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Towards Slow Earthquakes Forecasting

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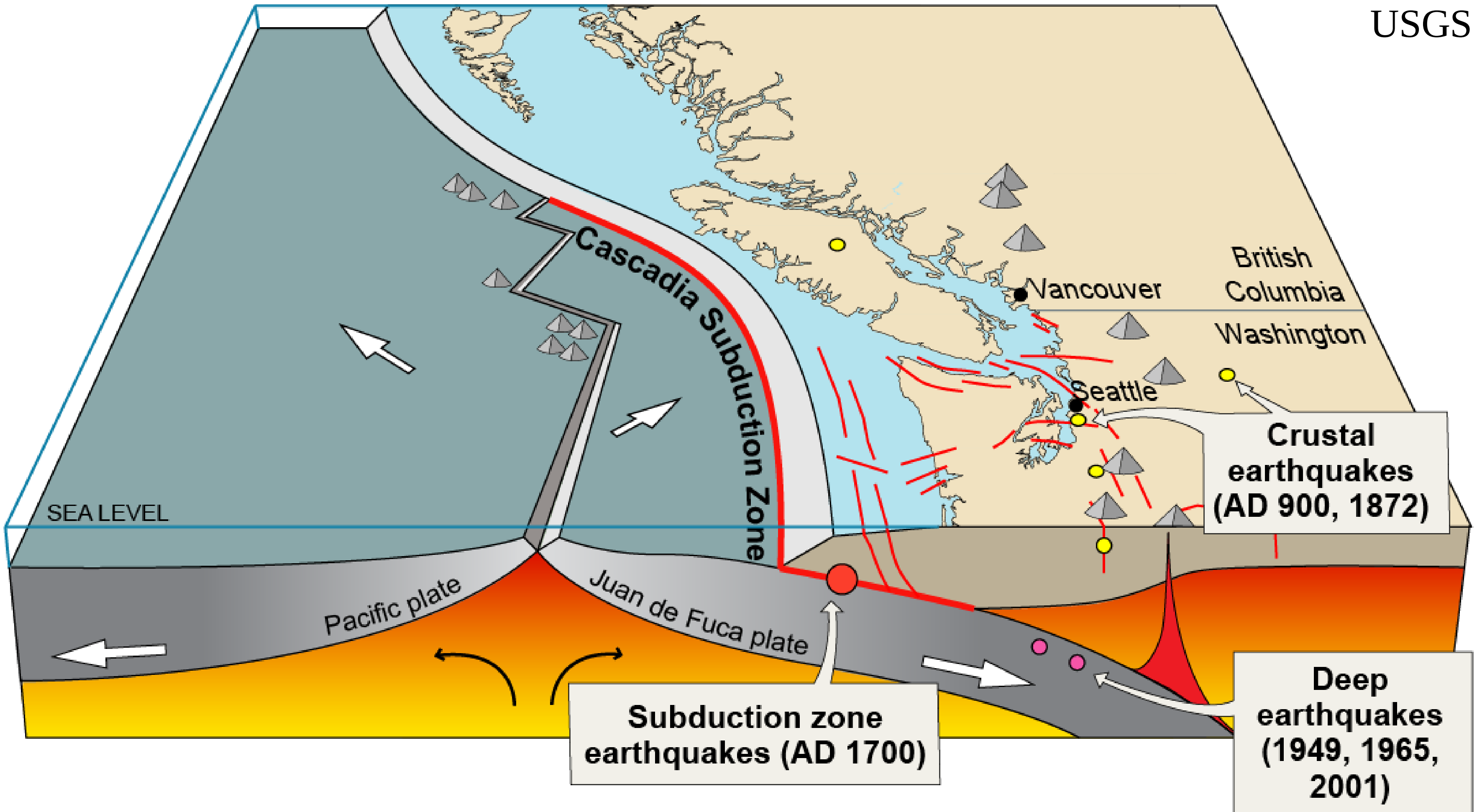
EGU General Assembly 2020

