A physically-based sandpile model for the prediction of solar flares using data assimilation

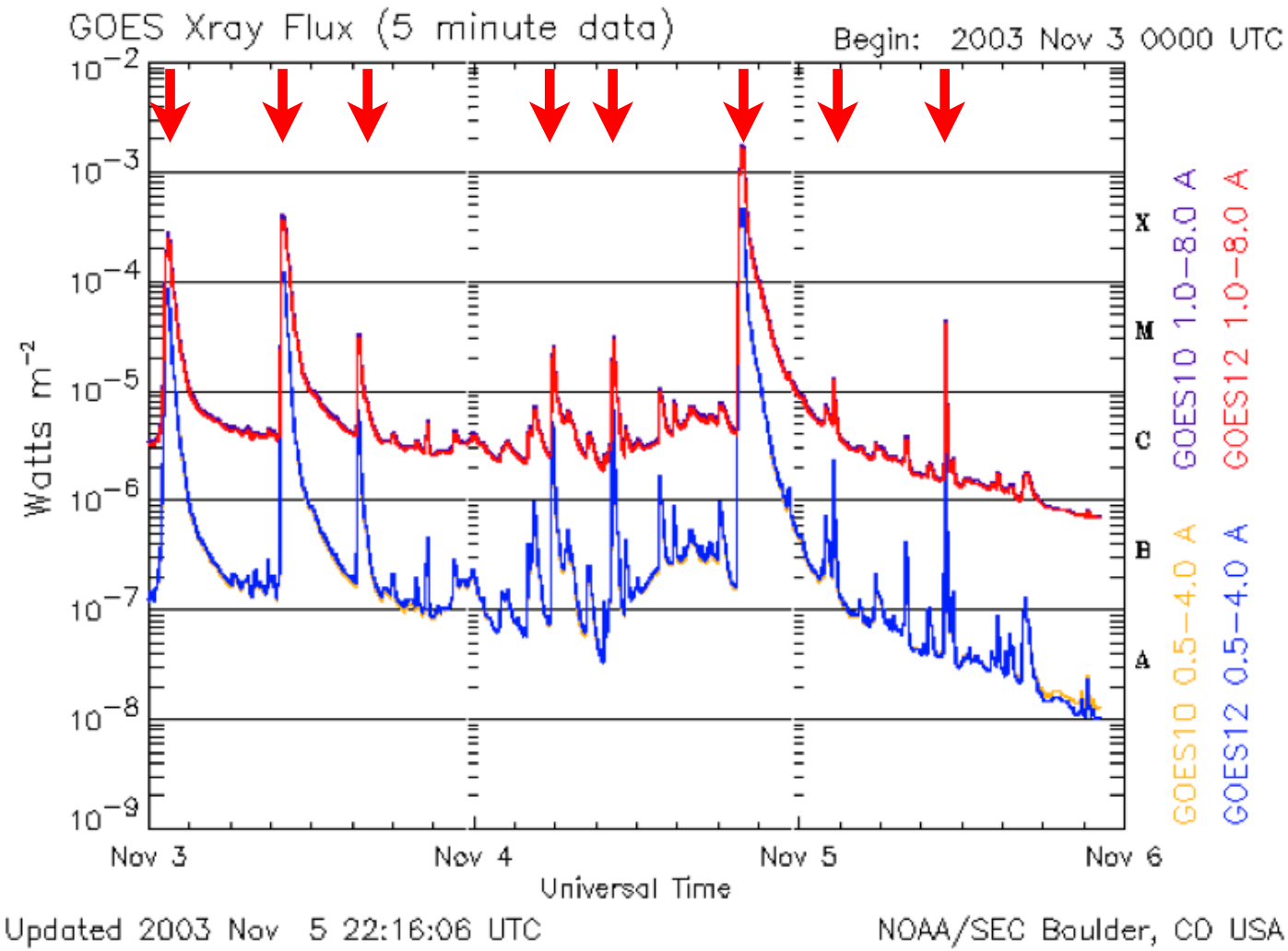
Antoine Strugarek

CEA/Saclay
Observatoire Paris-Meudon
Université de Montréal

solar orbiter

With R. Barnabé, A.S. Brun, P. Charbonneau, N. Vilmer

Detection of solar flares in X-rays

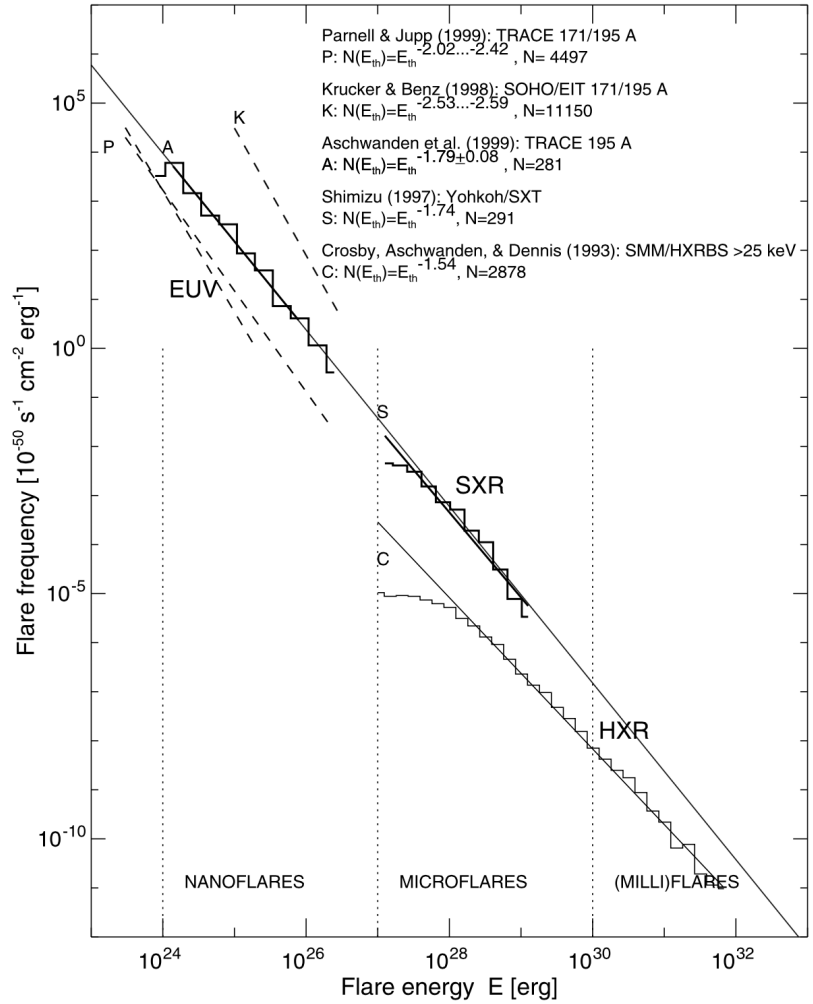


Flare classification and statistics

[Bhatnagar & Livingston 2005]

Hα classification			Radio flux at 5000 MHz in s.f.u.	Soft X-ray class	
Importance Class	Area (Sq. Deg.)	Area 10^{-6} solar disk		Importance class	Peak flux in 1-8 Å w/m^2
S	2.0	200	5	A	10^{-8} to 10^{-7}
1	2.0–5.1	200–500	30	B	10^{-7} to 10^{-6}
2	5.2–12.4	500–1200	300	C	10^{-6} to 10^{-5}
3	12.5–24.7	1200–2400	3000	M	10^{-5} to 10^{-4}
4	>24.7	>2400	3000	X	$>10^{-4}$

$$1 \text{ s.f.u.} = 10^4 \text{ jansky} = 10^{-2} \text{ W m}^{-2} \text{ Hz}^{-1}$$



[Aschwanden+, 2014]

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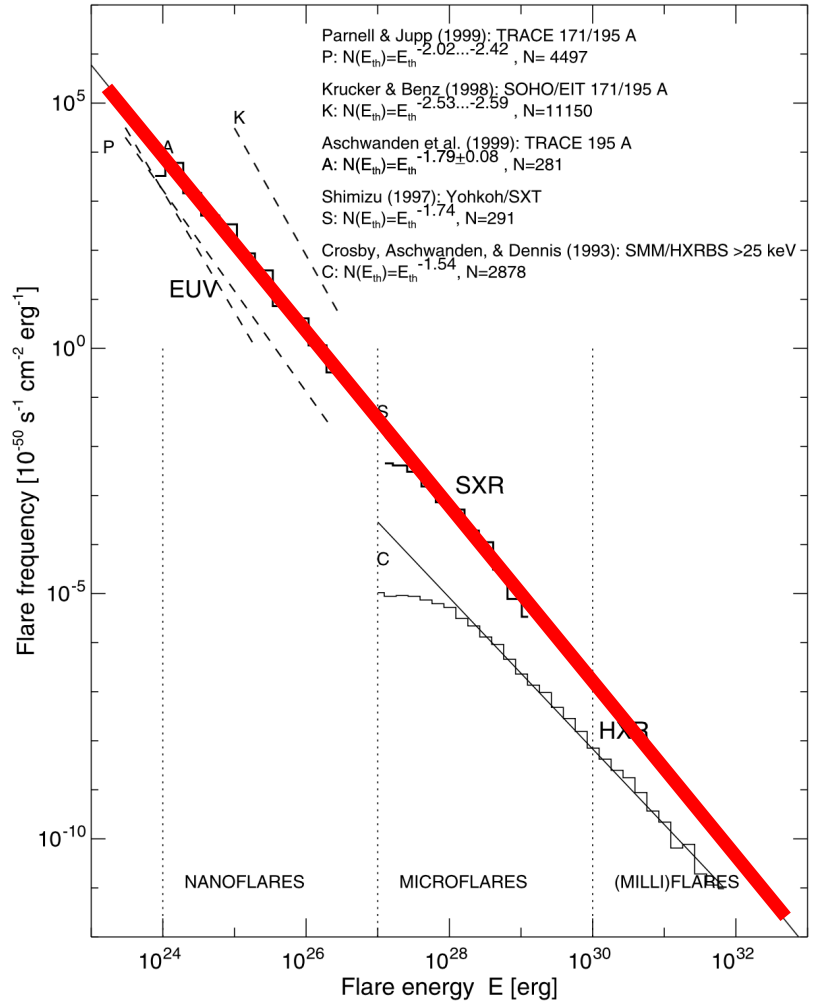

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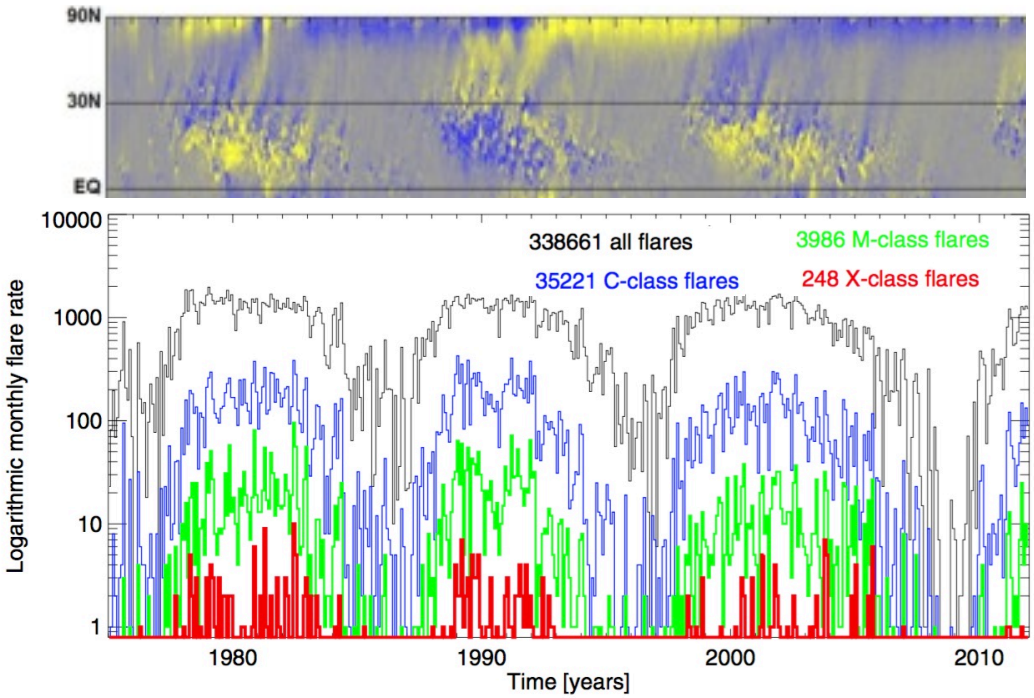
The number of flares strongly varies during the solar cycle



Line of sight magnetic field in the north hemisphere of the Sun

[Aschwanden & Freeland 2012]

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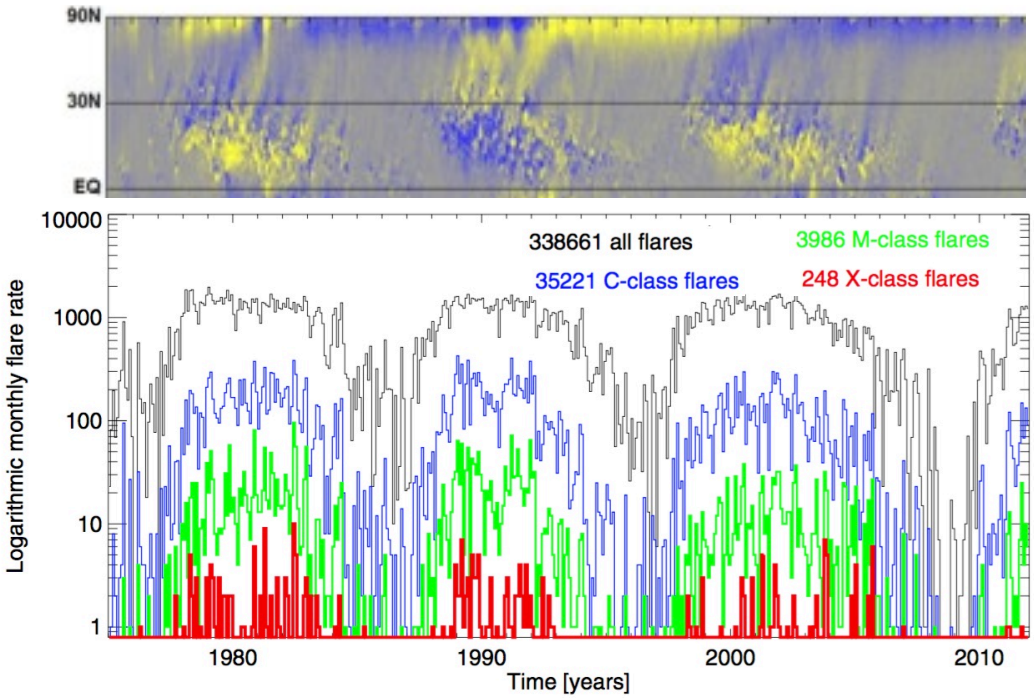
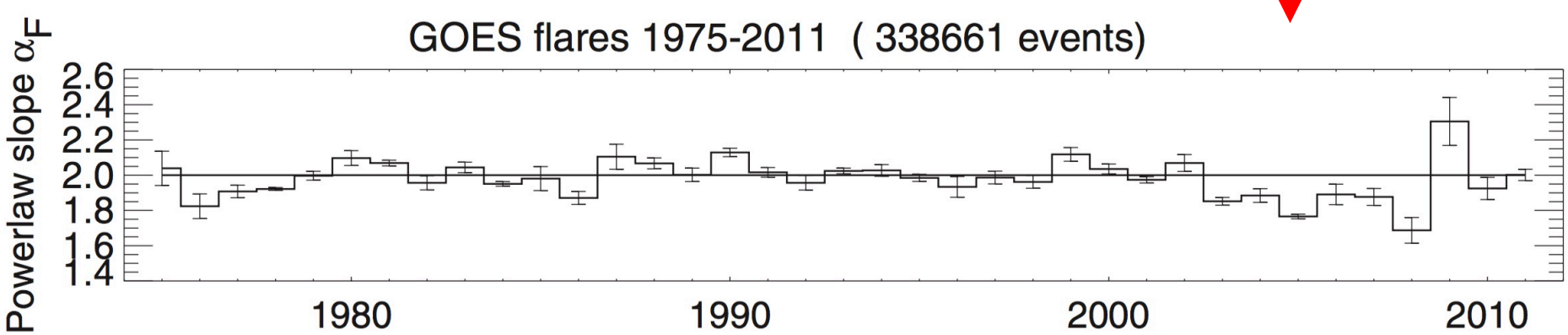


Line of sight magnetic field in the north hemisphere of the Sun

But no correlation of the power-law slope of the peak X-ray flux during flares



[Aschwanden & Freeland 2012]

Outline

Sandpile model and solar flares

Strugarek+ 2014, Solar Physics

Predicting individual (large) events with a stochastic model?

Strugarek & Charbonneau 2014, Solar Physics

Data assimilation: towards the Solar Orbiter era

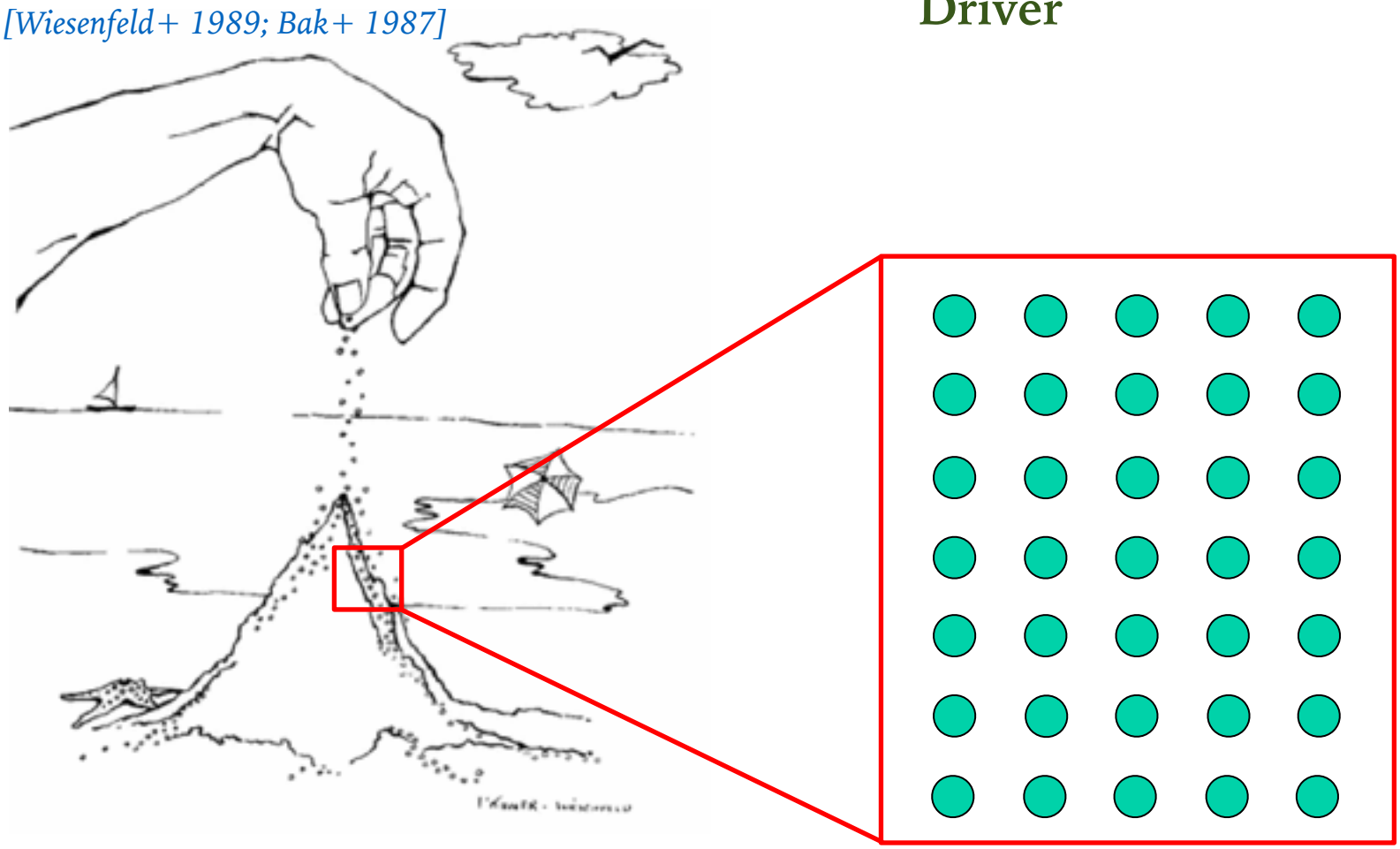
R. Barnabé's PhD thesis (AIM)

Basics of sandpile models (I)

Basic model ingredients:

Driver

[Wiesenfeld+ 1989; Bak+ 1987]



'Self-Organized Criticality'

[Lu & Hamilton 1993]

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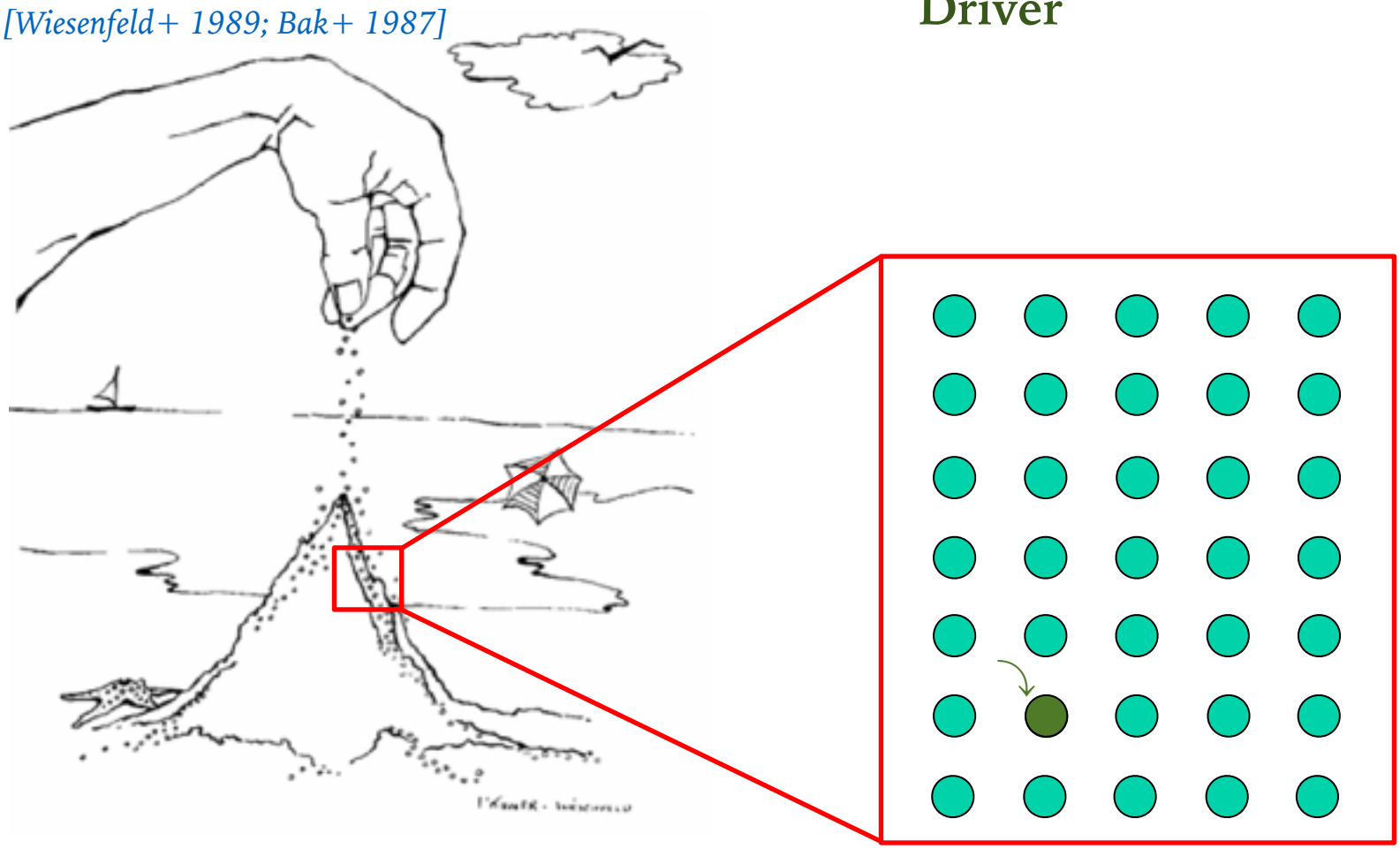

