The National IOR Centre of Norway

Workshop on ensemble-based 4D seismic history matching
The National IOR Centre of Norway
October 14-15, 2020

Wednesday 14th October

12.00-12.15: Randi Valestrand, NORCE: Welcome and introduction

12.15-12.45: Vedad Hadziavdic, Wintershall Dea: "Ensemble based modelling and 4D in Wintershall Dea – experience and challenges."

12.45-13.15: Tao Feng, Equinor: "Conditioning reservoir models on Well2Seis attributes."

13.15-13.45: Rolf J. Lorentzen, NORCE: "A workflow for 4D seismic history matching demonstrated on the Norne field."

13.45-14.00: Break

14.00-14.30: Geir Evensen, NORCE: "Consistent Formulation and Error Statistics for Reservoir History Matching: Implications for Seismic History Matching."

14.30-15.00: Dario Grana, University of Wyoming: "Geophysical monitoring of CO_2 sequestration in deep saline aquifers."

Thursday 15th October

12.00-12.05: Welcome

12.05-12.30: Tuhin Bhakta, NORCE: "Discrimination of changes in pressure-saturation and porosity fields from time-lapse seismic data using an ensemble-based method."

12.30-13.00: Jarle Haukås, Schlumberger: "4D seismic history matching workflows in DELFI."

13.00-13.30: Romain Chassagne, Heriot-Watt University: "The locks within Seismic History Matching."

13.30-13.45: Concluding remarks

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ENSEMBLE BASED MODELLING AND 4D IN WD

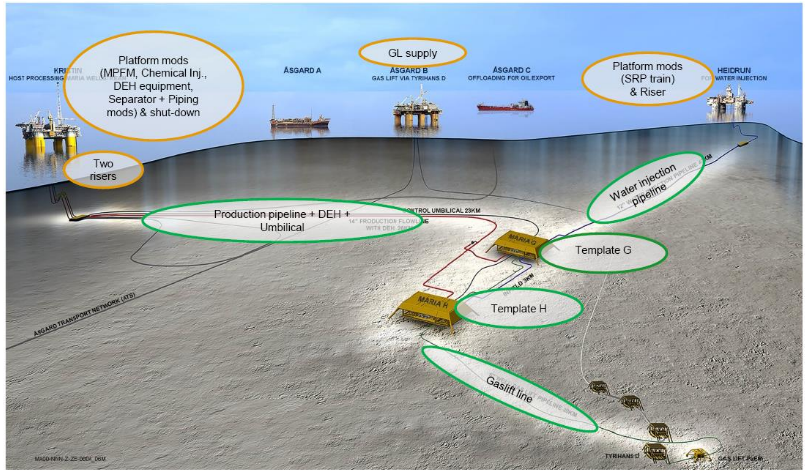
EXPERIENCE AND CHALLENGES

VEDAD HADZIAVDIC

ENSEMBLE METHODS AND 4D

INTRODUCTION

- No experience with including 4D in ensemble-based history matching in Wintershall Dea (as far as I know)
- 4D experience from several operated and non-operated fields (including Brage)
- Ensemble based history matching on operated (Maria and Brage) and several non-operated fields
- *My two cents:*
    - *If I wanted to include 4D in ensemble-based HM, these are the questions I would pose.*



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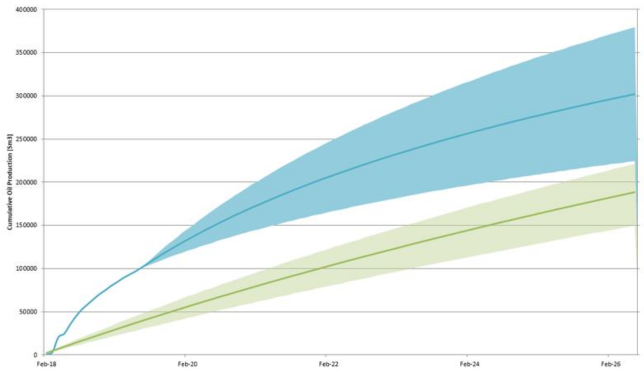
ENSEMBLE BASED METHODS AND 4D

PREDICTIONS

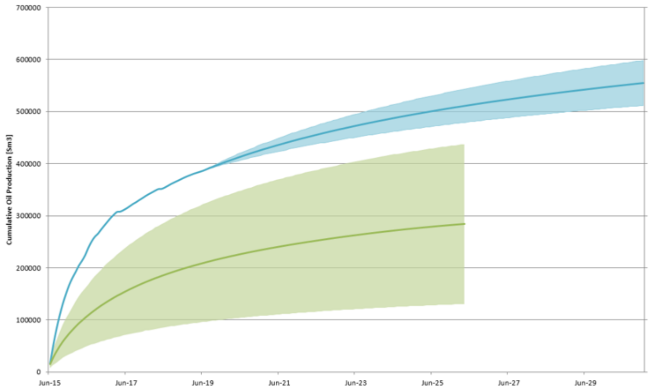
- In Brage, on average, reserve predictions are is close to what is proven by the wells. On individual well level, proven reserves are often far away from P50 predictions.
- We are obviously performing uncertainty analysis – without apparent success.
- Improvement potential
  - Are key uncertainties included?
  - Can we reduce prediction uncertainty?

AFE/DG2

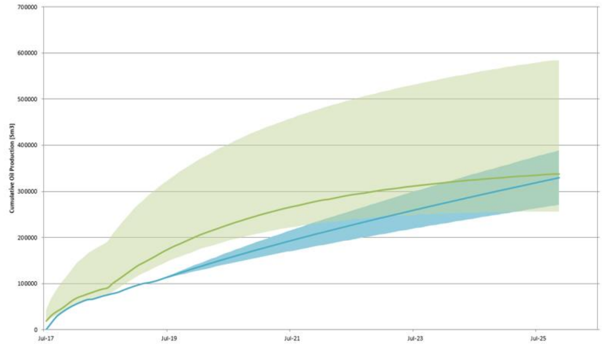
ACTUAL/BP2020 FC



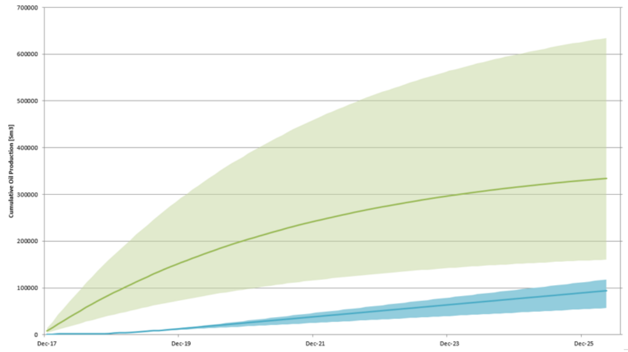
- A-08B oil production (Statfjord)



- A-18C oil production (Fensfjord)



- A-25A oil production (Statfjord)



- A-23E oil production (Fensfjord)

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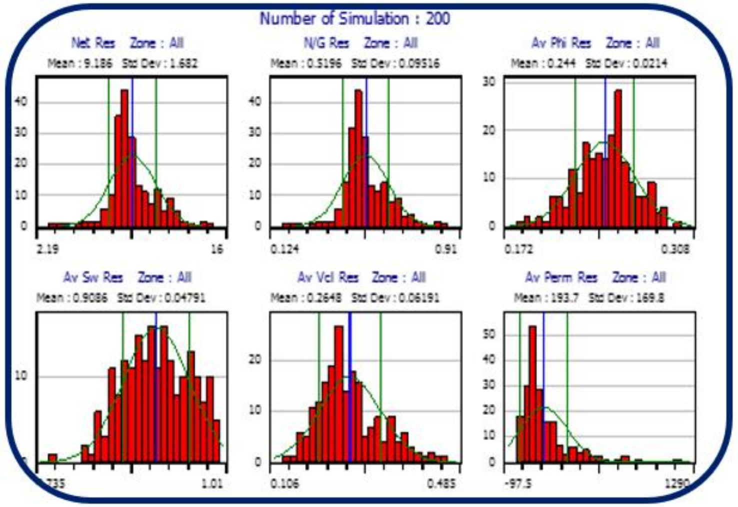
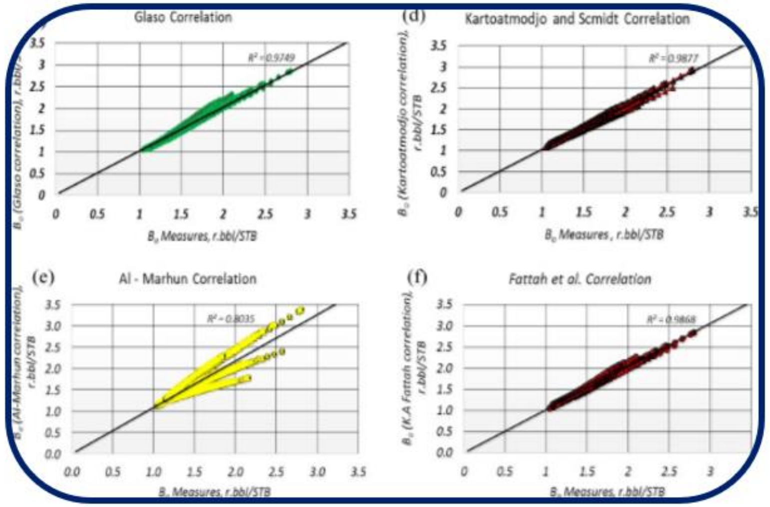
ENSEMBLE BASED METHODS

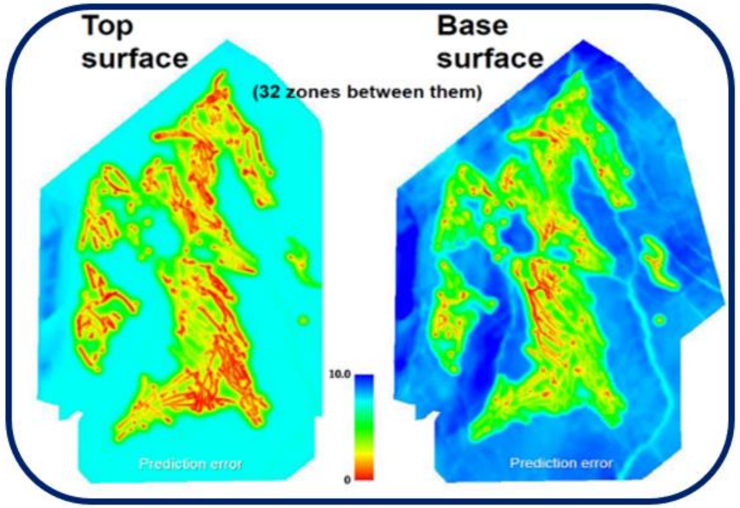
UNCERTAINTIES



Porosity, N/G, permeability, saturation, fluid contacts, isocores, upscaling



PVT, relative permeability, fault transmissibility, aquifier support



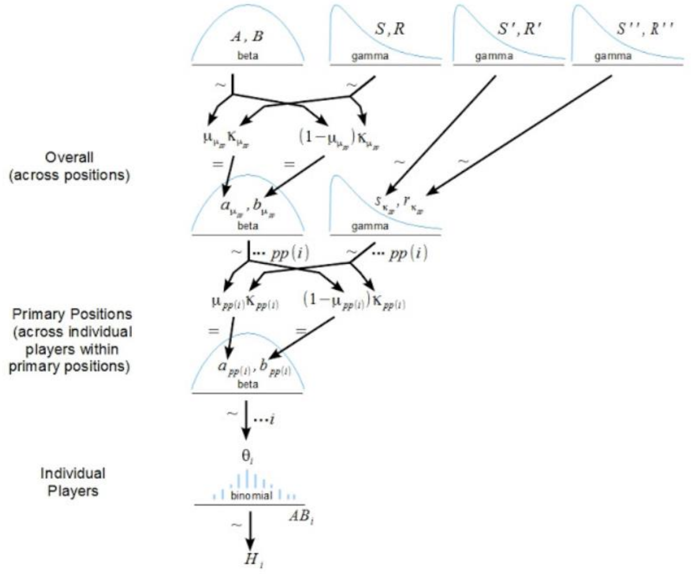
Seismic interpretation, velocity model, markers, well paths

- Leaving out uncertainties in input, leads to overconfidence in prediction.

THE POWER OF CONDITIONING

- Conditioning is one of the most important principles of statistical inference
  - Data are conditioned on how they get sampled
  - Posterior distributions are conditional on the data.
  - Model-based inference is conditional on the model
  - Every inference is conditional on something, whether we notice it or not.

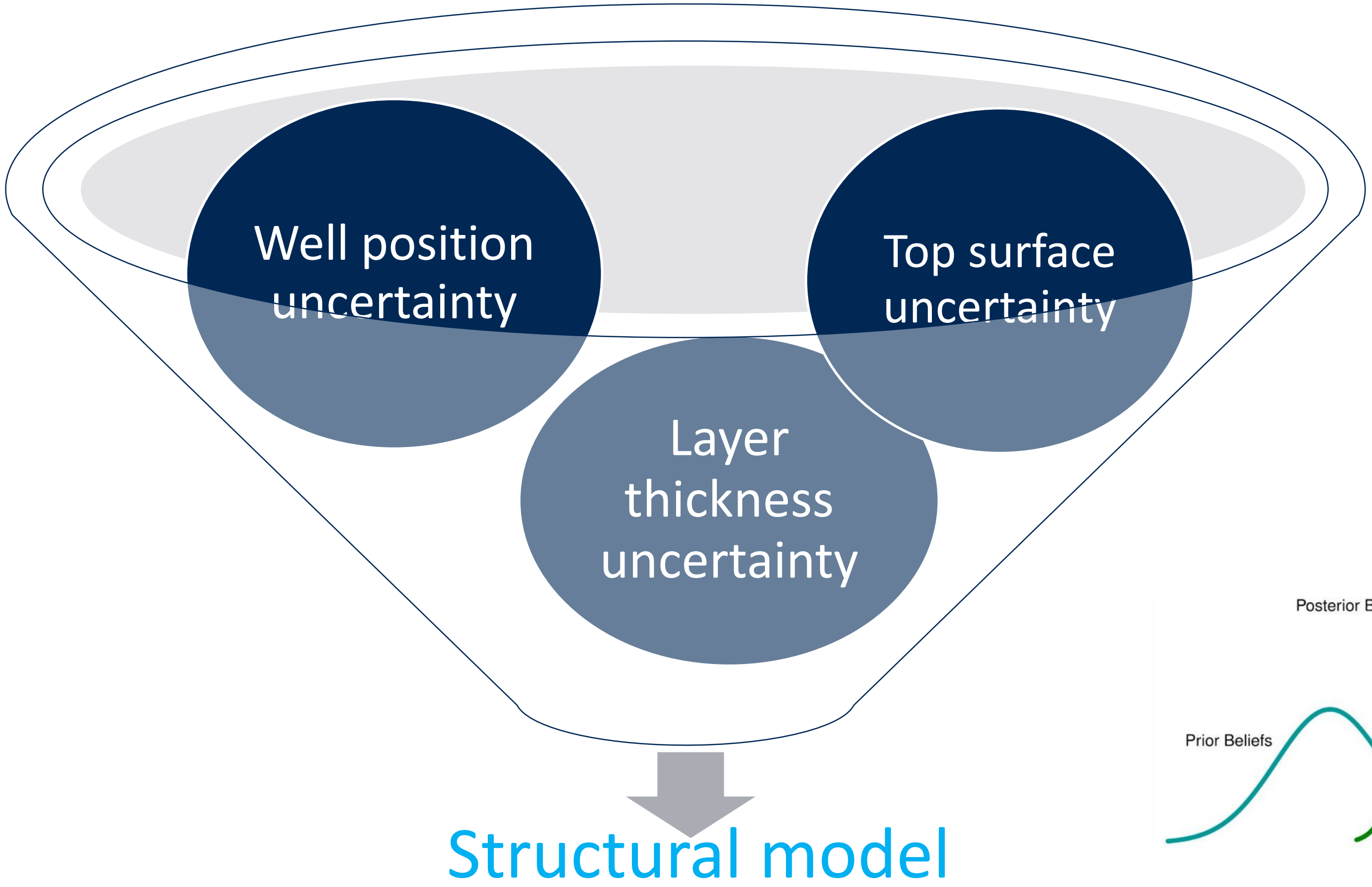
The power of statistical modelling comes from the ability to condition probability on different aspects.

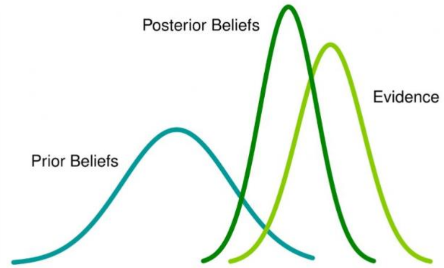


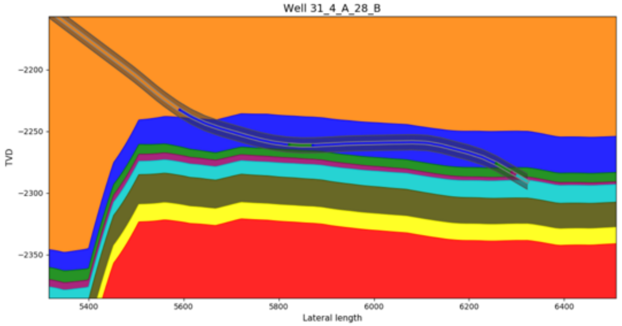
- Bayesian hierarchical models

UNCERTAINTY AND PREDICTION IN SUBSURFACE

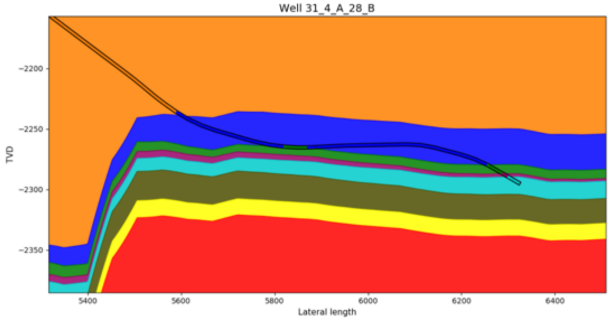
UNCERTAINTY REDUCTION







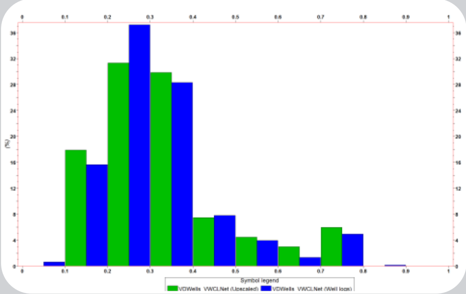
Prior uncertainty in well path TVD in the reservoir section – 5.6m to 6.3m (1std)

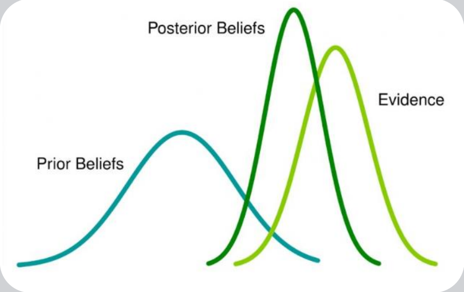


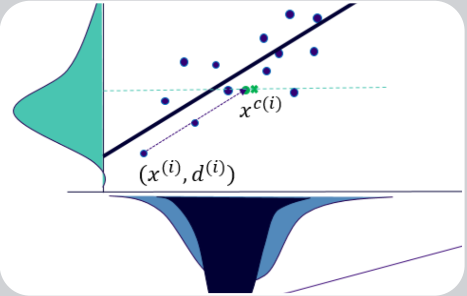
Posterior uncertainty in well path TVD in the reservoir section – 1.2m to 2.2m (1std)

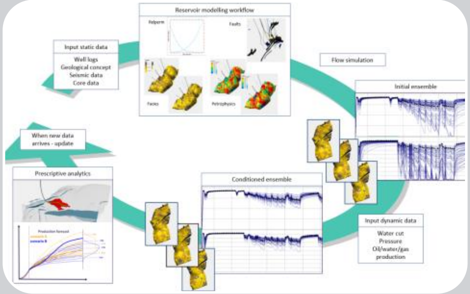
UNCERTAINTY AND PREDICTION IN SUBSURFACE

OBJECTIVE









Quantify uncertainty and include it in the model

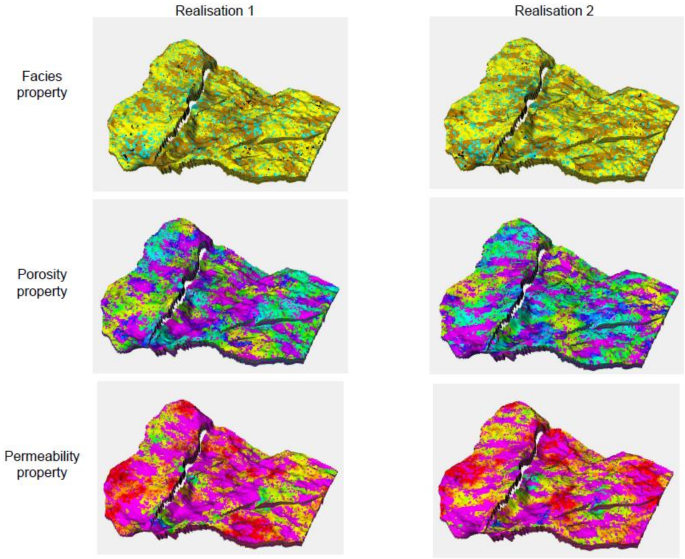
Integrate data to reduce uncertainty

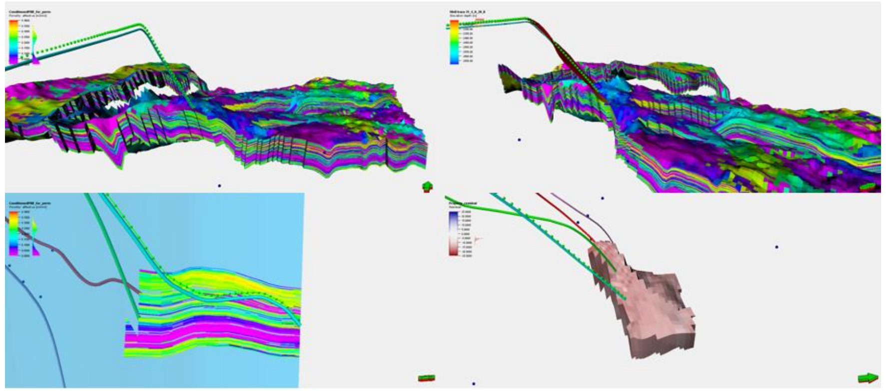
Predict outcomes and associated probabilities

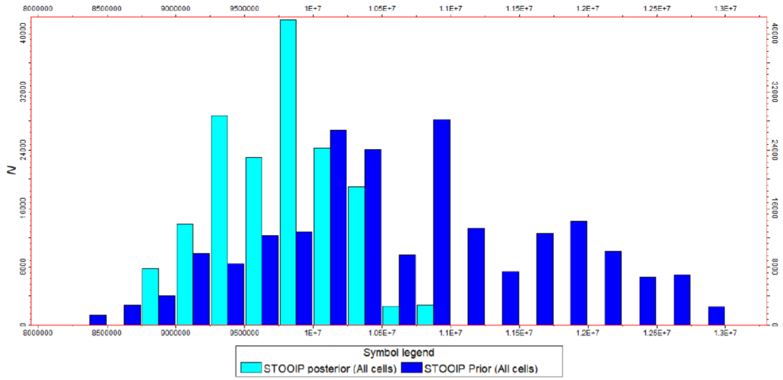
Update model consistently and rapidly with new data

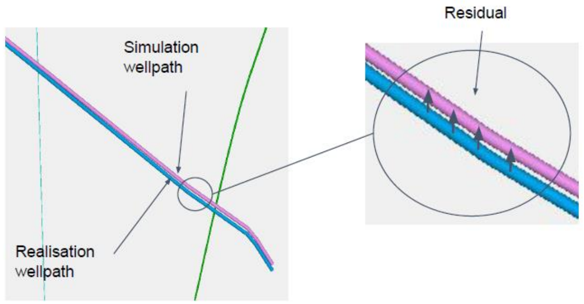
UNCERTAINTY AND PREDICTION IN SUBSURFACE

UNDERSTANDING RESULTS – RE AND STATISTICS









"This is the right answer to the question of combining this model and the data. But it's your responsibility to process the answer and make sense of it."
Richard McElreath

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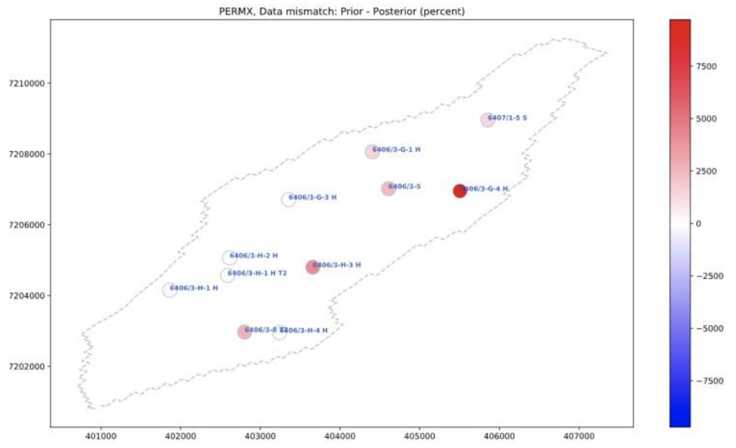
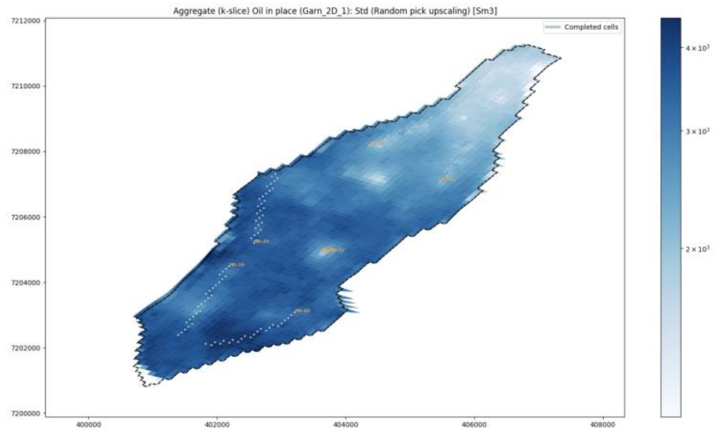
ENSEMBLE AND 4D

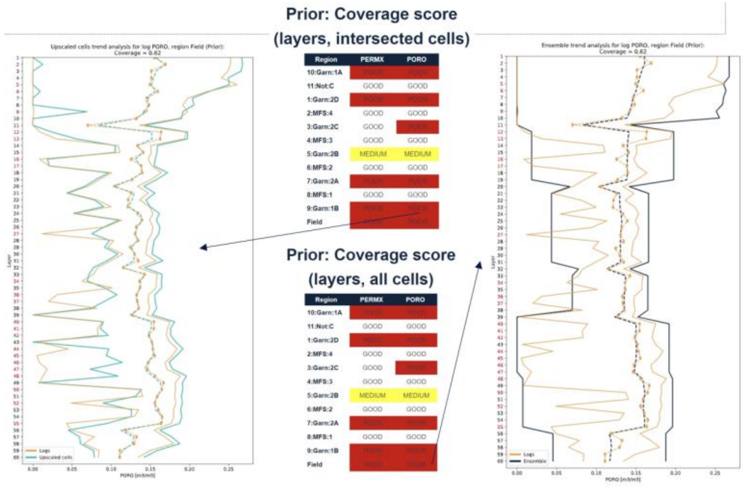
ANALYSIS



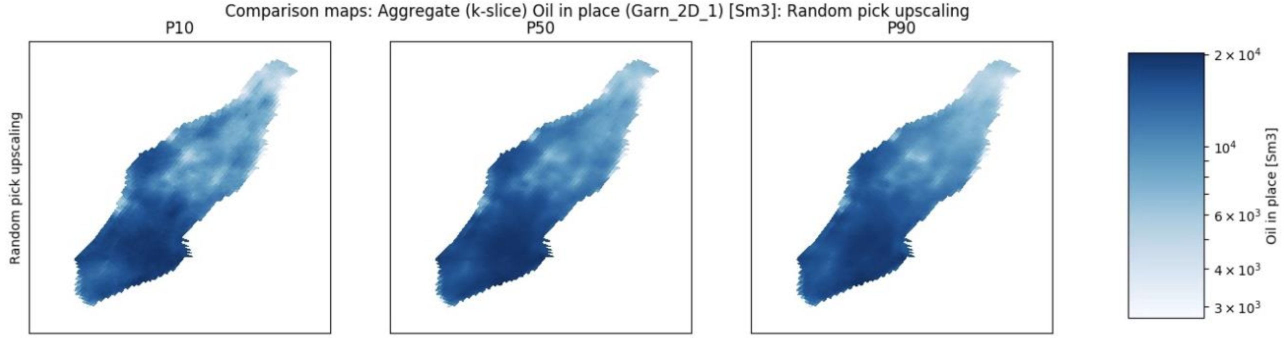
Prior - posterior



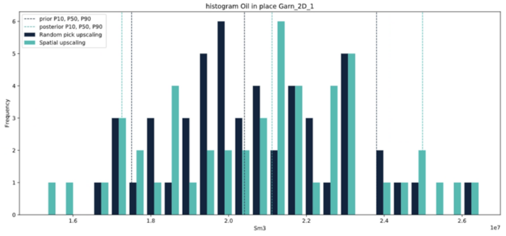
Aggregate oil in place



Coverage score



Percentiles



Histograms

ENSEMBLE METHODS AND 4D

WHERE ARE WE?

- Brage:
  - Brent ensemble model (finished, limited usage)
  - Fensfjord model (under construction)
    - Will be used to plan a campaign with several wells
    - Campaign will be evaluated probabilistically (management approval challenge)
    - Partnership is supportive but have little in-house competence on ensemble-based modelling
  - Maria:
    - Second (improved) model is under construction
    - Partnership is supportive and competent (with some in-house modelling capabilities)

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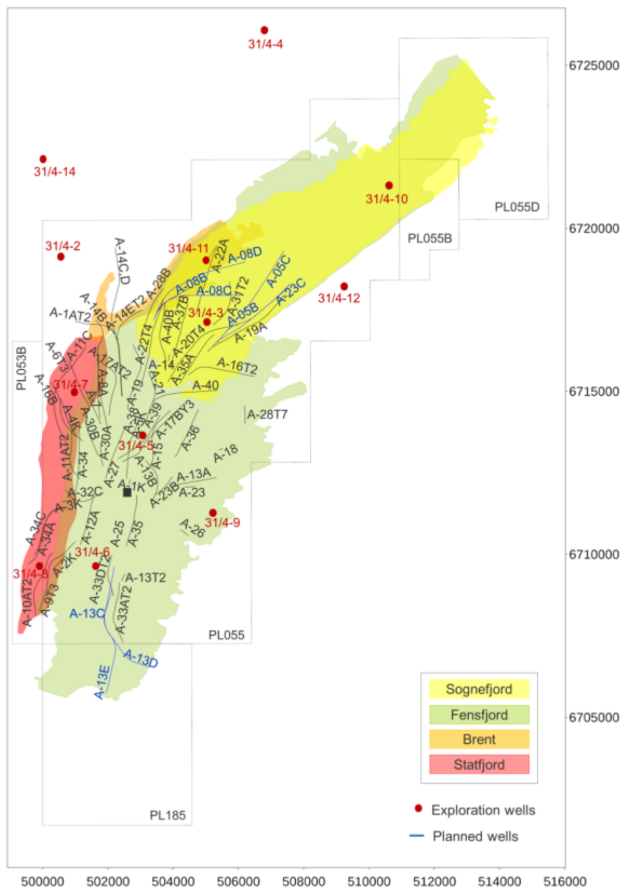
ENSEMBLE METHODS AND 4D

4D – BRAGE CASE

- Brage reservoirs and 4D feasibility:
  - Fensfjord – limited
  - Sognefjord - limited
  - Statfjord - good
  - Brent – very good

- 4D application in modelling/history matching:
  - In none of the reservoirs were 4D maps used quantitively in modelling/history matching
  - In Statfjord, a barrier was introduced by RE based on 4D observations

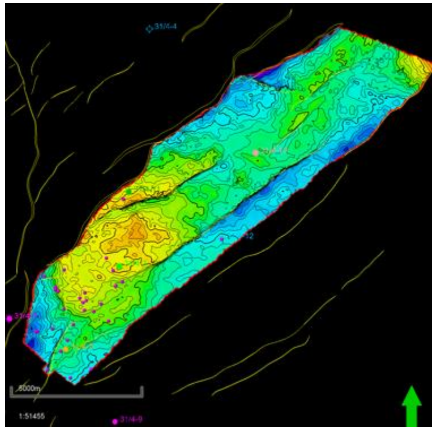
Brage Reservoirs (2013)

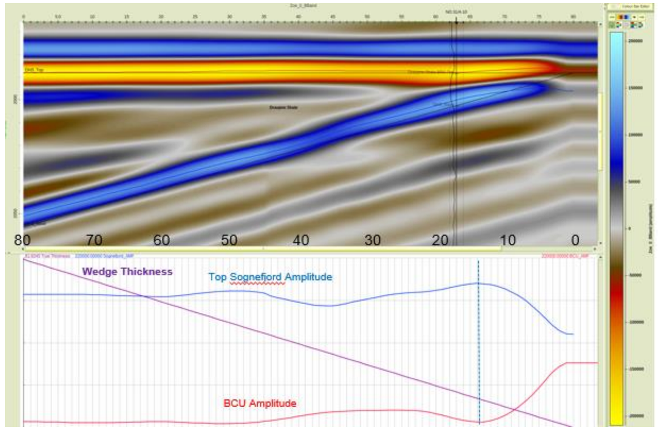


ENSEMBLE METHODS AND 4D

FENSFJORD/SOGNEFJORD – THE TROUBLESOME CHILDREN

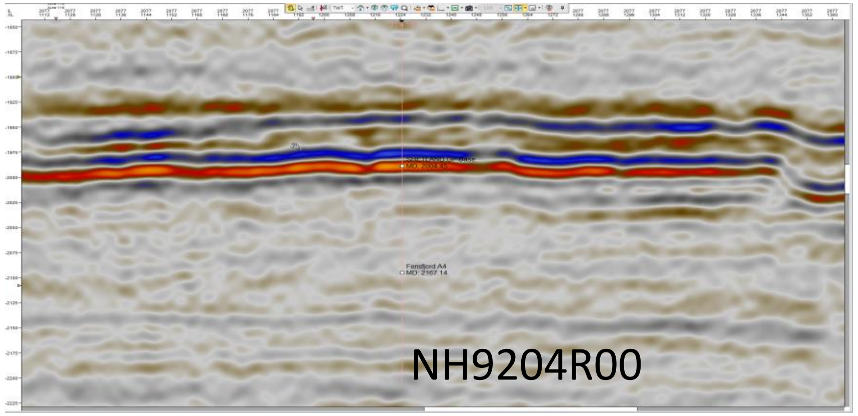
- Fensfjord - reservoir with largest remaining potential on Brage, difficult to identify drilling targets – business candidate for 4D?
- Sognefjord – gas cap and oil leg. Compartmentalized. Where is the remaining oil leg?

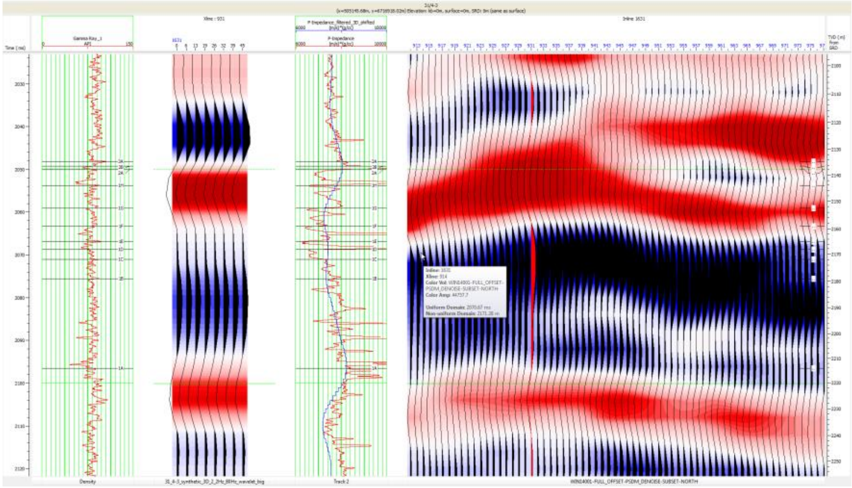




Sognefjord

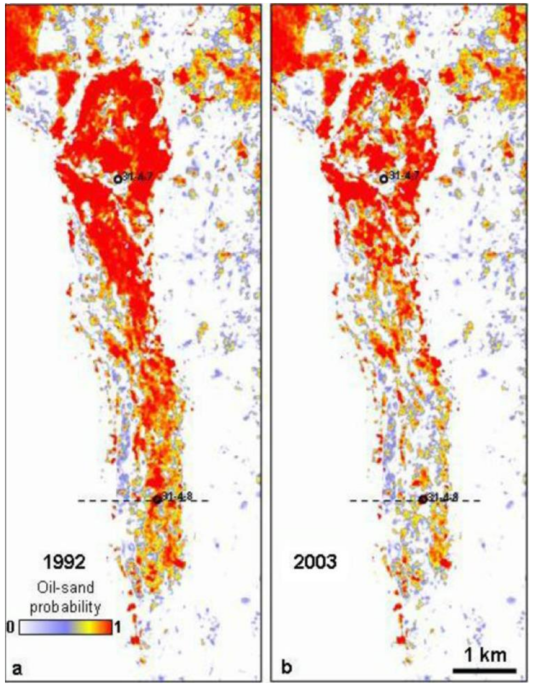
Fensfjord



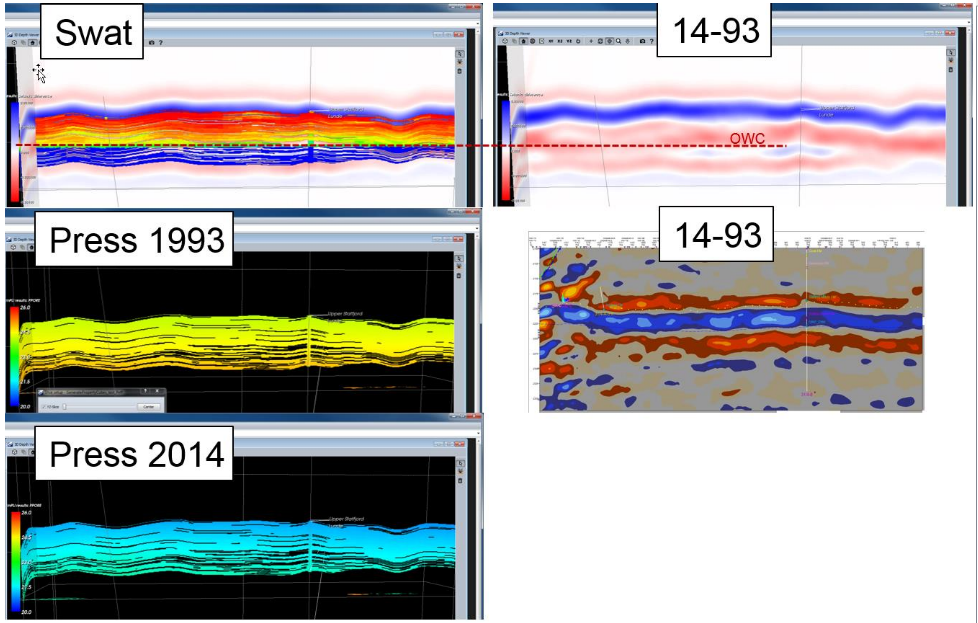


ENSEMBLE METHODS AND 4D

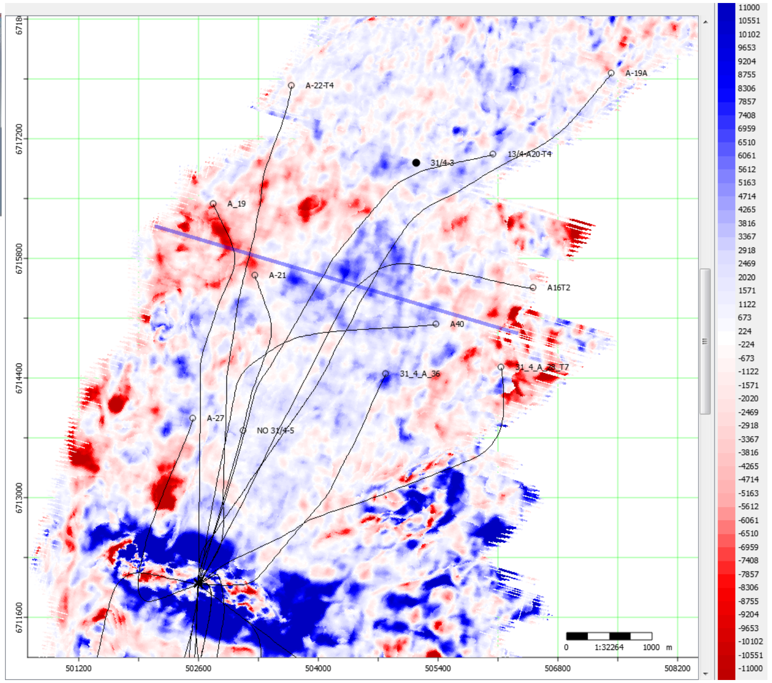
4D INTERPRETATION STRATEGIES



4D inversion on Statfjord reservoir in Brage, CGG 2009 – Bayesian fluid classification



