



— 70 years —
1950-2020

A machine learning based monitoring framework for CO₂ storage

EGU-2020

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CASE STUDY

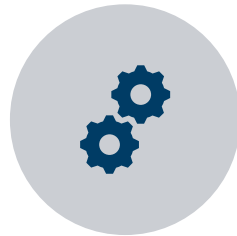


CONCLUSIONS
AND PERSPECTIVES

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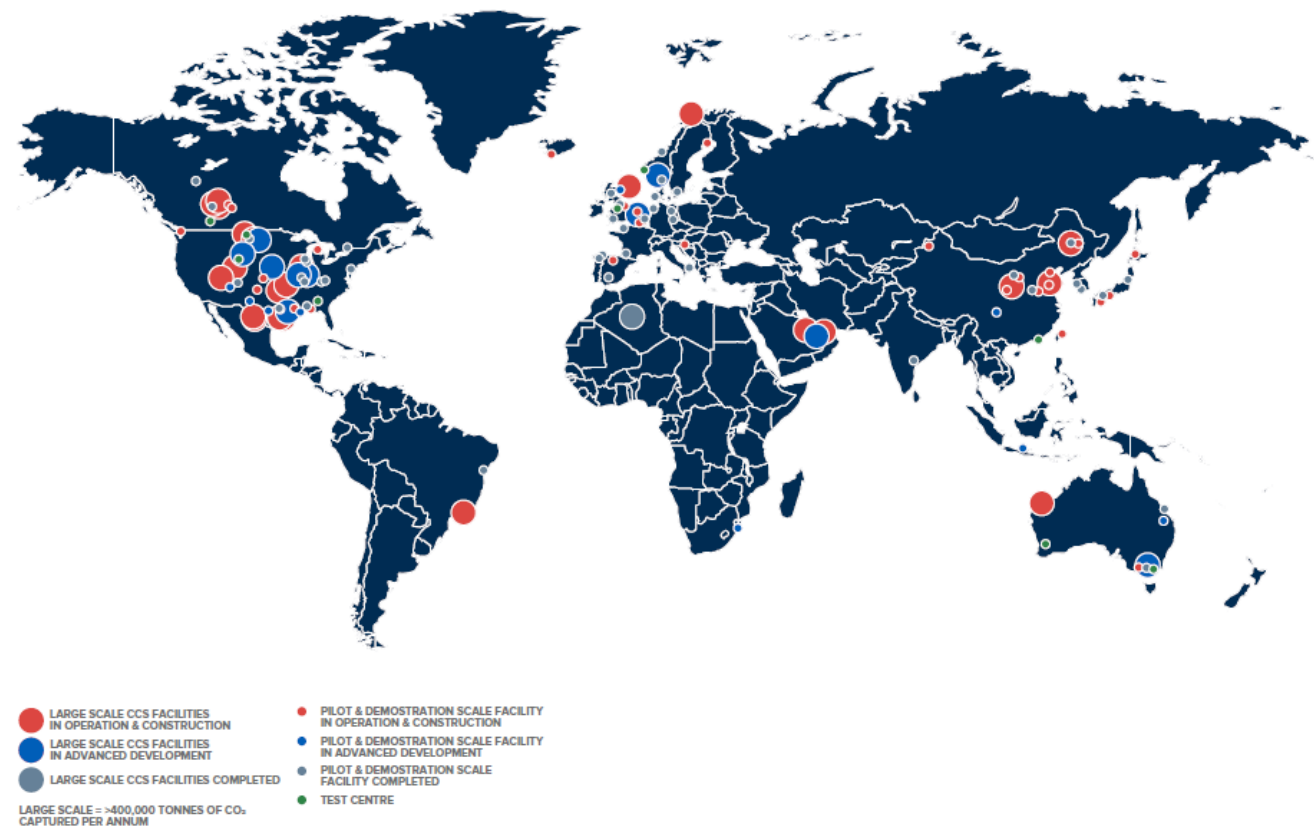
CONCLUSIONS
AND PERSPECTIVES

Background

- 19 operating large-scale facilities
 - 2 in Norway
 - More than 25 Mtons stored in 2019
- CCS (carbon capture and storage) is gathering pace, but the rates are still insufficient to make a significant impact on green house gas emissions
- There is a lot at stake. CCS requires high investments



Cost efficiency, including in monitoring is a must



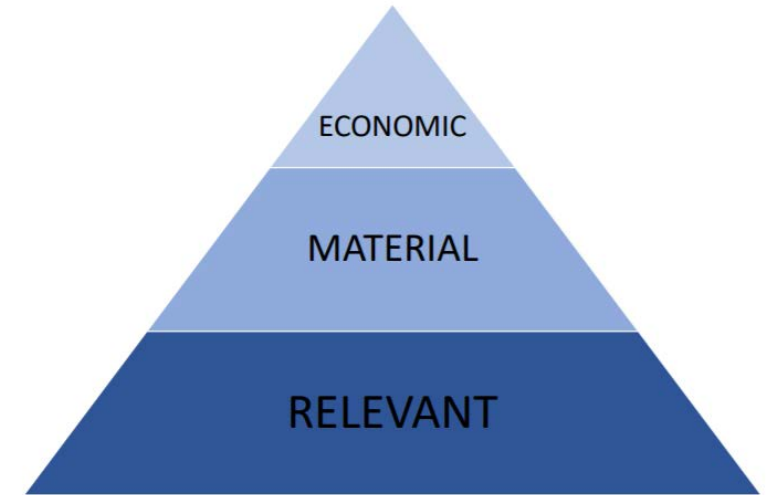
CCS facilities around the world.

(source: global status of ccs, <http://www.globalccsinstitute.com>)

Background

Geophysical monitoring

- Important for conformance and containment verification
 - conformance: CO₂ behaviour in the storage site is consistent with model-based forecasts
 - containment: demonstrate security of CO₂ storage
- Geophysical monitoring is very valuable but can be costly.
 - Example: Time lapse 3D seismic
- Acquire data if the value is larger than the acquisition cost, need for:
 - Dealing with uncertainties
 - The right kind of information
 - The right amount of information

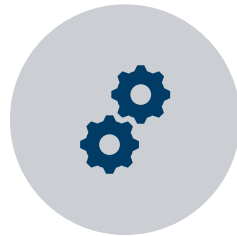


Criteria for information to be valuable

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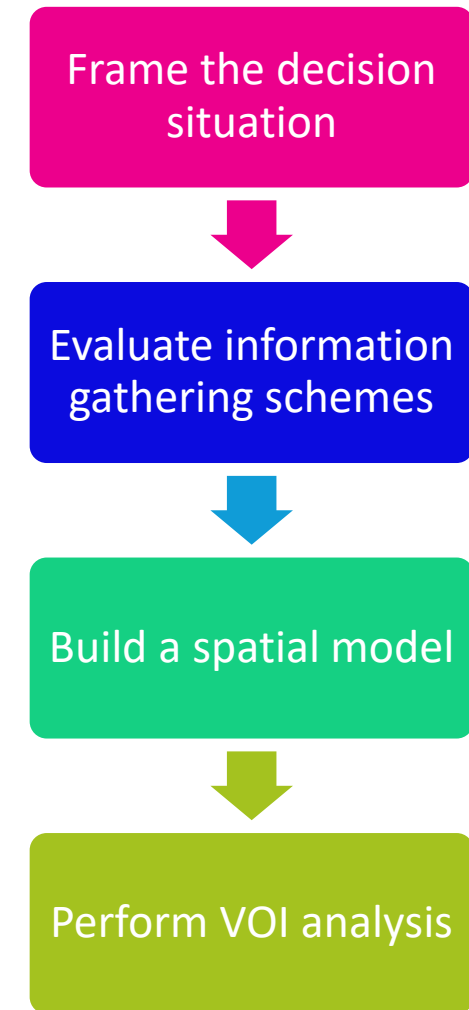
Value of information (VOI)

Why VOI analysis?