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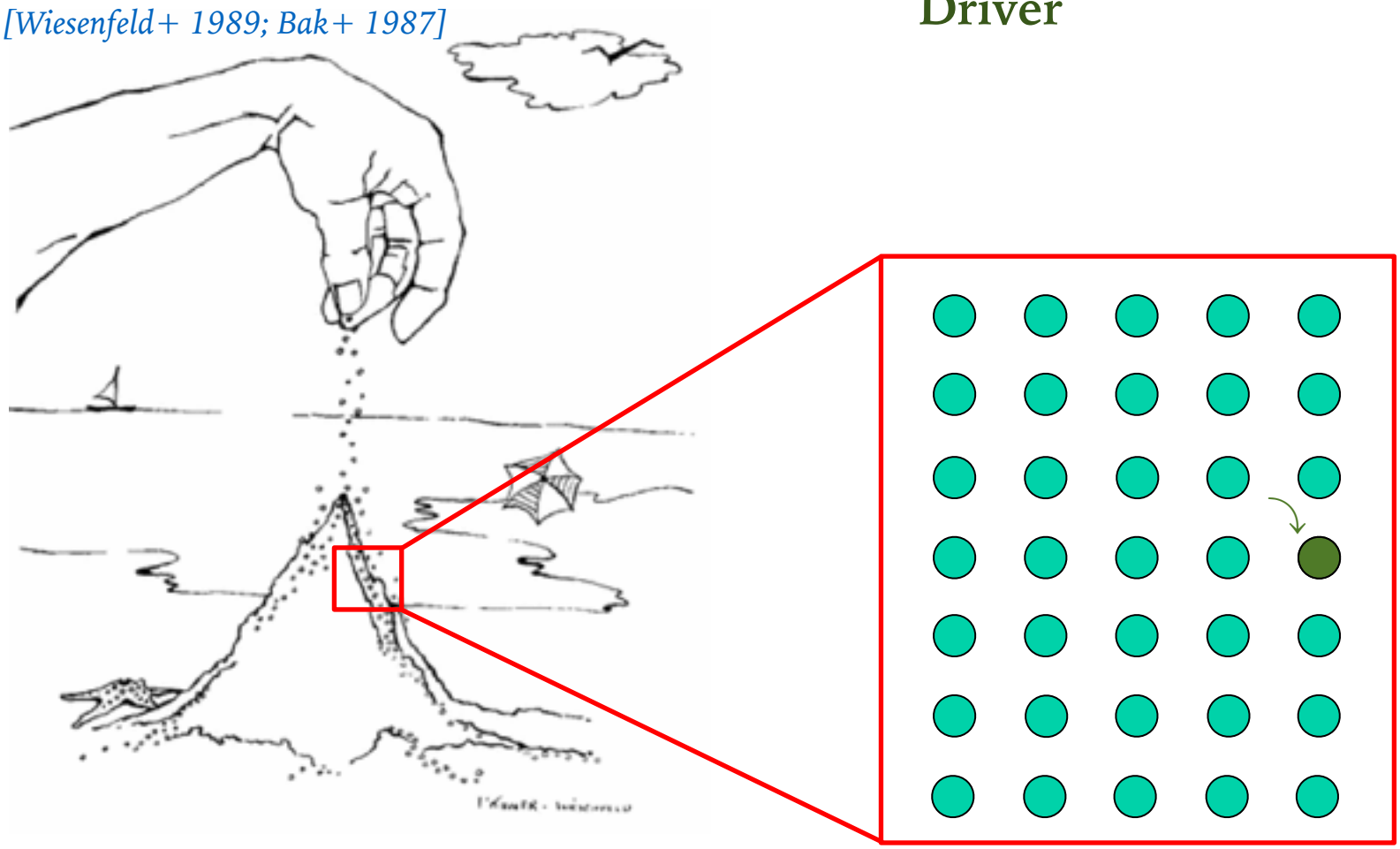

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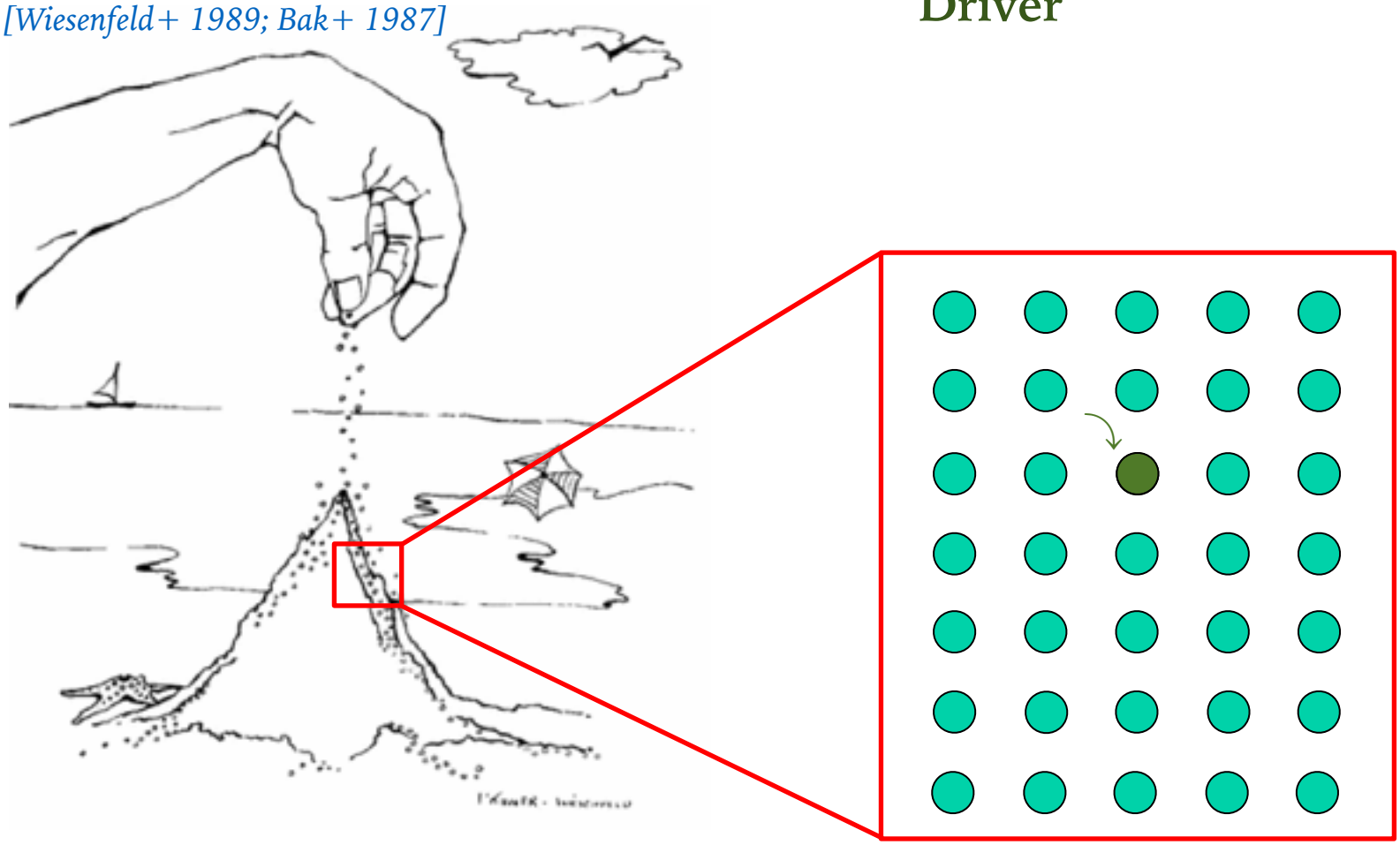

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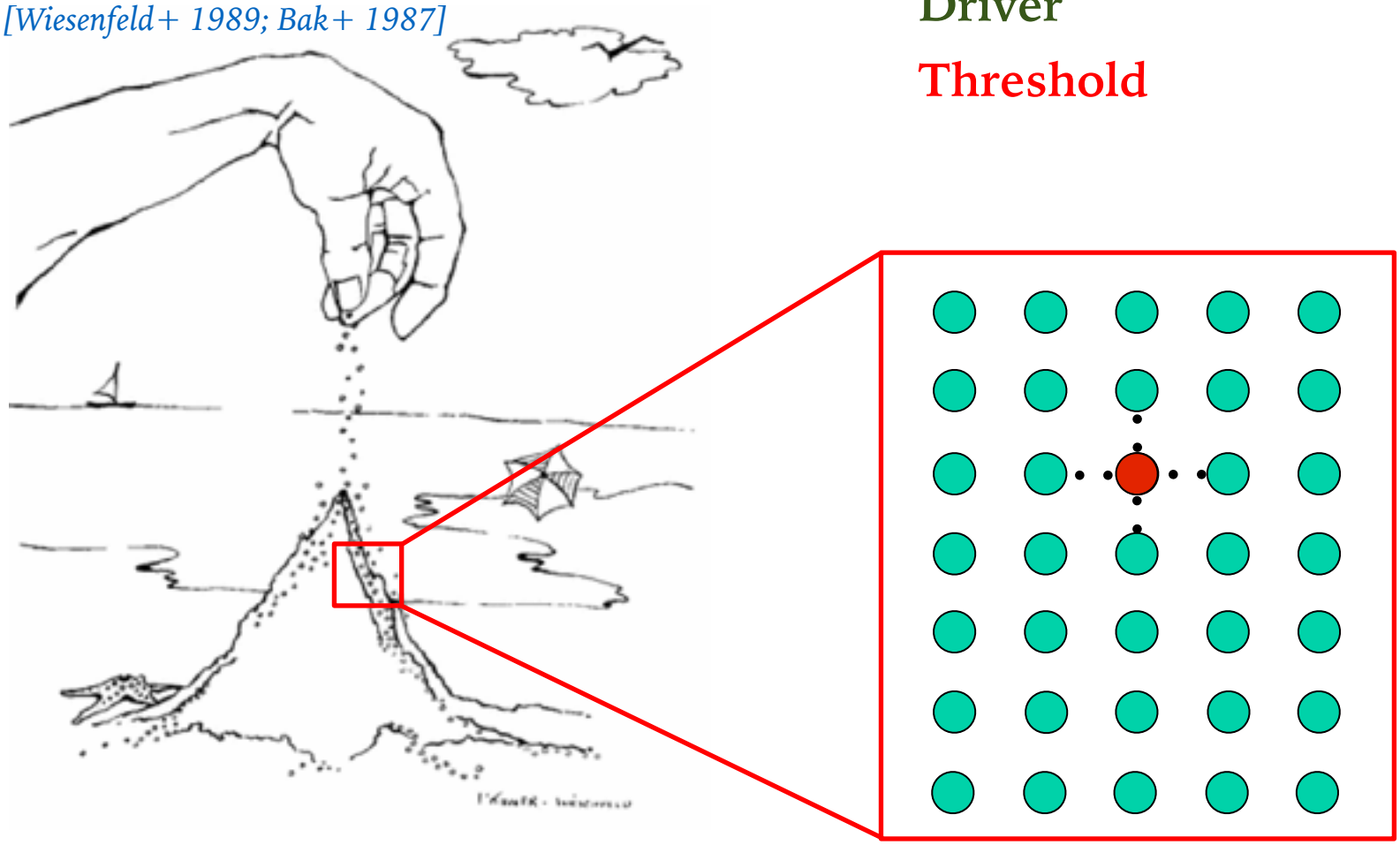

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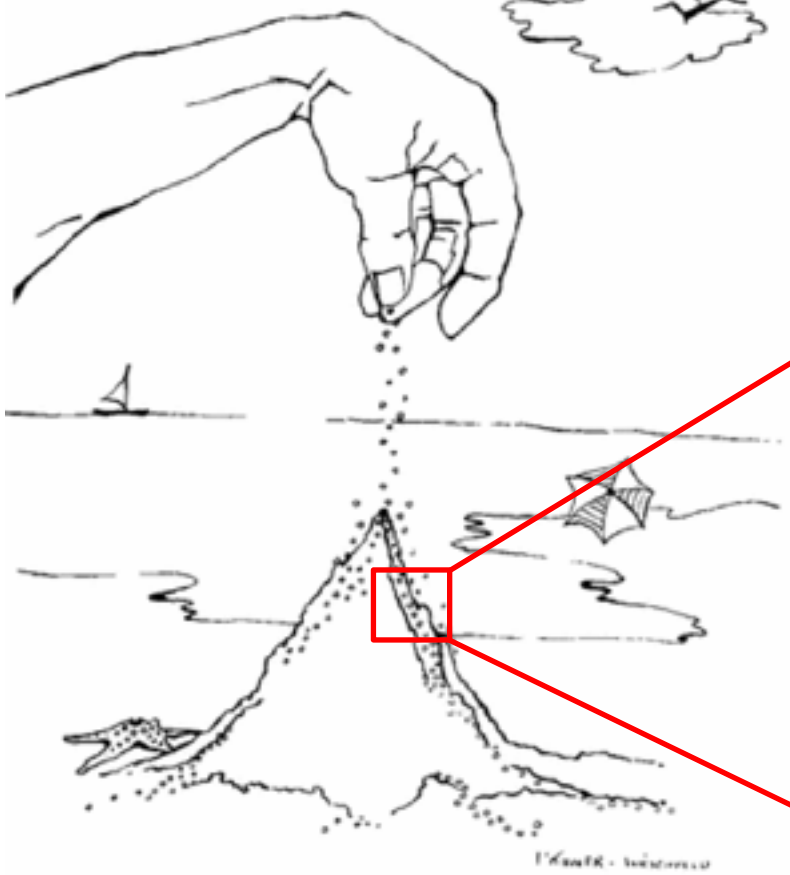
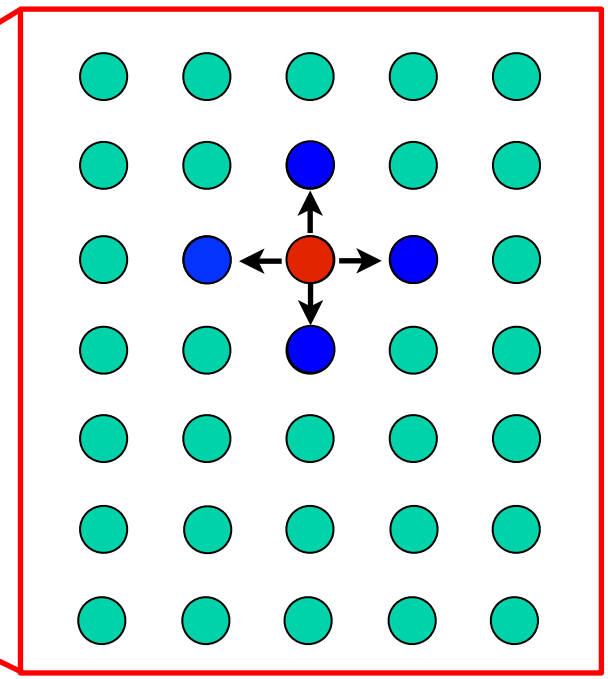
Redistribution rule

[Wiesenfeld+ 1989; Bak+ 1987]





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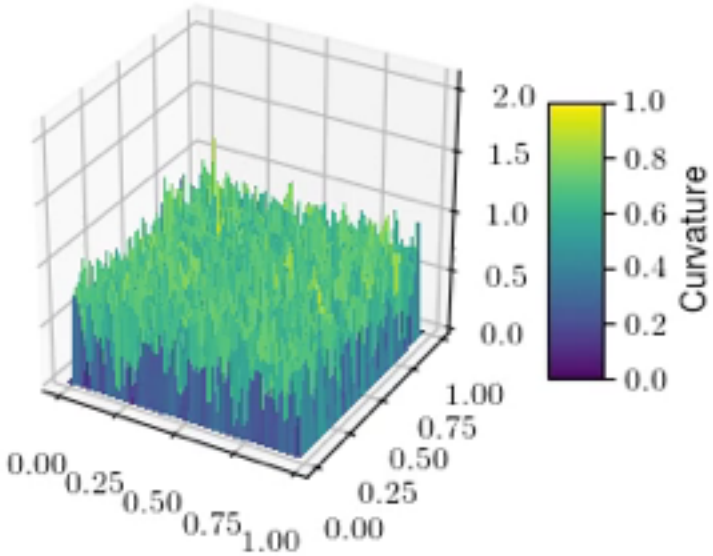
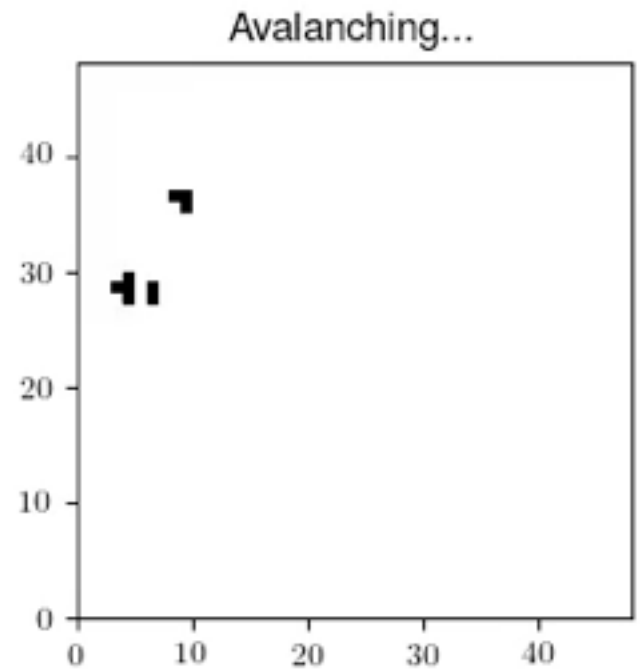
Basics of sandpile models (II)





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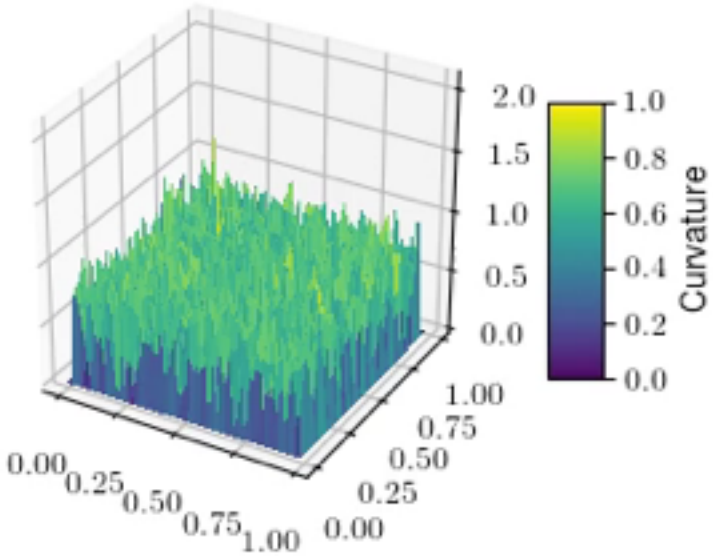
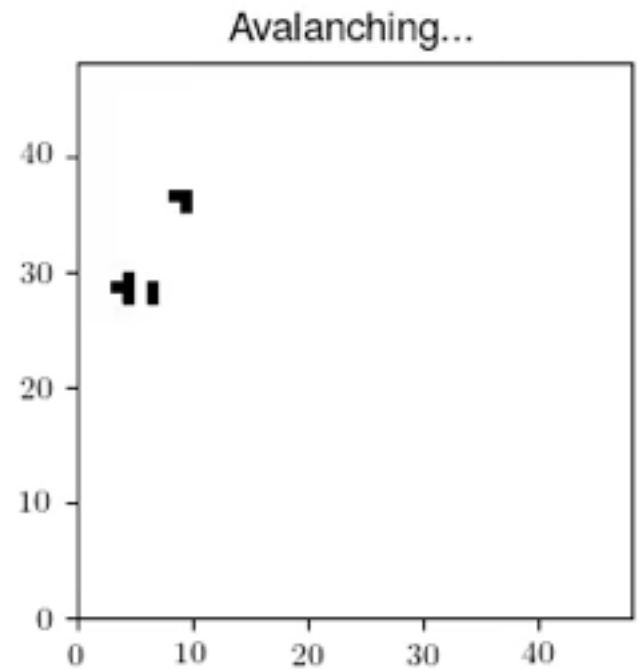
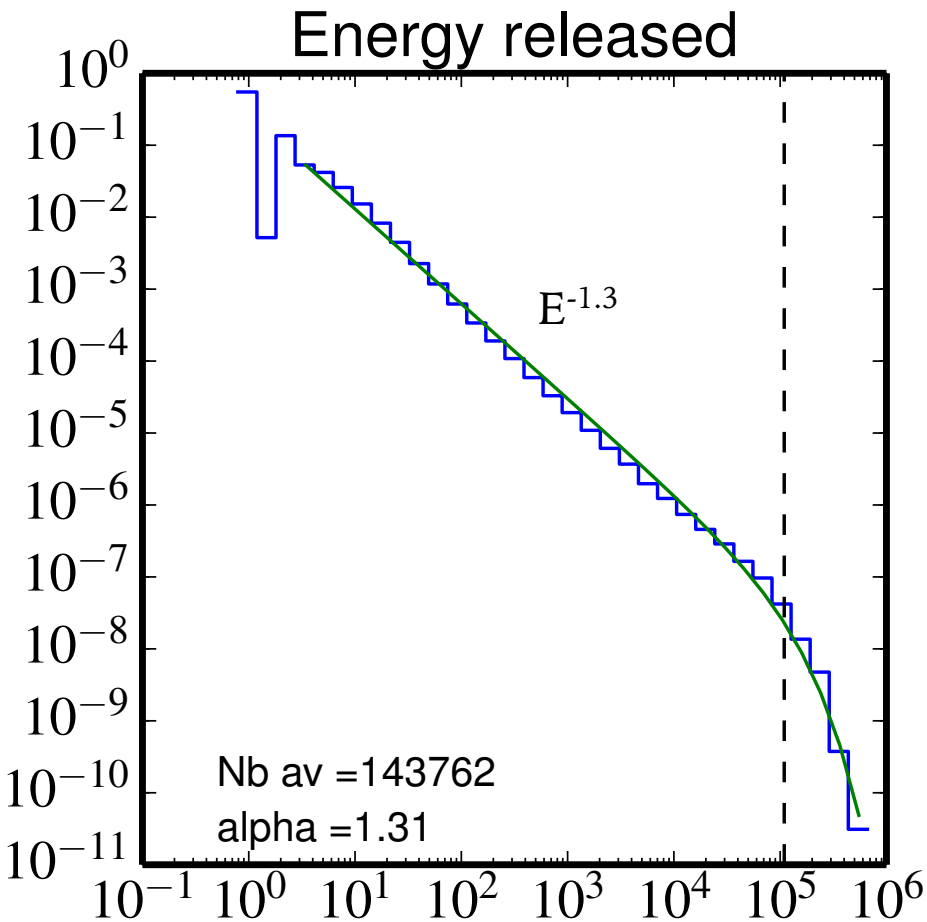


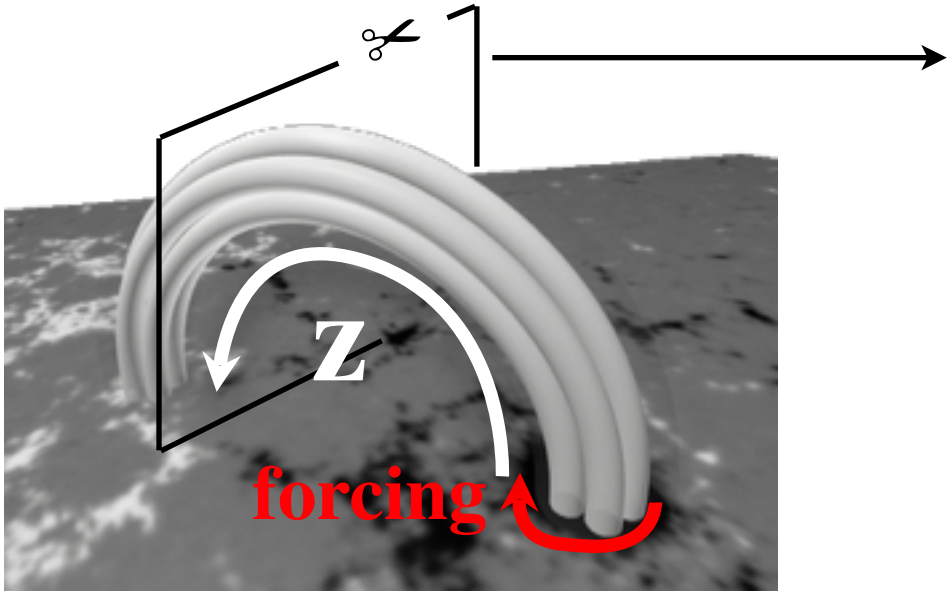


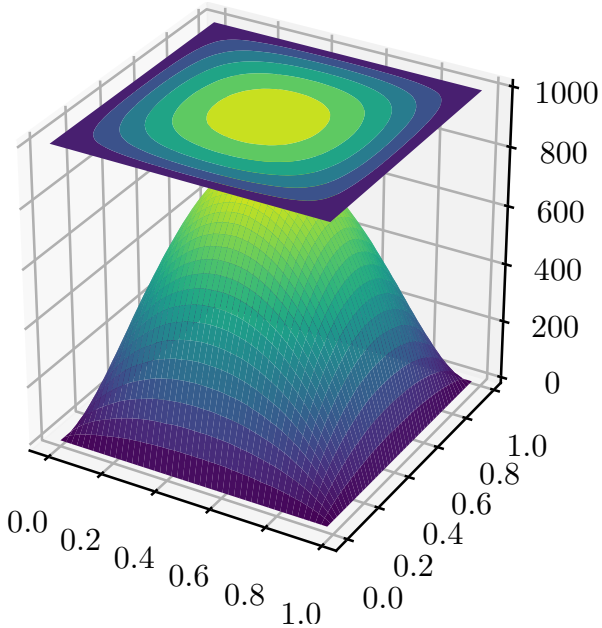
Basics of sandpile models (III)



Power law obtained for the **energy release**, **peak energy** during the avalanche, and also **duration** and **area** covered by the avalanche

A physical interpretation of sandpiles





Coronal Loop	Sandpile
Magnetic potential A_z	Height
Turbulent twisting of loop	Homogenous forcing
Currents	Curvature
Magnetic reconnection	Stochastic redistribution

[Strugarek+ 2014]

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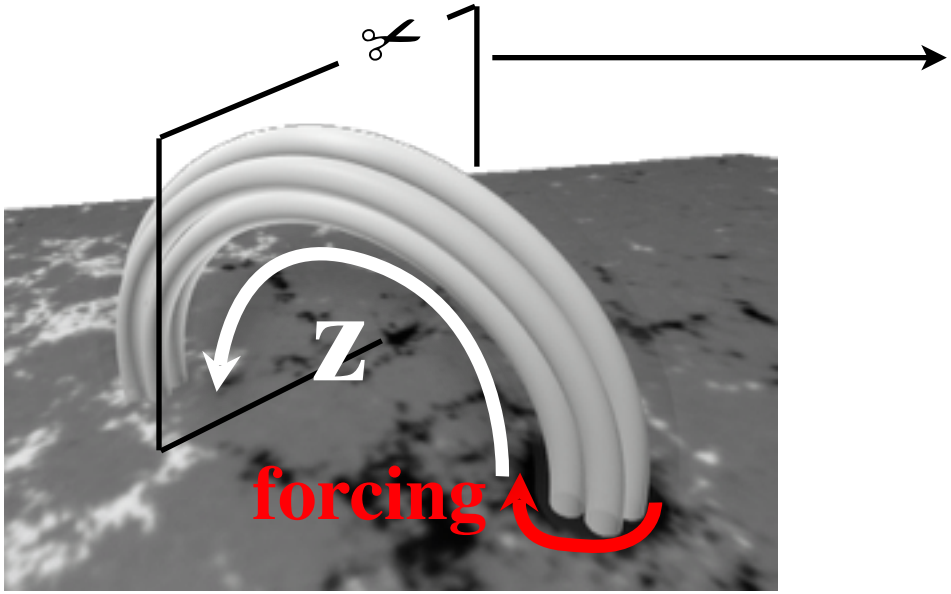

