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## A statistical learning approach to model the uncertainties in reservoir quality for the assessment of CO<sub>2</sub> storage performance in the Lower Permian Rotliegend Group in the Mid North Sea High Area

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### Abstract

It has been identified that the Rotliegend sandstone reservoir in the Mid North Sea High region, in the UK Quadrants 27-29, has a large-scale CO<sub>2</sub> storage potential of national importance. In this paper, the authors develop a reservoir model using extensive datasets available from seismic interpretations and core analysis. An advanced statistical learning approach was applied to characterise the uncertainties in the spatial distribution of reservoir quality. The model was used to assess the CO<sub>2</sub> injection performance and the preliminary results obtained thusfar indicate promise in the available storage capacities.

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### 1. Introduction

An initiative to explore unproven plays located in the frontier areas, spanning the Mid North Sea High (UK Quadrants 27-29) and its immediate surrounding areas, was jointly undertaken by the UKOOA and DTI in 2001. In a

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hydrocarbon prospectivity review of the area conducted by an industry consortium (Coots, Fox Oil and GTO Ltd.) in 2008, using a database comprising of vintage 2D seismic line data and well locations, at least five structural closures were identified in blocks 28/25, 29/21 and 29/22 (see Fig. 1). It was initially suggested that the Lower Permian Rotliegend Auk sandstone formation, having a mixed fluvial and aeolian sedimentation, which extends across these blocks, could contain multiple trillion cubic feet of gas. The formation is also known to host oil fields in the neighbouring blocks, namely the Auk field (block 30/16) and the Ardmore (formerly Argyll), Duncan and Innes fields (blocks 30/24 and 30/25a). It was thus envisaged that the formation could potentially lend itself to become a large-scale CO<sub>2</sub> storage reservoir of national importance.

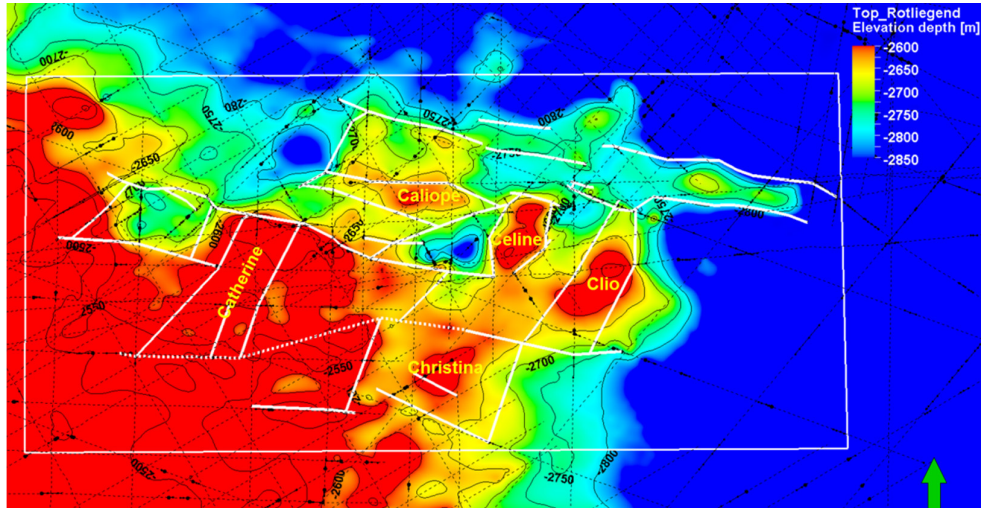


Fig. 1. The study area containing structural closures

Table 1 lists the upper and lower bounds of the estimated pore volume (in billion cubic metres) of the structural closures that were identified.