- VOI has the potential to support decision making around information gathering
- It allows the decision maker to perform a reasonable evaluation before the information is purchased and therefore revealed
- If the decision maker can model value using monetary units, then VOI is also in monetary units
- Can incorporate the spatial dependence of subsurface uncertainties, the gathered information, and the decision situation



Robust and general framework to support decision making



Framework for VOI analysis
(Eidsvik et al., 2015)

Value of information

- We need to define:
 - Alternatives: $a \in A$
 - Uncertainty/Scenario class: $x \in \Omega$
 - Time (if the VOI analysis is time dependent): t
 - Value derived from the decision situation: $v_t(x, a)$
 - Purchased data (at time t): \mathbf{y}_t
- The VOI is defined by the difference between posterior (PoV_t) and the prior value (PV_t).

$$\begin{aligned} \text{VOI}_t &= \text{PoV}_t - \text{PV}_t \\ &= \int \max_a \{E[v_t(x, a)|\mathbf{y}_t]\} p(\mathbf{y}_t) d\mathbf{y}_t - \max_a \{E(v_t(x, a))\} \end{aligned}$$

Value of information

- The posterior value can be hard to calculate with imperfect information
- Monte Carlo sampling and approximate conditional probabilities $\hat{P}(X = x|y_t)$ can be used to approximate PoV_t and calculate the VOI

$$\begin{aligned} PoV_t &= \int_{\mathbf{y}_t} \max_{a \in A} \{E[v_t(x, a)|\mathbf{y}_t]\} p(\mathbf{y}_t) d\mathbf{y}_t \\ &\approx \frac{1}{B_{test}} \sum_{b=1}^{B_{test}} \max_{a \in A} \{E[v_t(x, a)|\mathbf{y}_t^b]\}, \\ E[v_t(x, a)|\mathbf{y}_t^b] &= \sum_x v(x, a_t) P(X = x|\mathbf{y}_t^b) \approx \sum_x v(x, a_t) \hat{P}(X = x|\mathbf{y}_t^b). \end{aligned}$$

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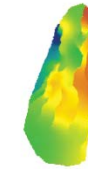


CONCLUSIONS
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Case study Smeaheia

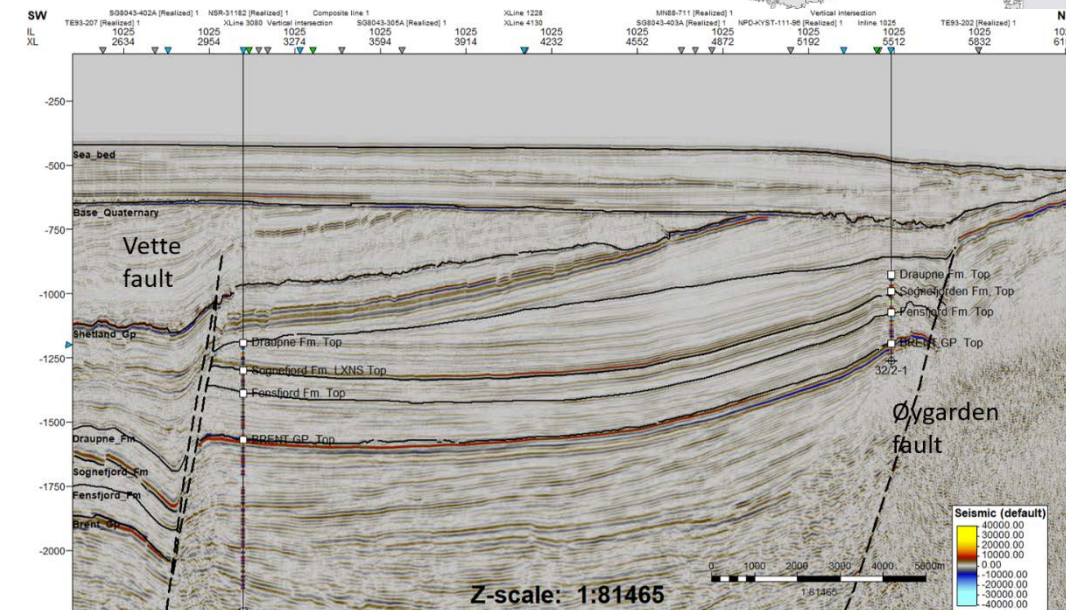
- Possible storage candidate for the Norwegian full-scale CCS project
- Possible injection @ 1200-1500m deep in Sognefjord, Fensfjord or Krossfjord formations under Draupne shale overburden.
- Uncertainties related to:
 - Reservoir and caprock properties
 - Fault properties

Location of Smeaheia area. The top of the Fensfjord (reservoir) formation is displayed



Bergen

Stavanger



Example of a 2D extracted seismic section from the Smeaheia area. The main faults, interpreted horizons, and well locations are indicated.

Case study

Decision problem

- An operator wants to inject CO₂ for a period of 25 years.
- It is uncertain whether the site will leak or not
- During this injection period, the operator has the possibility to do one seismic survey and decide whether to continue or stop the injection.
- When should the survey be done?



Time dependent VOI analysis of seismic data related to leakage detection.

Case study

Decision problem

- Alternatives: $a \in A = \{0,1\}$, to continue ($a = 1$) or to stop the injection ($a = 0$) at time t
- Uncertainty/Scenario class: $x \in \Omega = \{0,1\}$, whether CO₂ will leak ($x = 1$) or not ($x = 0$)
- Time (if the VOI analysis is time dependent): $t \in (0,25)$
- Value derived from the decision situation: $v_t(x, a)$
- Purchased data (at time t): \mathbf{y}_t seismic data

- 25 years injection time
- One unit injected per year
- Fixed cost if injection is done: 5
- Cost of injecting per unit CO₂ : 0.2
- Fixed cost if leakage: 2
- Fine if leakage per unit of injected CO₂ : 1.2
- Cost of not injecting per unit CO₂ : 0.8



Many assumptions and simplifications

Case study

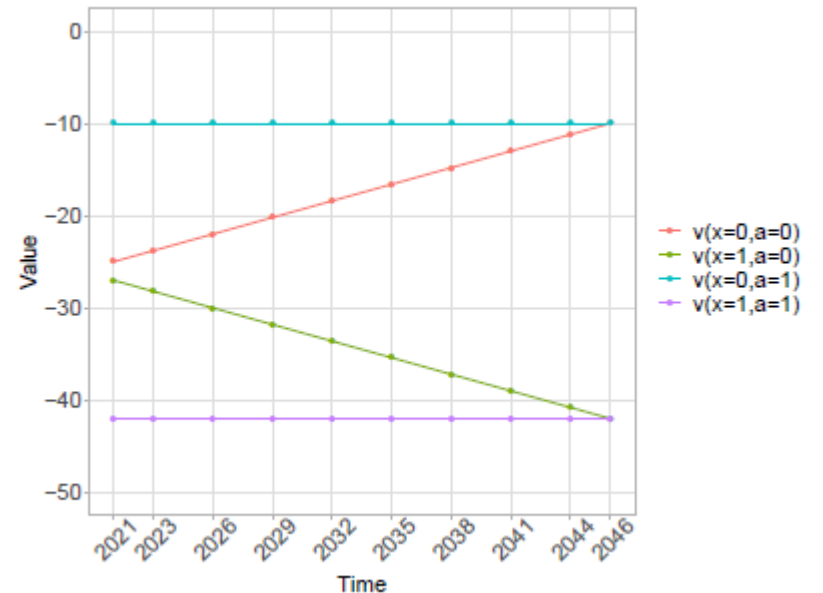
Decision problem

- Alternatives: $a \in A = \{0,1\}$, to continue ($a = 1$) or to stop the injection ($a = 0$) at time t
- Uncertainty/Scenario class: $x \in \Omega = \{0,1\}$, whether CO₂ will leak ($x = 1$) or not ($x = 0$)
- Time (if the VOI analysis is time dependent): $t \in (0,25)$
- Value derived from the decision situation: $v_t(x, a)$
- Purchased data (at time t): y_t seismic data

