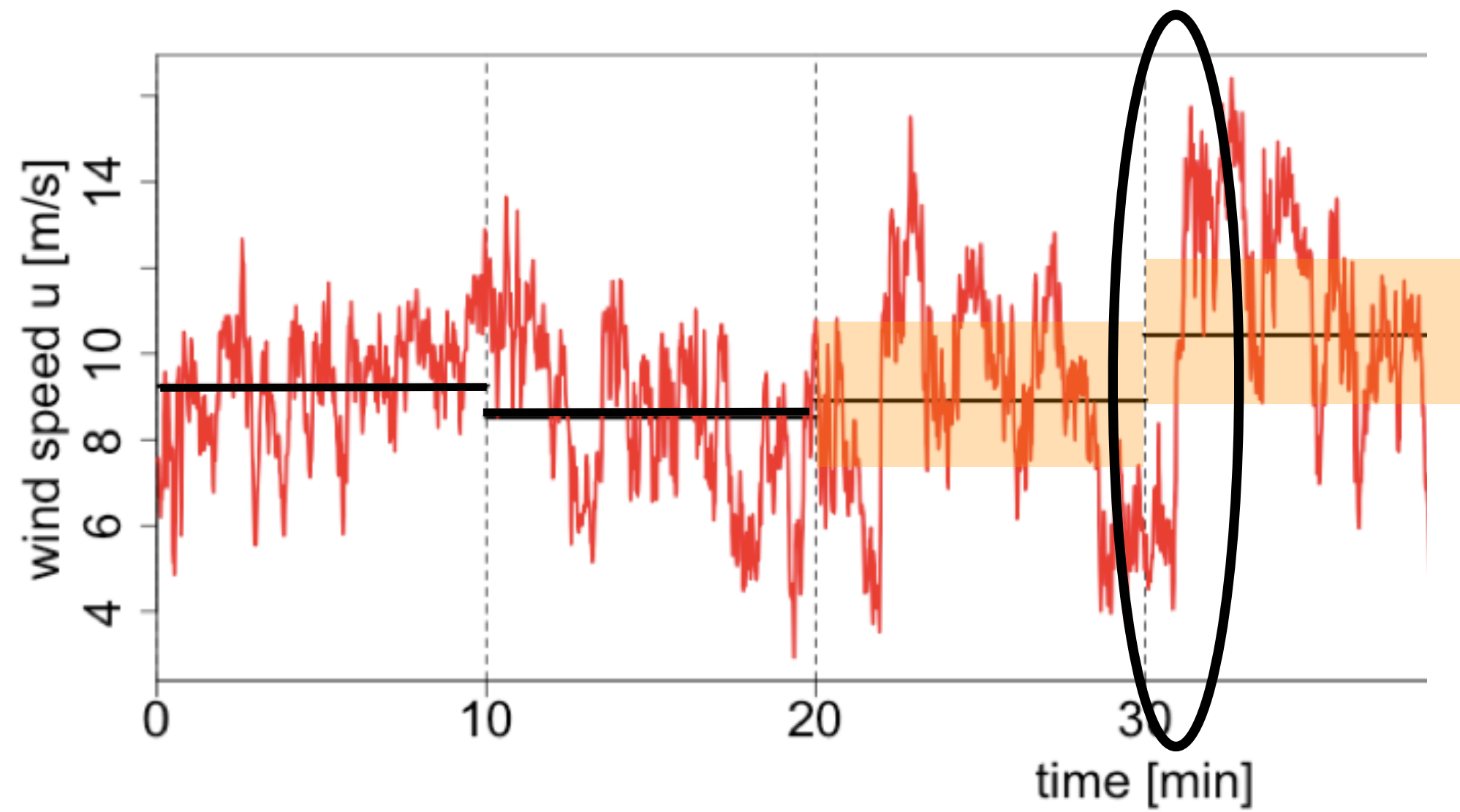


measured time series



wind measurements and data analysis

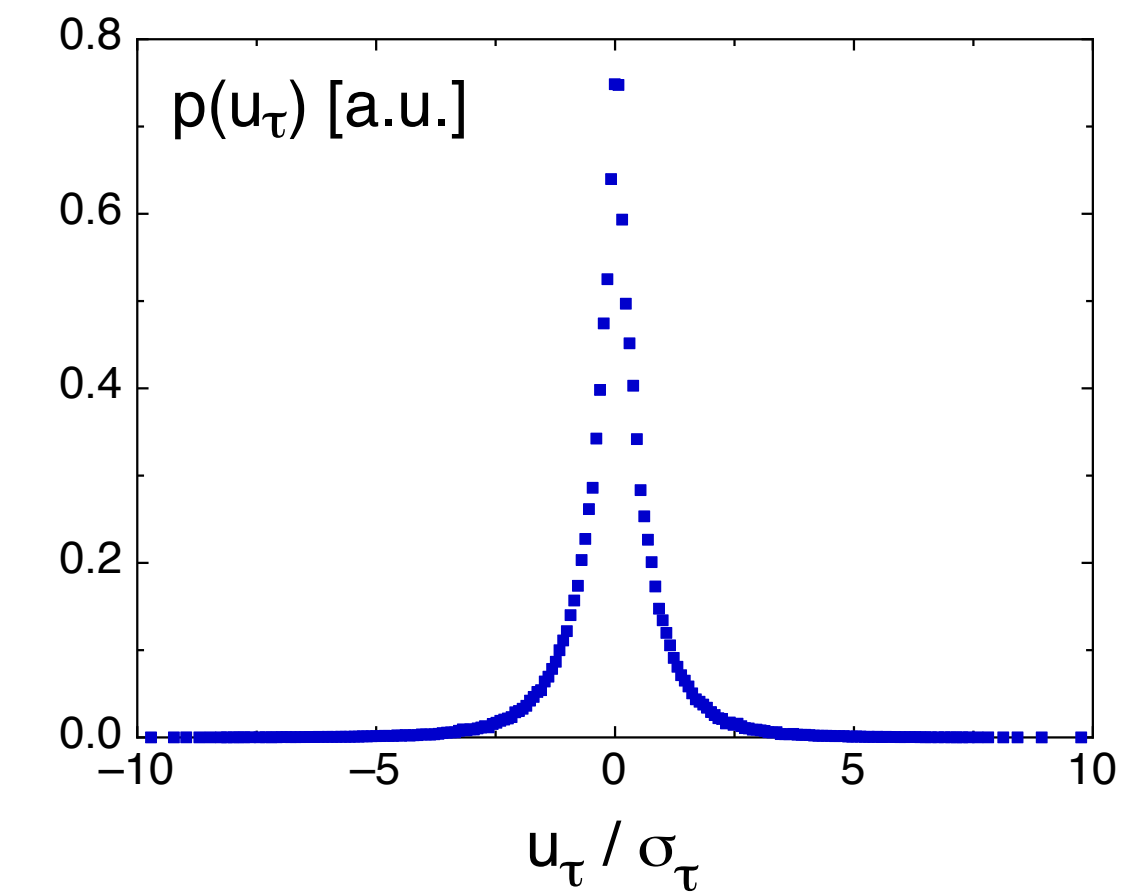
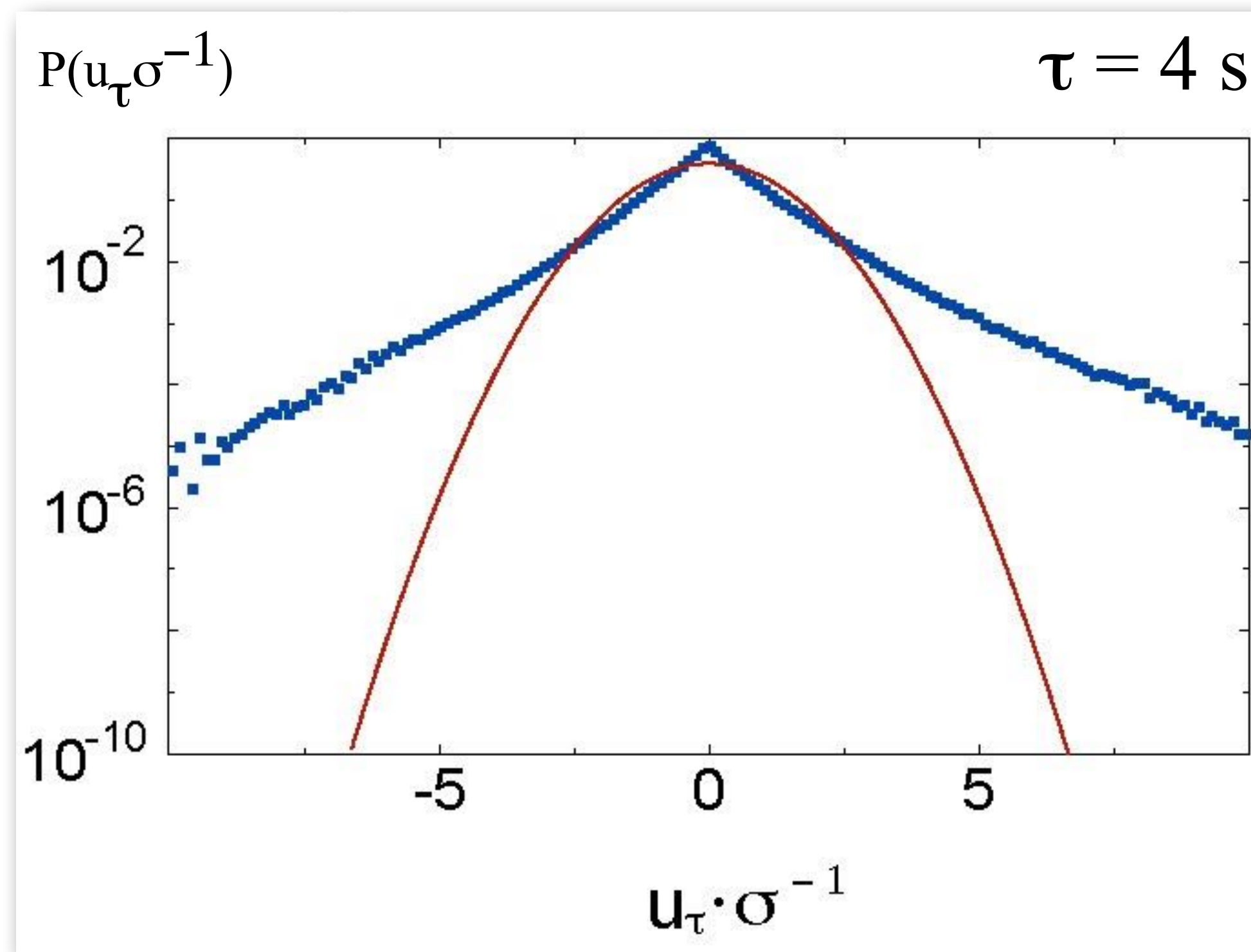
▼ characterisation after IEC norm



statistics of gusts

▼ wind fluctuations can be measured by velocity increments

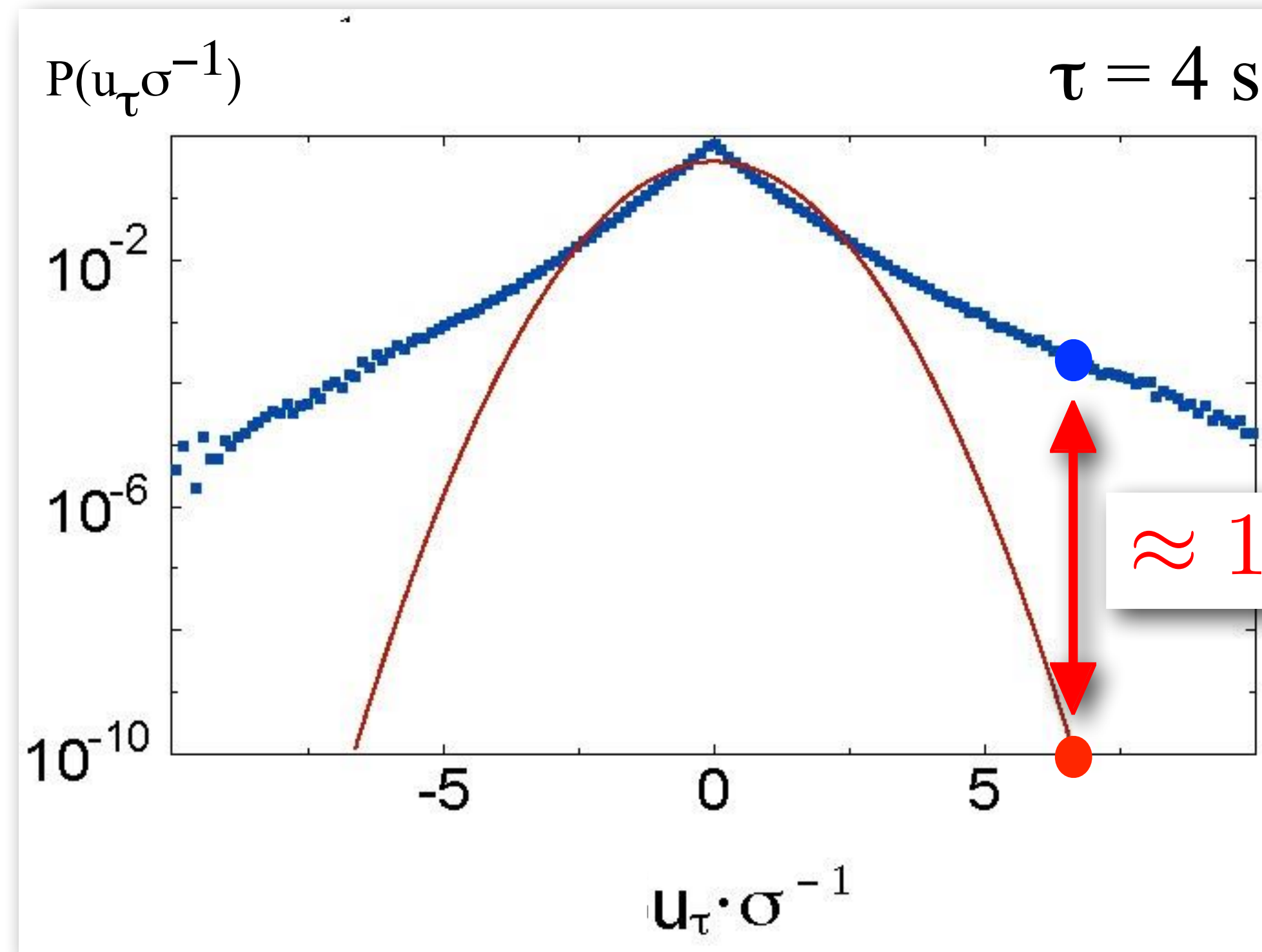
$$u_{\tau} = u(t + \tau) - u(t)$$



Boundary-Layer Meteorology **108** (2003)

statistics of gusts

non-Gaussian called intermittency



$$Prob(u_\tau > 6\sigma) \approx 10^{-4}$$

1/day

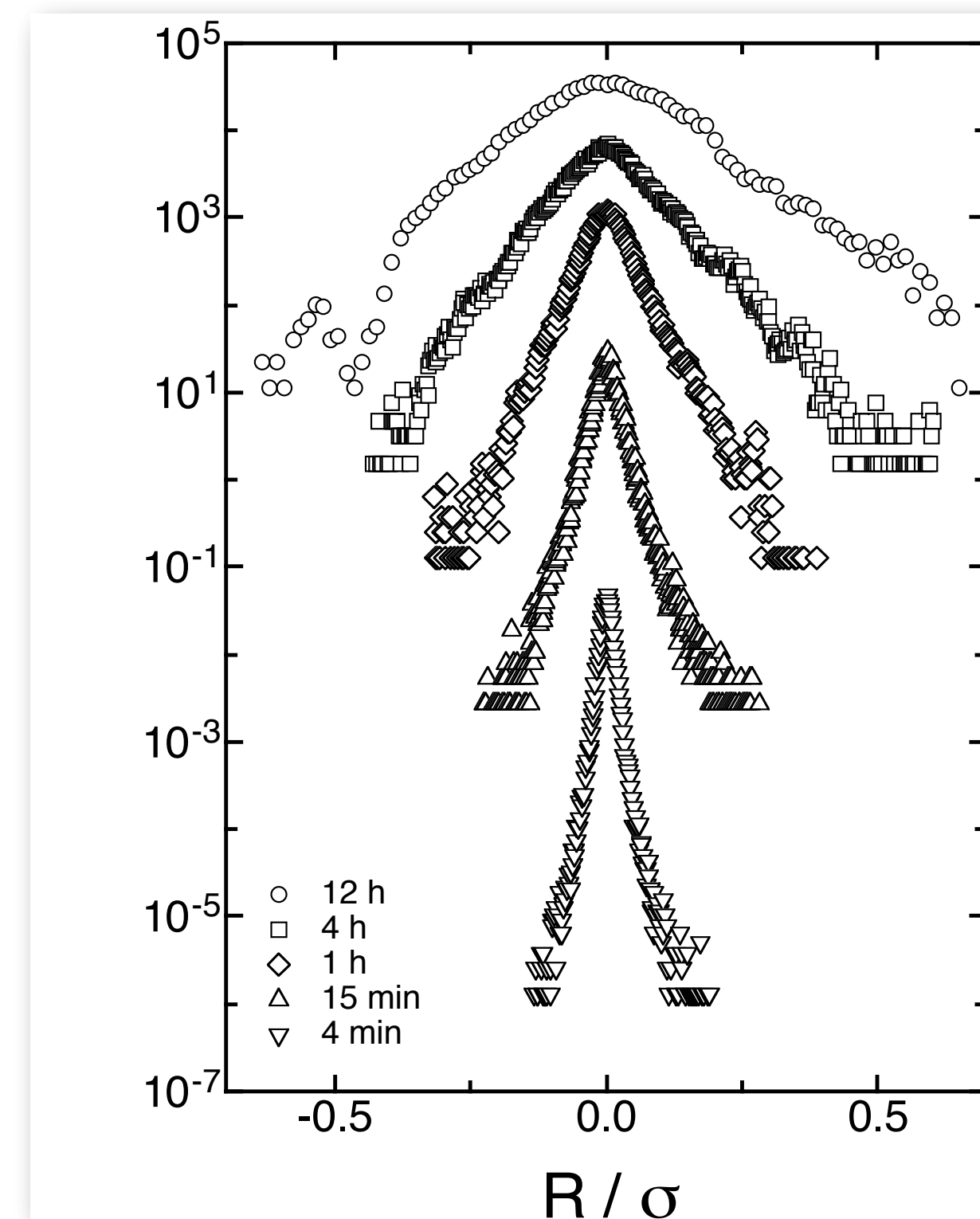
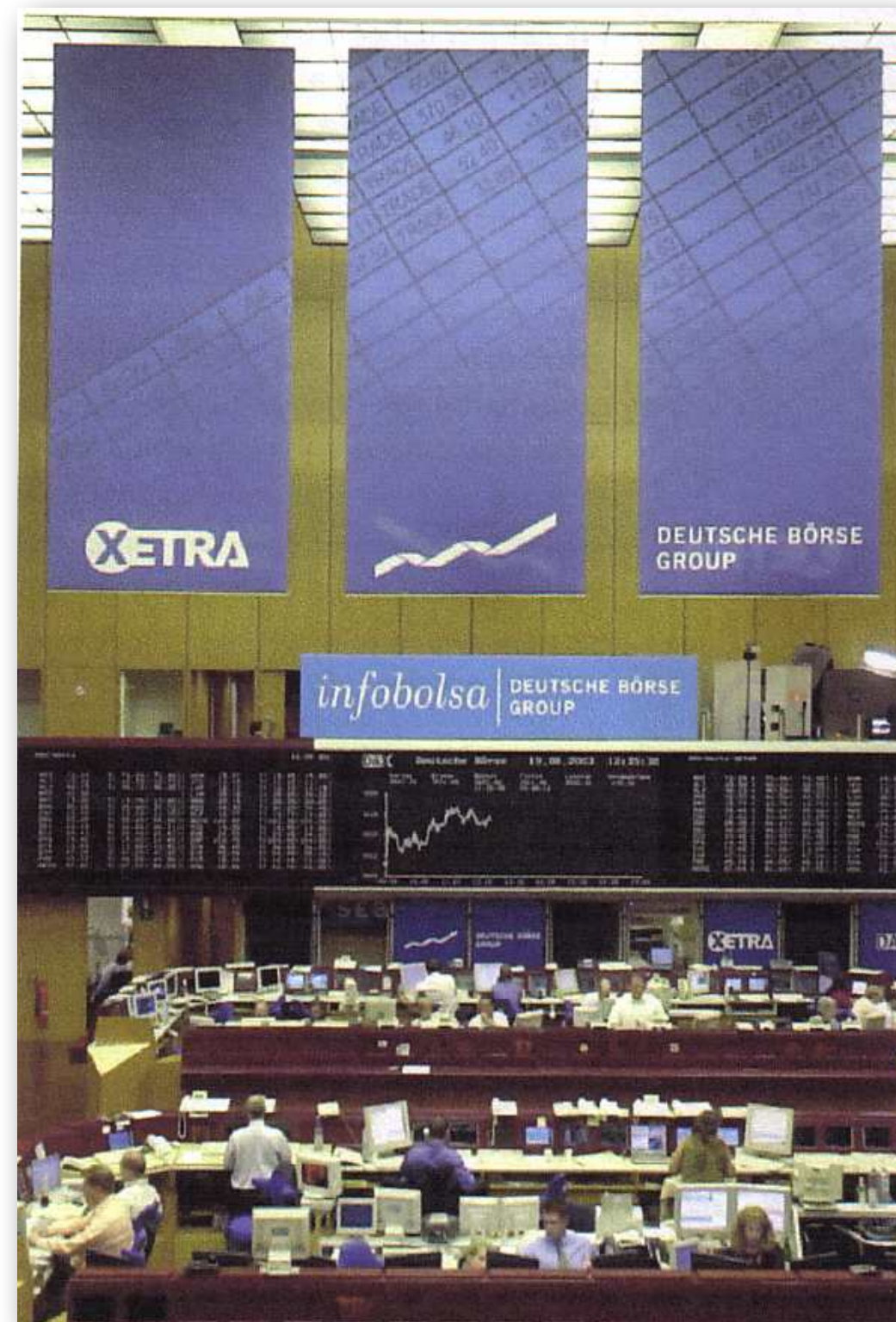
=> Importance of statistics $p(x)$

$$Prob(u_\tau > 6\sigma) \approx 10^{-10}$$

1/3000 years

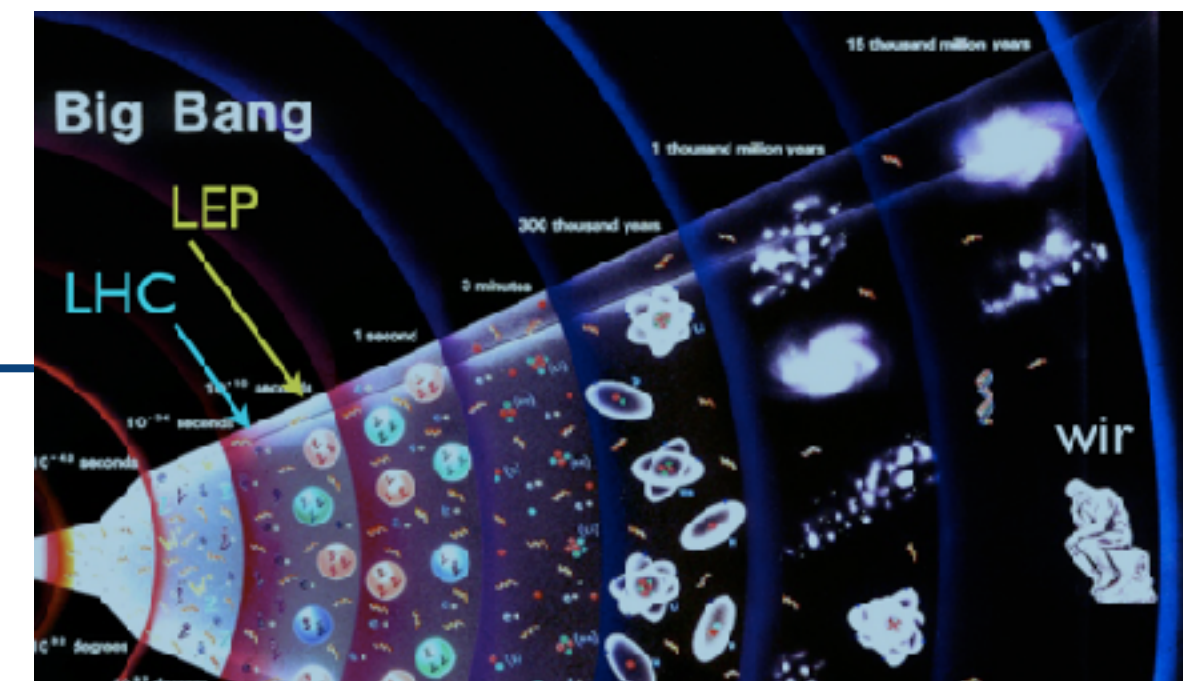
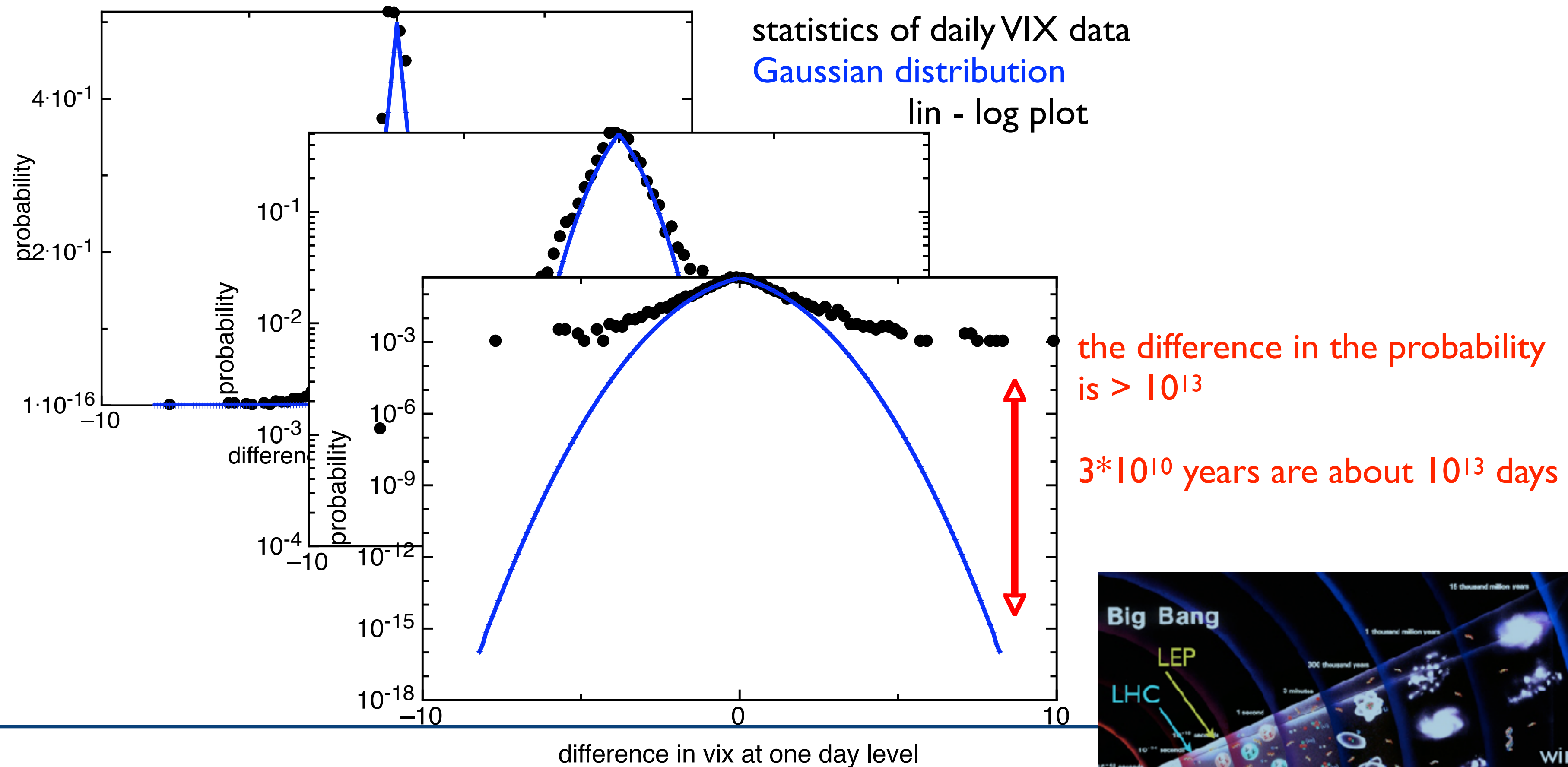
Scale dependent quantity for measuring the disorder
return or log return for different time scales

$$Q(x, r) \Rightarrow r(t, \tau) = \frac{x(t + \tau) - x(t)}{\tau} \quad \text{or} \quad R(t, \tau) = \log r(t, \tau)$$



extreme events

- „According to Goldman and Sachs, the latest jump in Vlx (a measure of stock-market volatility) took it **eight standard deviations** from its average. If conventional models are correct, such an event should have happened in the history of the known **universe**.“



rare or extreme events **categories:**

1) **Extreme events :**

- based on statistics
- based on effect - outcome
 - **above threshold** leads to damage
 - coupled to a system - same event may be extrem or not

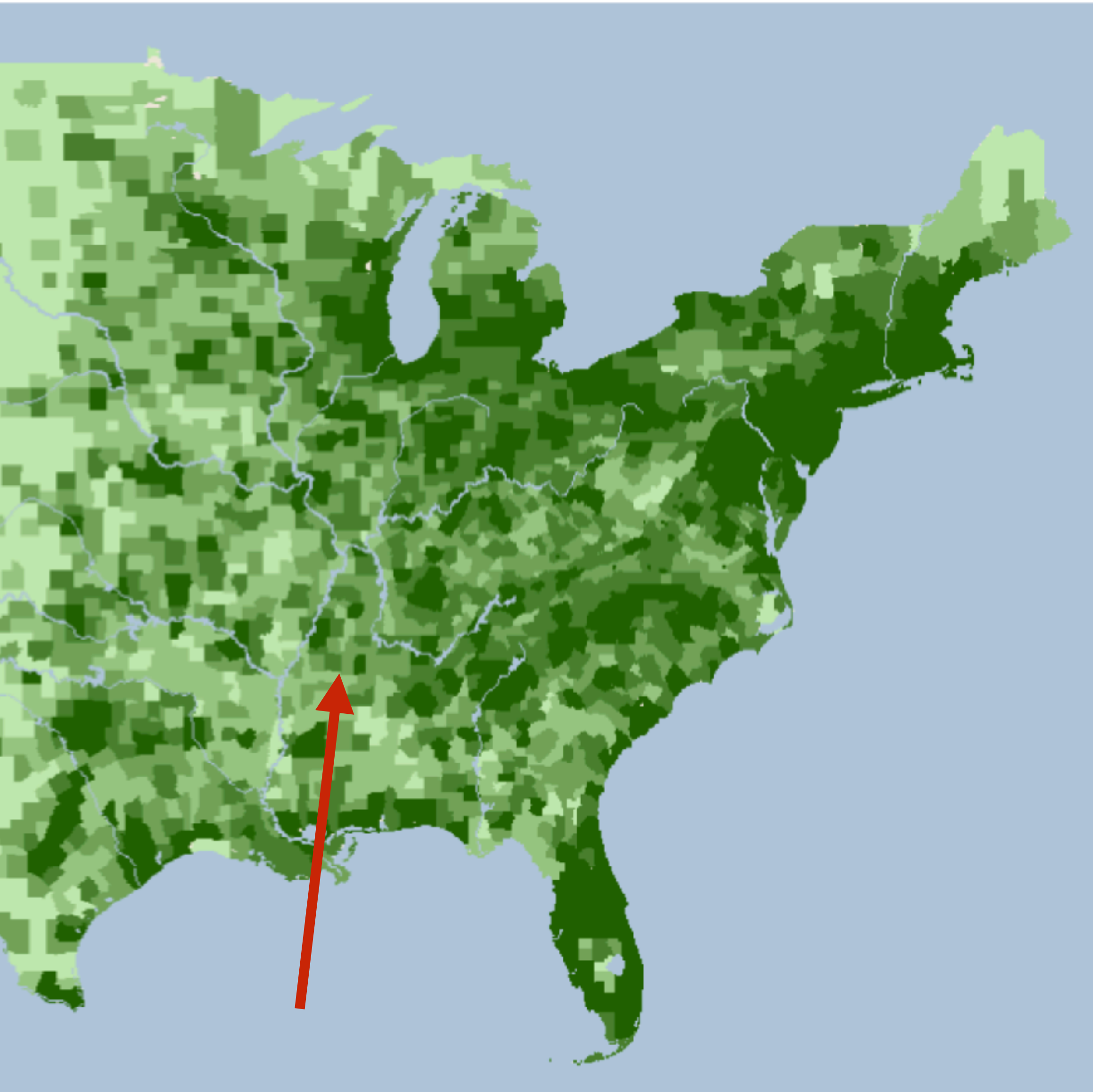


rare or extreme events **categories:**

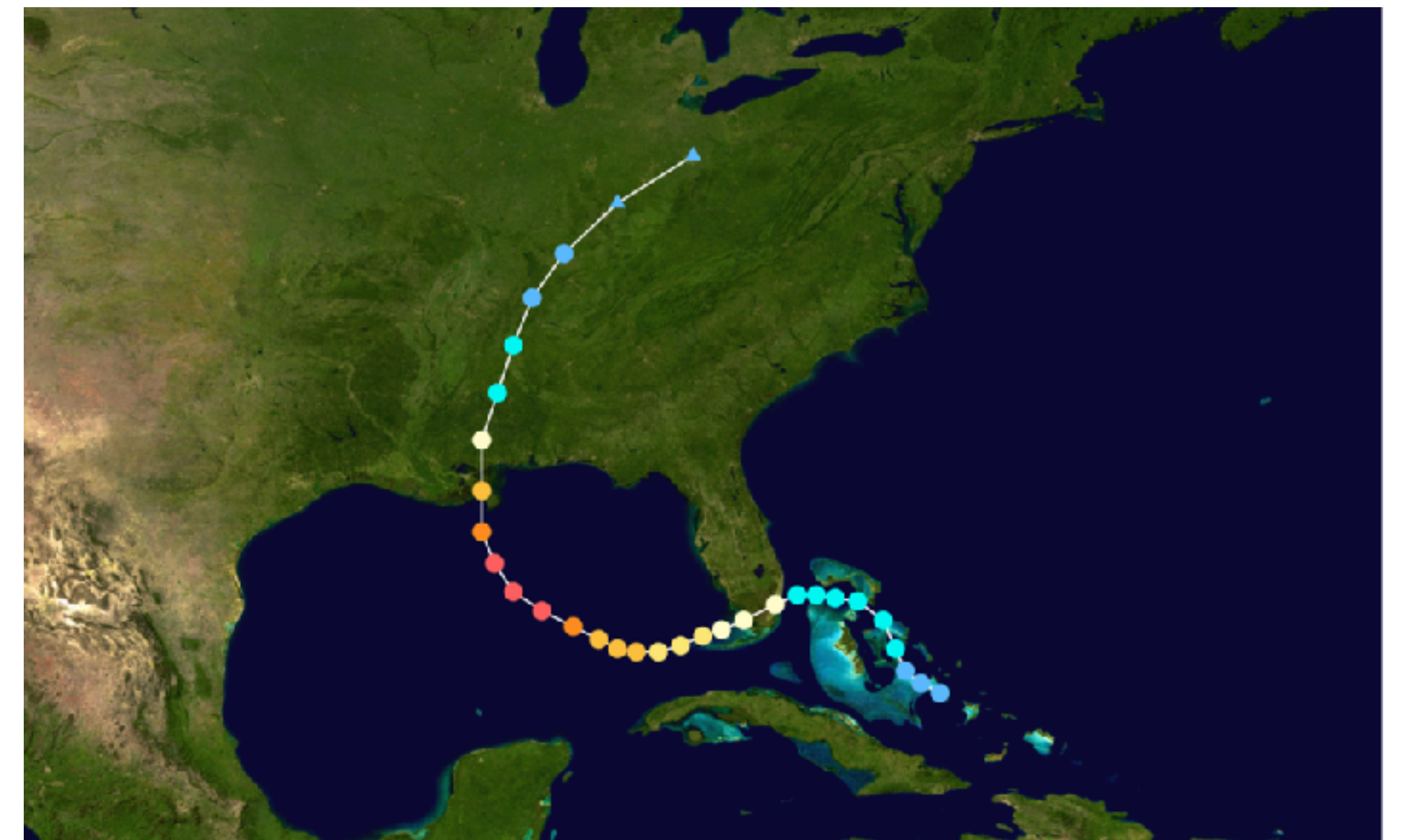
1) **Extreme events :**

- based on statistics
- based on effect - outcome
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 - **coupled to another system** - same event may be extrem or not

Distribution of wealth



The event being extreme depends on the
Wealth distribution



rare or extreme events **categories:**

1) Extreme events :

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2) event and system

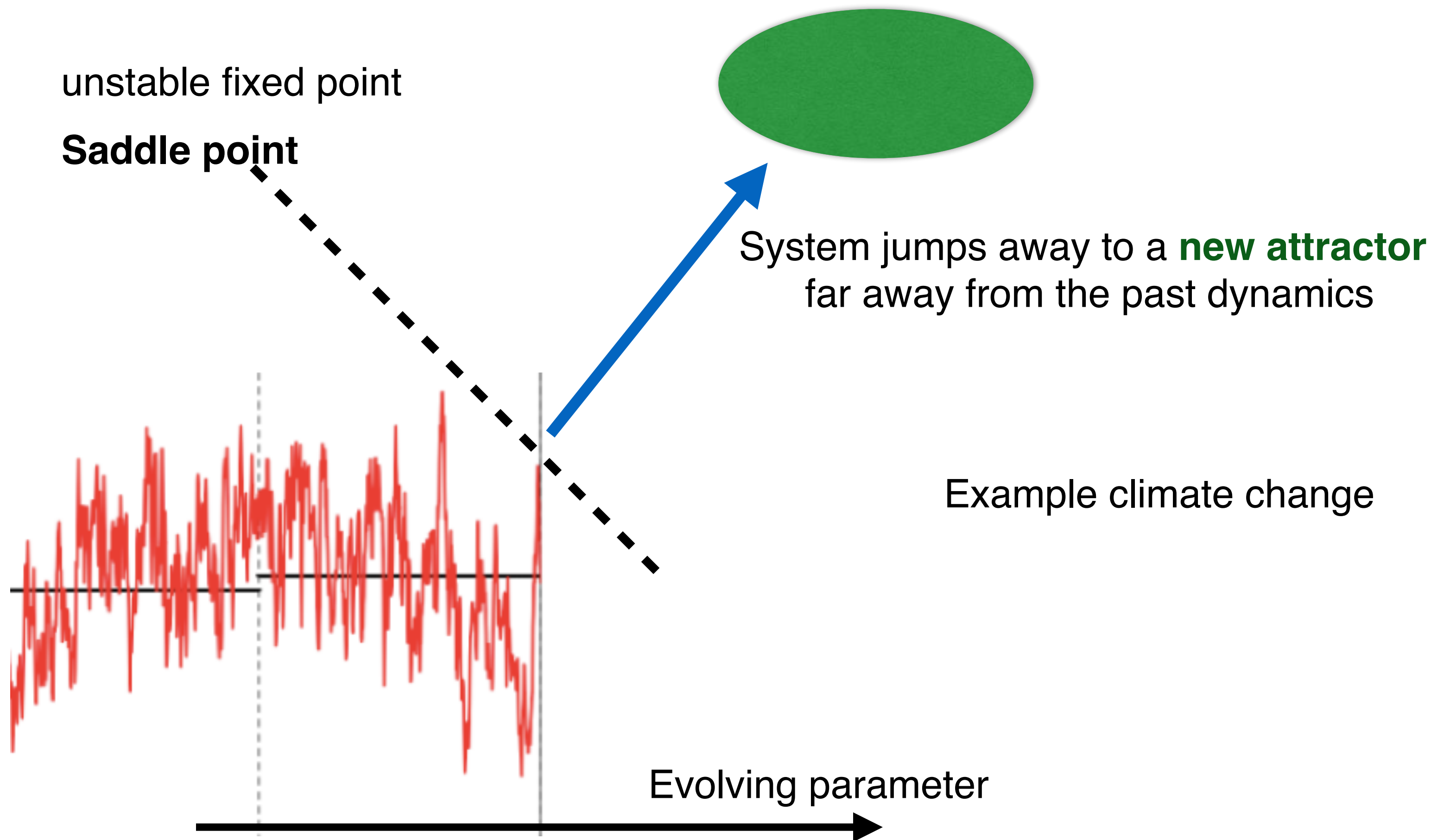
- **outside** of the system, driven by **external** parameters
- intrinsic feature of a system

events driven from outside

- Changing parameters

Extrem events :

- **blue sky catastrophe**
- in phase space a non local effect



rare or extreme events **categories:**

1) Extreme events :

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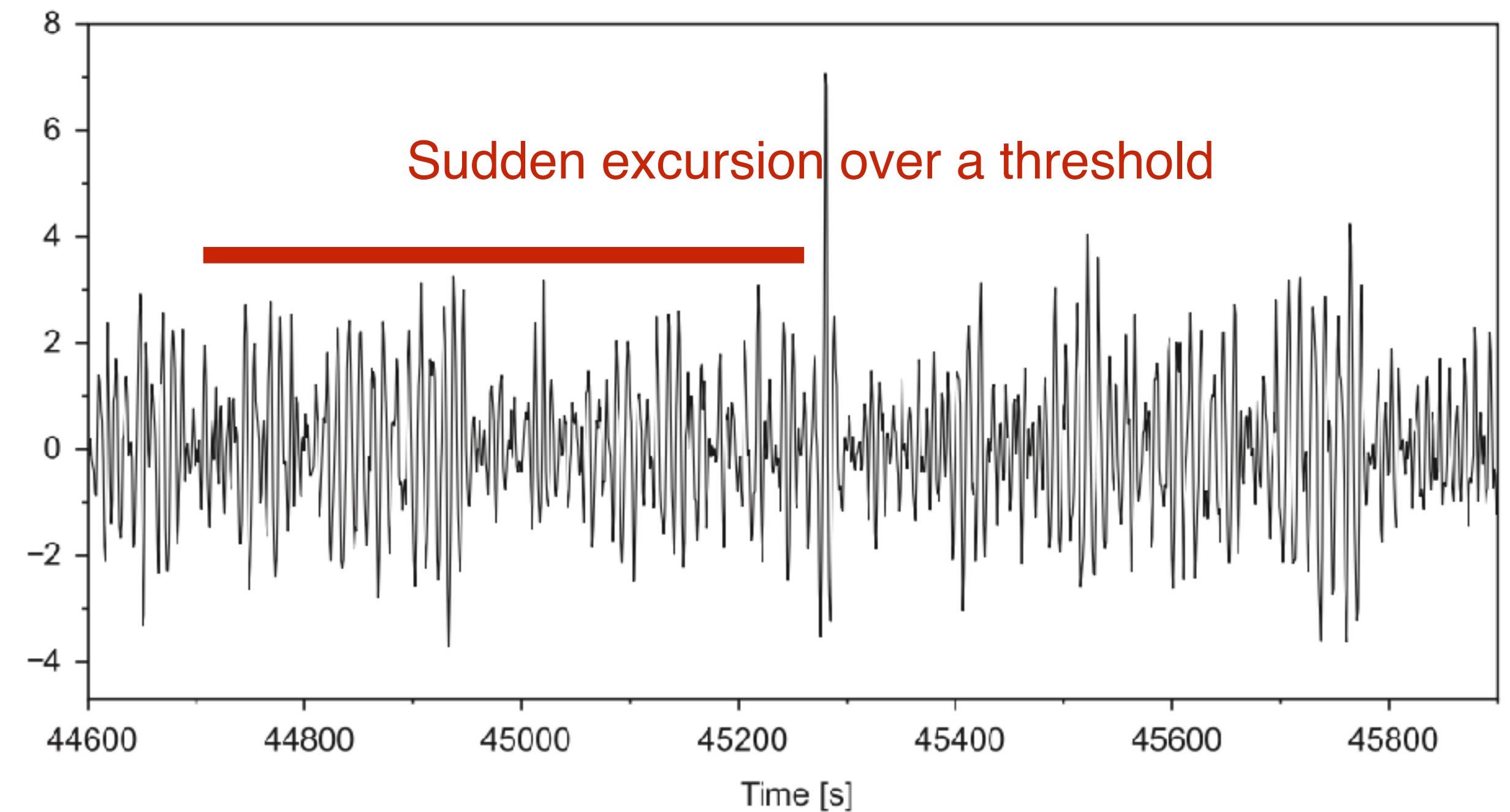
events and the system

Extrem events :

- **blue sky catastrophe** - in phase space a non local effect
- **event within the system**

Reason may be

- **intrinsic system property**



events and the system

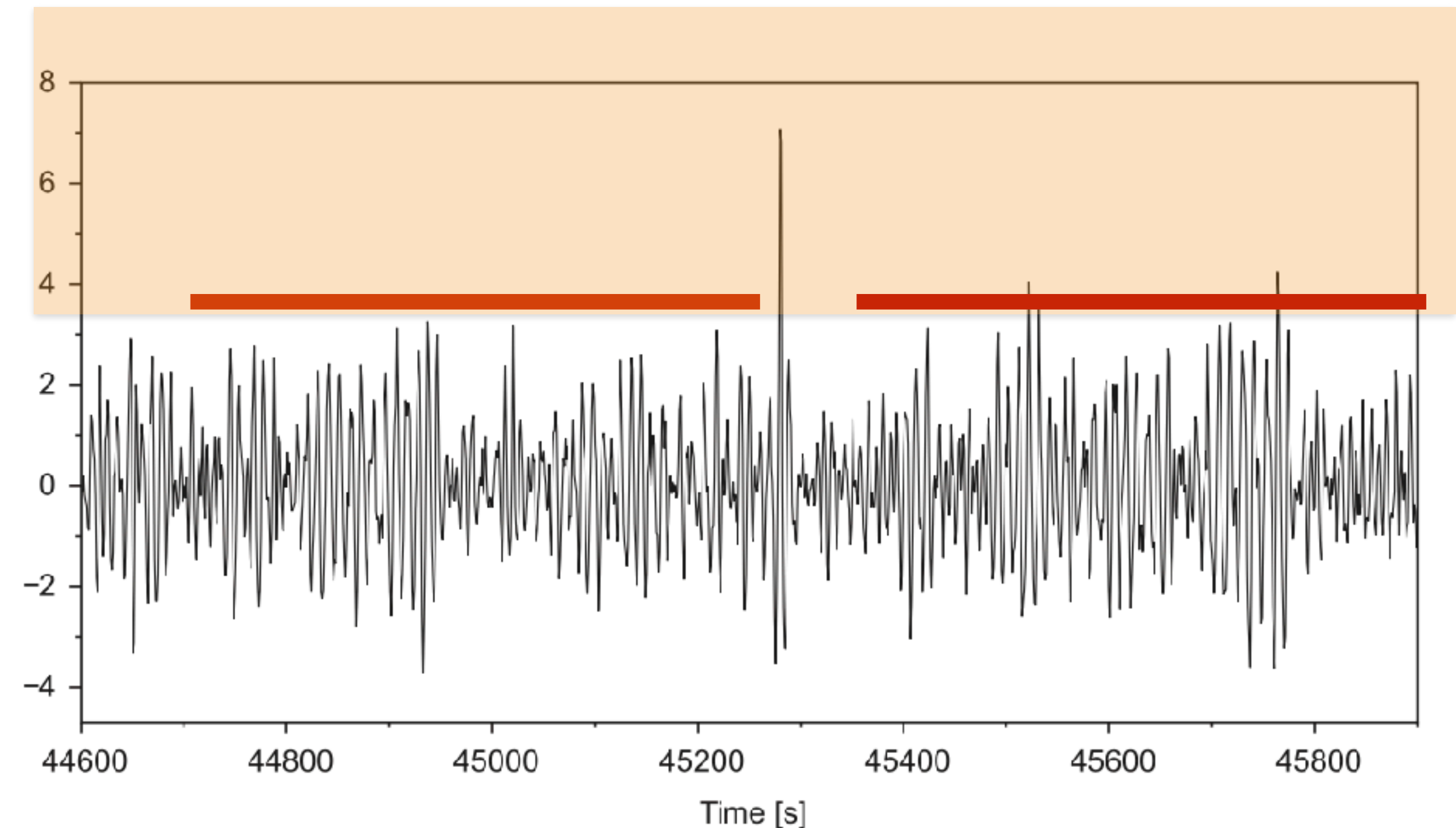
Extrem events :

- **blue sky catastrophe** - in phase space a non local effect
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Reason may be

- **intrinsic system property**

Extreme value statistics - extreme events are rare and independent



events and the system

Extrem events :

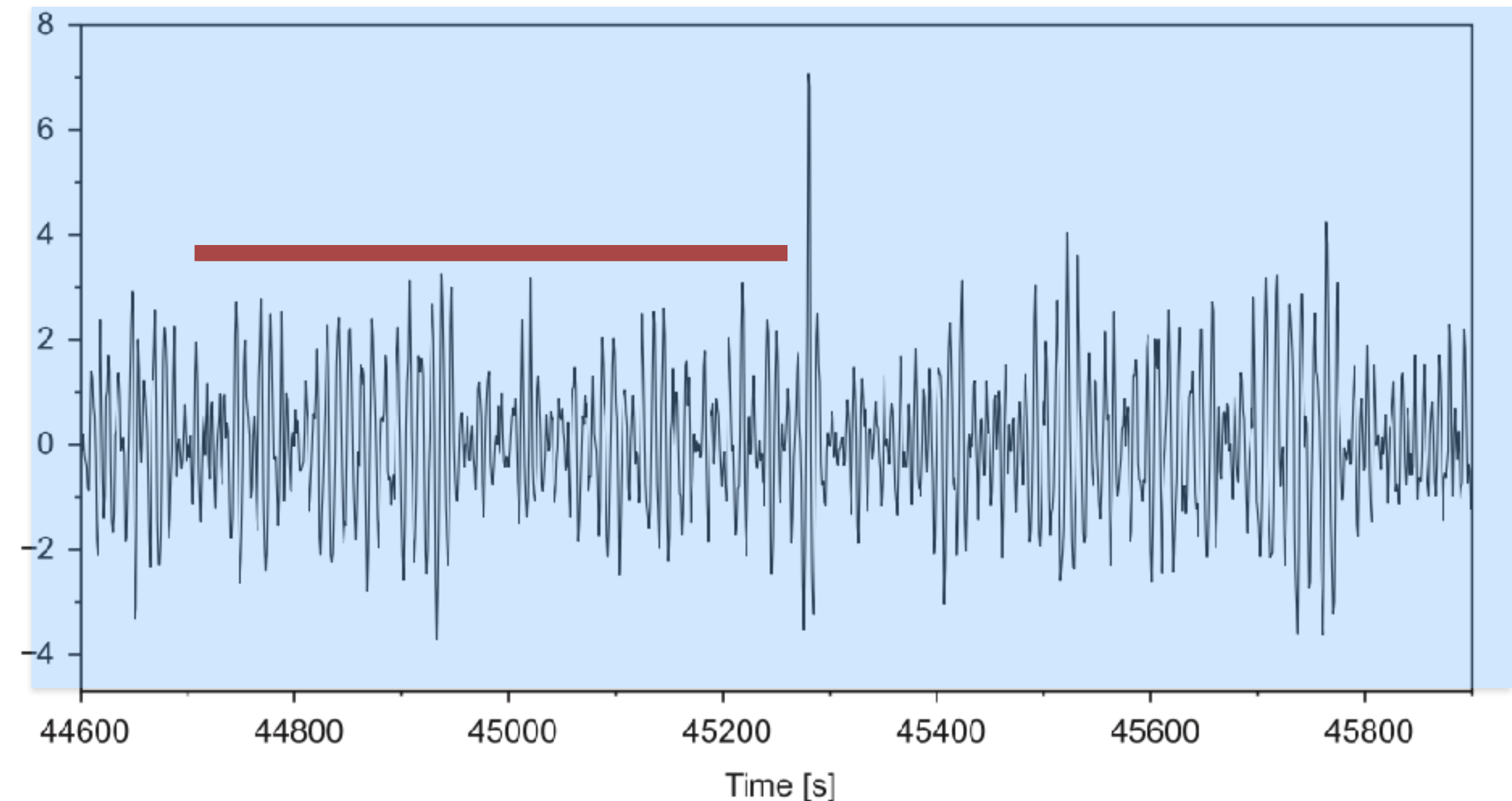
- **blue sky catastrophe** - in phase space a non local effect
- **event within the system**

Reason may be

- **intrinsic system property**

Extreme values are part of the whole system

Of all data



rare or extreme events categories: — take home message

1) Extreme events :

- based on **statistics**
- based on effect - **outcome**
 - above threshold leads to damage
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2) events and the system

- outside of the system, driven by **external** parameters
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Earth's Future



RESEARCH ARTICLE

10.1002/2017EF000686

Defining Extreme Events: A Cross-Disciplinary Review

Lauren E. McPhillips¹ , Heejun Chang² , Mikhail V. Chester³ , Yaella Depietri⁴ ,
Erin Friedman⁵ , Nancy B. Grimm⁶ , John S. Kominoski⁷ , Timon McPhearson^{4,8} ,
Pablo Méndez-Lázaro⁹ , Emma J. Rosi⁸ , and Javad Shafiei Shiva¹⁰ 

rare or extreme events **categories:**

1) Extreme events :

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- outside of the system, driven by external parameters
- intrinsic feature of a system

3.) what do we want to know?