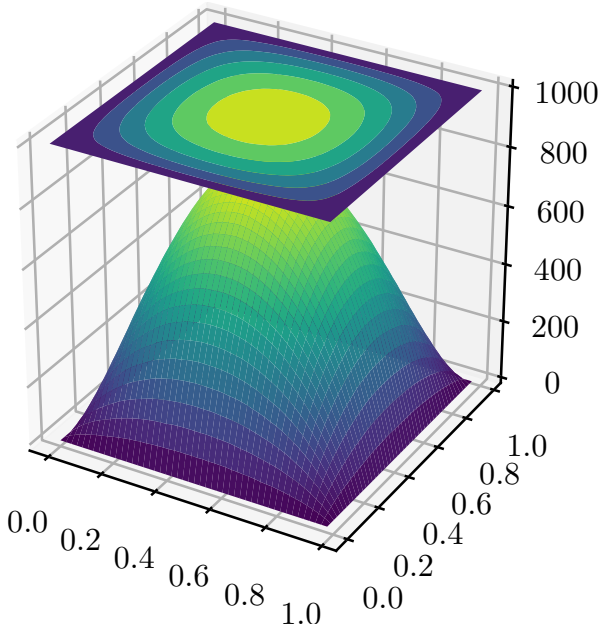

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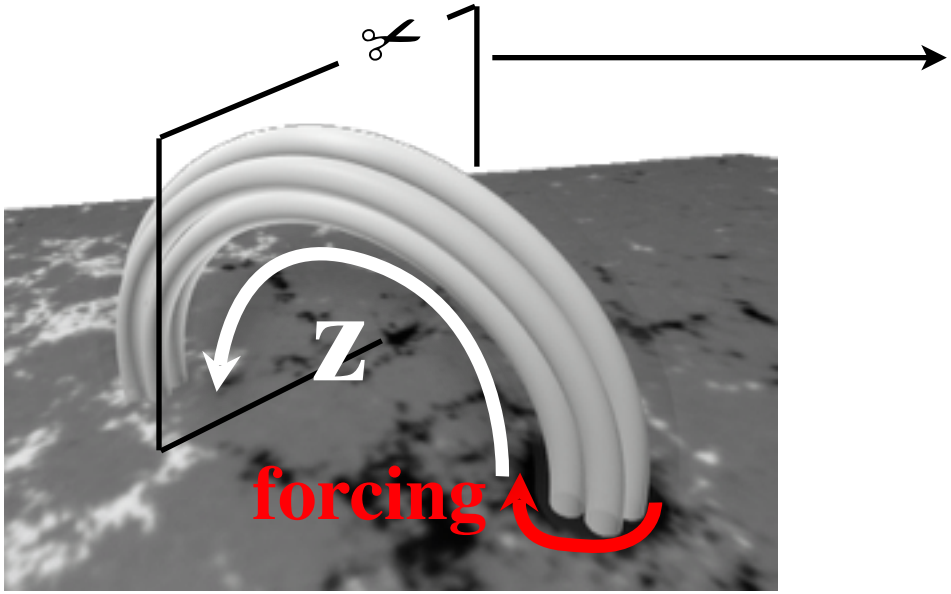

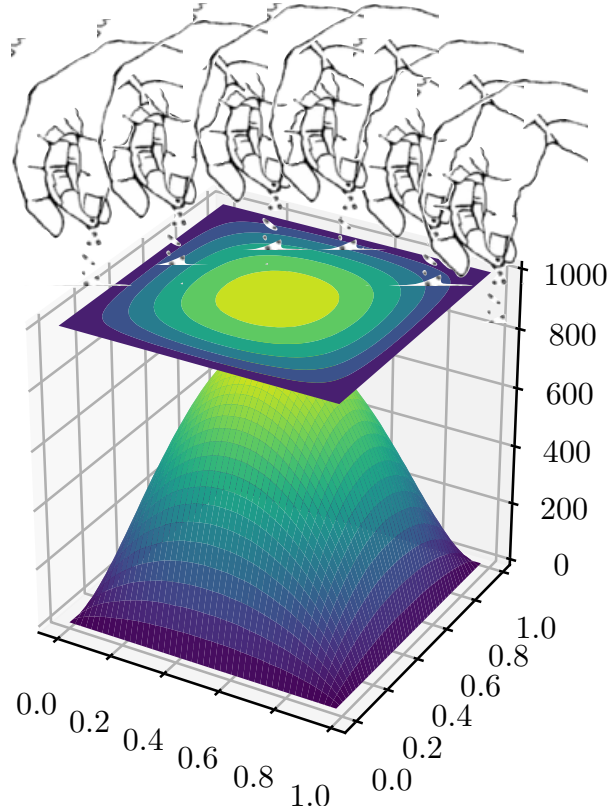

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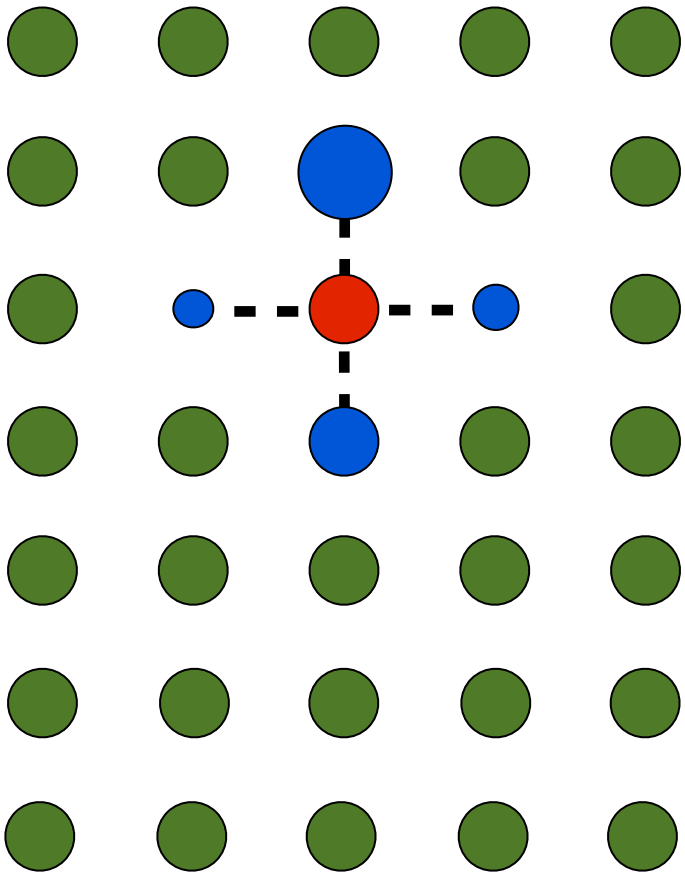
Deterministically-driven sandpile models



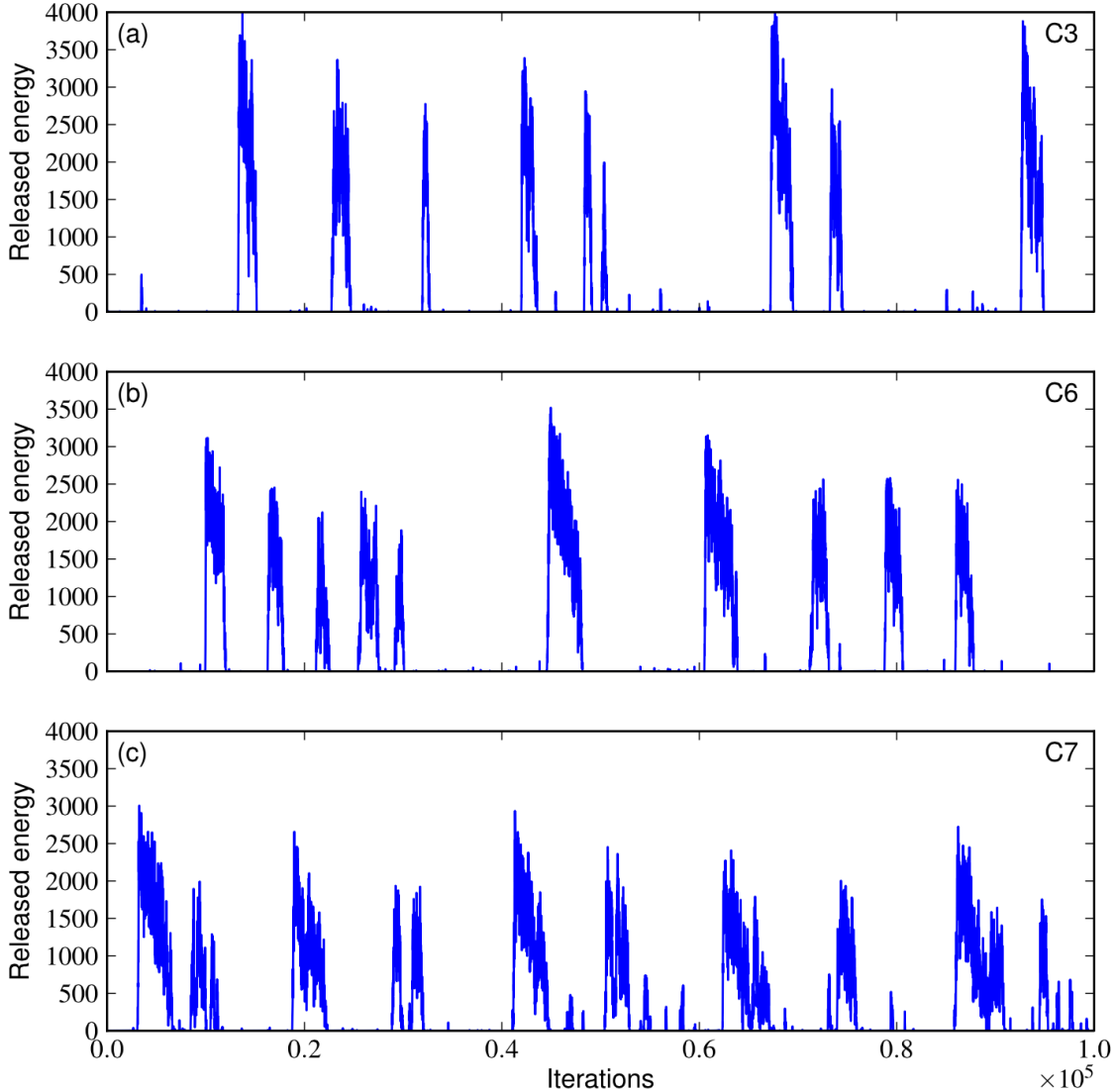
Deterministic driving on **all nodes**

(**Non)-Conservative** redistribution rule

Random process in **threshold**, **redistribution** and/or **extraction**

[Strugarek+ 2014]

Conservative models do not reach the 'SOC' state



Random extraction

Random extraction
+
Random redistribution

Random extraction
+
Random redistribution
+
Random threshold

[Strugarek+ 2014]

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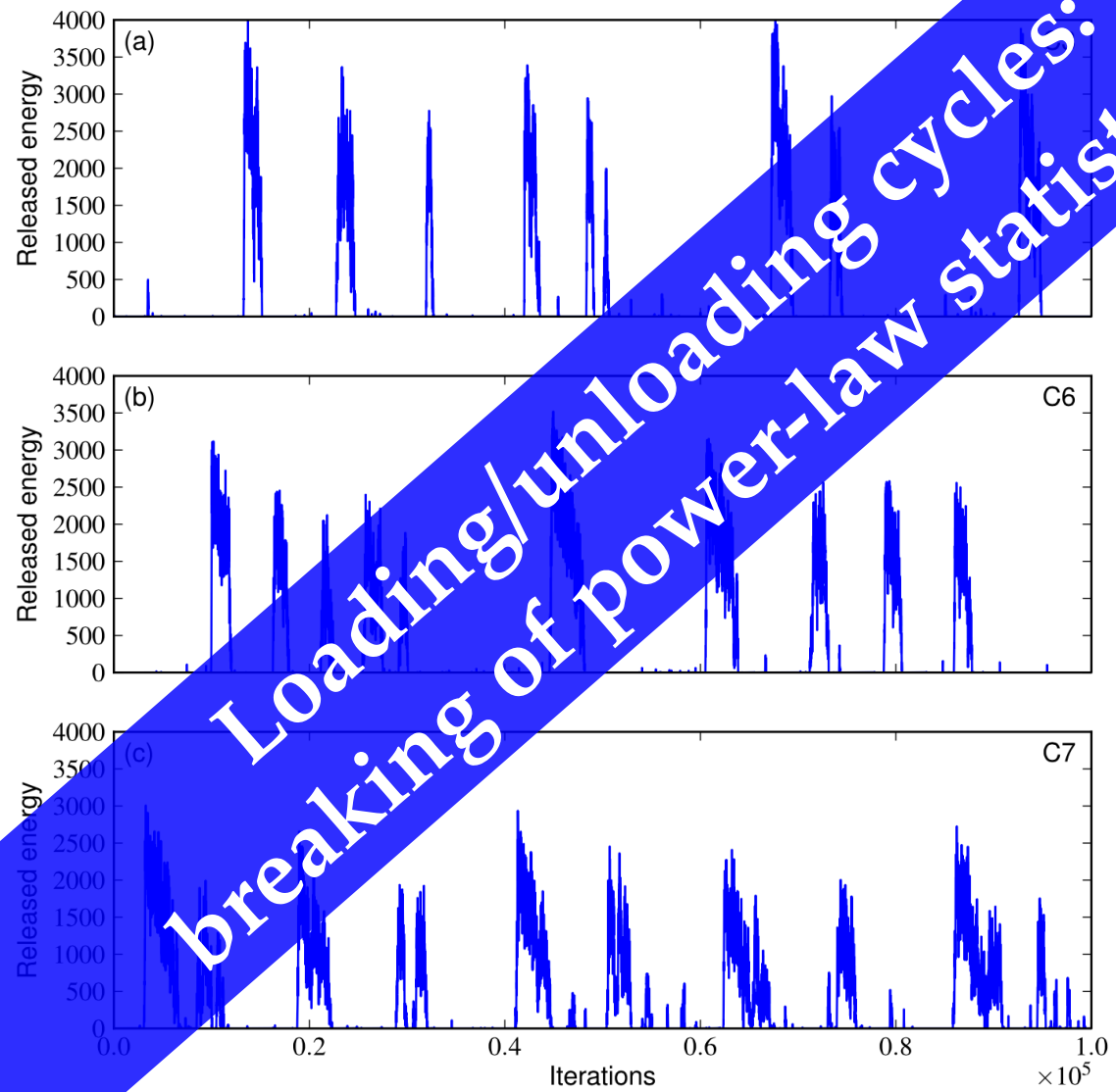

Loading/unloading cycles:
breaking of power-law statistics…

Random extraction

Random extraction
+
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Random extraction
+
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+
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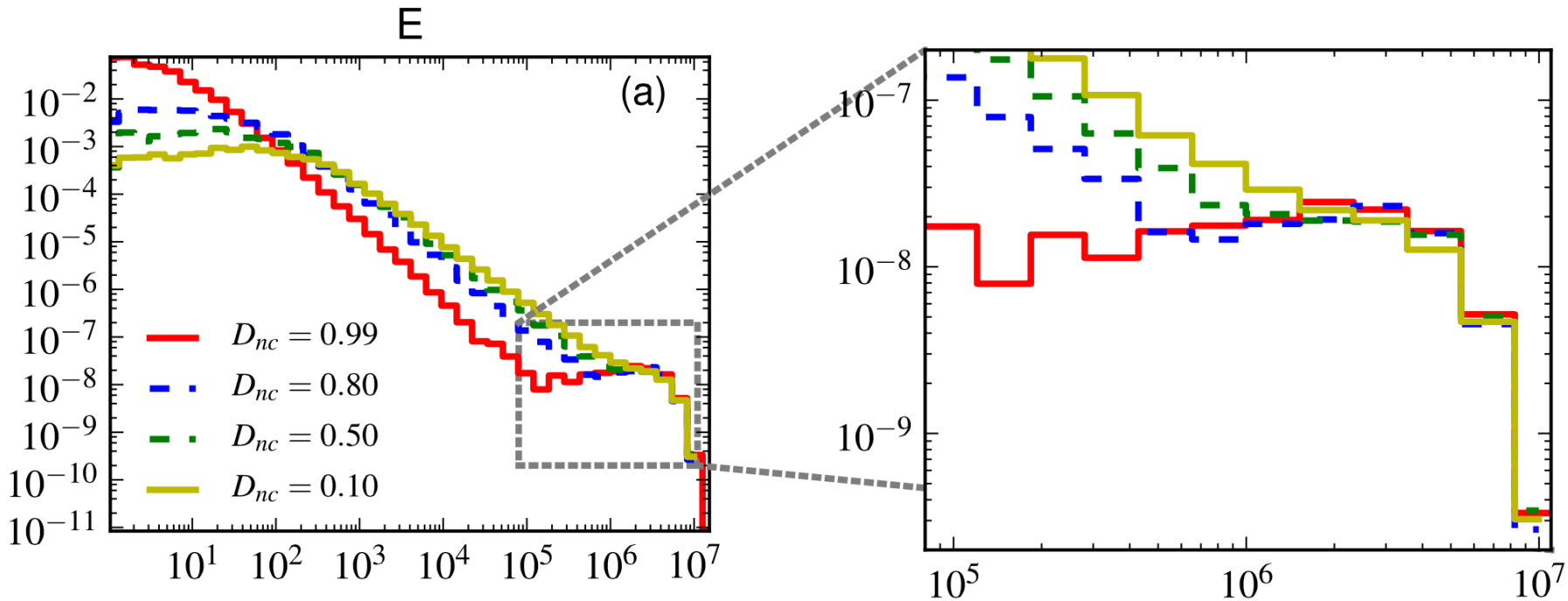
[Strugarek+ 2014]

Non-conservative models manage to recover SOC

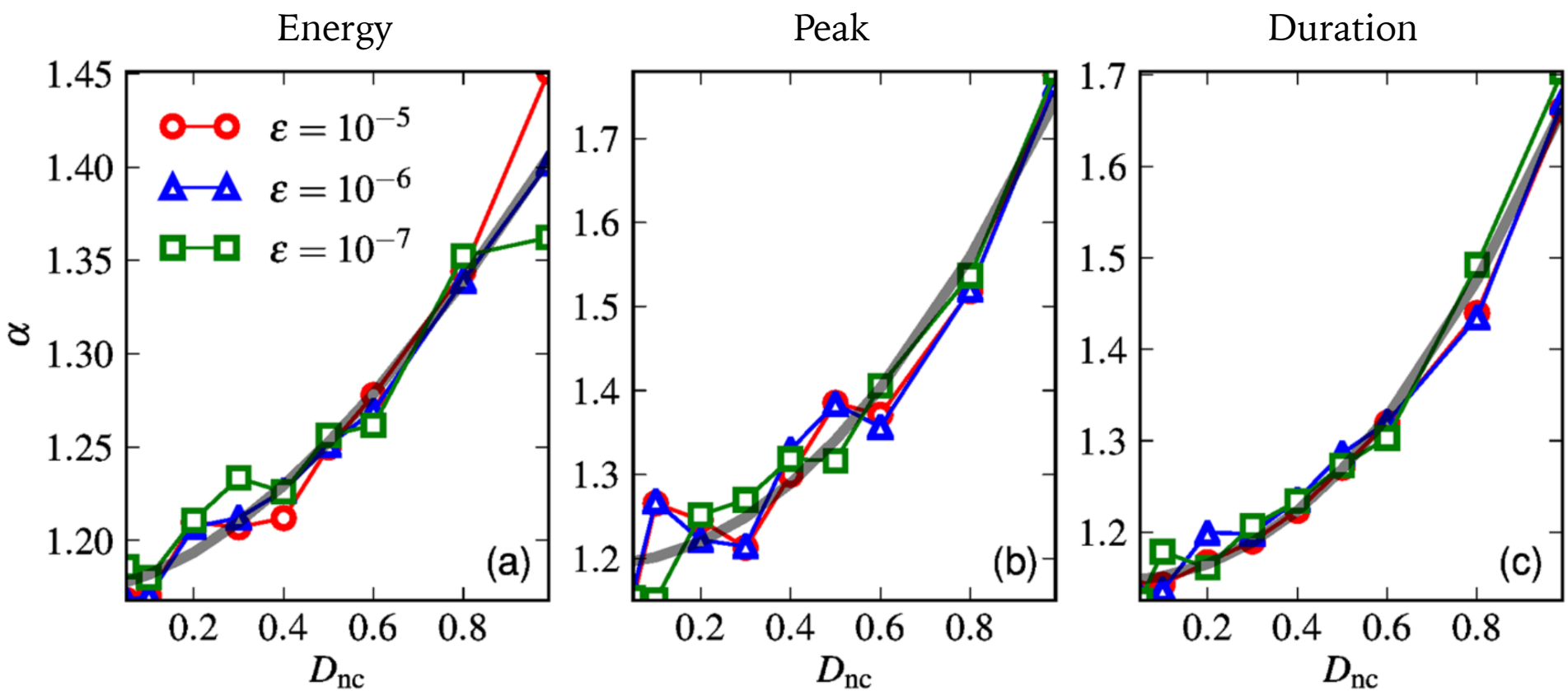


D_{nc} = Non-conservation parameter

(D_{nc}=1 for conservative model)

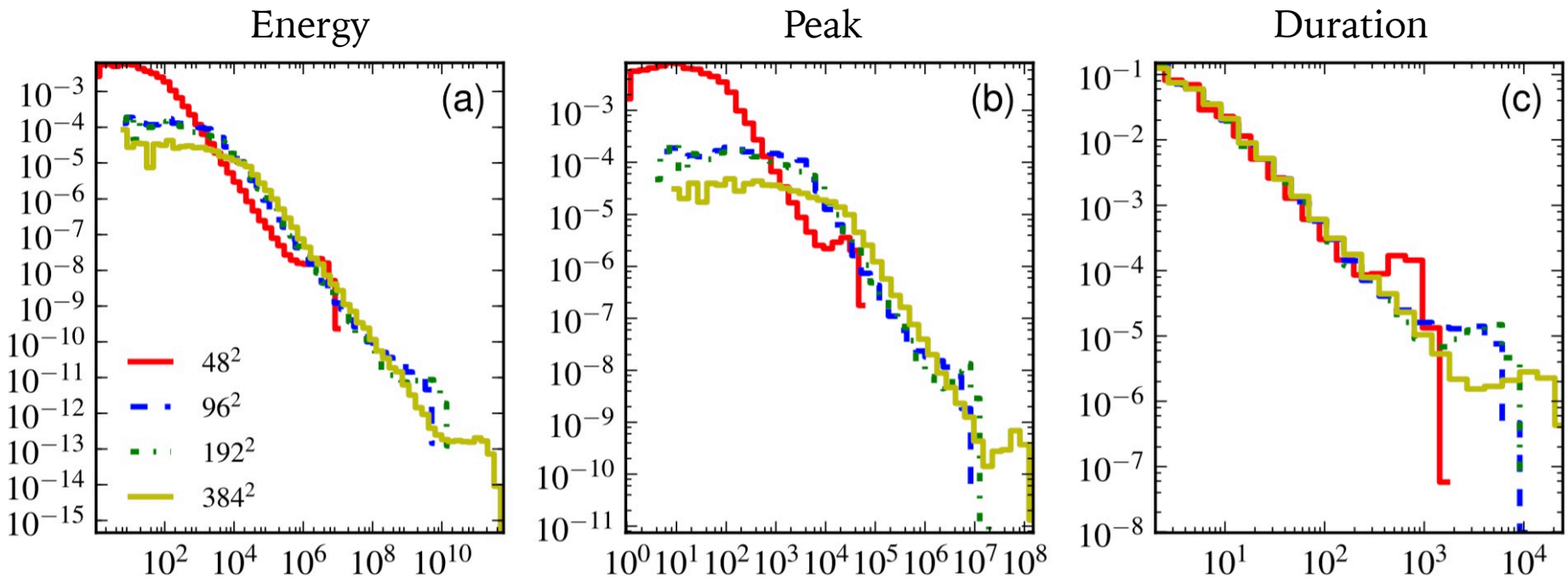
[Strugarek+ 2014]

Power-law exponents in the D-models



[Strugarek+ 2014]

Lattice size: it only affects the accessible energy range



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Motivation: predicting solar flares still gives us a hard time

THE ASTROPHYSICAL JOURNAL, 829:89 (32pp), 2016 October 1 doi:10.3847/0004-637X/829/2/89

CrossMark

A COMPARISON OF FLARE FORECASTING METHODS. I. RESULTS FROM THE "ALL-CLEAR" WORKSHOP

G. BARNES[1], K. D. LEKA[1], C. J. SCHRIJVER[2], T. COLAK[3], R. QAHWAJI[3], O. W. ASHAMARI[3], Y. YUAN[4], J. ZHANG[5], R. T. J. MCATEER[6], D. S. BLOOMFIELD[7,14], P. A. HIGGINS[7], P. T. GALLAGHER[7], D. A. FALCONER[8,9,10], M. K. GEORGOULIS[11], M. S. WHEATLAND[12], C. BALCH[13], T. DUNN[1], AND E. L. WAGNER[1]

When a comparison was made in this fashion, no one method clearly outperformed all others, which may in part be due to the strong correlations among the parameters used by different methods to characterize an active region. For M-class flares and above, the set of methods tends toward a weakly positive skill score (as measured with several distinct metrics), with no participating method proving substantially better than climatological forecasts.