Values before any monitoring data is purchased

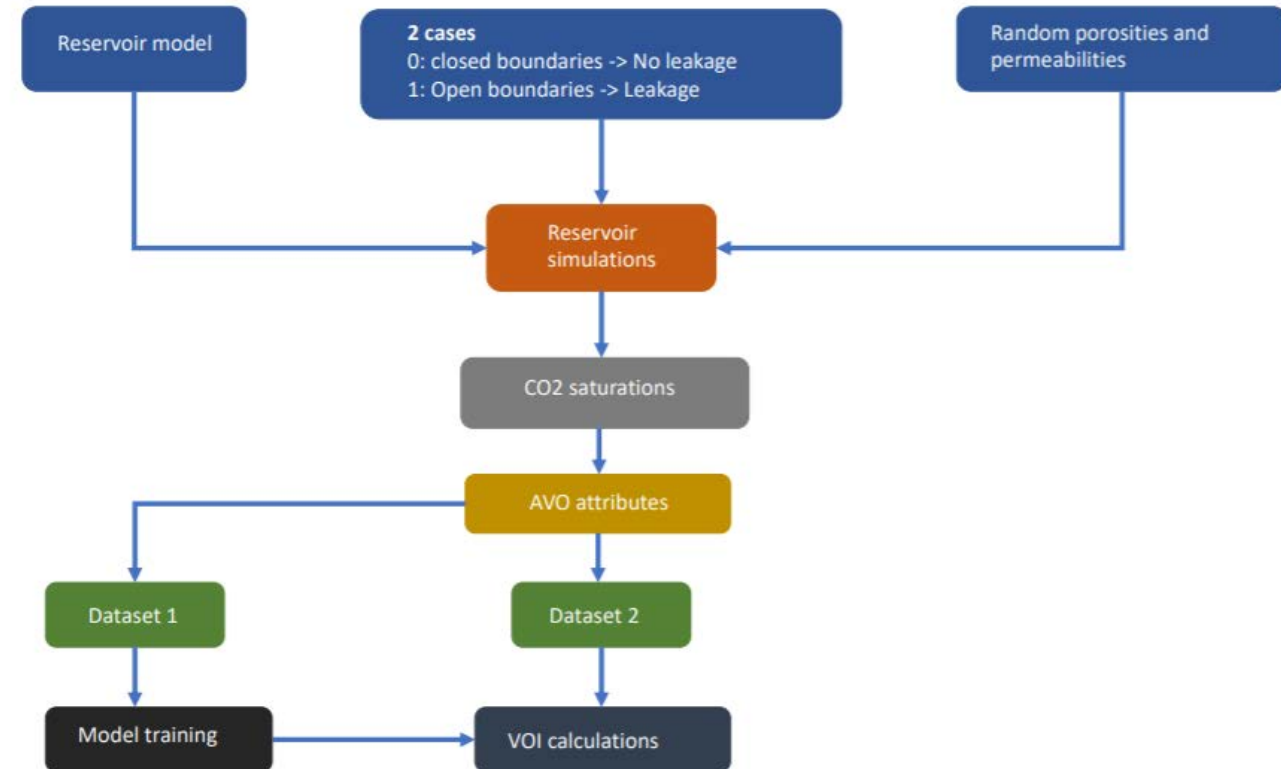
- $v_t(x = 0, a = 0) = -5 - 0.2t - 0.8(25 - t) = -25 + 0.6t$
- $v_t(x = 1, a = 0) = -5 - 0.2t - 0.8(25 - t) - 2 - 1.2t = -27 - 0.6t$
- $v_t(x = 0, a = 1) = -5 - 0.2 * 25 = -10$
- $v_t(x = 1, a = 1) = -5 - 0.2 * 25 - 2 - 1.25 * 25 = -42$

Objective: compare the expected values with monitoring data to the one without monitoring data



Case study Workflow

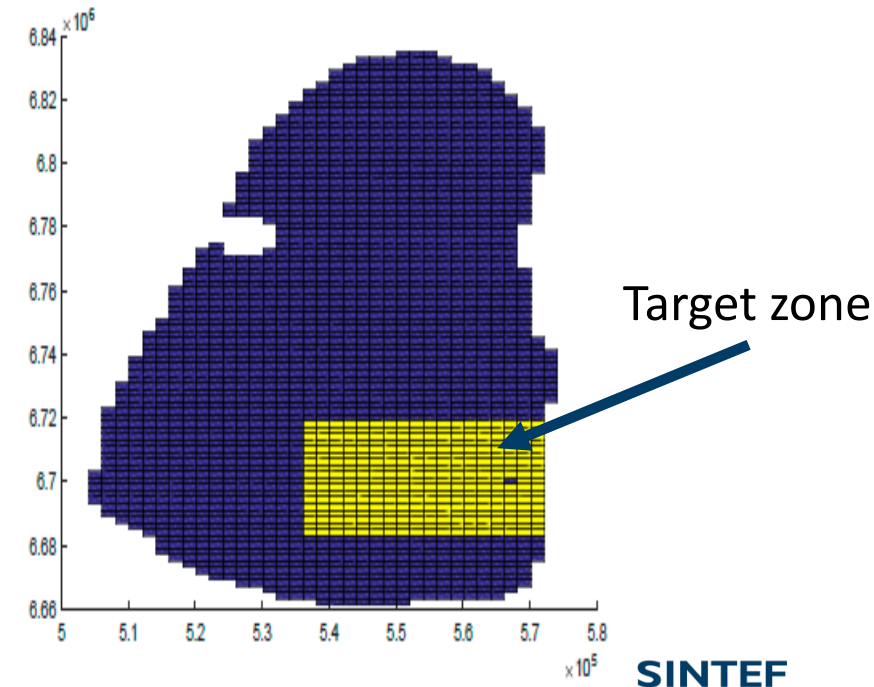
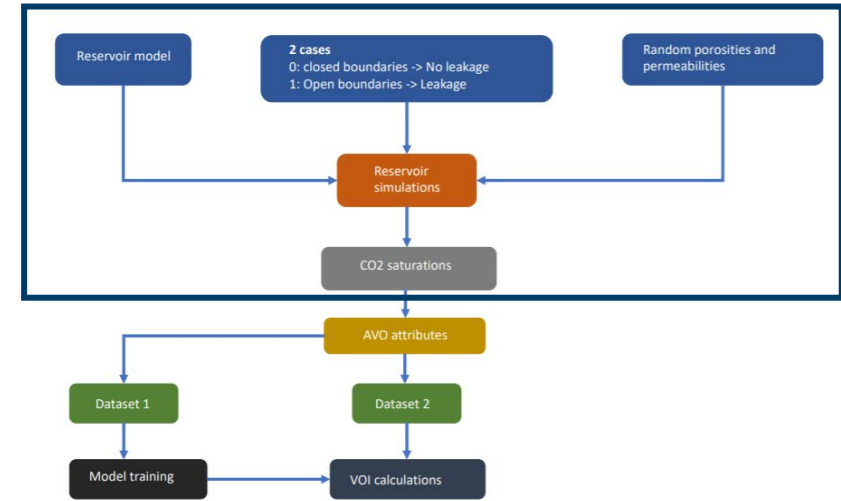
1. Reservoir simulation
2. AVO attributes
3. ML
4. VOI analysis