How likely is an event

Forecasting of events

rare or extreme events categories:

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- outside of the system, driven by external parameters
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3.) what do we want to know?

How likely is an event

Forecasting of events

Part B :

Aim of this talk

Rare events :

Statistics and structures
as intrinsic features of a complex system

Turbulence - wind gusts

Water waves - monster waves

Content - Part B

Systems of extreme events

multi-point statistics — main idea

scale-dependent Fokker-Planck equations

consequences

waves and turbulence

Nonlinear Schrödinger equation (NLSE)

$$i \frac{\partial \psi}{\partial x} + \frac{1}{2} \frac{\partial^2 \psi}{\partial t^2} + |\psi|^2 \psi = 0$$



Navier Stokes equation (NSE)

$$\partial_t \vec{u} + (\vec{u} \cdot \nabla) \vec{u} = -\frac{1}{\rho} \nabla p + \nu \Delta \vec{u}, \quad \nabla \cdot \vec{u} = 0$$

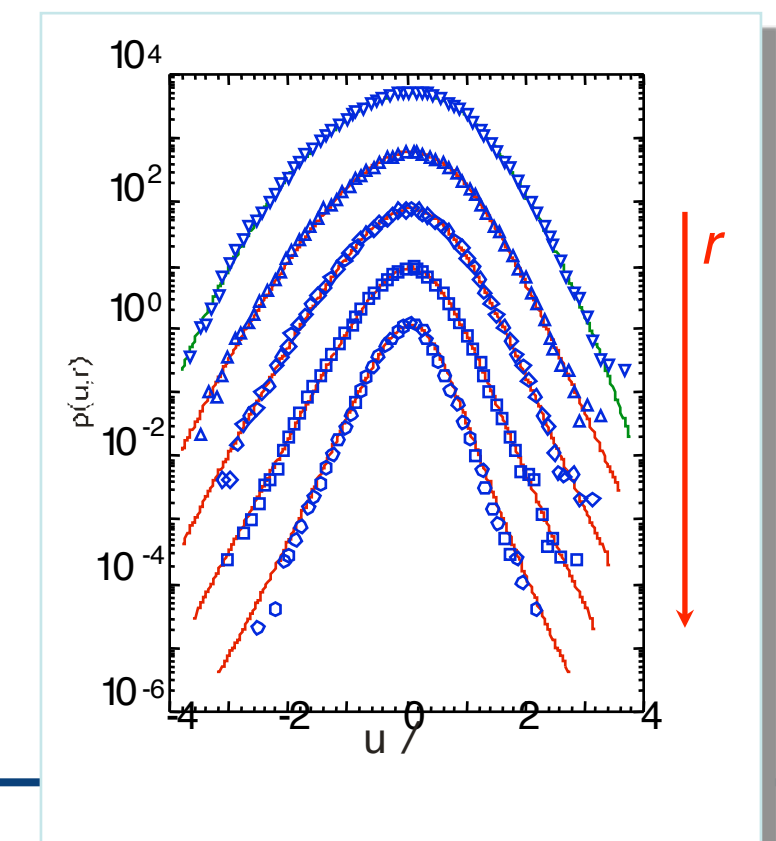
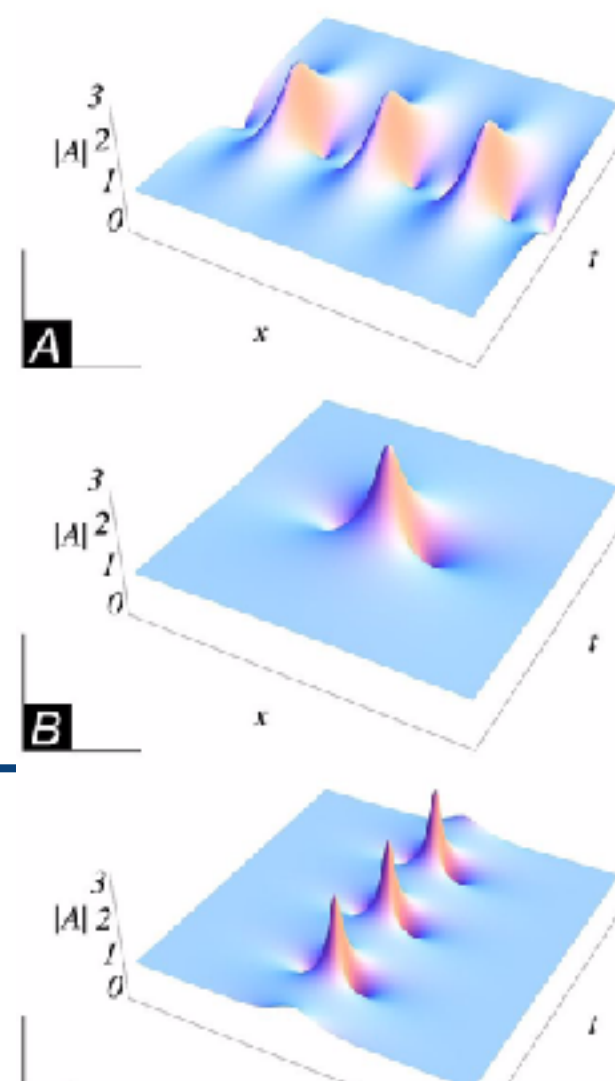


How to approach?

coherent structures
(Instabilities)

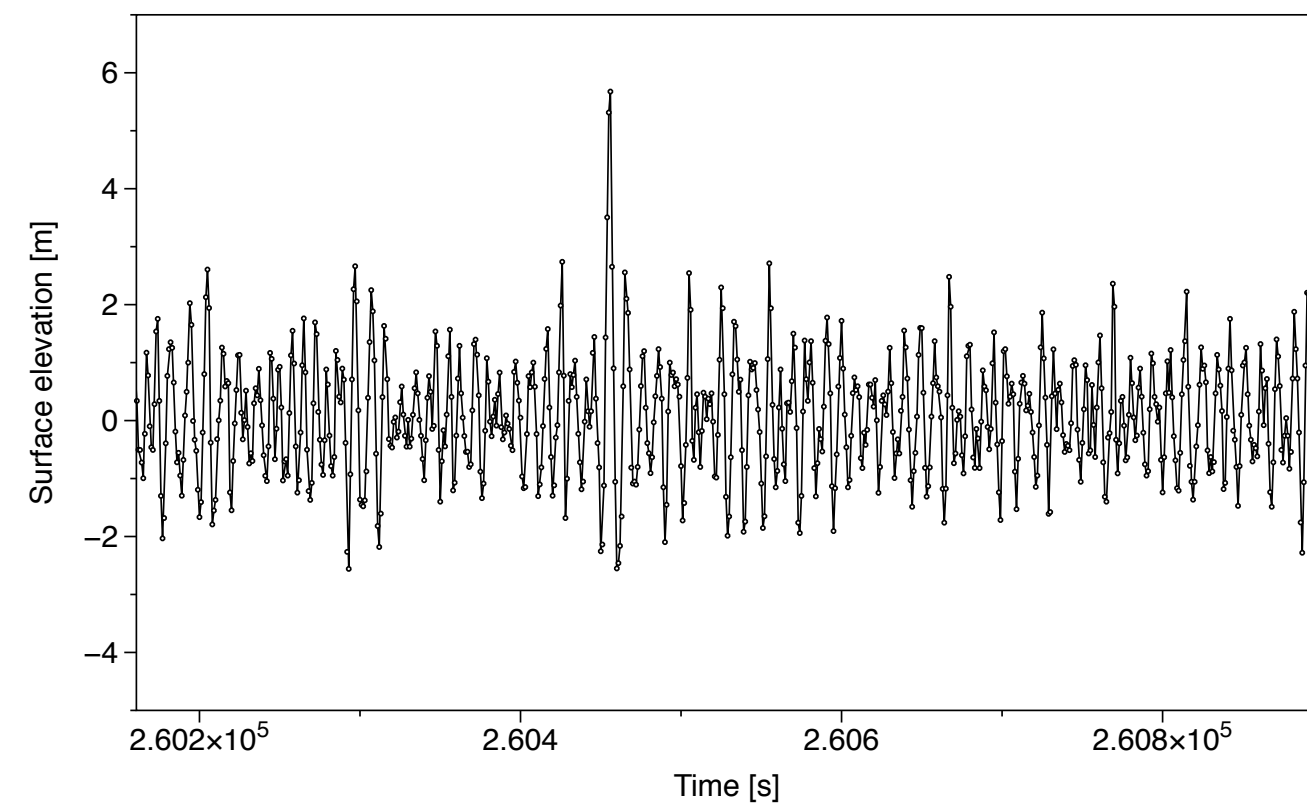
statistical approach-
extreme events

**Aim - general joint multipoint
statistics combines both sides**



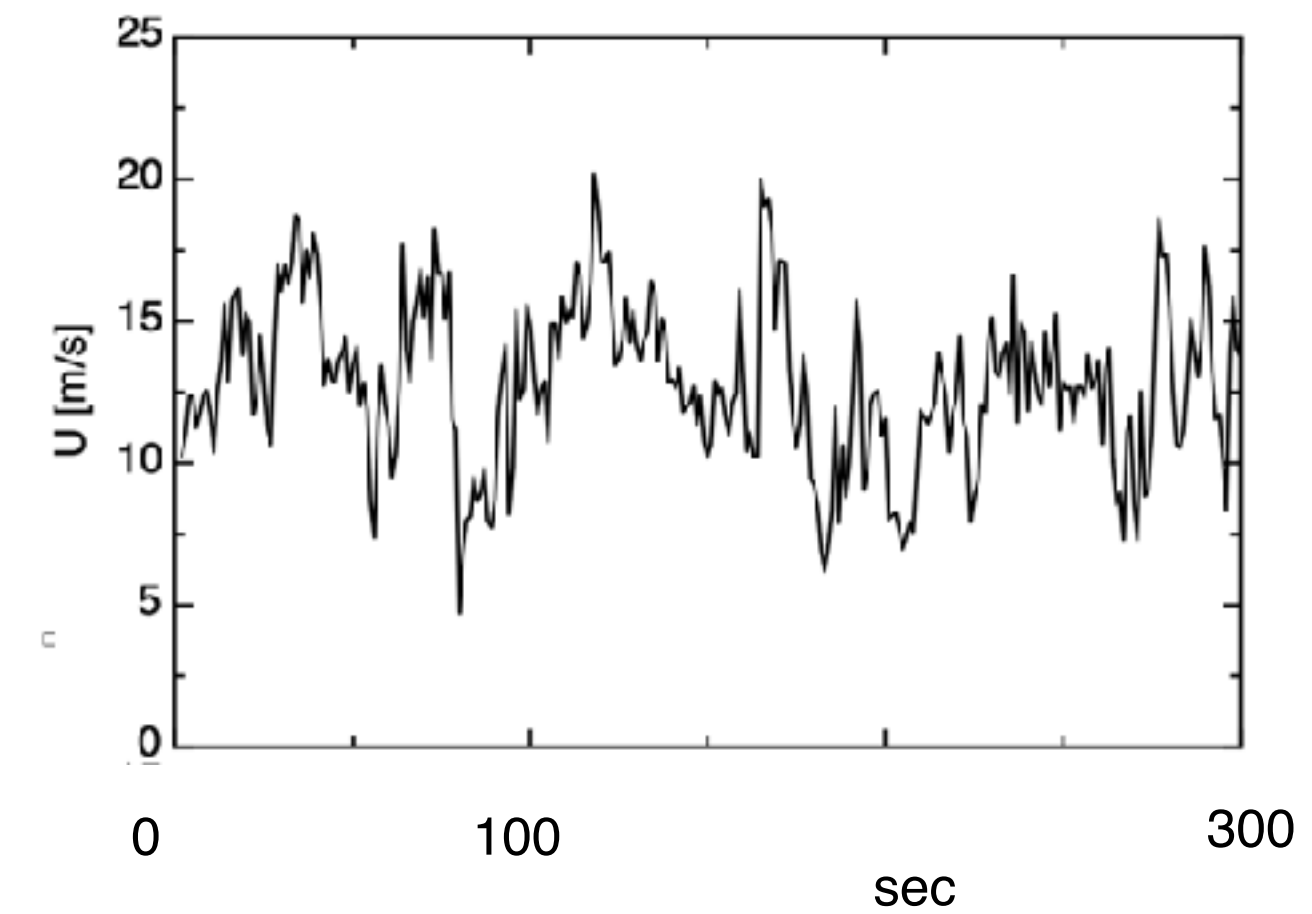
rogue wave - measured data

Sea of Japan data from N. Mori



Wind data

What is an exeme event?



0 100 sec 300

Content - Part B

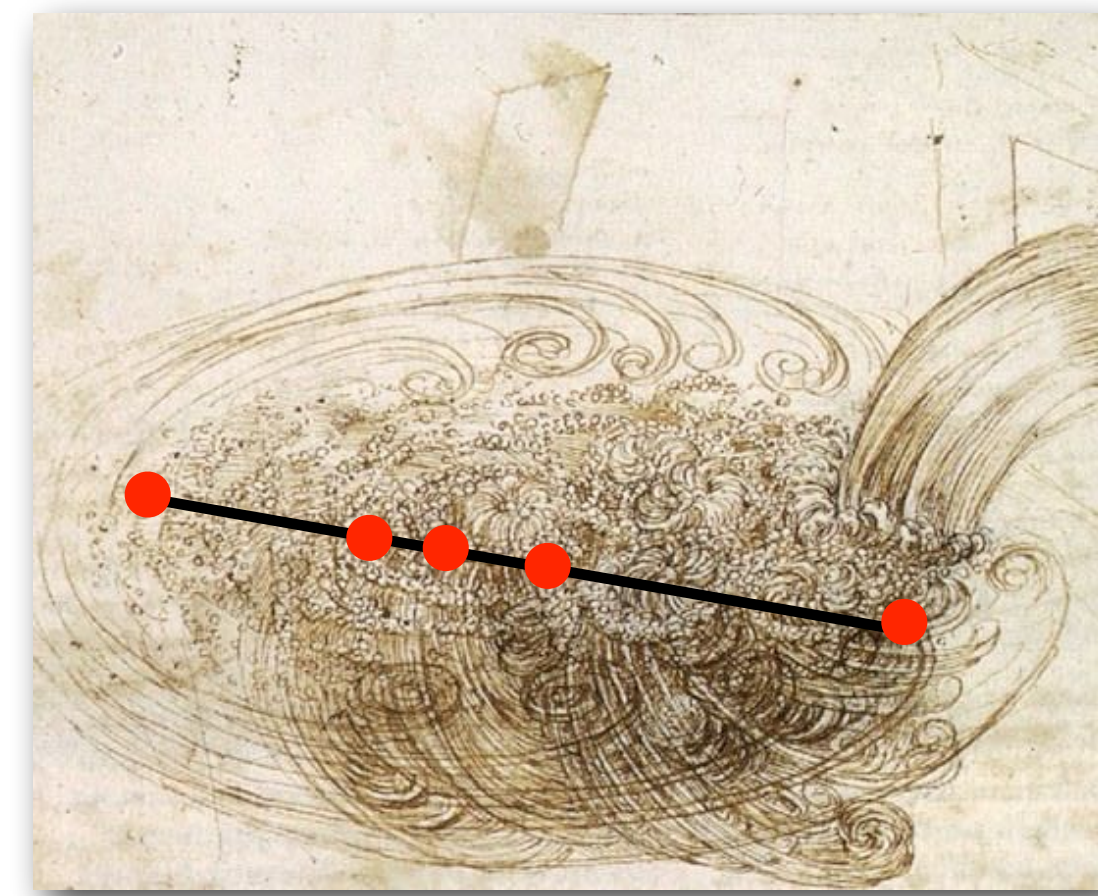
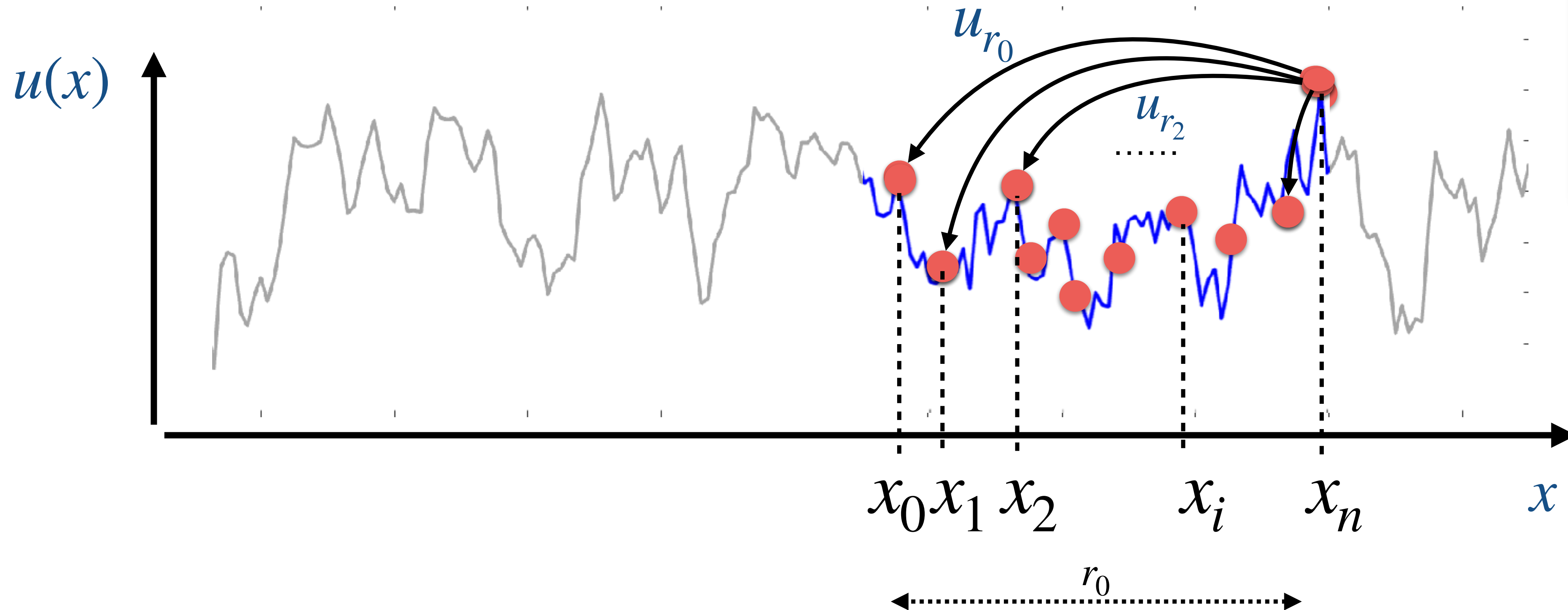
Extreme events

multi-point statistics <— main idea - > we want to get statistics and structures

scale-dependent Fokker-Planck equations

consequences

Data set $u(x) / h(x)$



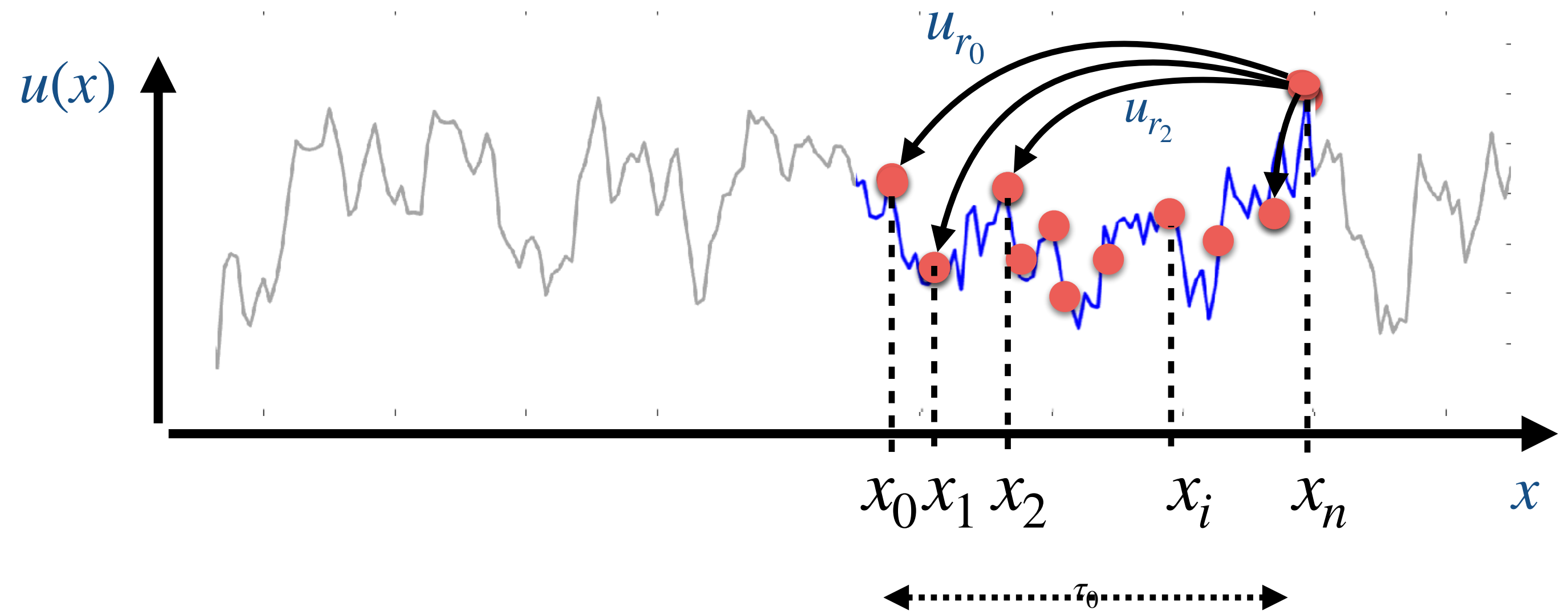
Aim to get the joint multi-time statistics $p(u(x_0), u(x_1), \dots, u(x_n))$

can be expressed by statistics of **increments** $u_r = u(x + r) - u(x)$

$$p(u(x_0), u(x_1), \dots, u(x_n)) = p(u_{r_0}, u_{r_1}, \dots, u_{r_{n-1}}, u(x_n))$$

J.P., et al., Annu. Rev. Condens. Matter Phys., 10 (2019) 107

Data set $u(x) / h(x)$



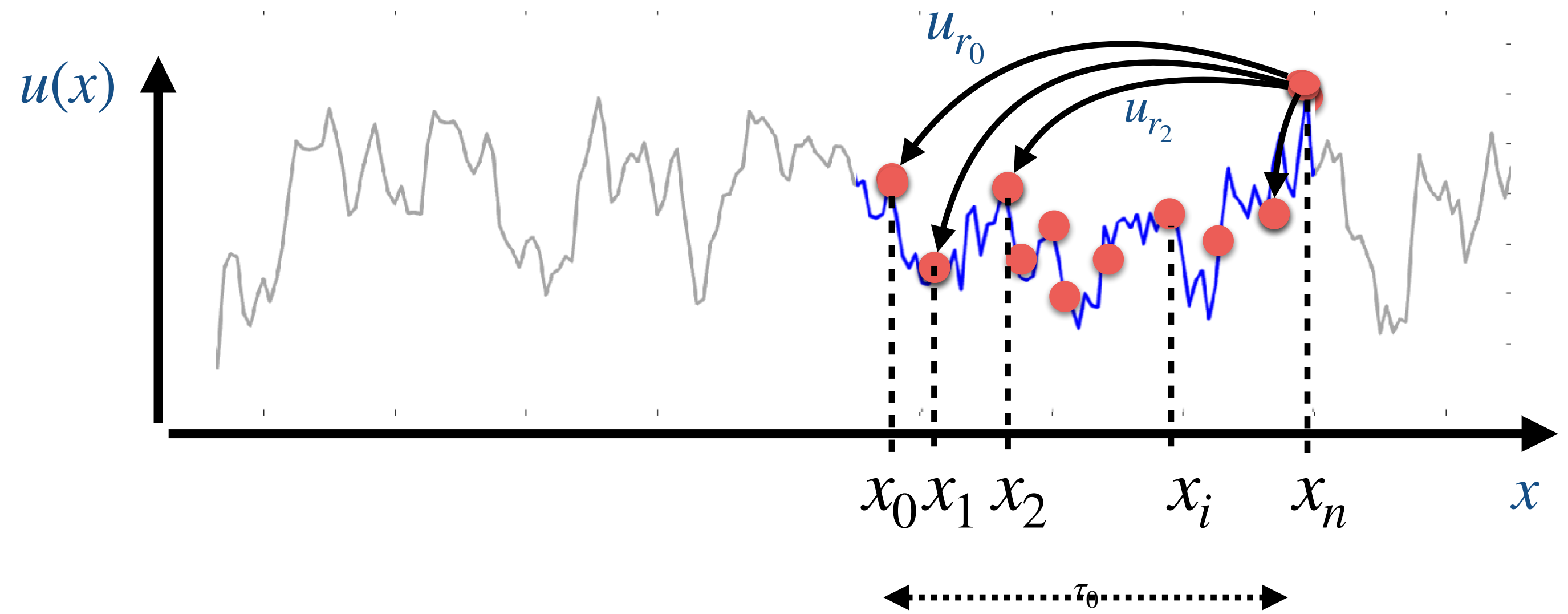
How to simplify

$$p(u(x_0), u(x_1), \dots, u(x_n)) = p(u_{r_0}, u_{r_1}, \dots, u_{r_{n-1}}, u(x_n))$$

Connection to set of increments - typical turbulent cascade description

J.P., et al., Annu. Rev. Condens. Matter Phys., 10 (2019) 107

Data set $u(x) / h(x)$



How to simplify - use conditional pdfs

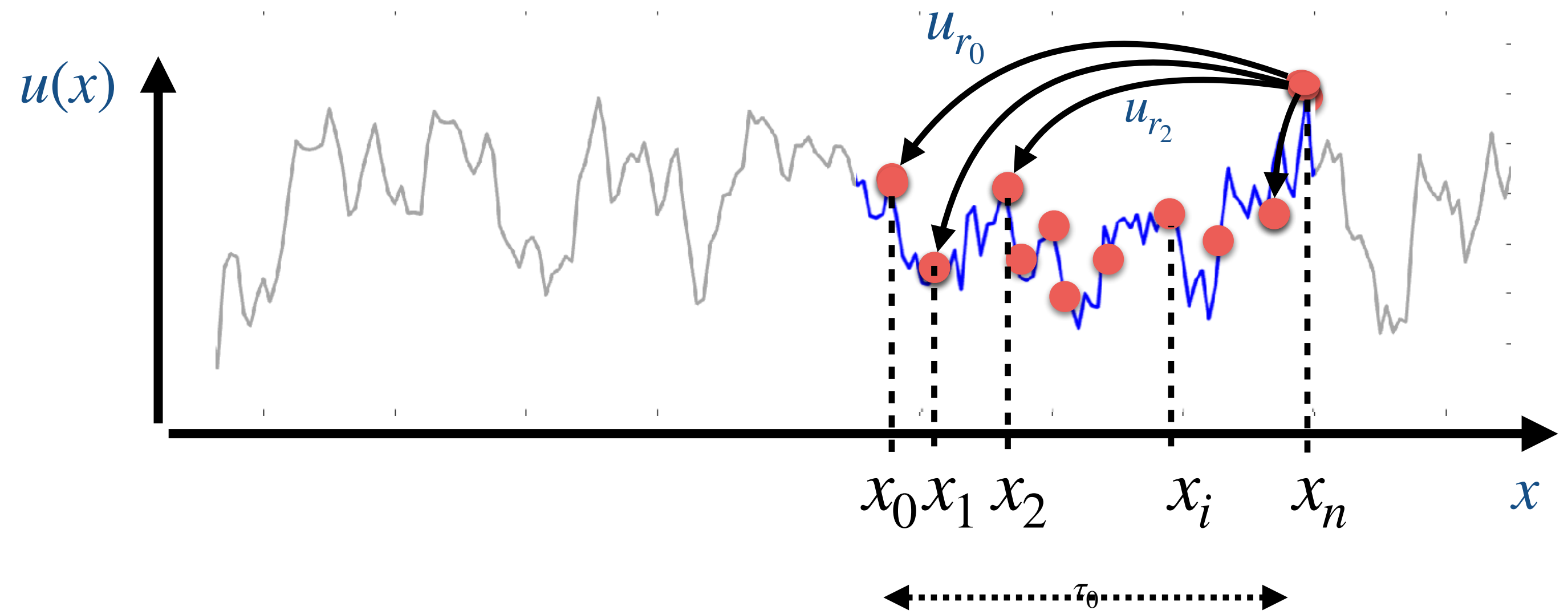
$$\begin{aligned}
 p(u(x_0), u(x_1), \dots, u(x_n)) &= p(u_{r_0}, u_{r_1}, \dots, u_{r_{n-1}}, u(x_n)) \\
 &= p(u_{r_0}, u_{r_1}, \dots, u_{r_{n-1}} | u(x_n)) p(u(x_n)) \\
 &= \dots \\
 &= p(u_{r_{n-1}} | u_{r_{n-2}}, \dots, u_{r_0}, u(x_n)) p(u_{r_{n-2}} | \dots) \dots p(u_{r_0} | u(x_n)) p(u(x_n))
 \end{aligned}$$

Simplification of multi-conditioned pdfs

$$\begin{aligned}
 p(u_{r_i} | u_{r_{i-1}}, \dots, u_{r_0}, u(x_n)) &=? \\
 &\stackrel{?}{=} p(u_{r_i} | u_{r_{i-1}}, u(x_n)) \\
 &\stackrel{?}{=} p(u_{r_i})
 \end{aligned}$$

J.P., et al., Annu. Rev. Condens. Matter Phys., 10 (2019) 107

Data set $u(x) / h(x)$

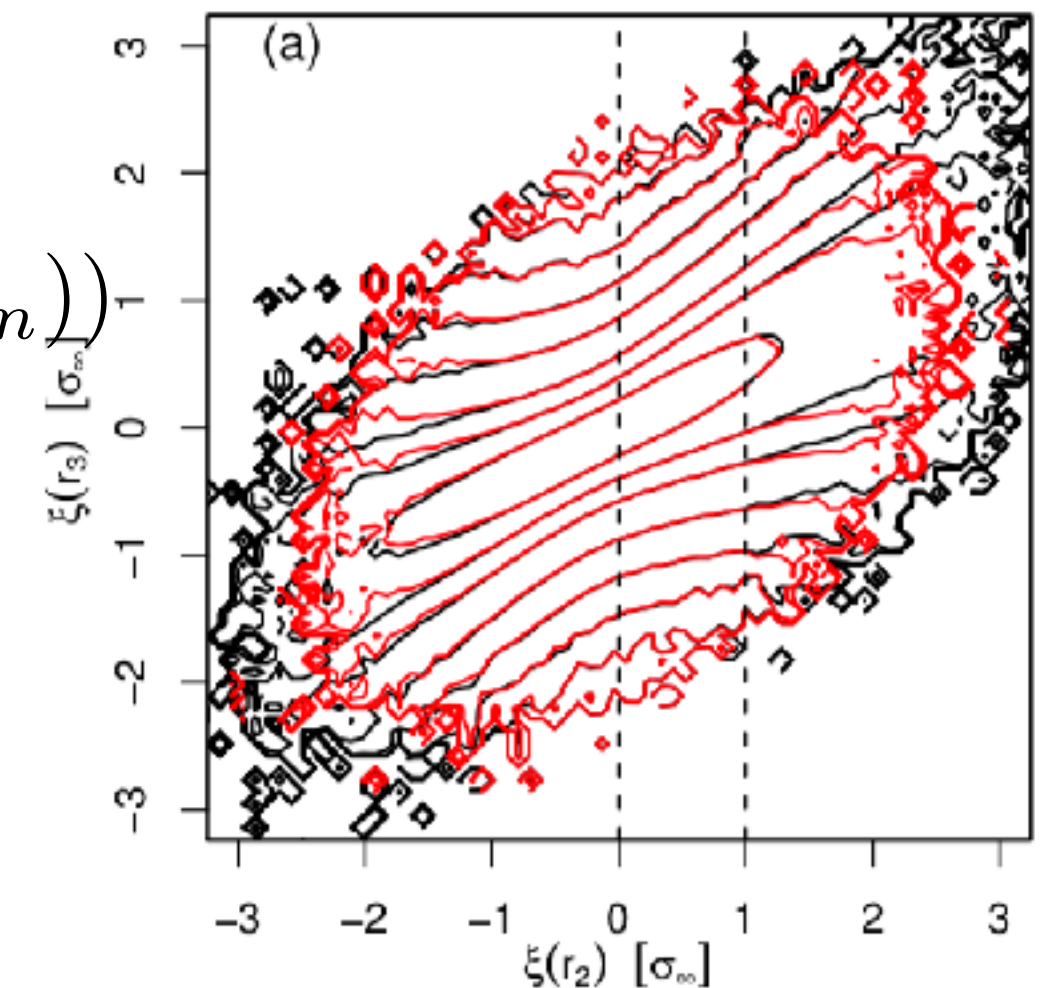


How to simplify - use conditional pdfs

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 \end{aligned}$$

Simplification of multi-conditioned pdfs

$$\begin{aligned}
 p(u_{r_i} | u_{r_{i-1}}, \dots, u_{r_0}, u(x_n)) &=? \\
 &= p(u_{r_i} | u_{r_{i-1}}, u(x_n)) \quad \text{Holds - three point closure} \\
 &\neq p(u_{r_i})
 \end{aligned}$$

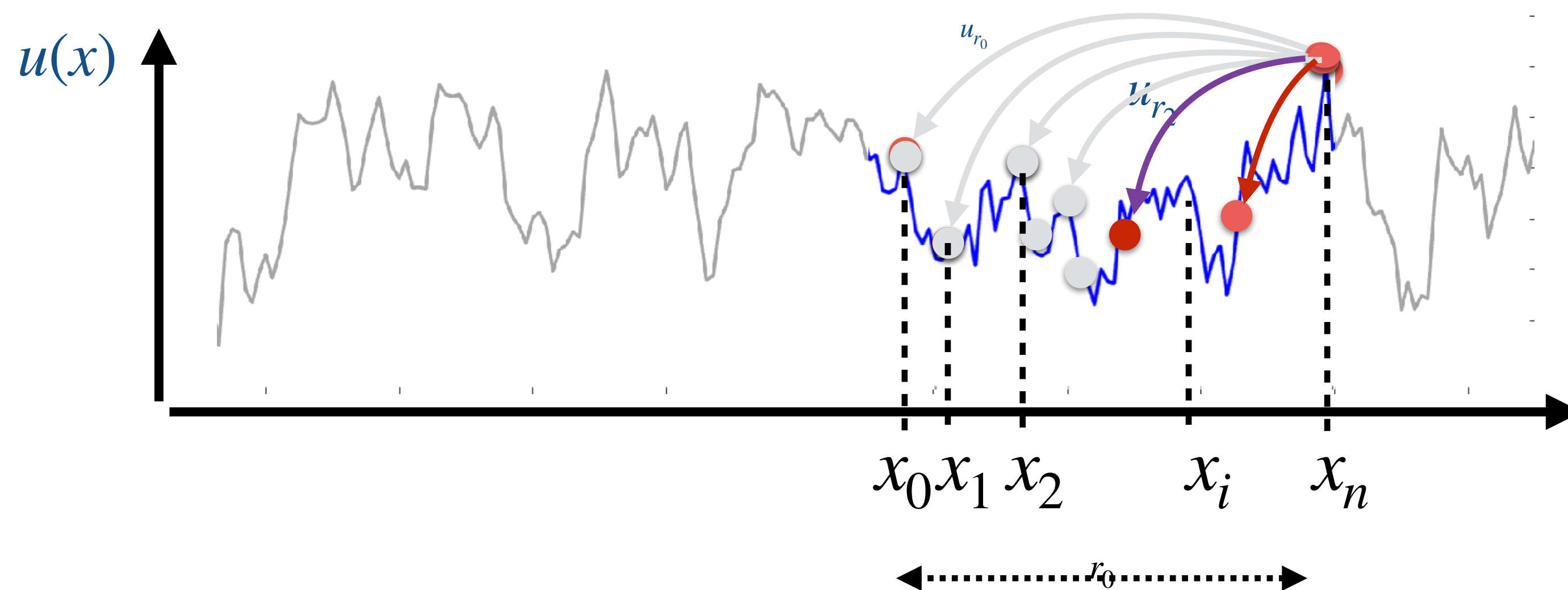


Joint- n-point statistics simplifies:

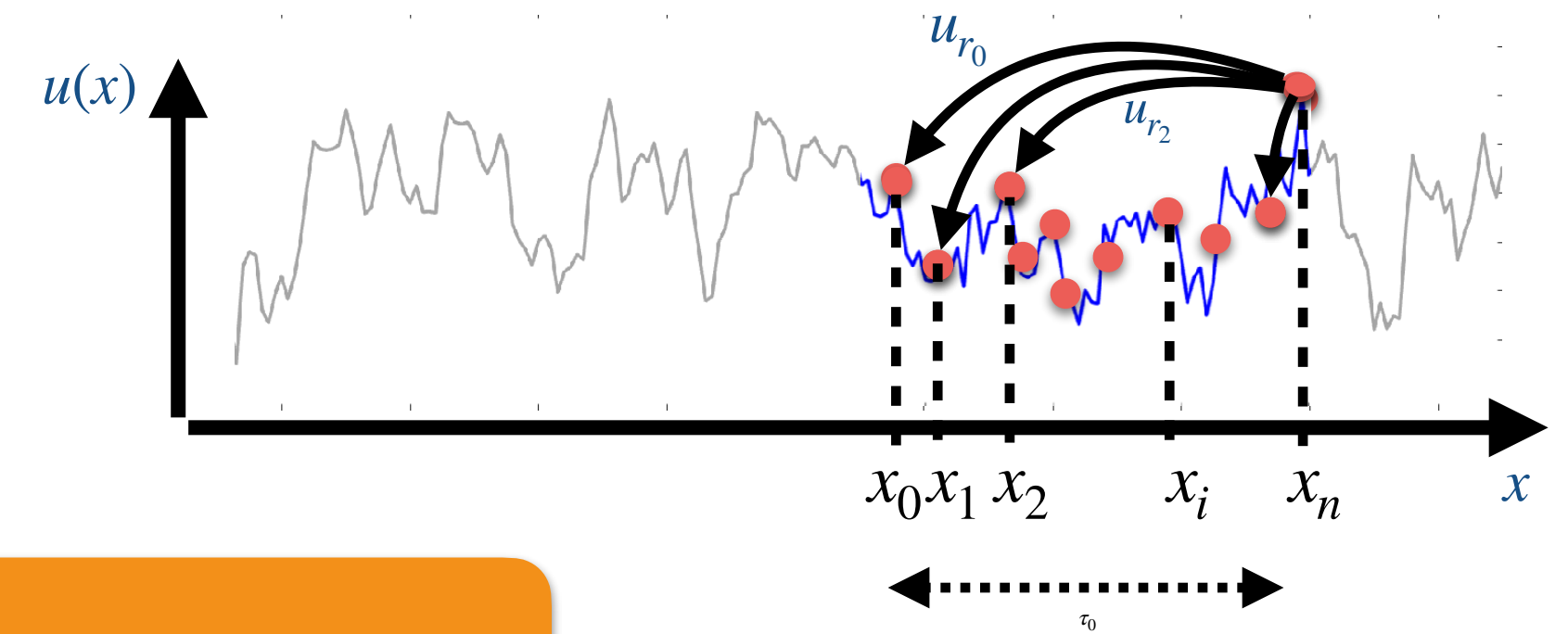
$$p(u_{r_{n-1}} | u_{r_{n-2}}, \dots, u_{r_0}, u(x_n)) p(u_{r_{n-2}} | \dots) \dots p(u_{r_0} | u(x_n)) p(u(x_n)) = p(u_{r_{n-1}} | u_{r_{n-2}}, u(x_n)) p(u_{r_{n-2}} | u_{r_{n-3}}, u(x_n))$$

$$p(u_{r_i} | u_{r_{i-1}}, \dots, u_{r_0}) = p(u_{r_i} | u_{r_{i-1}}, u(x_n))$$

Simple conditioned pdf = 3 point quantity



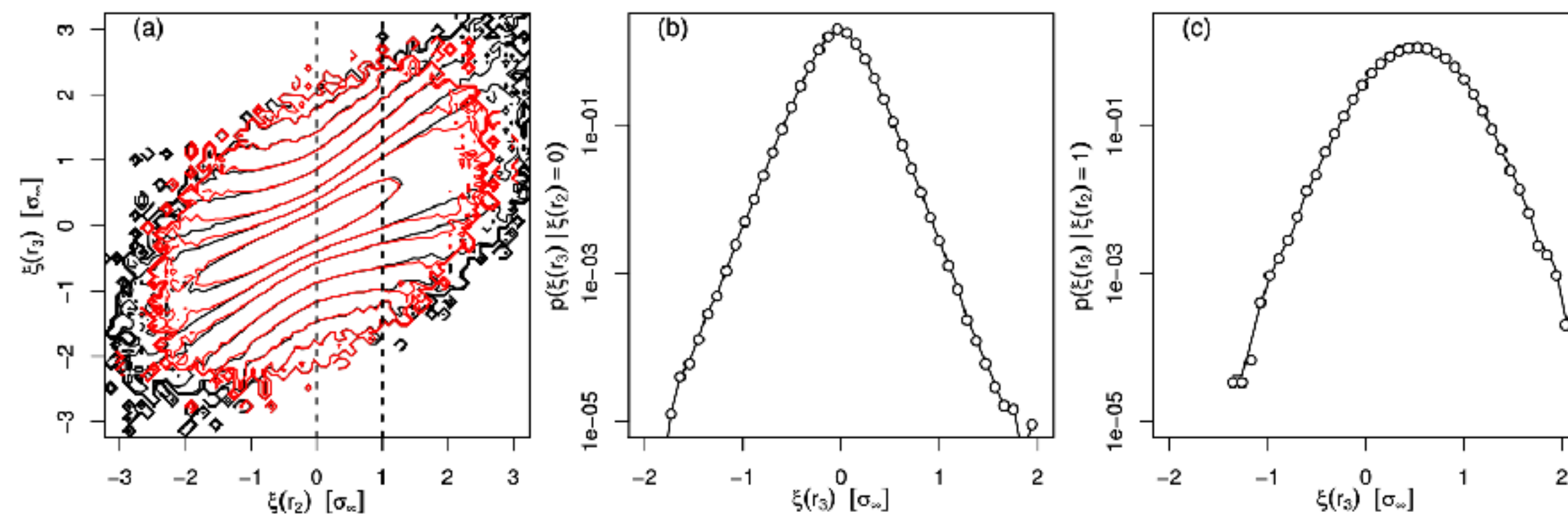
Joint- n-point statistics simplifies:



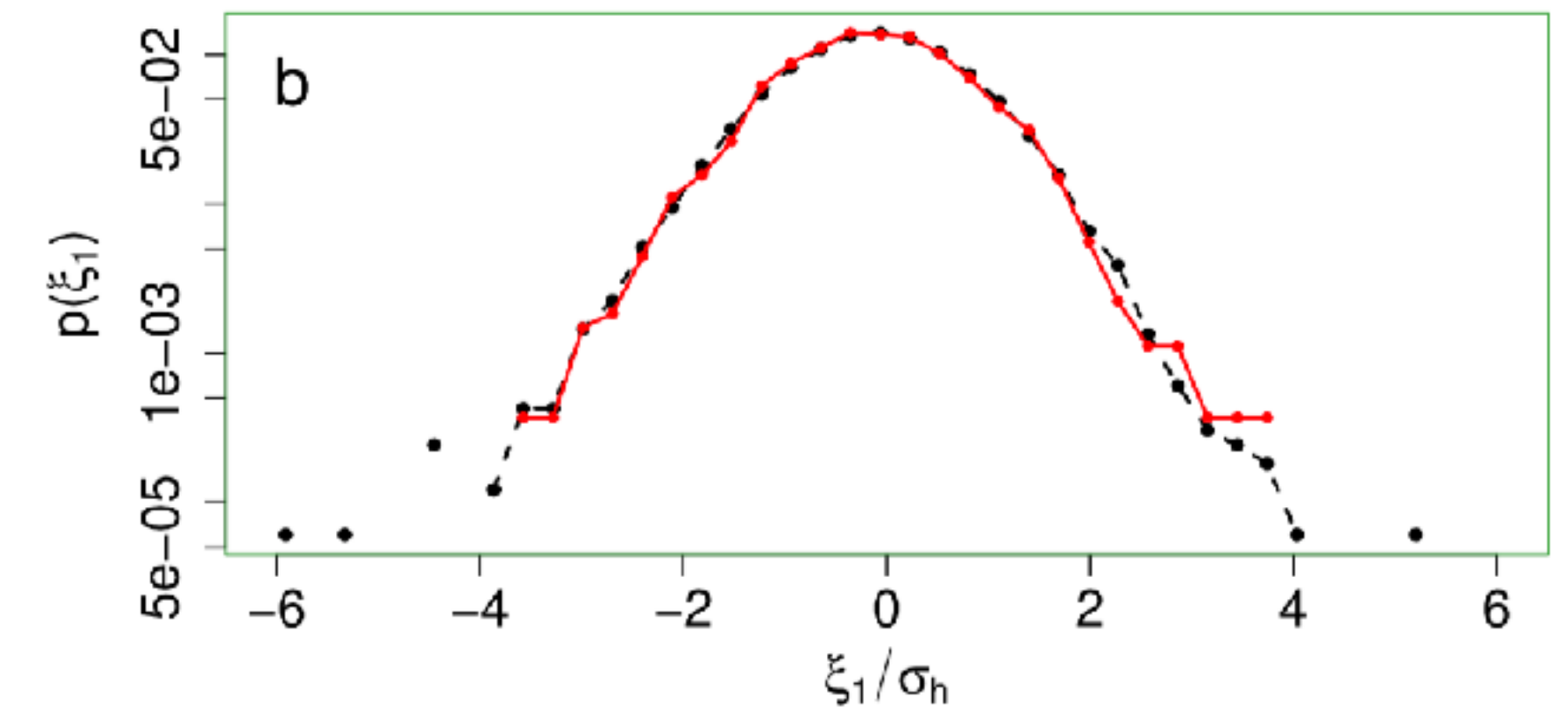
$$p(u_{r_{n-1}} | u_{r_{n-2}}, \dots, u_{r_0}, u(x_n)) p(u_{r_{n-2}} | \dots) \dots p(u_{r_0} | u(x_n)) p(u(x_n)) = p(u_{r_{n-1}} | u_{r_{n-2}}, u(x_n)) p(u_{r_{n-2}} | u_{r_{n-3}}, u(x_n))$$

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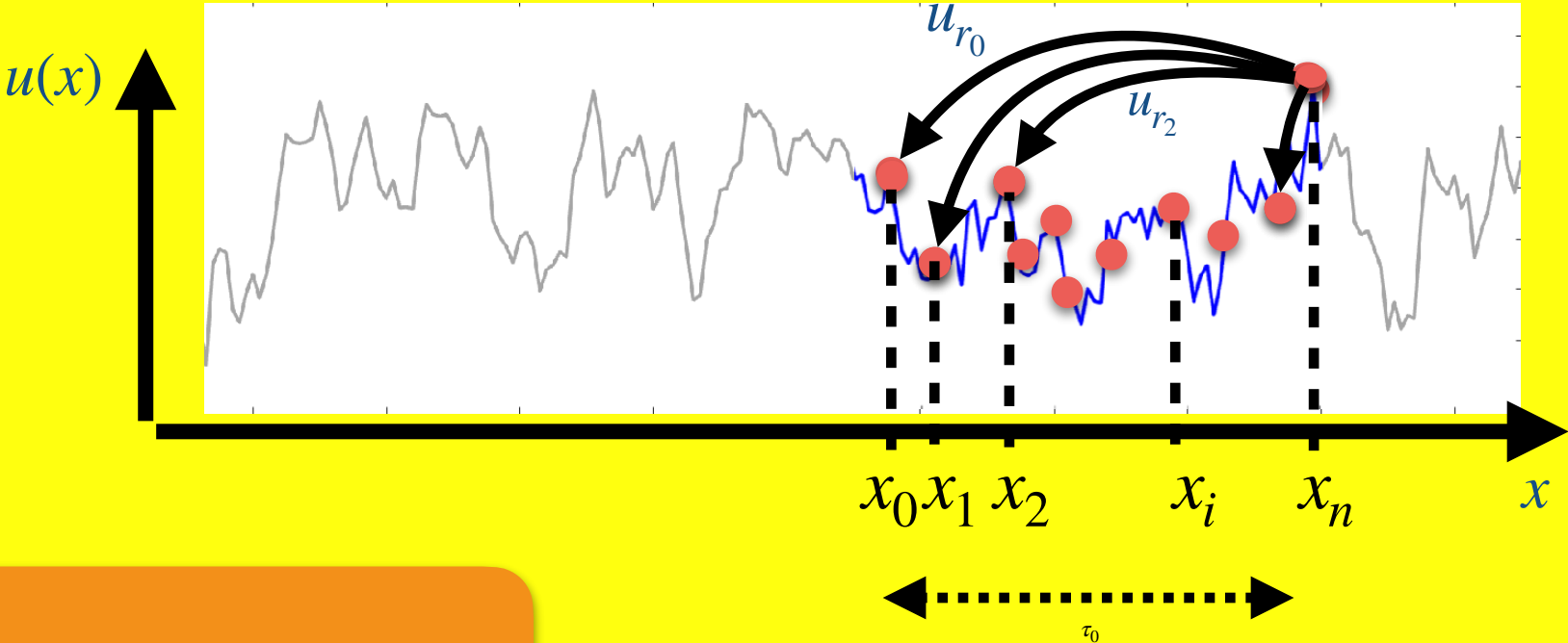
Turbulence



Waves



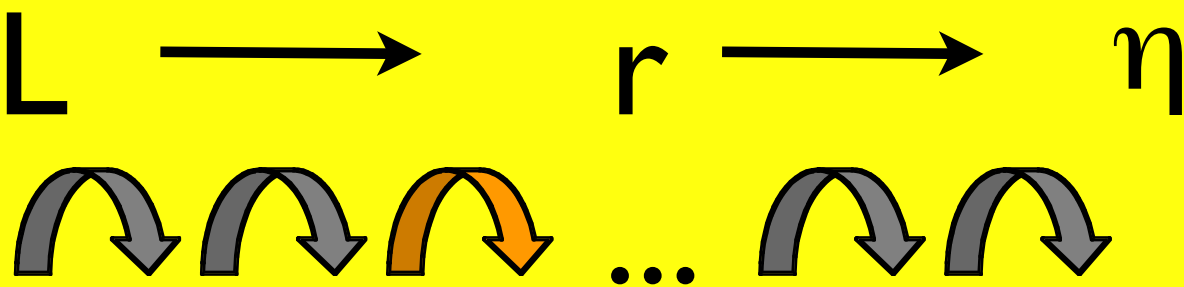
Joint- n-point statistics simplifies: Three point closure