Simulator-to-seismic and 4D signal prediction on Statfjord, Brage



4D amplitude difference 2003-1992 on Fensfjord, Brage

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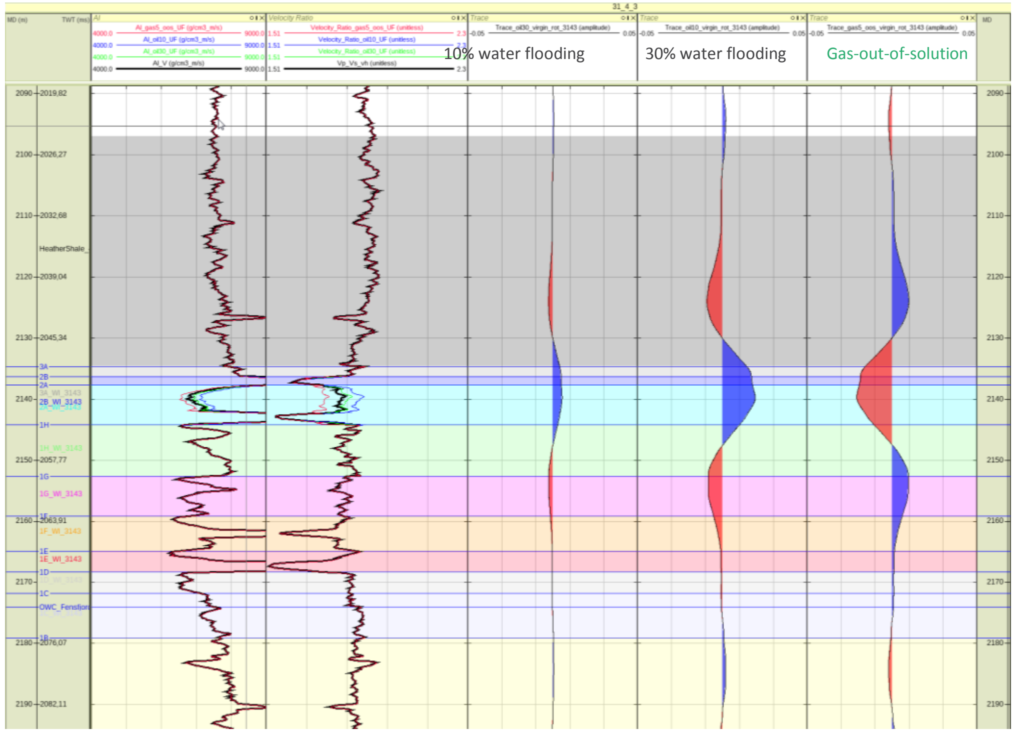
ENSEMBLE METHODS AND 4D

ECNOUNTERED ISSUES

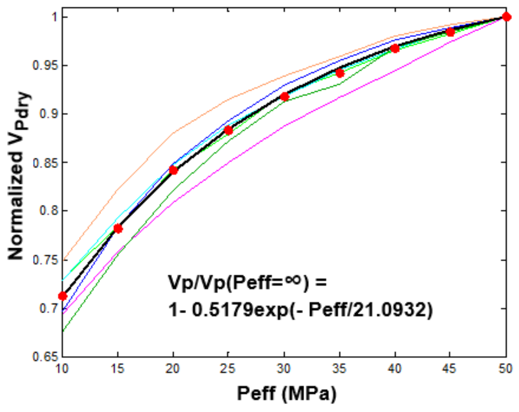
Fluid substitution

- Water flooding with remaining commercial saturation
- Water flooding with only residual oil
- Gas injection or gas-out-of-solution

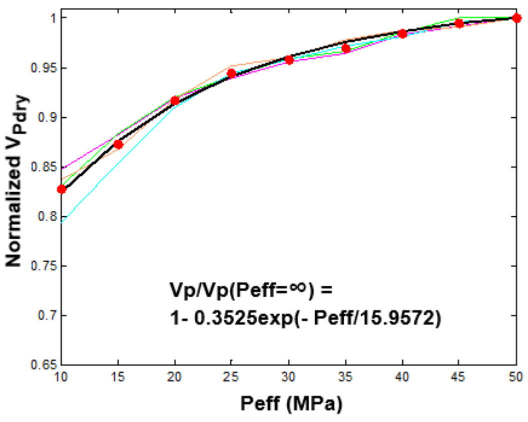


ENSEMBLE METHODS AND 4D

ENCOUNTERED ISSUES

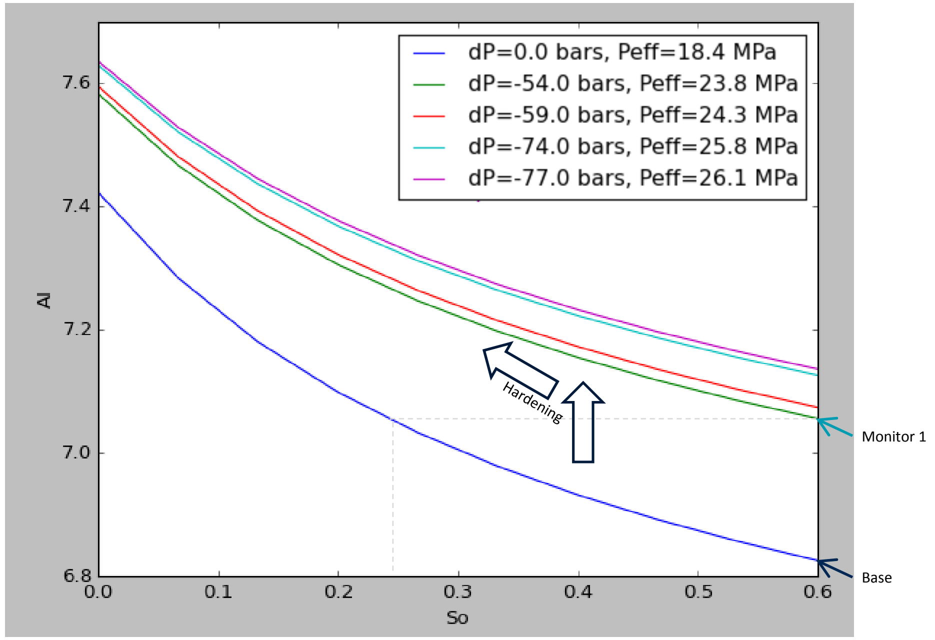


Fensfjord



Sognefjord

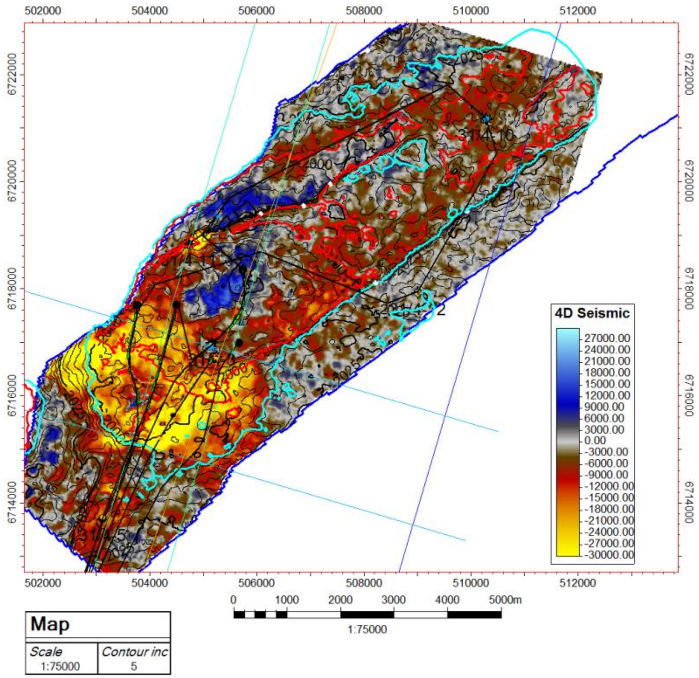
Velocity vs pressure



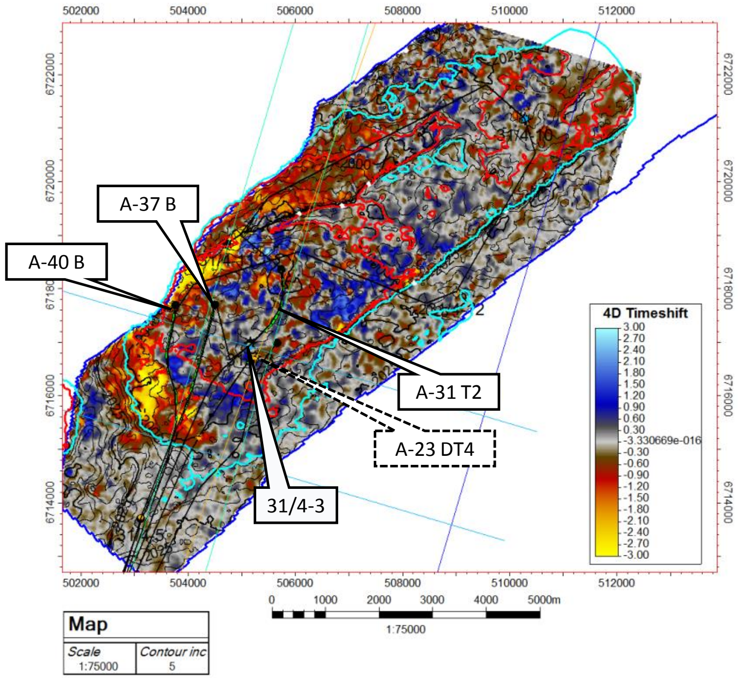
Hardening both with fluid and pressure depletion
Effects of pressure depletion may (by mistake) be interpreted as fluid change (e.g. Monitor1)

ENSEMBLE METHODS AND 4D

ENCOUNTERED ISSUES



Rel AI diff

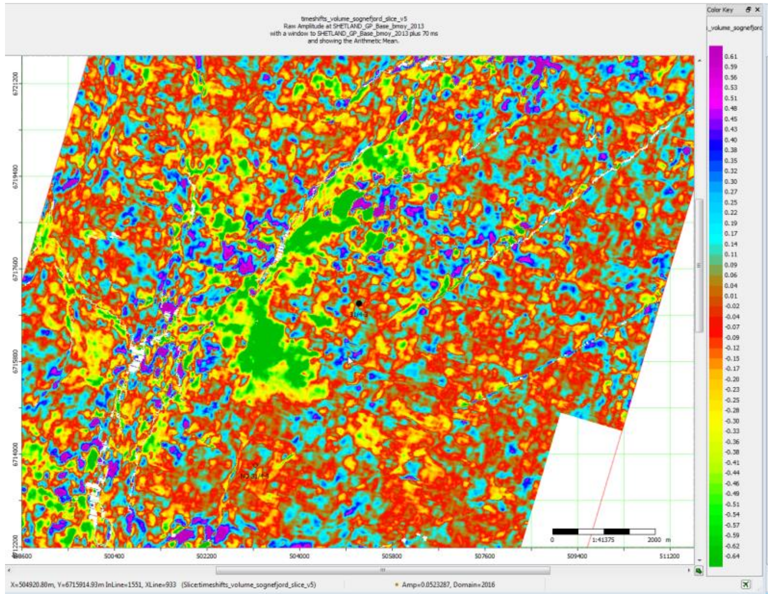


Time-shift

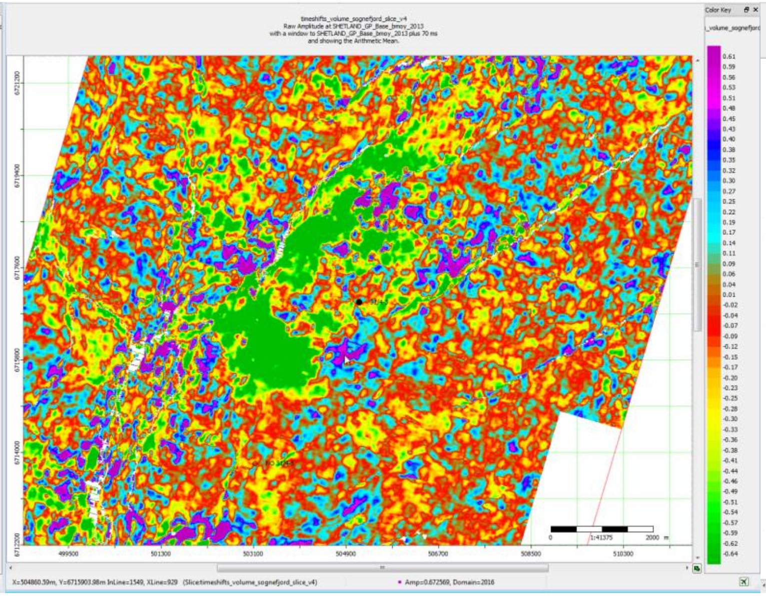
- **Low correlation between Relative AI different maps (amplitude) and time-shift maps.**

ENSEMBLE METHODS AND 4D

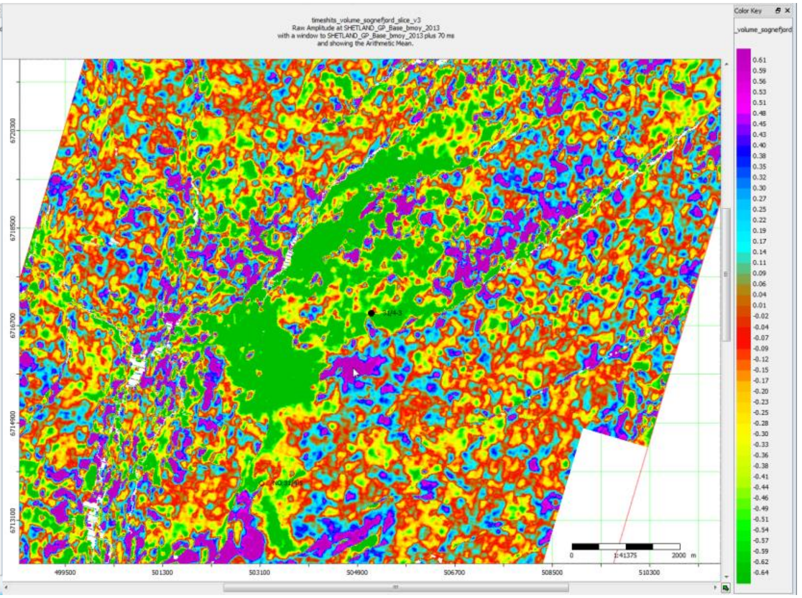
ENCOUNTERED ISSUES



100ms gate



70ms gate



40ms gate

Choice of parameters for calculation

SUMMARY

- Uncertainties:
  - Pressure vs fluid effect on the amplitude
  - Weighting of different attributes
  - Parameter choices
  - Attribute choices
  - Choice of time steps

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SPIRIT ENERGY

petoro

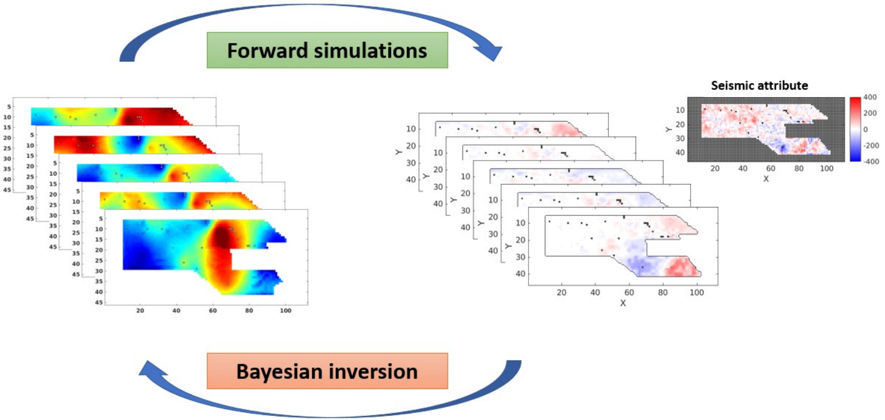
THANK YOU

A workflow for 4D seismic history matching demonstrated on the Norne field

Workshop on ensemble-based 4D seismic history matching

Rolf J. Lorentzen, NORCE / The National IOR Centre

Ensemble-based history matching



Ensemble-based history matching

- Provides uncertainty quantification for the reservoir model
  - Improved decision making
  - Better reservoir management
- Established for history matching of production data
  - First application to reservoir models: Nævdal et. al, 2002, SPE 75235
  - Methodology is applied world-wide, and is commercialized
  - Norne field: Evensen & Eikrem, 2018; Chen & Oliver, 2014, SPE-164902-PA
- Use of 4D seismic data
  - Problem with handling of large data sets (terabytes or petabytes)
  - Quantification of measurement noise is difficult
  - Norne field: Lorentzen et. al, 2019, Computational Geosciences
  - https://github.com/rolfjl/Norne-Initial-Ensemble

Iterative ensemble smoother

$$m_j^{i+1} = m_j^i + S_m^i (S_d^i)^T [(1+\lambda^i) C_d + S_d^i (S_d^i)^T]^{-1} (d_j^{\mathrm{obs}} - g(m_j^i))$$

$$\begin{aligned} S_m^i &= (N-1)^{-\frac{1}{2}} [m_1^i - \bar{m}^i, \ldots, m_N^i - \bar{m}^i] \\ S_d^i &= (N-1)^{-\frac{1}{2}} [g(m_1^i) - g(\bar{m}^i), \ldots, g(m_N^i) - g(\bar{m}^i)] \end{aligned}$$

N: Ensemble size

More information: Luo et. al, 2015, SPE-176023-PA

Truncated Singular Value Decomposition (TSVD)

$$[(1+\lambda^i)C_d + S_d^i(S_d^i)^T]^{-1} \in \mathbb{R}^{N_d \times N_d}$$

$$\downarrow \text{TSVD}$$

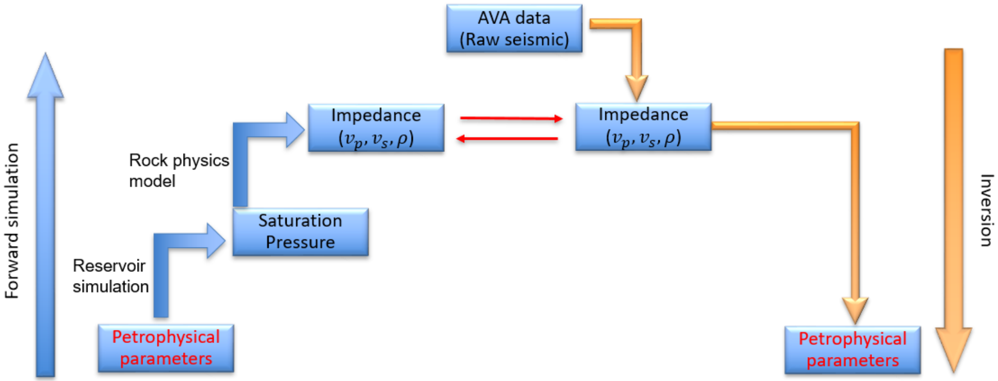
$$\begin{aligned} S_d &\approx U_p W_p V_p^T, \quad p < N \\ C_d &\approx S_\epsilon S_\epsilon^T, \quad S_\epsilon \in \mathbb{R}^{N_d \times N} \end{aligned}$$

$$\Downarrow$$

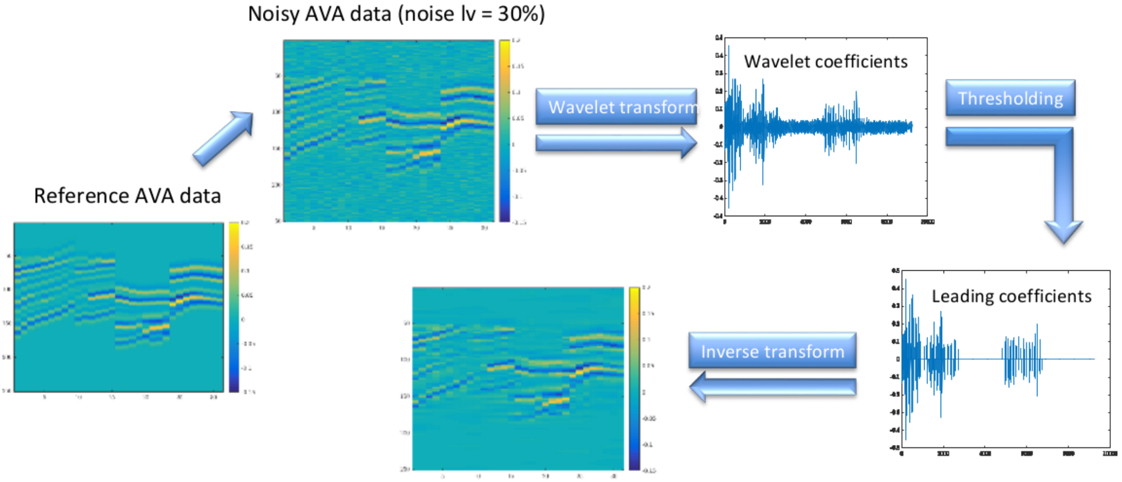
$$[(1+\lambda^i)C_d + S_d^i(S_d^i)^T]^{-1} \approx A^i \cdot B^i \cdot C^i$$

$$A^i \in \mathbb{R}^{N_d \times p}, \ B^i \in \mathbb{R}^{p \times p}, C^i \in \mathbb{R}^{p \times N_d}$$

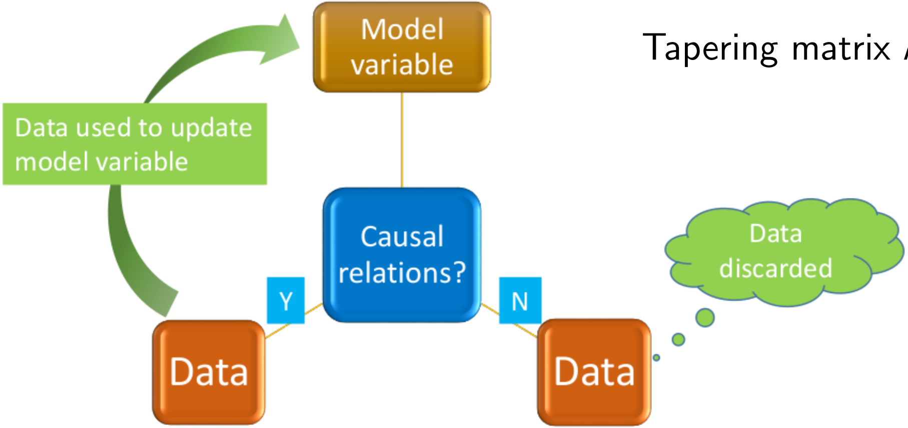
Inclusion of 4D seismic data



Data compression (denoising)

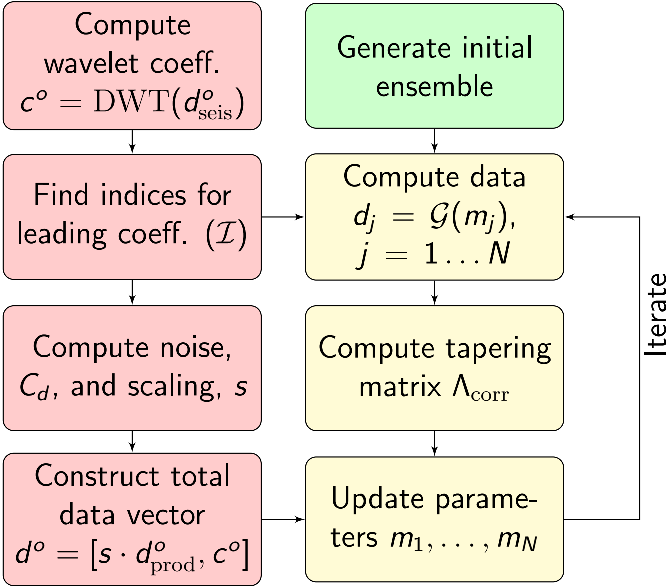


Correlation-based adaptive localization



Tapering matrix Λ_{corr}

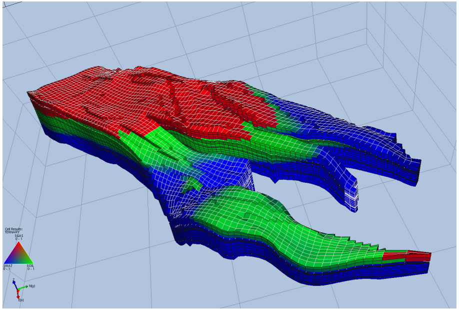
More information: Luo et. al, 2018, SPE-185936-PA.


Compute wavelet coeff. $c^o = \mathrm{DWT}(d^o_{\mathrm{seis}})$
Find indices for leading coeff. $(\mathcal{I})$
Compute noise, C_d, and scaling, s
Construct total data vector $d^o = [s \cdot d^o_{\mathrm{prod}}, c^o]$
Generate initial ensemble
Compute data $d_j = \mathcal{G}(m_j)$, $j = 1 \dots N$
Compute tapering matrix Λ_{corr}
Update parameters $m_1, \dots, m_N$
Iterate

Norne field

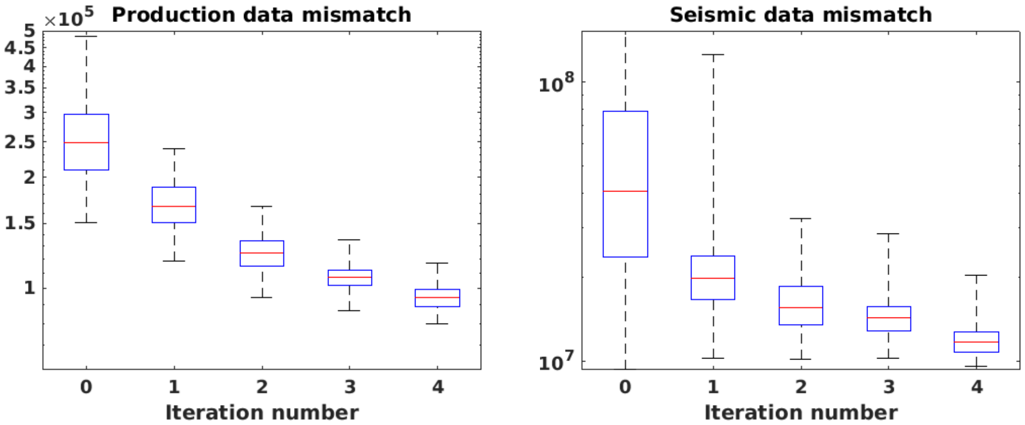
- Oil & gas field in Norwegian sector
- 5 formations
- Hydrocarbon column approx. 135 m
- Original oil-in-place: 160 million Sm^3
- Most of the sandstones are good reservoir rocks
- Wells: 9 injectors, 27 producers
- Production history: Nov. 1997–2006
- 4 seismic surveys (2001, 2003, 2004, 2006)
- 3×9 km

- Grid size: 46 x 112 x 22
- Active cells: 44927



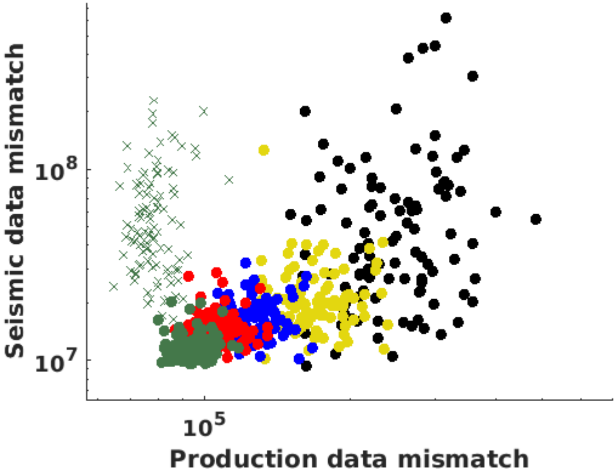
History matching the Norne field

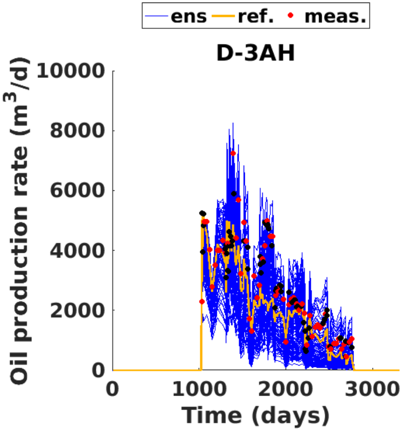
- Initial ensemble generated using Gaussian random fields
- Updates porosity, permeability, net-to-gross, transmissibility multipliers, relative permeability, initial oil-water contact
- Clay content defined as 1 minus ”net-to-gross”
- Data scaled based on initial data match
- Seismic data inverted for acoustic impedance at four points in time



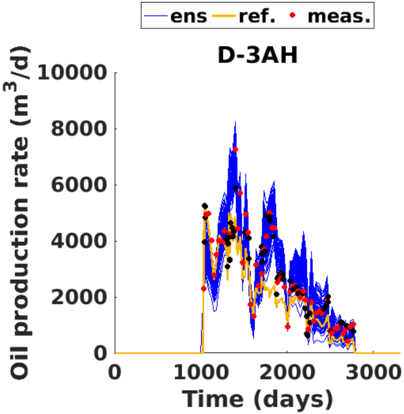
Production data mismatch
×10^5
5
4.5
4
3.5
3
2.5
2
1.5
1
0
1
2
3
4
Iteration number
Seismic data mismatch
10^8
10^7
0
1
2
3
4
Iteration number

Iteration crossplot

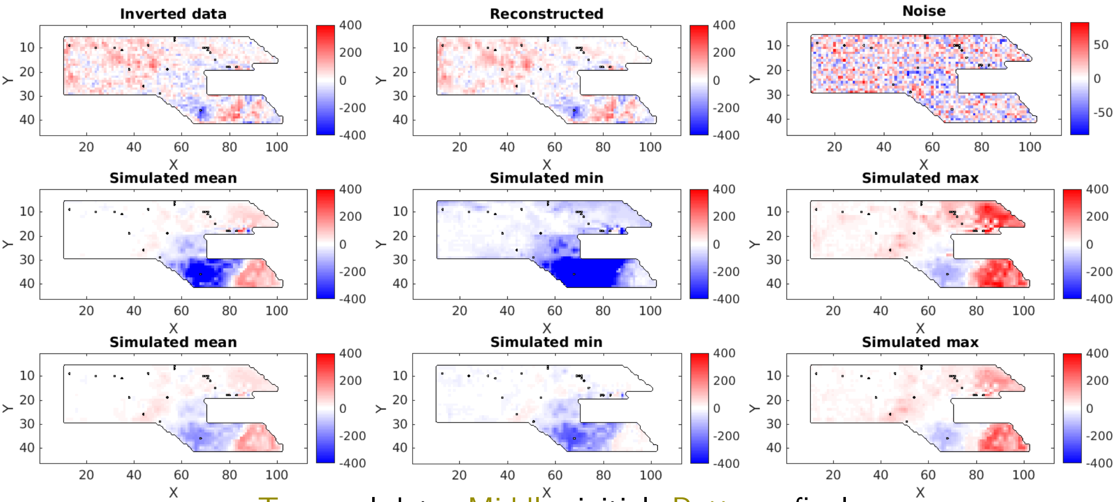




Initial

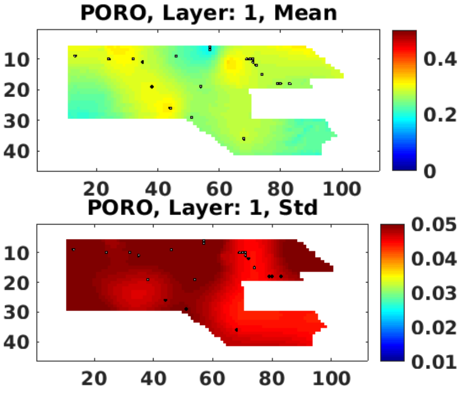


Final

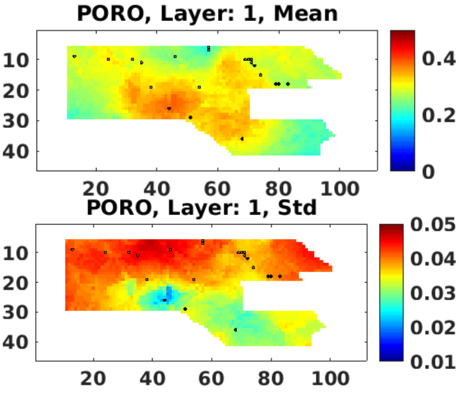


Top: real data. Middle: initial. Bottom: final.

Garn formation, Ip difference.



Initial



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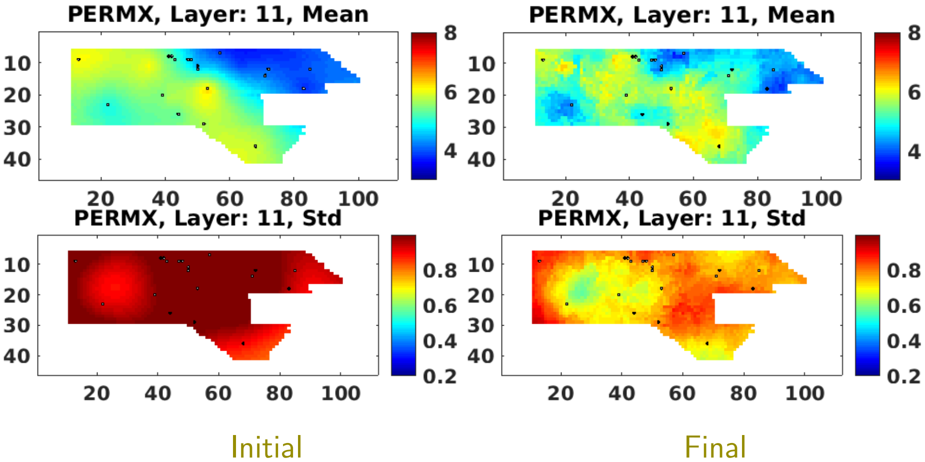
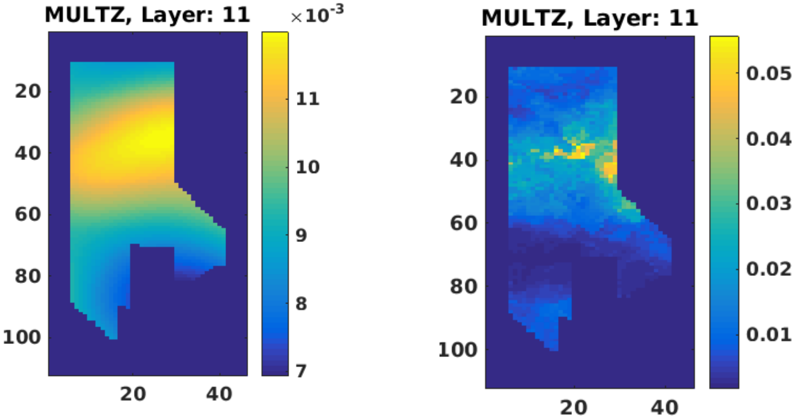
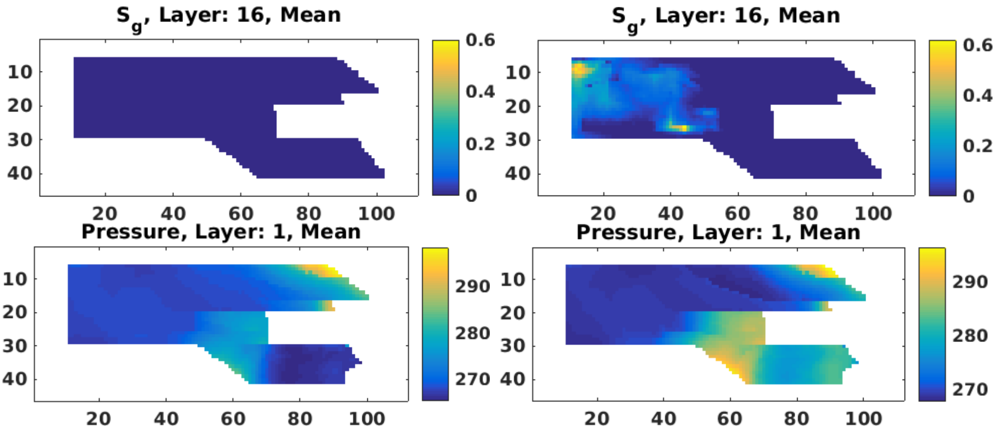

PERMX, Layer: 11, Mean
PERMX, Layer: 11, Mean
PERMX, Layer: 11, Std
PERMX, Layer: 11, Std
10
20
30
40
20
40
60
80
100
8
6
4
0.8
0.6
0.4
0.2
Initial
Final



Initial

Final



Mean gas saturation (*top*) and pressure (*bottom*)
at year 1997 (*left*) and 2006 (*right*).

Summary / Conclusions

- A workflow for history matching real production and seismic data is presented
- Methodology demonstrated on the Norne field
- Clay content and other petrophysical parameters updated
- Data match improved for both production and seismic data
- Updated static fields are geologically credible
- Used for reservoir management and uncertainty quantification
- Simulation of infill wells, EOR strategies and monitoring of EOR operations

NORCE

Acknowledgments

- The Research Council of Norway and the industry partners, ConocoPhillips Skandinavia AS, Aker BP ASA, Eni Norge AS, Total E&P Norge AS, Equinor ASA, Neptune Energy Norge AS, Lundin Norway AS, Halliburton AS, Schlumberger Norge AS, Wintershall Norge AS, and DEA Norge AS, of The National IOR Centre of Norway for main financial support.
- Eni, Petrobras, and Total, as well as the Research Council of Norway (PETROMAKS2), for financial support through the project "4D Seismic History Matching".
- Equinor (operator of Norne field) and its license partners ENI and Petoro for the release of the Norne data.
- IOR Center for Integrated Operations at NTNU for cooperation and coordination of the Norne Cases.
- Schlumberger and CGG for providing academic software licenses to ECLIPSE and HampsonRussell, respectively.

Measurement operator

The observation operator $\mathcal{G}$ comprises several steps summarized as:

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4. applying the discrete wavelet transform to get wavelet coefficients
5. using the leading indices $\mathcal{I}$ to get d_j

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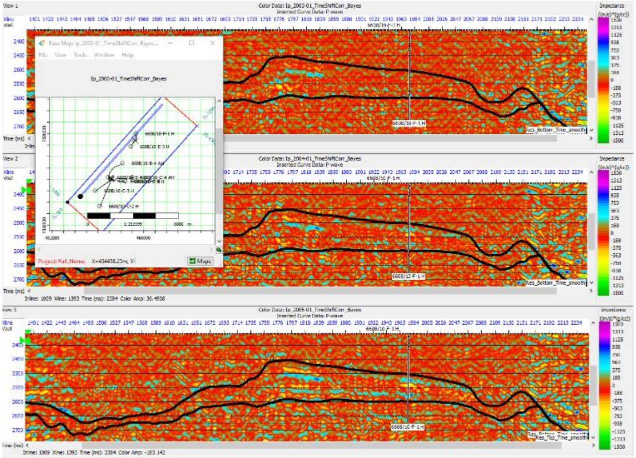
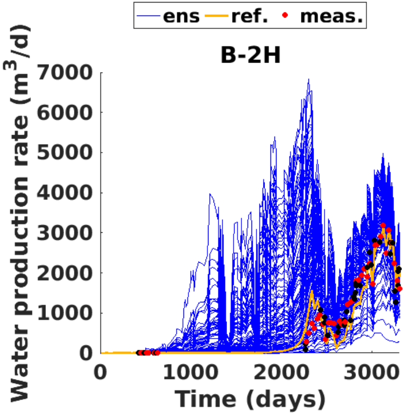
Seismic data inversion and transformation

- Time shift correction:
  Alfonzo et. al, 2017
- Linearized Bayesian approach:
  Buland and Omre, 2003
- Time to depth conversion:
  Provided Norne velocity model
- Upscaling:
  Petrel software
- Difference and averaging:
  $\overline{\Delta z}_p^o$

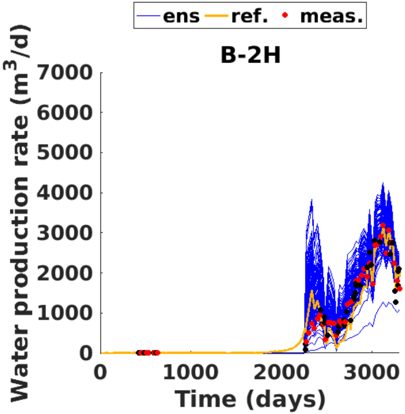


Petro-elastic model

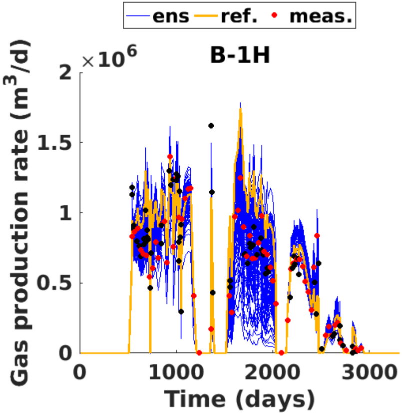
- Estimate mineral bulk and shear moduli:
  $[K_s, G_s] \leftarrow \mathrm{Hashin - Shtrikman}(K_{\mathrm{quartz}}, G_{\mathrm{quartz}}, K_{\mathrm{clay}}, G_{\mathrm{clay}}, V_{\mathrm{clay}})$
- Dry rock bulk and shear moduli (empirical):
  $[K_{\mathrm{dry}}, G_{\mathrm{dry}}] \leftarrow f(p, p_{\mathrm{ini}}, \phi)$
- Fluid substitution:
  $[K_{\mathrm{sat}}, G_{\mathrm{sat}}] \leftarrow \mathrm{Gassmann}(K_{\mathrm{dry}}, G_{\mathrm{dry}}, K_s, s_o, s_g, s_w)$
- P-wave velocity and rock density:
  $[v_p, \rho_{\mathrm{sat}}] \leftarrow \mathrm{Mavko}(K_{\mathrm{sat}}, G_{\mathrm{sat}})$
  $z_p = v_p \times \rho_{\mathrm{sat}}$



Initial



Final



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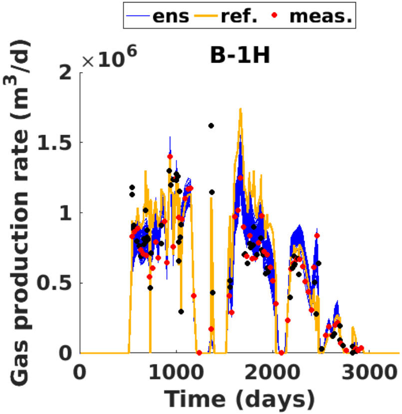

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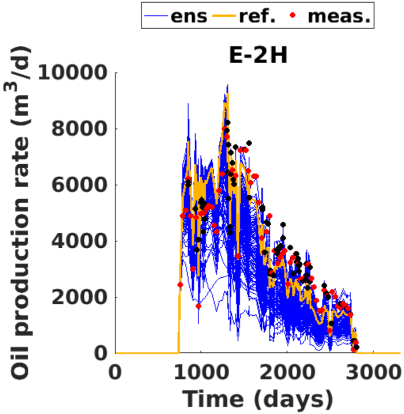
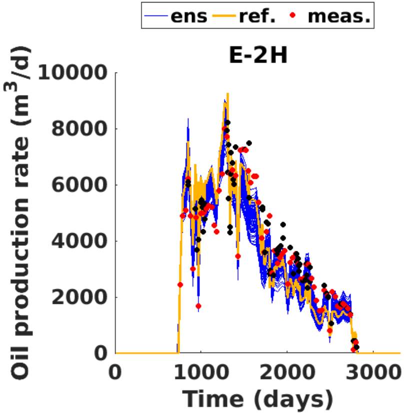


Initial



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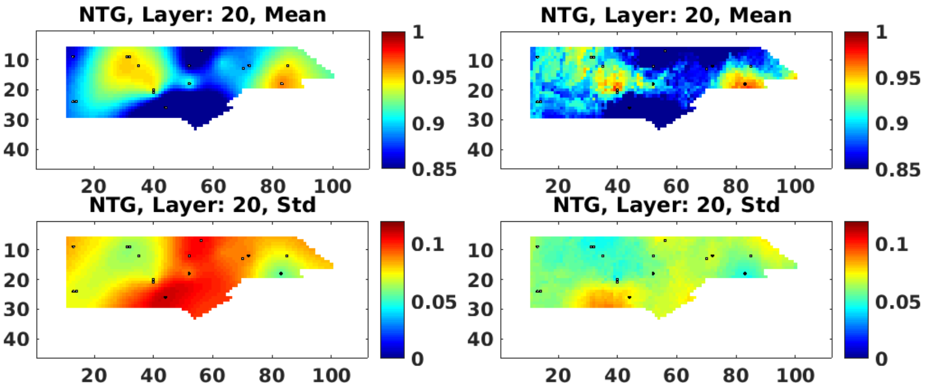

Initial

Final

Formulating the history-matching problem with consistent error statistics

Geir Evensen

NORCE

NORCE–Norwegian Research Center

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AkerBP equinor Lundin Petroleum NEPTUNE ENERGY BR PETROBRAS vår energi wintershall dea Universitetet i Stavanger

Issue 1

We sometimes force the model with some of the same data that we condition on!