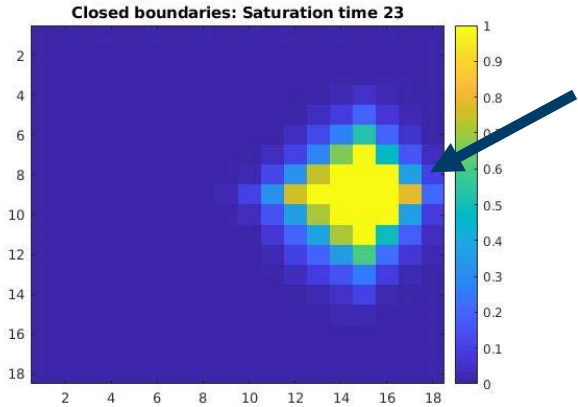
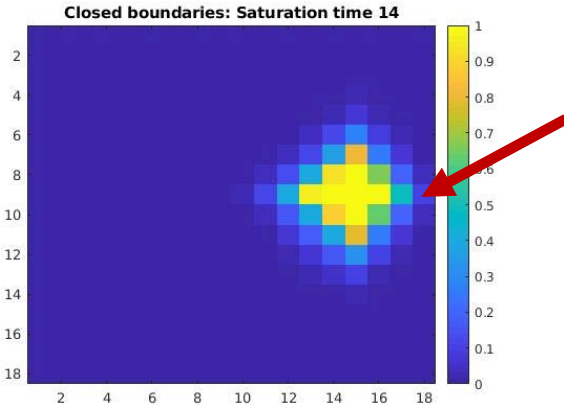
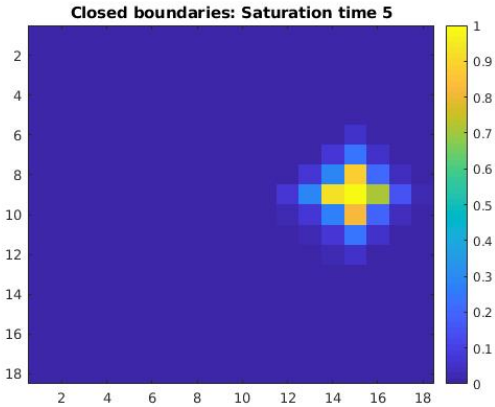
Workflow

Reservoir simulation

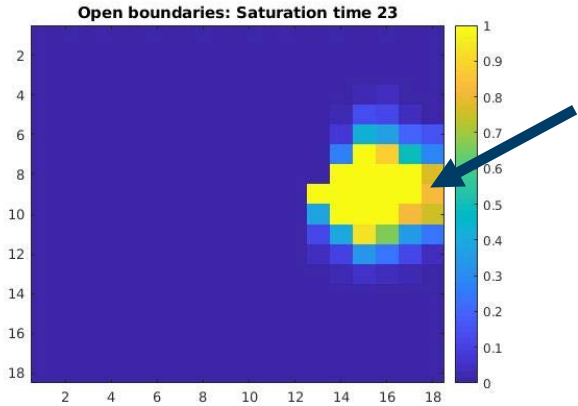
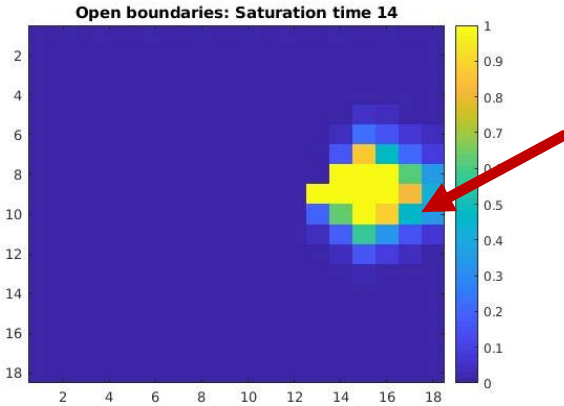
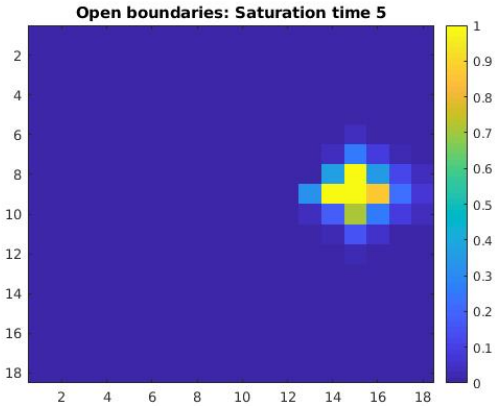
- MRST: MATLAB Reservoir Simulation Toolbox
 - Sognefjord formation
 - Vertical equilibrium model
 - 1000 realisations:
 - Reservoir boundaries set to open (leaking fault) or closed (sealing fault)
 - Uncertain porosity and permeability variables
 - Mean and variance estimated from log data.
 - Spatial correlation introduced



Workflow: Saturation maps – examples



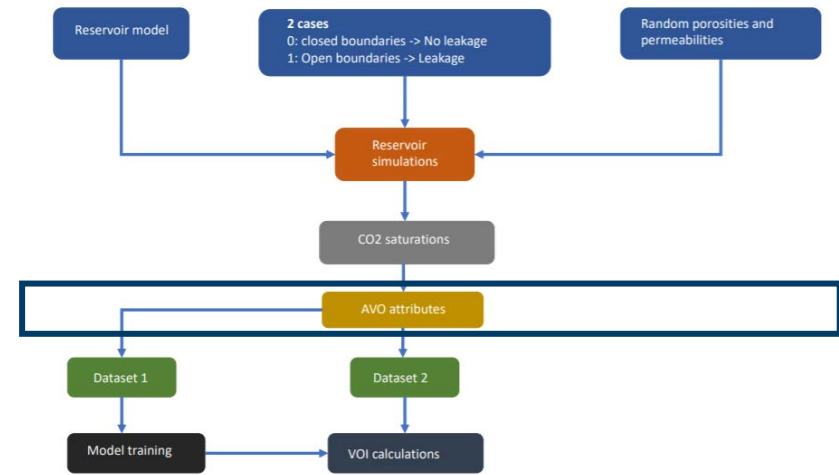
Closed boundaries



Open boundaries

Workflow

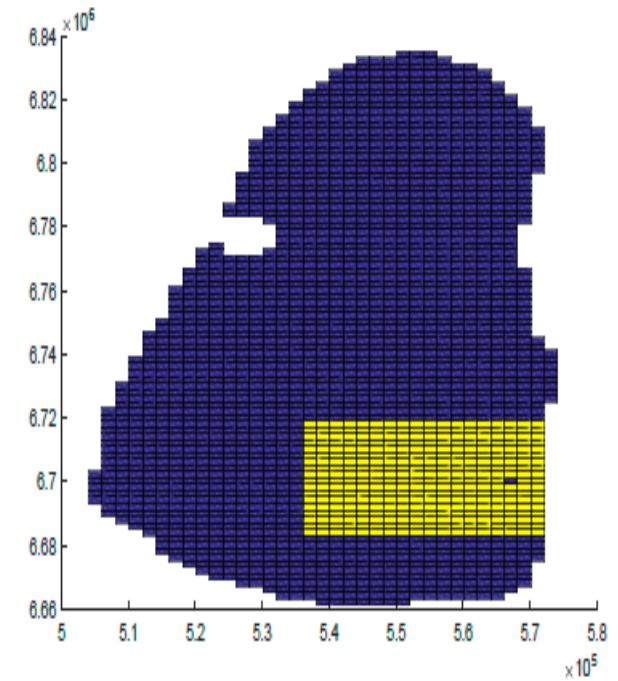
AVO attributes



- AVO attributes generated along the top reservoir zone
- Gassmann fluid substitution (from saturations to elastic properties)
- Noise (variance) added for both attributes
- Two different datasets:
 - R_0 (zero offset reflectivity) attribute
 - R_0 and G (AVO gradient) attributes (two attributes per cell)

