Waveform-based Bayesian Full Moment Tensor Inversion and Uncertainty Quantification for the Induced Seismicity in Oil/Gas Fields

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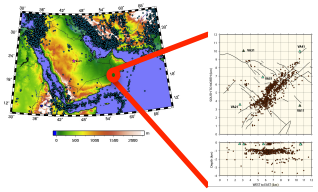
MIT Earth Resources Laboratory
2016 Annual Founding Members Meeting
May 18, 2016

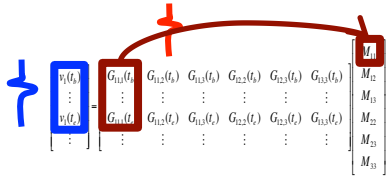
Earth Resources Laboratory

Massachusetts Institute of Technology

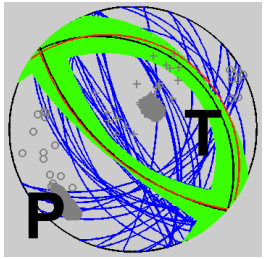
In many oil/gas fields and hydrofracking there are induced earthquakes due to fluid extraction or injection



- Research motivation – Source mechanisms of induced earthquakes and error bars

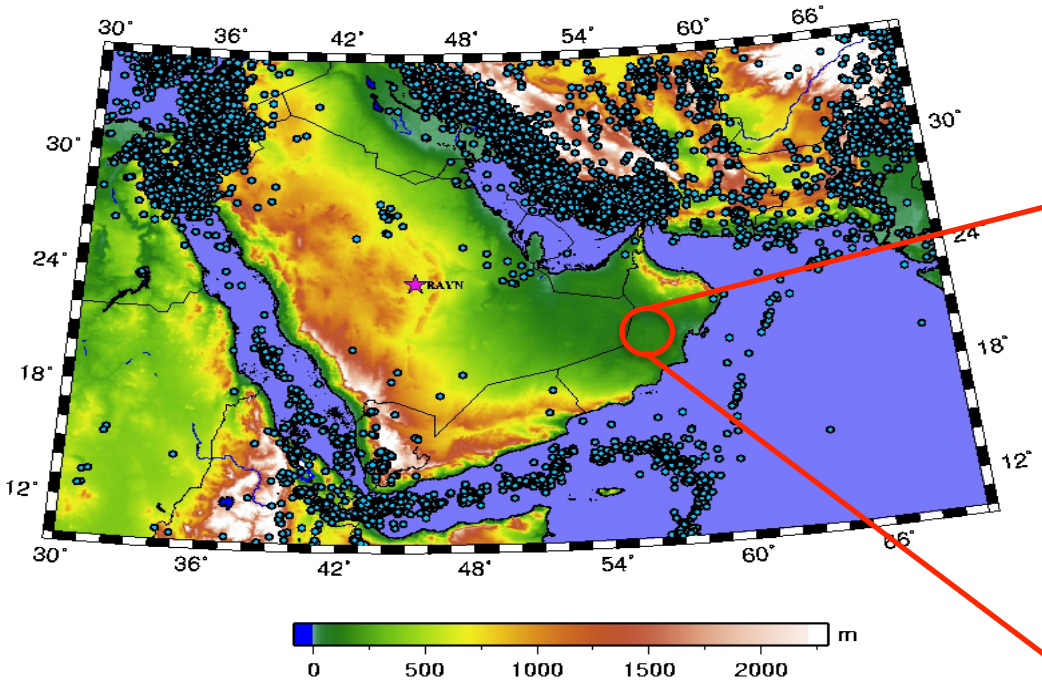


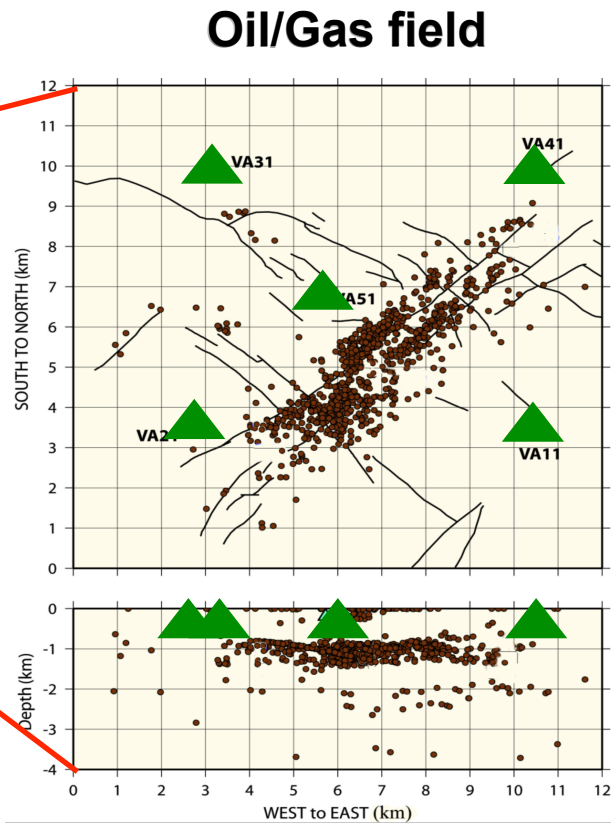
- Method – Waveform-based Bayesian moment tensor inversion



