Modelling subsidence: On the use of the particle filter for geomechanical parameter estimation

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Agenda

- Introduction
- Modelling subsidence
- Particle filter for parameter estimation
- Data assimilation experiments:
  - Point source (Mogi)
  - Fully coupled flow-geomechanical model (ADGPRS)
  - Fault-slip modeling with FEM package (Plaxis)
- Conclusions and Outlook

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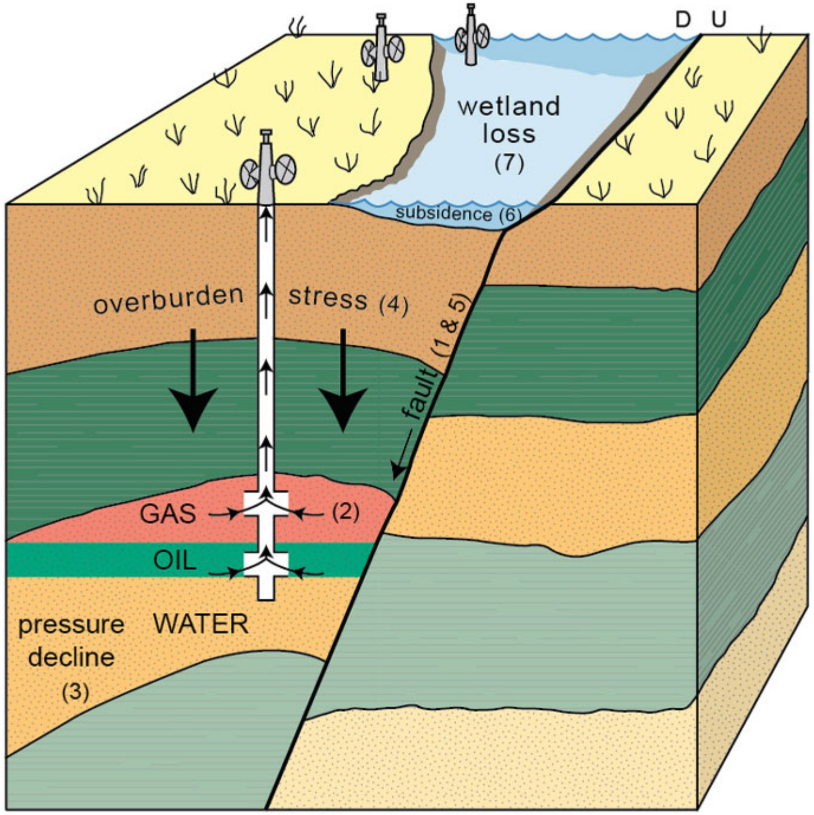
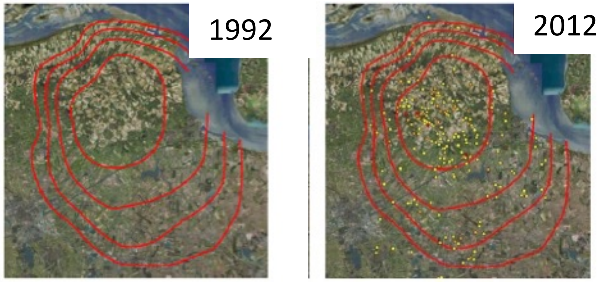
Examples of subsidence



1. Louisiana wetlands: fault activation *(USGS)*

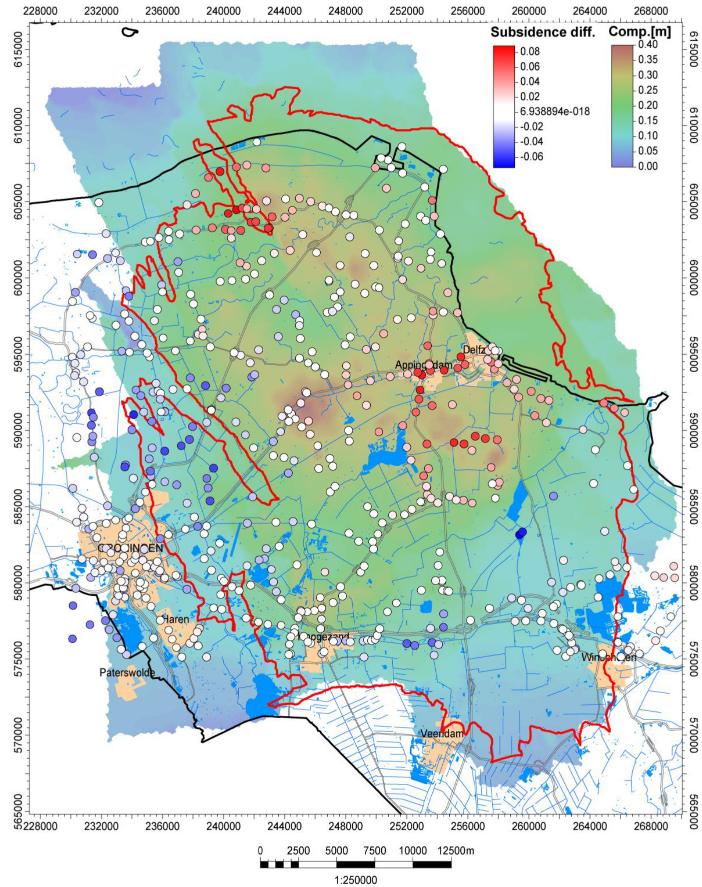


3. Groningen: seismic effects *(NAM)*

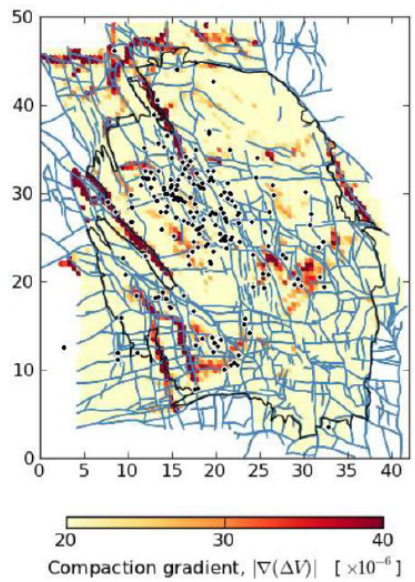
2. Venice: mixed effect of groundwater and gas extraction

Subsidence, induced seismicity

- Subsidence to first order related to pressure drop in reservoir (e.g. Geertsma, 1963)
- Relation with induced and natural seismicity poorly understood, for example in Groningen, San Jacinto, Basel.



Difference between calculated and modeled subsidence indicated at benchmark locations.
Van Thienen-Visser et al (2015)

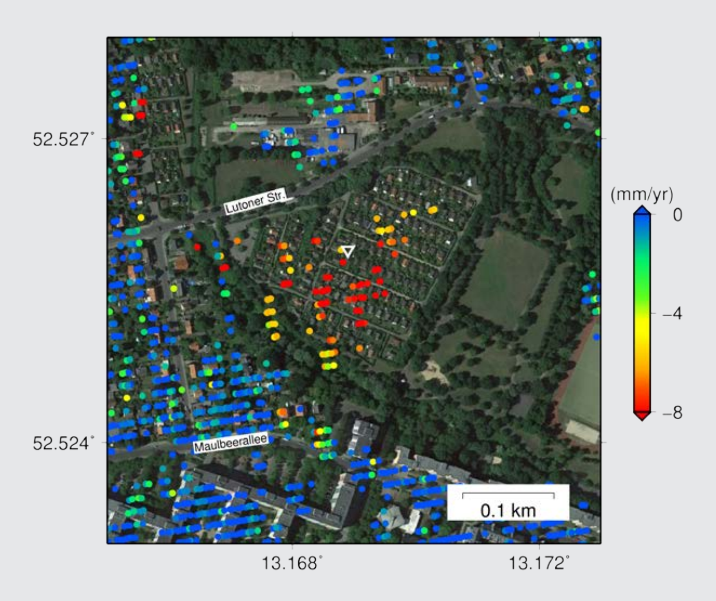


Bourne et al (2014)

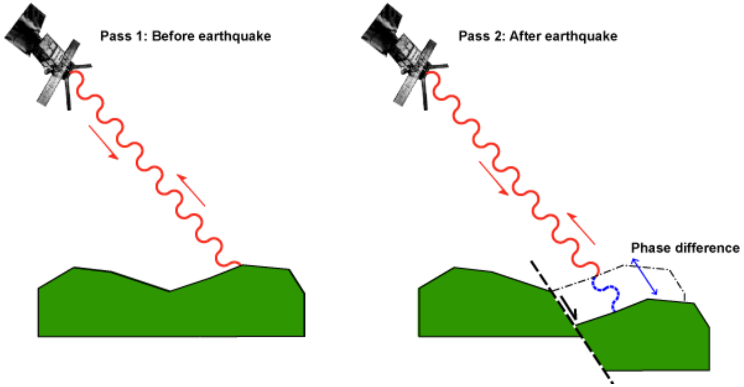
Geodetic monitoring

- Subsidence can be observed with satellites (InSAR, GPS) as well as in situ techniques (levelling)