Parameter/ Method	Statistical Method	C1.0+, 24 hr		M1.0+, 12 hr		M5.0+, 12 hr	
		ApSS	BSS	ApSS	BSS	ApSS	BSS
B_{eff}	Bayesian	0.12	0.06	0.00	0.03	0.00	0.02
ASAP	Machine	0.25	0.30	0.01	−0.01	0.00	−0.84
BBSO	Machine	0.08	0.10	0.03	0.06	0.00	−0.01
WL_{SG2}	Curve fitting	N/A	N/A	0.04	0.06	0.00	0.02
NWRA MAG 2-VAR	NPDA	0.24	0.32	0.04	0.13	0.00	0.06
$\log(\mathcal{R})$	NPDA	0.17	0.22	0.01	0.10	0.02	0.04
GCD	NPDA	0.02	0.07	0.00	0.03	0.00	0.02
NWRA MCT 2-VAR	NPDA	0.23	0.28	0.05	0.14	0.00	0.06
SMART2	CCNN	0.24	−0.12	0.01	−4.31	0.00	−11.2
Event Statistics, 10 prior	Bayesian	0.13	0.04	0.01	0.10	0.01	0.00
McIntosh	Poisson	0.15	0.07	0.00	−0.06	N/A	N/A

Stochasticity vs memory: the issue with classical sandpile

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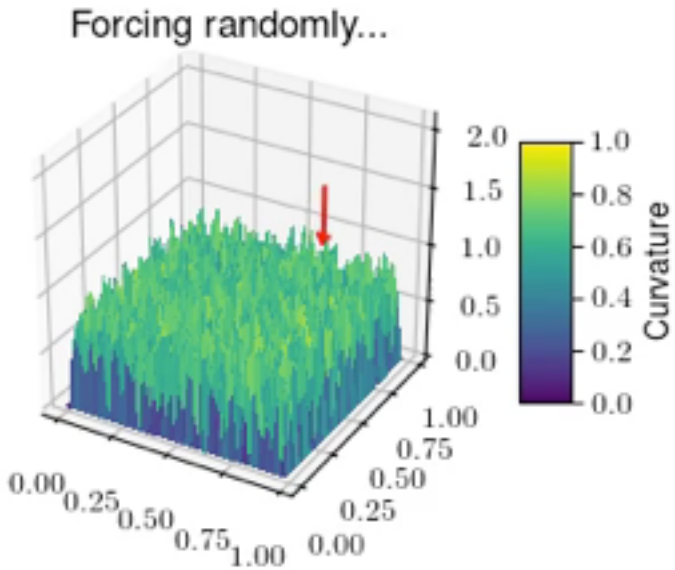
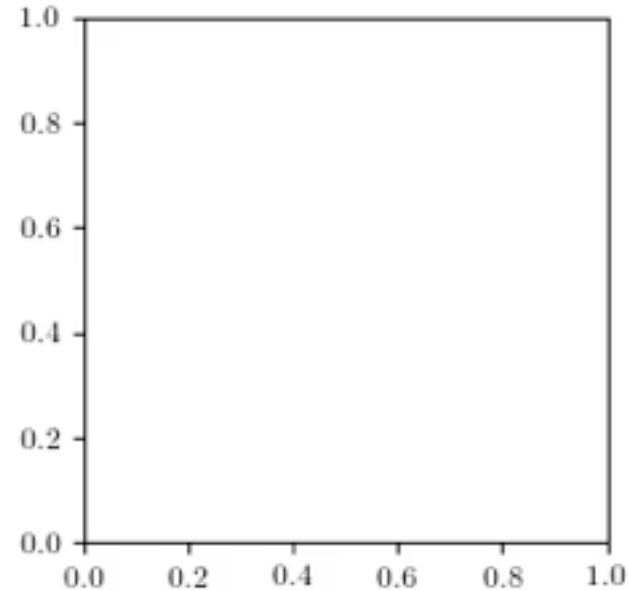
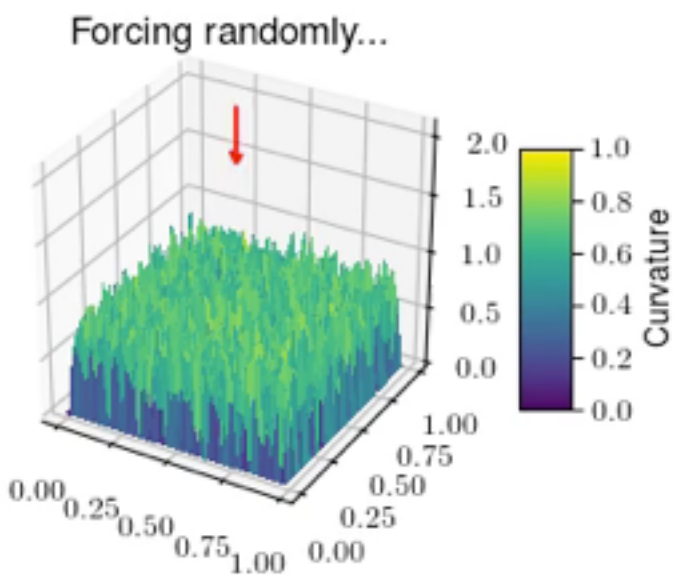
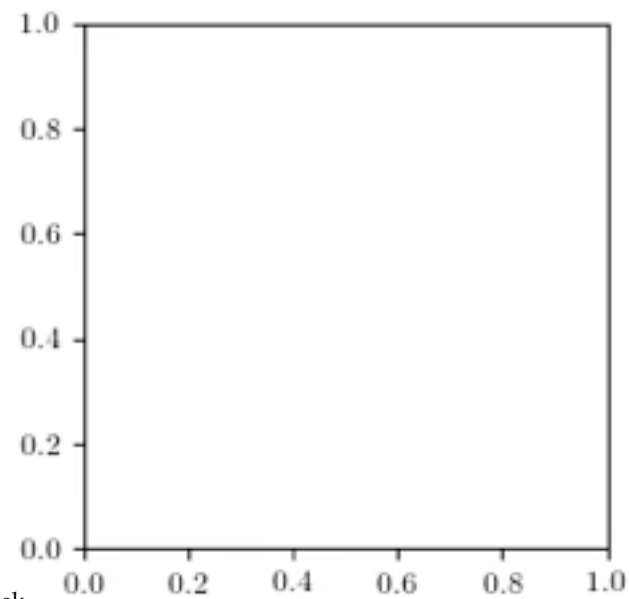




Standard sandpile model

Random seed #2





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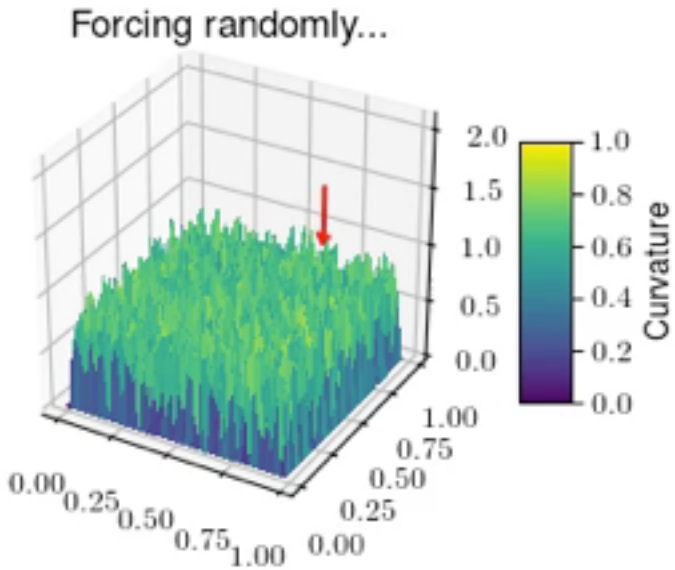

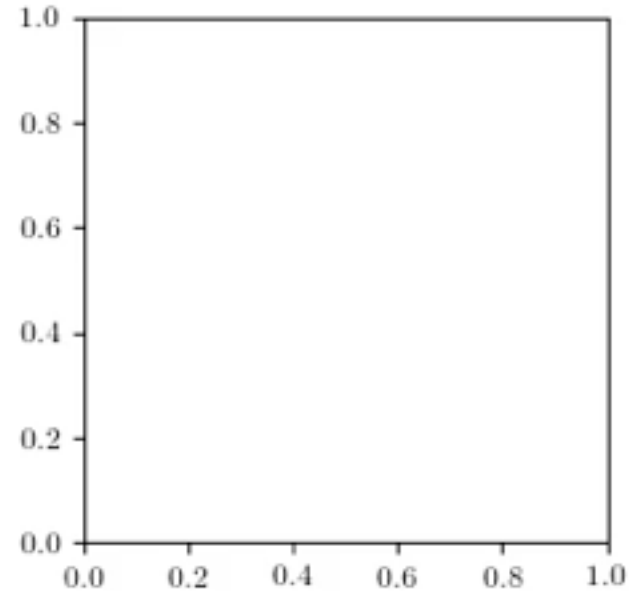

Standard sandpile model

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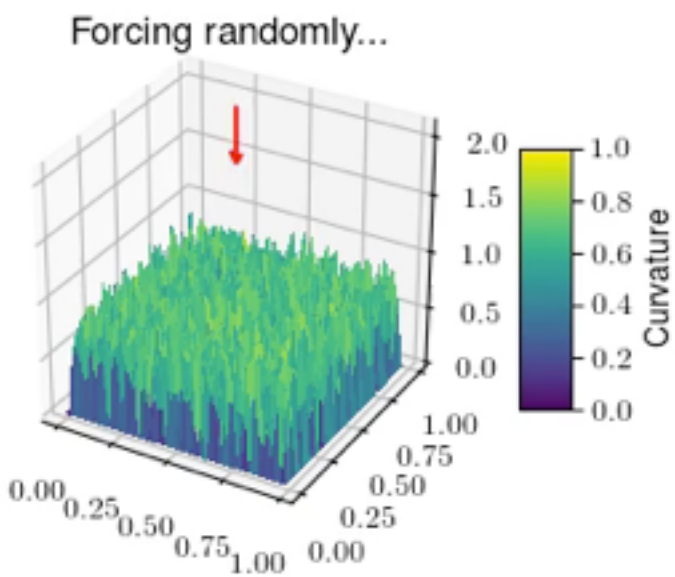

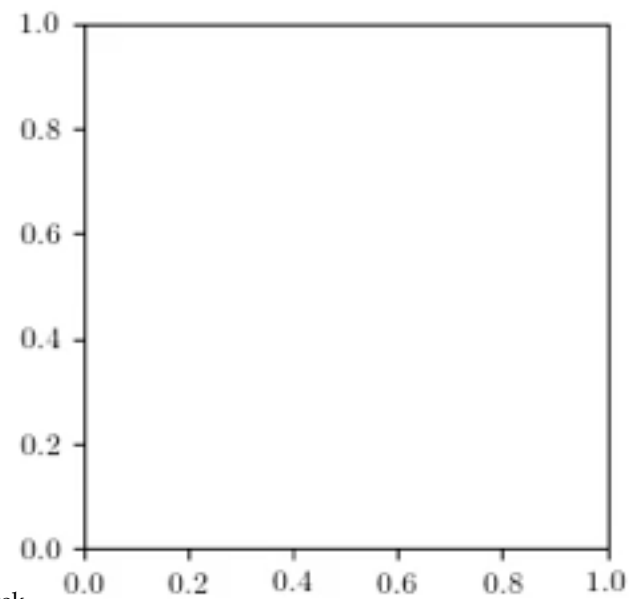

Stochasticity vs memory: D-models

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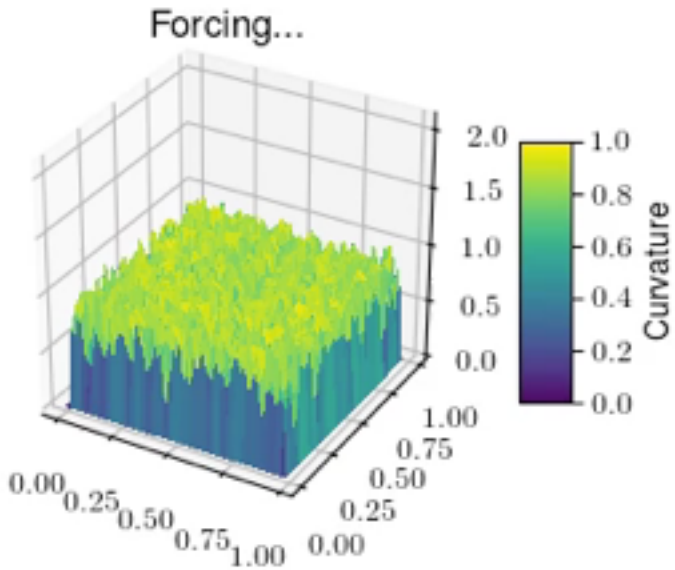
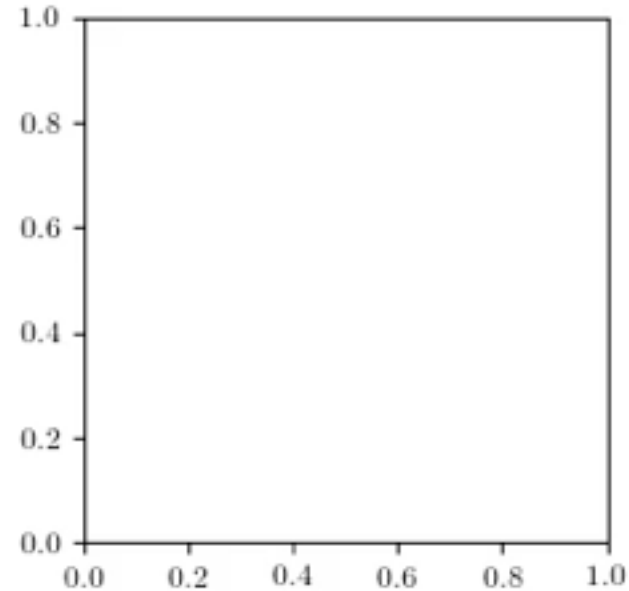
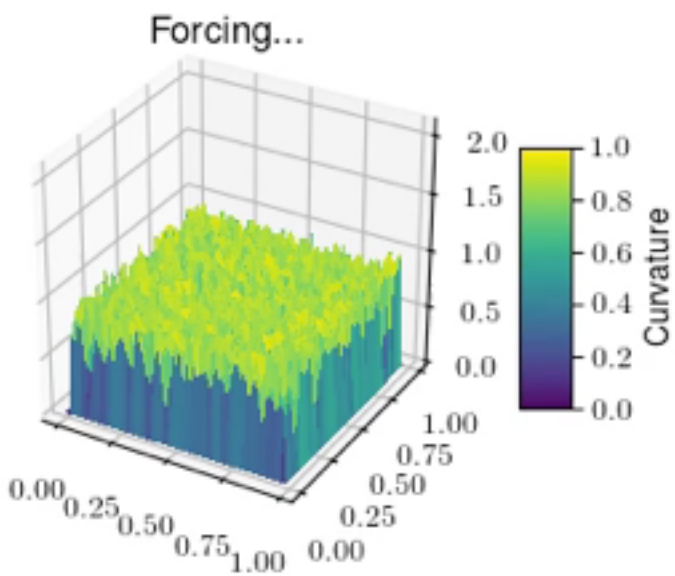
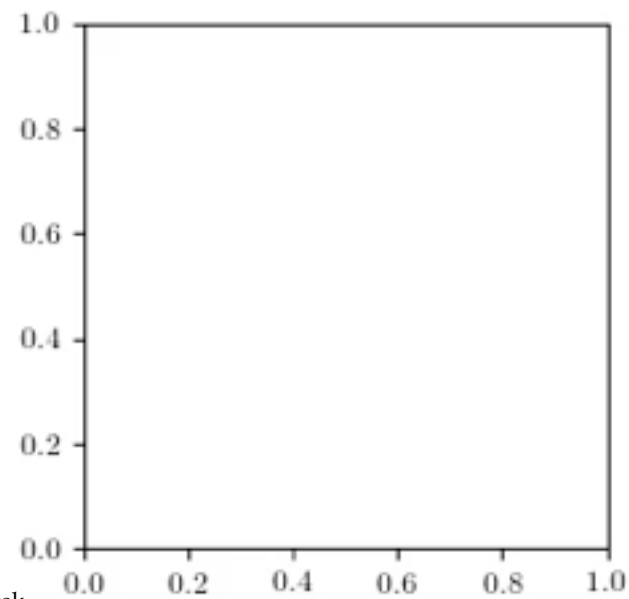




Non-Conservative sandpile model

Random seed #2





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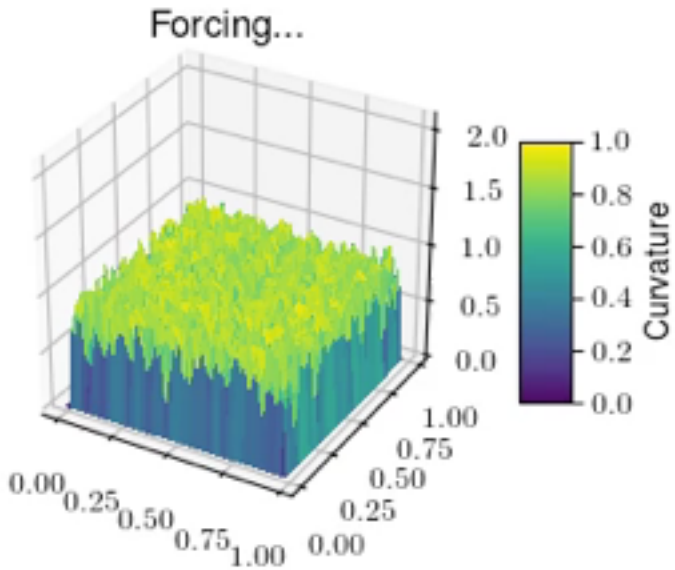
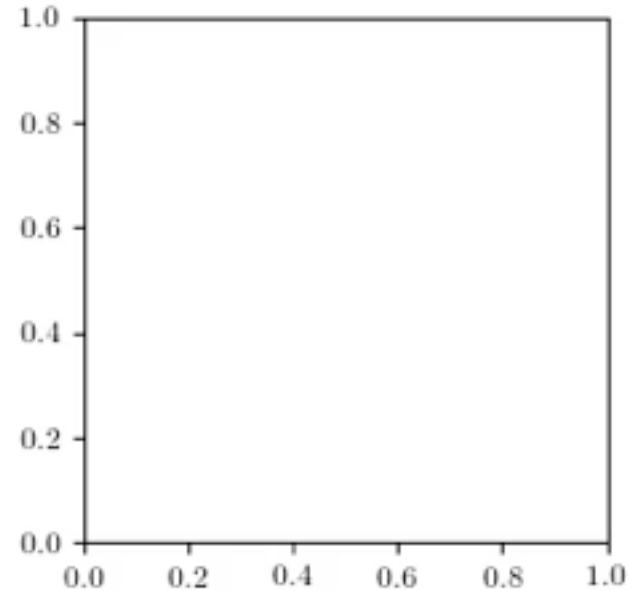
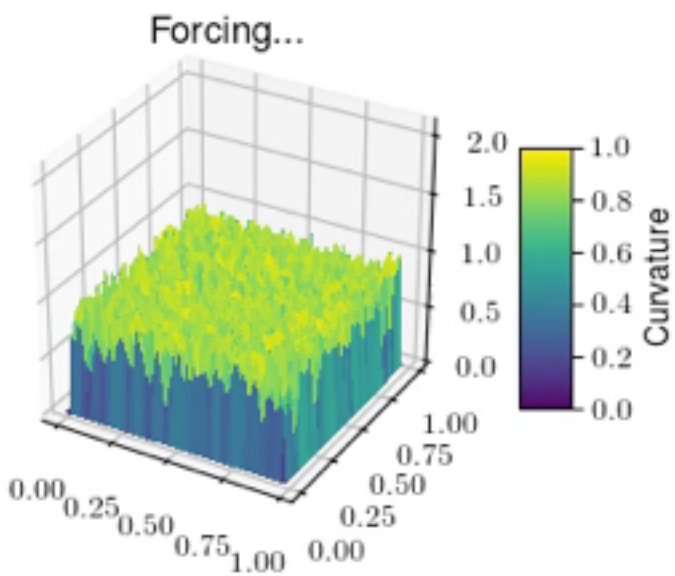
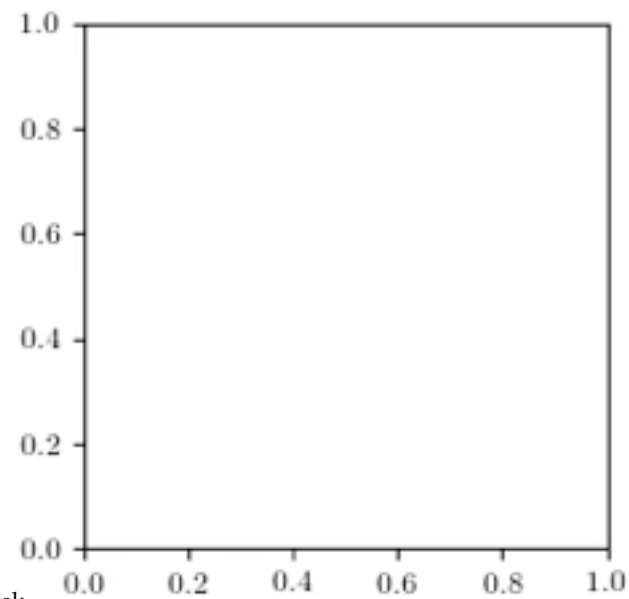




Non-Conservative sandpile model

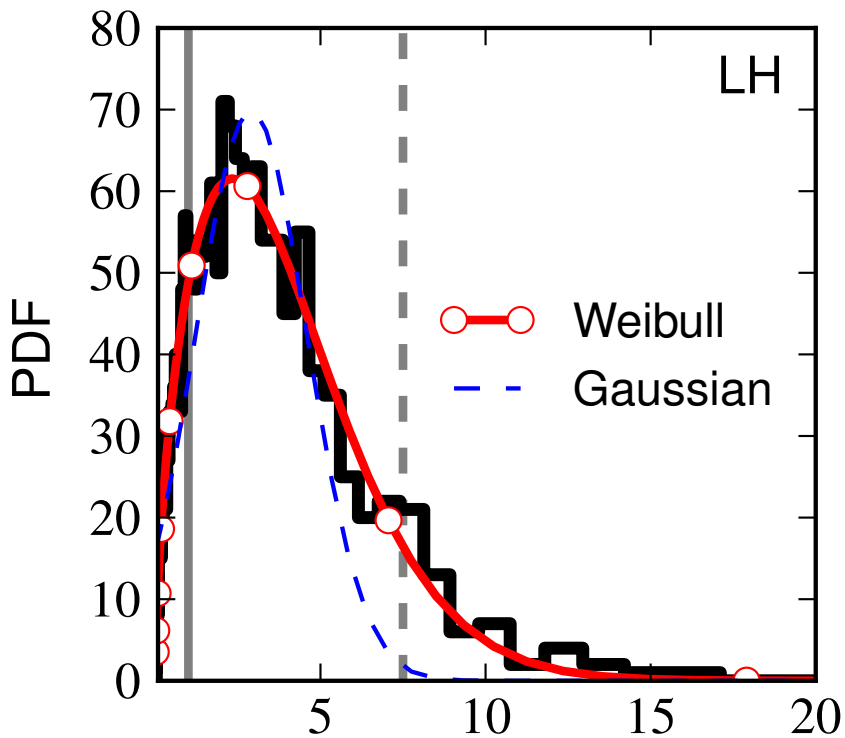
Random seed #2





Robustness of one large event (standard model)

Energy of the largest event
in the time window



2000 stochastic realisations

[Strugarek & Charbonneau 2014]

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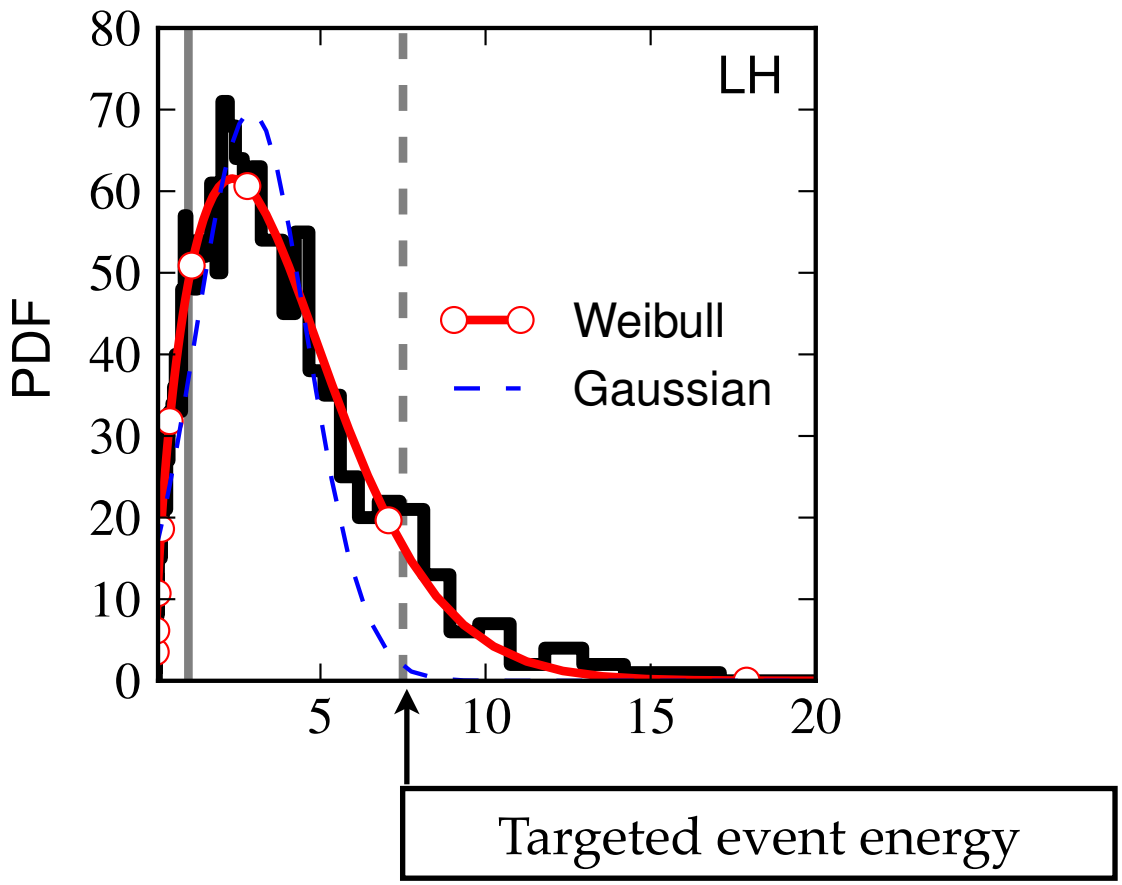