- Examples – Synthetics and an example from Oman

Motivation: Understand fracturing mechanisms, map microseismicity, and evaluate hydrofracking

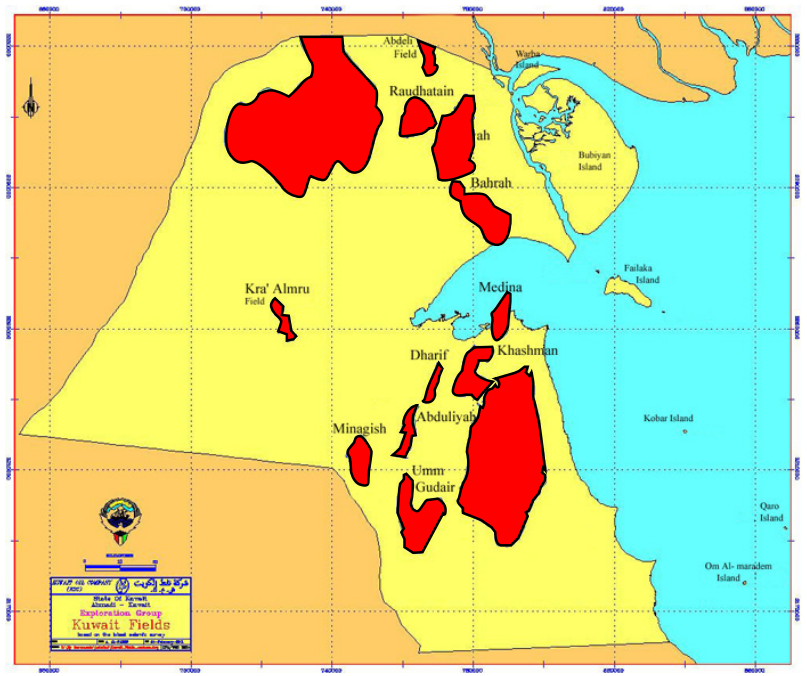




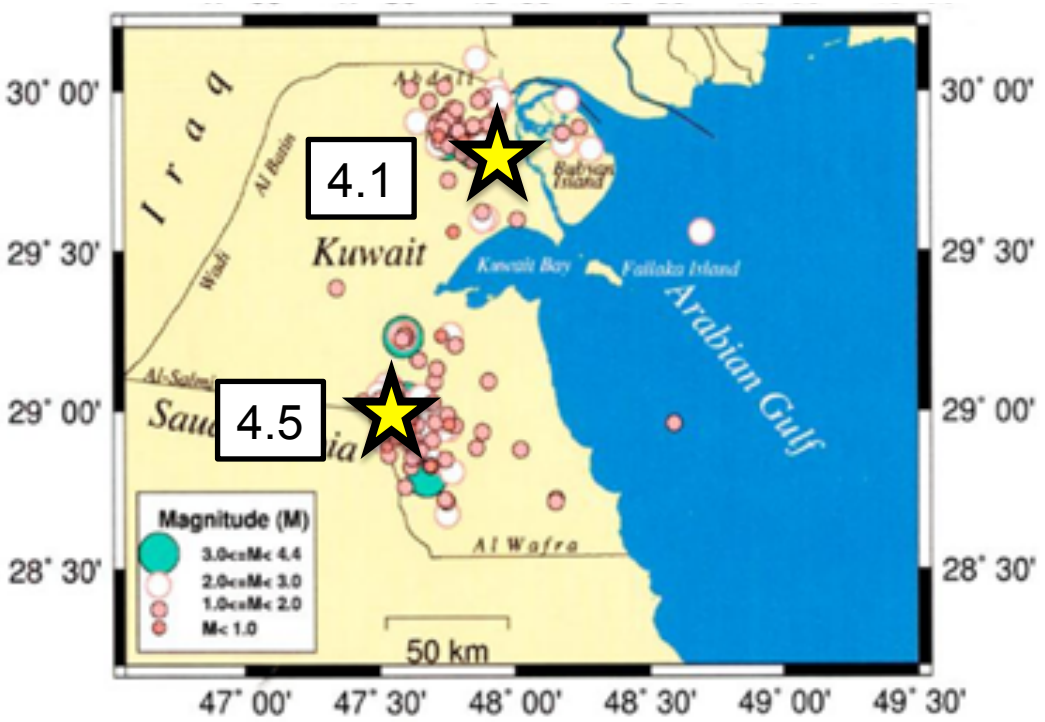
- More high-quality data
- In predictable places