Table 1. The lower (LB) and upper (UB) bounds of the estimated pore volumes

Structural Closure	LB pore volume (in m <sup>3</sup> )	UB pore volume (in m <sup>3</sup> )
Caliope	423	493
Catherine	694	809
Celine	238	316
Christina	275	341
Clio	788	854

In this paper, the authors describe the methodology followed to develop a reservoir model of the Rotliegend formation in the Mid North Sea High area. The objective of the study was to model the uncertainty in the spatial distribution of reservoir quality using the available datasets, and subsequently assess CO<sub>2</sub> storage performance using numerical simulations. XRF (X-Ray Fluorescence) measurements of core samples were used as training examples to perform the batch learning of fitting parameters using a regularised regression technique referred to as LASSO (least absolute shrinkage and selection operator) which aids in feature selection [1], *i.e.* the selection of key elements or compounds in the rock matrix that are statistically significant and control reservoir permeability. The fitting parameters were used to generate multiple realisations of 3D permeability distributions using geostatistical conditional simulations [2].

Despite the spatial uncertainty in reservoir quality of the Rotliegend formation owing to the sparse distribution of wells in the Mid North Sea High region area, the preliminary results obtained thus far suggest that it is possible to establish a range of injection strategies with a level of confidence using statistical learning.

## 2. Available Data

### 2.1. Seismic interpretations

The horizon surfaces for the Rotliegend reservoir and the overburden formations, namely the upper Permian Zechstein formation, Triassic Bunter sandstone and the Cretaceous and Chalk formations, were available from the industry consortium who conducted detailed structural interpretation using approximately 2,000 km of seismic database. Several faults have also been identified. Fig. 1 illustrates the geology of the study area and the results of the interpretation.

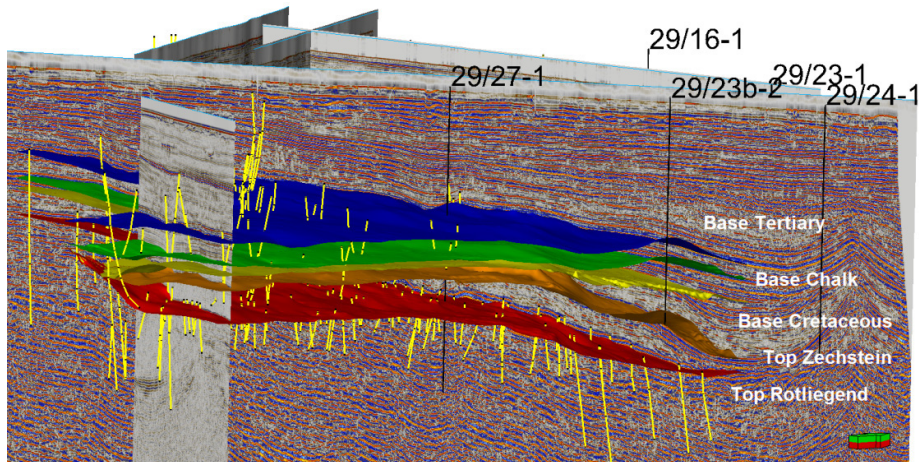


Fig. 2. Interpreted formation horizons and faults in the study area.

### 2.2. Data from cores and cuttings

A study was jointly commissioned by the University of Durham and Progressive Energy Ltd. on the Rotliegend Group encountered in wells 28/12-1, 28/18a-1, 29/23-1, 29/25-1 and 29/27-1 in the North Sea, UKCS, with the objective to determine the primary controls on permeability within a cored interval of well 29/25-1 by means of geochemical analysis, and thereby estimate the permeabilities over the un-cored study intervals of the remaining wells. A total of 82 samples were selected for chemical stratigraphic analysis, of which 19 are core samples and 63 are cuttings samples.

The geochemical analysis of the samples was undertaken based on non-destructive chemical analyses using XRF, with data being acquired for 43 elements, including the major elements Al, Si, Ti, Fe, Mn, Mg, Ca, Na, K, P, S and Cl, the trace elements Sc, V, Cr, Ni, Cu, Zn, Ga, Br, Rb, Sr, Y, Zr, Nb, Mo, Cd, Sn, Sb, I, Ba, Hf, Ta, W, Hg, Pb, Bi, Th and U, and the rare earth elements (REE) La, Ce, Eu and Gd. All of the major element data are quoted as %oxide values, while trace and rare earth element concentrations are in ppm (parts per million). Although data for more elements were acquired, these were not included in the raw dataset provided since the values for these elements are either below the limits of detection or the data are of poor quality.

