DNTNU Norwegian University of Science and Technology Ravesian seismic rock physic

Bayesian seismic rock physics inversion using a localized ensemble-based approach - with an application to the Alvheim field

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Outline

- Goals
- Case: Alvheim field
- Likelihood and geophysical forward model
- Prior model
- Posterior approximation
- Concluding remarks and further work



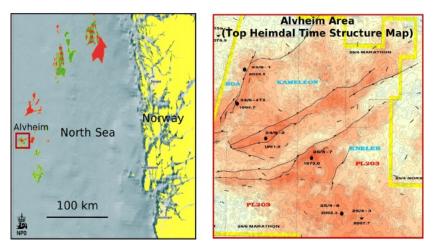
Goals

- Invert for the continuous reservoir parameters: oil and gas saturations and clay content
- Perform 2.5D inversion on top-reservoir using localised ensemble methods
- Condition on the seismic and well log data
- Provide more realistic uncertainty quantification by accounting for cementation and geology of the area

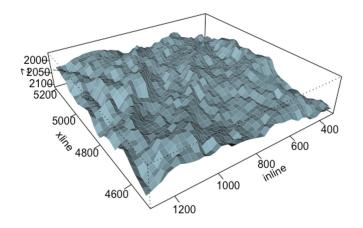


Case: Alvheim field

Traveltimes



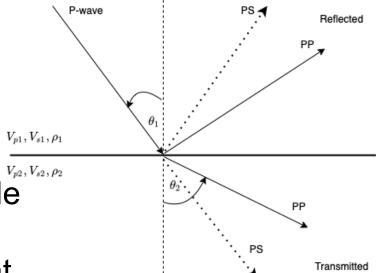
Source: Rimstad et al. *Hierarchical Bayesian lithology/fluid prediction: A North Sea case study*



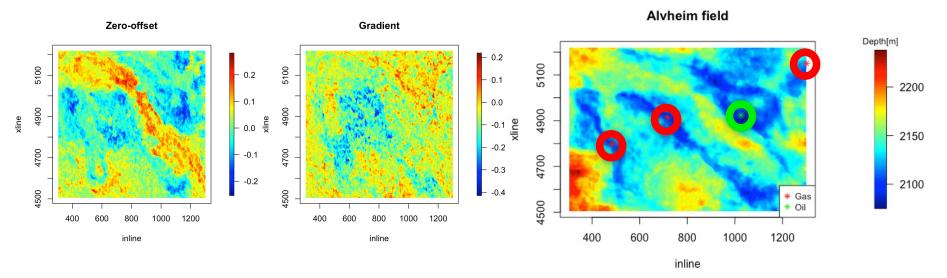
Traveltimes, top-reservoir

Amplitude versus offset - AVO

- Amplitude variation dependent on physical properties at the interface
- Zoeppritz equations
- Shuey approximation
- Linear fit of changes in amplitude vs incidence angles
- Extracting intercept and gradient at top-reservoir

