Kinematic point source moment tensor inversion using a hierarchical Bayesian approach

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1. Introduction

The seismic moment tensor (MT) reveals details about source processes within the Earth that cause earthquakes. Although uncertainties in MT inversions are important for estimating solution robustness, they are rarely available. When earthquake location is retrieved simultaneously with the MT, uncertainties in structural Green's functions also need to be included in the method. The problem becomes nonlinear and uncertainties in the source mechanism cannot be calculated in a simple manner.

2. Hierarchical Bayesian inversion for the centroid moment tensor

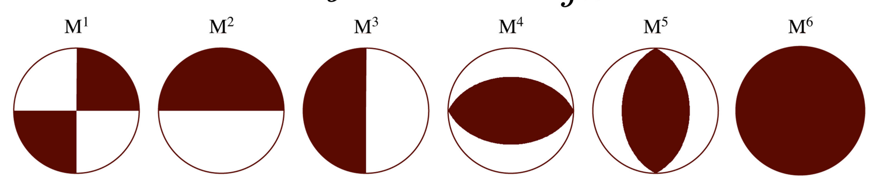
We have developed a method in a Bayesian probabilistic framework to study moderate earthquakes and explosions using waveform data. The parameter posterior probability distribution is determined by prior knowledge and information obtained from the data:

$$p(\mathbf{m}|\mathbf{d}) = c\,p(\mathbf{d}|\mathbf{m})p(\mathbf{m})$$

posterior ∝ likelihood × prior

Forward modelling is performed using the code AXITRA (Cotton and Coutant, 1997) to precompute the Green's functions and convolve them with six elementary tensors composing the seismic moment tensor

$$M_{jk} = a_n M^n_{jk}$$

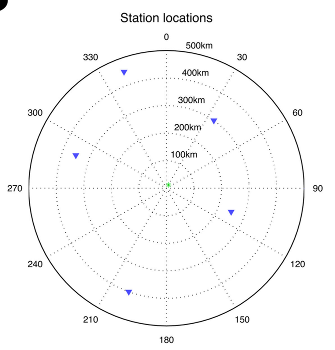


Two Markov chain Monte Carlo algorithms are run simultaneously: one for the location parameters and another for the moment tensor and noise level parameters.

Fig. 2: (right) Centroid locations for 5000 iterations in the Markov chain for locations, colored by the iteration number. Size is determined by the maximum variance reduction on each location. Subplot in the upper left corner shows the locations in 3D and the remaining subplots show cross sections through the input source location.

3. Synthetic experiments

Synthetic seismograms were computed for 5 stations (shown on the figure on the right) at regional distances and contaminated with uncorrelated or correlated random noise.