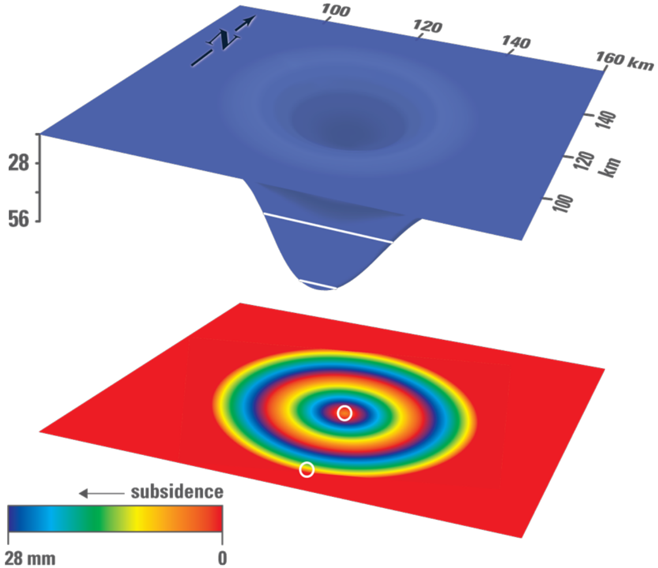
Subsidence and uplift at Egehlpfuhl (N of Potsdam) as observed by Sentinal-1 InSAR



Haghshenas and Motagh (GFZ & Leibniz Uni. Hannover), Zeitschrift für Geodäsie, Geoinformation und Landmanagement, 2017, www.geodaesie.info



http://comet.earth.ox.ac.uk/for_schools_radar4.html

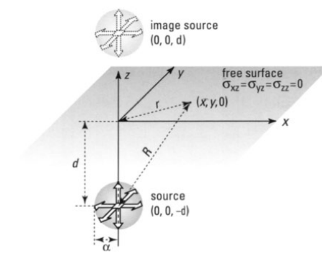


https://ca.water.usgs.gov/land_subsidence/california-subsidence-measuring.html

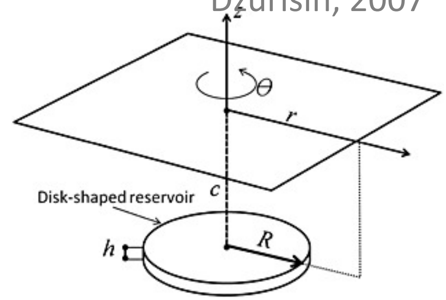
Modelling subsidence due to reservoir compaction

Increasingly nonlinear

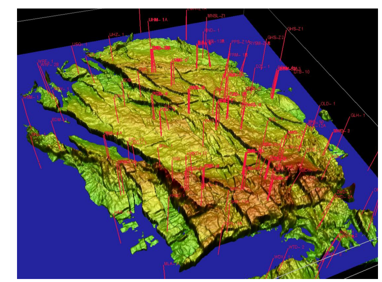
- **Time-independent deformation model**: represent reservoir compaction with a point source, following **Mogi** (1958).
- **Finite element geomechanical model** with single fluid flow (e.g. **Plaxis**)
- **Apply compaction model to reservoir pressure field**: Geertsma's analytical solution (1963), in combination with a time-dependent pressure distribution from a multi-layer reservoir model.
- **Fully coupled flow-geomechanics**: FEM geomechanical model coupled to finite difference model reservoir flow, e.g. **ADGPRS** (Garipov et al, 2016, Voskov and Tchelepi, 2012)
- **Integrated model** that includes geomechanics and multi-fluid, multi-phase flow



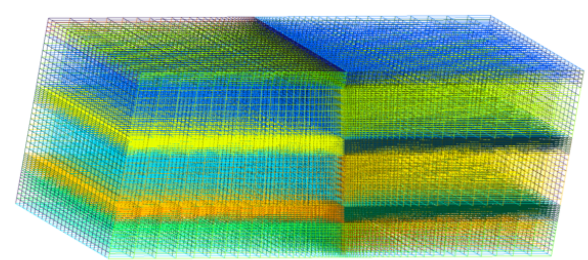
Mogi source, after Dzurisin, 2007



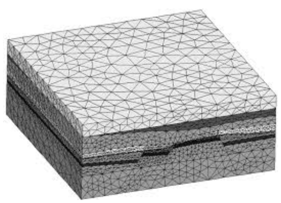
Bau (2014), after Geertsma (1963)



Groningen reservoir model
Mmax workshop March 2016, http://feitenencijfers.namplatform.nl

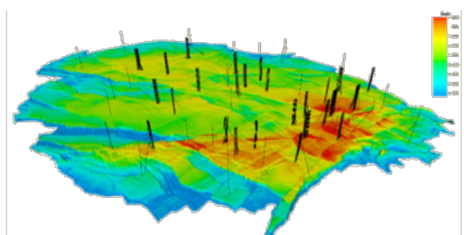


Data assimilation for parameter estimation

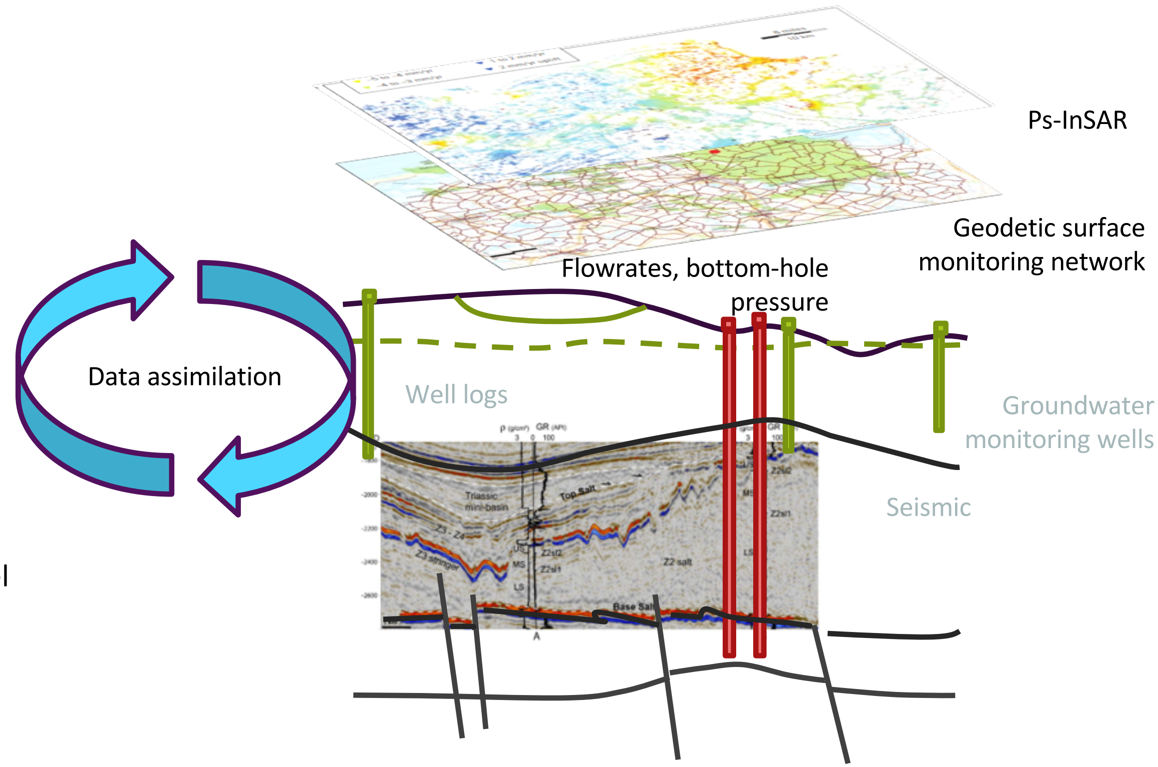


Geomechanical model

- Geomechanics:
  - Young's modulus
  - Poisson's ratio



Reservoir model



- Fluid flow:
  - Permeability
  - Porosity
  - Pressure
  - Saturation
- Geometry and geology
  - Layering
  - Faults and structure

- Subsurface and surface data reduce uncertainties in geometry, parameters and state variables

State and parameter estimation

Bayes' rule:

$$f(\psi \mid \mathbf{d}) = \frac{f(\mathbf{d}|\,\psi)f(\psi)}{f(\mathbf{d})}$$

Where ψ is the model state, and $\mathbf{d}$ are the observations. Assume state evolution can be described by Markov process:

$$d\,\psi = g(\psi;\gamma)dt + d\beta,$$

With γ the model parameters. Then the minimum variance estimate becomes:

$$\hat{\psi} = \int \psi\, f(\psi|\mathbf{d})d\psi$$

In subsurface flow estimation, several methods are being commonly used:

1. Ensemble Smoother (Van Leeuwen and Evensen, 1996)
2. Ensemble Kalman Filter (Evensen, 1994)
3. Ensemble Kalman Smoother (Evensen and Van Leeuwen, 2000)
4. Ensemble Square Root Filter (e.g., Zhang et al, 2010)
5. Randomized Maximum Likelihood (Oliver et al, 1996)
6. Particle Filters (review: Van Leeuwen, 2009)
7. Markov-Chain Monte Carlo (e.g., Oliver et al, 1996)

State and parameter estimation

Ensemble (Kalman) methods for state and parameter estimation can be seen as a summation of representer functions involving error covariances with coefficients:

$$\psi^a(\mathbf{x},\gamma,t^*) = \psi^f(\mathbf{x},\gamma,t^*) + \sum_{n=1}^{N^*} b_n \mathbf{r}(\mathbf{x},\gamma,t^*)$$

Where the coefficients b_n effectively weight a set of model realizations with their difference from the observations .