EGU2020-19639

On-line meeting

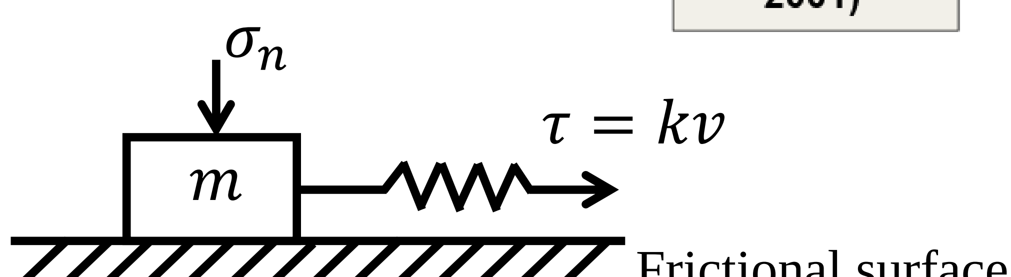
4-8 May 2020

Background



USGS

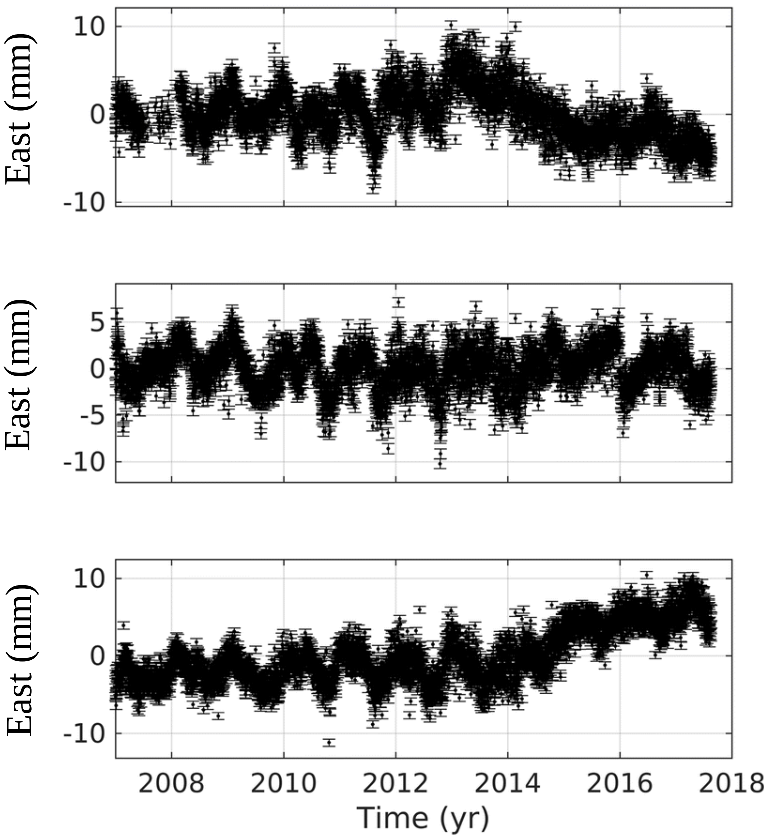
Spring-slider model

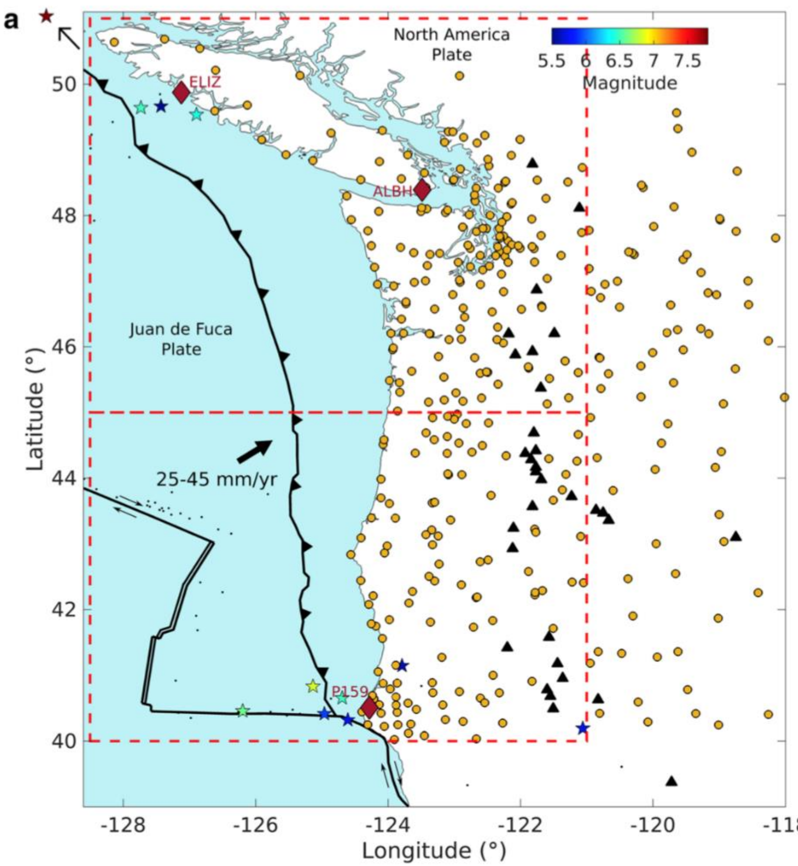


Tectonic setting and signal extraction

352 continuous GPS stations: 3-dim position every day for >10 yr (from 2007.0 to 2017.632)

Detrended and offsets corrected



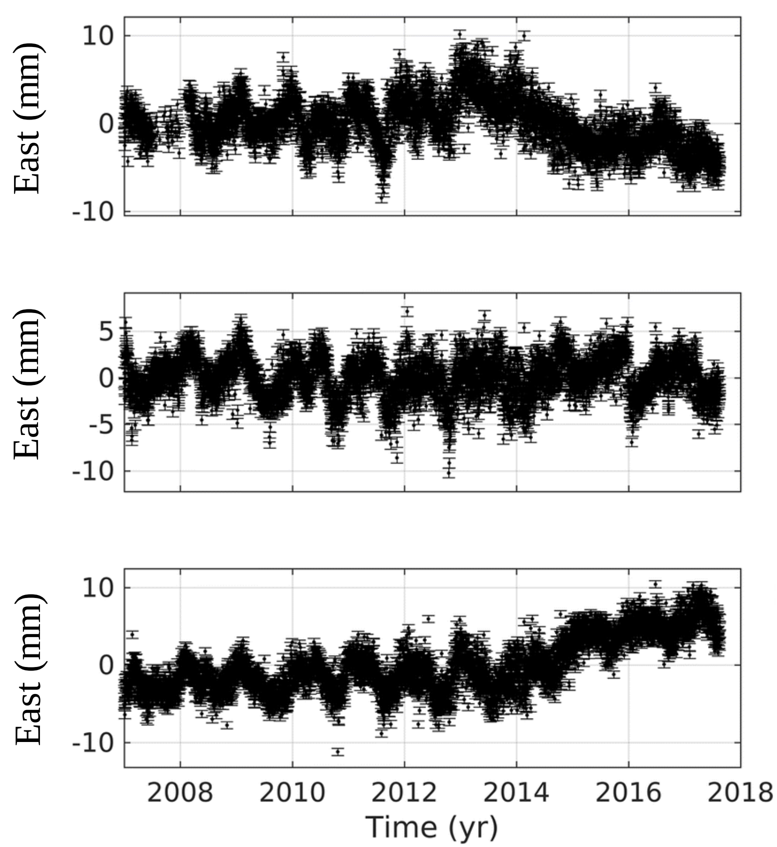


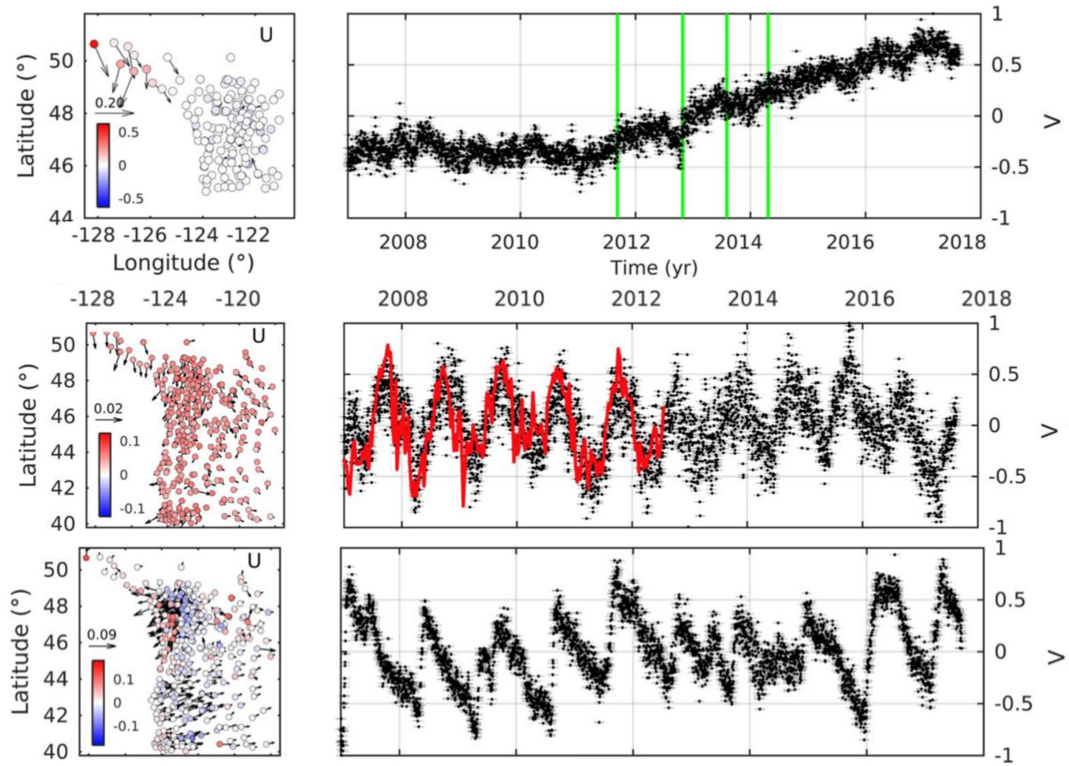
Tectonic setting and signal extraction

Surface displacement → **Linear decomposition** → **displacement linear components U_i**