Model: $\boldsymbol{y} = \boldsymbol{g}(\boldsymbol{x}, \boldsymbol{u})$

Likelihood: $f\big(\boldsymbol{d} \,|\, \boldsymbol{y}\big) = f\big(\boldsymbol{d} \,|\, \boldsymbol{g}(\boldsymbol{x}, \boldsymbol{u})\big)$

Validity of the standard Bayes formula for the HM problem?

Issue 2

We ignore errors in historical rates during ensemble simulation!

1. All model realizations are forced by the same rates.
2. Leads to underestimated prediction uncertainty.
3. Implications for the history matching?

It is possible to add stochastic rate errors in the schedule file.

Issue 3

How to handle stochastic model errors in iterative smoothers?

1. *Evensen* (2019) discussed the problem of including model errors in iterative smoothers.

We can include and estimate stochastic rates as part of the history-matching process.

Issue 4

We condition on observations assumed to have uncorrelated errors: $\boldsymbol{C}_{dd} = \boldsymbol{I}$.

Seismic data have errors with spatial correlations.

Rate data have highly correlated errors in time due to the use of allocation tables *Evensen and Eikrem* (2018).

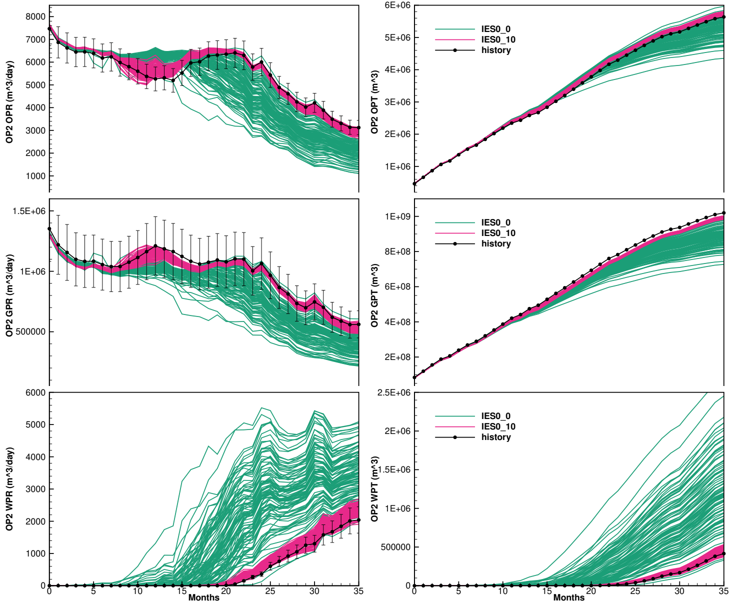
- Impact of neglecting these error correlations?
- Computational consequence of including these error correlations?

The subspace EnRML implementation (*Evensen et al.*, 2019) allows for a full $\boldsymbol{C}_{dd}$.

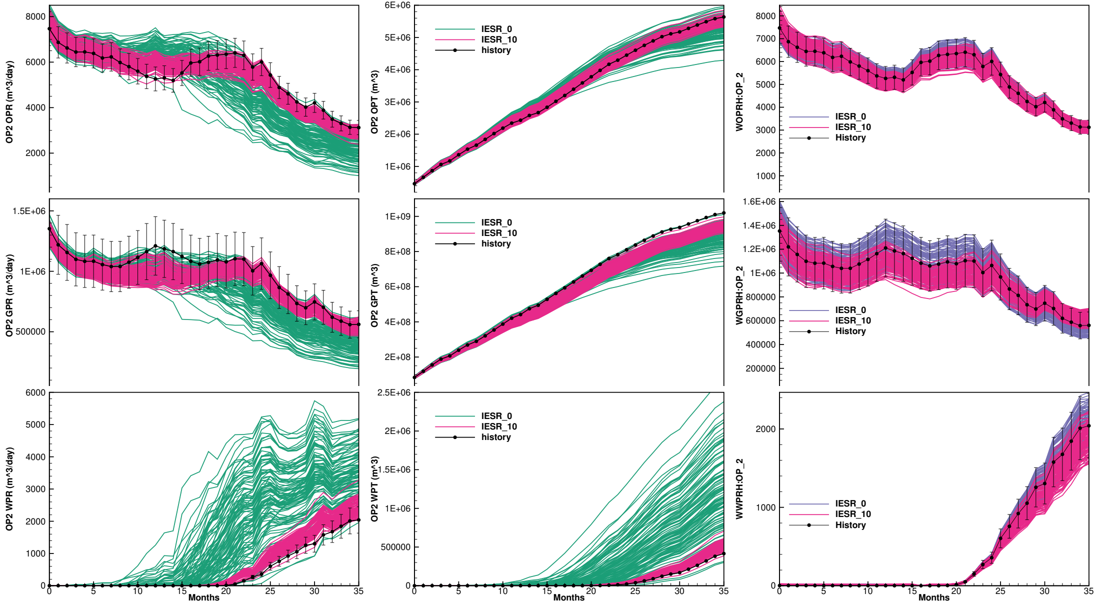
I propose a consistent HM formulation

- Rederive Bayes' formula for the HM problem.
- Include historical rates with stochastic errors during simulations.
- Update stochastic rates as part of the state vector.
- Include time-correlated rate data in a new subspace EnRML algorithm.

Leads to realistic posterior error statistics where we avoid "ensemble collapse."



G. Evensen, Formulating the history matching problem with consistent error statistics, Comp. Geosci. in revision, 2020


OP2 OPR (m^3/day)
OP2 OPT (m^3)
WOPRH:OP_2
OP2 GPR (m^3/day)
OP2 GPT (m^3)
WGPRH:OP_2
OP2 WPR (m^3/day)
OP2 WPT (m^3)
WWPRH:OP_2
IESR_0
IESR_10
history
History
Months

NORCE

HM problem becomes

Model

$$\boldsymbol{y} = \boldsymbol{g}(\boldsymbol{x}, \boldsymbol{u}) = \boldsymbol{g}(\boldsymbol{z}).$$

Bayes

$$f(\boldsymbol{z} \mid \boldsymbol{d}) \propto f(\boldsymbol{z}) f(\boldsymbol{d} \mid \boldsymbol{g}(\boldsymbol{z})).$$

Ensemble formulation for approximate sampling of $f(\boldsymbol{z} \mid \boldsymbol{d})$ (normal priors)

$$\mathcal{J}(\boldsymbol{z}_j) = \left(\boldsymbol{z}_j - \boldsymbol{z}_j^{\mathrm{f}}\right)^{\mathrm{T}} \boldsymbol{C}_{zz}^{-1} \left(\boldsymbol{z}_j - \boldsymbol{z}_j^{\mathrm{f}}\right) + \left(\boldsymbol{g}(\boldsymbol{z}_j) - \boldsymbol{d}_j\right)^{\mathrm{T}} \boldsymbol{C}_{dd}^{-1} \left(\boldsymbol{g}(\boldsymbol{z}_j) - \boldsymbol{d}_j\right).$$

We need to estimate the rates used to force the model as part of the state vector.

Subspace EnRML: (*Raanes et al.*, 2019)

Original cost functions

$$\mathcal{J}(\boldsymbol{z}_j) = \left(\boldsymbol{z}_j - \boldsymbol{z}_j^{\mathrm{f}}\right)^{\mathrm{T}} \boldsymbol{C}_{xx}^{-1} \left(\boldsymbol{z}_j - \boldsymbol{z}_j^{\mathrm{f}}\right) + \left(\boldsymbol{g}(\boldsymbol{z}_j) - \boldsymbol{d}_j\right)^{\mathrm{T}} \boldsymbol{C}_{dd}^{-1} \left(\boldsymbol{g}(\boldsymbol{z}_j) - \boldsymbol{d}_j\right).$$

Solution is contained in the ensemble subspace, thus

$$\boldsymbol{z}_j^{\mathrm{a}} = \boldsymbol{z}_j^{\mathrm{f}} + \boldsymbol{A}\boldsymbol{w}_j,$$

and,

$$\mathcal{J}(\boldsymbol{w}_j) = \boldsymbol{w}_j^{\mathrm{T}} \boldsymbol{w}_j + \left(\boldsymbol{g}\left(\boldsymbol{z}_j^{\mathrm{f}} + \boldsymbol{A}\boldsymbol{w}_j\right) - \boldsymbol{d}_j\right)^{\mathrm{T}} \boldsymbol{C}_{dd}^{-1} \left(\boldsymbol{g}\left(\boldsymbol{z}_j^{\mathrm{f}} + \boldsymbol{A}\boldsymbol{w}_j\right) - \boldsymbol{d}_j\right)$$

Reduces dimension of problem from state size to ensemble size.

$$\boldsymbol{w}_j^{i+1} = \boldsymbol{w}_j^{i} - \gamma \nabla \mathcal{J}_j^{i}$$

Iteration formula for $\boldsymbol{W}_i$ simplifies by setting $\boldsymbol{C}_{dd} = \boldsymbol{I}$

Standard form ($\mathcal{O}(m^3)$)

$$\boldsymbol{W}_{i+1} = \boldsymbol{W}_i - \gamma\Big(\boldsymbol{W}_i - \boldsymbol{S}_i^{\mathrm{T}}\left(\boldsymbol{S}_i\boldsymbol{S}_i^{\mathrm{T}} + \boldsymbol{C}_{dd}\right)^{-1}\boldsymbol{H}_i\Big)$$

From Woodbury, rewrite as

$$\boldsymbol{W}_{i+1} = \boldsymbol{W}_i - \gamma\Big\{\boldsymbol{W}_i - \left(\boldsymbol{S}_i^{\mathrm{T}}\boldsymbol{C}_{dd}^{-1}\boldsymbol{S}_i + \boldsymbol{I}_N\right)^{-1}\boldsymbol{S}_i^{\mathrm{T}}\boldsymbol{C}_{dd}^{-1}\boldsymbol{H}\Big\}$$

For $\boldsymbol{C}_{dd} = \boldsymbol{I}_m$ we have ($\mathcal{O}(mN^2)$)

$$\boldsymbol{W}_{i+1} = \boldsymbol{W}_i - \gamma\Big\{\boldsymbol{W}_i - \left(\boldsymbol{S}_i^{\mathrm{T}}\boldsymbol{S}_i + \boldsymbol{I}_N\right)^{-1}\boldsymbol{S}_i^{\mathrm{T}}\boldsymbol{H}\Big\}$$

Subspace inversion represents $\boldsymbol{C}_{dd} \approx \boldsymbol{E}\boldsymbol{E}^{\mathrm{T}}$

- Algorithm by *Evensen* (2004) works directly with $\boldsymbol{E}$.

$$
\begin{aligned}
&(\boldsymbol{S}\boldsymbol{S}^{\mathrm{T}} + \boldsymbol{E}\boldsymbol{E}^{\mathrm{T}}) \\
&\qquad \approx \boldsymbol{S}\boldsymbol{S}^{\mathrm{T}} + (\boldsymbol{S}\boldsymbol{S}^{+})\boldsymbol{E}\boldsymbol{E}^{\mathrm{T}}(\boldsymbol{S}\boldsymbol{S}^{+})^{\mathrm{T}} \\
&\qquad = \boldsymbol{U}\boldsymbol{\Sigma}\big(\boldsymbol{I}_N + \boldsymbol{\Sigma}^{+}\boldsymbol{U}^{\mathrm{T}}\boldsymbol{E}\boldsymbol{E}^{\mathrm{T}}\boldsymbol{U}(\boldsymbol{\Sigma}^{+})^{\mathrm{T}}\big)\boldsymbol{\Sigma}^{\mathrm{T}}\boldsymbol{U}^{\mathrm{T}} \\
&\qquad = \boldsymbol{U}\boldsymbol{\Sigma}\big(\boldsymbol{I}_N + \boldsymbol{Z}\boldsymbol{\Lambda}\boldsymbol{Z}^{\mathrm{T}}\big)\boldsymbol{\Sigma}^{\mathrm{T}}\boldsymbol{U}^{\mathrm{T}} \\
&\qquad = \boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{Z}\big(\boldsymbol{I}_N + \boldsymbol{\Lambda}\big)\boldsymbol{Z}^{\mathrm{T}}\boldsymbol{\Sigma}^{\mathrm{T}}\boldsymbol{U}^{\mathrm{T}}.
\end{aligned}
$$

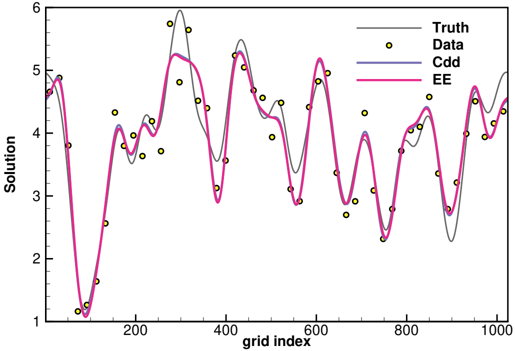
$$
\left(\boldsymbol{S}\boldsymbol{S}^{\mathrm{T}} + \boldsymbol{E}\boldsymbol{E}^{\mathrm{T}}\right)^{-1} \approx \boldsymbol{U}(\boldsymbol{\Sigma}^{+})^{\mathrm{T}}\boldsymbol{Z}\big(\boldsymbol{I}_N + \boldsymbol{\Lambda}\big)^{-1}\big(\boldsymbol{U}(\boldsymbol{\Sigma}^{+})^{\mathrm{T}}\boldsymbol{Z}\big)^{\mathrm{T}}
$$

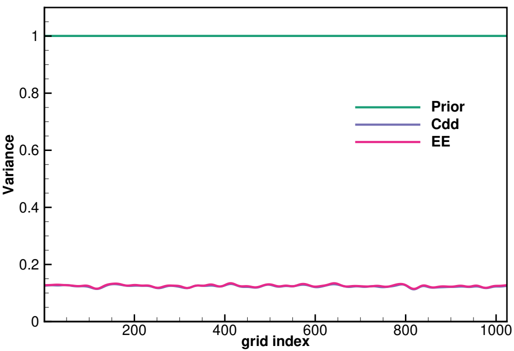
Computational cost is $\mathcal{O}(mN^2)$.

Subspace EnRML algorithm: (*Evensen et al.*, 2019)

Input: $\boldsymbol{X}_0 \in \Re^{n\times N}$ (prior model ensemble)
Input: $\boldsymbol{D} \in \Re^{m\times N}$ (perturbed measurements)
Input: $\boldsymbol{E}_0 \in \Re^{\hat{m}\times N}$ (initial measurement perturbations)
$\boldsymbol{W}_0 = 0$ $\qquad \boldsymbol{W} \in \Re^{N\times N}$
$\boldsymbol{\Pi} = \left(\boldsymbol{I} - \frac{1}{N}\boldsymbol{1}\boldsymbol{1}^{\mathrm{T}}\right)/\sqrt{N-1}$ $\qquad \boldsymbol{\Pi} \in \Re^{N\times N}$
$\boldsymbol{E} = \boldsymbol{D}\boldsymbol{\Pi}$ $\qquad \boldsymbol{E} \in \Re^{m\times N}$
i=0
repeat
    $\boldsymbol{Y}_i = \boldsymbol{g}(\boldsymbol{X}_i, \boldsymbol{E}_i)\boldsymbol{\Pi}$ $\qquad \boldsymbol{Y} \in \Re^{m\times N}$
    $\boldsymbol{\Omega}_i = \boldsymbol{I} + \boldsymbol{W}_i\boldsymbol{\Pi}$ $\qquad \boldsymbol{\Omega} \in \Re^{N\times N}$
    $\boldsymbol{S}_i = \boldsymbol{Y}_i\boldsymbol{\Omega}_i^{-1}$ $\qquad \boldsymbol{S} \in \Re^{m\times N}$
    $\boldsymbol{H}_i = \boldsymbol{S}_i\boldsymbol{W}_i + \boldsymbol{D} - \boldsymbol{g}(\boldsymbol{X}_i, \boldsymbol{E}_i)$ $\qquad \boldsymbol{H} \in \Re^{m\times N}$
    $\boldsymbol{W}_{i+1} = \boldsymbol{W}_i - \gamma\left(\boldsymbol{W}_i - \boldsymbol{S}_i^{\mathrm{T}}(\boldsymbol{S}_i\boldsymbol{S}_i^{\mathrm{T}} + \boldsymbol{E}\boldsymbol{E}^{\mathrm{T}})^{-1}\boldsymbol{H}_i\right)$
    $\boldsymbol{T}_i = \left(\boldsymbol{I} + \boldsymbol{W}_{i+1}\Big/\sqrt{N-1}\right)$ $\qquad \boldsymbol{T} \in \Re^{N\times N}$
    $\boldsymbol{X}_{i+1} = \boldsymbol{X}\boldsymbol{T}_i$
    $\boldsymbol{E}_{i+1} = \boldsymbol{E}_0\boldsymbol{T}_i$
    i=i+1
until convergence

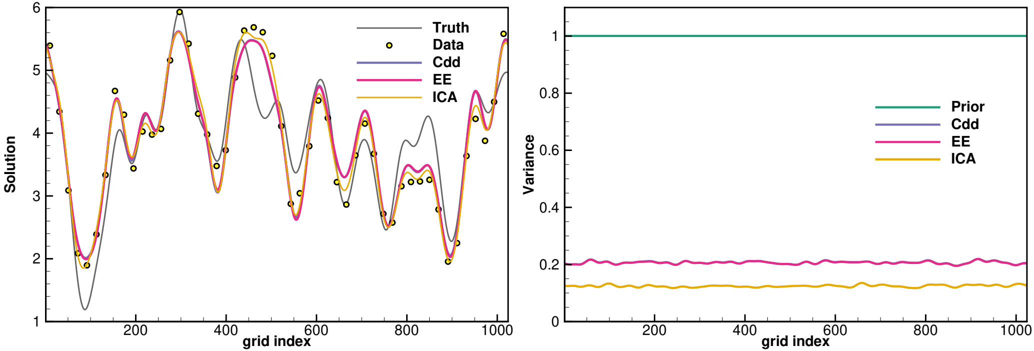
EnKF analysis with uncorrelated measurement errors





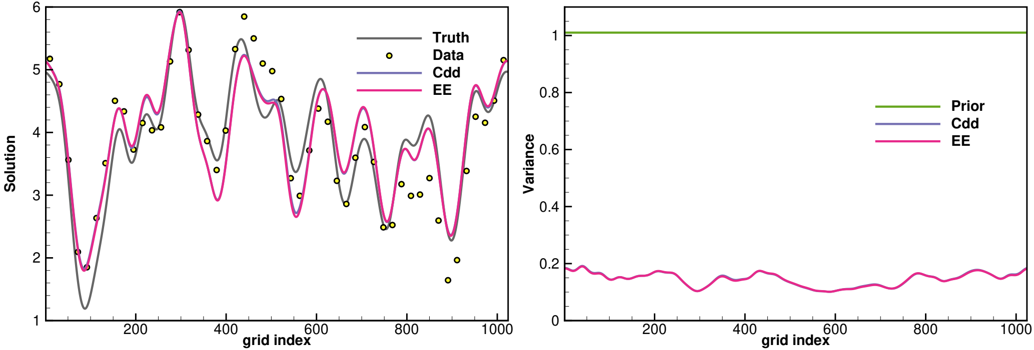
- Ensemble size $N = 2000$.
- Cdd is the solution with a full $\boldsymbol{C}_{dd}$.
- EE is the solution when using the measurement perturbations $\boldsymbol{E}$.
- Measurement error variance is 0.5.

EnKF analysis with correlated measurement errors



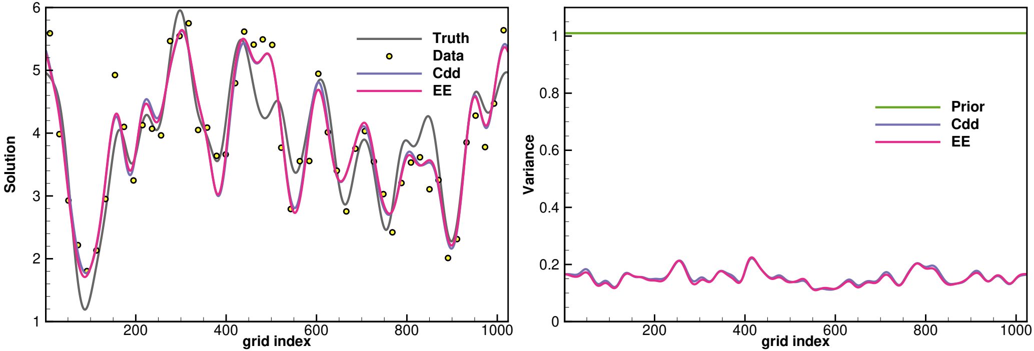
- Ensemble size $N = 2000$.
- Cdd is the solution with a full $\boldsymbol{C}_{dd}$.
- EE is the solution when using the measurement perturbations $\boldsymbol{E}$.
- ICA is inconsistent update erroneously assuming uncorrelated measurement errors.

EnKF analysis with smooth measurement errors



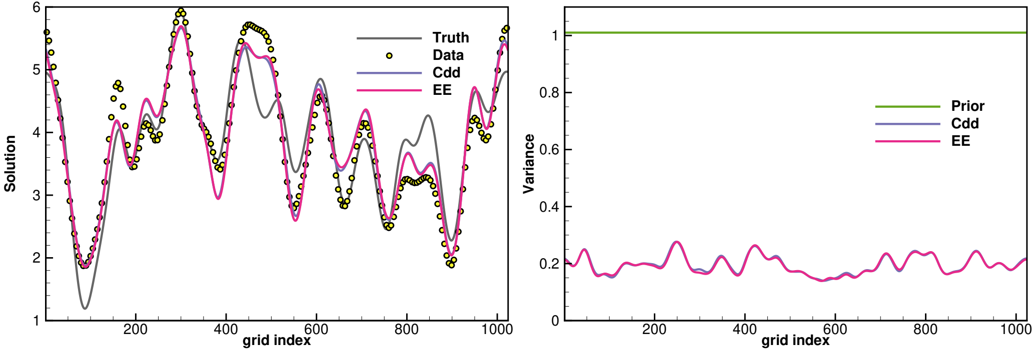
- Ensemble size $N = 100$, $\boldsymbol{E} \in \Re^{m \times 10N}$.
- Measurement error $r_d = 80$ while ensemble $r_d = 40$.
- Using $\boldsymbol{E}$ works perfectly.

EnKF analysis with non-smooth measurement errors



- Ensemble size $N = 100$, $\boldsymbol{E} \in \Re^{m \times 10N}$.
- Measurement error $r_d = 20$ while ensemble $r_d = 40$.
- Cannot represent scales in $\boldsymbol{E}$ shorter than $r_d = 40$.

EnKF analysis with many measurements



- Ensemble size $N = 100$, $\boldsymbol{E} \in \Re^{m \times 10N}$.
- Number of measurements 200.
- Correlated errors.

Approach

Simulate ensemble of correlated rate perturbations $\boldsymbol{E}_0$ and compute $\boldsymbol{D} = \boldsymbol{d} + \boldsymbol{E}_0$.

Iterate:

1. Run model ensemble using an ensemble of schedule files with perturbed rates.
2. Use $\boldsymbol{E}_0$ in analysis inversion

$$\boldsymbol{W}_{i+1} = \boldsymbol{W}_i - \gamma\Big(\boldsymbol{W}_i - \boldsymbol{S}_i^{\mathrm{T}}\left(\boldsymbol{S}_i\boldsymbol{S}_i^{\mathrm{T}} + \boldsymbol{E}_0\boldsymbol{E}_0\right)^{-1}\left(\boldsymbol{S}_i\boldsymbol{W}_i + \boldsymbol{D} - \boldsymbol{g}(\boldsymbol{X}_i, \boldsymbol{E}_i)\right)\Big)$$

3. Augment the rate perturbations to model state vector and update them

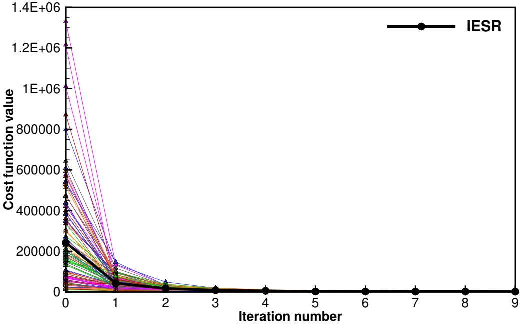
$$\begin{pmatrix}\boldsymbol{X}_i \\ \boldsymbol{E}_i\end{pmatrix} = \begin{pmatrix}\boldsymbol{X}_0 \\ \boldsymbol{E}_0\end{pmatrix}\Big(\boldsymbol{I} + \boldsymbol{W}_{i+1}/\sqrt{N-1}\Big).$$

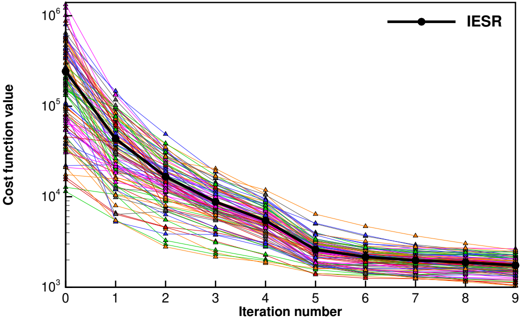
Cases

	Noise Model	C_{dd}	Schedule E_i	Update E_i
IES0	0	$\boldsymbol{I}$	no	no
IESnd	Red	$\boldsymbol{E}\boldsymbol{E}^{\mathrm{T}}$	no	no
IESR	Red	$\boldsymbol{E}\boldsymbol{E}^{\mathrm{T}}$	yes	yes

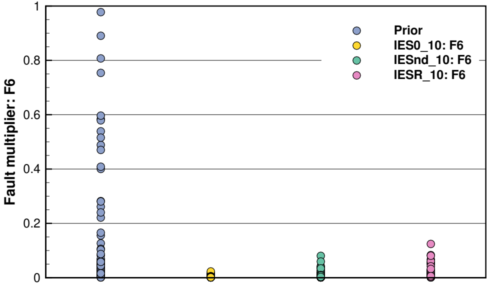
1. IES0 is the standard case with diagonal $\boldsymbol{C}_{dd} = \boldsymbol{I}$ and neglecting schedule forcing.
2. IESnd uses correlated errors through $\boldsymbol{C}_{dd} = \boldsymbol{E}\boldsymbol{E}^{\mathrm{T}}$, but neglects schedule forcing.
3. IESR uses $\boldsymbol{C}_{dd} = \boldsymbol{E}\boldsymbol{E}^{\mathrm{T}}$, updates $\boldsymbol{E}_i$, and includes schedule forcing.

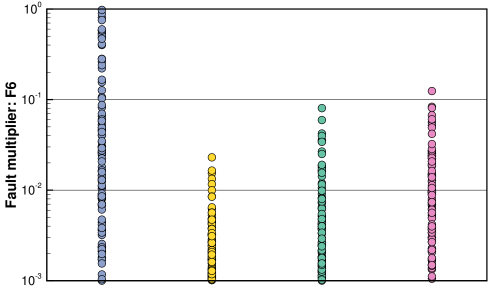
Ensemble of cost functions converges very fast

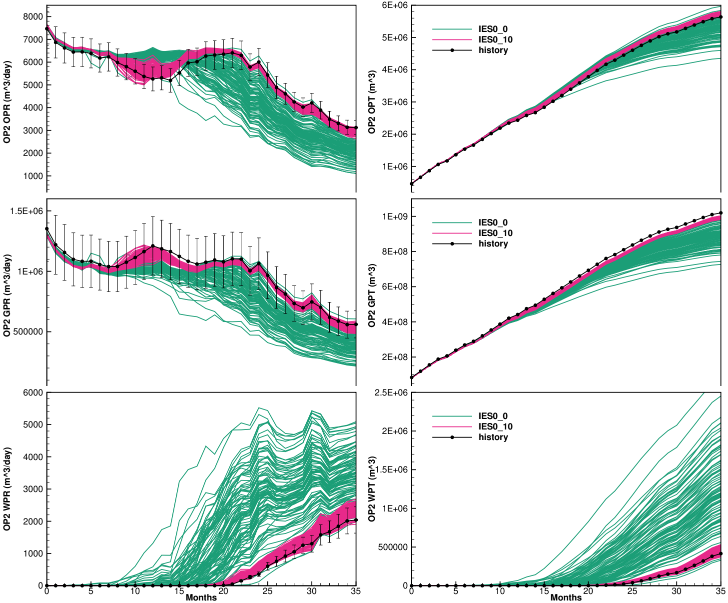




Fault multiplier F6



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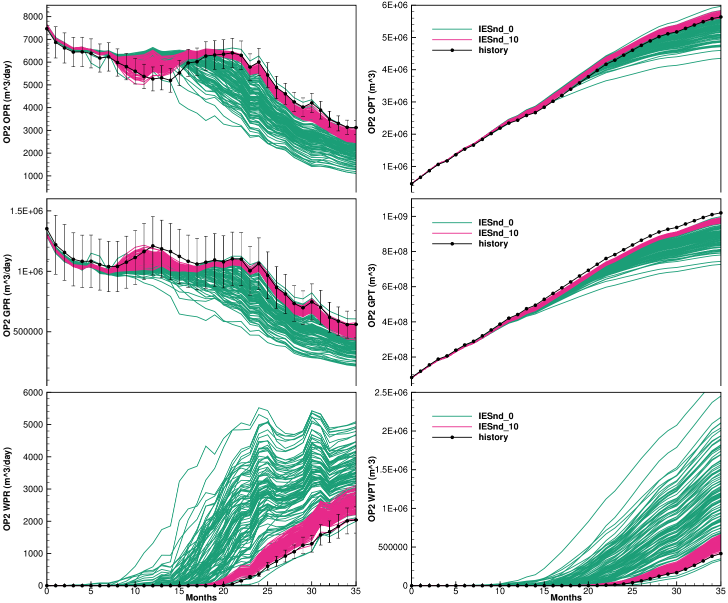
OP2 OPT (m^3)
OP2 GPR (m^3/day)
OP2 GPT (m^3)
OP2 WPR (m^3/day)
OP2 WPT (m^3)
IES0_0
IES0_10
history
Months



OP2 OPR (m^3/day)
OP2 OPT (m^3)
OP2 GPR (m^3/day)
OP2 GPT (m^3)
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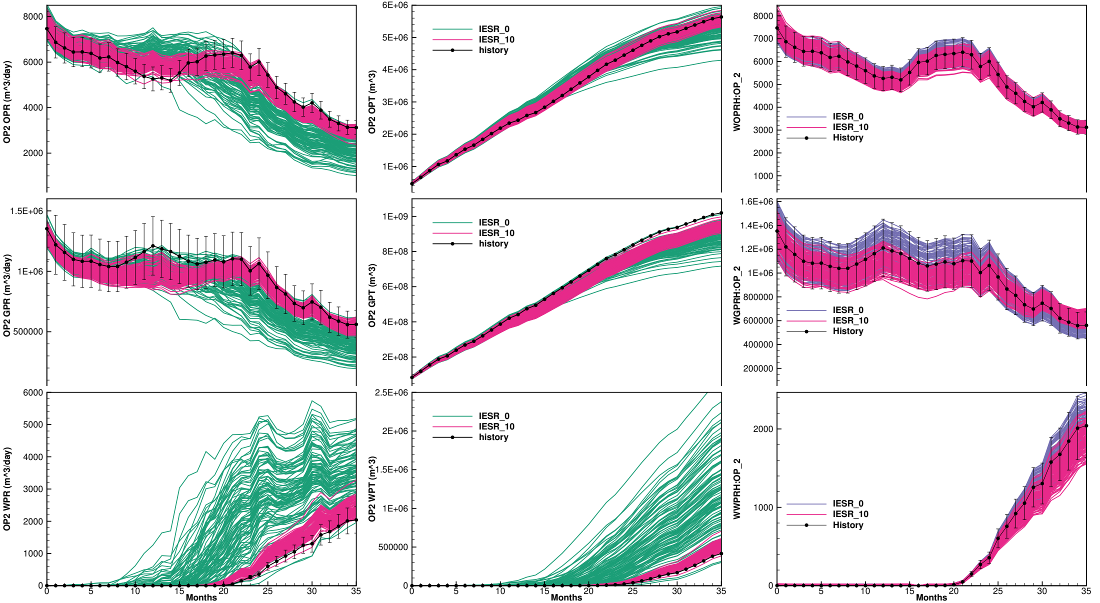
OP2 WPT (m^3)
IESnd_0
IESnd_10
history
Months
Months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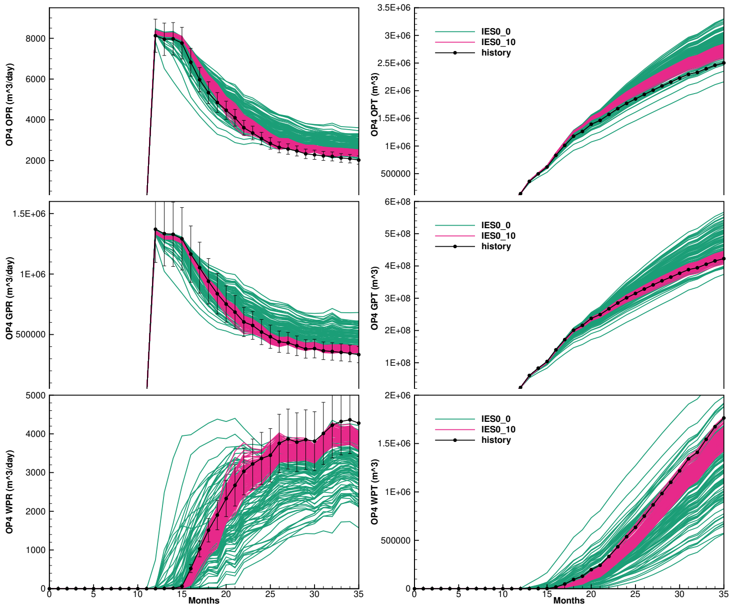
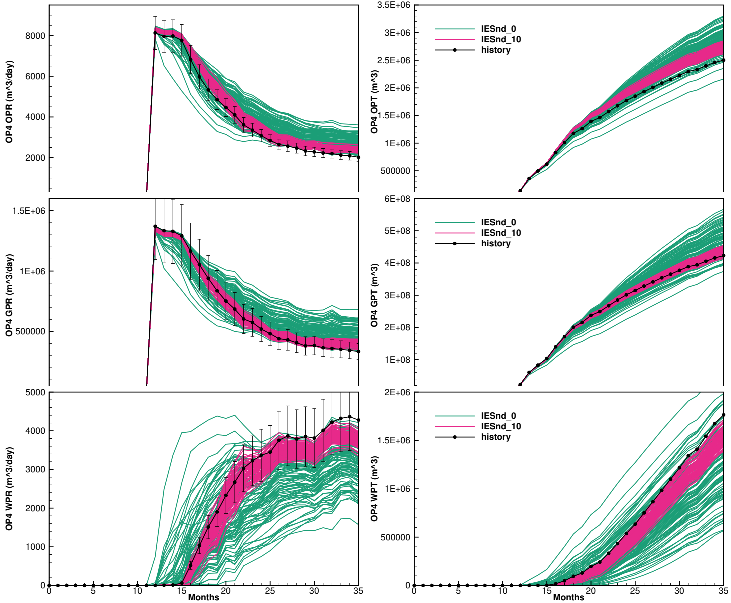
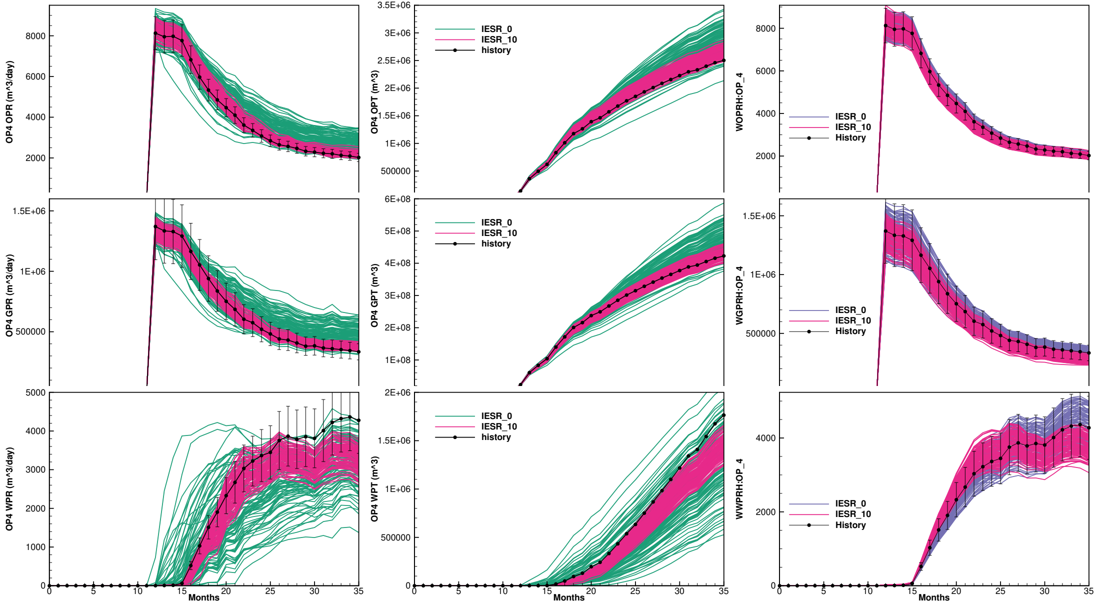
OP2 OPT (m^3)
WOPRH:OP_2
OP2 GPR (m^3/day)
OP2 GPT (m^3)
WGPRH:OP_2
OP2 WPR (m^3/day)
OP2 WPT (m^3)
WWPRH:OP_2
IESR_0
IESR_10
history
History
Months



OP4 OPR (m^3/day)
OP4 OPT (m^3)
OP4 GPR (m^3/day)
OP4 GPT (m^3)
OP4 WPR (m^3/day)
OP4 WPT (m^3)
IES0_0
IES0_10
history
Months
Months


OP4 OPR (m^3/day)
OP4 OPT (m^3)
OP4 GPR (m^3/day)
OP4 GPT (m^3)
OP4 WPR (m^3/day)
OP4 WPT (m^3)
IESnd_0
IESnd_10
history
Months
Months



OP4 OPR (m^3/day)
OP4 OPT (m^3)
WOPRH:OP_4
OP4 GPR (m^3/day)
OP4 GPT (m^3)
WGPRH:OP_4
OP4 WPR (m^3/day)
OP4 WPT (m^3)
WWPRH:OP_4
IESR_0
IESR_10
history
History
Months

Summary

- Discussed the formulation of the HM problem.
- Studied impact of correlated measurement errors on HM.
- Included historical rates with stochastic errors in simulations.
- Consistently updated stochastic rate errors.
- Used the new subspace EnRML algorithm.

$$\Downarrow$$

Consistent formulation of HM problem with more realistic error statistics.