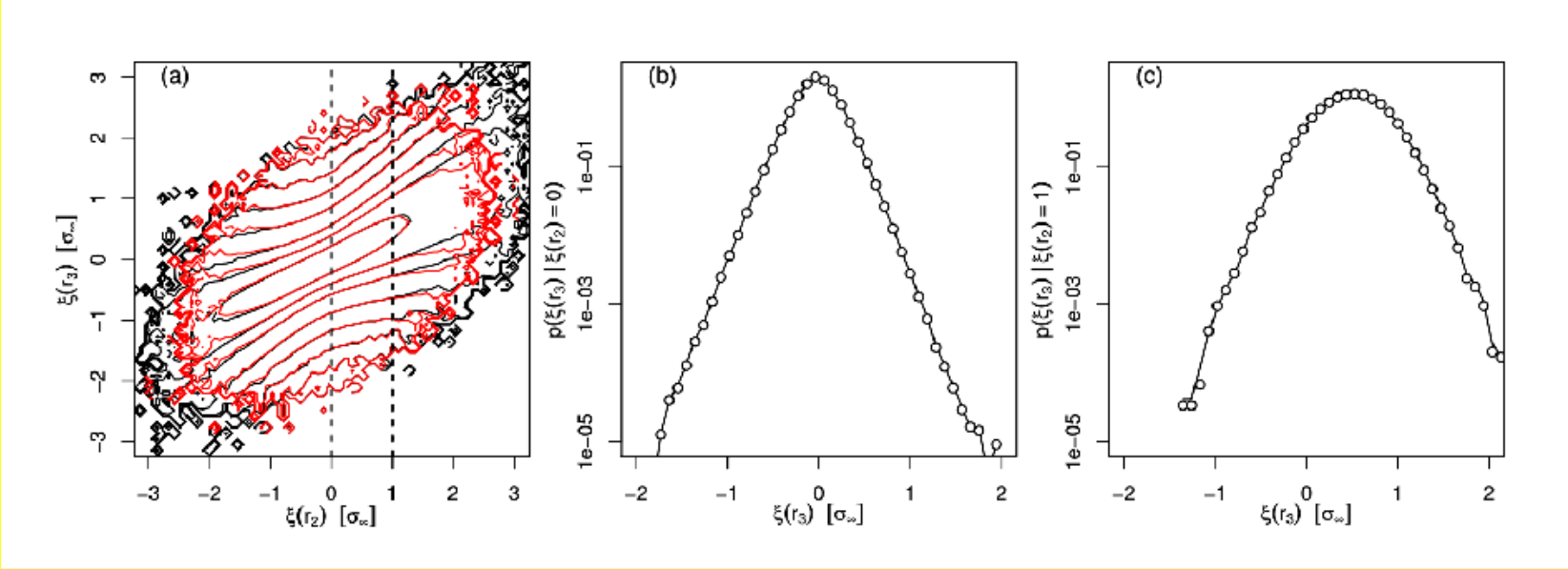
$$p(u_{r_{n-1}}|u_{r_{n-2}}, \dots, u_{r_0}, u(x_n))p(u_{r_{n-2}}|\dots) \dots p(u_{r_0}|u(x_n)) p(u(x_n)) = p(u_{r_{n-1}}|u_{r_{n-2}}, u(x_n))p(u_{r_{n-2}}|u_{r_{n-3}}, u(x_n))$$

$$p(u_{r_i}|u_{r_{i-1}}, \dots, u_{r_0}) = p(u_{r_i}|u_{r_{i-1}}, u(x_n))$$

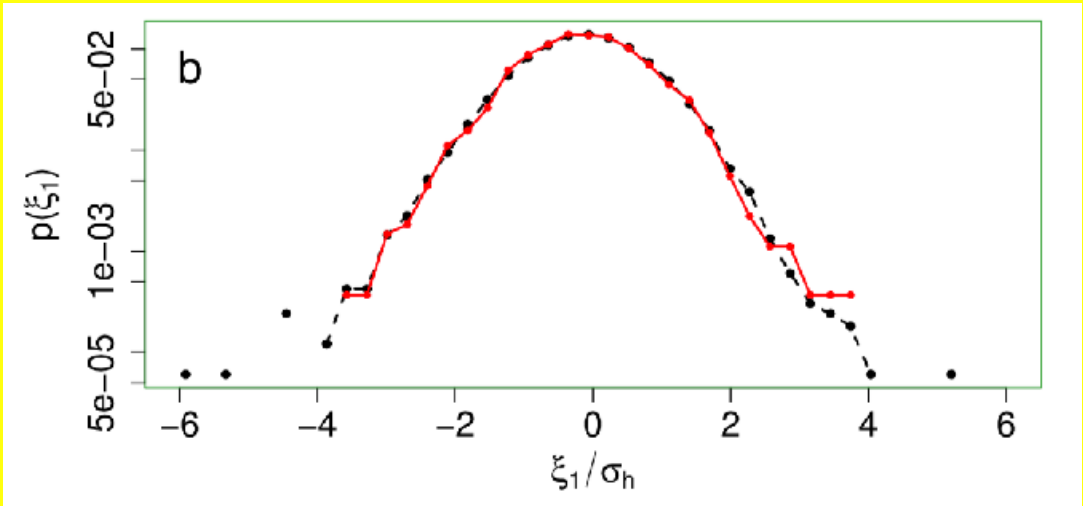
Idea of cascade - increments from large, L, to small scales η



Turbulence



Waves



Content

Extreme events

multi-point statistics

-> structures and forecasting

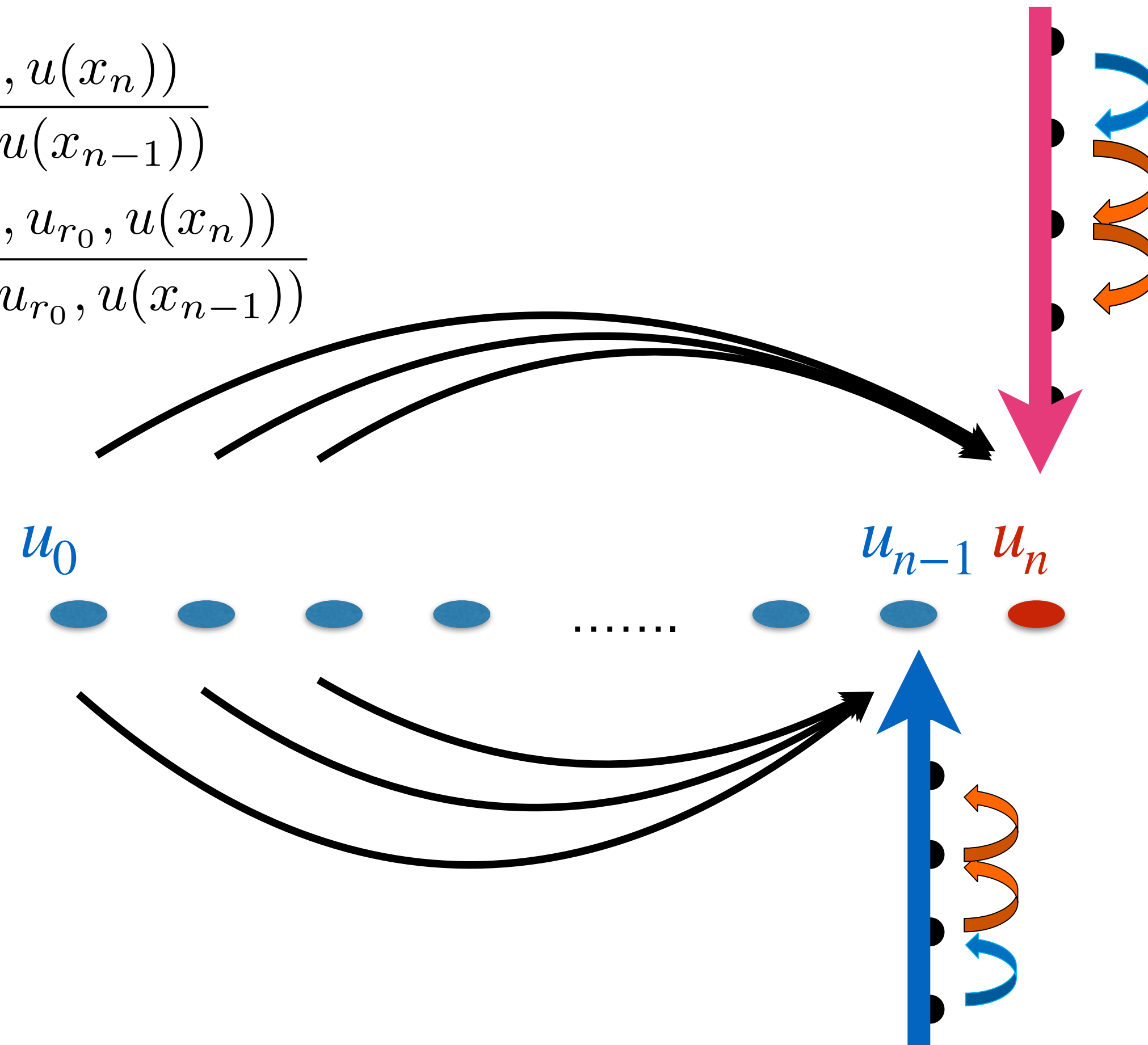
consequences

results and claims

cascade process in r and estimation of Fokker-Planck equation,

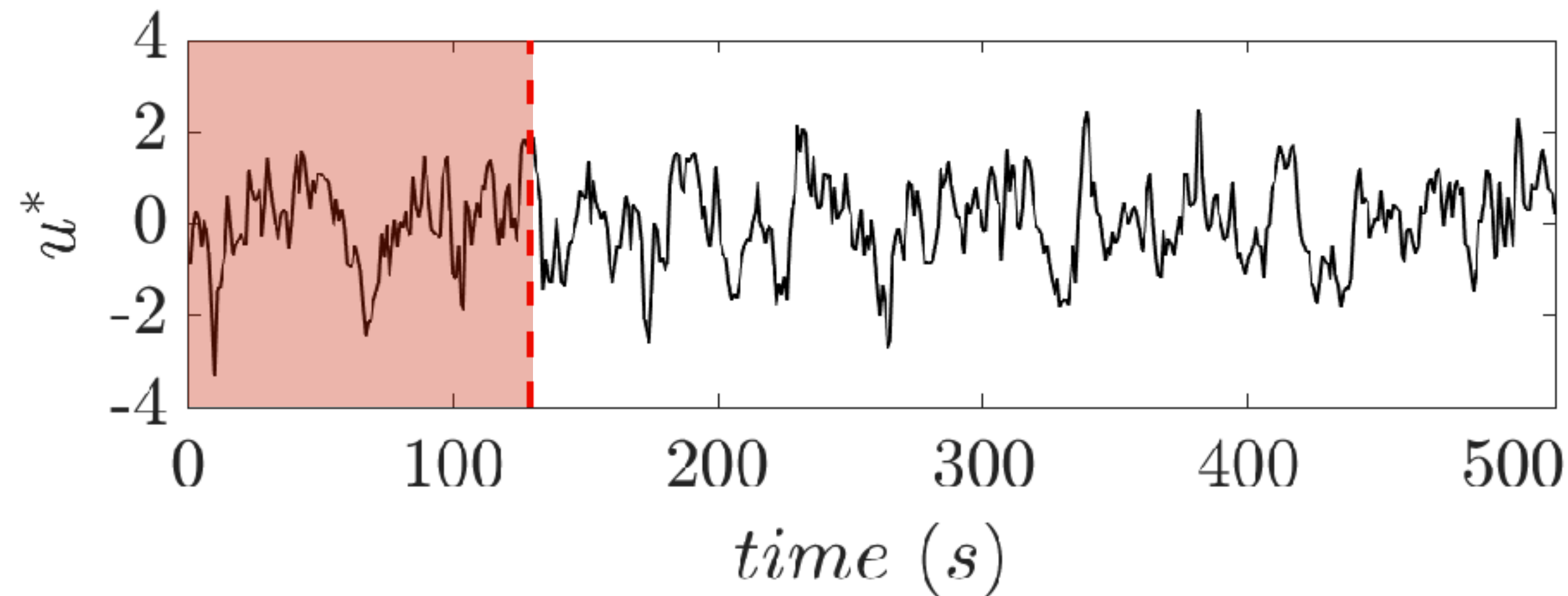
-> **new class of stochastic processes** for n-point statistics. => forecasting of future (here waves but also wind gusts...)

$$\begin{aligned} p(u(x_n)|u(x_{n-1}), \dots, u(x_0)) &= \frac{p(u(x_0), u(x_1), \dots, u(x_n))}{p(u(x_0), u(x_1), \dots, u(x_{n-1}))} \\ &= \frac{p(u_{r_{n-1}}, u_{r_{n-2}}, \dots, u_{r_0}, u(x_n))}{p(u_{r_{n-2}}, u_{r_{n-2}}, \dots, u_{r_0}, u(x_{n-1}))} \end{aligned}$$

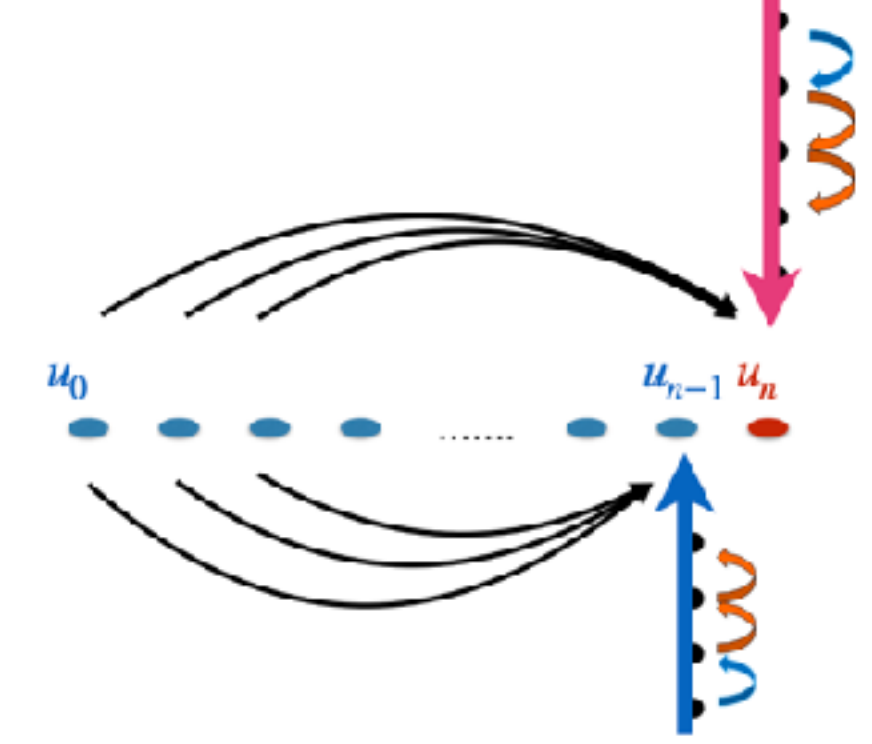
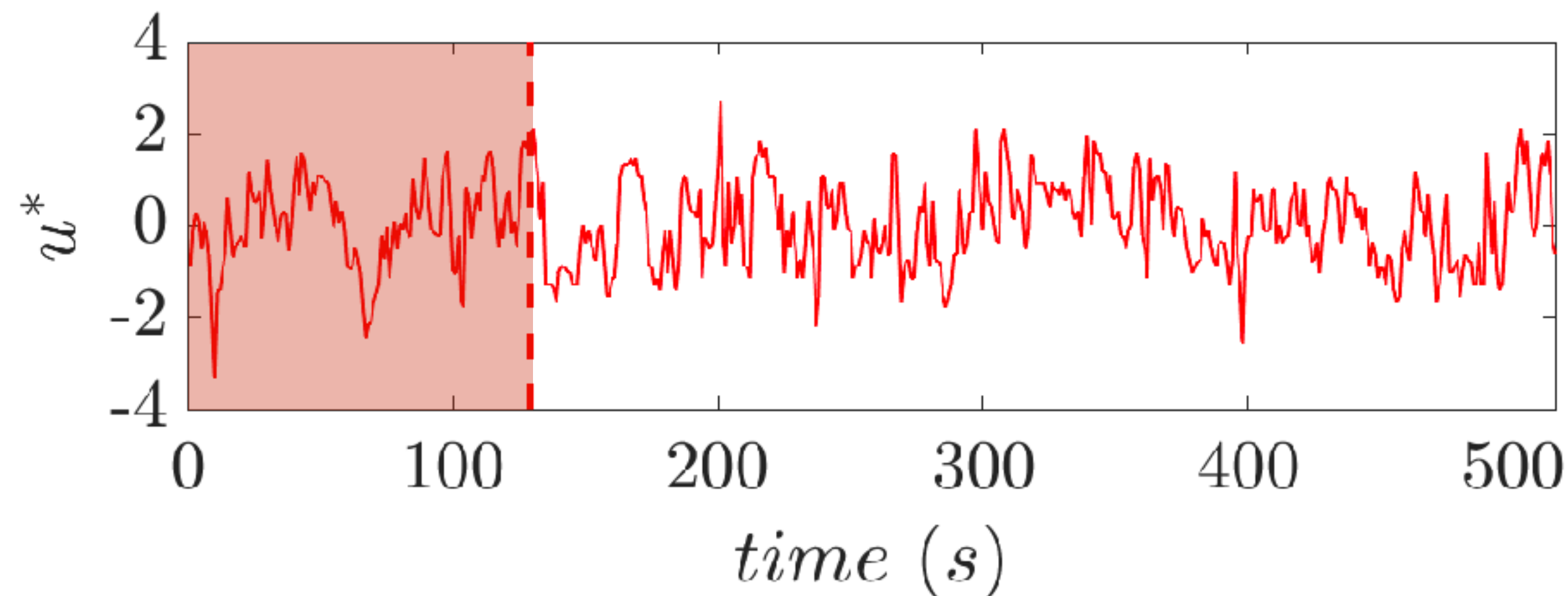


Surrogate wind speed fluctuations from Fokker-Planck Equation

Measured



Surrogates

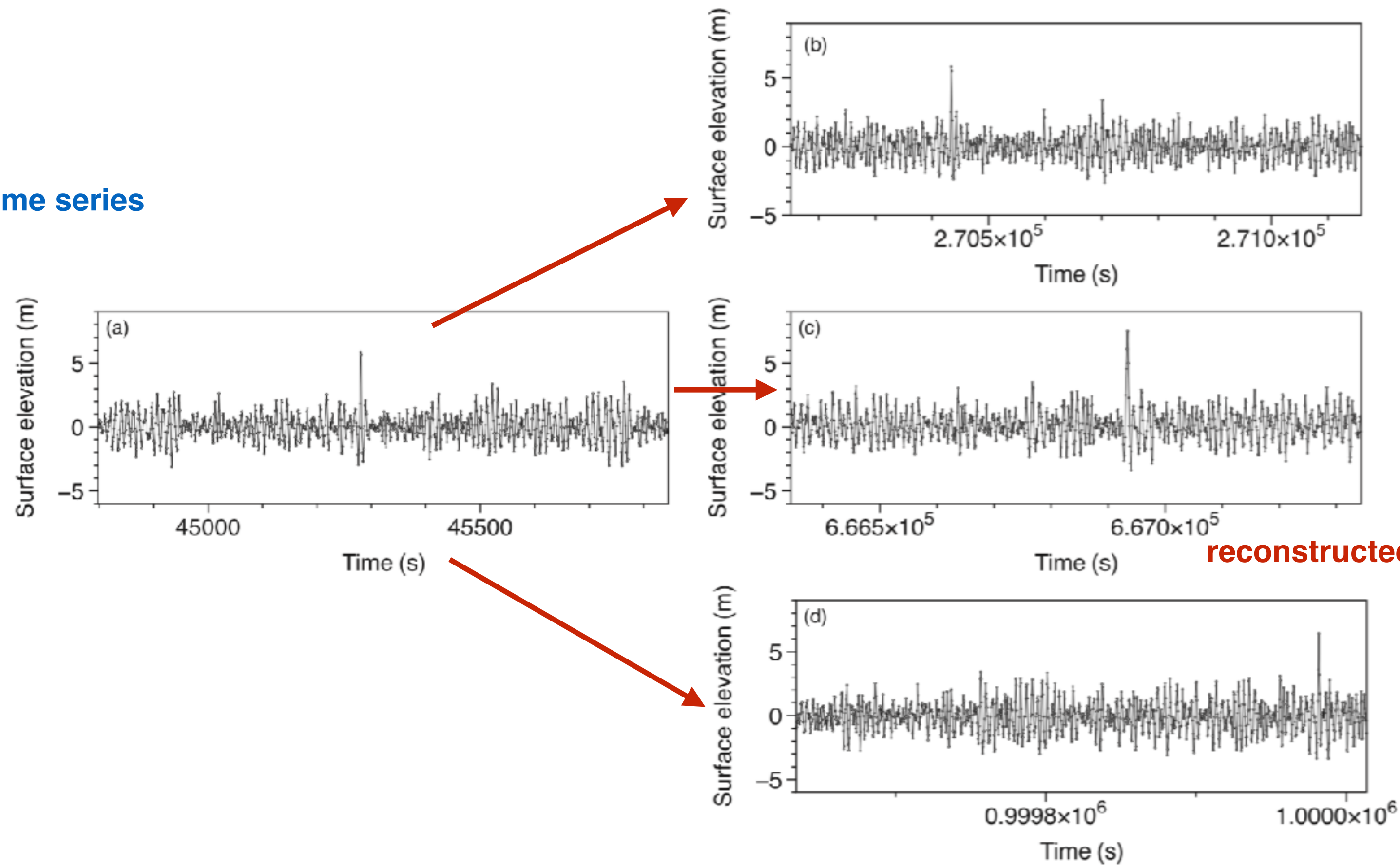


See also Poster F. Köhne

new data sets

-> new class of stochastic processes for n-point statistics

Measured time series

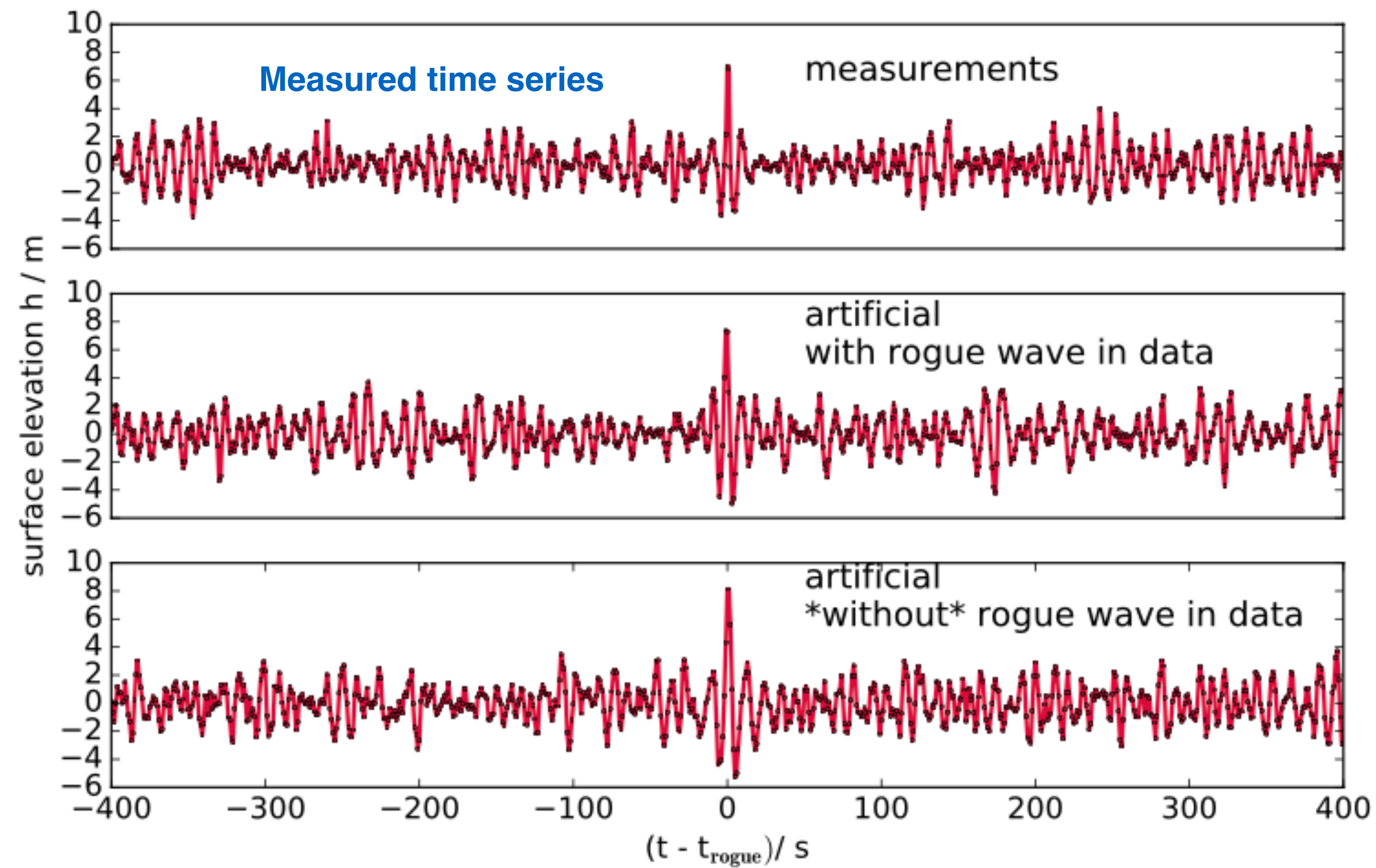


reconstructed time series



new data sets

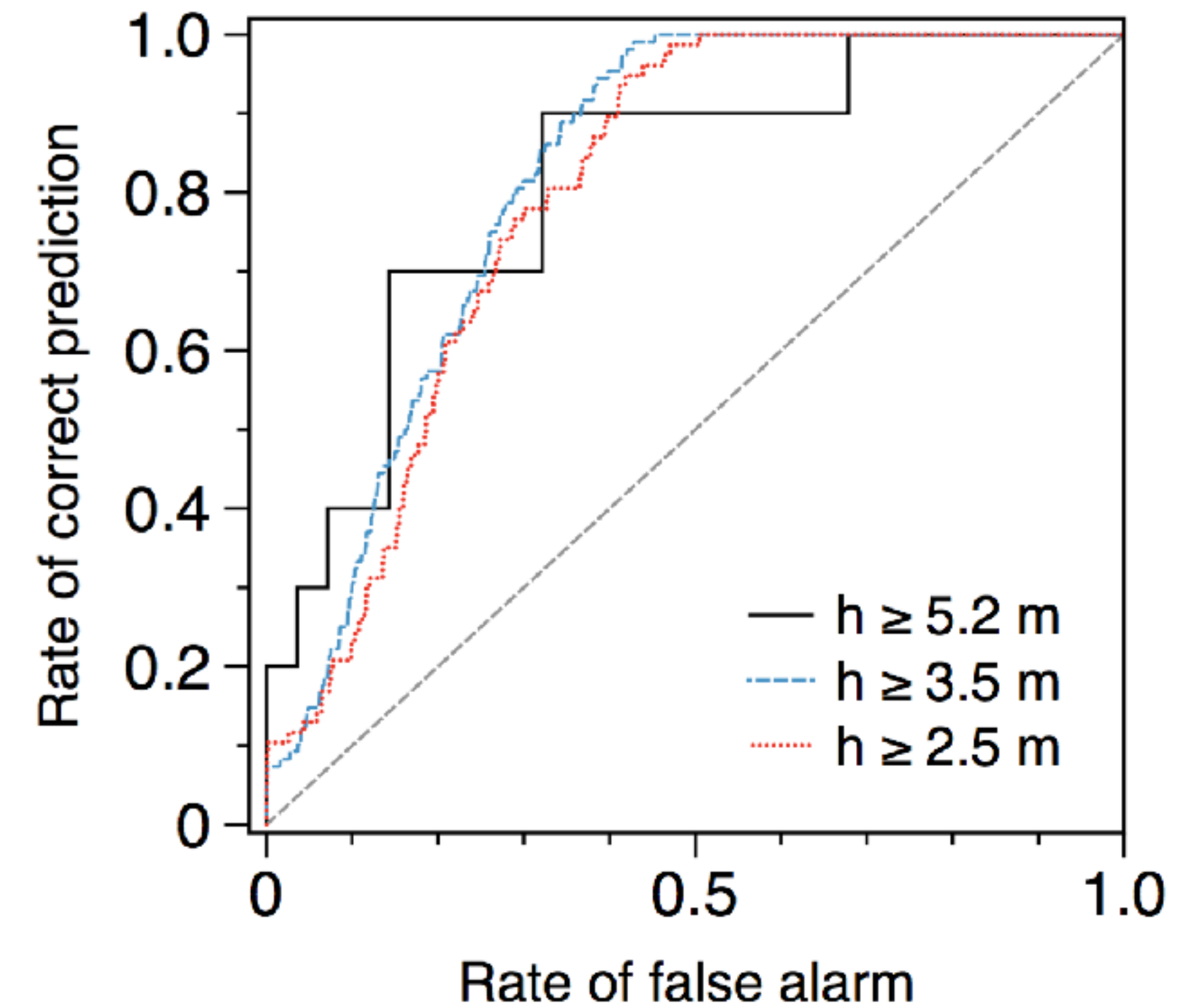
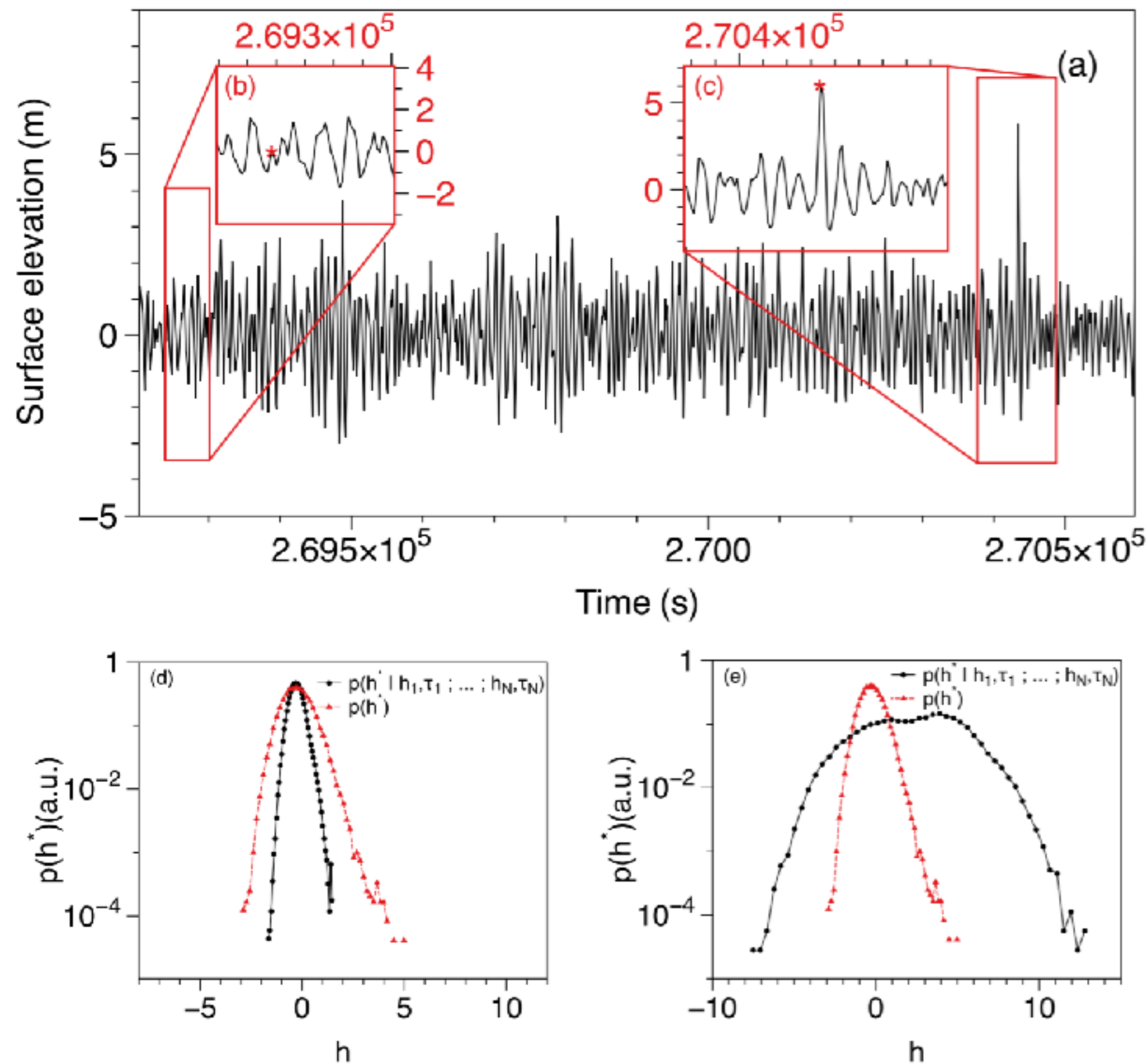
-> new class of stochastic processes for n-point statistics



reconstructed time series

Forecasting of rogue waves - ROC analysis

$$P_{\text{extreme}} = \int_{h_r}^{\infty} p(h^* | h_1, \tau_1; \dots; h_N, \tau_N) dh^*$$

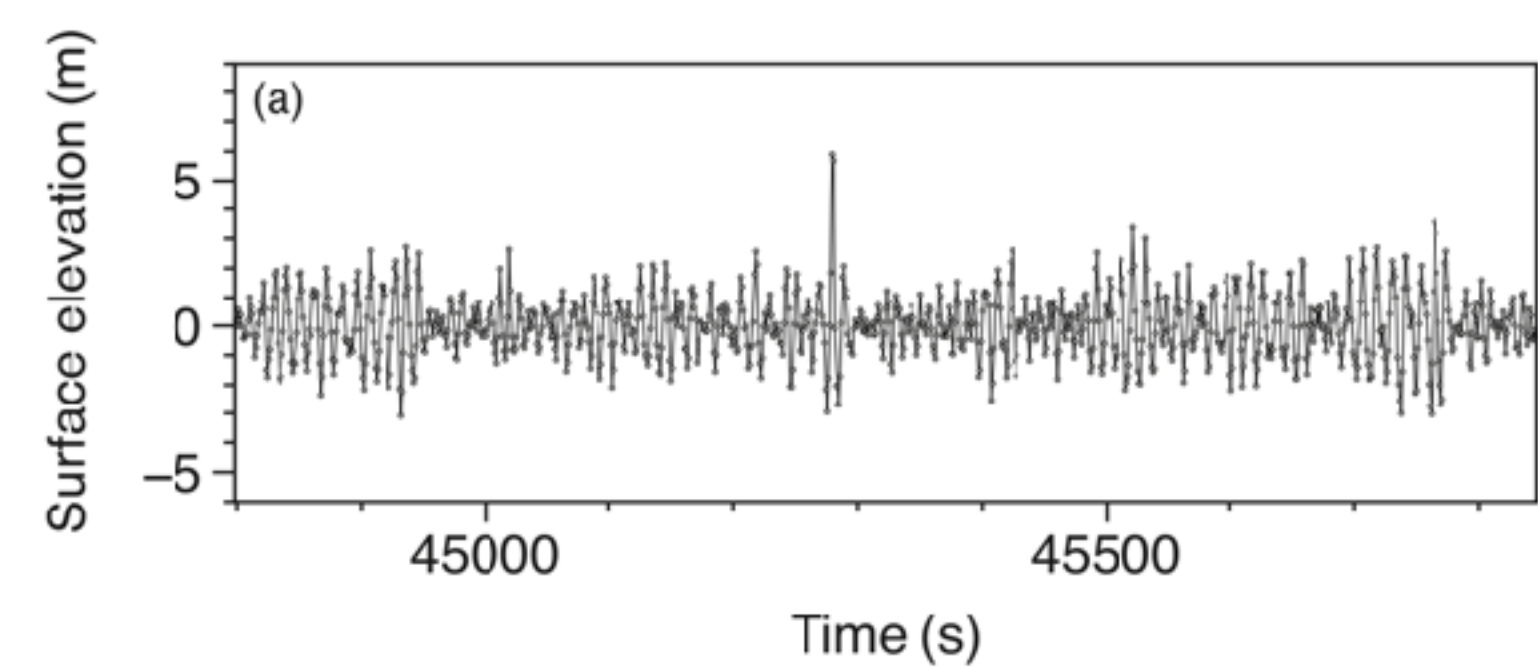
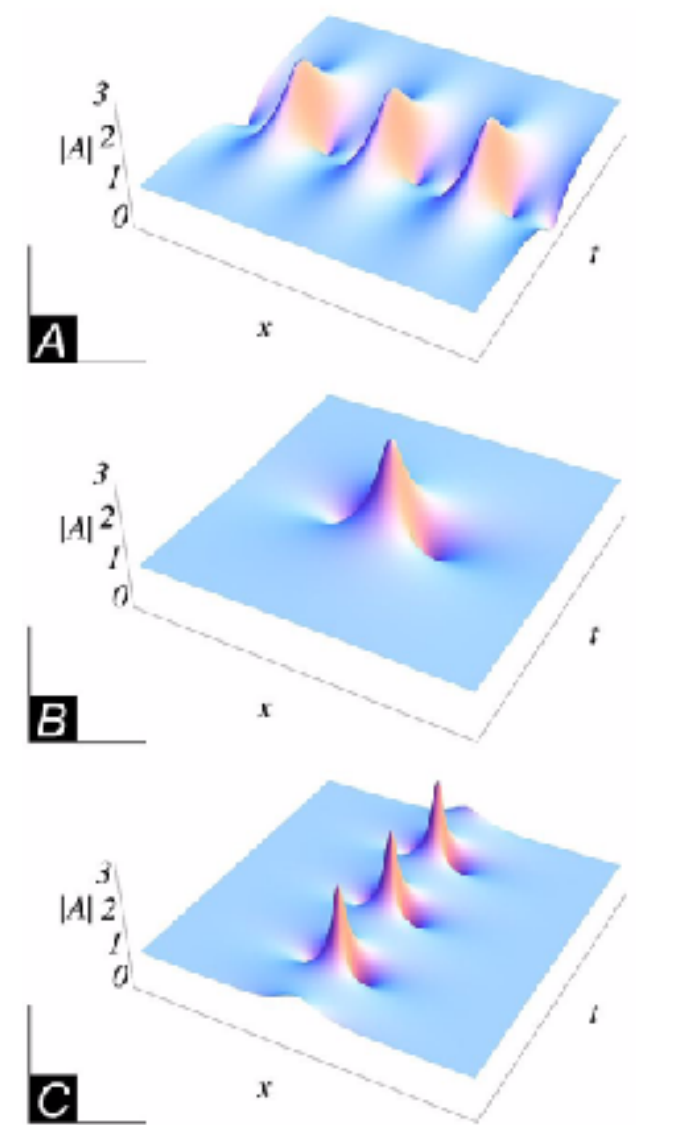


rogue wave - large deviation

Data from sea of Japan
=> F. P. Equation



non-linear Schrödinger equation
Predicts structures of rogue waves
Akhmediev Peregrine

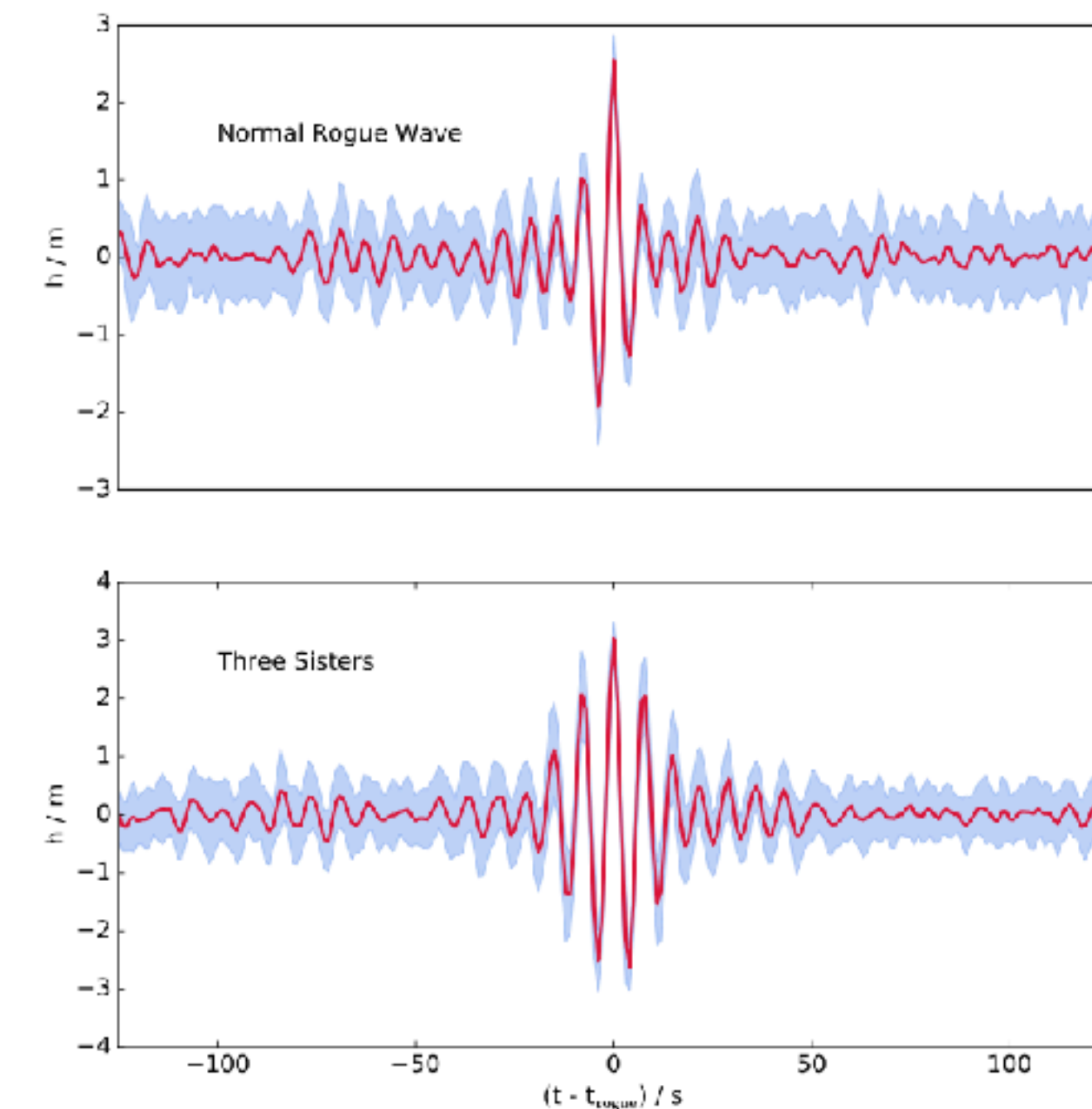


stochastic simulation of very rare events -

“Trajectory-Adaptive Multilevel Sampling” (TAMS)

Lestang, T. ; Ragone, F. ; Bréhier, C.-E. ; Herbert, C. ; Bouchet, F. :

Journal of Statistical Mechanics: Theory and Experiment 2018 (2018), Nr. 4, S. 043213



Multipoint statistics by 3-point closure leads to realistic data

- including extreme events and forecasting
- predicts also unseen events

We get correct

- probabilities,
- Spectra,
- higher order structure function

.....

Multipoint statistics by 3-point closure. - literature



Annual Review of Condensed Matter Physics

The Fokker–Planck Approach to Complex Spatiotemporal Disordered Systems

J. Peinke,^{1,2} M.R.R. Tabar,³ and M. Wächter¹

¹Institute of Physics and ForWind, University of Oldenburg, D-26111 Oldenburg, Germany; email: joachim.peinke@uni-oldenburg.de

²Fraunhofer Institute for Wind Energy Systems, D-26129 Oldenburg, Germany

³Department of Physics, Sharif University of Technology, Tehran 11155-9161, Iran

Annu. Rev. Condens. Matter Phys. 2019. 10:107–32

Physics of Fluids

An open source package to perform basic and advanced statistical analysis of turbulence data and other complex systems

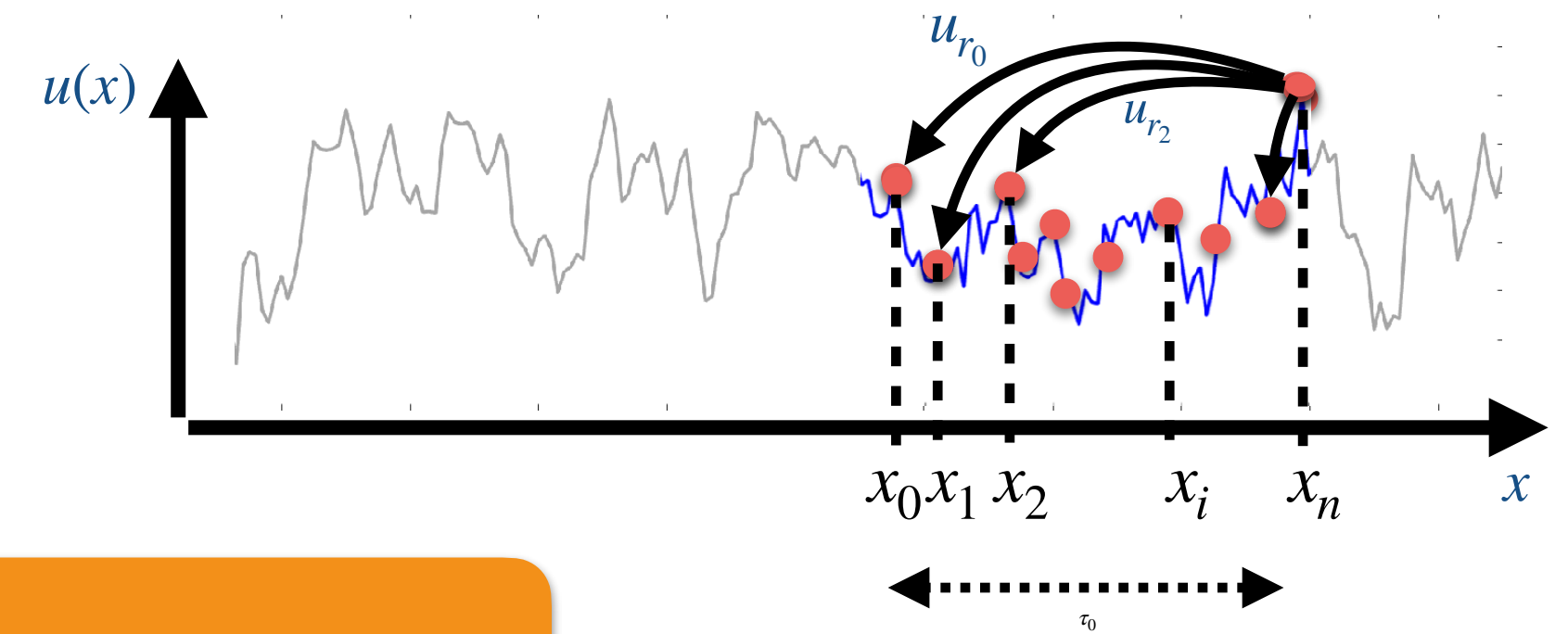
Cite as: Phys. Fluids **34**, 101801 (2022); <https://doi.org/10.1063/5.0107974>

Submitted: 07 July 2022 • Accepted: 16 September 2022 • Accepted Manuscript Online: 18 September 2022 • Published Online: 21 October 2022

http://github.com/andre-fuchs-uni-oldenburg/open_fpe_ift

2nd lecture ???

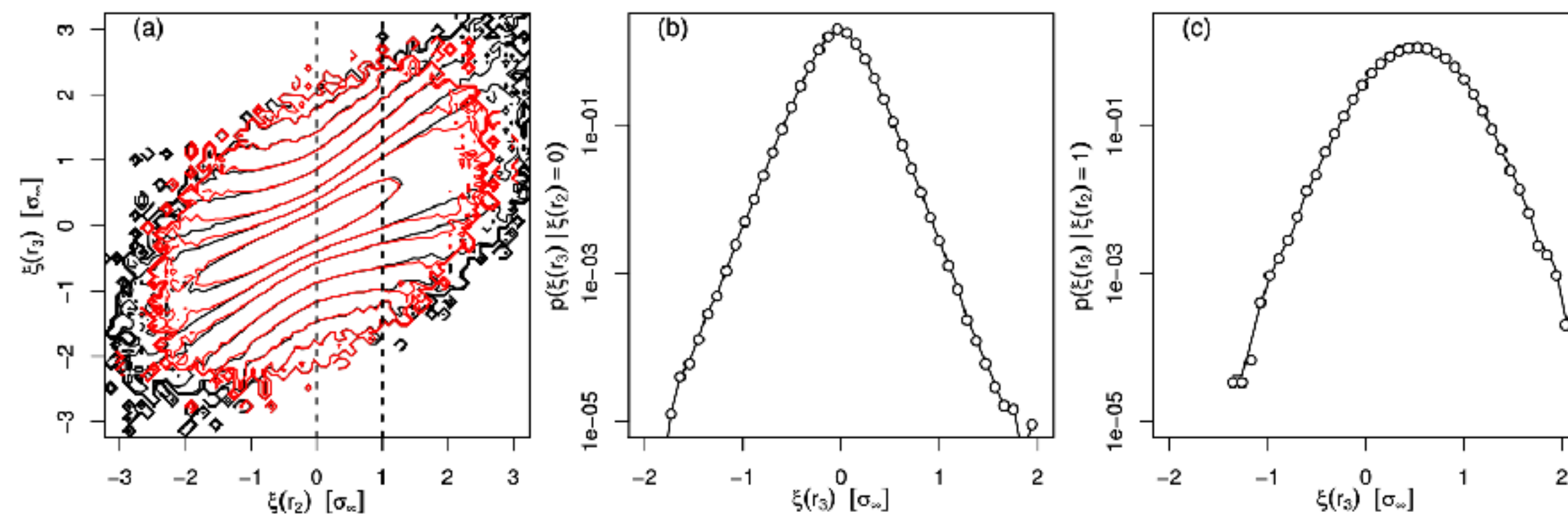
Joint- n-point statistics simplifies:



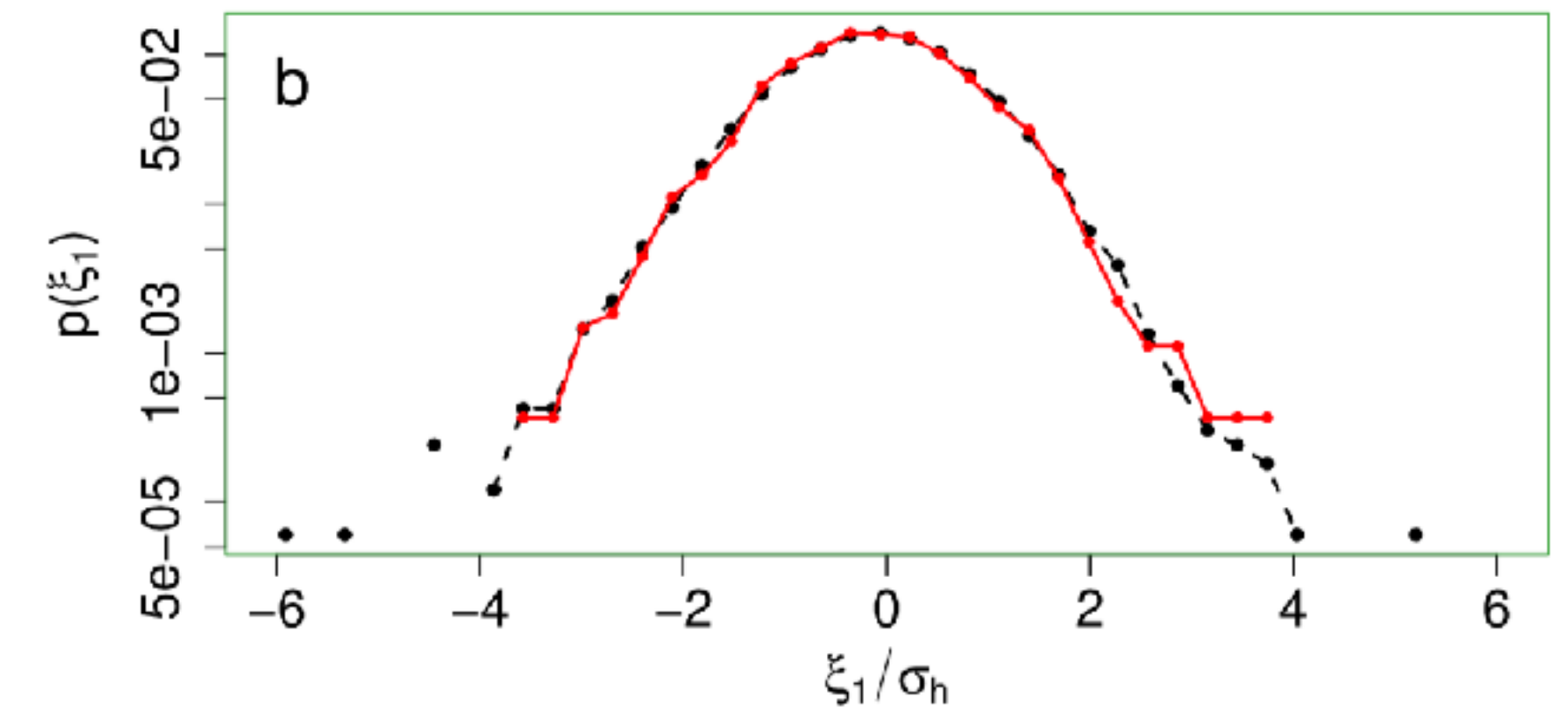
$$p(u_{r_{n-1}} | u_{r_{n-2}}, \dots, u_{r_0}, u(x_n)) p(u_{r_{n-2}} | \dots) \dots p(u_{r_0} | u(x_n)) p(u(x_n)) = p(u_{r_{n-1}} | u_{r_{n-2}}, u(x_n)) p(u_{r_{n-2}} | \dots, u_{r_{n-3}}, u(x_n))$$

$$p(u_{r_i} | u_{r_{i-1}}, \dots, u_{r_0}) = p(u_{r_i} | u_{r_{i-1}}, u(x_n))$$

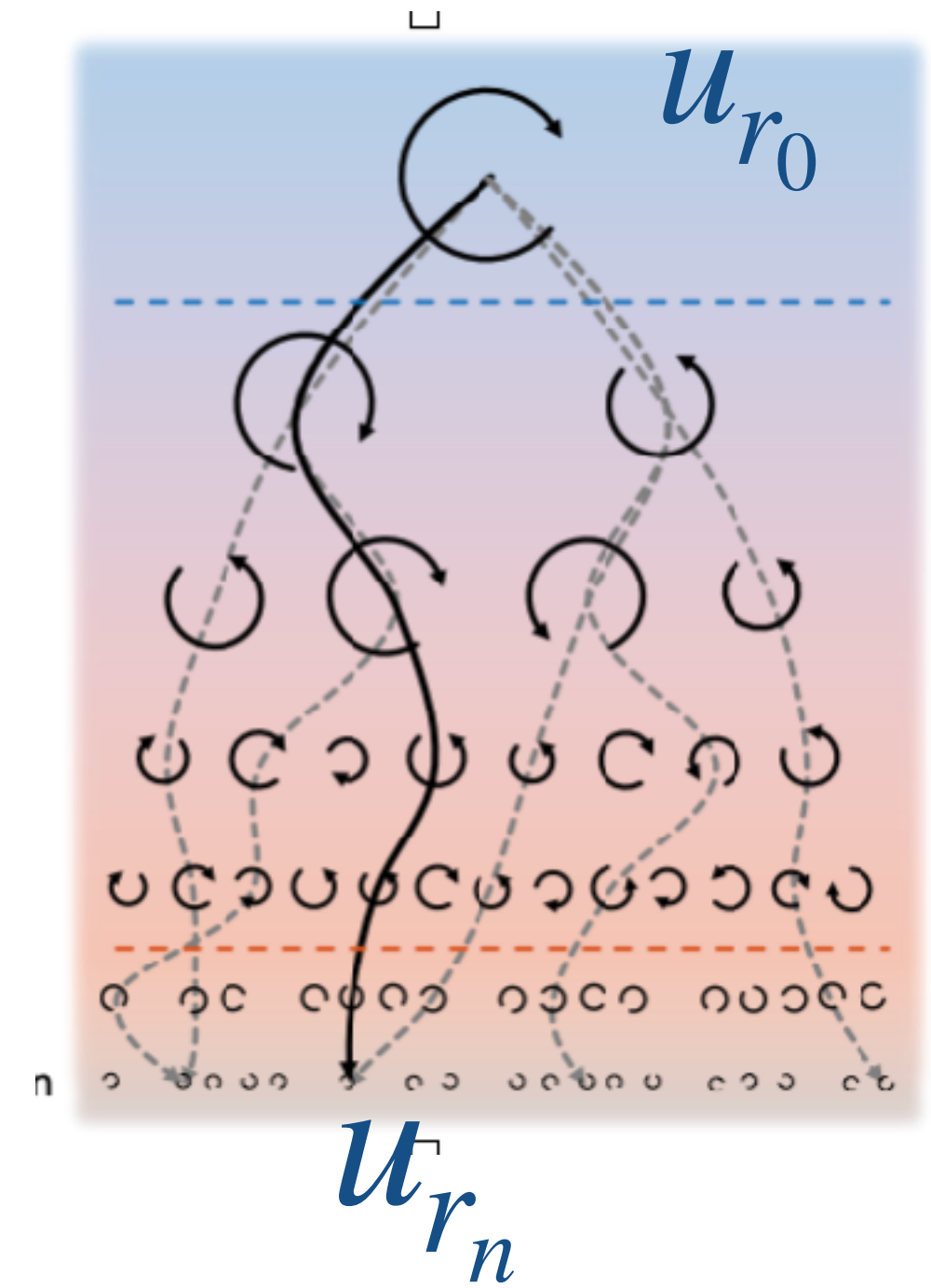
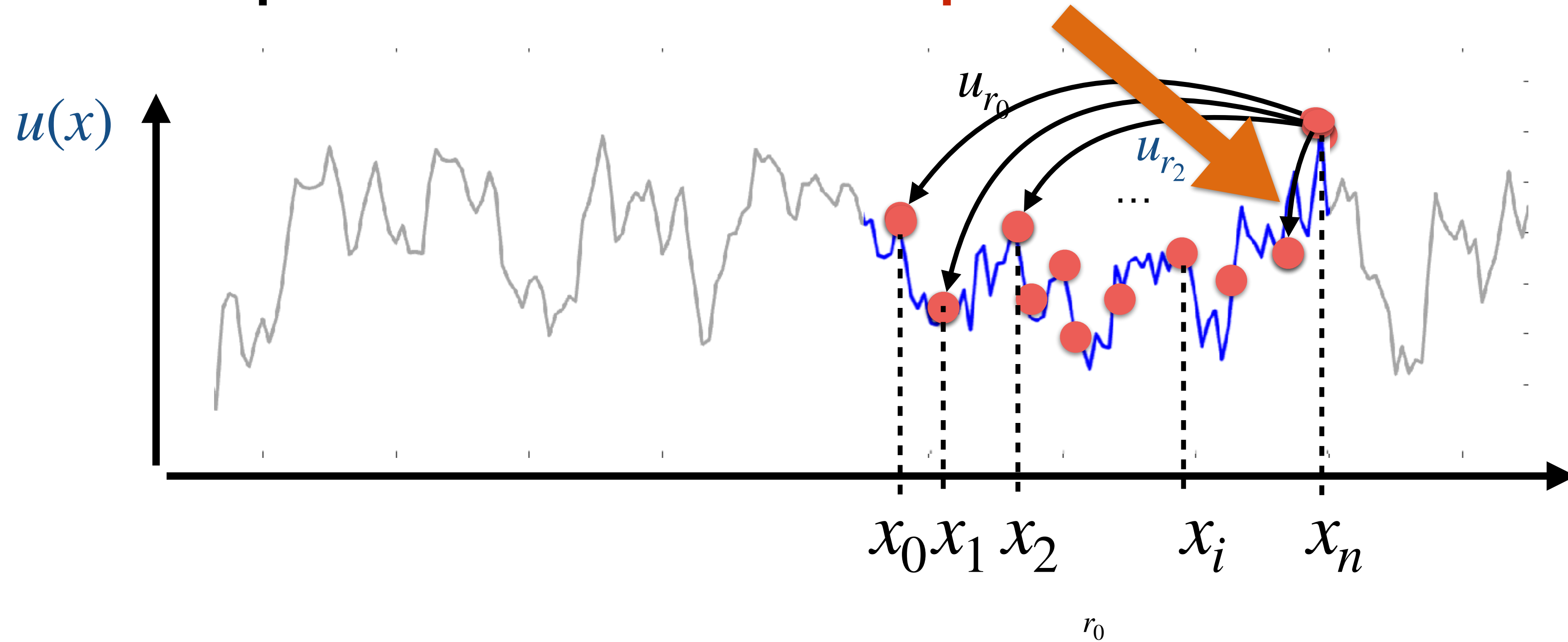
Turbulence



Waves



Joint- n-point statistics and **three point closure** => Markow process in scale



increments $u_r = u(x + r) - u(x)$

Cascade path $u(\cdot)$ goes from u_{r_0} to u_{r_n} and $r_0 > r_1 > \dots r > \dots r_n$

Markov- process in scale -> Fokker Planck equation (Kolmogorov equ.)

