

A clustering method for uncertainty quantification applied to CO₂ sequestration

What is CO₂ sequestration ?

In order to reduce the atmospheric emission of CO₂ due to human activities, one possibility is to store CO₂ in geological reservoirs. The principle is to extract the CO₂ produced by a polluting factory (a coal fired power plant for instance) and to inject it into a geological reservoir such as a deep saline aquifer. If the caprock's quality is good, the CO₂ will be trapped and will progressively turn into sediments.

The depth of the aquifer has to be greater than 800m to ensure a sufficiently high gas density. The duration of a site exploitation is around 20 years and the injection rate is between 1 and 15 megatons per year (Mt/y).

To check the viability of such project, one of the main challenges is to quantify the risk of CO₂ leakage. As all the leakage scenarii depend on the growth of the CO₂ plume, it is necessary to study its expansion by numerical simulation. However, the inputs of the simulation (permeability and porosity fields) are random, and simulating one single injection scheme takes around 2 days (20 years of injection with a 2 dimensional model).

Methodology

As classical Monte-Carlo methods are unaffordable, the method we use here is as described by Caers in [1].

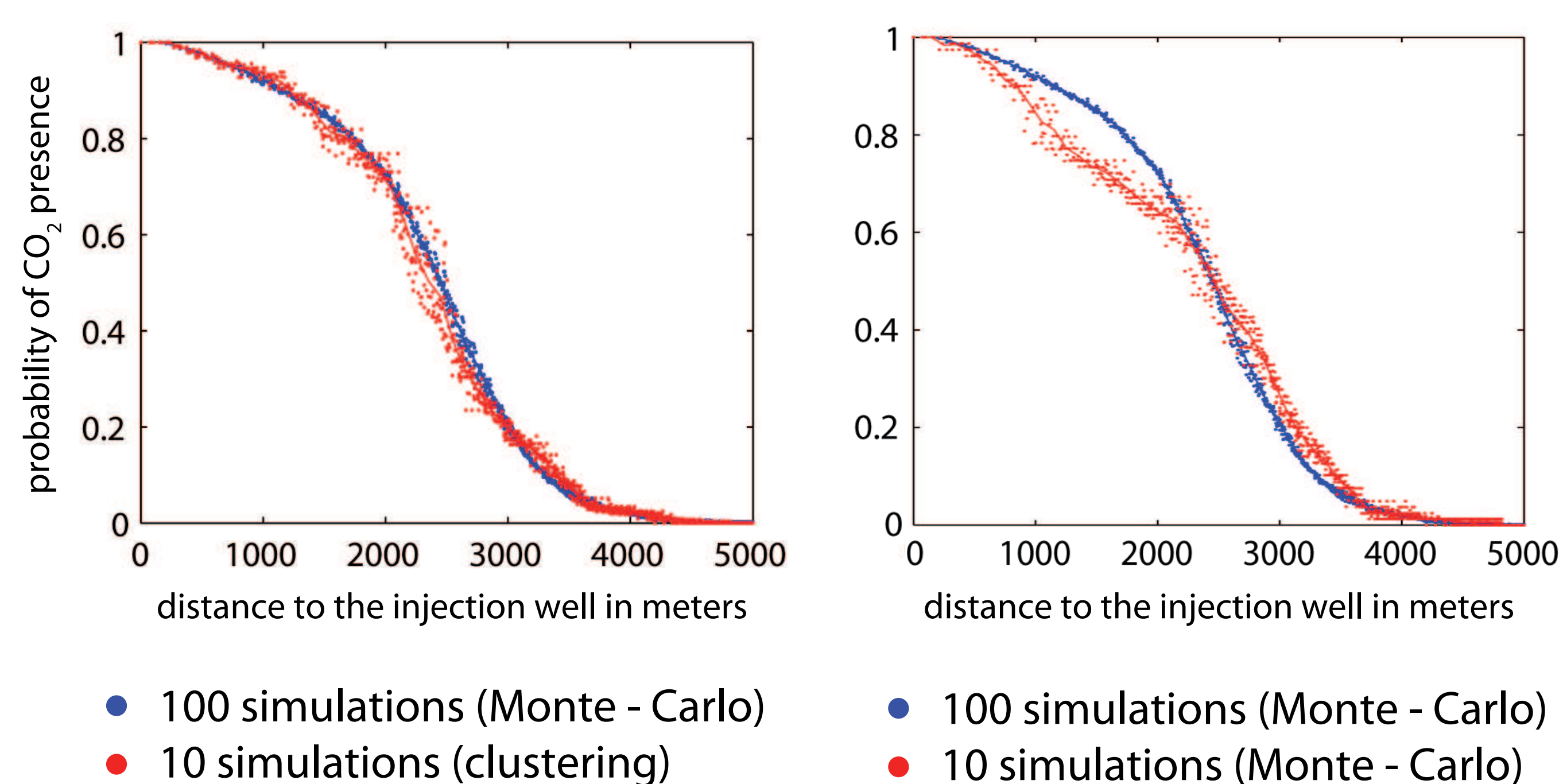
The aim is to select a limited number of simulation runs by applying a non intrusive method based on a *proxy simulator* (cheap-to-evaluate low-fidelity model). Following [2], kernel methods are used in order to linearize the data, which is supposed to improve the clustering procedure. The method consists of 5 steps:

Results

The flow simulation is performed using the software Tough2 with a 1 Mt/y injection rate during 20 years.

The proxy simulator is a shorten Tough2 simulation of a 1 year injection. The number of initial fields generated is $n=100$ and the number of complete simulations is $N=10$. In order to evaluate the efficiency of our method, we perform a classical Monte-Carlo analysis using 100 complete simulations.

Comparison between clustering method and Monte - Carlo

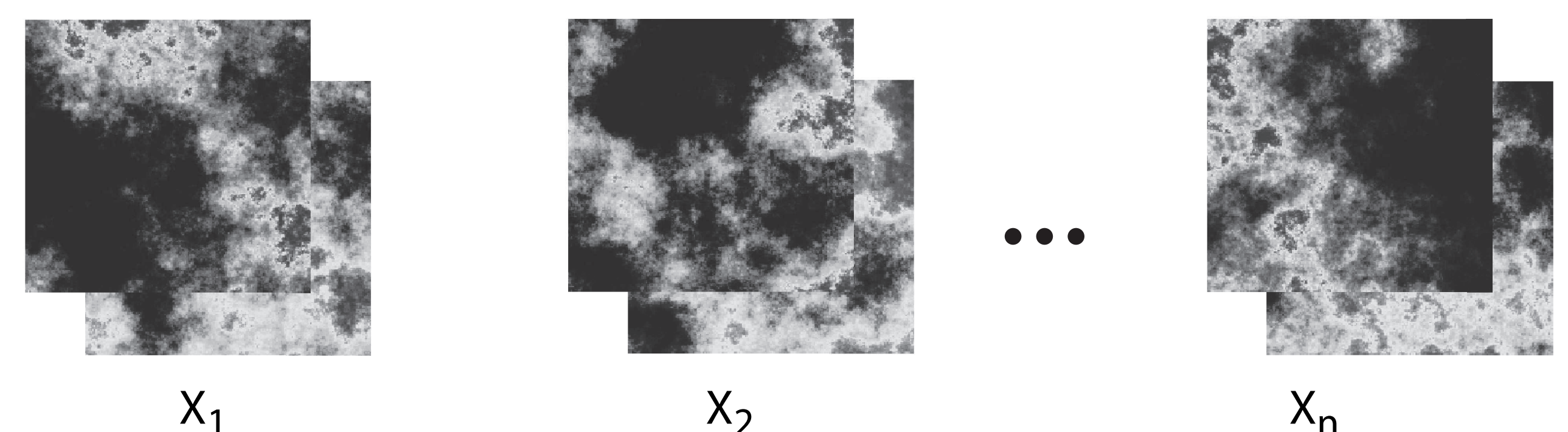


The ten simulations chosen using the clustering technique provide results almost similar to 100 Monte-Carlo simulations, while the ten Monte-Carlo fail to catch the response trend.