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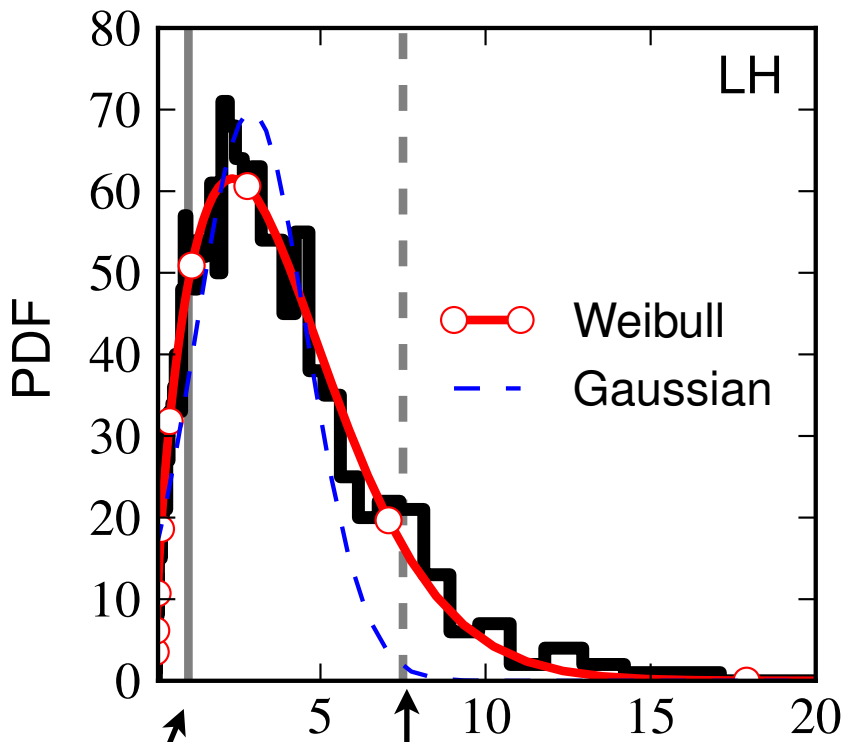

Targeted event energy

Statistical max in the time window

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[Strugarek & Charbonneau 2014]

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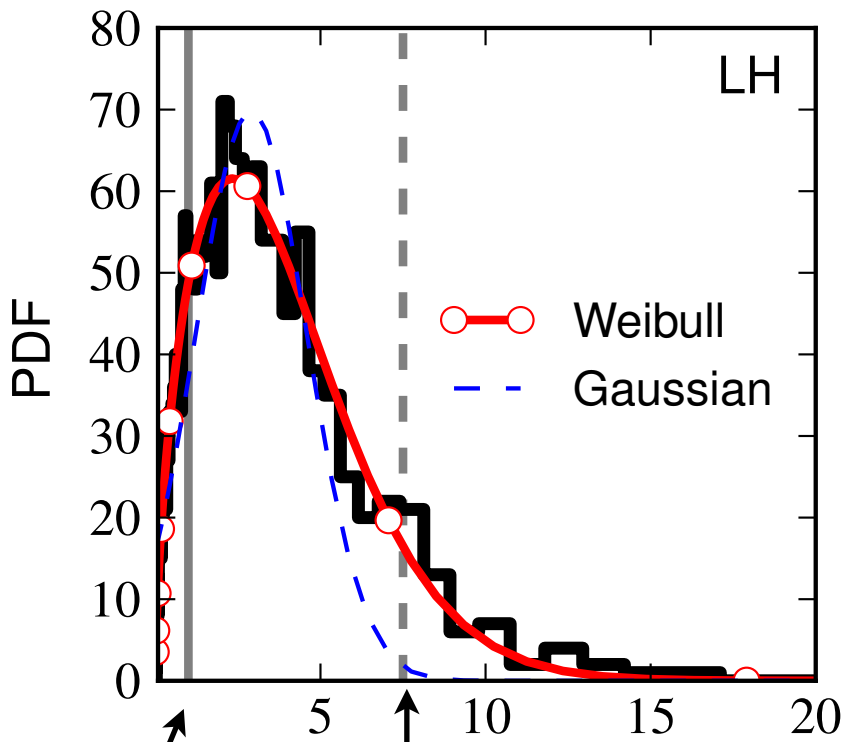
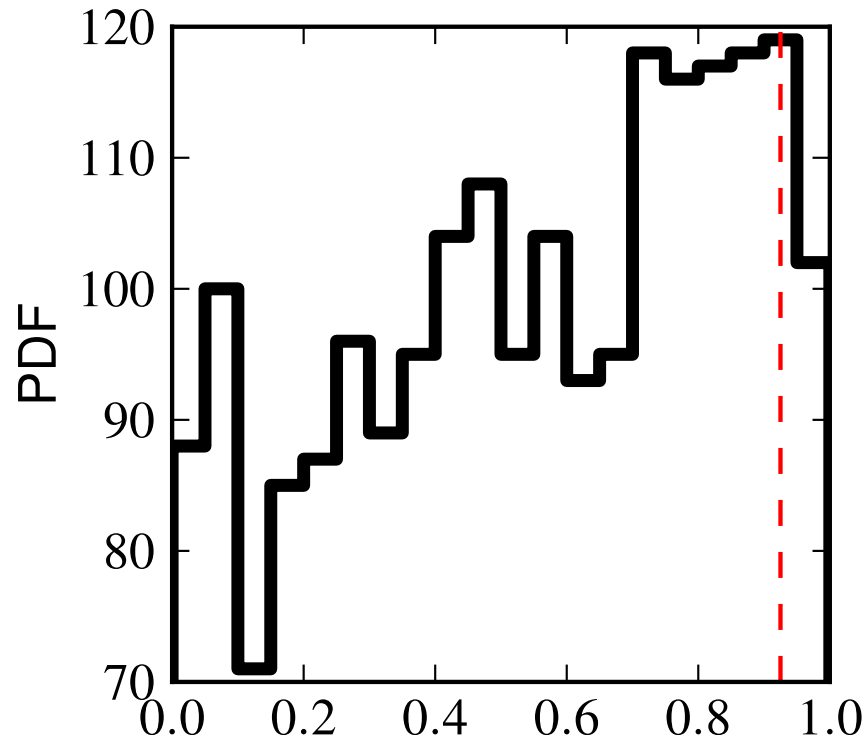


Occurence of the largest event in the time window



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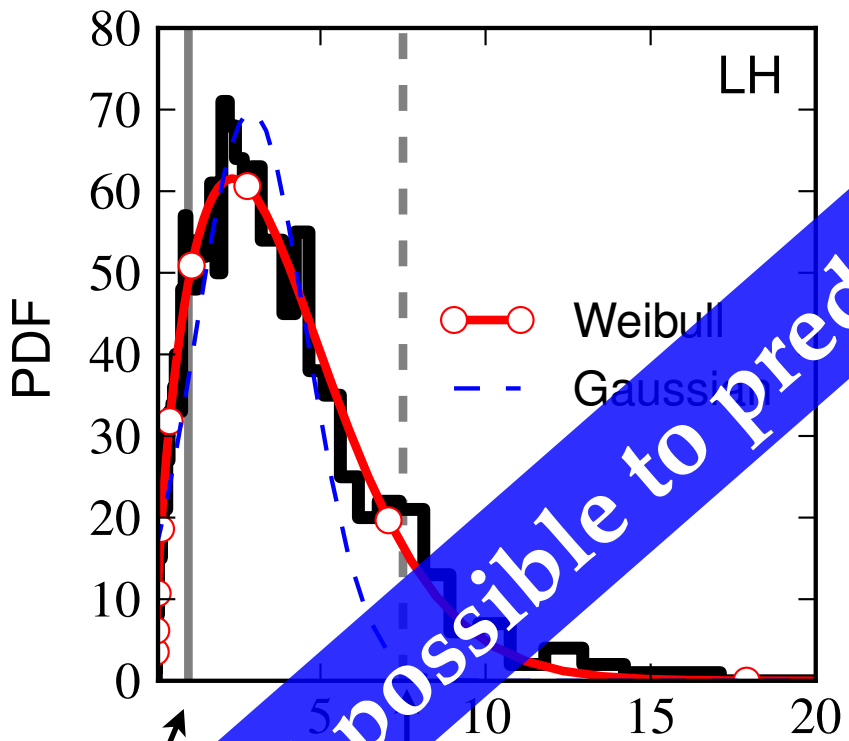

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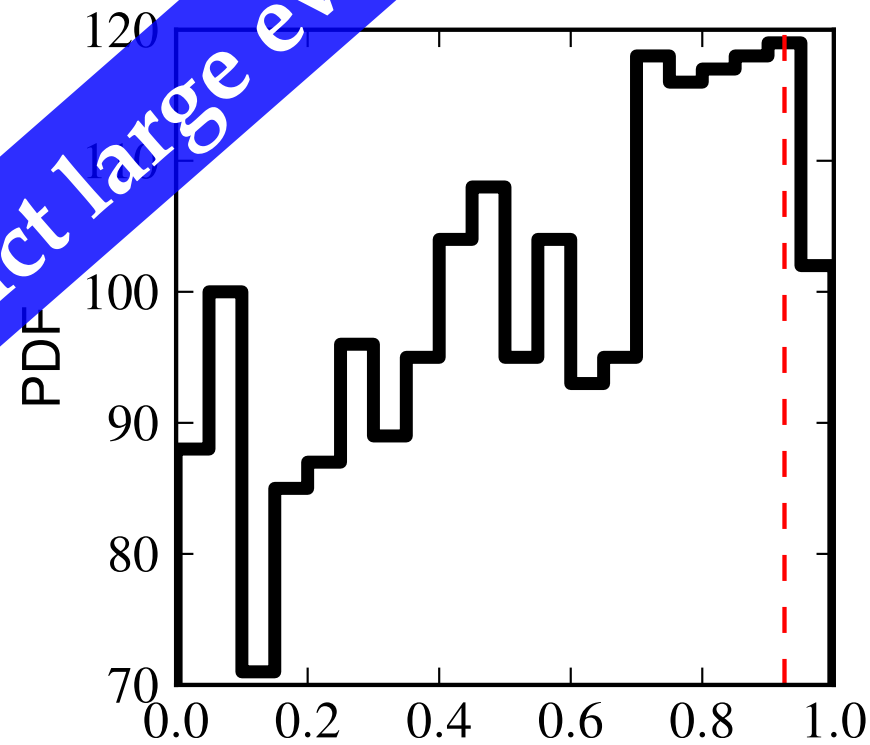


Not possible to predict large events…

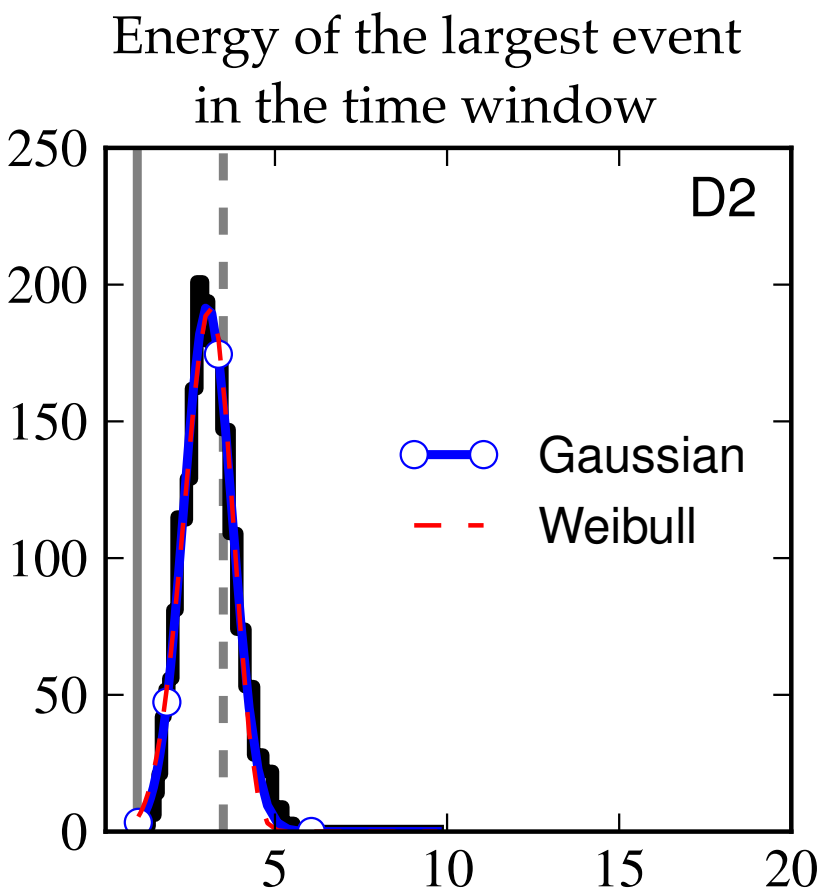
Targeted event energy

Statistical max in the time window

2000 stochastic realisations

[Strugarek & Charbonneau 2014]

Robustness of one large event (D model)



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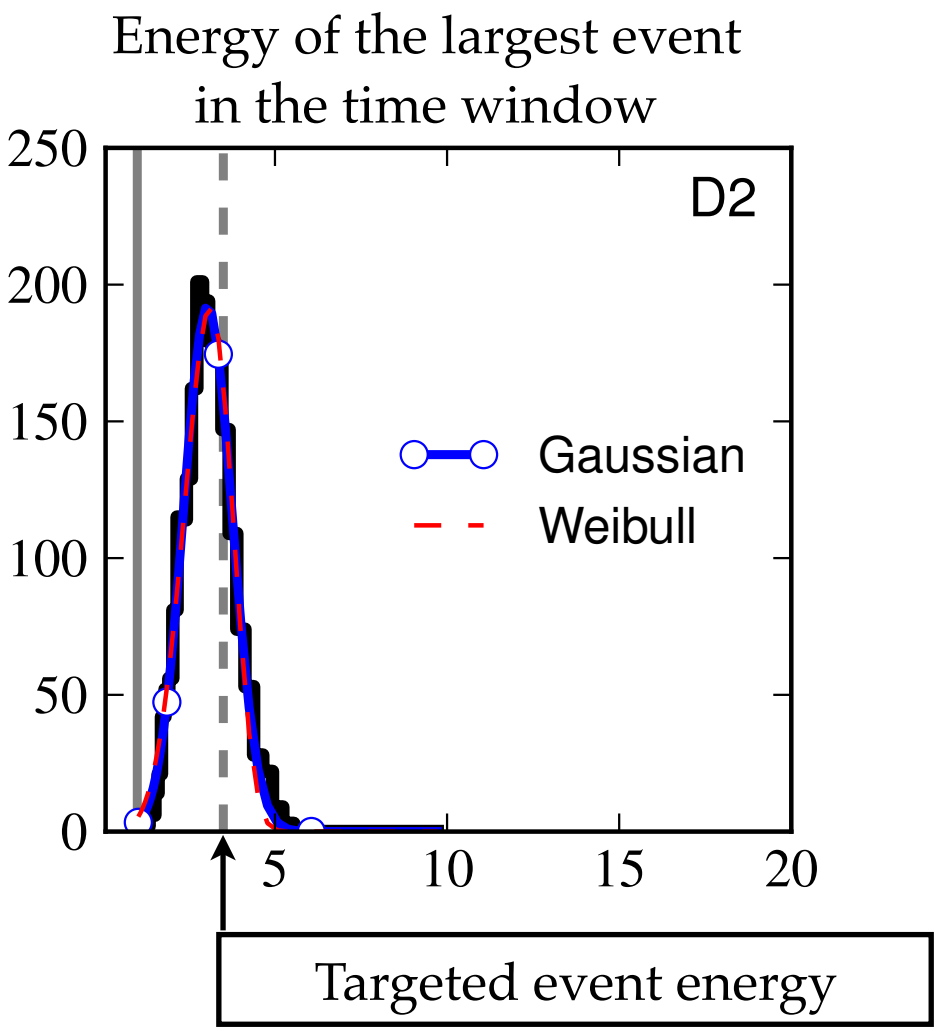

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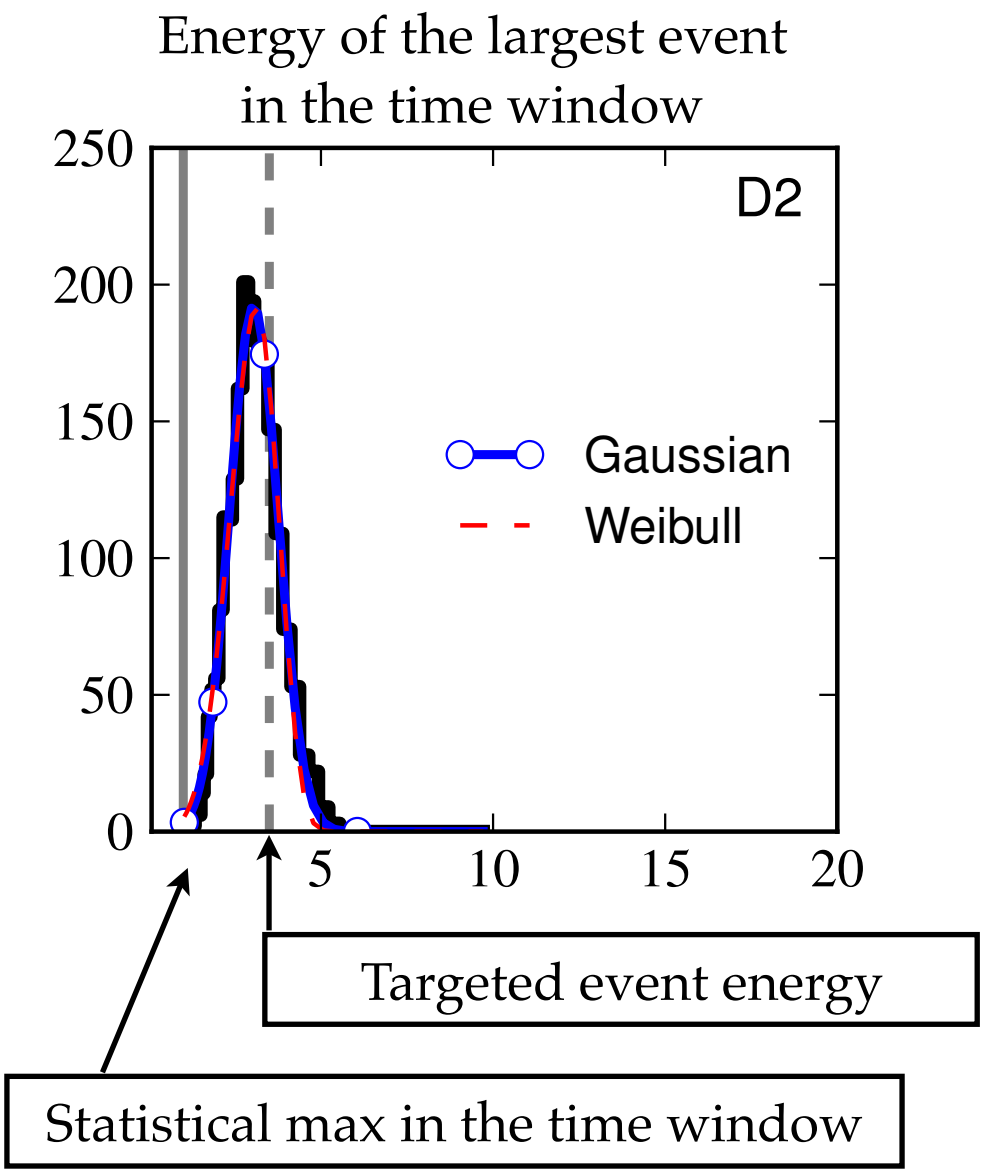

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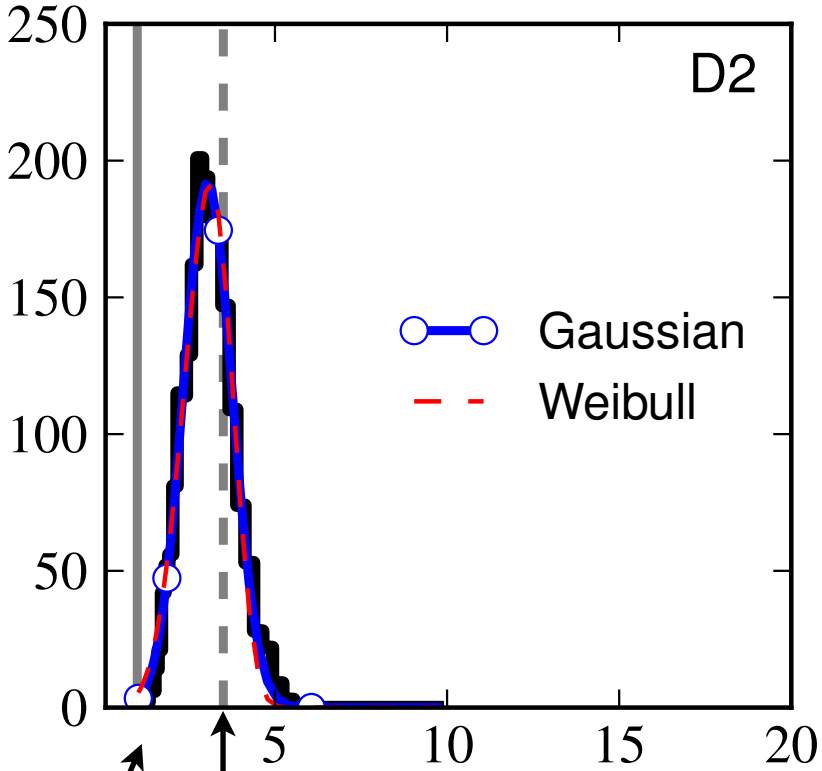

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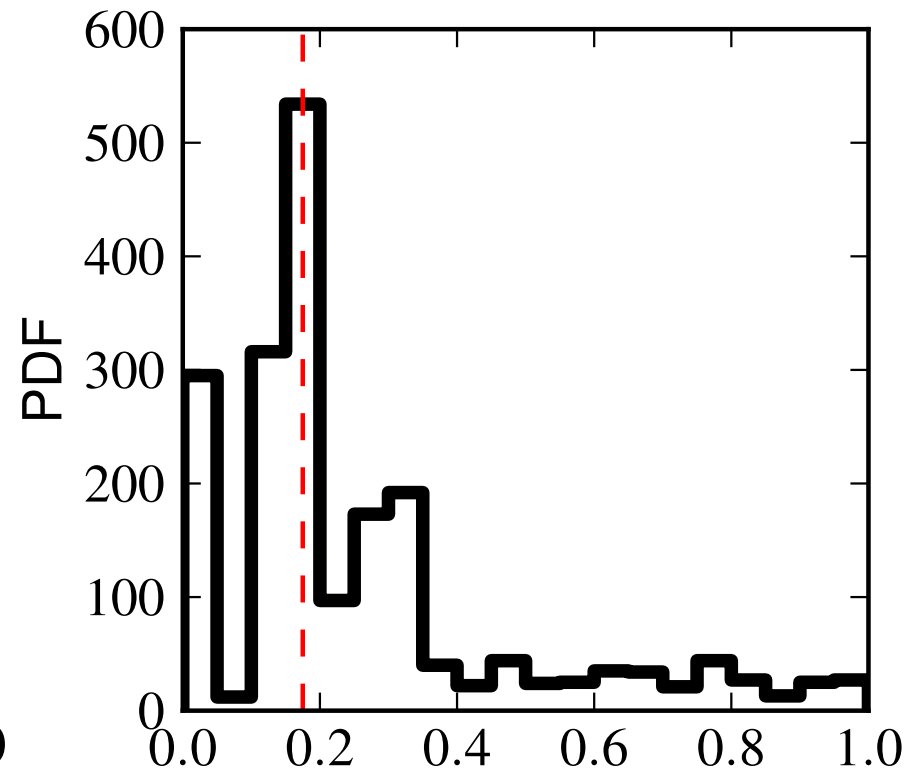

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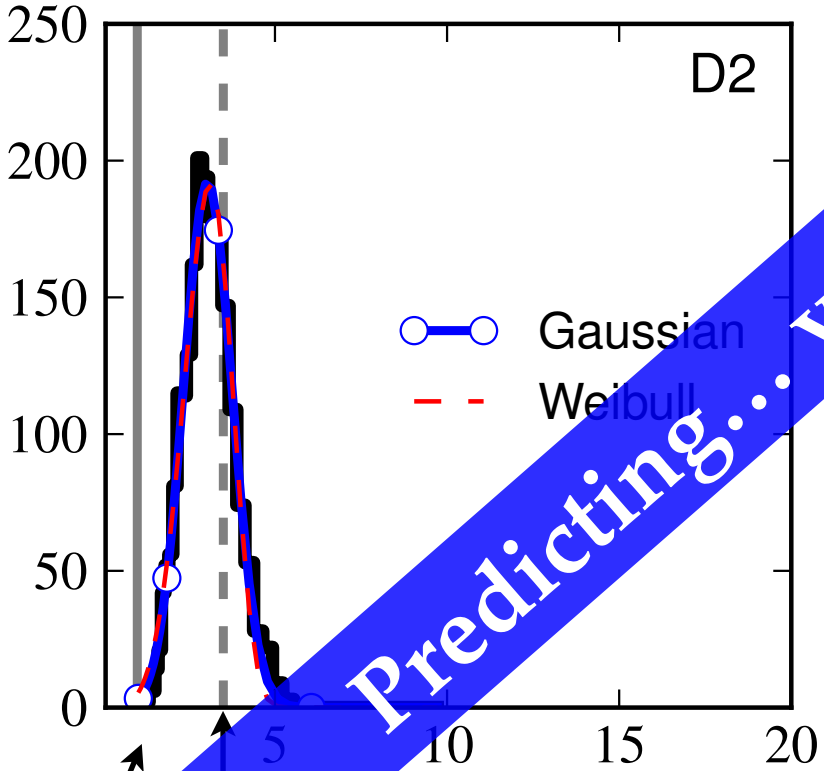

