

Bayesian inference in CO₂ storage monitoring: a way to assess uncertainties in geophysical inversions

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Motivation

- Conformance monitoring: convergence between models and monitoring data.
 - ➔ Requires quantitative estimates: pressure, saturation, stress changes,...
- Geophysical monitoring can provide quantification of relevant rock physics properties ➔ two-step inversion.
- Inverse problems (two steps) are non linear, highly underdetermined and ill-posed and have non unique solutions.
- Important to quantify/assess the uncertainty related to these measurements:
 - ➔ can be achieved with fully Bayesian formulation

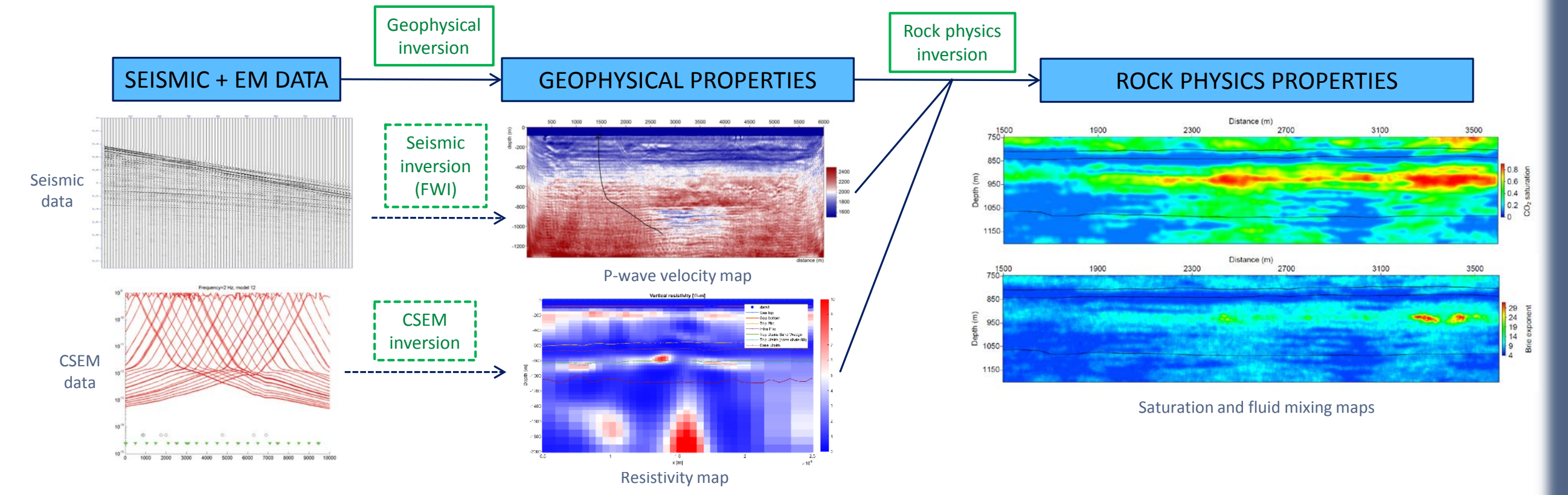


Figure 1: Two-step geophysical quantitative inversion. Figures from Romdhane and Querendez (2014), Bøe et al. (2017), Yan et al. (2018)

Bayesian formulation of inverse problems

- Review book of Tarantola, 2005
 - Bayes theorem: $P(A|B) = \frac{P(B|A) * P(A)}{P(B)}$
 - Inverse problem formulation: $C_{post}(\mathbf{m}) = c C_{prior}(\mathbf{m}) L(\mathbf{m}|d_{obs})$
 - Misfit function (L2 norm):
- $$L(\mathbf{m}|d_{obs}) = [d_{obs} - \mathbf{g}(\mathbf{m})]^T C_D^{-1} [d_{obs} - \mathbf{g}(\mathbf{m})]$$
- $P(B|A)$ = model posterior probability
 $P(B)$ = model prior probability
 $P(A|B)$ = data likelihood knowing the model
 \mathbf{m} = model vector; c = constant
 $C_{post}(\mathbf{m})$ = posterior probability distribution
 $C_{prior}(\mathbf{m})$ = prior probability distribution
 $L(\mathbf{m}|d_{obs})$ = data likelihood misfit function
 d_{obs} = observed data; $\mathbf{g}(\mathbf{m})$ = calculated data
 C_D = data covariance matrix (noise)

Full waveform inversion and uncertainty assessment

- Based on Bayesian inversion approach for tomographic methods (Tarantola, 2005; Eliasson and Romdhane, 2017).
- Posterior covariance determined from the Hessian H :

$$C_{post} = C_{prior}^{1/2} (C_{prior}^{1/2} H C_{prior}^{1/2} + I)^{-1} C_{prior}^{1/2}$$

- "Equivalent models" are sampled from posterior Gaussian probability density function. Parameter uncertainty proportional to range of values given by equivalent models.

