History matching real production and seismic data for the Norne field

EnKF Workshop 2018

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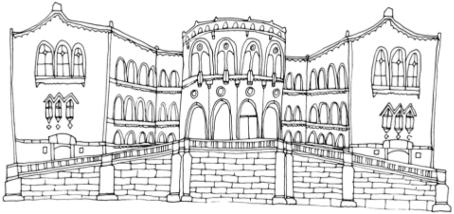
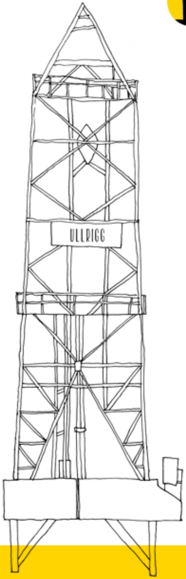
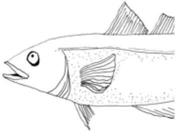






Introduction

- The full norne model is history matched using real production and seismic data
- Initial ensemble generated using Gaussian random fields
- Updates PORO, PERMX, NTG, MULTZ, MULTFLT, MULTREGT, KRW/KRG, OWC
- Clay content defined as VCLAY = 1 - NTG
- Sequential assimilation (production $\rightarrow$ seismic)
- Seismic data inverted for acoustic impedance at four points in time
- Iterative ensemble smoother, RLM-MAC, used (Luo et. al, SPE-176023-PA)
- Sparse representation using wavelets (data reduced by 86 %)
- Correlation based localization

Seismic data inversion and transformation

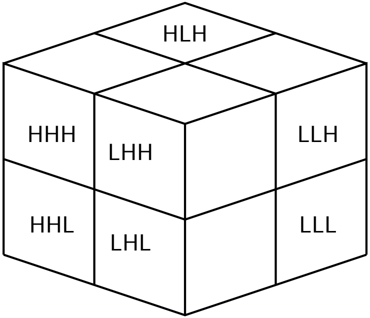
- Time shift correction:
  Alfonzo et al. 2017
- Linearized Bayesian approach:
  Buland and Omre, 2003: $S_{\mathrm{base}} = Gy_{\mathrm{base}} + e$
- Time to depth conversion:
  Provided Norne velocity model
- Upscaling:
  Petrel software
- Difference and averaging:
  $\overline{\Delta z}_p^o$

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:
  $[K_{\mathrm{sat}}, G_{\mathrm{sat}}] \leftarrow \mathrm{Gassman}(K_{\mathrm{dry}}, G_{\mathrm{dry}}, K_s, G_s)$
- P-wave velocity and rock density:
  $[v_p, \rho_{\mathrm{sat}}] \leftarrow \mathrm{Mavko}(K_{\mathrm{sat}}, G_{\mathrm{sat}})$
  $z_p = v_p \times \rho_{\mathrm{sat}}$

Sparse representation and image denoising

1. Transform seismic observations:
   $c_S \leftarrow \mathrm{DWT}(\overline{\Delta z}_p^o)$



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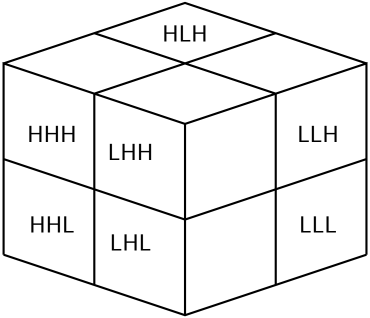

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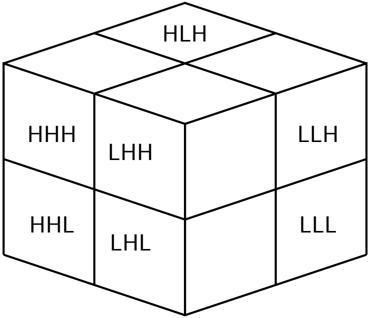

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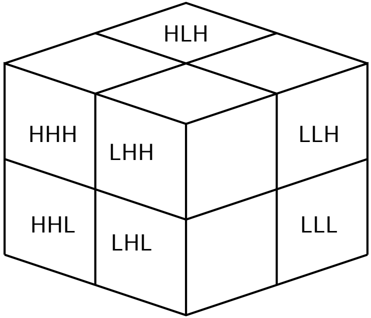