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https://github.com/equinor/libres/tree/master/lib/analysis/modules

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Evensen, G., P. Raanes, A. Stordal, and J. Hove, Efficient implementation of an iterative ensemble smoother for data assimilation and reservoir history matching, *Frontiers in Applied Mathematics and Statistics*, *5*, 47, 2019.

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Geophysical monitoring of CO_2 sequestration in deep saline aquifers

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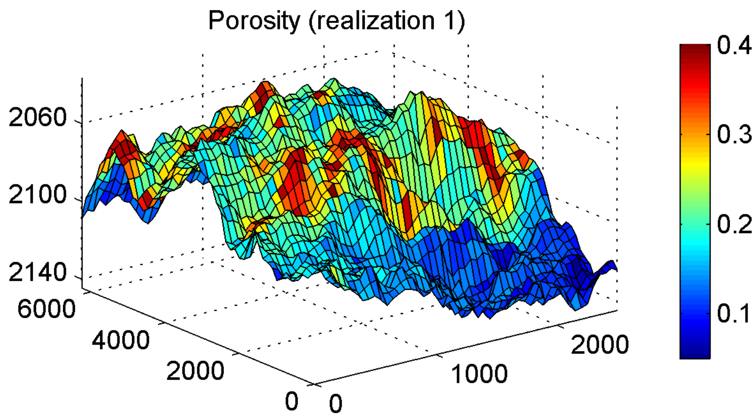
School of Energy Resources

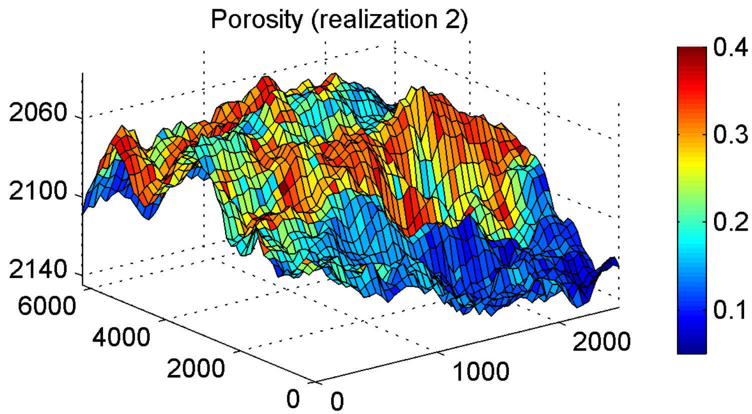
University of Wyoming

October, 2020

Motivation

- Dynamic model predictions (fluid flow simulations) are based on a static reservoir model.
- Static reservoir models are built using measured data at the well location and geophysical (seismic) measurements.
- Well data are sparse and geophysical data have low resolution, hence static reservoir models and dynamic model predictions are uncertain.





Content

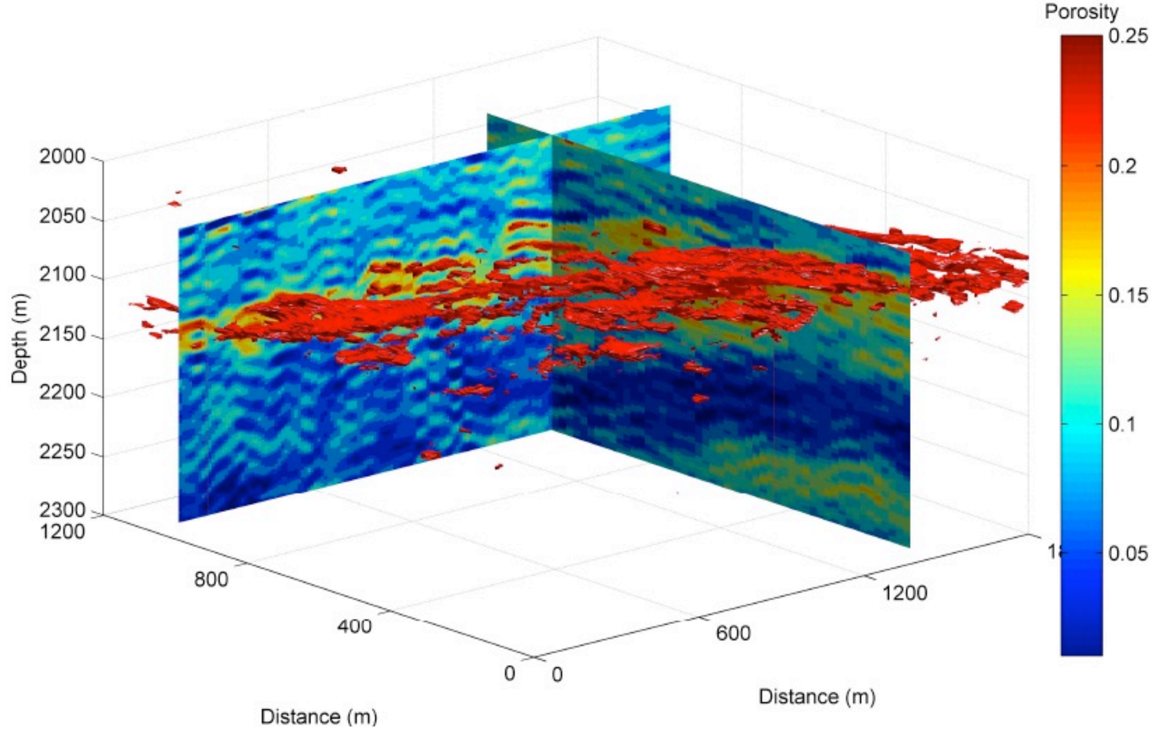
- **Introduction to reservoir geophysics**

- Ensemble-based methods:
  - Seismic inversion
  - Seismic history matching

- CO_2 sequestration

Reservoir geophysics

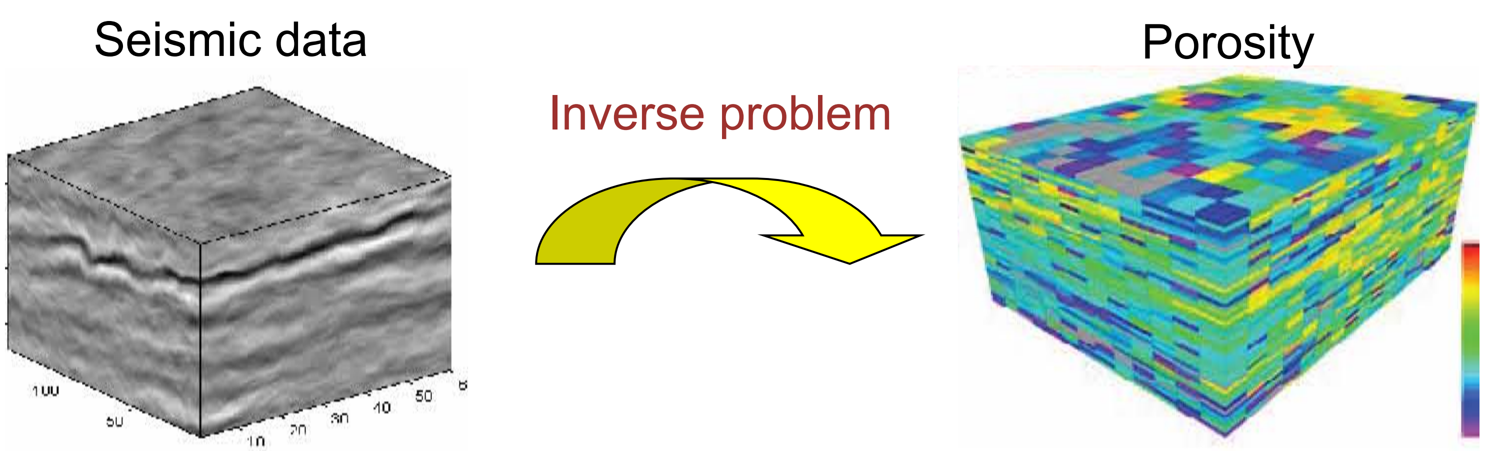
- In reservoir geophysics we aim to model rock properties: *porosity*, *lithology*, and *fluid saturations*.



Reservoir geophysics

Seismic inversion - Data: seismic amplitudes/traveltimes
Model parameters: elastic attributes

Petrophysical inversion - Data: elastic attributes
Model parameters: rock/fluid properties



Reservoir geophysics

- There are various approaches for ***quantitative estimation of reservoir properties*** from seismic data:
  - Deterministic methods
  - Probabilistic methods

- *Spatial variations* in reservoir properties and *inter-dependence* between different properties are complex to model.
- The ***probabilistic framework*** is ideally suited to model the uncertainty.

Bayesian inversion

- Goal: - Estimate reservoir properties **R**
  from seismic data **S**
  - Evaluate the model uncertainty

We estimate the posterior probability:

$$P(\mathbf{R} \mid \mathbf{S})$$

$$\mathbf{R} = [\phi, c, sw]$$

Porosity
Clay content
Water saturation

$$\mathbf{S} = [S(\theta_1), S(\theta_2), S(\theta_3)]$$

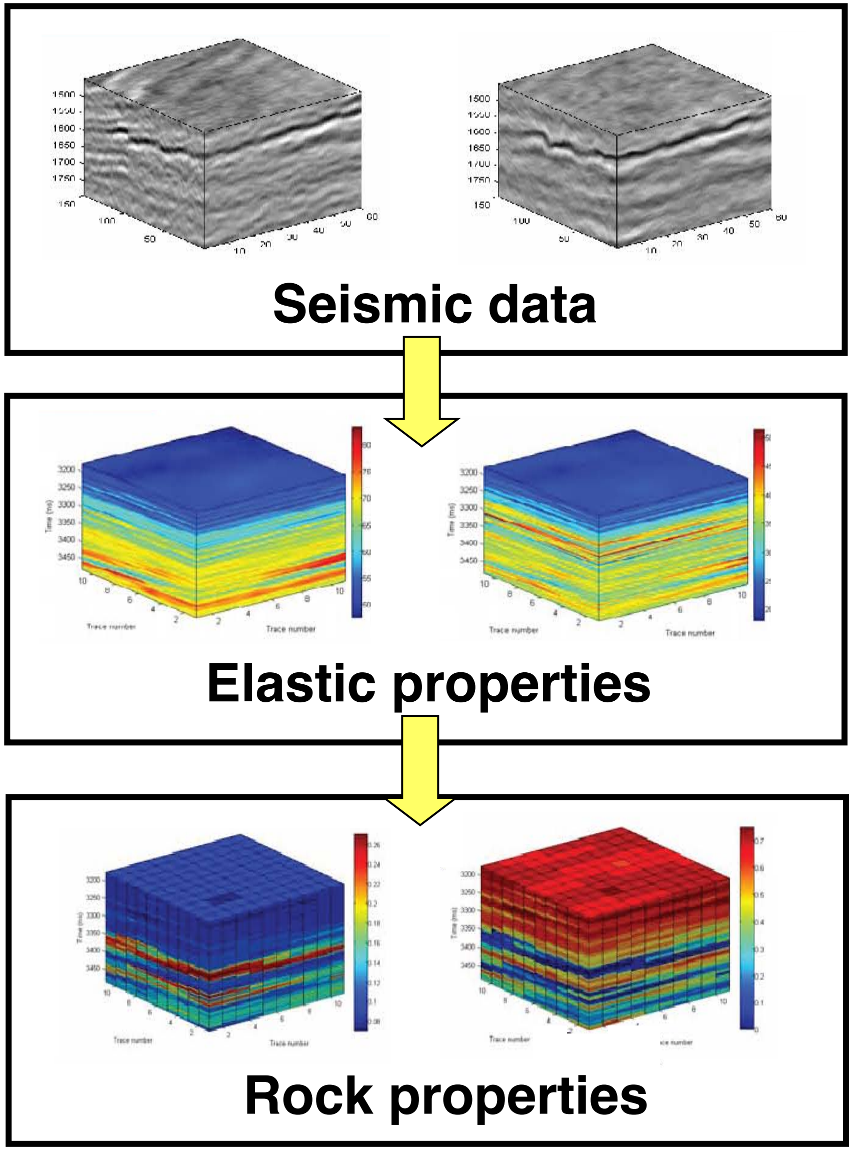
Partial-stack seismic data

Bayesian inversion

- Workflow:

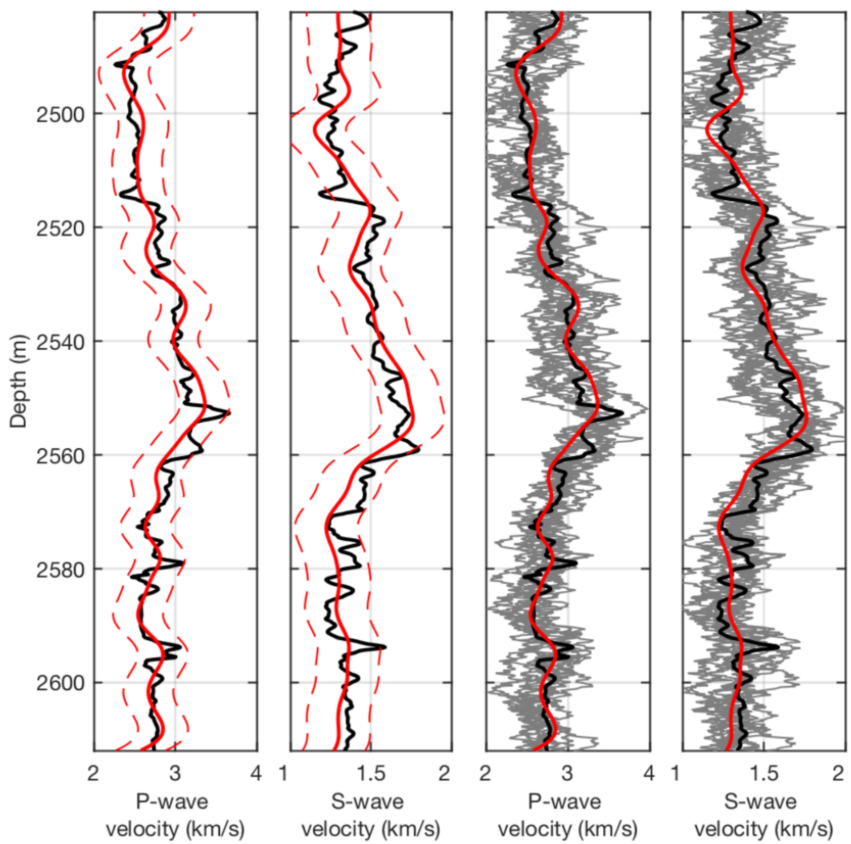
Bayesian seismic inversion
(e.g., Buland and Omre, 2003)

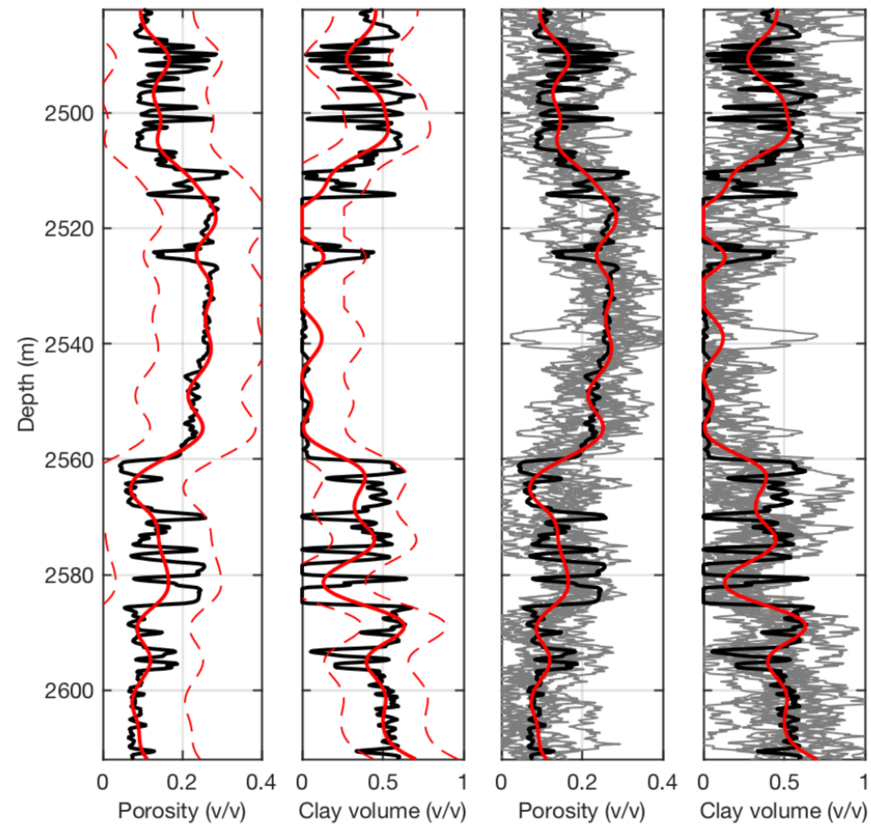
Bayesian petrophysical inversion
(e.g, Doyen, 2007)



Bayesian inversion

- Analytical vs numerical approaches





Bayesian geophysical inversion

- Seismic inversion
  - Log-Gaussian prior distribution – Linearized seismic model

    Buland and Omre, *Geophysics*, 2003

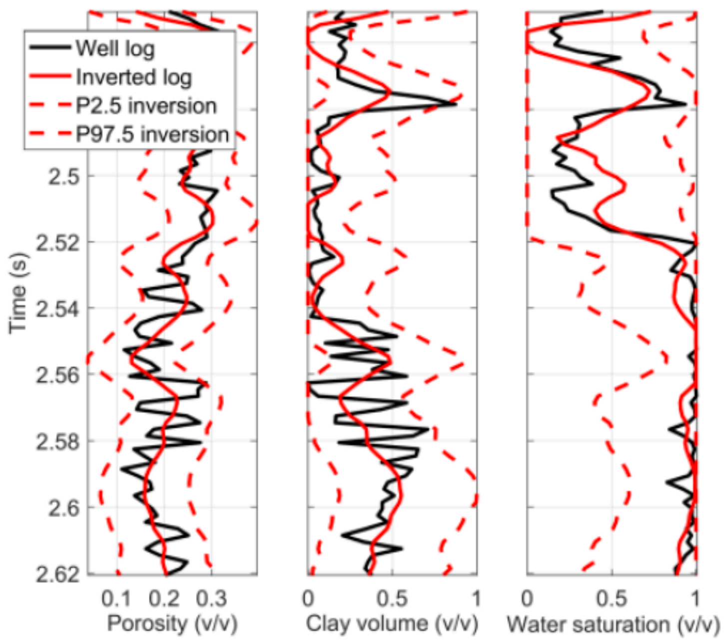
- Petrophysical inversion
  - Gaussian mixture prior distribution - Linearized rock physics model

    Grana and Della Rossa, *Geophysics*, 2010
  - Gaussian mixture prior distribution + Markov chain (facies) - Linearized rock physics model

    Grana, Fjeldstad, and Omre, *Math. Geo.*, 2017

Bayesian inversion

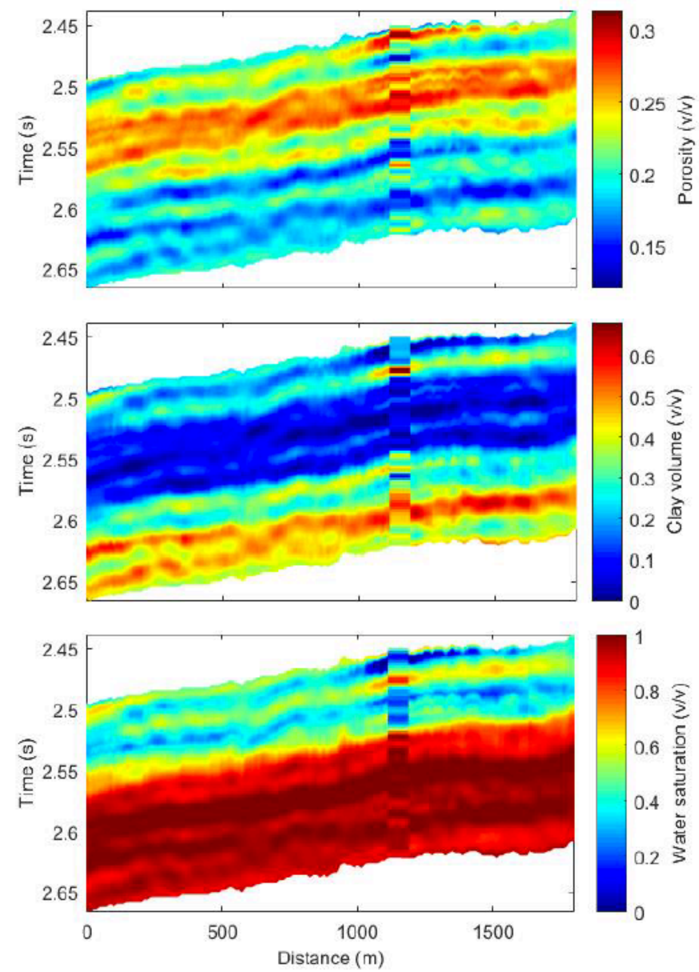
- Linearized forward model
- Real data example



Well log

Estimated log (Posterior mean)

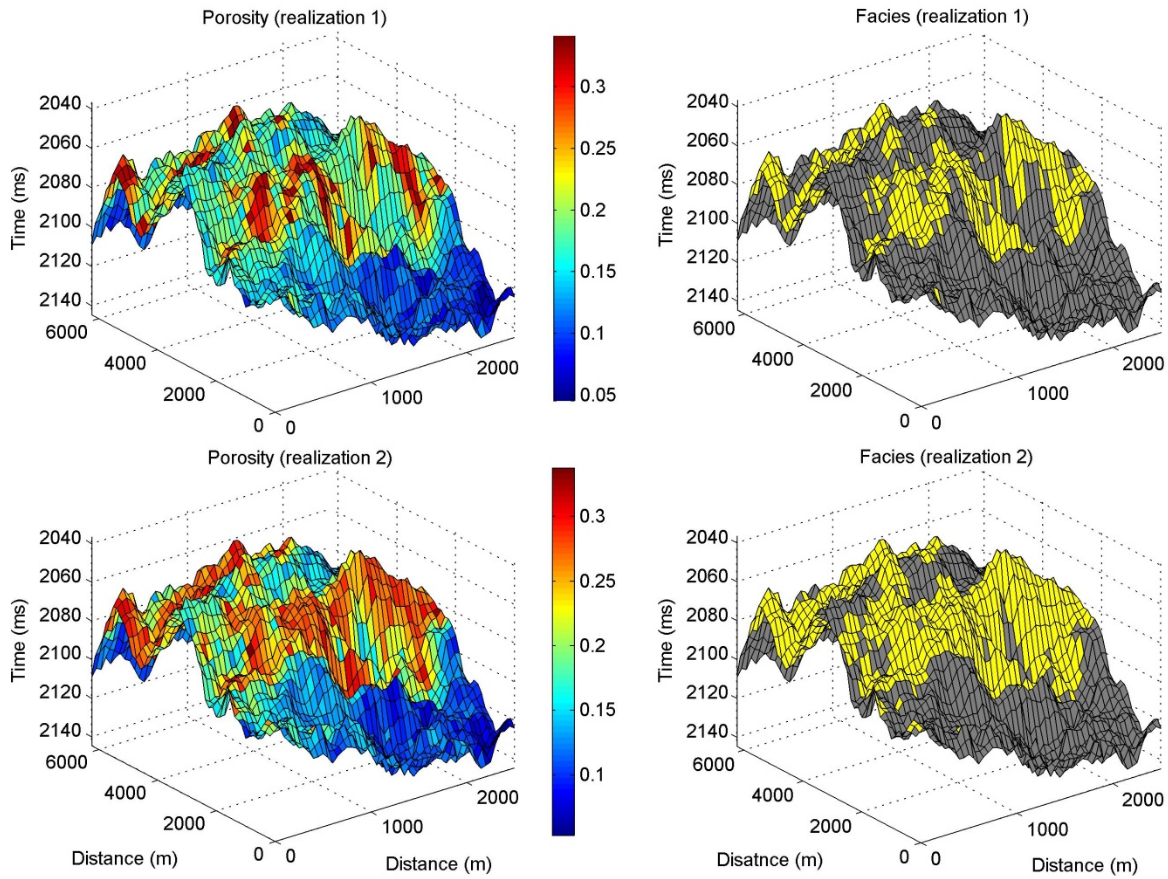
95% confidence interval (--)



Lang and Grana, 2017

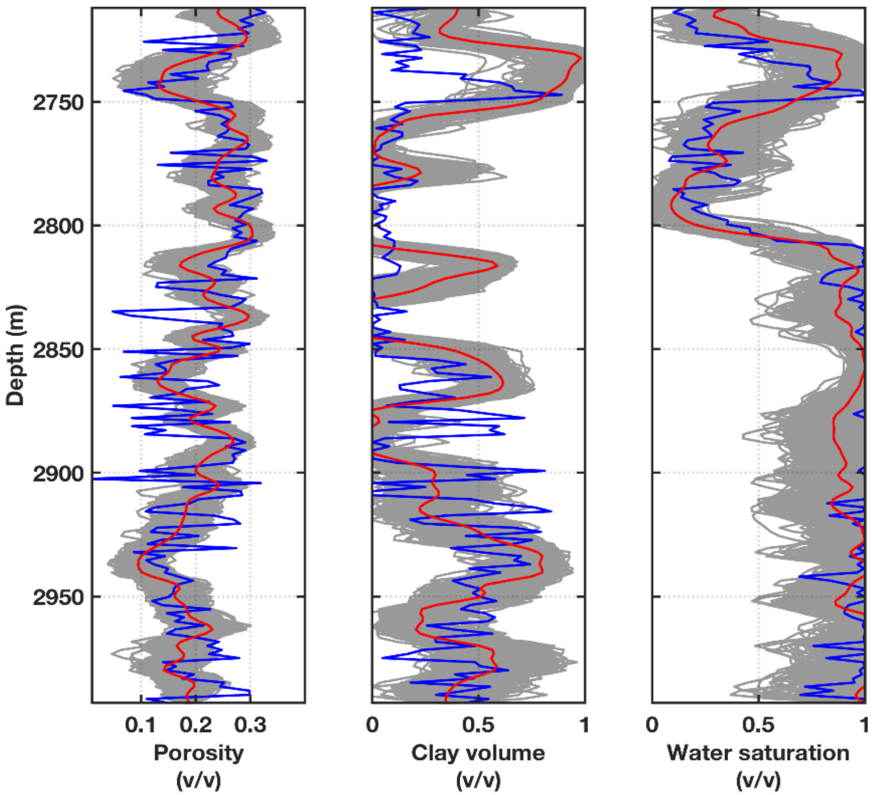
Geostatistical methods

- Multiple reservoir model realizations
- Uncertainty quantification

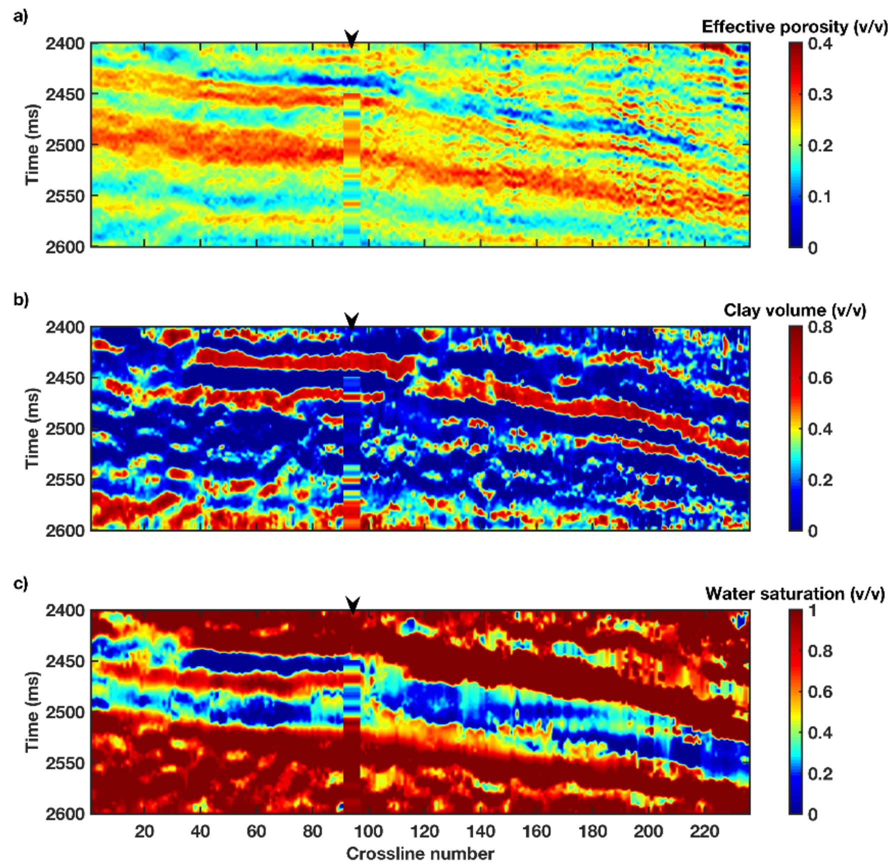


Geostatistical methods

- Stochastic optimization method (ES-MDA)
- Seismic and rock physics non-linear model



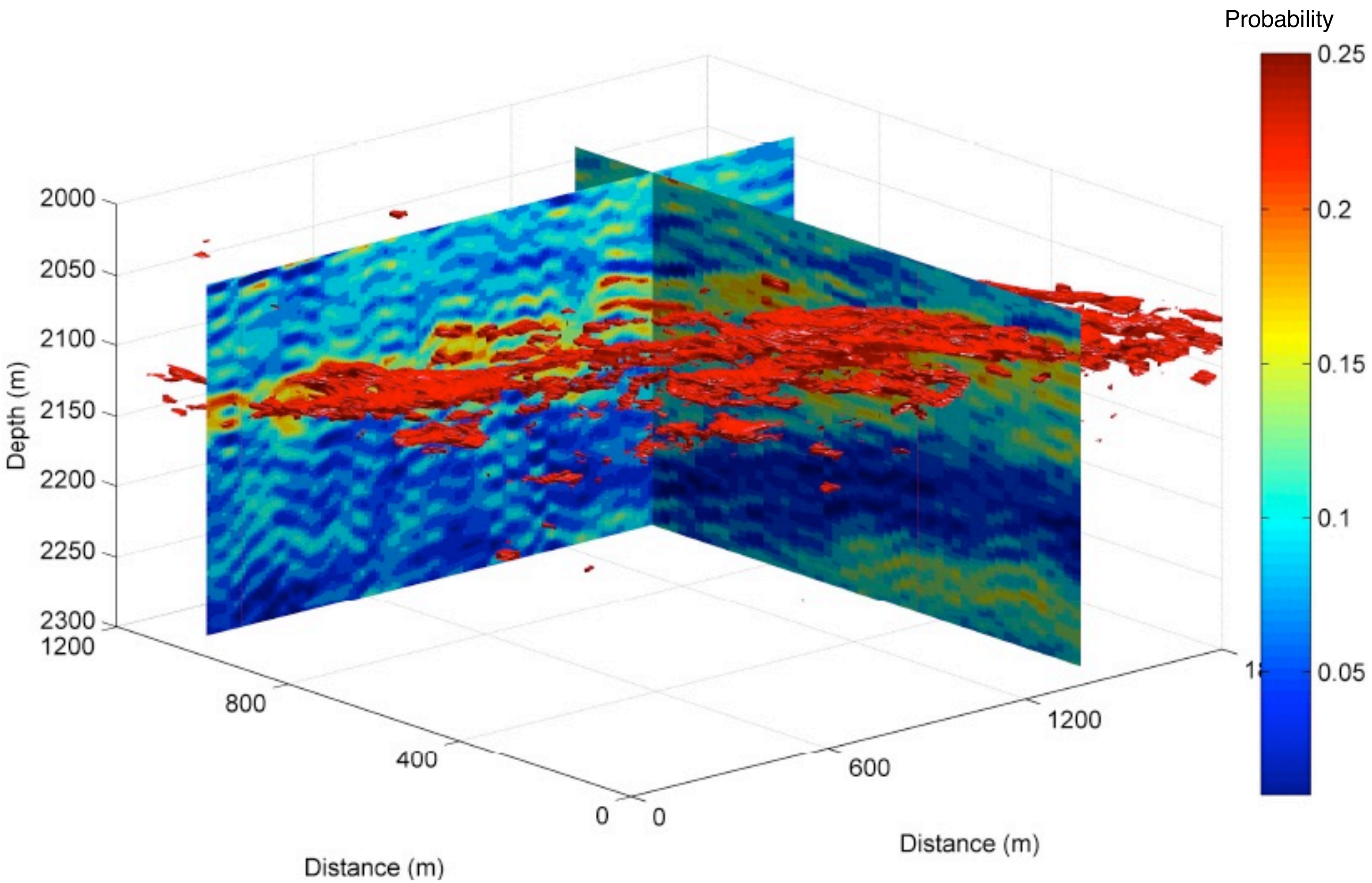
Well log data
Estimated model (Posterior mean)
Stochastic realizations



Liu and Grana, 2018

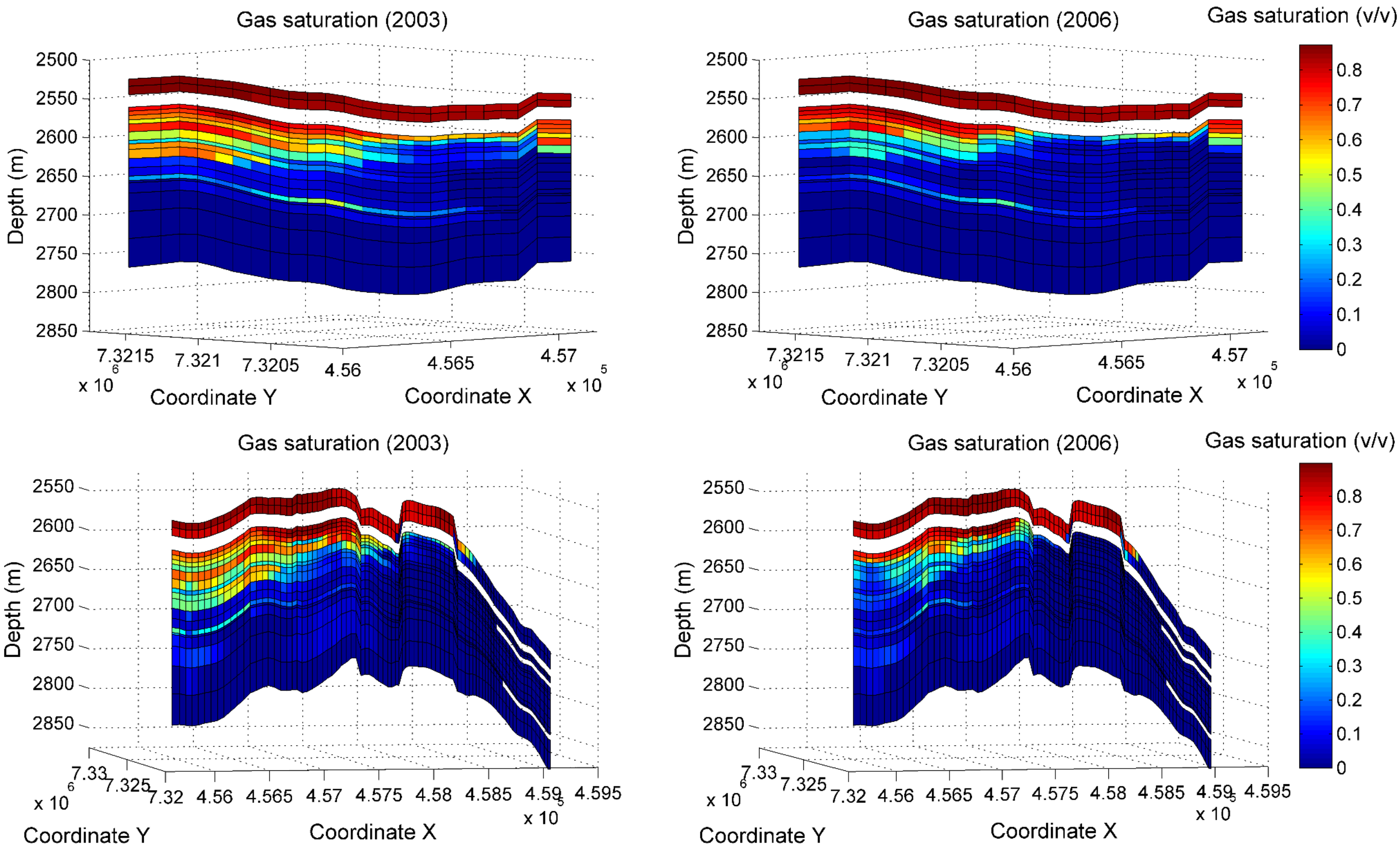
Example 1: Goliat – Barents Sea

Isoprobability surface of 70% probability of hydrocarbon sand



Grana and Della Rossa, 2010

Example 2: Norne – North Sea (4D)



Content

- Introduction to reservoir geophysics
- **Ensemble-based methods:**
  - Seismic inversion
  - Seismic history matching
- CO_2 sequestration

Ensemble-based methods

Find the unknown model parameters $m \in \mathcal{M}$ from noisy observations $d \in \mathcal{D}$

$$d = \mathcal{G}(m) + e$$

- $m \in \mathcal{M}$ model parameter vector / parameter function
- $\mathcal{G}: \mathcal{M} \rightarrow \mathcal{D}$ forward response operator ($\mathcal{M}$ and $\mathcal{D}$ are separable Hilbert spaces)
- d output / observations
- e measurement errors usually assumed to be Gaussian $\mathcal{N}(0, \Sigma)$
- Evaluation of $\mathcal{G}$ often expensive

Ensemble-based methods

Challenges for application to seismic inversion

Non-linear forward models

- Exact Zoeppritz equations
- Rock physics models
- Fluid flow simulation

Uncertainty quantification

- Bandlimited geophysical data
- Noisy measurement
- Imperfect models

High-dimensional data

- e.g. 3D seismic data
- Computationally prohibitive
- Ensemble collapse

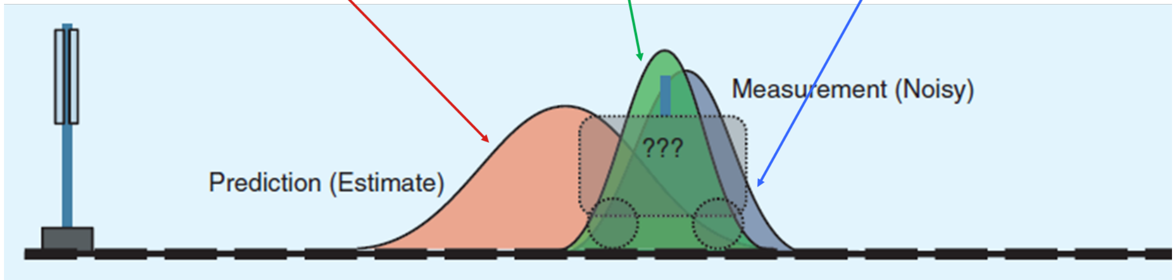
Ensemble-based methods

Bayesian formulation

$$f_{m|d}(\boldsymbol{m}|\boldsymbol{d}) = \frac{f_{d|m}(\boldsymbol{d}|\boldsymbol{m}) f_m(\boldsymbol{m})}{f_d(\boldsymbol{d})}$$

$f_m(\boldsymbol{m}) = \mathcal{N}(\boldsymbol{m}; \boldsymbol{\mu_m}, \boldsymbol{C_m})$

$f_{d|m}(\boldsymbol{d}|\boldsymbol{m}) = \mathcal{N}(\boldsymbol{d}|\boldsymbol{m}; 0, \boldsymbol{C_d})$



(Faragher, 2012)

Posterior distribution

Prior

Likelihood

$$\begin{aligned} f_{m|d}(\boldsymbol{m}|\boldsymbol{d}) &= \beta \exp\left\{-\frac{1}{2}(\boldsymbol{m}-\boldsymbol{\mu_m})^T \boldsymbol{C_m}^{-1}(\boldsymbol{m}-\boldsymbol{\mu_m})\right\} \times \exp\left\{-\frac{1}{2}(\boldsymbol{Gm}-\boldsymbol{d})^T \boldsymbol{C_d}^{-1}(\boldsymbol{Gm}-\boldsymbol{d})\right\} \\ &= \beta \exp\left\{-\left[\frac{1}{2}(\boldsymbol{m}-\boldsymbol{\mu_m})^T \boldsymbol{C_m}^{-1}(\boldsymbol{m}-\boldsymbol{\mu_m}) + \frac{1}{2}(\boldsymbol{Gm}-\boldsymbol{d})^T \boldsymbol{C_d}^{-1}(\boldsymbol{Gm}-\boldsymbol{d})\right]\right\} \\ &= \beta \exp\{-O(\boldsymbol{m})\} \end{aligned}$$

