BAYESIAN ROCK PHYSICS INVERSION FOR CO_2 STORAGE MONITORING

Bastien Dupuy, Pierre-Louis Nordmann, Anouar Romdhane, Peder Eliasson

Outline

- Why using Bayesian formulations in CO_2 storage monitoring?
- Two-steps inversion with uncertainty assessment.
- Sleipner case study
  - Time-lapse strategy
  - Rock physics models, partial saturation and joint inversion
  - Synthetic case
  - Real data case
- Conclusions

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Why quantitative monitoring?

Dean and Tucker, 2017

- Legal requirements for Measurement, Monitoring and Verification:
  - Containment: plume migration, potential leakages…
  - Conformance: **consistency between models and observed site behaviour**. Requires quantitative measurements: pressure, saturation, stress changes…
- How can geophysical monitoring provide **quantification** of relevant rock physics properties?
- What is the **uncertainty** related to these measurements? Link to operational decision making.
- Can we do this in a **cost-efficient** way over the whole duration of the injection (and hundred(s) years after the site is closed)?

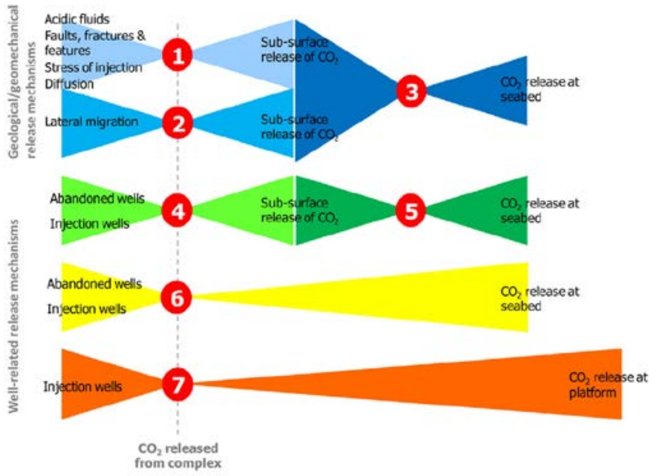

Fig. 6. The Goldeneye bowtie risk assessment required the use of multiple bowties.

Fig. 7. Ranking of monitoring technology options according to expected benefits and costs. Blue oval = in base MMV plan, green oval = pending on further assessment, yellow oval = not in base MMV plan. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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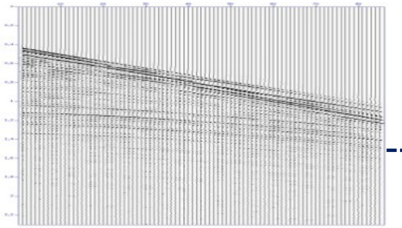
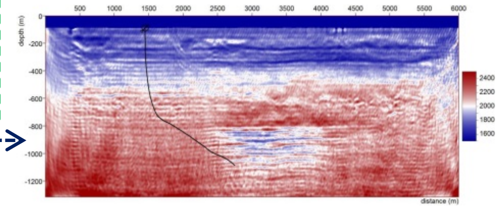
Two-step geophysical inversion

SEISMIC + EM DATA → Geophysical inversion → GEOPHYSICAL PROPERTIES → Rock physics inversion → ROCK PHYSICS PROPERTIES

Seismic data

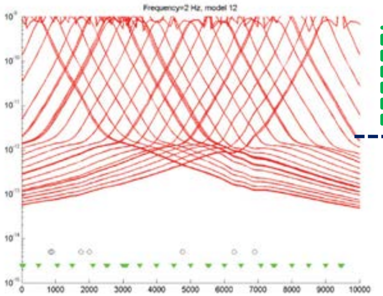


Seismic inversion (FWI)