This can also be written as:

$$\psi^a(\mathbf{x},\gamma,t^*) = \psi^f(\mathbf{x},\gamma,t^*) + \mathbf{C}_{\psi\psi}\mathbf{H}^T\left(\mathbf{H}\mathbf{C}^f_{\psi\psi}\mathbf{H}^T + \mathbf{C}_{dd}\right)^{-1}(\mathbf{d} - \mathbf{H}\psi^f(\mathbf{x},\gamma,t^*))$$

With covariances $\mathbf{C}_{\psi\psi}$ and $\mathbf{C}_{dd}$ representing uncertainty in model and data.

State and parameter estimation

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This can also be written as

Assuming Gaussianity

$$\psi^a(\mathbf{x},\gamma,t^*) = \psi^f(\mathbf{x},\gamma,t^*) + \mathbf{C}_{\psi\psi}\mathbf{H}^T\left(\mathbf{H}\mathbf{C}^f_{\psi\psi}\mathbf{H}^T + \mathbf{C}_{dd}\right)^{-1}(\mathbf{d} - \mathbf{H}\psi^f(\mathbf{x},\gamma,t^*))$$

With covariances $\mathbf{C}_{\psi\psi}$ and $\mathbf{C}_{dd}$ representing uncertainty in model and data.

Particle methods

- Start from Bayes:

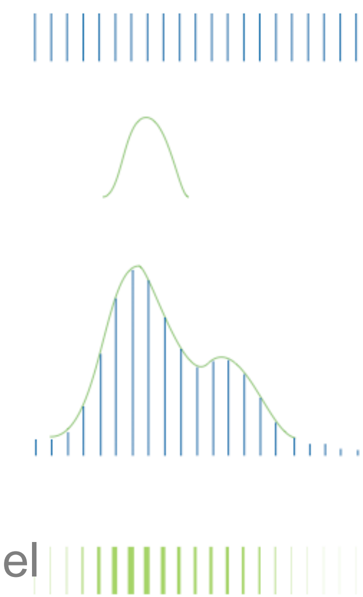
$$p_m(\psi \mid \mathbf{d}) = \frac{p_d(\mathbf{d} | \psi) p_m(\psi)}{p_d(\mathbf{d})}$$

- Approximate model probability density with ensemble of model realisations

$$p_m(\psi) = \frac{1}{N} \sum_{i=1}^{N} \delta(\psi - \psi_i)$$

- Minimum variance estimator is:

$$\hat{\psi} = \int \psi \, p_m(\psi | \mathbf{d}) d\psi = \frac{\int \psi p_d(\mathbf{d} | \psi) p_m(\psi) d\psi}{\int p_d(\mathbf{d} | \psi) p_m(\psi) d\psi} = \frac{\sum_{i=1}^{N} \psi_i p_d(\mathbf{d} | \psi_i)}{\sum_{i=1}^{N} p_d(\mathbf{d} | \psi_i)}$$



- In essence: weigh each particle with difference observation-model
- Can be used as a smoother or as a filter

Parameters and sensitivities in subsidence parameter estimation

- In these applications, the following (state) variables are observed:
  - Surface deformation
  - Reservoir pressure
  - Oil or gas rate
- While the following parameters are assumed to be unknown:
  - compaction coefficient/Young’s modulus
  - (in case of Mogi) source strength

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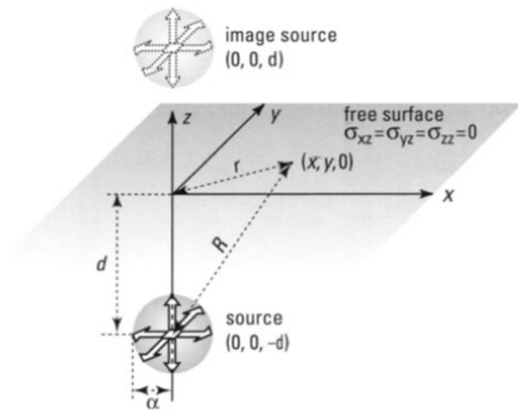
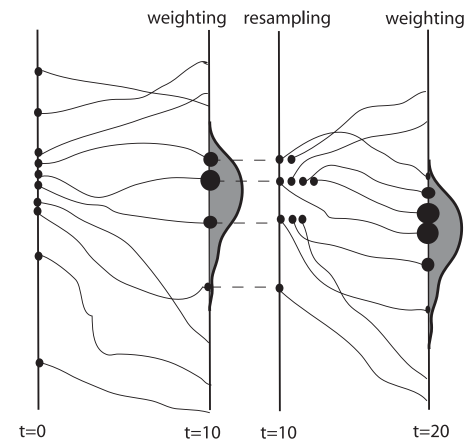
Particle Filter for Mogi point source of subsidence

- Modeling subsidence with so-called Mogi sources, spherical sources of strain
- Computationally inexpensive: possible to create large ensembles in particle filter
- System set-up for assimilation of InSAR surface deformation measurements in the Groningen area

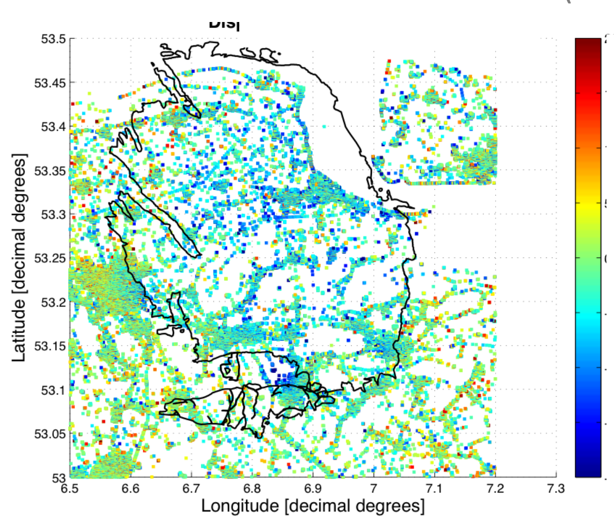
Mogi source, after Dzurisin, 2007



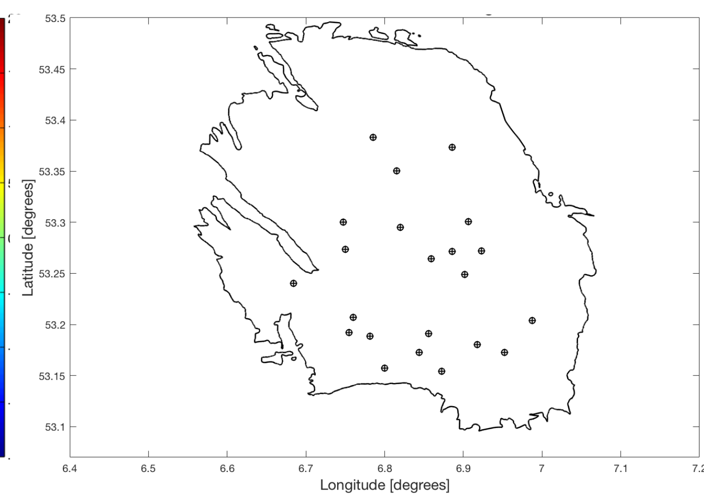
Particle filter with resampling (from Van Leeuwen, 2009)



InSAR data of 2009-2010 subsidence (mm)

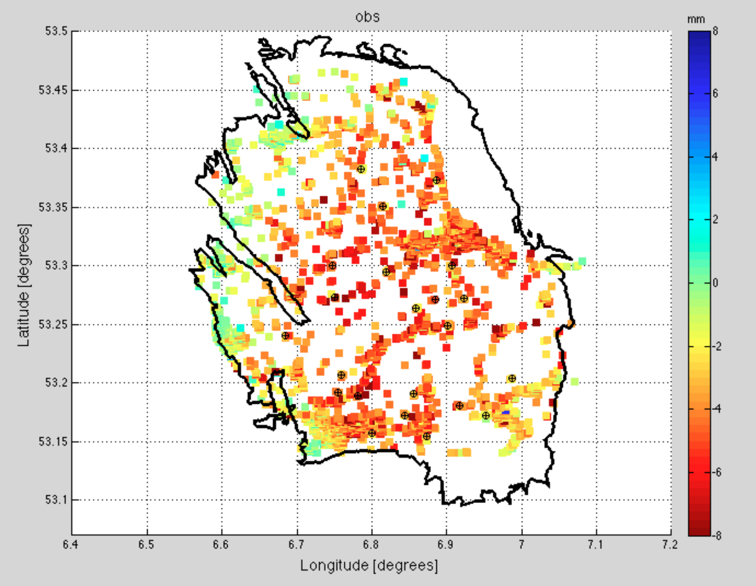


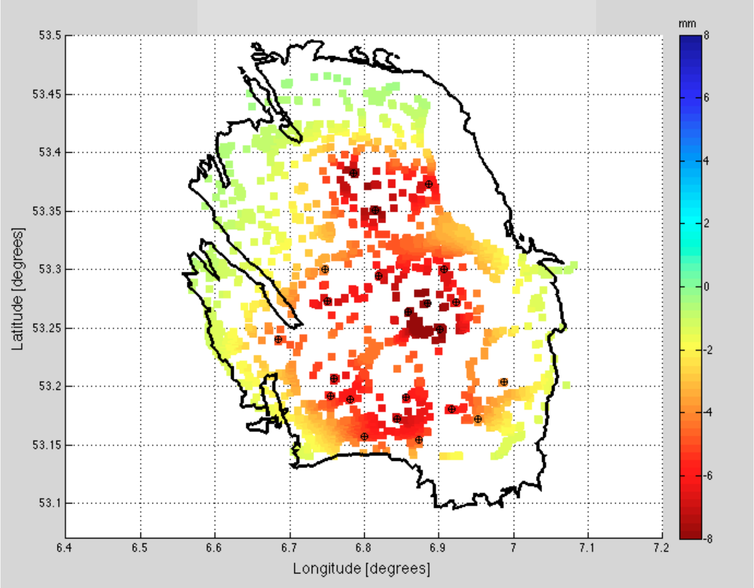
Represent compaction of reservoir by Mogi sources at well locations

