

Dynamic Stress Drop and Rupture Velocity for Mining Induced Seismicity

Wojciech Dębski

Institute of Geophysics Polish Acad. Sci.,

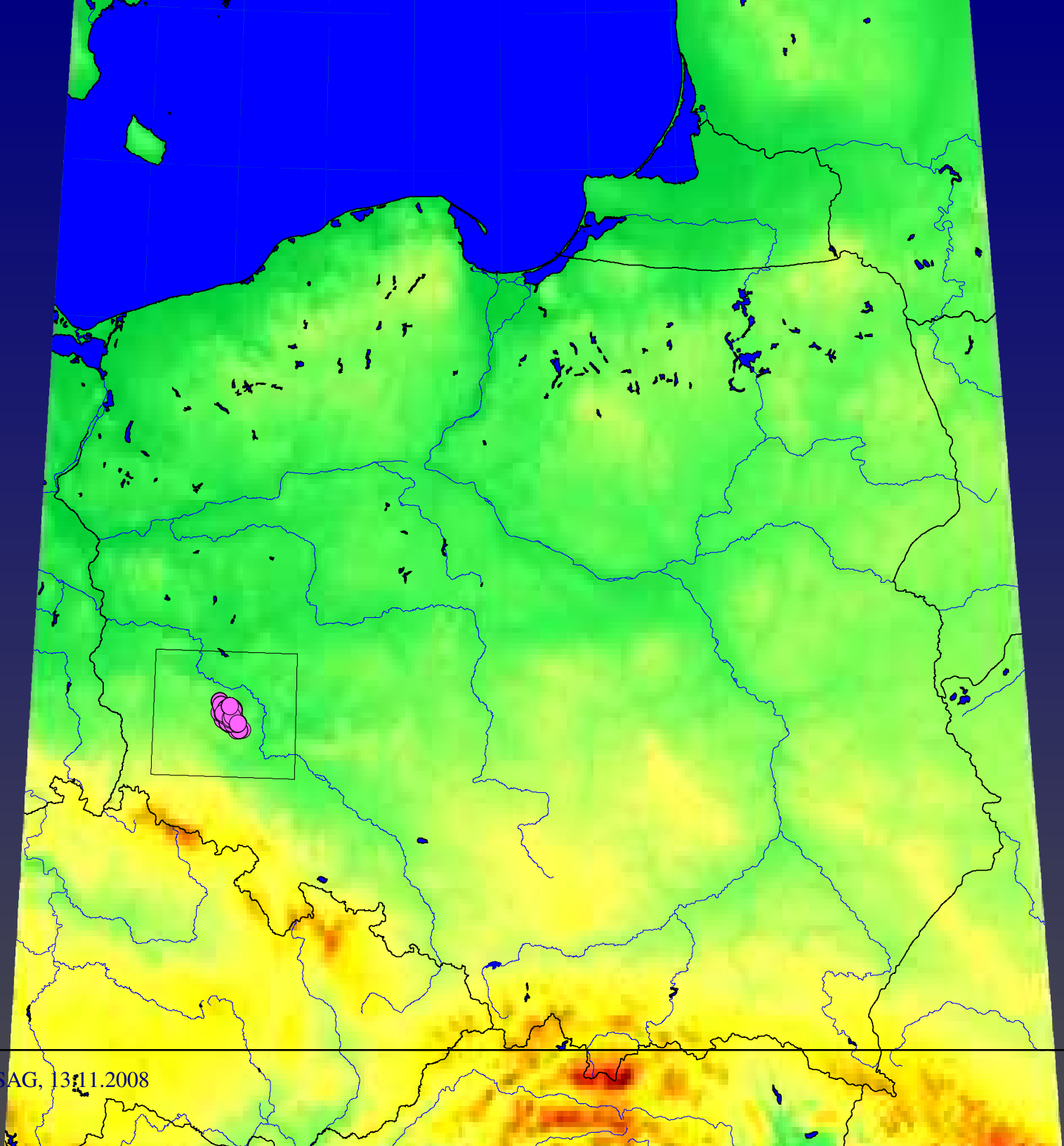
www.igf.edu.pl/~debski

debski@igf.edu.pl

13 listopada 2008

Plan of the talk

- ◆ Background review of the seismicity induced by mining in Poland
- ◆ Source parameters from seismic spectra
- ◆ *Rupture velocity and dynamic stress drop*
- ◆ Towards the dynamic source tomography
- ◆ An accuracy issue: Bayesian and MCMC sampling techniques



Mining technology



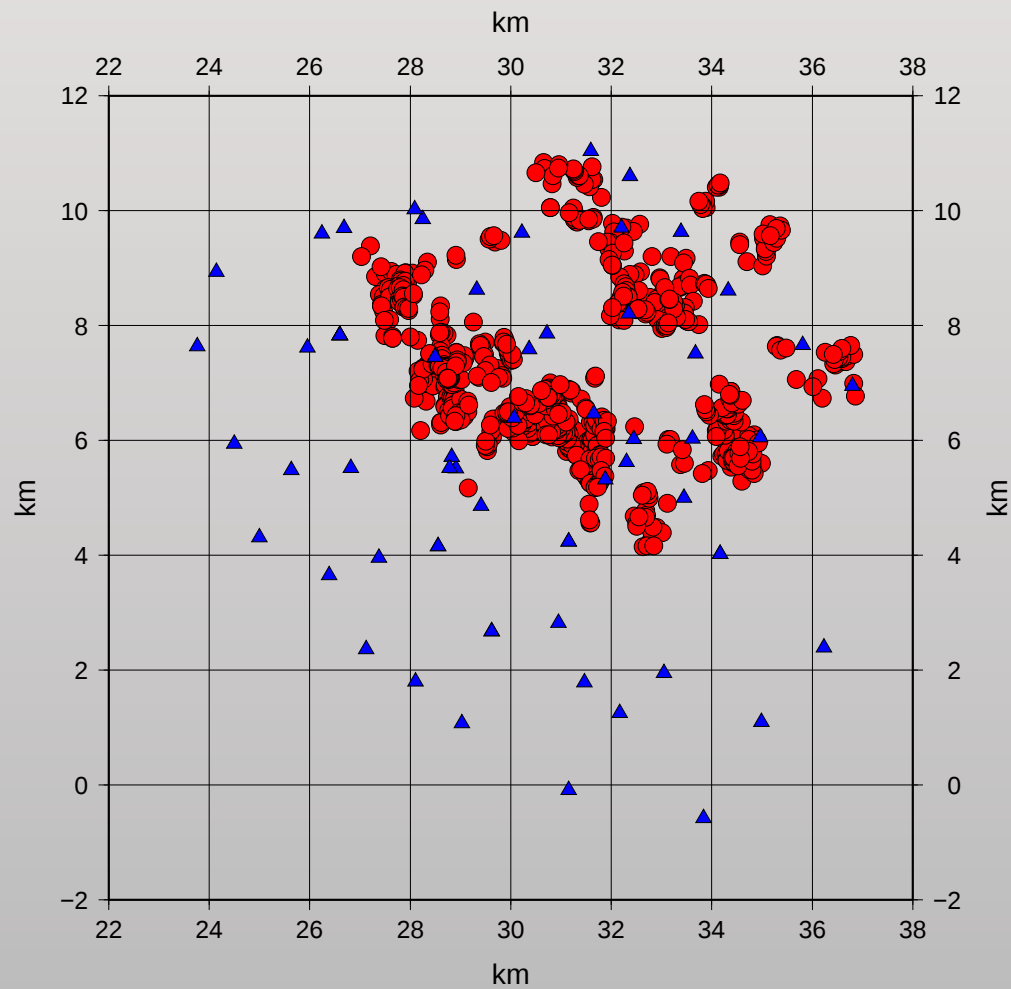
Mining technology (cd)



Mining technology (cd)