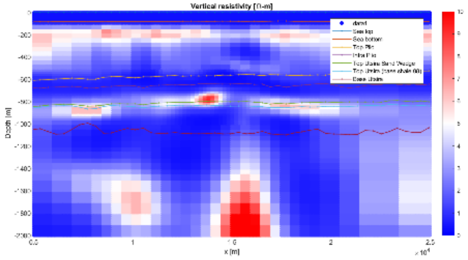


P-wave velocity map

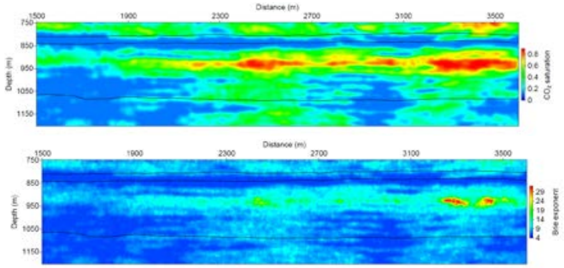
CSEM data



CSEM inversion



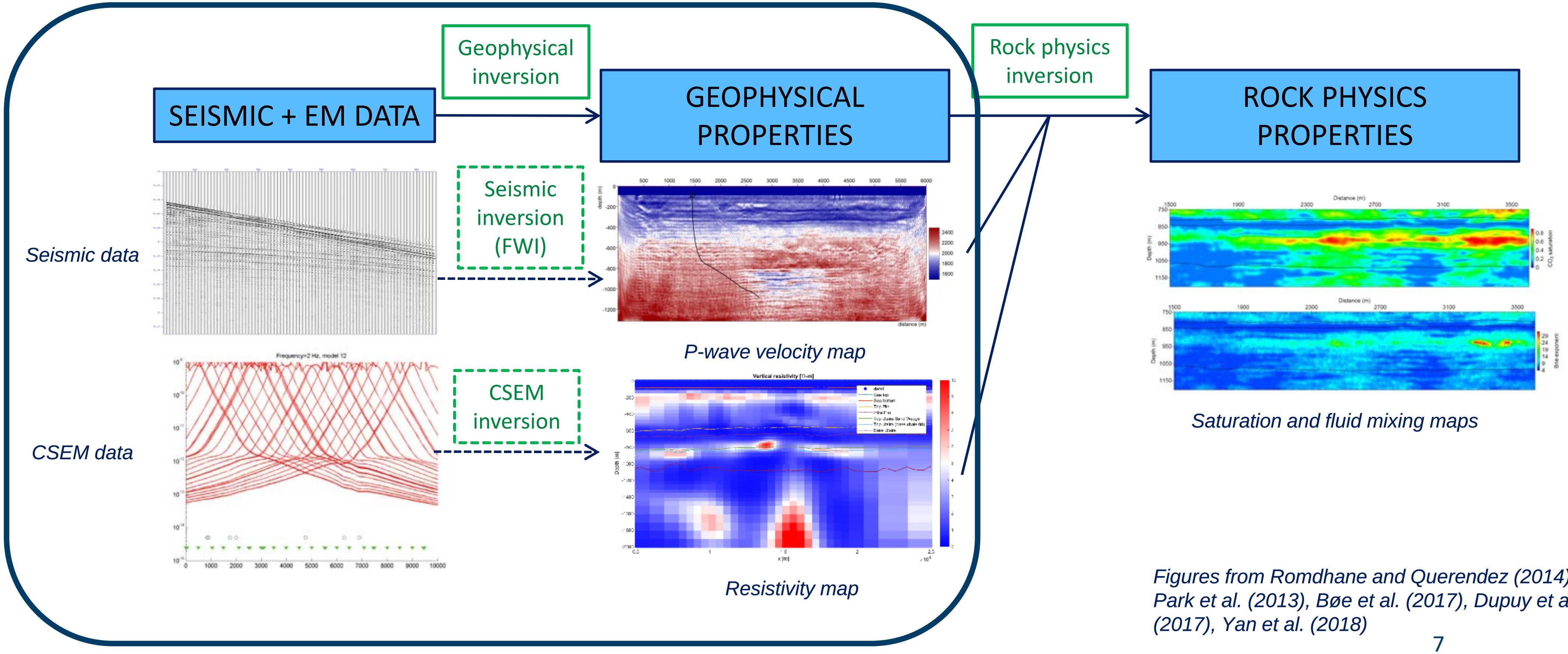
Resistivity map



Saturation and fluid mixing maps

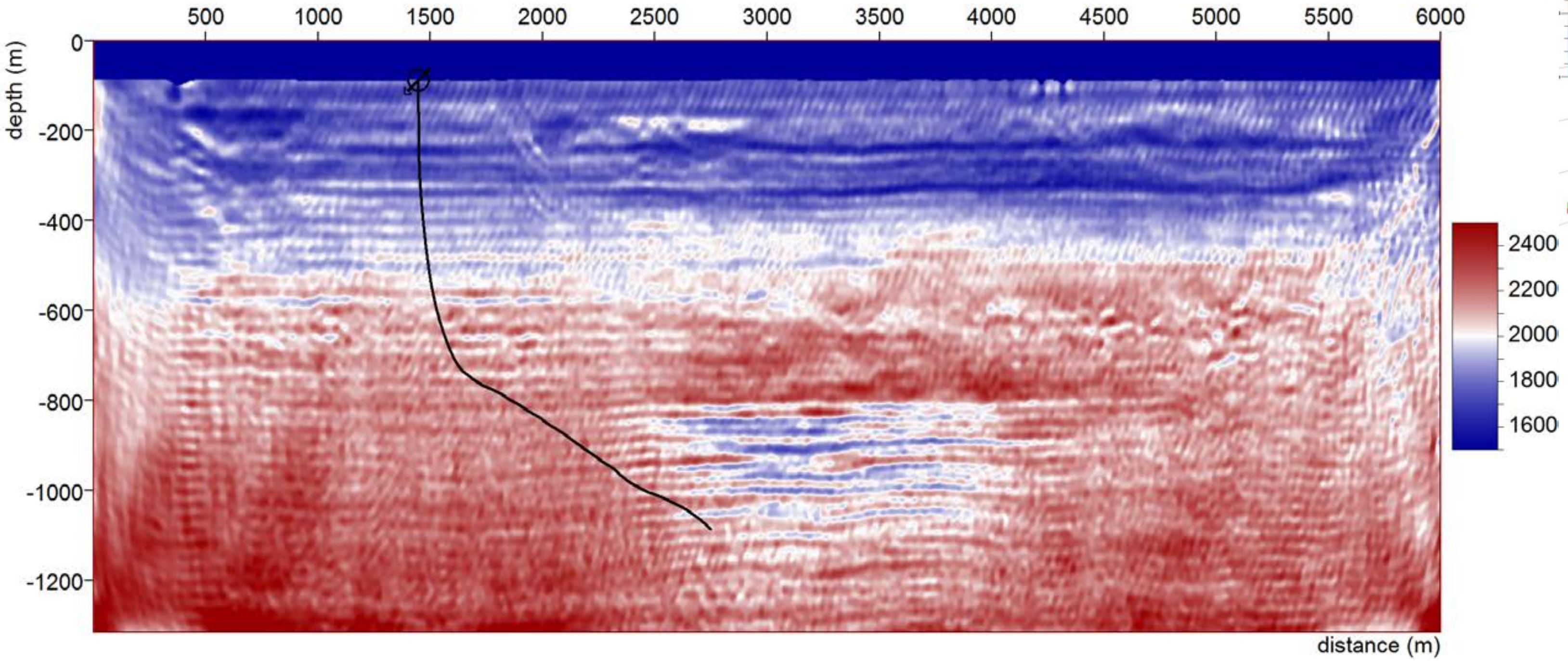
Figures from Romdhane and Querendez (2014), Park et al. (2013), Bøe et al. (2017), Dupuy et al. (2017), Yan et al. (2018)

Two-step geophysical inversion

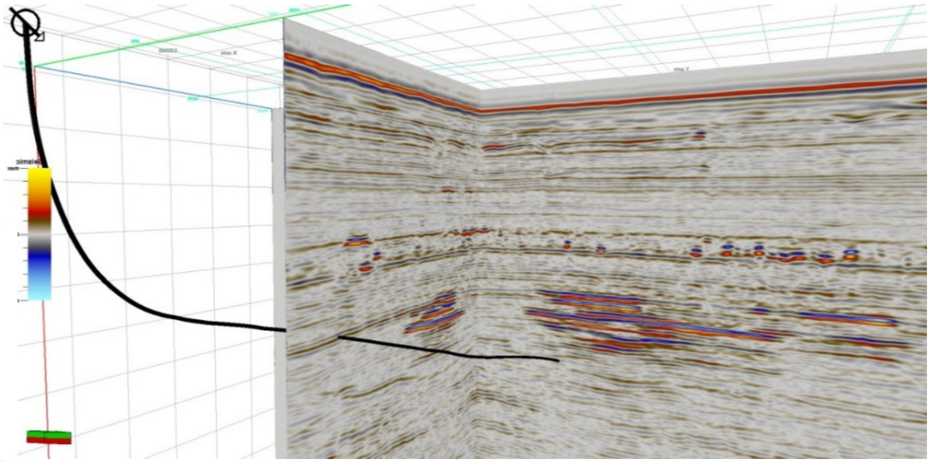


Figures from Romdhane and Querendez (2014), Park et al. (2013), Bøe et al. (2017), Dupuy et al. (2017), Yan et al. (2018)

Geophysical inversion
High resolution imaging at Sleipner



P-wave velocity model derived from FWI at Sleipner ; the black line corresponds to the injection well (15/9-A-16) in a projected view into the plane of the seismic section



Example of post-stack time migrated sections from the 2008 vintage

Romdhane and Querendez, 2014

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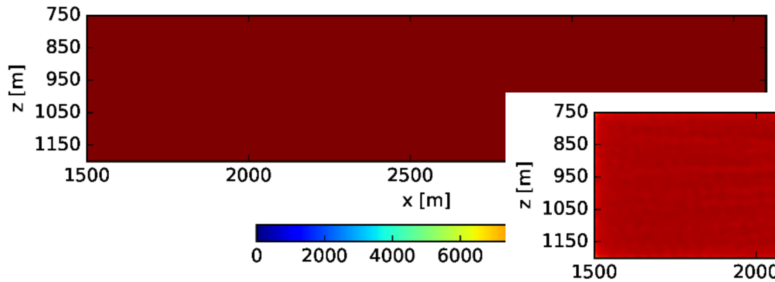
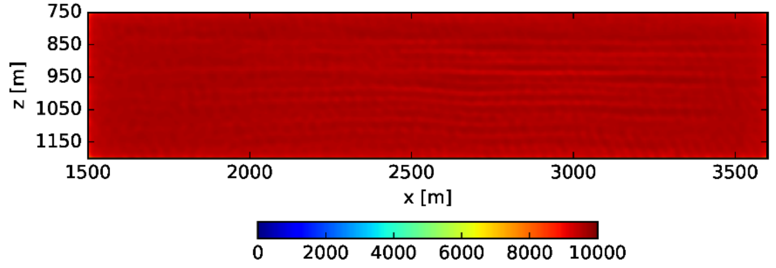
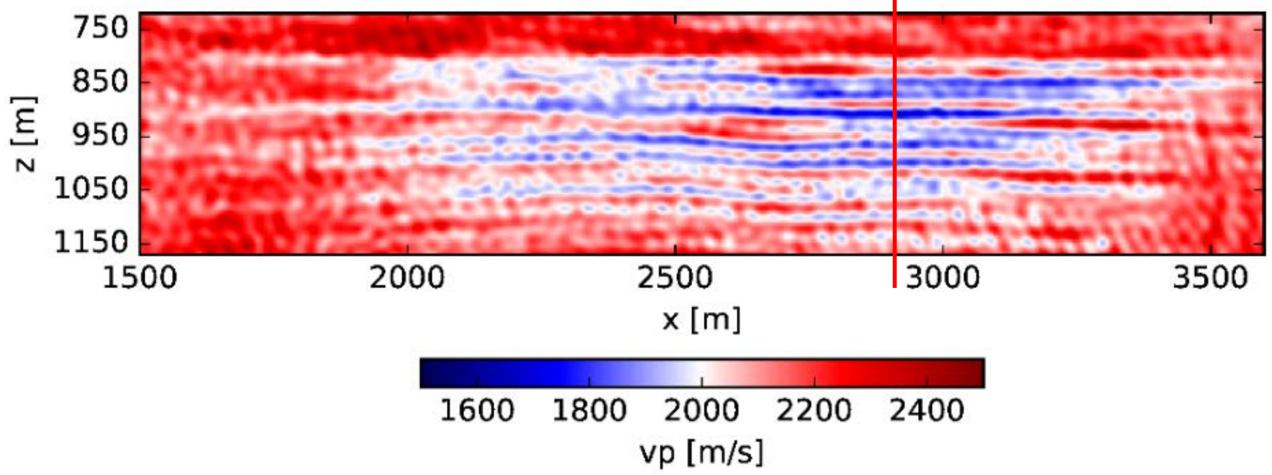
Geophysical inversion
Uncertainty assessment