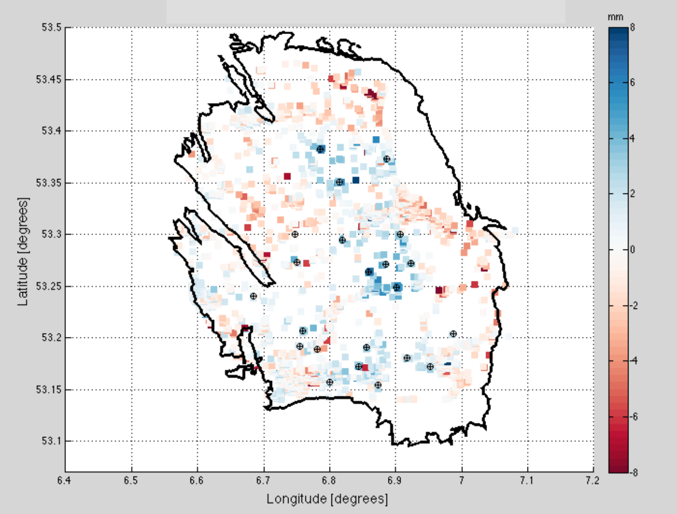


with Karlijn Beers, Ramon Hanssen

Reconstructed subsidence Groningen 2009-2010

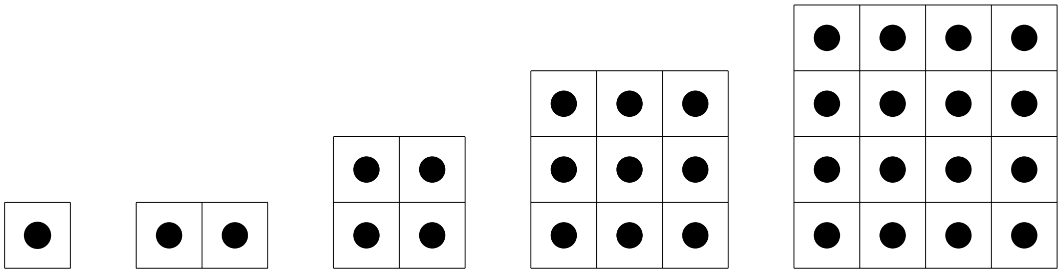


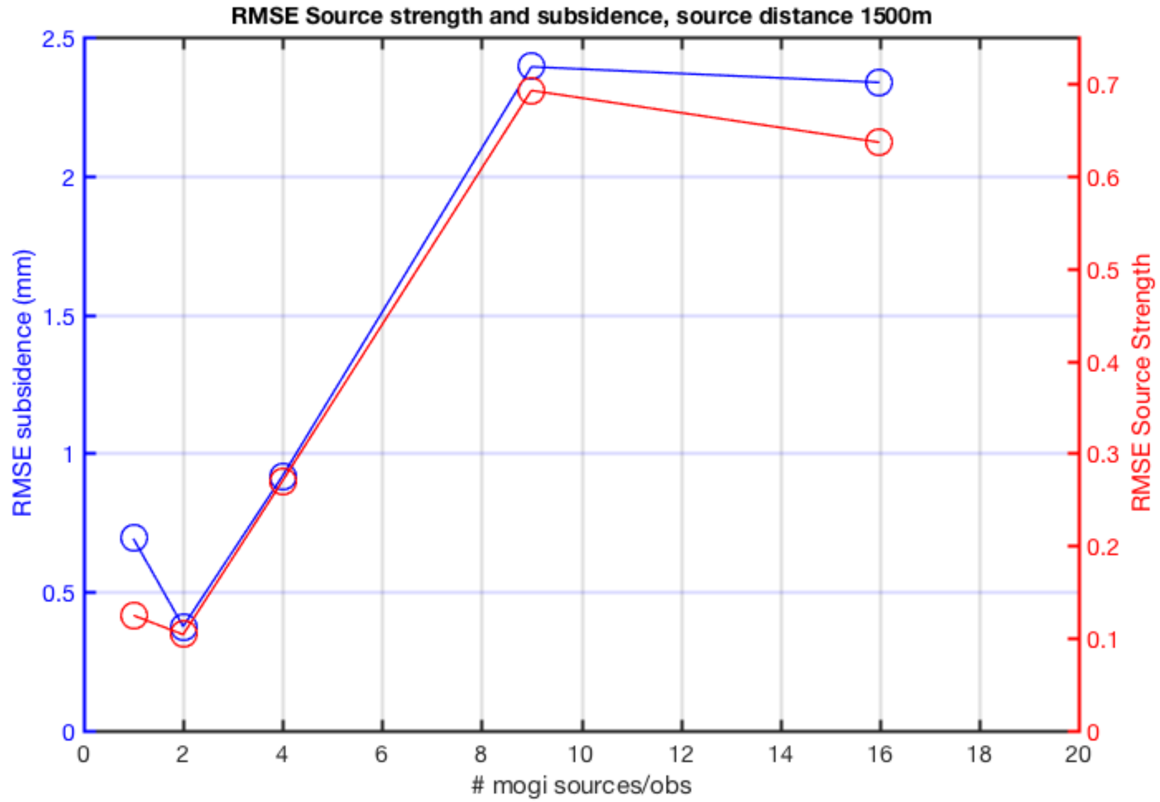




Quality of reconstruction Mogi strength

- Increasing number of Mogi sources, keeping ensemble size constant
  - Increasing ambiguity
  - Effectively decreasing search space
- Influence of observational error probability density function on performance





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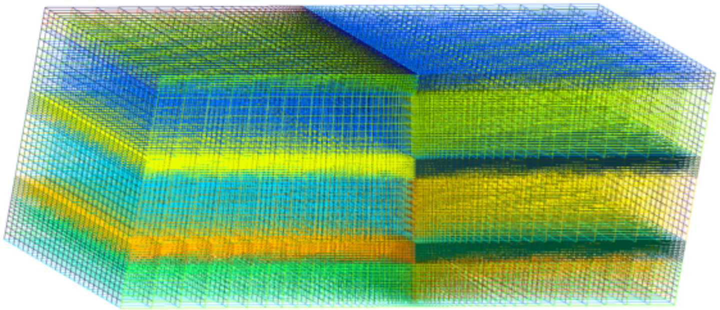
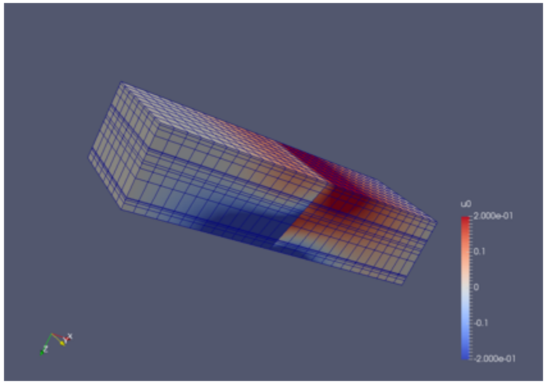
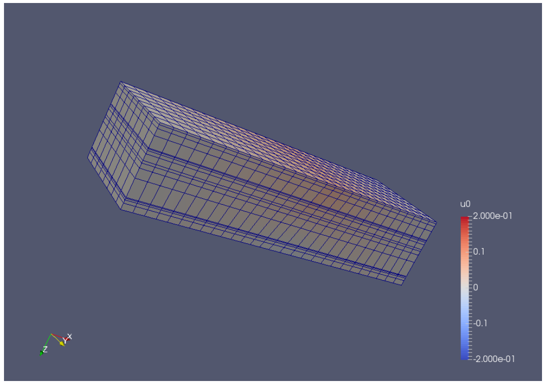
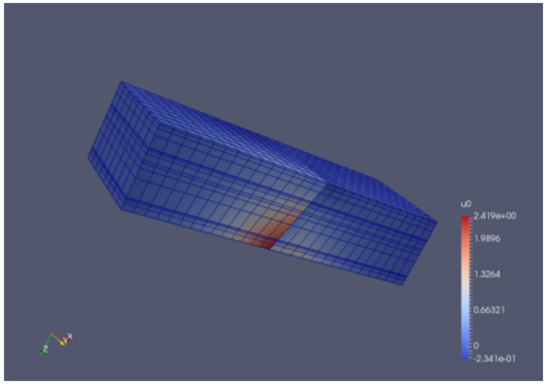
Coupled Flow-Geomechanical model ADGPRS









- Coupled reservoir-geomechanical model: AD-GPRS (Garipov et al, 2016, Voskov and Tchelepi, 2012)

