A global sensitivity methodology to guide risk assessment for CO2 geological storage in deep saline aquifers

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Géosciences pour une Terre durable
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CONTEXT

European Directive 2009/31/EC on the geological storage of carbon dioxide states: Annex I, *Step 3.2: Sensitivity characterisation*

« Multiple simulations shall be undertaken to identify the sensitivity of the assessment to assumptions made about particular parameters. The simulations shall be based on altering parameters in the static geological earth model(s), and changing rate functions and assumptions in the dynamic modelling exercise. Any significant sensitivity shall be taken into account in the risk assessment ».

Numerical models for risk assessment:

- **Multiple input parameters**
- **High non-linearities**
- **High computer time cost**

Need for appropriate tools to carry out sensitivity analysis based on limited number of model runs

METHODOLOGY

Response surface method (Box and Draper,1987)

f = "real" computing-intensive model
Y = output, $X = [x_1,\ldots,x_{nX}]$ = inputs
g = meta-model = surrogate "simpler" model to mimic *f* → "regression model"

$$Y = f(X) = f(x_1, x_2, \ldots, x_{nX})$$
$$f(X) \approx g(x_1, x_2, \ldots, x_{nX})$$

Evaluation of *g* is faster

Which meta-model ?

g can be of several form (Storlie and Helton, 2008) :

1. Linear regression ⇔ « One at a time »
2. Quadratic regression
3. Gaussian Process
4. Non parametric regression

When f highly non linear

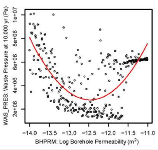
Work fairly well with a modest number of inputs

A method of nonparametric regression:
Recursive partitioning regression (Breiman et al., 1984)

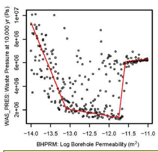
- Split a set S of observations into nP subgroups such that the observations within each subgroup PS are more homogeneous than they are over the whole set S;
- The model f is then estimated by a linear regression over each subgroup SG;
- g = piecewise linear function:

$$f(X) \approx g(X) = \sum_{s=1}^{s=nP} (a_s + b_s X) H_s(X)$$

$H_s(X)$ is the Heaviside function, $(a_s+b_s.X)$ is the linear fit to the data associated with *SG*.



Quadratic regression



Recursive partitioning

Extracted from Storlie and Helton, 2008 based on the « performance assessment for a radioactive waste disposal facility »

Step1: Mapping=training data

- Between the input and the output domain $\{X_j, Y_j\}$ with limited number of samples;
- **Latin hypercube sampling** method (McKay et al., 1979);
- Combined with the "maxi-min" space filling design criterion
- → **maximise the exploration of the input domain.**

Step2: Response surface construction

Objective: keep only the most important parameters in the surrogate model.

Step i. a 1dim. recursive partitioning regression model is constructed for each candidate parameter → *nX* 1dim response surface models. The parameter, for instance *x*1, associated with the best of these models is identified and selected;

Step ii. 2dim. recursive partitioning regression models are constructed using the best candidate *x*1 selected in the first step and each of the remaining *nX*–1 parameters. The parameter, for instance *x*2, associated with the best of these models is identified and selected;

Step iii.… Following the same principle, the third parameter is selected and the process is continued until a stopping criterion is reached…

Stopping criterion = p-value (statistical approach of hypothesis testing).

Step 3: Importance measure

Coeff. of determination R^2 ⇔ Goodness of fit:

$$R^2 = \sum_{i=1}^{Ns} \left(g(X^i) - Y_m\right)^2 \Big/ \sum_{i=1}^{Ns} \left(f(X^i) - \bar{Y}\right)^2$$

The order the input parameter enters the response surface = importance order;
At each step of the response surface construction **R^2 ≡ importance measure of the input parameter;**
Additional validation through **cross-validation** (use observations from the initial training data as the validation data, and the remaining samples as the new training data for a new response surface construction, e.g. Hjorth, 1994).

MODEL

Supercritical CO2 ≈ 1 Mt/y, 10y

P0= 180 bars, T0= 75 °C, Depth ≈ 1750 m

20 m

200 kms

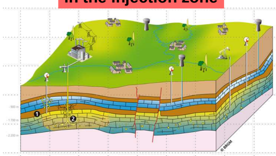
Input Parameter	Unit	min	MAX
Porosity	%	10	25
Intrinsic permeability	D	0,1	6
Capillary entry pressure P_0	Pa	20 000	81 000
Van Genuchten Parameter m(VG)	-	0,460	0,600
Residual gas saturation	%	5	25
Residual liquid saturation	%	20	50
Salinity	g/l	5	35
Pore compressibility	Pa^{-1}	4.5e-10	9.E-10

- 1d multiphase flow transport model;
- Dogger formation (Paris basin case);
- TOUGH2/ECO2n (Pruess, 2005);
- Based on Andre et al., 2007;
- Minimum grid cell of 50 cm;
- Total number of grid cells = 576;
- Number of input parameters=8;
- Number of samples=8x30=240.

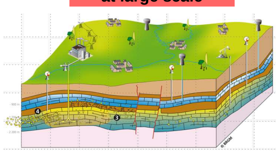
Based on: Andre et al., 2007, Bachu and Bennion, 2008, Birkholzer et al., 2009, Rojas et al., 1989

SENSITIVITY RESULTS

RISK in the injection zone



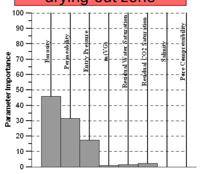
RISK at large scale



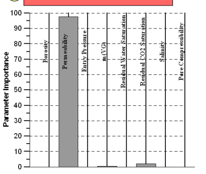
1. Leakage through wells
2. Local fracturing
3. Large scale over- pressurization
4. Expected lateral plume extent exceeded

Adapted from Bouc et al., 2009

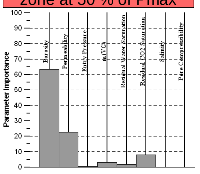
2 Extent of the drying-out zone



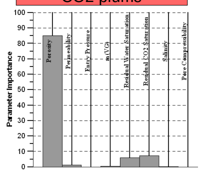
1 2 Maximum pressure



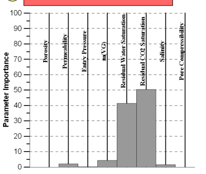
2 1 3 Extent of the over-pressurized zone at 50 % of Pmax



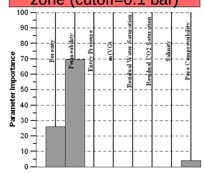
4 Extent of the CO2 plume



1 2 Total free gas



3 Extent of the over-pressurized zone (cutoff=0.1 bar)



- **Goodness of fit** R^2 >99.0 for all models;
- Coeff. of determination of the **cross-validation** Rcv^2 >98.0 for all models;
- The effect of **salinity** appears to be negligible;
- The **pore compressibility** should be taken into account for the large scale pressure impact;
- **Residual gas and liquid saturation** have an important effect considering trapping and has a moderate effect for CO_2 plume extent and over-pressurized zone (at 50 % of Pmax);
- Capillary entry pressure only affects the extent of the drying-out zone near the injector;
- Small effect of the **Van-Genuchten's parameter m**;
- **Both porosity & intrinsic permeability** ≈ 80 % of the effect on all considered risk outputs.

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