Motivation: Understanding earthquake dynamics, hazard assessment, and damage measurement

Oil fields in Kuwait

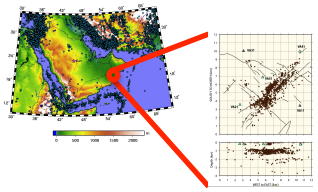


Induced earthquakes



Note: Earthquakes occur in the same place of Oil/gas fields

In many oil/gas fields and hydrofracking there are induced earthquakes due to fluid extraction or injection



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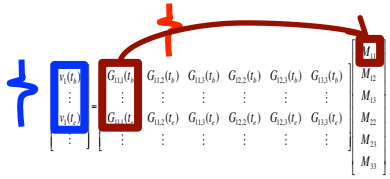

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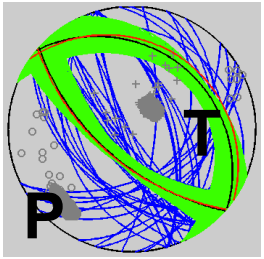
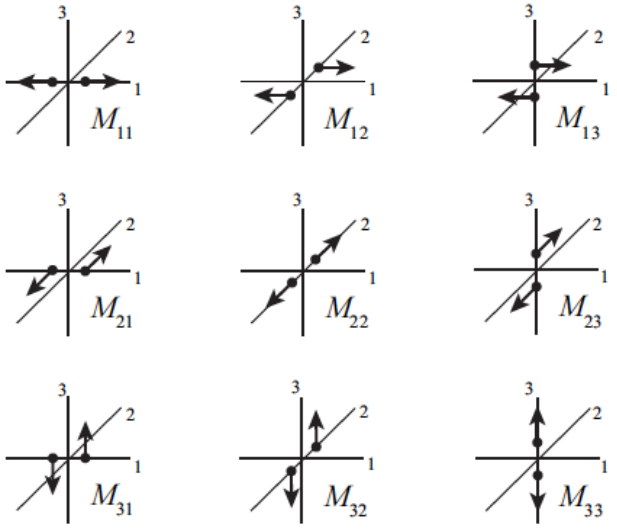


- Examples – Synthetics and an example from Oman

Moment Tensors of Earthquakes

- The mechanisms of the greatest majority of tectonic earthquakes can be described by a “Double Couple” – “DC”, corresponding to a shear fracture
- However some events exhibit more complex source mechanism such as volumetric component (ISO) and “Compensated Linear Vector Dipole” – “CLVD”.
- A complete moment tensor including all these components can be written as:

$$MT = \begin{bmatrix} M_{11} & M_{12} & M_{13} \\ M_{21} & M_{22} & M_{23} \\ M_{31} & M_{32} & M_{33} \end{bmatrix}$$

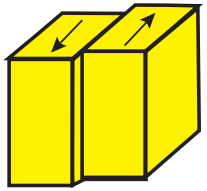


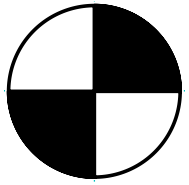
Aki and Richards (1980)

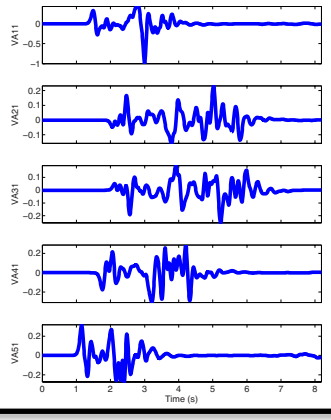
Moment Tensors of Earthquakes

DC

$$\frac{1}{\sqrt{2}}\begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

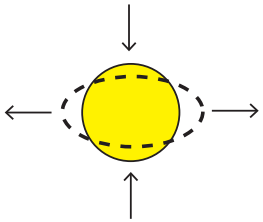


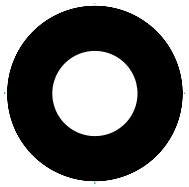


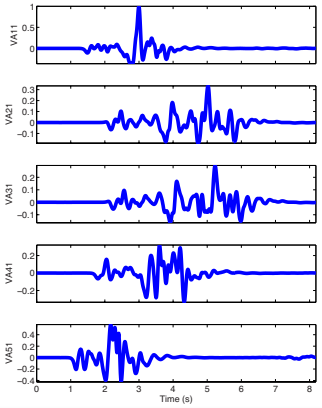


CLVD

$$\frac{1}{\sqrt{6}}\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -2 \end{bmatrix}$$