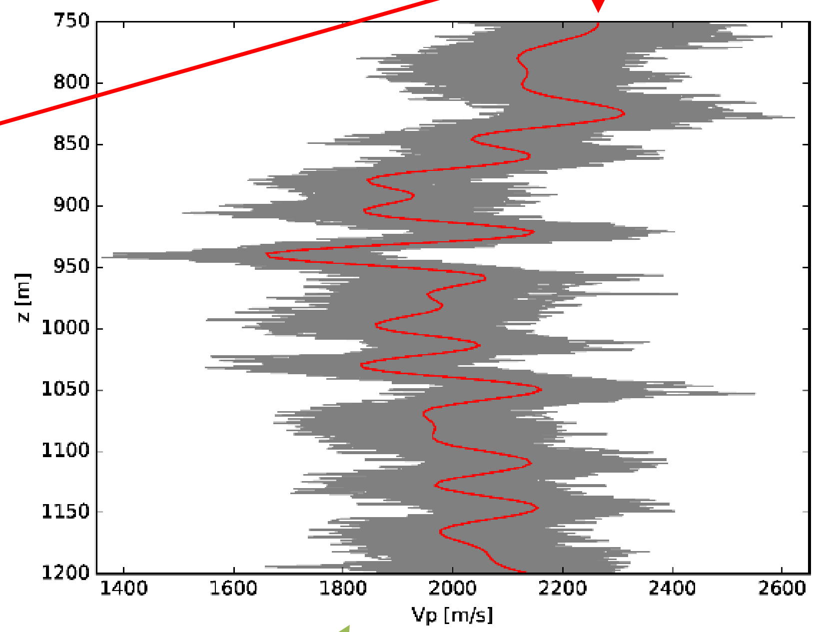
The inverse of the Hessian of the misfit function being minimized can be interpreted as the posterior covariance matrix in a local probabilistic sense (Tarantola, 2005; Zhu et al., 2016)



(left) Prior covariance. (right) Posterior covariance. Small but clear reduction.







Eliasson and Romdhane, 2017

(top) Close-up of plume region. (right) Extracted depth velocity profiles from 100 "equivalent models " at x=2916 m. The red line corresponds to the velocity of the final FWI model.

Successful uncertainty quantification and generation of equivalent models

Two-step geophysical inversion

SEISMIC + EM DATA

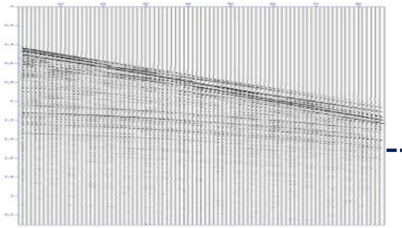
Geophysical inversion

GEOPHYSICAL PROPERTIES

Rock physics inversion

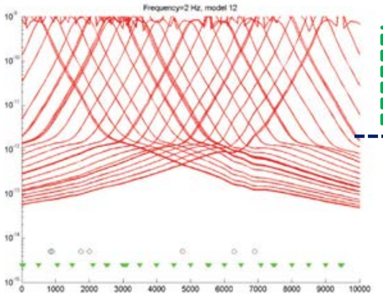
ROCK PHYSICS PROPERTIES

Seismic data

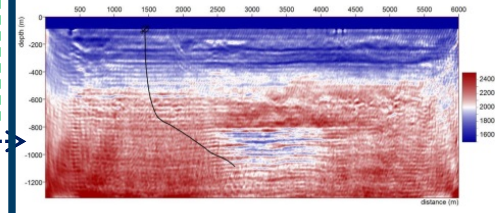


Seismic inversion (FWI)

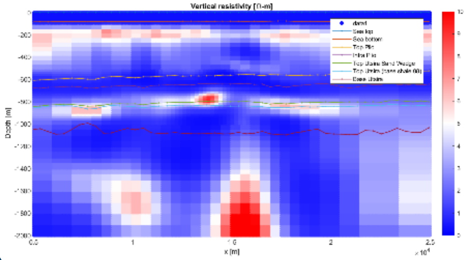
CSEM data



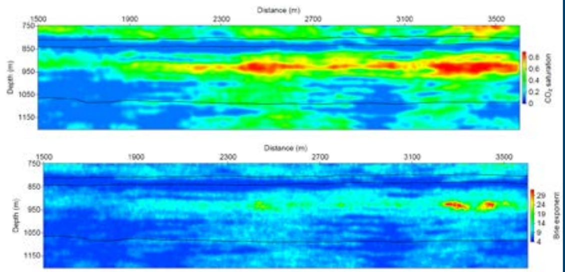
CSEM inversion



P-wave velocity map



Resistivity map



Saturation and fluid mixing maps

Figures from Romdhane and Querendez (2014), Park et al. (2013), Bøe et al. (2017), Dupuy et al. (2017), Yan et al. (2018)

Rock physics inversion
Bayesian formulation

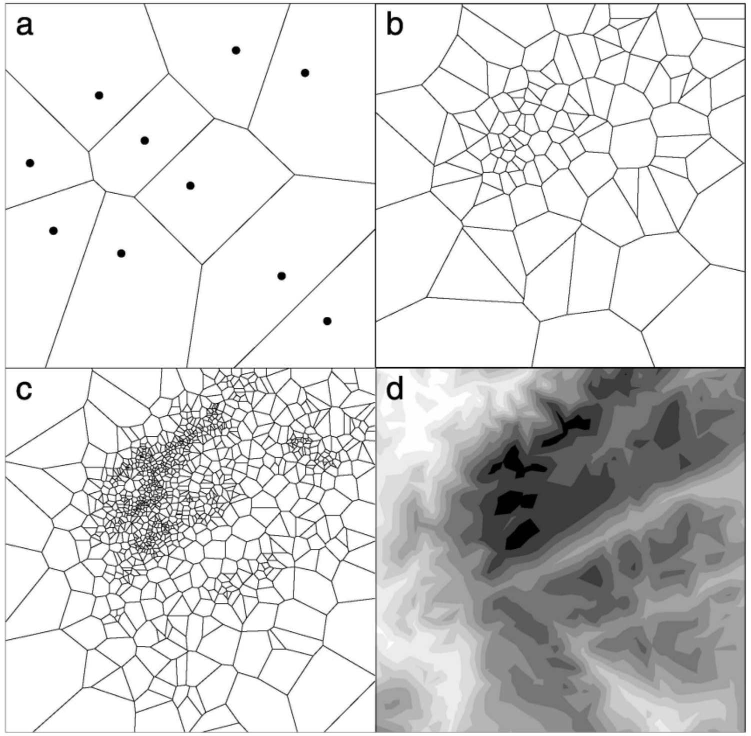
- Forward problem: $\boldsymbol{d} = g(\boldsymbol{m})$
- g^{-1} cannot be computed analytically ➔ **optimization method**: deterministic inversion (search maximum of the PPD) or stochastic/probabilistic inversion (produce samples from the PPD).
- Data likelihood function: $L(\boldsymbol{m}|\boldsymbol{d}_{obs}) = k \exp\left(-\frac{1}{2}\left(\boldsymbol{d}_{\boldsymbol{obs}} - g(\boldsymbol{m})\right)^T \boldsymbol{C}_D^{-1}\left(\boldsymbol{d}_{\boldsymbol{obs}} - g(\boldsymbol{m})\right)\right)$
- Bayesian inference: update of prior distribution to the posterior distribution by making use of the observed information (Tarantola, 2005).
- **Bayesian inverse problem formulation**: $\sigma_{post}(\boldsymbol{m}) = c\ \rho_{prior}(\boldsymbol{m})\ L(\boldsymbol{m}|\boldsymbol{d}_{obs})$

d=d$_{\mathbf{obs}}$=data vector (seismic, velocities, resistivities, densities, quality factors, impedances…)
m=model vector (rock physics properties: saturation, porosity…)
g= rock physics model (Biot-Gassmann equations, Archie Law…)

$\sigma_{post}(\boldsymbol{m})$ = posterior probability density (PPD)
c, k = normalization constants
$\rho_{prior}(\boldsymbol{m})$ = a priori probability density
$L(\boldsymbol{m}|\boldsymbol{d}_{obs})$ = data likelihood function
$\boldsymbol{C}_D$ = data covariance matrix

Rock physics inversion
Direct search with neighbourhood algorithm

- **Inverse problem difficult** because under-determined, non-linear and non-unique solutions.
- Linear or linearized local optimization not working, but fast and analytic forward problem ➔ **global exploration using Neighbourhood algorithm** (NA, *Sambridge, 1999*):
  - Only 2 control parameters.
  - Model space guided exploration.
  - Mix of good exploration of model space and "tendency" to look for the most likely models.
  - **Give an ensemble of models representing all "information".**
- Need to infer statistically meaningful information from the ensemble of models: **importance sampling**.



