DigiMon Deliverable D2.5: Project report and algorithms for integrated inversion of individual DigiMon data components

Digital monitoring of CO_2 storage projects

Prepared by

Tuhin Bhakta[a], Trond Mannseth[a], Martha Lien[b], Bob Paap[c], Vincent Vandeweijer[c]

[a]NORCE
[b]Octio Environmental

[c]TNO

DigiMon Deliverable D.2.5, December 2022

Scope

D2.5. Project report and algorithms for integrated inversion of individual DigiMon data components

Revision

Version	Date	Change	Page
1.0		Draft version	All
1.1		Check of document and minor updates of text and spelling.	All
1.2		Update after review	

Document distribution

ACT Coordinator

- Research Council of Norway

ACT national funding agencies

- Forschungszentrum Jülich GmbH, Projektträger Jülich, (FZJ/PtJ), Germany.
- Geniki Grammatia Erevnas kai Technologias/The General Secretariat for Research and Technology (GSRT), Greece.
- Ministry of Economic Affairs and Climate/Rijksdienst voor Ondernemend Nederland (RVO), the Netherlands.
- The Research Council of Norway (RCN), Norway.
- Gassnova, Norway.
- Development and Executive Agency for Higher Education, Research, Development and Innovation Funding (UEFISCDI), Romania.
- Department for Business, Energy and Industrial Strategy (BEIS), UK.
- Department of Energy (DoE), USA.

DigiMon partners

- NORCE Norwegian Research Centre AS
- OCTIO Environmental Monitoring AS
- NTNU Norwegian University of Science and Technology
- University of Bristol
- University of Oxford
- CRES Centre for Renewable Energy Sources and Saving
- Helmholtz–Centre for Environmental Research
- Sedona Development SRL
- TNO Nederlandse Organisatie voor toegepast -natuurwetenschappelijk Onderzoek
- Geotomographie GmbH
- LLC Lawrence Livermore National Security
- SILIXA LTD
- EQUINOR ASA
- REPSOL –NORGE AS

Table of contents

1 Introduction

Different data types carry different information about the subsurface, so there should be advantages in combining information from different data types when seeking to infer subsurface properties such as changes in CO_2 saturation and pressure with time. We have considered the following data types: conventional seismic data; gravimetric data, and; distributed acoustic sensors (DAS) data. These data types, and the corresponding forward-modelling techniques, are described in Vandeweijer et al., 2021, Bhakta et al., 2023.

An important aim for the DigiMon project is to qualify a *cost-efficient* monitoring system for use with large-scale CO_2 sequestration. It is therefore of particular interest to assess if it is possible to obtain satisfactory monitoring results without using the most acquisition-expensive data type(s). Acquisition of conventional seismic data is considerably more costly than acquisition of gravimetric and DAS data combined. In addition to comparing the monitoring performances of the individual data types, we have therefore also compared the performance of gravimetric and DAS data combined, to that of conventional seismic data.

We have developed a modelling framework for geophysical monitoring with the abovementioned geophysical data types that in addition to a best estimate of the monitoring target also quantifies the uncertainty in that estimate. The framework uses an ensemble-based implementation of Bayesian (and sequential Bayesian) statistics to achieve this at an affordable computational cost for the numerical examples studied. If the correct monitoring results are known, which they will be if a study with *synthetic* data is conducted, we can therefore assess with what certainty a particular data type produced better results than another data type for the study example in question.

We test the performances of the different data types (including relevant data-type combinations) by applying this framework on a sector of the Smeaheia reservoir model with synthetic data. Smeaheia is a saline aquifer offshore Norway (Mulrooney et al., 2020) under development for long term CO_2 storage, see Figure 1.