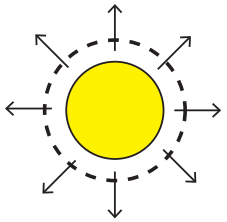


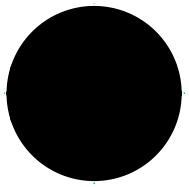


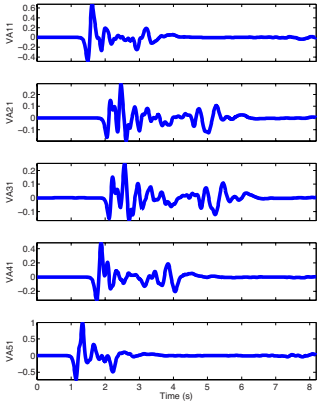


ISO

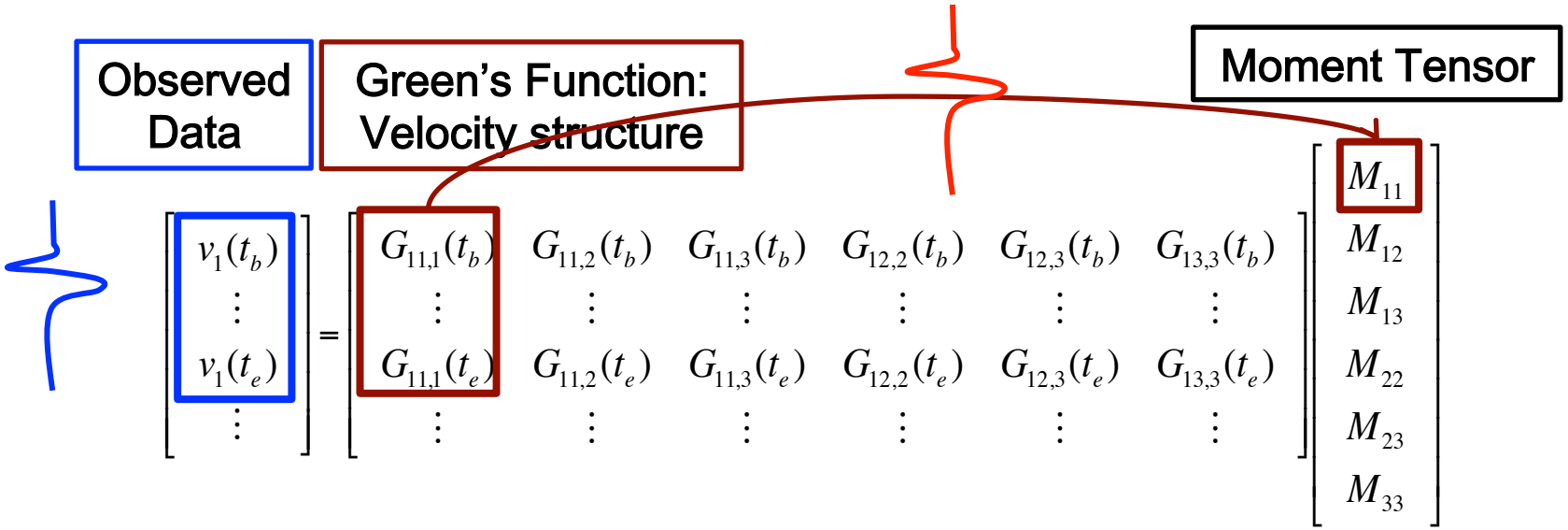
$$\frac{1}{\sqrt{3}}\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$







Least Square vs. Bayesian inversion

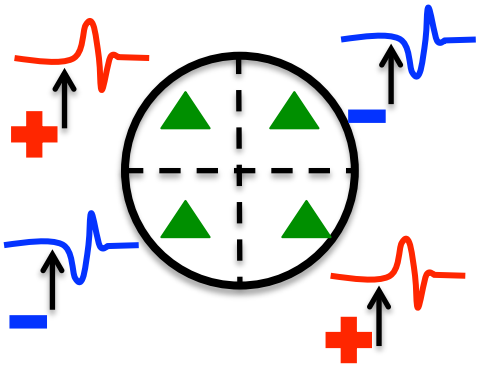


- Least square method: cannot quantify the uncertainty well
- Bayesian inversion method: estimate the *probability density function* of moment tensor solutions

Waveform-based Bayesian inversion (Adaptive Metropolis MCMC)

Prior	Information we know about the distribution of M_{ij} before we do any inversion *Here we use the first P-wave polarity.*	$\pi_0(M_{ij}) \propto \begin{cases} 1, & pol(M_{ij}) = pol_{obs}, \\ 0, & pol(M_{ij}) \neq pol_{obs}. \end{cases}$
Likelihood	How the waveform data are distributed for a given M_{ij}	$P(d \mid M_{ij}) \propto P_{\varepsilon}(d - G(M_{ij}), \sigma_{\varepsilon}^2)$
Posterior	The distribution of M_{ij} solutions given the data	$\pi(M_{ij} \mid d) \propto P(d \mid M_{ij}) \pi_0(M_{ij})$