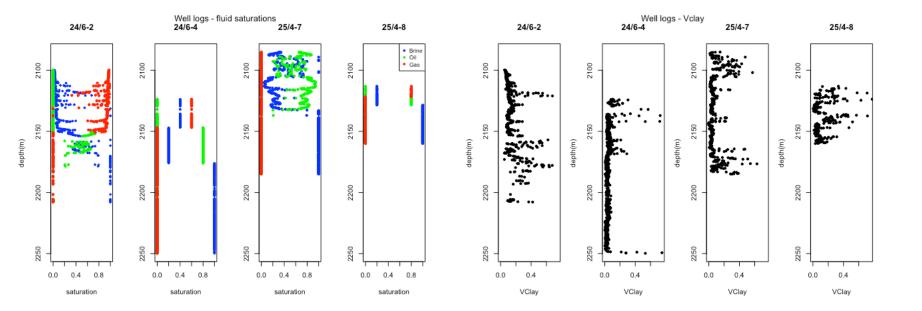


Case: Alvheim AVO data at top-reservoir





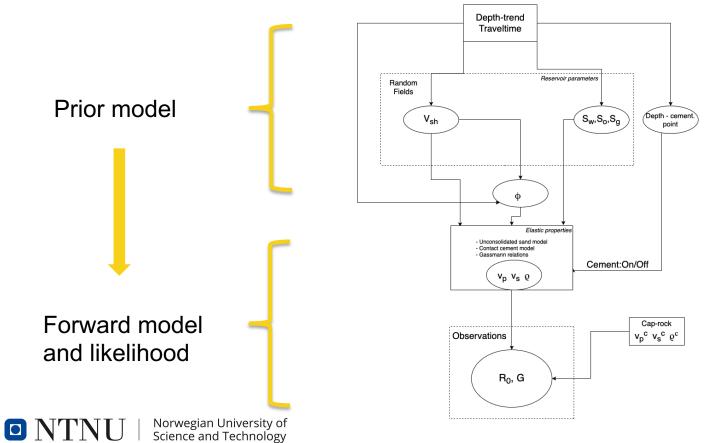
Case: Alvheim well log data



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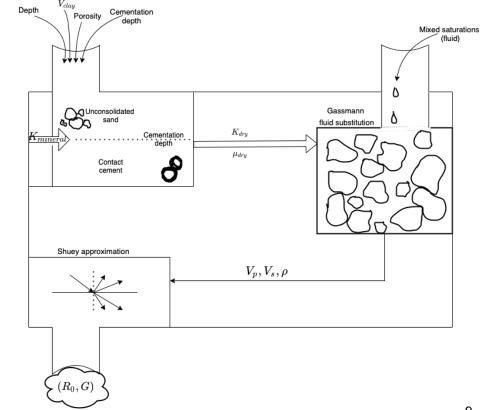
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Geophysical model



Zooming in on the seismic forward model

- Forward model
 - Unconsolidated sand model
 - Contact cement model (Dvorkin-Nur)
 - Gassmann relations
 - Shuey approximation



Bayesian framework

• Bayes rule

 $p(\mathbf{x}|\mathbf{y}) \propto p(\mathbf{y}|\mathbf{x})p(\mathbf{x})$

• Prior model

 $p(\boldsymbol{x^e}) \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$

- Likelihood
 - Observation model: $y^e = h(x^e) + \epsilon$
 - Non-linear forward model; dependent on depth, cementation point, porosity
 - $\epsilon \sim N(0, R)$, *R*-block diagonal

Prior model

Gaussian prior

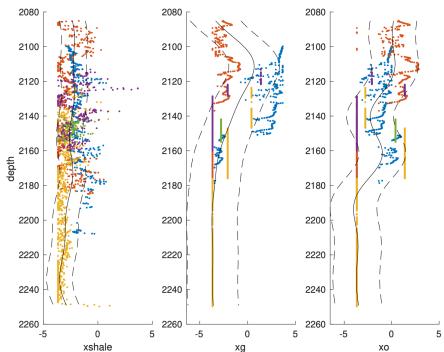
 $egin{aligned} oldsymbol{x}^g &\sim N(oldsymbol{\mu}^g, oldsymbol{\Sigma}^g) \ oldsymbol{x}^0 &\sim N(oldsymbol{\mu}^o, oldsymbol{\Sigma}^o) \ oldsymbol{x}^{cl} &\sim N(oldsymbol{\mu}^{cl}, oldsymbol{\Sigma}^{cl}) \end{aligned}$

- Mean trends estimated from well logs (depth dependence)
- Gaussian spatial correlation function
- Ensembles generated using the FFT-routine
- Logistic transformation