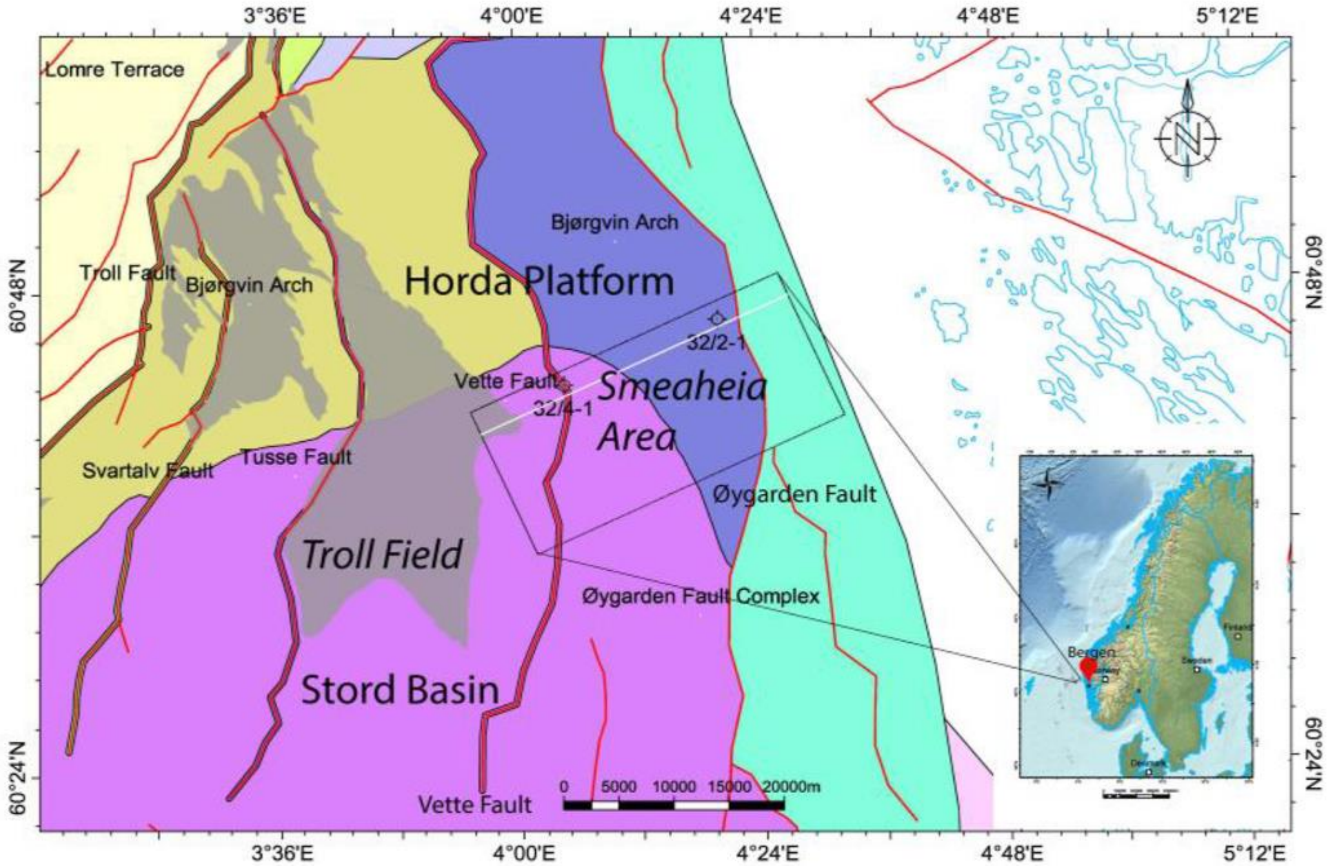

Figure 1: Location of the Smeaheia CO2 storage site offshore Norway (modified after Fawad et al., 2021)

2 Inversion methodology

The main ingredients of the inversion methodology applied for the modelling of the monitoring is described below in a high-level fashion, that is, avoiding details. A full description of the methodology can be found in Bhakta et al., 2023.

2.1 Bayesian inversion

When facing a problem where some data are to be inverted, there is often information available about the problem in addition to the data. With Bayesian inversion, this additional information is utilized to build a statistical model of the unknown quantities before the data is applied, i.e., a *prior model*. Both the data and the unknown quantities are considered as random variables. Subsequently, the data are inverted, taking also the prior model into account, resulting in the *posterior model* for the unknown quantities. The posterior model is thus a statistical model from which a best estimate (the mean) and a measure of the uncertainty in that estimate (the standard deviation) can be extracted.

2.2 Sequential Bayesian inversion

With sequential Bayesian inversion of two data types, Bayesian inversion of one of the data types is performed first, resulting in the posterior model for that data type. That posterior model then becomes the prior model for Bayesian inversion of the second data type, resulting in the final posterior model. (If there had been more than two data types available, the posterior model after inversion of two data types would have become the prior model for the third data type, and so on.)