Waveform-based Bayesian inversion



$\pi_0(M_{ij})$

Polarity

$\pi(M_{ij} \mid d)$

M_{ij} solution distribution

Waveforms

$P(d \mid M_{ij})$

Waveform-based Bayesian inversion

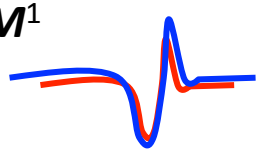
$\pi_0(M_{ij})$

Polarity

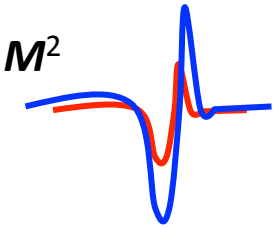
$\pi(M_{ij} \mid d)$

M_{ij} solution distribution

High Probability M^1



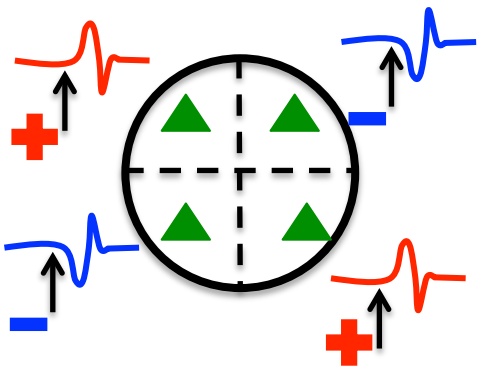
Low Probability M^2



Waveforms

$P(d \mid M_{ij})$

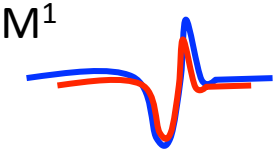
Waveform-based Bayesian inversion



$\pi_0(M_{ij})$

Polarity

High Probability M^1



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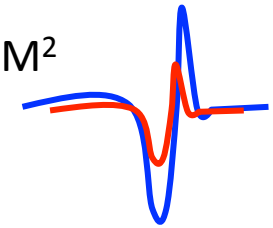


Waveforms

$P(d \mid M_{ij})$

$\pi(M_{ij} \mid d)$

M_{ij} solution distribution

Synthetic test: Experiment setup

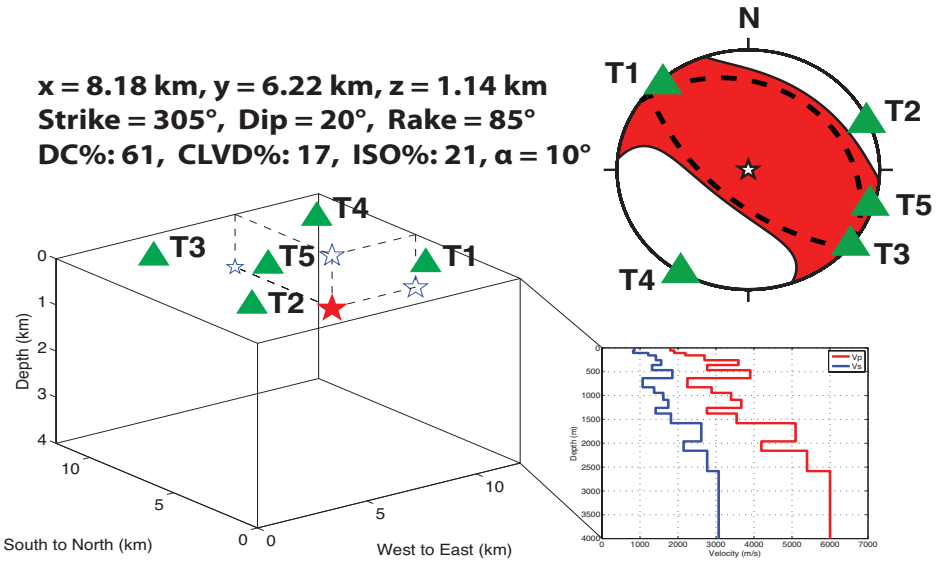
Step 1: Use a known synthetic source inside a layered structure