IRIS

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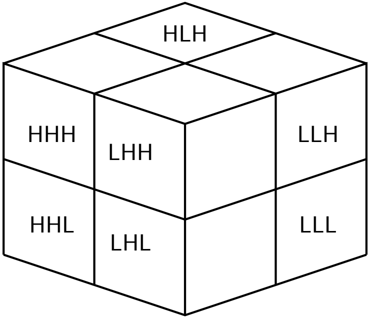
5. Apply hard thresholding:
   $c_s \rightarrow c_s > T_S, \quad d^o = c(\mathcal{I})$



Ensemble smoother

$$m_j^{i+1} = m_j^i + S_m^i (S_d^i)^T [S_d^i (S_d^i)^T + \gamma^i C_d]^{-1} \times [d^o + \epsilon_j - d_j^i]$$

$\downarrow$ TSVD

$$m_j^{i+1} = m_j^i + \tilde{K}^i \Delta \tilde{d}_j^i$$

$\Delta \tilde{d}_j^i \in \mathbb{R}^{p \times 1}, \ p \leq N$: Projected ("effective") data innovation.

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   $\xi_{kl} = 1, \text{ if} |\rho_{kl}| \geq \lambda_l, \; 0 \text{ otherwise}$
6. Updated Kalman gain matrix (see also Luo and Bhakta, 2017):
   $\hat{K} = \xi \circ \tilde{K}$

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4. applying the DWT to get c_j
5. using the leading indices $\mathcal{I}$ to get $d_j = c_j(\mathcal{I})$

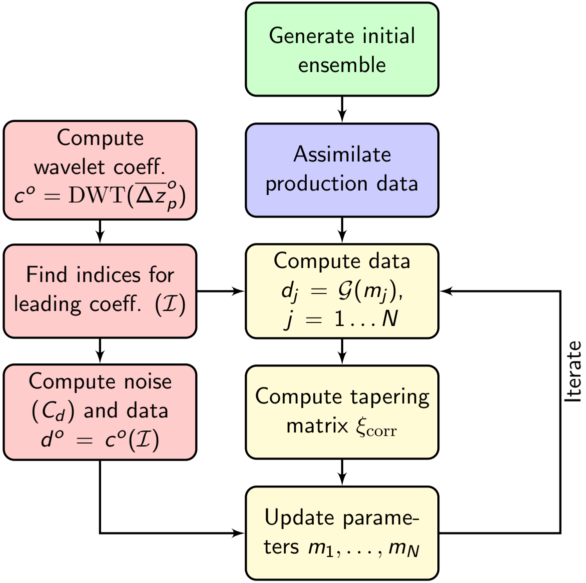
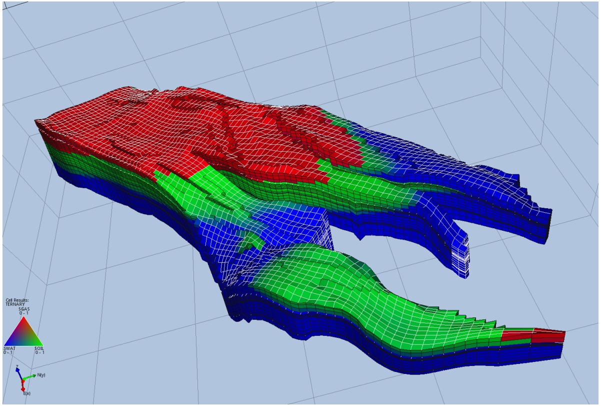
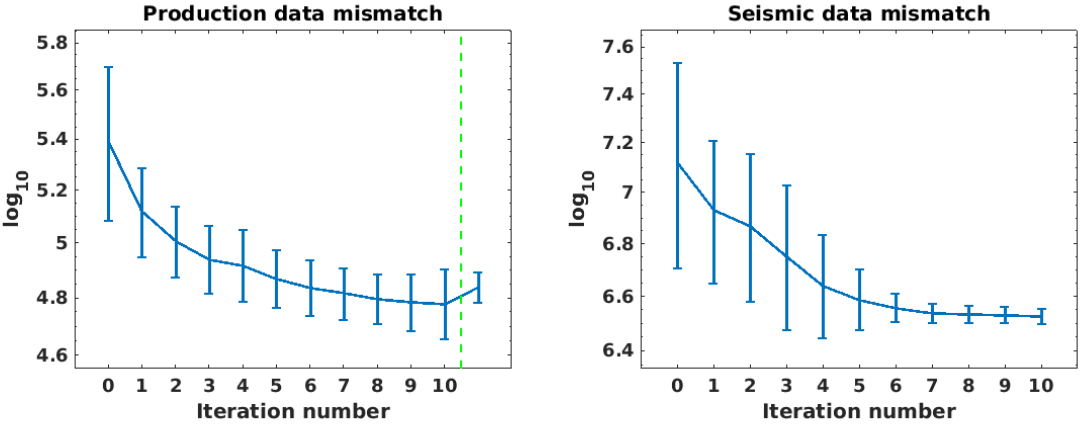


Figure: Workflow for assimilating seismic data.