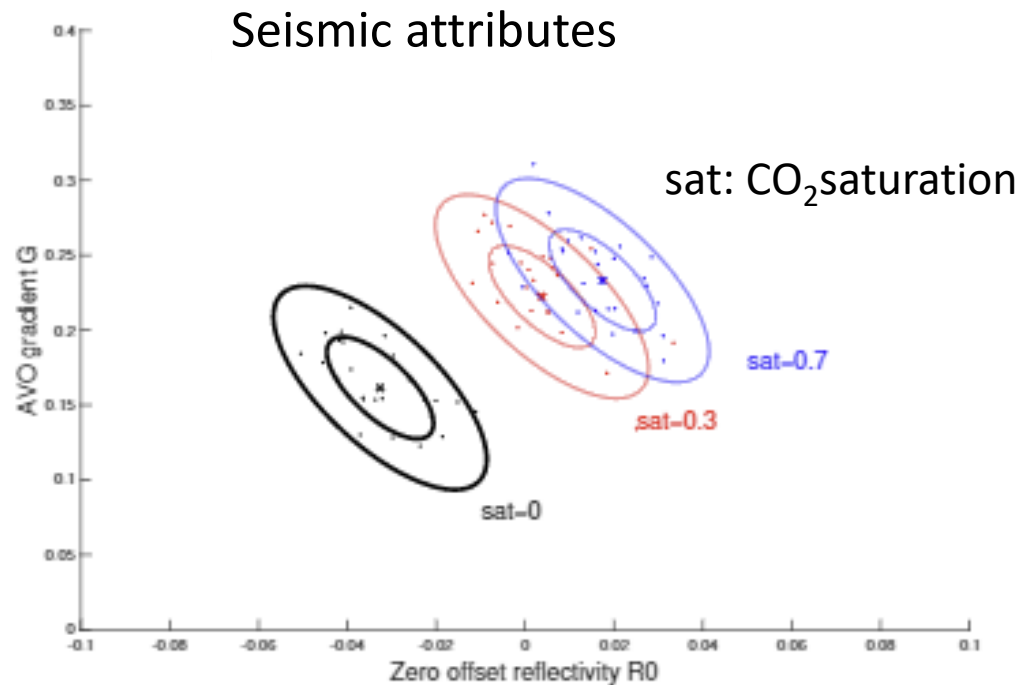
$$R_0 = \frac{1}{2} \left(\frac{\Delta V_p}{V_{pm}} + \frac{\Delta \rho}{\rho_m} \right),$$

$$G = \frac{1}{2} \frac{\Delta V_p}{V_{pm}} - 2 \left(\frac{V_s}{V_p} \right)^2 \left(2 \frac{\Delta V_s}{V_{sm}} + \frac{\Delta \rho}{\rho_m} \right)$$



Workflow

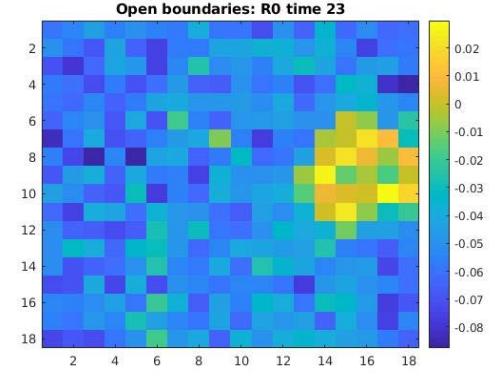
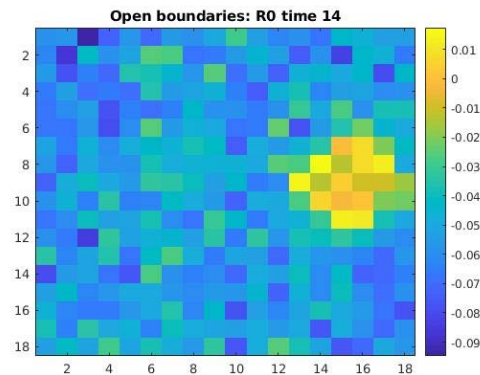
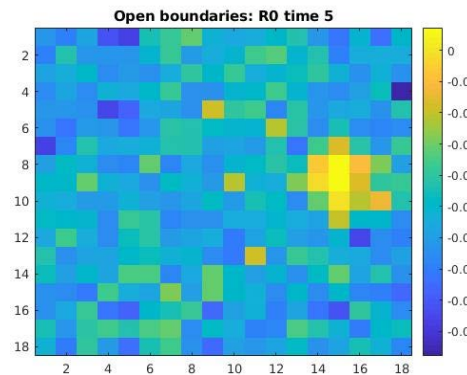
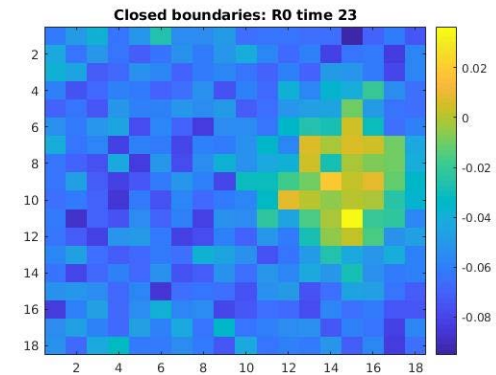
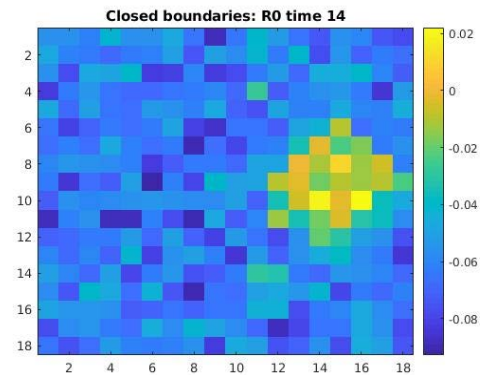
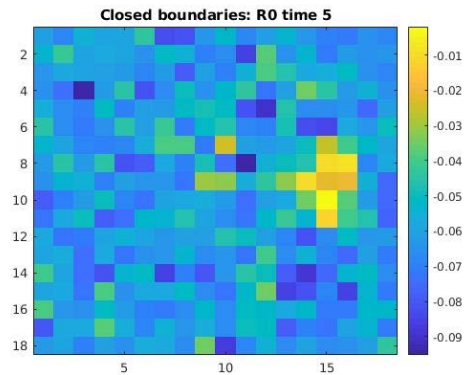
AVO attributes