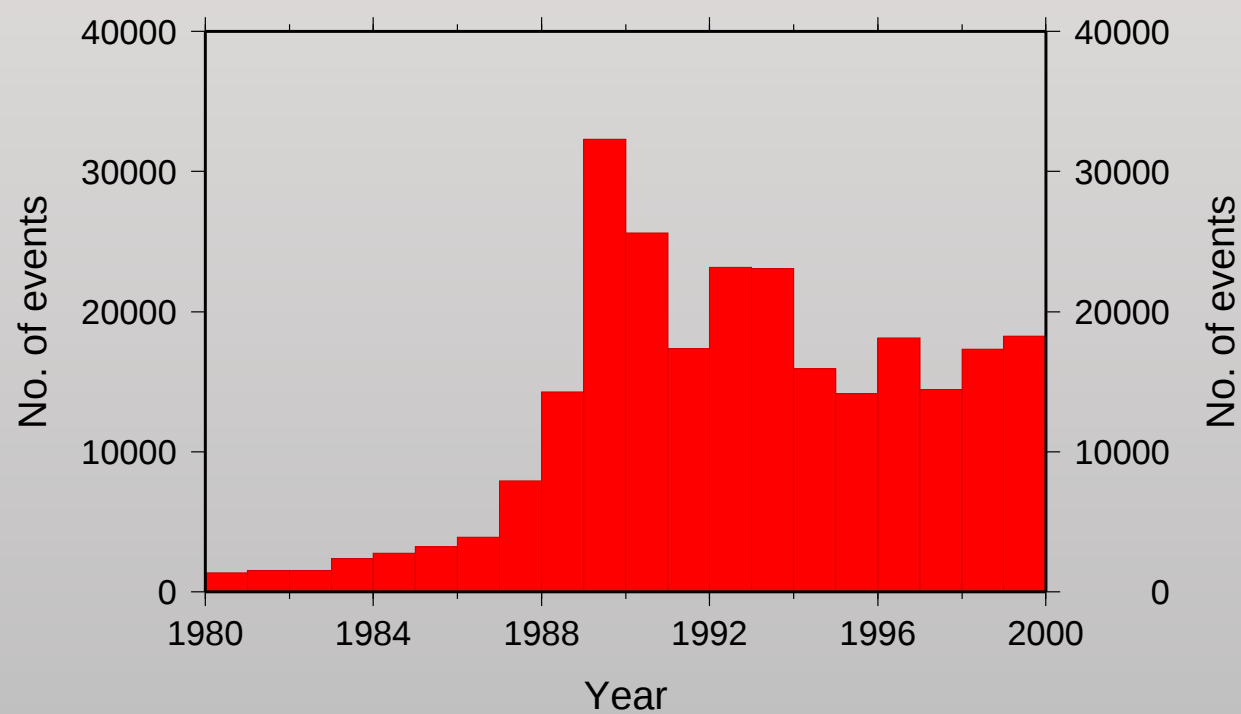


Polish copper mines



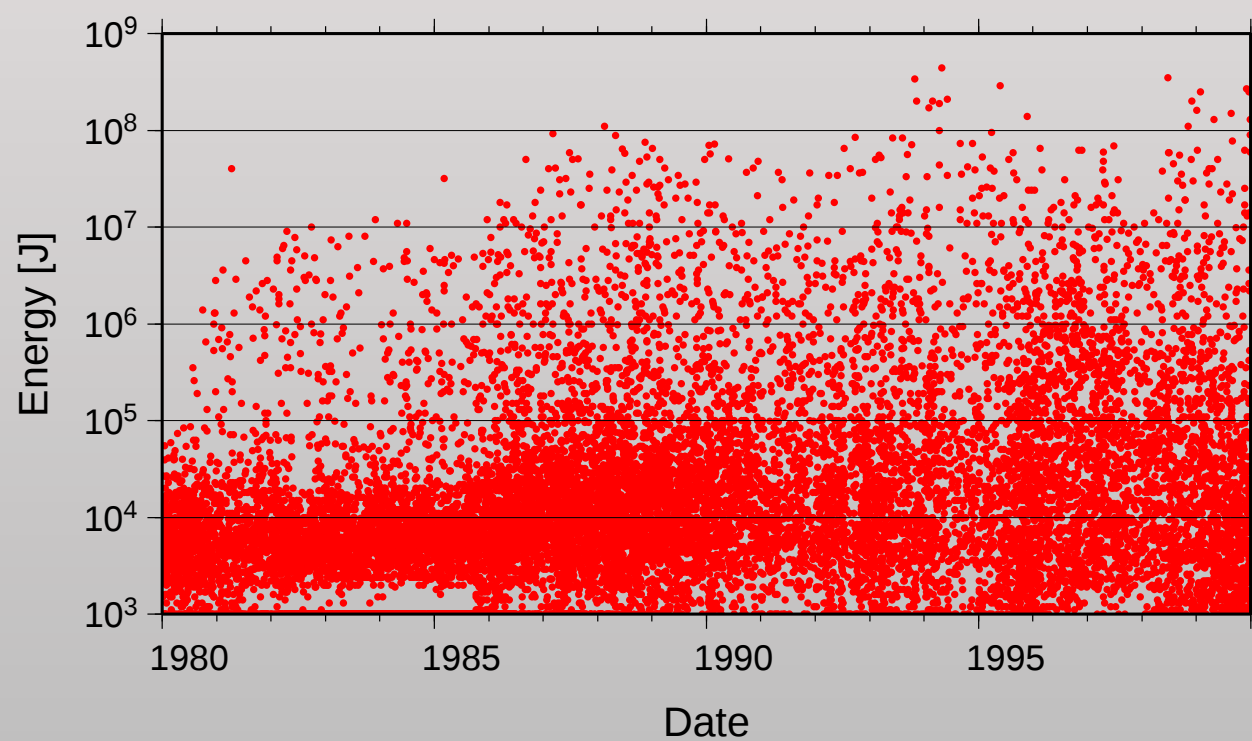
LGOM Seismicity

1980–1999



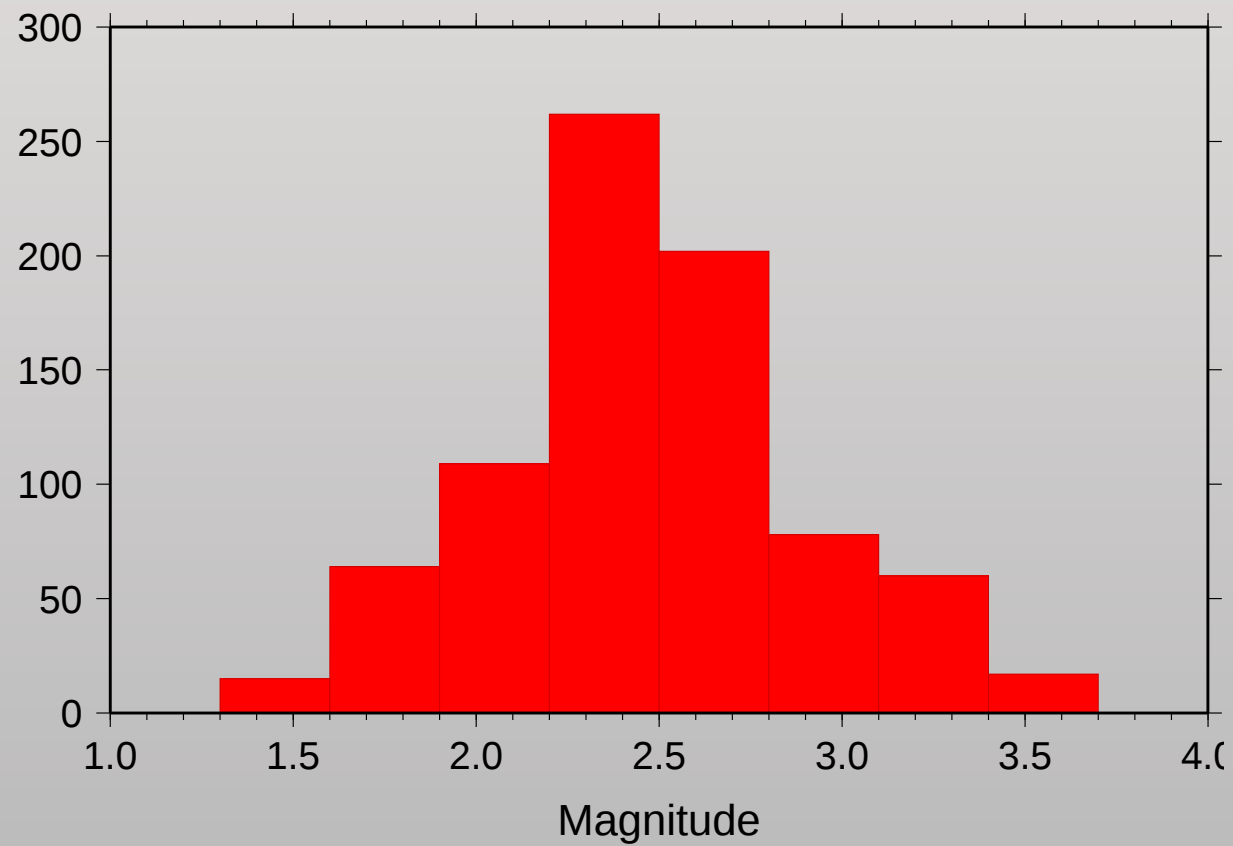
LGOM Seismicity

1980–1999

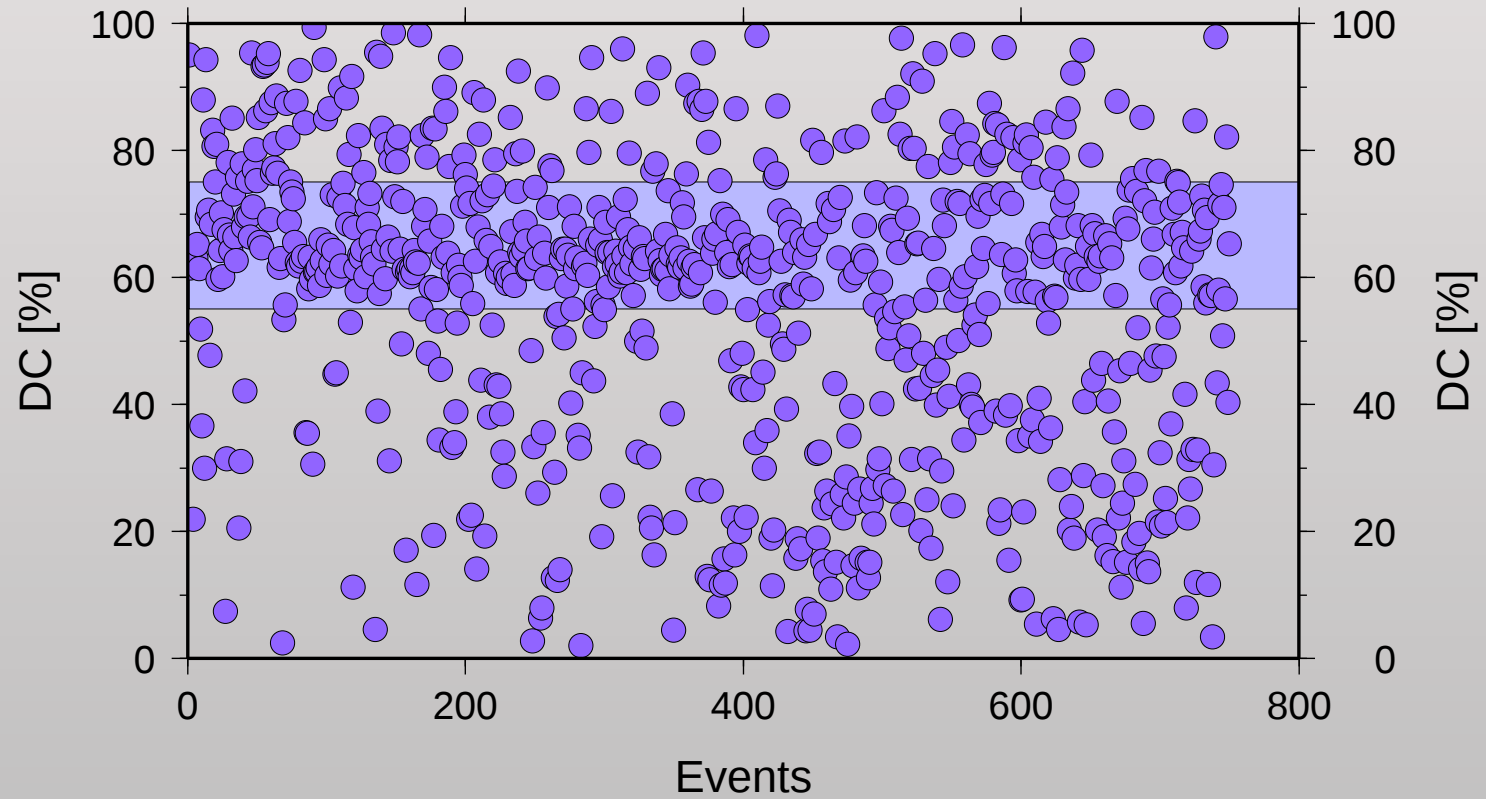


Analyzed data

1994–2006

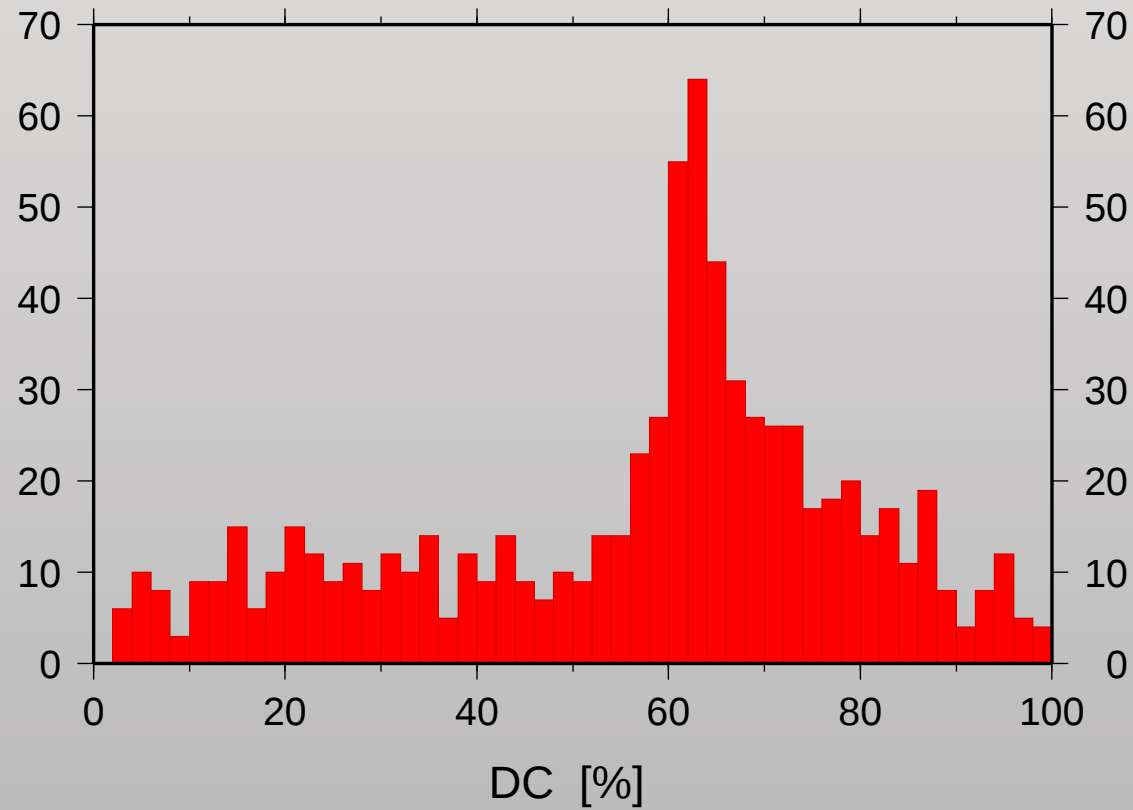


Moment Tensor

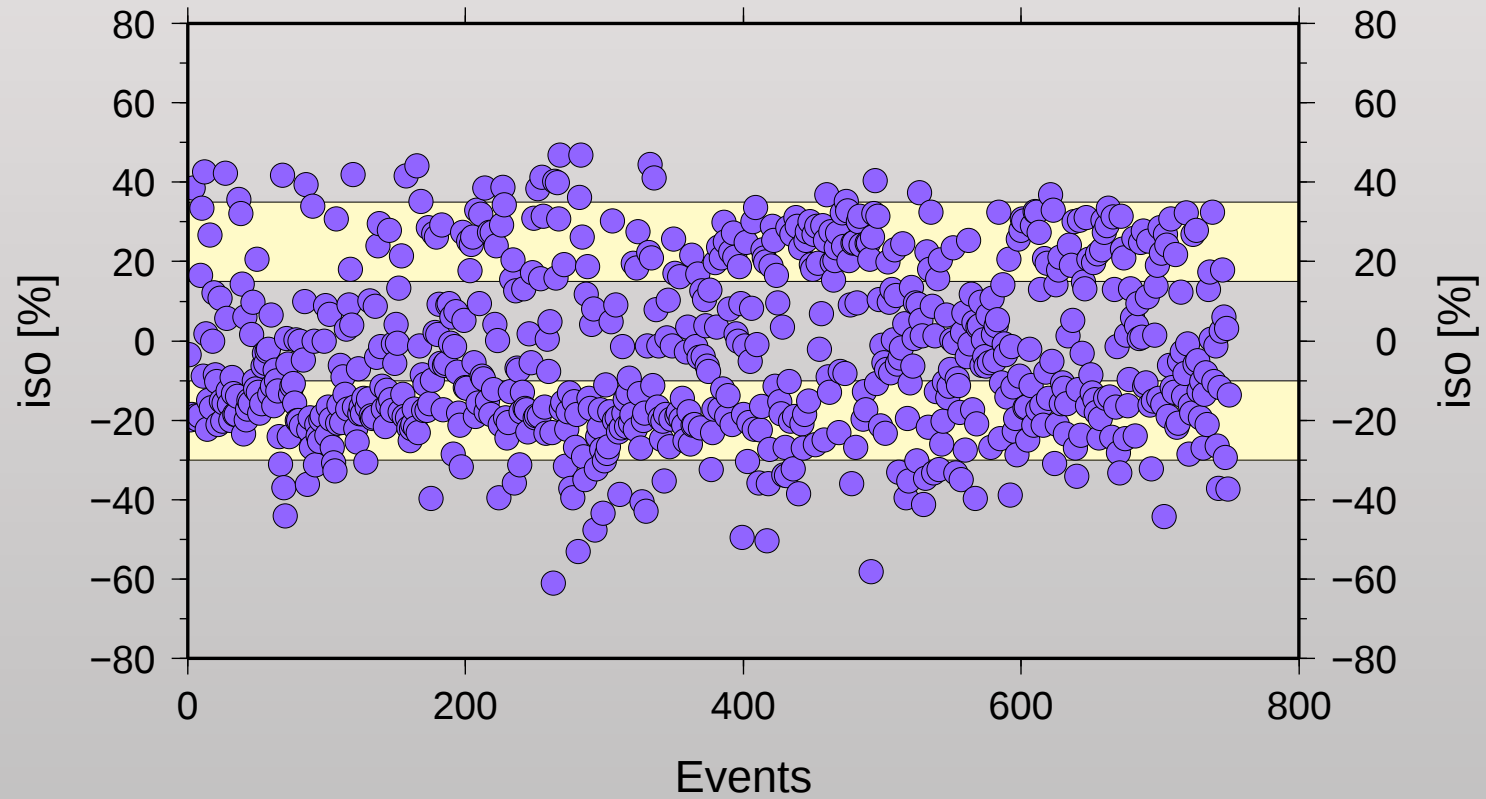


Moment Tensor

2003–2008

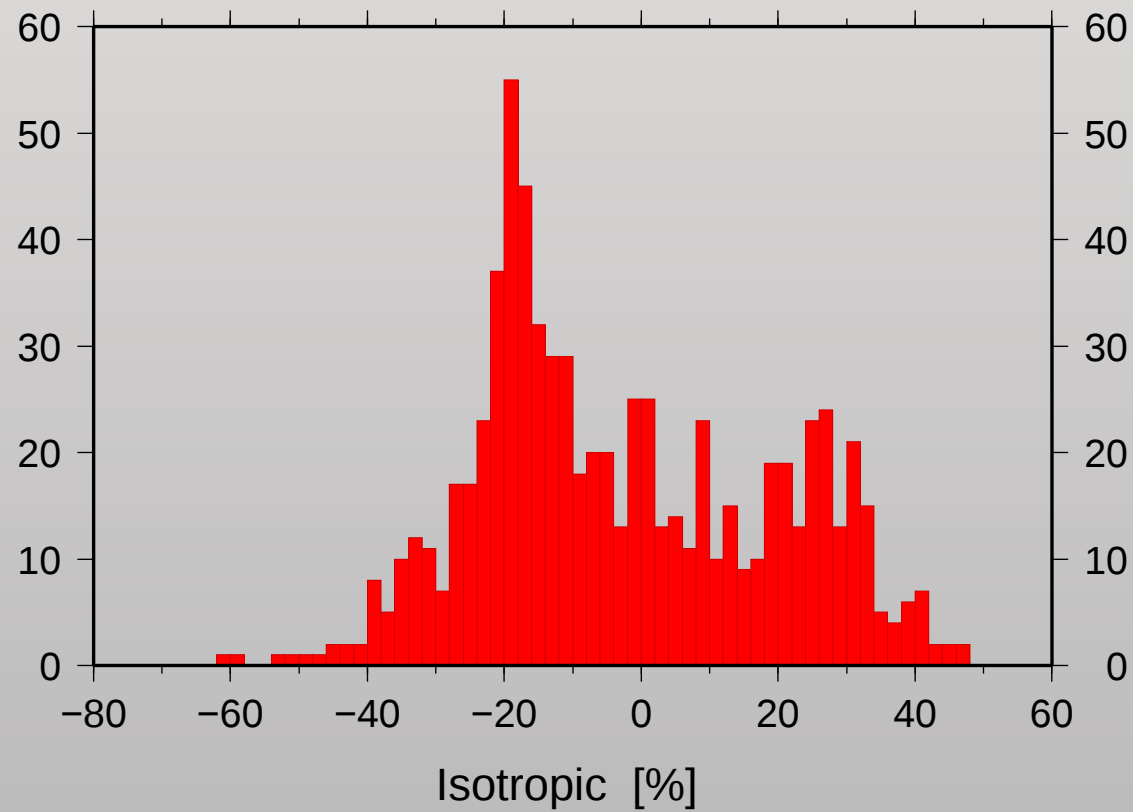


Moment Tensor



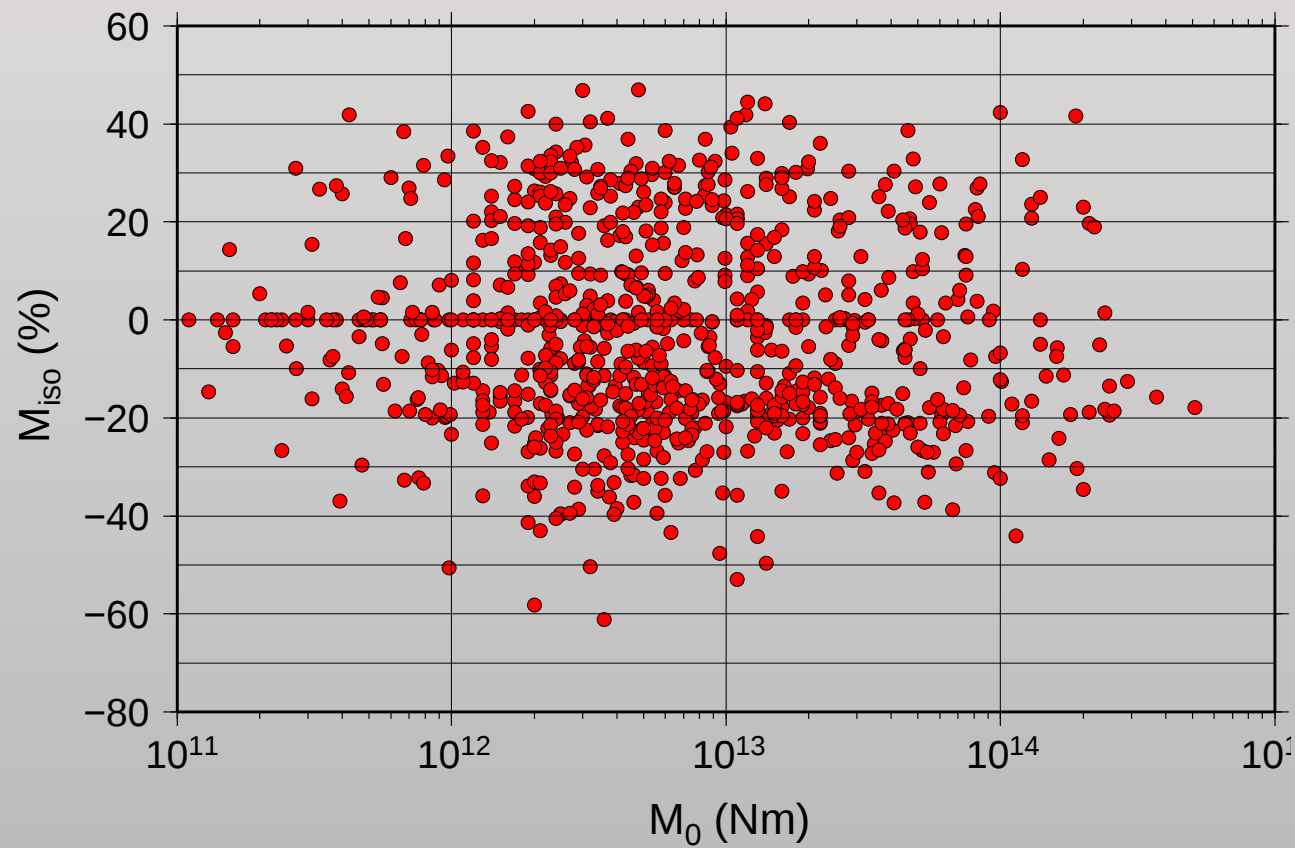
Moment Tensor

2003–2008



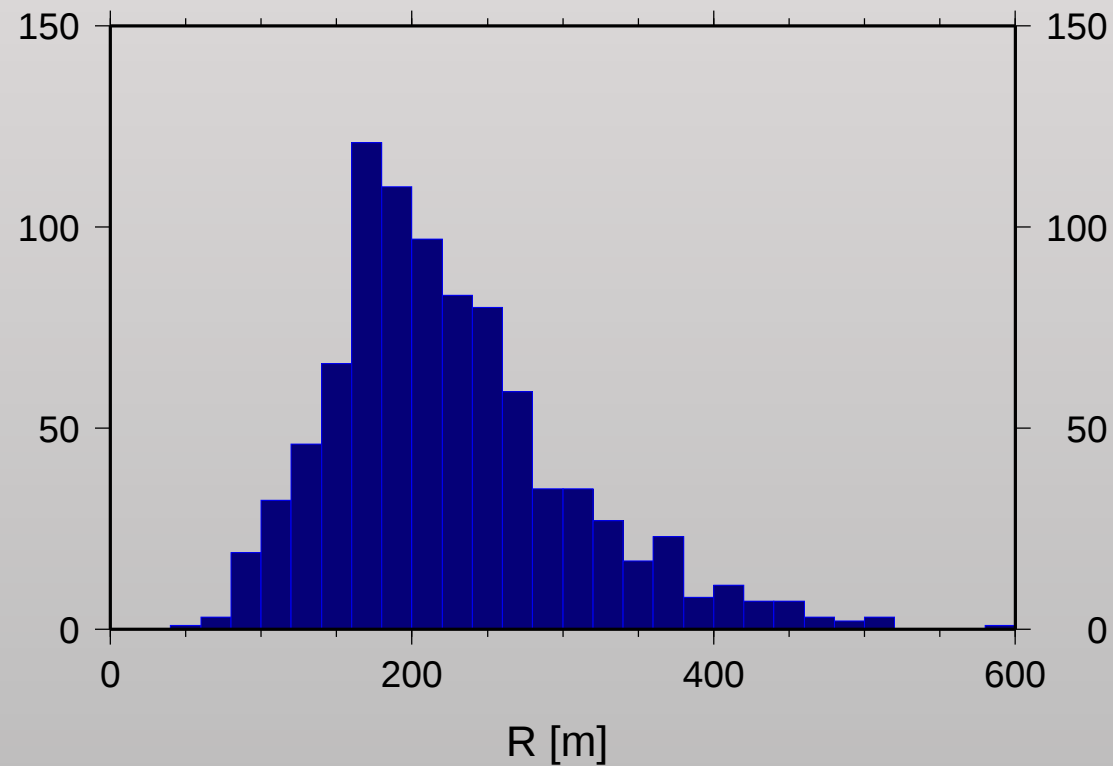
Moment Tensor

1994–2006

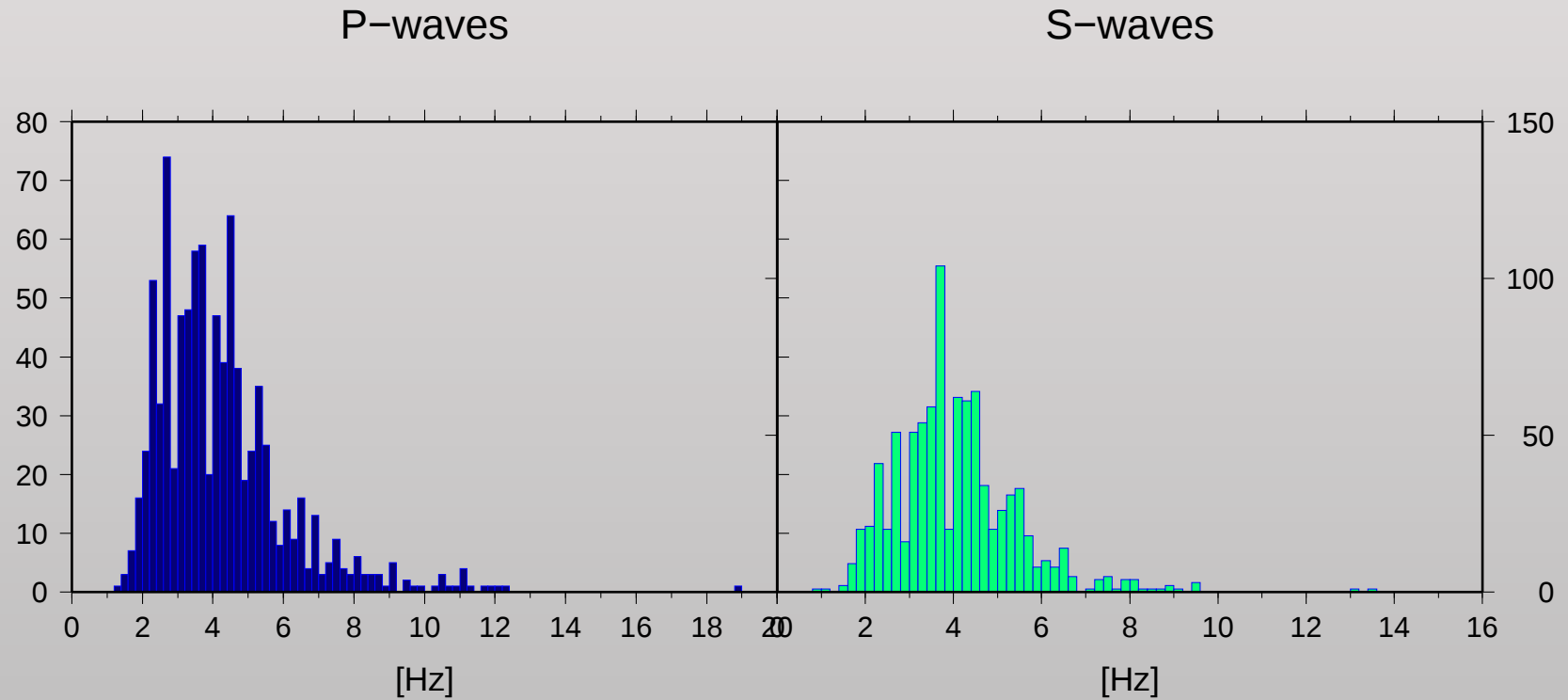


Spectral parameters

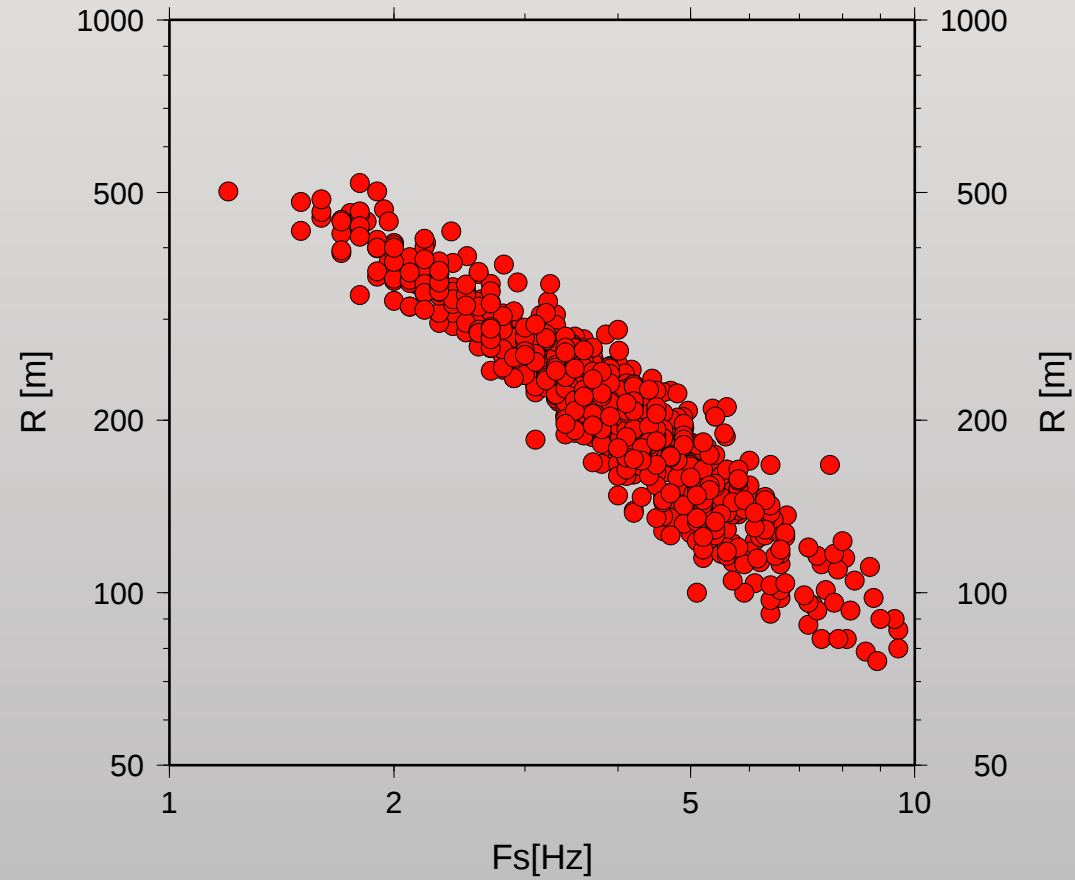
2003–2008



Spectral parameters

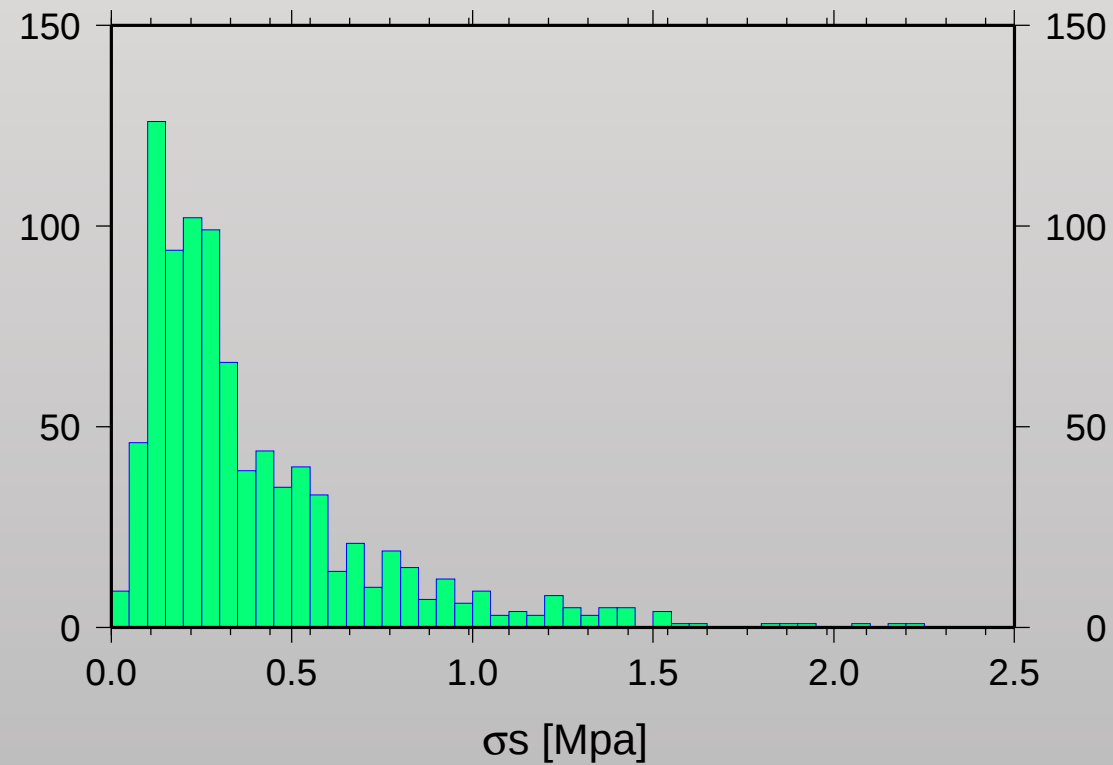


Spectral parameters



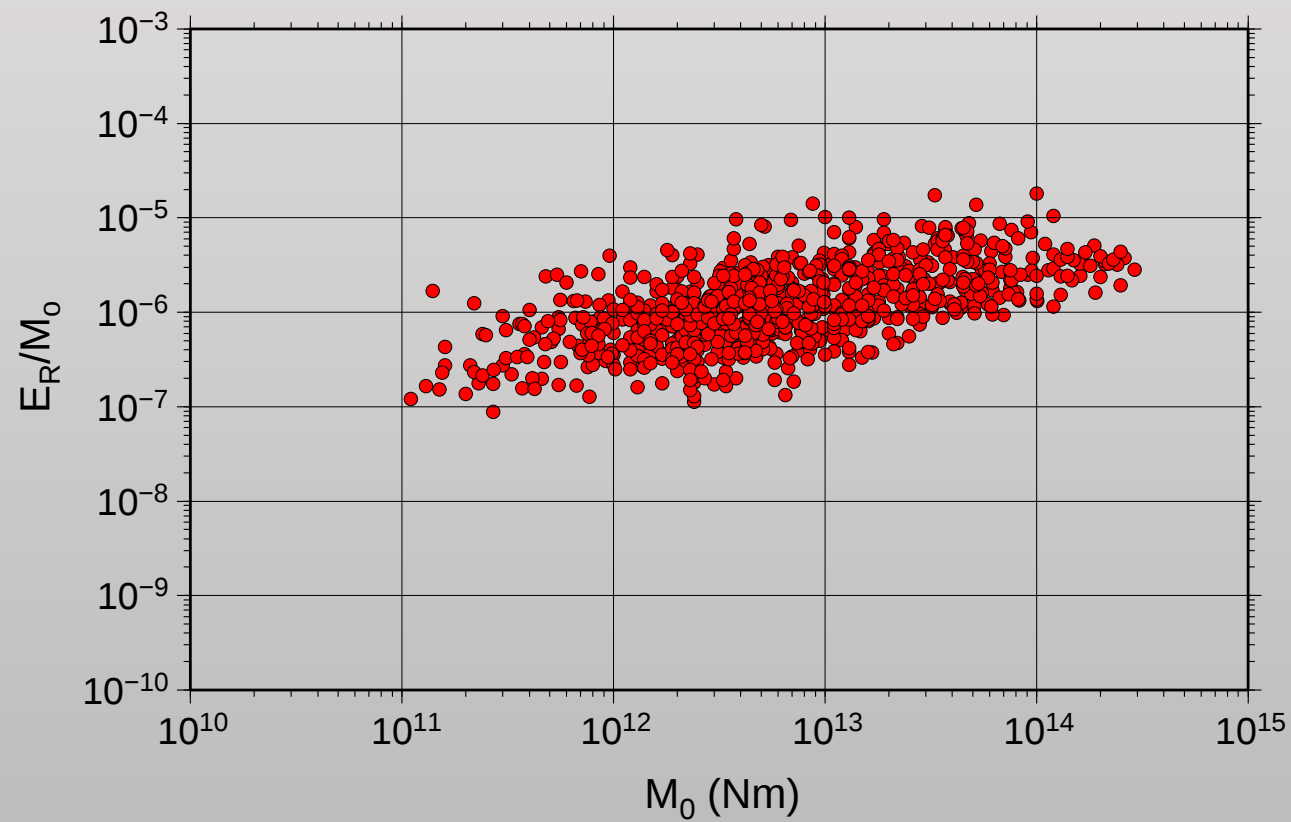
Spectral parameters

Static stress drop



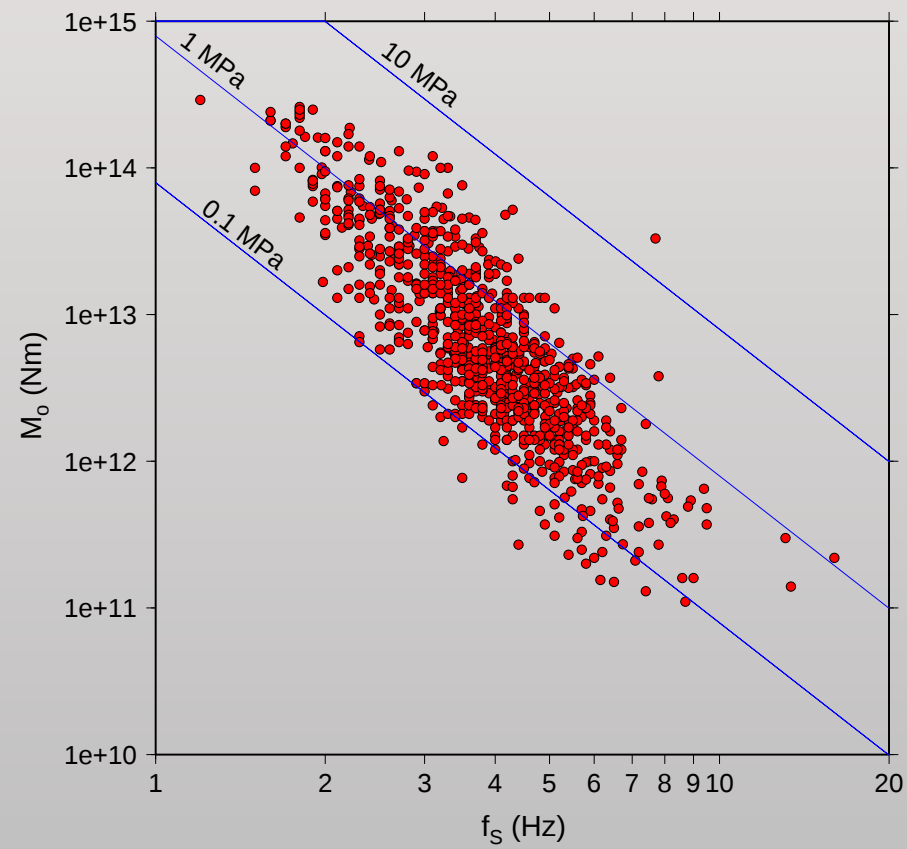
Spectral parameters

1994–2006



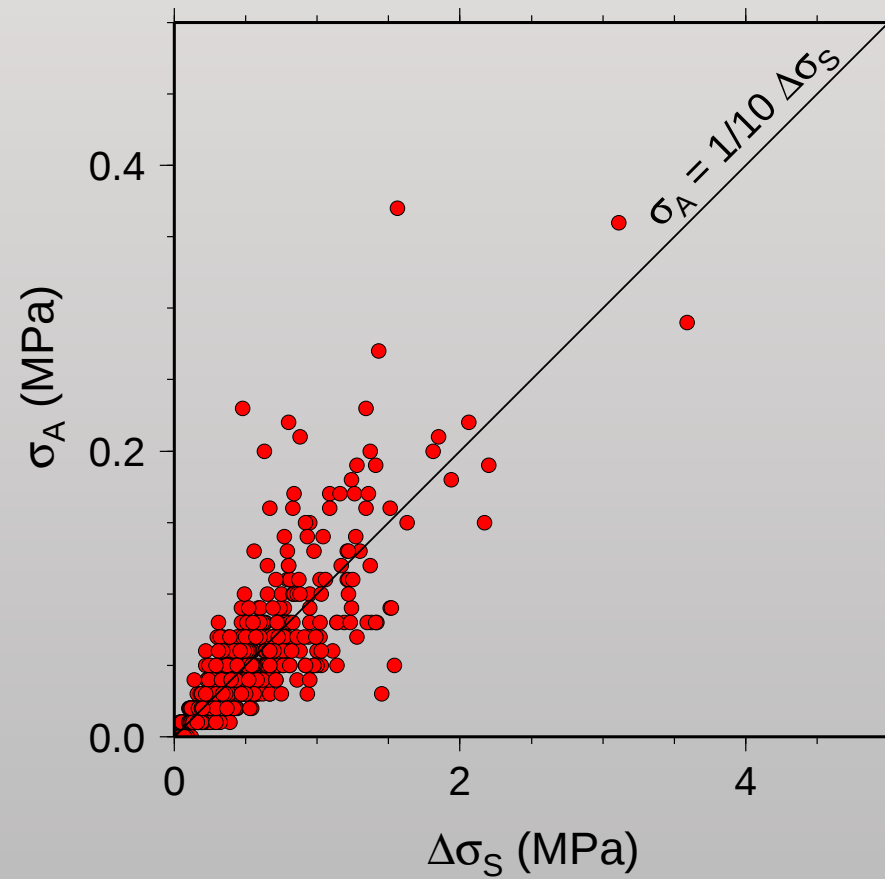
Spectral parameters

1994–2006



Spectral parameters

1994–2006



Stress drops - classical estimators

- ◆ Static (Brune) stress drop $[\sigma_0 - \sigma_1]$