Number of generated models:
a) 10
b) 100
c) 1000
d) Fit map

Rock physics inversion
Appraisal step and importance of sampling

Geophys. J. Int. (1999) **138**, 727–746

Geophysical inversion with a neighbourhood algorithm—II. Appraising the ensemble

Malcolm Sambridge
Research School of Earth Sciences, Institute of Advanced studies, Australian National University, Canberra, ACT 0200, Australia. E-mail: malcolm@rses.anu.edu.au

- We use **Sambridge (1999) neighbourhood algorithm**.
- Adapted to different search methods (simulated annealing, MC, genetic algorithms, neighbourhood algorithm…).
- Calculate **approximated PPD** everywhere in model space which is then used for evaluation of **Bayesian integrals**.
  - Use Voronoï cells for multi-dimensional interpolant, then use Gibbs sampler in neighbour cells (random walks).
- We can then calculate Bayesian integrals: posterior mean model, posterior model covariance matrix, resolution matrix and **marginal distributions**.

- **Appraisal step implemented in Python and Go**: soon available open source (github).

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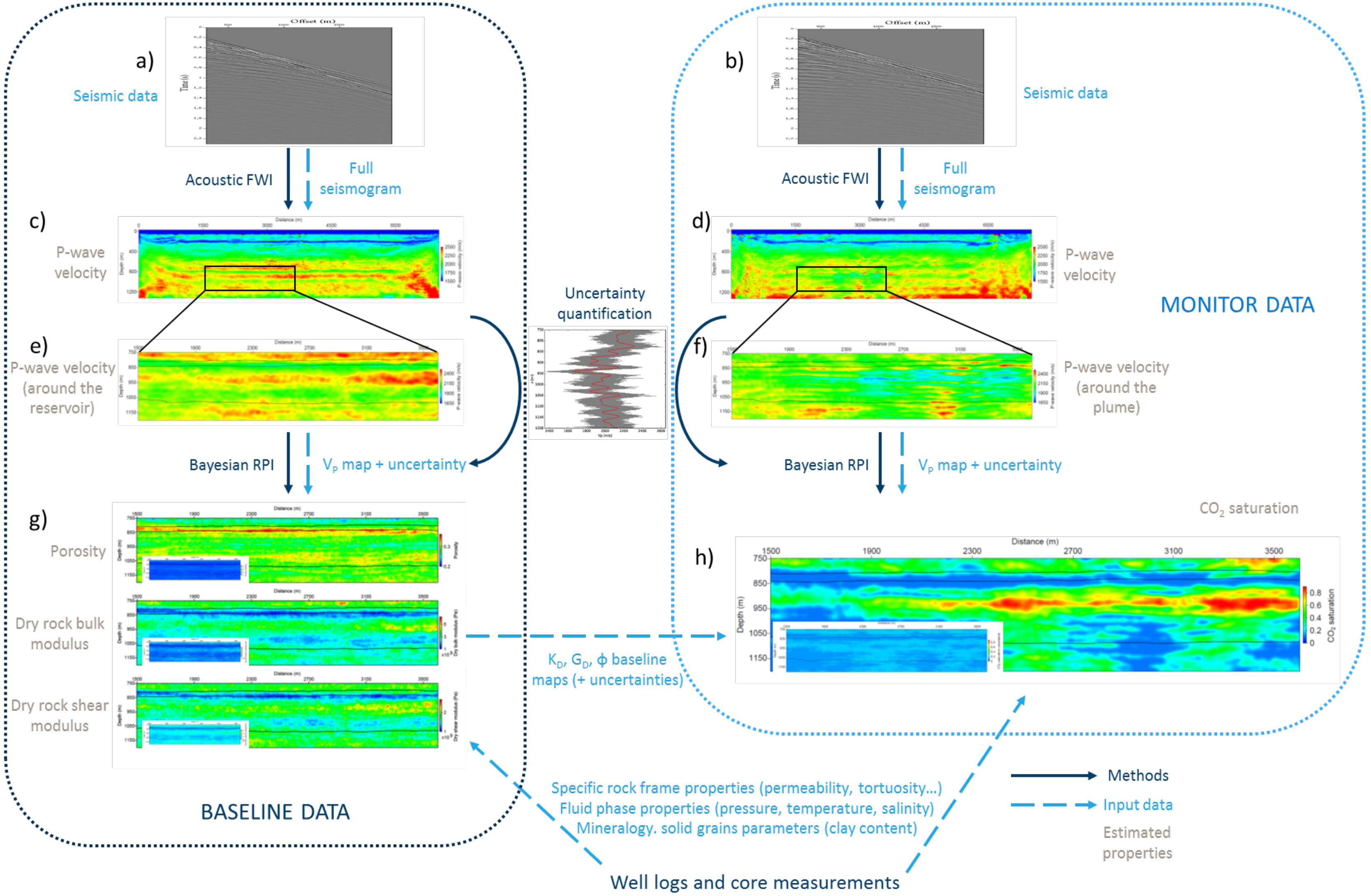
Sleipner case study
Time-lapse strategy



<u>Workflow:</u>

1. FWI + uncertainty analysis provides observed data $\mathbf{d_{obs}}$ and associated uncertainty $\mathbf{C_D}$ for second inversion and
2. Baseline data (1994): mapping of porosity + moduli (K_D, G_D)
3. Monitor data (2008): mapping of CO_2 saturations using baseline porosity and moduli maps as a priori input $\rho_{prior}(\boldsymbol{m})$

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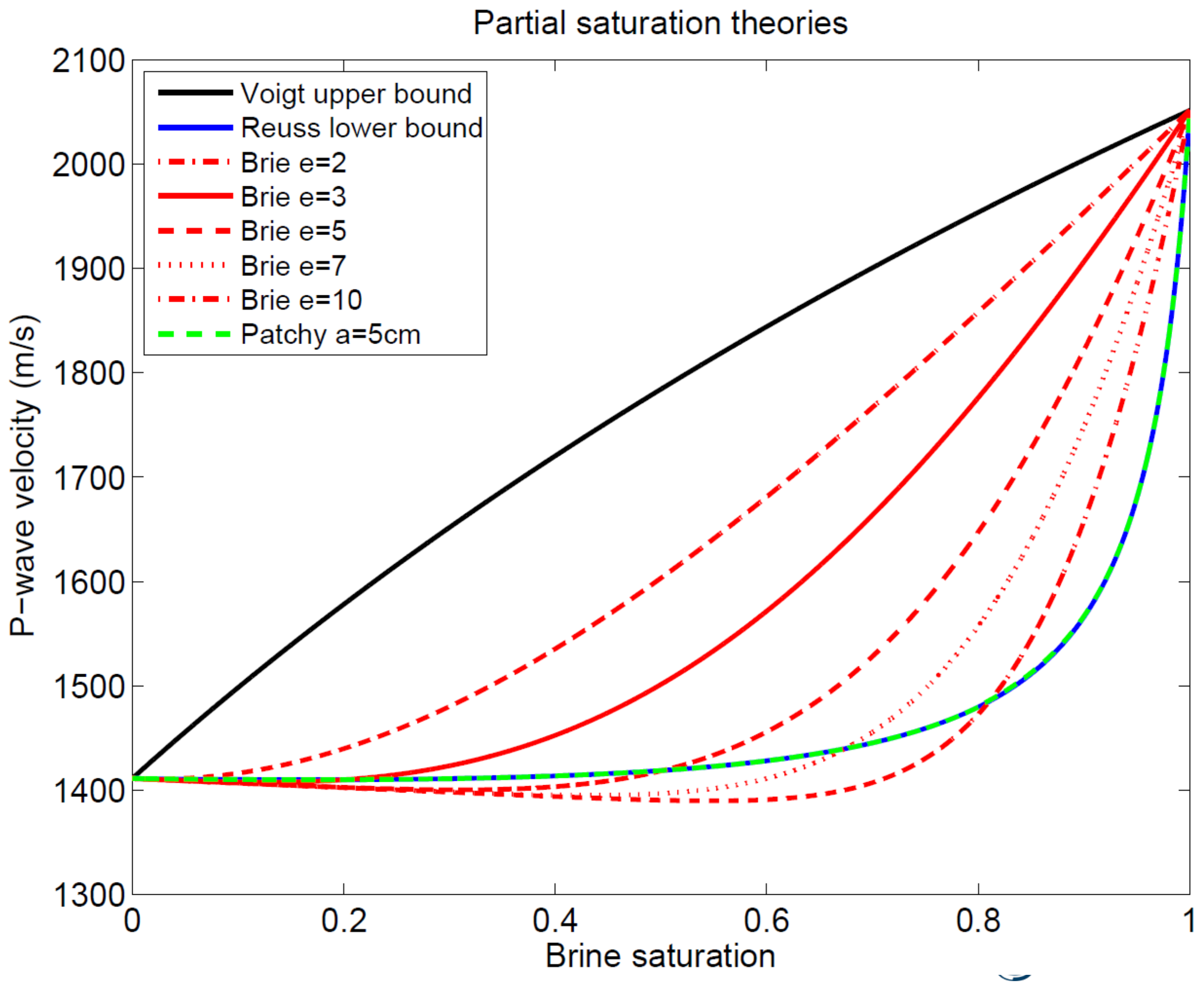
Sleipner case study
CO_2 partial saturation rock physics models

- Effective fluid phase plugged into *(Biot-) Gassmann* equations: different ways of calculating **effective fluid bulk modulus**.