Step 2: Calculate synthetic seismograms at five stations

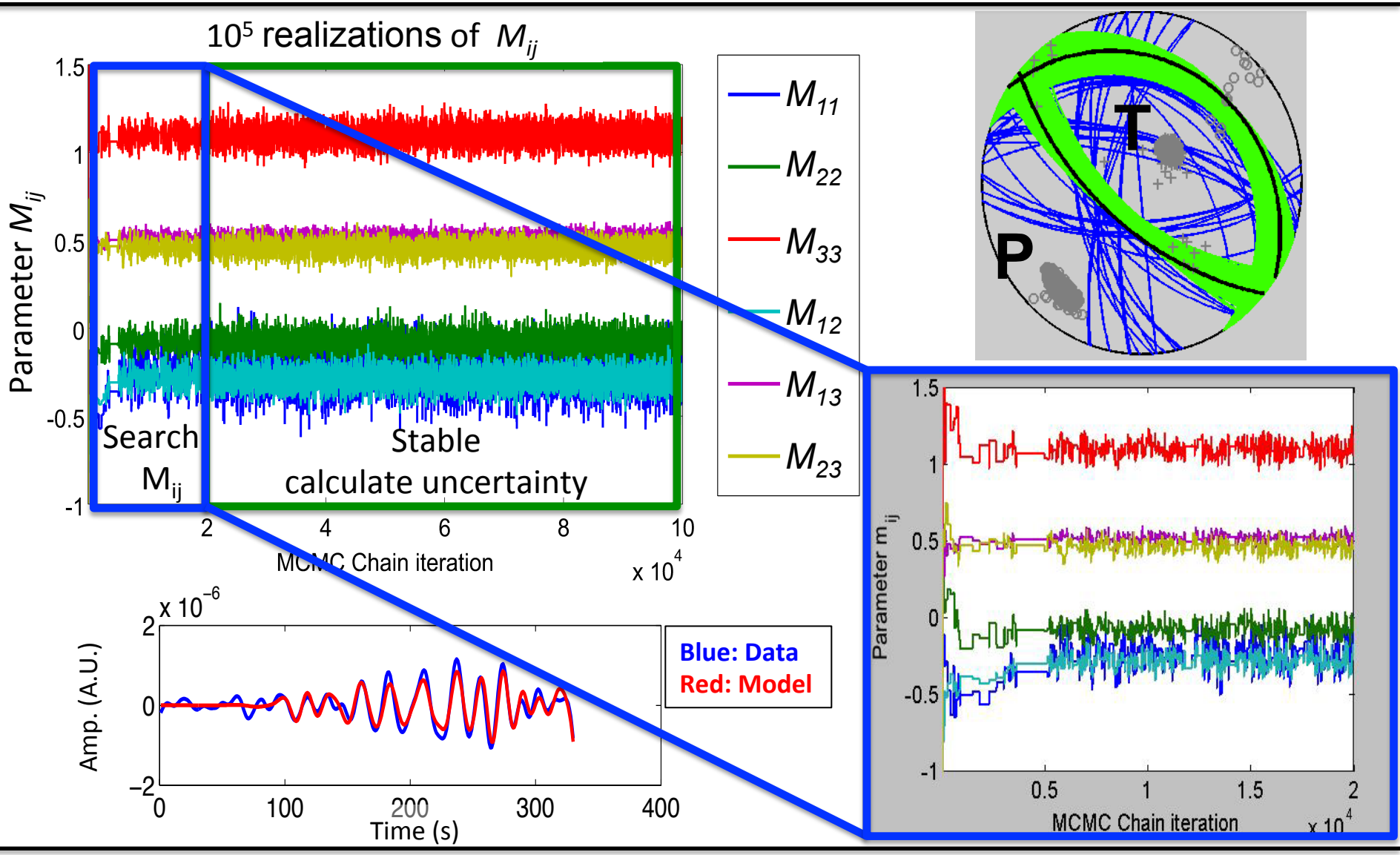
Step 3: Add 10% Gaussian noise

Step 4: Estimate the moment tensor using the “observed” data

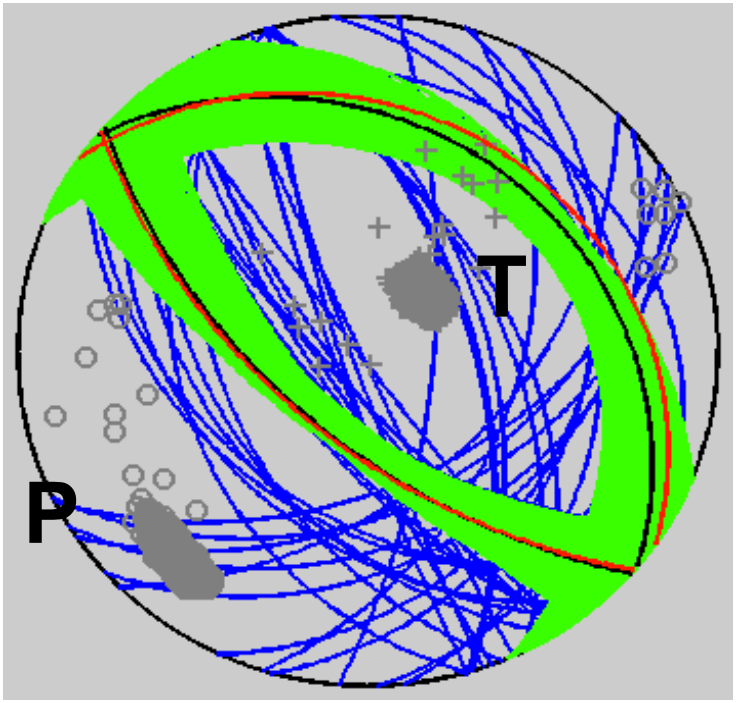
Step 5: Quantify the uncertainties



Synthetic test: AM MCMC Bayesian Inversion

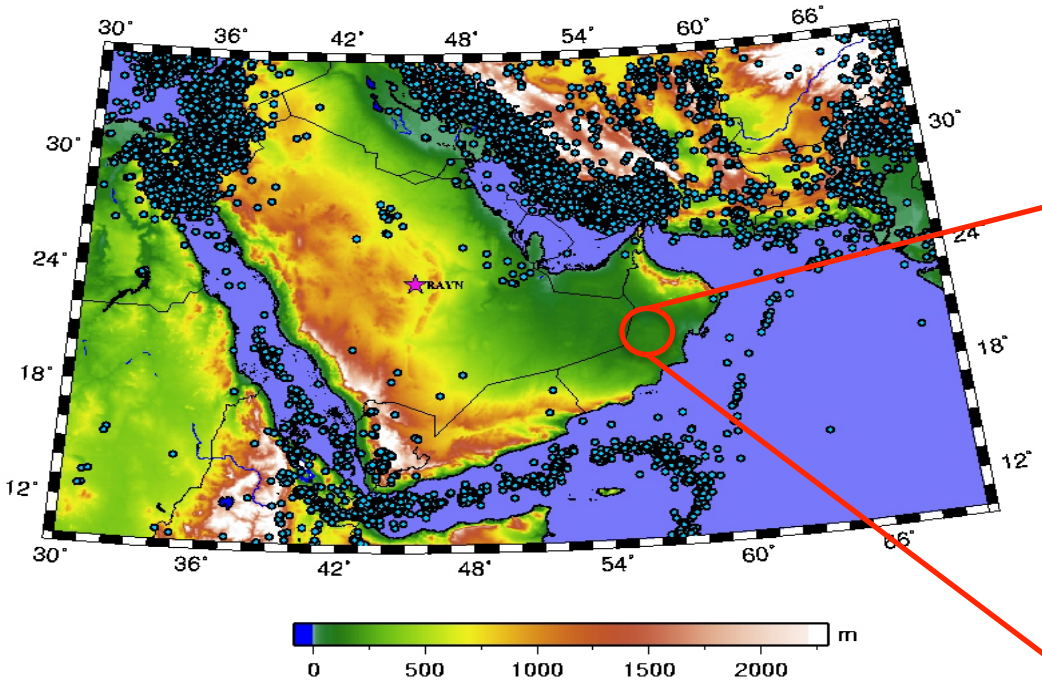


