CrossMark

Large-Scale CO_2 Storage in a Deep Saline Aquifer: Uncertainties in Predictions Due to Spatial Variability of Flow Parameters and Their Modeling

Sarah Bouquet[1,2] (iD) · **Dominique Bruel[1]** ·
Chantal de Fouquet[1]

Abstract Scarce data and uncertainties in the spatial variation of geological properties lead to different possible models of these heterogeneities. The aim of this study is to compare the pressure results and CO_2 behavior of different permeability field models for a large-scale CO_2 injection in a deep saline aquifer. Five ways of representing heterogeneities are tested and compared. The simplest representation defines homogeneous equivalent properties over the entire domain. A second representation is obtained by considering homogeneous layers. Two other models represent the lateral and vertical variations in permeability in greater detail by geostatistical methods with either a continuous model or a discontinuous model (discrete values). The last model is the semi-homogeneous model combining a heterogeneous area and a homogeneous area depending on the complexity of the flow process. Highly variable predictions arise from the heterogeneities, and significant differences in estimates are obtained using the various modeling methods. The optimum resolution depends on the type of response to be estimated. Averaged properties at large scale are not adequate to estimate the critical pressure propagation far from the well. Averaged properties in the injection area are not sufficient to assess the maximum increase in pressure or the extent of CO_2 migration. Lateral and vertical connectivities, and reservoir compartmentalization modeling are required to obtain reliable results. But the resolution requirements are not to be at the finest scale: The discontinuous model (discrete values) gives satisfactory results compared to the continuous model. The way to represent spatial variability of porosity and pore compressibility is also studied. The influence of these two properties is far lower than that of permeability.

Keywords Spatial variability · CO_2 storage · Heterogeneities modeling · Permeability · Optimum resolution · Uncertainties

✉ Sarah Bouquet
  bouquet.sarah@gmail.com

1 MINES ParisTech, Geosciences Centre, 35 rue Saint Honore, 77300 Fontainebleau, France

2 Present Address: IFPEN, Avenue de Bois-Preau, 92852 Rueil-Malmaison Cedex, France

🙂 Springer

1 Introduction

Flow parameters related to rock properties, such as permeability, capillarity, porosity, and pore compressibility, have a major effect on CO_2 storage feasibility (e.g. Birkholzer et al. 2009; Doughty 2009; Farajzadeh et al. 2011; Lengler et al. 2010; Mathias et al. 2013; Zhou et al. 2010). Thus, spatial variability of rock properties could cause variations in several orders of magnitude in CO_2 storage capacity predictions (Keating et al. 2011), but its representation is problematic since geological data are generally sparse (Nordbotten et al. 2012).

Since the characterization of geological parameters is, in most cases, limited, how can these parameters be represented spatially, at regional scale, so as to reproduce their influences on system responses resulting from CO_2 injection?

Marsily et al. (2005) deal with this problem in a hydrogeological framework based on progress for the exploitation of hydrocarbon and mineral resources. They point out the different methods of heterogeneity modeling and their efficiencies according to the application framework, from the definition of equivalent permeability (averaging), to the description of the spatial variability of properties by continuous or discontinuous geostatistical models [Boolean models, Indicator or Truncated Gaussian models (Fouquet et al. 1989), etc.] or by genetic models which reproduce the depositional and rock formation processes. According to Marsily et al. (2005), the resolution requirements of heterogeneity modeling should mainly depend on:

- the scale of the problem. Averaged properties could be used for predictions at regional or basin scale since flow and transport would be averaged by crossing different heterogeneous structures
- the type of processes to be characterized. Averaged properties, based on well testing, could be sufficient for flow problems but not for transport or diphasic problems.
- the type of response studied. For example, averaged properties can be sufficient if a contaminant transfer rate has to be assessed, but the assessment of a maximum contaminant concentration requires a detailed description of heterogeneities. The assessment of the CO_2 drainage area and the maximum dissolution rate may also require different descriptions of heterogeneities.

In the case of a CO_2 storage study, can we ignore, even partly, the spatial variability of rock properties?

For CO_2 leakage risks and storage capacity, both flow and transport processes have to be characterized. CO_2 migration and dissolution have to be defined, and we need to determine whether well pressure remains below the maximum admissible pressure (risks of fracturing). For the risks of fluid-in-place leakage and of interference between injection wells, the extent of pressure perturbations has to be known, in particular to define the area of review. This area of review depends partly on the extent of a critical pressure perturbation, which could induce fluid-in-place migration through water resource formations if potential leakage pathways existed in the area. Transport and diphasic flow processes occur mainly in the injection area, which could justify describing the spatial variability only in this area. However, averaged rock properties in the area where simpler flow processes occur are not always necessarily appropriate. The description of system perturbations based on model with averaged rock properties may not be sufficiently detailed for the risk assessment in a CO_2 storage context. The risk assessment cannot rely on average results. In addition, the problem of uncertainties in geological media may have to be addressed through stochastic modeling (Renard 2007; Koch et al. 2014). Multiple realizations of a geological model could be needed to obtain uncertainty estimates. Thus, it seems important to define whether a simplified model, in terms

of heterogeneities, could represent a maximum scenario of pressure perturbation propagation and CO$_2$ migration.

The Snohvit project, a CO$_2$ storage project in the North Sea, demonstrates the critical consequences on injectivity predictions of a lack of knowledge of heterogeneities and of a lack of model details on connectivities in the storage formation. The low injectivity could not be predicted because the vertical heterogeneities in the storage formation were not described prior to the injection (Hansen et al. 2013; Shi et al. 2013).

The main studies of CO$_2$ injection at basin scale generally assume a negligible influence of the lateral variability of petrophysical properties to evaluate the system response. Basins are mostly represented as multilayered systems, either in the aquifer (Zhou et al. 2010; Yamamoto et al. 2009; Zhao et al. 2012; Birkholzer et al. 2011) or for an alternating aquifers/aquitards system (Birkholzer et al. 2009; Rohmer and Seyedi 2010). In any case, aquifers are not vertically or laterally homogeneous at basin scale in reality. Yet, in Zhao et al. (2012) study, even though the preliminary geological studies indicated great heterogeneities in the injection formation, the permeability of the members of this formation was represented by an averaged and uniform value for each main member. In Birkholzer et al. (2011) study, models are represented by alternating continuous layers of sand and shale; and in the study by Doughty (2009) based on geological data for the same basin (Southern San Joaquin Valley) but at a smaller scale (injection area), these alternating sand/shale layers are represented as lenses with a lateral extent of several kilometers. These two studies do not analyze the same performance [pressure behavior for Birkholzer et al. (2011) and CO$_2$ plume migration and dissolution for Doughty (2009)]. This would partly explain the differences in modeling methods and why results are not comparable. However, we may examine the pressure-response consequences of modeling as continuous layers rather than as discontinuous lenses which would modify the vertical connectivity. For transport modeling, Refsgaard et al. (2012) underlines this tendency of interpreting geology as continuous layers although field data may describe less continuous layers. Refsgaard et al. (2012) show that more heterogeneity in stochastic model based on field data can give better results than model with geological layers assumed to be continuous. The Sleipner project is another example where the heterogeneities in shale layers played a key role in transport: Modeling this discontinuities in shale layers was needed to predict the CO$_2$ plume migration (Holloway 2003).

Three studies were carried out for the Mt Simon aquifer with different resolutions for the spatial variability of rock properties (Zhou et al. 2010; Person et al. 2010; Bandilla et al. 2012). In Person et al. (2010) and Bandilla et al. (2012), lateral variability was modeled on the entire domain, inferred from linear relationships between depth and porosity, and porosity and permeability. Because of the lack of data, relationships were simplified by linearization and more complex heterogeneities were not represented, even though they could possibly influence the pressure propagation (Person et al. 2010). Bandilla et al. (2012) observed that pressure perturbations propagated preferentially in highly permeable, shallow areas (depth and permeability are correlated). They also examined the effect of vertical and lateral variability of rock properties (compared to lateral variability only). The discretization by layers led to a reduction in the thickness of the injection interval and a decrease in the vertical plume migration. Consequently, the increase in pressure was higher at the injection point, and globally, the pressure perturbation of the aquifer system increased. The pressure perturbations could propagate farther, and new interference between injection areas appeared. Moreover, a basin model calibrated for groundwater modeling (Nicot 2008) indicated that a local permeability barrier (single-phase simulation of large-scale CO$_2$ injection) could cause a local increase in pressure that was critical for the system integrity.

The sensitivity to heterogeneity modeling still needs to be addressed to assess the resulting uncertainties in a feasibility study of CO_2 storage (Lemieux 2011). The aim of the present study is to compare the performances of different methods for modeling heterogeneities based on 200 stochastic realizations and to assess the uncertainties that arise due to the choice of spatial variability modeling. The results help to understand the resolution requirements for the characterization of heterogeneities in CO_2 storage studies. Conclusions based on this study have to take into account the limitations of the models (short timescale and 2D models representing a vertical section of a reservoir: the lateral variations or connectivities are restricted to only one direction; see the next sections).

We analyze results in terms of pressure response at the well and its propagation from the well, and in terms of CO_2 behavior for a large-scale CO_2 injection problem. The spatial variations and the scatter of these results are studied according to the various models.

2 Approach

2.1 Different Methods for the Spatial Modeling of Rock Properties

As the resolution requirements will depend on the scale of the problem, the type of processes and responses, we compare different scales of modeling the spatial variability of rock properties from the coarsest resolution to the finest: averaging at large scale (i.e., for the entire reservoir), at layer scale (averaged laterally), and at local scale and the combination of two scales (far from the well and close to the well). We do not study upscaling methods related to mesh resolution (same mesh size for all models).