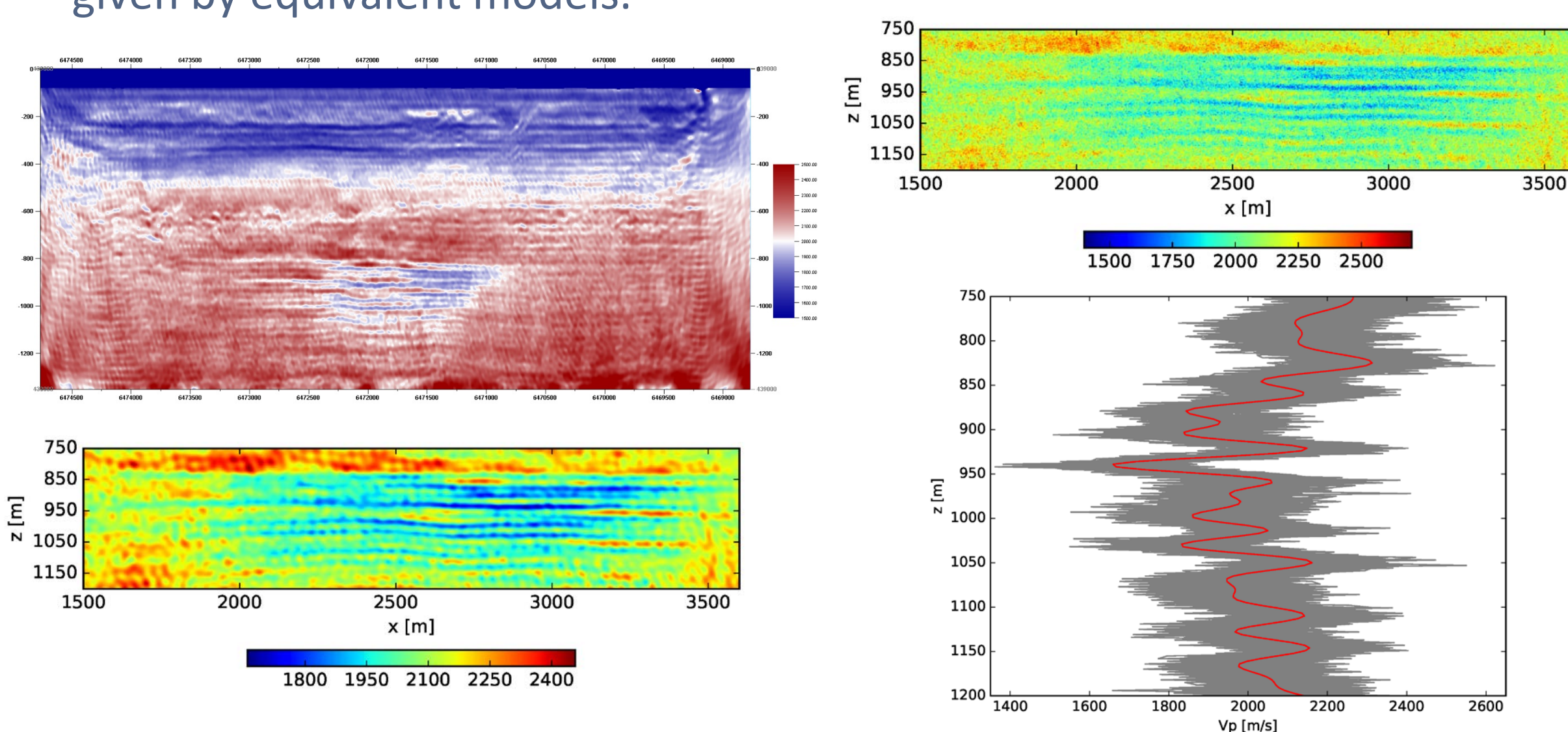
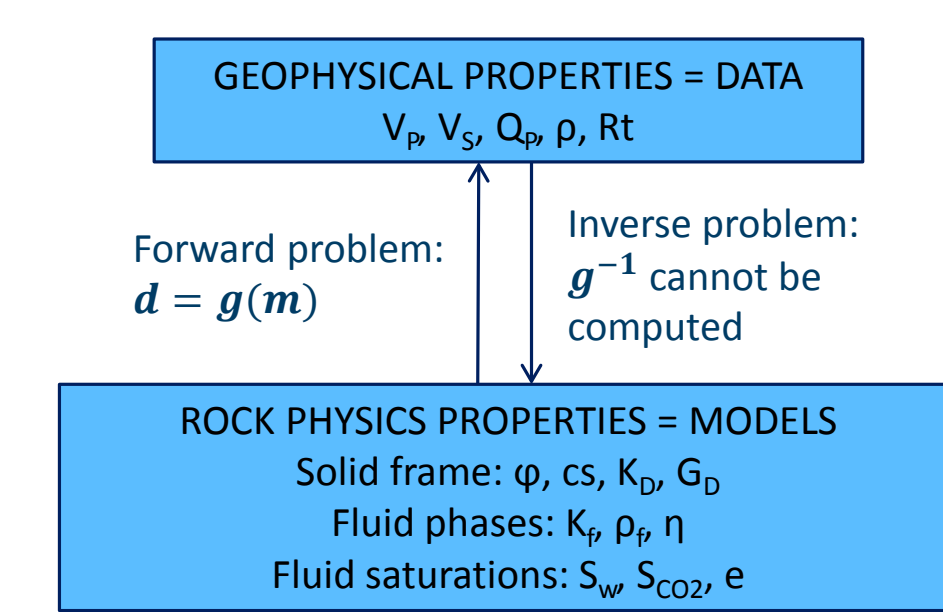