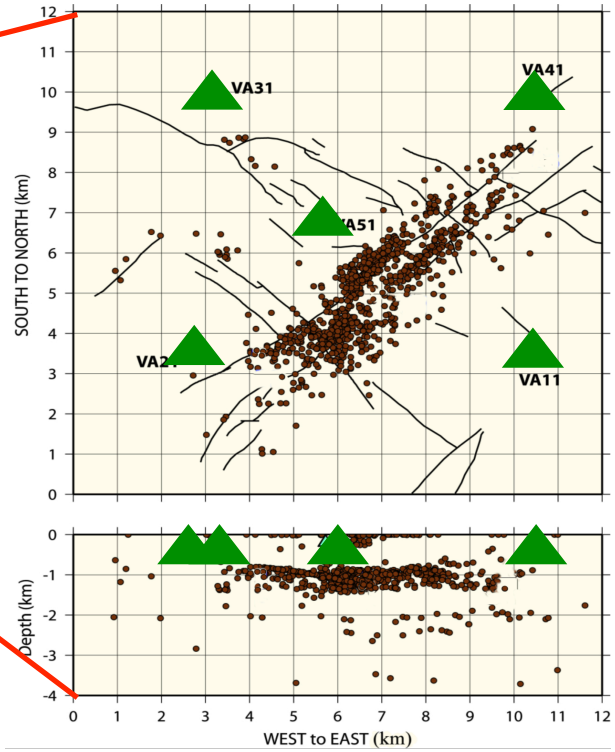
Synthetic test: Uncertainty Quantification



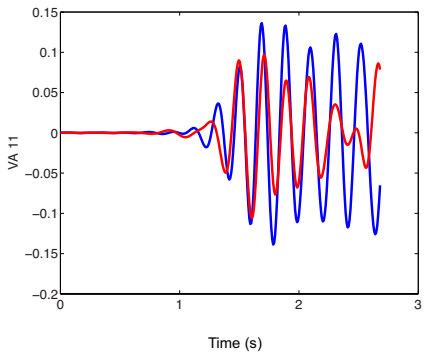
Source Parameters	True Value	Posterior Mean	Standard Deviation
Strike	305°	304°	7°
Dip	20°	19°	3°
Rake	85°	85°	6°
DC%	61.3%	63.4%	7.7%
CLVD%	17.2%	17.7%	5.6%
ISO%	21.5%	18.9%	3.2%
α	10°	10°	4°