(a) Model homogenization with one value over the entire domain. This value corresponds to a mean of the available data or can be inferred from well testing (Marsily et al. 2005). Equivalent, uniform properties are assumed to approximate the flow behavior at large scale. In this study, this model is used to examine whether results from a homogeneous model can come close to the statistical properties of results from heterogeneous models.

(b) Layered models with a laterally averaged value per layer (vertically heterogeneous, one value per layer over the entire domain). Layered models are often explained by the site geology, but, at regional or basin scale, rock properties of the layers are probably not homogeneous. The assumption of lateral homogeneity, even if it seems justified at local scale, is sometimes too restrictive (e.g. Refsgaard et al. 2012) and specially for a CO_2 storage study (e.g. the Sleipner project Holloway 2003). This layering can be represented as an upscaling of lenses or an upscaling of the lateral correlation length. This model is used to assess whether vertical variability modeling alone is sufficient to represent the main constraints on CO_2 migration and pressure response.

(c) Geostatistical simulations for modeling lateral and vertical spatial variabilities. In this study, the variability is represented either by a continuous model with a fine variability resolution (continuous spatial variability) or by a discontinuous model for which properties are discretized by classes. The model by classes assesses the influence of fine variability resolution: either the necessity to characterize heterogeneities finely (e.g., within a facies) or the predominant influence of the contrasts in rock properties (contrasts higher than one order of magnitude) on the system response. In this study, notice that the lateral variability is defined in only one lateral direction (2D models).

(d) Combination of a fine resolution model in the injection area (area of major nonlinear processes) and homogeneous model where flow processes are simpler (semi-

homogeneous model). If this type of model is sufficient to represent the variability of results due to heterogeneities, then the characterization of rock properties could be limited to the injection area.

For the modeling, we assume that the data available to describe the aquifer properties are scarce (e.g., pre-injection stage). Only some data on permeability distribution are known. We compare the most detailed heterogeneous model with the models using averaged values. The continuous spatial variability model is used as the base case (the most detailed model, 200 stochastic realizations based on the moving average method). In general, simple models are first used, and then, more details are added as the amount of available data increases. Here, a backward approach is adopted: Models are built on the basis of the continuous model to keep some consistency among models. Equivalent permeabilities are based on the permeability distribution of the continuous model (not calculated by numerical simulation). Multiphase flow simulations are applied to each model (from continuous to homogeneous models).

A similar study was carried out by Li et al. (2011) on a 3D geological model of an aquifer. From a fully heterogeneous model, they built a facies model, a layered model, and a homogeneous model. They compared the models' predictions in terms of CO$_2$ migration and dissolution, average reservoir pressure with different boundary conditions. The facies model gave a satisfactory description of pressure and CO$_2$ behaviors. In contrast, results from the layered model were the least reliable, even when compared to the results of the homogeneous model. The homogeneous model would be sufficient to estimate the average reservoir pressure, which is consistent with the findings of Marsily et al. (2005). However, for open boundaries, the differences in pressure between homogeneous and heterogeneous models may not be negligible (up to 10 MPa) and, as mentioned earlier, the average pressure is not an adequate criterion for risk assessments.

In this study, we use a stochastic approach (200 realizations for all types of heterogeneous models: continuous, by classes, by homogeneous layers and semi-homogeneous models) to take the uncertainties in the spatial variability of rock properties into account. Additionally, to the CO$_2$ migration and well pressure, the spatial variability of pressure response is studied since the area of review depends on the propagation of pressure perturbations. The main limit of this study is the geometry of the model: Models are in 2D so as to obtain results rapidly for the stochastic approach. This study is also limited to an infinite-acting aquifer.

We first study the sensitivity to the resolution of spatial variability on permeability and related capillary pressure (Leverett 1941). The spatial variability of these parameters is assumed to have a predominant influence on results. The influence of the spatial variability of other rock properties (relative permeability, porosity, pore compressibility) is assumed negligible. These properties are uniform over the entire domain. This assumption is based on results from Chadwick et al. (2009) and Buscheck et al. (2012). For uniform values, porosity has little impact on pressure response or on plume migration [CO$_2$ breakthrough time for Buscheck et al. (2012)] compared to the influence of permeability.

However, in most cases, rock properties are correlated and considering the related spatial variability of these parameters is a more realistic approach. So, in a second part, the validity of the previous assumption is evaluated. We progressively study the influence of permeability, porosity, and pore compressibility spatial variability on pressure and CO$_2$ migration at regional scale.

2.2 Modeling Basis and Hypothesis

We used 2D conceptual models representing a vertical section of a reservoir at regional scale (height 154 m, lateral extent 140 km, section width 7 m) and its horizontal well (Fig. 1). With
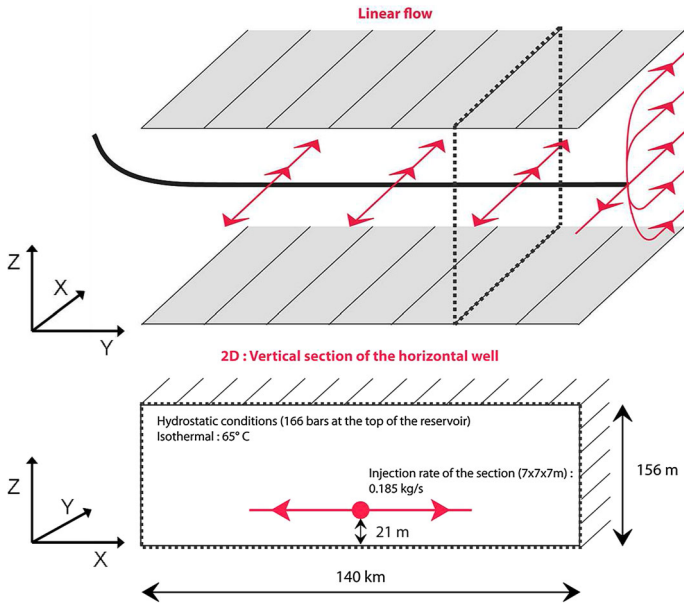
Fig. 1 2D models representing the *vertical* section of an aquifer with a *horizontal* well. The finest cell measures 7*7*7 m (injection cell). The *shading lines* represent the closed boundaries. The *red lines* are a schematic representation of the linear flow from the well

Table 1 Models input parameters

Reservoir parameters	Values
Depth (top of reservoir)	$-1550\,$m
Thickness	$154\,$m
Boundary conditions	Closed
Initial pressure (hydrostatic)	166E+05 Pa
Temperature (isothermal)	$65\,°$C
Porosity	$12\,\%$
Pore compressibility	$9.65 \times 10^{-10}\,\mathrm{Pa}^{-1}$
Relative permeability and capillary pressure	cf. Andre et al. (2007)
Salinity	$20\,$g/L
Blocks size in y- and z-direction	$7\,$m
Blocks size in x-direction	Increases from 7 m up to 14 m from 0 to 8 km of the injection point and up to 595 m at the boundaries

the large extent of the model, the lateral boundary conditions do not influence the system response.

The model parameters are defined in Table 1 and Fig. 2. Values and uncertainty intervals are based on data collected on the Dogger aquifer in order to keep the values and intervals realistic. However, the 2D models do not specifically describe the geology of the Dogger
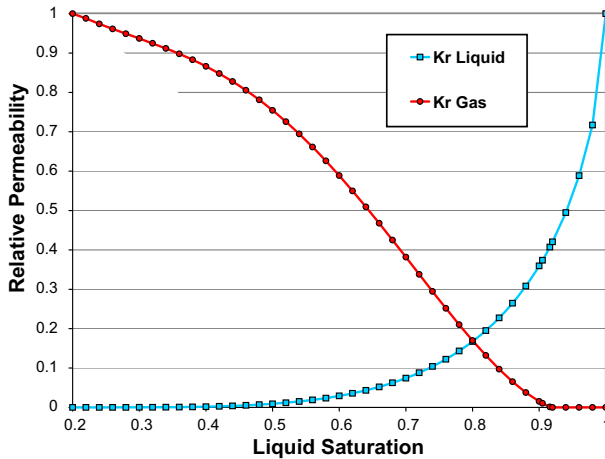
Fig. 2 Relative permeability curves based on Dogger aquifer data from Andre et al. (2007)

aquifer; they are conceptual models of carbonate aquifers intended to test the methodology for modeling rock properties.

The 2D model setting (intersection of a horizontal well) implies the assumption of a linear flow, perpendicular to the well. To respect the conditions of linear flow and to keep a realistic well setting, only a short-term injection period is studied: 1 year of injection. For a well length between 1.5 and 4 km, with an injection rate of 0.185 kg/s in the section, the total injection rate is equivalent to 1.25 up to 3.3 Mt/year. CO$_2$ injection is simulated via the multiphase flow simulator TOUGH2/ECO2N (Pruess and Oldenburg 1999).

The 2D model setting takes account of the major flow and transport processes that could be affected by vertical and lateral (in one direction) heterogeneities but does not take into account the connectivity in the third dimension. It may be considered that grouping realizations of heterogeneous models according to the third direction would bring out the influence of heterogeneities on system response. However, it is unlikely that sections would behave independently of each other. The linear flow is a strong assumption for heterogeneous media, even if the temporal design is set to respect the period during which the linear flow is valid. The short timescale needs also to be taken into account when concluding on this study.

Therefore, this model is not used to give accurate predictions but for general indications on pressure and CO$_2$ migration behaviors during the injection.

Despite their limitations, the 2D models are useful for the description and understanding of the underlying phenomena for large-scale CO$_2$ injection while reducing the computing cost, in particular for the 200 realizations of heterogeneous models.

