

Proposal Number: 07084

Title: Computing time to failure probabilities using interseismic constitutive relationships inferred from lab experiments

Principal Investigators:

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Other Participants:

Spiers, Chris his PhD stud

Our previous SCEC grant supported me as a postdoc working with PI Norman Sleep. Before coming to Stanford, Dr. Fitzenz worked at the USGS on the interseismic behavior of faults. She continued to study compaction within fault zones and its effect on fluid pressure. Physically, fluid pressure may build up within the fault zone between earthquakes. This may allow earthquakes to occur at laboratory values ~ 0.7 of the coefficient of friction at relatively low shear traction. It is a viable mechanism for weak faults like the San Andreas. In general, fault zones may heal interseismically by processes like pressure solution that cannot be represented by simple extrapolations of rate and state friction.

She concentrated in getting laboratory data into a physically well-characterized form for export to crustal fault zones [1]. Such data were collected for other purposes and experimental durations comparable to even a ~ 100 year seismic cycle are clearly intractable. With this in mind, she developed an inverse method that uses effective pressure-porosity-time histories. A Bayesian framework allowed us to make use of all available prior knowledge (e.g., lithology, permeability and porosity, as well as spatial heterogeneity in these parameters) and to take into account what we know about the data acquisition. This approach is limited by the fact that existing experimental data are rarely adequate to completely define a single constitutive relationship for a given fault gouge mineralogy and grain size distribution over temperature and effective confining pressures of relevance to actual fault zones.

She made special effort to the tracking of the uncertainties. Indeed, all laboratory measurements contain a statistical error and some noise, as well as uncertainties associated with extrapolation to natural conditions. It is important to both know the error and the noise on sensitive "input" variables such as temperature, porosity, and gouge grain size, and on the derived model parameters, if we want to evaluate the robustness of the model results. Rather than using separate sets of data points to fit separately for the stress dependence and the temperature dependence, she considered all of the data and their standard deviation within a Bayesian framework to determine the probability density functions of the model parameters. An intermediate step of reformulating the problem in terms expressions combining physical parameters that approximately affect observed quantities in a linear manner made the inversion tractable and stable.

These results are an interesting statistical application. Fitzenz presented posters at a Gordon conference and the Fall AGU. She was unable to present results at the MaxEnt meeting in San Jose during August because of recent maternity. Norm Sleep presented instead.

At the time of the last report, our paper was about to appear in the MaxEnt volume [1]. The main interest of this paper was in the fact that it was proposing a methodology to choose the range of temperature and pressure conditions, as well as the duration of the experiments, ahead of time, so that the porosity time series would be well suited for a quantitative analysis.

The year 2007 (when this proposal was accepted) saw the publication of the natural follow-up of this study [3]: 1. the application to real experiments of hydrothermal quartz deformation data

produced by the HPT Lab at Utrecht University by Andre Niemeijer and Chris Spiers [2] (Figure 1), and 2. the integration of the so-derived compaction law and probability density functions for its parameters into a simple model of seismogenesis (Figure 2). That model was based on 3 main ingredients: the constant tectonic loading rate, an interseismic fault pressurization module using the lab-derived compaction law and the conservation of fluid mass, and finally a Coulomb failure criterion.

In a first set of simulations, the properties of the homogeneous fault after an earthquake were perfectly known (porosity, pore pressure, shear and normal stress, static friction). Then we proceeded to a Monte Carlo sampling of the compaction parameters (with their covariance) and computed the time-to-failure. We obtained histograms for time-to-failure and properties at failure.

The remarkable result was that the time-to-failure distribution was well fitted by a lognormal close to the optimum but that it had a heavier tail (in fact, even heavier than that of a Brownian Passage Time (BPT) distribution). So, without prescribing the shape of the renewal model, just by having the complexity come from the compaction model, we were getting a renewal model not too different from what is currently used in Probabilistic Seismic Hazard Assessment, at least for times less than twice the optimal time.

A second set of simulations checked how the shape of the renewal model evolves when we introduce another source of uncertainties: a Gaussian distribution for the porosity just after an earthquake. We found that the shape is still close to a lognormal. The distribution of the log of time to failure was well fitted by a Gaussian with same mean as in the fixed porosity case, but with a larger standard deviation.

