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Detection of Reservoir Sorting Characteristics from Seismic Data

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SUMMARY

It is usually the case that rock permeabilities do not correlate especially well with elastic properties, so seismic based methods for estimating permeability are not conventionally viewed with much optimism. However, there are certain kinds of permeability variation that are driven chiefly by variations in sorting, and these sorting or grain-size distribution variations have a much more direct impact on elastic properties. We present an overview of modeling work applied to some deepwater field data where the turbidite reservoir facies has substantial grain size polydispersity, and this is shown to have significant seismic and permeability expressions. The effect of poor sorting on elastic properties is well captured by a simple model that takes into account the effect of non-load bearing (or 'floating') grains in the rock fabric. This model has ample corroboration from well logs, core permeability measurements, experimental laser-grain studies and numerical rock-assembly models. It is implemented as part of an open source stochastic seismic inversion. The statistical outputs of the inversion show that the sorting parameter is detectable in the field data.

Introduction

A systematic shift of the relationship of the compressional velocity (vp) to density (rho) inspired the development of a new rock physics model where some of the solid material is "floating" or not involved in load support. The shift in the vp-rho relationship, is directly related to the floating fraction by this model. It was also found by core analysis that the floating fraction is linearly related to the sorting of the sandstone. Two relationships are found from a regression of the core analysis: one that determines the capture fraction of small grains into the matrix, and a second that relates the porosity and floating grain fraction to the permeability. The two relationships together allow the determination of the permeability from the seismic reflectivity. The model is further understood by the analysis of numerical rock assemblies. The detectability is verified by a stochastic model based inversion which implemented the new rock physics model.

Rock Physics Model

The rock physics model is based on some of the solid material being "floating", as is shown in Fig. 1. The details of this model can be found in DeMartini and Glinsky, 2006.

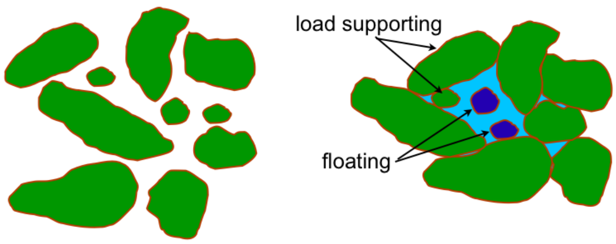

Figure 1 *Assembly of a set of grain of two different grain sizes showing some floating grains and a capture fraction of 1/3.*

The essential characteristics of this model are a systematic shift in the vp-rho relationship shown in Fig. 2, and found in the well data.

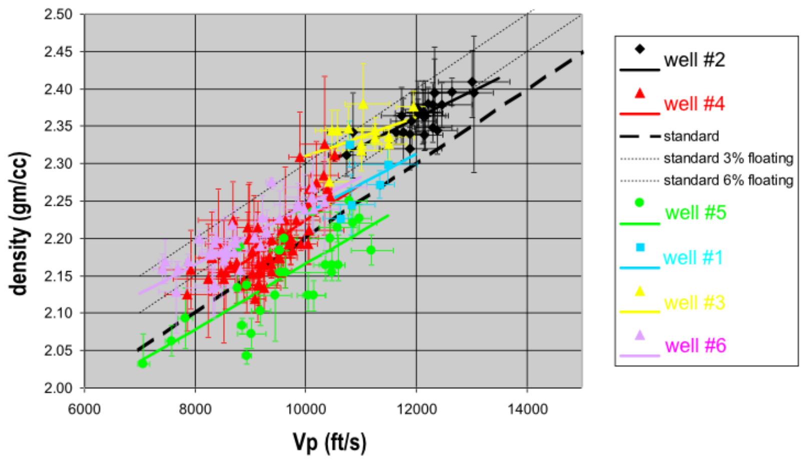

Figure 2 *Reference vp-rho relationship for a well sorted sand compared to the theoretical shift in that relationship due to floating grains and the observations in several wells (from well logs).*

The model predicts no change in the vp-vs relationship as observed in the data. Analysis of the core shows a linear relationship between the average floating grain fraction inferred by each well's vp-rho relationship, and the sorting parameter measured by the laser grain size analysis of the core. This is shown in Fig. 3. Note the significant difference in the grain size distributions. Two thin sections on core photos are shown: one for the well with the best sorting, and another for the well with the poorest sorting. Both have the same porosity, but one has a permeability of 500 mD and the other 10 mD. The second part of the figure demonstrates the linear relationship between floating grain fraction and the sorting parameter.

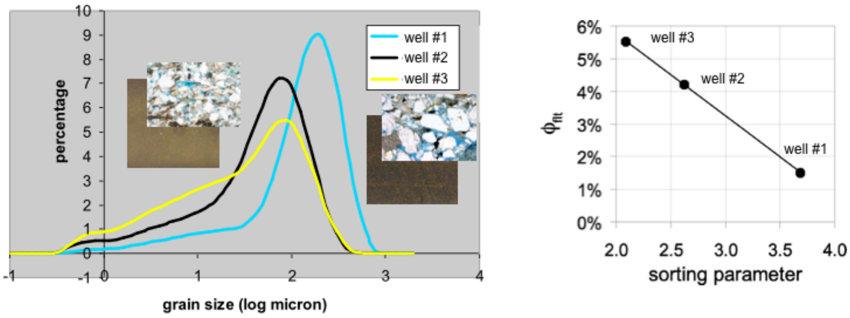

Figure 3 *Laser grain size sorting from the core for three of the wells are shown along with thin sections and core photographs for well #1 and well #3. Linear relationship between the floating grain fraction and sorting parameter (mean grain size / standard deviation) is shown on the right.*

A typically poor relationship between permeability and porosity is shown on the left of Fig. 4. A much improved regression is shown on the right by including the floating grain fraction.