The number of 200 realizations of heterogeneous models was selected by considering the differences in results between sets of 100, 150, 200, and 250 realizations. Comparing the results of the different sets, we observe a results' stabilization (mean, percentile, …) with 200 realizations. Moreover, the mean results obtained by bootstrapping on the 200 realizations are superimposed for the pressure results (Appendix, Figs. 17, 18) and fall within a small interval for the plume extent. Thus, the method error is quite low, and the use of the 200 realizations seems relevant to represent the main result variations due to the spatial variability of permeability.

Table 2 Labels of permeability field models

Model	Label
Continuous spatial variability model (log-normal distribution, $\sigma_{\text{Log}} = 1.5$, mean $= 100$ mD, median $= 32.5$ mD)	K_{HE}
Model by classes (discontinuous)	K_{Classes}
Semi-homogeneous model, arithmetic mean	$K_{\text{semief}-A}$
Semi-homogeneous model, geometric mean	$K_{\text{semief}-G}$
Model by layers	K_{Layers}
Homogeneous model, arithmetic mean	$K_{\text{ef}-A}$
Homogeneous model, geometric mean	$K_{\text{ef}-G}$

For computational efficiency, the mesh is irregular with fine discretization close to the well and length in x-direction increasing with distance from the well.

2.3 Modeling of Permeability Fields

1. The continuous spatial variability model was built up through unconditional geostatistical simulations (moving average method, 200 realizations). Variables were correlated following a circular variogram (Chilès and Delfiner 1999) with a geometrical anisotropy (correlation length of 600 m in X direction and 20 m in Z direction (normal to the bedding plane), no nugget effect, and the sill is equal to 1 before gaussian anamorphosis). This anisotropy was based on previous studies of the Dogger aquifer which used a ratio of 1/30 for the vertical and horizontal ranges (Diedro 2009). Moreover, geothermal studies indicate a productive thickness of about a dozen meters and marked lateral variability of the productive unit, making their correlations at kilometer scale difficult (Lopez et al. 2010; Rojas et al. 1989).

   The permeability field had a log-normal distribution (Table 2), and 99% of values lay between 0.31 mD and 3.16 D (consistent with local data for the Dogger aquifer (e.g., Delmas et al. 2010; Rohmer and Seyedi 2010; Brosse et al. 2010; Casteleyn et al. 2010; Lopez et al. 2010; Rojas et al. 1989)).

   Stochastic simulations were applied on an initial fine and regular mesh (cell size of 7*7*7 m). To obtain the previously mentioned irregular mesh, the geometric mean of permeability values was calculated as an equivalent permeability. On this specific model, this upscaling technique gave consistent flow results with results on the fine mesh (Bouquet et al. 2013).

2. For the model by classes (discontinuous), permeability values were discretized depending on threshold values applied to the permeability fields (realizations) of the continuous model. Low variations of permeability values were eliminated.

   Eight classes of permeability values (from the continuous model) are defined with a factor of ten between each class (Table 3). The value allocated to each cell is equal to the median of the class to which the cell belonged. This model by classes is close to facies models, but a facies model is generally defined according to the rock types and depositional environments, which are not modeled in this study. Results with the chosen discretization were compared to those of the continuous model in order to determine the resolution of heterogeneities necessary for relevant CO_2 storage predictions.

3. For the layered model, the permeability for the entire layer was approximated by the geometrical mean of cell values around the well from the continuous model. Cells were

Table 3 Distribution of permeability coefficients (multiplier of 10^{-13} m^2) of the continuous model

Log$_{10}$K$_{inf}$	Log$_{10}$K$_{sup}$	Mean	Min	Max	Median	Class mean	Log$_{10}$K
−4.5	−3.5	0	5	0	0	0.02	−4
−3.5	−2.5	0	5076	0	0	28	−3
−2.5	−1.5	0	28, 667	0	0	1804	−2
−1.5	−0.5	0	27	0	14, 214	14,817	−1
−0.5	0.5	33, 763	0	18	19, 556	15,153	0
0.5	1.5	7	0	28, 339	0	1938	1
1.5	2.5	0	0	5397	0	30	2
2.5	3.5	0	0	16	0	0.08	3

Selection of eight classes of permeability coefficients for the model by classes. Each row represents a class. The column "Log$_{10}$K'" gives the coefficient assigned to each class. Log$_{10}$K$_{inf}$ and Log$_{10}$K$_{sup}$ = the bounds of the class interval. Class Mean column = mean number of cells belonging to each class (from the 200 realizations, the sum is equal to the total number of model cells: 33,770). Mean (or Min, Max, or Median) column = Number of cells in the "Mean model" which fall within each class interval. The "Mean model" is obtained by calculating the mean value in each cell based on the 200 realizations (similar for Min, Max, or Median)

included in the mean calculation if they could be included in a hypothetical investigation radius of well testing. An intermediate radius value of about 100 m was chosen. Each of the 200 realizations, transformed into a layered model, had 22 permeability values, one for each layer.

Figure 3 is an example of the models by classes and by layers from the continuous model, for one realization.

4. For the homogeneous model, the equivalent permeability was calculated by averaging the permeability distribution of the continuous model (one isotropic permeability value for the entire aquifer). Two cases were considered:

   (a) the arithmetic mean ($K_{ef-A} = 100$ mD), i.e., the upper limit of the equivalent permeability [default value for few available data as in Zhao et al. (2012)].
   (b) the geometric mean ($K_{ef-G} = 32.4$ mD), i.e., the equivalent value for a 2D parallel flow for an isotropic, log-normal permeability distribution (Matheron 1967).

5. For the semi-homogeneous model, the influence of spatial variability of permeability was assumed to be significant in the diphasic, nonlinear process area, where perturbations are the most significant. Thus, permeability values from the continuous model were preserved in the injection area, over a distance of about 8.7 km from the well. For the injection period, CO$_2$ should not migrate outside this zone. Outside this zone, averaged properties could be used since the system was monophasic and perturbations were weaker. In this zone, the permeability value is equal to either the arithmetic mean or to the geometric mean ($K_{semief-A}$ or $K_{semief-G}$).

For all of these models, the same correlation was used between permeability and capillary pressure. Capillary pressure is scaled according to the permeability values, following the J-Leverett function (Leverett 1941). Therefore, the spatial variability of the capillary pressure was similar to that of permeability. Table 2 summarizes the models and the labels used to refer to each of them.
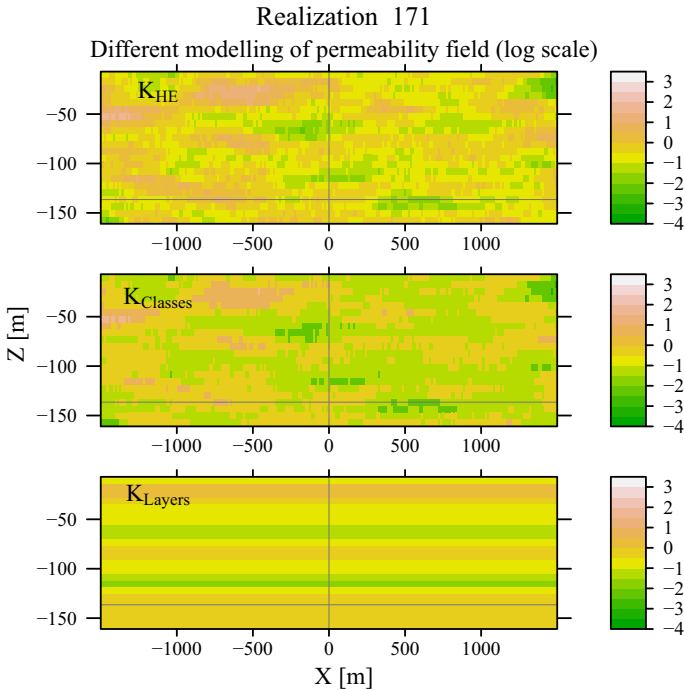
Fig. 3 Example of the relations between the three spatial variability models for one realization. Injection area (well at $X = 0$ m, $Z = -136.5$ m) of one realization of the models: continuous (*top*), by classes, by homogeneous layers (*bottom*). The intersection of the two *gray lines* represents the injection point

3 Sensitivity to the Spatial Variability of Permeability and its Representation

3.1 Pressure Response

On well pressure (Figs. 4, 5):

(i) The spatial variability led to a large spread of well pressure results up to 3 MPa (continuous spatial variability model results: spread of points on the horizontal axis, Fig, 4). The relationship between permeability at the injection point and increase in pressure is not linear (black symbols, Fig. 5). The increase in pressure can be smaller for a lower permeability at the well than in some realizations with a higher permeability, sometimes by several orders of magnitude. We also get a large spread of results for a similar permeability at the injection point. So, the pressure response at the well not only depends on the permeability at the injection point, but it is also strongly influenced by the permeability field around the well. This underlines the importance of connectivities modeling, at least in the injection area.

(ii) Well pressure results from semi-homogeneous and continuous models were identical (triangle and diamonds, Fig. 4).