Figure 2: Final model derived from FWI at $f = 39.5$ Hz for inline 1874 from Sleipner 2008 vintage (top left). Close-up of the plume-region (bottom left). Random sample ("equivalent model") drawn from the posterior distribution (top right). Extracted depth velocity profiles from 100 samples at $x = 2916$ m (bottom right). Red line corresponds to the velocity of the final model from FWI.

Rock physics inversion and neighbourhood algorithm



Fast and analytic forward problem/rock physics model (Pride, 2005).

➔ Neighbourhood algorithm (Sambridge, 1999):

- Only 2 control parameters
- Model space guided exploration
- Fit quality and uncertainty

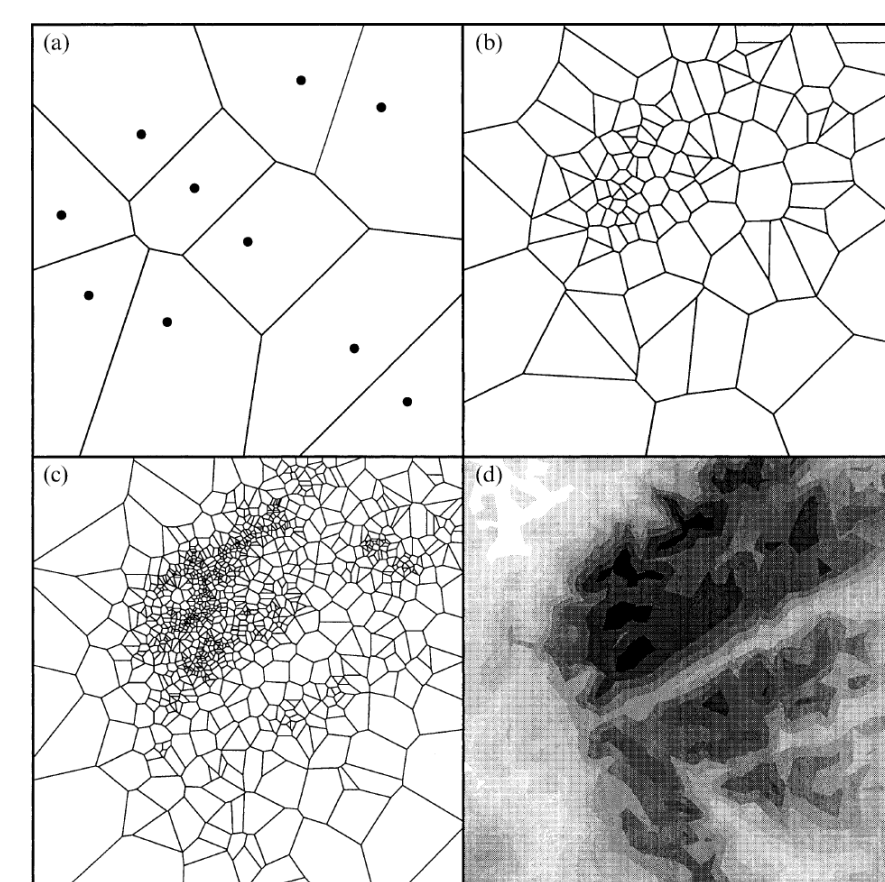


Figure 3 (from Sambridge, 1999): (a) Selection of 10 quasi-uniform random points in the 2D model space. (b) The Voronoi cells about the first 100 samples generated by a Gibbs sampler using the neighbourhood approximation. (c) Similar to (b), but for 1000 samples. (d) Contours of the test objective function.