$$\Delta\sigma_s = \frac{7}{16} \frac{M_0}{R^3}$$

- ◆ Apparent stress

$$\sigma_a = \frac{\mu E}{M_0}$$

$$\sigma_a \approx 1/10 \Delta\sigma \quad (\text{Rudna copper mine})$$

Stress drops - classical estimators

◆ Dynamic stress drop $[\sigma_0 - \sigma_d]$

$$\Delta\sigma_d = \frac{M_0}{4\pi v_r^3 I} (1 - \xi^2)^2 \frac{dS}{dt}$$

$$I = \int_0^T S(t) dt$$

- ◆ M_0 - seismic moment
- ◆ v_r - constant (assumption!) rupture velocity
- ◆ ξ - geometrical (directional) factor - assumed to be 0.75
- ◆ S - STF
- ◆ T - rupture duration time

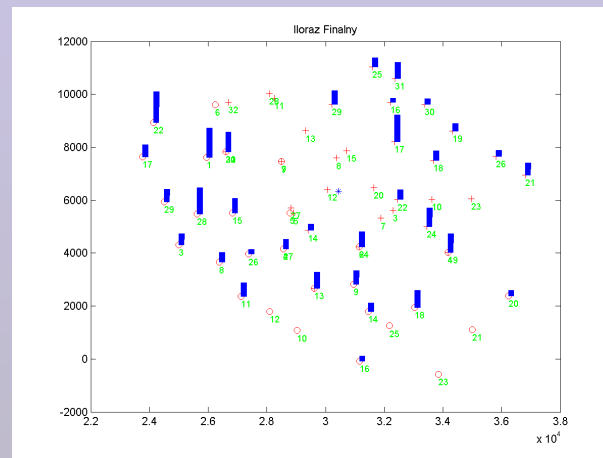
Partial stress drop/overshooting

$$\gamma_d = \Delta\sigma_d / \Delta\sigma_s \approx \frac{\sigma_0 - \sigma_d}{\sigma_0 - \sigma_1}$$

$$\gamma_d \left\{ \begin{array}{lll} = 1 & \text{Orowan's model} & \sigma_d = \sigma_1 \\ > 1 & \text{partial stress drop} & \sigma_d < \sigma_1 \\ < 1 & \text{"overshooting"} & \sigma_d > \sigma_1 \end{array} \right.$$

Rupture velocity

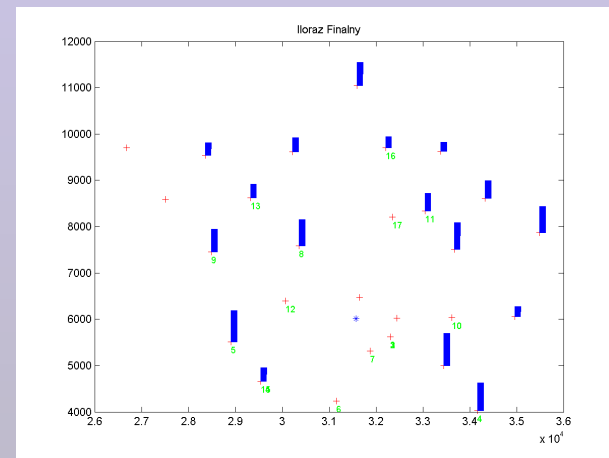
“circular type”



no visible directivity

$$V_r = 0.5V_s$$

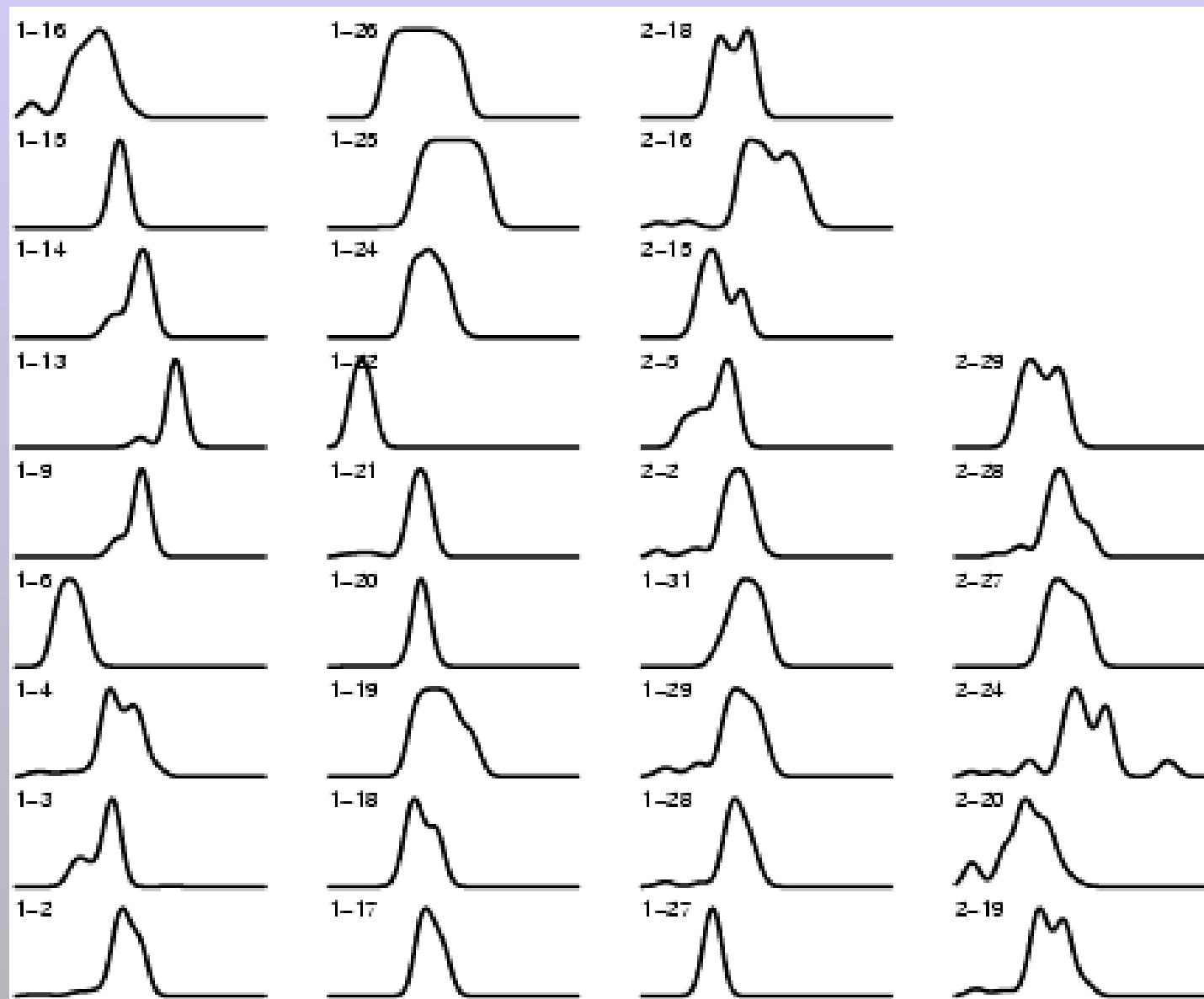
“unilateral type”