Norne field

- Grid size:
  46 x 112 x 22
  (113344)
- Active cells:
  44927
- Wells:
  9 injectors,
  27 producers
- Production: 3312 days




Production data mismatch
5.8
5.6
5.4
5.2
5
4.8
4.6
log10
0 1 2 3 4 5 6 7 8 9 10
Iteration number
Seismic data mismatch
7.6
7.4
7.2
7
6.8
6.6
6.4
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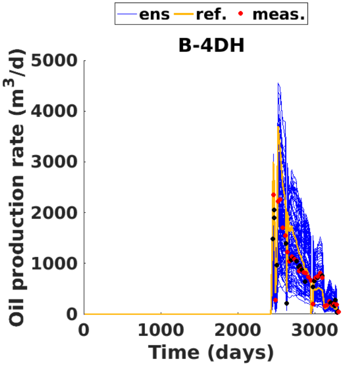
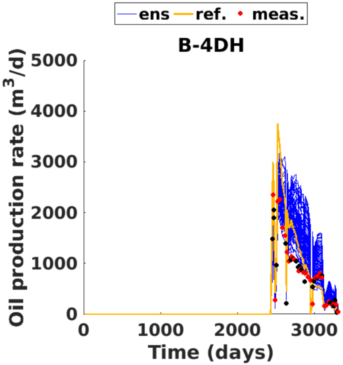
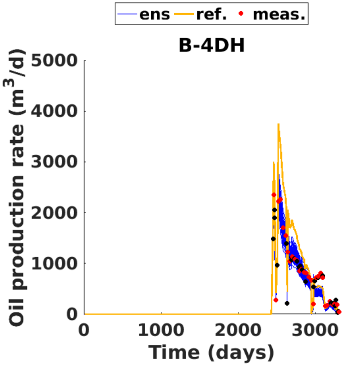


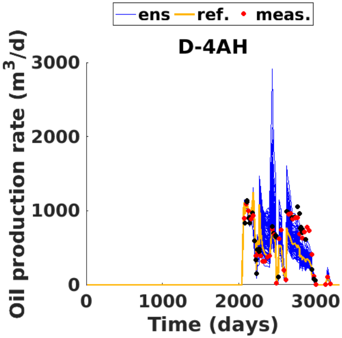
Initial



Production



Seismic



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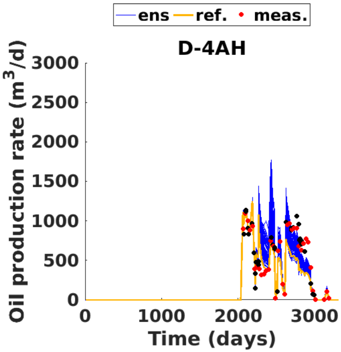

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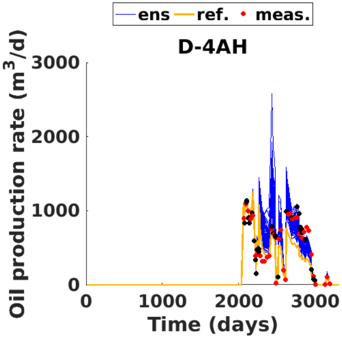

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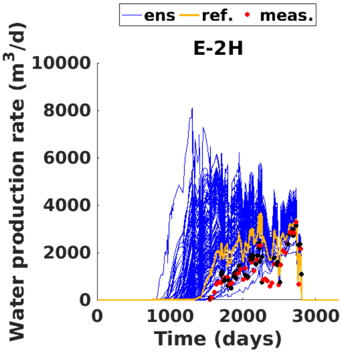

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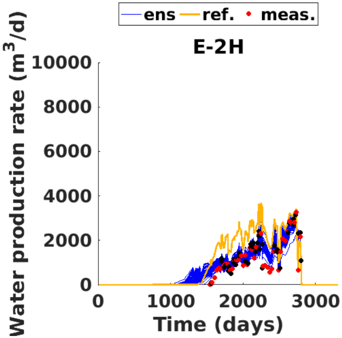