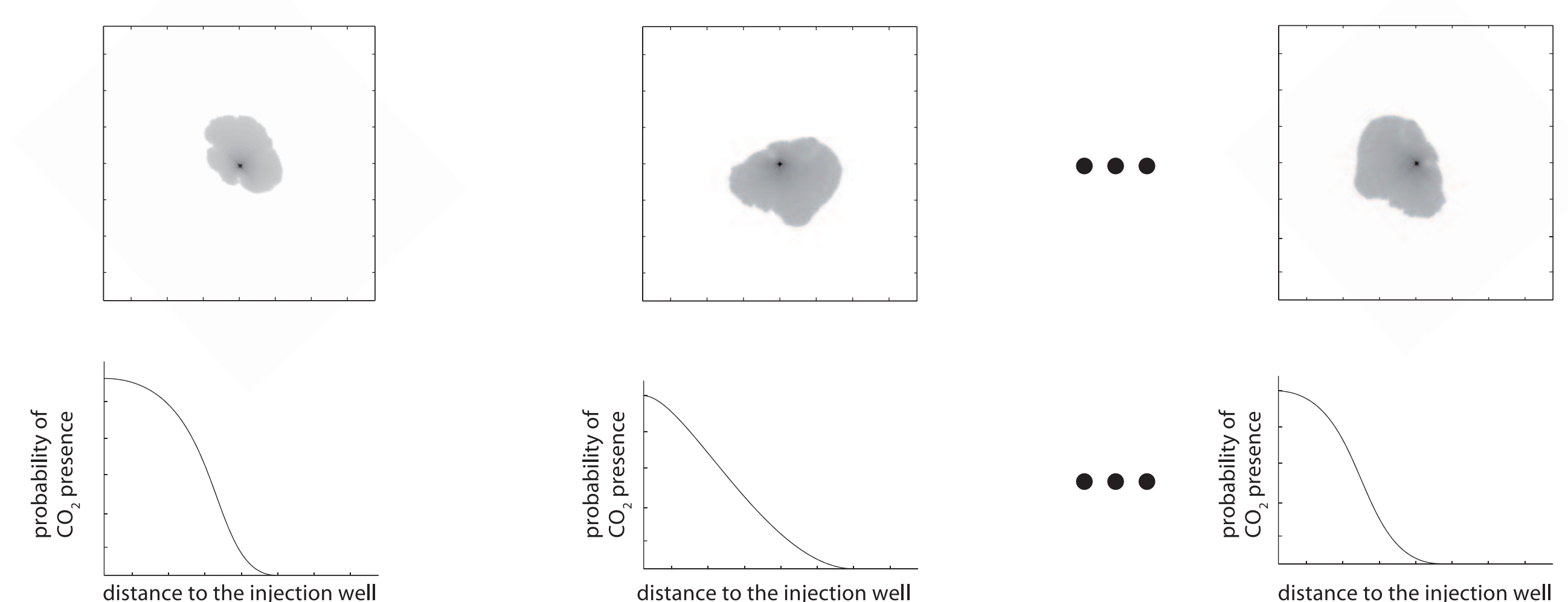
Conclusion

This work illustrates that proxy simulators can be used to efficiently select representative simulations. Here the CPU simulation time can be divided by one order of magnitude while keeping good estimates of the probability of presence of CO₂. However the distance definition seems to have a great impact on the final results. Future works may focus on the issue of selecting well-suited distances for importance sampling.