$$X_{cen} \cong \sum_{i=1}^{R} \mathbf{U}_i S_{ii} \mathbf{V}_i'$$

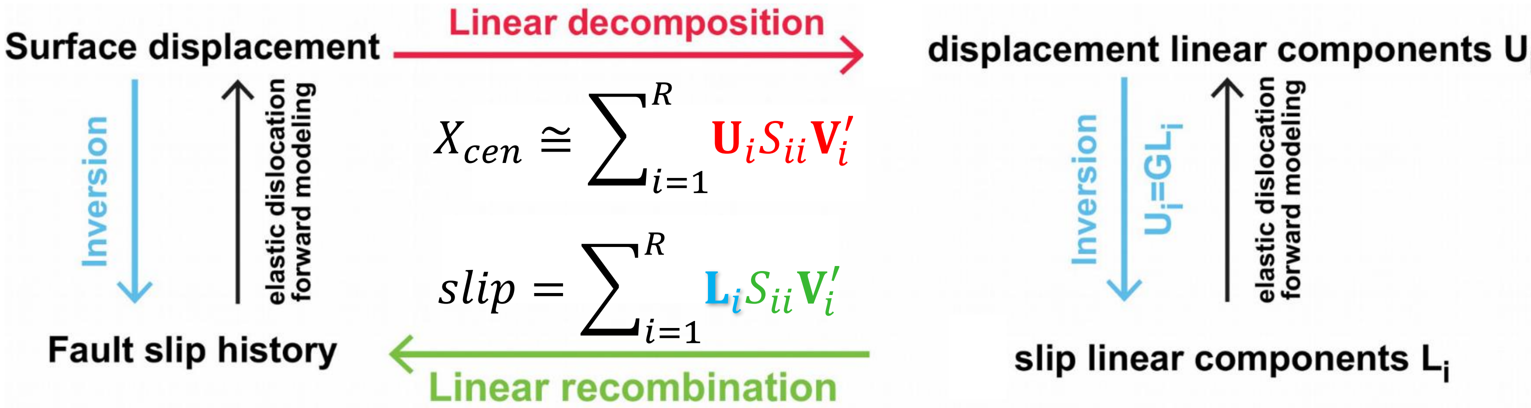
Modified from Kositsky and Avouac, 2010, *JGR*
Gualandi et al., 2016, *J. of Geod.*
Variational Bayesian Independent Component Analysis (vbICA)