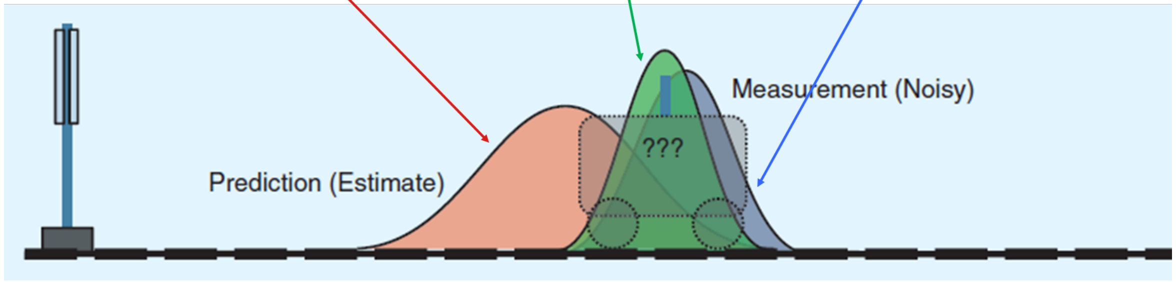
Ensemble-based methods

Bayesian formulation

$$f_{m|d}(\boldsymbol{m}|\boldsymbol{d}) = \frac{f_{d|m}(\boldsymbol{d}|\boldsymbol{m}) f_m(\boldsymbol{m})}{f_d(\boldsymbol{d})}$$

$$f_m(\boldsymbol{m}) = \mathcal{N}(\boldsymbol{m}; \boldsymbol{\mu_m}, \boldsymbol{C_m})$$

$$f_{d|m}(\boldsymbol{d}|\boldsymbol{m}) = \mathcal{N}(\boldsymbol{d}|\boldsymbol{m}; 0, \boldsymbol{C_d})$$



(Faragher, 2012)

Maximum a posterior

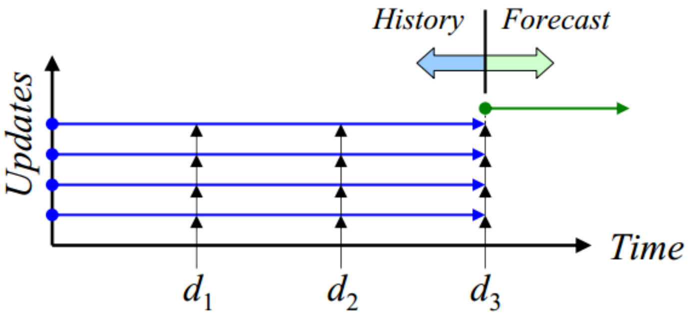
$$\boldsymbol{m}_{MAP} = \arg\min_{m} O(\boldsymbol{m}) = \boldsymbol{\mu_{m|d}} = \boldsymbol{\mu_m} + \boldsymbol{K}(\boldsymbol{d} - \boldsymbol{G}\boldsymbol{\mu_m})$$

$$\boldsymbol{K} = \boldsymbol{C_m}\boldsymbol{G}^T(\boldsymbol{G}\boldsymbol{C_m}\boldsymbol{G}^T + \boldsymbol{C_d})^{-1}$$

$$\boldsymbol{C_{m|d}} = \boldsymbol{C_m} - \boldsymbol{K}\boldsymbol{G}\boldsymbol{C_m}$$

Ensemble-based methods

Ensemble Smoother with Multiple Data Assimilation (ES-MDA)



$$\boldsymbol{m}_j^u = \boldsymbol{m}_j^p + \widetilde{\boldsymbol{K}}\left(\widetilde{\boldsymbol{d}}_j - \boldsymbol{d}_j^p\right)$$

$$\widetilde{\boldsymbol{K}} = \boldsymbol{C}_{\boldsymbol{md}}^p\left(\boldsymbol{C}_{\boldsymbol{dd}}^p + \boldsymbol{C}_{\boldsymbol{d}}\right)^{-1}$$

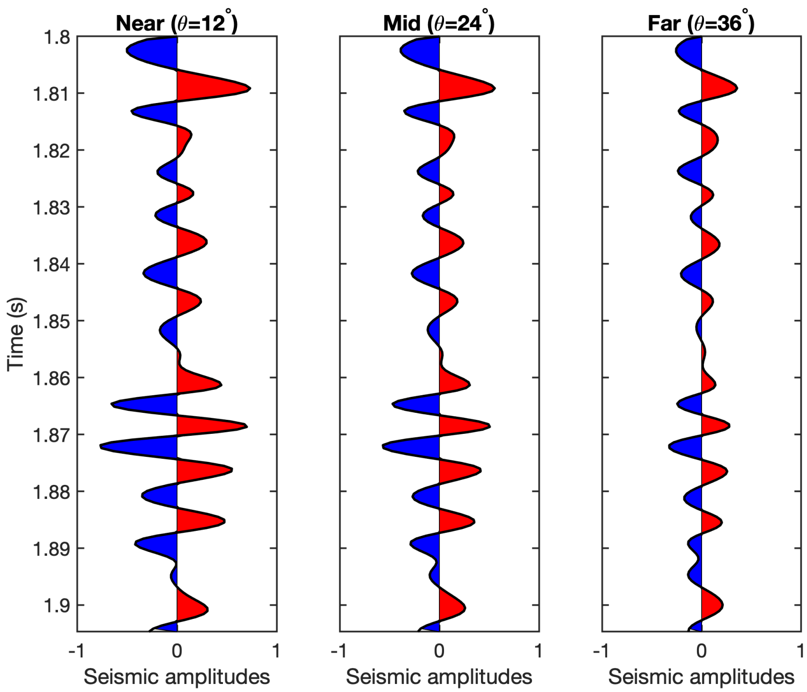
$$\widetilde{\boldsymbol{C}}_{\boldsymbol{md}}^p = \frac{1}{N_e - 1}\sum_{i=1}^{N_e}(\boldsymbol{m}_j^p - \overline{\boldsymbol{m}}^p)(\boldsymbol{d}_j^p - \overline{\boldsymbol{d}}^p)^T = \boldsymbol{C}_{\boldsymbol{m}}\boldsymbol{G}^T$$

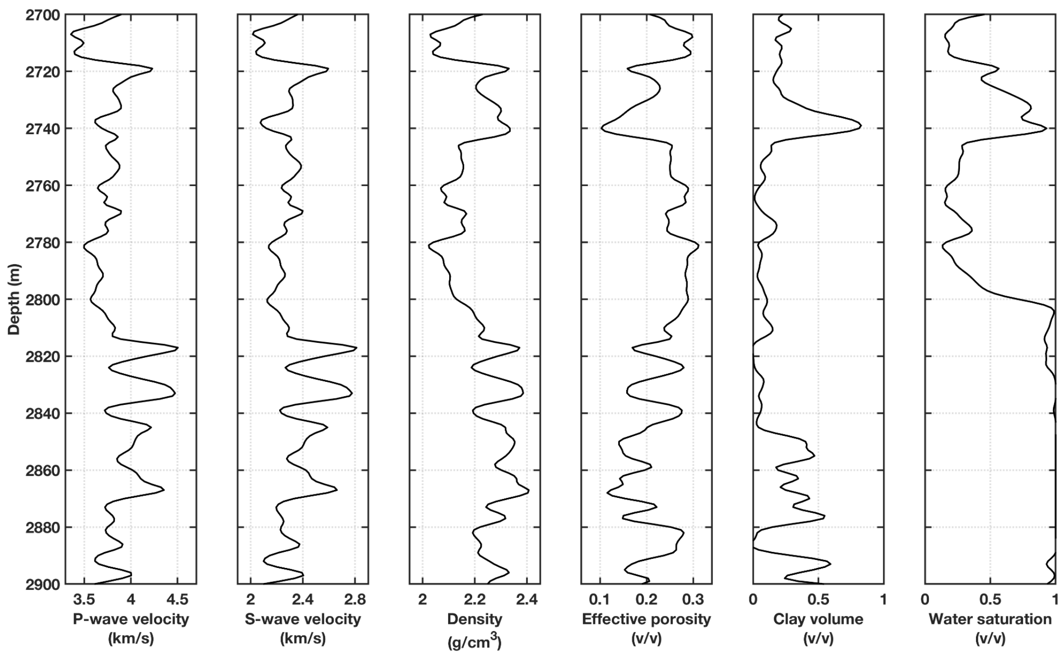
$$\widetilde{\boldsymbol{C}}_{\boldsymbol{dd}}^p = \frac{1}{N_e - 1}\sum_{i=1}^{N_e}(\boldsymbol{d}_j^p - \overline{\boldsymbol{d}}^p)(\boldsymbol{d}_j^p - \overline{\boldsymbol{d}}^p)^T = \boldsymbol{G}\boldsymbol{C}_{\boldsymbol{m}}\boldsymbol{G}^T$$

- Simultaneously assimilate all the observations available
- ES faster and easier to implement than EnKF
- To guarantee the convergence, the model updating is performed multiple times
- EnKF and ES are effectively the same as updating each ensemble member by doing one iteration of the Gauss-Newton method using the same average sensitivity matrix for all ensemble members.

Ensemble-based seismic inversion: example

Measured dataset at the well location





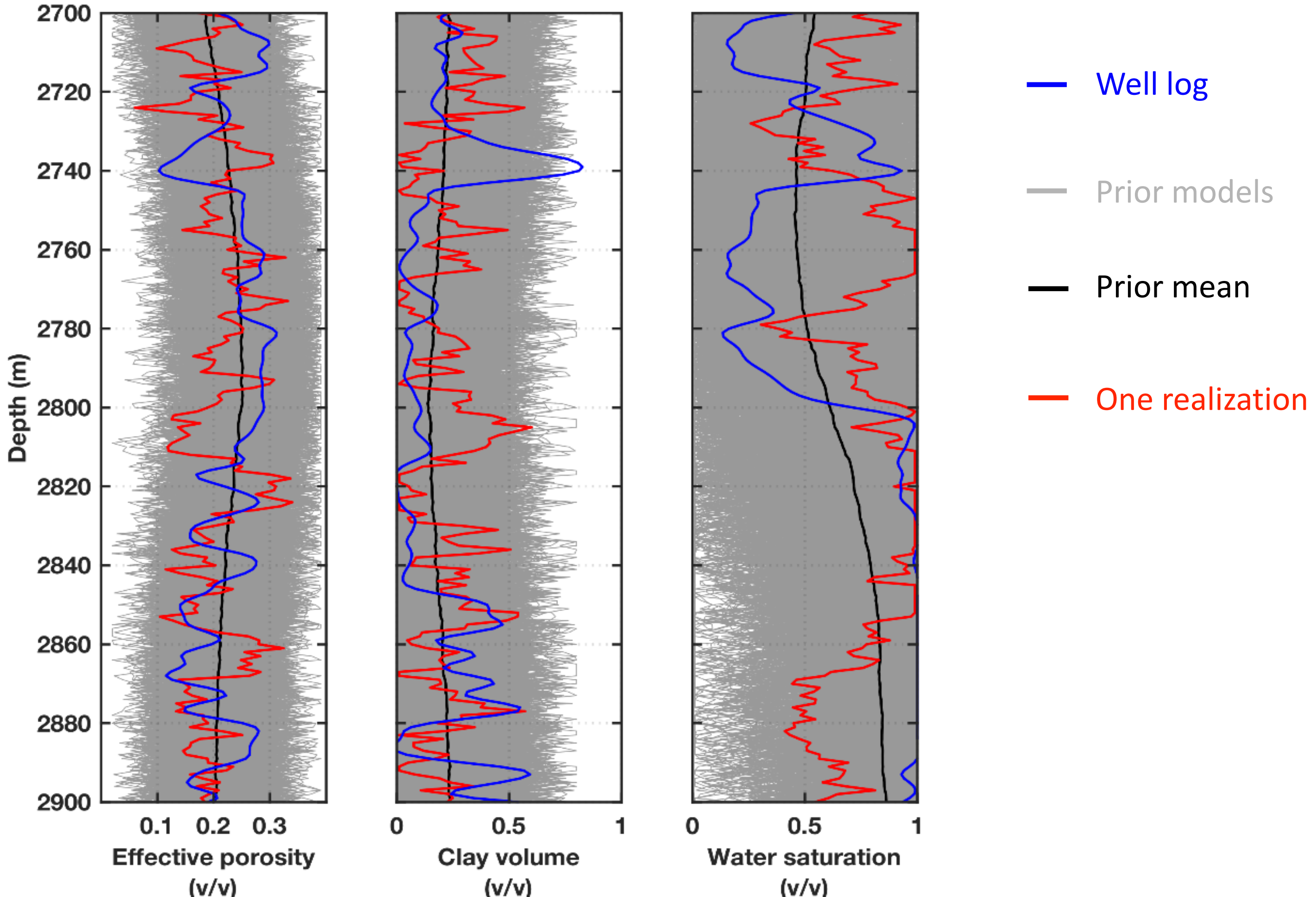
Pre-stack seismic response

Elastic attributes

Petrophysical properties

Ensemble-based seismic inversion: example

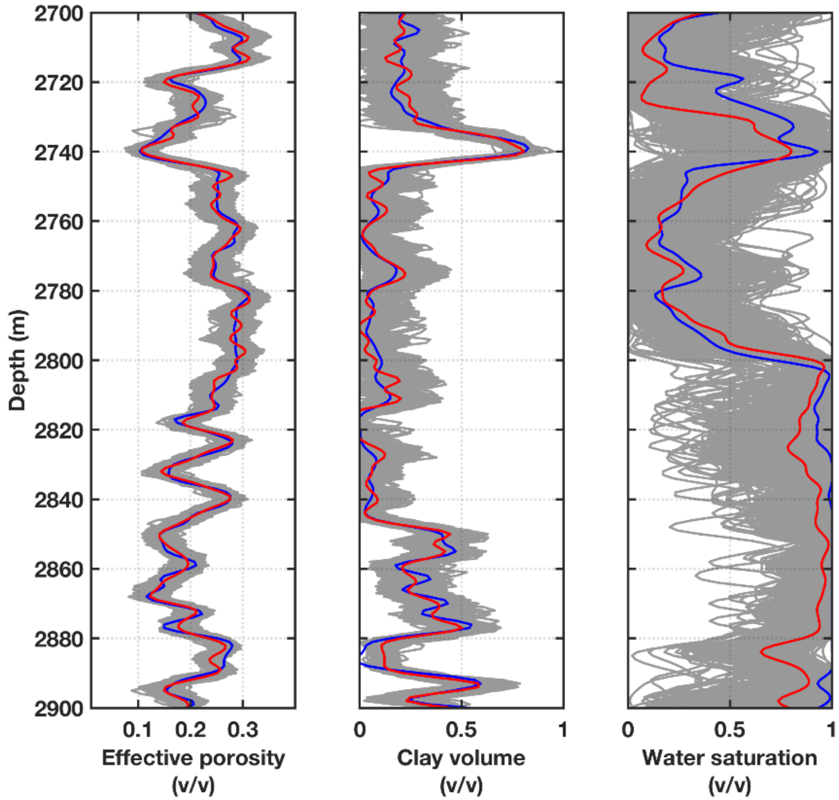
Prior Models



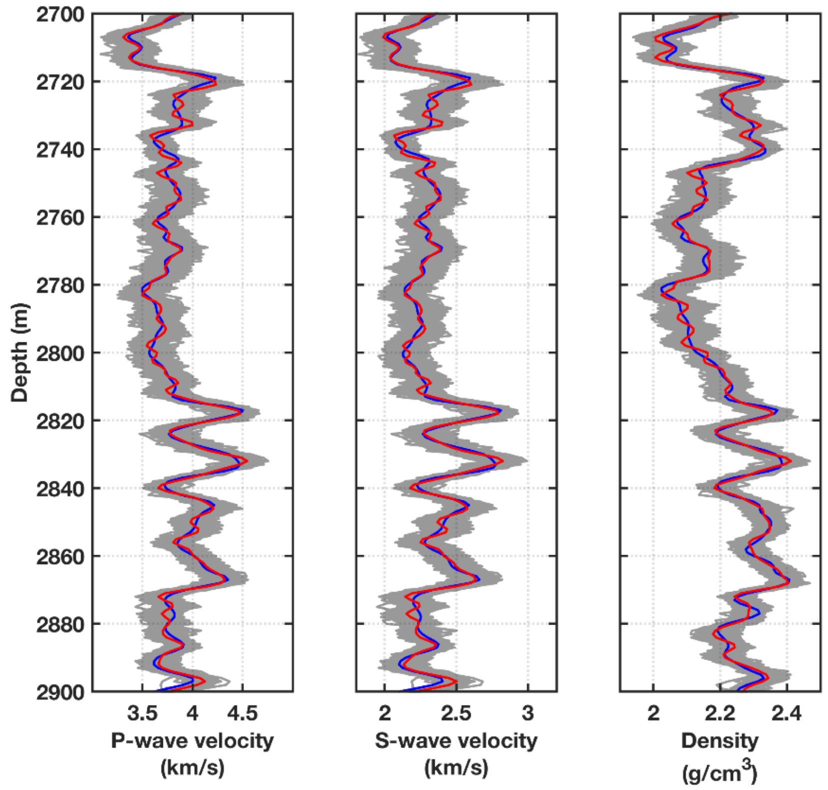
Ensemble-based seismic inversion: example

Posterior Models

Posterior petrophysical models



Posterior elastic models



Well log   Post. models   Post. mean

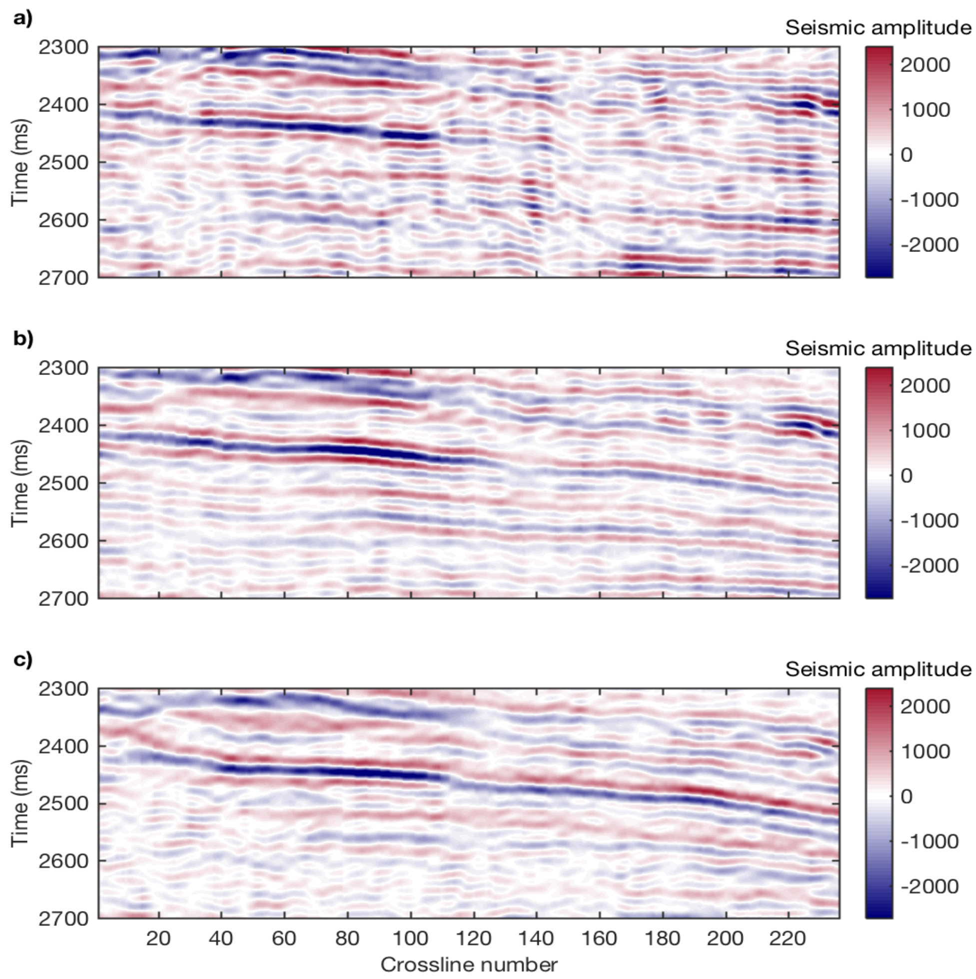
Ensemble-based seismic inversion: example

Case history: Norne field

Near stack (10^o)

Mid stack (23^o)

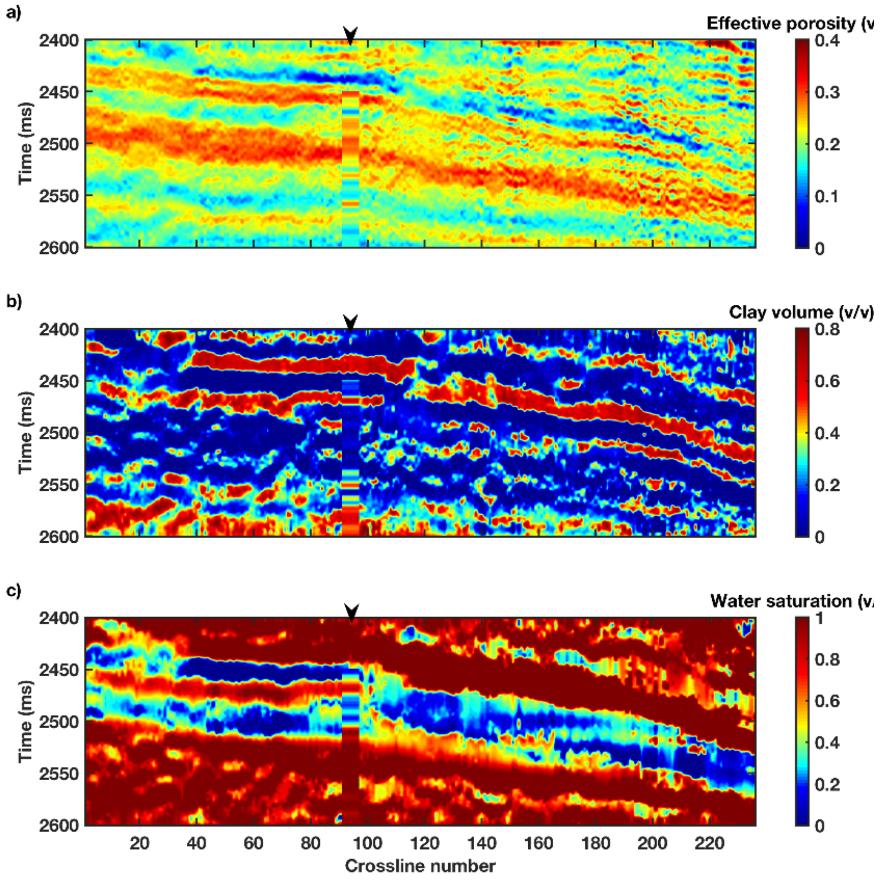
Far stack (35^o)



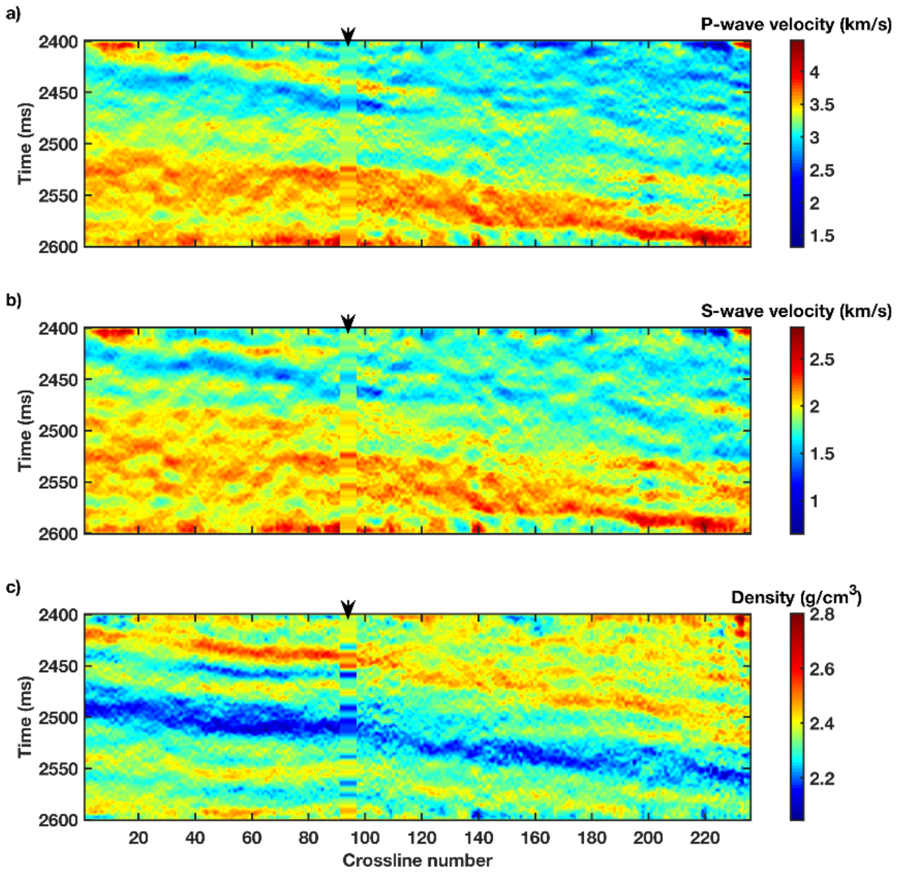
Ensemble-based seismic inversion: example

Case history: Norne field

Posterior mean of petrophysical models



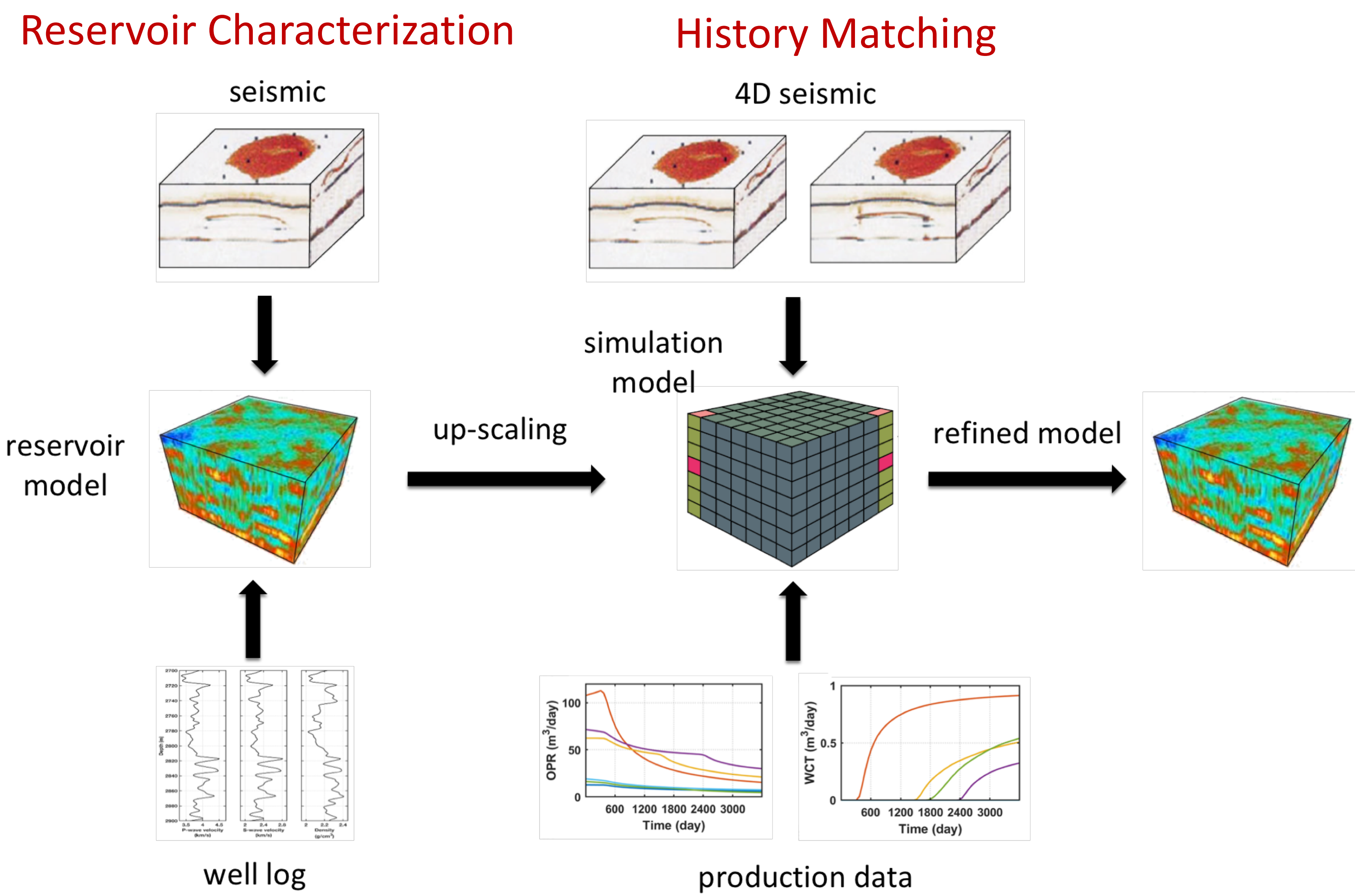
Posterior mean of elastic models



Dimensionality reduction

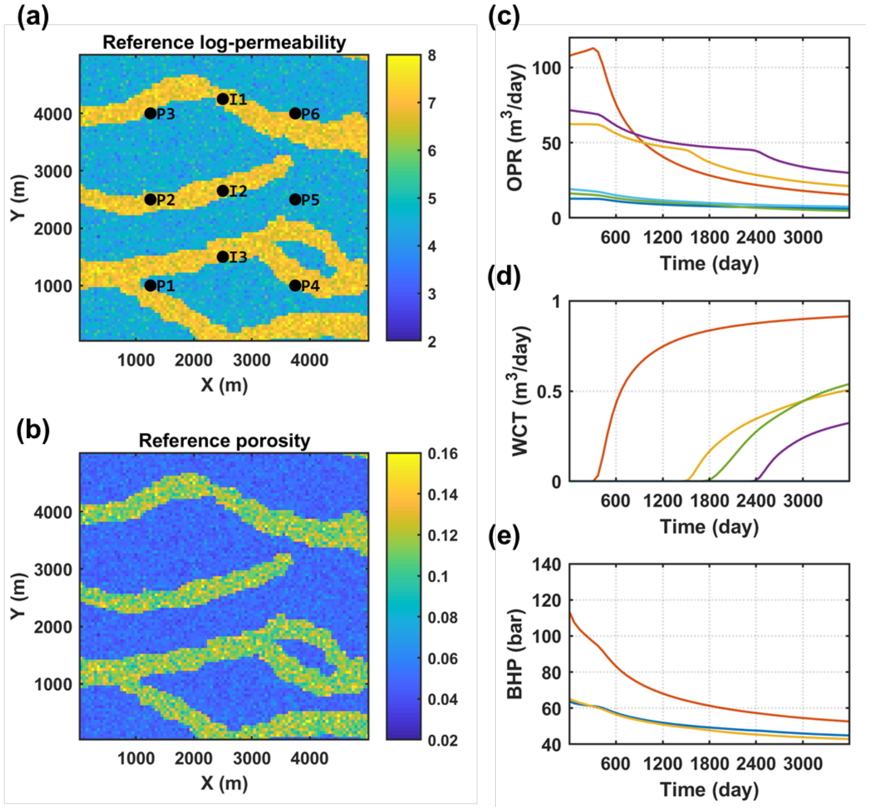
- The number of observations are much larger than the number of simulated models
- The forward modeling is often a highly time-consuming procedures
- How to avoid ensemble collapse due to the big size of seismic data?
  - Covariance localization
  - Data order reduction
    - SVD
    - DEIM
    - DCAE

Seismic history matching



Seismic history matching

- Goal: Estimation of porosity and permeability
- Method: Ensemble Smoother MDA

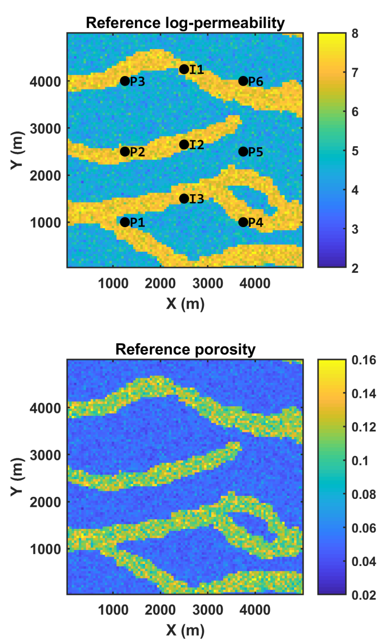


True model   Production data

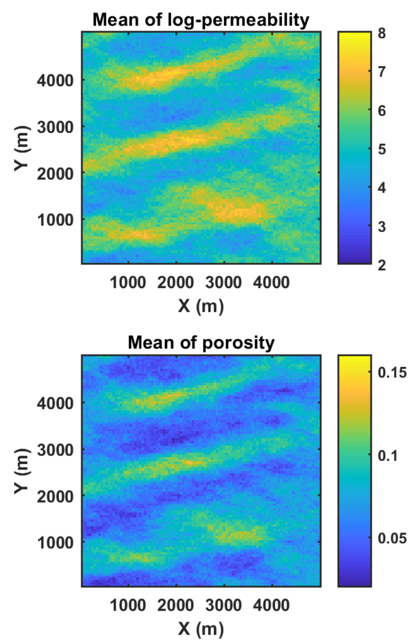
Seismic history matching

Results - Production data only

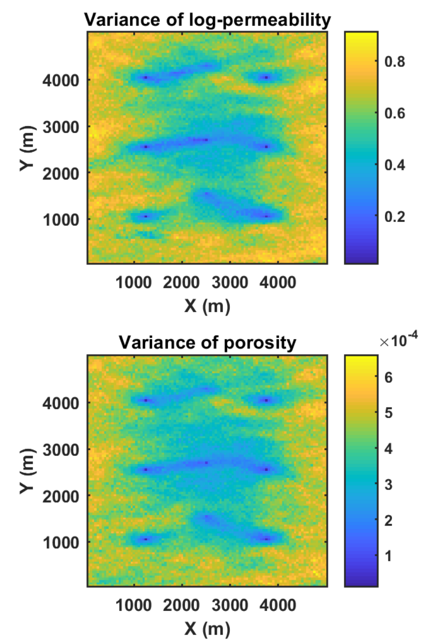
Only captures the trend near the well locations



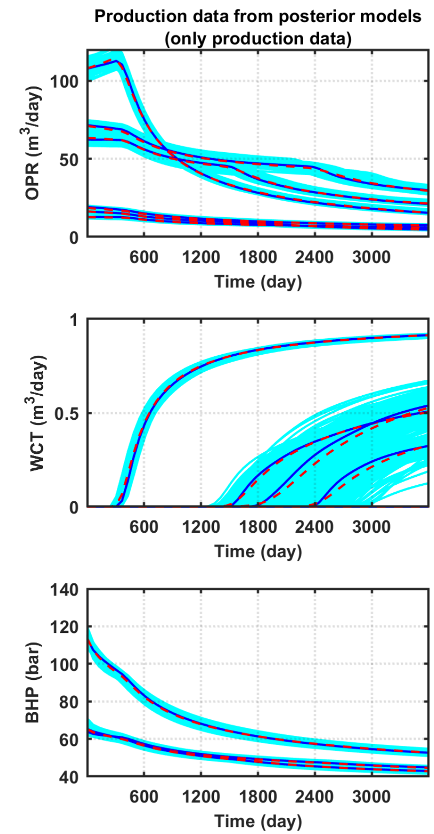
Reference Model



Posterior Mean



Posterior Variance



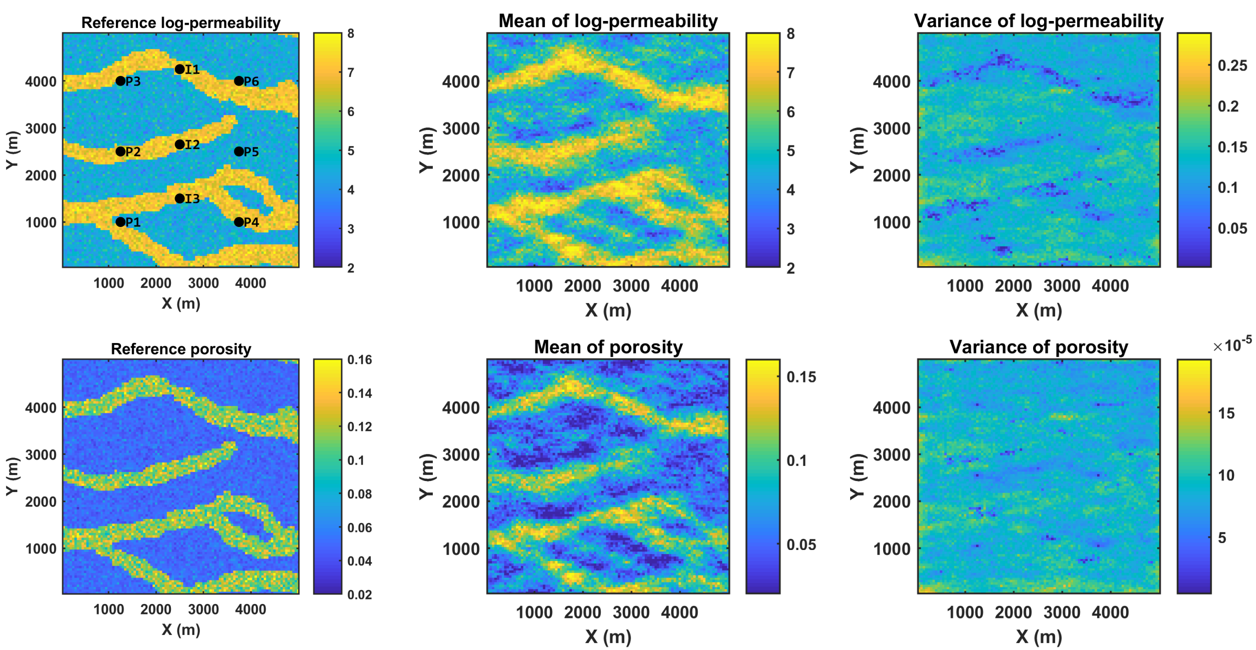
Predicted Production Data

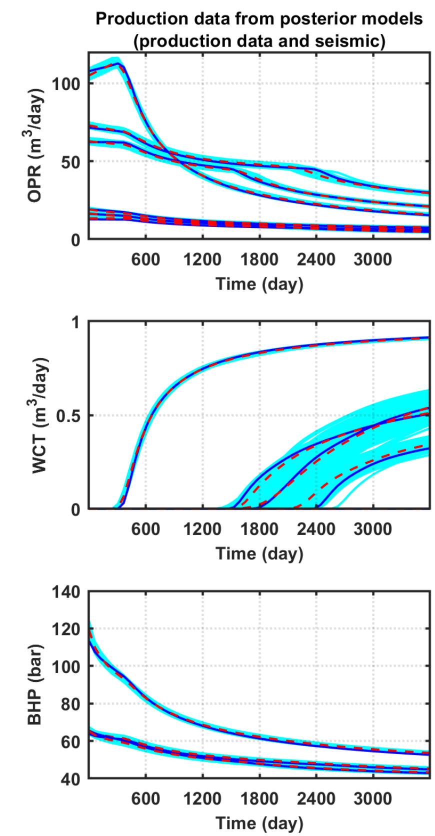
Liu and Grana, 2018b

Seismic history matching

Results - Production + Seismic data

Accurately captures the spatial trend of the reservoir model





Reference Model　Posterior Mean　Posterior Variance　Predicted Production Data

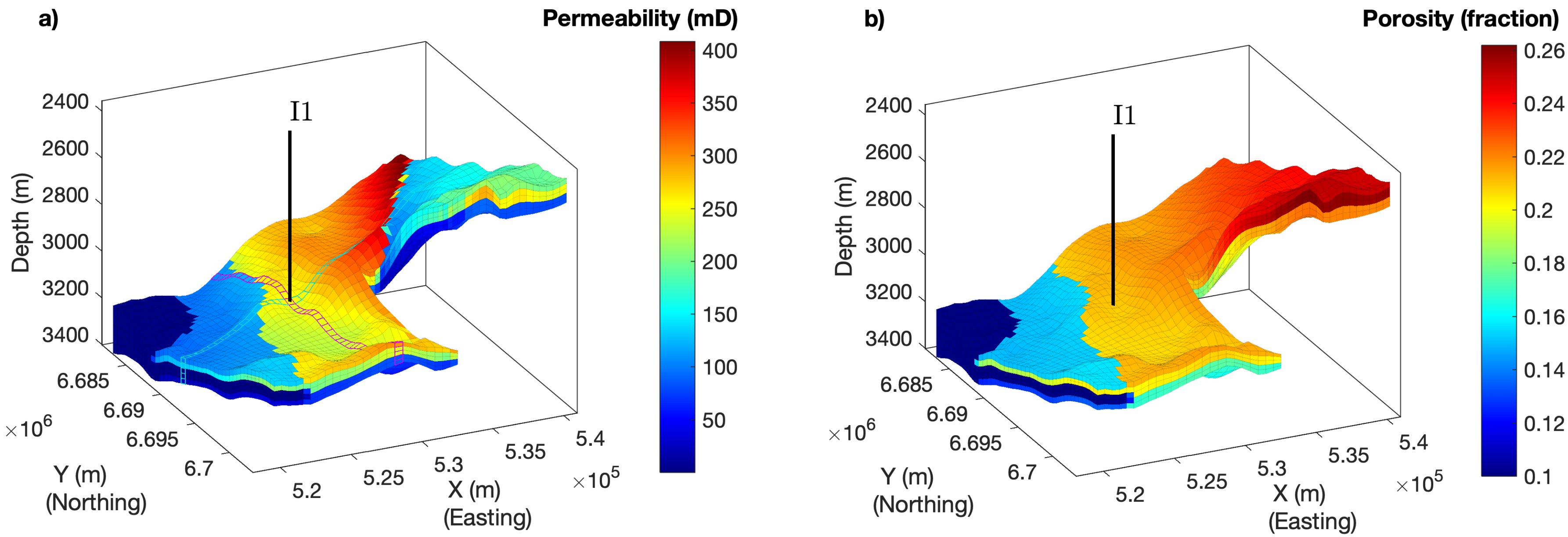
Liu and Grana, 2018b

Content

- Introduction to reservoir geophysics
- Ensemble-based methods:
  - Seismic inversion
  - Seismic history matching
- **CO_2 sequestration**