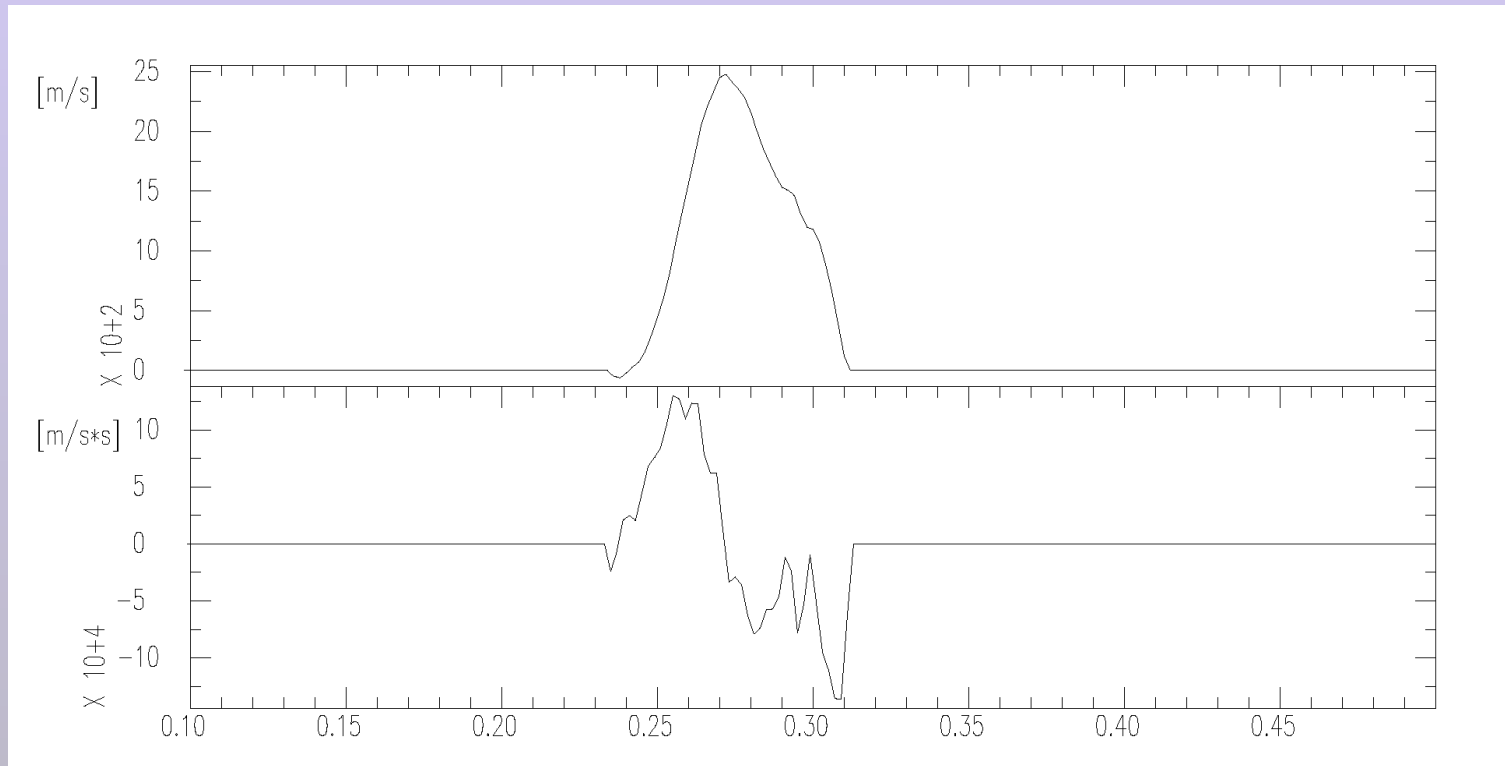
directivity of T distribution

$$T(\theta) = \frac{L}{V_r} - \frac{L}{V_P} \cos(\theta)$$

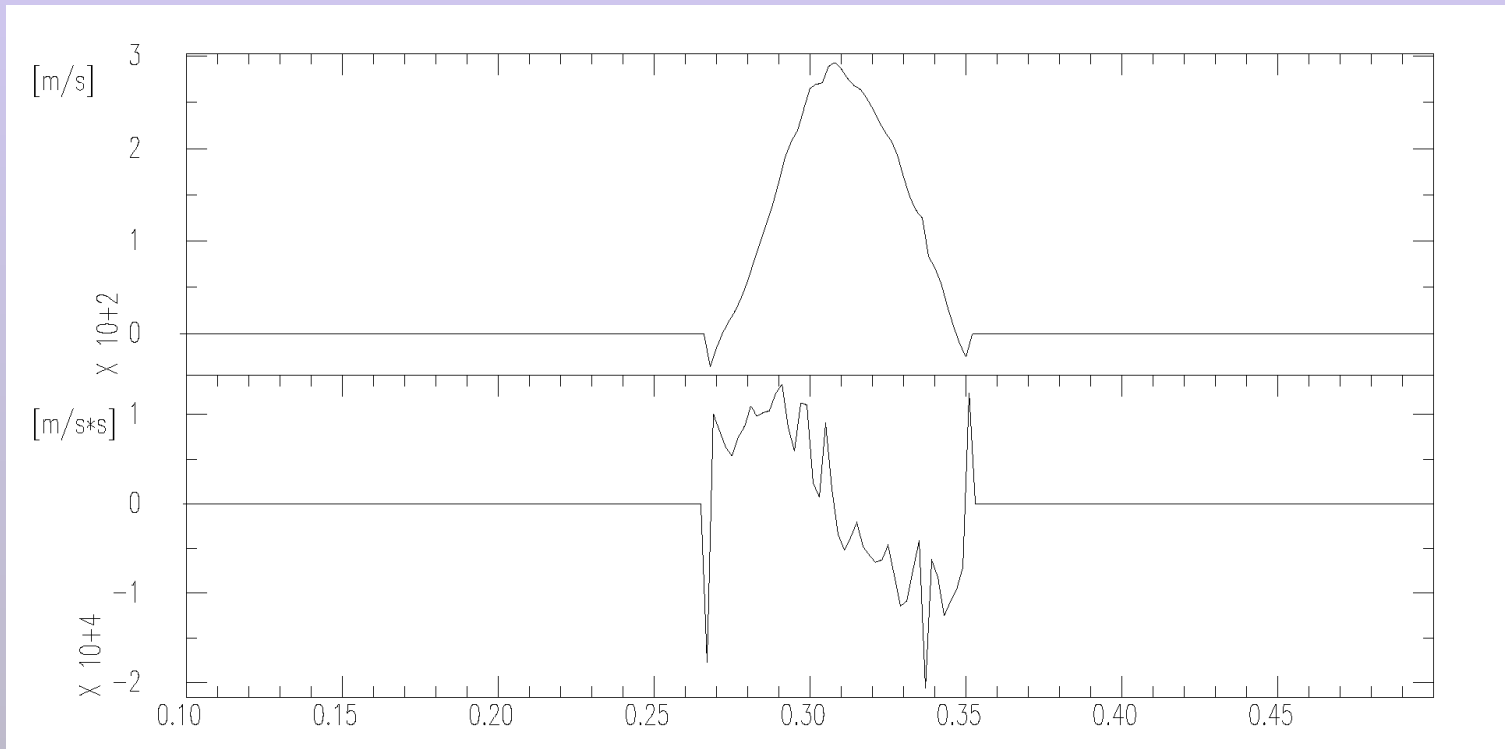
STF- spatial distribution



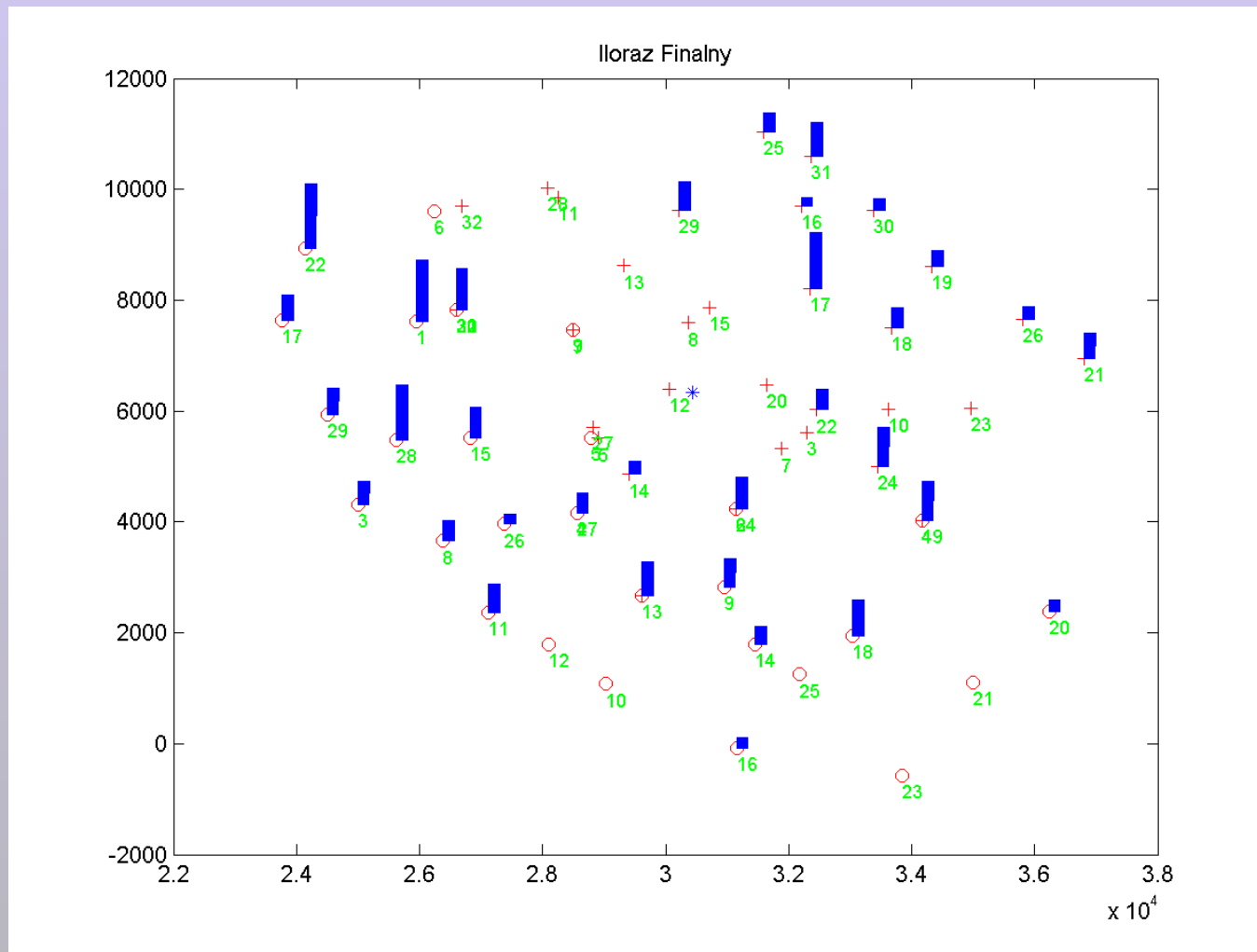
Source Time Function



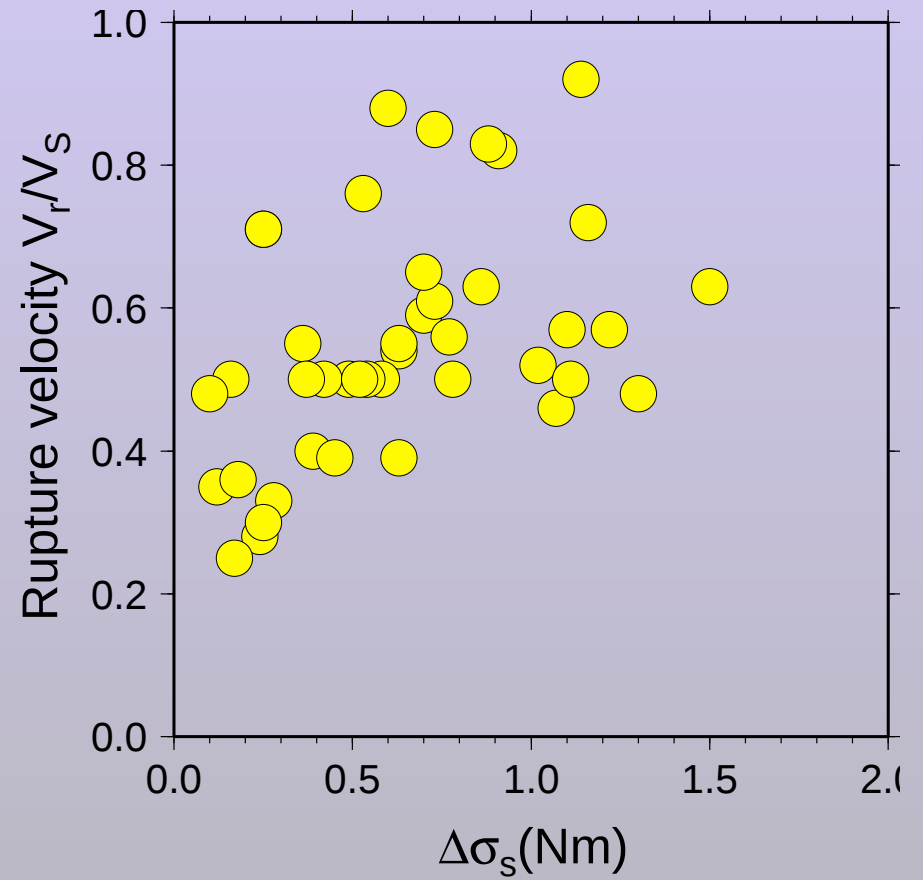
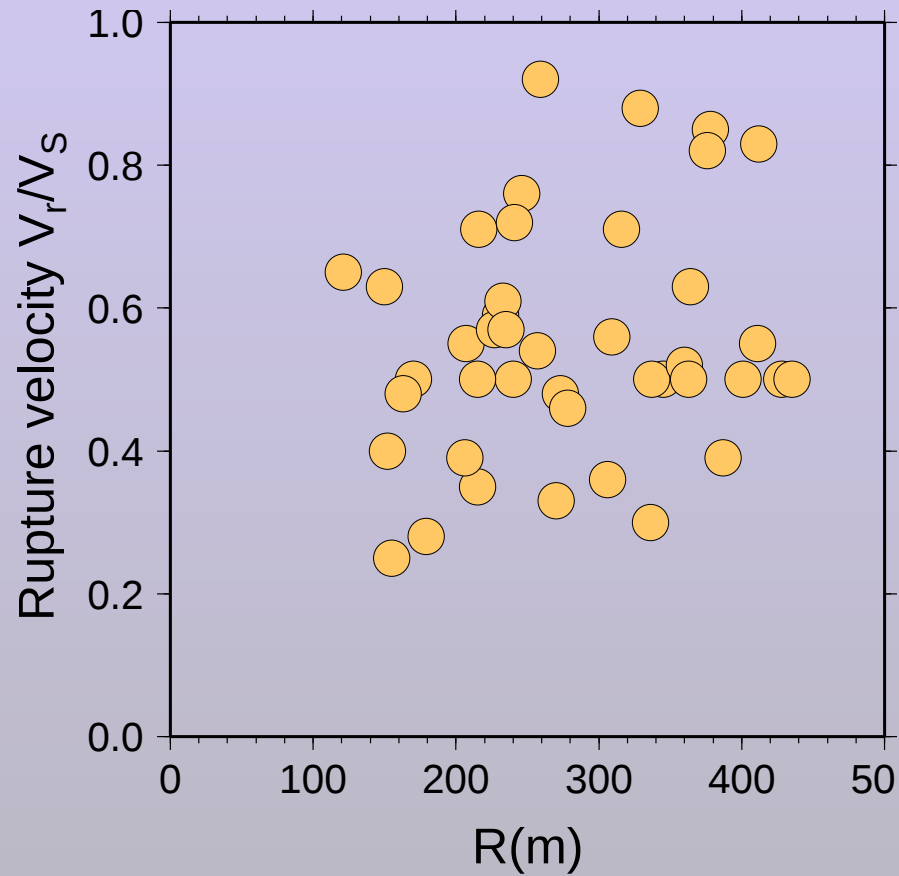
Source Time Function