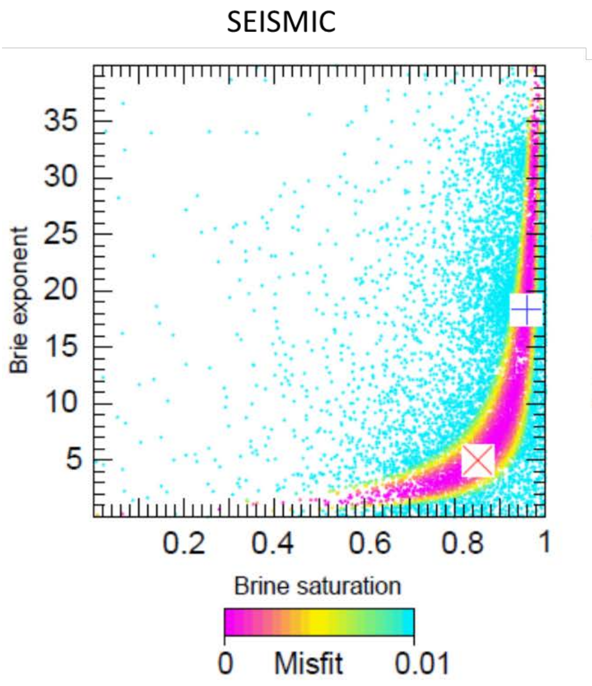
- Brie equation (*Brie et al., 1994*):

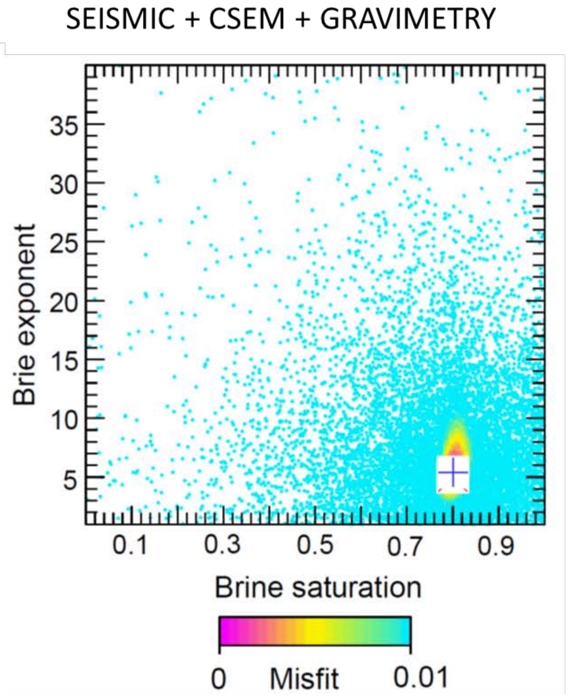
$$K_f = \left(K_w - K_{CO_2}\right) S_w^e + K_{CO_2}$$

- Patchiness/Brie exponent e:
  - e = 40 ➔ uniform mixing
  - e = 1, 3, 5? ➔ patchy mixing