a) Generate n fields of permeability and porosity



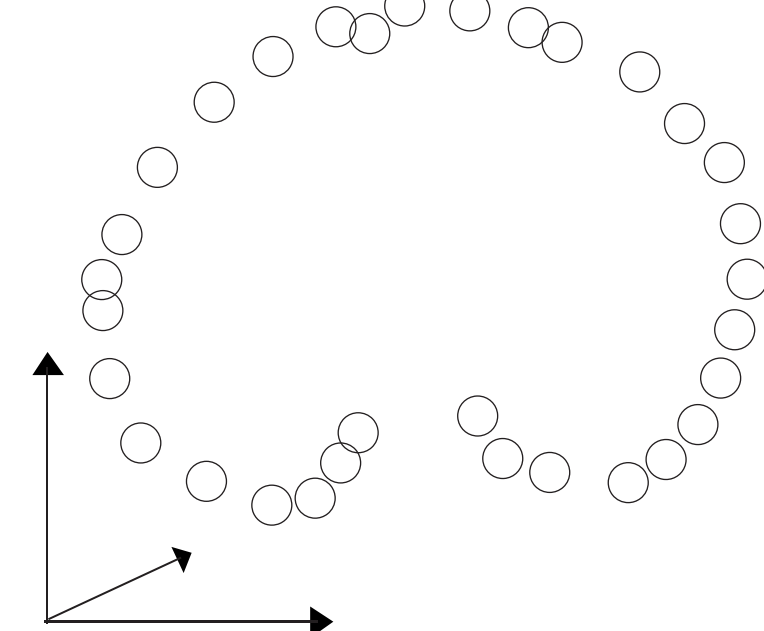
b) Use a proxy simulator to compute the n approximate solutions



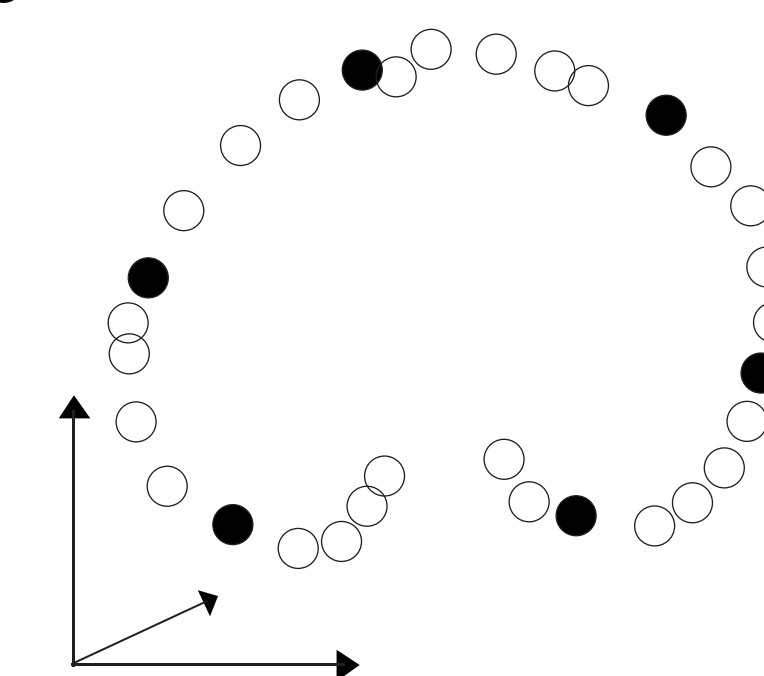
c) Define a distance between the solutions and create a mapping.
This transformation may be based on kernel methods for greater linearity

$$\delta'_{ij} = \text{dist}(X_i, X_j)$$
$$M_D = \begin{pmatrix} \delta'_{11} & \delta'_{12} & \dots & \delta'_{1n} \\ \delta'_{21} & \delta'_{22} & \dots & \delta'_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \delta'_{n1} & \delta'_{n2} & \dots & \delta'_{nn} \end{pmatrix}$$

mapping



d) Find N centres of clusters



e) Run the simulator for the N selected points.

[1] J. Caers. Distance-based stochastic modeling : theory and applications. Technical Report 21, Stanford University, Energy resources Engineering Dep., 2008

[2] C. Scheidt, J. Caers. Uncertainty quantification using distances and kernel methods - application to a deepwater turbidite reservoir. Technical report, Stanford University, Energy resources Engineering Dep., 2008

[3] V. Vapnik. The Nature of Statistical Learning Theory. Springer, 1995