Johansen formation

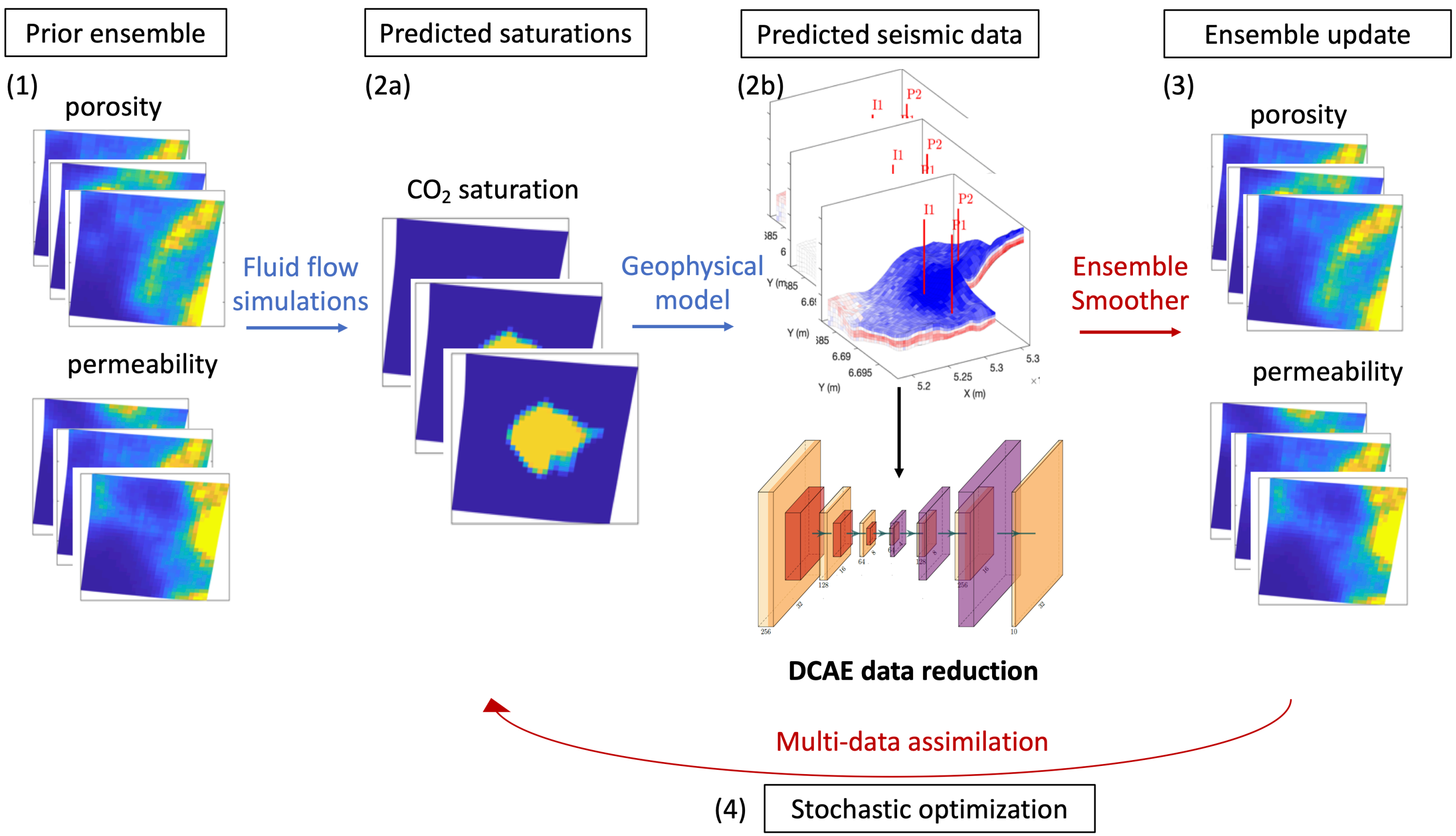
- Deep saline aquifer located under the Troll field
- Potential CO_2 storage unit



(Eigestad et al., 2009; Bergmo et al., 2011)

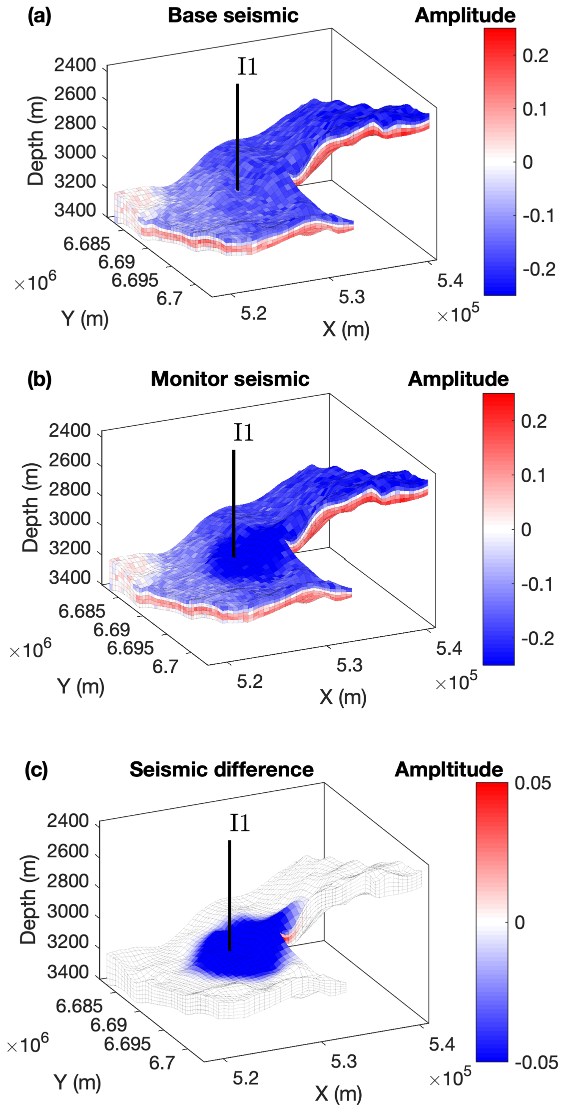
Geophysical history matching

- Geophysical history matching:
  - Seismic and CSEM surveys
  - Injection and monitoring well data

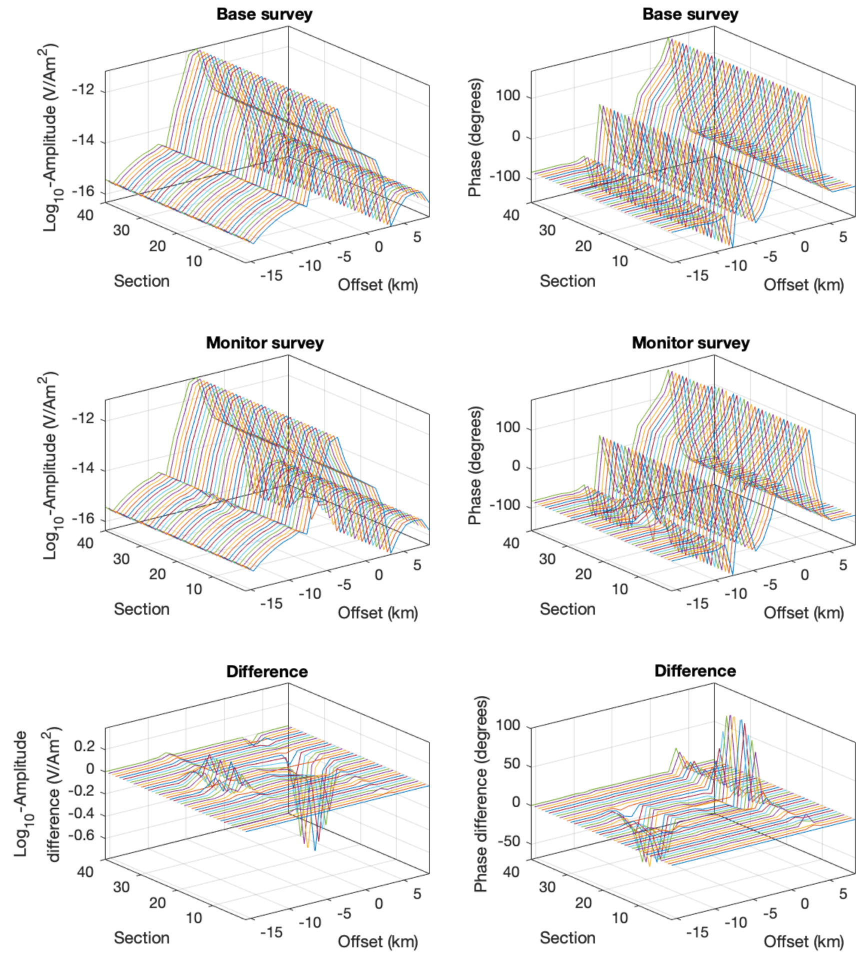


Geophysical history matching

4D seismic data

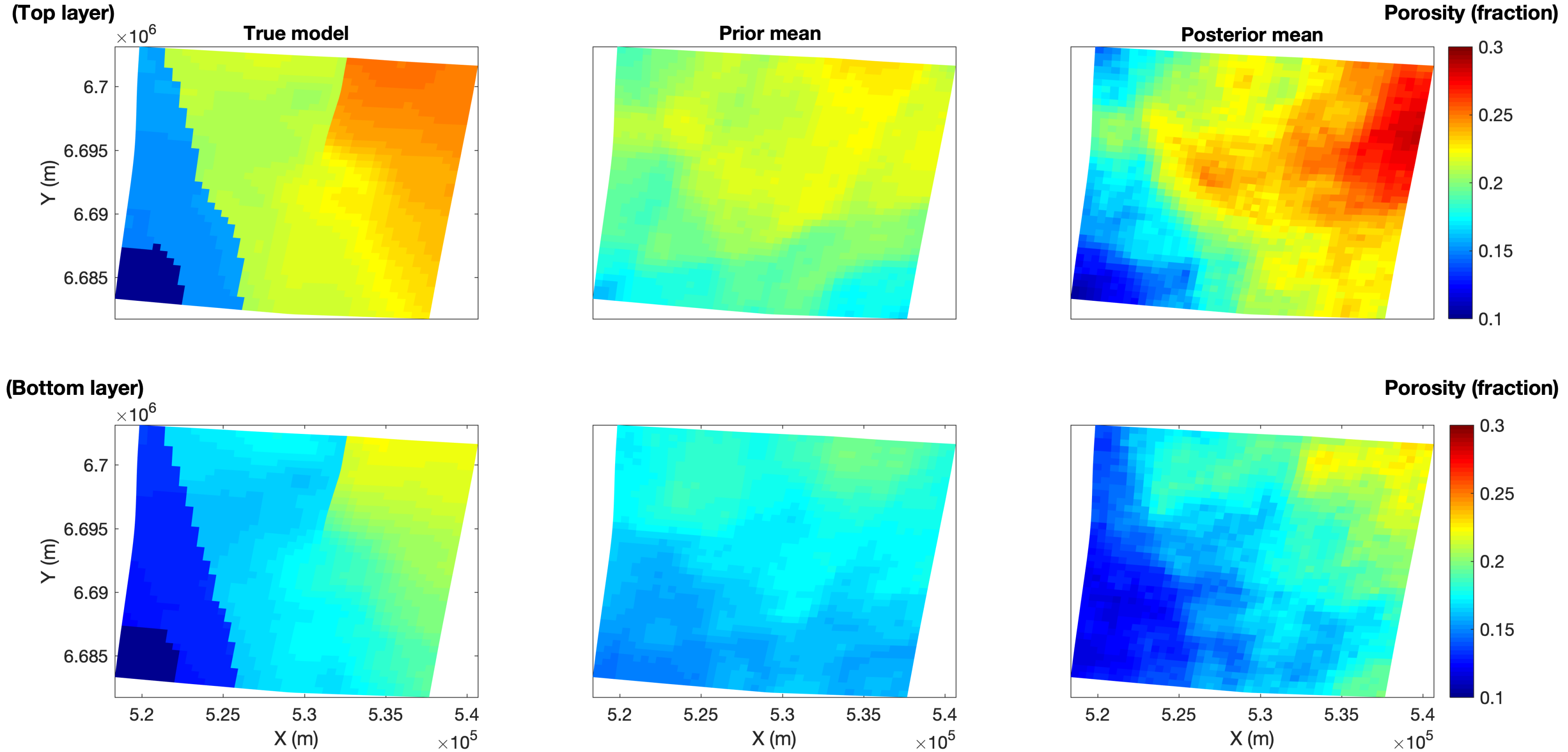


4D CSEM data



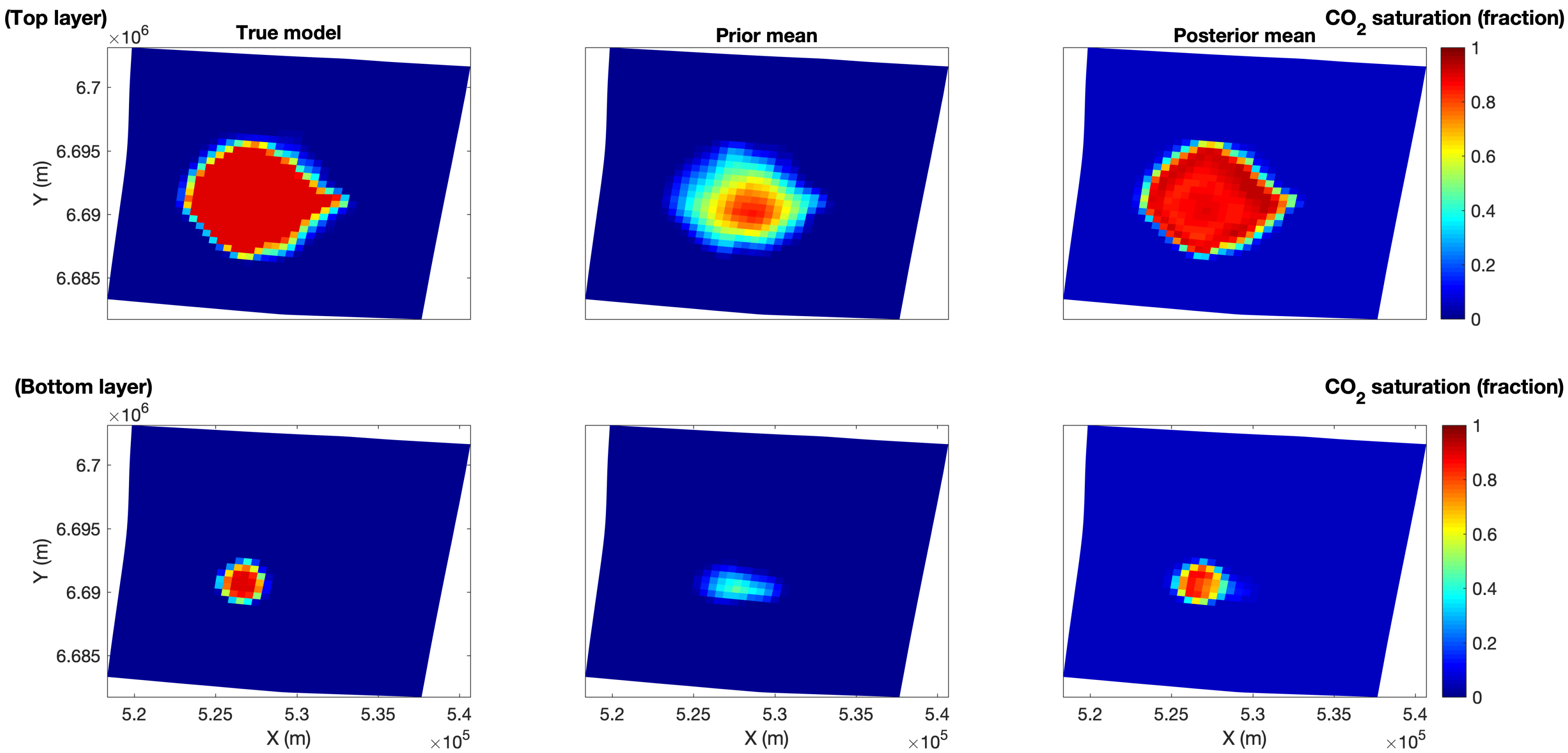
Geophysical history matching

Porosity prediction (pre-injection)



Geophysical history matching

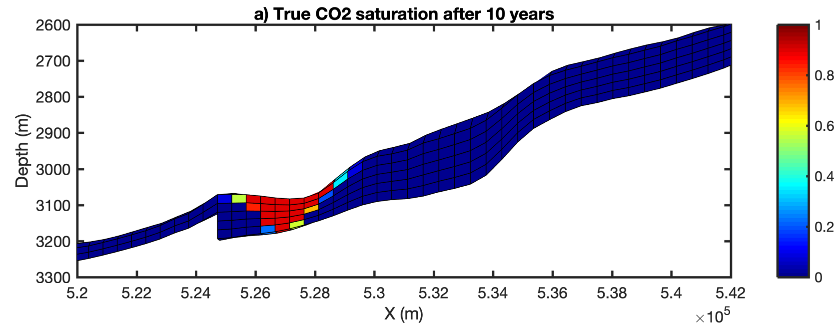
CO_2 saturation (year 110)



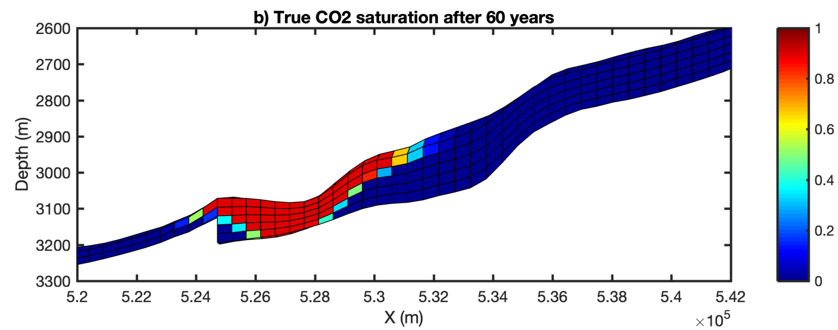
Geophysical history matching

- CO_2 saturation

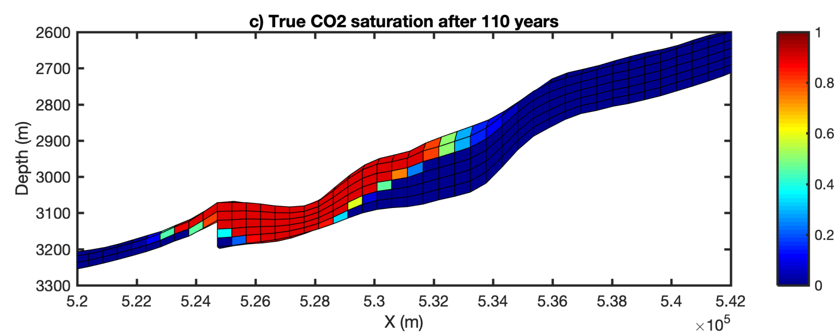
Year 10



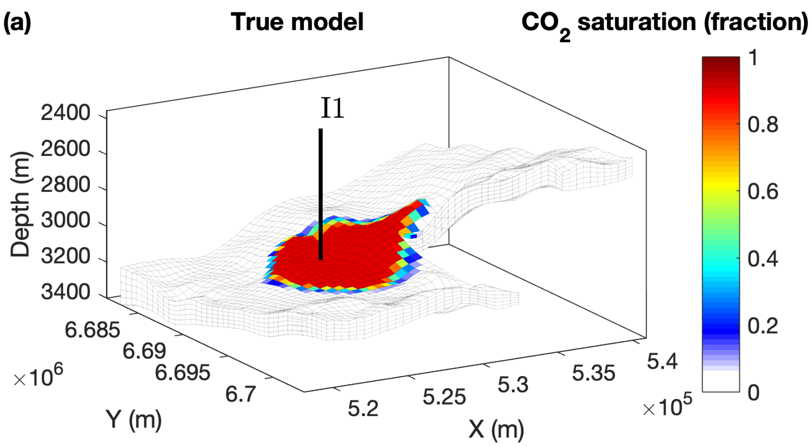
Year 60

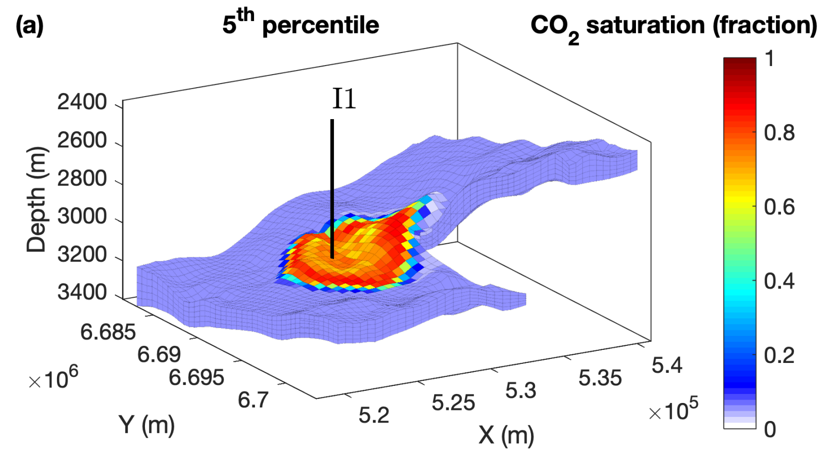


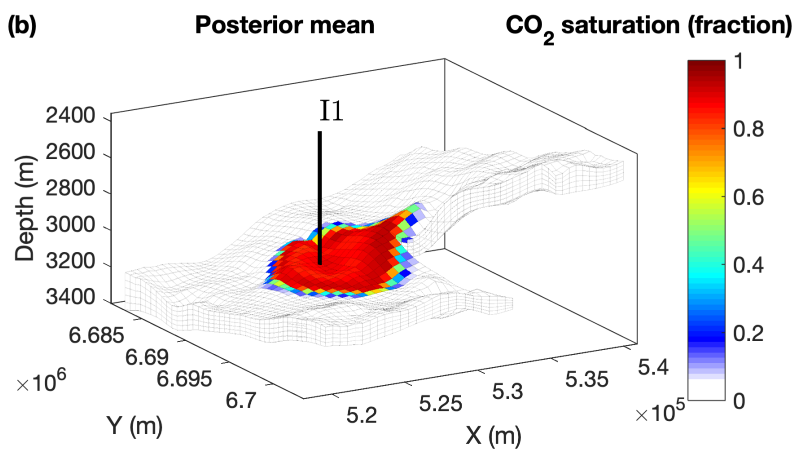
Year 110

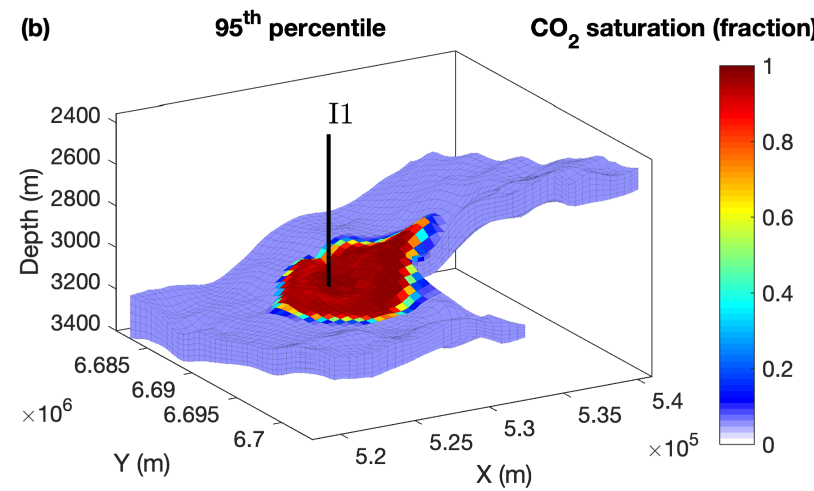


Geophysical history matching









Conclusions

- Surface geophysical data provide useful information to constrain the spatial distribution of reservoir properties;
- Data are dense but resolution is limited and signal to noise ratio low, hence uncertainty quantification is required;
- Ensemble-based methods provide a mathematical tool for model optimization and uncertainty quantification.

Acknowledgements

Thanks for your attention

Discrimination of changes in pressure-saturation and porosity fields from time-lapse seismic data using an ensemble-based method

Tuhin Bhakta*, Norwegian Research Centre AS (NORCE); Evgeny Tolstukhin and Carlos Pacheco, ConocoPhillips Norway; Xiaodong Luo and Geir Nævdal, Norwegian Research Centre AS (NORCE)

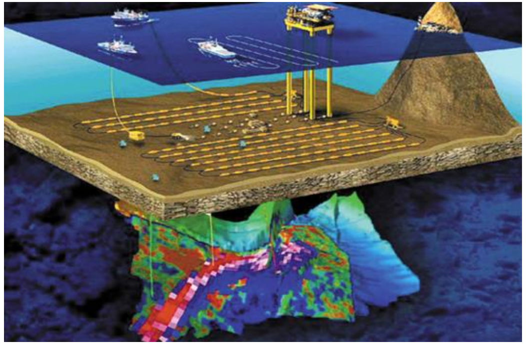
IOR Centre Workshop
14-15 Oct, 2020

Outline

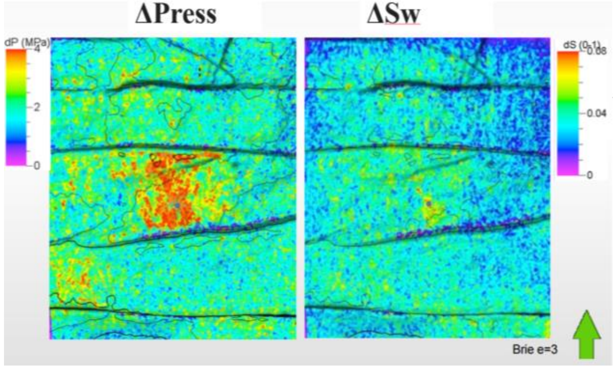
- Background and motivation
- Proposed framework and methodology
- Numerical examples
- Conclusions and future works

Motivation of the work

- Repeated seismic (4D) surveys provide information about:
  - Production related changes (changes in pressure, saturations)
  - Compaction related changes (change in porosity)
- This work addresses estimation of reservoir parameters (Saturations (SWAT, SGAS), Pressure (PRESS) and Porosity (PORE)) from seismic data
  - an ensemble-based methodology is implemented and tested
  - uncertainty quantification of the estimated parameters



(Courtesy http://csegrecorder.com/articles/view/what-comes-up-must-have-gone-down)



(Courtesy http://www.uis.no/getfile.php/IOR-senter/21%20Martin%20Landr%C3%B8%20Komplett%20IOR-NORWAY-2015-ML_a.pdf)

Review of methods

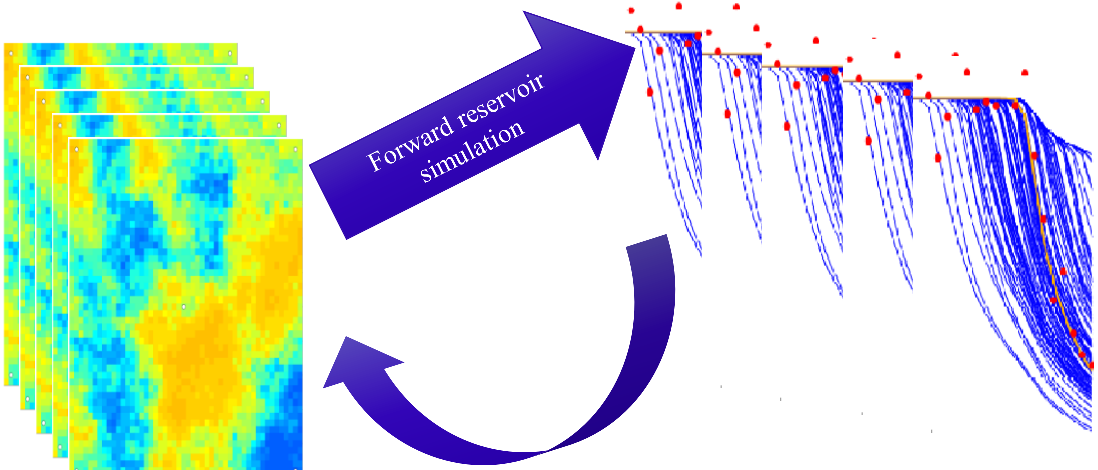
- Ensemble-based method for reservoir characterization
  - ➢ A new ensemble-based data-assimilation method, Ensemble Kalman Filter (EnKF), was published for use in oceanography and meteorology (Evensen, 1994)
  - ➢ The method was introduced in reservoir community by Næavdal and Lorentzen (2000). The method is now a well-established history matching tool (Næavdal et., 2005; Aanonsen et al., 2009, Chen and Oliver, 2013)
  - ➢ Investigation by integrating seismic data (Skjervheim et al. , 2007; Trani et al., 2012; Luo et al., 2016; Lorentzen et al. , 2019)
- Recent applications of the method in seismic inversions:
  - ➢ Estimation of pressure-saturation changes using time-lapse acoustic impedance data (ΔIp) (Emerick, 2014)
  - ➢ Simultaneous inversion of pressure-saturation and porosity fields from Ip data (Bhakta et al., 2017a)
  - ➢ Inversions of pressure-saturation and porosity fields using AVA data (Bhakta et al., 2017b)
  - ➢ Extend the method for compacting reservoir scenario (Bhakta et al., 2018)
  - ➢ Implementation of the method in real field case (Liu and Grana, 2018)
  - ➢ Investigation of the method using both PP- and PS- seismic data (Liu and Grana, 2018)
- Here, we demonstrate the workflow for compacting reservoir scenario :
  - ✓ To estimate changes in both dynamic and static parameters. Decoupling of production and compaction related changes.
  - ✓ Time-lapse Ip (ΔIp) data is used for the inversion

Background and motivation

Ensemble-based history matching for hydrocarbon reservoir characterization

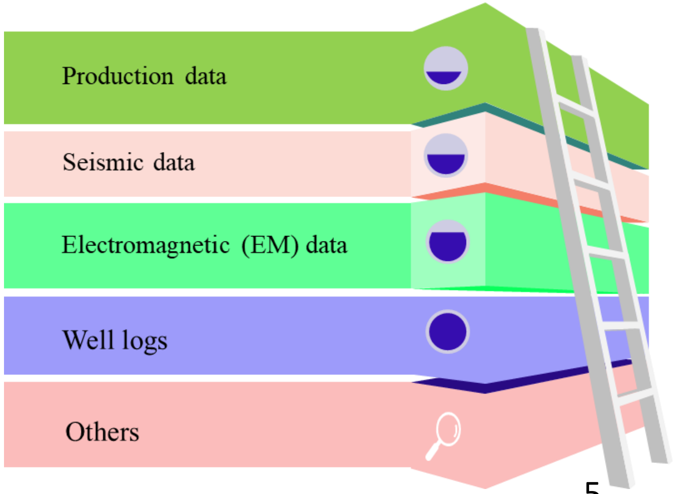
Reservoir models

Observations (real and simulated)



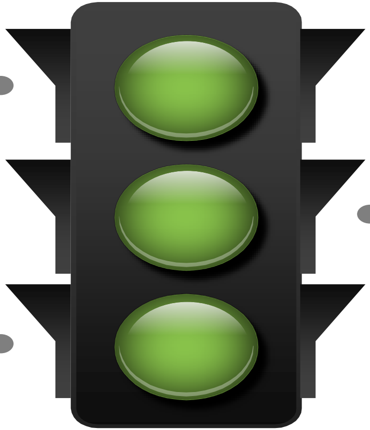
History matching (a.k.a. data assimilation) for the update of reservoir models

- ✓ Ensemble-based history matching methods provide a means of ***uncertainty quantification (UQ)*** for the estimation results



Background and motivation

Seismic data



- Amplitude versus angle (AVA);
- or, Raw seismic data

- Impedances (I_p, I_s);
- or, Velocities (v_p, v_s) and density

- Dynamic parameters (Saturation and pressure)
- Static parameter (Porosity)

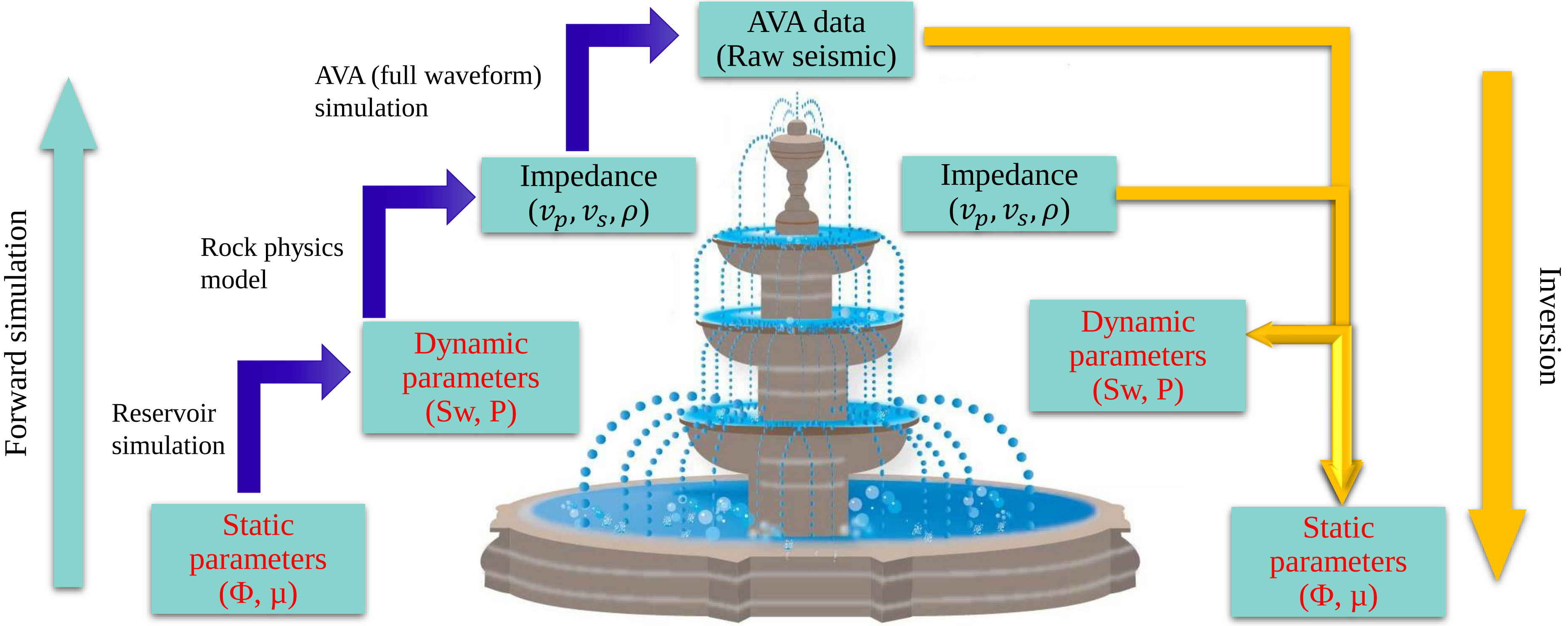
How to obtain from seismic data

Seismic data at different "levels"*

Feng, T., J. Skjervheim, and G. Evensen. "Quantitative use of different seismic attributes in reservoir modeling." *ECMOR XIII-13th European Conference on the Mathematics of Oil Recovery*. 2012.

Background and motivation

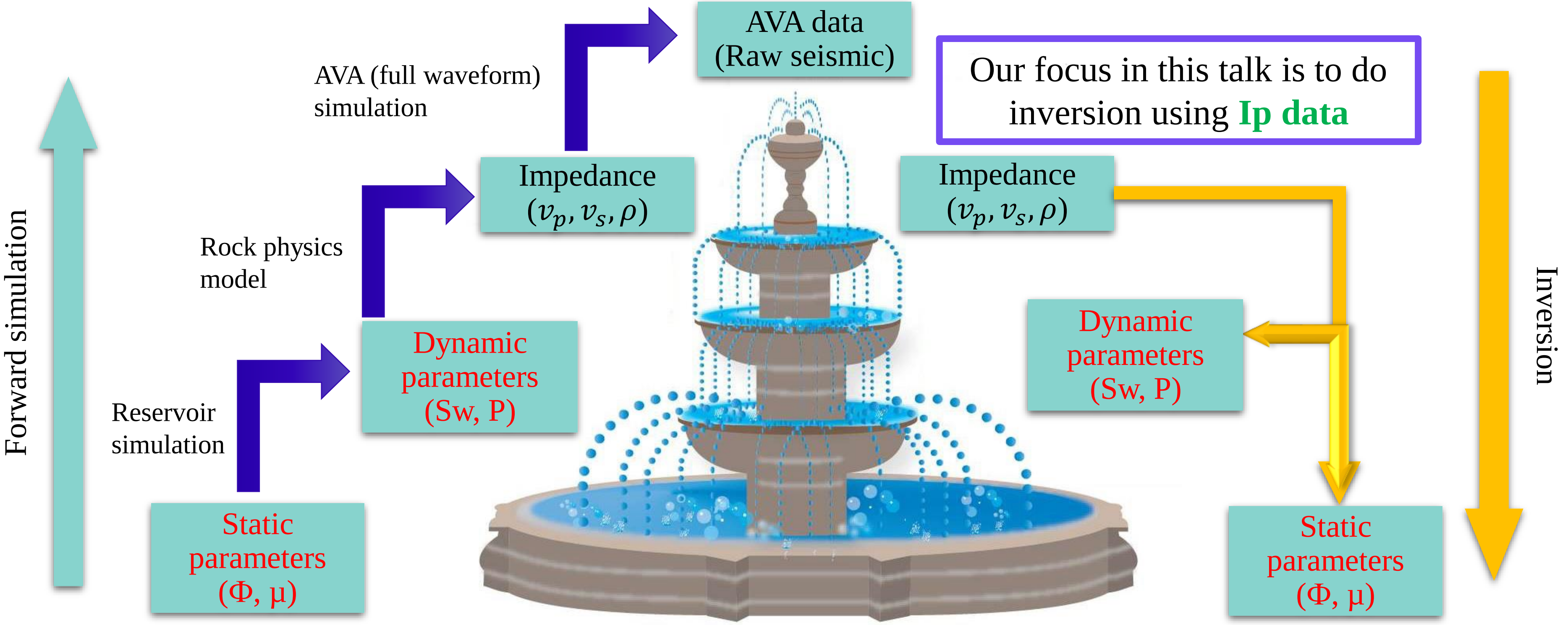
Relation between reservoir petro-physical parameters and seismic data at different levels



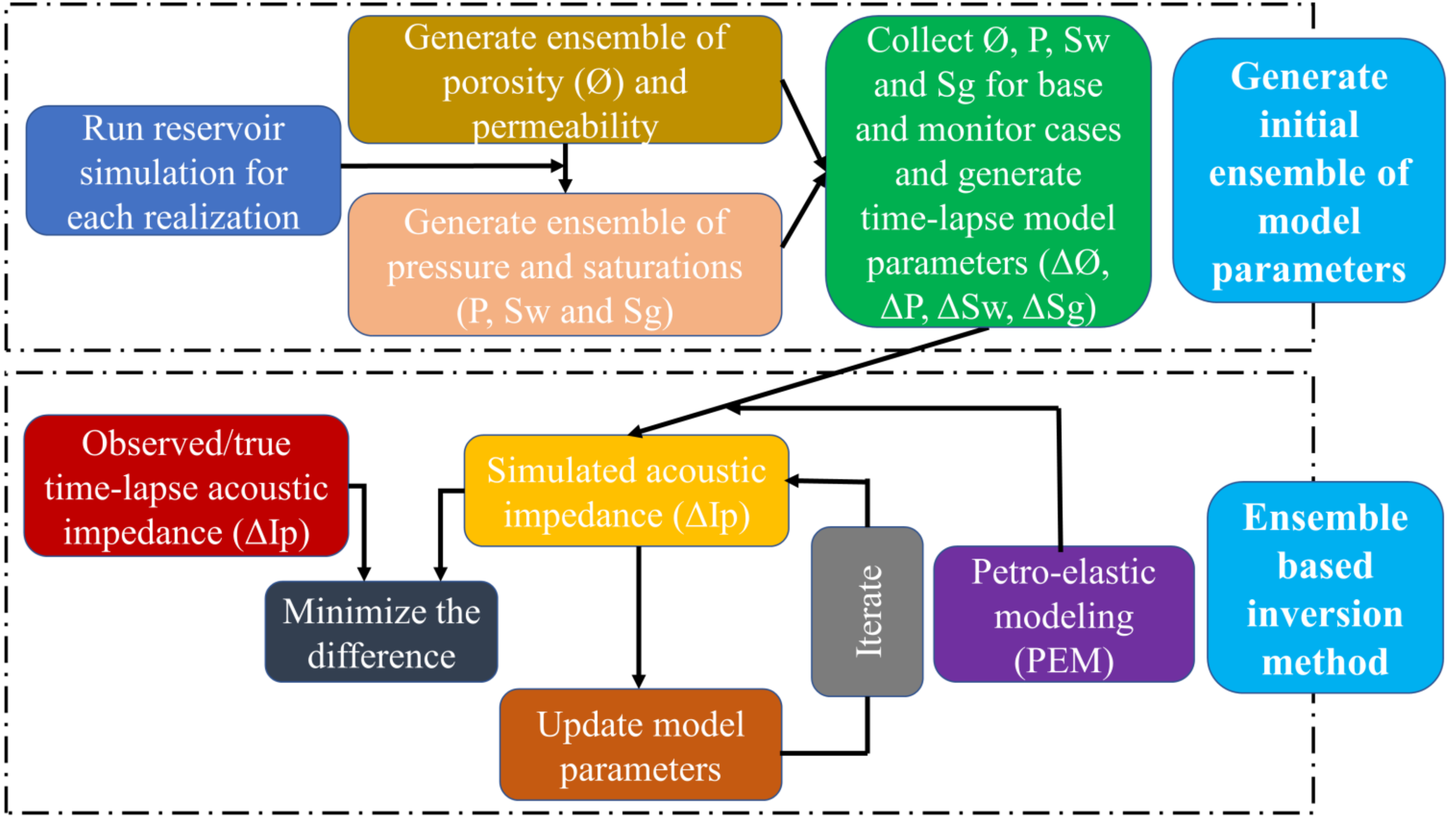
* For compacting reservoir, porosity also changes over the production life of the field.