It is good practice to invert the different data types according to their expected resolutions, i.e., starting with the data type with the lowest expected resolution and finishing with the data type with the highest expected resolution. The idea is then that inversion of a data type with a coarser resolution provides an improved starting point for the inversion of a data type with finer resolution, see, e.g., Tveit et al., 2020, Tveit &Mannseth, 2022. We note that sequential Bayesian inversion is a particular instance of co-operative inversion (Lines et al., 1988).

2.3 Ensemble-based Bayesian inversion

An analytical expression for the posterior model is only feasible when the prior model is Gaussian and the forward model is linear (with more than a single data type, all involved forward models must be linear). If this is not the case, the posterior model must be characterized through sampling. Markov-chain Monte Carlo methods can sample correctly from the posterior model, but they are prohibitively computationally expensive for realistic geophysical problems. Ensemble-based methods (see, Aanonsen et al., (2009) for a review of ensemble-based methods), where all calculations and inferences are based on samples (i.e., an ensemble) from the relevant distributions, represent a computationally much less expensive, approximate alternative.

We have applied the iterative ensemble smoother (Chen&Oliver, 2012, Luo et al., 2015) in our work. The computational challenge is still considerable for realistic geophysical problems, which means that we cannot apply an ensemble that is sufficiently large to avoid unwarranted uncertainty reduction. The conventional remedy for a too small ensemble is localization (Houtekamer&Mitchell, 1998). We have applied a correlation-based localization technique (Luo et al., 2018). To handle the huge amount of data present in geophysical inversion we have applied a wavelet-based data compression (Luo et al., 2017) that removes redundant information before inversion.

The result of a successful ensemble-based Bayesian inversion is an ensemble of representatives for the unknown quantity that adequately approximates a sample from the (correct) posterior model for that quantity. Figure 2 illustrates the workflow with a single data type (time-lapse DAS data) when the unknown quantity is the time-lapse CO_2 saturation. As indicated on the figure, the prior-model realizations of time-lapse CO_2 saturations are generated from reservoir simulations with an ensemble of reservoir properties.