(iii) Well pressure results from the model by classes were close to those of the continuous model (red squares, Fig. 4). The predominant influence of connectivities on well pressure was also clear: The pressure differences between realizations of the model by
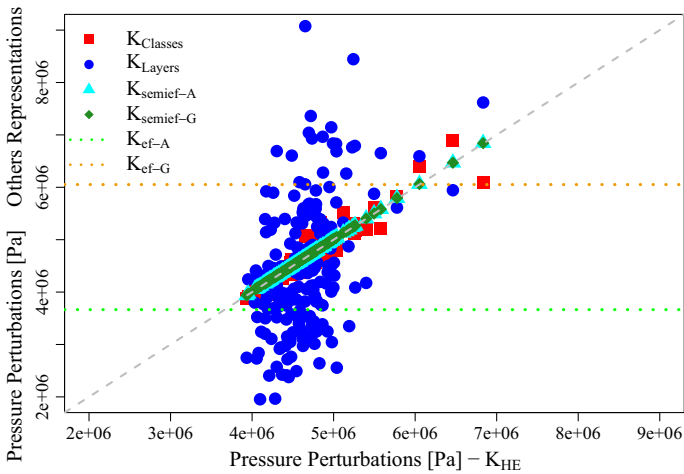
Fig. 4 Comparison of well pressure perturbations between permeability field models (homogeneous, semi-homogeneous, by layers and by classes) and results from the continuous model. Two hundred realizations for each model except for the homogeneous model (two homogeneous models). Results after an injection period of 1 year
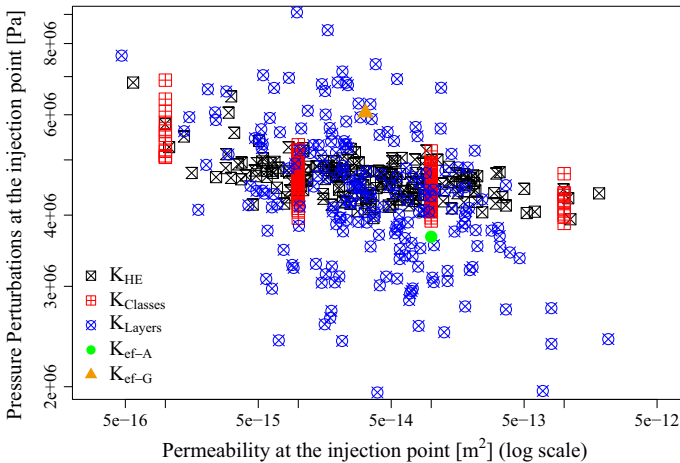

Fig. 5 Well pressure perturbation versus permeability value at the well for the different permeability field models. Results after an injection period of 1 year

classes were between 1 and 2 MPa for an identical permeability value at the well (red squares, Fig. 5).

(iv) The model by layers overestimated maximum pressure results compared to the continuous model, and inversely for minimum results (blue circles, Fig. 4). Maximum well pressure results from the layered model were obtained when there was a low-permeability layer above the injection point, and not for the lowest permeability value at the injection point itself (blue symbols, Fig. 5). This effect could have been attenuated if this low-permeability layer had presented some lateral variability. The inverse effect is also observed on the Fig. 5 (i.e., the lowest well pressure is not observed for
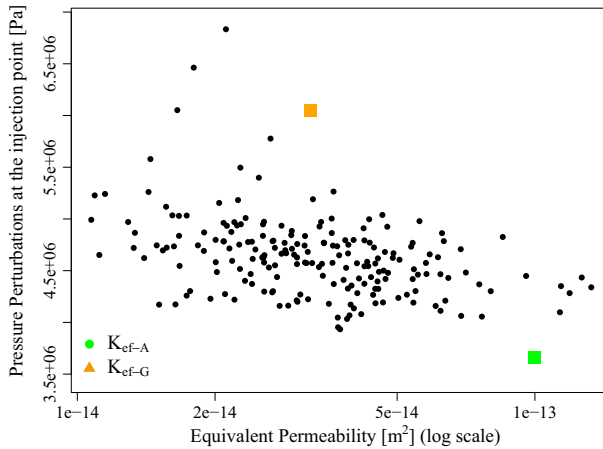
Fig. 6 Well pressure perturbation versus equivalent permeability value at the well for the continuous model and for homogeneous models. Results after an injection period of 1 year

the highest permeability value but for a value around 4.10^{-14} m^2). So, well pressure is strongly influenced by the vertical connectivity. The objective of injection in the highest permeability layer may not be relevant in regard to this vertical connectivity.

(v) To compare well pressure results from homogeneous and heterogeneous models, we calculate the equivalent permeability from each continuous model (based on values close to the well, within a radius of 100 m). We draw (Fig. 6) the well pressure results from the continuous model versus its calculated equivalent permeability and the results from both homogeneous models. According to the continuous model, we would have expected a lower pressure perturbation at the well for an equivalent permeability similar to the K_{ef-G} model and a higher pressure perturbation for an equivalent permeability similar to the K_{ef-A} model. In particular, the well pressure results from the K_{ef-A} model is weaker than all results for the realizations of the continuous model (Fig. 5). Averaged value of the permeability values in the injection area failed to reproduce the pressure behavior due to the heterogeneities (and so variable connectivities) close to the injection point.

On the propagation of pressure perturbations (pressure profiles, Figs. 7, 8, 9, 10):

(i) As for the well pressure, the spatial variability (continuous model) led to a large spread of pressure perturbations (about 1 MPa up to 10 km from the injection point, Fig. 7). The spread (stochastic dispersion) reached several kilometers for pressure perturbations of 0.05 and 1 MPa (Fig. 11).

(ii) The results from semi-homogeneous models were close to those from the continuous model up to 7 km from the well (Fig. 8).

(iii) Pressure profiles from the model by classes were similar to those of the continuous model (Fig. 9).

(iv) Maximum and minimum pressure profiles (Fig. 9), and standard deviation results (Fig. 10) from the model by layers were drastically different from those of the continuous model. In contrast, mean pressure behaviors were relatively close for both models. For pressure perturbations lower than 1 MPa, layered models overestimated the maximum extent and underestimated the minimum extent compared to the continuous
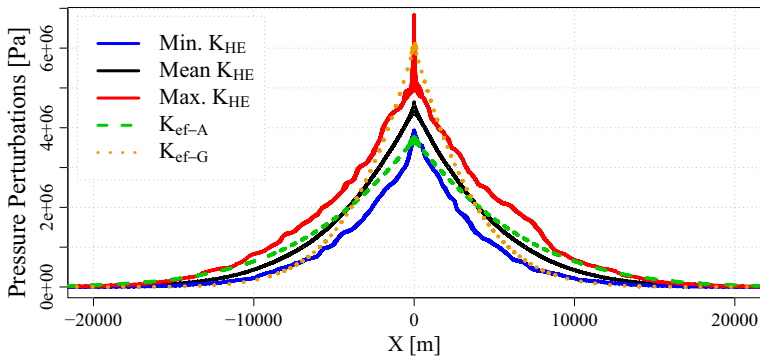
Fig. 7 Minimum, mean, and maximum pressure perturbation profiles from the 200 realizations of the continuous model and profiles from the homogeneous models. Results after an injection period of 1 year. Minimum, mean, and maximum profiles are based on, respectively, minimum, mean, and maximum values in each cell from the 200 realizations. Thus, minimum and maximum profiles do not correspond to a specific realization but give the dispersion of the results. Results are given for all cells along z, but the pressure is vertical at equilibrium except closed to the injection point
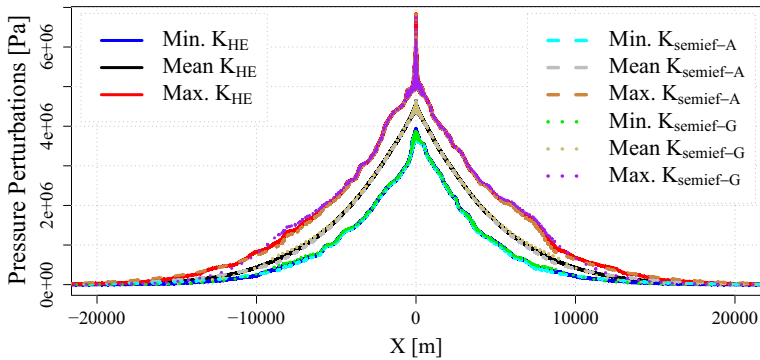

Fig. 8 Minimum, mean, and maximum pressure perturbation profiles from the 200 realizations of the continuous model and the semi-homogeneous models. Results after an injection period of 1 year
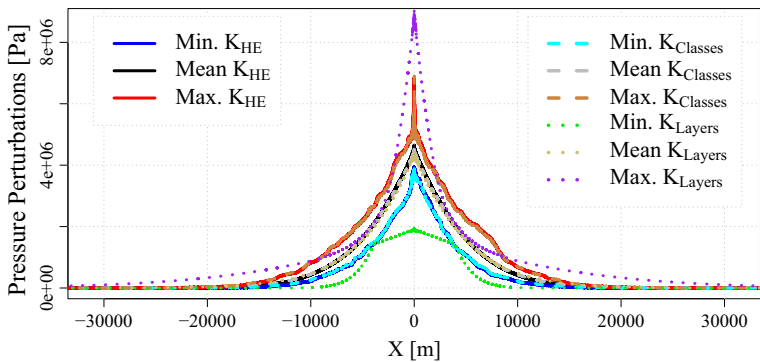

Fig. 9 Minimum, mean, and maximum pressure perturbation profiles from the 200 realizations of the continuous model, model by classes, and model by layers. Results after an injection period of 1 year
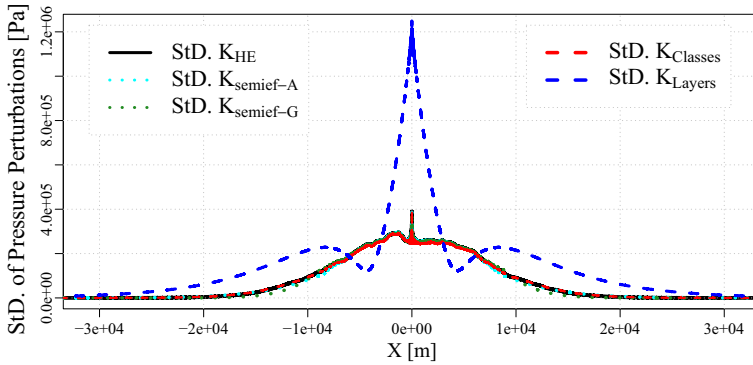
Fig. 10 Standard deviations of pressure perturbation profiles at 1 year of injection for models with different spatial variability of permeability (continuous, by classes, by layers, and semi-homogeneous)

model (Fig. 9). Differences in the propagation of pressure perturbations of 0.05 MPa reached several kilometers (up to 17 km for the maximum extent, Fig. 11)

(v) Both homogeneous models underestimated the maximum extent of high pressure perturbations (e.g. 1 MPa) compared to the continuous model (differences up to several kilometers, Fig. 11). For lower pressure perturbations, far from the well (e.g. 0.05 MPa), results from the continuous model fell within the range of results given by the two homogeneous models. But the uncertainty interval of homogeneous models was significantly larger than the stochastic dispersion[1] of the continuous model (7.5 vs. 4 km at 1 year). Likewise, the mean behavior of the continuous model was between those of the two homogeneous models, but the interval was large (Fig. 7).