Background and motivation

Relation between reservoir petro-physical parameters and seismic data at different levels



Proposed framework



Rock physics model for compacting reservoir*

- Estimate water saturated bulk modulus for varying porosity:

$$[K_{wet}] \leftarrow \text{modified Voigt model}(\emptyset, \emptyset_c, hf)$$

- Calculate dry moduli from K_{wet}:

$$[K_{dry_1}, G_{dry_1}] \leftarrow \text{Gassmann and rock Poisson's ratio } (K_{wet}, Pr)$$

- Inclusion of pressure effects:

$$[K_{dry}, G_{dry}] \leftarrow \text{Hertz–Mindlin and lower Hashin–Shtrikman}(K_{dry_1}, G_{dry_1}, \emptyset, \emptyset_c)$$

- Fluid substitution:

$$[K_{sat}, G_{sat}, \rho_{sat}] \leftarrow \text{Gassmann}(K_{dry}, G_{dry}, \emptyset, S_{water}, S_{oil}, S_{gas})$$

- P-wave velocity and acoustic impedance:

$$V_p \leftarrow (K_{sat}, G_{sat}, \rho_{sat})$$

$$I_p \leftarrow V_p \rho_{sat}$$

* Das, Agnibha, et al. "Dynamic rock physics modeling for compacting chalk reservoirs." SEG Technical Program Expanded Abstracts 2013. Society of Exploration Geophysicists, 2013. 2792-2796.

Methodology [iterative Ensemble Smoother (iES)]

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The posterior realizations can be expressed as (RLM-MAC algorithm*):

$$m_j^{i+1} = m_j^i + K^i \Delta y_j$$

where, $m_j^i = \begin{bmatrix} \Delta\emptyset \\ \Delta P \\ \Delta S_w \\ \Delta S_g \end{bmatrix}$

$i =$ iteration step number

$j =$ ensemble member number

$$K^i \equiv S_m^i \left(S_d^i\right)^T \left(S_d^i \left(S_d^i\right)^T + \gamma^i C_d\right)^{-1}$$ (Kalman-type gain matrix)

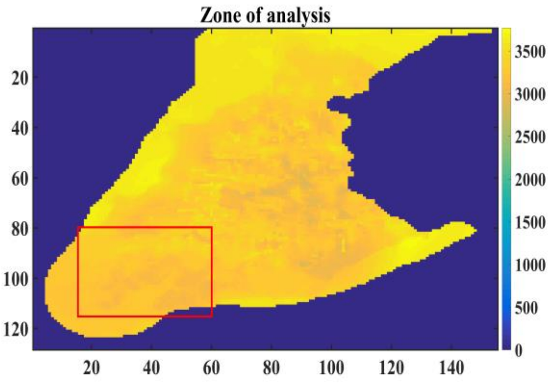
$$S_m^i = \frac{1}{\sqrt{N_e - 1}}\left[m_1^i - \bar{m}^i, m_2^i - \bar{m}^i, \dots \dots \dots, m_{N_e}^i - \bar{m}^i\right]$$ (Model square root matrix)

$$S_d^i = \frac{1}{\sqrt{N_e - 1}}\left[g(m_1^i) - g(\bar{m}^i), g(m_2^i) - g(\bar{m}^i), \dots, g(m_{N_e}^i) - g(\bar{m}^i)\right]$$ (Square root matrix of simulated data)

$$\bar{m}^i = \frac{1}{N_e}\sum_{j=1}^{N_e} m_j^i \qquad \Delta y_j = (d_{obs} - g(m_j^i))$$

*Luo, X., et al. (2015). "Iterative ensemble smoother as an approximate solution to a regularized minimum-average-cost problem: theory and applications." SPE Journal, 20, 962 - 982, paper SPE-176023-PA.

Numerical example: 3D Sector model of a compacting reservoir



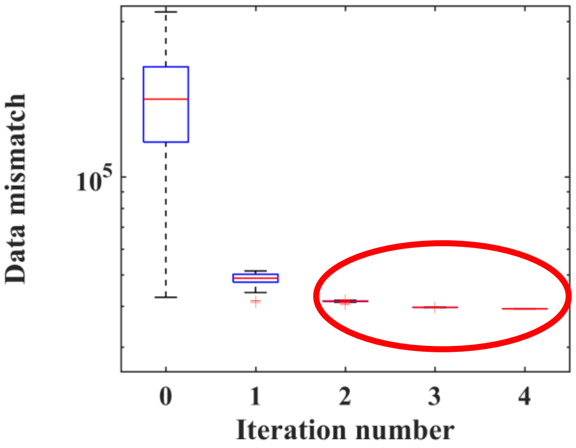
Experimental settings	
Model size	Full model dimension: 128×155×22 Part of the model is used: 36×45×22, with 31313 out of 35640 being active cells
Parameters to estimate	ΔPORE, ΔPRESSURE, ΔSWAT and ΔSAG. Total number is 4×31313 = 125,252
Gridblock size	Irregular. Average ΔX ≈ 120m, ΔY ≈ 120m, and average ΔZ ≈ 20m
Reservoir simulator	PSim (ConocoPhillips)
Number of wells	10 injectors and 30 producers
Production period	14600 days
Seismic data	Time-lapse acoustic impedance (ΔIp) data at each grid block at survey times.
Noise to the measurements	Gaussian noise is added to ΔIp (Standard deviation (σ) = 25 000 $Kg\ m^{-2}\ s^{-1}$)
Inversion method	iES (RLM-MAC) with an ensemble of 100 reservoir models*
Localization	Correlation based localization*
Number of ensemble members	100

*Luo, X., et al. (2015). "Iterative ensemble smoother as an approximate solution to a regularized minimum-average-cost problem: theory and applications." SPE Journal, 20, 962 - 982, paper SPE-176023-PA.

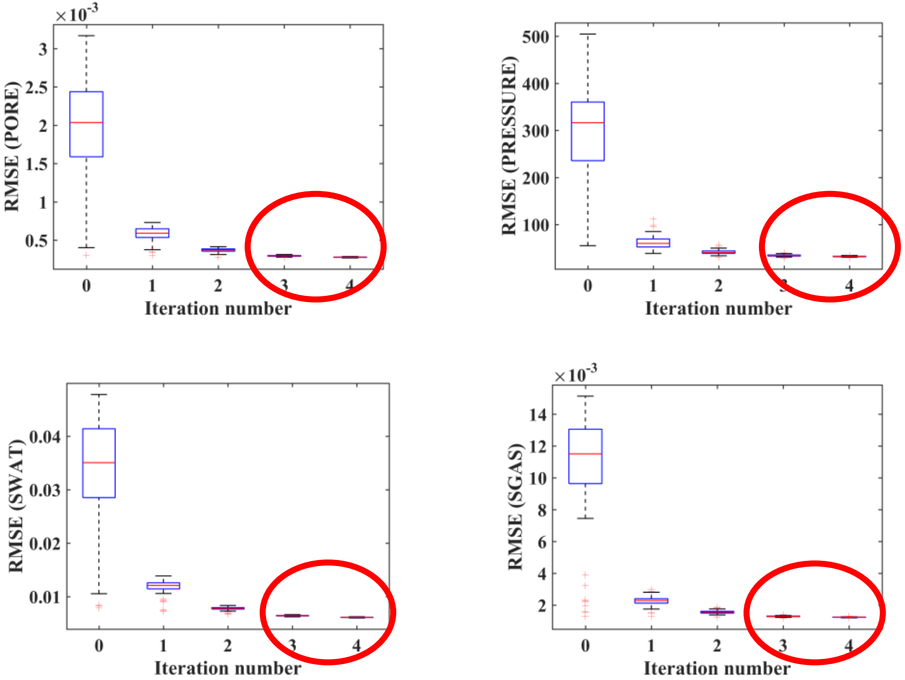
*Luo X., Bhakta T. and Nævdal, G. Data Driven Adaptive Localization For Ensemble-Based History Matching Methods, SPE Bergen One Day Seminar, 5 April 2017. SPE-185936-MS

Numerical example: 3D Sector model

Results without localizations



Seismic data mismatch

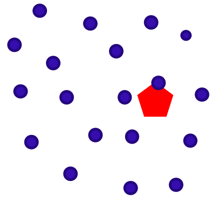


RMSE of model parameters

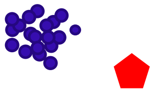
Methodology

Ensemble collapse: a practical challenge for ensemble-based inversion

Desired scenario



Reality: ensemble collapse (small ensemble size + large dataset)



Estimates

Truth

Impact of ensemble collapse

- ❑ Poor UQ performance
- ❑ Stop assimilating observations into reservoir models

- ❑ **Ensemble collapse**: a phenomenon in which estimated reservoir models become almost identical with very few varieties

Methodology

Effect of localization on an ensemble-based inversion algorithm

$$m_i^u = m_i^f + \sum_j K_{ij}\,\Delta y_j \qquad \text{(original update formula)}$$
$$m_i^u = m_i^f + \sum_j \xi_{ij} K_{ij}\,\Delta y_j \qquad \text{(update formula with localization)}$$

- ❑ The tapering coefficient $\xi_{ij} \in [0,1]$ depends on the specific localization method
- ❑ For instance, in a distance-based localization method, ξ_{ij} depends on the distance between the physical locations of the jth observation element and the ith model variable

➢ We use correlation-based localization method that

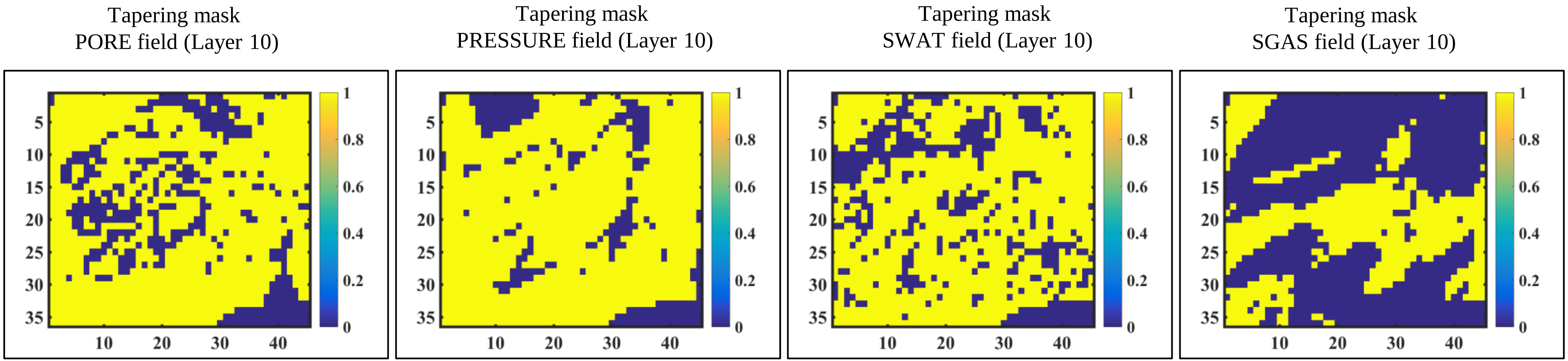
- ✓ does not rely on physical locations of model variables and/or observations
- ✓ works for both local and non-local observations

Methodology

❑ Correlation-based localization*

$m_i^u = m_i^f + \sum_j \xi_{ij} K_{ij}\, \Delta y_j$ (update formula with localization)

Thresholding: $\xi_{ij} = I\left(\left|\rho_{ij}^N\right| \geq \lambda_j^N\right) \equiv \begin{cases} 1, if \left|\rho_{ij}^N\right| \geq \lambda_j^N \\ 0, \ otherwise \end{cases}$ independent of physical locations of model variables and/or observations

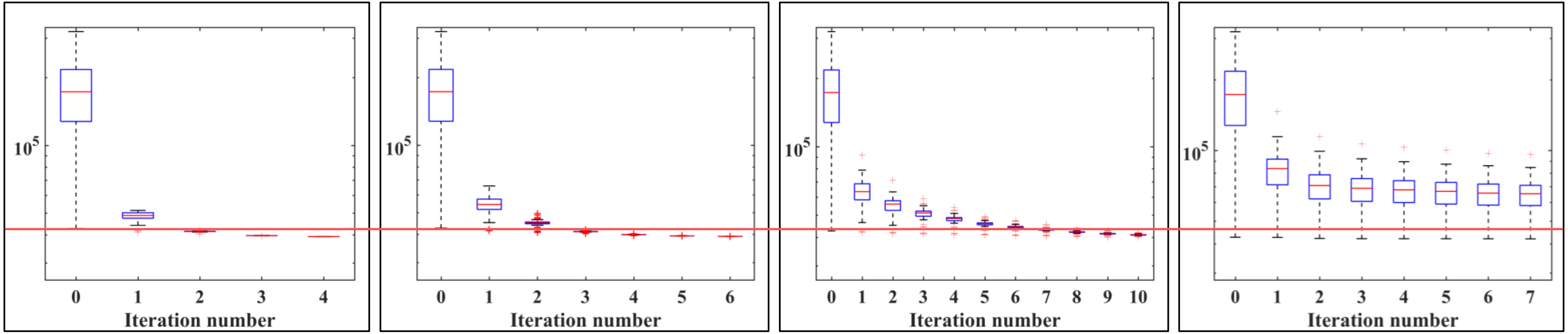


- ✓ Data selection based on correlations between model variables and observations
- ✓ Here, tapering fields for 1st element of the data are shown

*Luo X., Bhakta T. and Nævdal, G. Data Driven Adaptive Localization For Ensemble-Based History Matching Methods, SPE Bergen One Day Seminar, 5 April 2017. SPE-185936-MS

Numerical example: 3D Sector model

Results with localizations



No localization

Localization
(Threshold = 0.10)

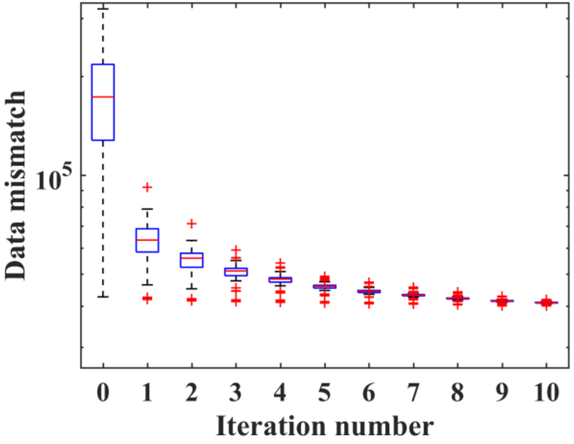
Localization
(Threshold = 0.20)

Localization
(Threshold = 0.35)

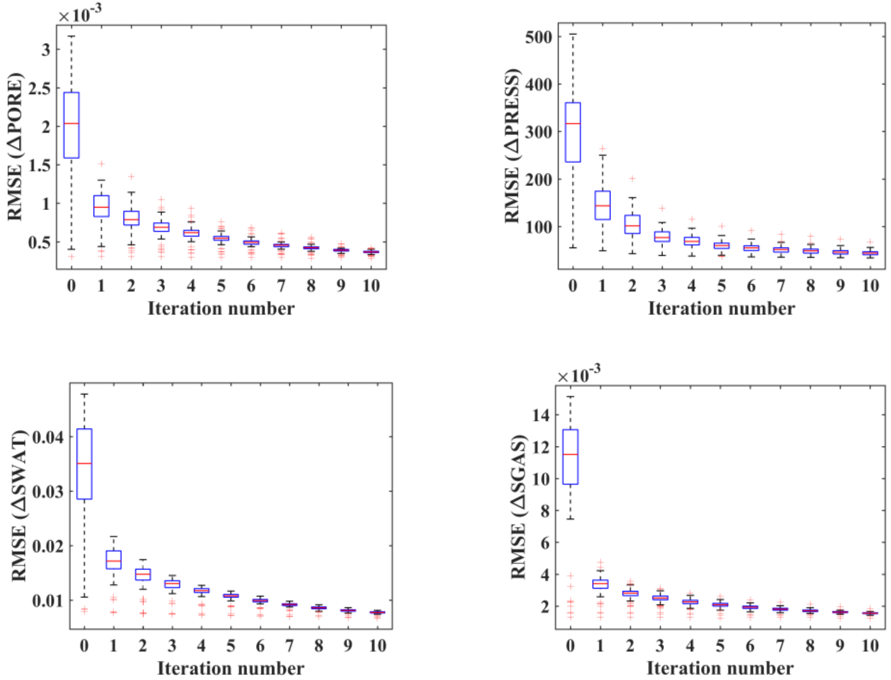
Seismic data mismatch

Numerical example: 3D Sector model

Results with localizations (Threshold = 0.20)



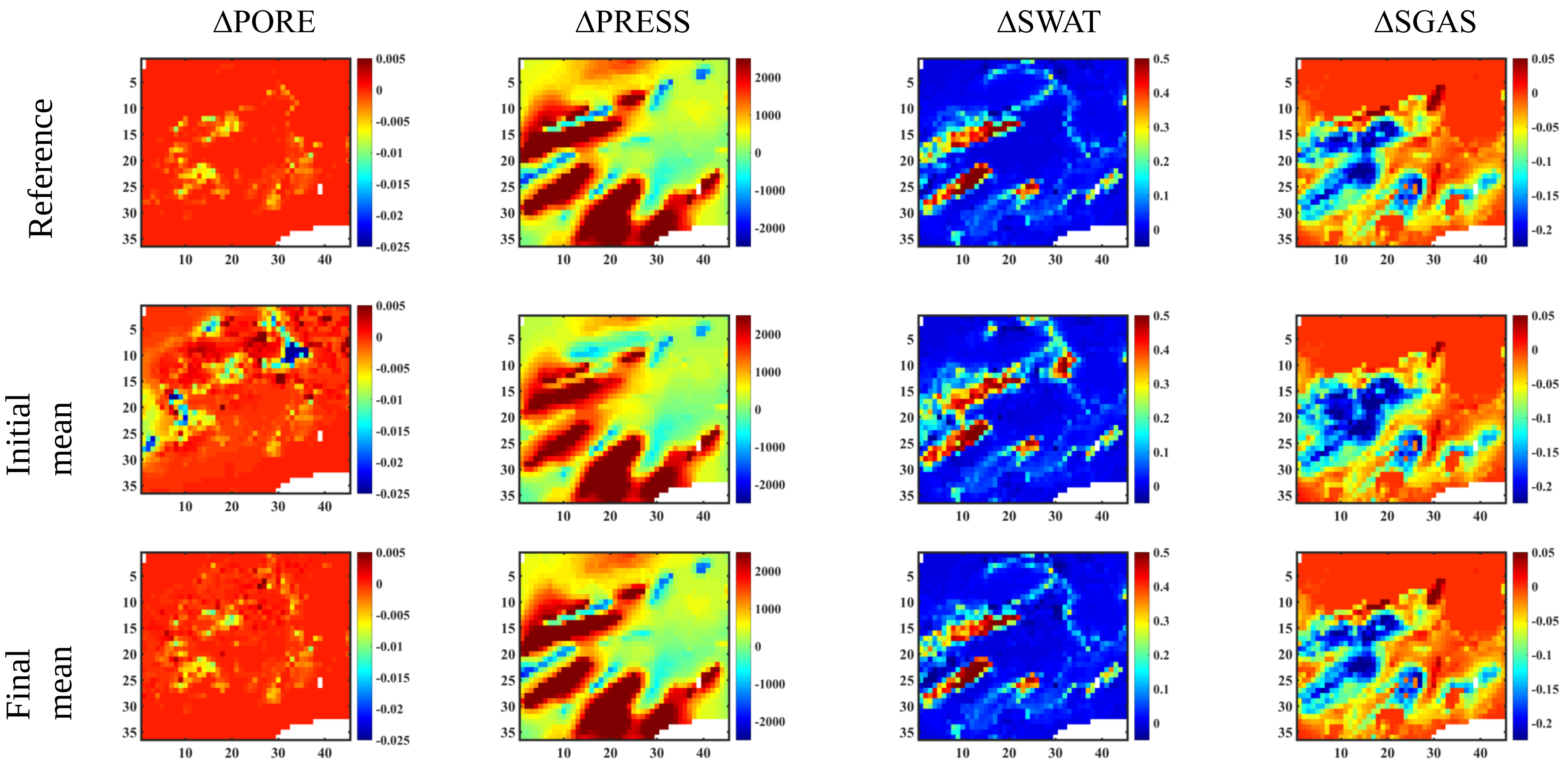
Seismic data mismatch



RMSE of model parameters

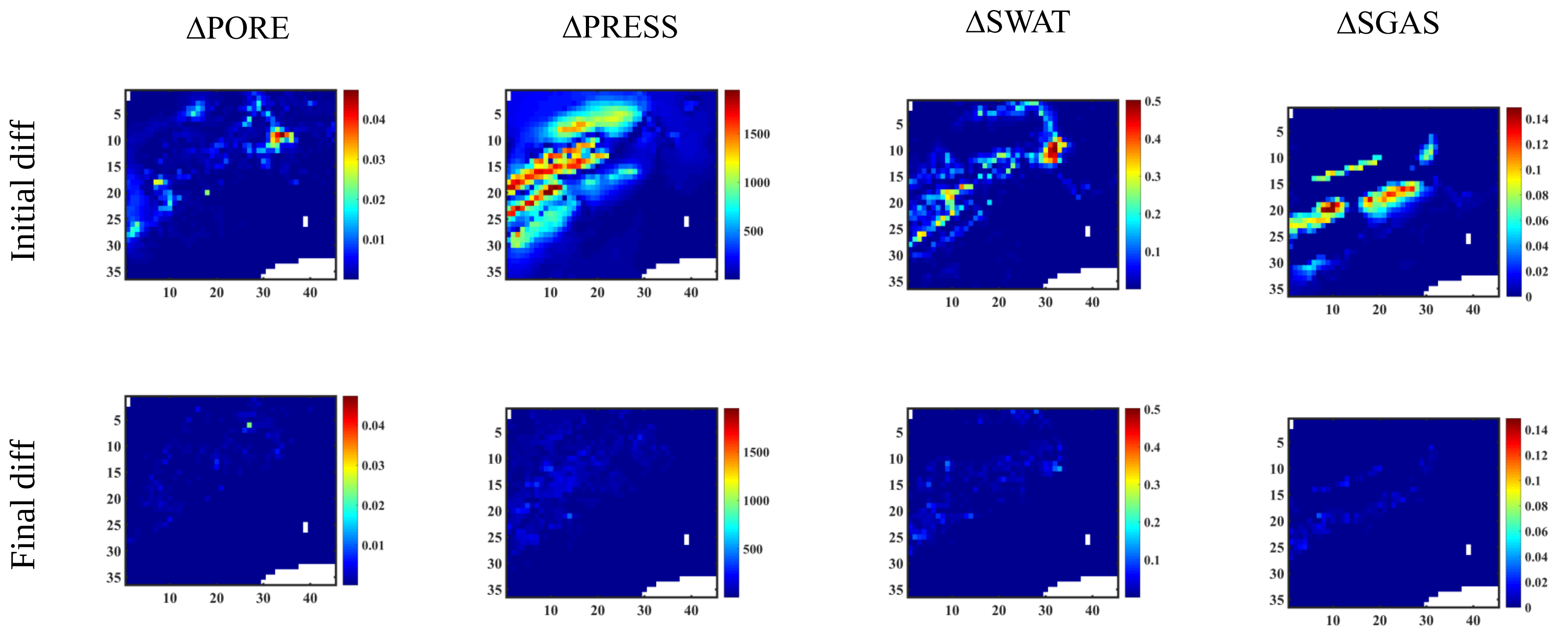
Numerical example: 3D Sector model

Results with localizations (Threshold = 0.20) – for Layer 10



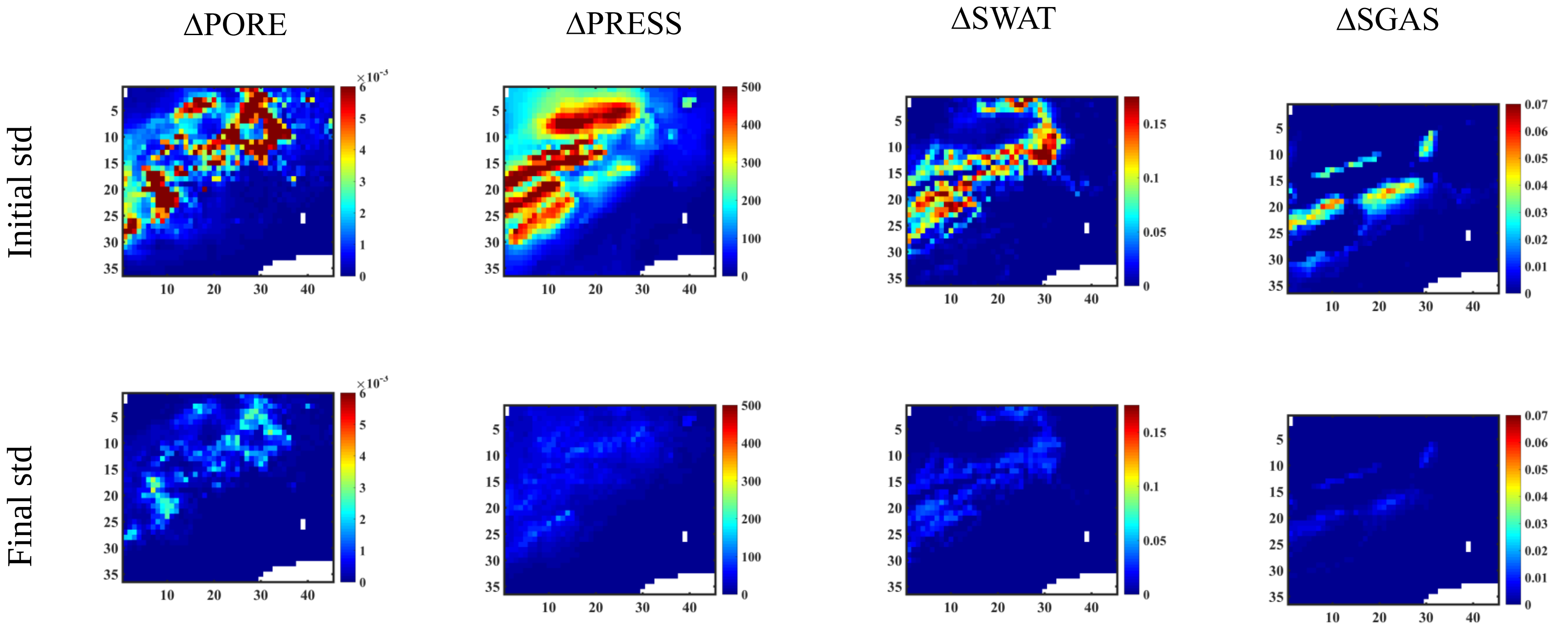
Numerical example: 3D Sector model

Results with localizations (Threshold = 0.20) – for Layer 10



Numerical example: 3D Sector model

Results with localizations (Threshold = 0.20) – for Layer 10



Conclusions and future works

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Advantages in using ensemble-based inversion method

- Estimations of both static and dynamic parameters simultaneously
- Uncertainty quantification of the estimated parameters
- Applicability to various types of seismic data (coming from different levels)

Conclusion and future works

Possible future investigations

- Field case studies
- Various types of seismic data/ attributes

Acknowledgements

The authors acknowledge the Research Council of Norway and the industry partners, ConocoPhillips Skandinavia AS, Aker BP ASA, Vår Energi AS, Equinor ASA, Neptune Energy Norge AS, Lundin Norway AS, Halliburton AS, Schlumberger Norge AS, and Wintershall DEA, of The National IOR Centre of Norway for support.

Thank You / Questions

4D seismic history matching in DELFI

Jarle Haukås, Schlumberger Norway Technology Centre, Stavanger

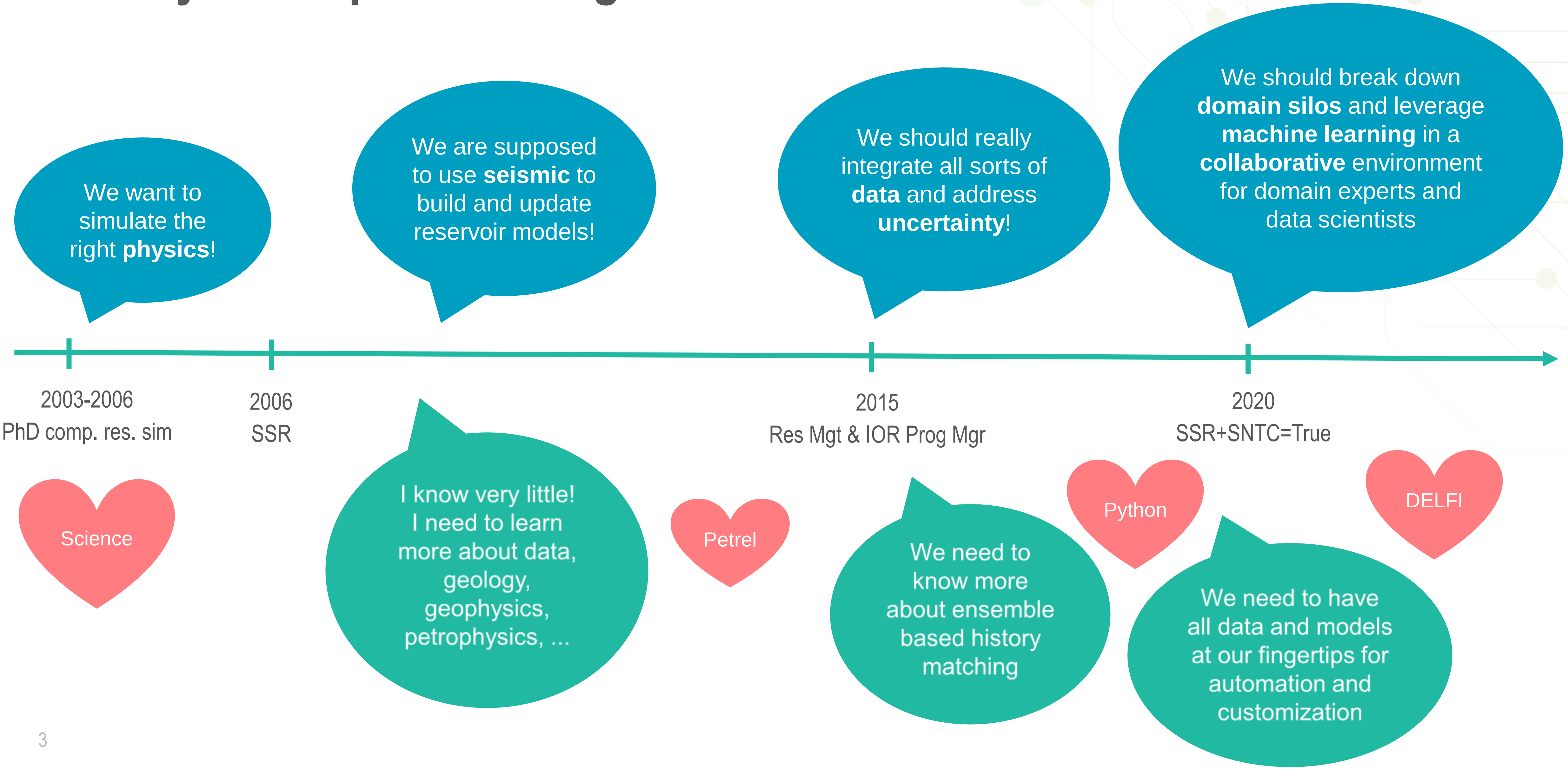
Workshop on ensemble-based 4D seismic history matching, October 14-15, 2020

Schlumberger

Outline

- Introduction
- Ensemble based 4D seismic history matching – experience and lessons learned
- Data, models and compute resources at your fingertips – new ways of working?
- Summary and outlook

Journey from specialist to generalist



Motivation

Poor cross-domain integration

«How is the new time-lapse seismic working out?»
«I think the geophysicists are happy about it»

«I pushed the data processing vendor to deliver time-lapse data 10 days after the last shot. I handed the interpretations over to the reservoir engineering team, eager to see the impact on the reservoir model. Two weeks later I came back and asked how it was going. They replied that they hadn't had time to look at it yet.»

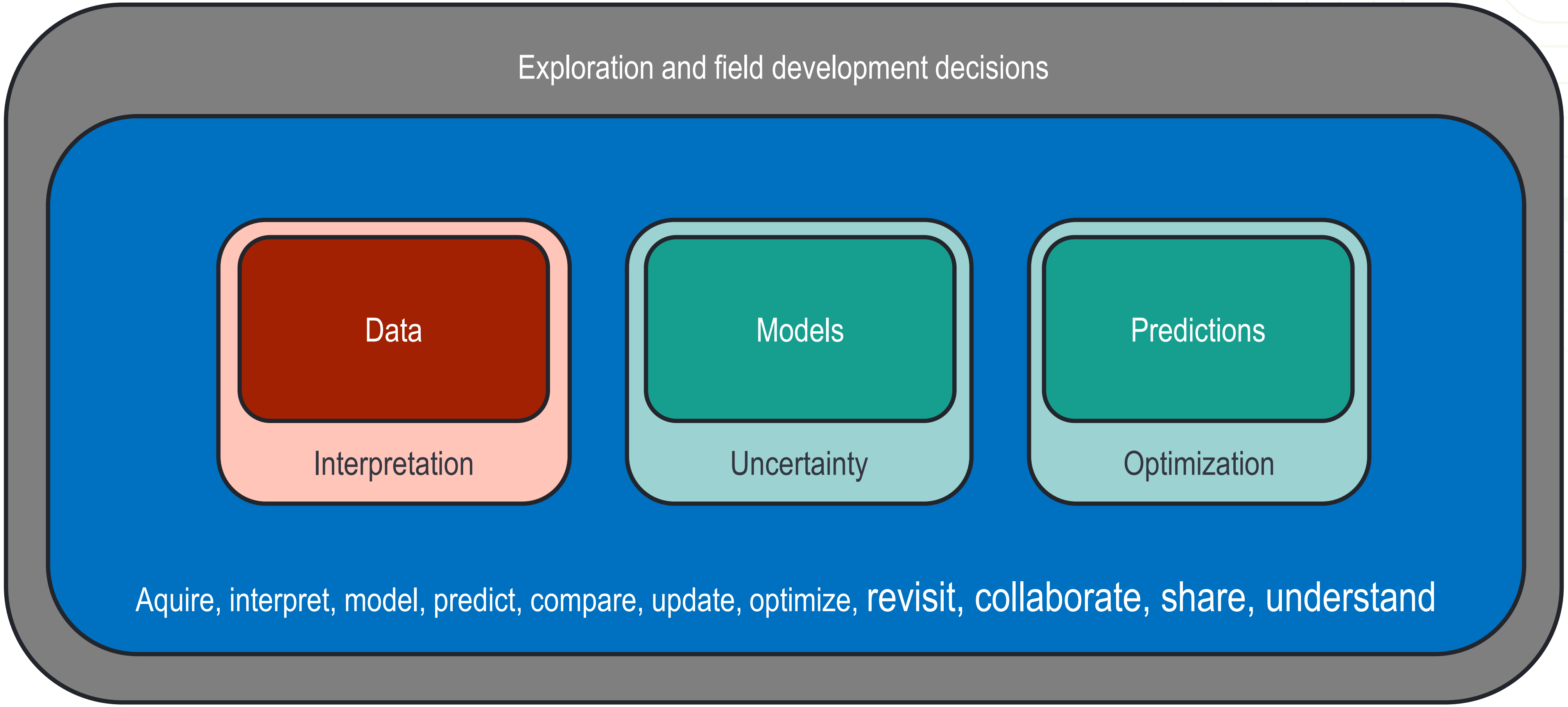
Lack of automation and efficiency

«Based on time-lapse seismic data, I did a quick sketch of what could potentially be the water front. Some time later, I discovered that my sketch had been copied into a series of PowerPoint presentations as a picture of the actual water front.»

«The acquisition and processing of time-lapse seismic data has been automated and is very efficient, but it takes up to 6 months to bring the results into the reservoir model.»