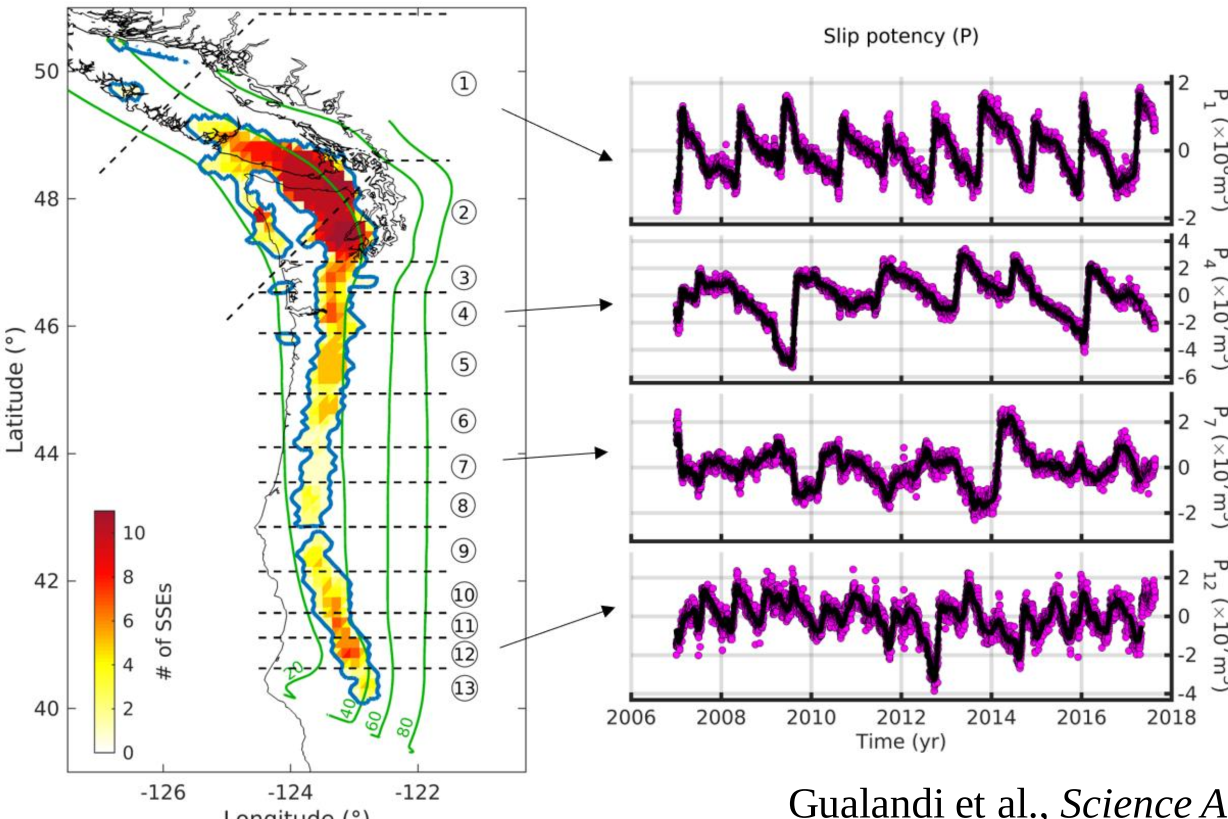




Michel et al., 2019 *PAGEOPH*

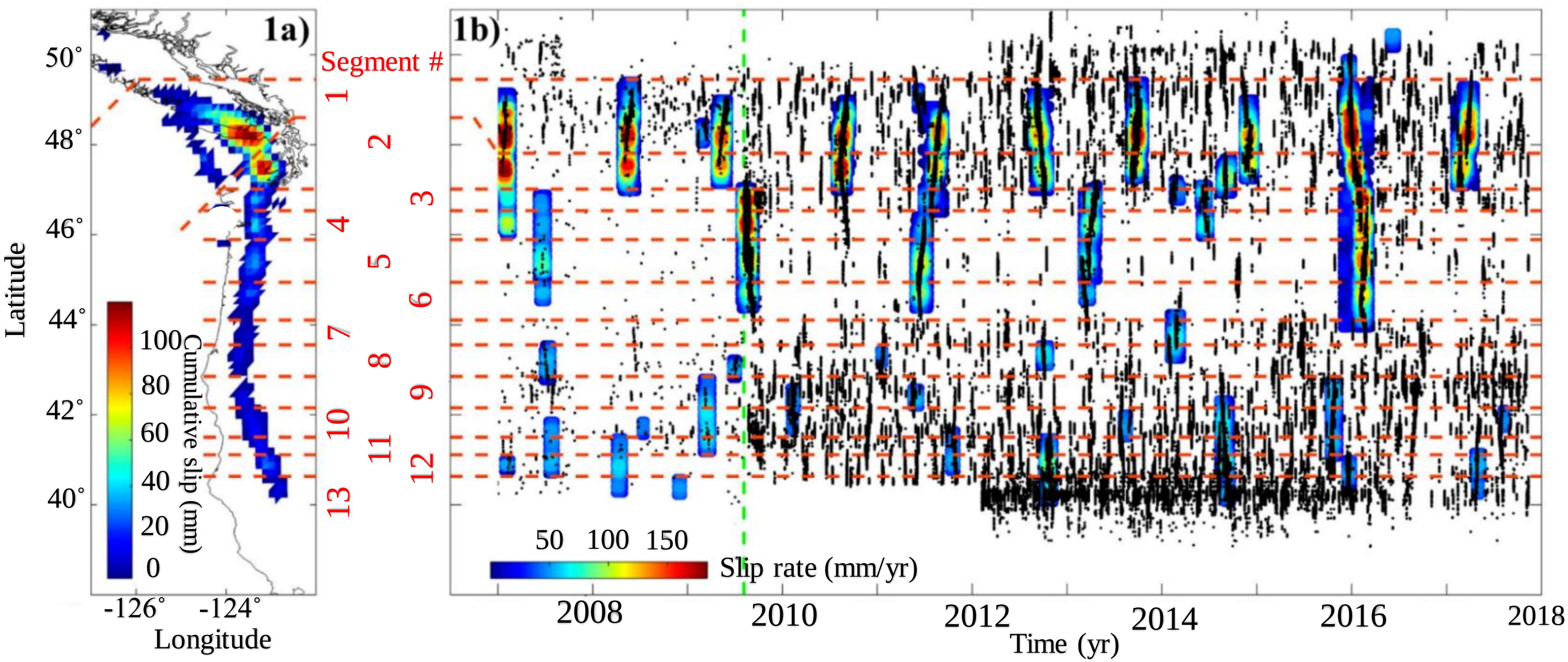
Tectonic setting and signal extraction

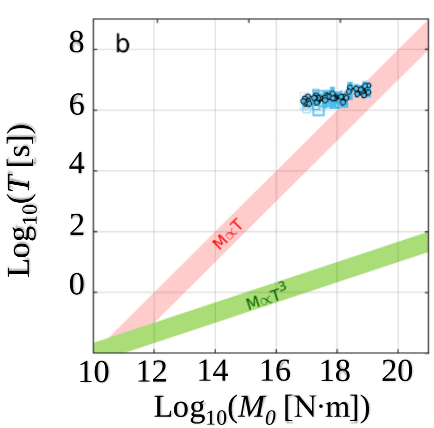


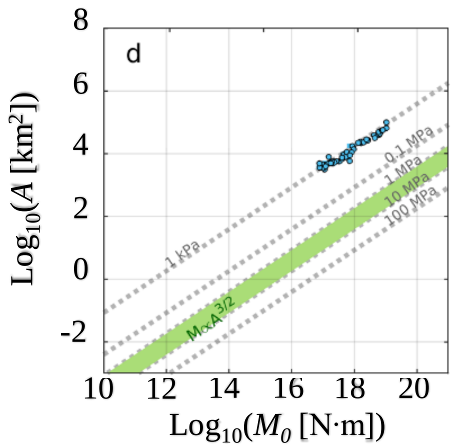


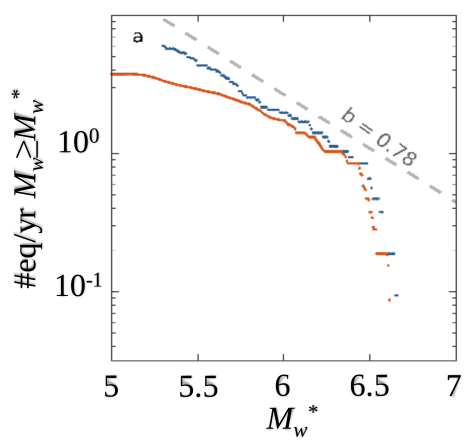
Gualandi et al., *Science Advances* (accepted)