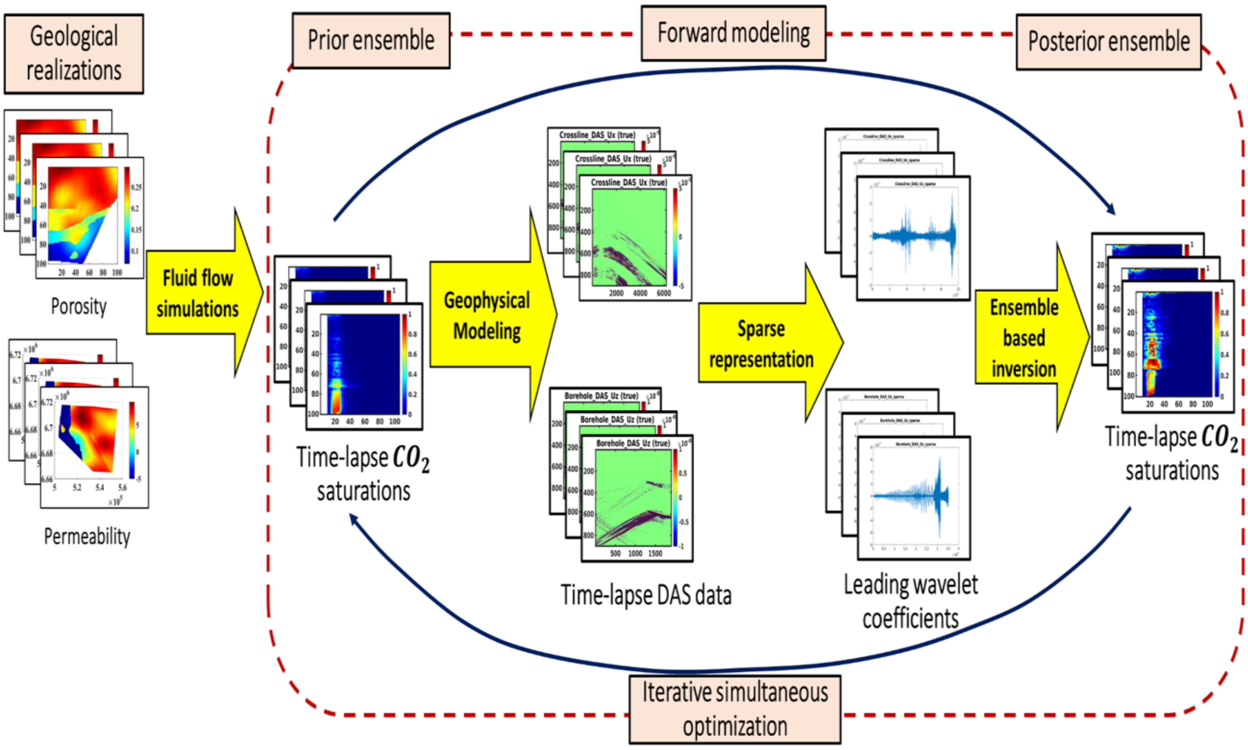

Figure 2: The proposed ensemble-based inversion framework with a single data type (time-lapse DAS data).

3 Numerical experiments

3.1 Setup

We give a high-level description of the setup of the numerical experiments. All details of the setup of the numerical experiments can be found in Bhakta et al., 2023.

The numerical experiments are conducted on a sector model of the Smeaheia saline aquifer. CO_2 is injected in a single well, and data are acquired right before injection starts (base survey, year 2022) and after 13 years of injection (monitor survey, year 2035). The data types used for the study are: conventional seismic data; gravimetric data, and; gravimetric and DAS data in combination. The prior ensemble of 100 CO_2 saturation and pressure changes is generated by running 100 reservoir simulations with different realizations of the subsurface rock properties (permeability and porosity).

Synthetic data to be applied in the inversions are generated as follows: First, an additional realization of the rock properties is used to generate the reference CO_2 saturation and pressure changes. Then, the reference CO_2 saturation and pressure changes are run through the respective domain-specific forward models to obtain domain-specific reference forecasts. Finally, synthetic data (gravimetric, conventional seismic, and DAS) are generated by adding random errors drawn from domain-specific statistical error models to the respective reference forecasts. The domain-specific error models is obtained from collaboration with project-partner specialists on gravimetry (Octio) and seismics (TNO).

We use full-waveform (FW) seismic modelling for accuracy. Running FW seismic modelling on 100 ensemble members (which would be required as part of the inversion) in 3D is computationally too expensive. We therefore perform the seismic inversions (conventional and DAS) on a 2D slice of the Smeaheia sector model. The gravimetric modelling is computationally much less expensive. We perform gravimetric inversion in 3D and extract results on the 2D slice where the seismic inversions were performed for comparisons, and for building the prior model for the DAS inversion part of the combined gravimetric and DAS inversion.

3.2 Summary of results

In Bhakta et al., 2023, we compare the following quantitative measures of the inversion results: Data mismatch and root mean squared error (RMSE) between reference and estimated CO_2 saturation and pressure changes. Furthermore, we compare plots of means of the CO_2 saturation and pressure changes from the prior and posterior ensembles to the corresponding reference quantities. Finally, we compare plots of standard deviations of the CO_2 saturation and pressure changes from the prior and posterior ensembles, to assess changes in the uncertainty. Below, we give a summary of these results. All details of these results can be found in Bhakta et al., 2023. Additional results with these data types can be found in Bhakta et al., 2021, Bhakta et al., 2022.

Gravimetric data provides a direct measurement of the mass changes in the reservoir and is not sensitive to pressure changes alone. Hence, gravity provides a tool to separate saturation and pressure changes during the injection. Inversion of gravimetric data resulted in a clear improvement of both the data match and the RMSE with respect to the prior model when inverting for saturation changes. The results showed robust toward different degrees of geological uncertainty. This is supported by visual inspection of the plots.

To reduce the impact of geological uncertainty in the forward modelling in the inversion of conventional seismic data, also the porosity field was estimated in addition to CO_2 saturation and pressure changes. The best results with conventional seismic data were obtained when first using the data from the base survey to update porosity, and then use the estimated porosity when inverting time-lapse conventional seismic data for CO_2 saturation and pressure changes. These results (data match improvement, RMSE, and plots) were generally better than those obtained with gravimetric data.

