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Stochastic Seismic Inversion to Estimate the Pore Volume for CO2 Injection in the St. Flavien Reservoir, Quebec, Canada

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SUMMARY

The estimation of the volume of pores available is of prime importance when evaluating the potential of a site for the geological storage of CO2. Sequential Bayesian simulations, using well logs and acoustic impedance cube are completed to model the porosity field and its variability in the Beekmantown Group reservoir of the Saint-Flavien region, Québec, Canada. We use stochastic seismic inversion to better recover the whole bandwidth of acoustic impedance distribution observed at well logs, needed to reproduce the distribution of porosity observed on well logs. This methodology is of prime importance in the Saint-Flavien context, as the average porosity is extremely low, and only a fraction of the reservoir, identified as Family 3 by Gaussian mixture models, exhibits higher porosity where CO2 injection would be possible. Comparison of the porosity fields simulated using the deterministic acoustic impedance cube and one realisation of a stochastic inverted acoustic impedance cube clearly show that zones of higher porosity are better reproduced by the latter option. The use of stochastic seismic inversion is needed to obtain a more realistic estimate of available pores for CO2 injection in the Beekmantown Group reservoir in the Saint-Flavien region.

Introduction

The estimation of pore volume is of prime importance when evaluating the potential of a site for the geological storage of CO_2. The porosity field and its variability are usually evaluated by geostatistical simulations using well logs and, when possible, guided with a 3D acoustic impedance (AI) cube (Mukerji et al., 2001; Mavko et al., 2009). Because of the low vertical resolution of surface seismic data and conventional deterministic inversion algorithm, it is however not possible to recover the whole bandwidth of the AI distribution fitted on well logs. This gives smoothed porosity estimates, which often result in biased estimation of the volume of available pores. This problem is even more evident in fractured reservoir, where porosity can be extremely low except for a few localized zones of higher porosity. Recently, developments of stochastic seismic inversion algorithm (Escobar et al., 2006) permit to generate high frequency AI models of reservoir by optimally integrating seismic traces and well logs in a geostatistical framework (Dubrule, 2003; Doyen, 2007). AI models are then used to infer the porosity field, based on variograms and porosity-AI kernel (Dubrule, 2003; Grana and Della Rossa, 2010). In the presence of multiple geological families, we use an empirical Gaussian mixture to model the three petrophysical families within a sequential Bayesian simulation scheme (Dubreuil-Boisclair et al., 2011, 2012). This workflow is applied to the Saint-Flavien gas field (Québec, Canada). One of the challenges lies in the fact that the porosity of the reservoir is extremely low and the statistical relation with the AI is at the limit of the resolution of the method.