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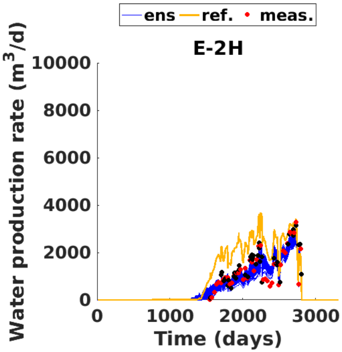

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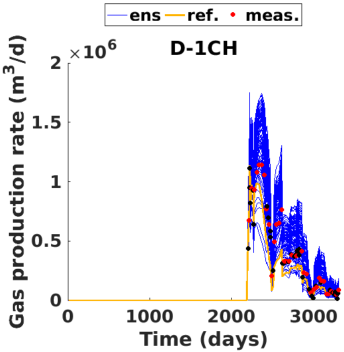

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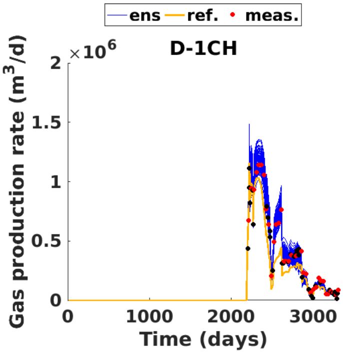

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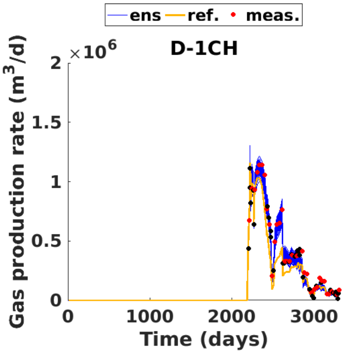

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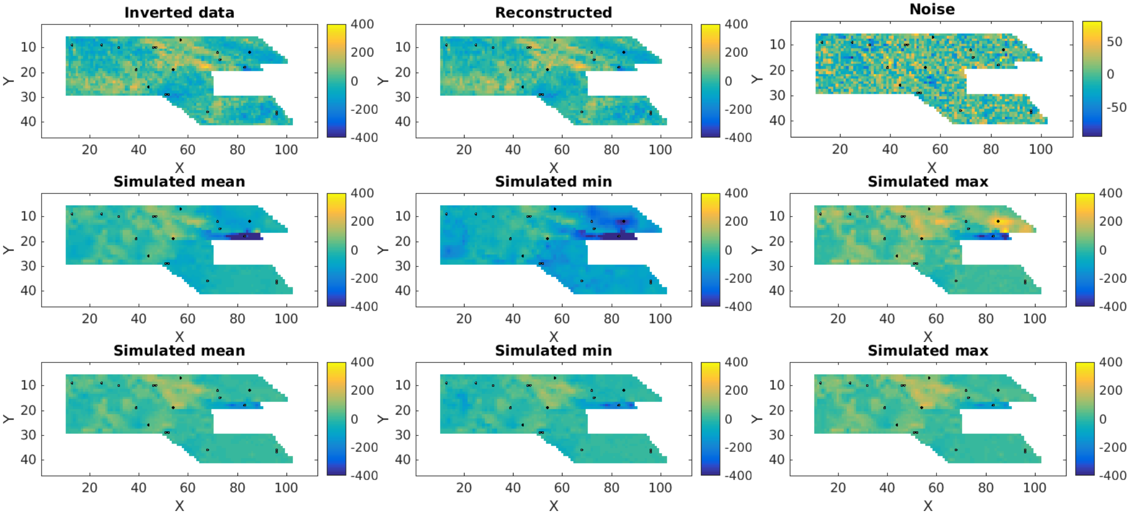
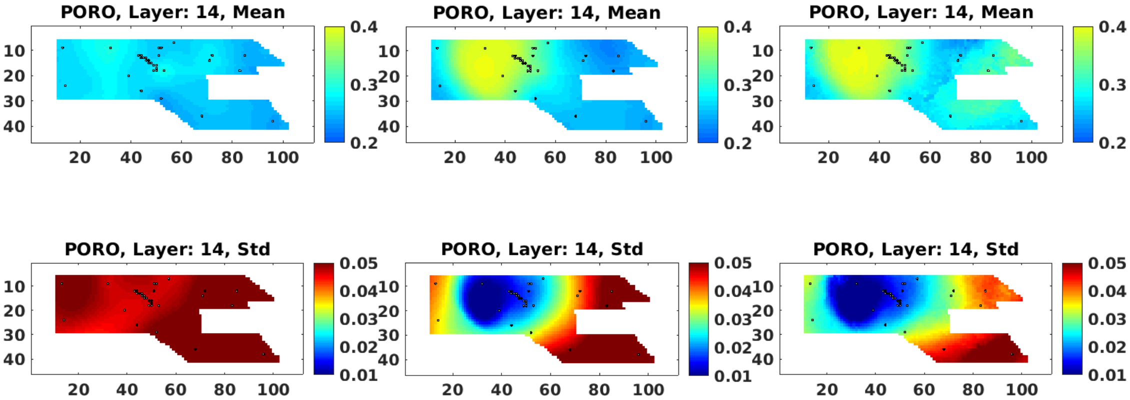