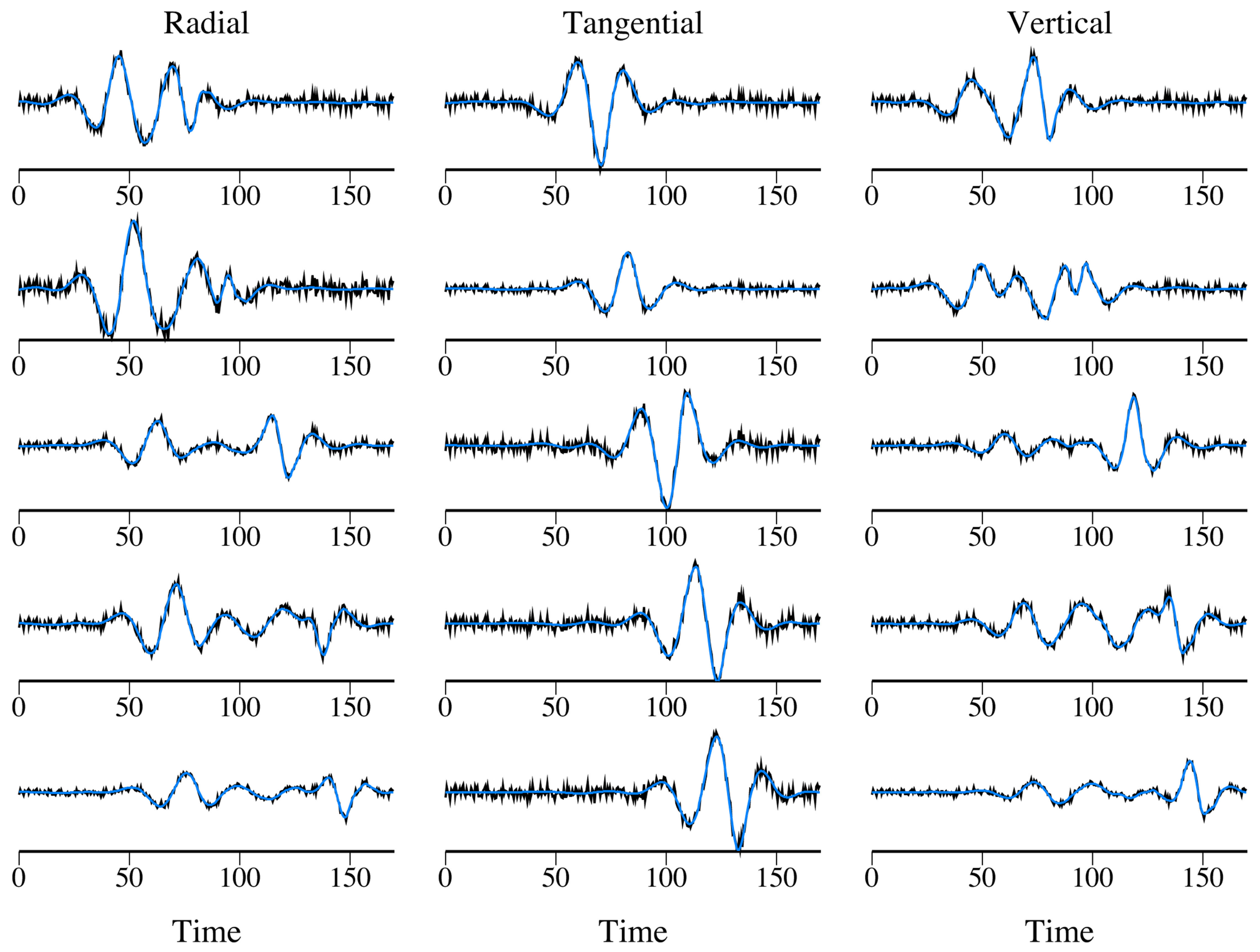
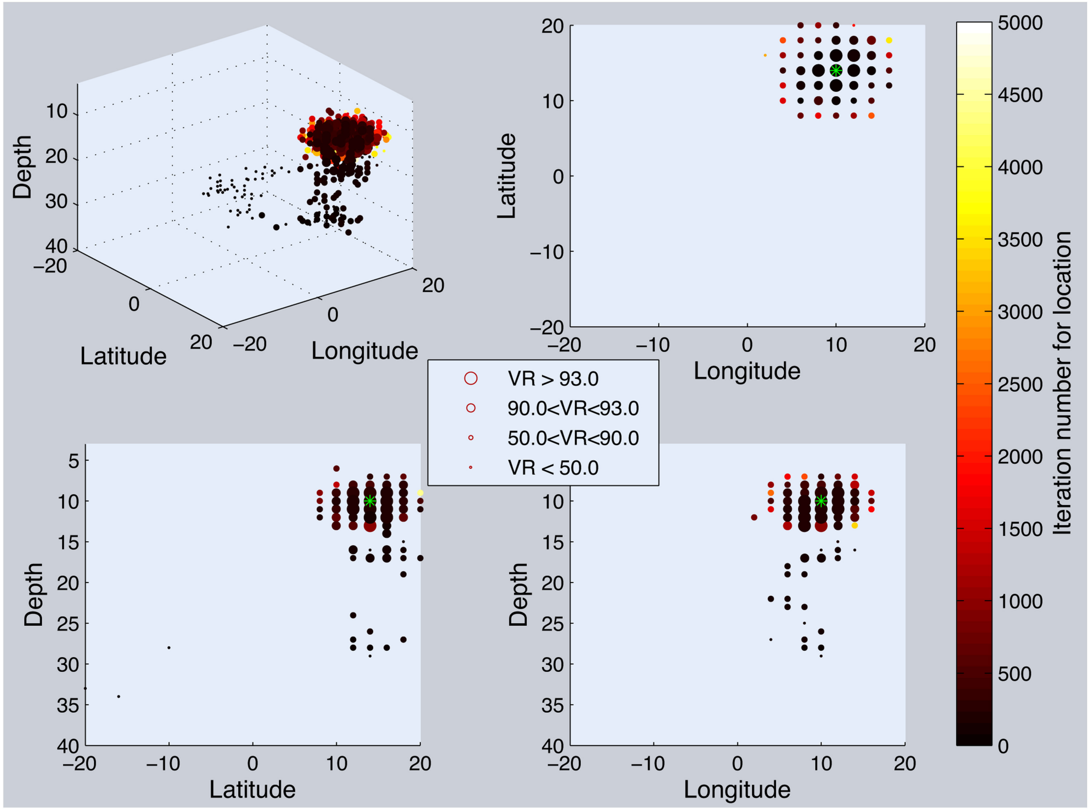