## 3. Geological model

The structural model spans an area of  $30.5 \times 13.5$  km and has an average thickness of 230 m. The model was constructed with the horizon surfaces and the fault data using the pillar gridding approach. The model grid has an average resolution of  $50 \times 50 \times 25$  m. Multiple faults exist in the model domain and these were assumed as steep normal faults with negligible offset. Fig. 3 illustrates the 3D model of the study area wherein the structural closures of interest are highlighted.

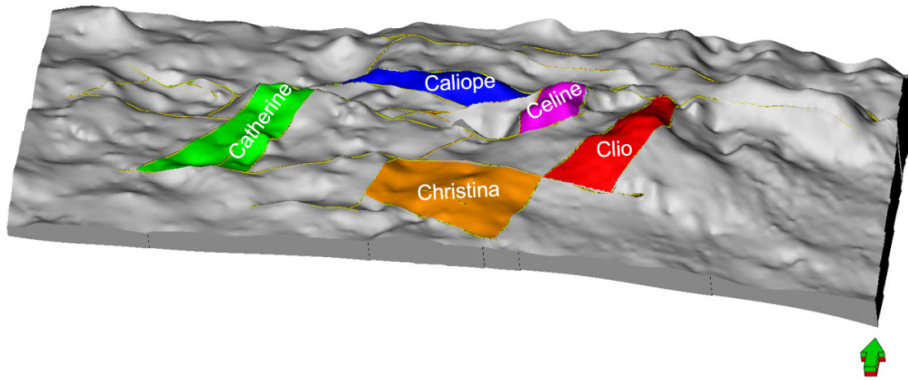


Fig. 3. The structural model of the study area indicating the structural closures of interest.

The petrophysical attribution was carried out using a combined approach of statistical analysis and validation using data from the literature [1]. The XRF and permeability measurements for the samples obtained from the well 29/25-1 were used as training data in order to fit a multiple regression model based on LASSO, which performs both variable selection and regularisation in order to enhance the permeability estimation accuracy for the unknown samples. The LASSO parameters vector ( $\beta$ ) was estimated by minimising the following regularised error function [1]:

$$\hat{\beta} = \arg \min_{\beta} \left\{ \frac{1}{2} \sum_{i=1}^n \left( y_i - \beta_0 - \sum_{j=1}^p x_{ij} \beta_j \right)^2 + \lambda \sum_{j=1}^p |\beta_j| \right\} \quad (1)$$

where,  $x$  is the vector of input features (XRF analysis data) vector,  $y$  is the output (permeability) vector, and  $\lambda$  is the L1-regularisation parameter. The lasso parameters were then used to estimate the permeabilities of the samples obtained from the remaining wells in the region, namely 28/12-1, 28/18a-1, 29/23-1, and 29/27-1. The estimated permeability values were further validated using the data ranges reported by Trewin and Bramwell [3] for the Auk field in the neighbouring block 30/16 and are found to be in good agreement.

A total of 82 samples were used to further fit the geostatistical parameters for estimating multiple stochastic realisations of 3D permeability distributions in the model using conditional simulations [2]. Fig. 4 illustrates an example realisation of permeability distribution obtained using the proposed approach.

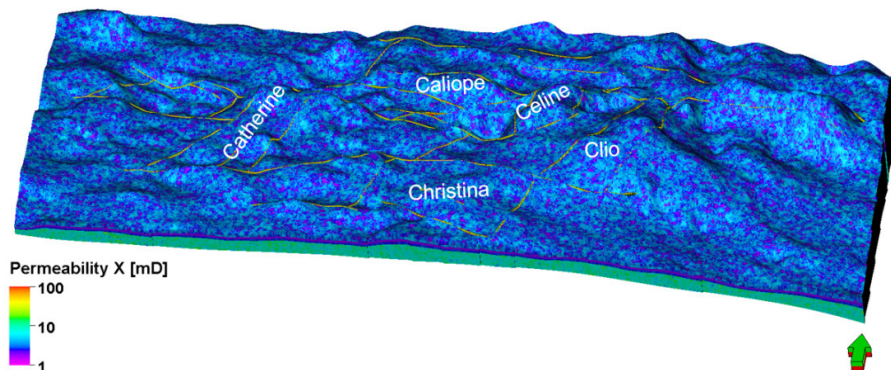


Fig. 4. An example realisation of the 3D permeability model.