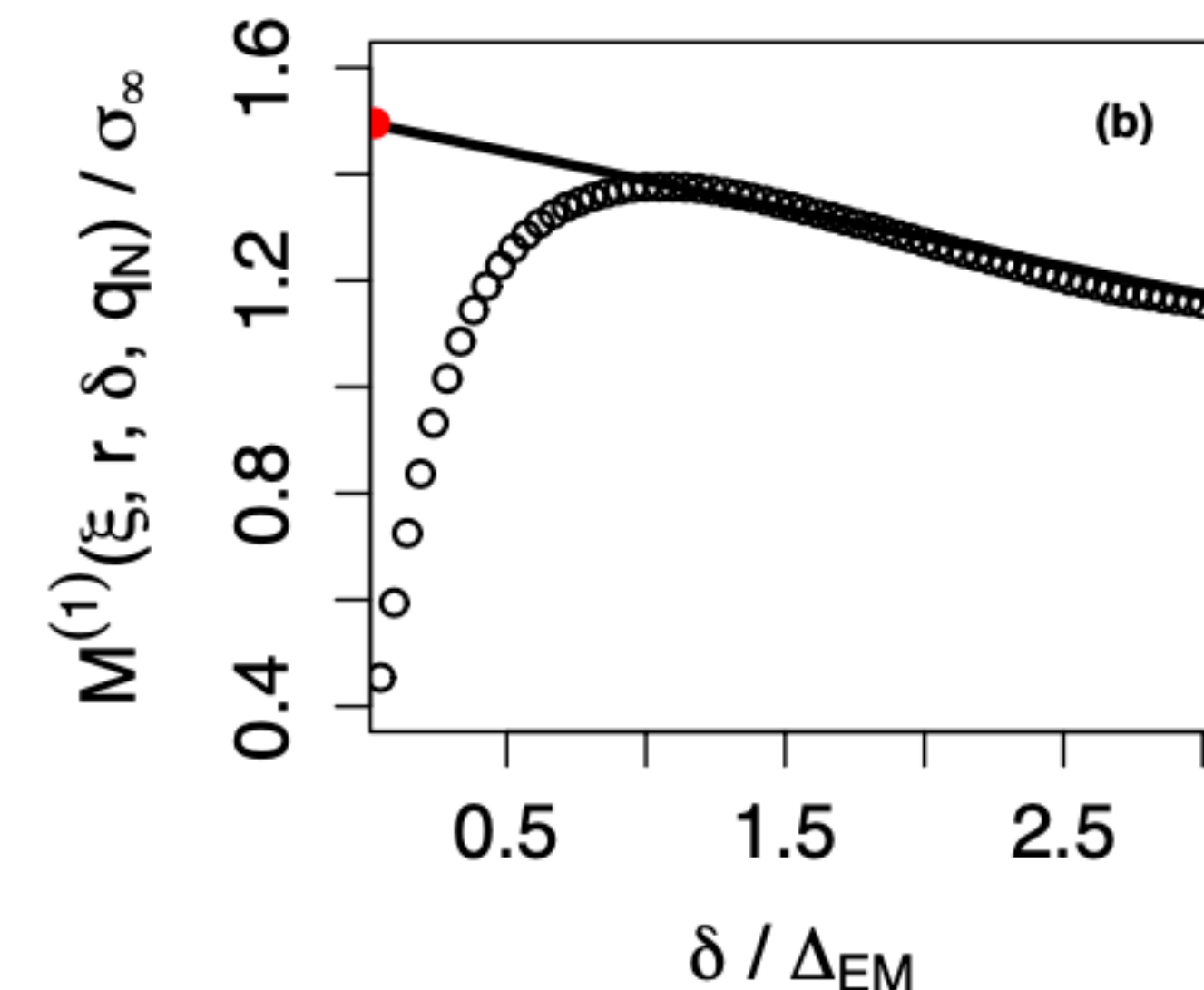
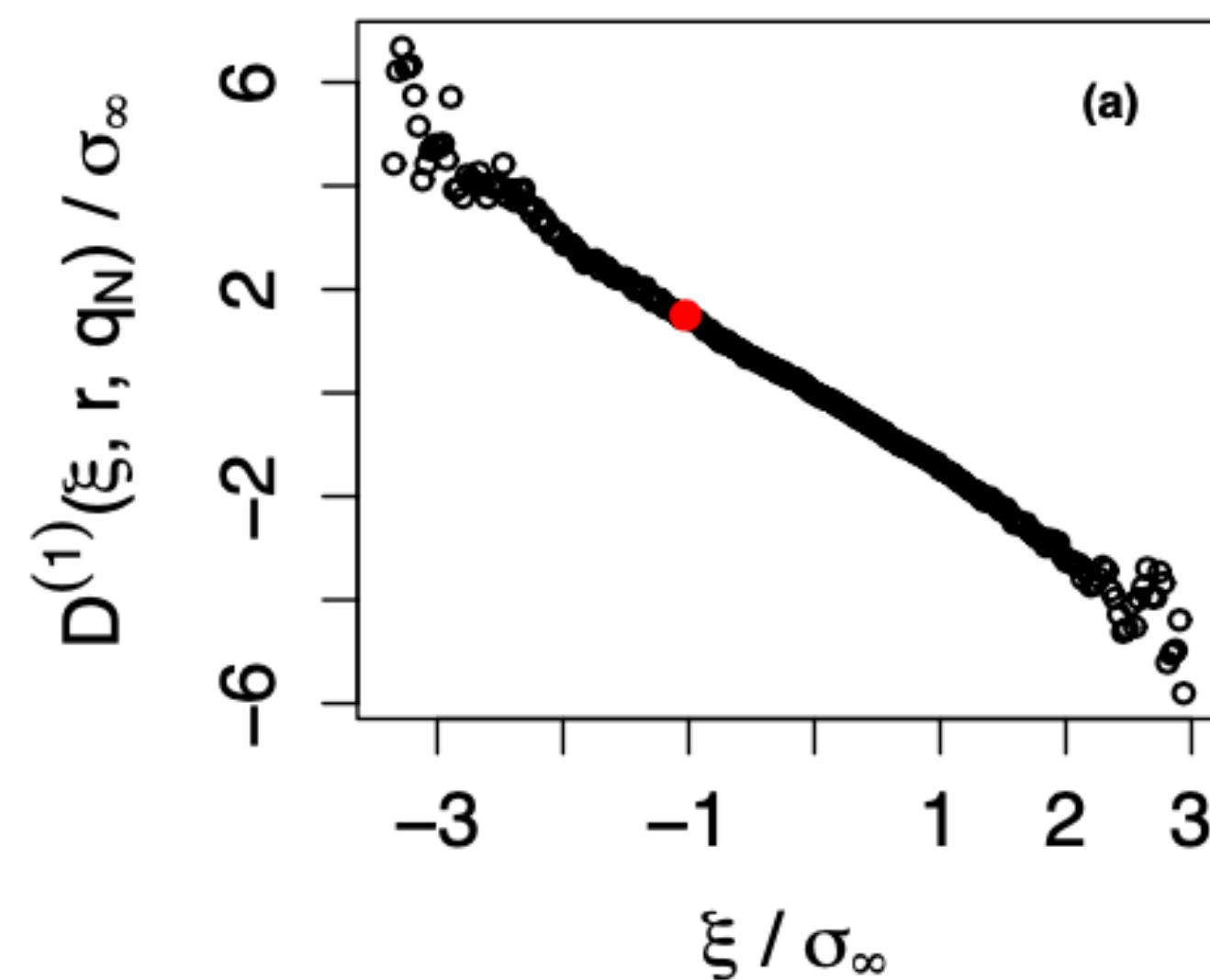
$$-r_j \frac{\partial}{\partial r_j} p(u_{r_j} | u_{r_k}, u(x_1)) = \left\{ -\frac{\partial}{\partial u_{r_j}} D^{(1)}(u_{r_j}, r_j, u(x_1)) + \frac{\partial^2}{\partial u_{r_j}^2} D^{(2)}(u_{r_j}, r_j, u(x_1)) \right\} p(u_{r_j} | u_{r_k}, u(x_1))$$

Drift and Diffusion coefficient can be “measured”

Kramer_Moyal coeff.

$$D^{(k)}(u, r) = \lim_{\Delta r \rightarrow 0} \frac{r}{k! \Delta r} M^{(k)}(u, r, \Delta r),$$

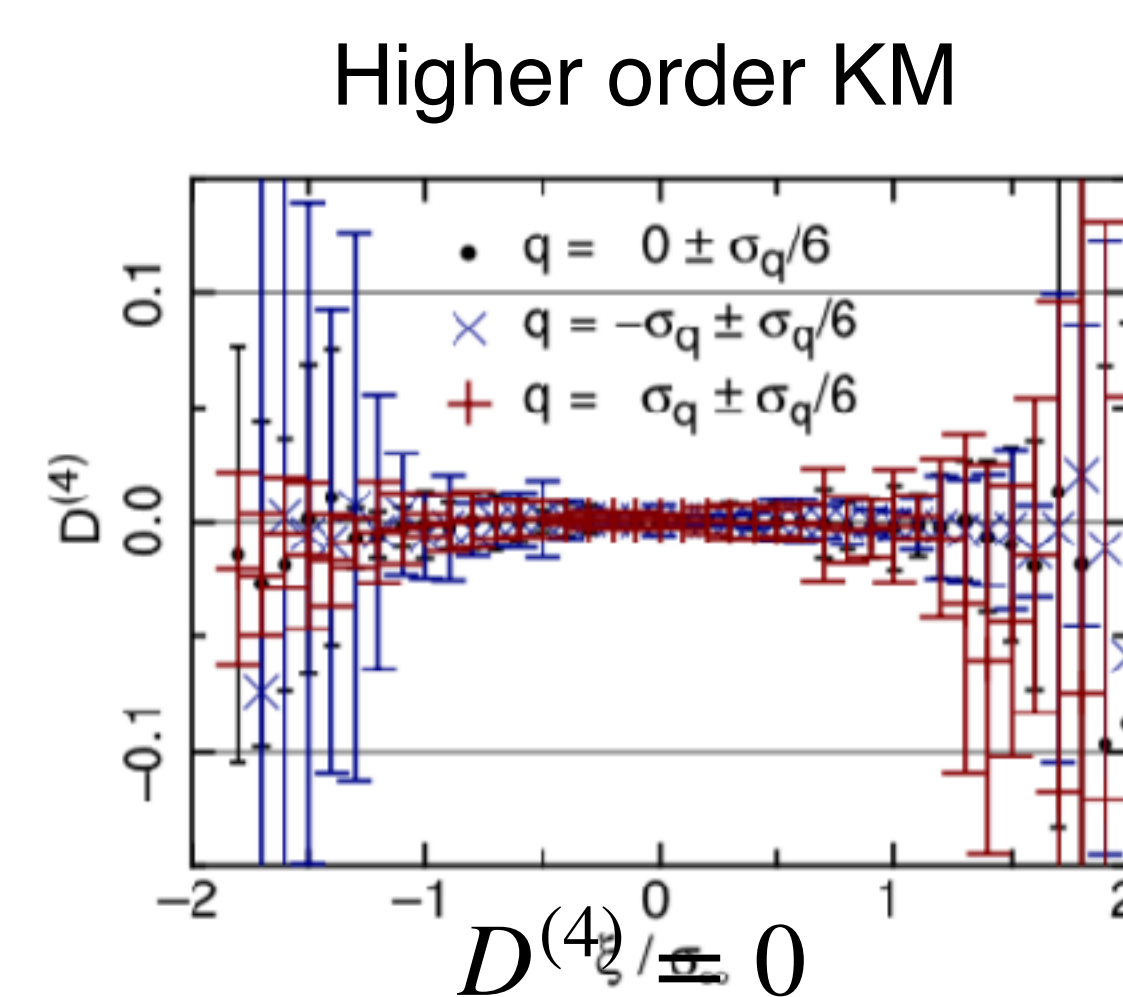
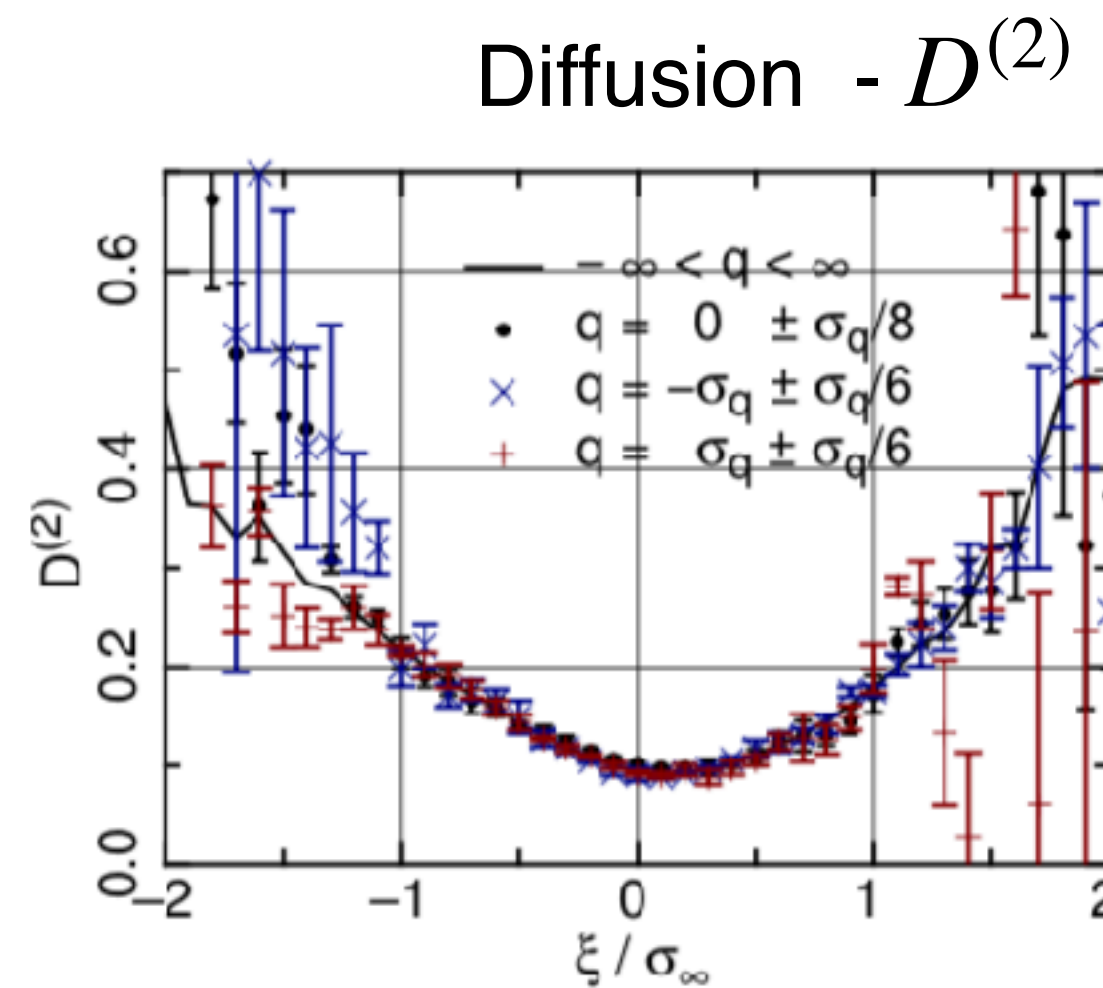
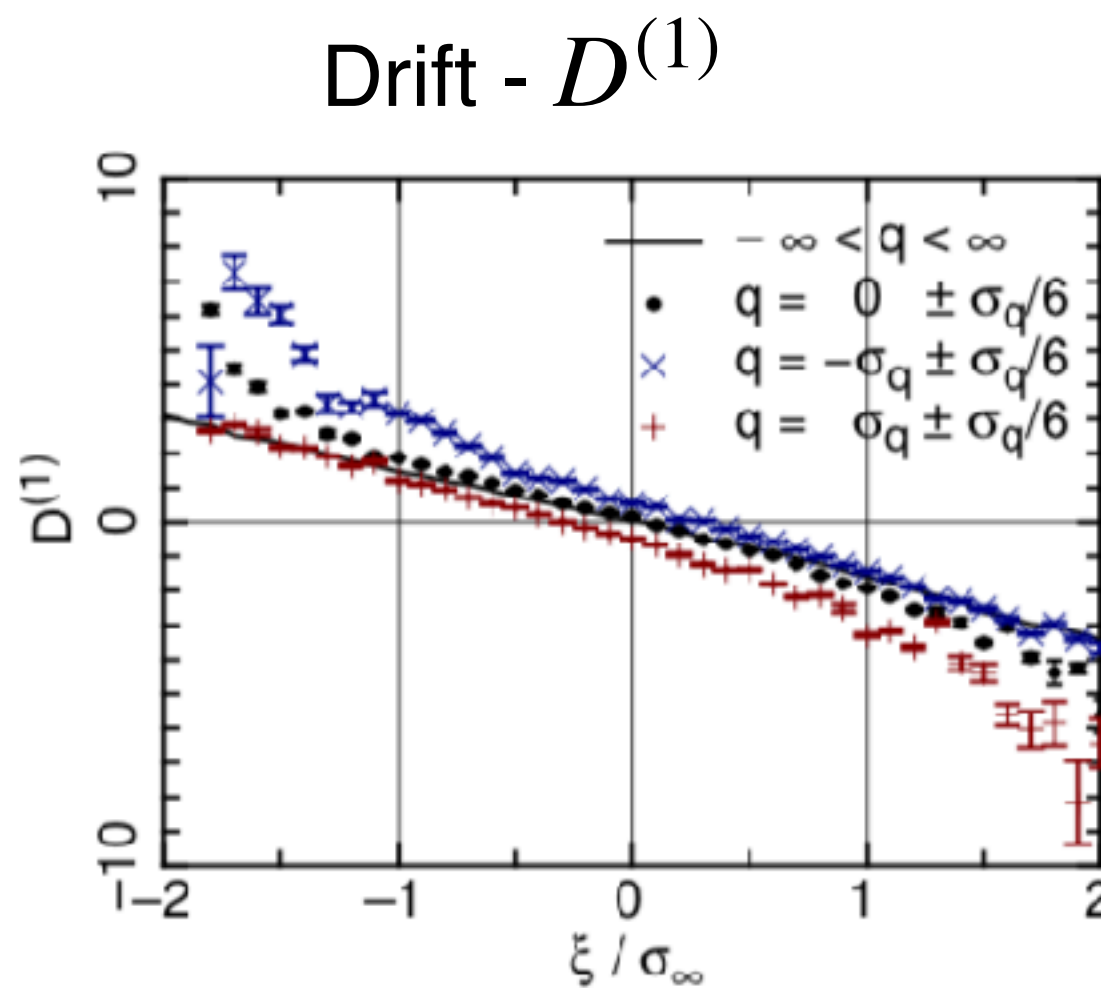
$$M^{(k)}(u, r, \Delta r) = \int_{-\infty}^{+\infty} (\tilde{u} - u)^k p(\tilde{u}, r - \Delta r | u, r) d\tilde{u}$$



multi-point characterisation (FP for turbulence)

$$-r_j \frac{\partial}{\partial r_j} p(u_{r_j} | u_{r_k}, u(x_1)) = \left\{ -\frac{\partial}{\partial u_{r_j}} D^{(1)}(u_{r_j}, r_j, u(x_1)) + \frac{\partial^2}{\partial u_{r_j}^2} D^{(2)}(u_{r_j}, r_j, u(x_1)) \right\} p(u_{r_j} | u_{r_k}, u(x_1))$$

Drift and Diffusion coefficient can be “measured”



White noise - **Paula theorem**

=> Langevin equ

And Fokker-Planck equ.

$$D^{(1)} \propto u_r$$

$$D^{(2)} \propto A + u_r^2$$

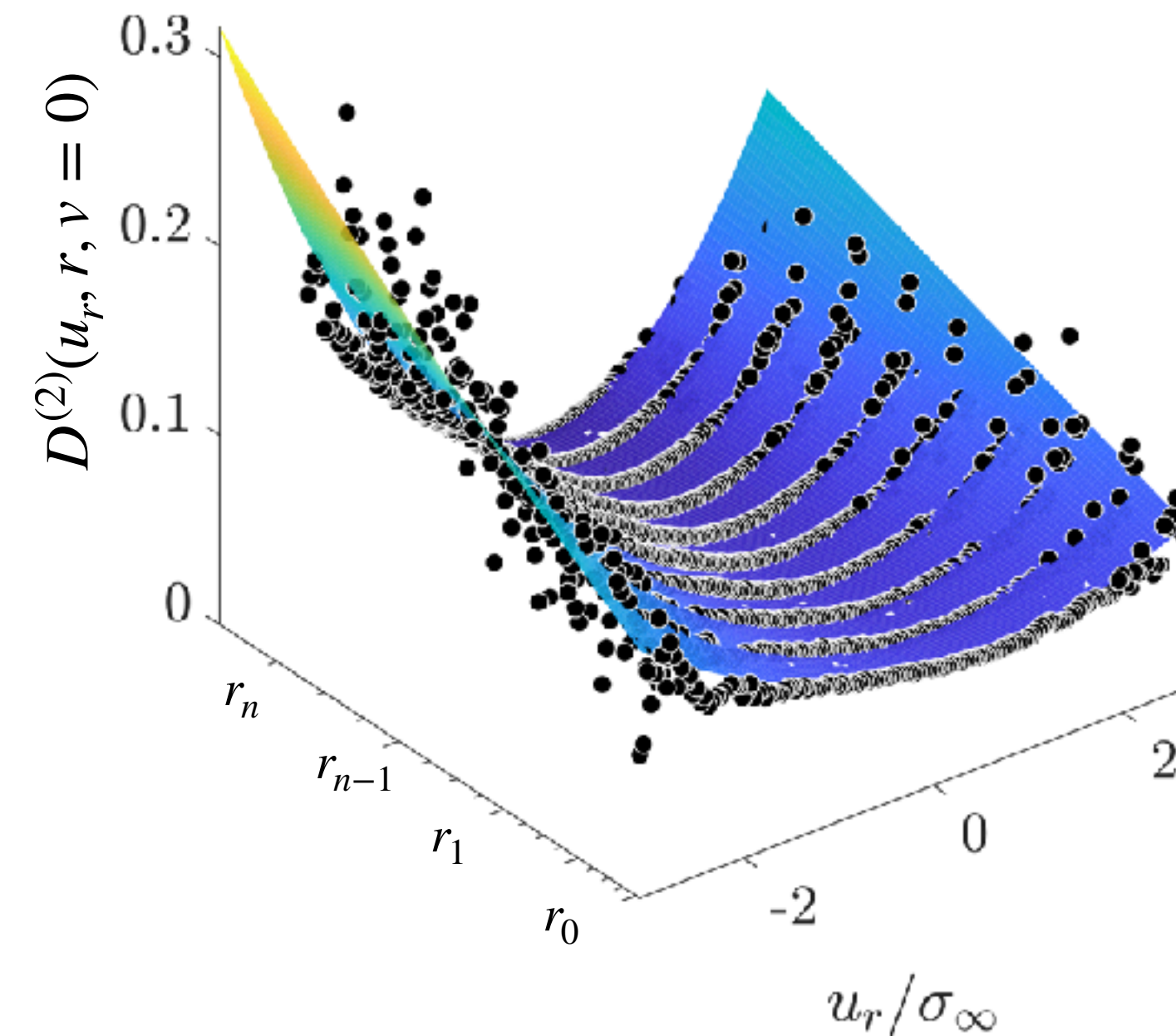
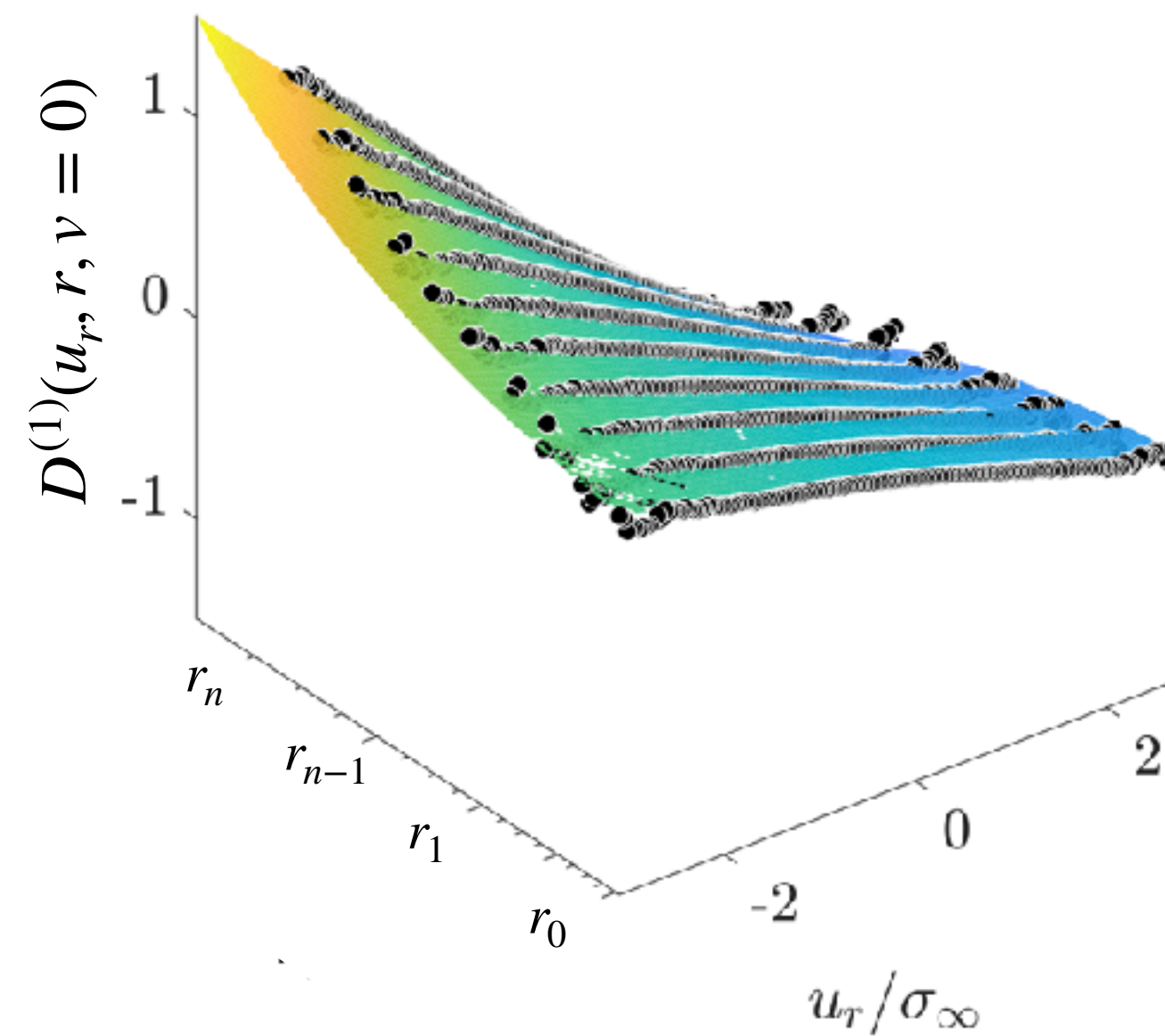
Stresing et.al. New Journal of Physics **12** (2010)

Renner et.al JFM (2001)

multi-point characterisation (FP for turbulence)

$$-r_j \frac{\partial}{\partial r_j} p(u_{r_j} | u_{r_k}, u(x_1)) = \left\{ -\frac{\partial}{\partial u_{r_j}} D^{(1)}(u_{r_j}, r_j, u(x_1)) + \frac{\partial^2}{\partial u_{r_j}^2} D^{(2)}(u_{r_j}, r_j, u(x_1)) \right\} p(u_{r_j} | u_{r_k}, u(x_1))$$

Drift and Diffusion coefficient as a function of r can be “measured”



Recipe for stochastic analysis

data

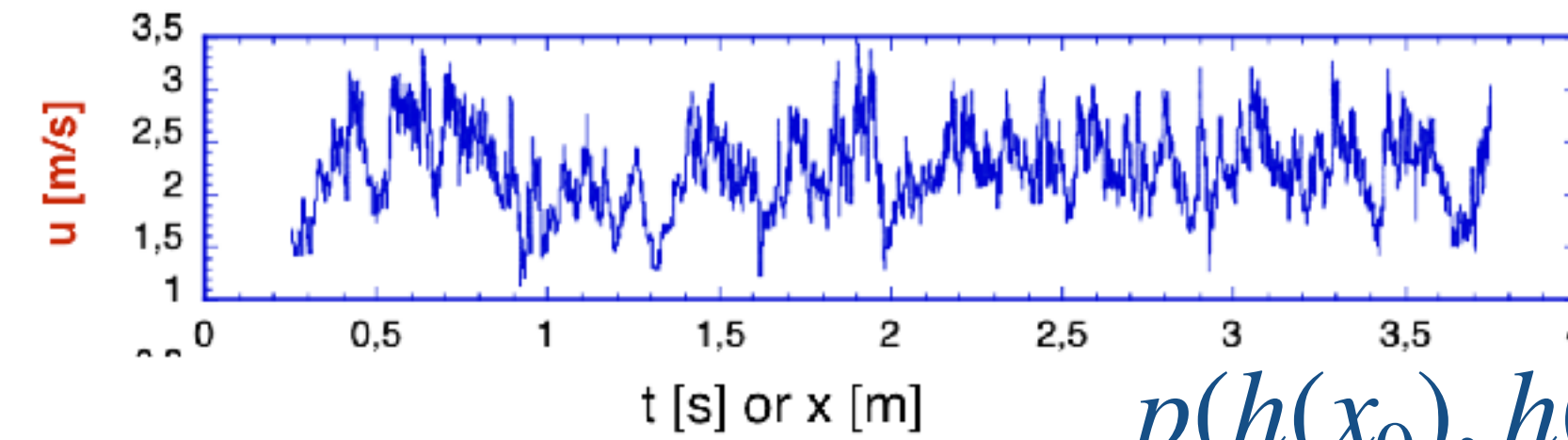
Joint - n-point statistics reduces to

conditional pdfs

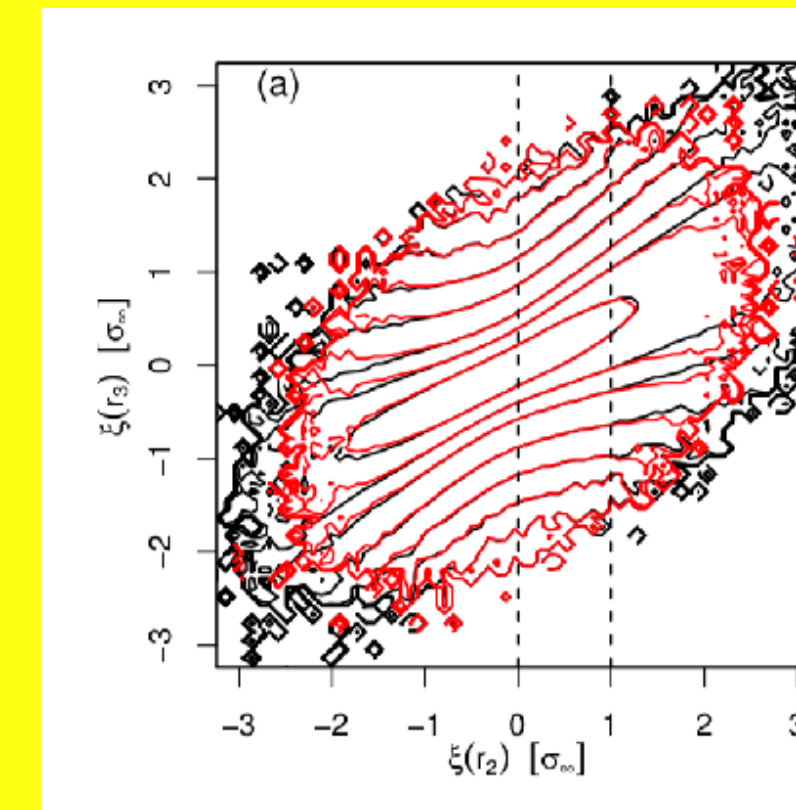
$$\begin{array}{ccccc} \mathbf{L} & \longrightarrow & \mathbf{r} & \longrightarrow & \boldsymbol{\eta} \\ \text{(curved arrows)} & & & & p(u_{r_i} | u_{r_{i+1}}, u(x_n)) \\ & & & & p(h_{r_i} | h_{r_{i+1}}, h(x_n)) \end{array}$$

Fokker-Planck equation describes the cond- pdf

$$p(u(x_0), u(x_1), \dots, u(x_n))$$

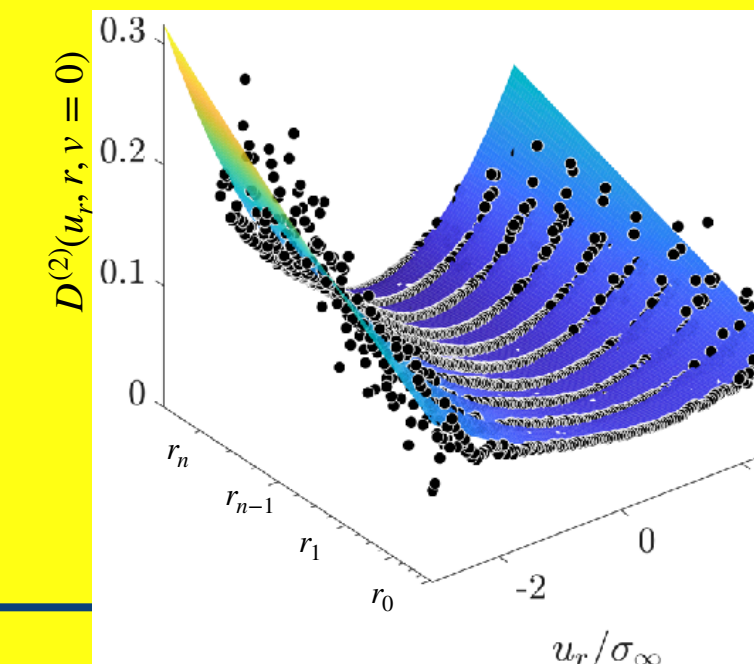
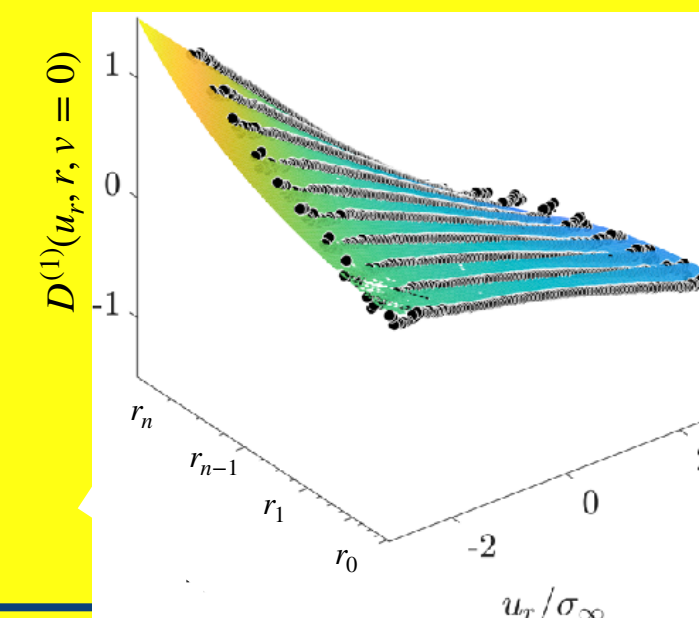


$$p(h(x_0), h(x_1), \dots, h(x_n))$$



Drift - $D^{(1)}$

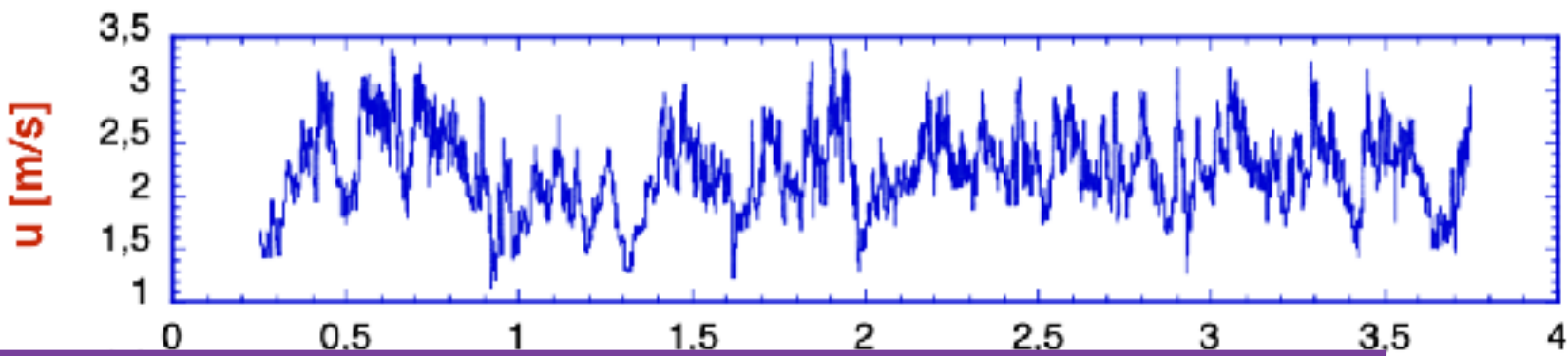
Diffusion - $D^{(2)}$



Recipe for stochastic analysis

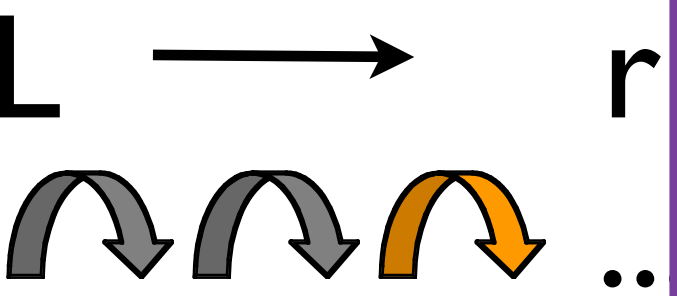
$$p(u(x_0), u(x_1), \dots, u(x_n))$$

data



$$), h(x_1), \dots, h(x_n))$$

Joint - n-point sta



Fokker-Planck eq

Physics of Fluids

TUTORIAL

scitation.org/journal/phf

An open source package to perform basic and advanced statistical analysis of turbulence data and other complex systems

Cite as: Phys. Fluids **34**, 101801 (2022); doi: [10.1063/5.0107974](https://doi.org/10.1063/5.0107974)
Submitted: 7 July 2022 · Accepted: 16 September 2022 ·
Published Online: 21 October 2022

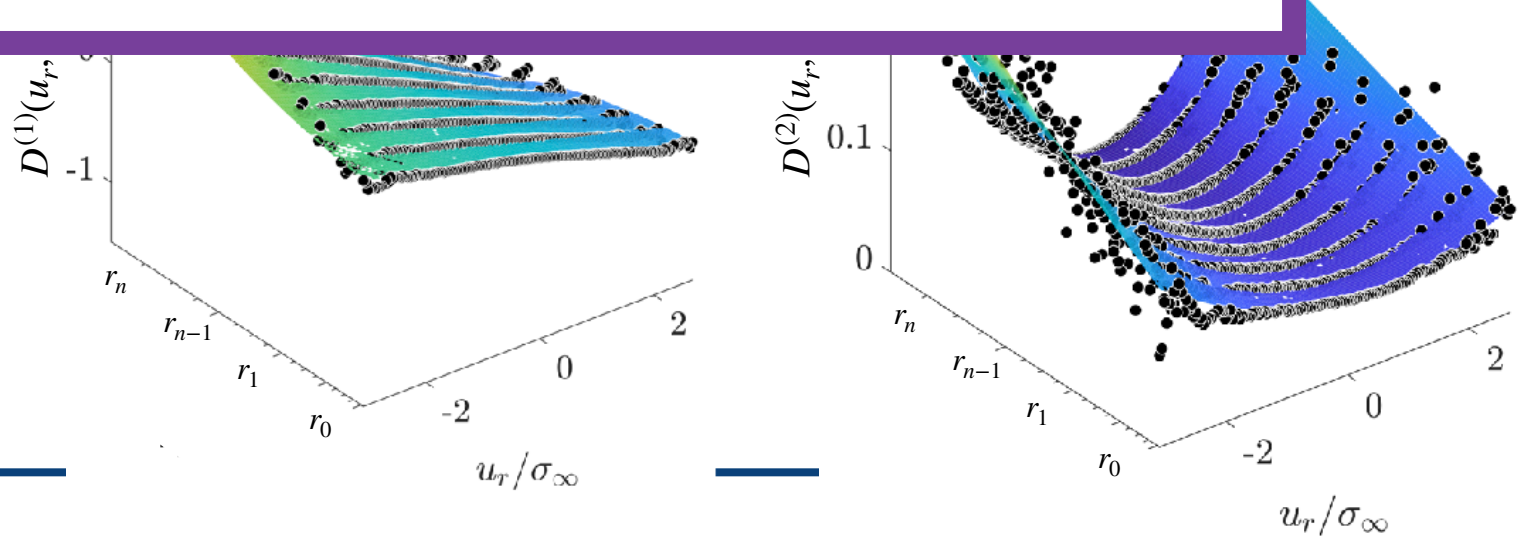
View Online

Export Citation

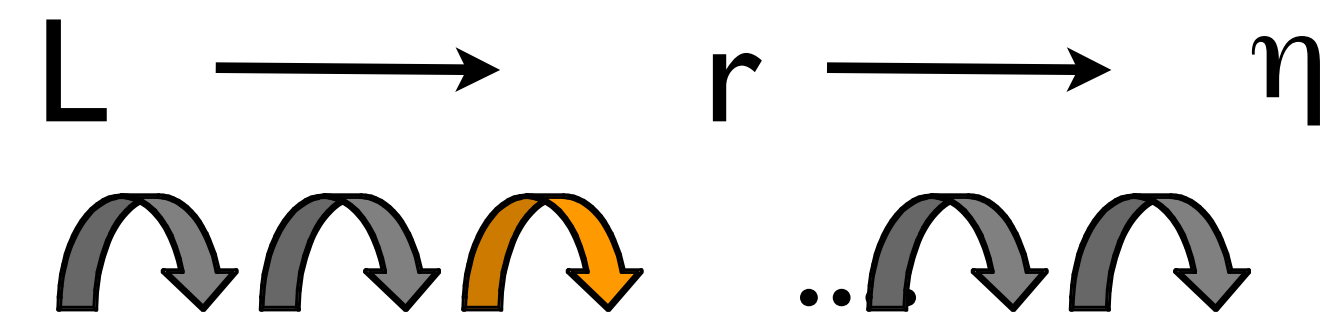
CrossMark

André Fuchs,^{1,a)}  Swapnil Kharche,² Aakash Patil,³  Jan Friedrich,¹  Matthias Wächter,¹ 
and Joachim Peinke¹ 

$D^{(2)}$

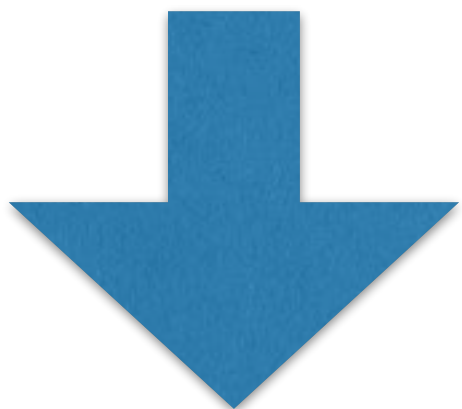


stochastic cascade process: Fokker - Planck equation



$$-r_j \frac{\partial}{\partial r_j} p(u_{r_j} | u_{r_k}, u(x_1)) = \left\{ -\frac{\partial}{\partial u_{r_j}} D^{(1)}(u_{r_j}, r_j, u(x_1)) + \frac{\partial^2}{\partial u_{r_j}^2} D^{(2)}(u_{r_j}, r_j, u(x_1)) \right\} p(u_{r_j} | u_{r_k}, u(x_1))$$

What can we do with this?