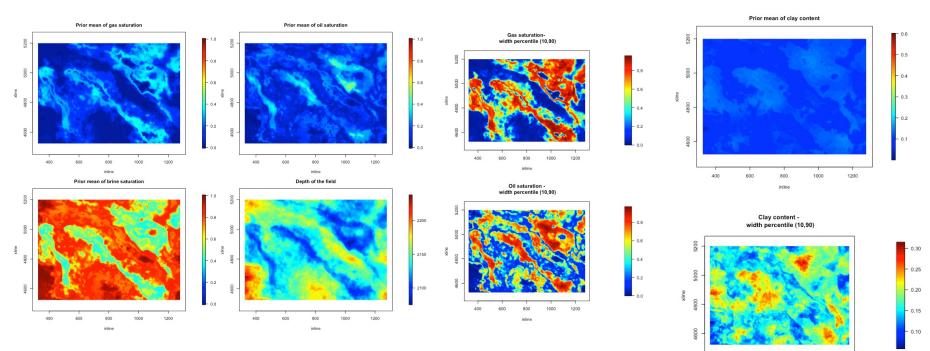
$$S_g = rac{\exp(x^g)}{1 + \exp(x^g) + \exp(x^o)}$$



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Prior: mean and uncertainty from realisations





inline

Conditioning on well data

Prior mean of oil saturation

1.0

- 0.8

0.6

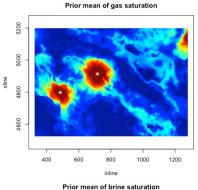
0.4

0.2

2200

2150

2100



5200

5000

4800

4600

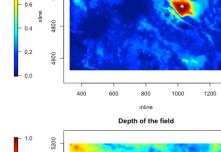
400

600

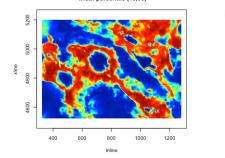
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inline

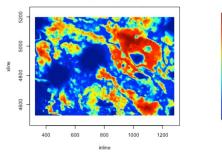
xline



Gas saturationwidth percentile (10,90)









1200

1000

1.0

0.8

5200

5000

- 0.8

- 0.6

- 0.4

- 0.2

- 0.8

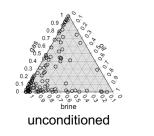
- 0.6

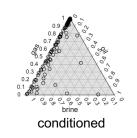
- 0.4

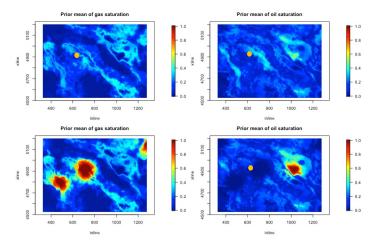
- 0.2

Conditioning on well data

 Difference in saturation at inline 624, xline 4928 for 100 realisations

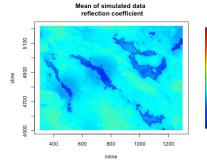


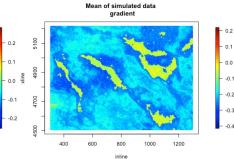






Simulated seismic data





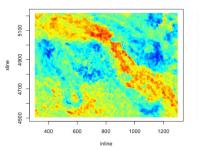
0.0

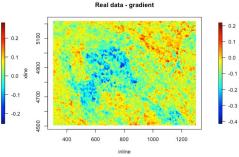
-0.1 -0.2

- -0.3

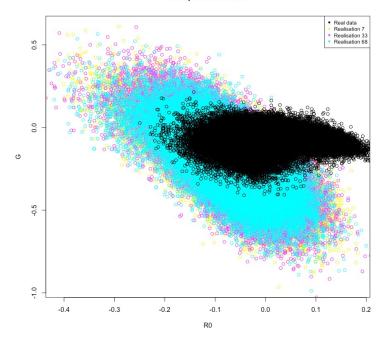
-0.4

Real data - reflection coefficient





Crossplot of AVO data





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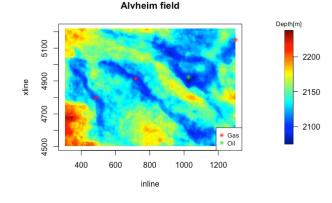
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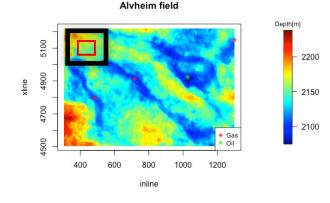
- Approximate realisations of the posterior
- Localised Ensemble Transform Kalman Filter