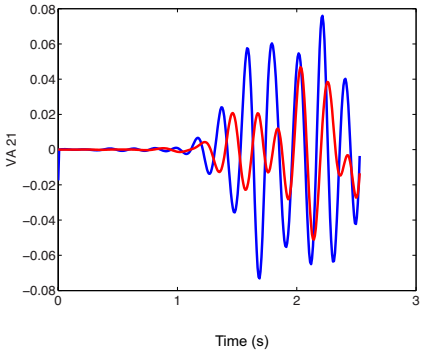
Induced Earthquakes from an Oil/Gas field in Oman

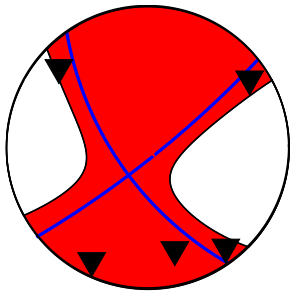


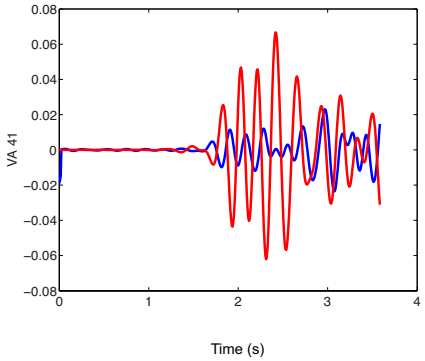


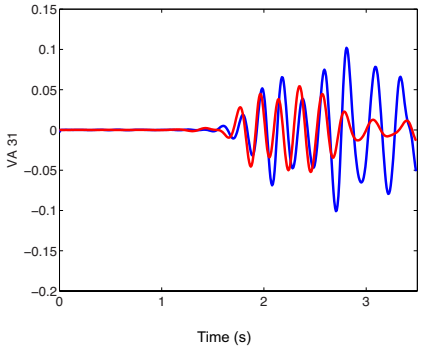
Oman: induced earthquake seismograms

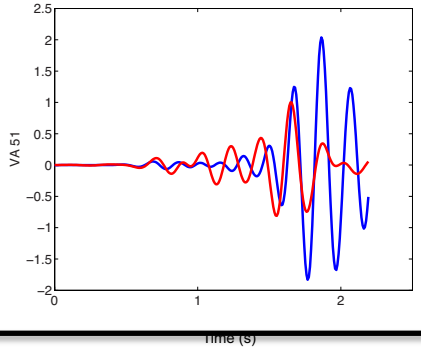






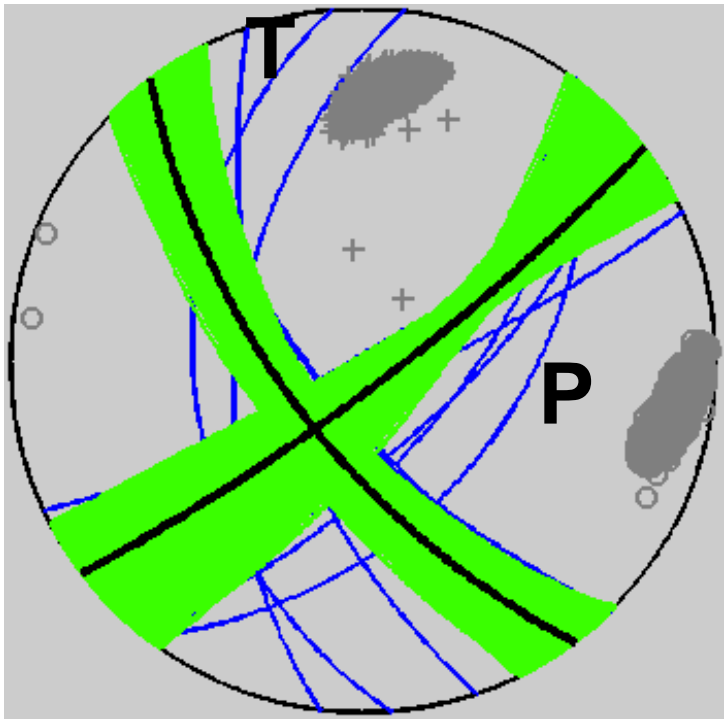






Blue: Data
Red: Model

Oman: Uncertainty Quantification



Source Parameters	Posterior Mean	Standard Deviation
Strike	53°	5°
Dip	81°	3°
Rake	154°	5°
DC%	70%	6%
CLVD%	7%	6%
ISO%	22%	4%
α (°)	4°	4°

Summary

Conclusions

- Waveform-based Bayesian inversion can estimate the full moment tensor of seismicity and quantify the uncertainties of source parameters.

Future work

- Stress triggering analysis and geodynamic modeling
- Hazard assessment and damage measurement

Acknowledgement

- This research was supported by the Kuwait-MIT Center (CNRE).
- We thank Petroleum Development Oman for providing seismic data in Oman.
- We also thank Dr. A. Al-Enezi and Ms. F. Al-Jeri for providing seismic data in Kuwait and assisting in the analysis.

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Thank you!

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