

# **COMPARISON OF STATISTICAL METHODS FOR RANKING THE IMPORTANCE OF MODEL AND PARAMETER UNCERTAINTIES: A CASE STUDY WITH** NUMERICAL FLOW SIMULATIONS OF CO2 SEQUESTRATION

### **General context**

- Uncertainty analysis is a key component of modelling flow processes
- Flow modelling:
  - Two types of uncertainties : parameter and model Ο
  - Potentially large computation time cost (>hours)
- **Global sensitivity analysis (GSA) :** 
  - what sources of uncertainty contribute the most to the

# Within-method

- analysis
  - Three criteria for assessing the impact of the number of simulation results N and the robustness to the parametrization of each method:

1) Convergence of the sensitivity



- uncertainties in the flow simulation results?
- how to rank these sources of uncertainties?  $\bigcirc$
- how to **set priorities** for future investigations? Ο

**Observation :** different SA approaches can be used for computing sensitivities, **BUT** they may result in a different importance ranking.

#### Question : which GSA methods are best applicable regarding the specificities of the situation ?

# Objective

- Test the feasibility of the available methods/approaches for dealing with GSA with respect to parameter and model uncertainties
- 4 types of approaches tested:
  - **DGSA:** distance-based generalized sensitivity analysis 0 developed by Fenwick et al. (2014) and further extended by Park et al. (2016) based on the Regionalized sensitivity analysis **RSA** method (Spear and Hornberger 1980);
  - **PAWN:** a density-based GSA (aka moment-independent) developed by Pianosi & Wagener (2015);
  - M-VBSA: combination of variance-based GSA (Saltelli et Ο al. 2008) and metamodeling techniques adapted to situations using continuous and categorical variables (Storlie et al. 2013);
  - **RF:** a machine learning approach based on the random Ο

indices: reached if the values of the indices remain stable;

2) **Convergence of ranking:** achieved if the ordering between the parameters remains stable;

3) Convergence of screening: reached if the partitioning between non- and -influential parameters remains stable.



A) Permutation-based Variable Importance measure **PVIM of RF model B) Significance p-value** 



#### **Between-method analysis**

 $\Rightarrow$ Clear similarity among most methods

 $\Rightarrow$ The importance ranking of the other

 $\Rightarrow$ The normalized sensitivity measures

parameters is less straightforward

cannot be compared

regarding *kr* largest importance

**BUT**:

•Normalization of the sensitivity measures with respect to the maximum value reached for each method considering N=250

forest technique (e.g., Wei et al. 2015).

### **Case study**

Same as in Manceau and Rohmer (2016) :dataset of 1000 simulations available

Injection of 30 Mt of CO<sub>2</sub> during 30 years in the lower Triassic sandstone formation based on a potential project in the Paris basin (France).

Sensitivity analysis on the quantity of mobile CO<sub>2</sub> 150y. after the injection stops





#### Comparison of the methods form a practical point of view

	X-axis			PROS	CONS	
OP1 Samah			M- VBSA	Intuitive and rigorous interpretation as a proportion of variance; Feedbacks in a large variety of domains	<ul><li>Sensitivity to the number of simulations, which imposes a careful examination of the predictability of the metamodel.</li><li>Convergence analysis when using Monte-Carlo algorithm.</li></ul>	
Sg,mob       Depth (m)         OP1 = 3,8 Mt       Depth (m)         OP1 = 3,8 Mt       Depth (m)         Scale study geological model [Manceau and Rohmer, 2016]			RF	Little influence of the RF parameters (mtry, ntree, nodesize and even split rule); Robustness to the number of simulations	Sensitivity of the p-value algorithm to the number of permutations. Difficulties in the interpretation of the sensitivity measure (here as a decrease in predictability)	
			RSA	Easy to compute, and possible even for low number of samples and for categorical inputs. Adapted when the outputs can be naturally divided into two different groups, and useful for factor mapping.	<ul> <li>Do not account for interactions among input parameters.</li> <li>No procedure for factor fixing.</li> <li>Cannot handle more than two groups, and very much influenced by the choice of these two groups: may lead to difficulties in interpretation.</li> </ul>	
Input variables and associated uncertainties:				Can handle <b>multiple groups of outputs</b> .	The proposed statistical test might lead to a strong <b>sensitivity to the number of simulations.</b>	
Parameter	Uncertainty type	Representation	DGSA	DGSAProvide a lot of information on interactions among parameters (two-way interactions) Can help fixing parameters to the less influential value/rangePAWNRelatively good convergence for sensitivity analysis, ranking and fixing with the number of simulations. Compared to other density-based GSA, rely on CDF whose approximation is easier than PDF	<sup>3</sup> The test for statistically significant interactions require a <b>high number</b> of simulations.	
Porosity	Parametric	Probability density			difficulties in interpretation	
Permeability	Parametric	Probability density	PAWN		Dependent on the <b>choice of the statistic</b> : may lead to difficulties in interpretation.	
Permeability anisotropy	Model	3 scenarios ( $k_v/k_h = 0.1$ ; 0.5 and 1)			accounted for.	
Regional hydraulic	Madal	2 scenarios (hydrostatic and 0.01 m/m)		References Fenwick et al., 2014, Math. Geosci., 46(4), 493-511 / Manceau and Rohmer, 2016, Comput. Geosci., 20(6), 1251-1267 / Park al., 2016, Comput. Geosci., 97, 15-29 / Pianosi and Wagener, 2015, Environ. Modell. Softw., 67, 1-11 / Saltelli et al., 2008, T Primer. John Wiley & Sons, Chichester. / Spear and Hornberger, 1980, Water Res., 14, 43-49 / Storlie et al., 2013, Reliab. Er		
gradient	INICACI					
Relative permeability	Model	10 scenarios (10 different relative		Syst. Safe., 113, 30-41 / Wei et al., 2015, Reliab. Eng. Syst. Safe., 142, 399-432		
		permeability datasets)		Authors		
Capillary pressure	Model	2 scenarios (no-capillary pressure and		Jean-Charles Manceau, Jérémy Rohmer and Pascal Audigane Contact: jc.manceau@brgm.fr		
		"strong" capillary pressure)			WWW.BRGM.FR	