Fig. 1: Input synthetic seismograms with uncorrelated random noise (with a variance of 25% signal RMS) (black) and the best fit (minimum L2 misfit) solution (blue).

3.1. Location parameters

In most cases, the algorithm rapidly converges to the input centroid location.



3.2. Moment tensor parameters

- Well determined (narrow posterior distributions)
- Average of posterior models can be influenced by outliers

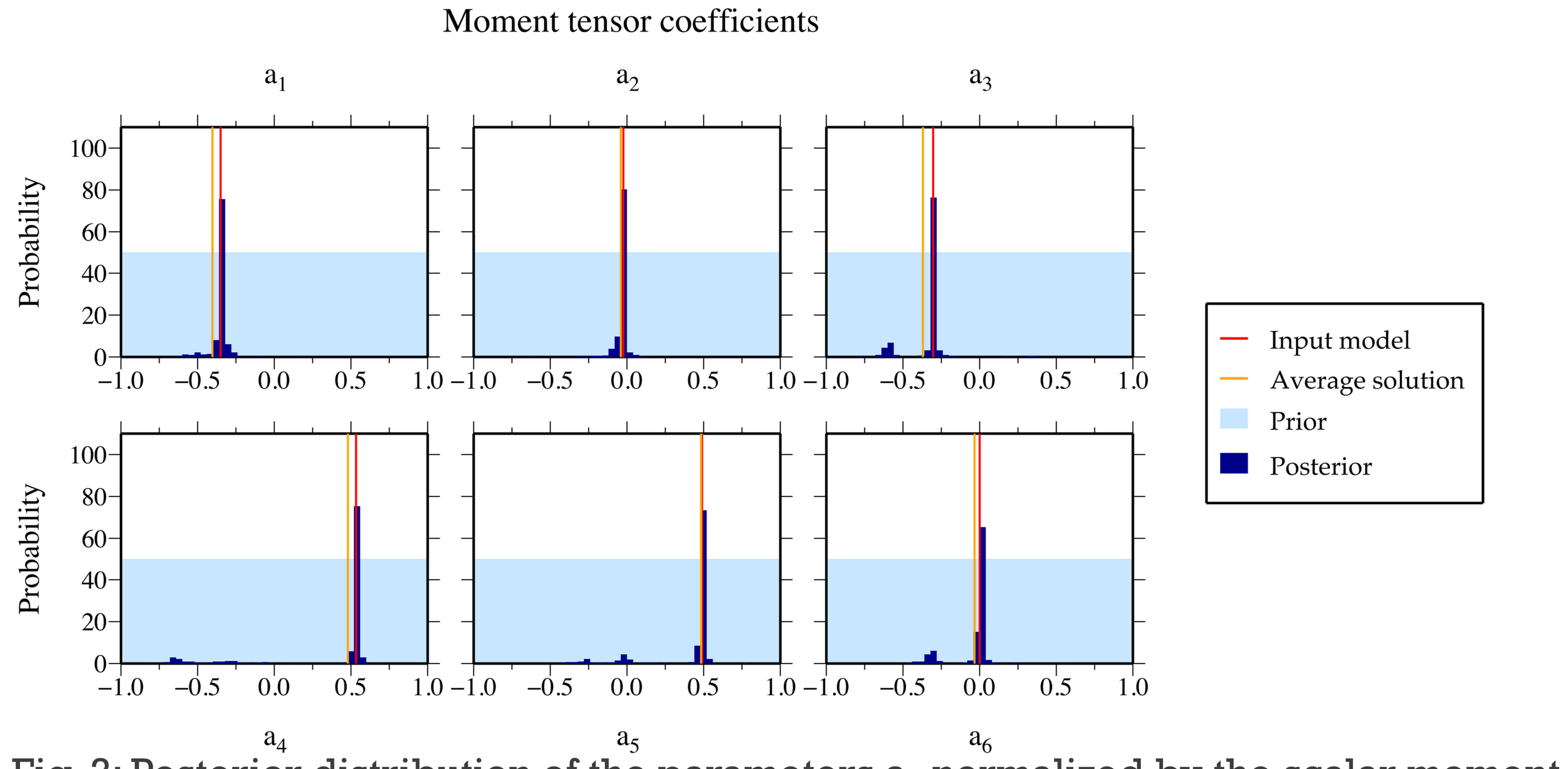
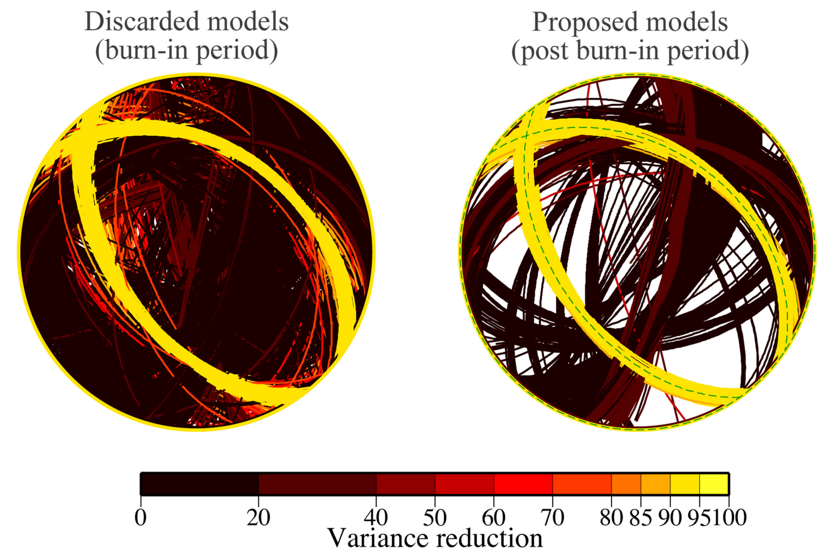