Algorithm 1: Localized Ensemble
Transform Kalman Filter
Prior
$oldsymbol{x}^e \sim p(oldsymbol{x}) = N(oldsymbol{x};oldsymbol{\mu},oldsymbol{\Sigma}), e=1,,n_e;$
$oldsymbol{y}^e = h(oldsymbol{x}^e) + oldsymbol{\epsilon}, oldsymbol{\epsilon} \sim N(oldsymbol{\epsilon}; 0, oldsymbol{R});$
$ar{y}_n = 1/n_e \sum_{e=1}^{n_e} y_n^e, n = 1,, N;$
$oldsymbol{Y}=(oldsymbol{y}^1-ar{oldsymbol{y}},,oldsymbol{y}^{n_e}-ar{oldsymbol{y}});$
$ar{x}_n = 1/n_e \sum_{e=1}^{n_e} x_n^e;$
$m{X} = (m{x}^1 - ar{m{x}},, m{x}^{n_e} - ar{m{x}});$
For each patch $j = 1,, J$
$oldsymbol{H}_j = [oldsymbol{Y}_j^Toldsymbol{R}_j^{-1}oldsymbol{Y}_j + (n_e-1)oldsymbol{I}]^{-1}$
$oldsymbol{K}_j = oldsymbol{X}_j oldsymbol{H}_j oldsymbol{Y}_j^T oldsymbol{R}_j^{-1}$
$ar{oldsymbol{x}}^a = ar{oldsymbol{x}} + oldsymbol{K}_j (oldsymbol{y}_j^0 - ar{oldsymbol{y}})$
$oldsymbol{E}_j = oldsymbol{ar{x}}^a + oldsymbol{X}_j [(n_e-1)oldsymbol{H}_j]^{1/2};$
Result: $\boldsymbol{E} = (\boldsymbol{E}_1, \dots, \boldsymbol{E}_j)$

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- Approximate realisations of the posterior
- Localised Ensemble Transform Kalman Filter



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Algorithm 1: Localized Ensemble
Transform Kalman Filter
Prior
$oldsymbol{x}^e \sim p(oldsymbol{x}) = N(oldsymbol{x};oldsymbol{\mu},oldsymbol{\Sigma}), e=1,,n_e;$
$oldsymbol{y}^e = h(oldsymbol{x}^e) + oldsymbol{\epsilon}, oldsymbol{\epsilon} \sim N(oldsymbol{\epsilon}; 0, oldsymbol{R});$
$ar{y}_n = 1/n_e \sum_{e=1}^{n_e} y_n^e, n = 1,, N;$
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$\bar{x}_n = 1/n_e \sum_{e=1}^{n_e} x_n^e;$
$oldsymbol{X} = (oldsymbol{x}^1 - oldsymbol{ar{x}},, oldsymbol{x}^{n_e} - oldsymbol{ar{x}});$
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$oldsymbol{K}_j = oldsymbol{X}_j oldsymbol{H}_j oldsymbol{Y}_j^T oldsymbol{R}_j^{-1}$
$ar{oldsymbol{x}}^a = ar{oldsymbol{x}} + oldsymbol{K}_j (oldsymbol{y}_j^0 - ar{oldsymbol{y}})$
$m{E}_j = ar{m{x}}^a + m{X}_j [(n_e-1)m{H}_j]^{1/2};$
Result: $\boldsymbol{E} = (\boldsymbol{E}_1, \dots, \boldsymbol{E}_j)$