SSEs: earthquakes in slow motion





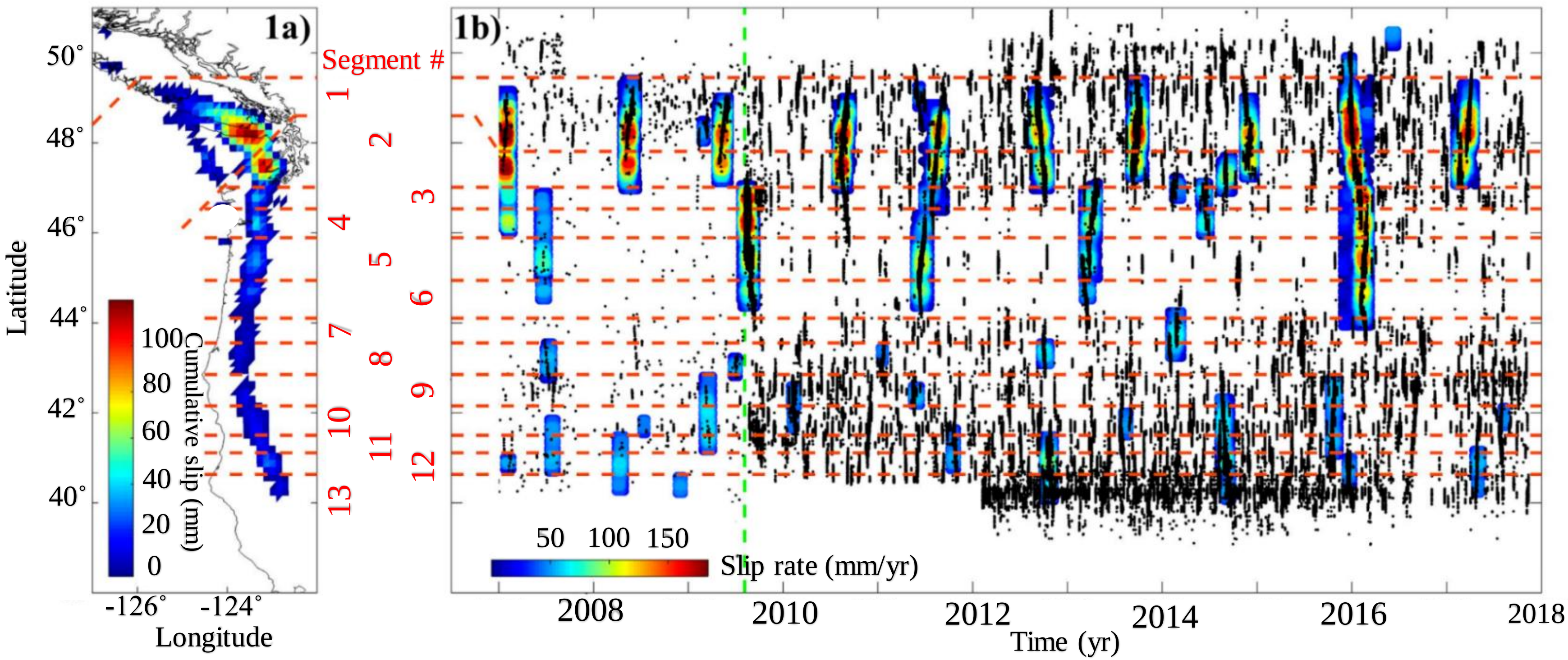


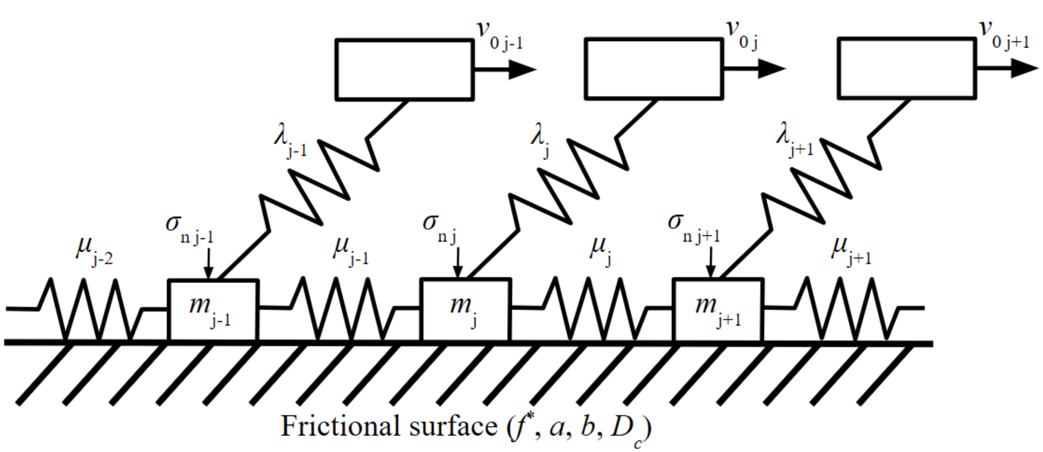


Slow and regular earthquakes share similar scaling laws

Michel et al., 2019, *Nature*

SSEs: earthquakes in slow motion





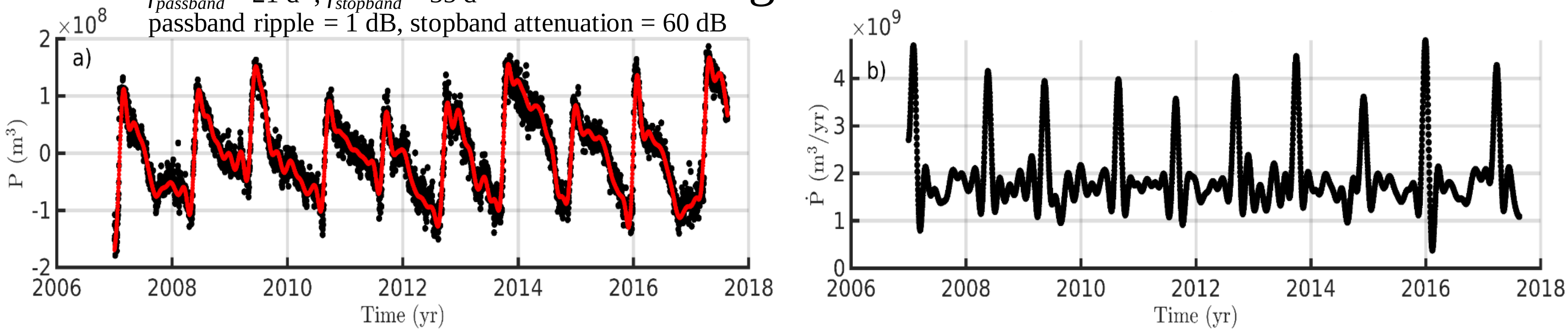
Along-strike segmentation: similar to a multibody system

Michel et al., 2019, *Nature*

Dynamical system study

Segment 1

$f_{passband} = 21\ d^{-1}$, $f_{stopband} = 35\ d^{-1}$
passband ripple = 1 dB, stopband attenuation = 60 dB



$M_0 = \mu A \delta$ Seismic moment $P = A\delta$ Slip potency

- **Can we characterize the SSEs dynamical system?**
  (… better than Poissonian process)

- Extreme Value Theory (EVT) applied to dynamical systems
  (e.g., Faranda et al., 2017, *Sci. Rep.*)
- Instantaneous and average dimensions
- Instantaneous extremal index and metric entropy
- Implications for SSEs predictability

Gualandi et al., *Science Advances* (accepted)