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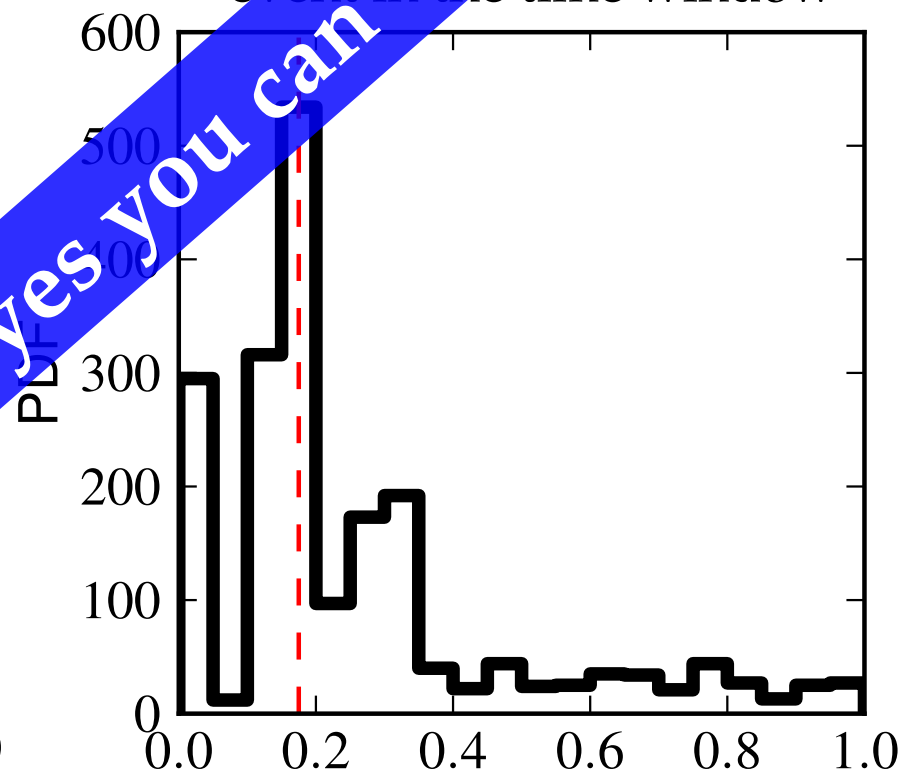


Predicting… yes you can

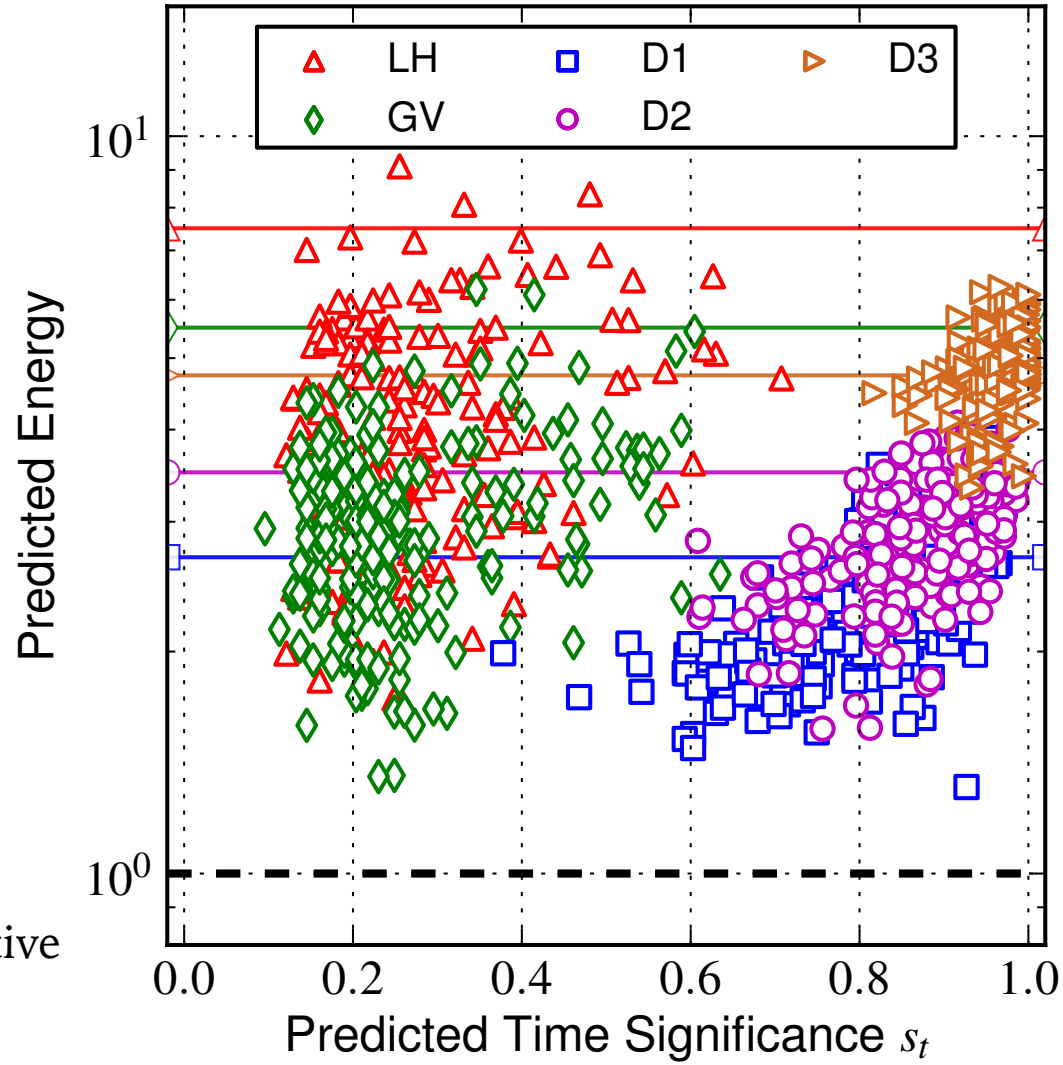
Targeted event energy

Statistical max in the time window

2000 stochastic realisations

[Strugarek & Charbonneau 2014]

Predictive performance of sandpile models

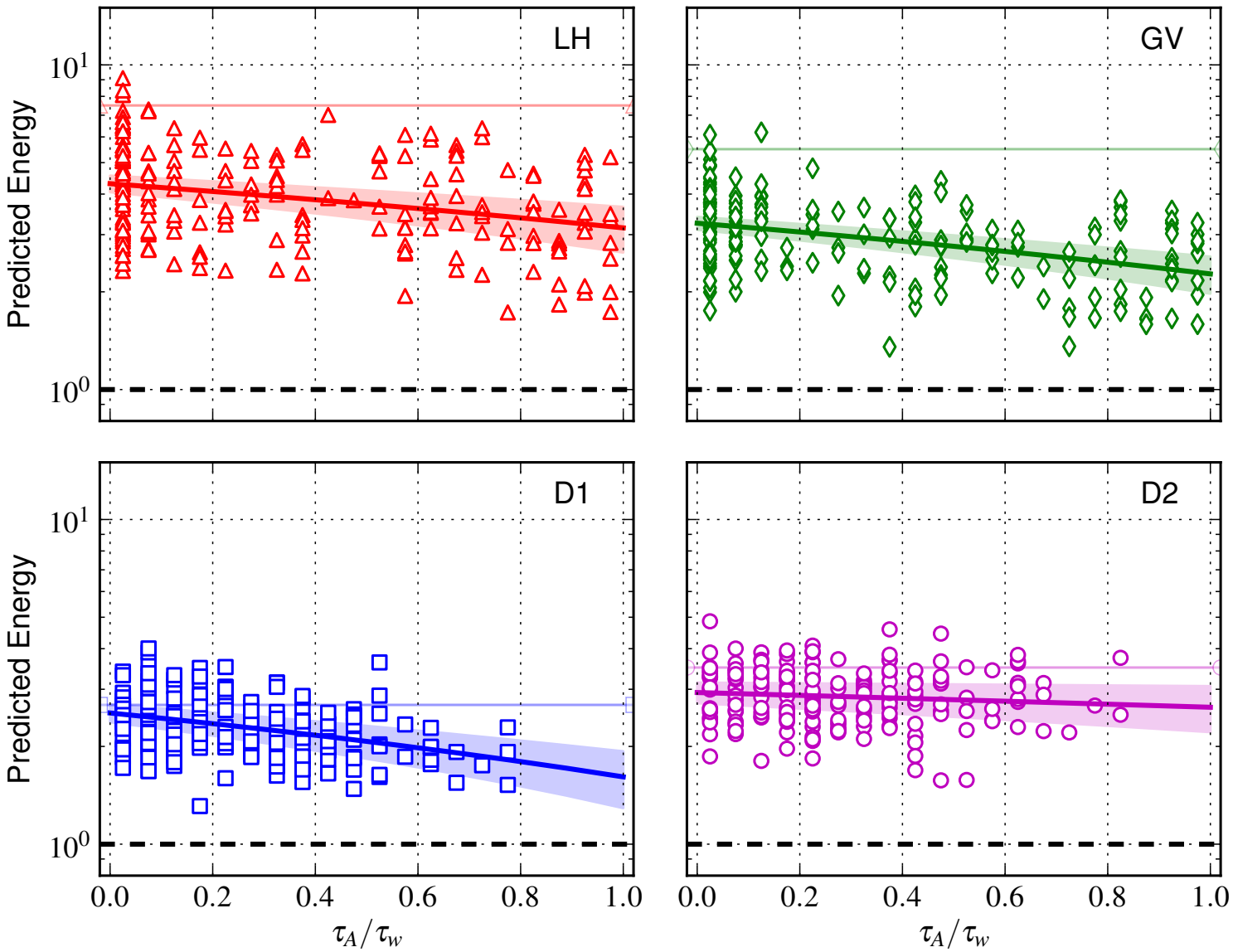


Good predictive capabilities

Bad predictive capabilities

[Strugarek & Charbonneau 2014]

Bias with occurence in the time window



[Strugarek & Charbonneau 2014]

Outline

- Sandpile model and solar flares

Strugarek+ 2014, Solar Physics

- Predicting individual (large) events with a stochastic model?

Strugarek & Charbonneau 2014, Solar Physics

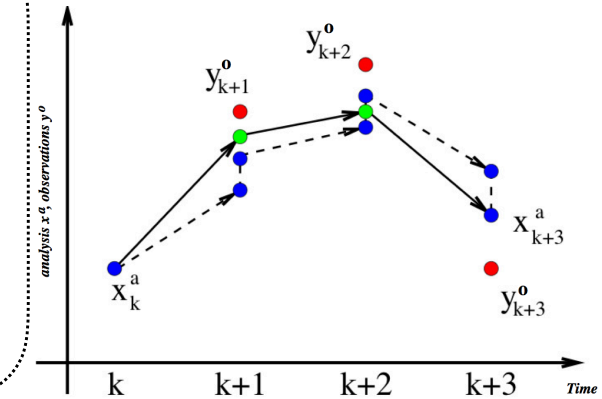
- Data assimilation: towards the Solar Orbiter era

R. Barnabé's PhD thesis (AIM)

Data assimilation in sandpile models: FlarePredict

Initial condition
(+model parameters)

Variational data assimilation



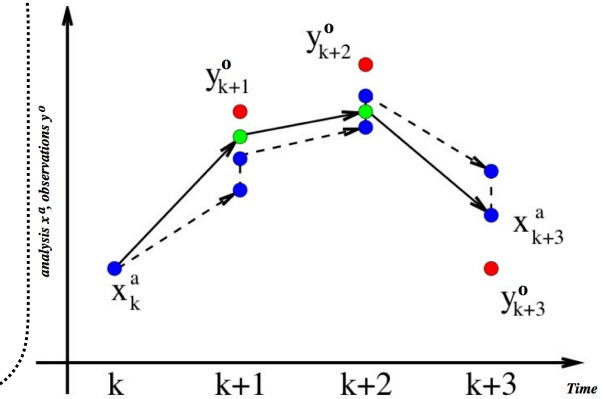
Data assimilation in sandpile models: FlarePredict

Initial condition
(+model parameters)

→

A) Compare model *vs* observations

Variational data assimilation



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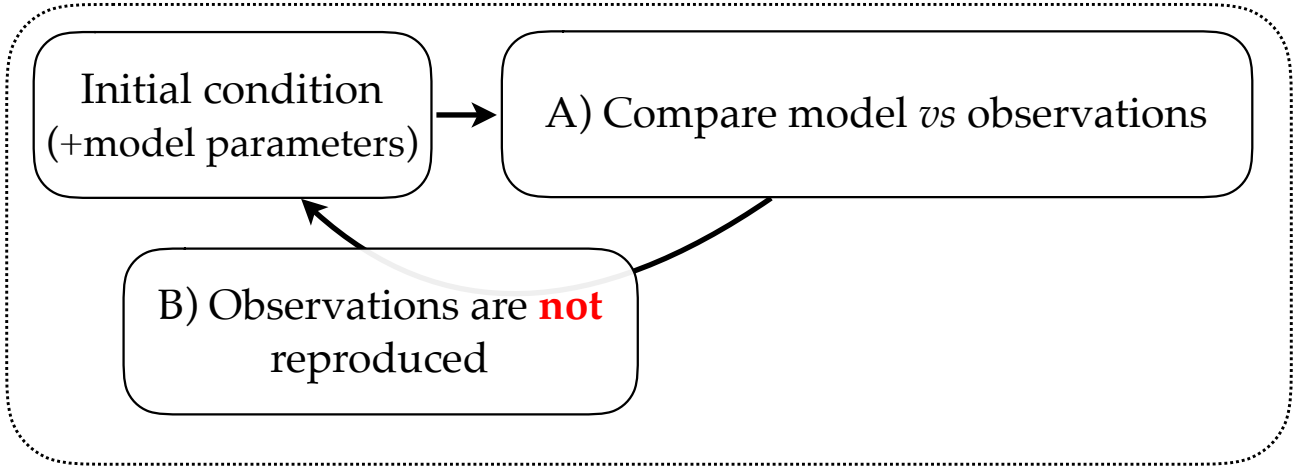

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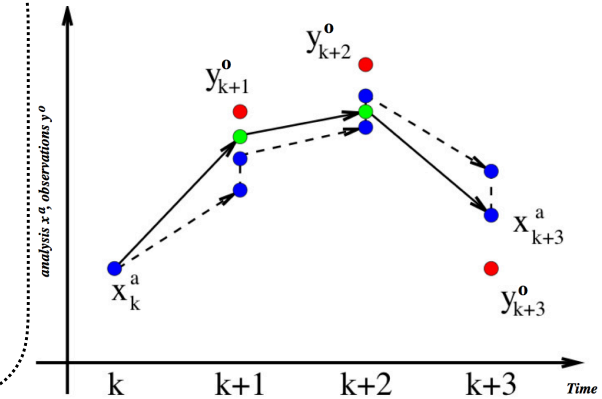

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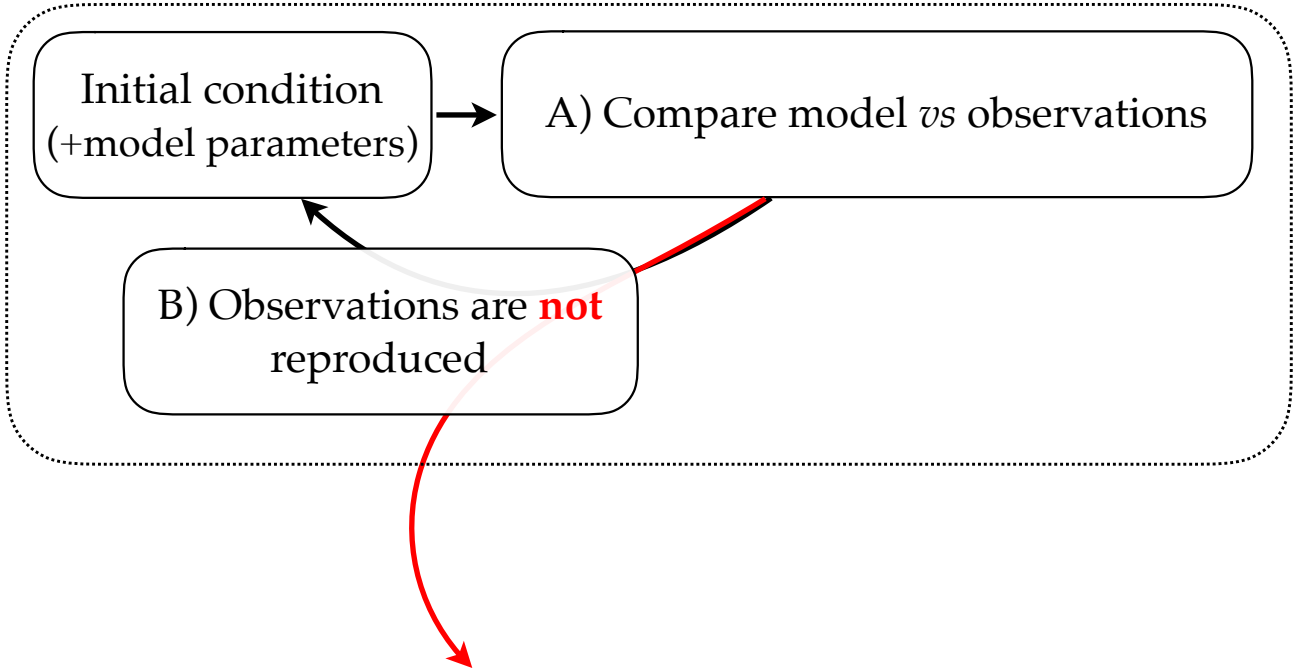

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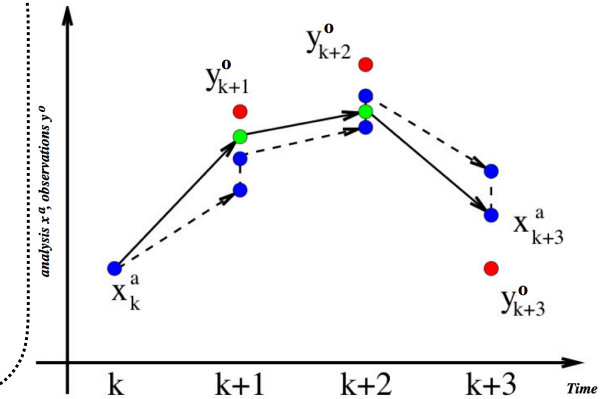

Promising technique: **simulated annealing**

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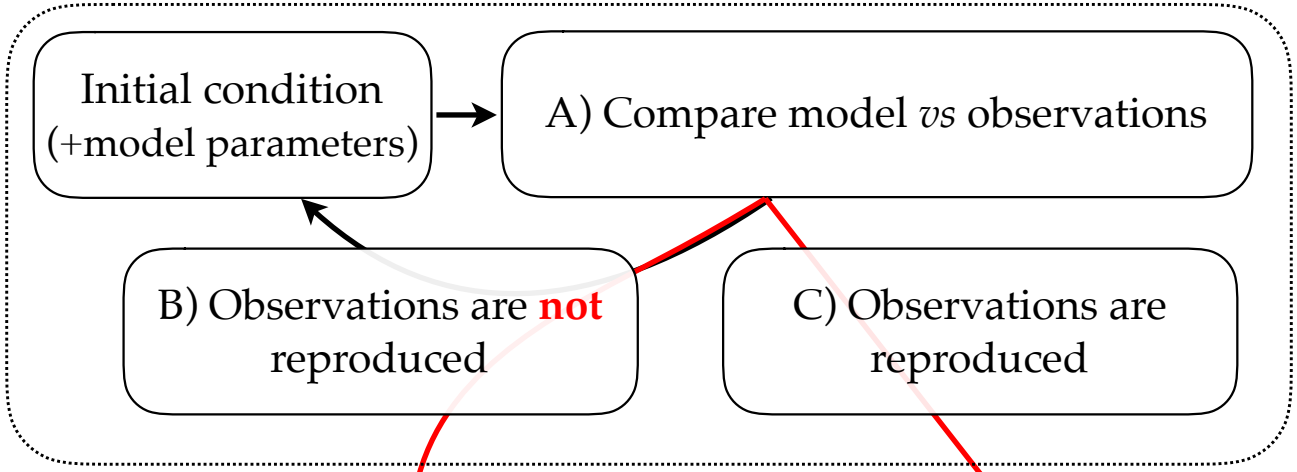

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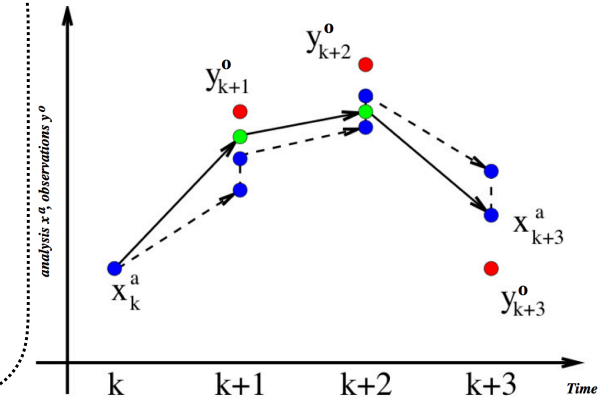
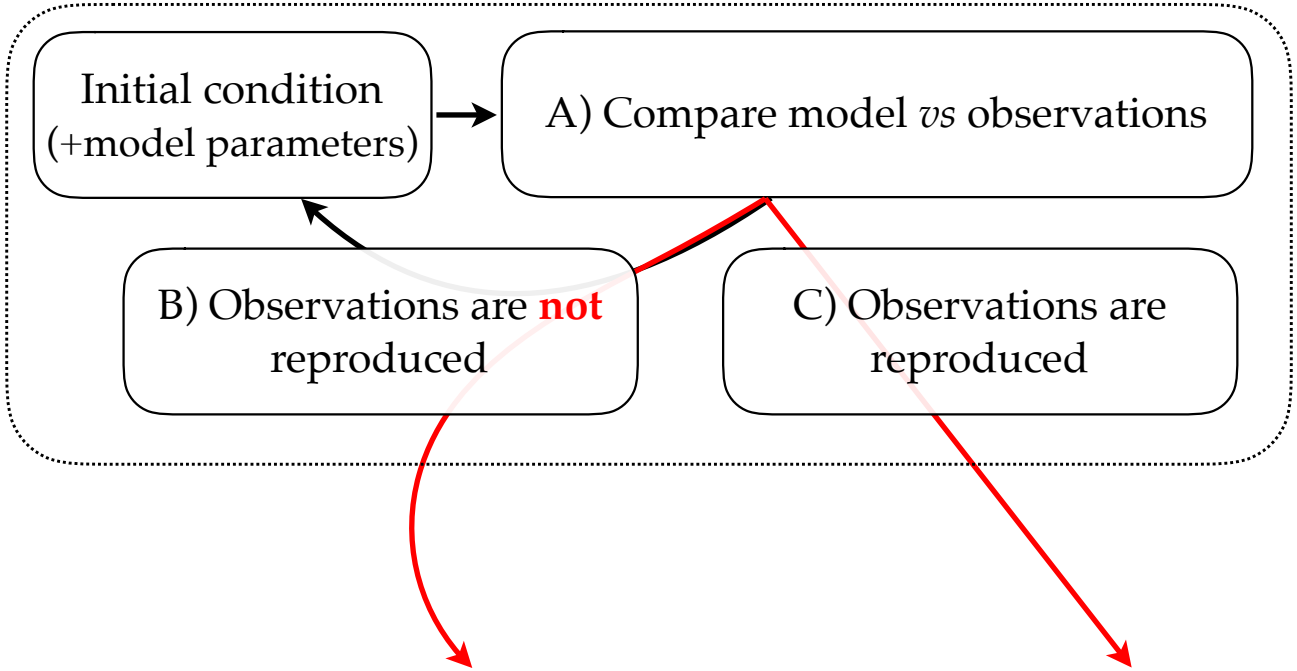


Promising technique: **simulated annealing**

Determine eruptive probability (prediction)

'Hindcasting' on past records first

Data assimilation in sandpile models: FlarePredict



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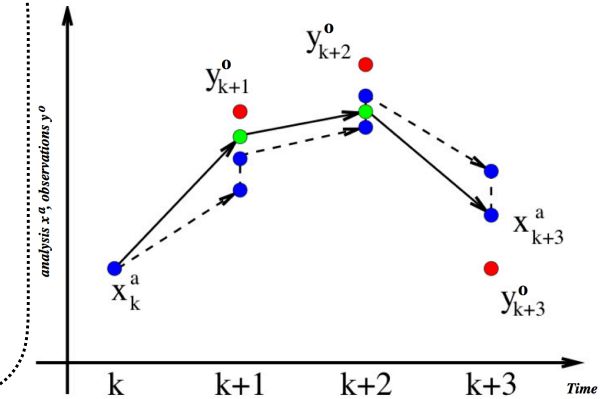

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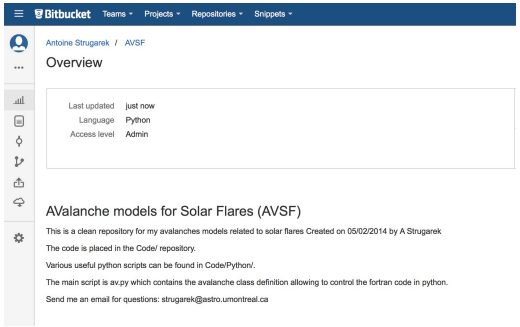
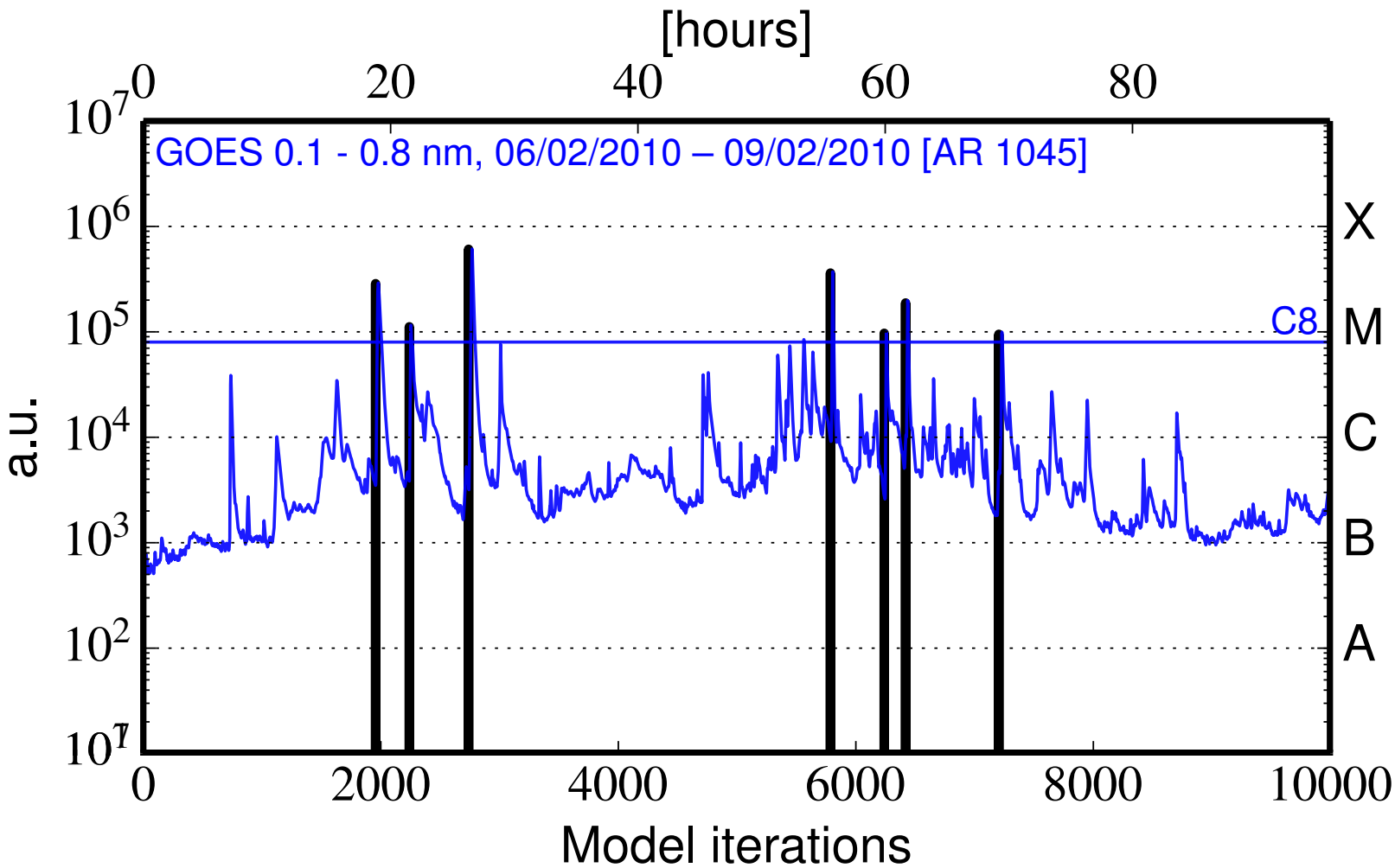