Statistical non-equilibrium physics

IOP PUBLISHING

REPORTS ON PROGRESS IN PHYSICS

Rep. Prog. Phys. **75** (2012) 126001 (58pp)

[doi:10.1088/0034-4885/75/12/126001](https://doi.org/10.1088/0034-4885/75/12/126001)

Stochastic thermodynamics, fluctuation theorems and molecular machines

Udo Seifert

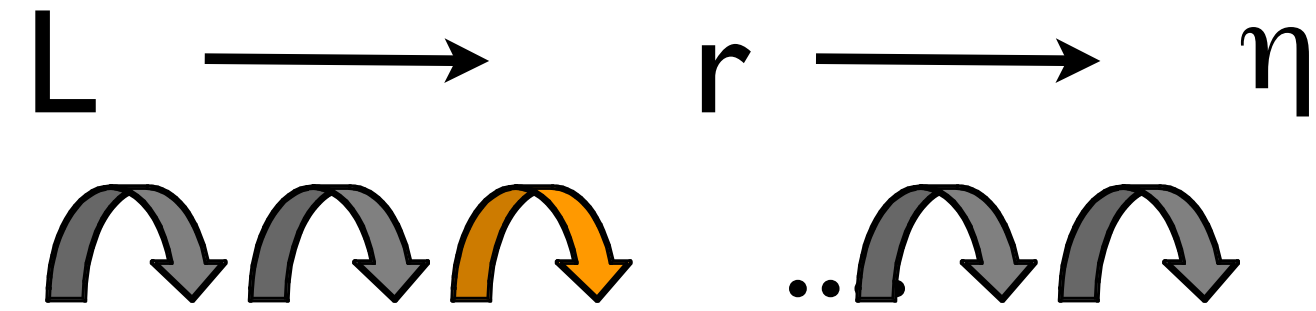
II. Institut für Theoretische Physik, Universität Stuttgart, 70550 Stuttgart, Germany

Received 18 May 2012, in final form 6 August 2012

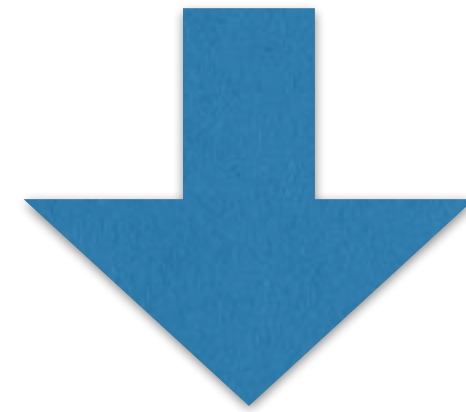
Published 20 November 2012

Online at stacks.iop.org/RoPP/75/126001

stochastic cascade process: Fokker - Planck equation



$$-r_j \frac{\partial}{\partial r_j} p(u_{r_j} | u_{r_k}, u(x_1)) = \left\{ -\frac{\partial}{\partial u_{r_j}} D^{(1)}(u_{r_j}, r_j, u(x_1)) + \frac{\partial^2}{\partial u_{r_j}^2} D^{(2)}(u_{r_j}, r_j, u(x_1)) \right\} p(u_{r_j} | u_{r_k}, u(x_1))$$



- **non equilibrium thermodynamics**
 - **Entropy** (Seifert 2005)
 - **Fluctuation Theorem**
 - Hamiltonian for cascade - instantones

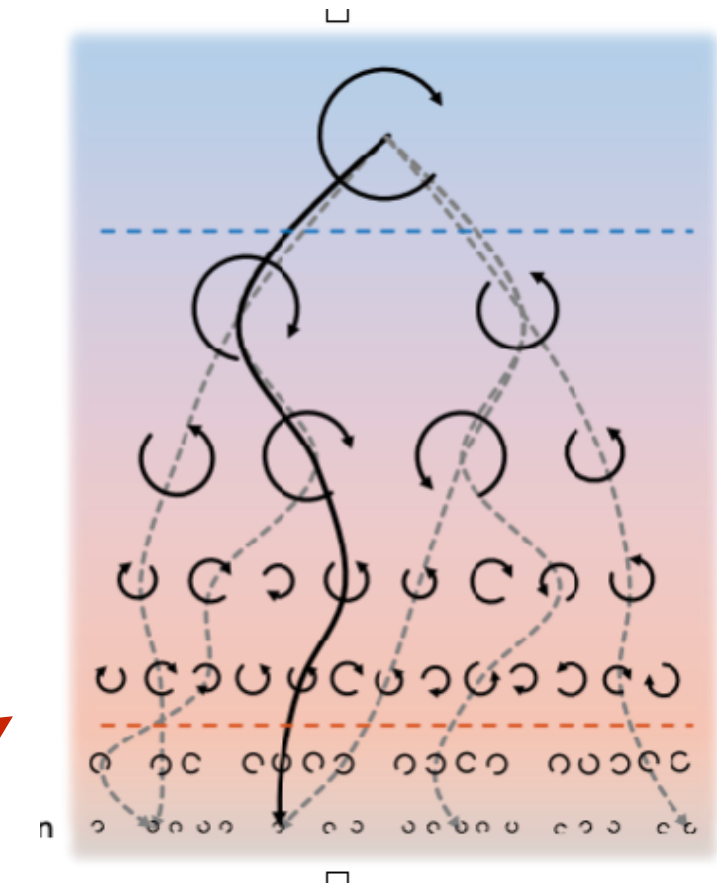
entropy of cascade trajectories

2nd law : entropy balance

there are two contributions of the entropy (cf. Seifert 2005) to the subsystem

$$S_{tot}(u_r) = S_m(u_r) + \Delta S$$

(1) interaction with the medium results in **power done on the subsystem**



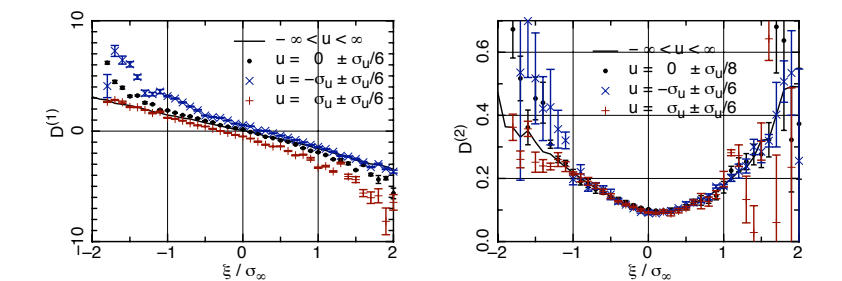
for the cascade path u_r

$$\dot{x}F = \dot{x}\partial_x\varphi$$

$$S_m(u_r) = - \int_L^\lambda \partial_r u_r \partial_u \varphi(u_r, r) dr$$

$$\varphi(u_r) = \ln D^{(2)}(u_r, r) - \int_{-\infty}^{u_r} \frac{D^{(1)}(u', r)}{D^{(2)}(u', r)} du'$$

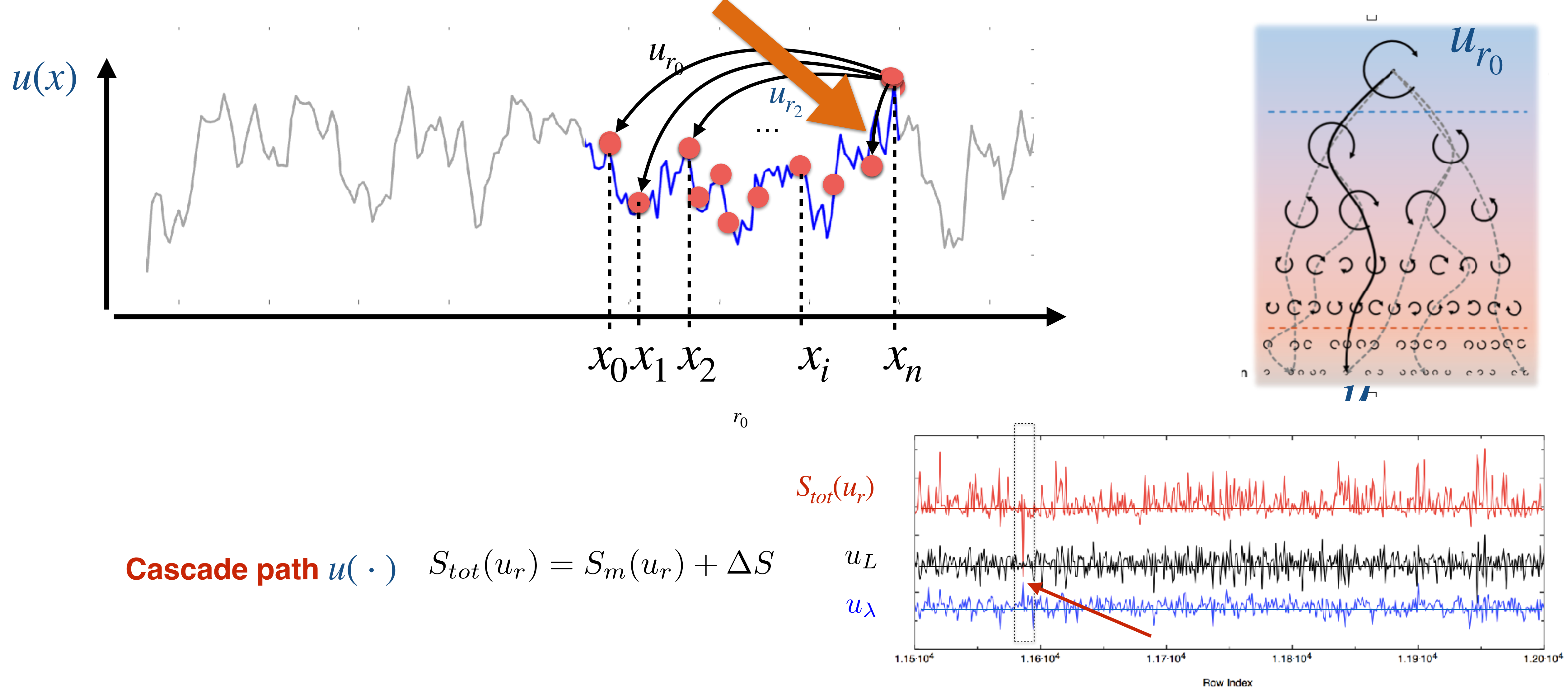
$$\Delta S = -\ln \frac{p_\lambda(u_\lambda)}{p_L(u_L)}$$



shift of drift function, no u -dependence of diffusion function

► Nickelsen Engel PRL 110 (2013)

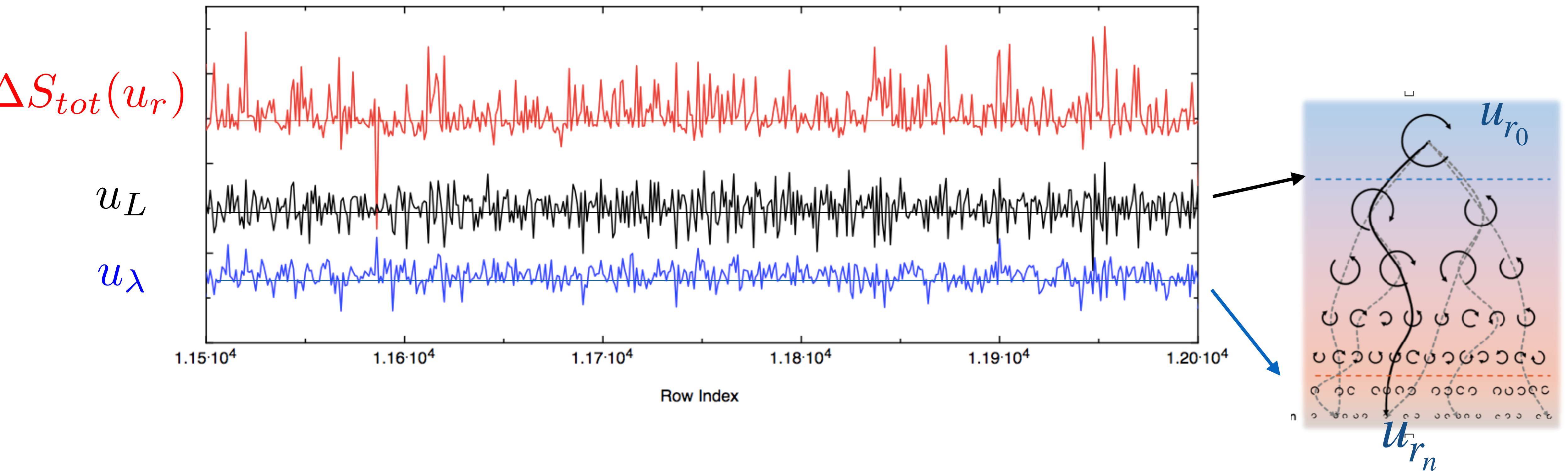
For each trajectory we get an entropy production term



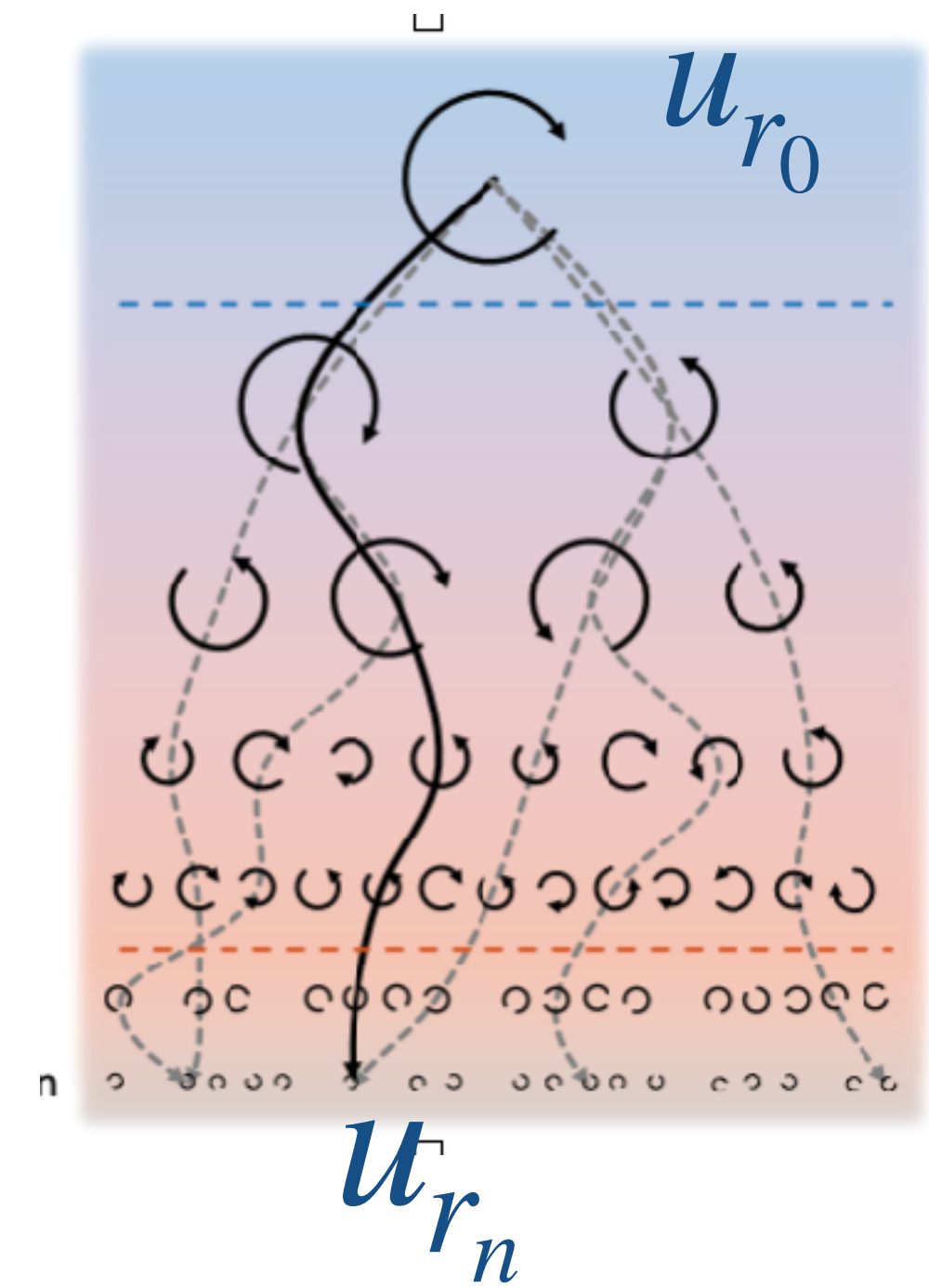
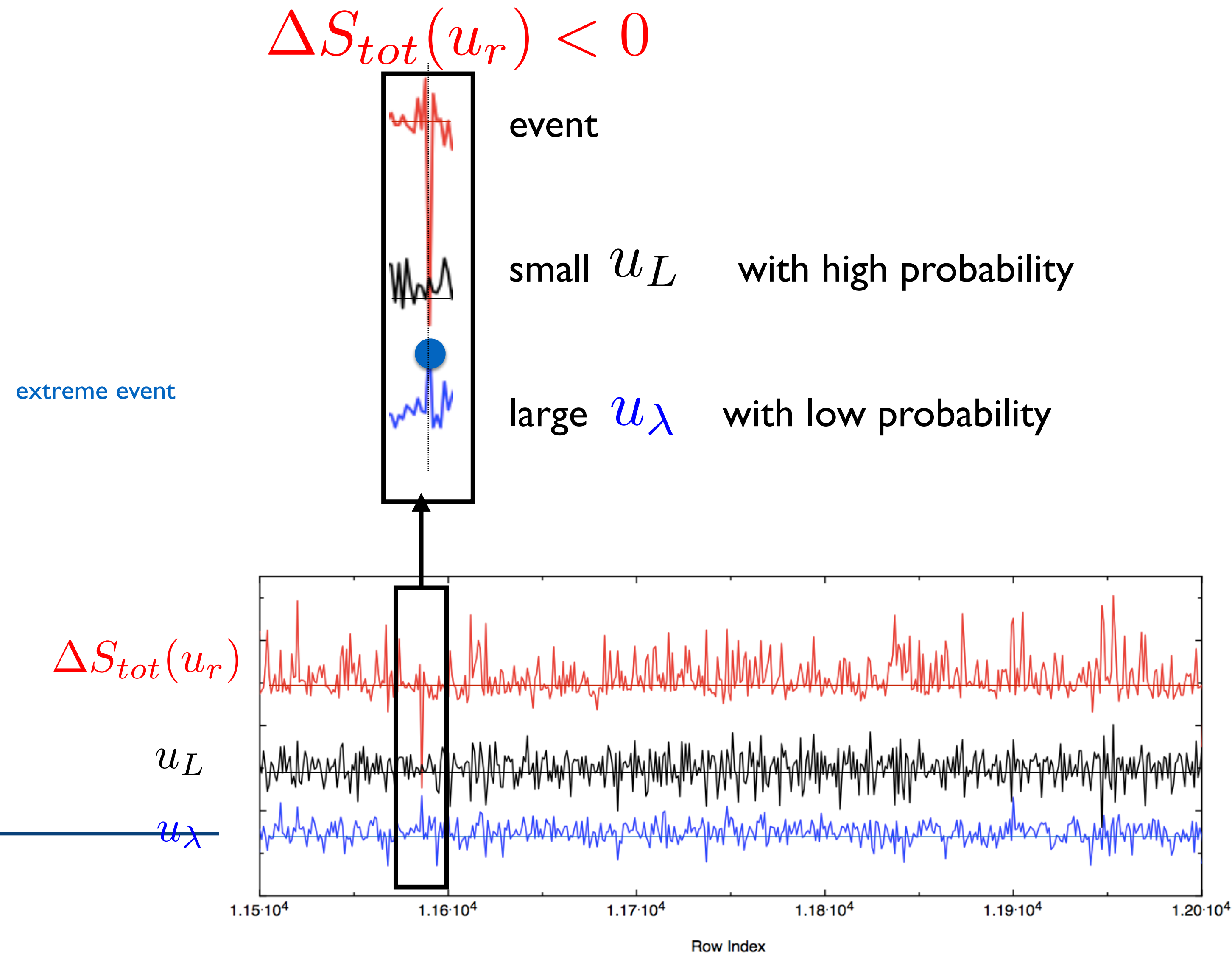
For each trajectory we get an entropy production term

for each cascade path $u(\cdot)$: $u_L \rightarrow u_r$ an entropy value is obtained

ΔS is a fluctuating quantity with positive and negative values

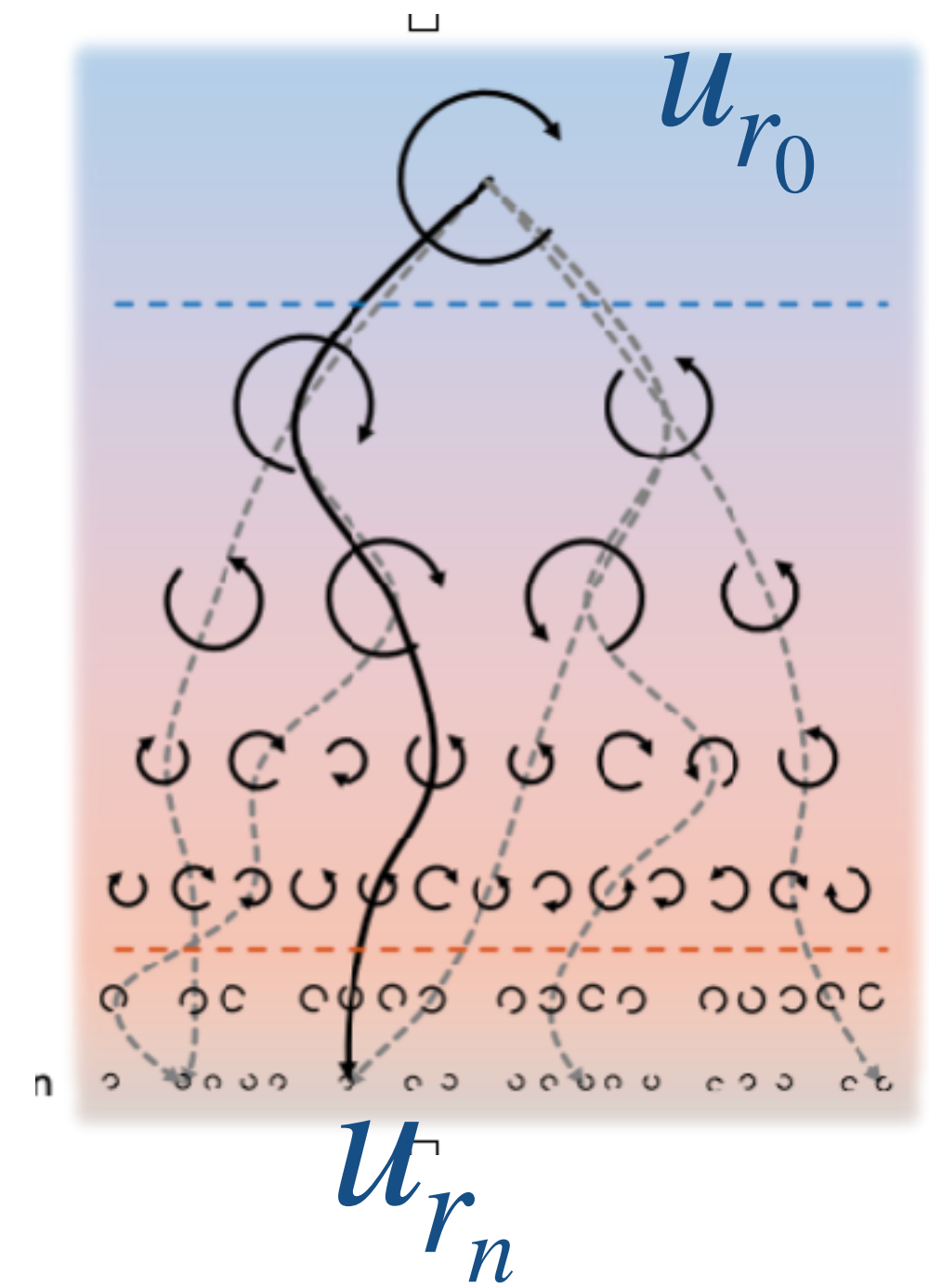
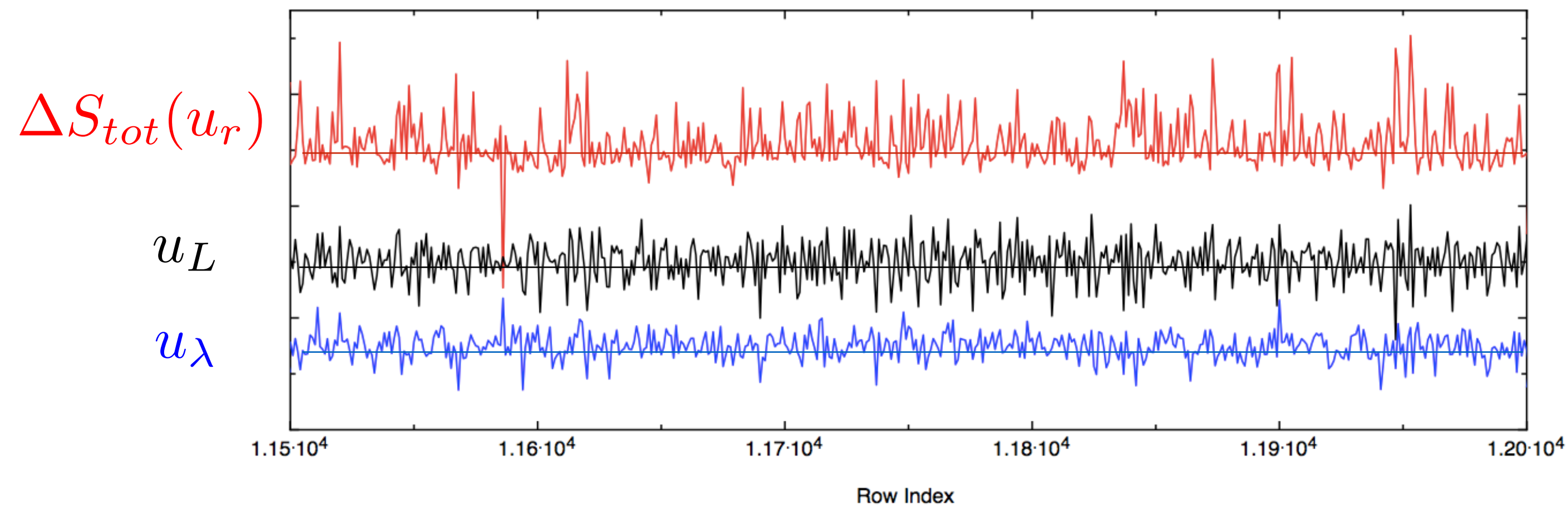


For each trajectory we get an entropy production term



For each trajectory we get an entropy production term

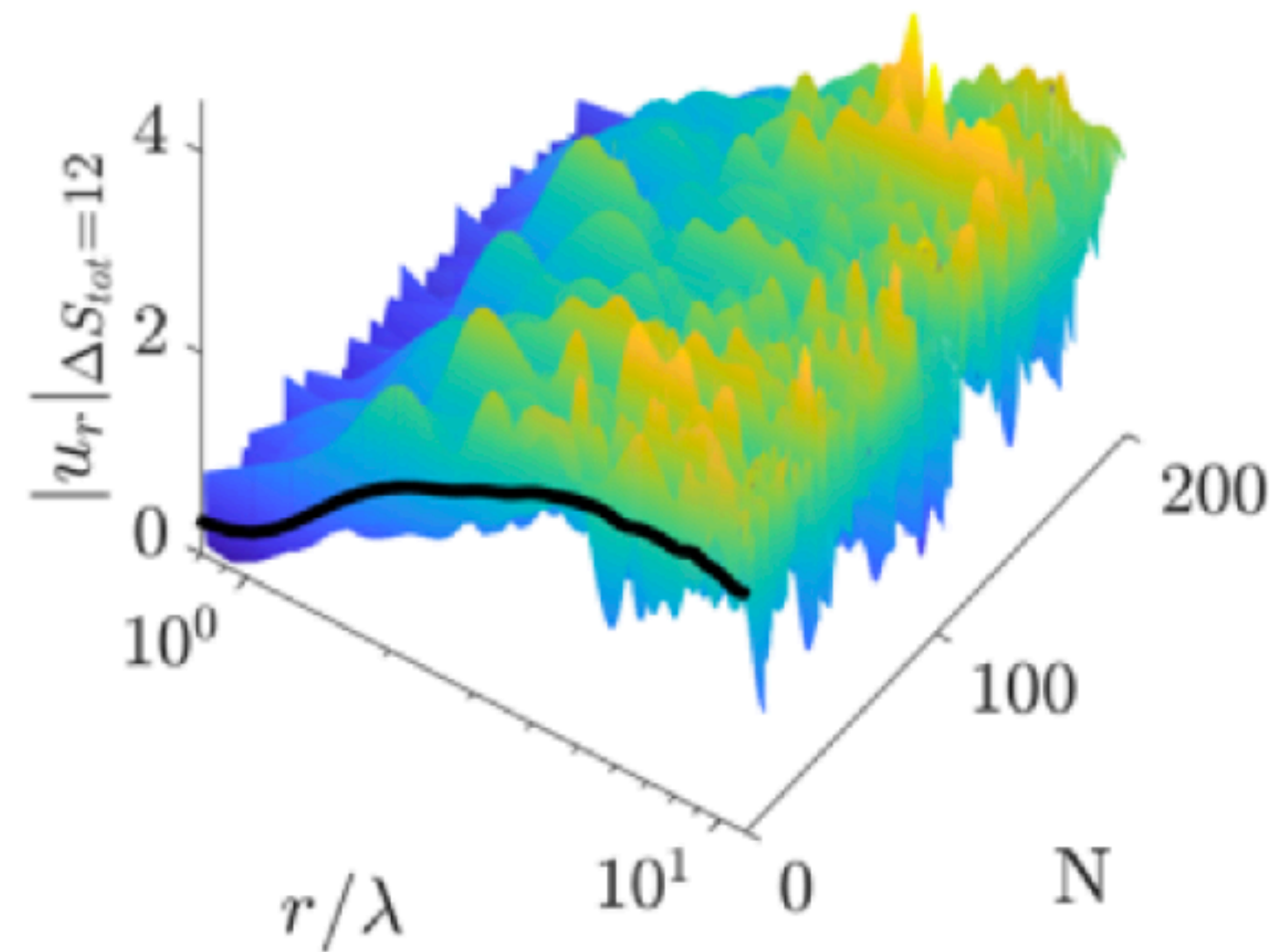
So what?



with positive entropy

$$u(\cdot)|_{S_{tot} > 0}$$

(a)



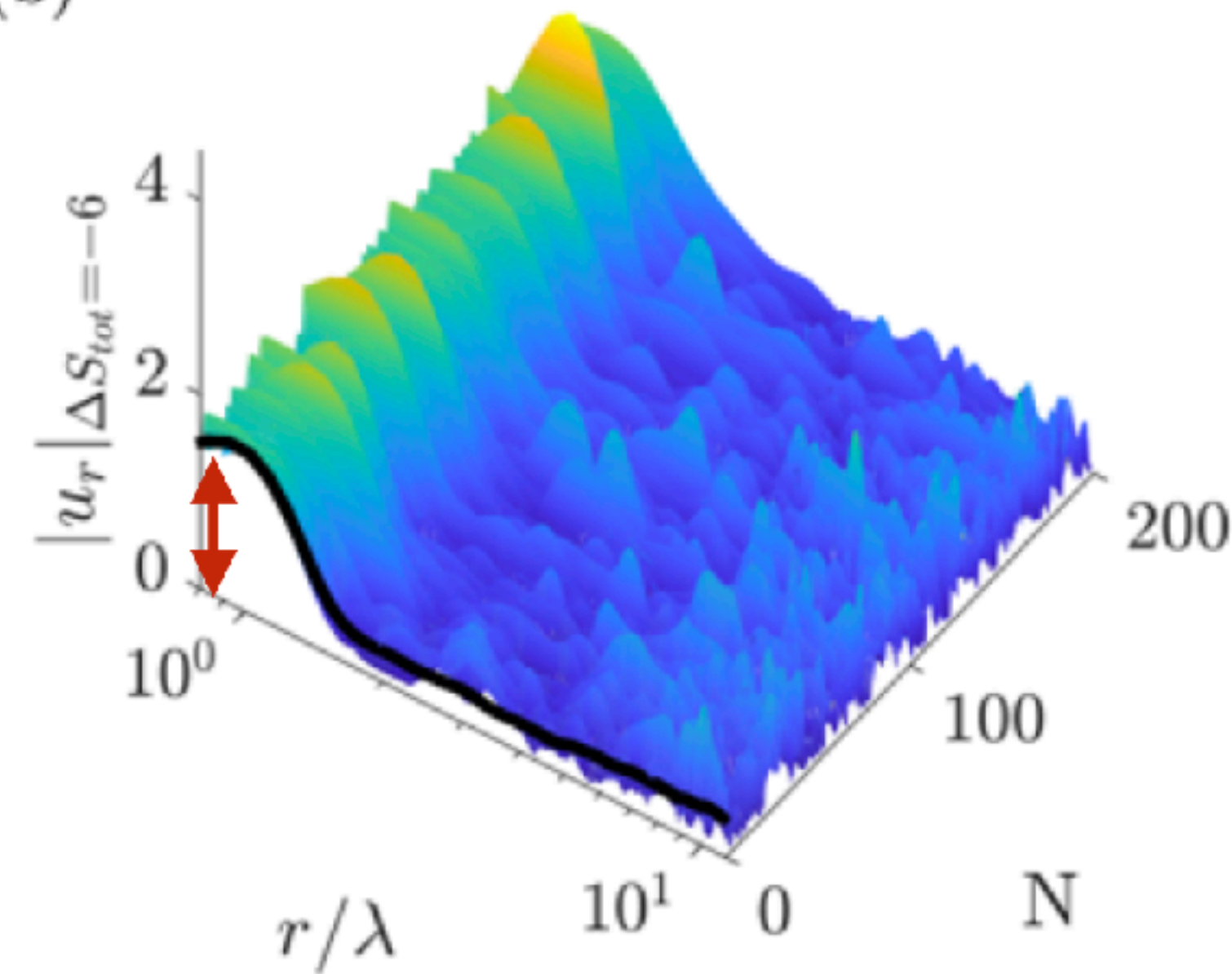
$$u_r \rightarrow 0 \text{ for } r \rightarrow 0$$

$$\text{Kolmogorov 41} \quad u_r \sim r^{1/3}$$

with negative entropy

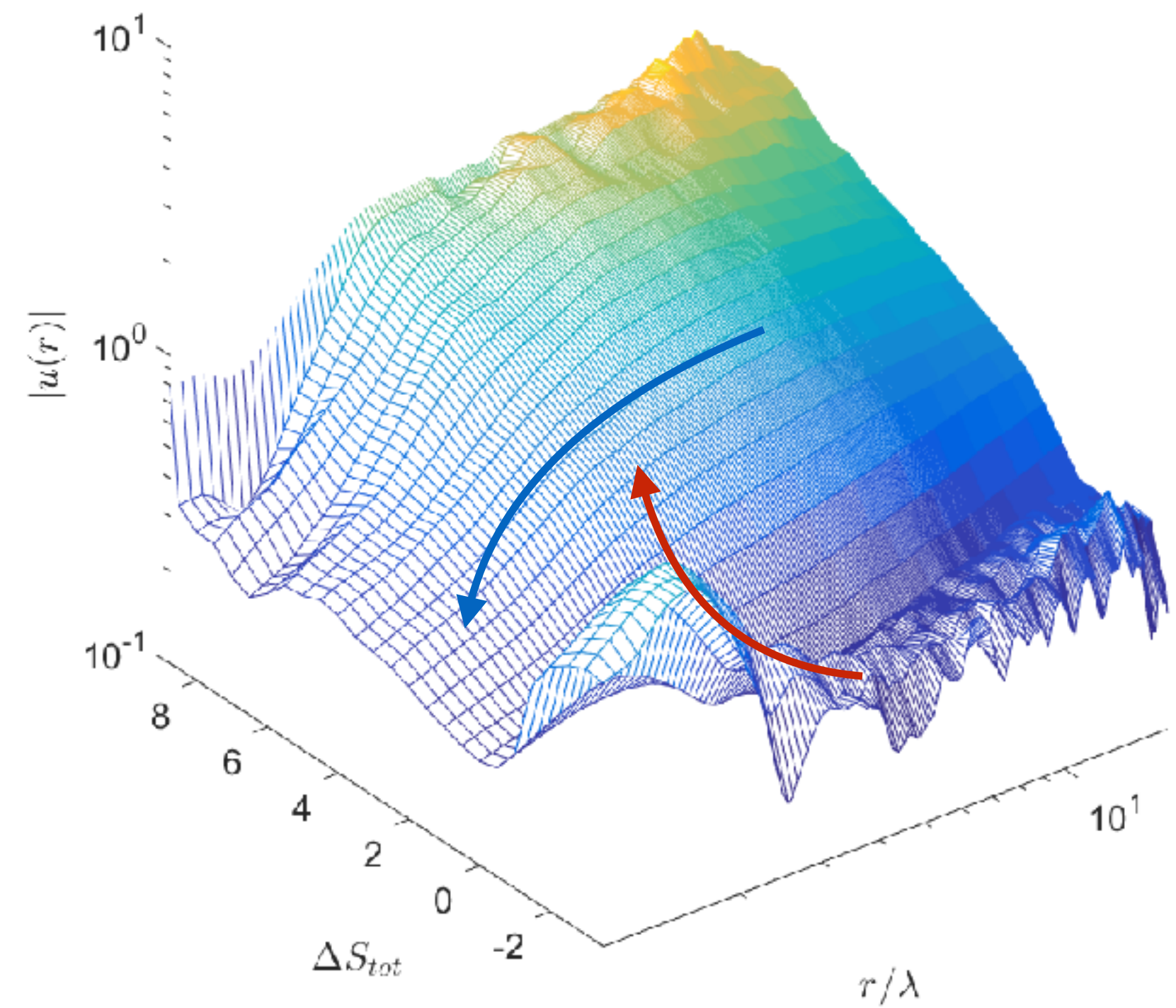
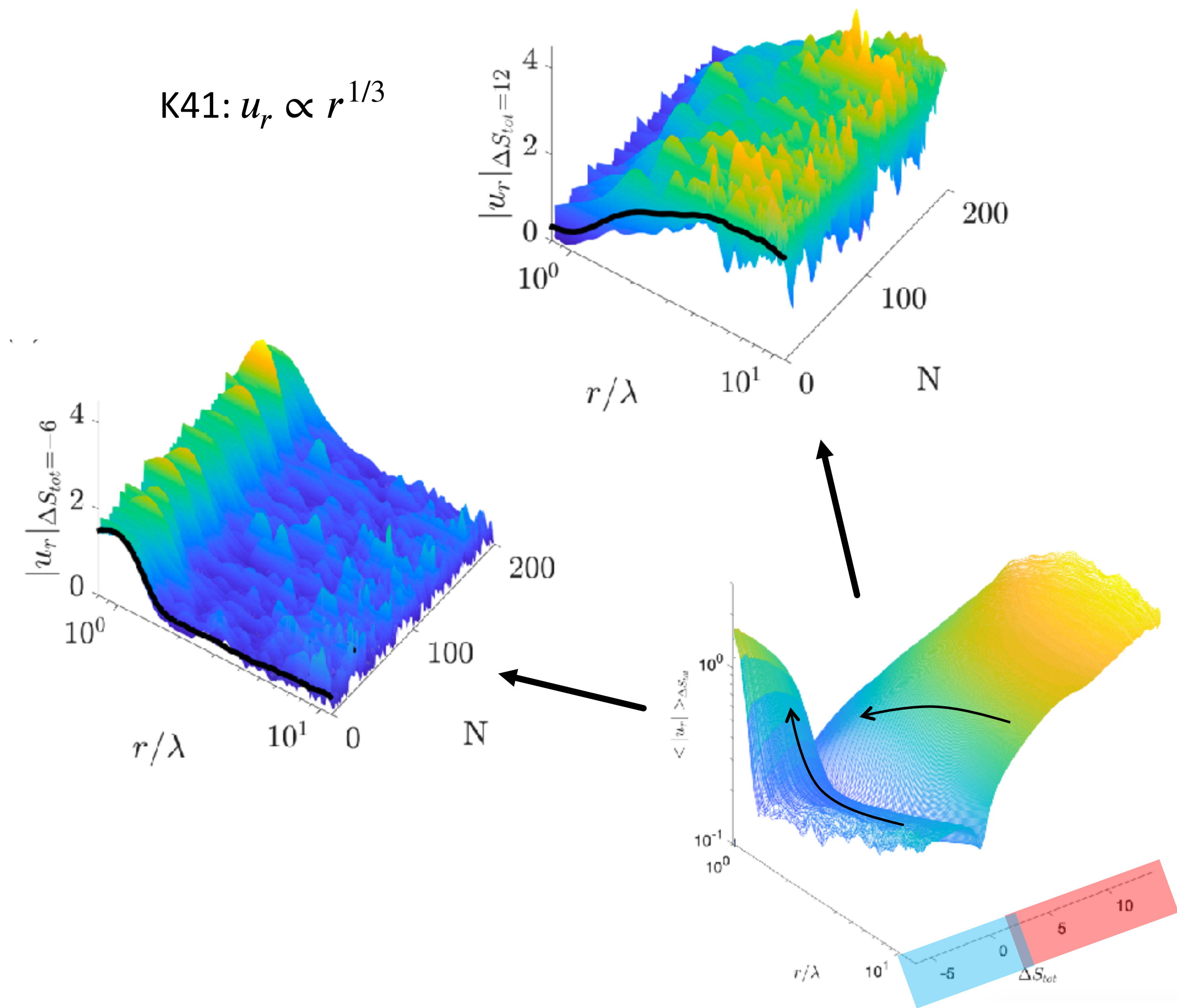
$$u(\cdot)|_{S_{tot} < 0}$$

(b)



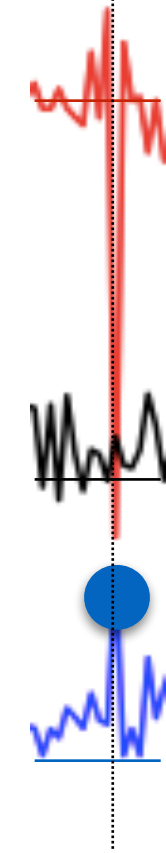
$$u_r > 0 \text{ for } r \rightarrow 0$$

$\Delta S_{tot} [u(\cdot)]$ is linked to distinct local turbulent flow structures



$$\Delta S_{tot}(u_r) < 0$$

extreme event



event

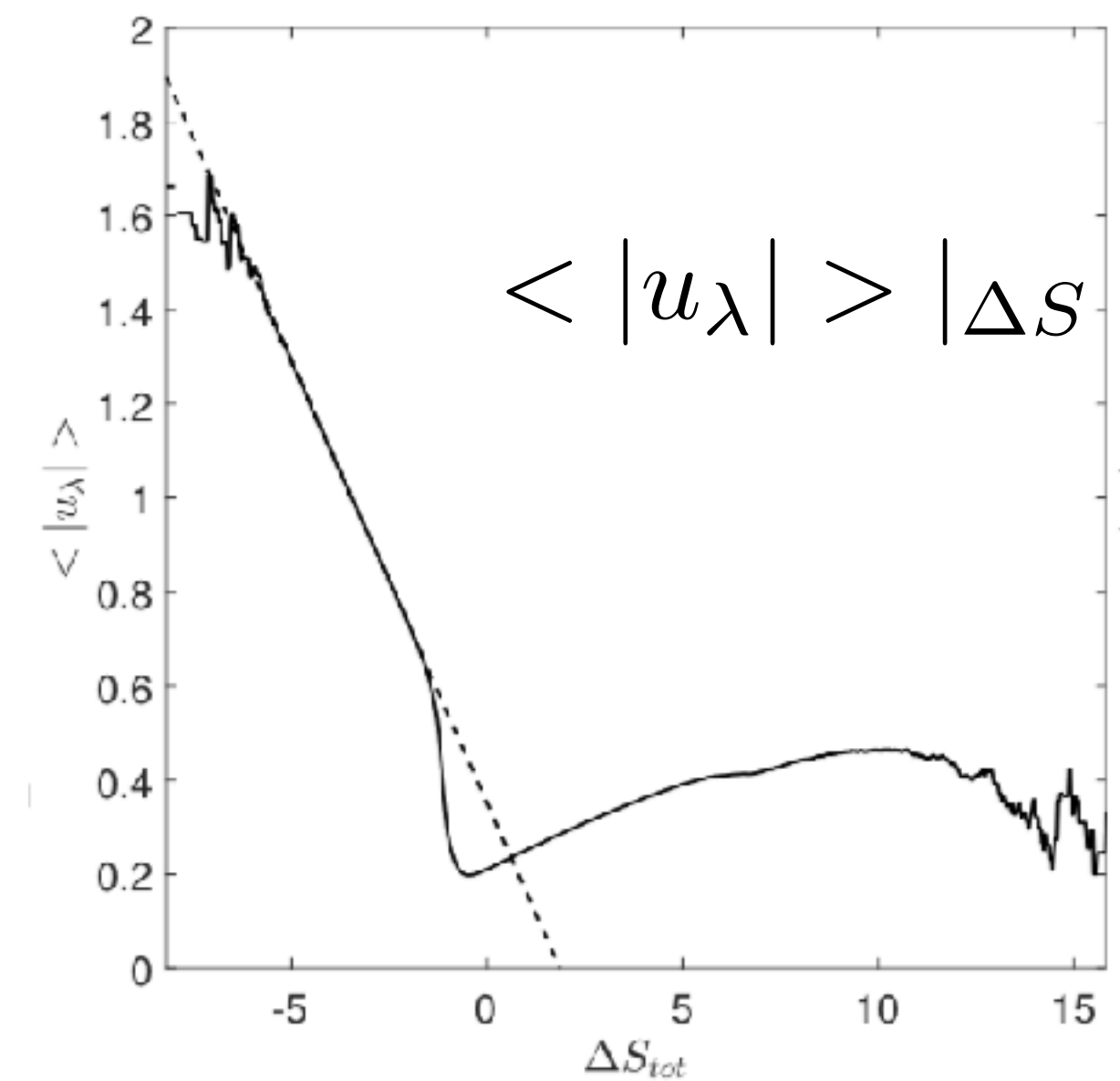
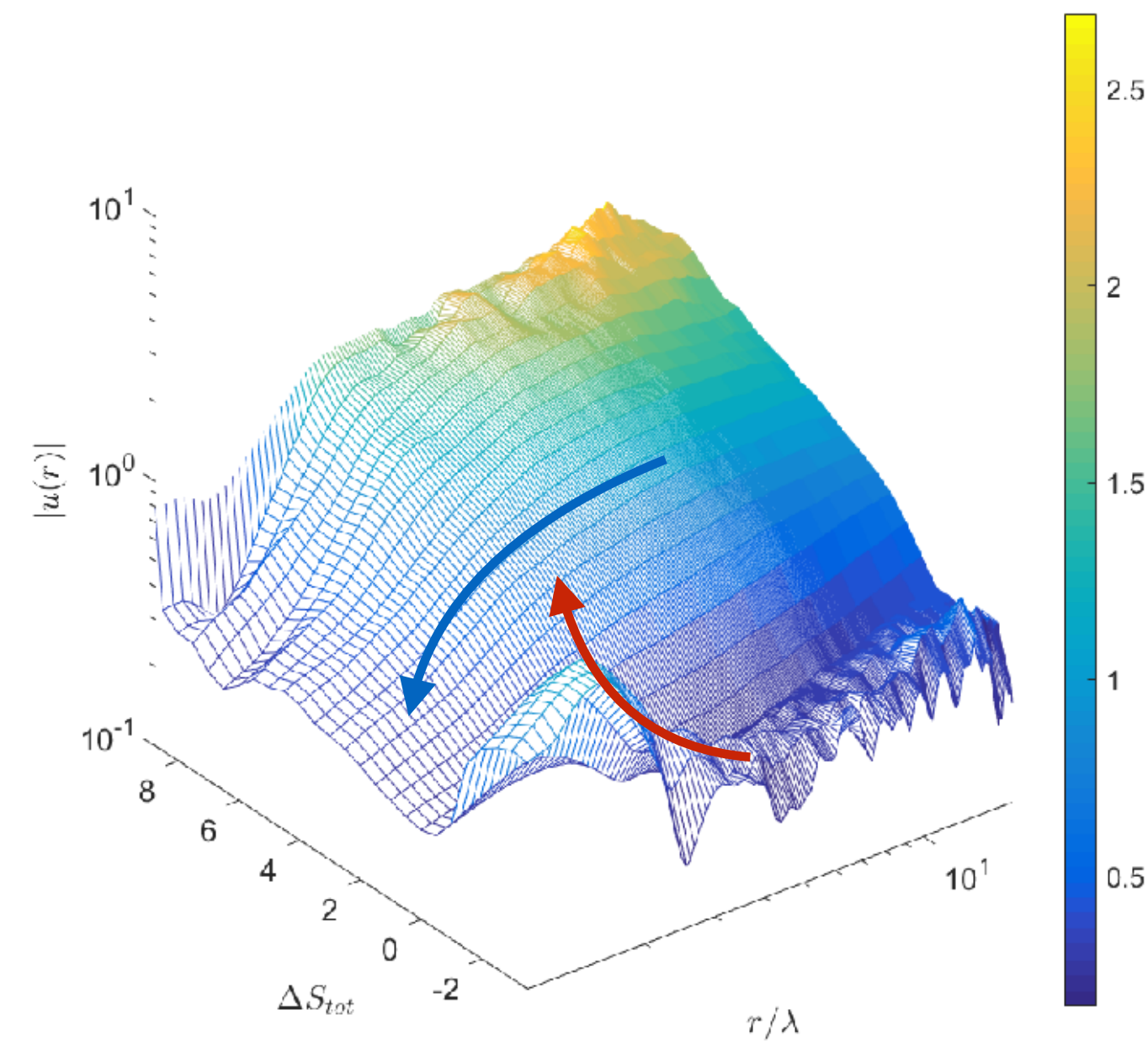
small u_L with high probability

large u_λ with low probability

Negative entropy events are small scale structures !!!!