Instantaneous dimension d

ζ point on a strange attractor

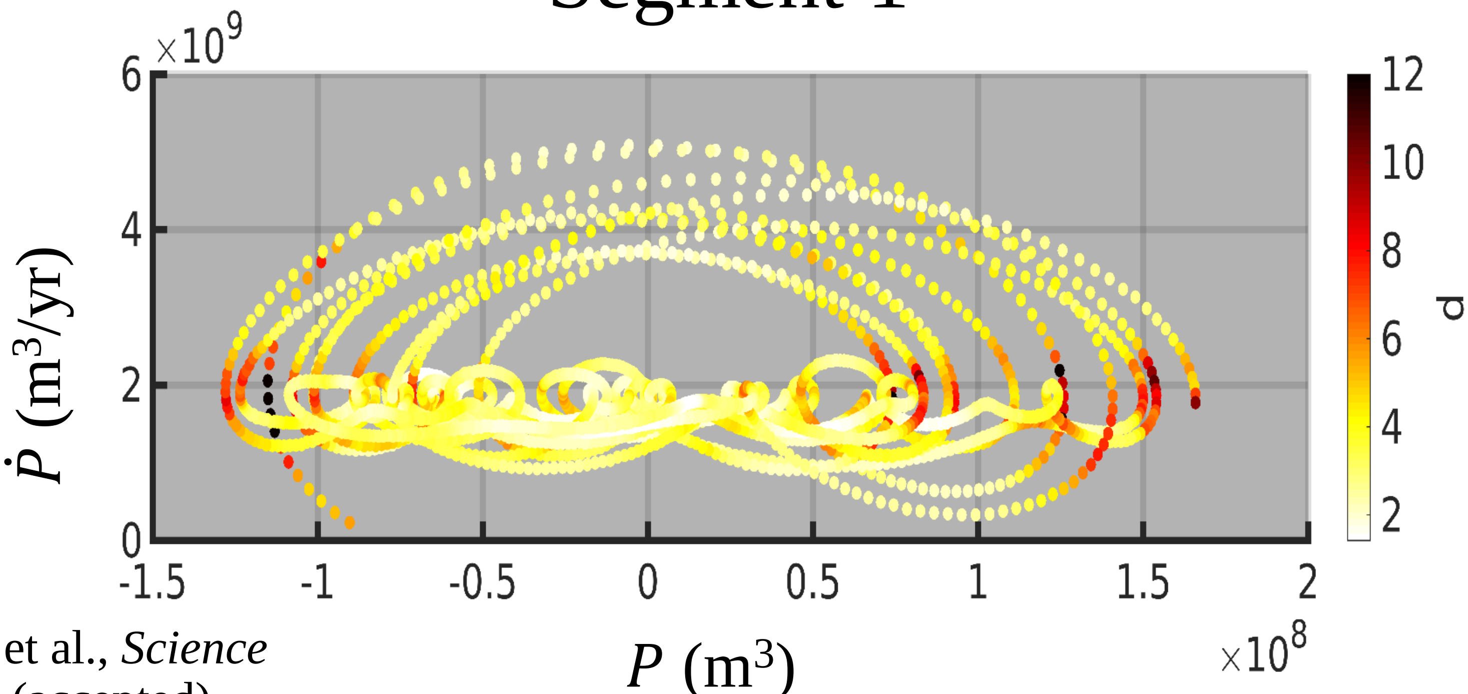
Faranda et al., 2017, *Sci. Rep.*

d density of neighbors around ζ (instantaneous dimension)

Hypothesis: The observed slip potency rate $\dot{P}(t)$ represents a state of the system and approximates a point ζ on the attractor

Segment 1

$3 < D = \bar{d} < 4$



Gualandi et al., *Science Advances* (accepted)

Surrogate data

Can we trust the calculated dimension?

Autocorrelated noise can fool dimension estimation

Solution: Surrogate data

Null hypothesis

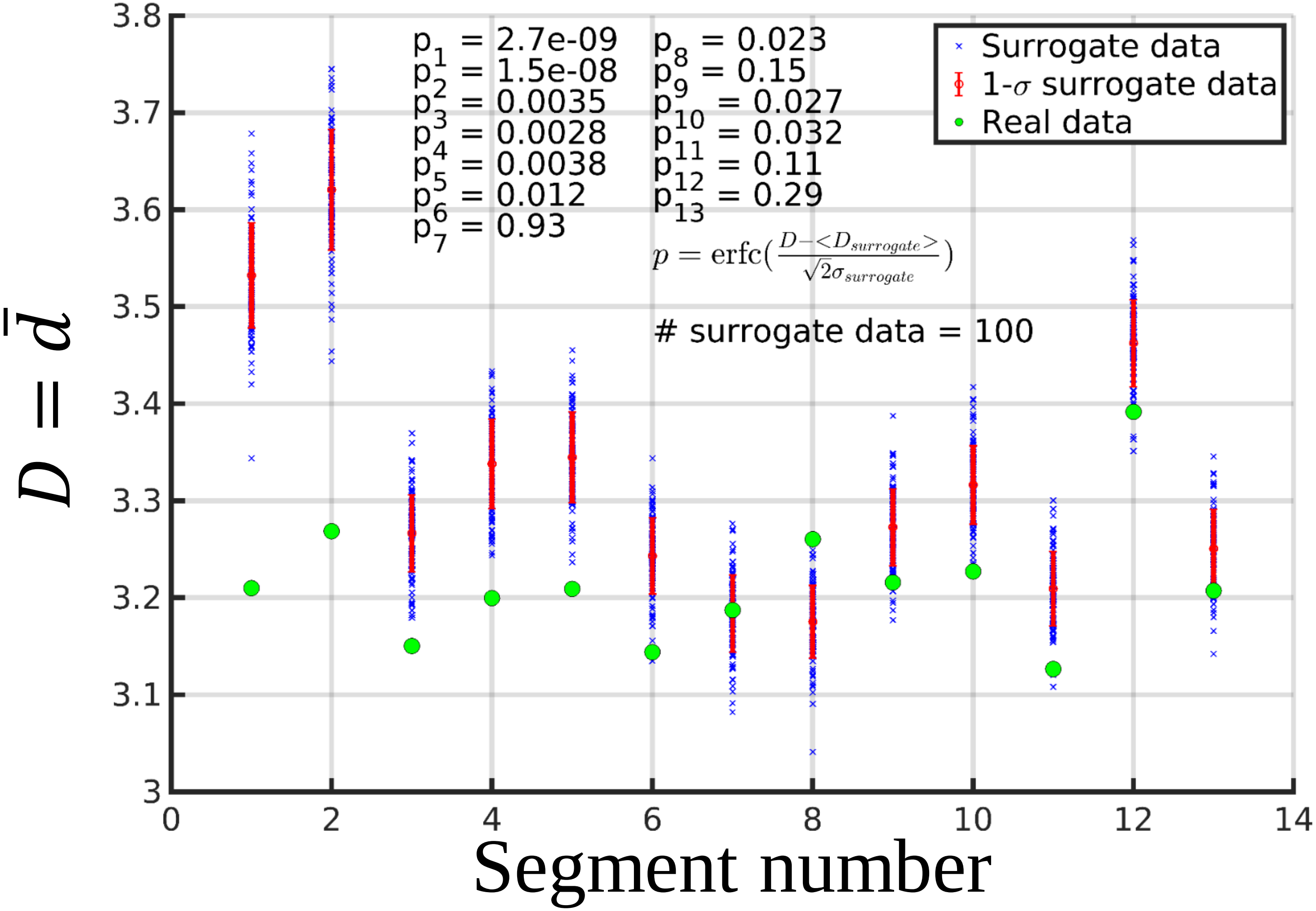
All the structure in the time series is given by the Fourier power spectrum

- Generate surrogate data randomizing the phase of the Fourier transformed data and calculate *D*
- Extension to multivariate time series

Theiler et al., 1992, *Physica D*;
Prichard and Theiler, 1994, *Phys. Rew. Lett.*

Gualandi et al., *Science Advances* (accepted)