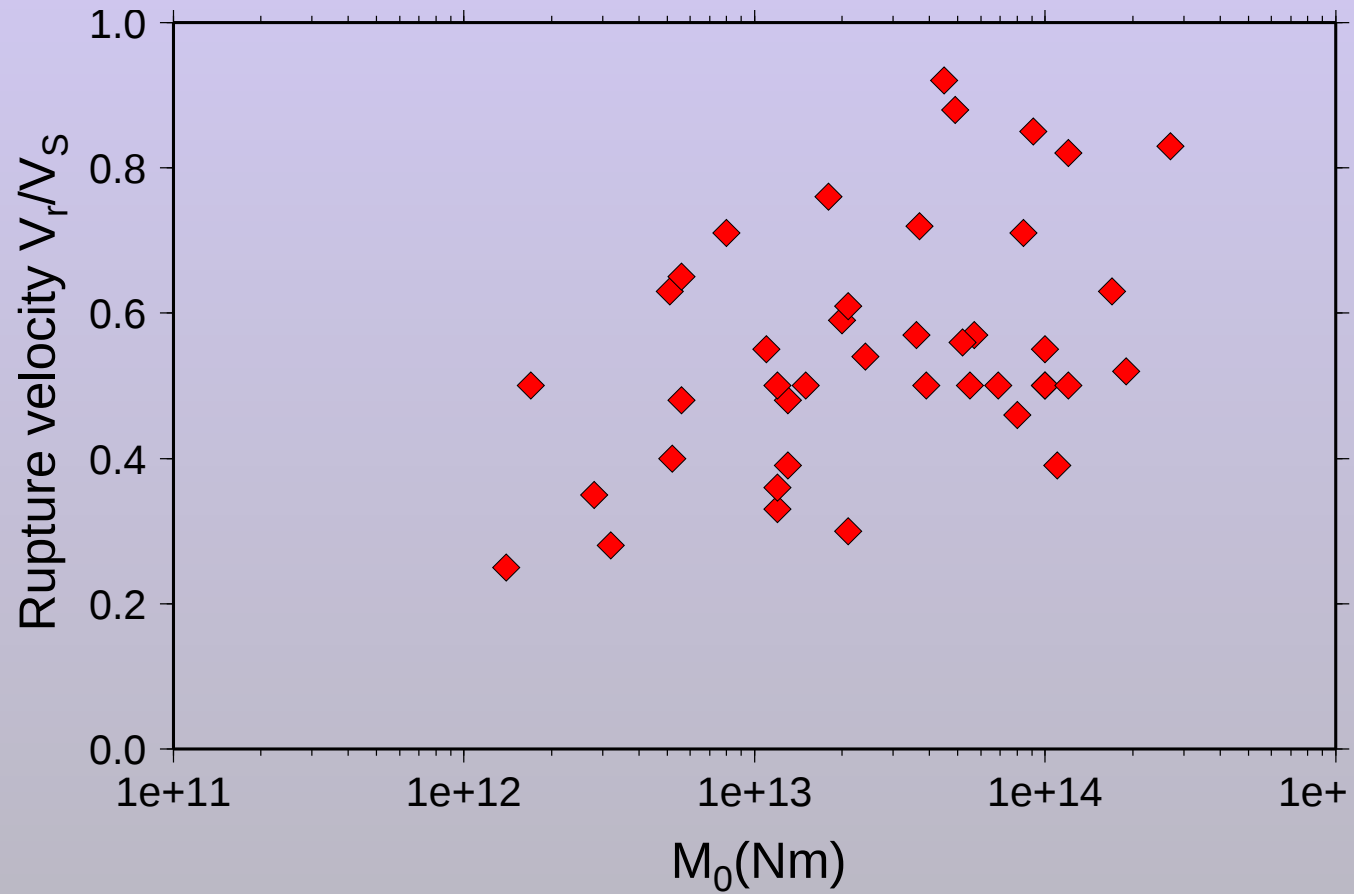
STW width - spatial distribution



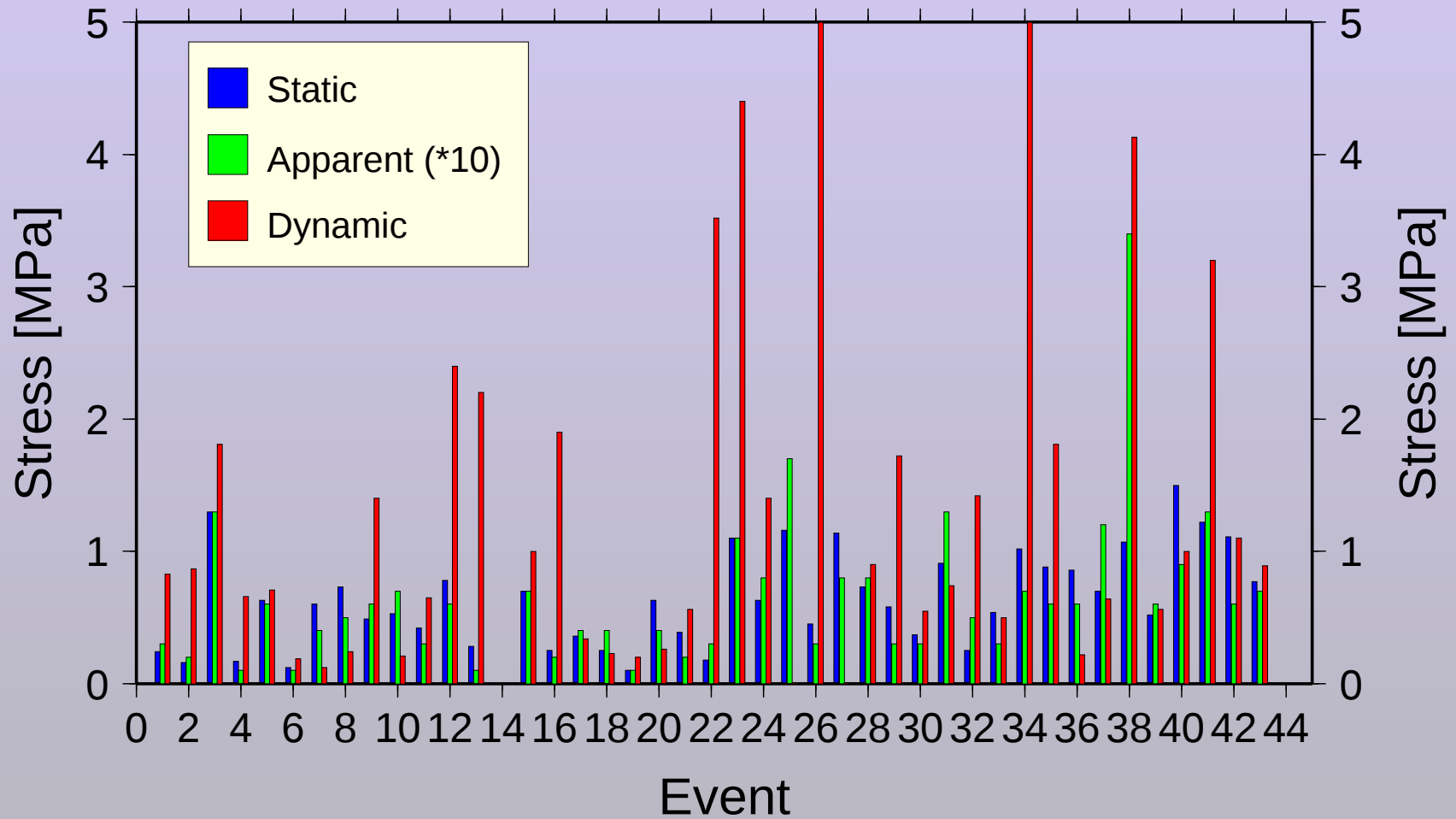
Rupture velocity



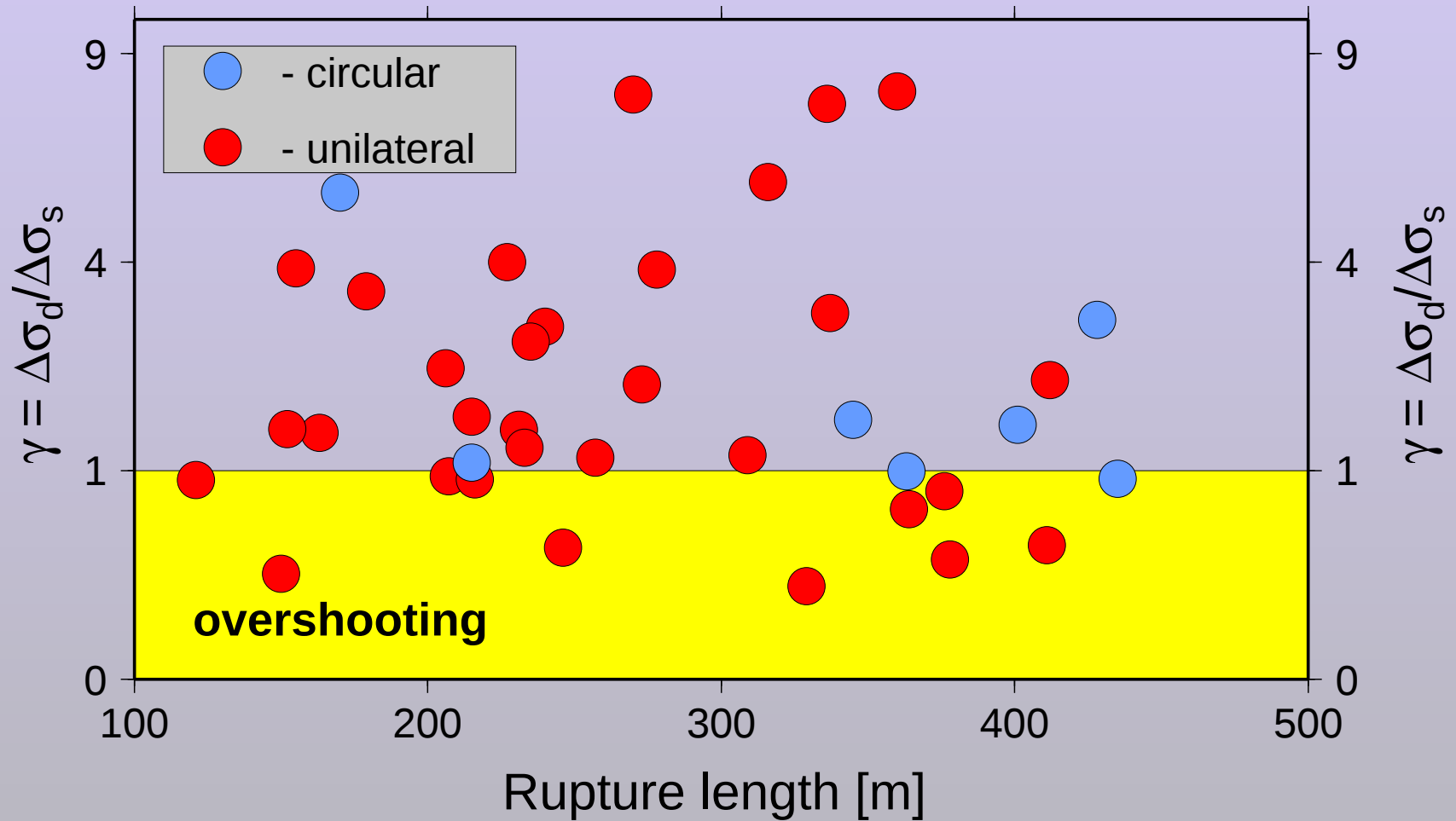
Rupture velocity



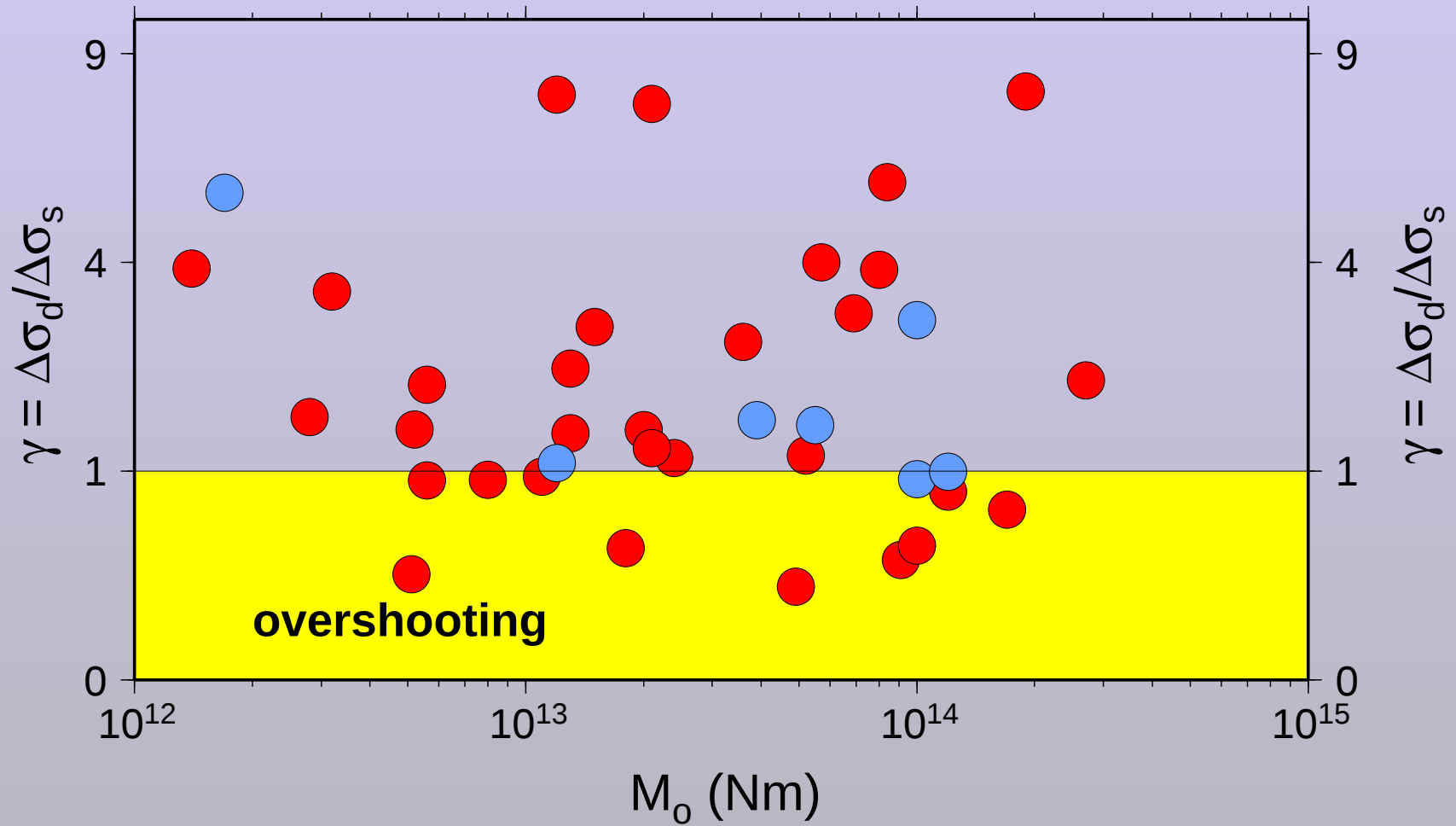
Stress estimates



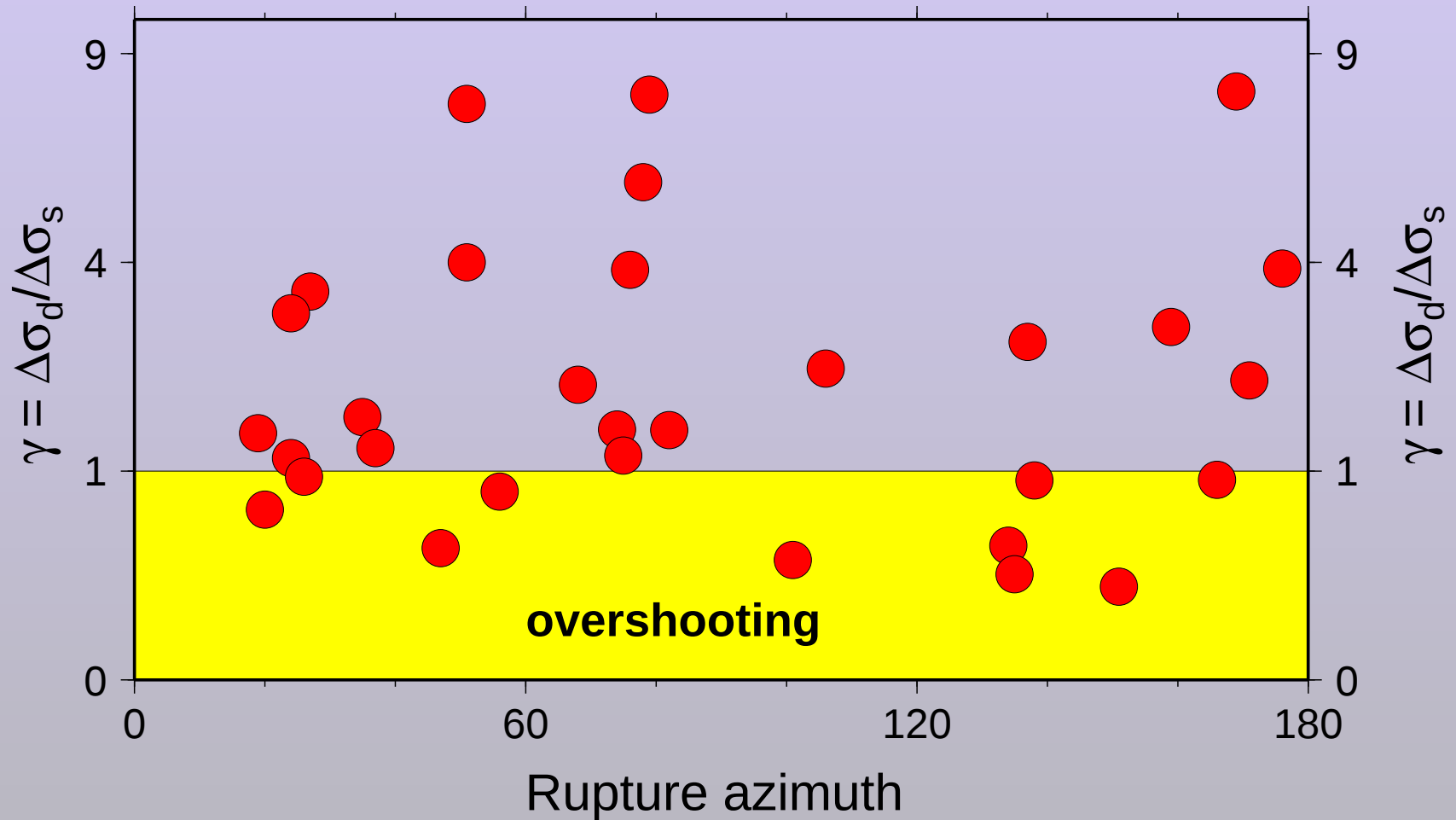
Correlations



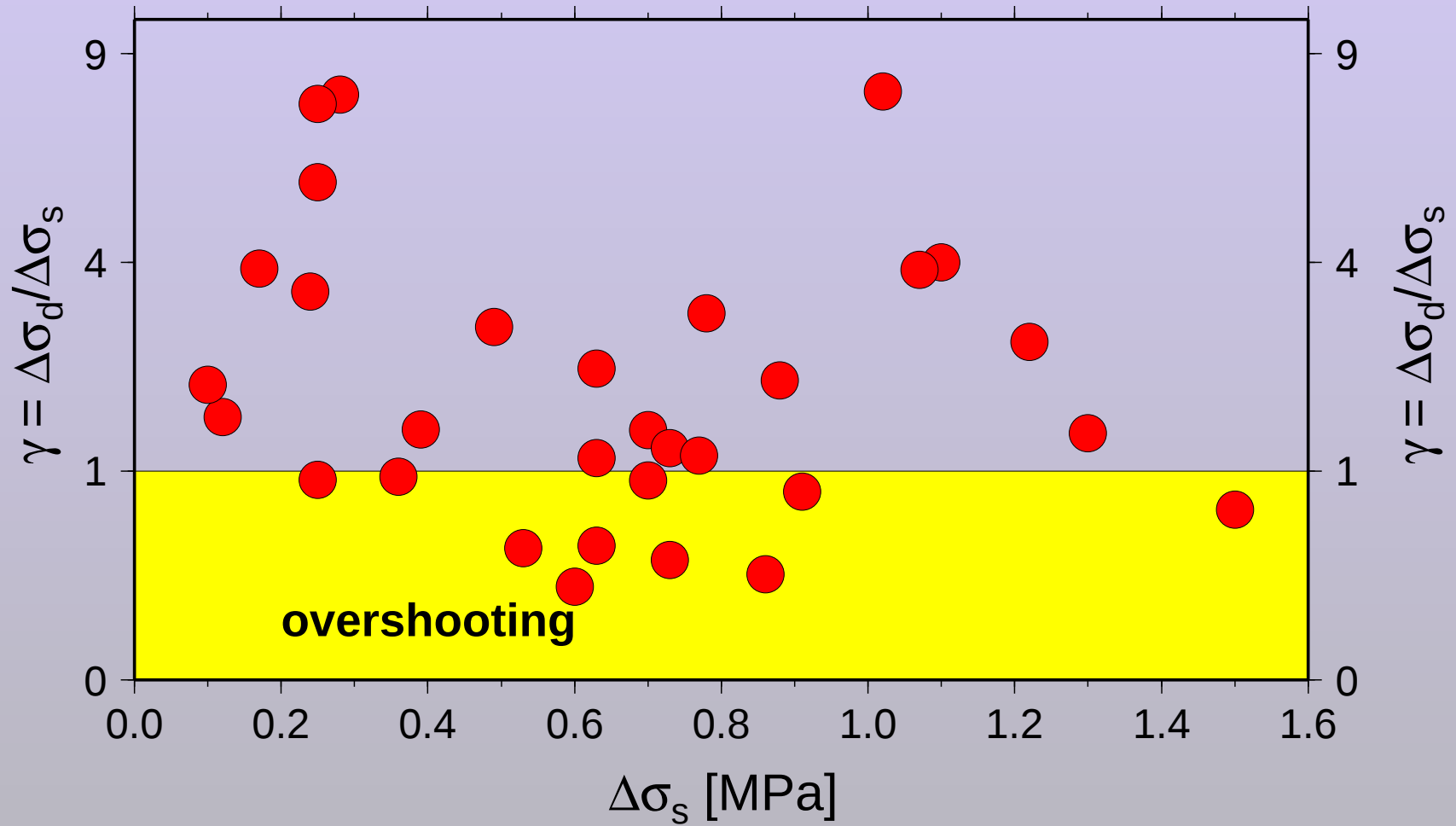
Correlations



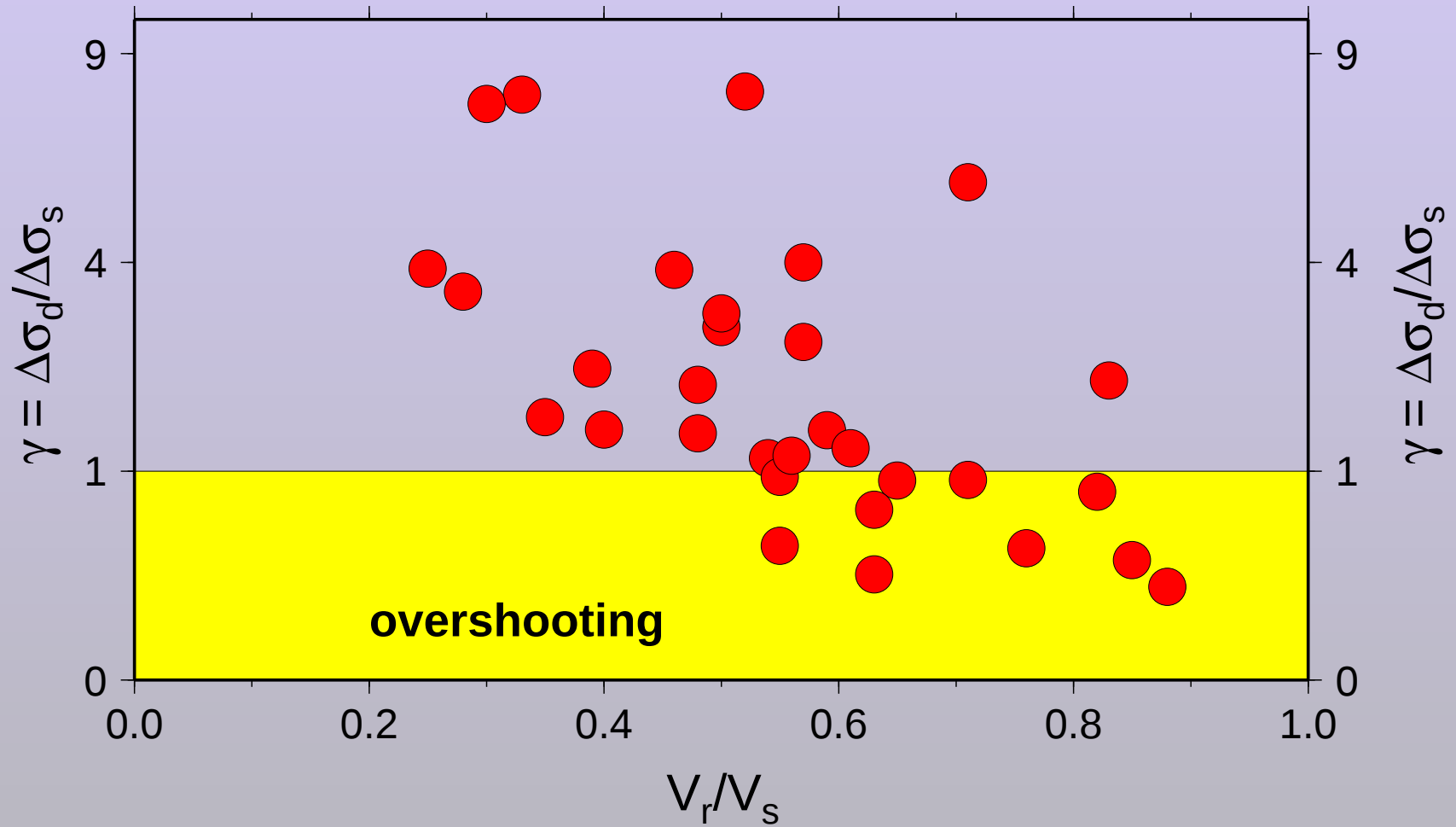
Correlations