Sleipner case study
CO_2 partial saturation rock physics models





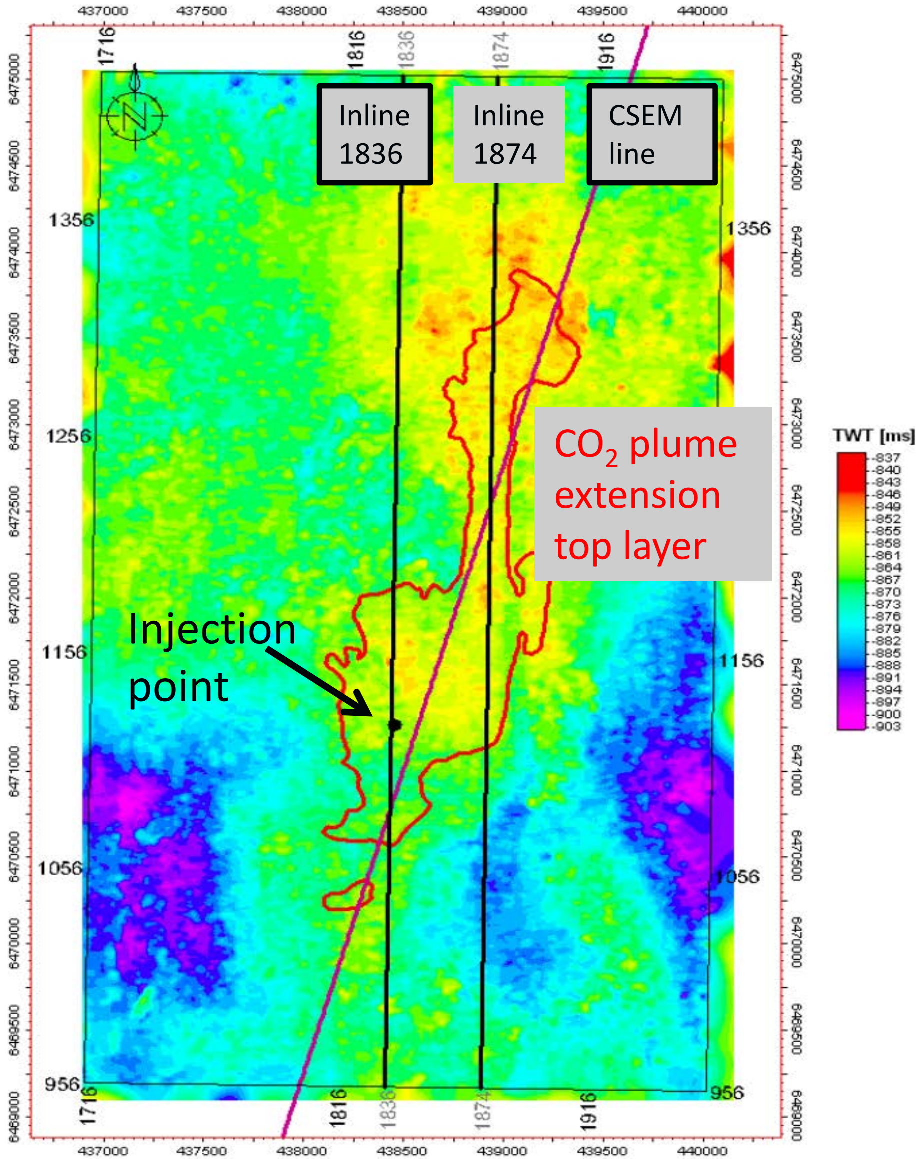
S_{CO2} = 20 %

X True model

\+ Lowest misfit model

Inversion of saturation and Brie exponent

Dupuy et al., 2018



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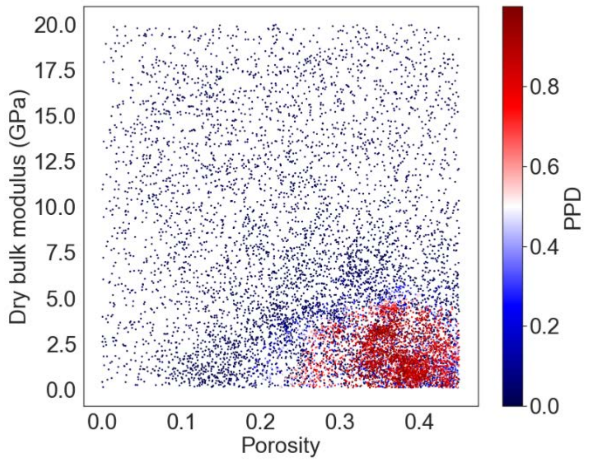
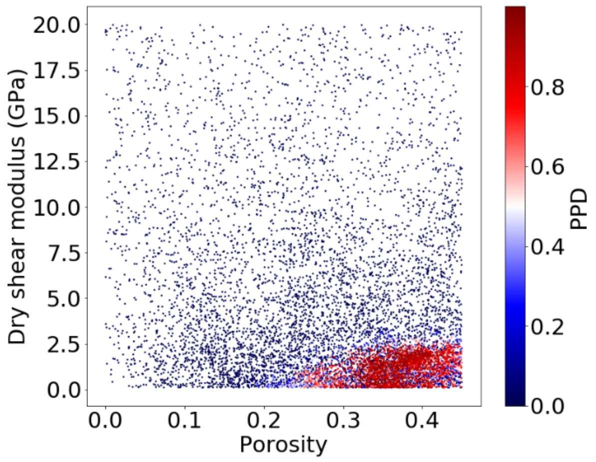
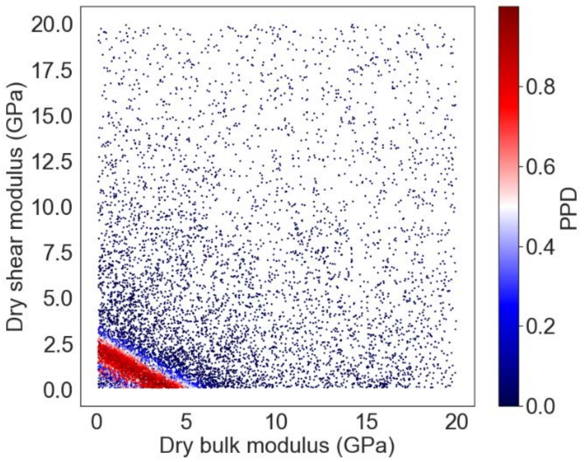
Synthetic case
Baseline, porosity search step and PPD after appraisal

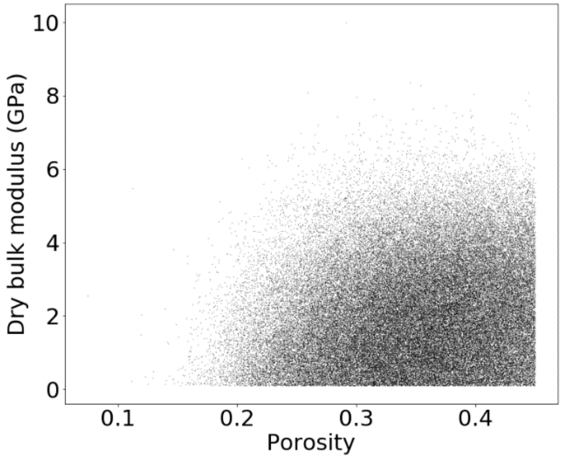
<u>True model</u>:
$\phi = 0.36$
$K_D = 2.56$ GPa
$G_D = 0.75$ GPa

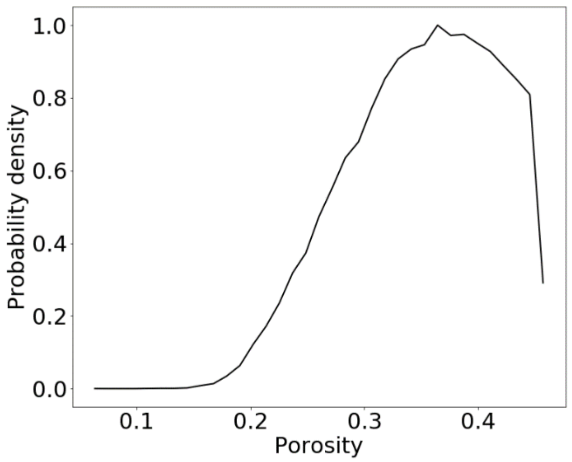


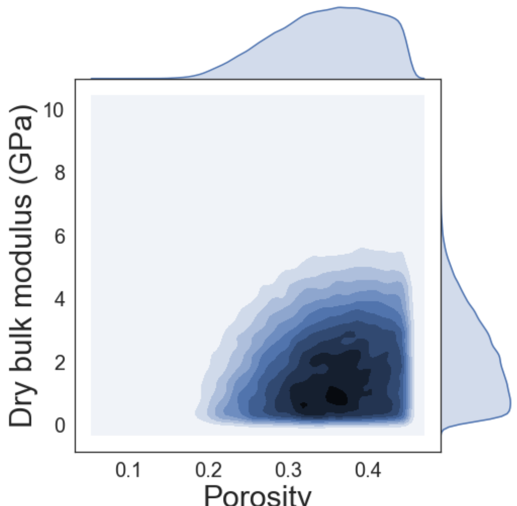




<u>Search step</u>: 2D slices of 3D model space, models with likelihood



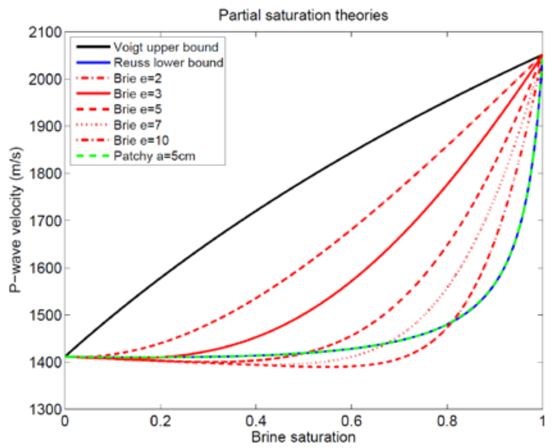


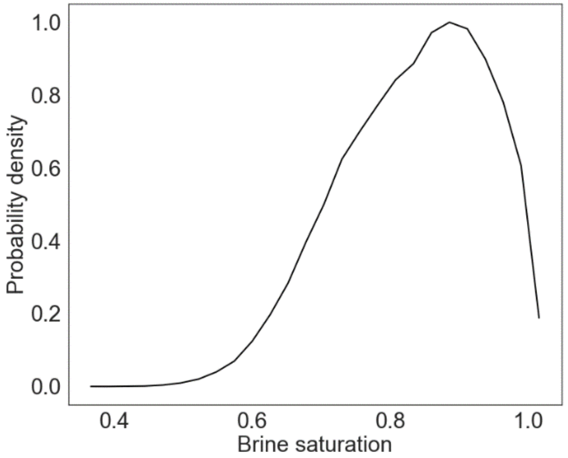


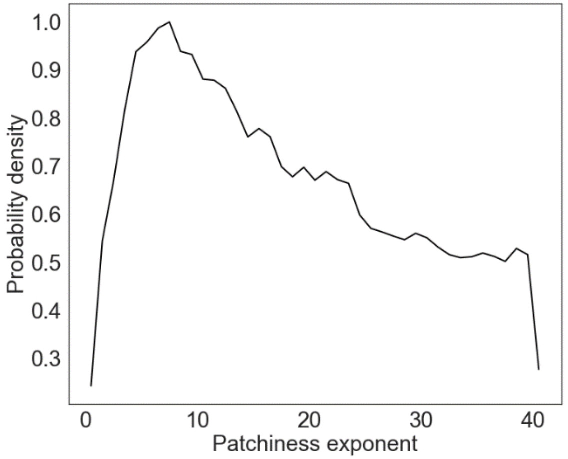
<u>Appraisal step</u>:
2D slice of resampled 3D model space (left)

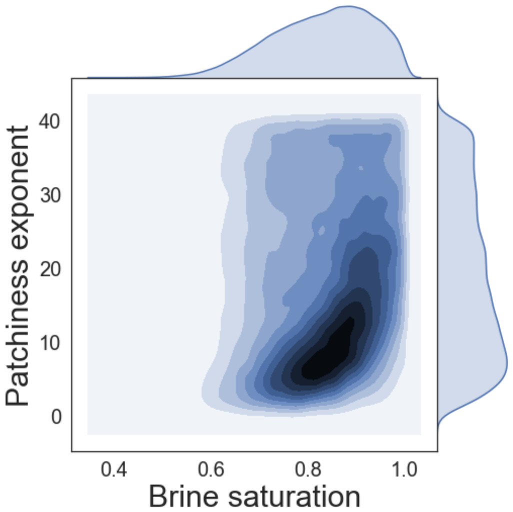
1D (middle) and 2D (right) marginal probability densities