In summary, the homogeneous model results bracketed the mean pressure behavior of the continuous model, but the interval between both homogeneous models' results is large. Averaged properties at large scale are only a rough approximation of the averaged pressure propagation and did not approximate the spread of results found in the continuous spatial variability model. Both homogeneous models fail to represent the potentially maximum pressure behavior either at the well or further away from the well. Because of the considerable loss of accuracy, the homogeneous model does not constitute a valid representation for studying pressure response to CO_2 injection.

Since pressure results from the model by classes and the continuous model are similar, the fine resolution of the spatial variability of permeability and capillary pressure (here, lower than one order of magnitude) can be neglected for the pressure response. However, major connectivity modeling (vertical and lateral connectivities, here, in one direction), even in the single-phase area, is required to obtain relevant predictions for the feasibility of storage (significant differences between the continuous, homogeneous, semi-homogeneous, and layered models).

3.2 CO_2 Migration and Dissolution

The results from the homogeneous models mainly present the influence of permeability on the gravity forces and thus on CO_2 migration. With a high permeability, the plume quickly reaches the top of the reservoir where it migrates laterally, whereas a lower permeability slows

---

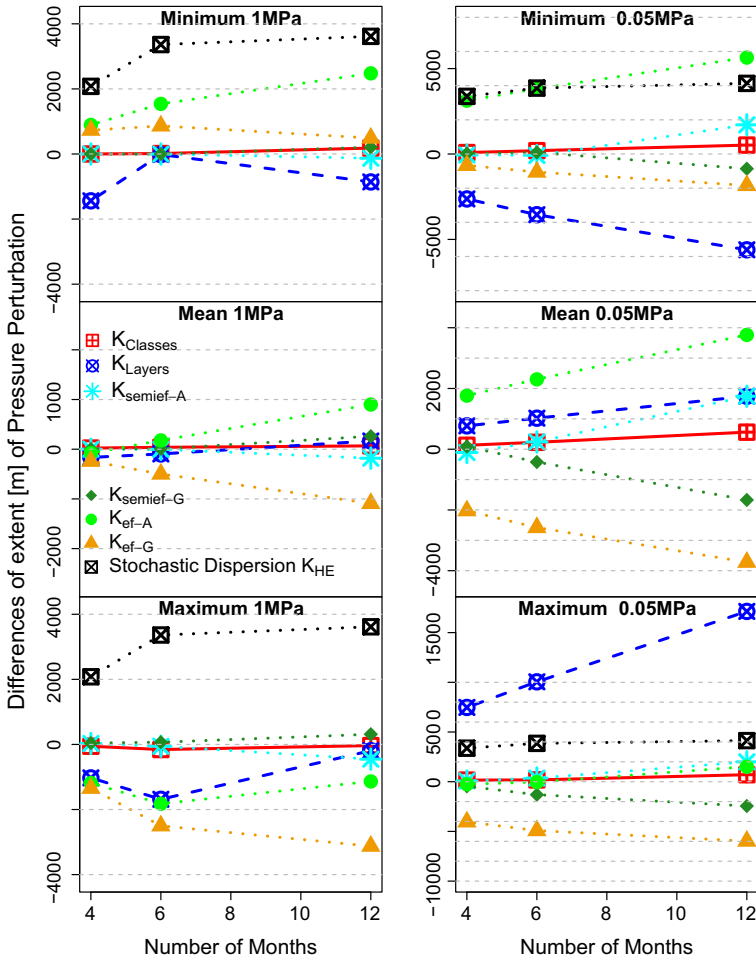[1] Differences between minimum and maximum pressure perturbations.

Fig. 11 Comparison of the extent of pressure perturbations propagating from the well (1 MPa, on the *left*; and 0.05 MPa, on the *right*) from permeability field models compared to the continuous spatial variability model. Two hundred realizations for each model (except for the homogeneous models). Differences of the minimum extent (*top*), mean extent, and maximum extent (*bottom*). The stochastic dispersion is defined as the differences between minimum and maximum pressure perturbations of the continuous spatial variability model

down the vertical migration and so the lateral migration at the top. Nevertheless, the lateral sweep efficiency throughout the thickness of the reservoir is improved (Fig. 12, differences between K_{ef-A} and K_{ef-G}).

The lateral extent at the top of the reservoir given by the homogeneous model of higher permeability (K_{ef-A}) is similar to the mean lateral extent of the continuous model. For the continuous model, the maximal extent is not at the top of the reservoir but at the same level as the injection point. Because of preferential migration pathways and local permeability barriers, the CO$_2$ plume of the continuous model has an irregular shape and, mostly, a larger lateral extent.

Moreover, the homogeneous models tend to underestimate the dissolution rate (Table 4) compared with the continuous model. This underestimation is associated with CO$_2$ migration.
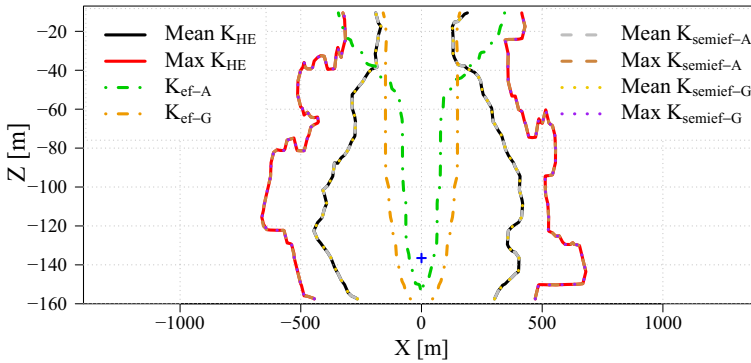
Fig. 12 Maximum and mean gas saturation profiles ($Sg = 0.01$) from the 200 realizations of the continuous model and semi-homogeneous models, and gas saturation profiles from the homogeneous models. Results after an injection period of 1 year. The *blue* cross represents the injection point

Table 4 Dissolution rate differences (minimum, mean, and maximum) between permeability field models

Dissolution rate differences [%]	$\delta(K_{\text{Classes}})$	$\delta(K_{\text{Layers}})$	$\delta(K_{\text{semief}-A}$ and $K_{\text{semief}-G})$	$\delta(K_{\text{ef}-A}$ and $K_{\text{ef}-G})$
Min. dissolution rate	0.47	2.44	<0.001	[−0.7; −4.1]
Mean dissolution rate	−0.9	−0.08	<0.01	[4.45; 1]
Max. dissolution rate	2.13	1.11	<0.001	[8.8; 5.4]

The label δ(type_Model) refers to the difference between continuous model results and type_Model results. N.B: The stochastic dispersion of the continuous models is equal to 9.5%

The drainage areas are more widely distributed for the continuous model, thus increasing the brine-CO_2 interface area and consequently the dissolution rate.

CO_2 plumes and dissolution rates from the semi-homogeneous and continuous models are identical (Fig. 12; Table 4). The homogenization, beginning at 8 km from the well, does not affect the transport process close to the well, for an injection period of 1 year.

Profiles of the CO_2 plume from the model by classes are close to those from the continuous model (Fig. 13). The modeling by classes will be sufficient to assess the connectivities between permeable areas and to capture the preferential migration pathways.

The model by layers overestimates the maximum and mean lateral migrations compared to the continuous model and exacerbates particular cases. For example, if the injection layer has a high permeability but the layer above has a low one, then CO_2 will migrate only laterally, while, for the same realization but for the continuous model or the model by classes, other connectivities will allow vertical CO_2 migration. The assessment of CO_2 migration, and so the risk assessment of CO_2 leakage could be dramatically different depending on the type of model used.

3.3 Discussion on Permeability Field Models

The following discussion is drawn from this study based on 2D models (lateral connectivity refers to connectivity in only one lateral direction) with various spatial variability modeling and based on a short-time injection period.
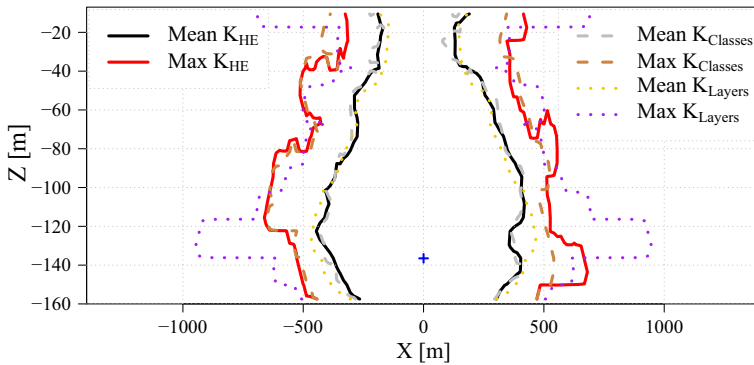
Fig. 13 Maximum and mean gas saturation profiles ($Sg = 0.01$) from the 200 realizations of the continuous model, the model by classes, and model by layers. Results after an injection period of 1 year. The *blue* cross represents the injection point

Based on the bootstrapping of the results from the different modeling methods (continuous, classes, and layers) and compared to results from homogeneous and semi-homogeneous models, one can say that method errors remain below the differences between the results from permeability field models (Figs. 17, 18 in appendix).