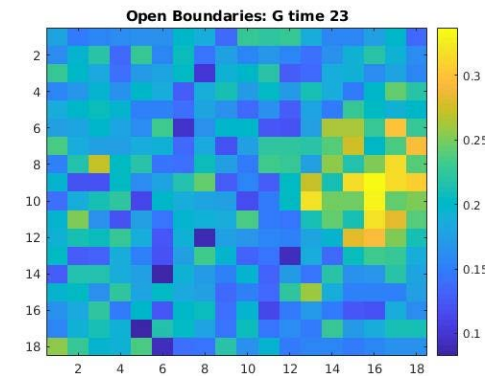
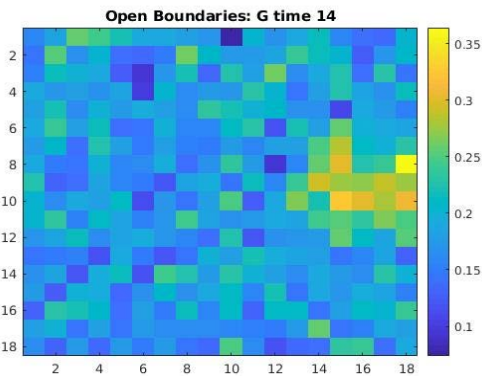
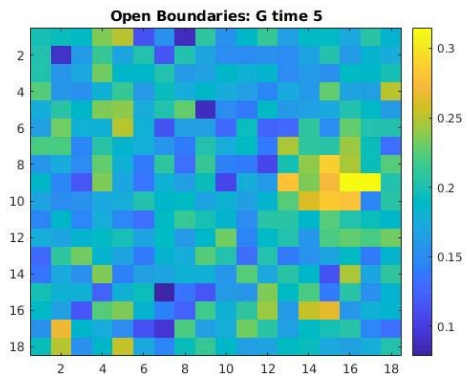
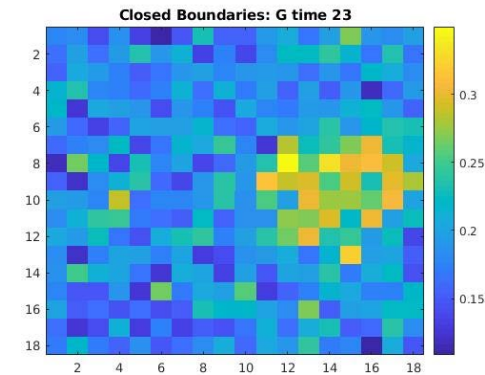
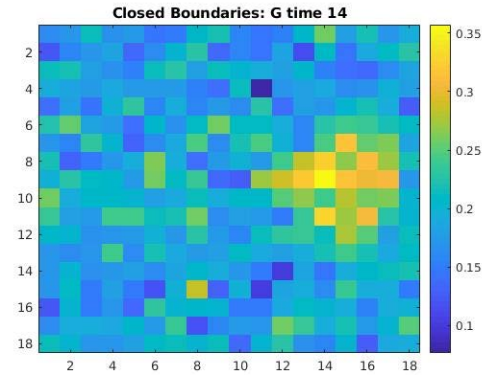
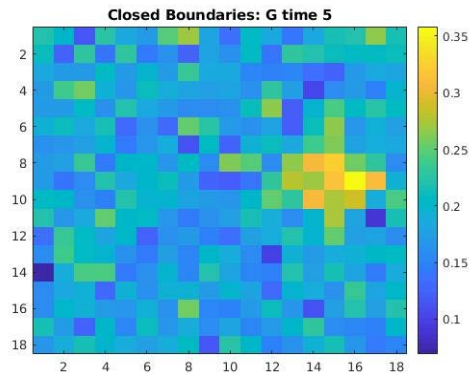
Not straightforward to differentiate CO₂ saturation levels with AVO attributes

Expected seismic AVO response (dots) for different levels of CO₂ saturation along with 50 % and 80 % uncertainty contours in the seismic AVO observation model.

Workflow: R0 maps– examples



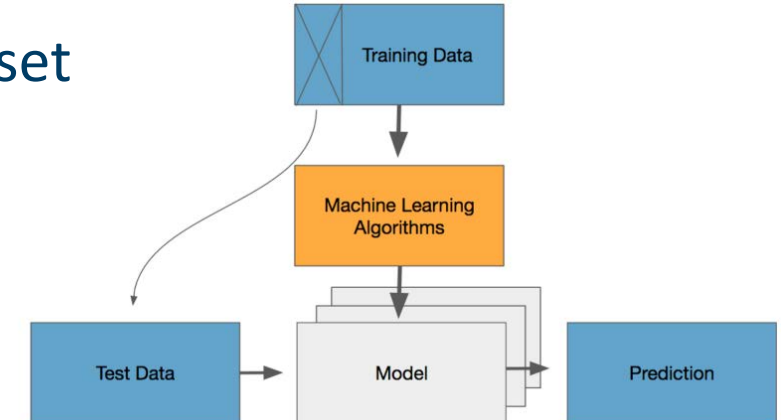
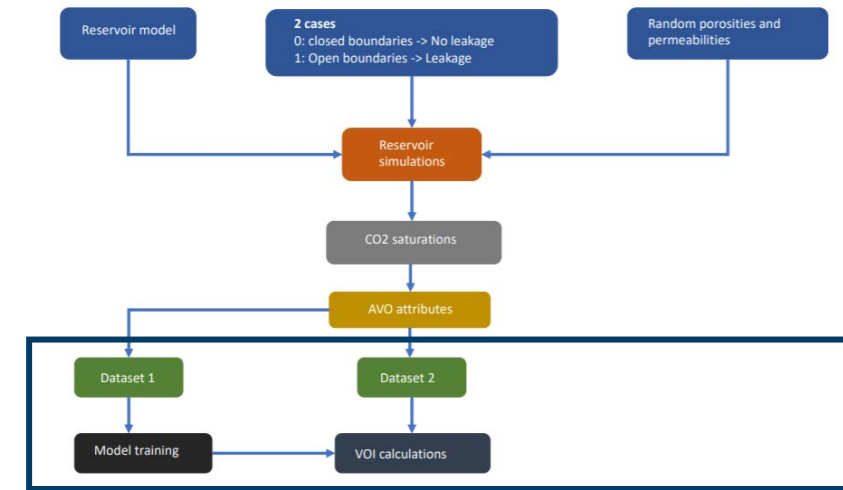
Workflow: G maps– examples



Workflow

Machine learning

- Objective: classify probabilities of seal and leak scenario ($\hat{P}(X = x|y_t)$, $x \in \{0,1\}$) needed for the PoV calculation
- We split the data generated through reservoir simulation and AVO modelling into training (80%) and testing (20%) dataset
 - Training can be performed using different ML algorithms
- Input data: AVO attribute(s) in each grid of the top of the reservoir
- Output: seal or leak class by comparing $\hat{P}(X = 1|y_t^b)$ and $\hat{P}(X = 0|y_t^b)$