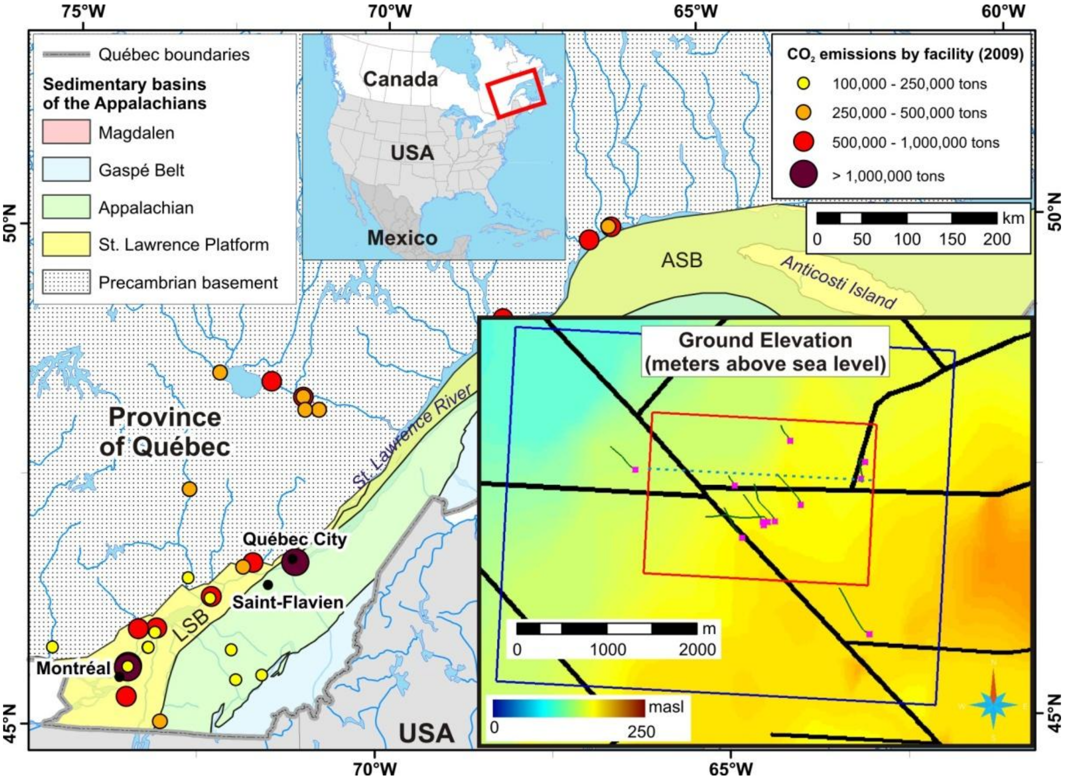

Figure 1: *Location of the Saint-Flavien gas field in Québec, Canada. Bottom-right inset shows the outline of the reservoir model (red square), the outline of the 1993 seismic cube (blue square), the location of 11 wells included in the model (pink square is surface location, green lines are trajectory), the position of the profile shown in Figure 3 (cyan), and the roads in Saint-Flavien (black lines).*

Geological Context and Available Data

The Saint-Flavien gas field is located 50 kilometres southwest of Quebec City, Canada (Figure 1). The reservoir is located within a fold-thrust belt in the middle unit of the Lower Ordovician Beekmantown Group of the St. Lawrence sedimentary platform, at an average depth of 1500 m (Bertrand et al., 2003). Porosity in the Saint-Flavien reservoir has been mostly produced by fracture-controlled dissolution of calcite in intertidal dolomitic slightly porous facies. Within the reservoir modelling area (red square of inset of Figure 1), the AI and effective porosity logs are evaluated at 11 wells at the reservoir level. Data from a 3D seismic survey conducted in 1993 were inverted to get a deterministic AI cube. The seismic cube, sampled at 2 ms, covers an area of 3.94 by 4.88 km^2. The dominant frequency is estimated at 35 to 40 Hz at reservoir depth. In the reservoir, the seismic velocity is 5000 to 5500 m/s. Thus, we estimate the seismic wavelength to be between 125 m and 150 m, corresponding to a vertical resolution of 31.25 m to 37.5 m (a quarter of the seismic wavelength). The spacing of the modelling grid is the same as the seismic grid, 20 m laterally and 2 ms vertically.

Acoustic Impedance and Porosity at Well Logs

Acoustic impedance and effective porosity logs are evaluated at a vertical resolution between 10 cm and 15 cm. The logs are converted in TWT and upscaled at the grid resolution of 2 ms. We identify three petrophysical families in the Beekmantown reservoir from well logs analysis. The histograms of upscaled acoustic impedance from well logs of each family in the Beekmantown reservoir are presented in Figure 2a. The red lines outline the mean acoustic impedance, plus or minus one standard deviation. The histograms of effective porosity of all three families are presented in Figure 2b, showing a logarithmic distribution of the porosity at the reservoir level. The 2D probability distribution function between the acoustic impedance and the effective porosity in the Beekmantown Group is shown in Figure 2c. This relation is the cornerstone of sequential Bayesian simulation of a porosity field using well logs and the AI cube. At each cell of the reservoir where the porosity is simulated, we use the AI value determined from the seismic cube to stochastically draw a value of porosity from the probability distribution function of each family, determined by Gaussian Mixture Models (Dubreuil-Boisclair et al., 2012; Grana et al., 2012). The identification of Family 3 (red histograms and curves in Figure 2) is of prime importance in this project, corresponding to the family containing some relatively high porosity and where the expected relation between porosity and AI is better defined. The probability to select every family with respect to the acoustic impedance is plotted in Figure 2d.