We think this type of approach (Bayesian analysis of data to constrain modules in models of seismogenesis) can open new perspectives for the development of physics-based renewal models, to be tested against or in combination with the usual Poisson, Weibull, lognormal and BPT models.

We recently developed a method able to use datasets complementary to catalogs of large events and trench data, such as dated cumulative offsets [4,5]. This Bayesian method allows to update our belief on the best renewal models and their parameters. Once priors and datasets are chosen, it allows for a reproducible, quantitative model selection or combination. Not only is the parameter space of each model defined, but the evidence of each model is computed, and the evidence ratios give the relative weights of each model in the model combination best representing our belief (priors and datasets). No expert judgement is needed at this point.

We hope that in the future, physics-based models will be tested as alternative viable models to the usual candidates models.

The money that SCEC awarded to this proposal 07084 was only for travel to attend the SCEC annual meeting. Because I later found out I was pregnant, and it was not an easy pregnancy, I had to cancel my plans of travelling from France to California for the meeting...and I did not realize I had to write a report nonetheless.

References

[1] -Fitzenz, D. D., A. Jalobeanu, S. H. Hickman, and N. Sleep, 2005, Integrating laboratory compaction data with numerical fault models: a bayesian framework, Bayesian inference and maximum entropy methods in science and engineering : 25th International Workshop on Bayesian

Inference and Maximum Entropy Methods in Science and Engineering, San Jose, California, August 2005, Melville, N.Y. : American Institute of Physics

[2] Niemeijer, A., C. J. Spiers, and B. Bos (2002), Compaction creep of quartz sand at 400–600°C: Experimental evidence for dissolution-controlled pressure solution, *Earth Planet. Sci. Lett.*, 195, 261–275.

[3] Fitzenz, D. D., A. Jalobeanu, S. H. Hickman, 2007, Integrating Laboratory Creep Compaction Data with Numerical Fault Models: a Bayesian Framework, *J. Geophys. Res.*, 112, B08410, doi: 10.1029/2006JB004792

[4] Fitzenz, D. D., M. A. Ferry, and A. Jalobeanu (2010), Long-term slip history discriminates among occurrence models for seismic hazard assessment, *Geophys. Res. Lett.*, 37, L20307, doi: 10.1029/2010GL044071

[5] D.D. Fitzenz, A. Jalobeanu, and M.A. Ferry, accepted Jan 2012, A Bayesian Framework to Rank and Combine Candidate Recurrence Models for Specific Faults, BSSA-D-11-00087