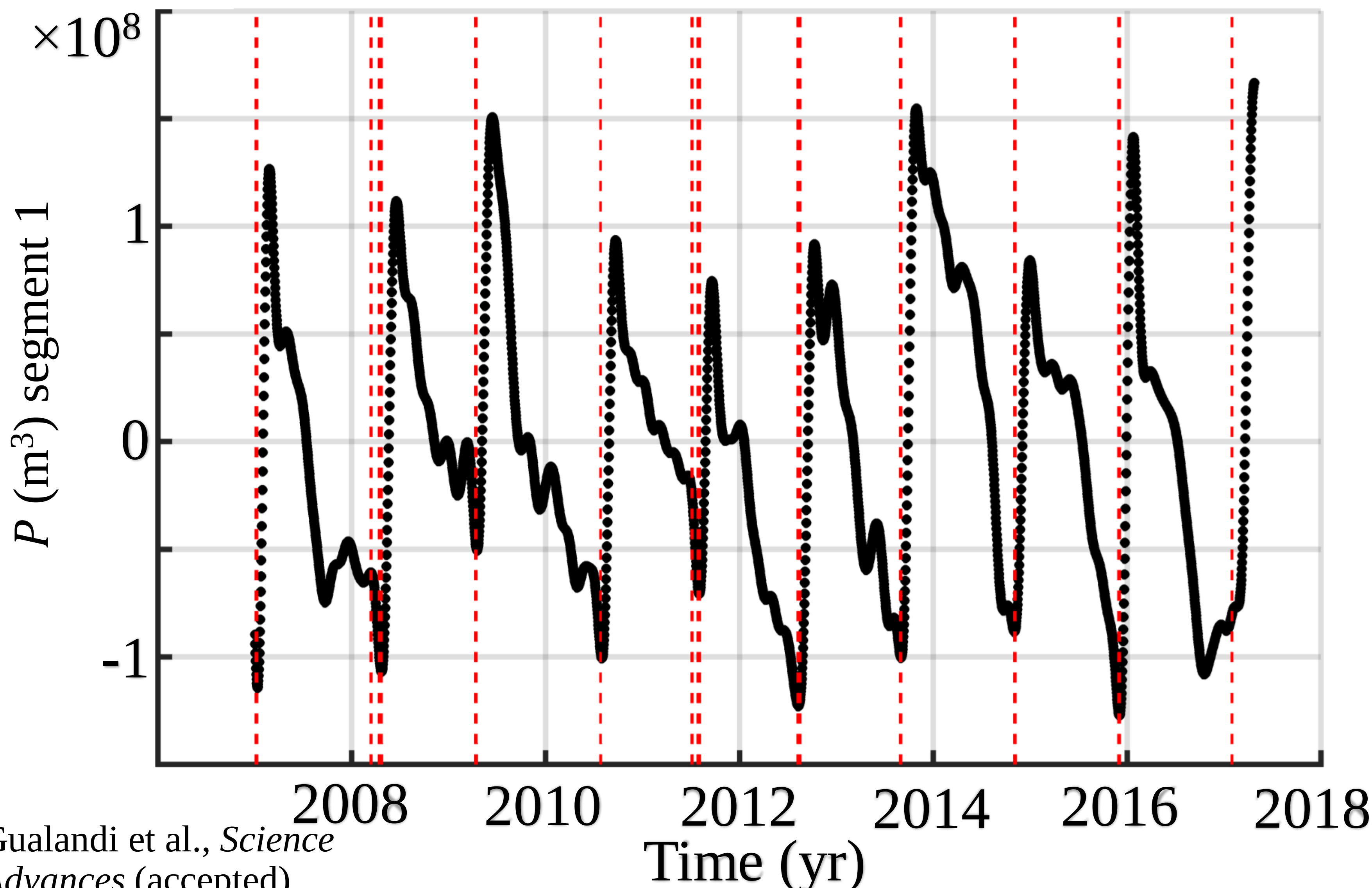
Surrogate data



If D derived from the data is significantly (p<0.001) lower than D derived from the surrogate data
$\Longrightarrow$ we can reject the null hypothesis for which the data can be described via a linear stochastic model and we infer that the time series are deterministic, low-dimensional and chaotic

d as an instability precursor

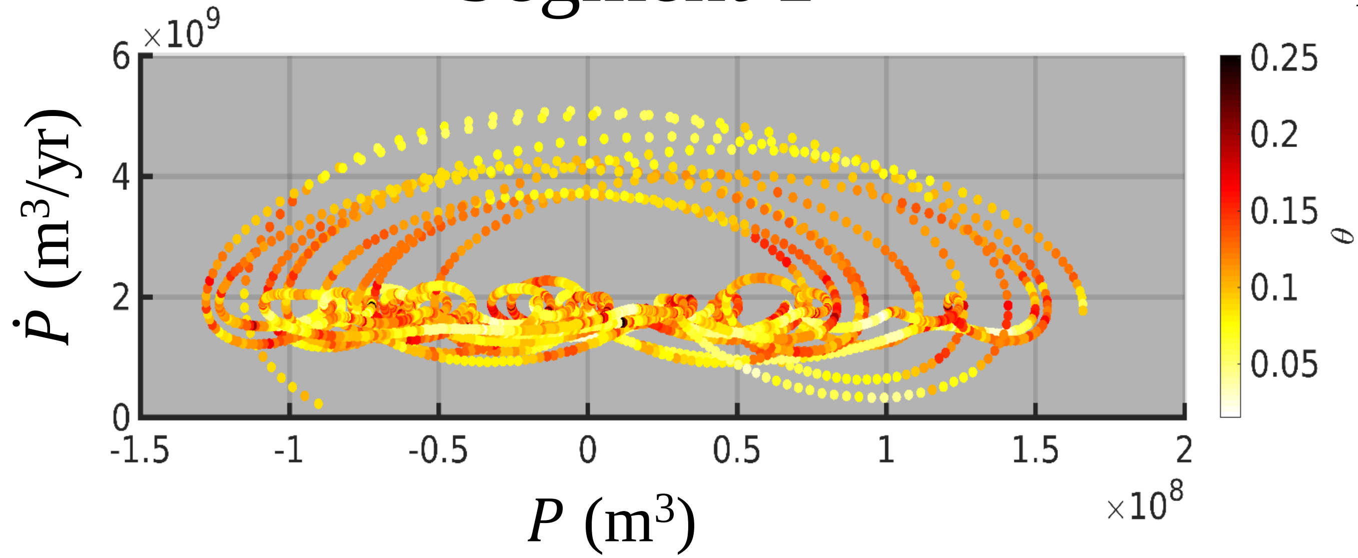
$d \geq 95th$ quantile of d and $P < 50th$ quantile of P



Gualandi et al., *Science Advances* (accepted)

Extremal index and metric entropy

Segment 1



Gualandi et al., *Science Advances* (accepted)