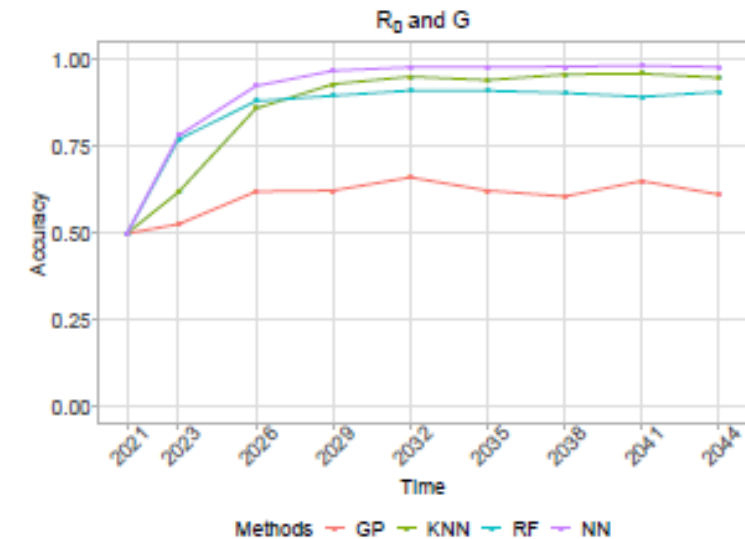
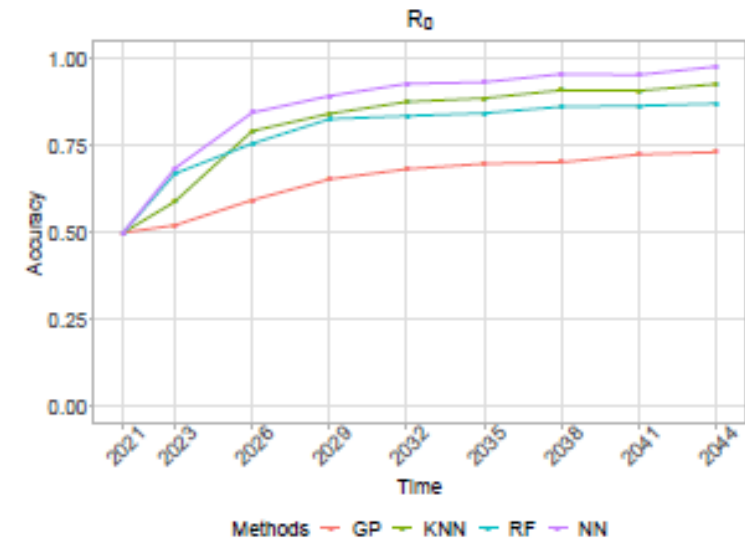
Workflow

Machine learning

- Accuracy score (ACC) to evaluate the performance of the prediction

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}$$

- Methods tested:
 - Gaussian process (GP)
 - K-Nearest neighbours (kNN)
 - Random forest (RF)
 - Neural network (NN)

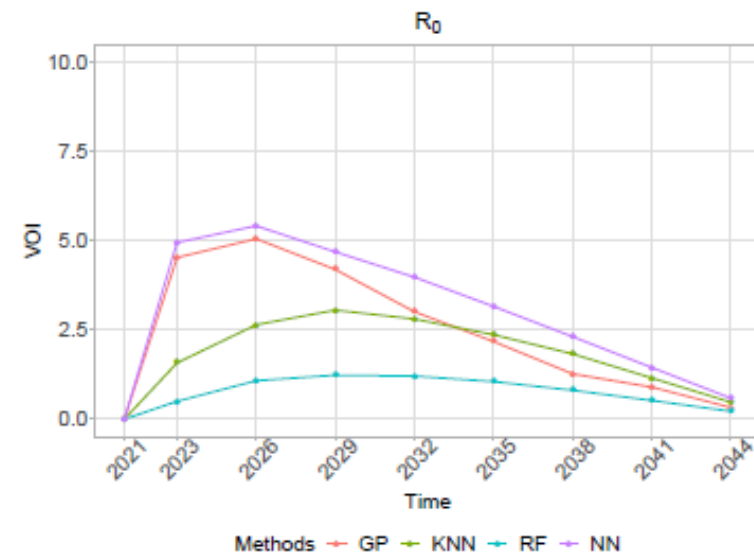


The accuracy values plotted as a function of the year of monitoring

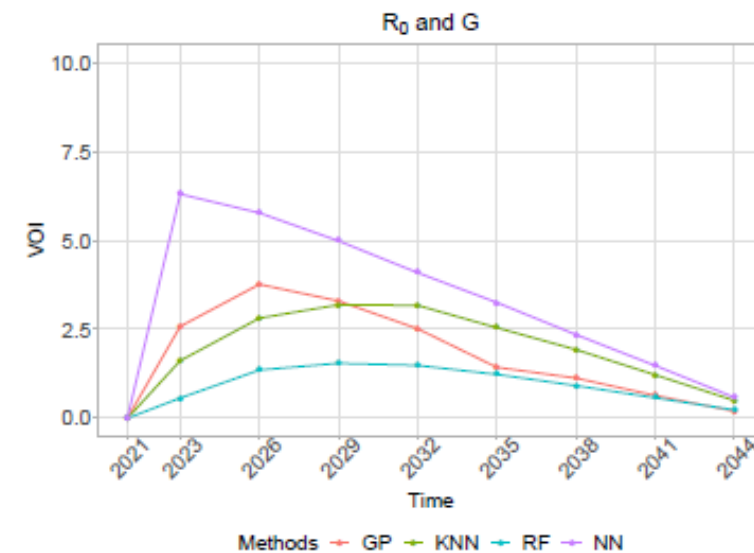
Results

VOI for the different models

- Increase and decrease in all models
- Optimum time around year 2026-2029
- Largest value provided by the NN
- With both seismic attributes, the optimal monitoring time is shifted towards earlier times → possible to detect leakage earlier with more info



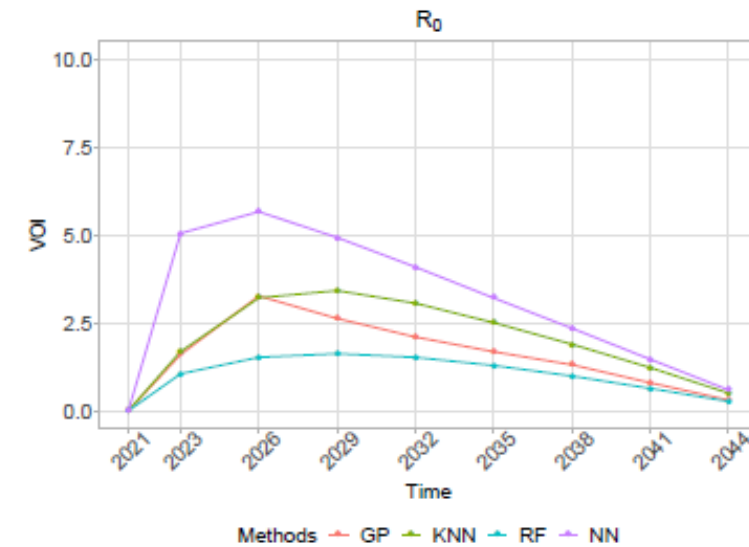
(a) VOI of zero-offset seismic AVO attribute.



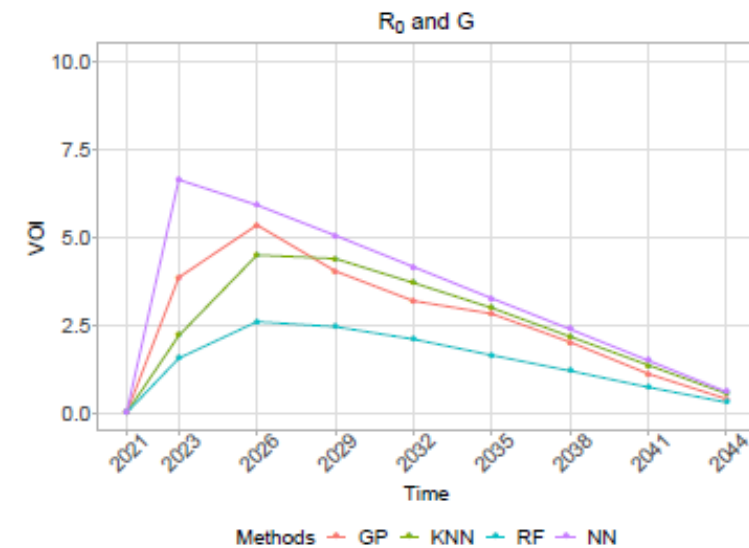
(b) VOI of zero-offset and AVO gradient.