Top: real data. Middle: production. Bottom: seismic.



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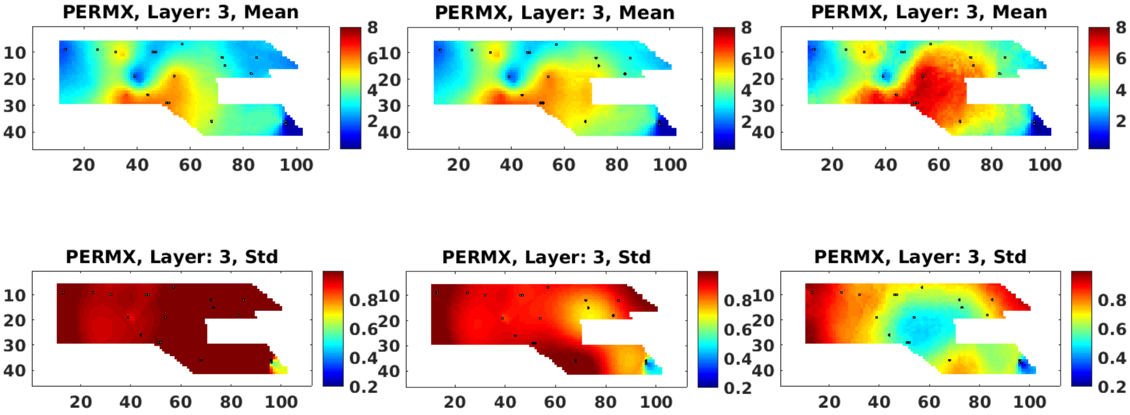

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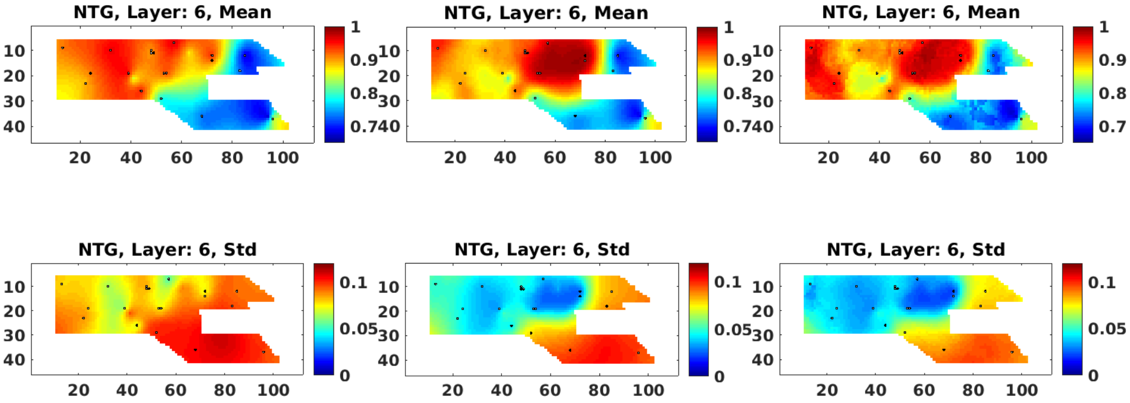

Initial

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Seismic

Summary / Conclusions

- A workflow for history matching real production and seismic data is presented
- Clay content and other petrophysical parameters updated
- Data match improved for both production and seismic data
- Updated static fields are geologically credible
- Potential for simulating infill wells or EOR strategies

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