#### 4. CO<sub>2</sub> injection simulations

The stochastic realisations were implemented in Eclipse 300 to simulate CO<sub>2</sub> injection, assuming an injection rate of 1 Mt/year per well. It was also assumed that the number of injection wells is fixed and their placement locations are known apriori. Injection into the structural closures were considered separately in order to assess the time it takes on for the plume to spill outside the closures, and the regional pressure build-up in each scenario. It was additionally assumed that all the faults were transmissible and non-sealing since they generally have a negligible offset.

Fig. 5 illustrates the plume footprint at the top of the storage reservoir after simulating CO<sub>2</sub> injection for 100 years in different structural closures. Table 2 summarises the results for the five scenarios considered. From the results obtained thusfar, it can be inferred that injection into Christina closure allows a relatively better utilisation of the capacity of the structural closure, while injection into Caliope leads to an early spillage. The pressure change observed for the simulated cases inside and outside the closures ranges between 0-20 bars, which is well within the fracture pressure limit of the reservoir.

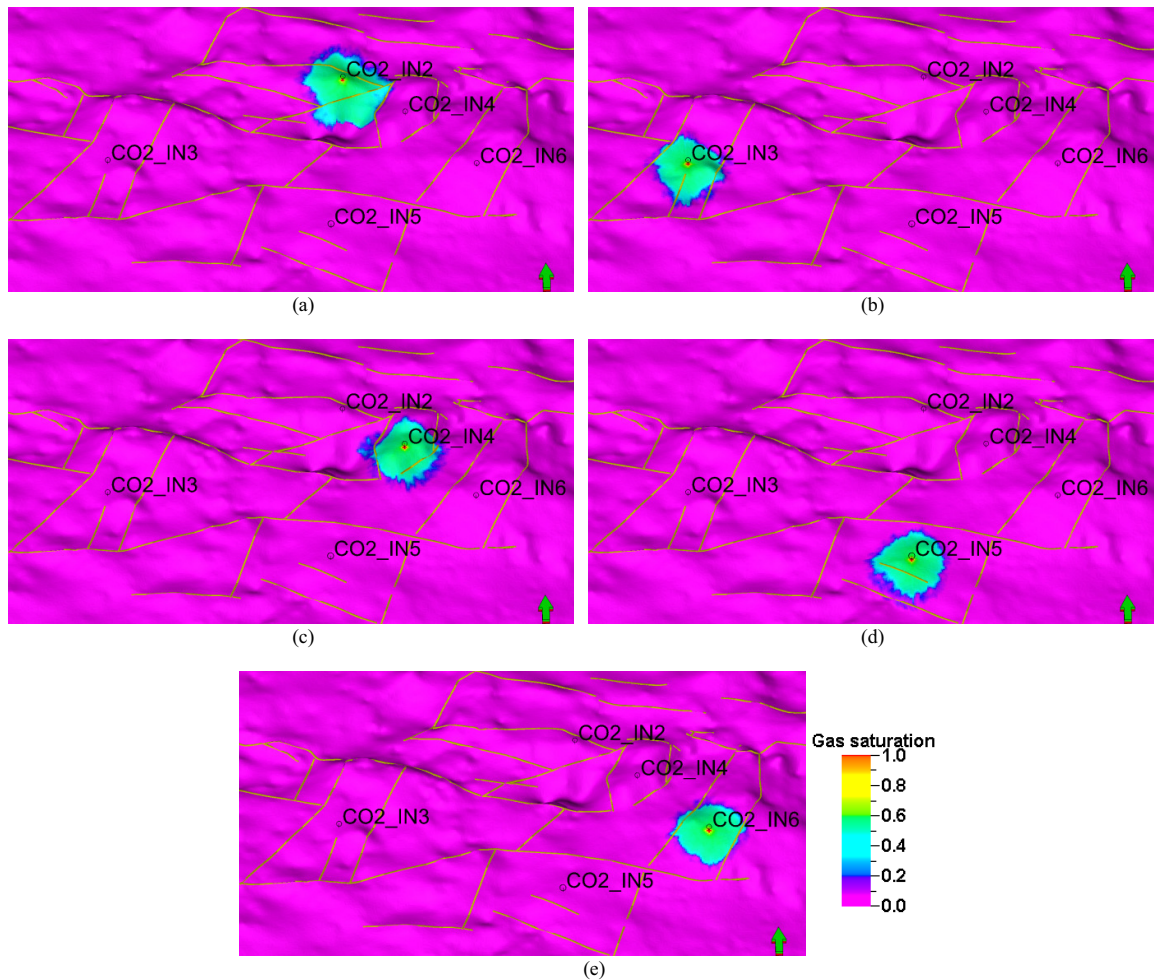


Fig. 5. The plume footprint at the top of the Rotliegend formation after simulating 100 years of CO<sub>2</sub> injection at: (a) Caliope; (b) Catherine; (c) Celine; (d) Christina; and (e) Clio.

Table 2. A summary of the simulation results for different scenarios (injection for 100 years).

Injection Scenario (1Mt/year)	Time taken for spillage (in years)						Change in pressure (in bars)					
	Caliope	Catherine	Celine	Christina	Clio	Outside closures	Caliope	Catherine	Celine	Christina	Clio	Outside closures
Caliope	0	-	37	-	-	4	12.6	5.1	15.7	6.3	7.8	0.2
Catherine	-	0	-	-	-	24	7.4	19.7	3.5	4.9	2.2	0.2
Celine	68	-	0	-	-	13	10.6	3.3	17.1	8.9	15.8	0.2
Christina	-	-	-	0	-	47	5.9	4.2	8.0	11.7	6.9	0.2
Clio	-	-	-	-	0	24	5.7	1.9	15.5	7.7	18.19	0.2