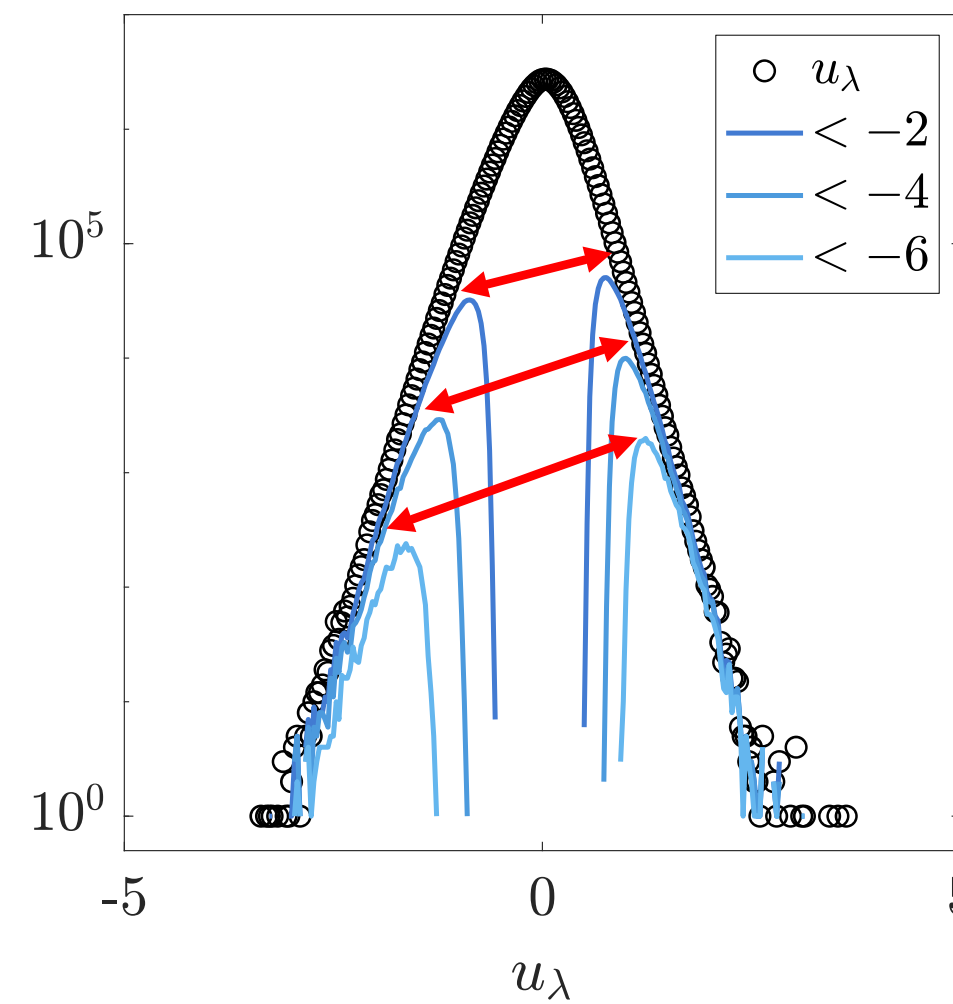
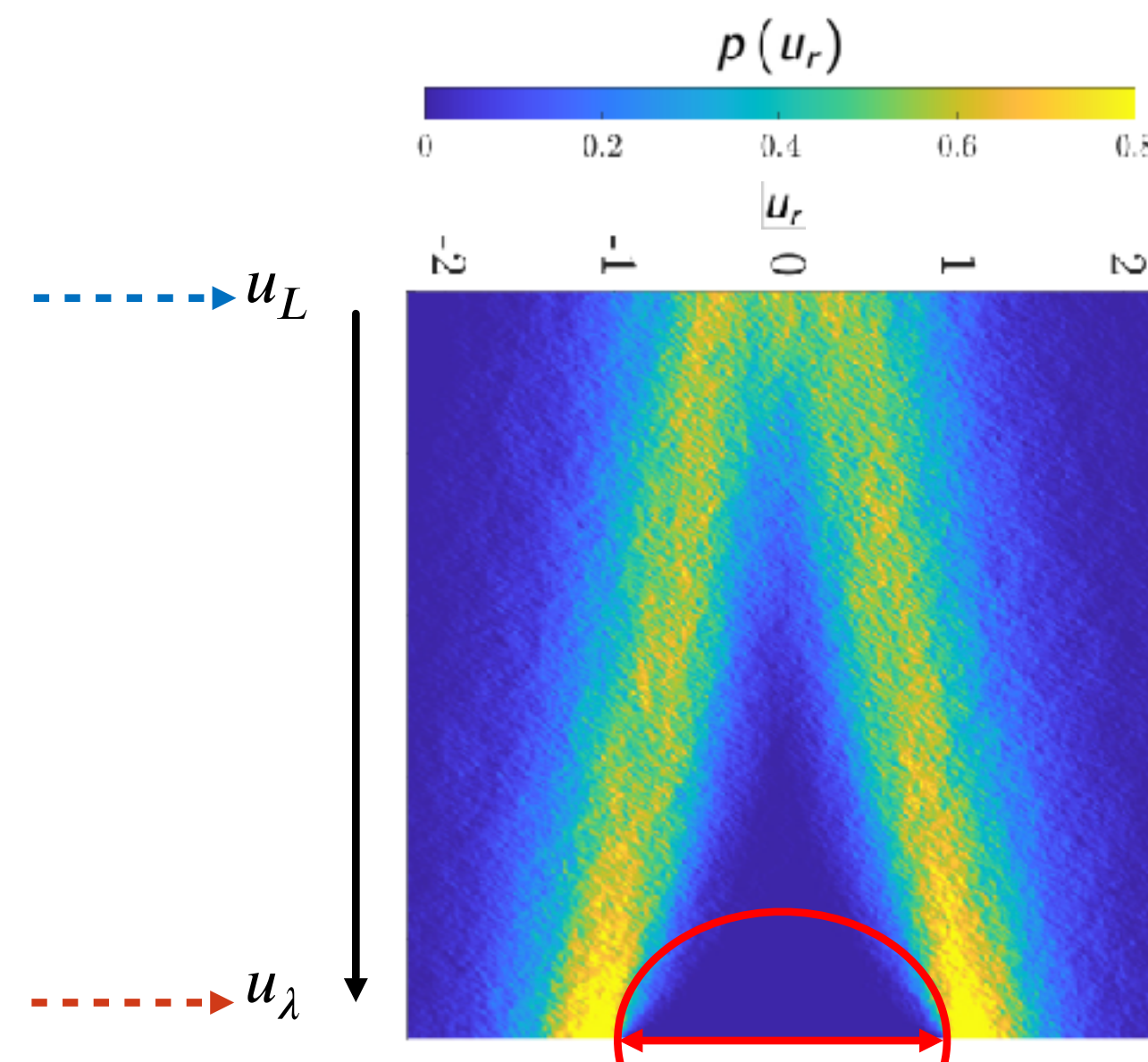
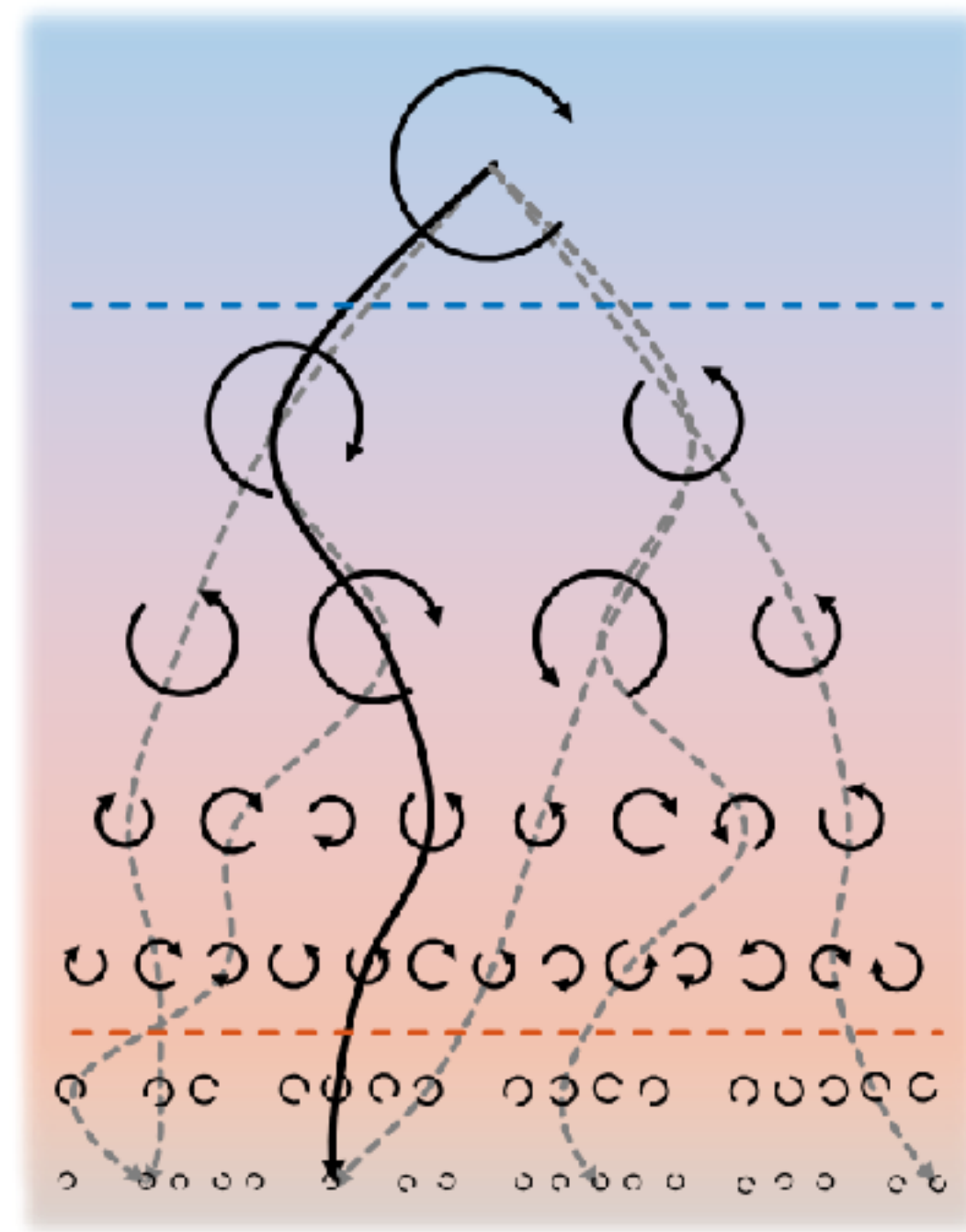
Are these indication of shocks?

$$\langle |u_r| \rangle \propto |\Delta S|$$

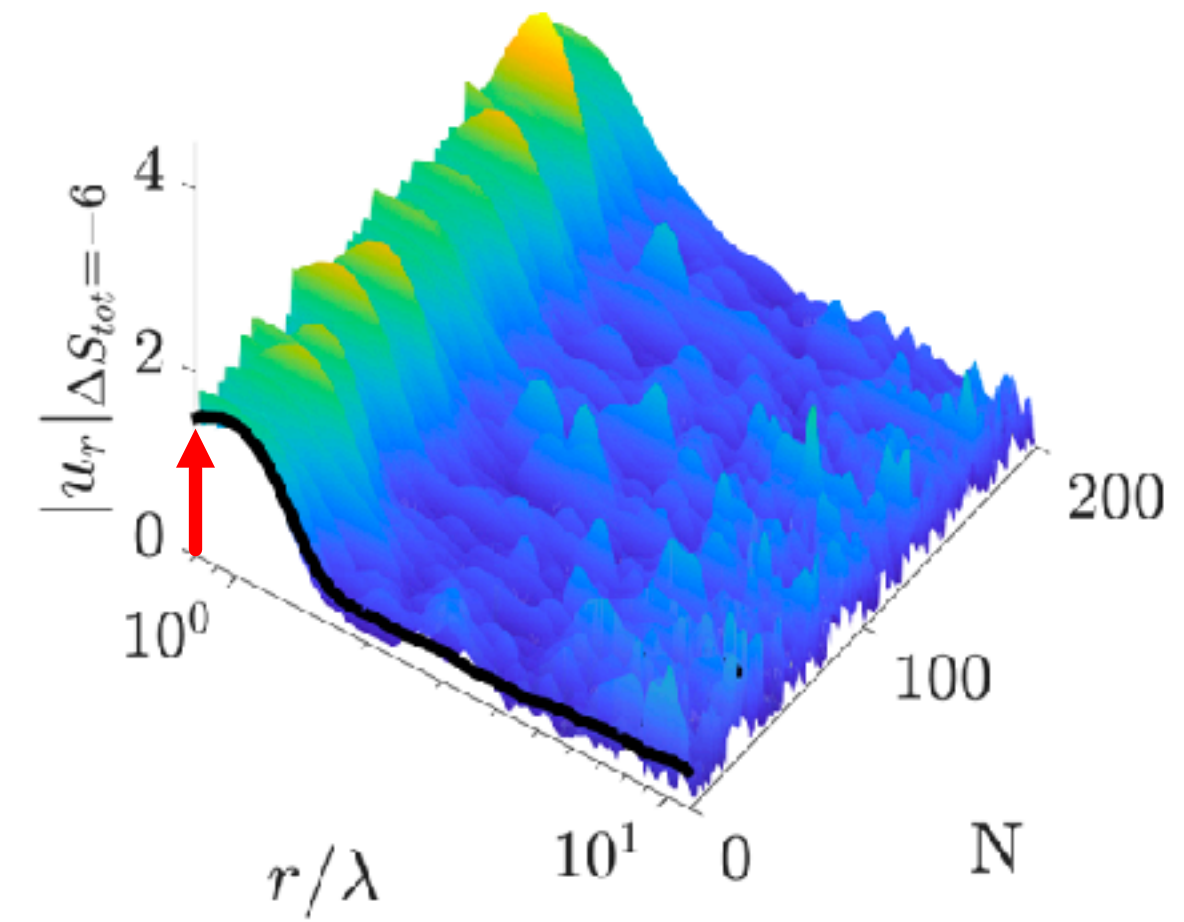


$$\langle |u_\lambda| \rangle \propto |\Delta S|$$

Negative entropy provides access to intermittency



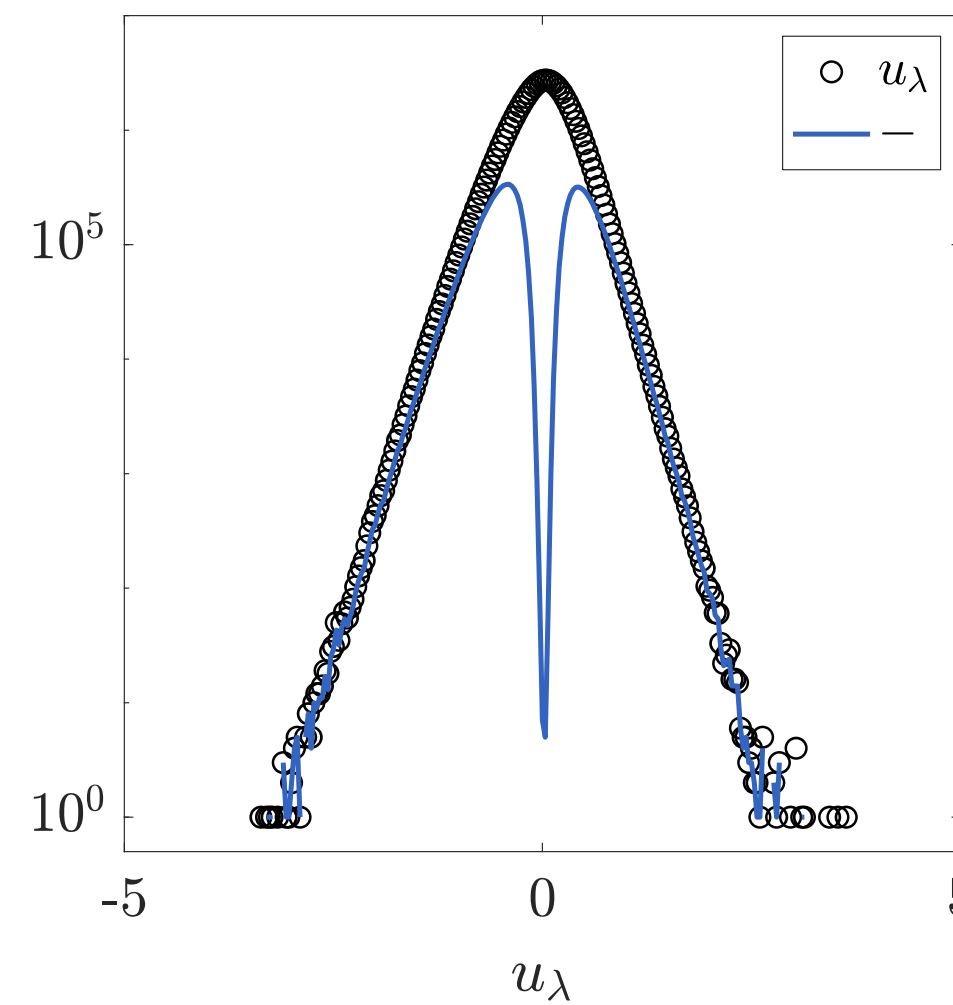
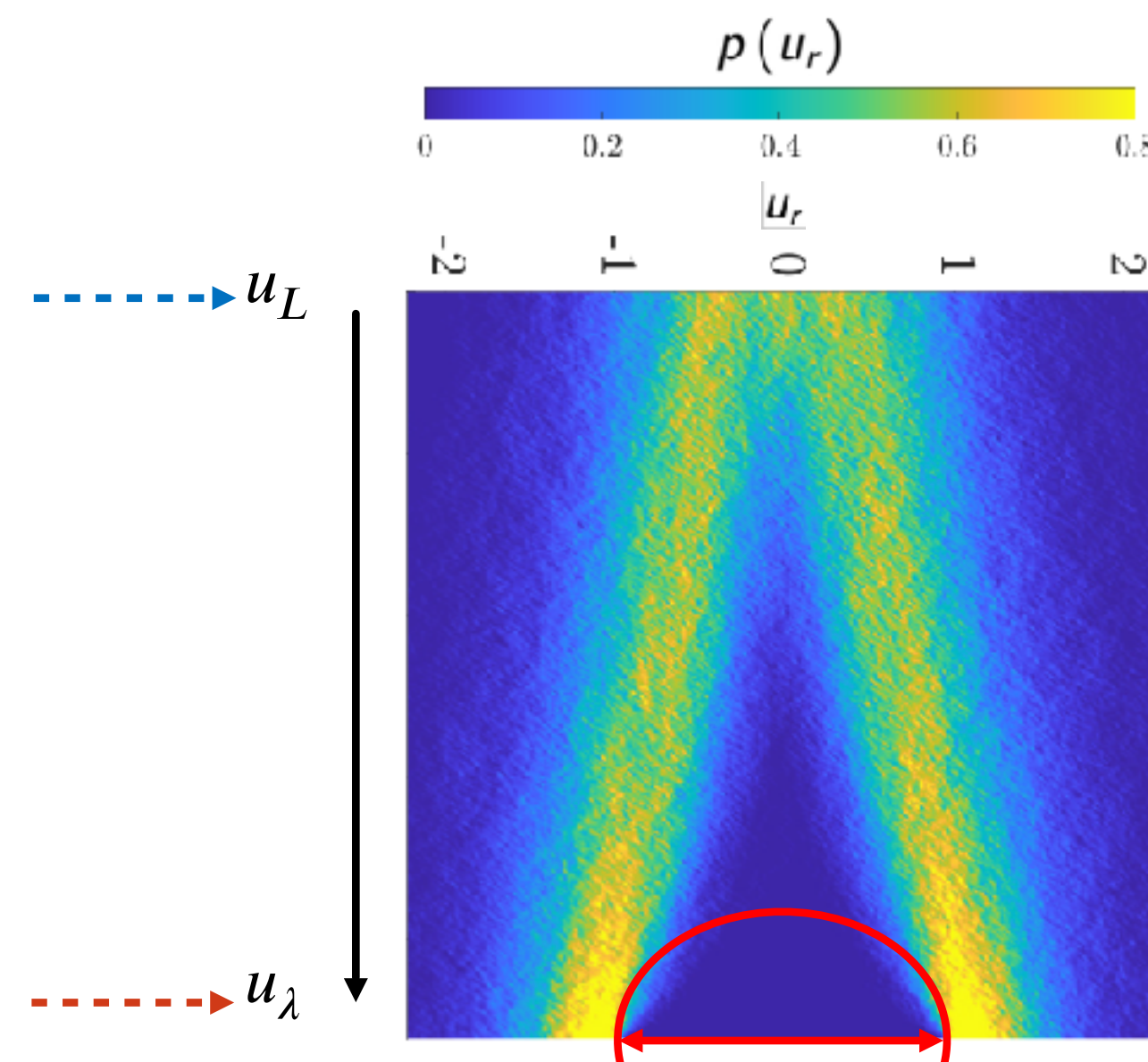
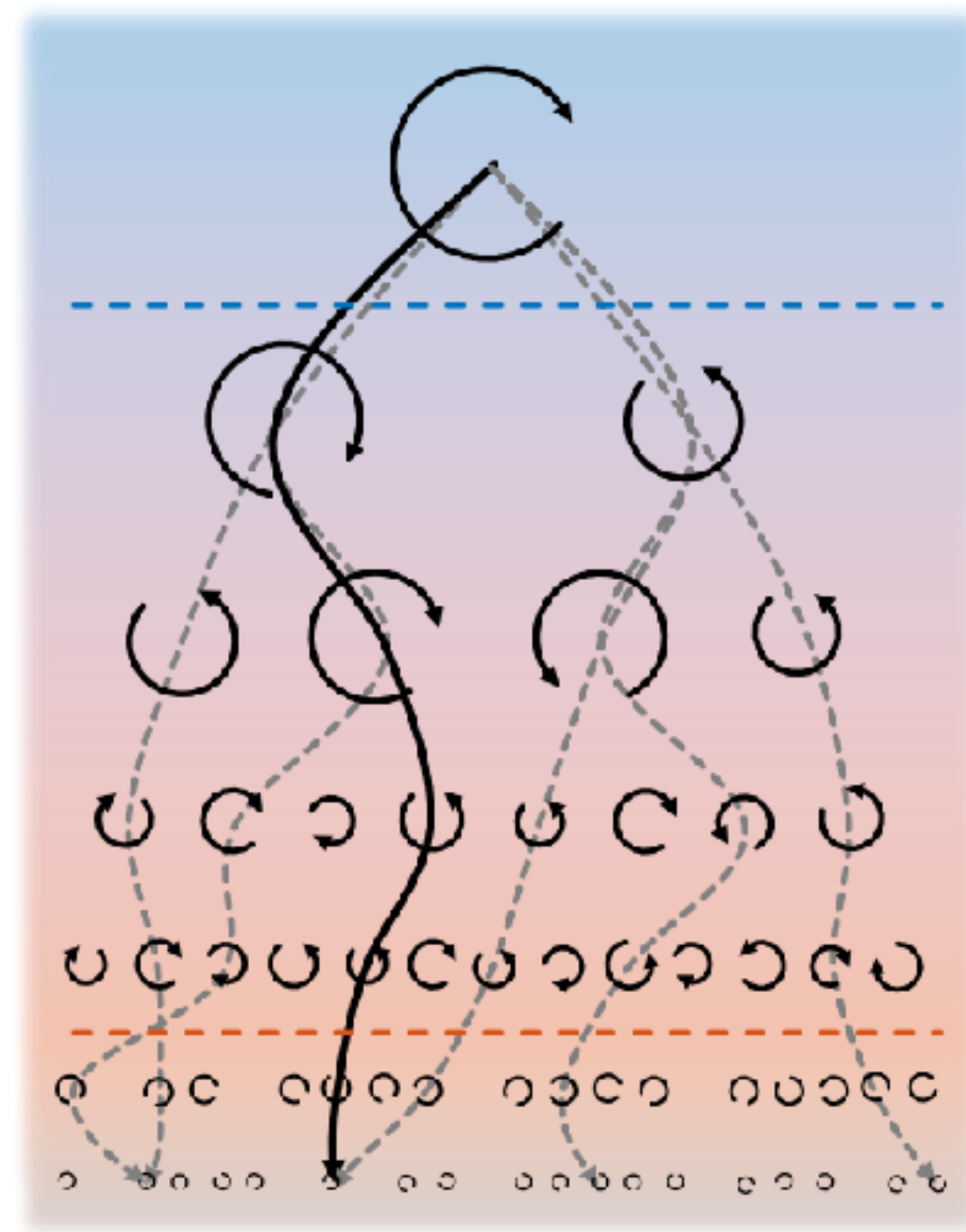
$$\Delta S = -6$$



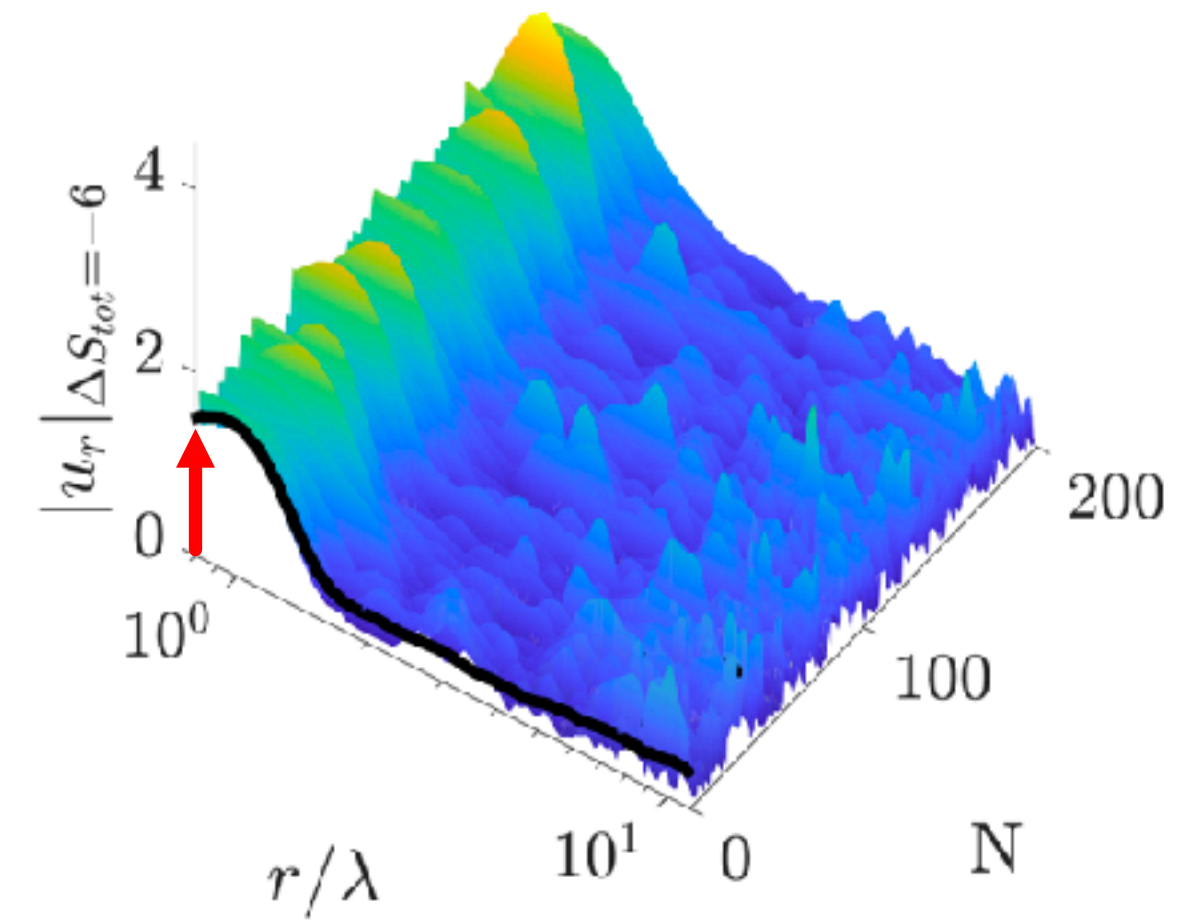
finite increment at small scales

$$|u_r| > 0 \text{ for } r \rightarrow \lambda$$

Negative entropy provides access to intermittency

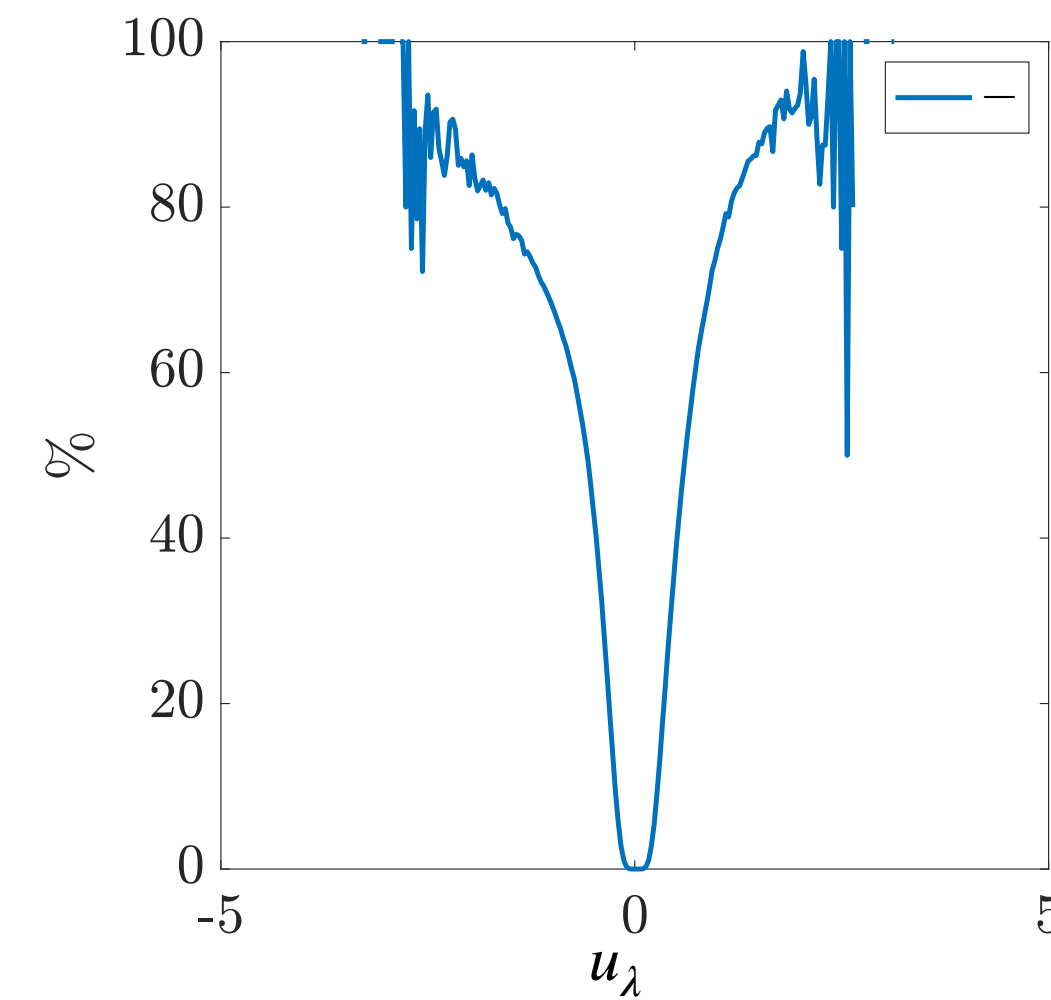


$$\Delta S = -6$$



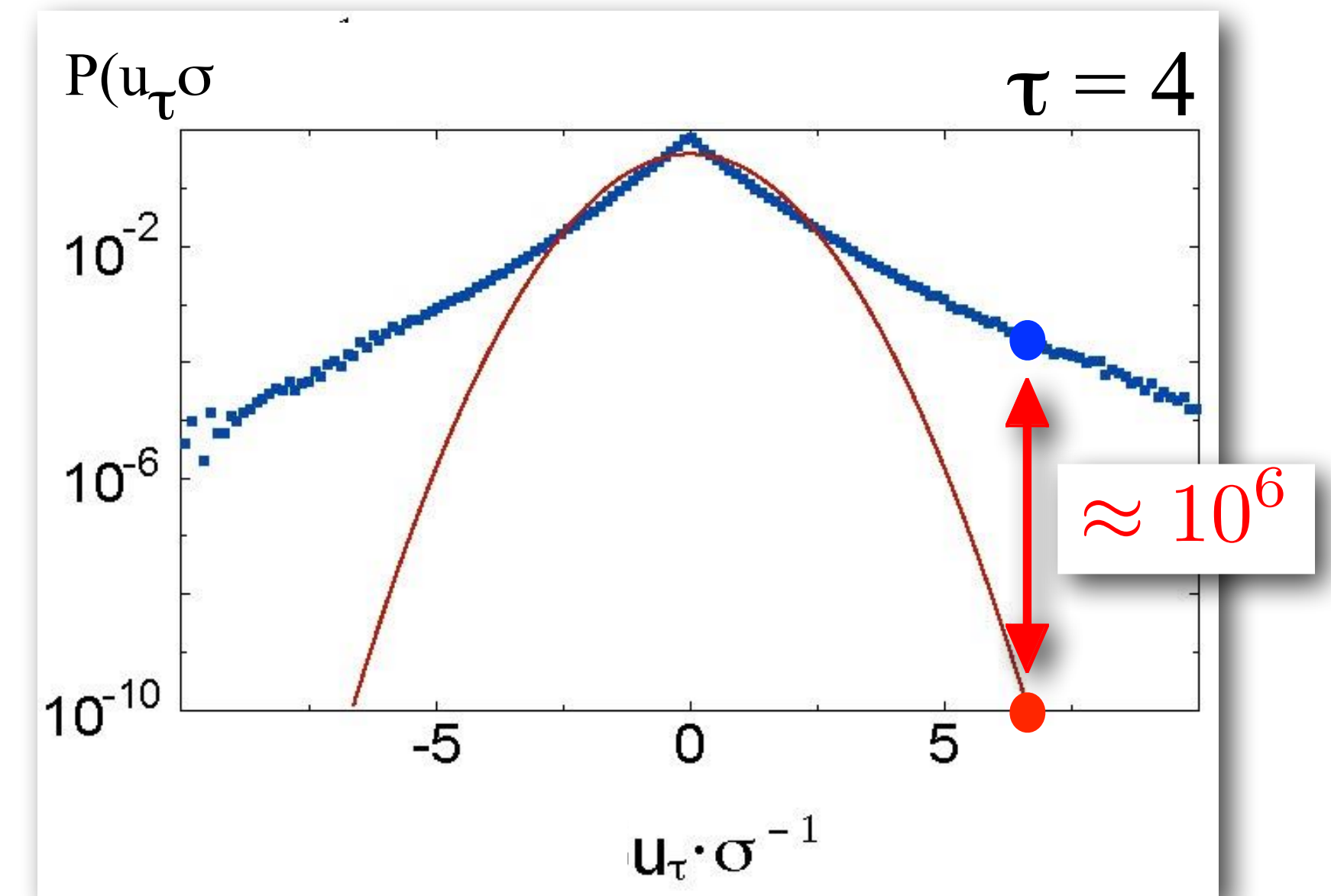
finite increment at small scales

$$|u_r| > 0 \text{ for } r \rightarrow \lambda$$



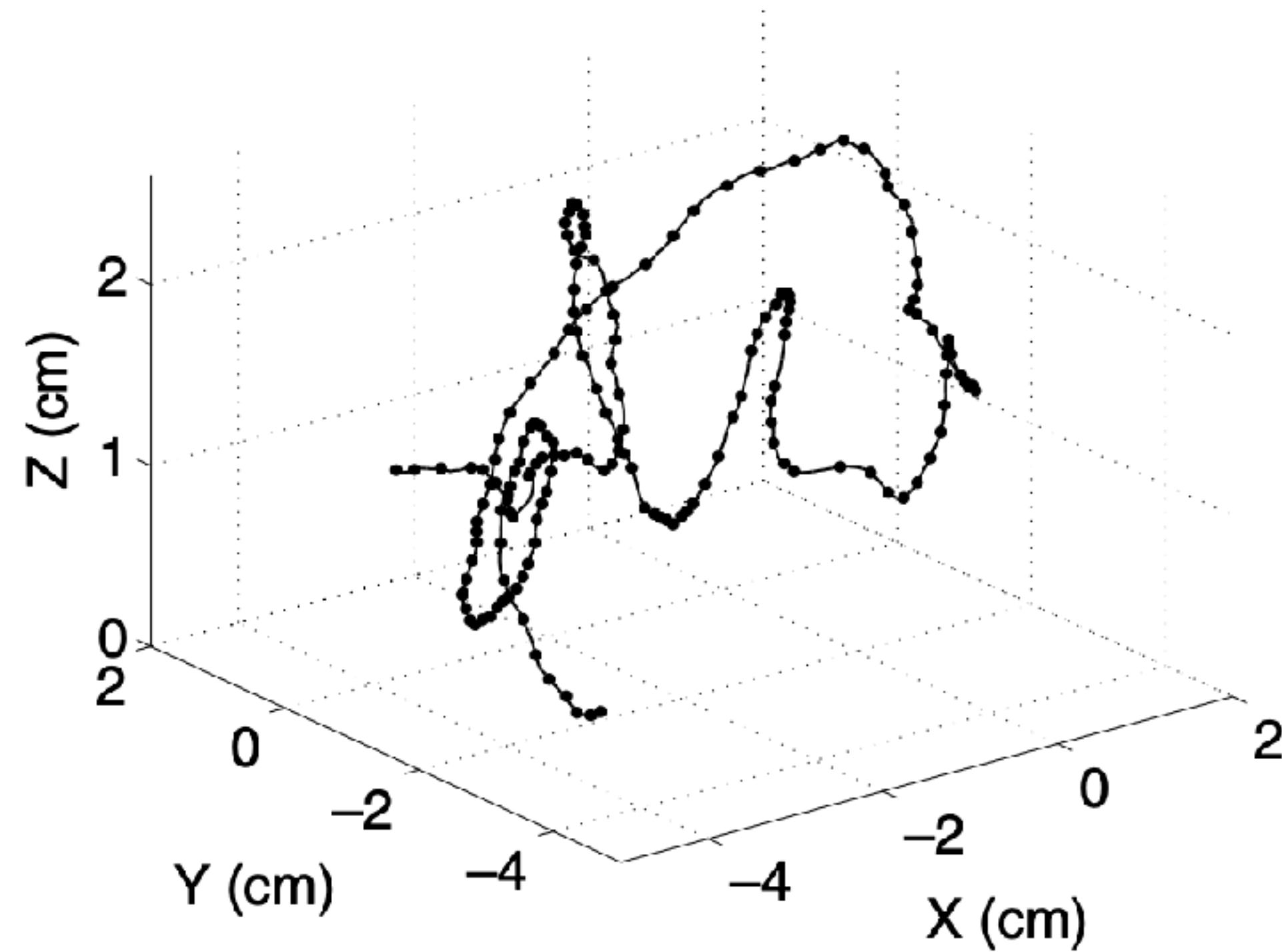
Negative entropy provides access to non-Gaussian statistics intermittency - small scale structures

Further examples -
Waves and Lagrange turbulence

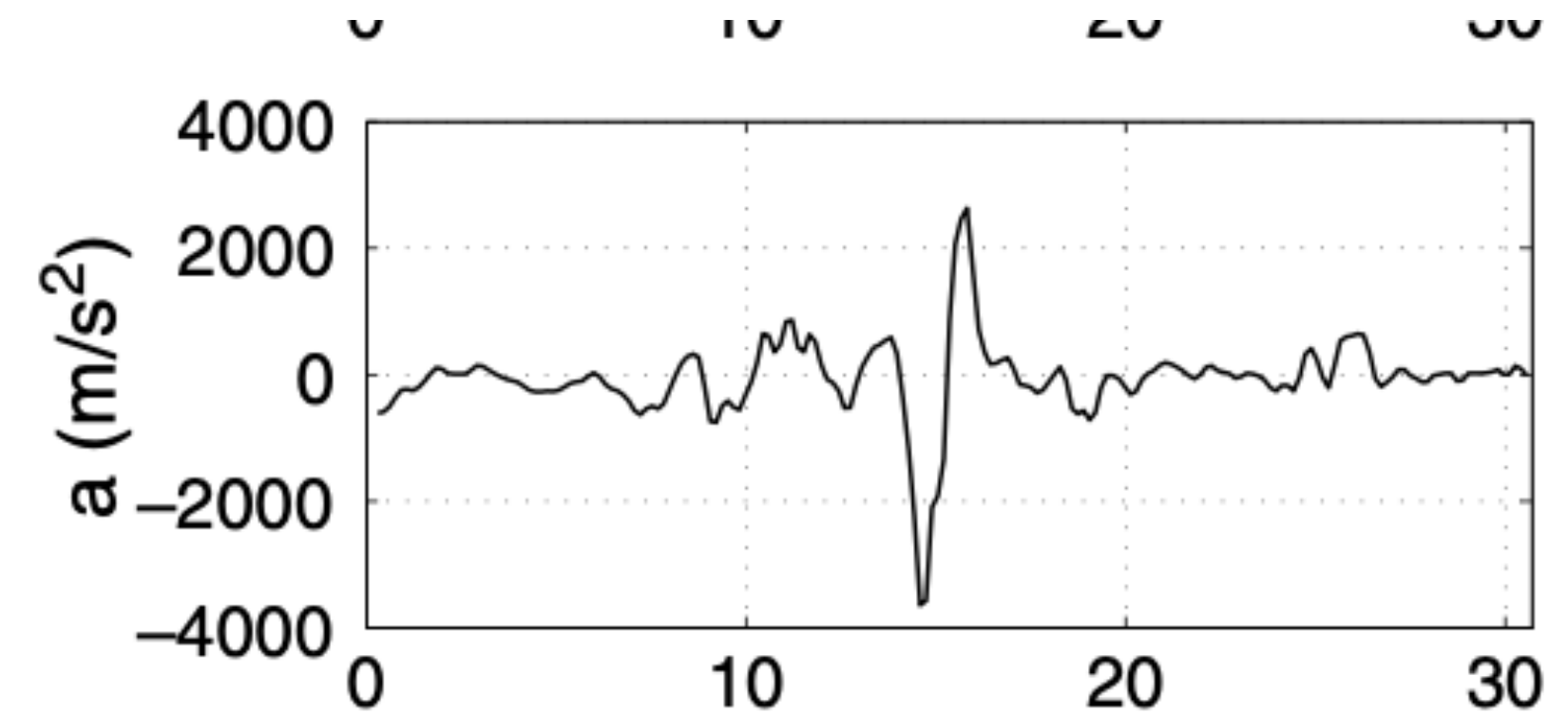


u_λ

Lagrangian particles in turbulent flow - old challenge



Typical trajectories



Events of high particle accelerations

Nicolas Mordant et al. New Journal of Physics 6 (2004) 000

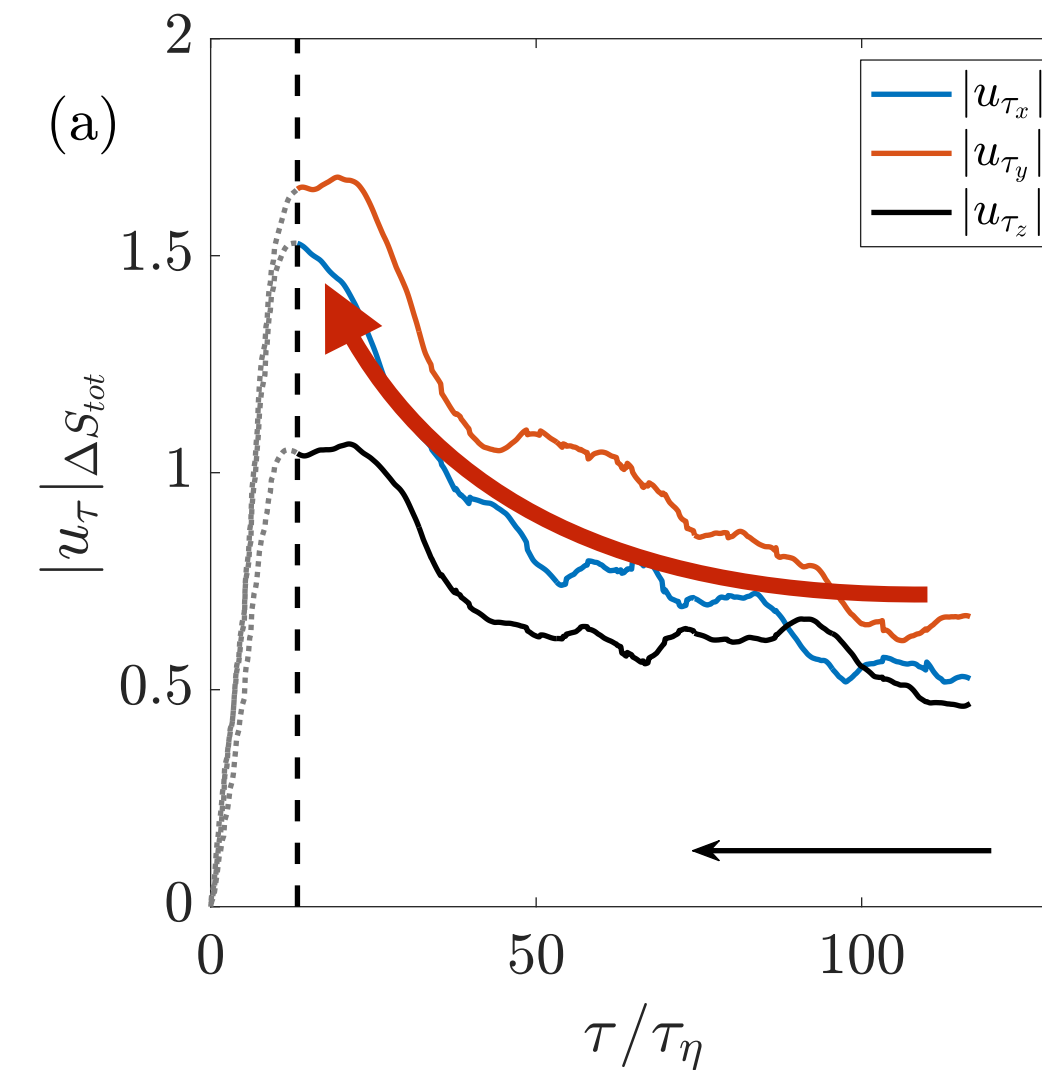
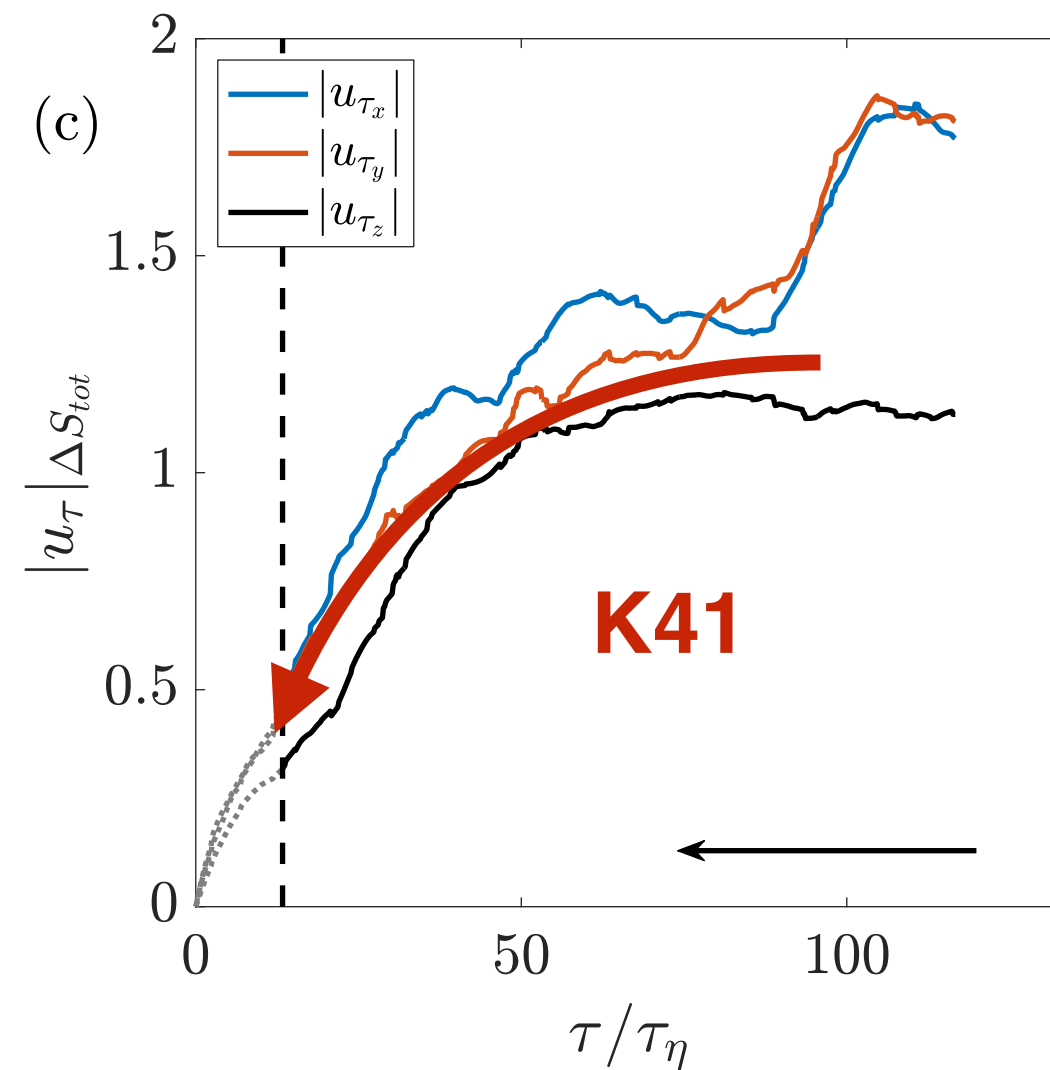
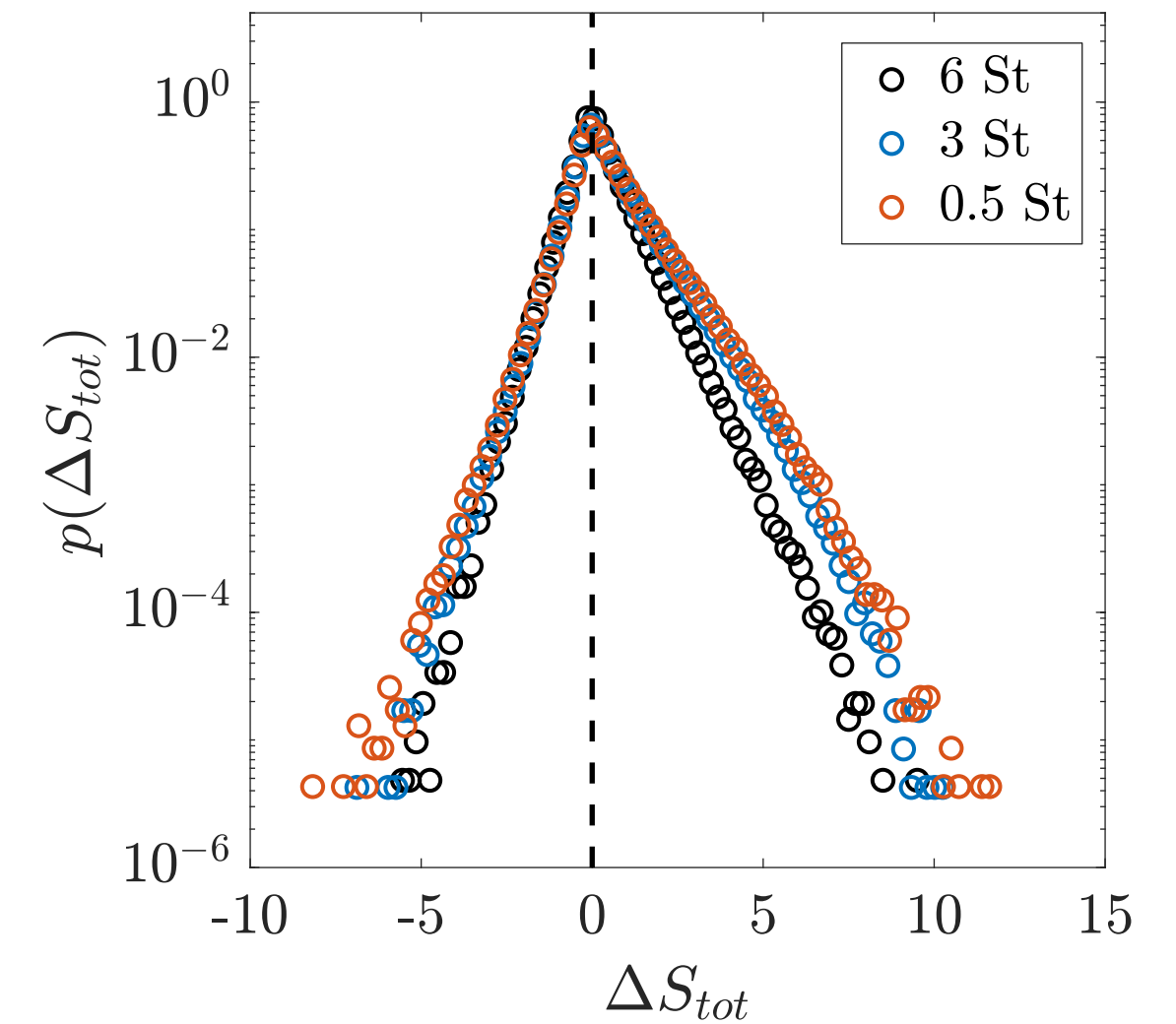
Consequences of stochastic process of u_τ

- For path $u(\cdot)$ an **entropy** can be defined, fluctuating quantity

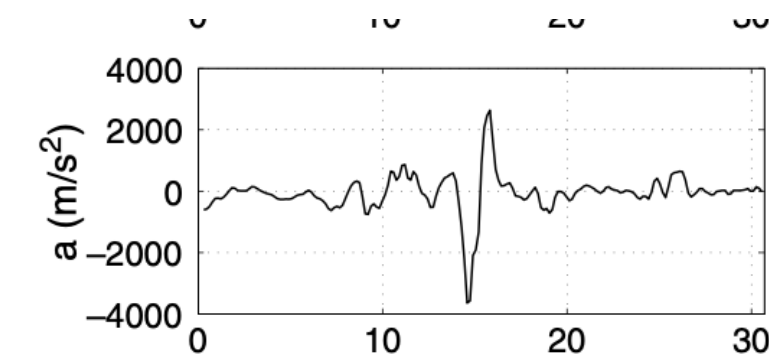
$$\Delta S_{tot} [u(\cdot)] = \Delta S_{sys} [u(\cdot)] + \Delta S_{med} [u(\cdot)]$$

- Negative entropy events $\rightarrow$ biggest $u_{\Delta_{EM}}$ (or acceleration: $a = u_{\Delta_{EM}} / \Delta_{EM}$ events)
- Positive entropy events $\rightarrow$ small $u_{\Delta_{EM}}$

Entropy are connected with structures of Lagrangian turbulence



Anormal - intermittent



Negative entropy provides access to intermittency - small scale structures

Further examples -

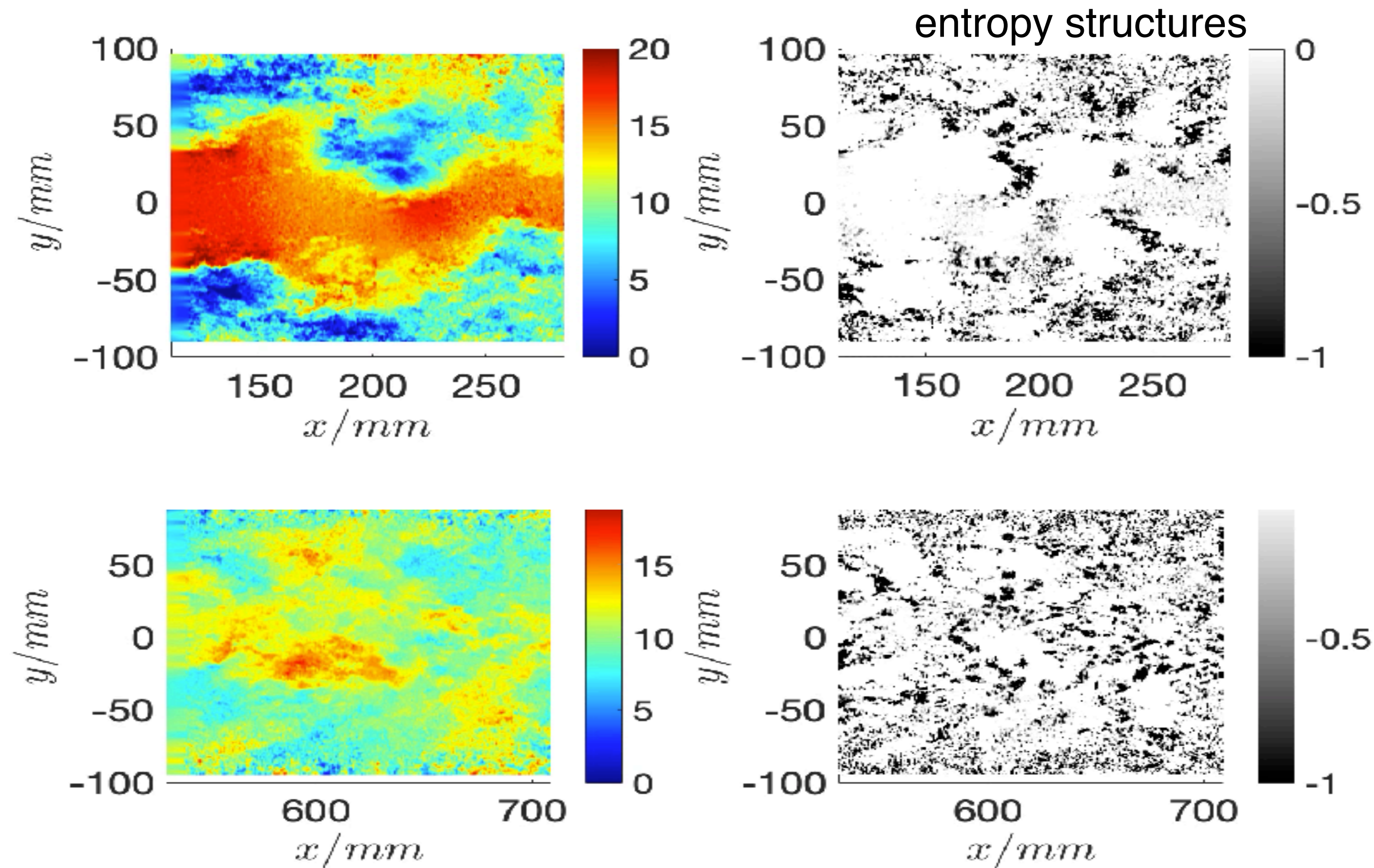
Waves and Lagrange turbulence

2-dim flow structures

u_λ

entropy and structures

application to high speed PIV measurements:



Negative entropy provides access to intermittency - small scale structures

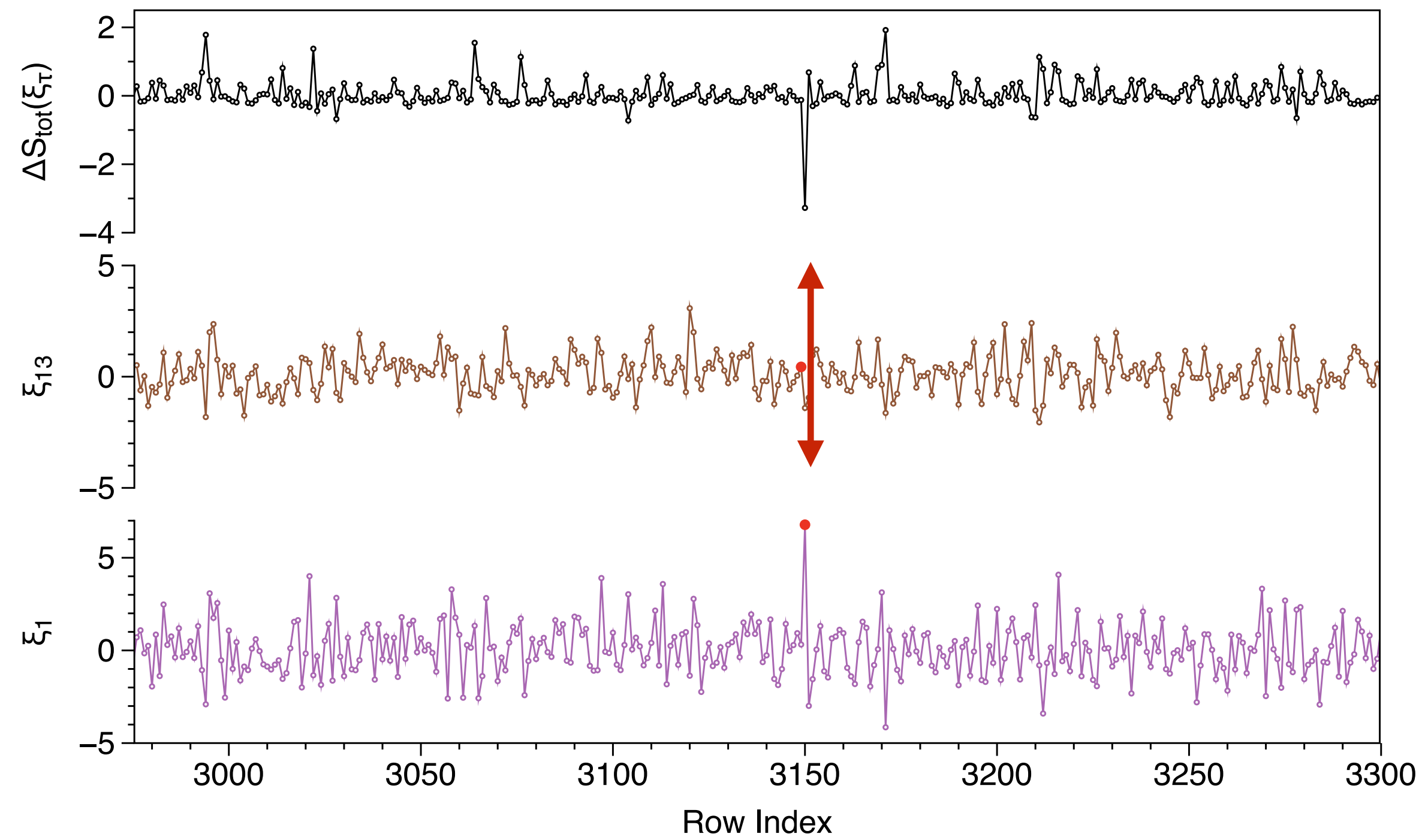
Further examples -

Waves and Lagrange turbulence

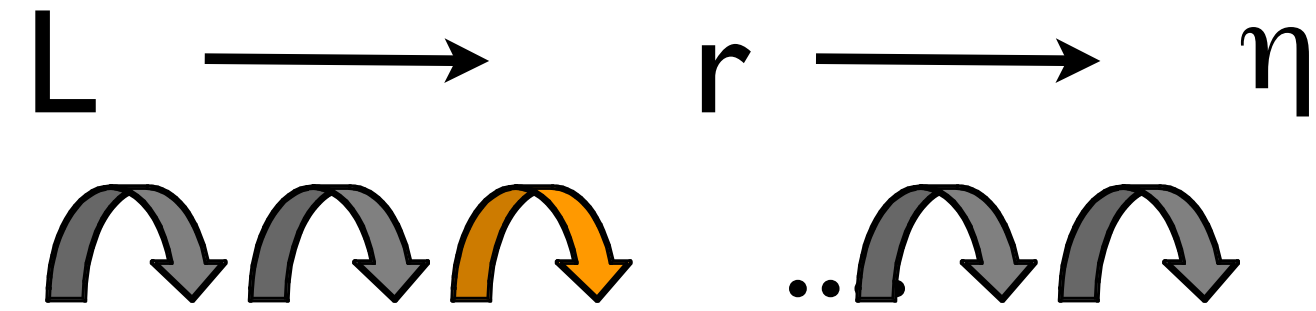
2-dim flow structures

u_λ

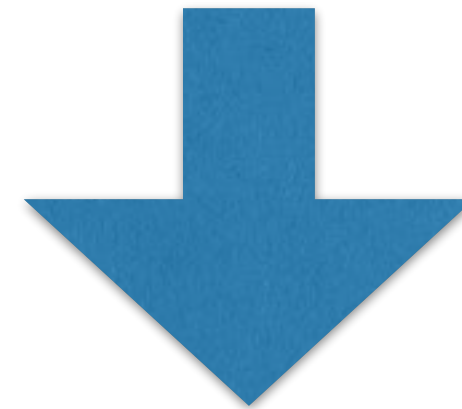
rogue wave: event of negative entropy production



stochastic cascade process: Fokker - Planck equation



$$-r_j \frac{\partial}{\partial r_j} p(u_{r_j} | u_{r_k}, u(x_1)) = \left\{ -\frac{\partial}{\partial u_{r_j}} D^{(1)}(u_{r_j}, r_j, u(x_1)) + \frac{\partial^2}{\partial u_{r_j}^2} D^{(2)}(u_{r_j}, r_j, u(x_1)) \right\} p(u_{r_j} | u_{r_k}, u(x_1))$$

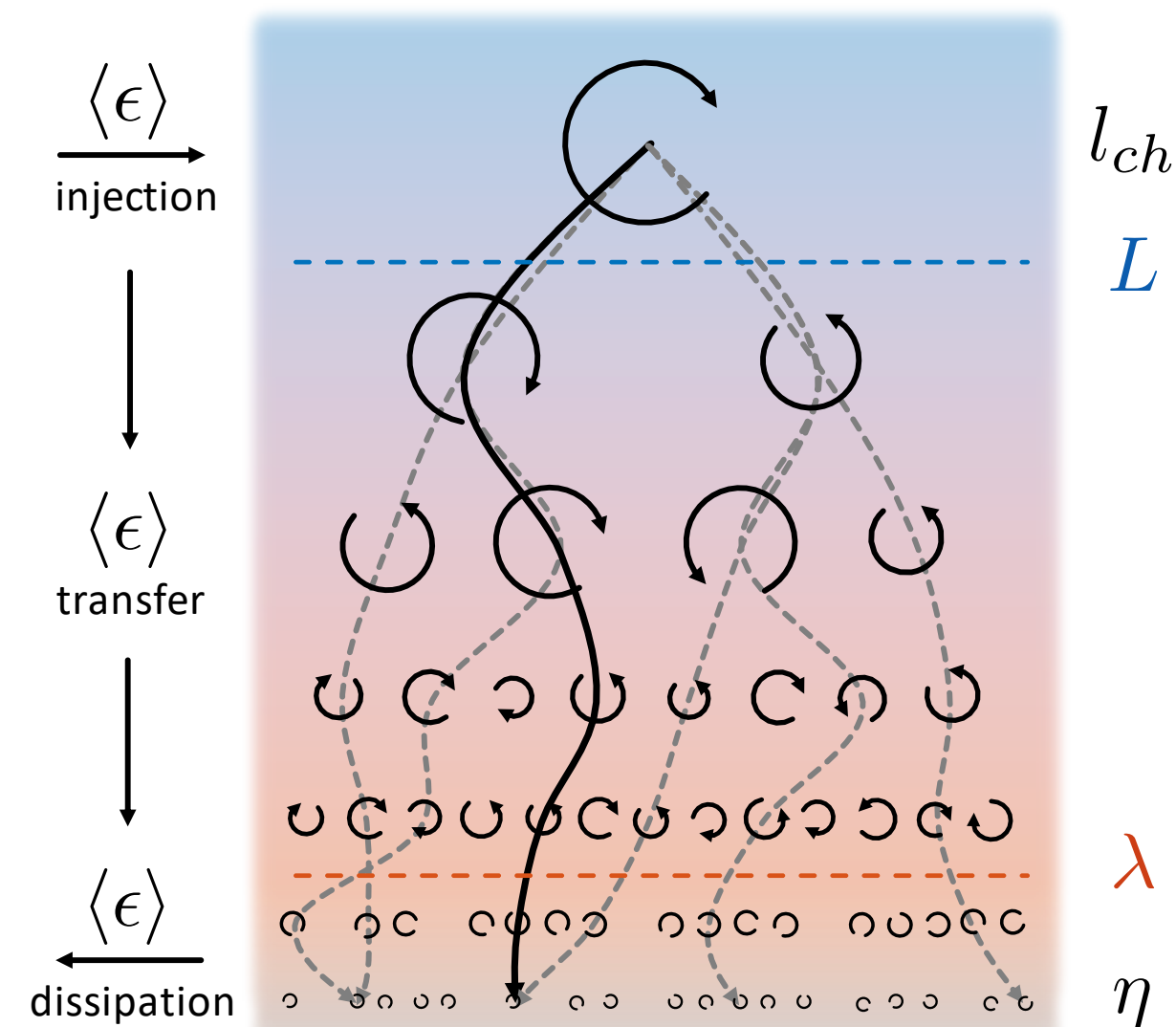


Statistical approach: multipoint statistics, **new data sets**

- **non equilibrium thermodynamics**
 - **Entropy** (Seifert 2005)
 - **Fluctuation Theorem**
 - Hamiltonian for cascade - instantones

entropy of cascade trajectories - non-equilibrium thermodynamics

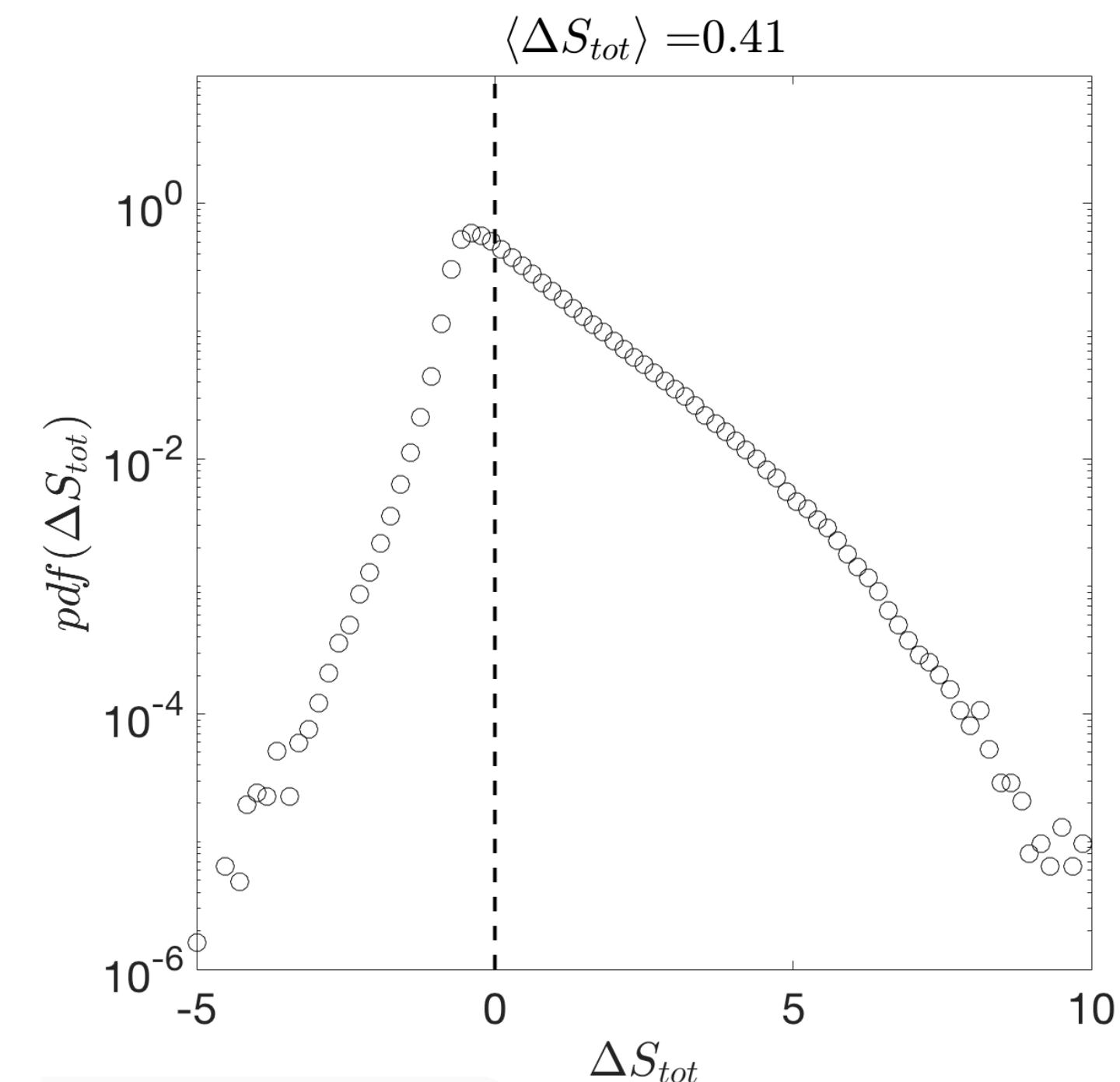
Cascade trajectories $\mathbf{u}(\cdot)$ set of increments for fixed x and changing r , $L > r > \eta$



- entropy of cascade trajectories

- Statistics of entropy

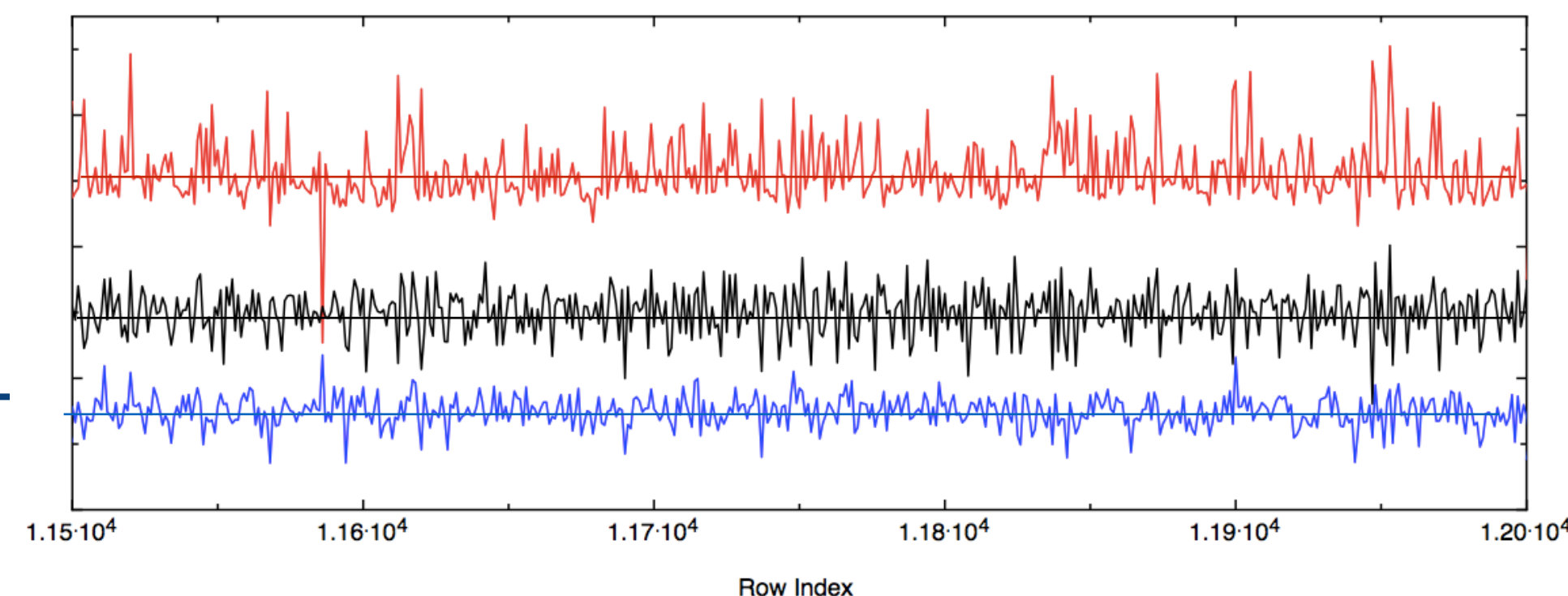
- Fluctuations



$\Delta S_{tot}(u_r)$

u_L

u_λ



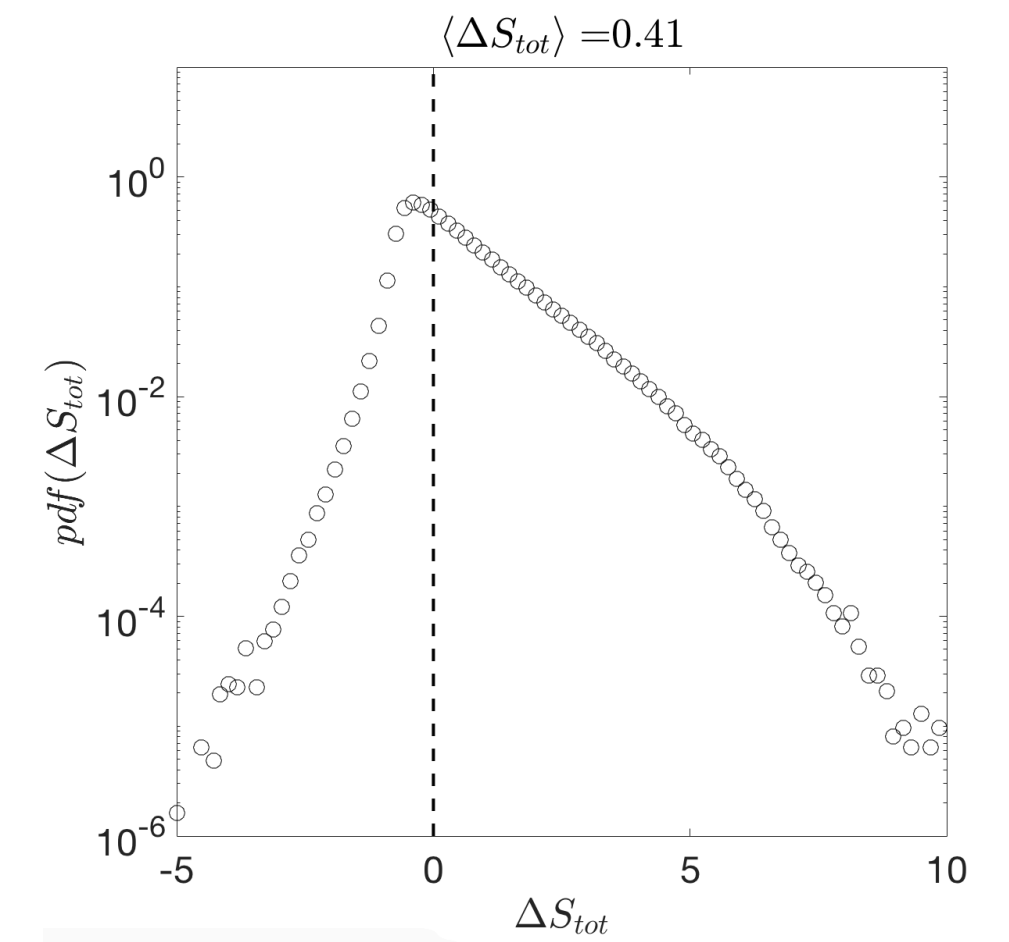
integral fluctuations theorem a new precision law

nonequilibrium thermodynamics

- a new rigorous entropy law for turbulence

$$\langle e^{-\Delta S_{tot}} \rangle = 1$$

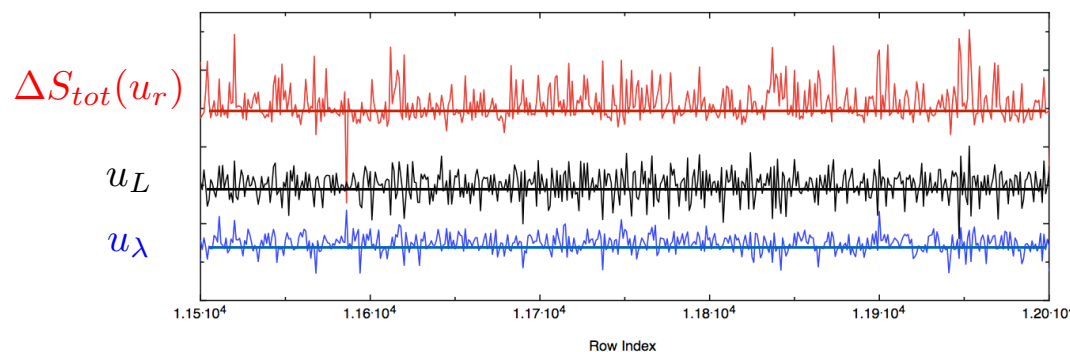
integral fluctuation theorem
Seifert (2005) (and Jarzynski)



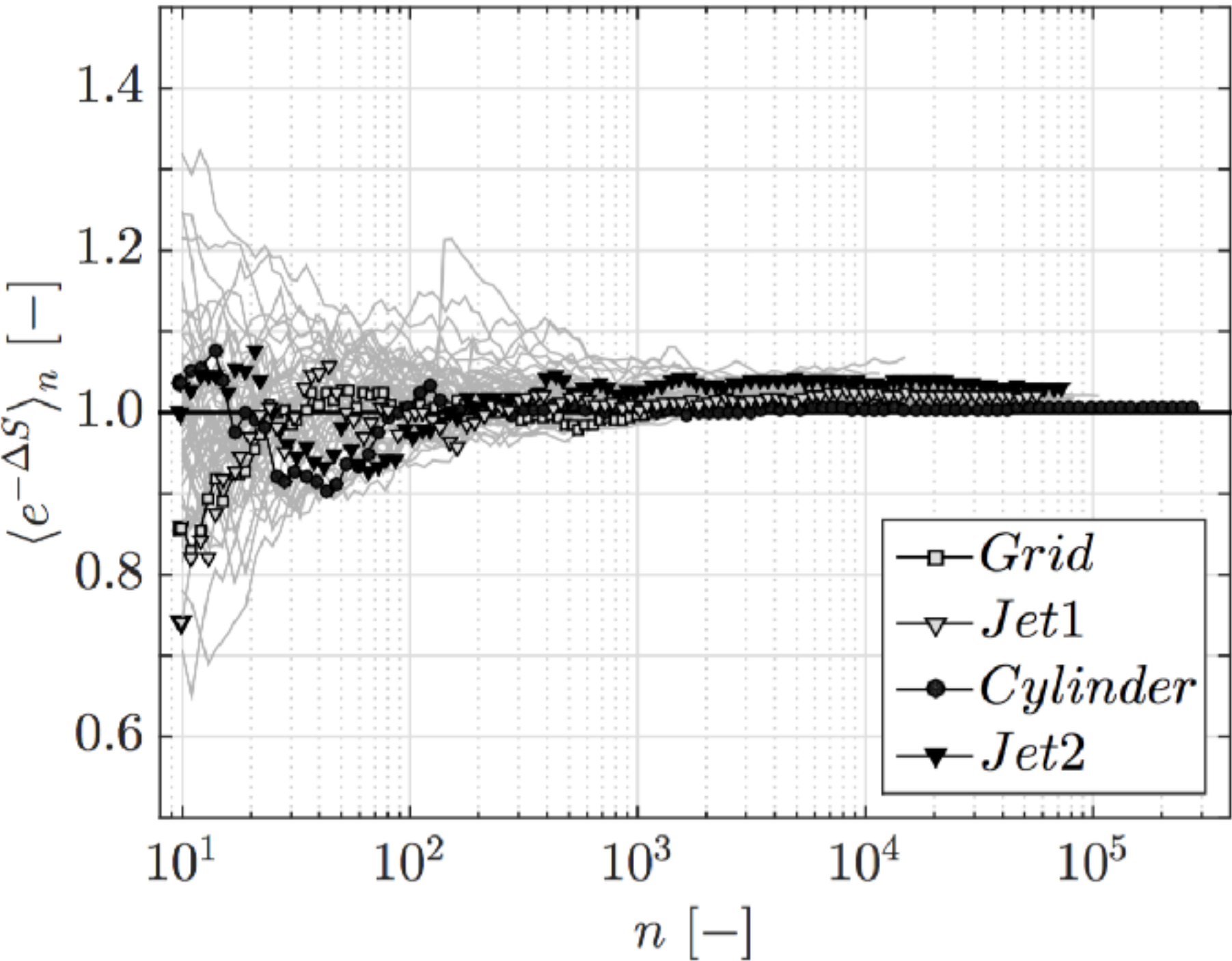
- should hold, if the non-equilibrium thermodynamics is given by a Fokker_Planck equation

integral fluctuations theorem a new precision law

IFT for 60 different data sets



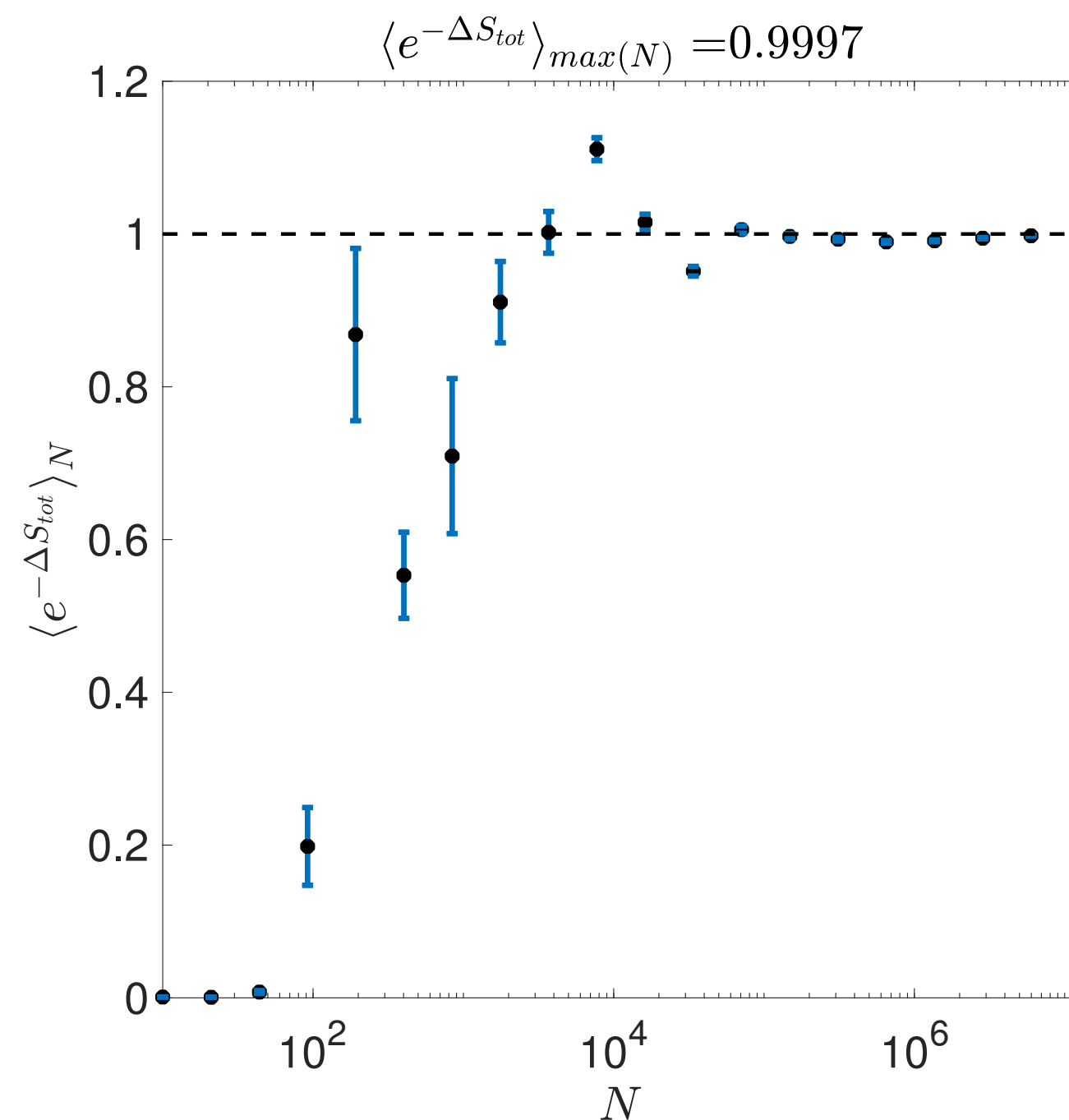
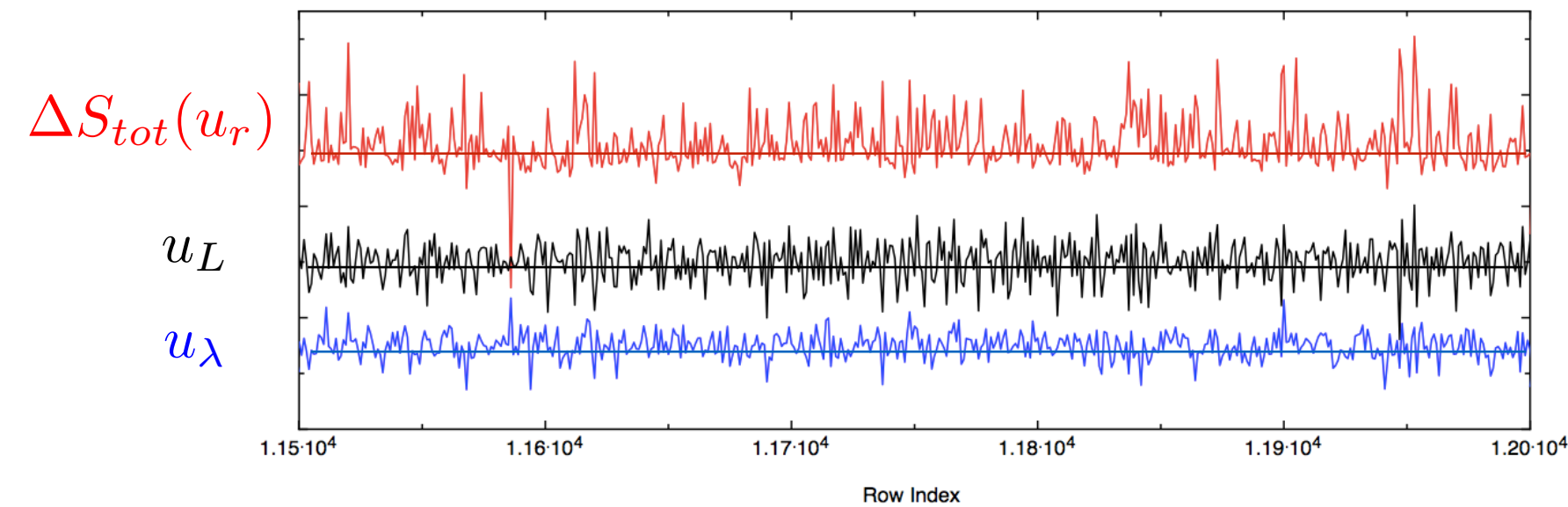
$$\langle e^{-S_{tot}(u_r)} \rangle = 1.01 \pm 0.01$$



Dataset	$Re_\lambda [-]$	$L[mm]$	$\lambda [mm]$
i) grid	153	25.0	2.61
iii) cylinder	894	25.2	3.35
iv) jet (2)	996	1.95	0.186
vii) jet (1)	166	62.5	5.84

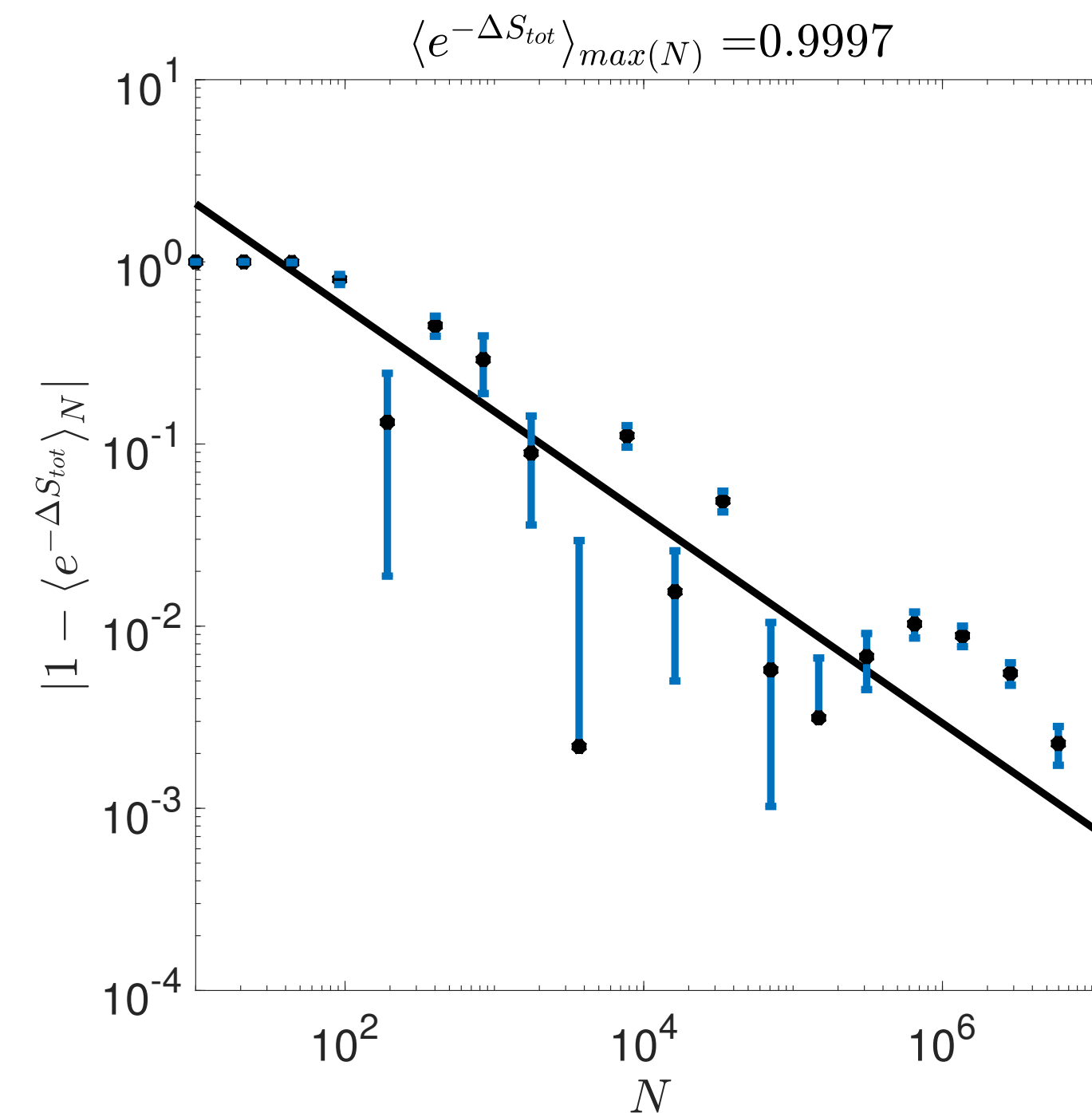
N. Reinke et al. JFM 2018

integral fluctuations theorem a new precision law



$$\langle e^{-S_{tot}(u_r)} \rangle = 1$$

fulfilled to 10^{-3}



Data Renner et.al J. Fluid Mech. 433, pp. 383–409 (2001)

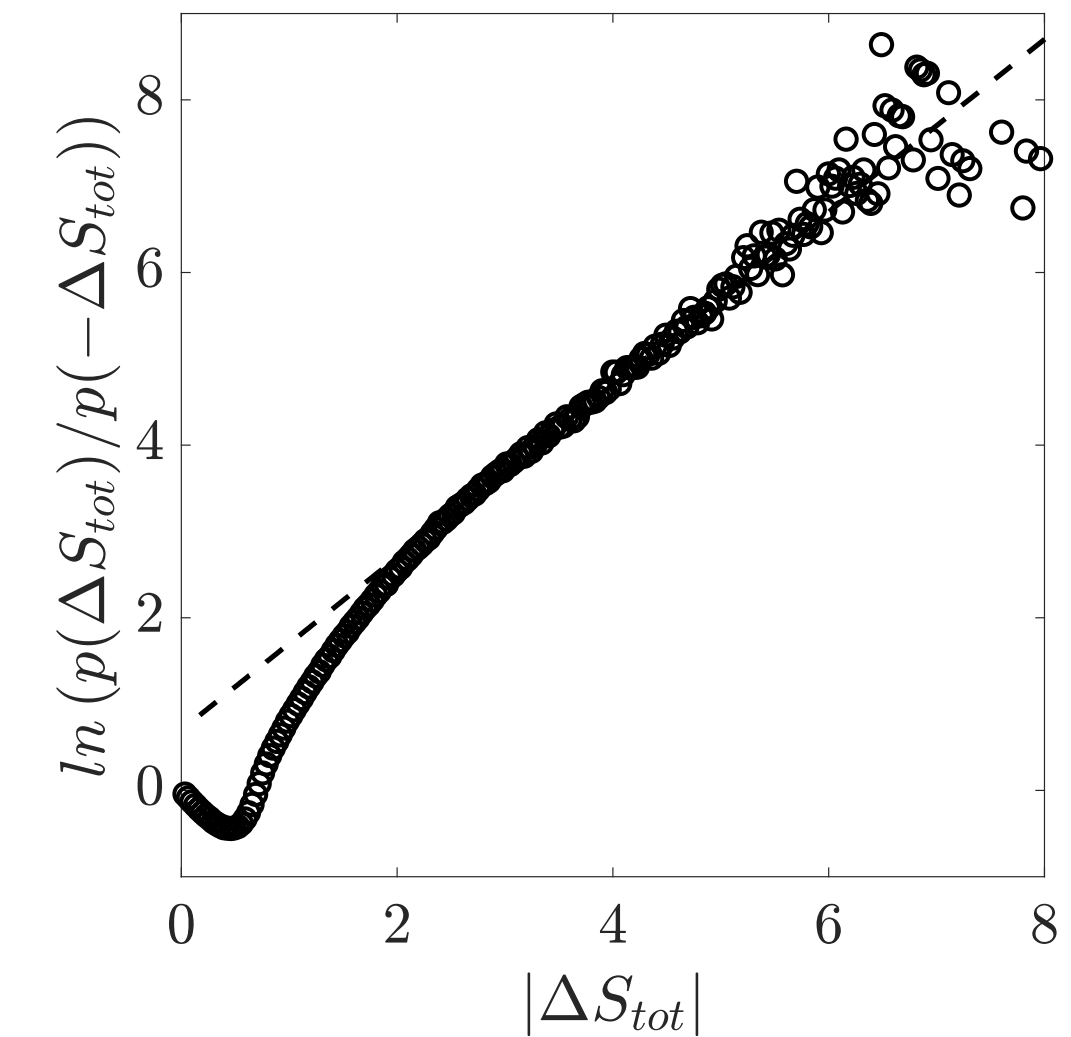
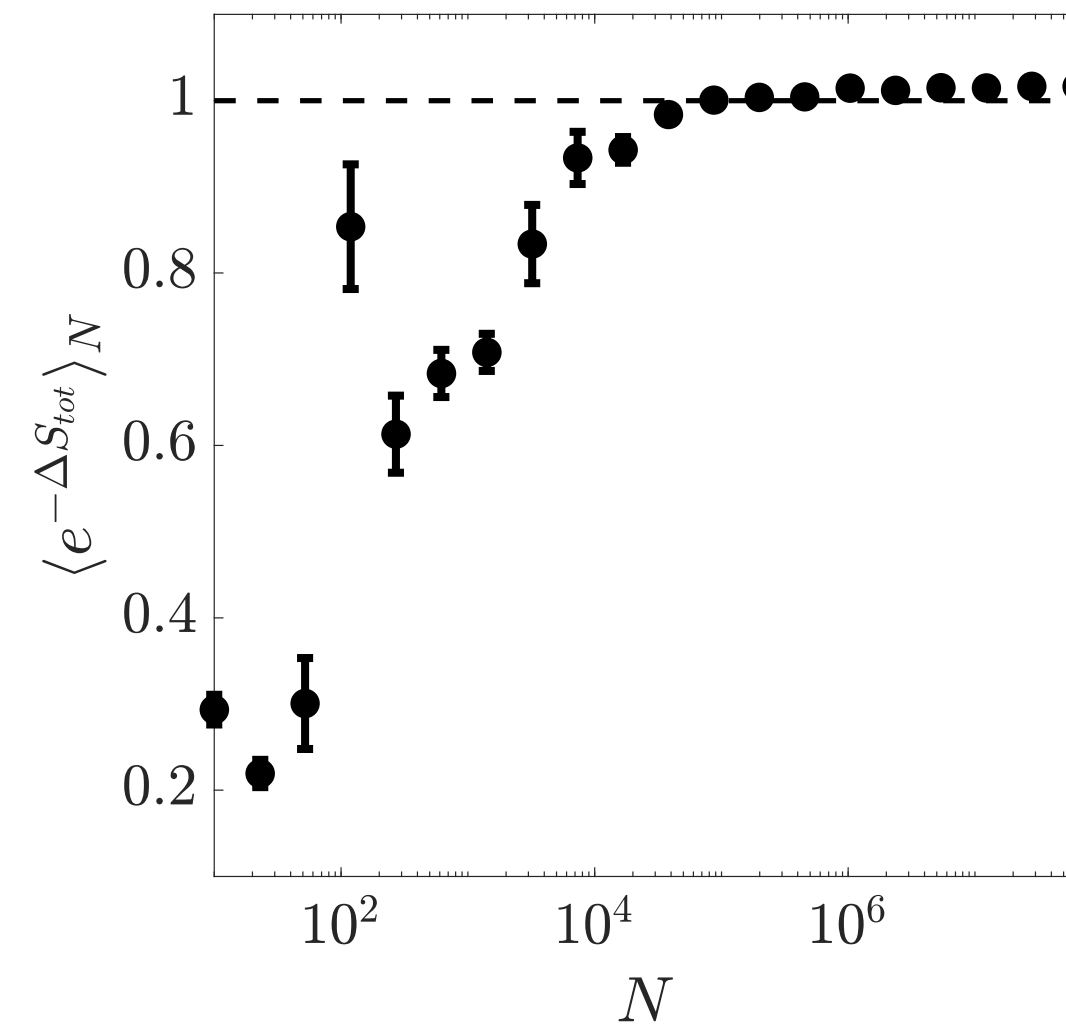
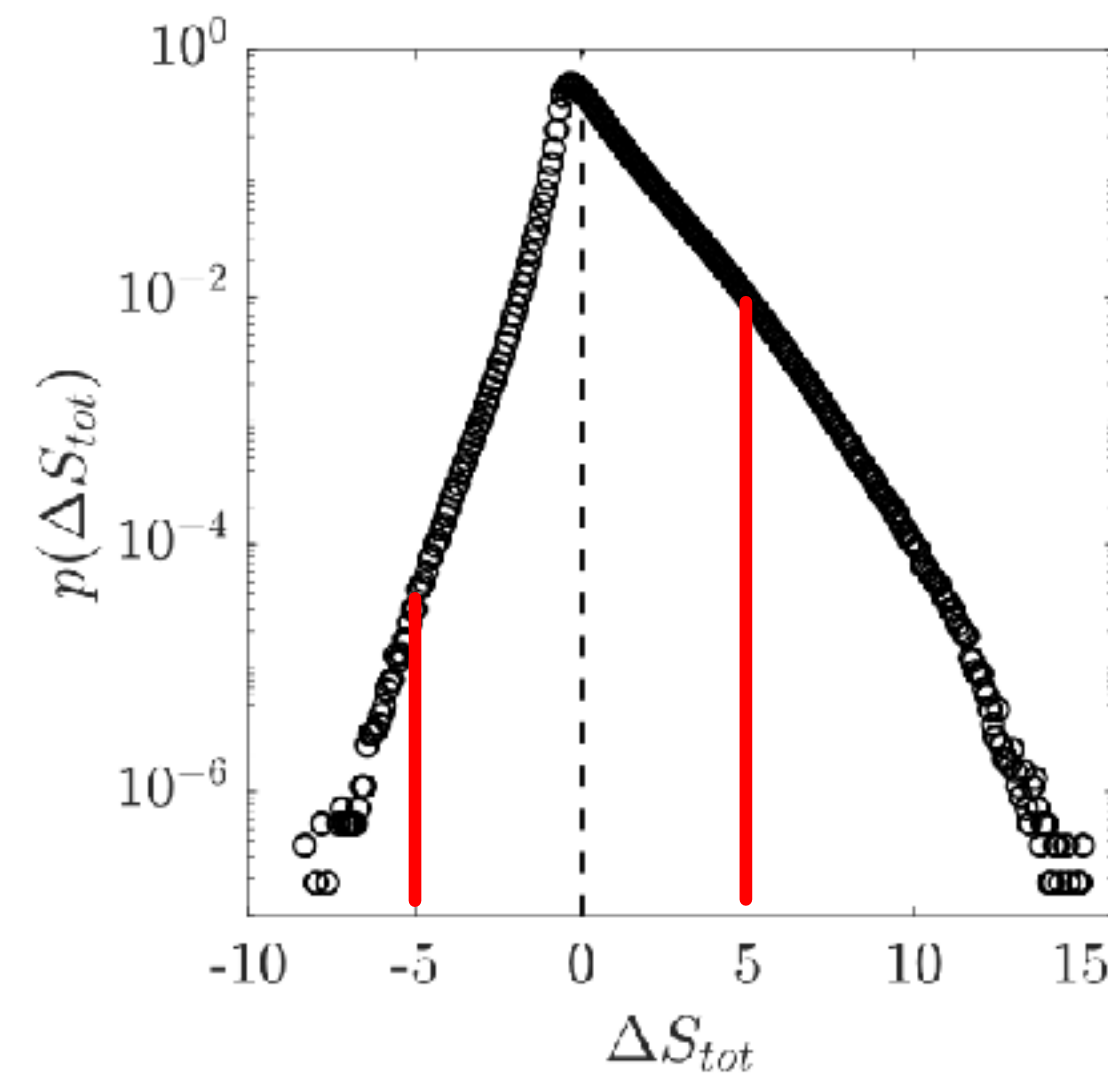
A. Fuchs et al, A Rigorous Entropy Law for the Turbulent Cascade Turbulent Cascades II. Springer, Cham, 2019. 17-25.