Uncertainty not captured / communicated

Contributing to the big picture



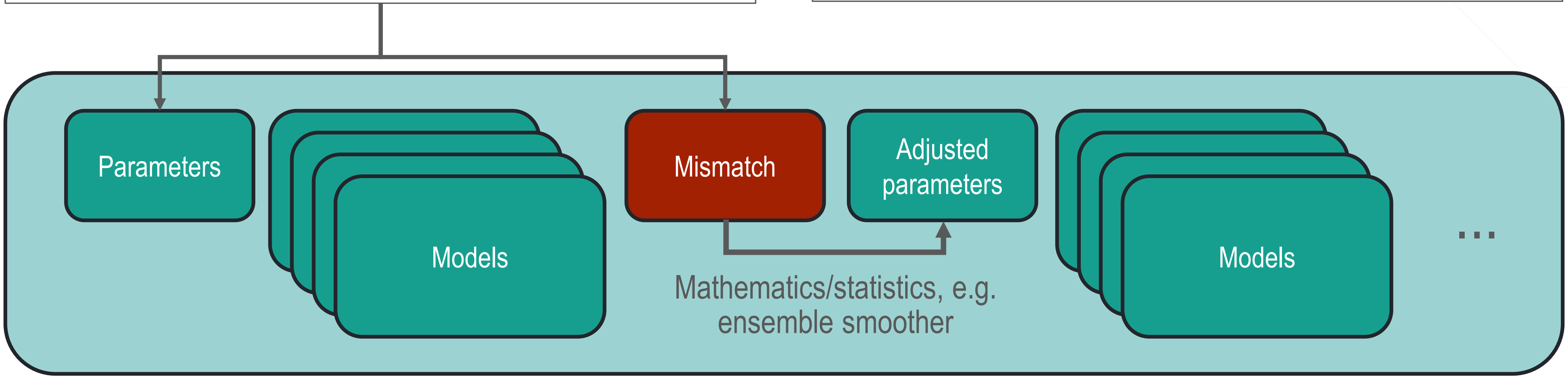
Ensemble based history matching

<u>Where can domain experts influence the system?</u>

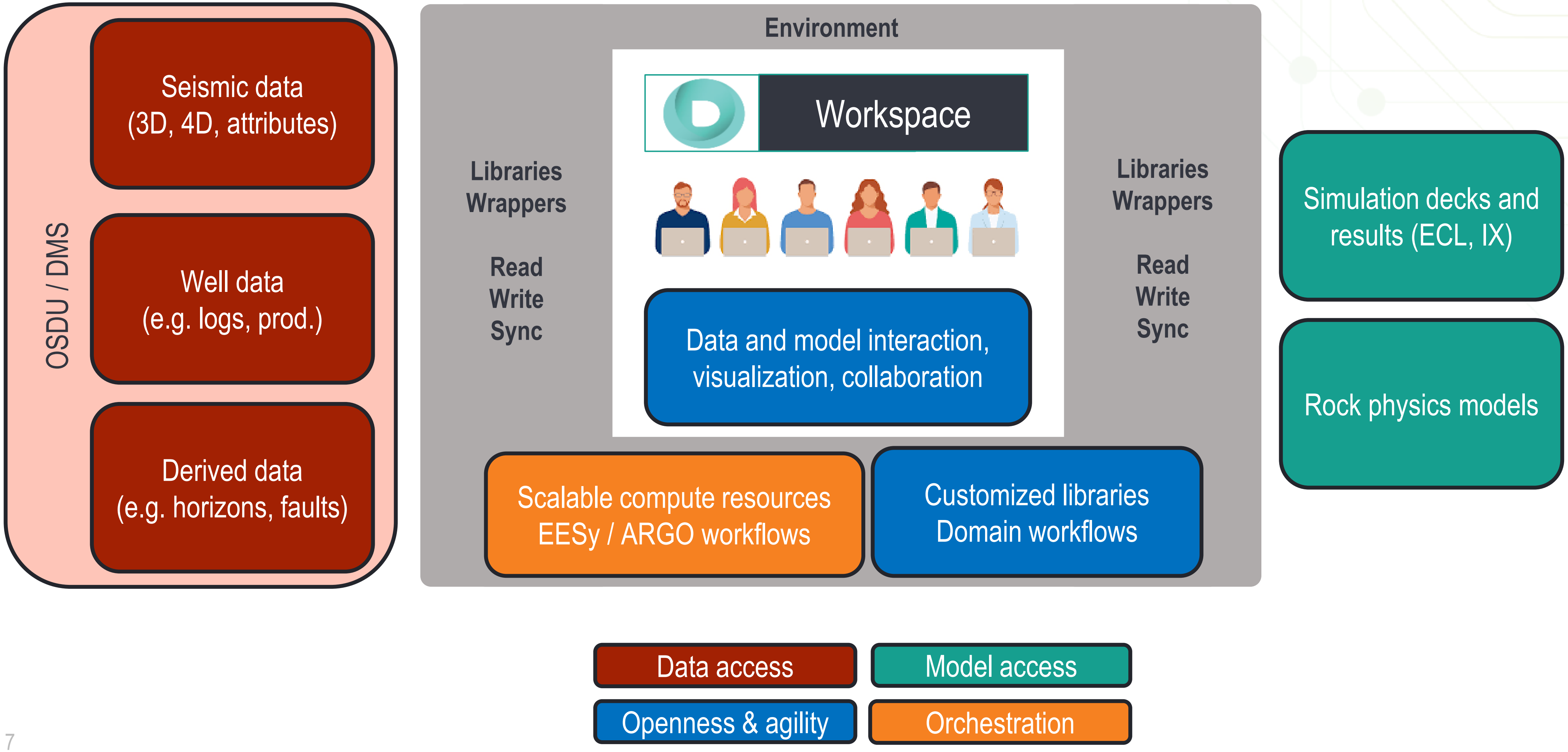
- Impose geological realism
- Flag and help quantify interpretation uncertainties
- Flag and help quantify modeling uncertainties
- Define uncertainty consistently for all domains
- Define appropriate mismatch function for all domains

<u>Which new tools are needed?</u>

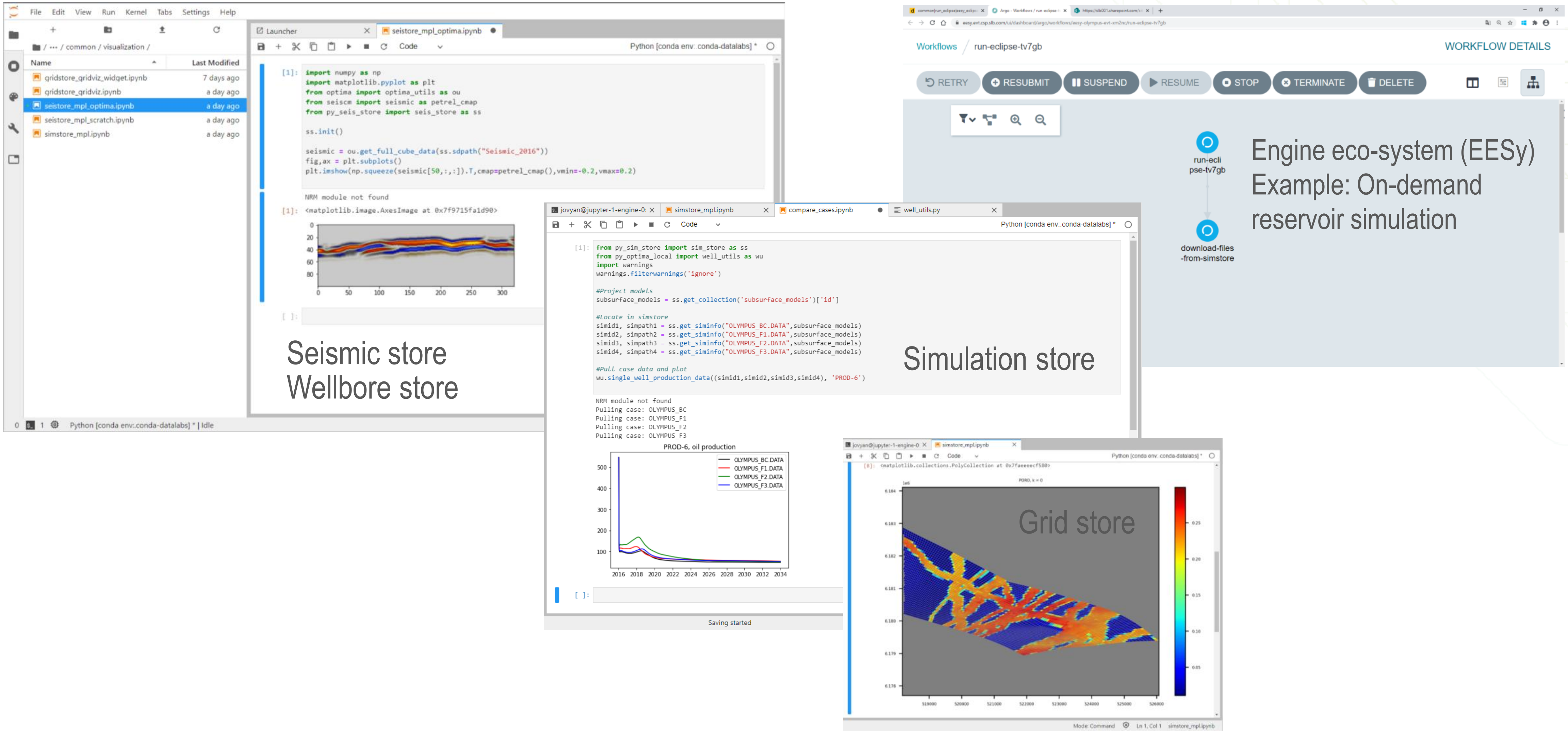
- *Parametrized* interpretation and modeling
  - Horizons, faults, properties, 3D models
  - Fluid and pressure fronts (thresholds)
- Extract relationships (e.g. constraints) from data
- End-to-end sensitivity checks
- Composability and customization



Workspace for Integrated Geoscience and RE Workflows in DELFI



Cloud access to data, models, engines



Challenges adressed

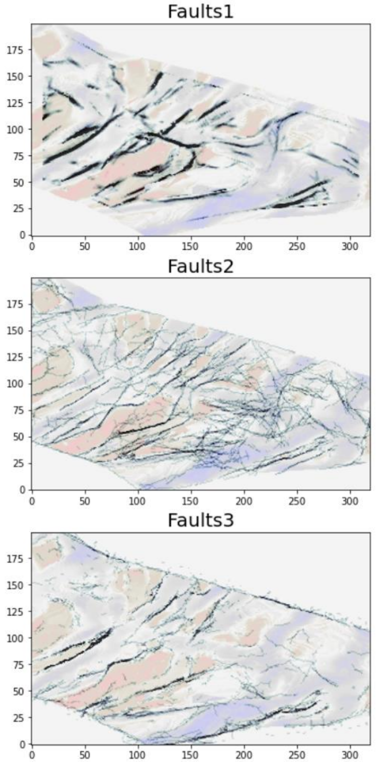
- Break down domain silos
- Utilize data across all domains

- Scalable compute and storage
- Composable workflows – combine own and 3rd party components
- Customization, e.g. field specific rock physics models

- Bring research prototypes faster to market
- Collaborate and share
- Connect to machine learning solutions – discover relationships in data and models

Data, models and engines at your fingertips – new ways of working?

Example developed together with geologist with no programming background

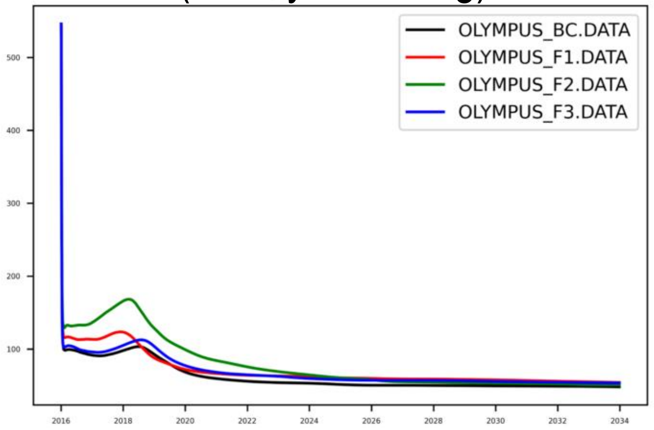


RE workflow Eclipse

Input data for simulation:

- Grid geometry
- Static properties (PORO, NTG, PERM)
- Faults and fault transmissibilities
- Fluid and rock properties (rhof, kr, Pc)
- Equilibration (Pinit, OWC)
- Wells
- Development strategy (inj, prod, hist/pred)

Production forecast (history matching)



Goal: Geologically consistent parametrization

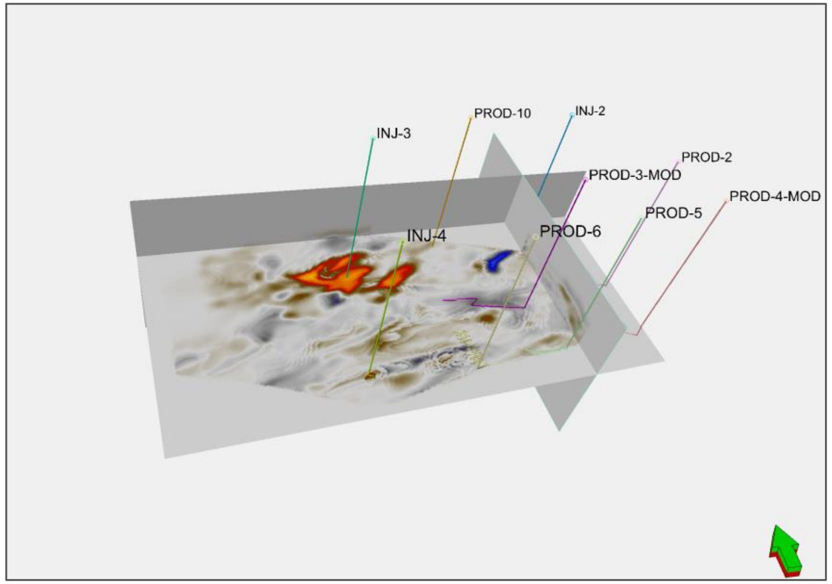
Automated orchestration

End-to-end sensitivity check

Both deterministic and machine learning solutions included (EESy engines)

4D seismic history matching – integrated approach

1. Locate significant and interpretable 4D seismic anomalies – connected to well event
2. Swept volume tracking, pressure fronts, fluid fronts – observed versus simulated
3. Quantify mismatch – overall or well-by-well basis



Well events that could / should have an impact on 4D

In [1]:

```
from olympus.py_sim_store import sim_store as ss
from olympus.py_optima_local import well_utils as wu
from olympus.py_auth import auth
import warnings
warnings.filterwarnings('ignore')

auth.init()

#Locate in simstore
simid, simpath = ss.get_siminfo("OLYMPUS_BC.DATA")

#Pull case data and plot
wu.wells_list_events_simulated(simid,wells=('INJ-4','PROD-6'))
```

Read directly from cloud storage

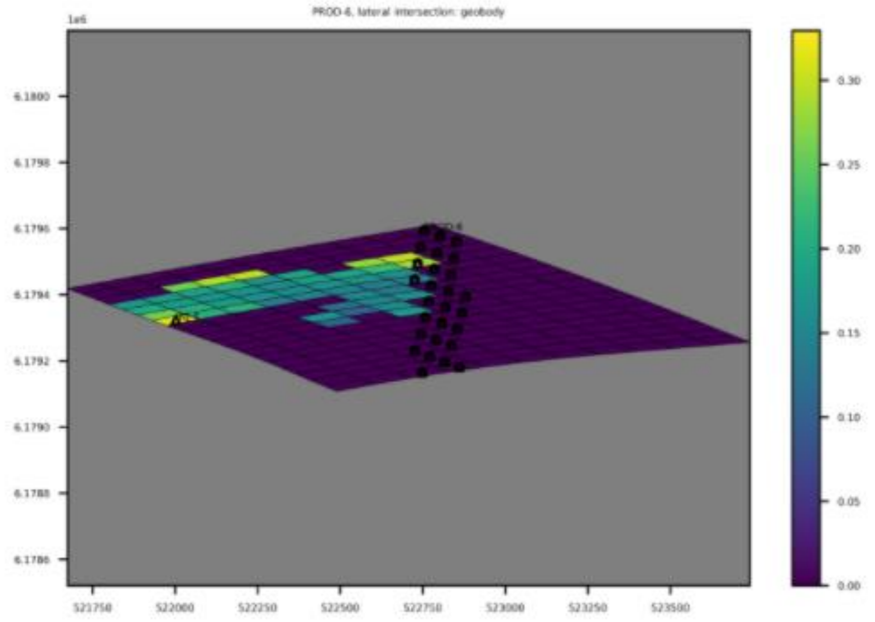
```
Pulling case: OLYMPUS_BC
Case links established.

Well: INJ-4
- Type: WINJ

-    INTERVAL     WELL_STATUS   WELL_IMPACT   THP_IMPACT   BHP_IMPACT    FLUID
-  2016 - 2018       INIT          MINI         None          MAXI         W
-  2018 - 2020       OPEN          SOME         None          None         W
-  2020 - 2022       OPEN          SOME         None          None         W
-  2022 - 2024       OPEN          SOME         None          None         W
-  2024 - 2026       OPEN          SOME         None          None         W
-  2026 - 2028       OPEN          SOME         None          None         W
-  2028 - 2030       OPEN          SOME         None          None         W
-  2030 - 2032       OPEN          SOME         None          None         W
-  2032 - 2034       OPEN          MAXI         None          None         W

Well: PROD-6
- Type: PROD

-    INTERVAL     WELL_STATUS   WELL_IMPACT   THP_IMPACT   BHP_IMPACT    FLUID
-  2016 - 2018       INIT          MINP         None          MIND         O
-  2018 - 2020       OPEN          SOME         None          None       OW_WBT
-  2020 - 2022       OPEN          SOME         None          None         OW
-  2022 - 2024       OPEN          SOME         None          None         OW
-  2024 - 2026       OPEN          SOME         None          None         OW
-  2026 - 2028       OPEN          SOME         None          None         OW
-  2028 - 2030       OPEN          SOME         None          None         OW
-  2030 - 2032       OPEN          SOME         None          None         OW
-  2032 - 2034       OPEN          MAXP         None          None         OW
```

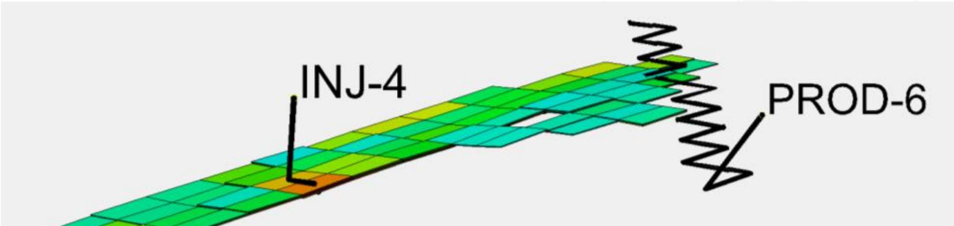
- Start-up
- Shut-down
- Pressure increase
- Pressure drop
- Gas breakthrough
- Water breakthrough

Swept volume at time of water breakthrough

```
In [1]: from olympus.py_sim_store import sim_store as ss
        from olympus.py_optima_local import property_utils as pu
        from olympus.py_auth import auth
        import warnings
        warnings.filterwarnings('ignore')

        auth.init()

        #Locate in simstore
        simid, simpath = ss.get_siminfo("OLYMPUS_F1.DATA")

        #Zoom in
        well = 'PROD-6'
        well_zoom = ('INJ-4','PROD-6')
        t1 = (2016,1,1)
        t2 = (2020,1,1)

        #Run workflow
        pu.swept_volume_at_well(simid,well,t1,t2,well_zoom=well_zoom)
```

```
Pulling case: OLYMPUS_F1
Processing grid ...
Grid setup completed.
Case links established.
Get closest restart, t1
Restart files: ['81ekfnxs6yy0er3m6t7r6gmrte']
Note: time 2016-01-01 00:00:00 requested, closest date found was 2016-01-01 00:00:00
Get closest restart, t2
Restart files: ['81ekfnxs6yy0er3m6t7r6gmrte']
Note: time 2020-01-01 00:00:00 requested, closest date found was 2020-12-30 00:00:00

Anomaly overlaps with well INJ-4
```

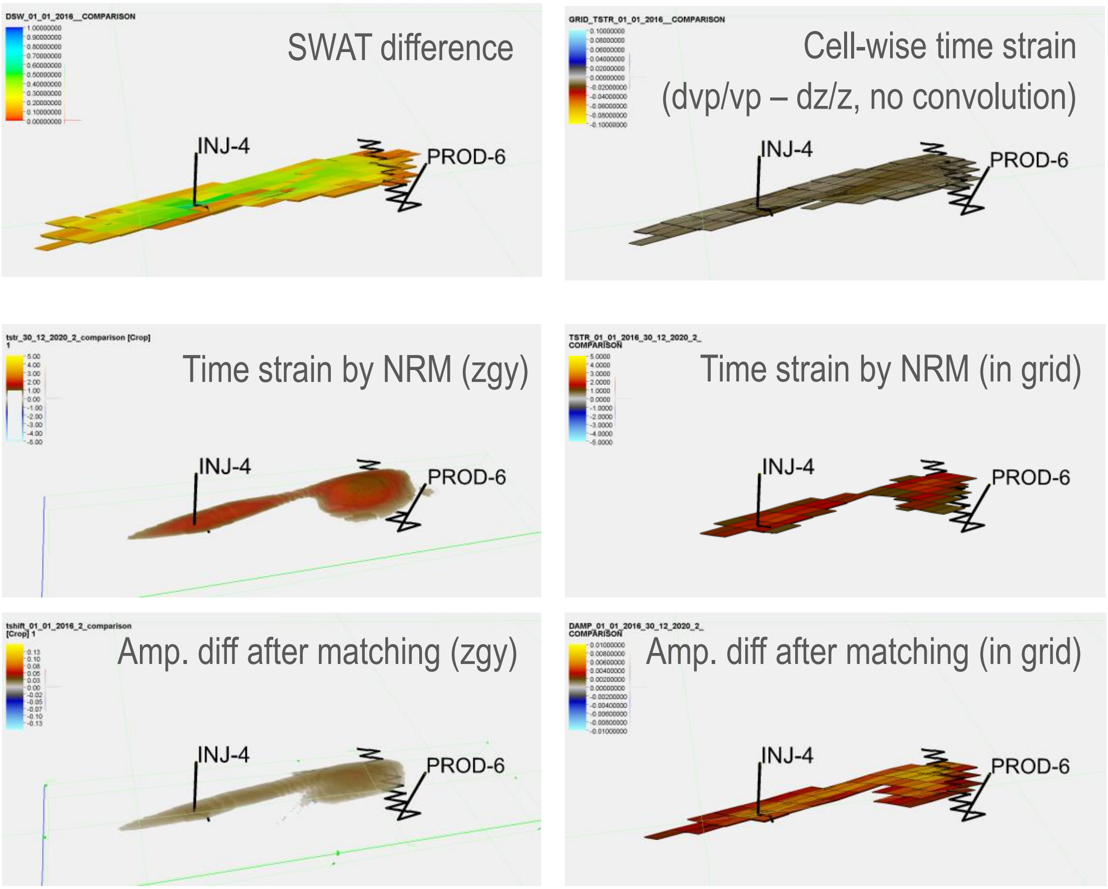




Petrel view (.grdecl import)

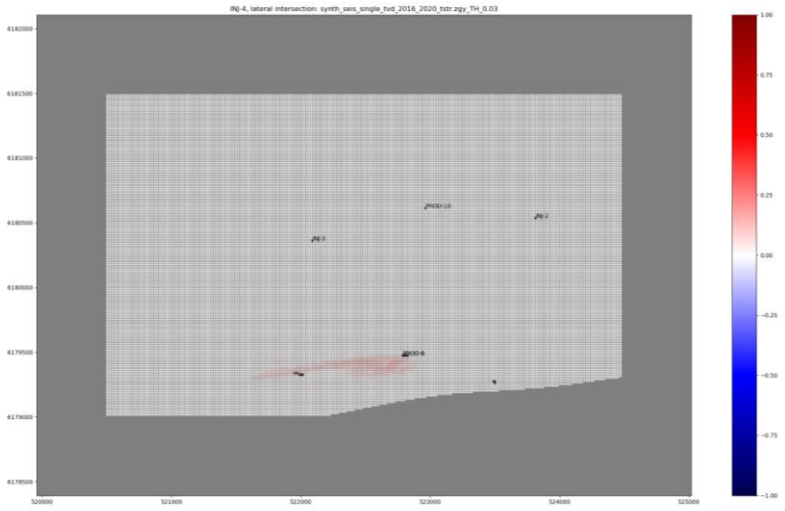
Different for different realizations!

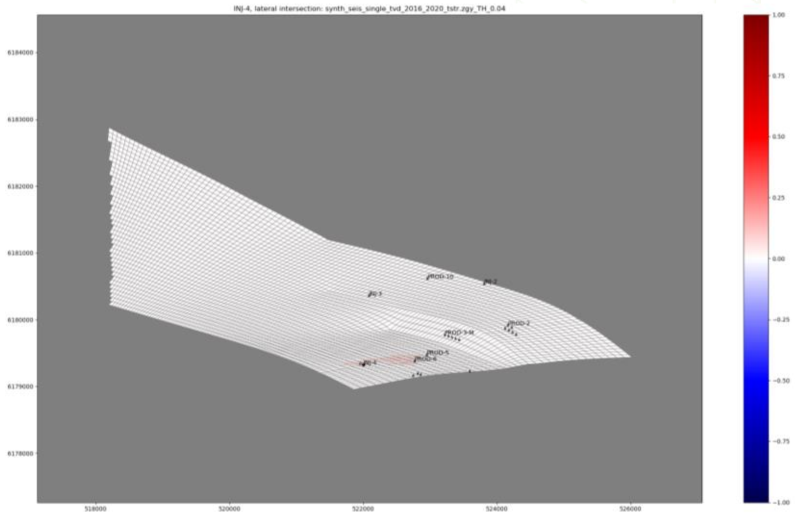
Synthetic 4D difference at water breakthrough

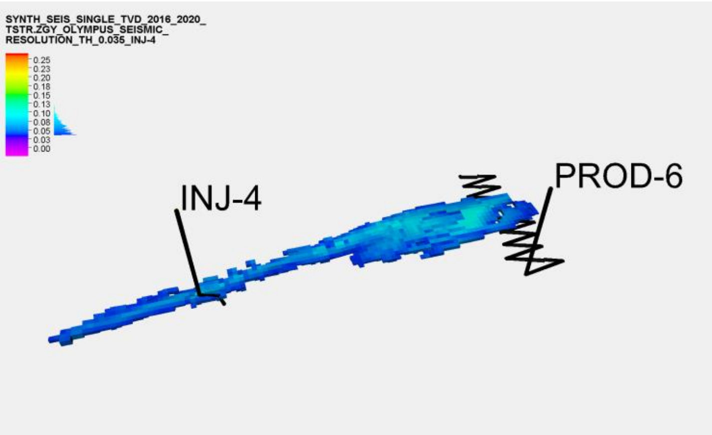


Notice loss of resolution / accuracy – important for comparison with real 4D data

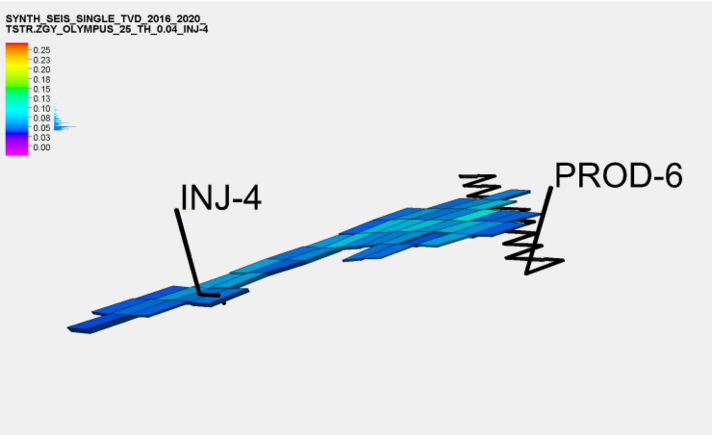
Observed 4D seismic anomaly at water breakthrough





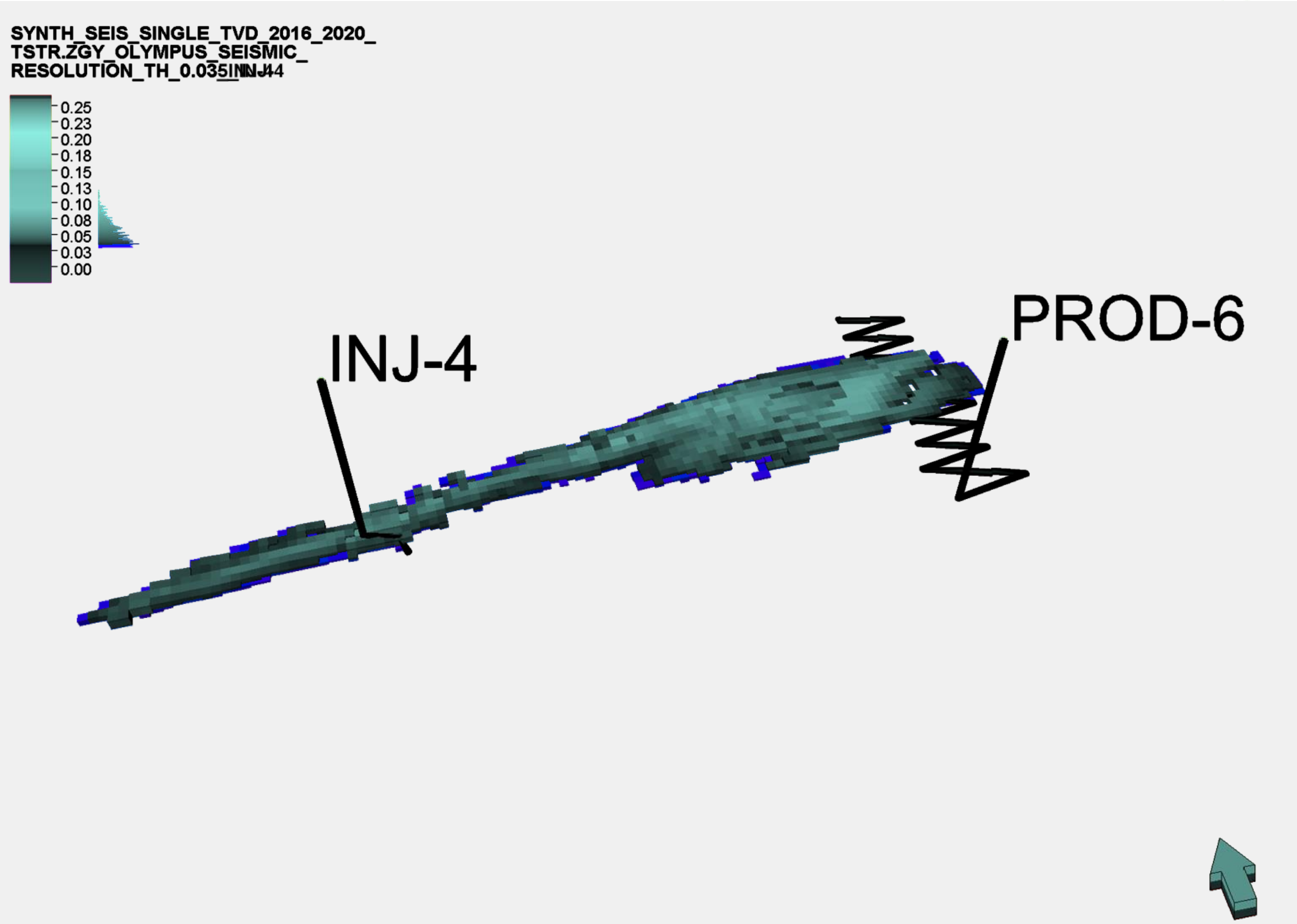


Seismic grid resolution



Simulation grid resolution

Interpretation / extraction uncertainty – threshold sensitivity



4D seismic model vs data mismatch

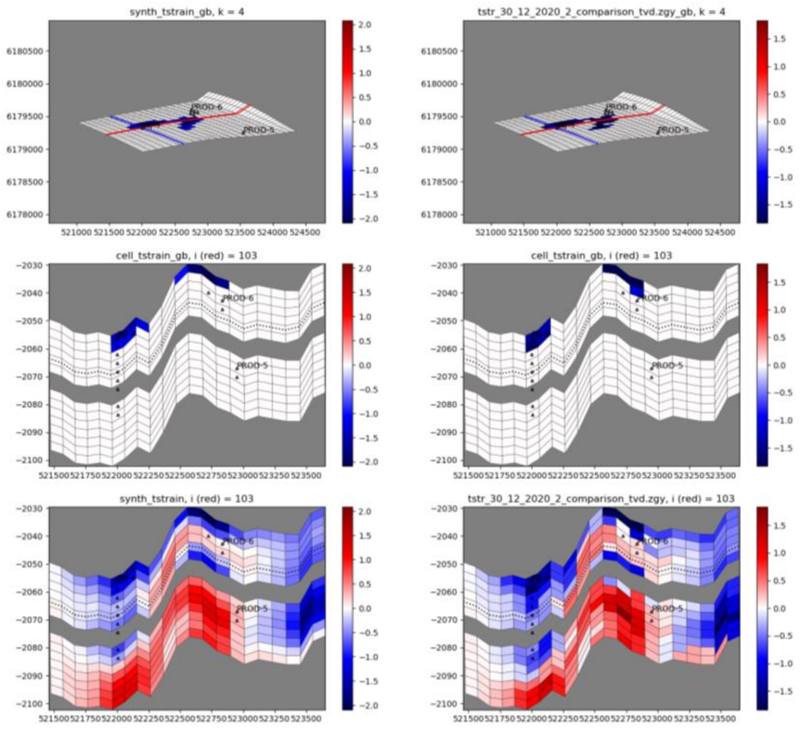
Time strain

```
MISMATCH:
Size of footprint: -0.02
    Missing parts:  0.17
     Excess parts:  0.15
```

Footprint

Threshold

Original



Simulated 4D attr

«Observed» 4D attr

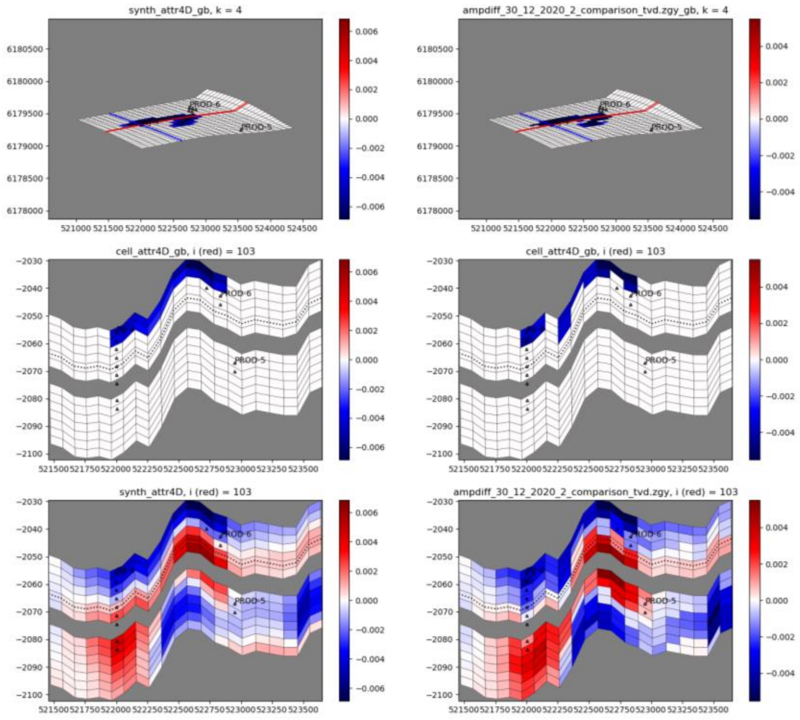
Amplitude difference

```
MISMATCH:
Size of footprint:  0.00
    Missing parts:  0.10
     Excess parts:  0.10
```

Footprint

Threshold

Original



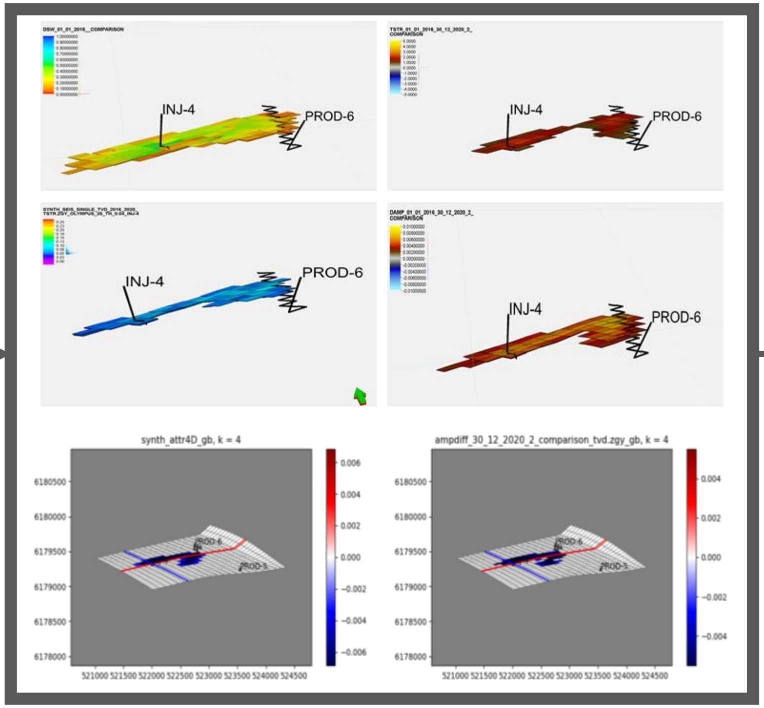
Simulated 4D attr

«Observed» 4D attr

Scripts put in sequence – consistent tracking of events

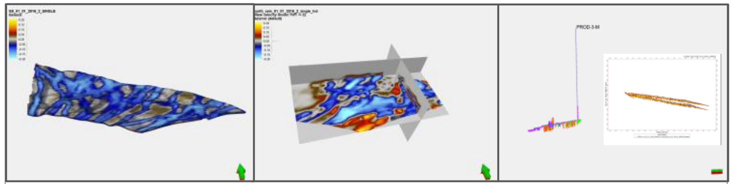
Well: PROD-6
- Type: PROD

-	INTERVAL	WELL_STATUS	WELL_IMPACT	THP_IMPACT	BHP_IMPACT	FLUID
-	2016 - 2018	INIT	MINP	None	MIND	
-	2018 - 2020	OPEN	SOME	None	None	OW_WBT
-	2020 - 2022	OPEN	SOME	None	None	
-	2022 - 2024	OPEN	SOME	None	None	OW
-	2024 - 2026	OPEN	SOME	None	None	OW
-	2026 - 2028	OPEN	SOME	None	None	OW
-	2028 - 2030	OPEN	SOME	None	None	OW
-	2030 - 2032	OPEN	SOME	None	None	OW
-	2032 - 2034	OPEN	MAXP	None	None	OW

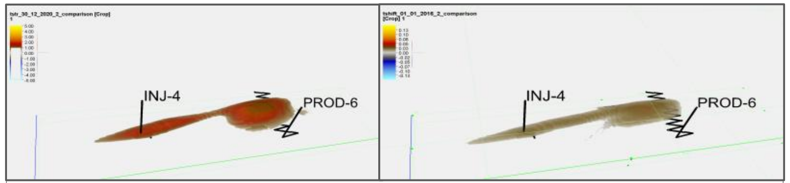



```
MISMATCH:
Size of footprint: -0.02
    Missing parts:  0.17
     Excess parts:  0.15
```

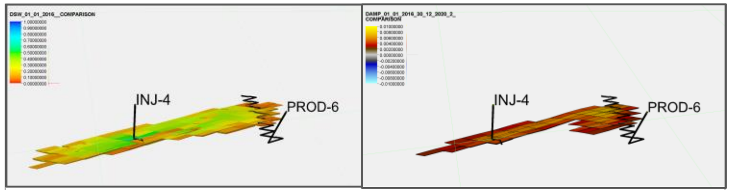
Composability and extensibility – working together to fill the gaps



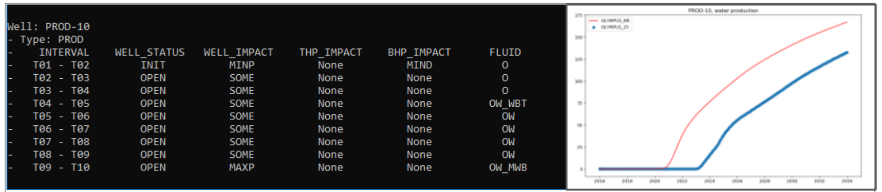
Auto-generate synthetic seismic & logs
from simulation input and results (3D, 4D by non-rigid matching)



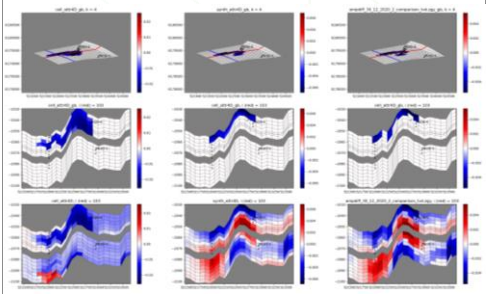
Auto-extract seismic anomalies
(geobodies from 3D & 4D seismic)



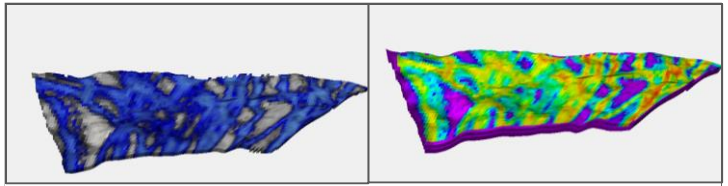
Auto-extract swept volumes
from simulation results & via synthetic 4D seismic



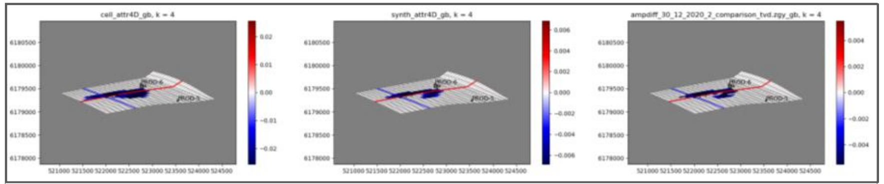
Auto-characterize well events
simulated and observed data



Auto-generate customized displays
Well-centric, data & model coviz

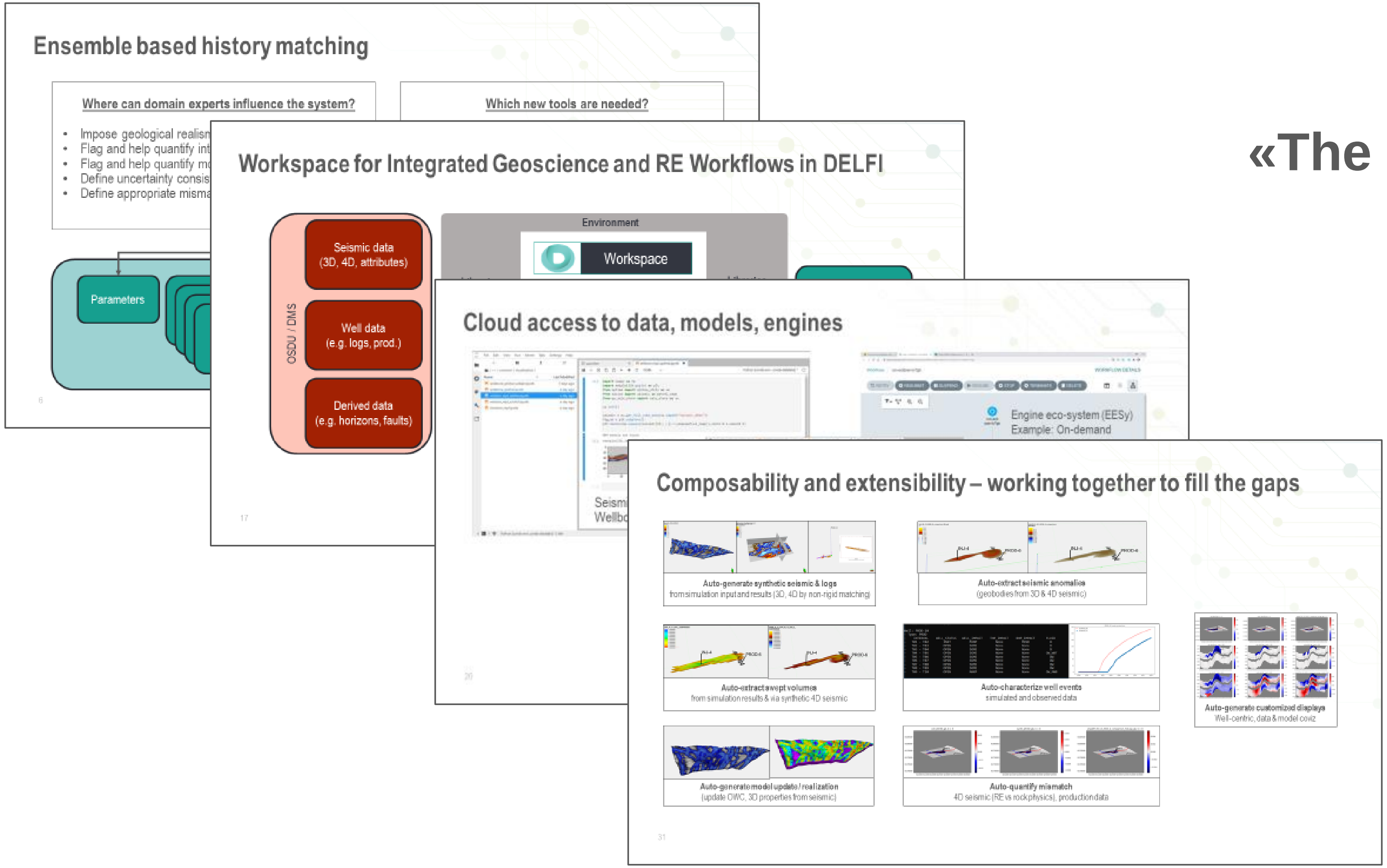


Auto-generate model update / realization
(update OWC, 3D properties from seismic)



Auto-quantify mismatch
4D seismic (RE vs rock physics), production data

Summary and outlook



«The future is open»