## 5. Conclusions

An industry consortium had previously carried out a review of the Mid North Sea High region and identified structural closures that demonstrated the availability of a large-scale CO<sub>2</sub> storage potential of national importance. The horizon surfaces for the Rotliegend reservoir and the overburden formations were available from the industry consortium who had conducted detailed structural interpretation using approximately 2,000 km of seismic database. Furthermore, a detailed chemical analysis of core samples from the well bores in the region was conducted using the XRF technique. These datasets, together with the publicly available literature, form an extensive host of information known about the Rotliegend sandstone reservoir in the region.

In this paper, the authors developed a geological model of the reservoir using an advanced statistical approach referred to as lasso (least absolute shrinkage and selection operator). The technique was used to characterise the uncertainties in the spatial distribution of reservoir quality. The estimated permeability values were found to be in good agreement with the ranges of values reported in literature on the neighbouring Auk field.

The model was subsequently used to simulate scenarios of CO<sub>2</sub> injection at a rate of 1 Mt/year in the structural closures, assuming that the number of wells and their locations are known *a priori*. The results obtained thusfar indicate that the pressure increase in the reservoir ranges between 0-20 bars, and is well within the fracture pressure limit. Hence, pressure it is not a limiting factor for injection. Moreover, plume migration analysis also suggests that it is possible to inject CO<sub>2</sub> for upto 50 years without spillage outside the structural closures. However, in order to maximise the storage capacity utilisation, the current work requires an extension using simultaneous injection strategies based on an optimisation framework.

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## References

- [1] Tibshirani, R.. Regression Shrinkage and Selection via the lasso. J R Stat Soc Series B Stat Methodol. 1996; 58(1):267-288.
- [2] Chilès J.P, Delfiner P. Geostatistics: Modeling Spatial Uncertainty, Second Edition. N.Y.:Wiley 2012: 734p.
- [3] Trewin, N.H, Bramwell, M.G. The Auk Field, Block 30/16, UK North Sea. From Abbotts, I. L. (ed.), United Kingdom Oil and Gas Fields, 25 Years Commemorative Volume, Geological Society Memoir 1991; 14:227-236.