Figures

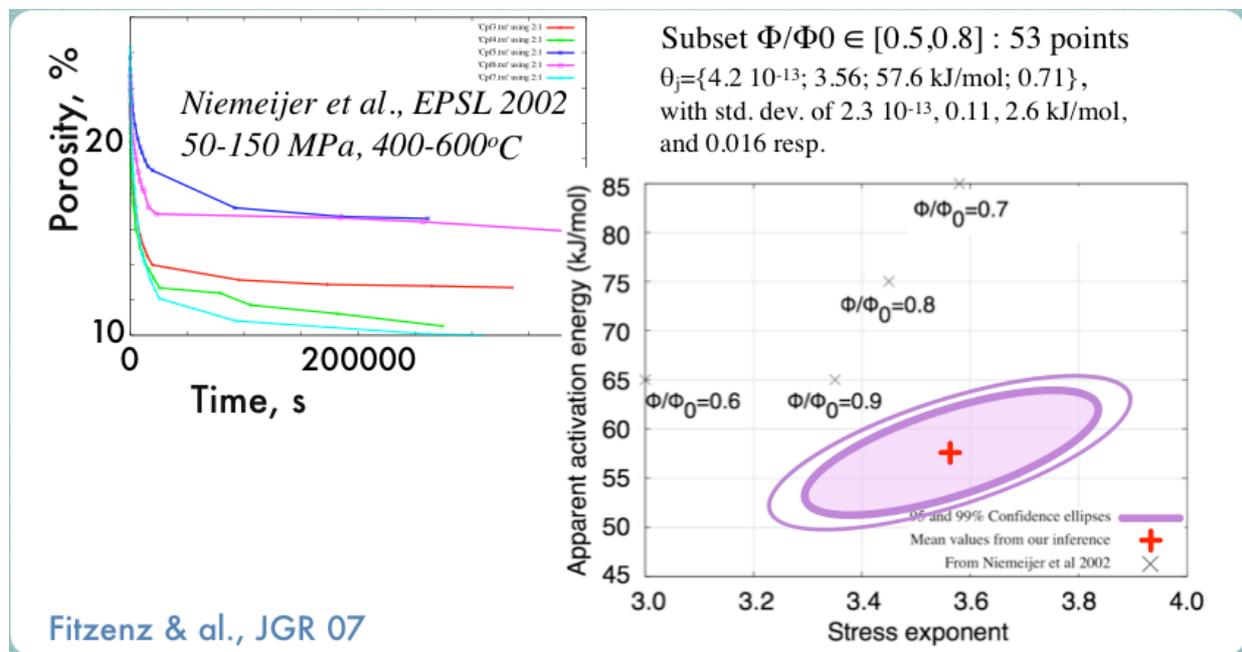


Figure 1. From porosity time series to the probability density functions for the compaction parameters

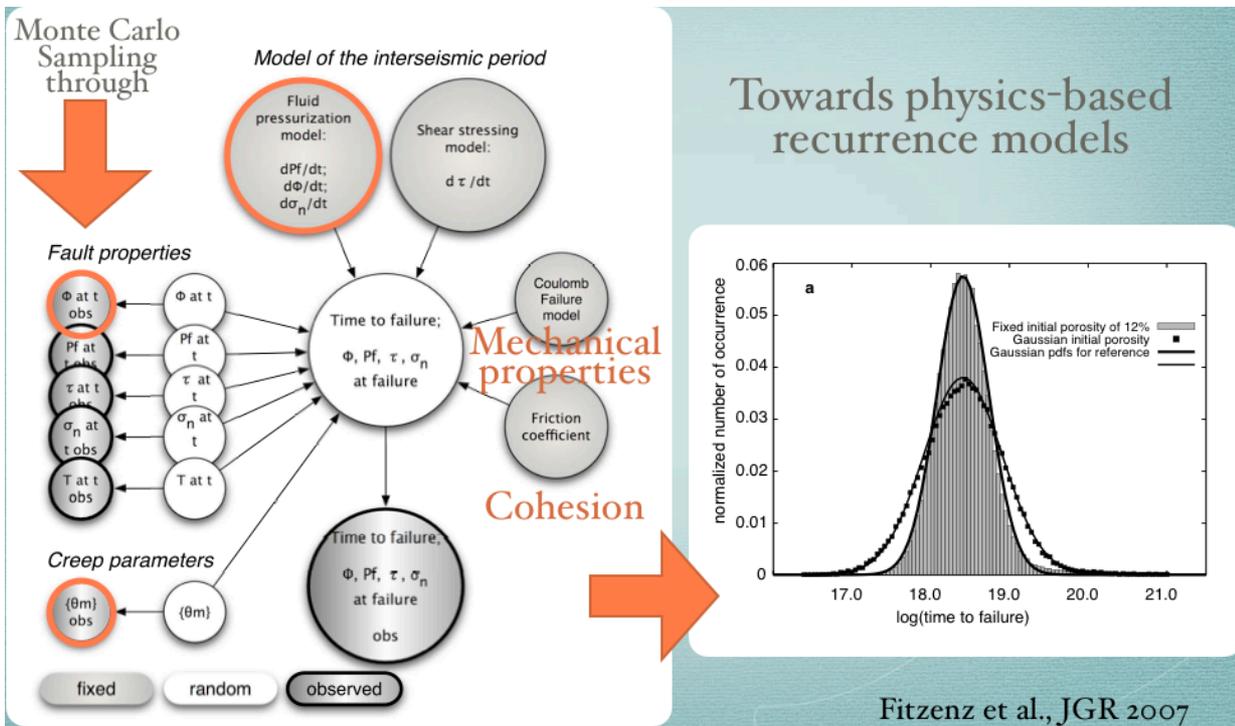


Figure 2. Sampling through the probability density functions for the compaction parameters to get to the shape of the time-to-failure distribution using a simple model of seismogenesis