Fig. 3: Posterior distribution of the parameters aᵢ, normalized by the scalar moment is shown in dark blue. Prior distribution is given in light blue, the true model (i.e. the input value) in red and the average solution in orange.

Fig. 4: Double-couple part of models from the burn-in period (before they are collected for the ensemble) and models proposed afterwards.



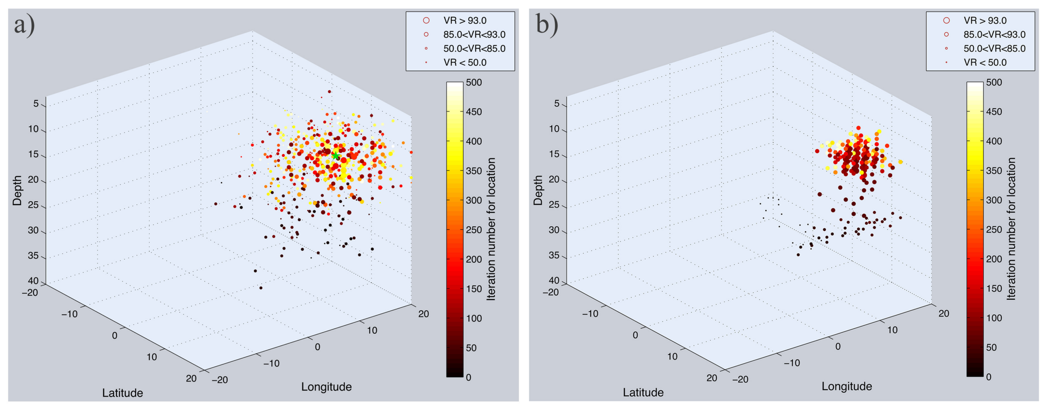
3.3. Noise parameters: the hierarchical formulation