The different blocks are included in a general framework called **FlarePredict** (under development)

A) Comparing observational data with our model (I)

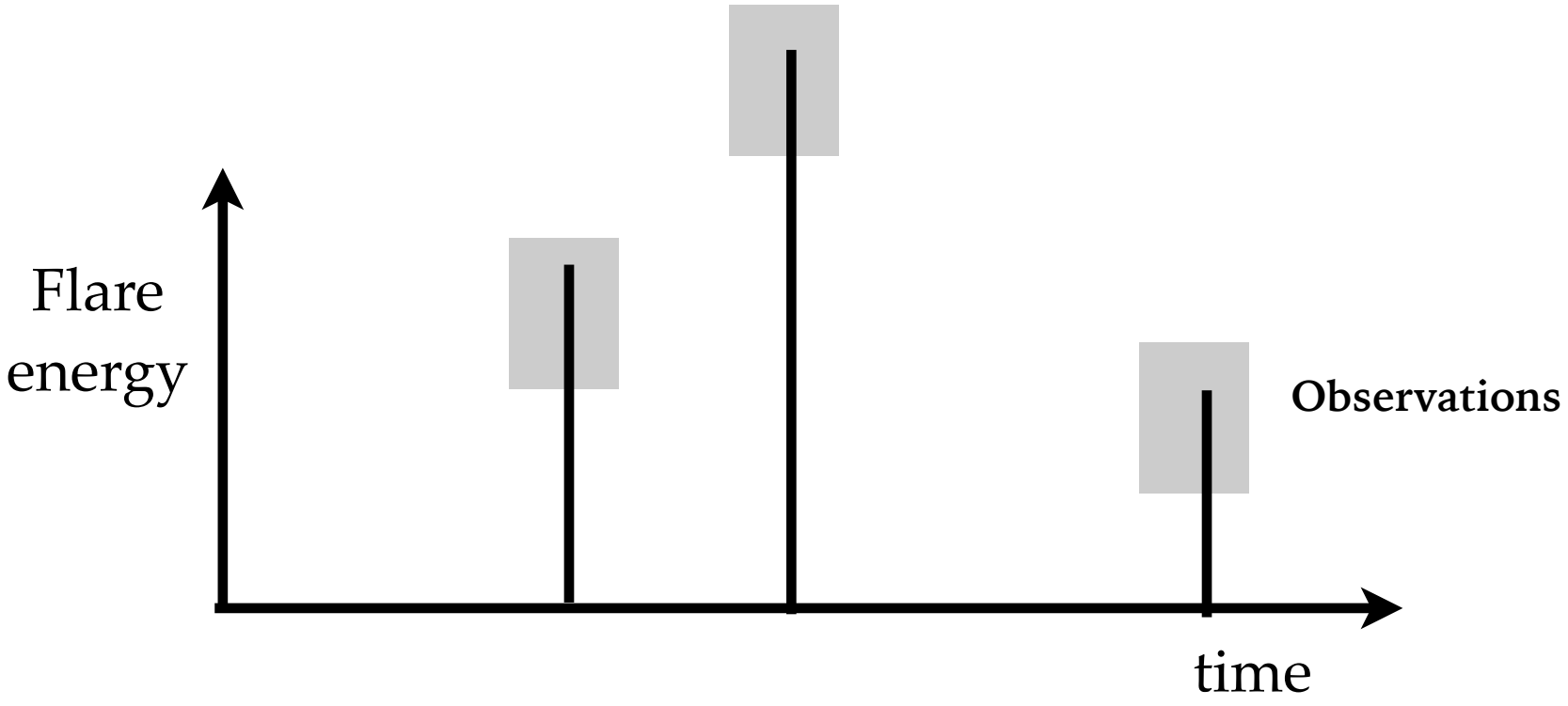


[Aschwanden & Freeland 2012]

A) Comparing observational data with our model (II)

Least squares not efficient because of the discrete character of the events

Defining a versatile **cost function**:



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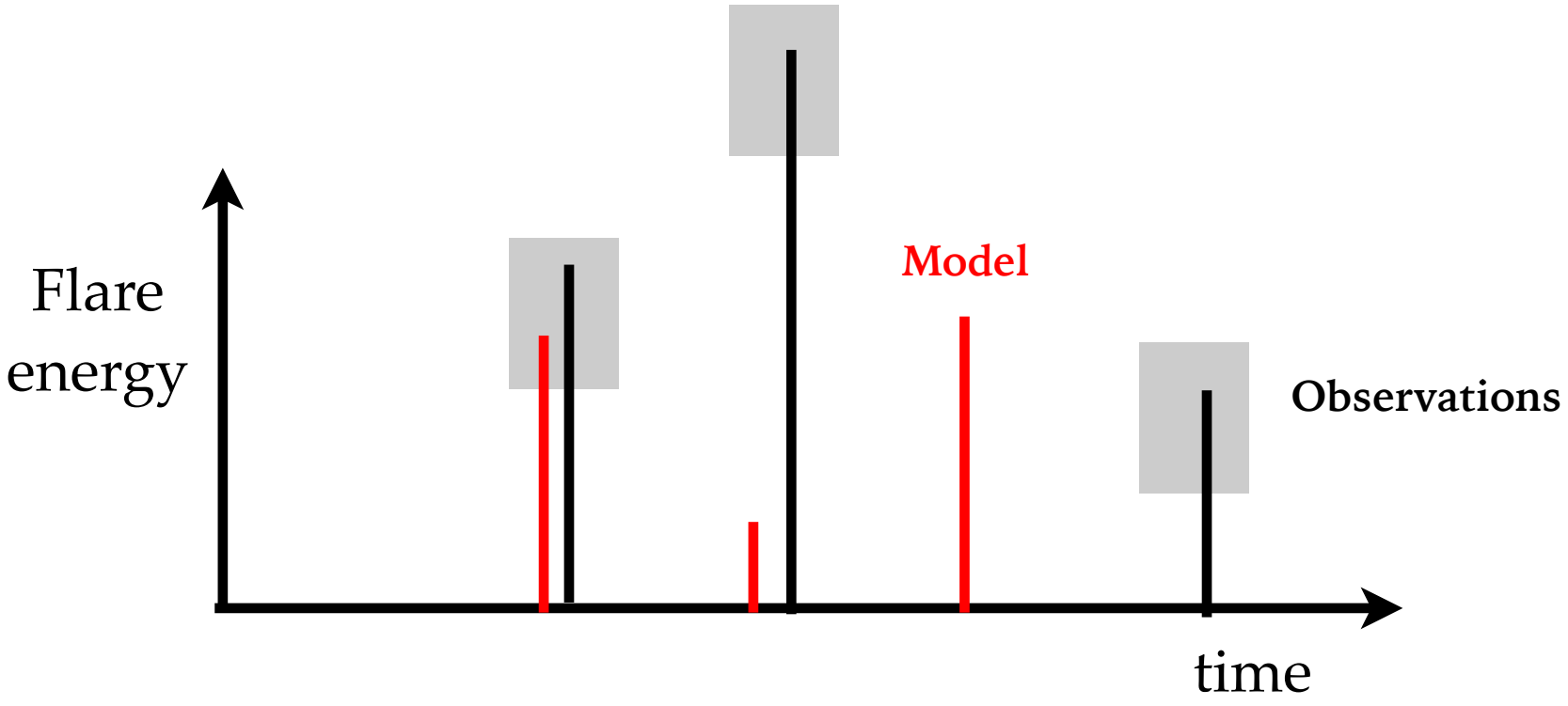

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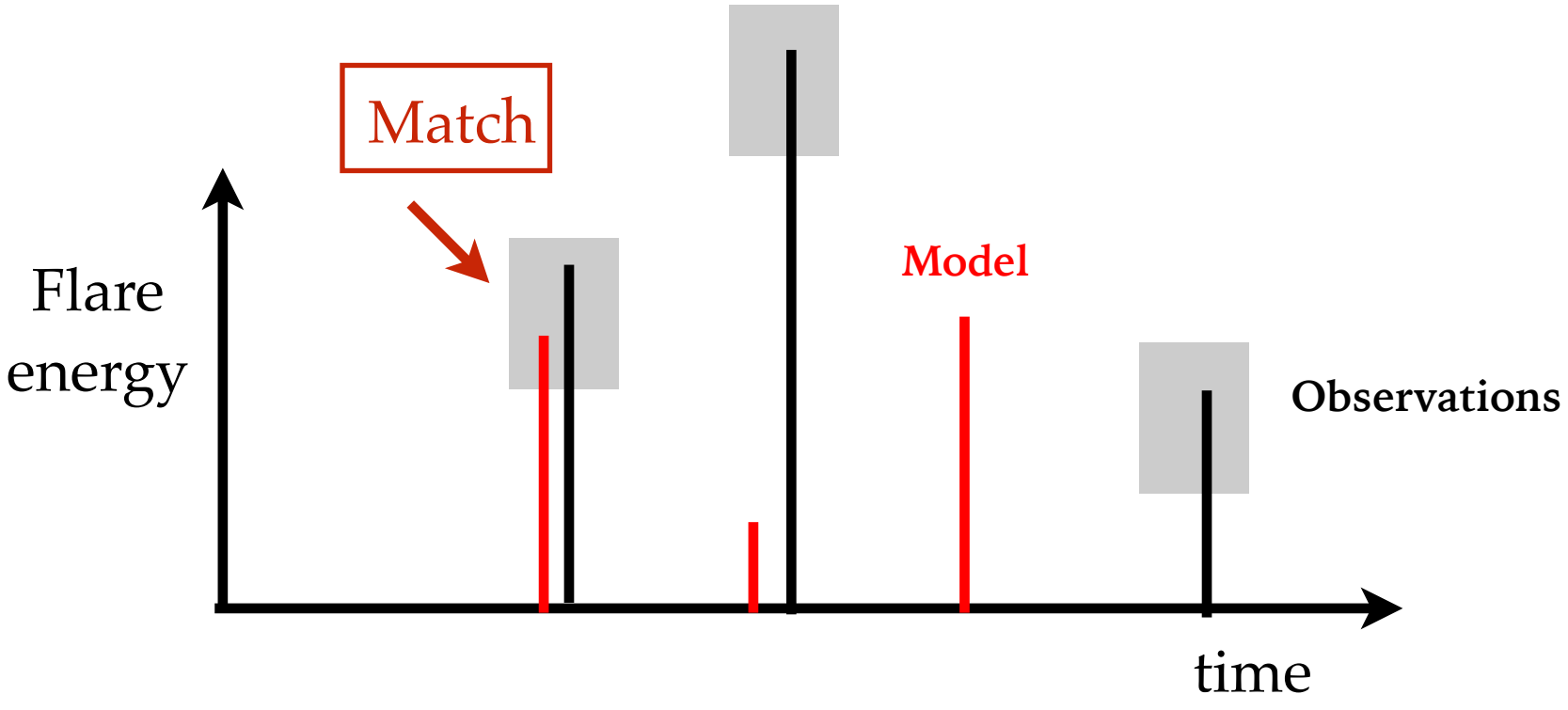

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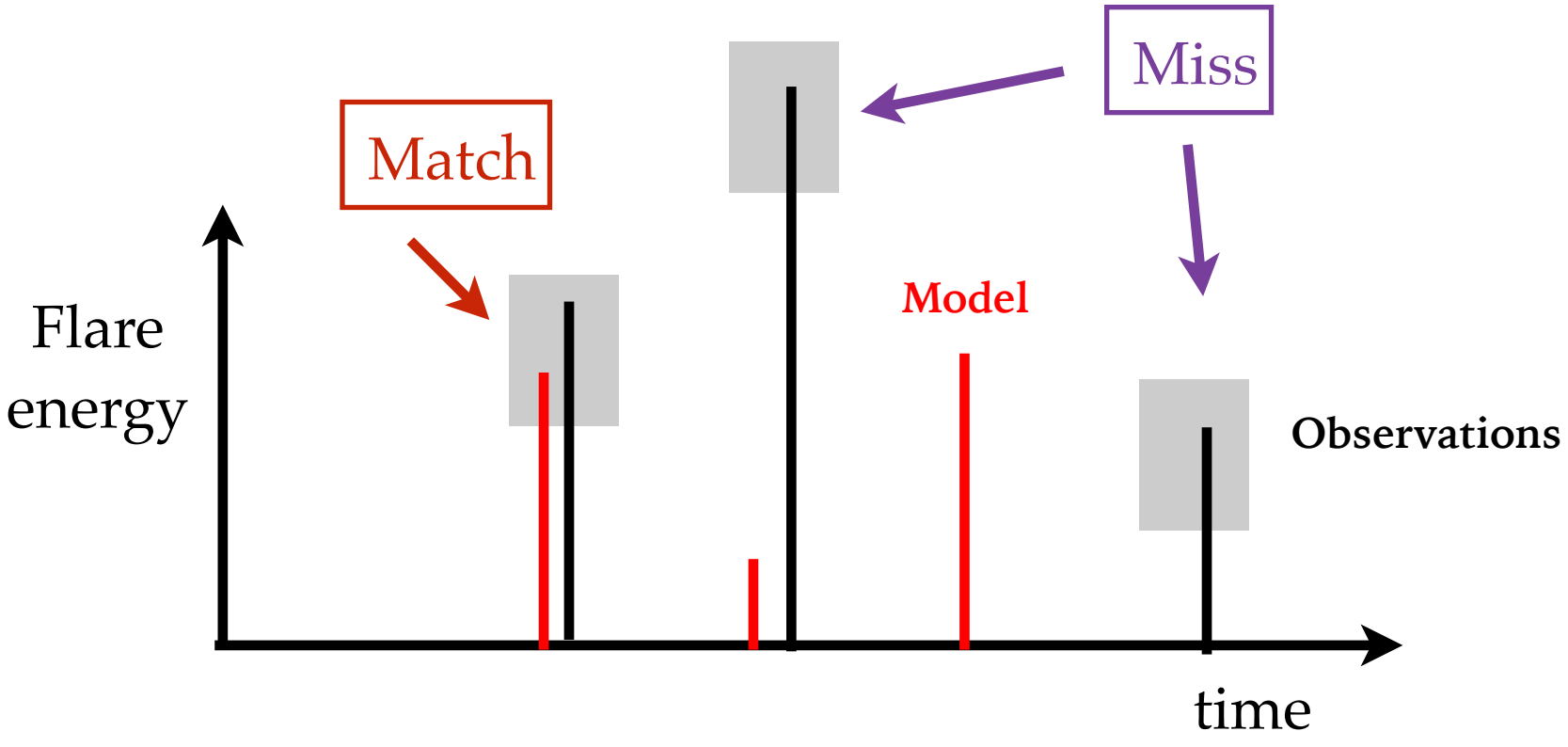

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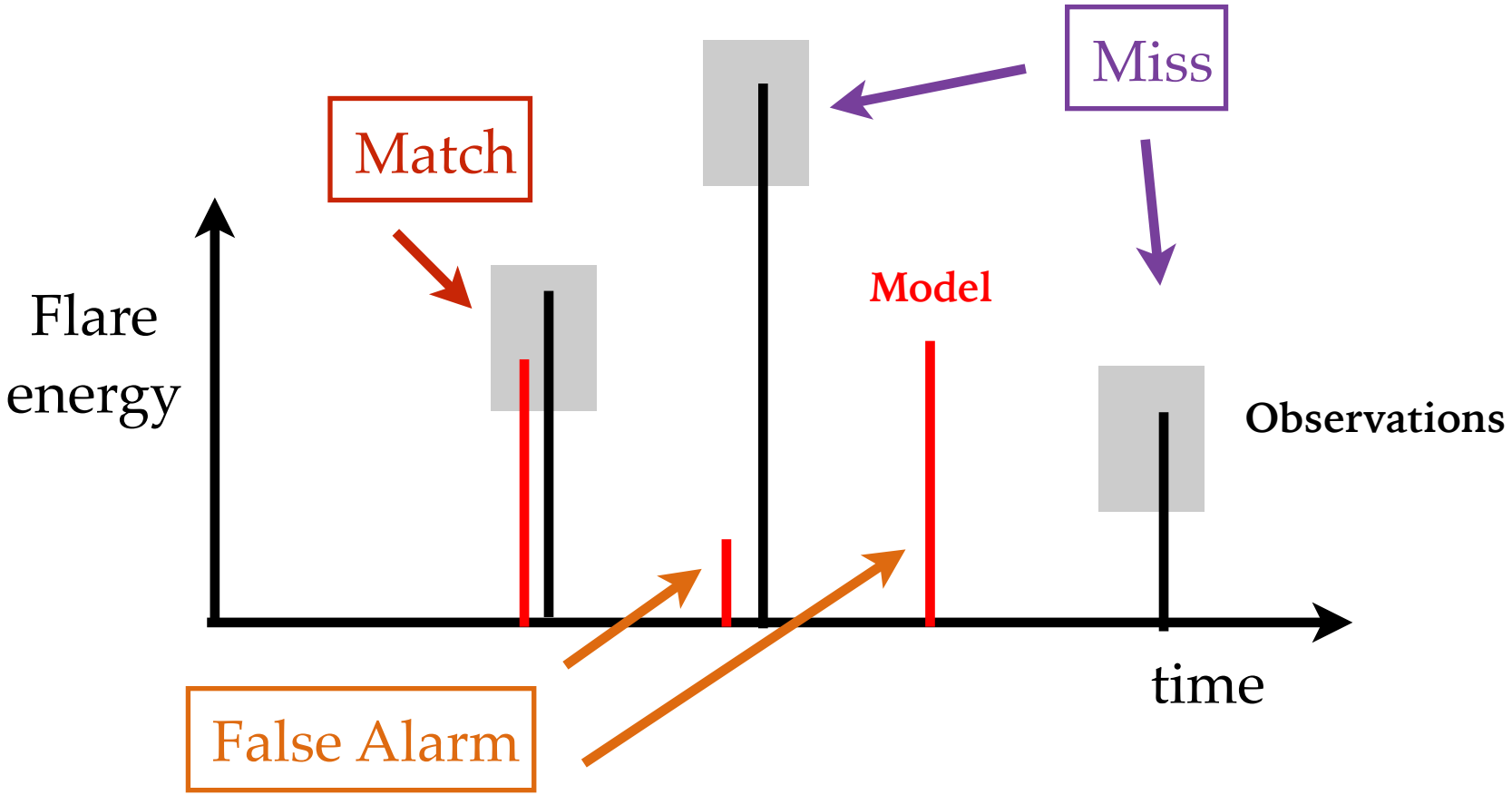
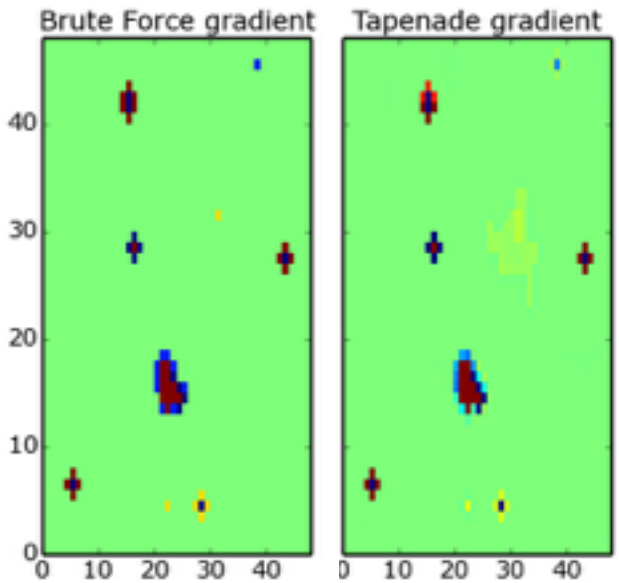


B) Finding a new initial condition reproducing the data (I)

Using the gradient of the cost function



Adjoint method

B) Finding a new initial condition reproducing the data (I)

Using the gradient of the cost function

Adjoint method

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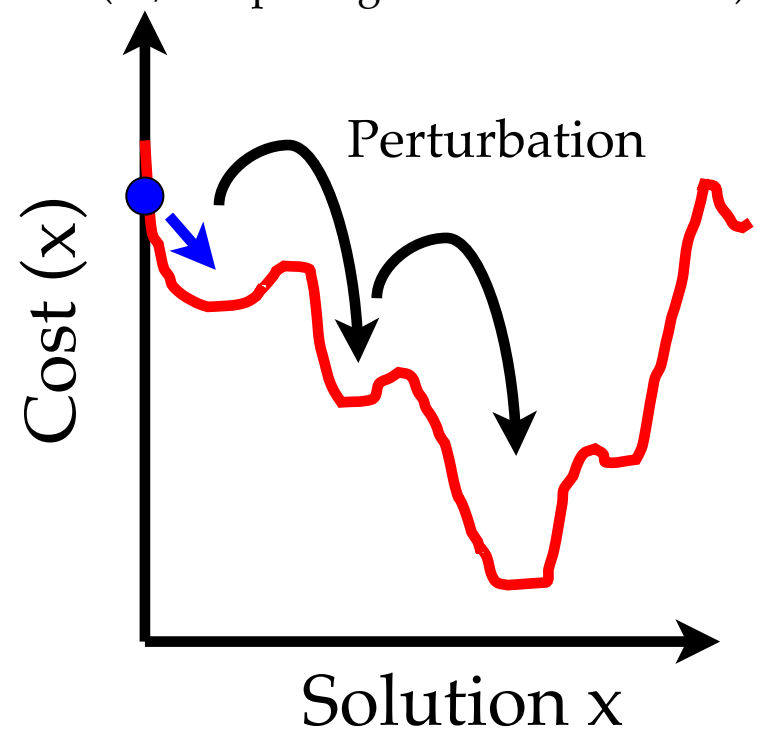
Using the gradient of the cost function

Too many local minima

Adjoint method

Using more robust but more expensive methods
(w/o explicit gradient calculation)

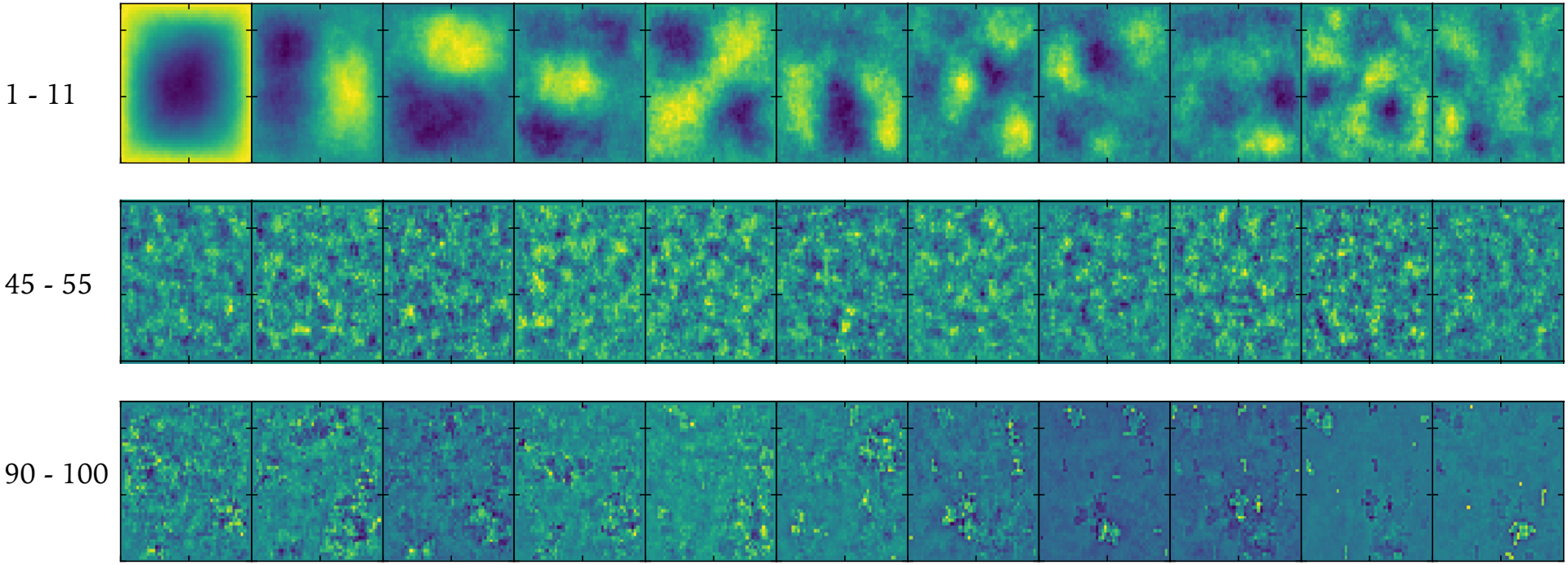


Simulated annealing

B) Finding a new initial condition reproducing the data (II)