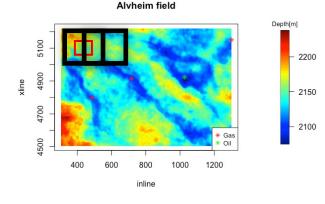
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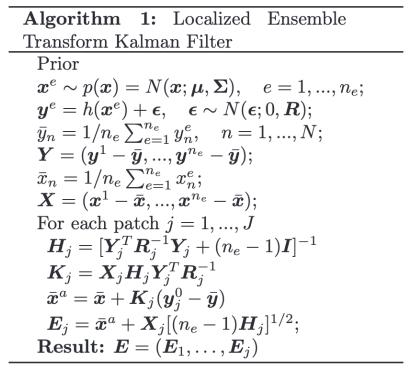
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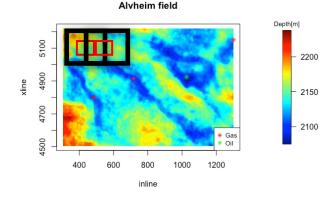
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- Approximate realisations of the posterior
- Localised Ensemble Transform Kalman Filter



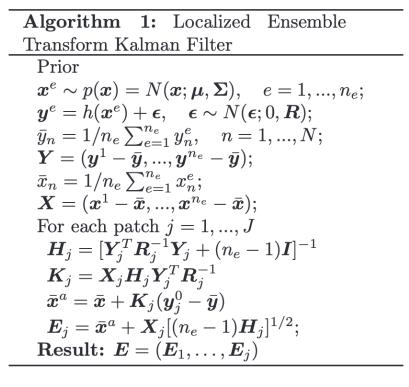


- Approximate realisations of the posterior
- Localised Ensemble Transform Kalman Filter



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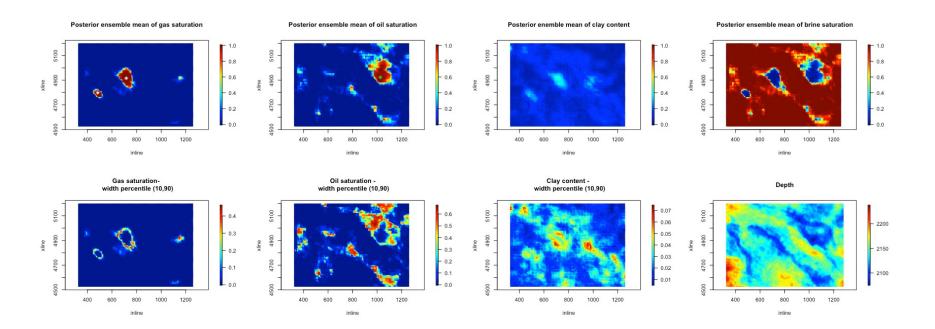
Posterior approximation – IEnKS

- Localised IEnKS
- For each patch we run the IEnKS for *j* number of iterations
- Data assimilation window (DAW) corresponds to the observation patch