References

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 • Romdhane A. and Querendez E. 2014. CO₂ characterization at the Sleipner field with full waveform inversion: application to synthetic and real data. Energy procedia, 63, 4358-4365.
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Sensitivity tests

Inversion of CO₂ saturation, porosity and patchiness exponent from P-wave velocity and resistivity with different levels of noise/uncertainty in the data.

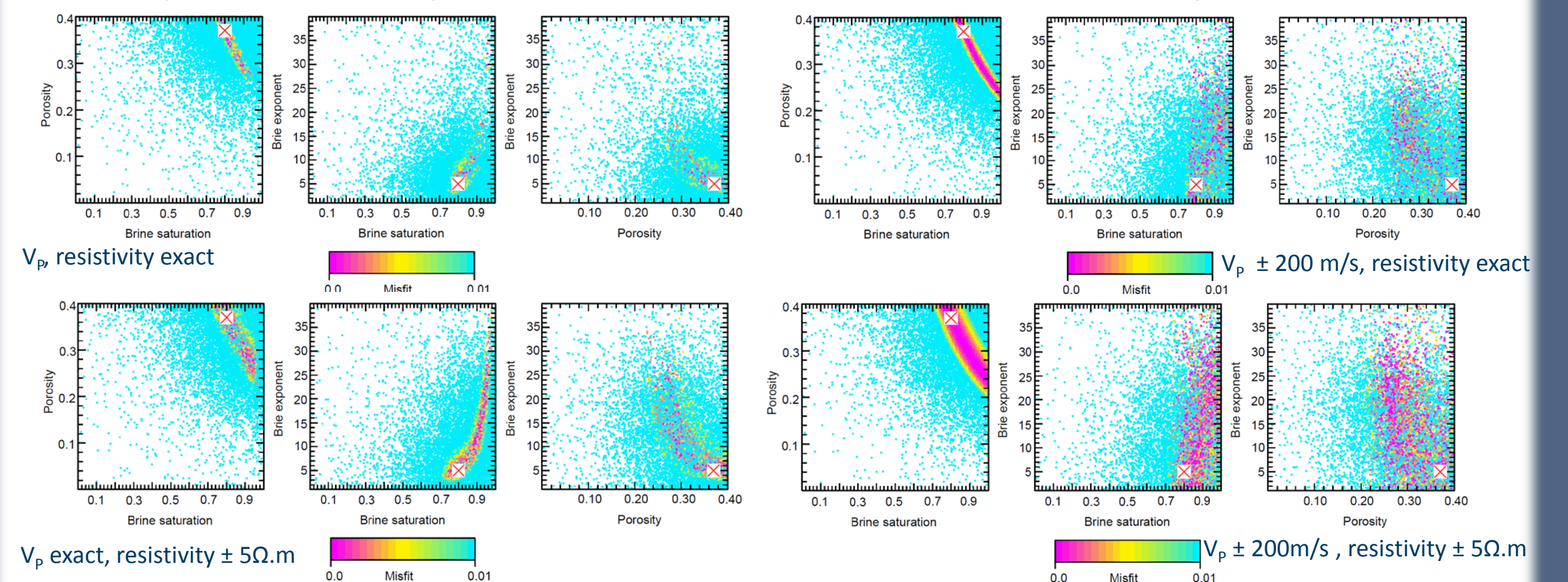


Figure 4: 2D slices of 3D model space where the inverted parameters are CO₂ saturation, porosity and Brine exponent. Each dot corresponds to a model with a misfit given by the color scale (absolute values). The red crosses stand for the true model.