These differences between the results from permeability field models underline the uncertainties introduced by the modeling, either on interference predictions or on the definition of the area of review: differences in pressure propagations at the scale of a kilometer or dozens of kilometers, differences in CO₂ migration extent, that could lead to unexpected leakage, or on injectivity predictions (differences of several MPa). The misestimation of well pressure could lead to economic consequences or risks of fracturing and microseismicity. Other parameters, such as brine production wells (e.g., Buscheck et al. 2012; Li et al. 2011), may reduce in some extent these uncertainties on system response (decrease in the stochastic dispersion).

Even when only one model of spatial variability (i.e. 200 realizations) is considered, pressure and CO₂ migration results are also highly scattered. Spatial variability of permeability has a predominant impact on the predicted results for both. The uncertainty on variance and correlation length of permeability could also increase the spread of results (e.g., De Lucia 2008; Lengler et al. 2010; Diedro 2009). Well and model setting could also contribute to the variability of the results. For example, the spatial variability of properties mostly increases the efficiency of dissolution as observed by Farajzadeh et al. (2011) and Flett et al. (2007), but here some dissolution rates of the heterogeneous model are lower than results from the homogeneous models. This particularity is due to a permeability barrier above the horizontal well: CO₂ migrates mainly laterally, and a low dissolution rate is obtained for the injection period.

The lack of lateral and vertical connectivities modeling causes a marked loss of information and a poor degree of confidence in models' predictions either for CO₂ migration and pressure response. The spatial variability of the pressure response shows the poor predictive quality of the homogeneous model for pressure propagation and injectivity which varies by several orders of magnitude, as shown by Lengler et al. (2010) and Heath et al. (2012). Modeling both lateral and vertical variabilities of rock properties is critical to characterize the system perturbation by CO₂ injection since the differences between the model by layers and the continuous model can be greater than those between the continuous and homogeneous models.

In contrast, the model by classes preserves the quality of predictions of pressure and CO_2 migration, even with the discretization of permeability variability. But, the discretization leads to a deviation of gas saturation values and consequently to a low accuracy of the minimum and maximum dissolution rates.

These conclusions agree with those of Li et al. (2011) except for the validity of the homogeneous model for the pressure response [mean pressure, one realization of heterogeneous model for Li et al. (2011)] and of the model by classes for the dissolution estimates, and are extended, here, for the multiple realizations of the heterogeneous model and for the spatial variability of the pressure response.

Additionally, we observe that the homogenization in the single-phase area, far from the well, also leads to a significant bias in the pressure response propagating in this area (semi-homogeneous model). In contrast, CO_2 migration and pressure results closer to the well are not influenced by the homogeneous area of the semi-homogeneous model and the model gives reliable predictions close to the well.

The validity and accuracy of the semi-homogeneous model rely on the distance between the injection well and the homogeneous area and on the perturbation to be estimated. The use of this model is justified if the response to be assessed is in the heterogeneous area, as it avoids the characterization of heterogeneities at larger scales and the bias due to boundary conditions. However, the semi-homogeneous model cannot be used for accurate predictions of pressure perturbations at regional scale: Even in the single-phase area, the heterogeneities affect significantly the propagation of pressure perturbations of the continuous models.

4 Sensitivity to Spatial Variability of Porosity and Pore Compressibility

To study the spatial variability of porosity and pore compressibility associated with the variability of permeability, the model by classes is used since this model gives reasonable results.

Each of the eight permeability classes has its associated porosity value. Generally, for a high effective porosity, rocks also present a high permeability value. Two cases are considered (cases a and b in Table 5).

A new model is also built with the spatial variability of pore compressibility (with the porosity values of case b, cf. Table 5). The pore compressibility value of each class is cal-

Table 5 Porosity and pore compressibility values for each class of permeability and related labels

Classes	−4	−3	−2	−1	0	1	2	3
Porosity case a [$K\Phi_{a\text{Classes}}$] (mean: 12.02 %)	4 %	6 %	9 %	11.5 %	12.5 %	15 %	18 %	20 %
Porosity case b [$K\Phi_{b\text{Classes}}$] (mean: 12.03 %)	4 %	6 %	8 %	10 %	14 %	16 %	18 %	20 %
Pore compressibility [$K\Phi_b CP_{\text{Classes}}$] (unit: 10^{-10} Pa^{-1}, mean: 10.26)	34.7	23.9	17.0	12.6	7.66	6.29	5.36	4.73

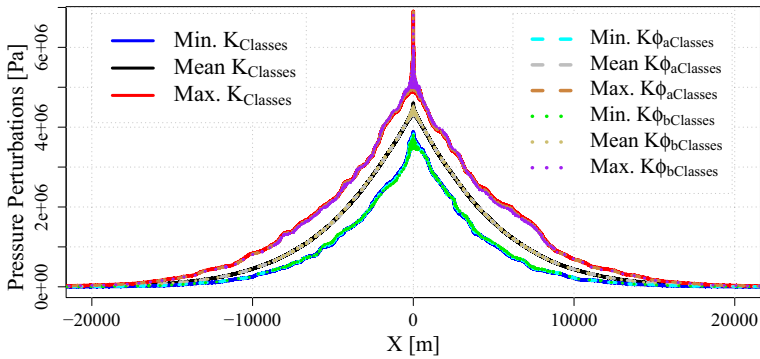The mean porosity value is close to the uniform porosity value of previous models

Fig. 14 Mean, minimum, and maximum pressure perturbation profiles (200 realizations) after 1 year of injection, model by permeability classes (K_{Classes}) or by permeability and porosity classes (cases a $K\Phi_{a\text{Classes}}$ and b $K\Phi_{b\text{Classes}}$, Table 5). Similar pressure results were obtained for the model by permeability, porosity, and pore compressibility classes ($K\Phi_b CP_{\text{Classes}}$)

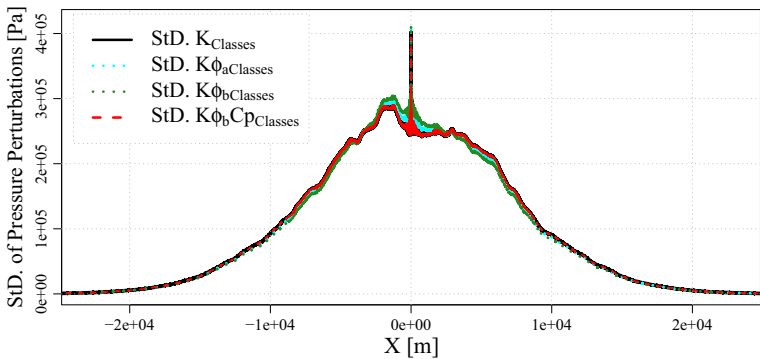**Fig. 15** Standard deviation of pressure perturbation profiles (200 realizations) after 1 year of injection, model by permeability classes (K_{Classes}) or by permeability and porosity classes (cases $K\Phi_{a\text{Classes}}$ and $K\Phi_{b\text{Classes}}$, table 5) or by permeability, porosity, and pore compressibility classes ($K\Phi_b CP_{\text{Classes}}$)

culated on the basis of Horne's correlation (Horne 1995) for carbonate rocks (the same correlation was used for the previous models with spatial variability of permeability only).

4.1 Influence on Pressure Response

Taking into account the spatial variability of porosity and/or pore compressibility does not significantly affect the pressure perturbation profiles (Fig. 14).

Slight differences are observed in the profiles of the standard deviation of pressure compared to the model with only the spatial variability of permeability (Fig. 15). The standard deviation values for case b, with the highest porosity variance and a uniform value of pore compressibility, are higher in the injection area. For the same spatial variability of porosity and with the spatial variability of pore compressibility, the differences decrease.

Pore compressibility values are inversely correlated to porosity values. Consequently, the increase in available pore volume brought by an increase in the porosity value is attenuated by the lower pore compressibility value. Thus, with an increase in pressure, low-porosity
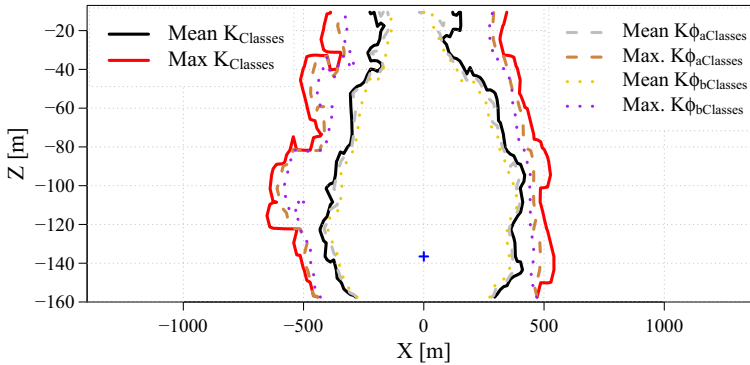
Fig. 16 Maximum and mean gas saturation profiles (200 realizations, $Sg = 0.01$) after 1 year of injection, model by permeability classes ($K_{Classes}$) or by permeability and porosity classes (cases $K\Phi_{aClasses}$ and $K\Phi_{bClasses}$, Table 5). Results from the model by permeability, porosity, and pore compressibility classes ($K\Phi_b CP_{Classes}$) are superimposed with those from the $K\Phi_{bClasses}$ model. The *blue* cross represents the injection point

areas may accumulate a fluid volume equal to the volume in a higher porosity area with a lower pore compressibility.