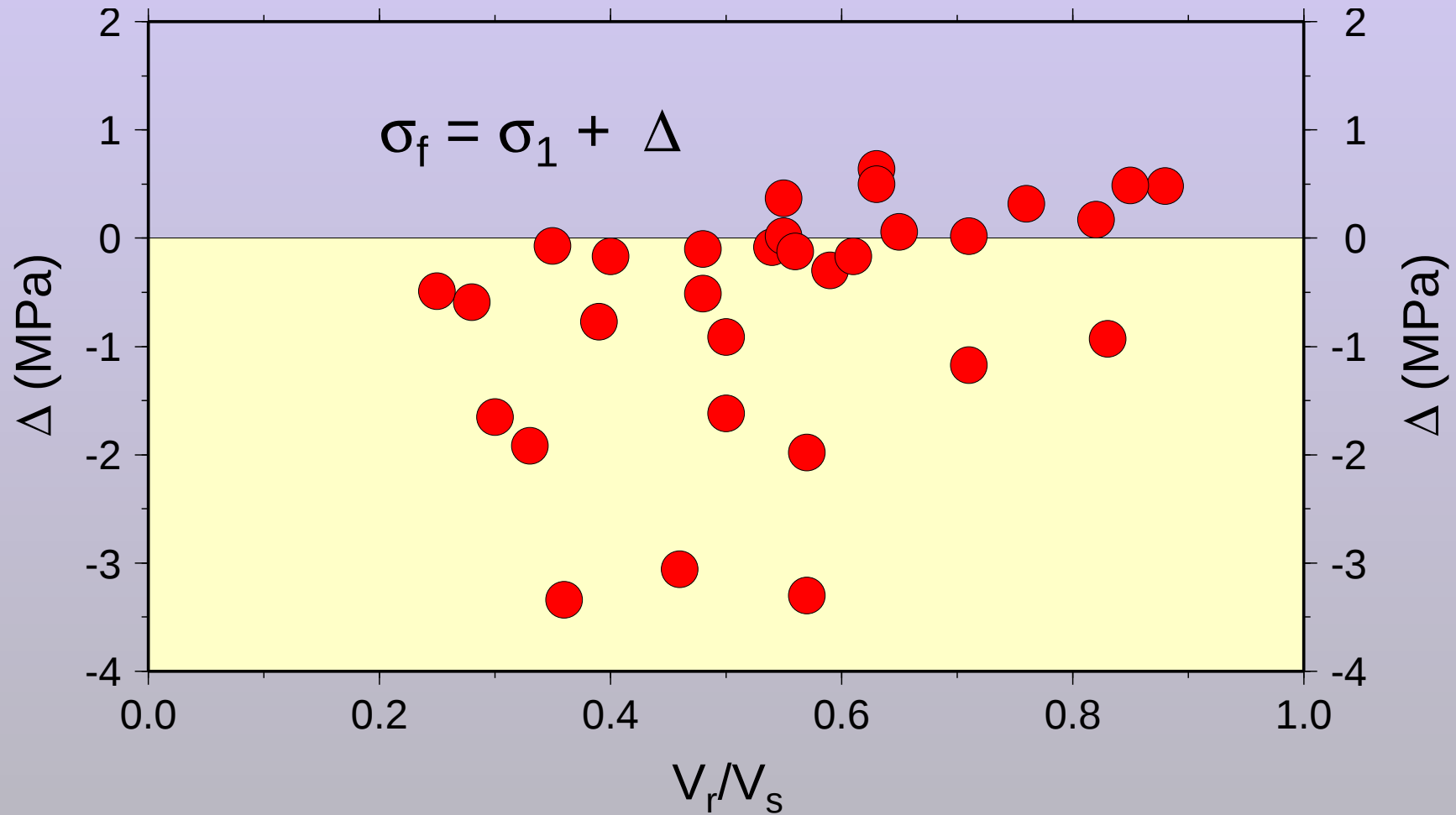
Correlations



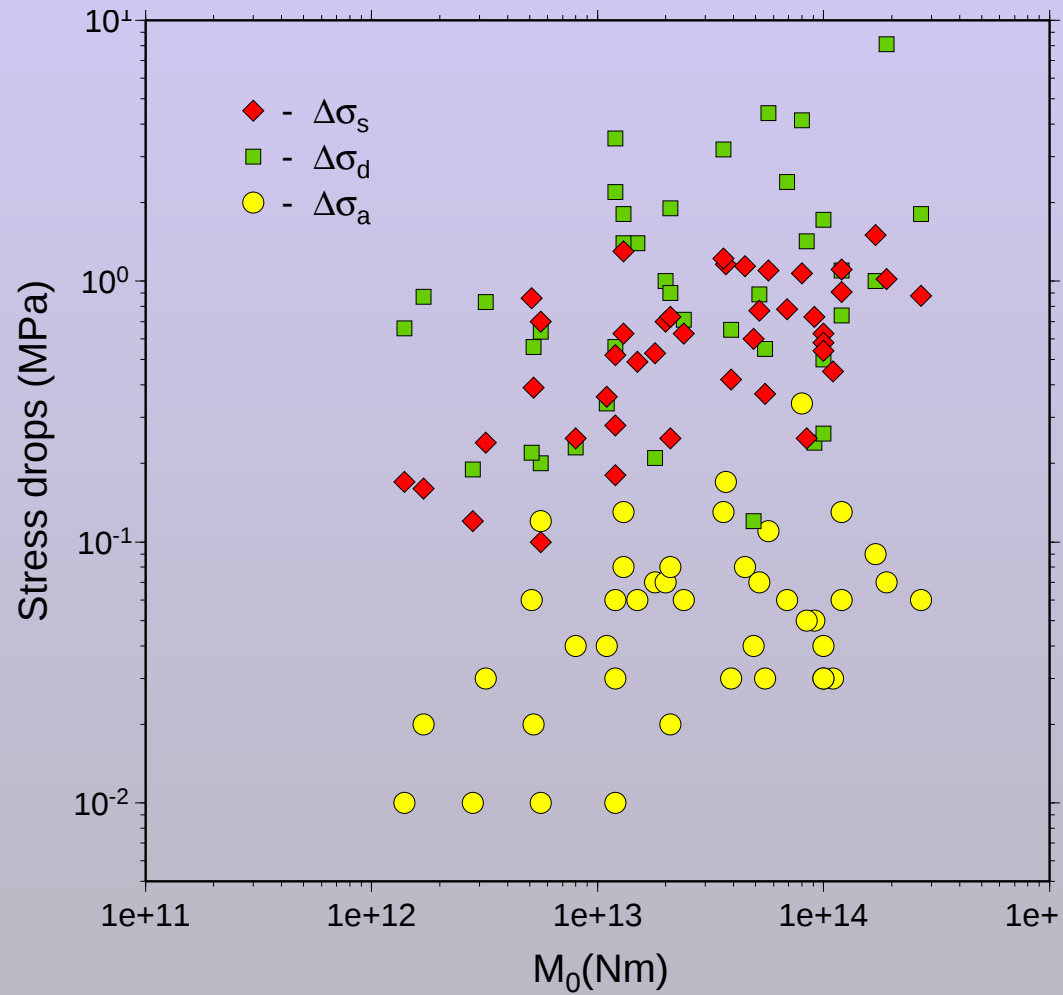
Velocity



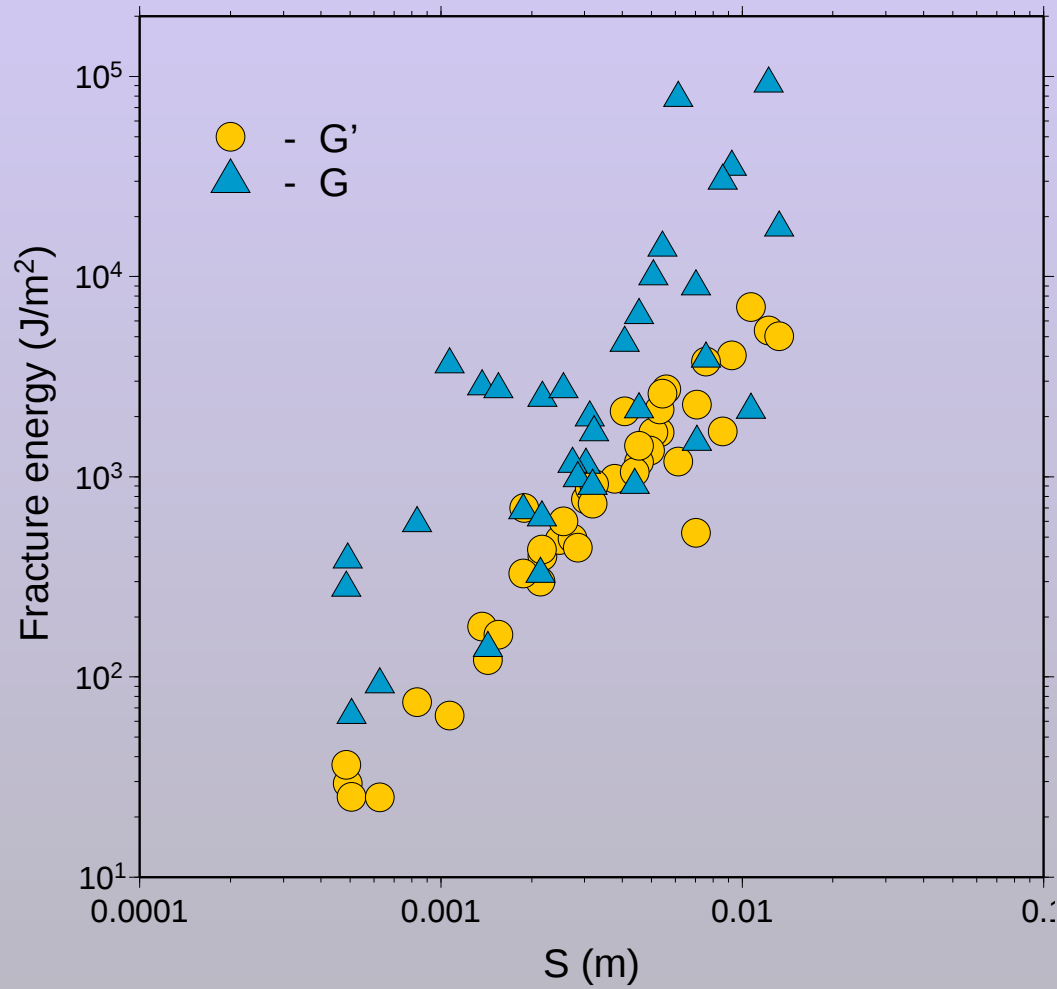
“Overshooting” stress



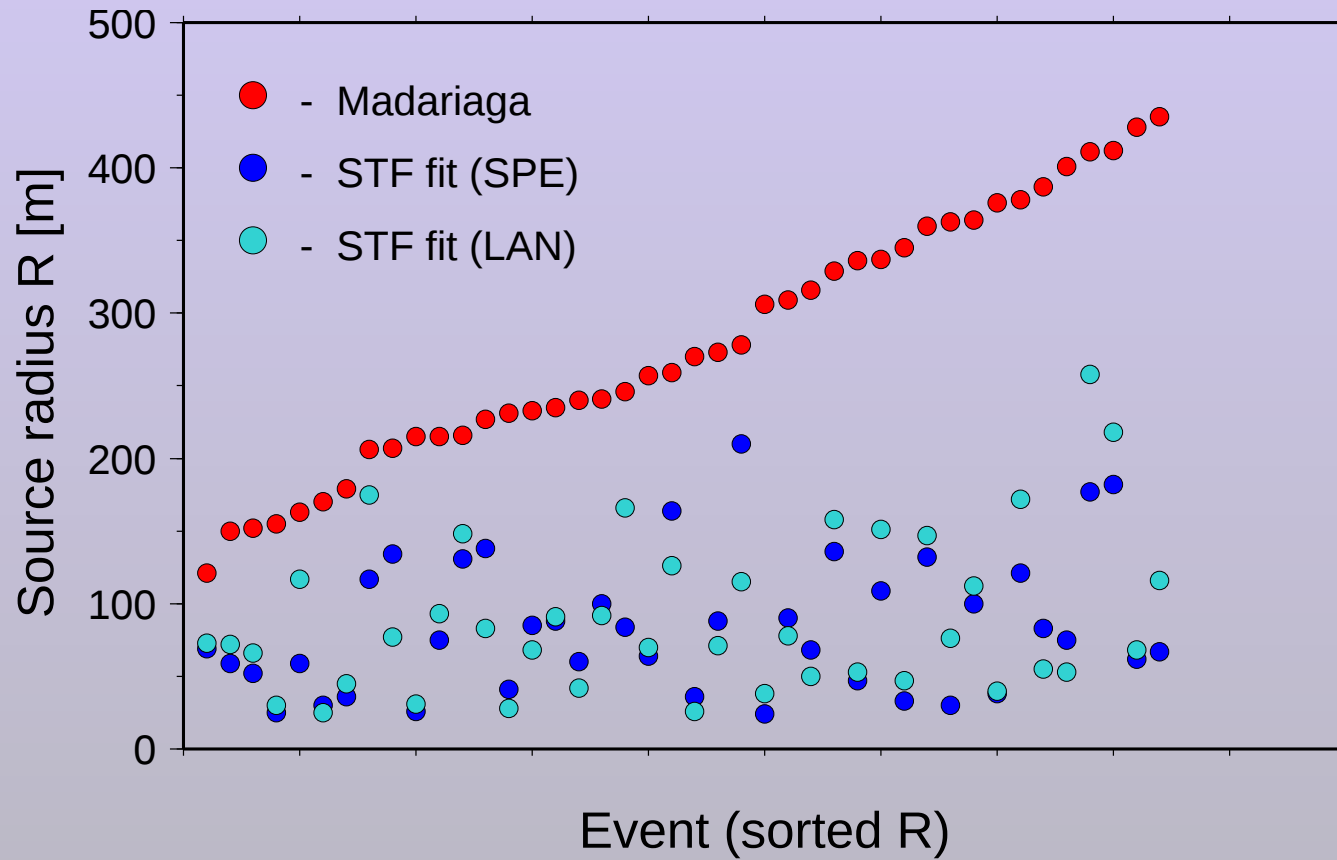
Scaling stresses with M_0



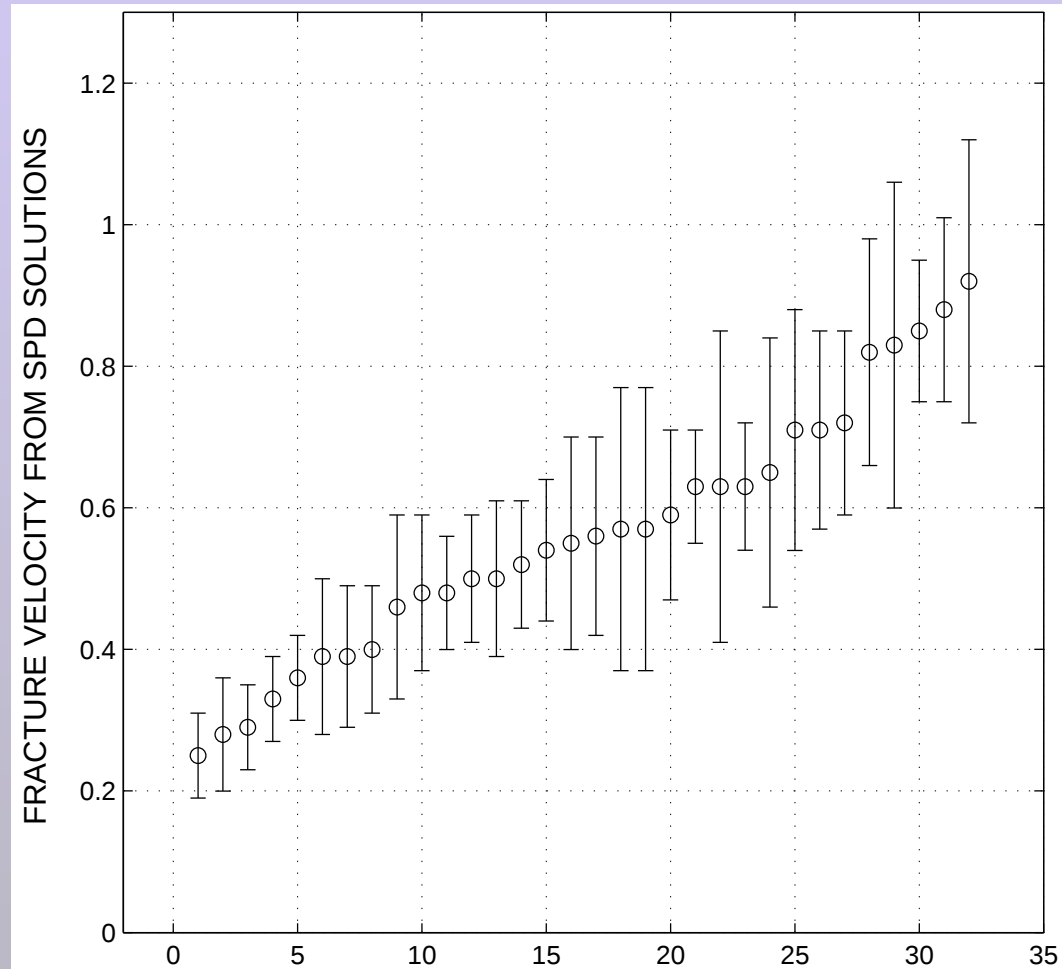
Fracture energy



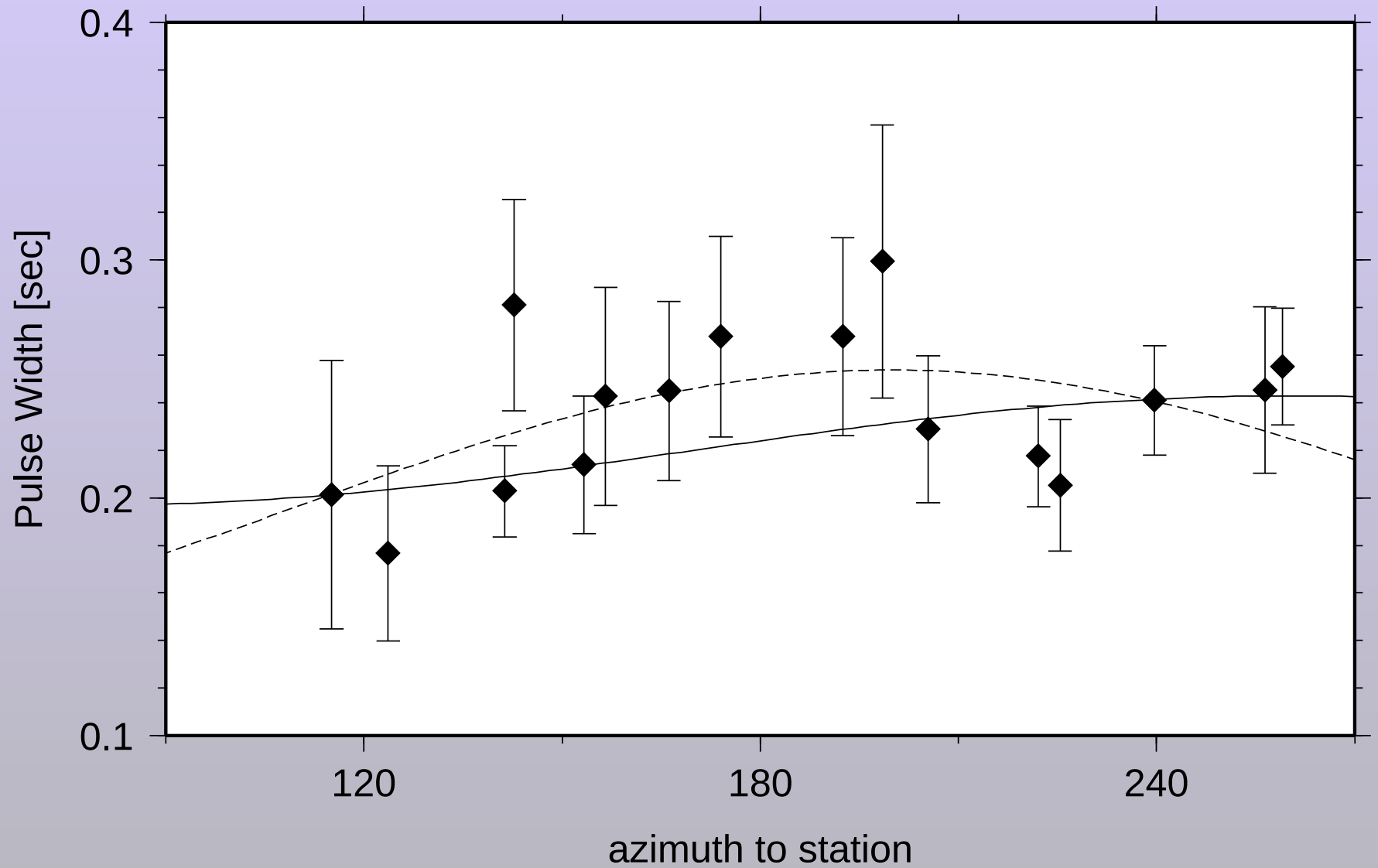
Source size: Madariaga, Brune, or ...



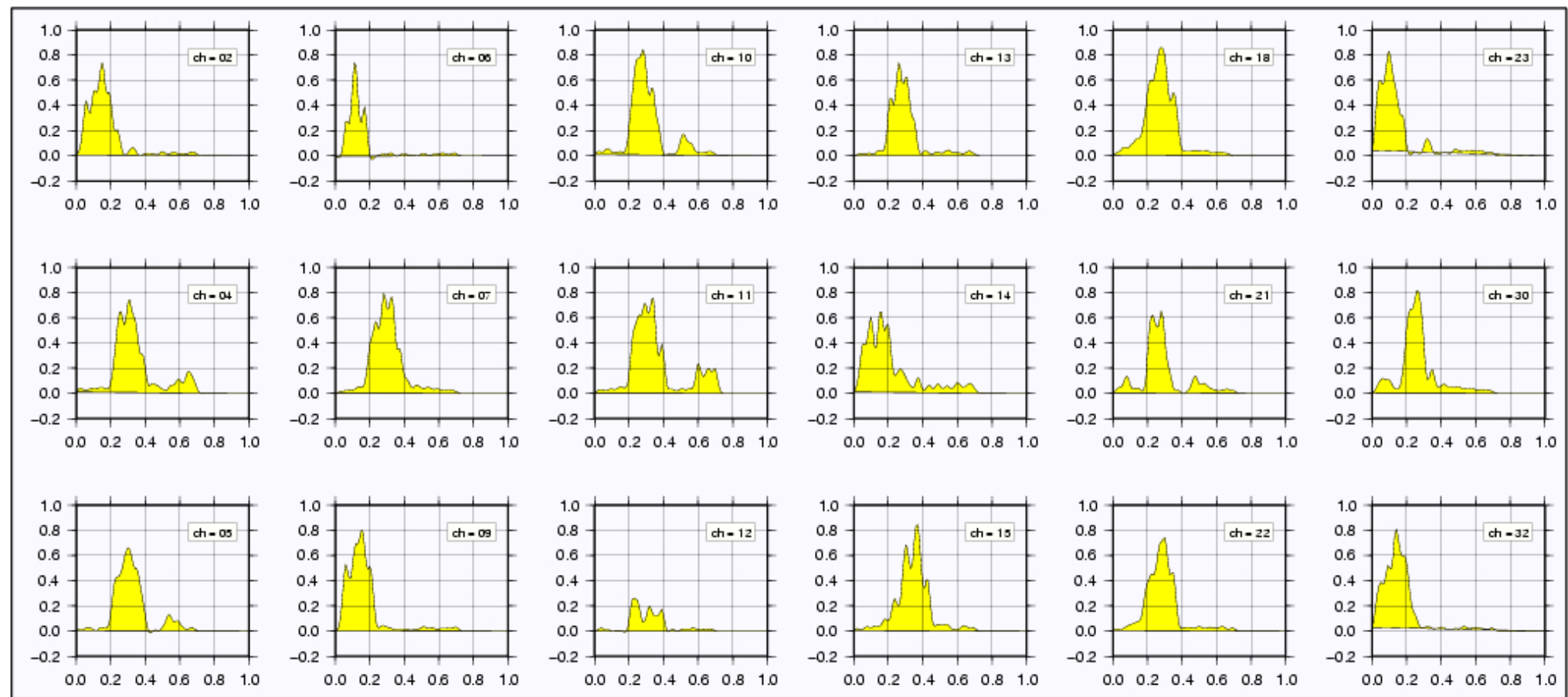
Uncertainties (a)