Sequential inversion of gravimetric and DAS data improved the gravimetric results, and they were comparable to conventional seismic results. For the examples considered, sequential inversion of gravimetric and DAS data therefore seems a less costly, viable alternative to conventional seismic data for monitoring of CO_2 sequestration. The investigation considered is, however, far from comprehensive, and more work is needed before any conclusion with some generality can be drawn. The inversion framework developed in the project is well suited to be applied in a more comprehensive investigation, aiming for more general conclusions.

4 References

S I Aanonsen, G Nævdal, D Oliver, A C Reynolds, B Valles: *The ensemble Kalman filter in reservoir engineering—a review*, SPE Journal **14**(3), pp 393-412, 2009

T Bhakta, M Lien, T Mannseth: *Monitoring of CO2 saturation plume movement from time-lapse inverted-seismic and gravity data using an ensemble-based method*, In 82nd EAGE Annual Conference & Exhibition, vol. 2021, no. 1, pp. 1-5. European Association of Geoscientists & Engineers, 2021.

T Bhakta, B Paap, V Vandeweijer, M Lien, T Mannseth: *Assessment of various geophysical data types for cost-efficient monitoring of CO_2 sequestration*, preliminary version - to be submitted to International Journal of Greenhouse gas Control, 2023

T Bhakta, B Paap, V Vandeweijer, T Mannseth: *Monitoring of CO2 plume movement using time-lapse distributed acoustic sensing (DAS) data*, In SEG/AAPG International Meeting for Applied Geoscience & Energy. OnePetro, 2022

Y Chen, D Oliver: *Ensemble randomized maximum likelihood method as an iterative ensemble smoother*, Mathematical Geosciences **44**, pp 1-26, 2012

M Fawad, M D J Rahman, N H Mondol: *Seismic reservoir characterization of potential CO_2 storage reservoir sandstones in Smeaheia area, northern north sea*, Journal of Petroleum Science and Engineering **205**, pp 108812, 2021, ISSN 0920-4105, doi: https://doi.org/10.1016/j.petrol.2021.108812. URL https://www.sciencedirect.com/science/article/pii/S0920410521004733

P L Houtekamer, H L Mitchell: *Data assimilation using an ensemble Kalman filter technique*, Monthly Weather Review **126**(3), pp 796-811, 1998

X Luo, T Bhakta, M Jakobsen, G Nævdal: *An ensemble 4D-seismic history-matching framework with sparse representation based on wavelet multiresolution analysis*, SPE Journal **22**, pp 985 – 1010, 2017, doi: http://dx.doi.org/10.2118/180025-PA. SPE-180025-PA

X Luo, T Bhakta, G Nævdal: *Correlation-based adaptive localization with applications to ensemble-based 4D-seismic history matching*, SPE Journal **23**(2), pp 396 – 427, 2018

X Luo, T Bhakta, A S Stordal, R J Lorentzen, G Nævdal*: Iterative ensemble smoother as an approximate solution to a regularized minimum-average-cost problem: Theory and applications*, SPE Journal **20**(5), pp 962 – 982, 2015, doi: 10.2118/176023-pa. URL28

M J Mulrooney, J L Osmond, E Skurtveit, J I Faleide, A Braathen*: Structural analysis of the Smeaheia fault block, a potential CO2 storage site, northern Horda Platform, North Sea*, Marine and Petroleum Geology **121**, pp 104598, 2020

B Paap, T Bhakta, V Vandeweijer, T Mannseth*: Modeling Approach for Evaluating Time-Lapse Effects of CO2 Storage on Particle Velocity and Strain Rate Data* In EAGE GeoTech 2022 Third EAGE Workshop on Distributed Fibre Optic Sensing, vol. 2022, no. 1, pp. 1-5. European Association of Geoscientists & Engineers, 2022.

S. Tveit, T. Mannseth, J. Park, G. Sauvin, R. Agersborg: *Combining CSEM or gravity inversion with seismic AVO inversion, with application to monitoring of large-scale CO_2 injection.* Computational Geosciences, **24**(3), 2020

S. Tveit, T. Mannseth: *Monitoring of large-scale CO_2 injection using CSEM, gravimetric, and seismic AVO data.* Geophysical Monitoring for Geological Carbon Storage, Geophysical Monograph **272**, edited by Lianjie Huang, American Geophysical Union, John Wiley & Sons, 2022