4.2 Influence on CO₂ Migration and Dissolution

Spatial variability of porosity tends to decrease the extent of the CO_2 plume (Fig. 16). In case b, the decrease in maximum lateral extent reaches 70 m (i.e., about one-tenth of the maximum lateral extent from the well). With the spatial variability of porosity, the injected CO_2 invades an equivalent pore volume but to a lower lateral extent than for the case with only the spatial variability of permeability.

Changes in CO_2 migration affect the dissolution rate. If the vertical migration is constrained by permeability barriers (mainly lateral migration), then the dissolution rate is lower with the spatial variability of porosity. The opposite is true if the CO_2 can drain vertically and laterally into the entire thickness of the reservoir. The spatial variability of porosity exacerbates the minimum and maximum CO_2 behaviors obtained with the spatial variability of permeability because of the change in brine volume at the interface between CO_2 and brine.

The spatial variability of pore compressibility does not influence CO_2 migration and dissolution.

4.3 Discussion on Porosity and Pore Compressibility Spatial Variability

The influence of the spatial variability of porosity becomes relevant for CO_2 migration and dissolution if the variance of porosity values is sufficiently high. But, the spatial variability of permeability has greater influence on pressure results and CO_2 behavior than the spatial variability of porosity and pore compressibility.

As in the sensitivity study on uniform porosity value (Chadwick et al. 2009; Buscheck et al. 2012), its spatial variability has a negligible influence on pressure results. On the contrary, previous studies on uniform pore compressibility values show its significant effects on pressure response (e.g., Birkholzer et al. 2009; Zhou et al. 2010; Person et al. 2010). But its spatial variability, related to those of permeability and porosity, has a low influence. We could possibly approximate the spatial variability of porosity and pore compressibility by an

equivalent, uniform value over the entire domain without a significant loss of information on the pressure response.

The spatial variability of other rock properties, such as relative permeability, could be considered. Spatial variability of relative permeability may influence CO$_2$ migration and dissolution and injection pressure according to its influence as a uniform value (Mathias et al. 2013; Flett et al. 2007).

5 Conclusion

Studies on CO$_2$ storage feasibility rely on the knowledge and quality of geological models. In case data on geological formations are scarce, averaged properties are often used to represent the storage formations. Here, we compared pressure response and CO$_2$ behavior in different averaged permeability field 2D models.

The significant differences of predictions among permeability field models show how critical the choice of spatial variability modeling and its related uncertainties may be for storage and risk assessments.

At the injection well, the singular behaviors and differences show that connectivities and migration pathways (i.e., lateral, here in one direction, and vertical variability of permeability) have to be described to ensure reliability of both pressure results and CO$_2$ migration predictions. According to our results, whereas the dissolution rate can only be derived from a fine description of the heterogeneities at the injection well, the main contrasts of permeability (here, one order of magnitude) are sufficient to characterize pressure perturbations and CO$_2$ migration.

At large scale, farther away from the well, the description of major connectivities is still required to describe the critical pressure perturbations. It appeared models averaging the lateral and/or the vertical variability of rock properties at large scale are not appropriate for CO$_2$ storage feasibility studies.

The model by classes and semi-homogeneous model are recommended as the most convenient models combining both simplified heterogeneities and reliable results. They provide sufficiently accurate results for the plume migration, injectivity, and pressure perturbations in the injection area. As the dissolution is only happening at the smaller plume, the semi-homogeneous model gives more accurate dissolution rate predictions than the model by classes. On the other hand, as the predominant influence of the large contrasts of rock properties was observed on pressure results, the model by classes is preferred for pressure perturbation estimates at large scale.

The spatial variability of porosity and the related pore compressibility were also considered. Results indicate a negligible influence of their spatial variability compared to the effects of the spatial variability of permeability. Their spatial variability could be approximated by a uniform value of porosity and pore compressibility.
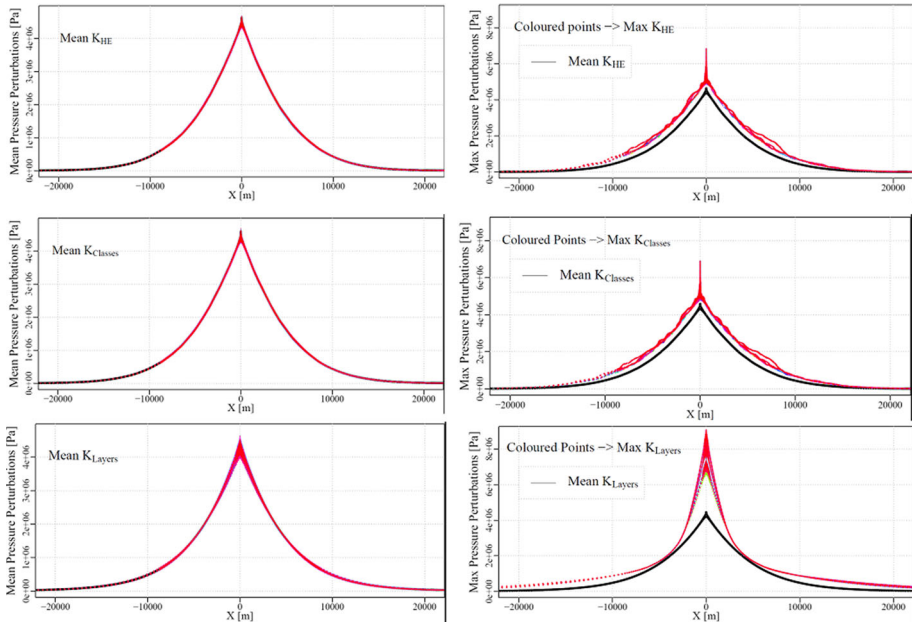
Appendix

See Figs. 17 and 18.

Fig. 17 Mean (*left*) and Maximum (*right*) pressure perturbation profiles after the bootstrapping of 200 realizations of the continuous model, model by classes, and model by layers (200 resampling for each model, i.e., 200 mean and maximum profiles). Results after an injection period of 1 year

Fig. 18 Maximum and mean gas saturation profiles ($Sg = 0.01$) after the bootstrapping of 200 realizations of the continuous model, model by classes, and model by layers (200 resampling for each model, i.e., 200 mean and maximum profiles). Results after an injection period of 1 year
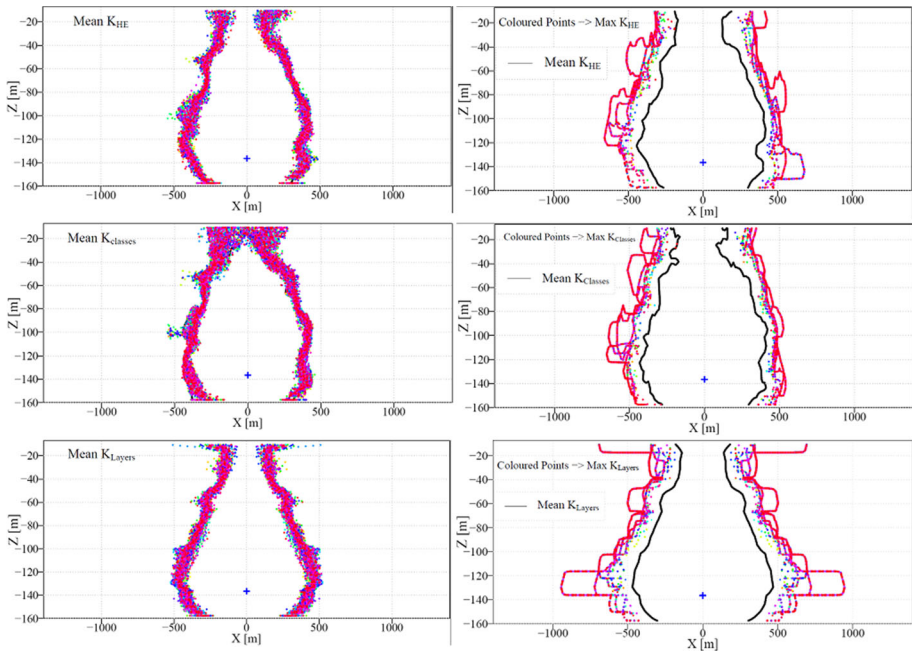
References

Andre, L., Audigane, P., Azaroual, M., Menjoz, A.: Numerical modeling of fluid-rock chemical interactions at the supercritical CO$_2$-liquid interface during CO$_2$ injection into a carbonate reservoir, the Dogger aquifer (Paris Basin, France). Energy Convers. Manag. **48**(6), 1782–1797 (2007)

Bandilla, K., Celia, M., Elliot, T., Person, M., Ellett, K., Rupp, J., Gable, C., Zhang, Y.: Modeling carbon sequestration in the illinois basin using a vertically-integrated approach. Comput. Vis. Sci. **15**(1), 39–51 (2012)

Birkholzer, J., Zhou, Q., Tsang, C.F.: Large-scale impact of CO$_2$ storage in deep saline aquifers: a sensitivity study on pressure response in stratified systems. Int. J. Greenh. Gas Control **3**(2), 181–194 (2009)

Birkholzer, J., Zhou, Q., Cortis, A., Finsterle, S.: A sensitivity study on regional pressure buildup from large-scale CO$_2$ storage projects. Energy Procedia **4**, 4371–4378 (2011)

Bouquet, S., Bruel, D., de Fouquet, C.: Influence of heterogeneities and upscaling on CO$_2$ storage prediction at large scale in deep saline aquifer. Energy Procedia **37**, 4445–4456 (2013)