Simulated annealing is not very efficient: N^2 realizations of the model are used to minimize the cost function

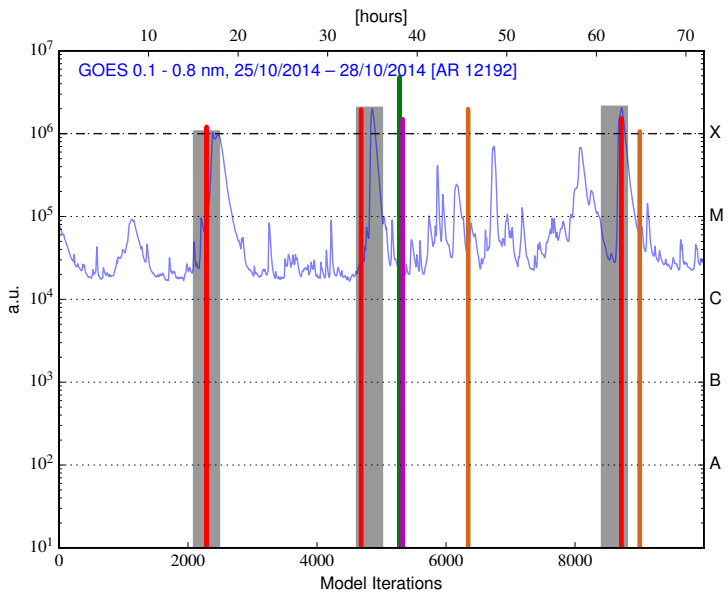
Work in progress: reduce this number by projecting the sandpile model on its **eigenvectors**

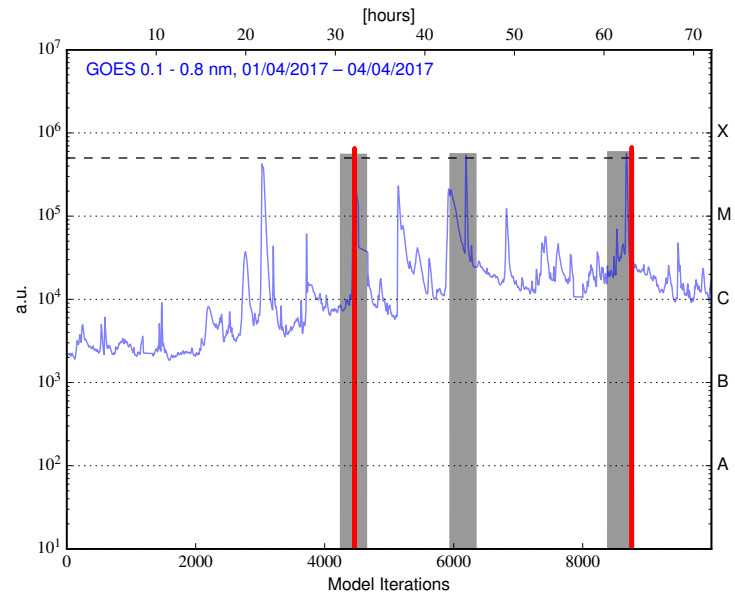


In this case, $\mathbf{N^2 = 2304}$ **eigenvectors** (N degrees of freedom)

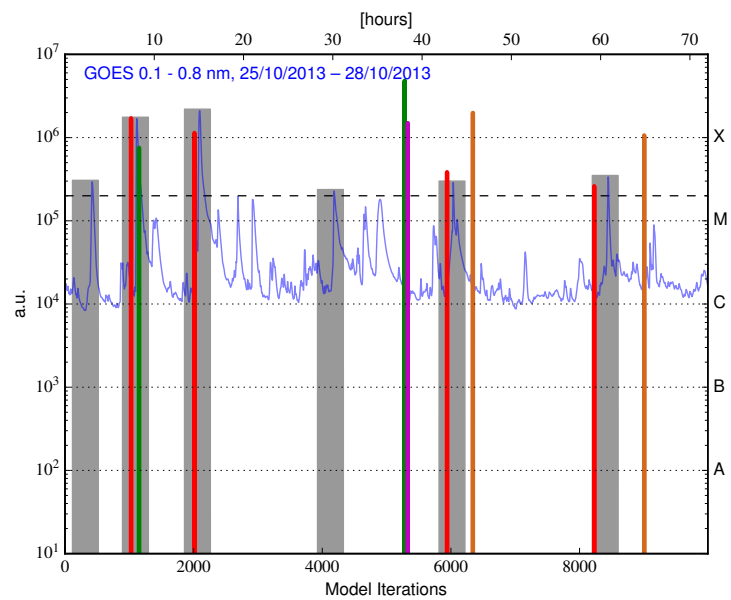
C) Towards a predictive tool…

3 X-flares





3 M-flares



2 X-flares
+
4 M-flares

Summary

Develop a 'physics-inspired' SOC model that reproduces the solar flare statistics

[Strugarek+ 2014]

Demonstrate the predictive capabilities of particular sandpile model(s)

[Strugarek & Charbonneau, 2014]

Reduce solar X-ray data to be used as an input of the data assimilation pipe-line

✔

Implement robust data assimilation techniques (minimization algorithm)

Under investigation: first results are very encouraging

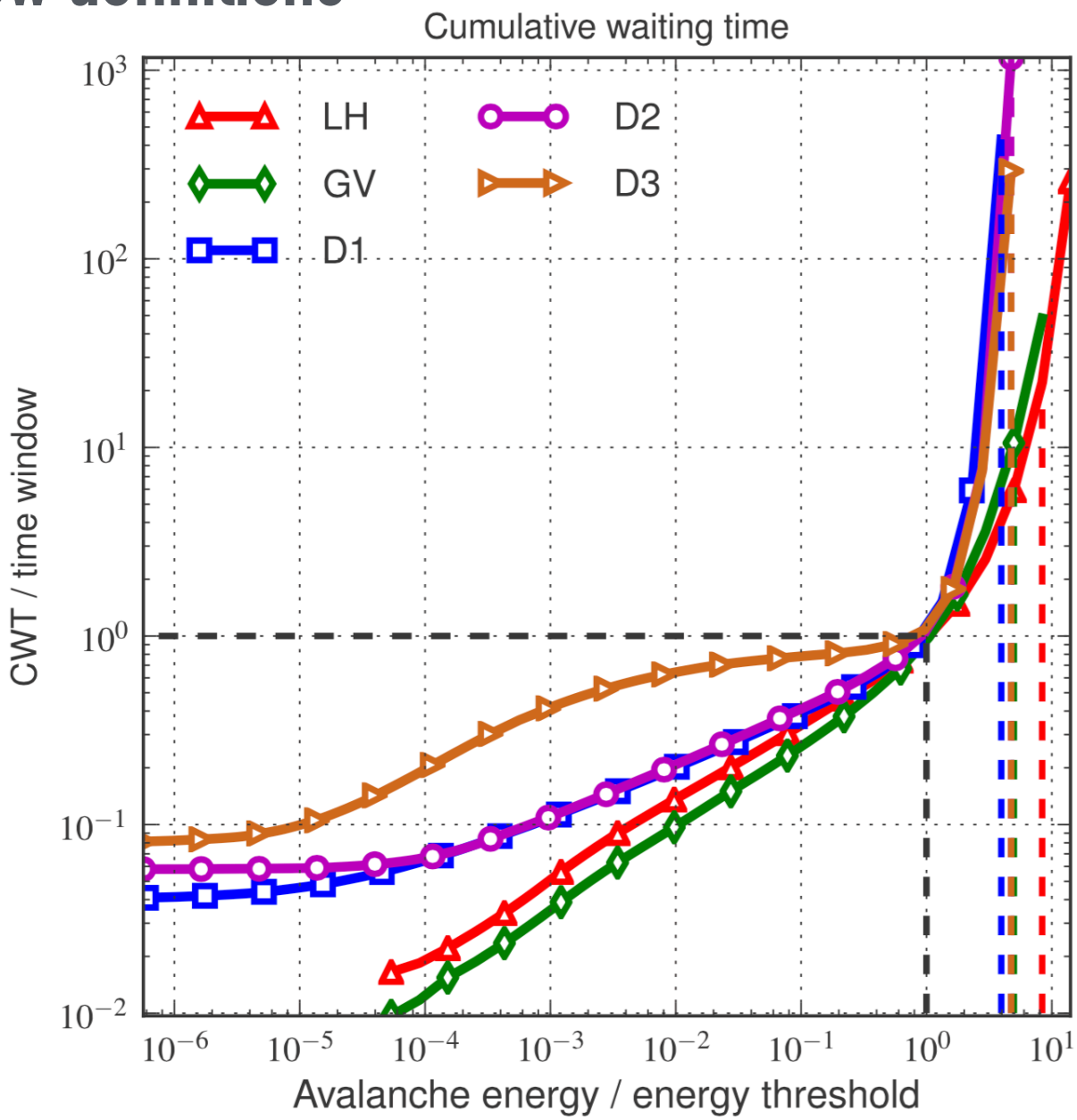
Test the prediction package with a statistically significant sample of real observations

Future: compare sandpile models with MHD models

Stay tuned!

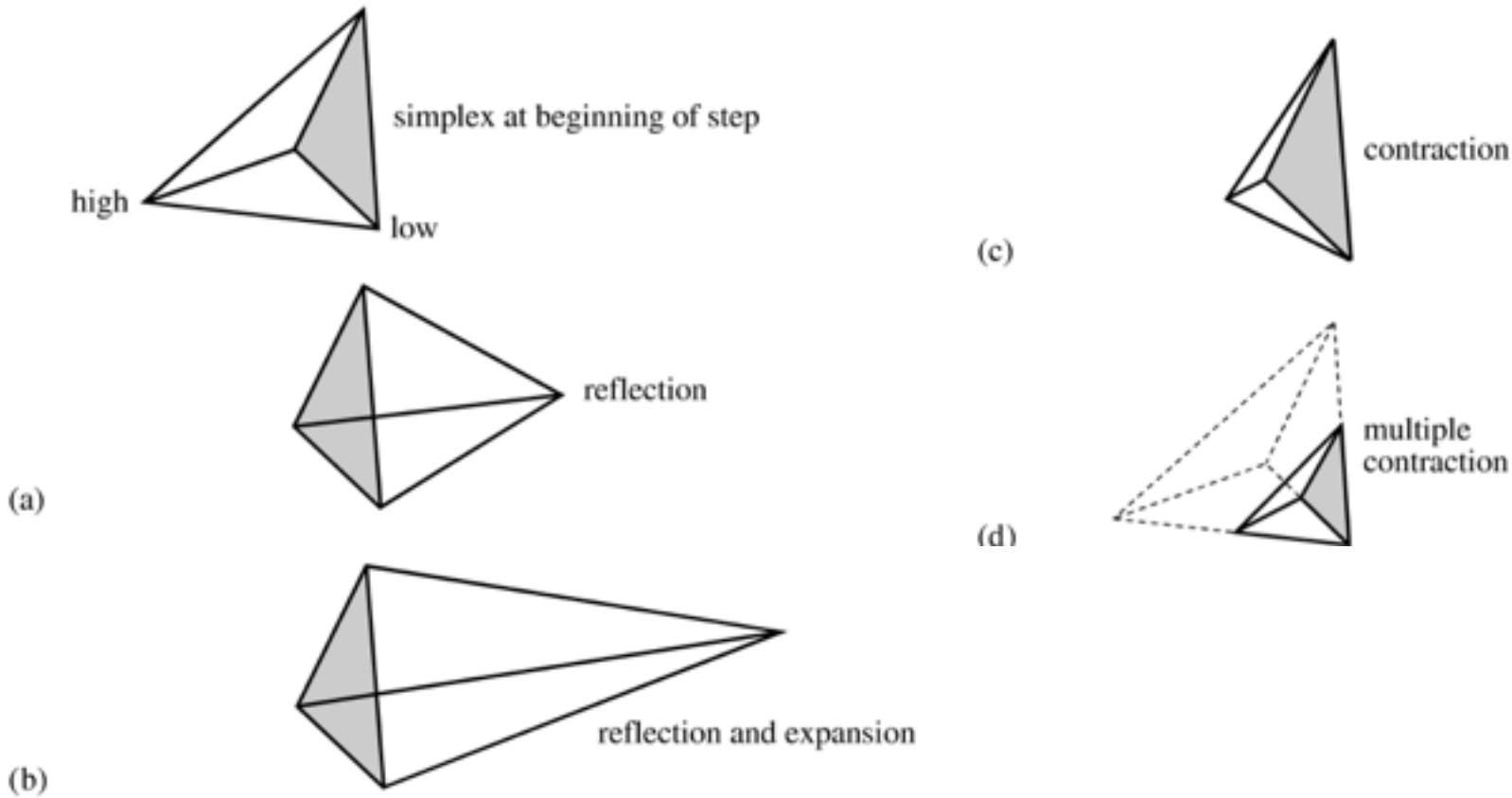
Thank you for your attention!

Time window definitions



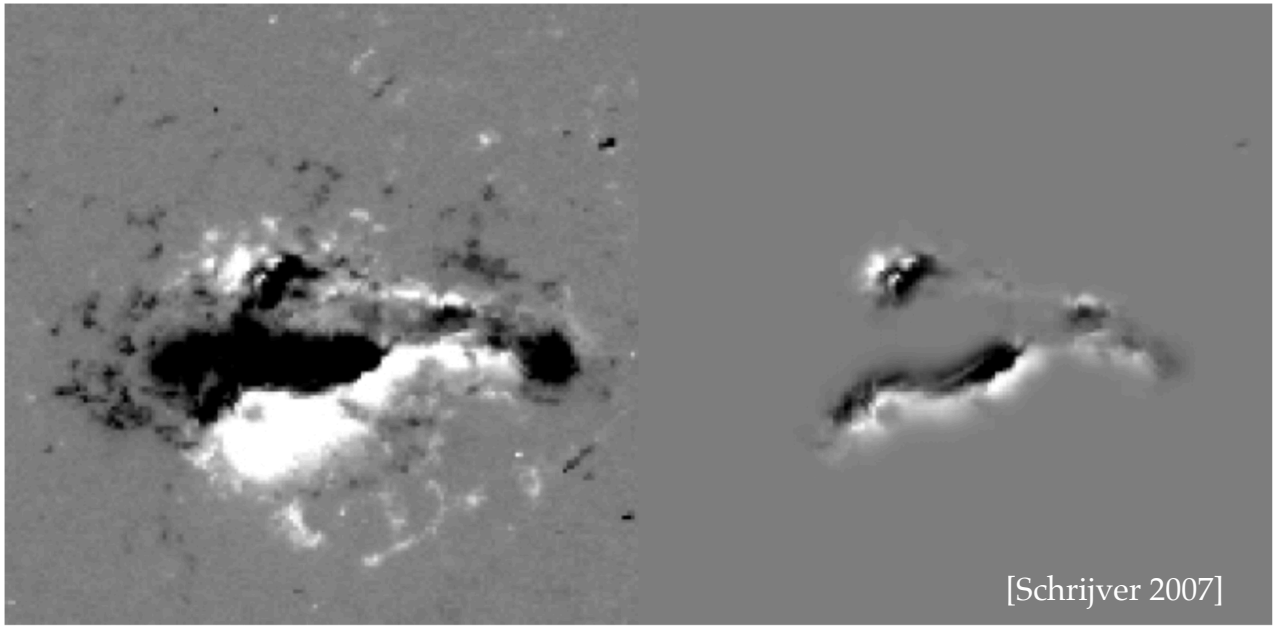
[Strugarek & Charbonneau 2014]

Simulated annealing with the simplex method



The largest flares are extremely hard to predict

Parameter	Success Rate
Climatology	0.908
Φ_{tot}	0.922
E_e	0.916
R	0.922
B_{eff}	0.913

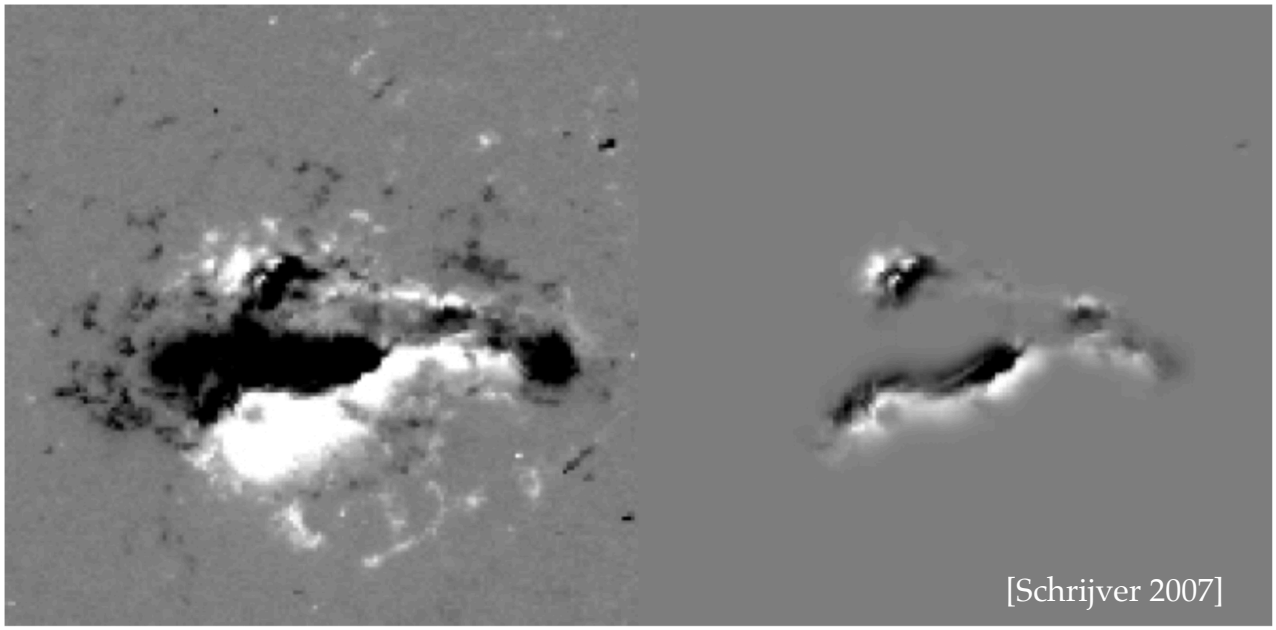


[Barnes & Leka, ApJ 2008]

The largest flares are extremely hard to predict

Parameter	Success Rate	Heidke Skill Score	Climatological Skill Score
Climatology	0.908	0.000	0.000
Φ_{tot}	0.922	0.153	0.197
E_e	0.916	0.081	0.231
R	0.922	0.144	0.242
B_{eff}	0.913	0.072	0.220

Improvement factor compared to an assumed statistics of events



All the estimates perform quite poorly for the large events

[Barnes & Leka, ApJ 2008]

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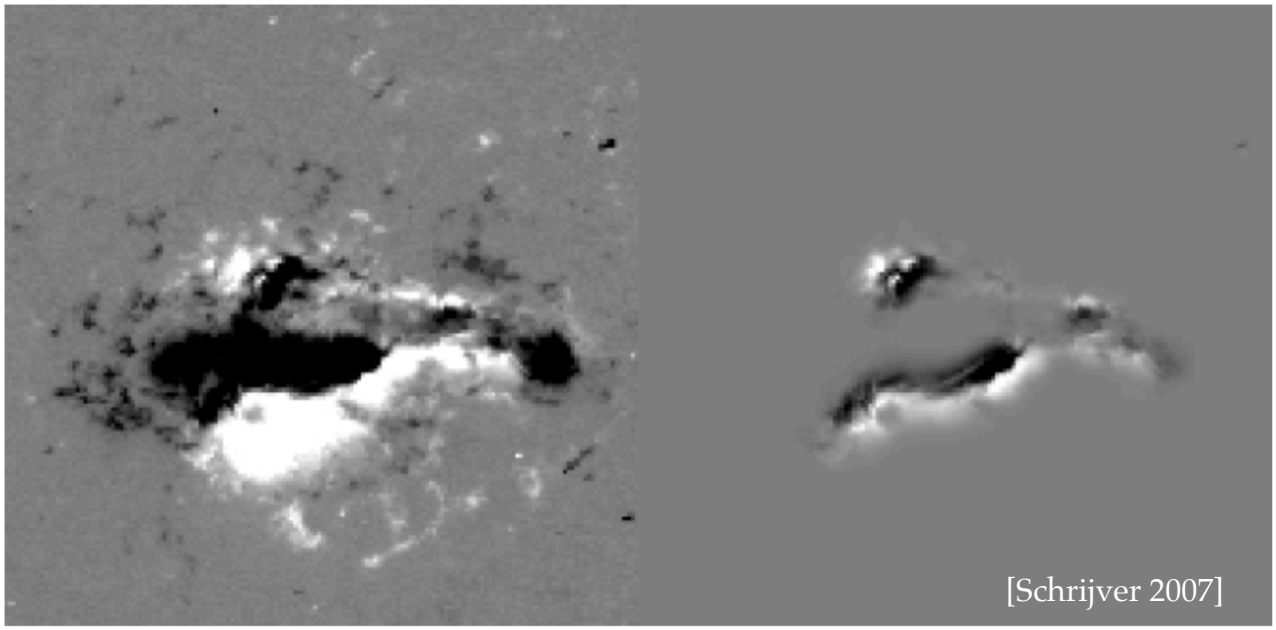


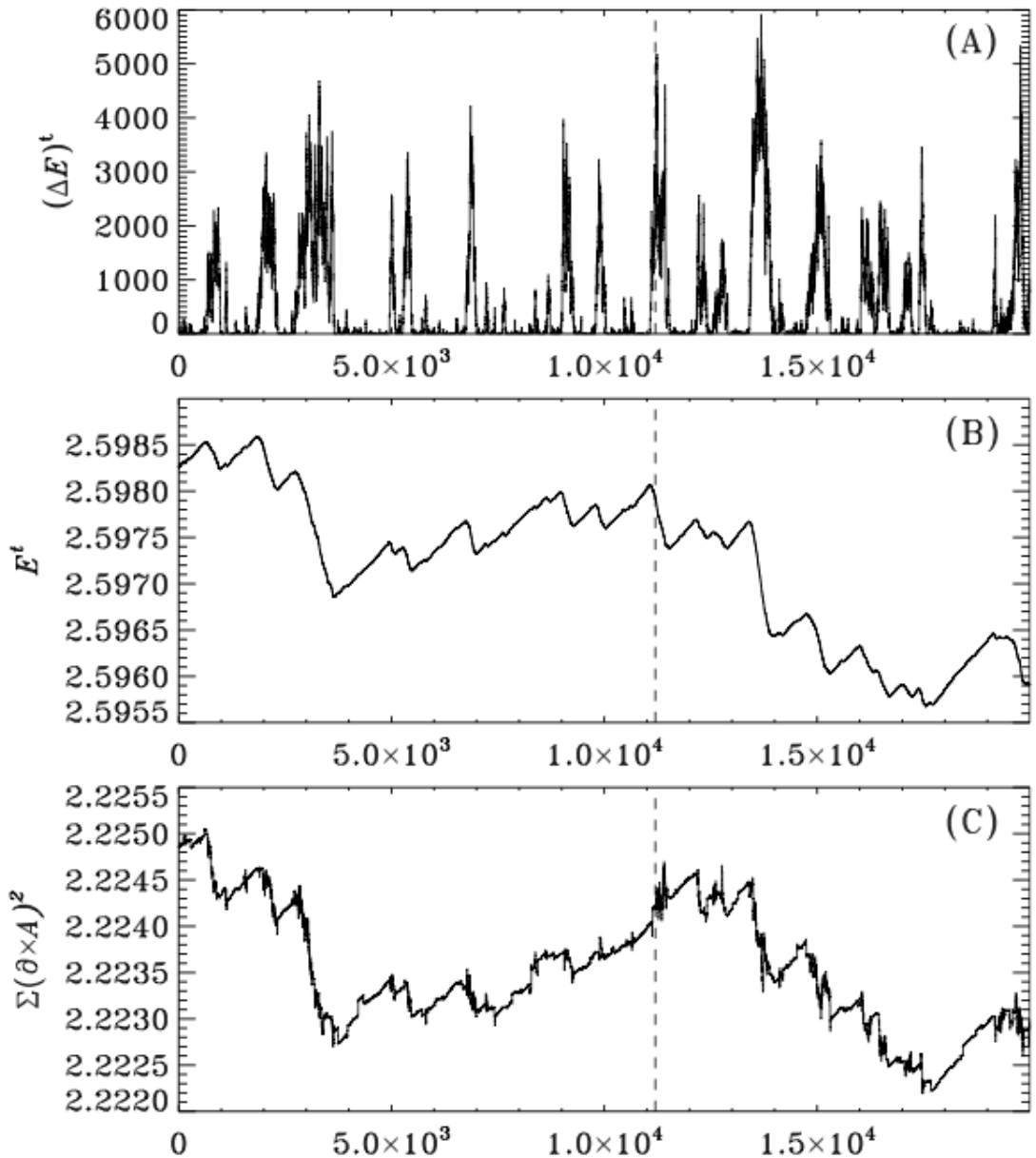
All the estimates perform quite poorly for the large events

Estimates using the statistical distribution of flares [Wheatland 2005] give *slightly* better results

[Barnes & Leka, ApJ 2008]

Physical interpretation of the nodal variable

[Charbonneau 2013]



Stochasticity in the D models

★ Where to put the random process?

✤ Random **extraction**

$$(Z_{i,j} > Z_c) \rightarrow \begin{cases} B_{i,j} & -= \quad 4\delta B_r \\ B_{i\pm1,j\pm1} & += \quad \delta B_r \end{cases}$$

✤ Random **threshold**

$$(Z_{i,j} > Z_c^r) \rightarrow \begin{cases} B_{i,j} & -= \quad 4\delta B \\ B_{i\pm1,j\pm1} & += \quad \delta B \end{cases}$$

✤ Random **redistribution**

$$(Z_{i,j} > Z_c) \rightarrow \begin{cases} B_{i,j} & -= \quad 4\delta B \\ B_{i\pm1,j\pm1} & += \quad \frac{r_k}{R}\delta B \end{cases}$$

$$r_k \text{ random deviate } \in [0,1] \ (k \in \{1,4\}) \qquad \sum_k r_k = R$$