Entropy balance for Eulerian/Lagrangian turbulence

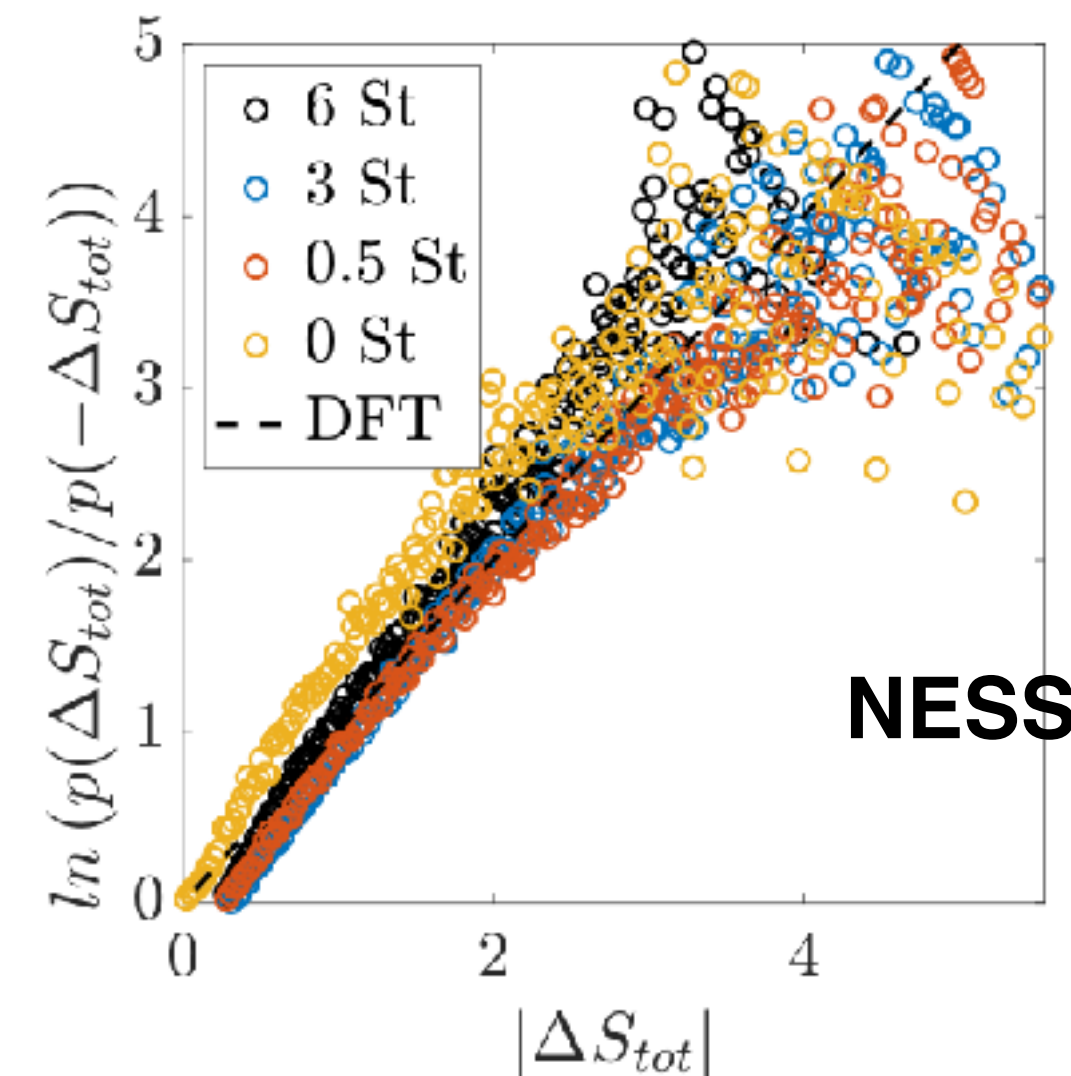
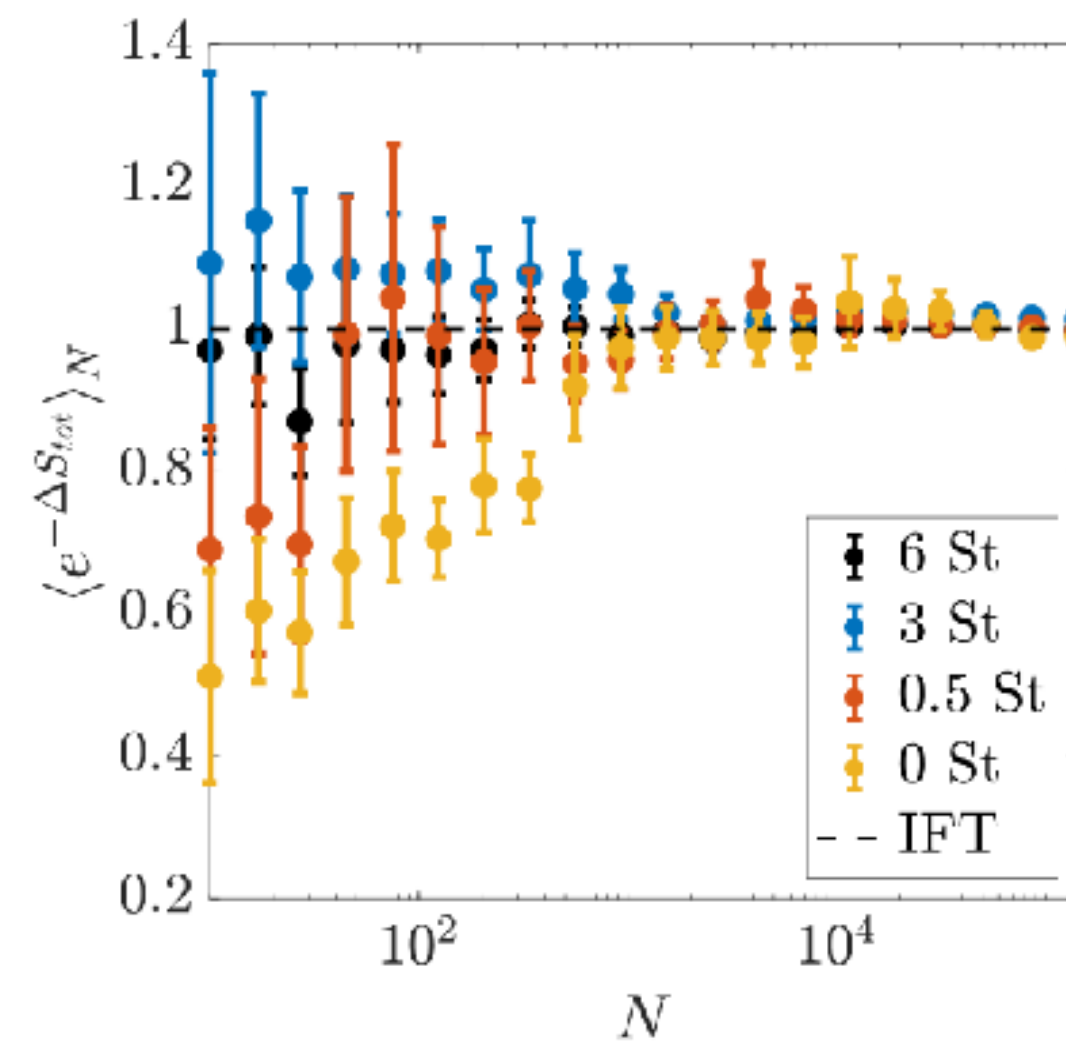
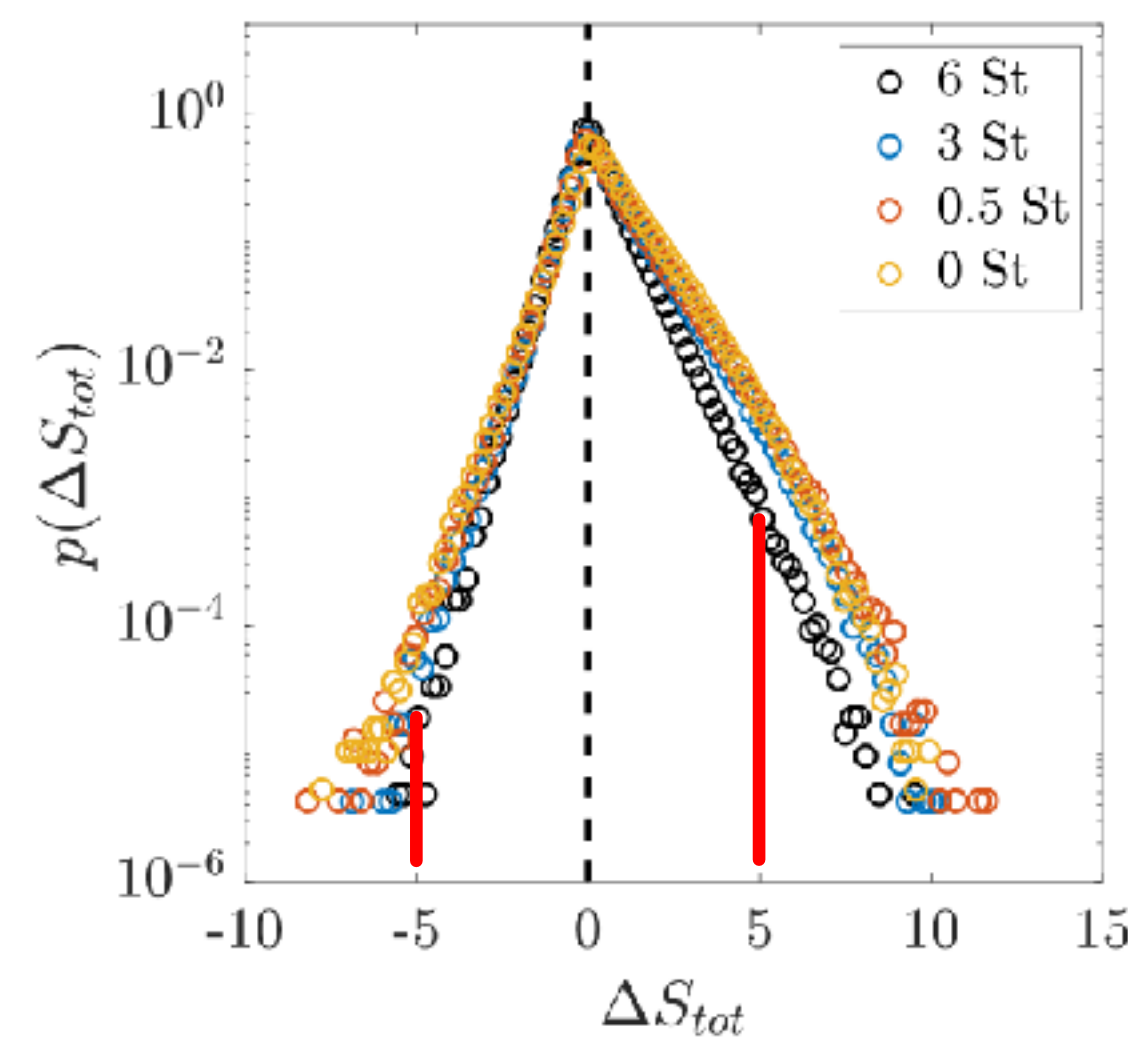
$$\ln \left(\frac{p(\Delta S_{tot})}{p(-\Delta S_{tot})} \right) \propto \Delta S_{tot}$$

$$p(\Delta S_{tot}) \propto p(-\Delta S_{tot}) e^{\Delta S_{tot}}$$

Eulerian



Lagrangian



NESS

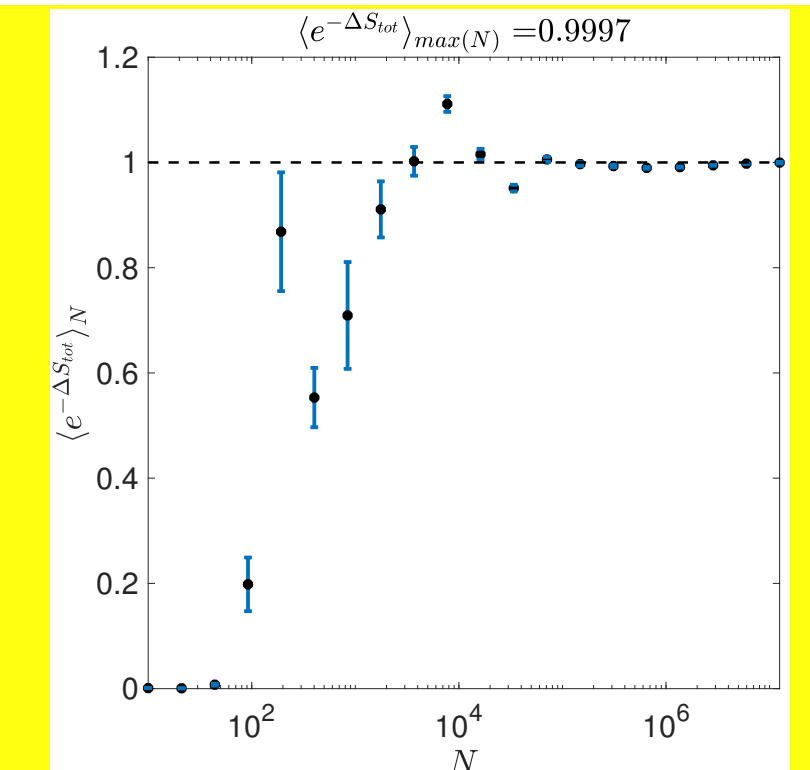
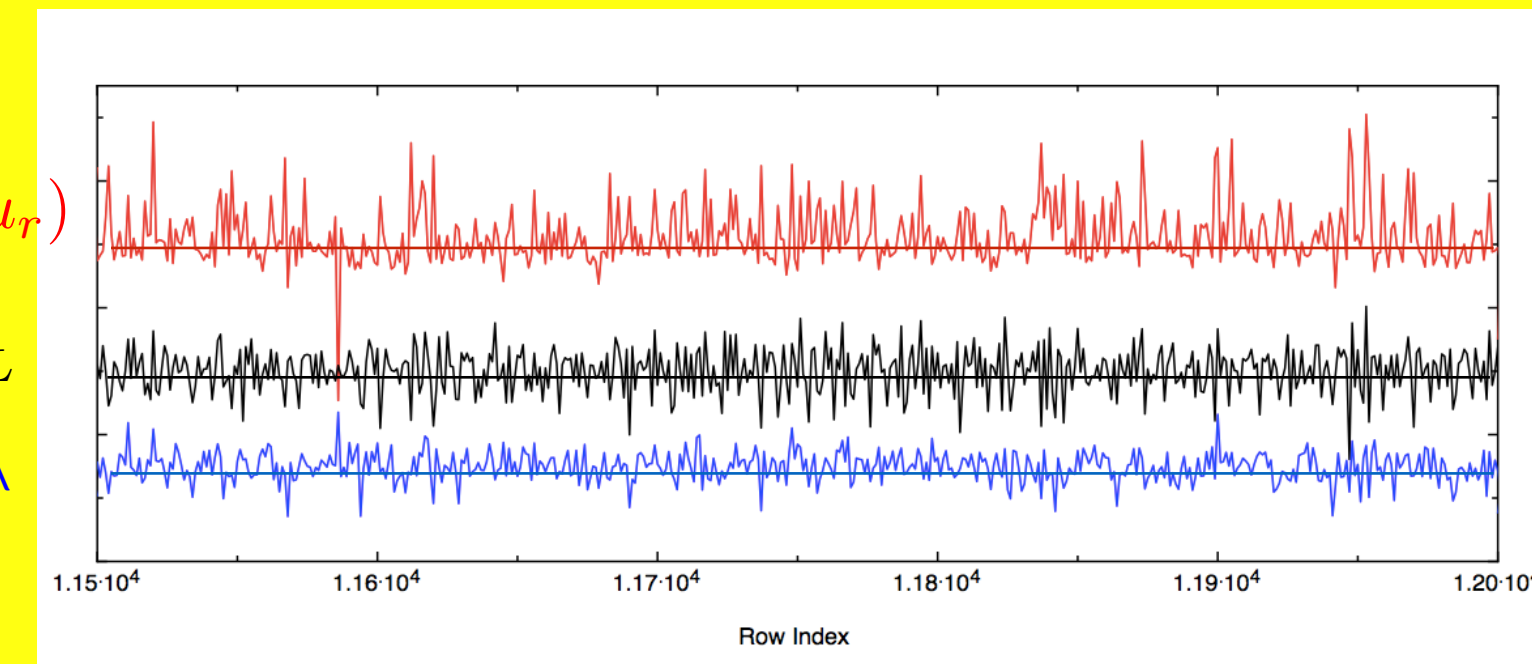
Integral and detailed fluctuations theorem

Give balance of negative & positive entropy events
And „explain“ non-Gaussian statistics

$$\Delta S_{tot}(u_r)$$

$$u_L$$

$$u_\lambda$$



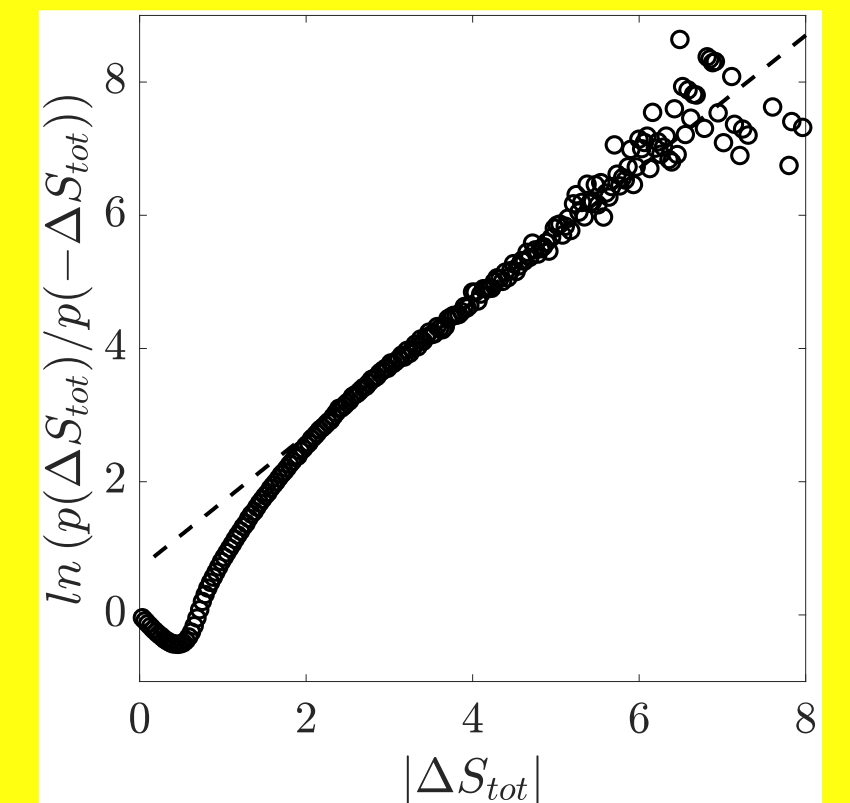
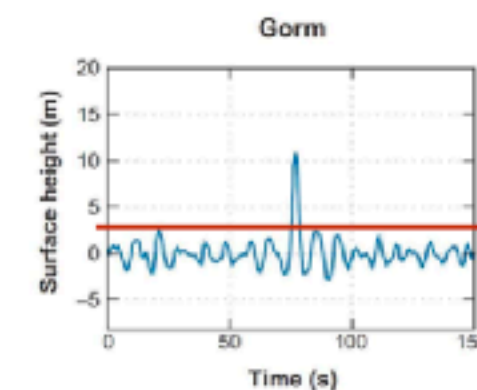
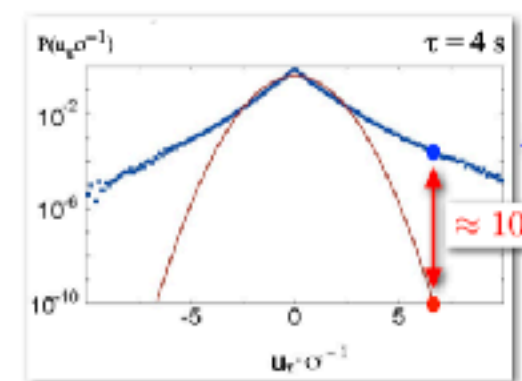
Introduction

- monster wave

Are extreme wave (extreme structures) part of the system or additional structures?

- wind gusts

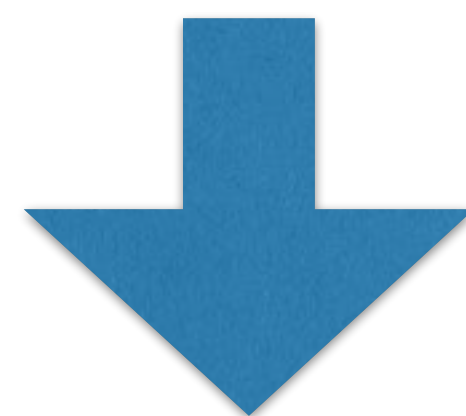
Non- Gaussian statistics of wind fluctuations



stochastic cascade process: Fokker - Planck equation



$$-r_j \frac{\partial}{\partial r_j} p(u_{r_j} | u_{r_k}, u(x_1)) = \left\{ -\frac{\partial}{\partial u_{r_j}} D^{(1)}(u_{r_j}, r_j, u(x_1)) + \frac{\partial^2}{\partial u_{r_j}^2} D^{(2)}(u_{r_j}, r_j, u(x_1)) \right\} p(u_{r_j} | u_{r_k}, u(x_1))$$



Statistical approach: multipoint statistics, **new data sets**

- **non equilibrium thermodynamics**
 - **Entropy** (Seifert 2005)
 - **Fluctuation Theorem**
 - **Hamiltonian for cascade - instantones & entropons**

- A.Fuchs , C. Herbert , J. Rolland , F. Bouchet , PRL 129 (2022)

Entropons: Instantons conditioned on entropy

Langevin equation for trajectories (stochastic process for cascade) $-\partial_r u_r = D^{(1)}(u_r, r) + \sqrt{D^{(2)}(u_r, r)}\Gamma(r)$

- Path integral formalism: probability of a trajectory is proportional to $e^{-\mathcal{A}[u(\cdot)]}$
- $\mathcal{A}$ is the Onsager-Machlup action given by

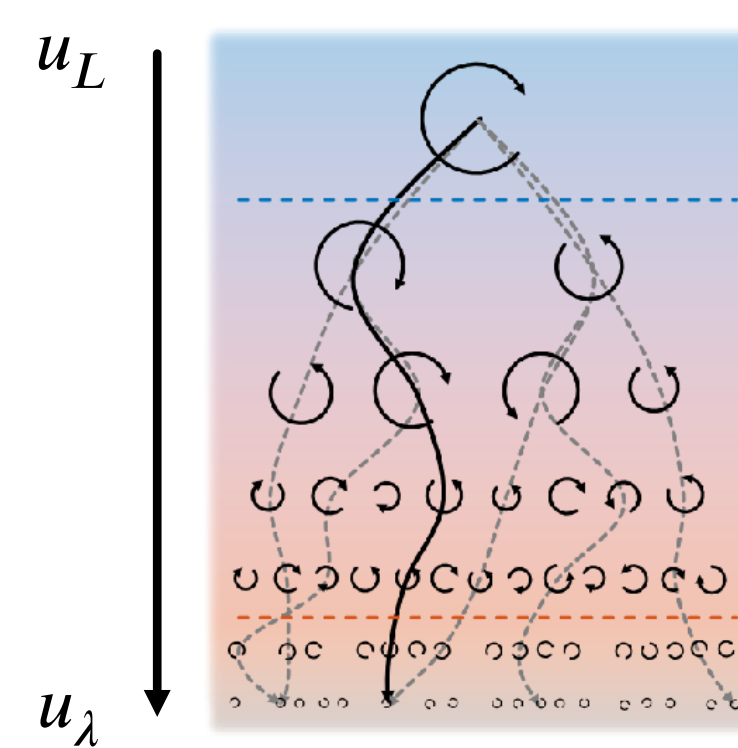
$$\mathcal{A}[u(\cdot)] = \int_L^\lambda \left[\frac{(\dot{u}_r - D^{(1)} + D^{(2)}/2)^2}{4D^{(2)}} + \frac{D^{(1)}}{2} \right] dr$$

Instantons are paths linking u_L and u_λ , given by the variational problem

$$A(u_L, u_\lambda) = \inf_u \{ \mathcal{A}[u(\cdot)] \mid u(L) = u_L, u(\lambda) = u_\lambda \}$$

Entropons: instanton for fixed entropy -> constrained variational problem

$$A(S) = \inf_{u_L} \{ A(u_L, \pm \tilde{u}_\lambda(S, u_L)) + f(u_L) \}$$



Entropons: Instantons for given entropy

path integral formalism probability of a trajectory is proportional to $\exp \left[-\mathcal{A} \left[u(\cdot) \right] \right]$, where $\mathcal{A}$ is an **action**

and given by

$$\mathcal{A} \left[u(\cdot) \right] = \int_{s_i}^{s_f} \left[\frac{\left(\dot{u}_s - \frac{D^{(1)} + D^{(2)}/2}{2} \right)^2}{4D^{(2)}} + \frac{D^{(1)}}{2} \right] ds$$

For path u_0 to u_f instantons are given by the variational problem

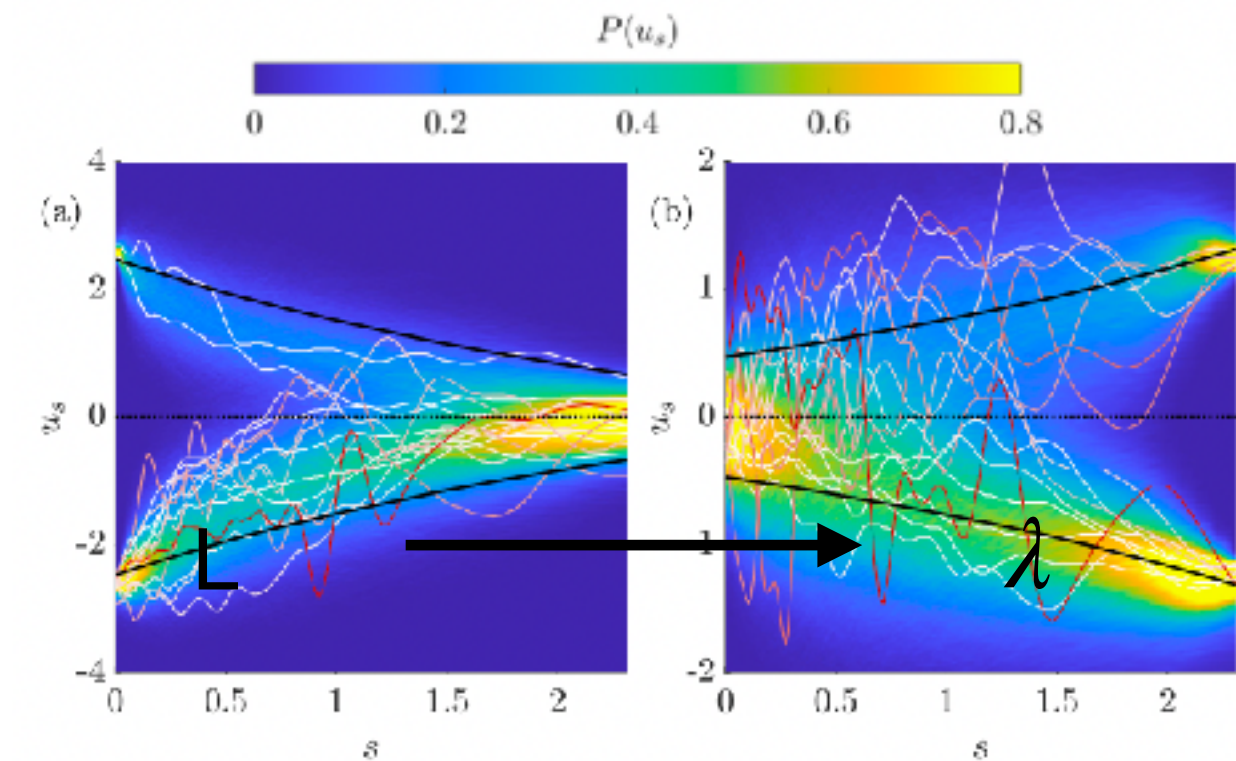
$$A(u_0, u_f) = \inf_u \left\{ \mathcal{A} \left[u(\cdot) \right] \mid u(s_i) = u_0, u(s_f) = u_f \right\}$$

Which leads to the **Hamiltonian**

$$\begin{aligned} H &= D^{(2)} p^2 + \left(D^{(1)} - \frac{D^{(2)}}{2} \right) p - \frac{D^{(1)}}{2}, \\ &= (\beta + \gamma u^2) p^2 - (\alpha + 2\gamma) u p + \frac{\alpha + \gamma}{2} \end{aligned}$$

J. Rolland
C. Herbert
F. Bouchet

$\mathcal{L} \longrightarrow \lambda$



For given entropy of the trajectory we get

$$A(S) = \inf_u \left\{ \mathcal{A} \left[u(\cdot) \right] + f(u_0) \mid \Delta S_{med} \left[u(\cdot) \right] = S \right\}$$

From what follows -

$$\tilde{u}_f(S, u_0) = \sqrt{\frac{\beta}{\gamma} \left(e^{-\frac{2\gamma S}{\alpha + 2\gamma}} - 1 \right)} + u_0^2 e^{-\frac{2\gamma S}{\alpha + 2\gamma}}$$

Entropons: Instantons conditioned on entropy

Langevin equation for trajectories (stochastic process for cascade)

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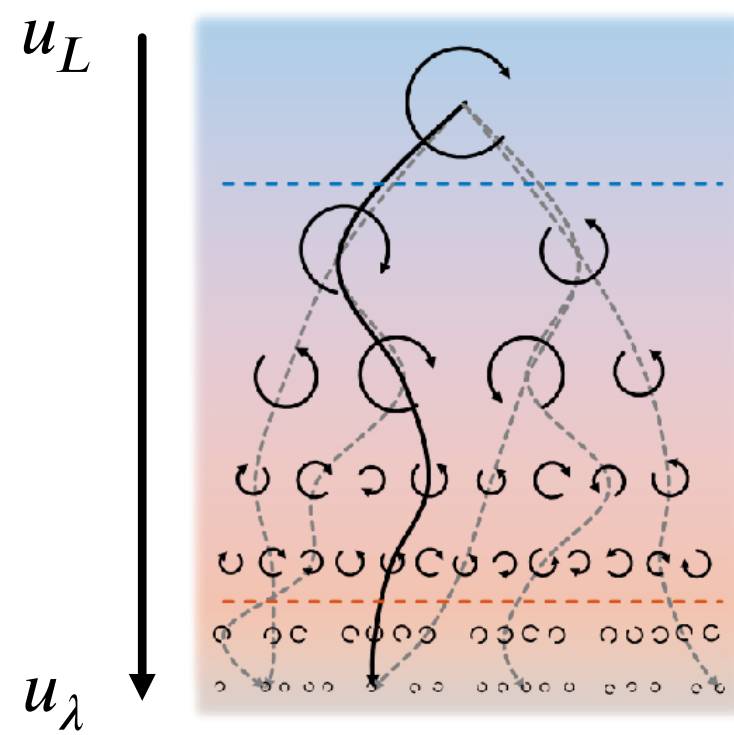
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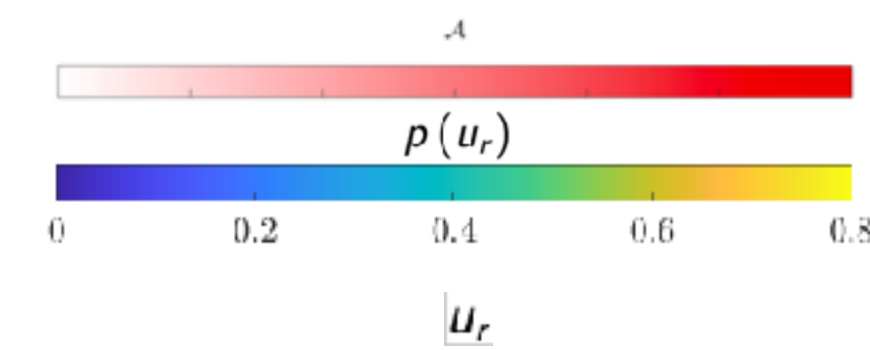


Simplified process

$$-\partial_r u_r = D^{(1)}(u_r) + \sqrt{D^{(2)}(u_r)} \Gamma(r)$$

$$\begin{aligned} D^{(1)}(u_r) &= -(\alpha + \gamma) u_r \\ D^{(2)}(u_r) &= \beta + \gamma u_r^2 \end{aligned}$$

Entropions are an underlying order within turbulence



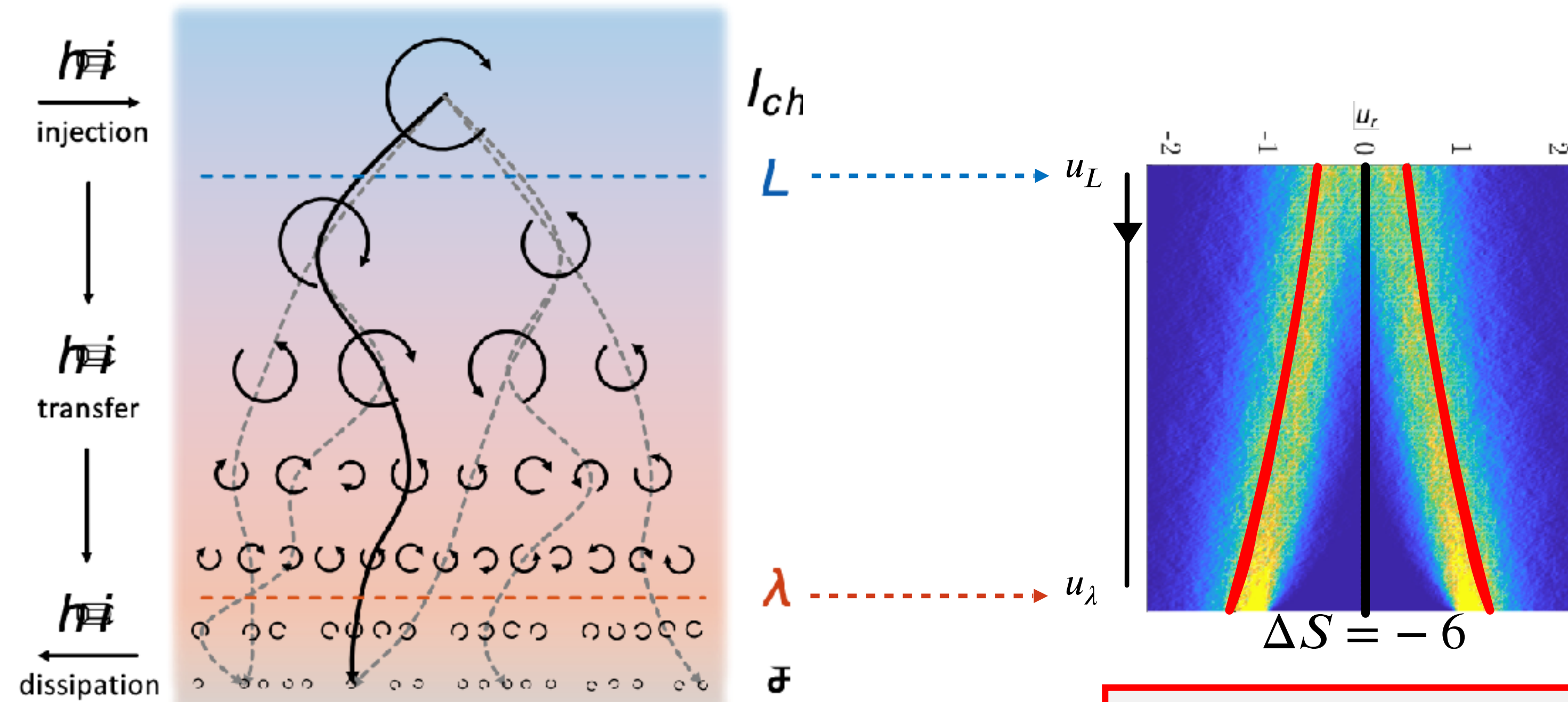
Simplified process

$$D^{(1)}(u_r) = -(\alpha + \gamma) u_r$$

$$D^{(2)}(u_r) = \underline{\underline{\beta + \gamma u_r^2}}$$

$(\beta = 0) \rightarrow$ Kolmogorov 62 scaling

$(\beta \neq 0) \rightarrow$ Intermittency correction



For given entropy of the trajectory we get

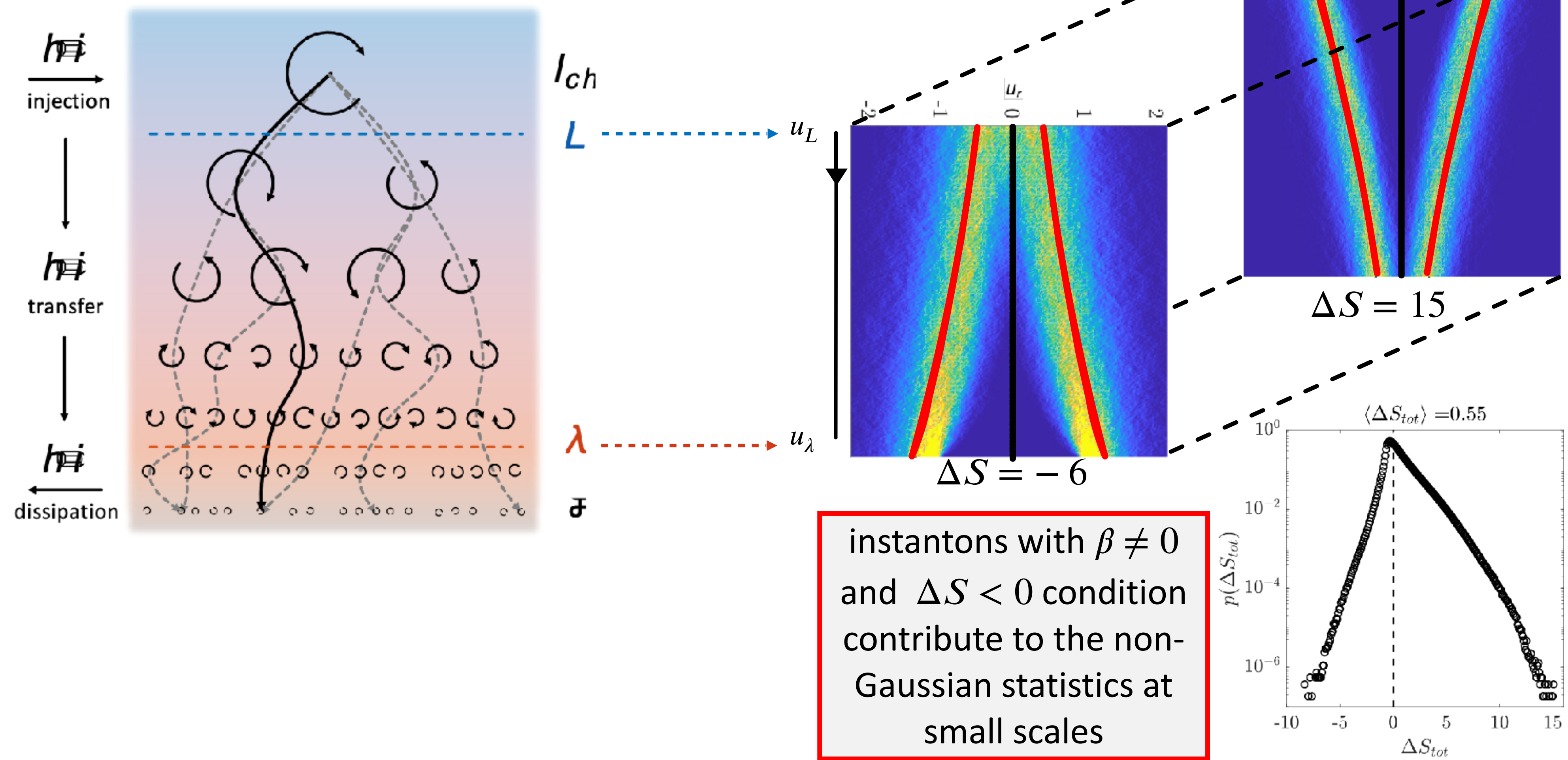
$$A(S) = \inf_u \left\{ \mathcal{A} [u(\cdot)] + f(u_0) \mid \Delta S_{med} [u(\cdot)] \right\}$$

From what follows -

$$\tilde{u}_f(S, u_0) = \sqrt{\frac{\beta}{\gamma} \left(e^{-\frac{2\gamma S}{\alpha + 2\gamma}} - 1 \right) + u_0^2 e^{-\frac{2\gamma S}{\alpha + 2\gamma}}}$$

instantons with $\beta \neq 0$ and $\Delta S < 0$ condition contribute to the non-Gaussian statistics at small scales

Entropions are an underlying order within turbulence



Simplified process

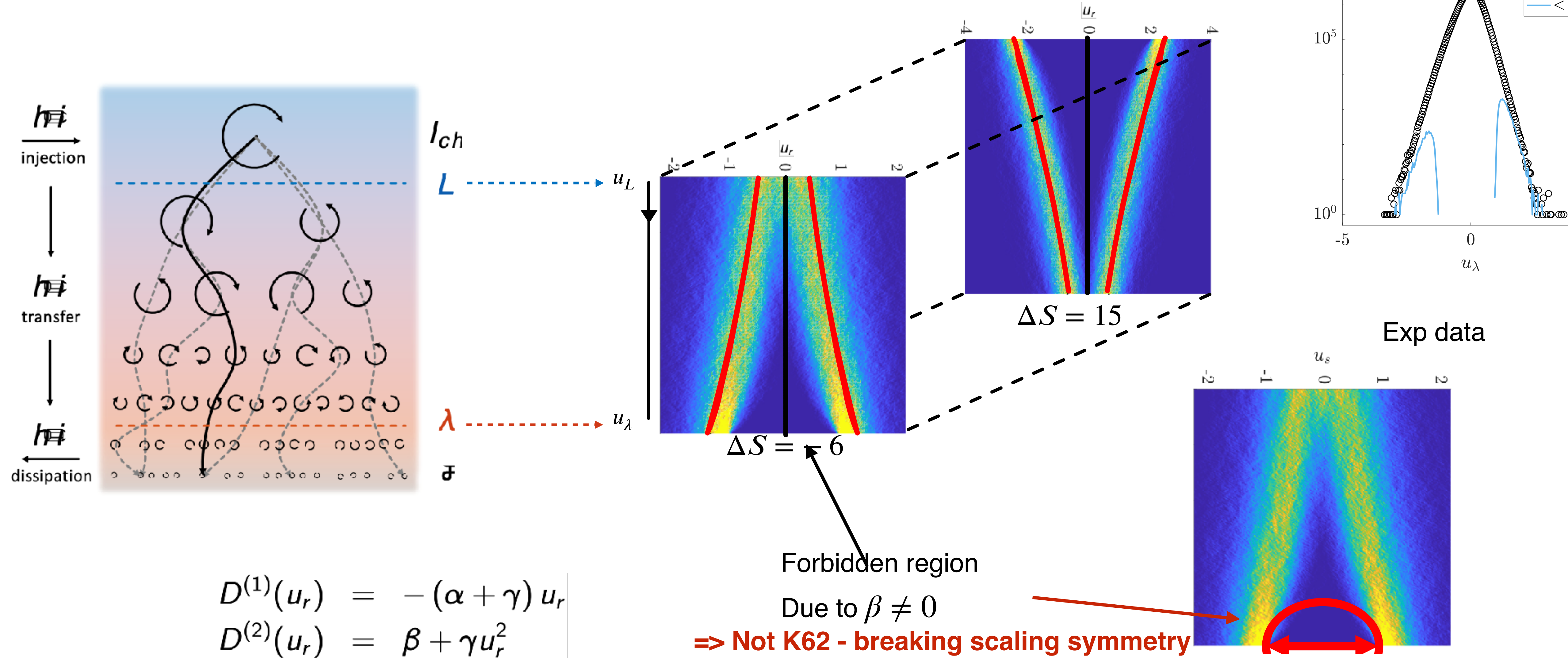
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$(\beta = 0) \rightarrow$ Kolmogorov 62 scaling

$(\beta \neq 0) \rightarrow$ Intermittency correction

IFT + DFT:
Statistical balance
of entropy events

Entropions are an underlying order within turbulence



Turbulence and rogue waves

Nonlinear Schrödinger equation (NLSE)

$$i \frac{\partial \psi}{\partial x} + \frac{1}{2} \frac{\partial^2 \psi}{\partial t^2} + |\psi|^2 \psi = 0$$



Navier Stokes equation (NSE)

$$\partial_t \vec{u} + (\vec{u} \cdot \nabla) \vec{u} = -\frac{1}{\rho} \nabla p + \nu \Delta \vec{u}, \quad \nabla \cdot \vec{u} = 0$$



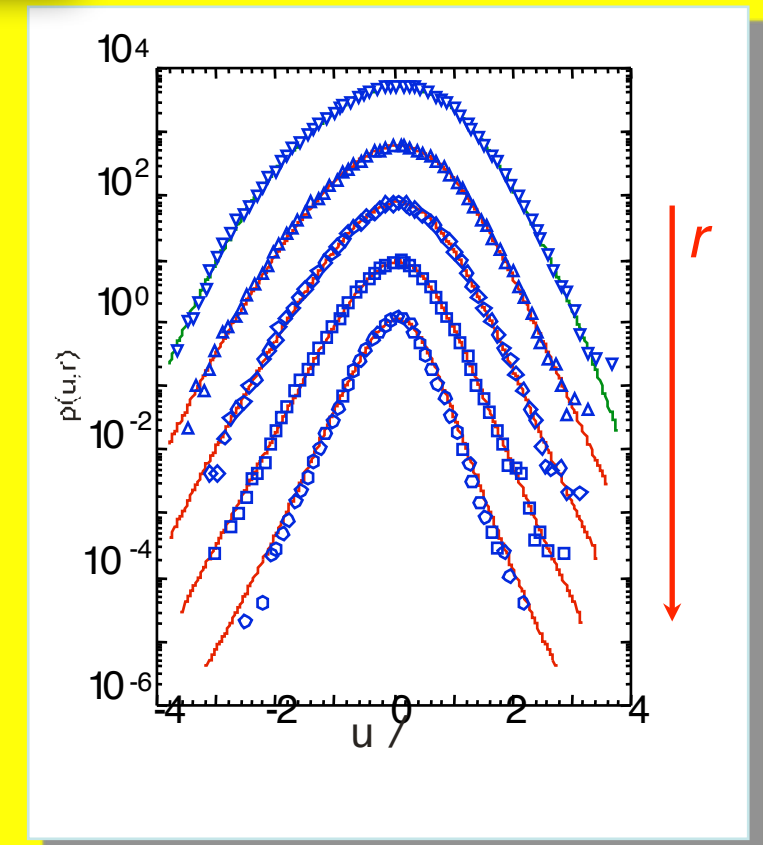
How to approach?

coherent structures
(Instabilities)

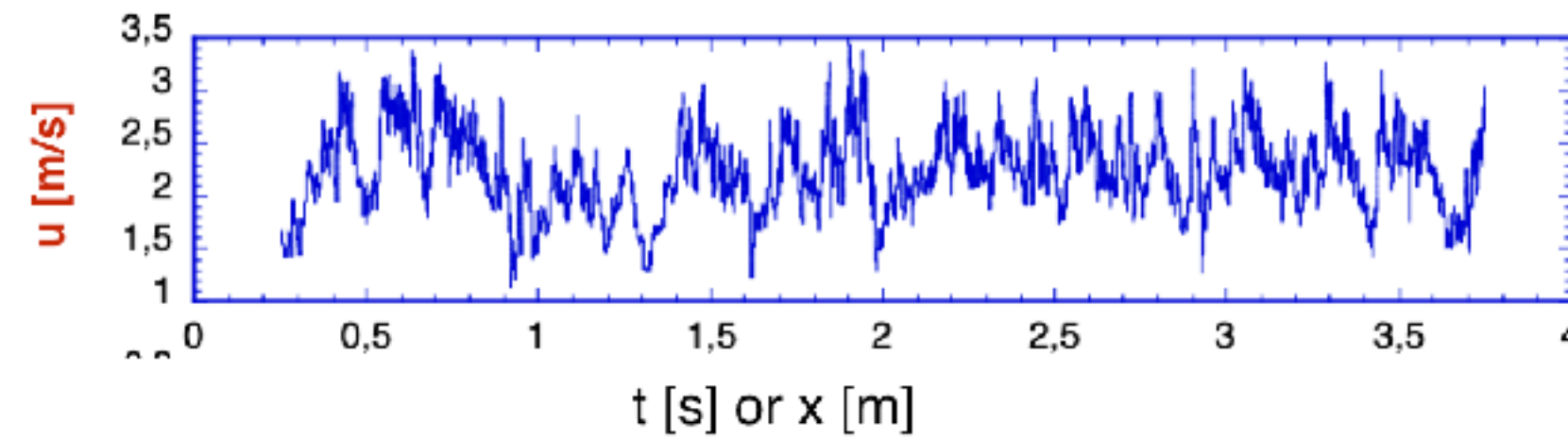
statistical approach-
extreme events

**Aim - general joint multipoint
statistics combines both sides**

$$-r_j \frac{\partial}{\partial r_j} p(u_{r_j} | u_{r_k}, u(x_1)) = \left\{ -\frac{\partial}{\partial u_{r_j}} D^{(1)}(u_{r_j}, r_j, u(x_1)) + \frac{\partial^2}{\partial u_{r_j}^2} D^{(2)}(u_{r_j}, r_j, u(x_1)) \right\} p(u_{r_j} | u_{r_k}, u(x_1))$$

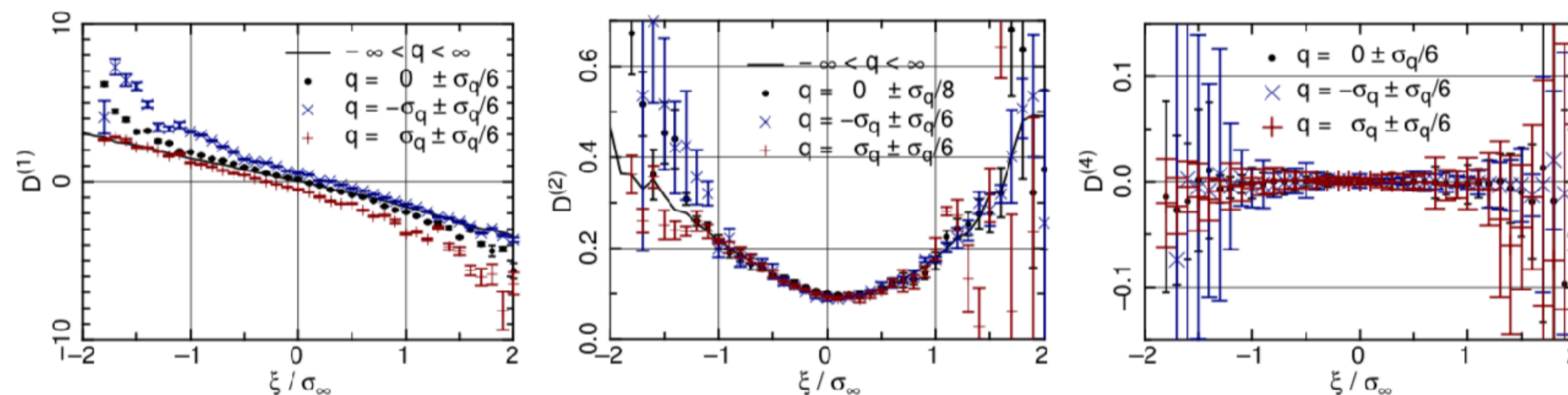


data



$$p(u(x_0), u(x_1), \dots, u(x_n))$$

Data analysis - ML (Machine learning) of stochastic equations



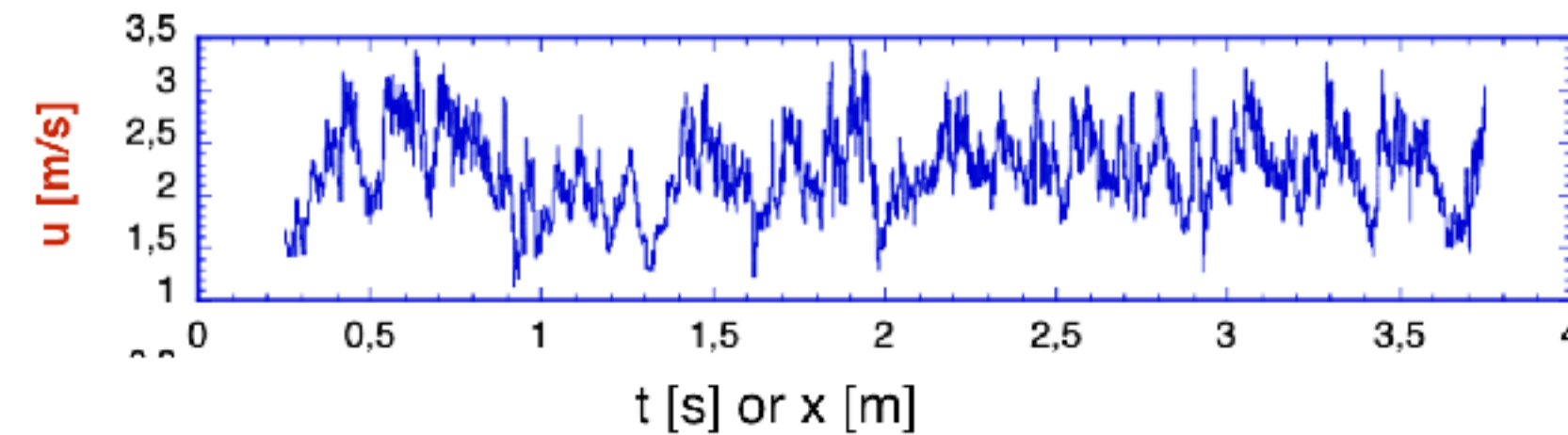
Fokker-Planck equation

$$-r_j \frac{\partial}{\partial r_j} p(u_{r_j} | u_{r_k}, u(x_1)) = \left\{ -\frac{\partial}{\partial u_{r_j}} D^{(1)}(u_{r_j}, r_j, u(x_1)) + \frac{\partial^2}{\partial u_{r_j}^2} D^{(2)}(u_{r_j}, r_j, u(x_1)) \right\} p(u_{r_j} | u_{r_k}, u(x_1))$$

Langevin equation

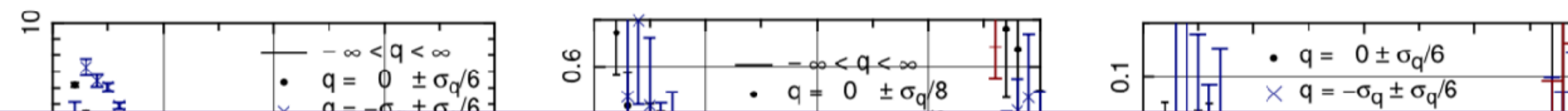
$$-r \frac{\partial}{\partial r} u_r = D^{(1)}(u_r, r) + \sqrt{D^{(2)}(u_r, r)} \eta(r)$$

data



$$p(u(x_0), u(x_1), \dots, u(x_n))$$

Data analysis - ML (Machine learning) of stochastic equations



Physics of Fluids

TUTORIAL

scitation.org/journal/phf

An open source package to perform basic and advanced statistical analysis of turbulence data and other complex systems

Cite as: Phys. Fluids **34**, 101801 (2022); doi: 10.1063/5.0107974

Submitted: 7 July 2022 · Accepted: 16 September 2022 ·

Published Online: 21 October 2022



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André Fuchs,^{1,a)} Swapnil Kharche,² Aakash Patil,³ Jan Friedrich,¹ Matthias Wächter,¹ and Joachim Peinke¹

Open questions

- Are nonlinear **partial diff. equation** equivalent to cascade **Fokker-Planck equations**?

$$\partial_t \vec{u} + (\vec{u} \cdot \nabla) \vec{u} = -\frac{1}{\rho} \nabla p + \nu \Delta \vec{u}, \quad \nabla \cdot \vec{u} = 0$$
$$i \frac{\partial \psi}{\partial x} + \frac{1}{2} \frac{\partial^2 \psi}{\partial t^2} + |\psi|^2 \psi = 0$$

$$-r_j \frac{\partial}{\partial r_j} p(u_{r_j} | u_{r_k}, u(x_1)) = \left\{ -\frac{\partial}{\partial u_{r_j}} D^{(1)}(u_{r_j}, r_j, u(x_1)) + \frac{\partial^2}{\partial u_{r_j}^2} D^{(2)}(u_{r_j}, r_j, u(x_1)) \right\} p(u_{r_j} | u_{r_k}, u(x_1))$$

- Is the fluctuation theorem of **entropy** a new constraint of extreme events (instabilities/structures)?
 - Entropons show the entropy is linked to structures - big increments

$$\langle e^{-\Delta S_{tot}} \rangle = 1$$

- what is the **role of noise**? For turbulence it is an intrinsic part of the system - for solitons?

$$\text{Diffusion} - D^{(2)} \propto u_r^2$$

Danke an

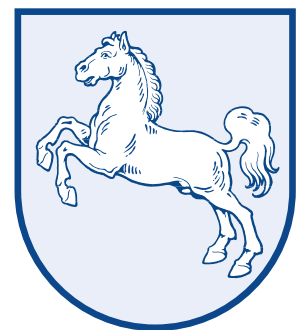
Thanks to my group m(A. Fuchs, M. Wächter,)
And F. Bouchet, R.M. Tabar, A. Girard



Forschungsverbund Windenergie



Dank für die Förderung von:



Forschungsbau Oldenburg



References

- [1] J. Peinke, M. R. R. Tabar, and M. Wächter, Annual Review of Condensed Matter Physics 10, 107-132 (2019)
- [2] A. Fuchs, C. Herbert, J. Rolland, M. Wächter, F. Bouchet, and J. Peinke, Phys. Rev. Lett. 129, 034502 (2022)
- [3] A. Fuchs, S. Kharche, M Wächter, and Joachim Peinke, Physics of Fluids 34 (10), 101801 (2022)