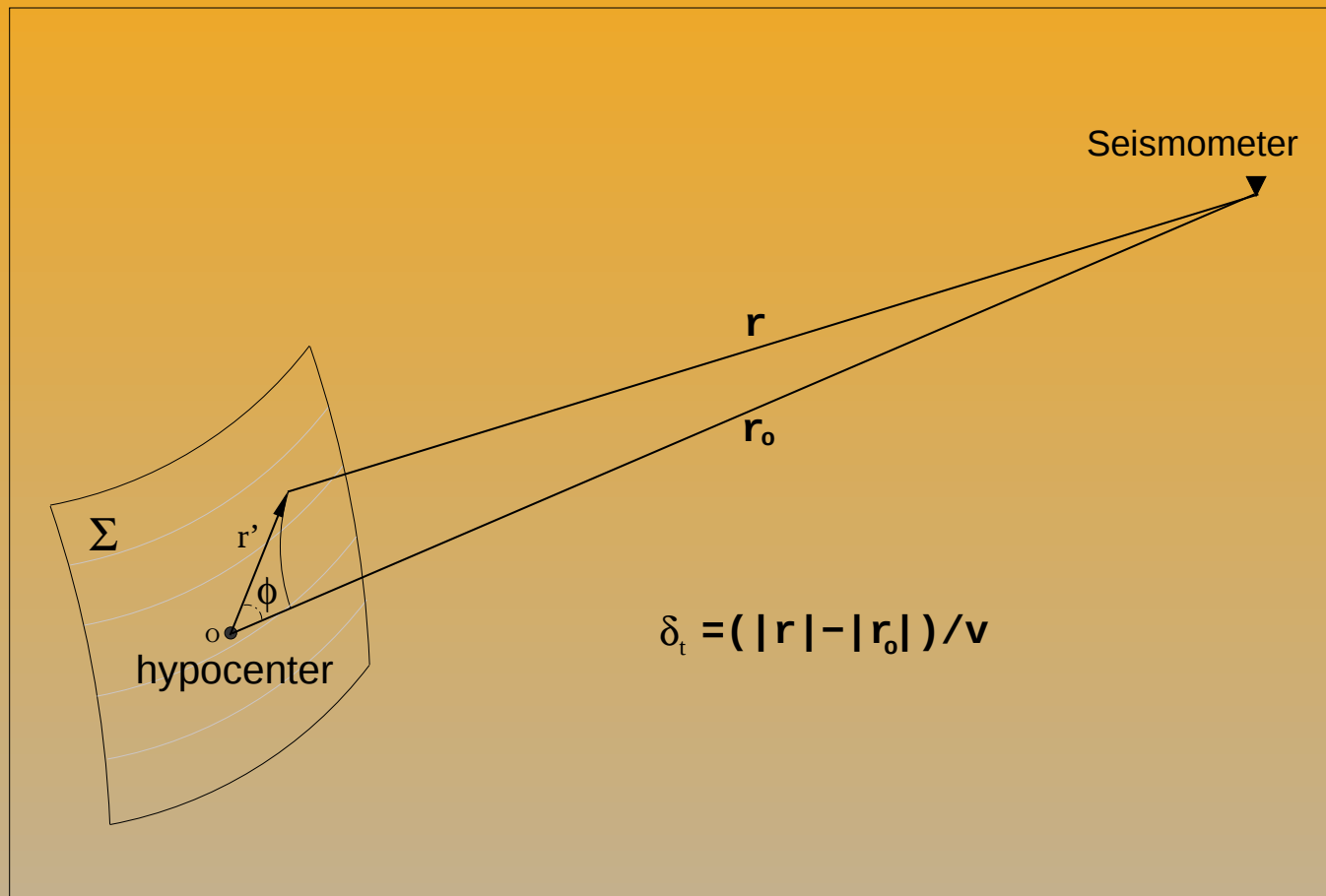
Uncertainties (b)



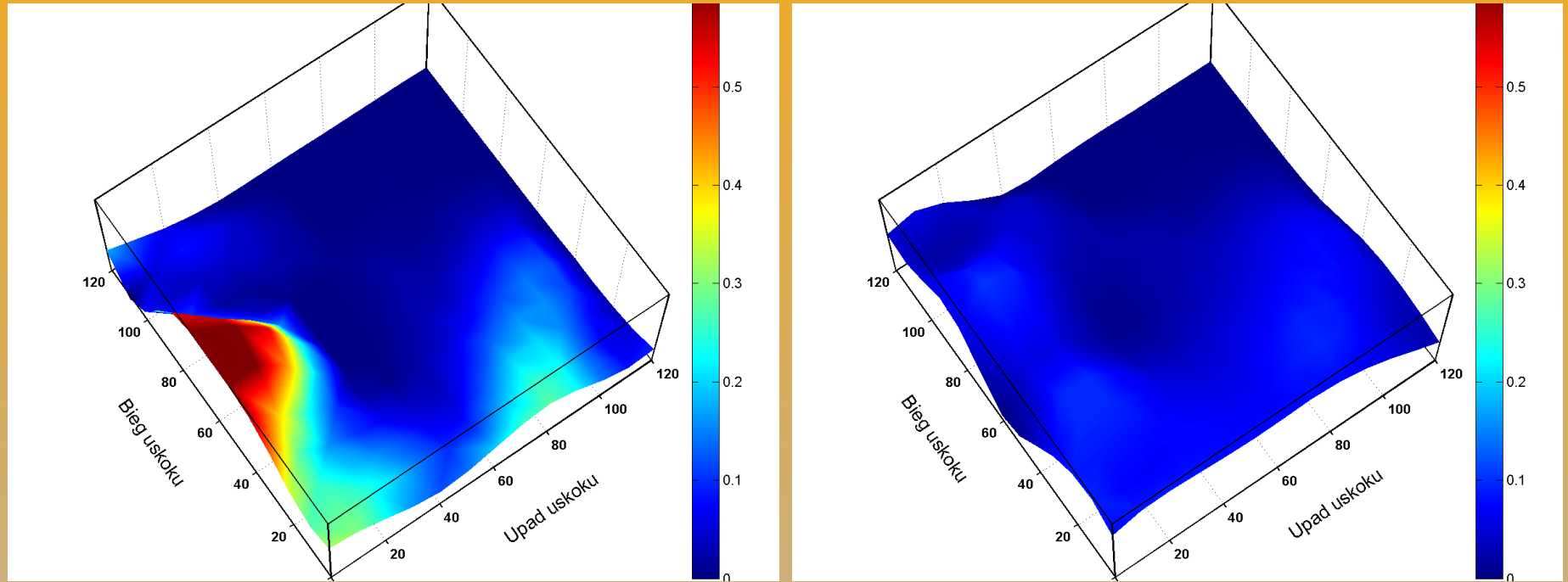
Finite size sources



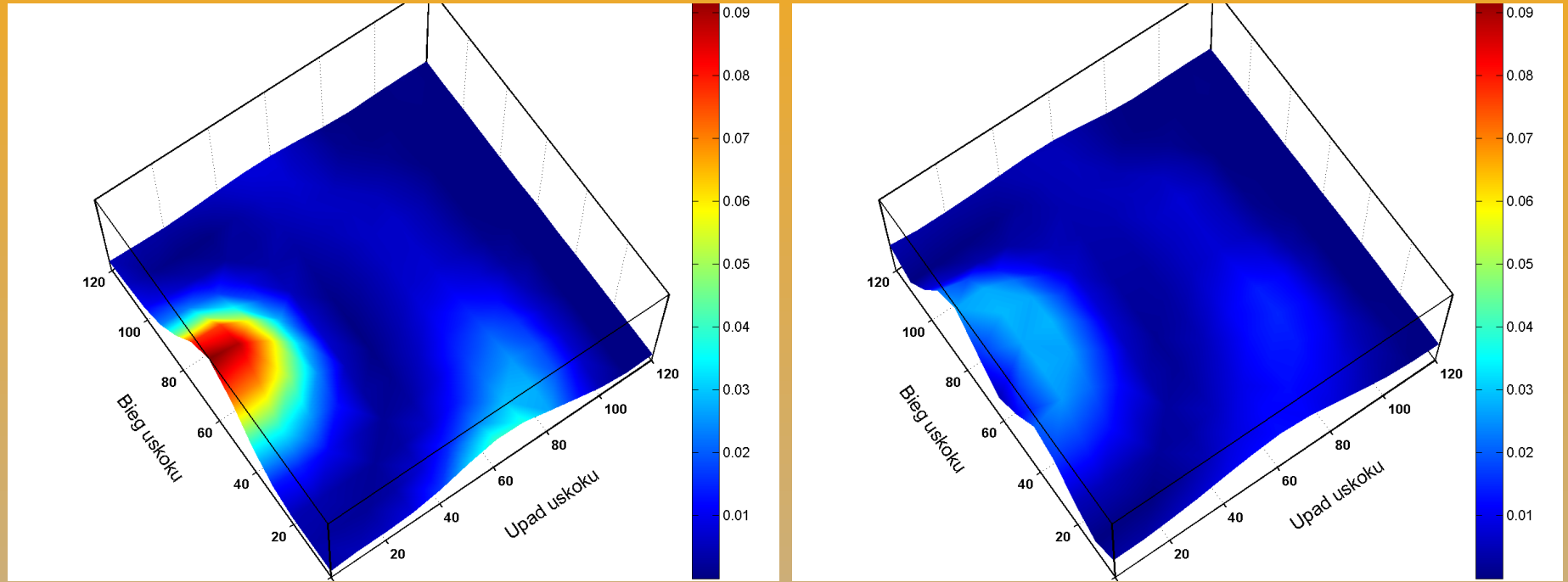
Finite size sources



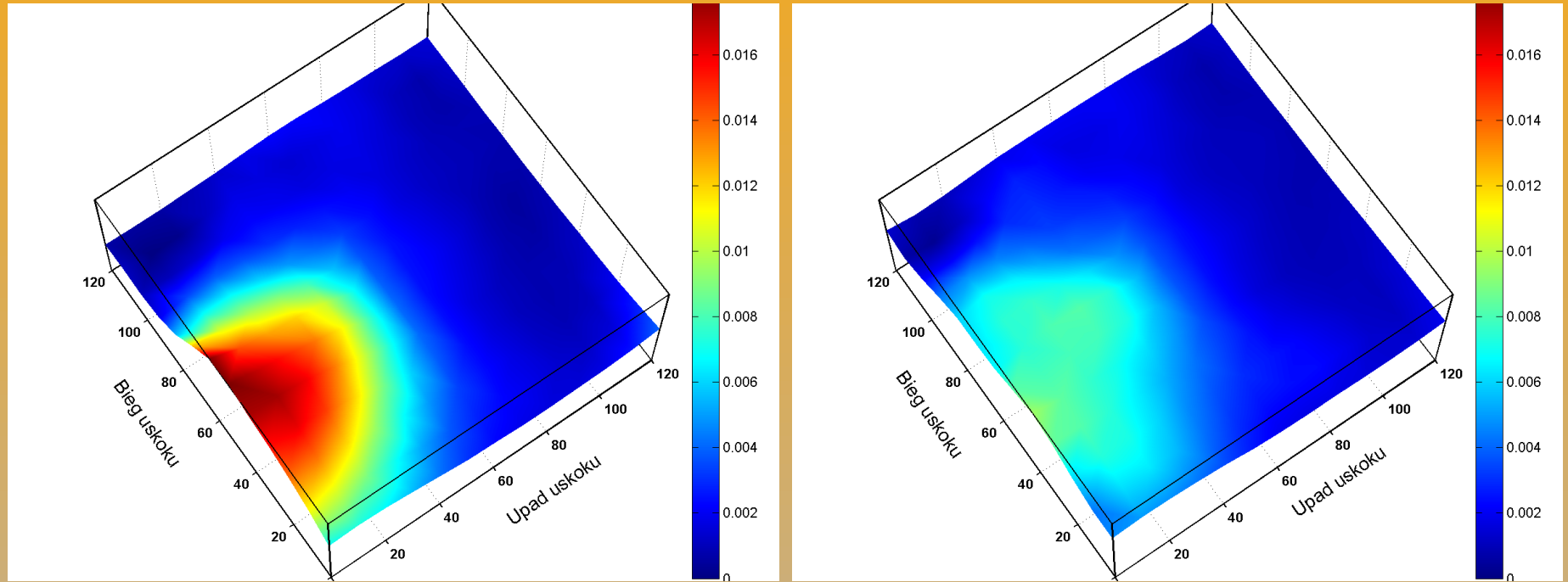
Case - A



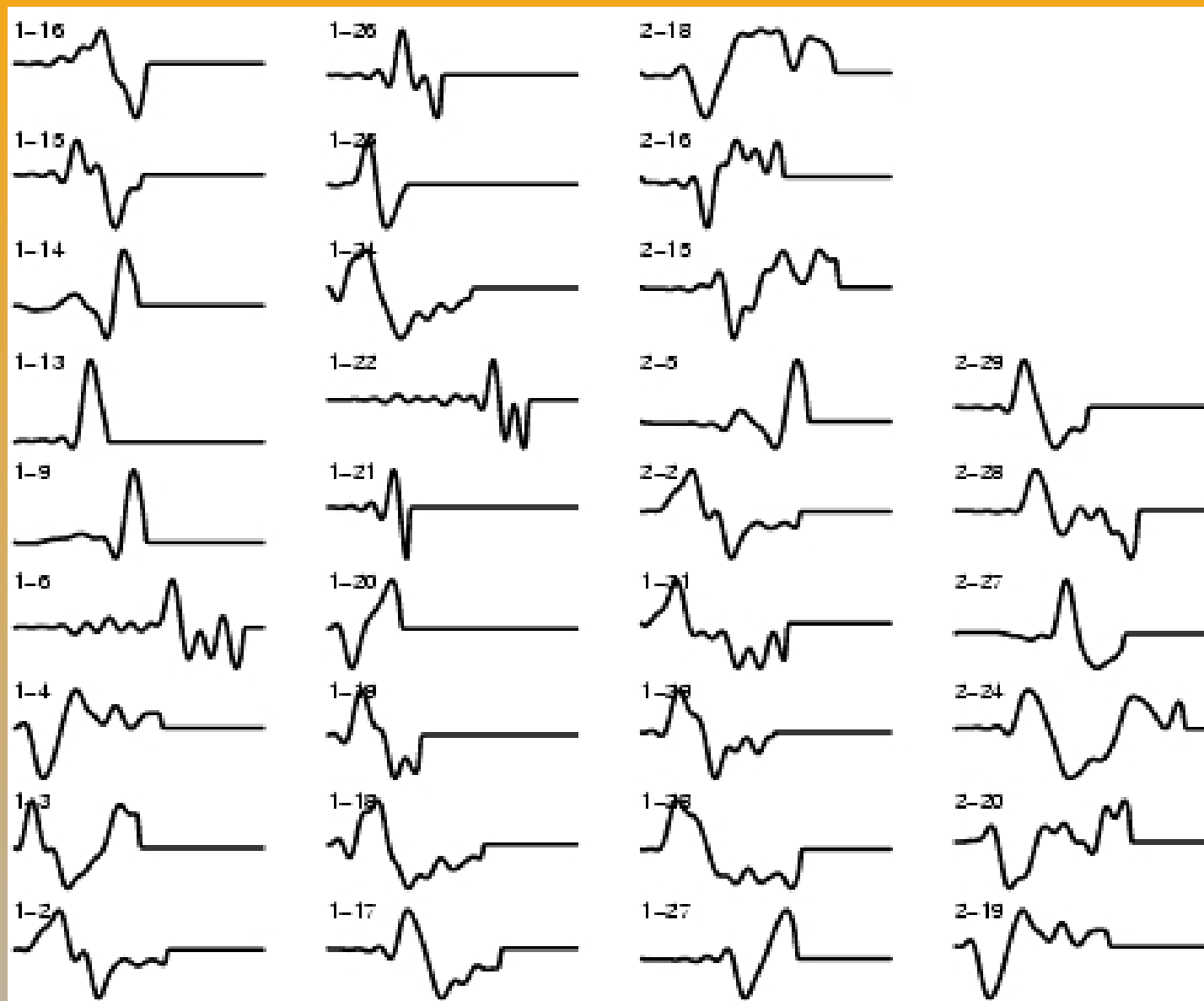
Case - B



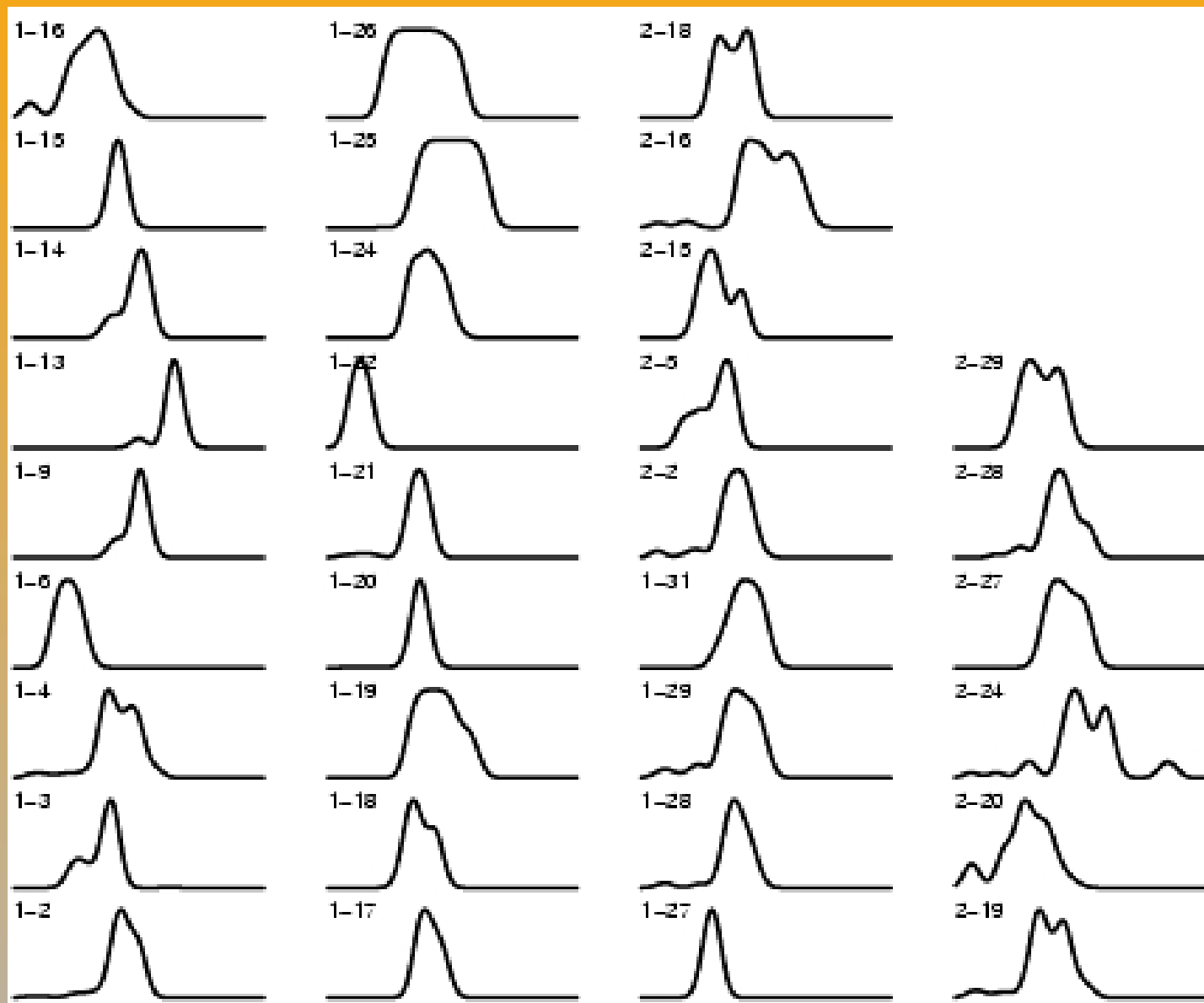
Case - C



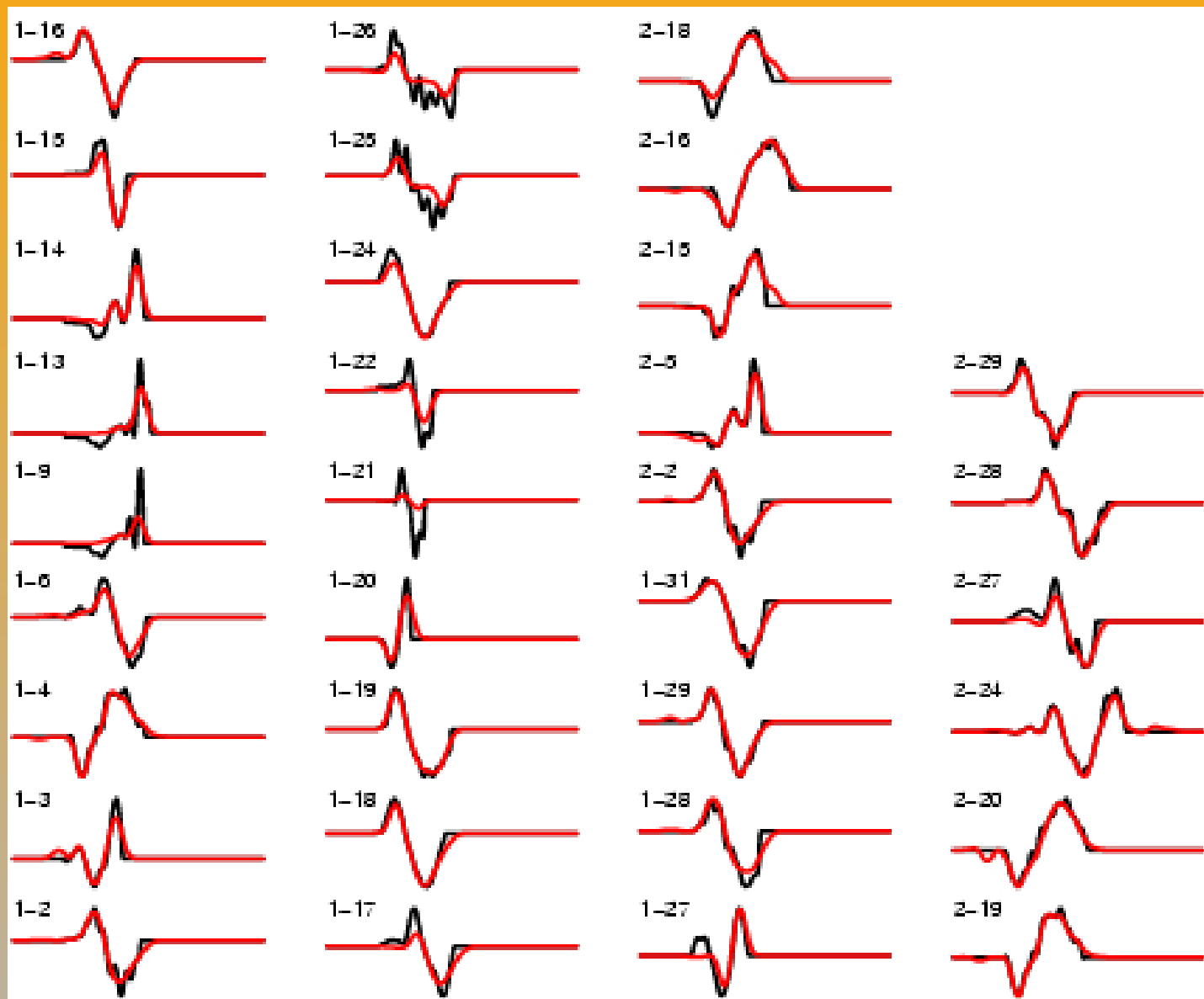
Empirical Green Functions



Source Time Function



Synthetics/Seismograms



Inverse problem - Indirect Measurements

$$\mathbf{d}^{obs} \implies \mathbf{m}$$

Solution

$$||\mathbf{d}^{obs} - \mathbf{d}^{th}(\mathbf{m})|| + \lambda ||\mathbf{m}^{ml} - \mathbf{m}^{apr}|| = \min$$