Coupled Flow-Geomechanical model ADGPRS

- Governing equations:

$$\frac{\partial(\rho_f \phi)}{\partial t} - \nabla \cdot \left[\rho_f \frac{k}{\mu_f}(\nabla p - \rho_f g)\right] - q = 0$$

mass conversation and Darcy's law

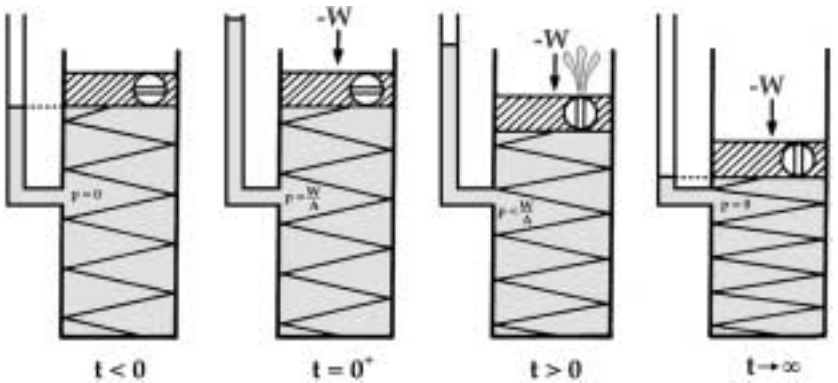
$$\phi = \phi_0 + \frac{(b-\phi_0)(1-b)}{K_d}(p - p_0) + b(\epsilon_v - \epsilon_v, o)$$

constitutive equation skeleton, assuming elasticity (Coussy, 2004)

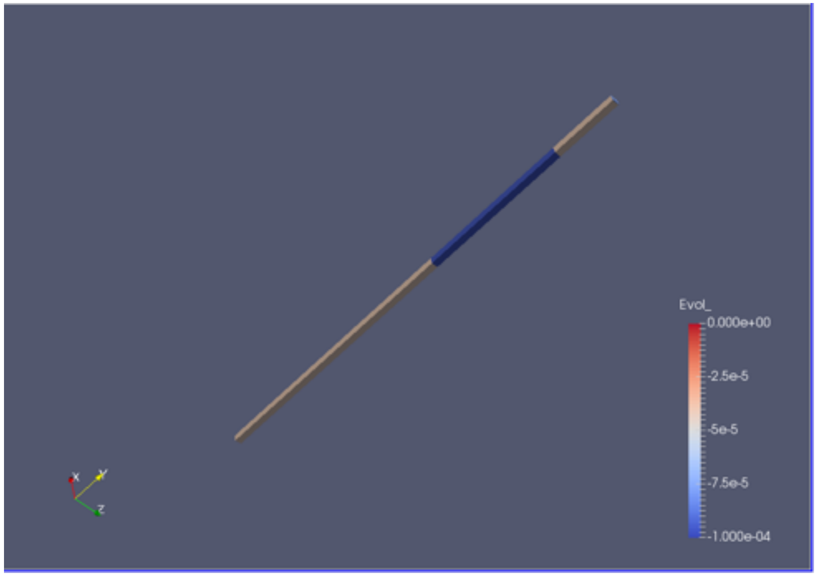
- Simplified geometry with full coupling, fully implicit methods makes model computationally efficient

Model set-up 1D ADGPRS

- Terzaghi's experiment: consolidation process where axial load is initially borne by fluid, and then shifted to skeletal frame

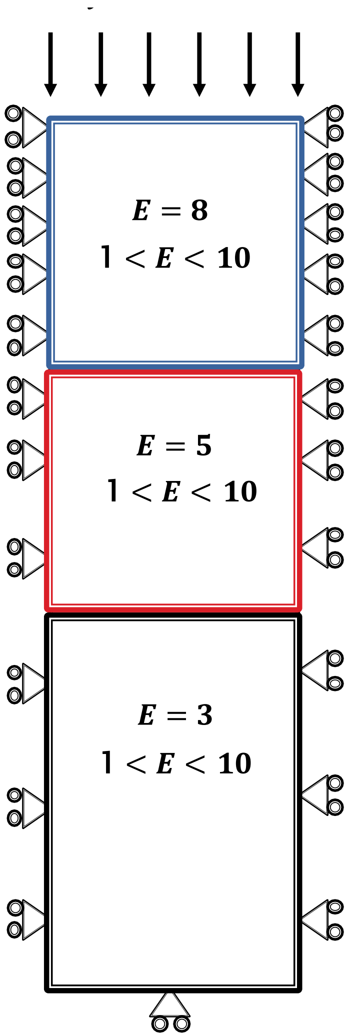


Terzaghi's uniaxially constrained soil consolidation, *Craig 1997*

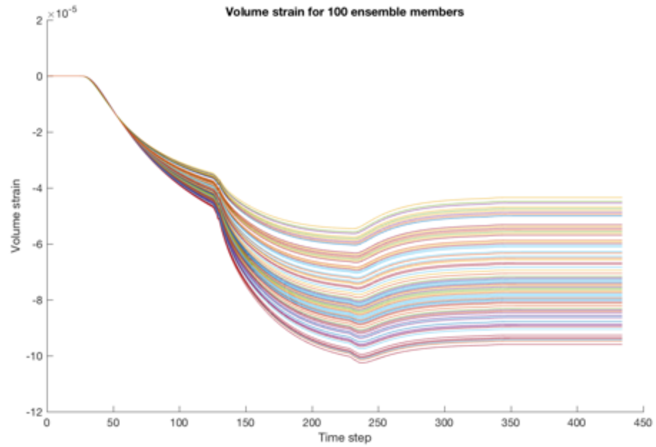


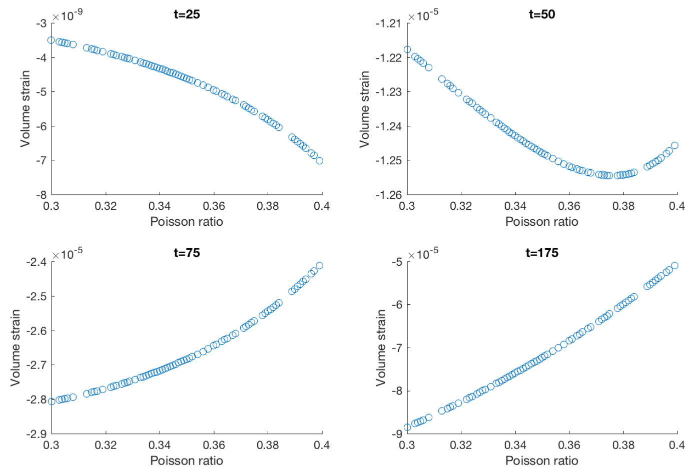
- Single column (19 cells)
- Deformation depends on bulk modulus K_d, which depends on Young's modulus and Poisson ratio

Intermediate results 1D ADGPRS

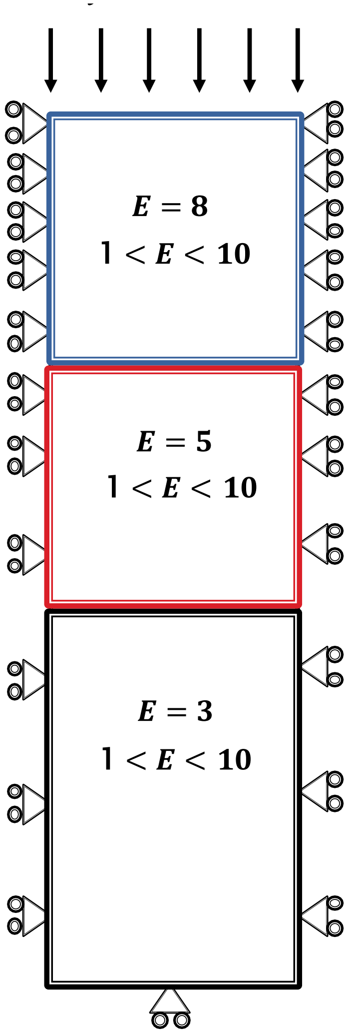


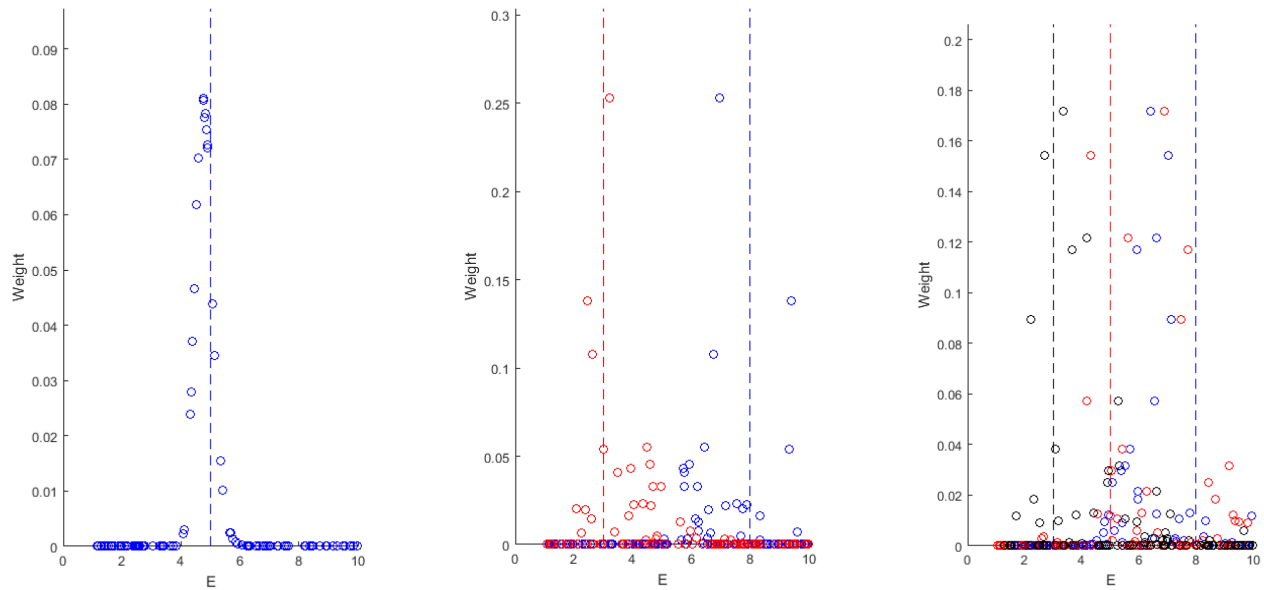
- 100 member ensemble for sensitivity study
- Varying Young's modulus (E) and/or Poisson's ratio (ν) in three subsurface layers
- Note: this 1D case is actually not as non-linear as a 3D case could be