Algorithm 2: Localized Iterative Ensemble Kalman Smoother

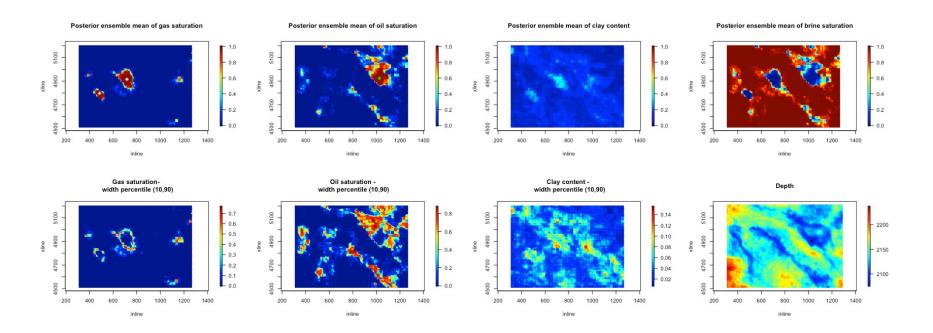
Prior ensemble $\boldsymbol{E}^f = \boldsymbol{E}^f_k$ $j=0, \boldsymbol{w}_{j}=\boldsymbol{0}, \boldsymbol{T}_{j}=\boldsymbol{I}_{n_{e}}$ $ar{m{x}}^f = m{E}^f m{1}/n_e$ $\boldsymbol{X}_{f} = \left(\boldsymbol{E}^{f} - \bar{\boldsymbol{x}}^{f} \boldsymbol{1}^{T} \right) / \sqrt{n_{e} - 1}$ Repeat $\boldsymbol{x}_i = ar{\boldsymbol{x}}^f + \boldsymbol{X}_f \boldsymbol{w}_i$ $\boldsymbol{E}_{j} = \boldsymbol{x}_{j} \boldsymbol{1}^{T} + \sqrt{n_{e} - 1} \boldsymbol{X}_{f} \boldsymbol{T}_{j}$ $\bar{\boldsymbol{y}} = h_k(\boldsymbol{E}_i) \mathbf{1}/n_e$ $\boldsymbol{Y} = \left[h_k(\boldsymbol{E}_i) - \bar{\boldsymbol{y}} \boldsymbol{1}^T\right] \boldsymbol{T}_i^{-1} / \sqrt{n_e - 1}$ $\nabla J = \boldsymbol{w}_{i} - \boldsymbol{Y}^{T} \boldsymbol{R}_{k}^{-1} \left(\boldsymbol{y}_{k}^{0} - \bar{\boldsymbol{y}} \right)$ $\mathbb{H} = \boldsymbol{I} + \boldsymbol{Y}^T \boldsymbol{R}_{\boldsymbol{\mu}}^{-1} \boldsymbol{Y}$ $oldsymbol{w}_{i+1} = oldsymbol{w}_i - \mathbb{H}^{-1}
abla J$ $\boldsymbol{T}_{i+1} = \mathbb{H}^{-1/2}$ i = i + 1termination criteria met $\boldsymbol{E}_{k} = \bar{\boldsymbol{x}}^{f} \boldsymbol{1}^{T} + \boldsymbol{X}_{f} \left(\boldsymbol{w}_{i-1}^{T} \boldsymbol{1}^{T} + \sqrt{n_{e} - 1} \boldsymbol{T}_{i} \right)$

Posterior approximation – results(ref. case) Observation patch: 16x16; Parameters 6x6;



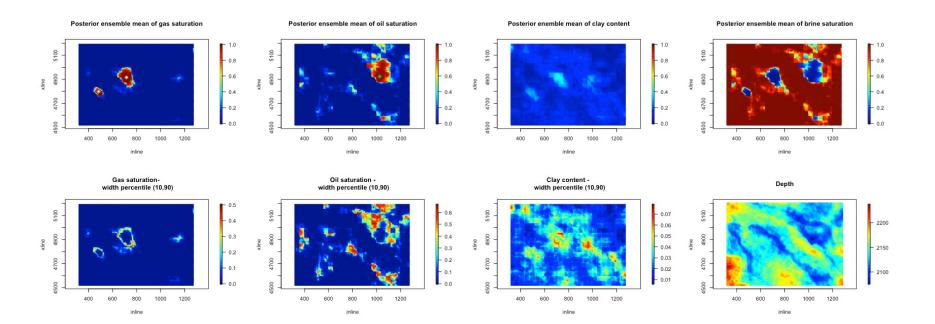


Posterior approximation – results Observation patch: 9x9; Parameters: 6x6;

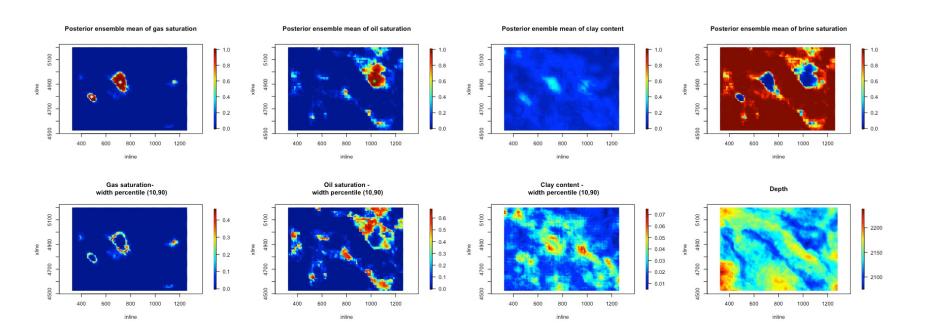




Posterior approximation – results Observation patch: 16x16; Parameters: 10x10;