Synthetic case
Monitor, PPD after appraisal



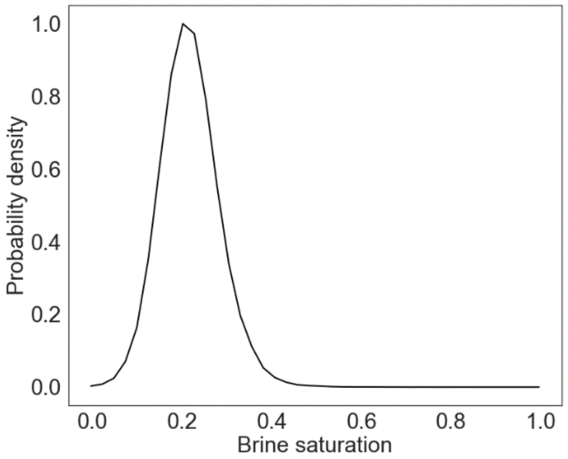


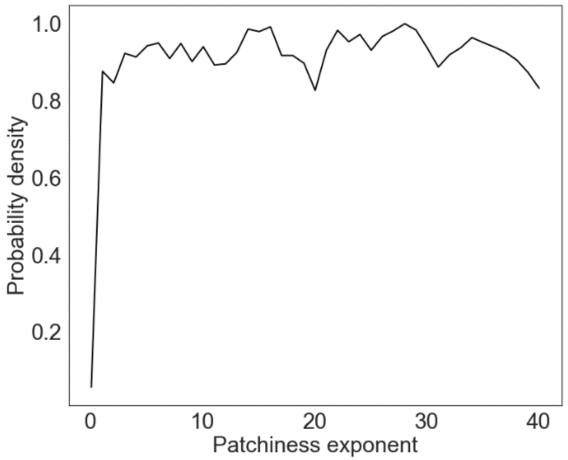


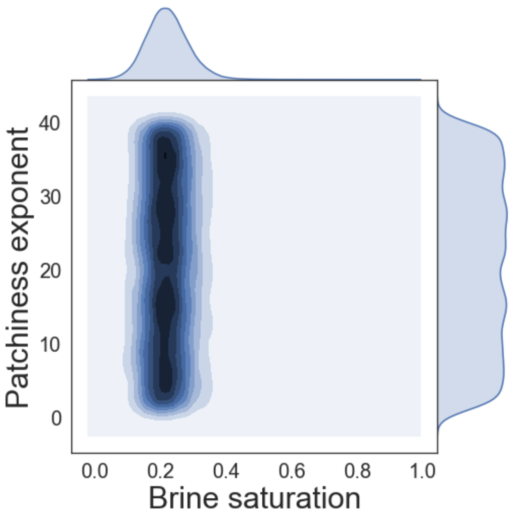


True model:
$S_{CO_2} = 20\%$
e = 5

1D and 2D marginal probability densities







True model:
$S_{CO_2} = 80\%$
e = 5

ϕ, K_D, G_D are also estimated with prior distribution from baseline (after appraisal, 99% confidence interval)

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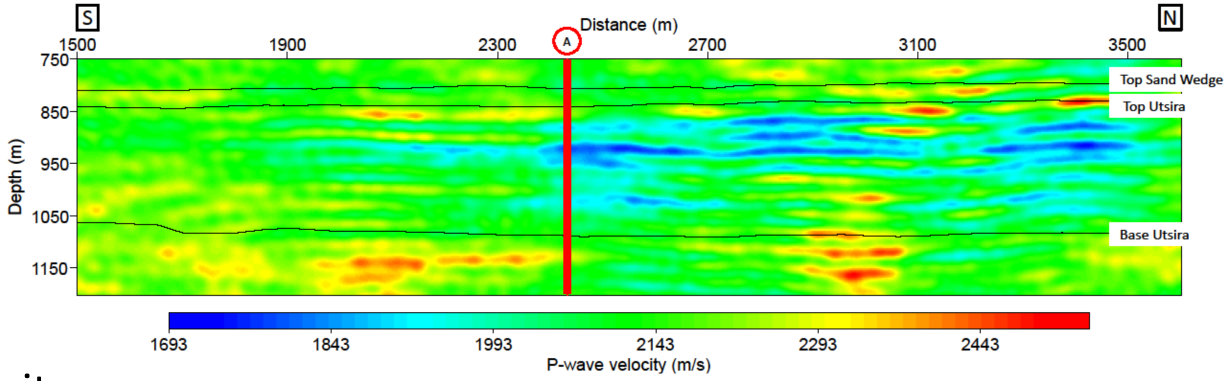
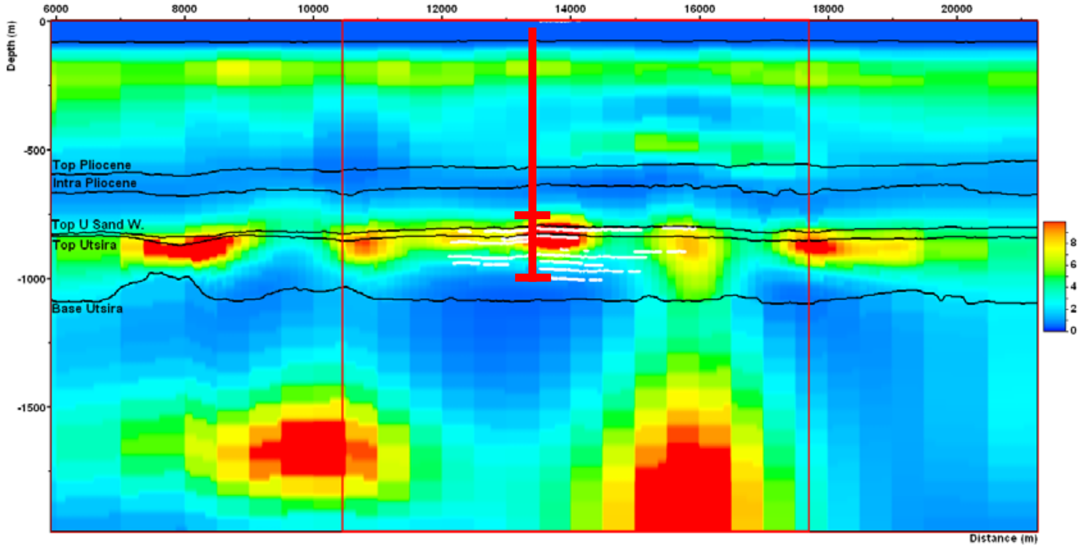
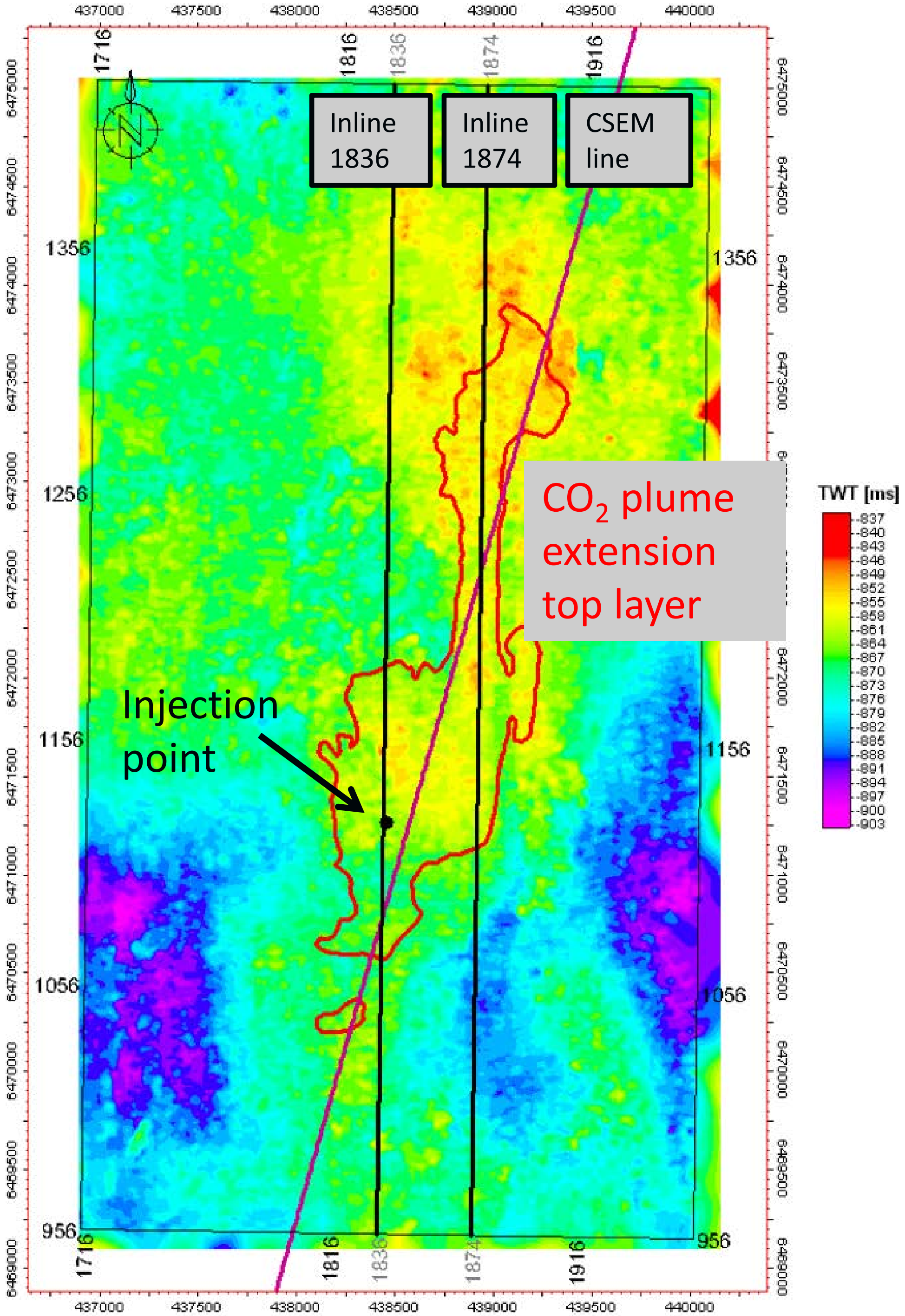
Sleipner real data case
Results of CSEM and seismic inversions