2D Sleipner case studies

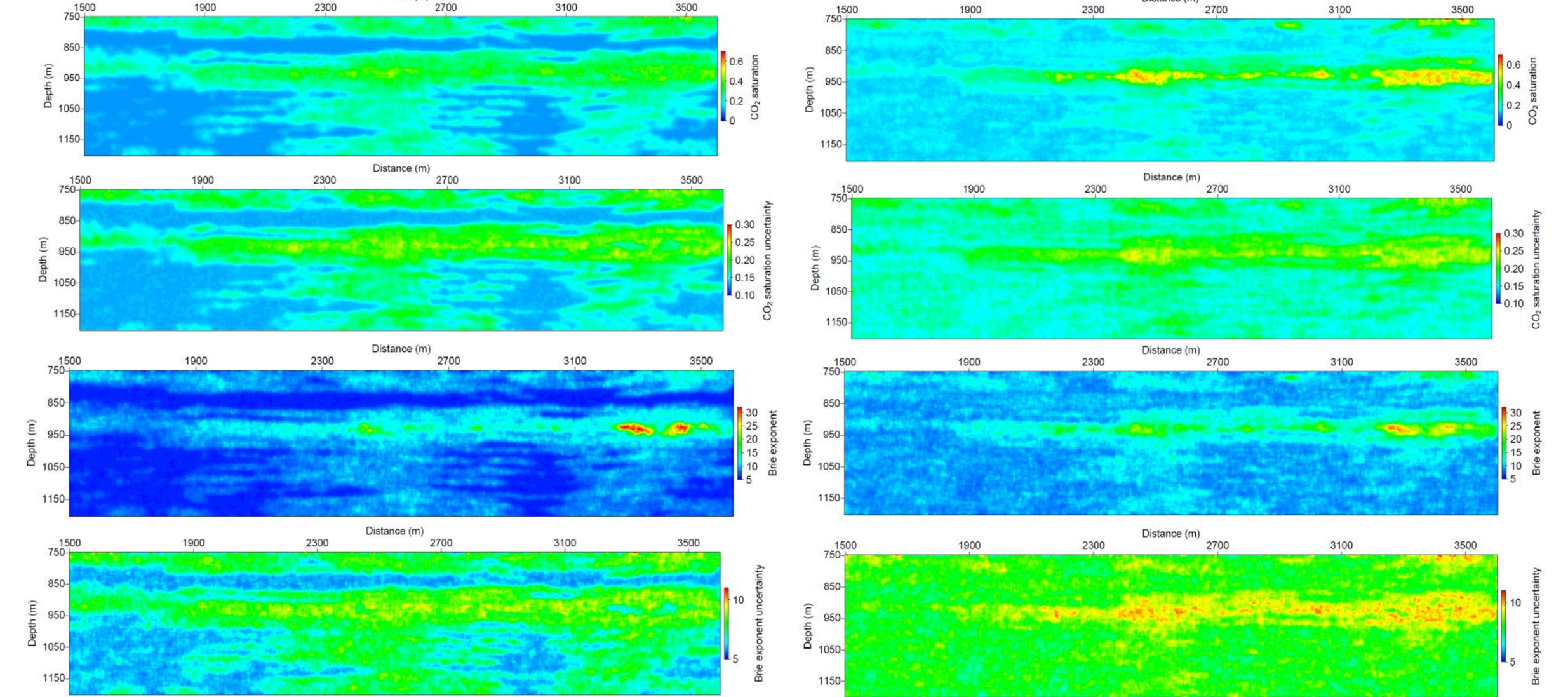


Figure 5: Inversion of CO₂ saturation and patchiness exponent for the inline 1838 with no uncertainty on data (left panels) and 100 m/s uncertainty on P-wave velocities (right panels). P-wave velocity is used as input.