Errors

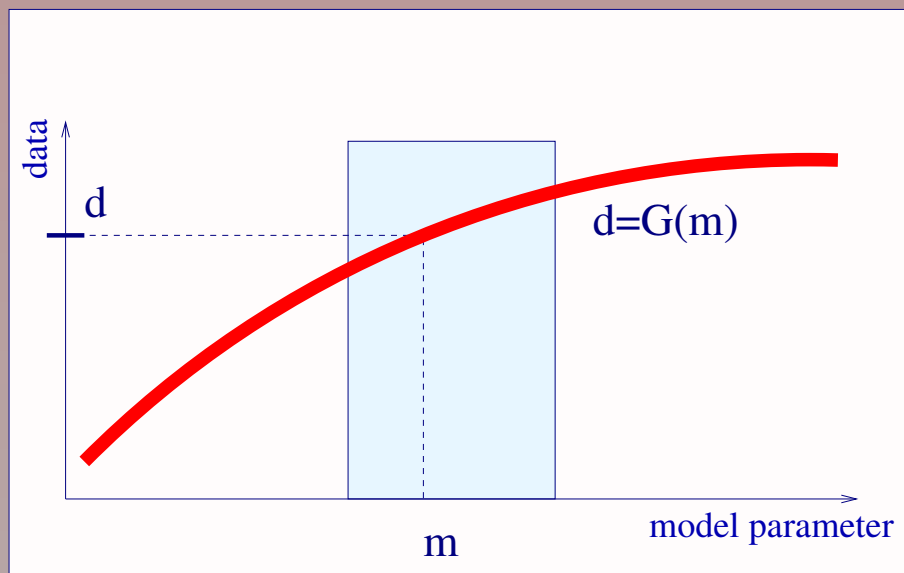
$$\mathbf{m}^{true} = \mathbf{m}^{ml} + \epsilon_{\mathbf{m}}$$

$$\epsilon_{\mathbf{m}} = ???$$

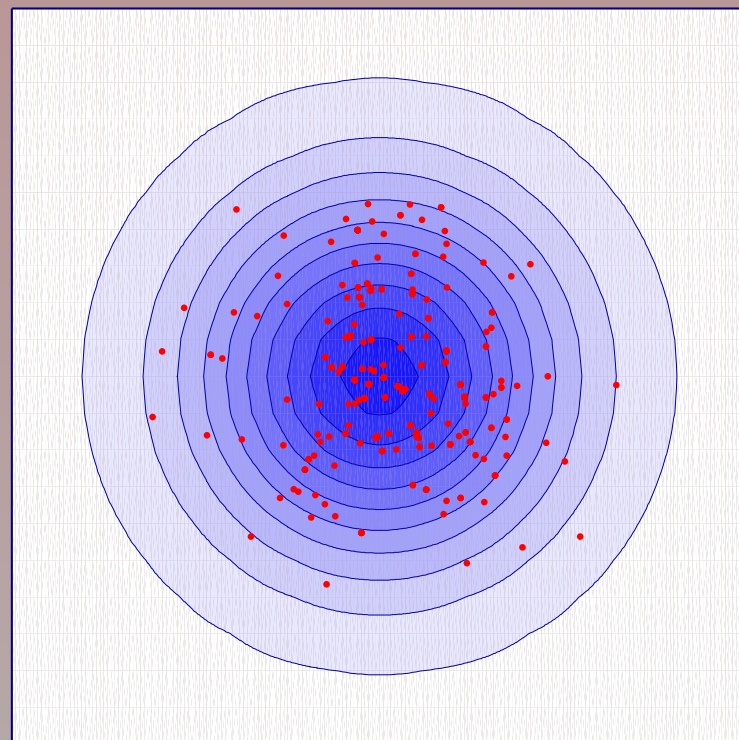
Inversion Algorithms

Method	Advantages	Limitations
Algebraic (LSQR) $\mathbf{m}^{ml} = (\mathbf{G}^T \mathbf{G} + \gamma \mathbf{I})^{-1} \mathbf{G}^T \cdot \mathbf{d}^{obs}$	- Simplicity - Large scale problems	- Only linear problems - Lack of robustness
Optimization $\ \mathbf{G}(\mathbf{m}) - \mathbf{d}^{obs}\ + \lambda \ \mathbf{m}\ = \min$	- Simplicity - Fully nonlinear	- Difficult error estimation
Bayesian $\sigma(\mathbf{m}) = f(\mathbf{m}) L(\mathbf{m}, \mathbf{d}^{obs})$	- Fully nonlinear - Full error handling	- More complex theory - Requires efficient sampler

Inversion algorithms

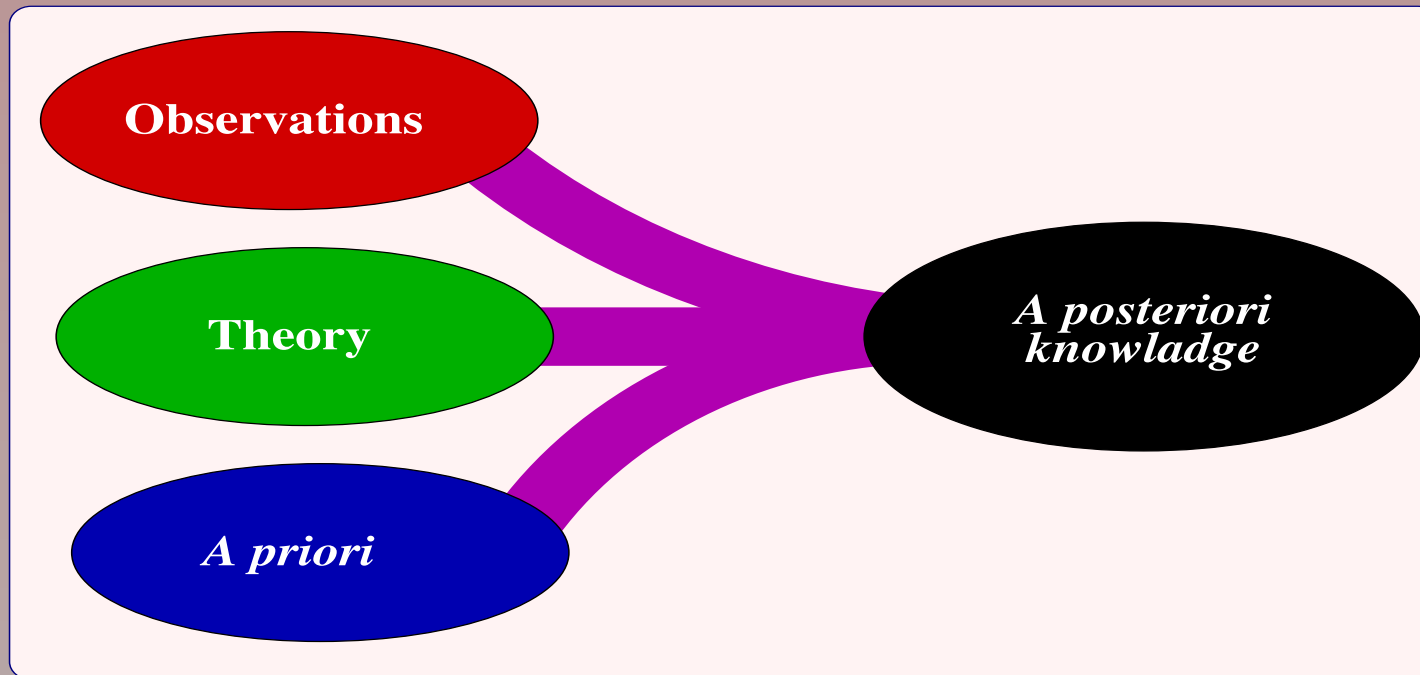


Back projection



Model space search

Bayesian Inversion - Basic Ideas



$$p_{post}(\mathbf{m}|\mathbf{d}) = \frac{p_{th}(\mathbf{d}|\mathbf{m})p_{apr}(\mathbf{m})}{p_{obs}(\mathbf{d})}$$

Probabilistic approach

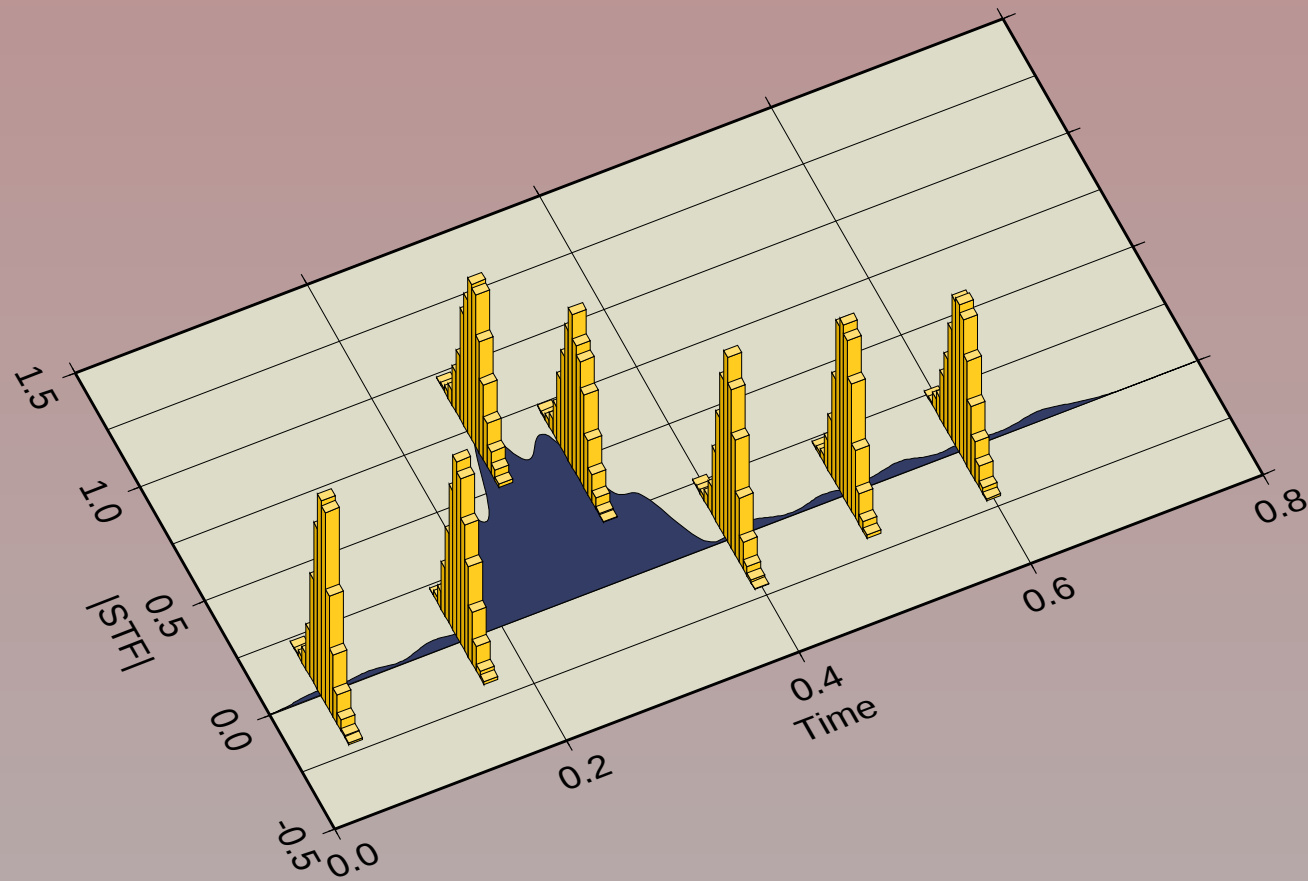
A *posteriori* pdf $\sigma(m, d)$:

- ♦ always exists
- ♦ is unique
- ♦ describes all information
- ♦ is the **solution** of an inverse problem

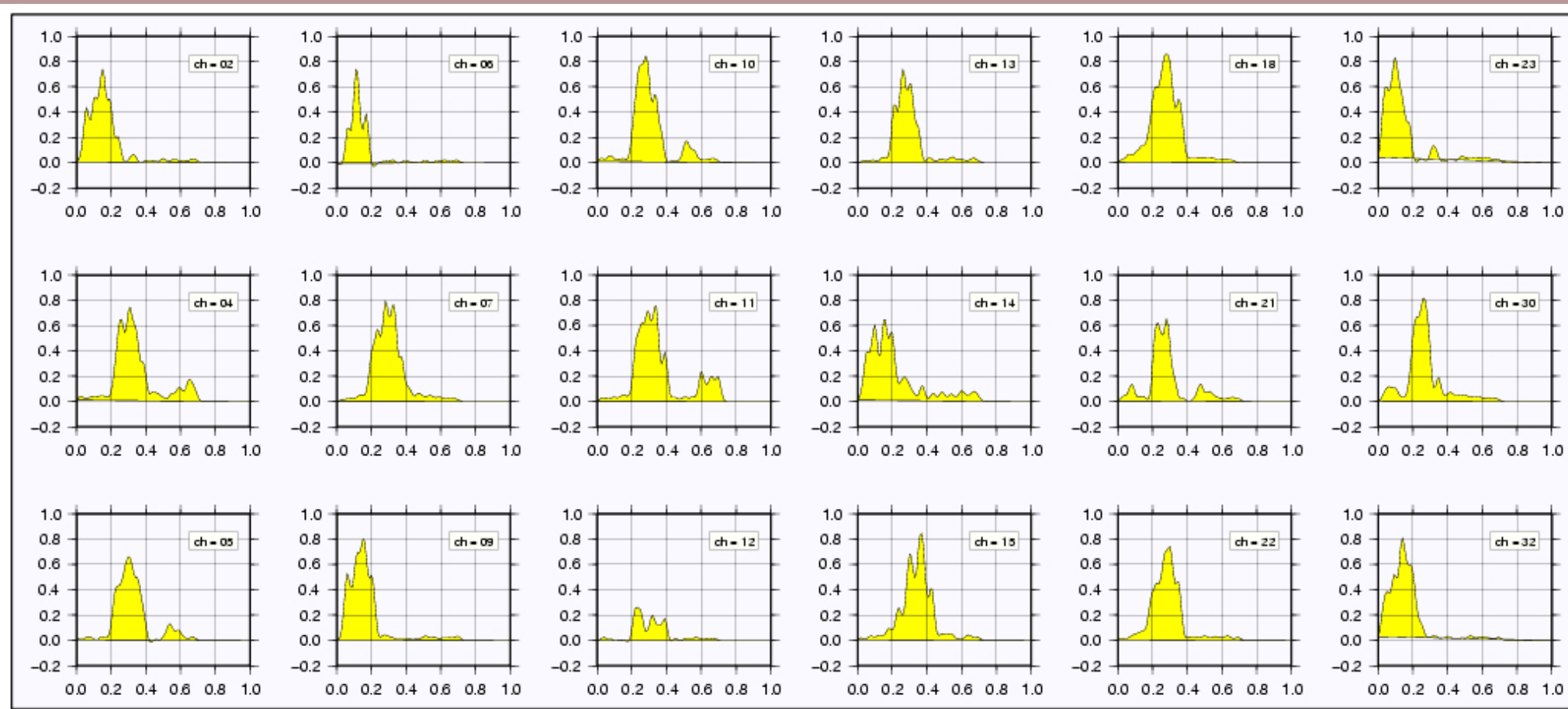
When and why we need to use this approach ???

ERROR ANALYSIS !!!

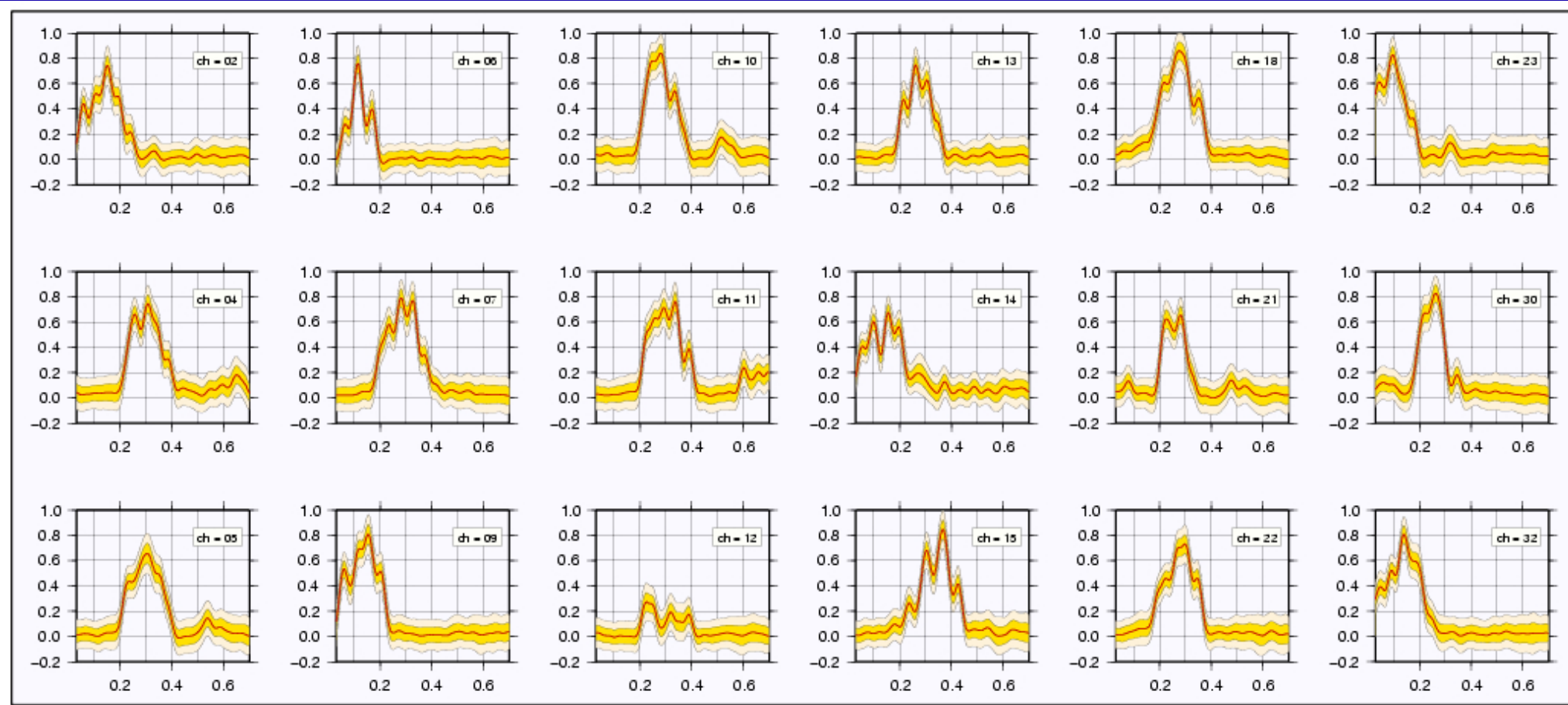
STF - channel 13



All channels



STF- errors



Warsaw team

- ◆ prof. S.J. Gibowicz
- ◆ dr P. Wiejacz
- ◆ dr B Domański
- ◆ dr G. Kwiatek (on leave GFZ, Potsdam)
- ◆ dr G. Lizurek
- ◆ L. Rudziński
- ◆ M. Dec
- ◆ dr hab. W. Dębski