Brosse, E., Badinier, G., Blanchard, F., Caspard, E., Collin, P., Delmas, J., Dezayes, C., Dreux, R., Dufournet, A., Durst, P., et al.: Selection and characterization of geological sites able to host a pilot-scale CO$_2$ storage in the paris basin (GéoCarbone-PICOREF). Oil Gas Sci. Technol.- Revue de l'Institut Français du Pétrole **65**(3), 375–403 (2010)

Buscheck, T., Sun, Y., Chen, M., Hao, Y., Wolery, T., Bourcier, W., Court, B., Celia, M., Friedmann, J., Aines, R.: Active CO$_2$ reservoir management for carbon storage: analysis of operational strategies to relieve pressure buildup and improve injectivity. Int. J. Greenh. Gas Control **6**, 230–245 (2012)

Casteleyn, L., Robion, P., Collin, P., Menendez, B., David, C., Desaubliaux, G., Fernandes, N., Dreux, R., Badiner, G., Brosse, E., Rigollet, C.: Interrelations of the petrophysical, sedimentological and microstructural properties of the Oolithe Blanche Formation (Bathonian, saline aquifer of the Paris Basin). Sediment. Geol. **230**(3–4), 123–138 (2010)

Chadwick, R., Noy, D.J., Holloway, S.: Flow processes and pressure evolution in aquifers during the injection of supercritical CO$_2$ as a greenhouse gas mitigation measure. Pet. Geosci. **15**(1), 59–73 (2009)

Chilès, J.-P., Delfiner, P.: Geostatistics: Modeling Spatial Uncertainty. Wiley, New York (1999)

De Lucia, M.: Influenza della variabilità spaziale sul trasporto reattivo—Influence de la variabilité spatiale sur le transport réactif. Ph.D. thesis, Universita di Bologna and MINES ParisTech (2008)

de Fouquet, C., Beucher, H., Galli, A., Ravenne, C.: Conditional simulation of random sets: application to an argillaceous sandstone reservoir. In: Armstrong, M. (ed.) Geostatistics, vol. 2, pp. 517–530. Kluwer Academic Publishers, Dordrecht (1989)

Delmas, J., Brosse, E., Houel, P.: Petrophysical properties of the middle jurassic carbonates in the PICOREF Sector (South Champagne, Paris Basin, France). Oil Gas Sci. Technol.- Rev. IFP **65**(3), 405–434 (2010)

Diedro, F.: Influence de la variabilité pétrophysique et minéralogique des réservoirs géologiques sur le transfert réactif. Ph.D. thesis, Ecole Nationale Superieure des Mines de Saint-Etienne (2009)

Doughty, C.: Investigation of CO$_2$ plume behavior for a large-scale pilot test of geologic carbon storage in a saline formation. Transp. Porous Media **82**(1), 49–76 (2009)

Farajzadeh, R., Ranganathan, P., Zitha, P., Bruining, J.: The effect of heterogeneity on the character of density-driven natural convection of CO$_2$ overlying a brine layer. Adv. Water Resour. **34**(3), 327–339 (2011)

Flett, M., Gurton, R., Weir, G.: Heterogeneous saline formations for carbon dioxide disposal: impact of varying heterogeneity on containment and trapping. J. Pet. Sci. Eng. **57**(1–2), 106–118 (2007)

Hansen, O., Gilding, D., Nazarian, B., Osdal, B.: Snøhvit: the history of injecting and storing 1 Mt CO$_2$ in the fluvial Tubåen Fm. Energy Procedia **37**, 3565–3573 (2013)

Heath, J.E., Kobos, P.H., Roach, J.D., Dewers, T.A., Mckenna, S.A.: Geologic heterogeneity and economic uncertainty of subsurface carbon dioxide storage. SPE Econ. Manag. **4**(1), 32–41 (2012)

Horne, R.N.: Modern Well Test Analysis: A Computer-Aided Approach, 2nd edn. Petroway Inc, Palo Alto (1995)

Holloway, S. (ed.): Best Practice Manual from SACS-Saline Aquifer CO$_2$ Storage Project. Statoil Research Center, Trondheim, Norway (2003)

Keating, G.N., Middleton, R.S., Viswanathan, H.S., Stauffer, P.H., Pawar, R.J.: How storage uncertainty will drive CCS infrastructure. Energy Procedia **4**, 2393–2400 (2011)

Koch, J., He, X., Jensen, K.H., Refsgaard, J.C.: Challenges in conditioning a stochastic geological model of a heterogeneous glacial aquifer to a comprehensive soft data set. Hydrol. Earth Syst. Sci. **18**(8), 2907–2923 (2014)

Lemieux, J.-M.: Review: the potential impact of underground geological storage of carbon dioxide in deep saline aquifers on shallow groundwater resources. Hydrogeol. J. **19**(4), 757–778 (2011)

Lengler, U., De Lucia, M., Kühn, M.: The impact of heterogeneity on the distribution of CO$_2$: numerical simulation of CO$_2$ storage at Ketzin. Int. J. Greenh. Gas Control **4**(6), 1016–1025 (2010)

Leverett, M.C.: Capillary behavior in porous solids. Trans. AIME **142**, 152–169 (1941)

Li, S., Zhang, Y., Zhang, X.: A study of conceptual model uncertainty in large-scale CO_2 storage simulation. Water Resources Research **47**(5), 5534 (2011)

Lopez, S., Hamm, V., Le Brun, M., Schaper, L., Boissier, F., Cotiche, C., Giuglaris, E.: 40 years of Dogger aquifer management in Ile-de-France, Paris Basin, France. Geothermics **39**(4), 339–356 (2010)

Marsily, G., Delay, F., Goncalves, J., Renard, P., Teles, V., Violette, S.: Dealing with spatial heterogeneity. Hydrogeol. J. **13**(1), 161–183 (2005)

Matheron, G.: Elements pour une théorie des milieux poreux. Mason, Paris (1967)

Mathias, S., Gluyas, J., de Miguel, G.González Martínez, Bryant, S., Wilson, D.: On relative permeability data uncertainty and CO_2 injectivity estimation for brine aquifers. Int. J. Greenh. Gas Control **12**, 200–212 (2013)

Middleton, R.S., Keating, G.N., Viswanathan, H.S., Stauffer, P.H., Pawar, R.J.: Effects of geologic reservoir uncertainty on CO_2 transport and storage infrastructure. Int. J. Greenh. Gas Control **8**, 132–142 (2012)

Nicot, J.-P.: Evaluation of large-scale CO_2 storage on fresh-water sections of aquifers: an example from the Texas Gulf Coast Basin. Int. J. Greenh. Gas Control **2**(4), 582–593 (2008)

Nordbotten, J., Flemisch, B., Gasda, S., Nilsen, H., Fan, Y., Pickup, G., Wiese, B., Celia, M., Dahle, H., Eigestad, G., Pruess, K.: Uncertainties in practical simulation of CO_2 storage. Int. J. Greenh. Gas Control **9**, 234–242 (2012)

Person, M., Banerjee, A., Rupp, J., Medina, C., Lichtner, P., Gable, C., Pawar, R., Celia, M., McIntosh, J., Bense, V.: Assessment of basin-scale hydrologic impacts of CO_2 sequestration, Illinois basin. Int. J. Greenh. Gas Control **4**(5), 840–854 (2010)

Pruess, K., Oldenburg, C.M.: TOUGH2 User's Guide, Version 2.0. Earth Sciences Division, Lawrence Berkeley National Laboratory, University of California, Berkeley, California 94720 (1999)

Refsgaard, J.C., Christensen, S., Sonnenborg, T.O., Seifert, D., Hjberg, A.L., Troldborg, L.: Review of strategies for handling geological uncertainty in groundwater flow and transport modeling. Adv. Water Resour. **36**, 36–50 (2012)

Renard, P.: Stochastic hydrogeology: what professionals really need? Ground Water **45**(5), 31–541 (2007)

Rohmer, J., Seyedi, D.: Coupled large scale hydromechanical modelling for caprock failure risk assessment of CO_2 storage in deep saline aquifers. Oil Gas Sci. Technol.-revue De L Institut Francais Du Petrole **65**(3), 503–517 (2010)

Rojas, J., Giot, D., Nindre, Y.M., Criaud, A., Lambert, M.: Caractérisation et modélisation du réservoir géothermique du Dogger Bassin Parisien, France rapport final. Technical report, Report BRGM/RR-30169-FR, BRGM, Orleans, France (1989)

Shi, J.-Q., Imrie, C., Sinayuc, C., Durucan, S., Korre, A.: Snøhvit CO_2 storage project : assessment of CO_2 injection performance through history matching of the injection well pressure over a 32-months period. Energy Procedia **37**, 3267–3274 (2013)

Wang, Y., Xu, Y., Zhang, K.: Investigation of CO_2 storage capacity in open saline aquifers with numerical models. Procedia Eng. **31**, 886–892 (2012)

Yamamoto, H., Zhang, K., Karasaki, K., Marui, A., Uehara, H., Nishikawa, N.: Numerical investigation concerning the impact of CO_2 geologic storage on regional groundwater flow. Int. J. Greenh. Gas Control **3**(5), 586–599 (2009)

Zhao, R., Cheng, J., Zhang, K.: CO_2 plume evolution and pressure buildup of large-scale CO_2 injection into saline aquifers in Sanzhao Depression, Songliao Basin, China. Transp. Porous Media **95**(2), 407–424 (2012)

Zhou, Q., Birkholzer, J.T., Mehnert, E., Lin, Y.-F., Zhang, K.: Modeling basin- and plume-scale processes of CO_2 storage for full-scale deployment. Ground Water **48**(4), 494–514 (2010)