θ: instantaneous extremal index. Inverse of the average persistence time around a state ζ of the phase space

$\Theta \in [0,1]$: reciprocal of the mean cluster size

Smith and Weissman, 1994, *Royal Statistical Society*

$$\Theta \sim 1 - e^{-H} \Rightarrow H \sim -\ln(1-\Theta)$$

Faranda and Vaienti, 2018, *Chaos*

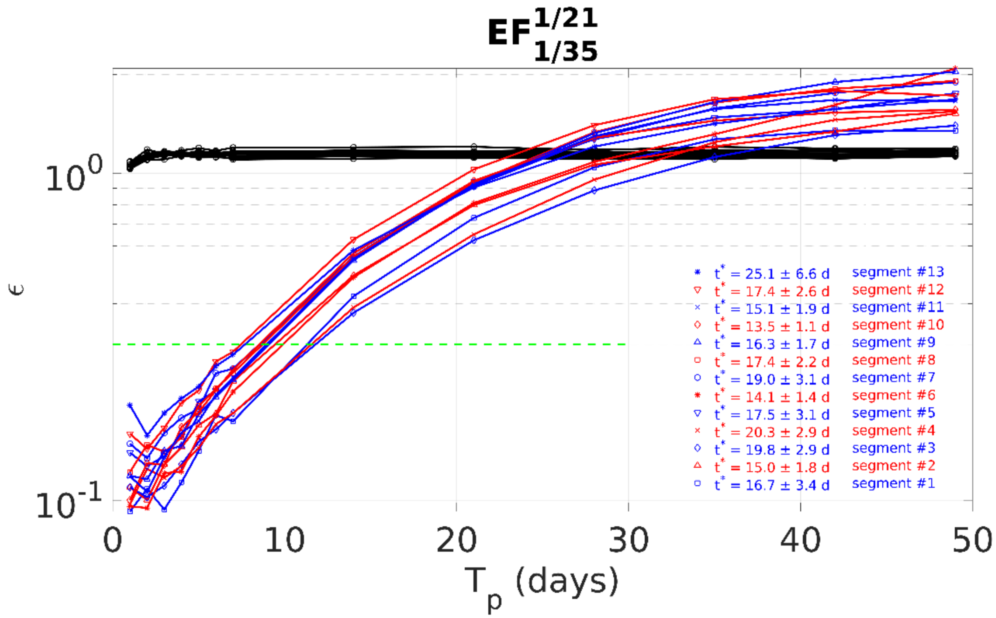
$$H = \sum_{j=1}^{L} \Lambda_j^+$$

Metric entropy = Sum positive Lyapunov exponents with multiplicity one

$$\Rightarrow 2\text{ d} \lesssim t^* = \frac{1}{H} \lesssim 65\text{ d}$$

Predictability horizon

Non-linear Forecasting Analysis



Gualandi et al., *Science Advances* (accepted), after Farmer and Sidorowich, 1987, *Phys. Rev. Lett.*

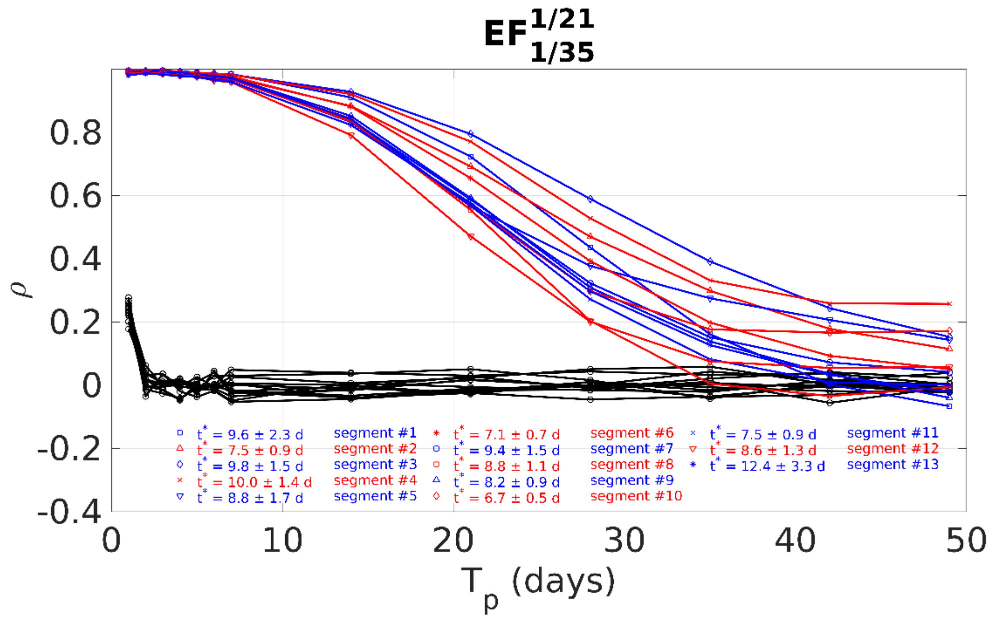
$$\epsilon = \frac{\sqrt{\left\langle \left[\hat{\dot{P}}(t, T_p) - \dot{P}(t + T_p) \right]^2 \right\rangle}}{\sqrt{\left\langle \left[\dot{P}(t) - \langle \dot{P}(t) \rangle \right]^2 \right\rangle}}$$

Black: unfiltered time series.
Red and blue: causally filtered time series.
Embedding delay time $\tau = 7$ days
Embedding dimension $m = 9$

$\hat{\dot{P}}(t, T_p)$ prediction of $\dot{P}$ at time $t + T_p$ using k nearest neighbor in embedded space of past data to train a local linear estimator

$t^* = 1/H$ calculated using points such that $\epsilon < \epsilon^* = 0.3$ (green dashed line)

Non-linear Forecasting Analysis



Gualandi et al., *Science Advances* (accepted), after Wales, 1991, *Nature*

ρ correlation coefficient between $\hat{\dot{P}}(t, T_p)$ and $\dot{P}(t + T_p)$

Black: unfiltered time series.
Red and blue: causally filtered time series.
Embedding delay time $\tau = 7$ days
Embedding dimension $m = 9$

$\hat{\dot{P}}(t, T_p)$ prediction of $\dot{P}$ at time $t + T_p$ using k nearest neighbor in embedded space of past data to train a local linear estimator

$t^* = 1/H$ calculated using points such that $\rho > 0.98$

Conclusions and Future Work

- SSEs: deterministic low-dimensional chaotic dynamics

- SSEs: $t^* \lesssim T \sim$ days – months

$\Rightarrow$ earthquakes: $t^* \lesssim T \sim$ seconds?
Long-term predictions seem intrinsically impossible.

- Weekly sampled data may be enough to predict SSEs, but noise reduction is needed if we want to apply this methodology in real time applications.

- Data Assimilation techniques, Unscentend Kalman Filter, or Machine Learning to predict time to failure and slip potency

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