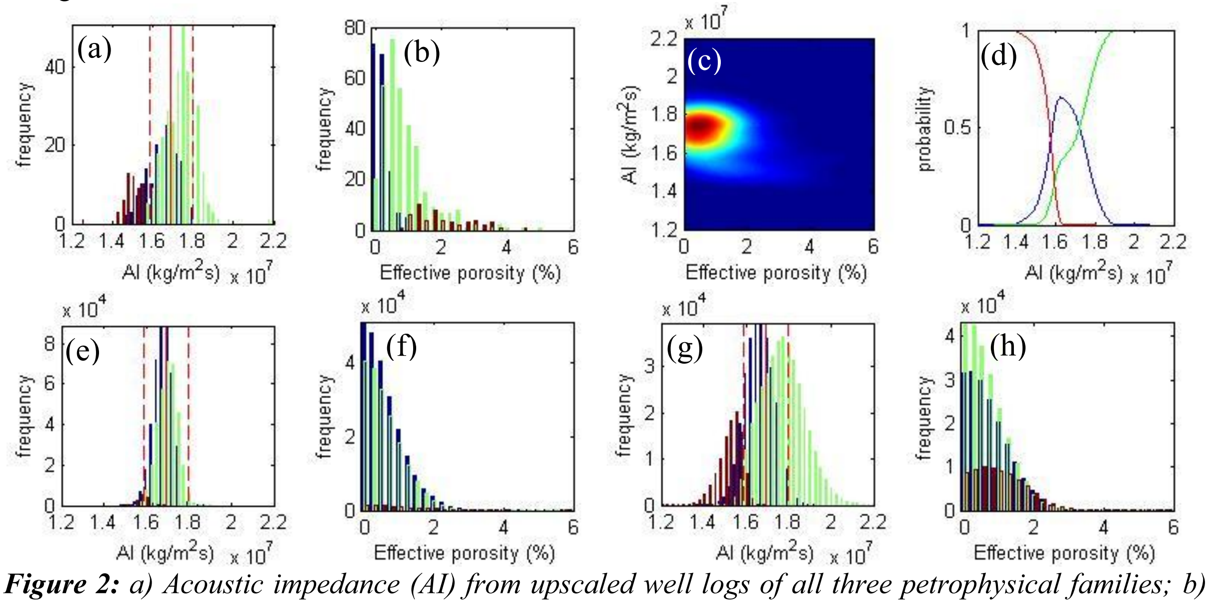

Figure 2: *a) Acoustic impedance (AI) from upscaled well logs of all three petrophysical families; b) Effective porosity from upscaled well logs; c) Global 2D probability distribution function computed from upscaled well logs; d) Probabilities of occurrence of every family with respect to AI values; e) AI from deterministic seismic cube; f) Effective porosity modelled by sequential Bayesian simulation using AI of the deterministic cube; g) AI from one stochastic simulation and; h) Effective porosity modelled by sequential Bayesian simulation using AI of the stochastic simulation cube.*

Deterministic Acoustic Impedance Cube

A deterministic AI cube was generated in 2000 (Figure 3a), with the same vertical resolution than the initial 3D seismic data. The histograms of the deterministic AI cube over the reservoir are plotted in Figure 2e. For comparison, the mean value plus or minus one standard deviation of the AI computed at well logs (Figure 2a) are also drawn. We notice that the mean of the deterministic AI agrees with the mean AI computed from well logs. However, we clearly observe that the variability of the AI of the deterministic cube cannot reproduce the variability observed at well logs. This induces a bias in the porosity estimation, the Family 3 (red histogram, lower AI values) being underrepresented by the deterministic cube. As a result, the histograms of modelled porosity obtained by sequential Bayesian simulations using the deterministic AI cube underestimate the porosity in the reservoir (Figure 2f).

Stochastic Seismic Inversion

To reduce the bias induced in the simulated porosity field by the use of the deterministic AI cube, we generate high frequency AI cubes by stochastic seismic inversion. The inversion procedure uses the deterministic AI cube as an initial low frequency impedance model, and uses a Bayesian scheme to update it with the seismic and the well logs, generating higher frequency models which agree both with the deterministic AI cube, the observed seismic amplitude cube, and the AI logs evaluated at 11 wells. The high-frequency variations away from the wells are guided by variogram models, spatially-variable if need be. We simulate five hundreds high frequency models, so the means of AI models and seismic amplitude models agree well with the initial deterministic AI cube (Figure 3a, b, c) and the observed seismic cube (Figure 3e, f, g). We randomly select a few of these models (Figure 3d, h) to simulate the porosity of the Saint-Flavien gas field.