Results-VOI for the different models- higher signal to noise ratio (SNR)

- Higher VOI with less noise
- Shift towards earlier times for GP, KNN, and NN
- Little changes with NN indicating possible overfitting



(a) VOI of zero-offset seismic AVO attribute.

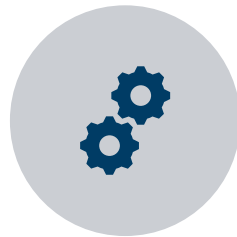


(b) VOI of zero-offset and AVO gradient

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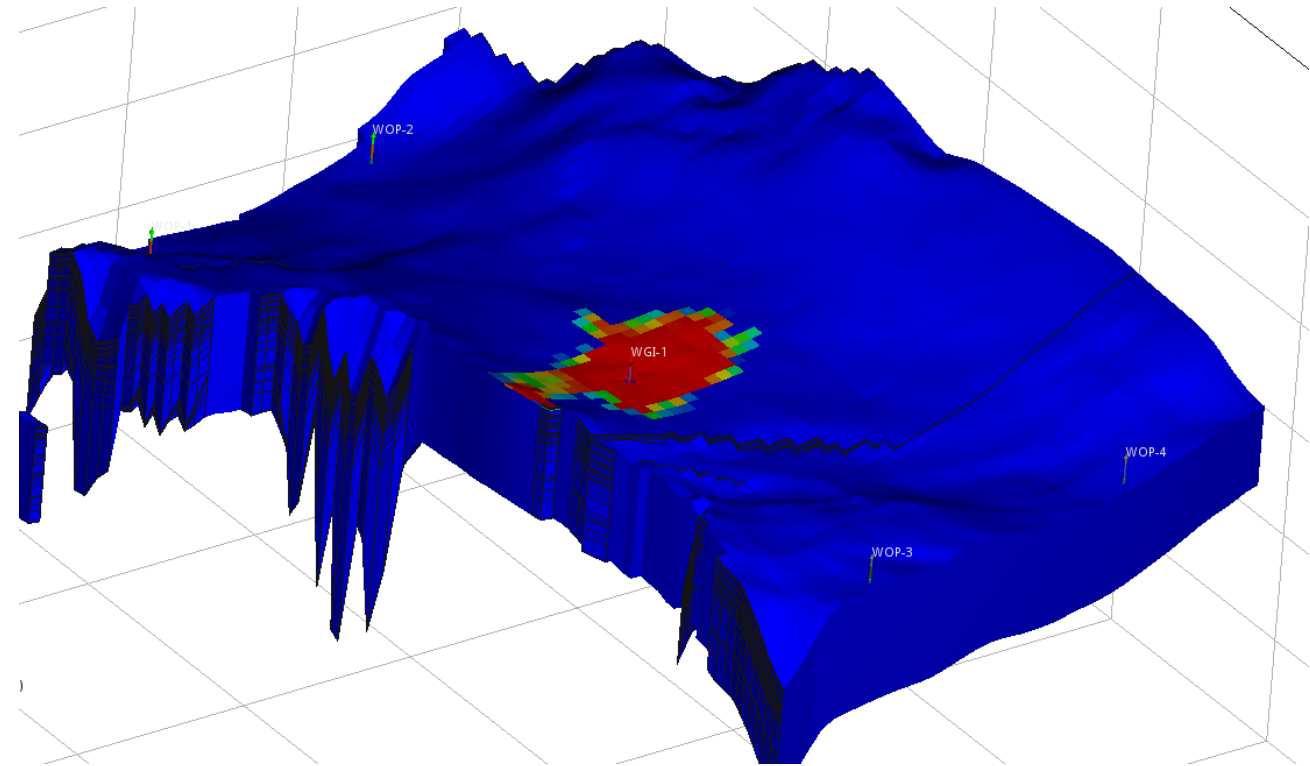
CASE STUDY



CONCLUSIONS
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Discussions/perspectives

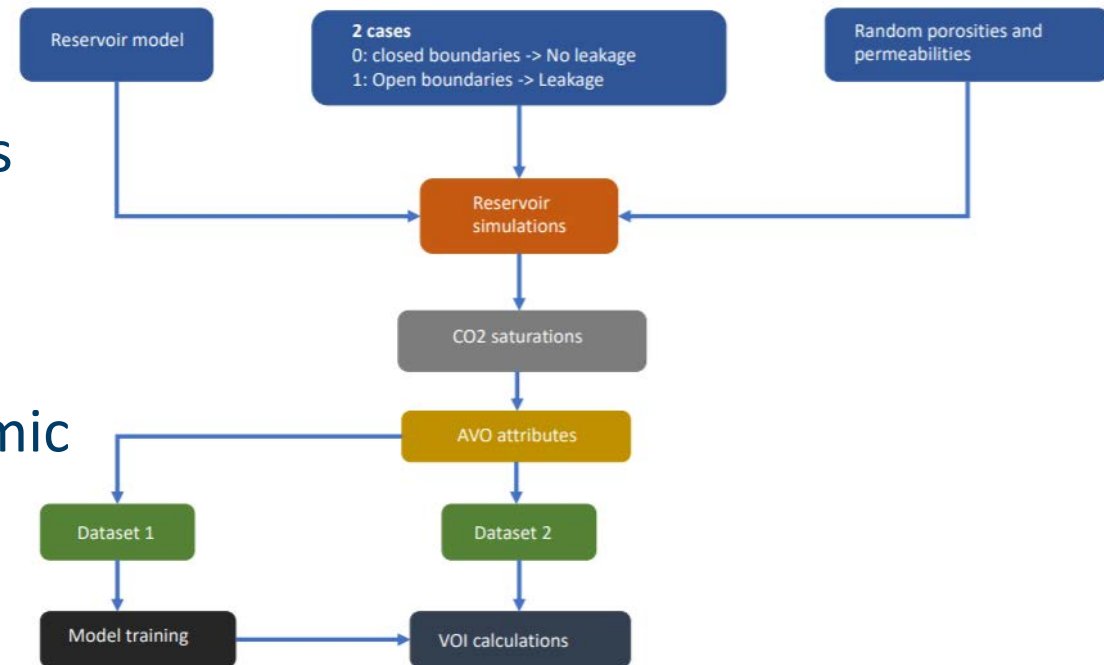
- More realistic model:
 - Grid size relatively large
 - Include a more detailed reservoir topography
 - Smaller blocks would likely lead to higher detail in the PDE solver and better separation (and hence classification) between open/close boundary realizations.



To be analysed against the computational burden to generate enough realizations

Summary

- Proposed workflow for CO₂ storage includes reservoir modelling, geophysical and rock physics analysis, VOI with elements of ML
- Simplified case study at Smeaheia with seismic data
 - MRST for reservoir modelling
 - Random porosity/permeability perturbations
 - Leaking/non leaking scenarios
- Various ML techniques tested



Discussions/perspectives

- More realistic model
 - Possibility to study
 - Sensitivity to compartmentalization
 - 3D connections of volumes
- Beyond binary leak or seal input
 - Could be generalized to partial leakage near the fault
- More complex decision problem, including options to:
 - Increase/decrease injection rate
 - Produce water
 - Study sensitivity to the decision framing parameters

Acknowledgements

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