P-wave velocity model, inline 1836

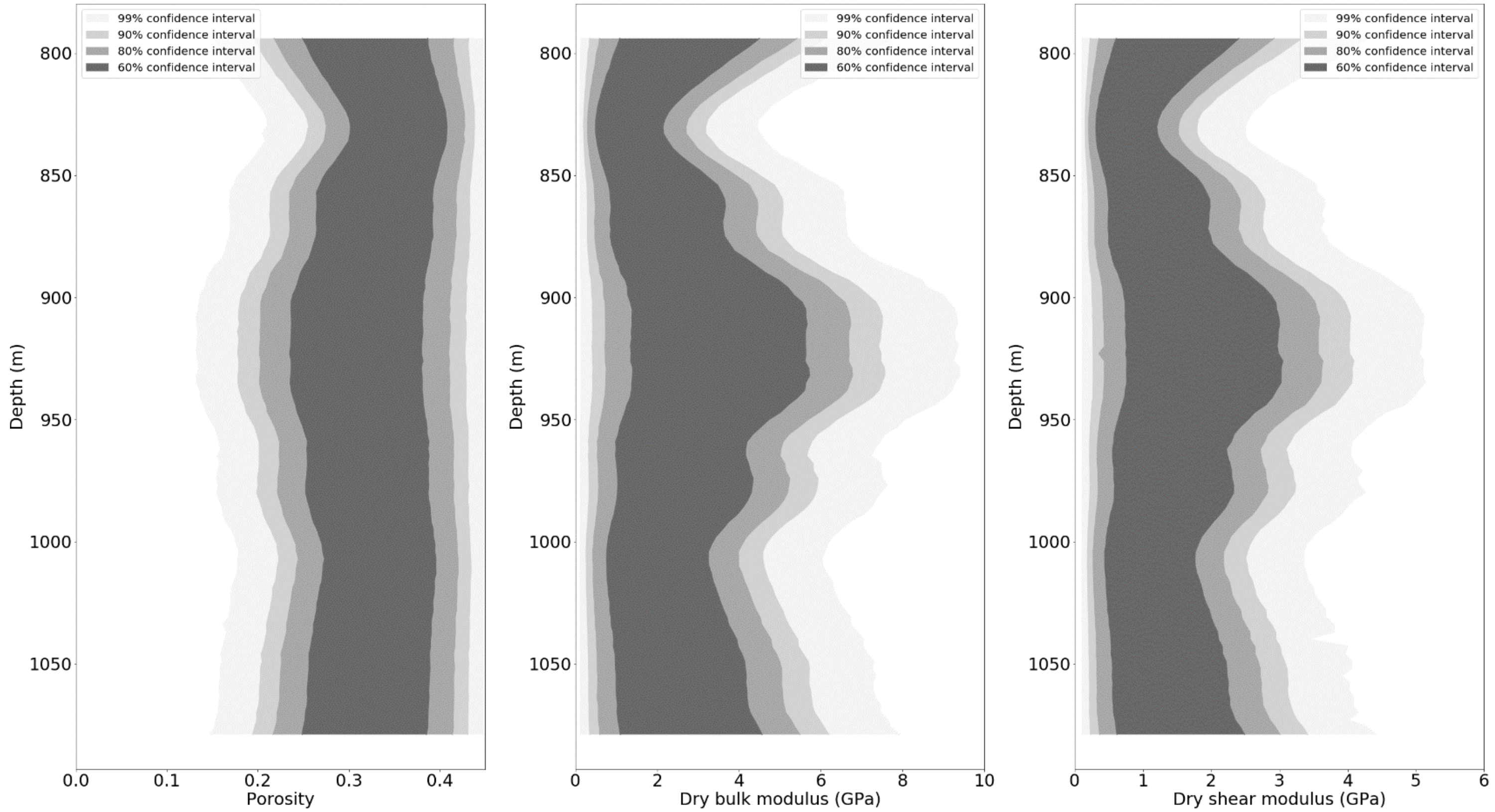


Resistivity model along CSEM line

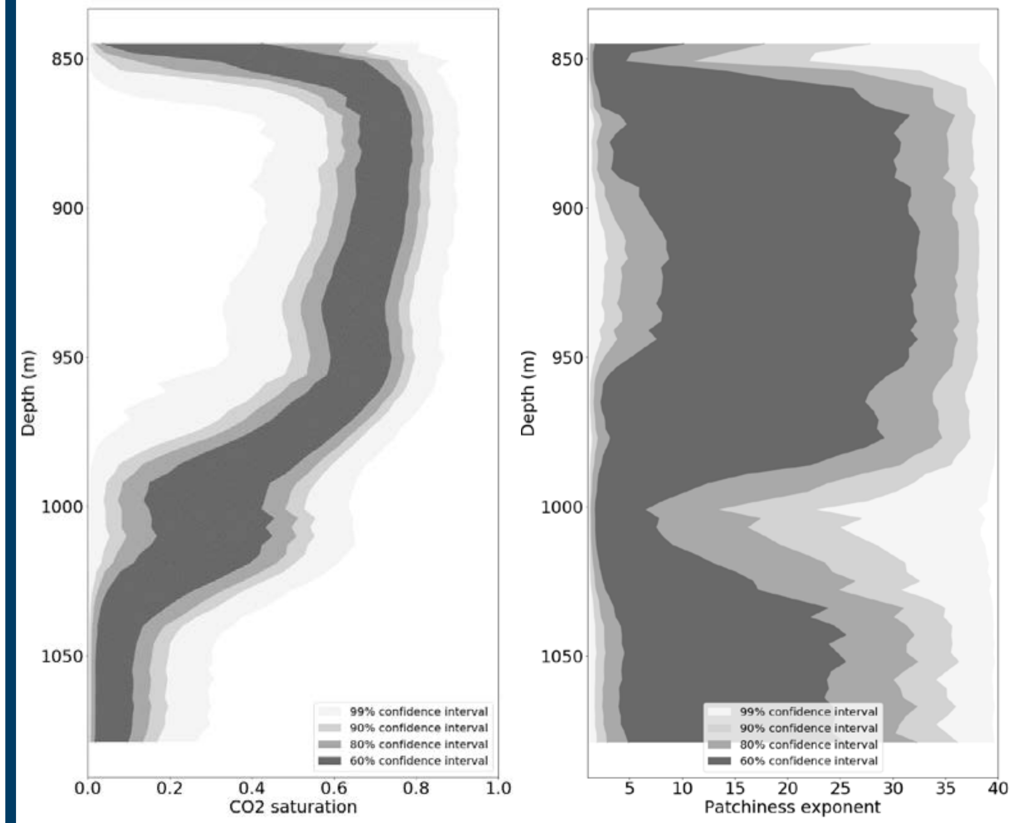


Sleipner real data case
Results of rock physics inversion after appraisal

99% confidence interval
90% confidence interval
80% confidence interval
60% confidence interval



<u>Baseline results</u>: porosity, dry bulk and shear moduli



<u>Monitor results</u>: CO_2 saturation and patchiness exponent

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Conclusions

- Bayesian inversion is crucial for uncertainty assessment/quantification in CO_2 storage monitoring to ensure conformance.
- Quantitative inversion carried out in two steps with uncertainty propagation.
- Time-lapse data allows for quantitative use of prior models derived from baseline data.
- Proper CO_2 saturation estimation requires joint inversion of seismic and EM data.
- Final uncertainty range in CO_2 saturation for real data is quite narrow.

Acknowledgments

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