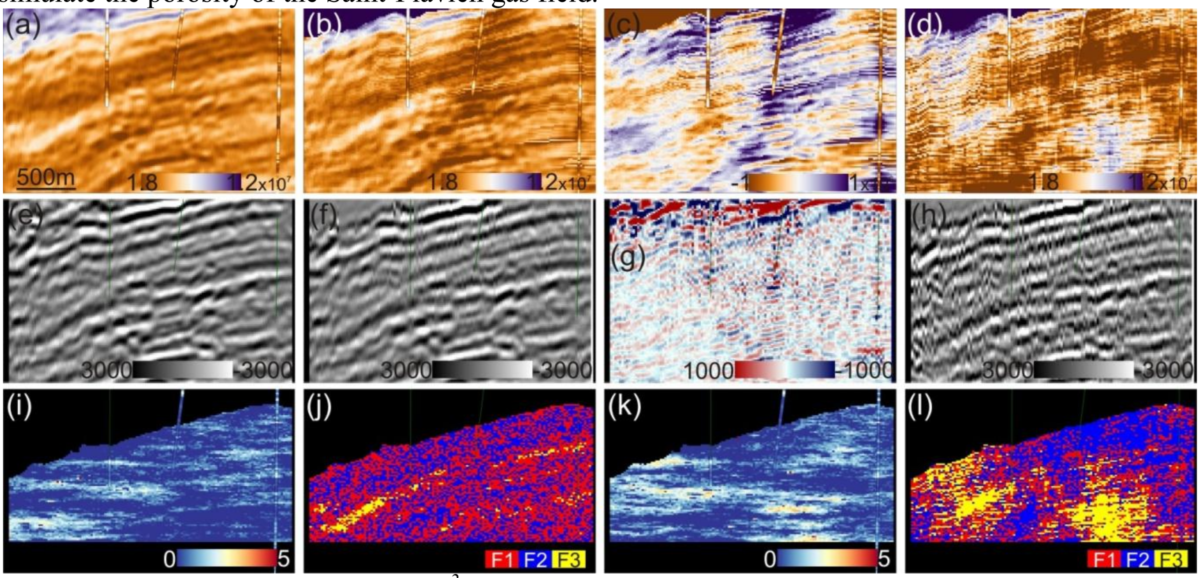

Figure 3: *a) Deterministic AI (kg/m^2s); b) Mean of 500 realisations of AI by stochastic seismic inversion; c) Difference between b and a; d) One realisation of AI by stochastic seismic inversion; e) Observed seismic amplitude; f) Mean of 500 realisations of seismic amplitude by stochastic seismic inversion; g) Difference between f and e; h) One realisation of seismic amplitude by stochastic seismic inversion; i,j) One realisation of porosity and family distributions simulated with deterministic AI presented in a; k,l) One realisation of porosity and family distributions simulated with the AI realisation presented in d. Vertical extent of panels is 230ms.*

Sequential Bayesian Simulation of Porosity

We simulate the porosity distribution in the reservoir by sequential Bayesian simulation, using Gaussian mixture models to account for the non-stationarity of the porosity field due to local changes in geology. We first use the deterministic AI cube to simulate the porosity and family fields (Figure 3i, j). We then use one realisation of high frequency AI cube obtained by stochastic seismic inversion to observe its impact on the simulations of the porosity and family fields (Figure 3k, l). We notice an increase in averaged porosity when modelling with the results of the stochastic seismic inversion (Figure 3k). Family 3 is also better represented, in a proportion which is closer of what is observed in well logs. We estimate the volume of pores by evaluating the volume of cells where the porosity is greater than 2%. We multiply the volume of each of these voxels by their porosity to obtain the total volume of pore available for CO_2 storage. Using the realisation shown in Figure 3i with the deterministic cube, we obtain of total pore volume of 530 000 m^3. This volume increases to 970 000 m^3 when we use the porosity field simulated with a high frequency AI realisation (Figure 3l).

Conclusion

Numerical simulations of the porosity field of the Beekmantown Group reservoir in Saint-Flavien show that stochastic seismic inversion of the deterministic acoustic impedance is essential to adequately represent the porosity and family distribution observed on well logs. Stochastic seismic inversion allows increasing the bandwidth of acoustic impedance to realistically evaluate the porosity by sequential Bayesian simulation. This allows a better representation of Family 3, associated with low acoustic impedance and higher porosity, which leads to a more realistic volume of pores available for CO_2 geological storage, which was underestimated when using the deterministic inversion cube. History-matching with production data acquired over 15+ years at the reservoir will be completed to better constrain the porosity field, and to evaluate the connectivity between high porosity zones.

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