- Noise in the data determines the model complexity
- Adequate treatment of noise results in required data fit
- Noise variances act as weights for each station
- The data noise covariance matrix can account for measurement and theory errors

$$p(\mathbf{d}|\mathbf{m}) = ((2\pi)^N |\mathbf{C_e}|)^{-1/2} \exp\left[-\frac{1}{2}(\mathbf{G}(\mathbf{m}) - \mathbf{d_{obs}})^T \mathbf{C_e}^{-1}(\mathbf{G}(\mathbf{m}) - \mathbf{d_{obs}})\right]$$

synthetic data   observed data

Fig. 5: Centroid locations for synthetics with correlated noise, when **uncorrelated noise** (a) and **correlated noise** (b) was **assumed in the inversion**.



3.4. Simulating signal generated noise

Additional tests were performed on synthetics with noise added in the frequency domain, simulating the propagation effects on the wavefield. Complex spectra were multiplied by $c(1 + r_1 + ir_2)$, which introduces a change in both amplitude and phase.

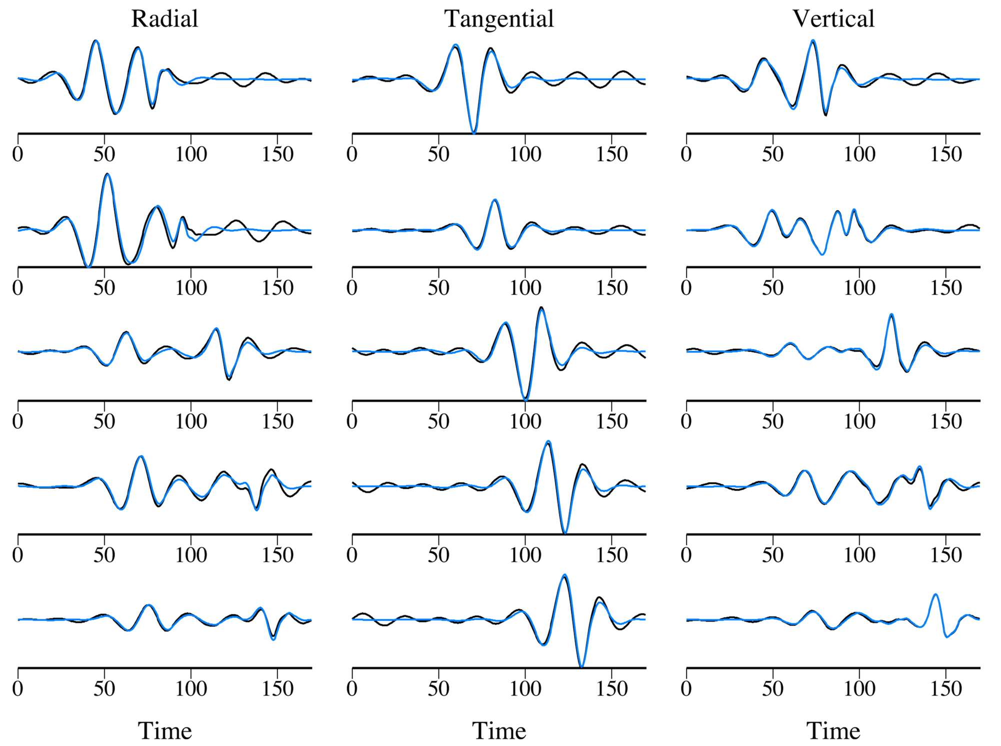


Fig. 6: (right) Input noisy synthetic seismograms for c=0.5 (black) and the best fit solution (blue).

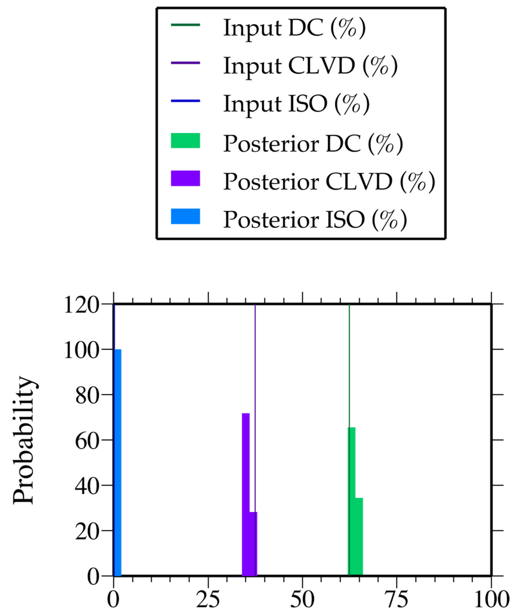


Fig. 7: Posterior distributions of the double couple (DC), compensated linear vector dipole (CLVD) and isotropic (ISO) components.