Consolidation results

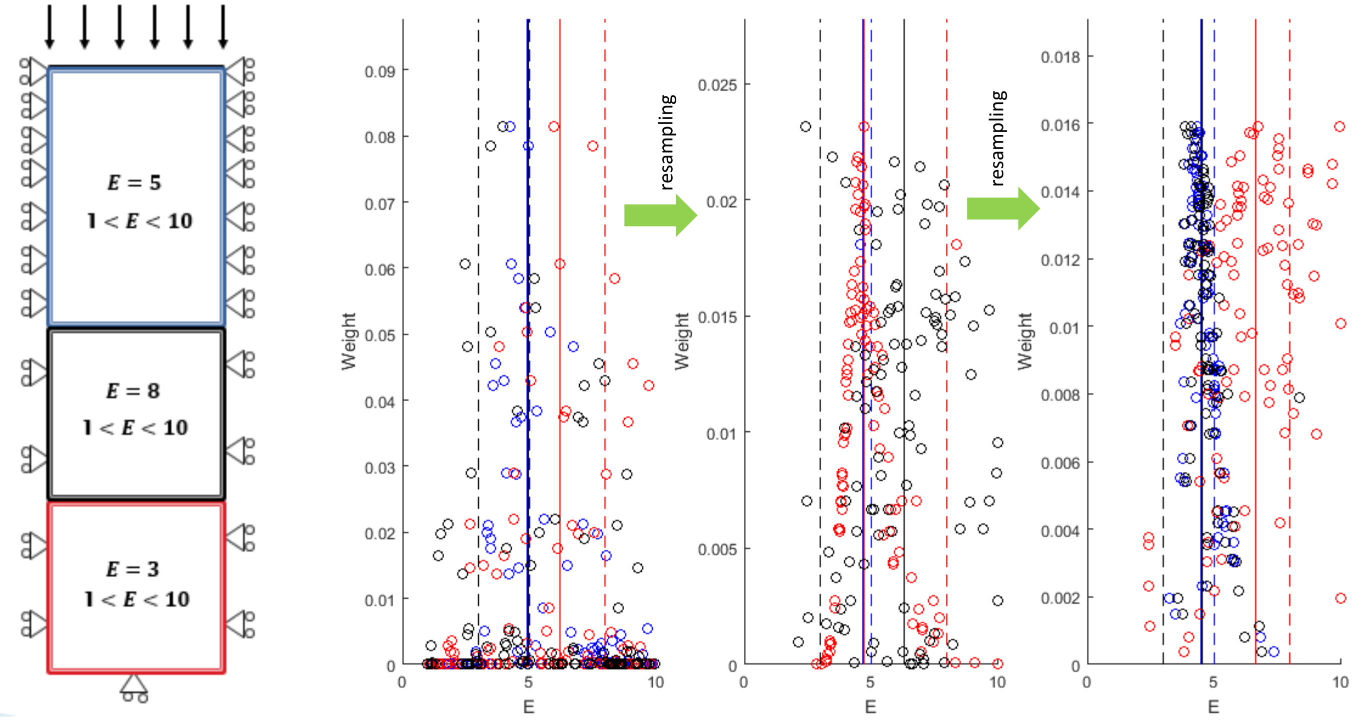




- Increasing number of unknowns, able to separate between the different rock properties for two top layers, for three layers this becomes challenging
- Comparison with Ensemble Kalman Filter and ES-MDA ongoing
- Investigating PF adjustments:
  - Incremental adjustments with adaptive weights (next slide)
  - Regularized particle filter
  - Proposal density function

Consolidation results PF adjustments

- Resampling with ‘jitter’
- Adaptive weighting in three iterations
- Further experiments ongoing…



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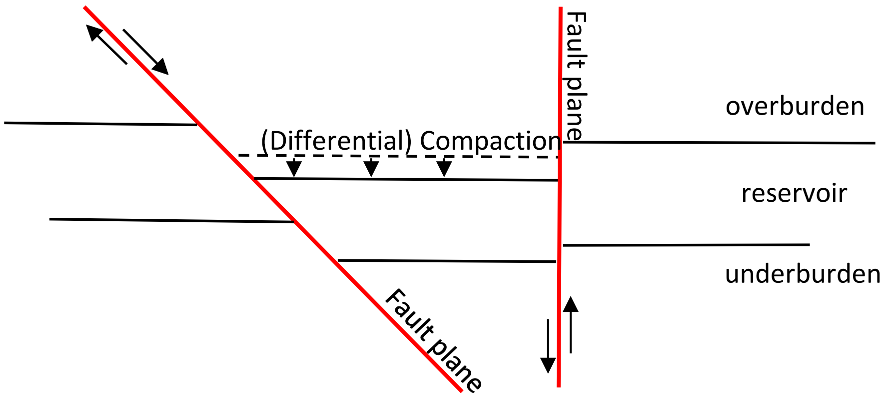
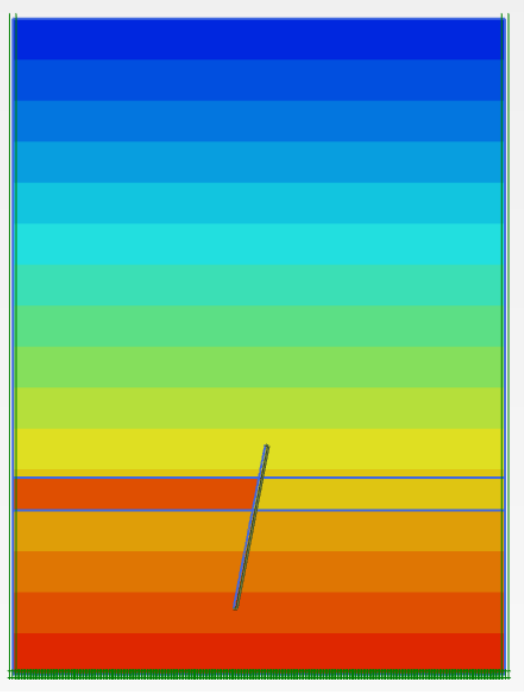
Fault reactivation in FEM (Plaxis)

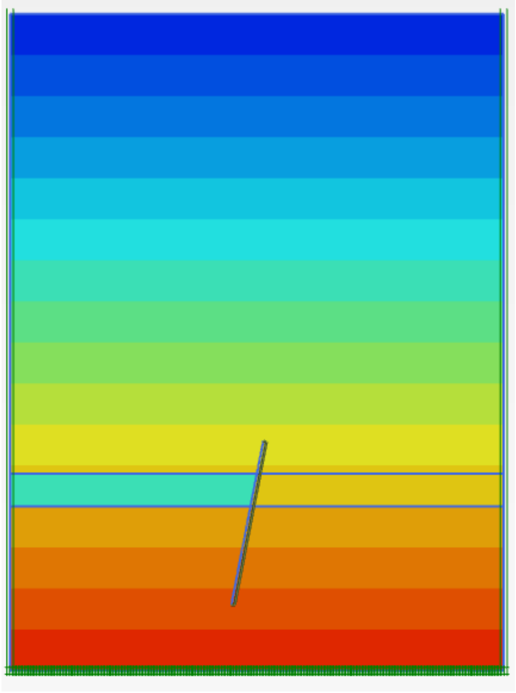
- Reservoir depletion on one side of a fault leads to differential pressure loading, which may lead to fault slip and induced seismicity

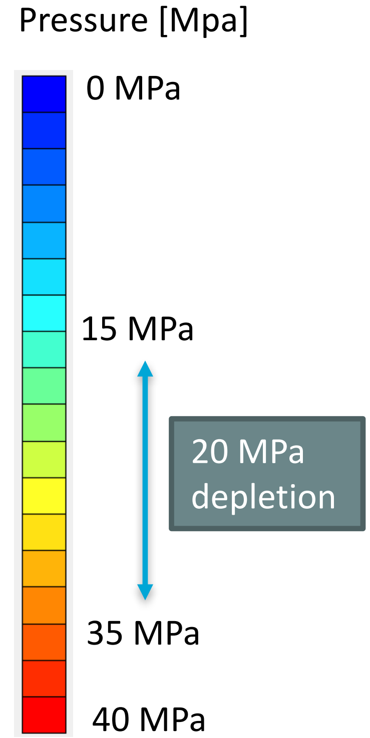


Initial pressure situation:



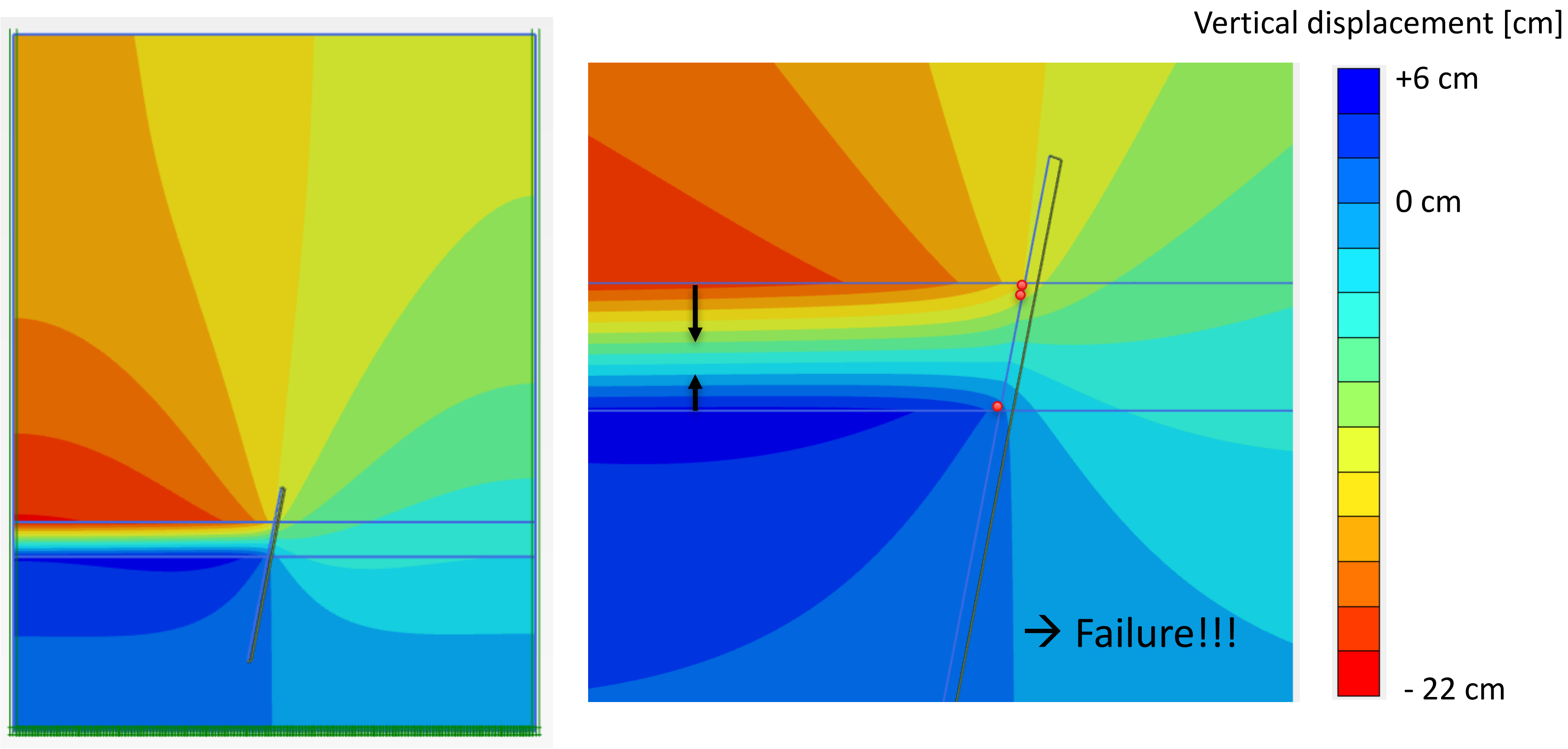
After 20 MPa depletion:





1MPa = 10 bar

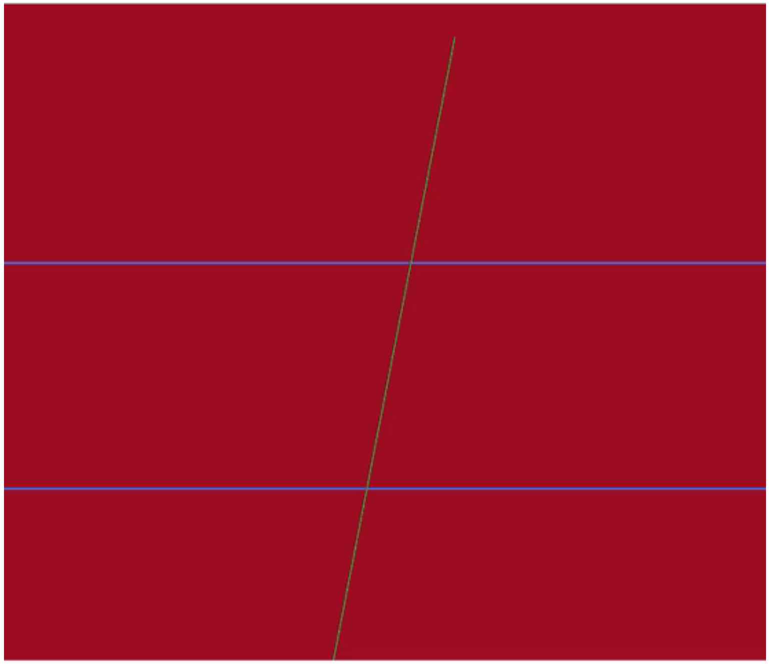
Vertical displacement fault reactivation



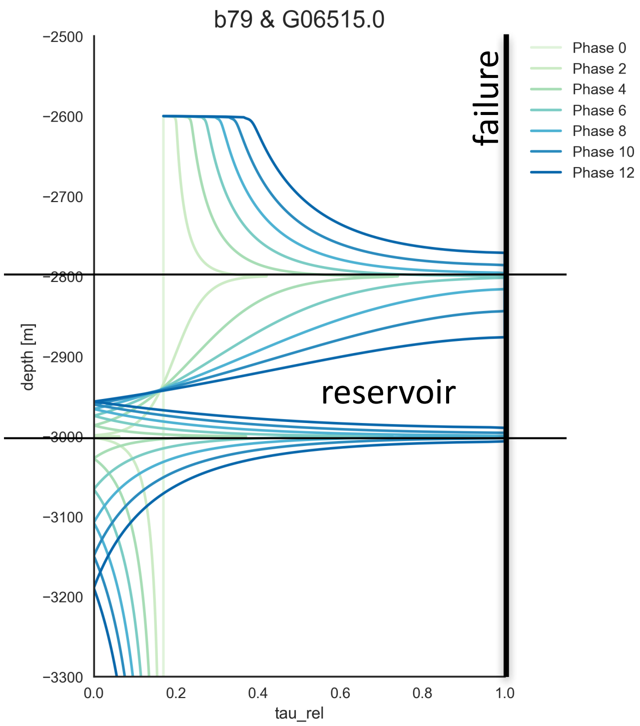
Failure points analysis

- At which pressure does fault failure occur?

Pressure: 35-30-25-20-15-10-5 MPa
Phase: 0- 2- 4- 6- 8- 10-12



Failure: just before pore pressure is 20 MPa (Phase 6)

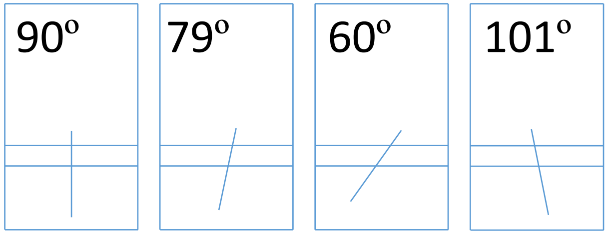


Fault reactivation sensitivities

Geometry parameter	Values
Reservoir radius [m]	500, 1000, 3000
Reservoir thickness [m]	50, 100, 200, 300
Fault angle [deg]	60, 79, 90, 101, (70, 120, 160, 20)
Fault throw [m]	0, +30, -30, +100, -100, + res. thickness, - res. thickness

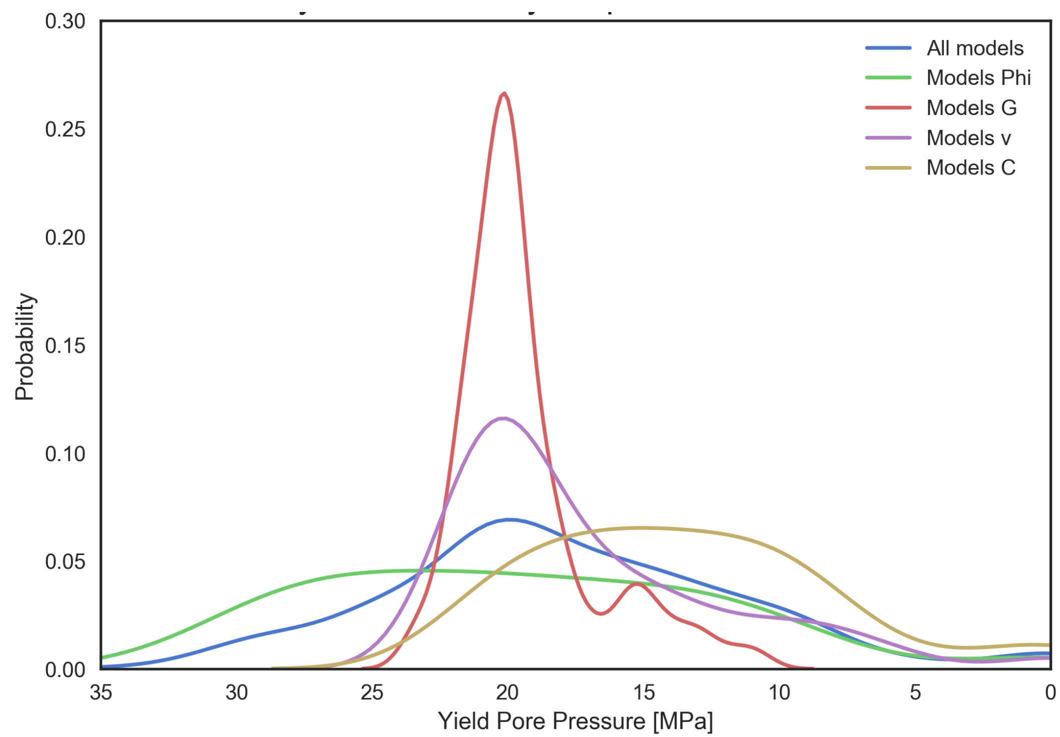
Rock/Fault parameter	Base	Min	Max	Variations
E (Young's modulus) [GPa]	15	5	25	9
v (Poisson's ratio)	0,15	0,1	0,3	6
C (Cohesion) [MPa]	0	0	10	5
Phi (friction angle) [deg]	25	15	40	9

e.g. fault angle:



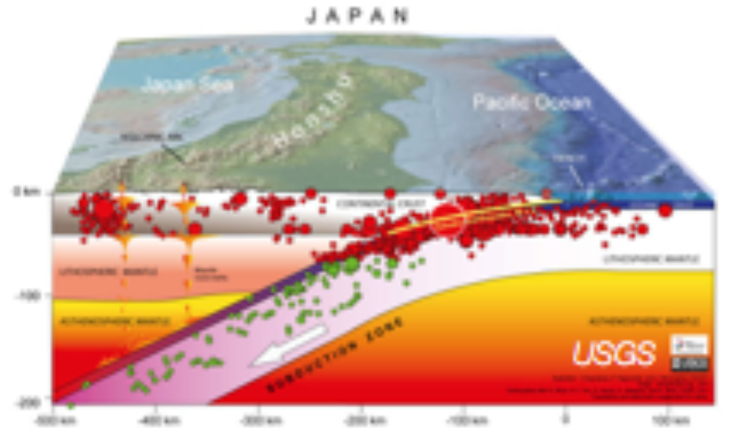
Fault reactivation sensitivities

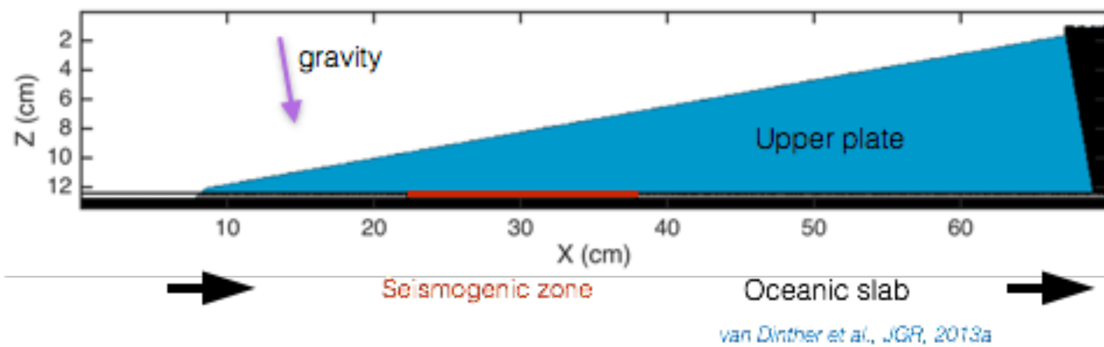
- Probability distributions derived from sensitivity studies for internal friction angle, Young's modulus, Poisson's ratio and a tuning factor for poro-elastic loading
- Shape of distribution can be used as a measure of sensitivity for each of the parameters
- Use these distributions for perturbations for data assimilation with sequential Monte Carlo methods

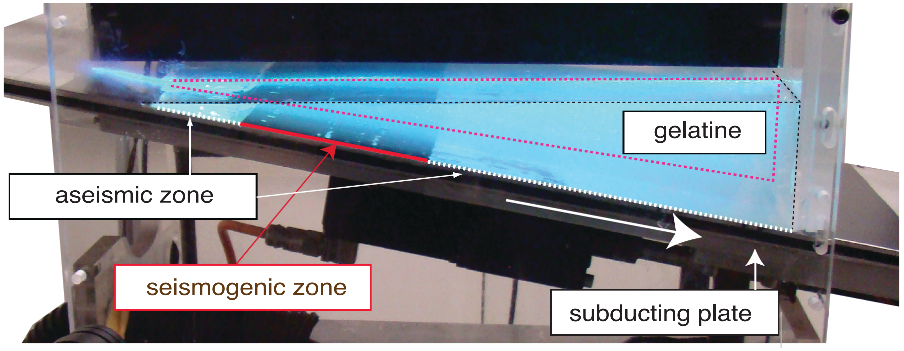


Data assimilation for fault slip modelling

- Collaboration with Ylona van Dinther and Marie Bocher (ETH Zürich)
- Understanding fault slip will help monitor and forecast earthquakes and their consequences
- Fault slip strongly depends on initial fault stresses and parameters
- Can we make use of what we know from observations? …and from laboratory experiments?

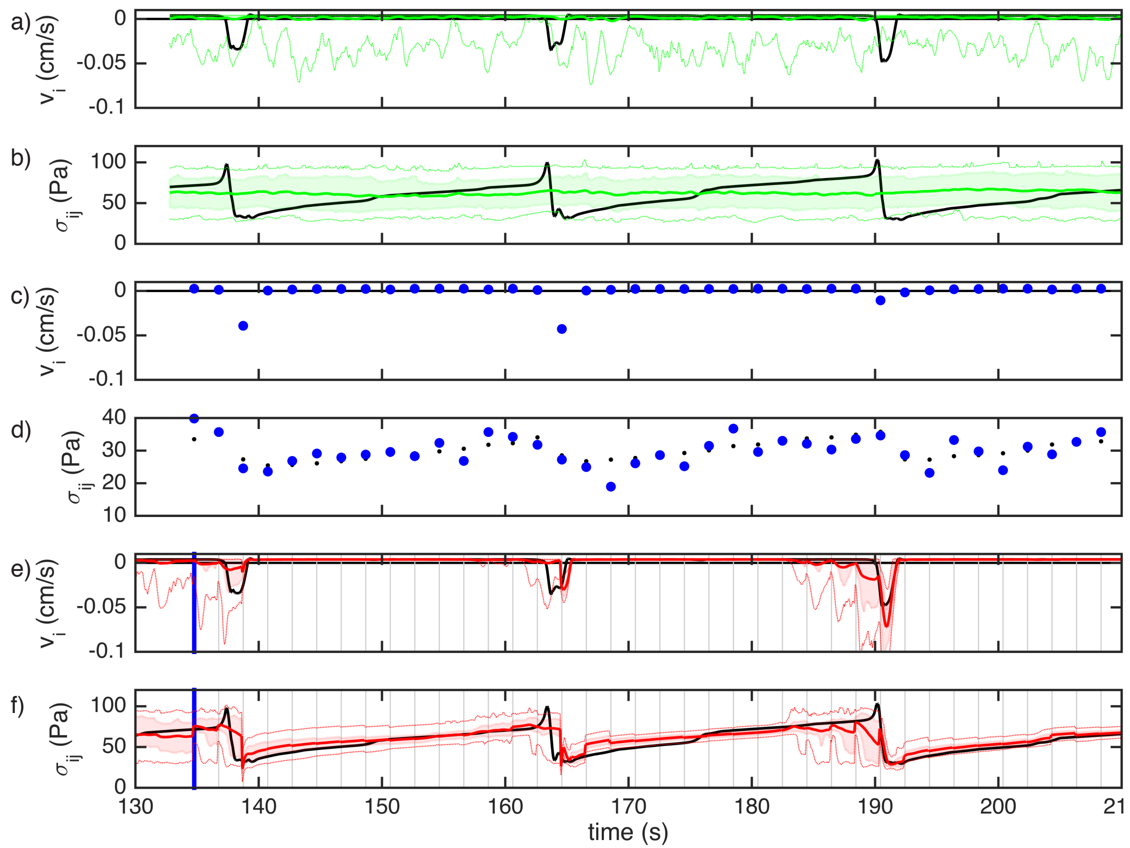






Data assimilation for fault slip -results so far

- Ensemble Kalman filter as a tool to estimate and forecast synthetic slip of laboratory earthquakes
- Updating the stress and strength fields using observations of borehole velocity, stress, and pressure in a simplified subduction zone



Limited applicability of the Ensemble Kalman Filter to strongly non-linear problems may be overcome by using the Particle Filter for data assimilation.

Conclusions and outlook

- Conclusions
  - A variety of models and data assimilation approaches are tested to infer reservoir compaction from subsidence observations
  - Non-linearities and coupled models ask for Sequential Monte-Carlo methodologies
- Outlook
  - Focus on more strongly nonlinear processes:
    - 3D heterogeneities in subsidence
    - fault slip and seismicity
  - Investigate Hybrid Monte Carlo/EnKF assimilation methods

Q&A