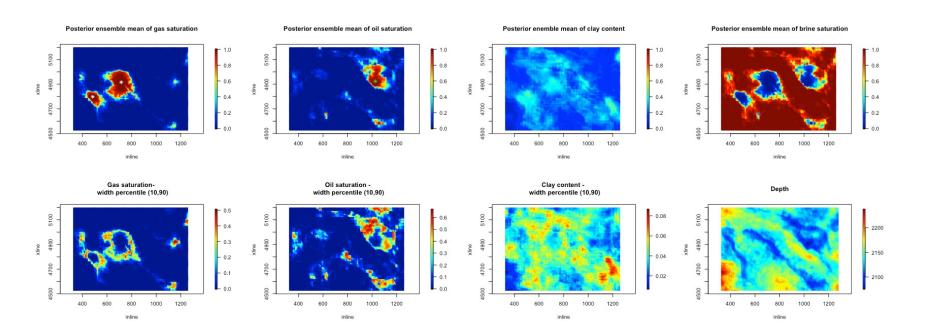


Posterior approximation – results Cem depth: 2110 m



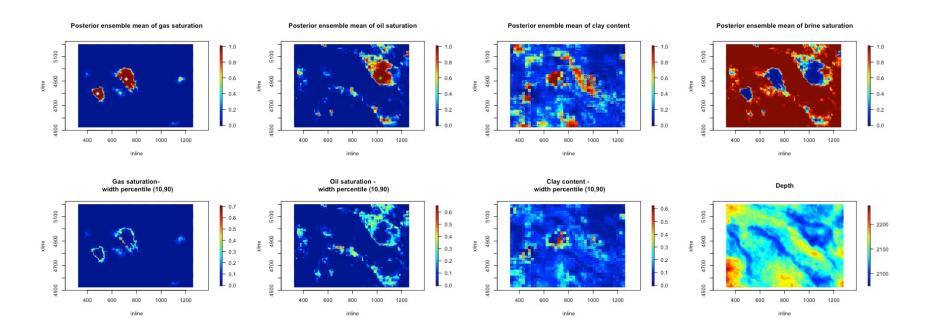


Posterior approximation – results Cem depth: 2162 m

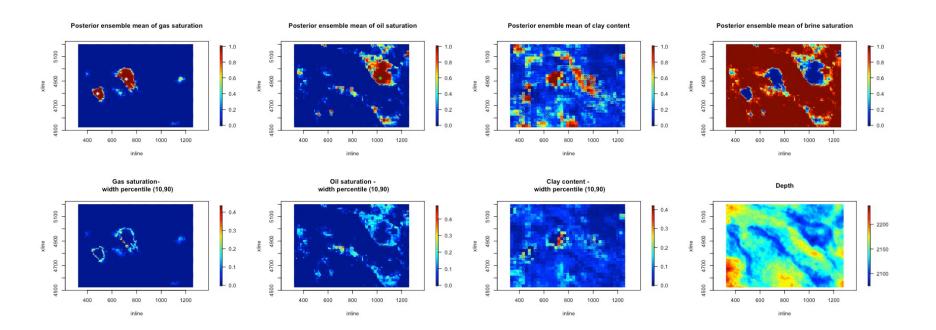




Posterior approximation – results One iteration



Posterior approximation – results Two iterations





Concluding remarks and further work

- Perform 2.5D inversion of the reservoir parameters
- Use localised ensemble methods to assimilate available seismic data
- Validation of the results using seismic data and sensitivity analysis
- Further improving forward model and conditioning on remaining well log data