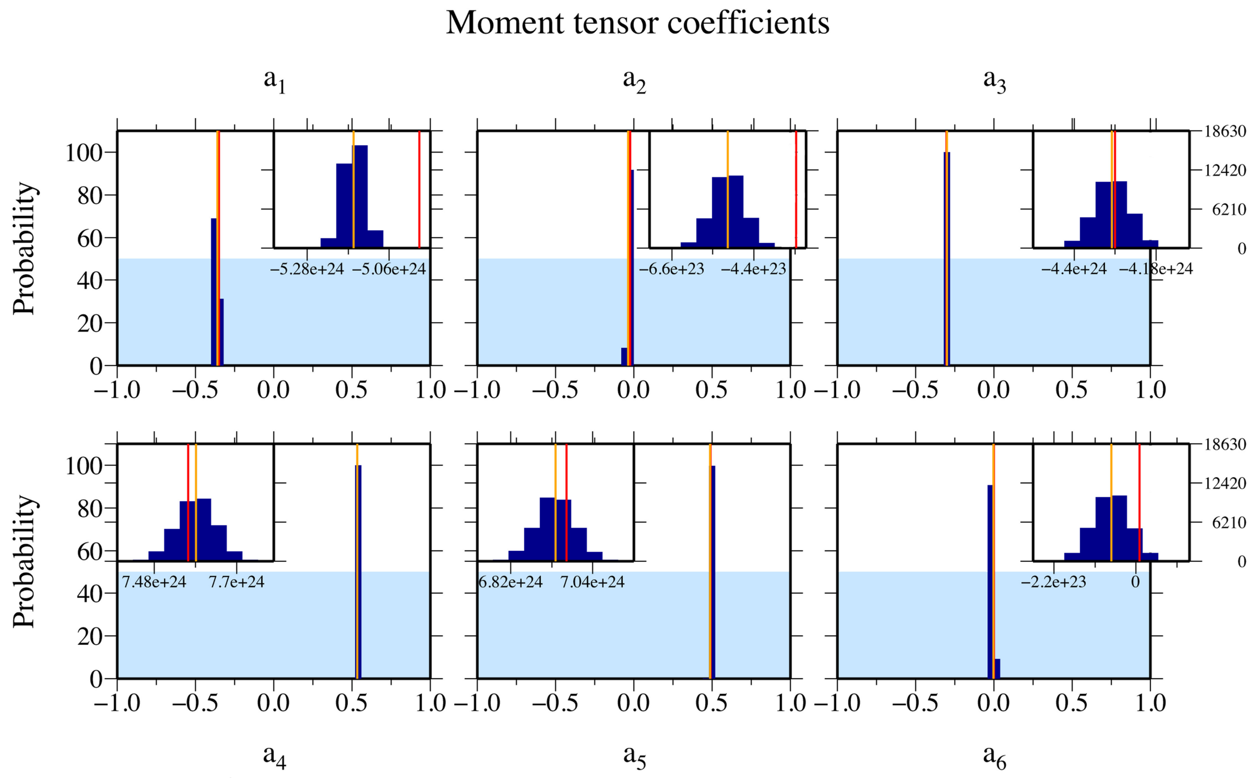


Fig. 8: As in Fig.3, with inserted histograms of unnormalized values for every coefficient of the MT.

4. Conclusions and future work

- A hierarchical Bayesian method was applied to the centroid moment tensor inversion of waveform data at regional distances
- Synthetic tests show successful retrieval of model parameters
- Uncertainties can be estimated from the posterior probabilities
- Furthermore, the noise covariance matrix accounts for measurement and theory errors and determines the model complexity
- Future work includes applying the algorithm on waveform data from various tectonic settings