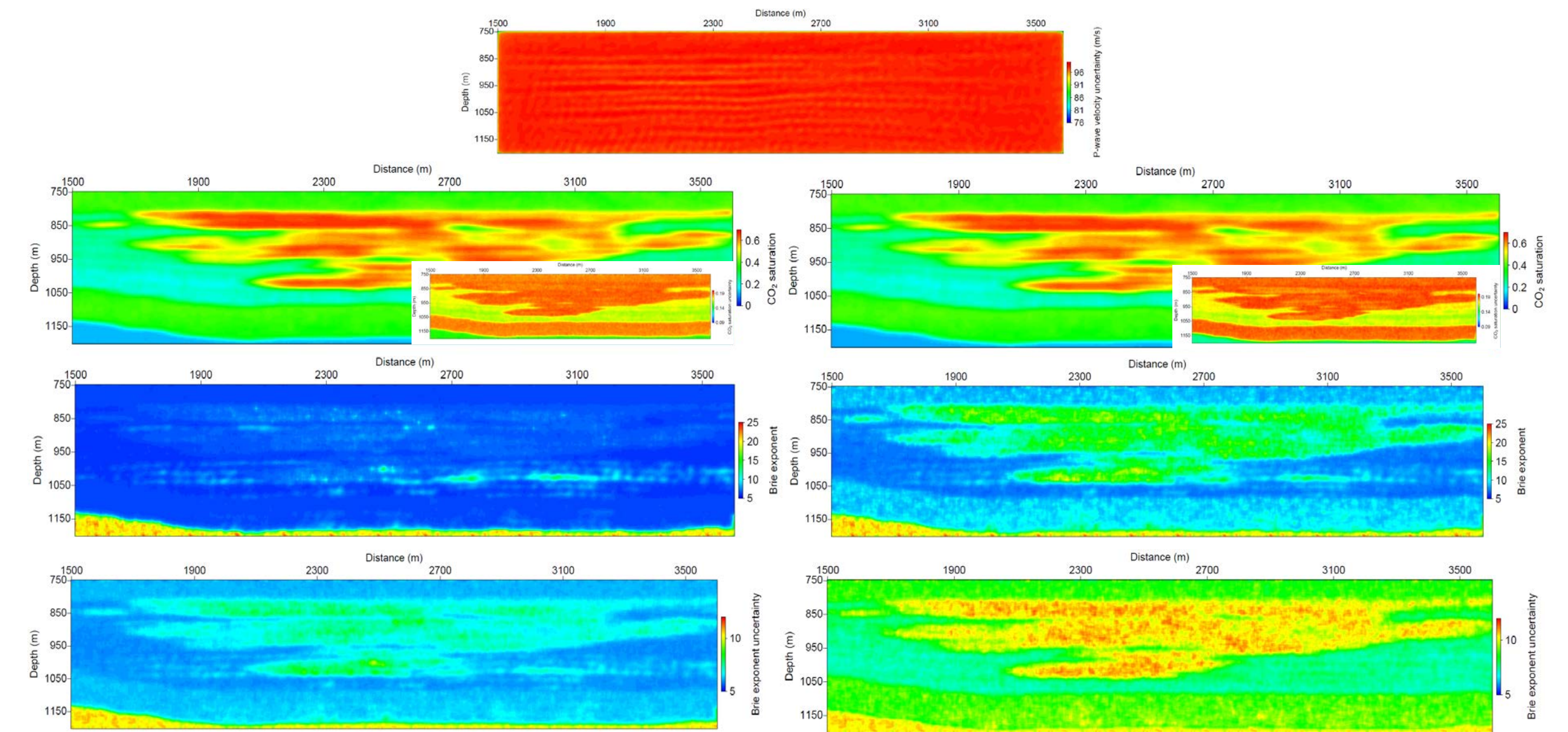


Figure 6: Inversion of CO₂ saturation and patchiness exponent for the inline 1874 with no uncertainty on data (left panels) and uncertainty on P-wave velocity [from uncertainty analysis after FWI, top figure] and 10 Ω.m uncertainty on R_t (right panels). P-wave velocity and resistivity are used as input.

Conclusions and way forward

- Successful propagation of uncertainty between the two inversion steps.
- Bayesian formulation allows to account for noise/uncertainty in the data and prior model distributions.
- Effect of uncertainty in geophysical properties is observed in the final results with an increase of CO₂ saturation and patchiness exponent uncertainties.
- Prior model distribution and spatial correlation need to be implemented in the rock physics inversion step.