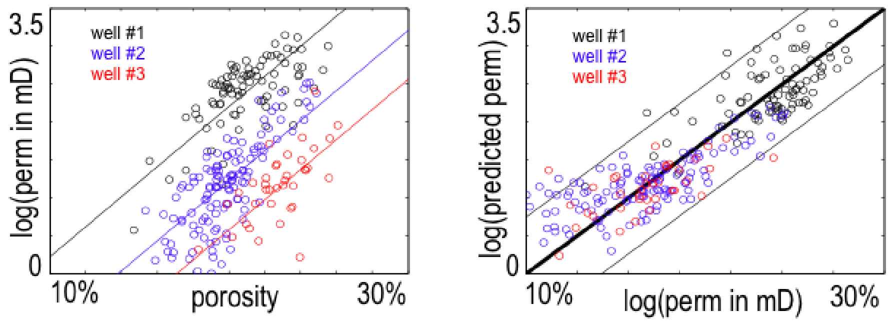

Figure 4 *Relationship between porosity and permeability. Improvement by including the floating grain fraction in a regression of porosity versus logarithm of the permeability, shown on right.*

Numerical Rock Assembly Modelling

Further understanding is gained by analysis of numerical rock assemblies (Bryant et al., 2009).

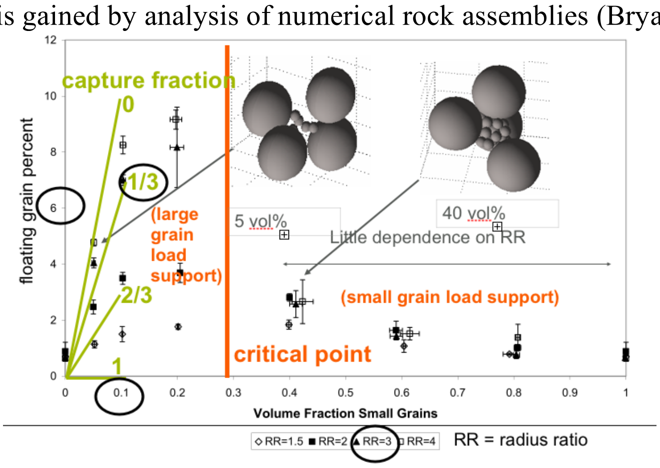

Figure 5 *Plot of the volume fraction of small grains versus the floating grain percent for various radius ratios of mixtures of two different size spheres. Note the critical point in volume fraction, 40%, beyond which the mixture is large spheres suspended in a matrix support of small spheres. Below this critical point there is large grain support. Capture fraction is shown as the slope of the relationship for small values of volume fraction of small grains.*

Note the critical behaviour of these assemblies in Fig. 5. Above a critical point of the volume fraction the small grains are grain supporting, there are few floating grains, and the floating grain fraction is independent of the radius ratio. Below this critical point the large grains are load supporting, there are significant numbers of floating grains, the number dependant on the radius ratio. The larger the radius ratio the greater the slope at zero volume fraction, the lower the capture fraction, and the greater the maximum floating grain fraction. It should be noted that there is a maximum, no matter how large the radius ration of about 10% for the floating grain fraction (as observed in the well data). There is also a critical point in the radius ratio of 4. Above this ratio the grains are rarely captured and the floating grain fraction again becomes independent of the radius ratio. Below this critical point the floating grain fraction does depend on the radius ratio, and a significant fraction of the some grains are captured into the matrix. The result is the phase diagram shown in Fig. 6.

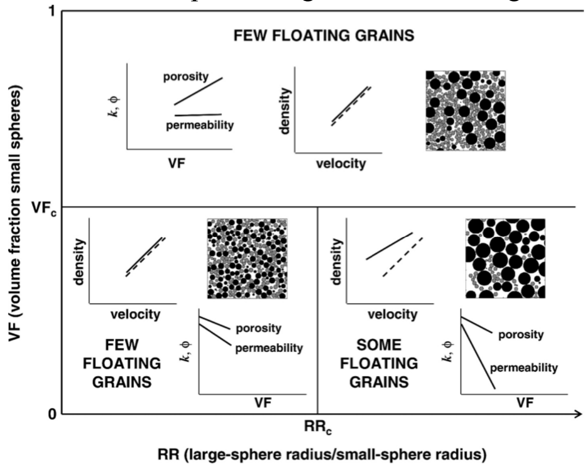

Figure 6 *Phase diagram of the assembly of a binary mixture of spheres. This is a function of radius ration and the volume fraction of small spheres.*

Seismic Detectability Using Bayesian Inversion

The rock physics model indicates that it might be possible to determine the permeability from the seismic data. There is a significant question to be answered – whether the permeability is detectable in the presence of uncertainty in the rock physics relationships, complex geological structure, uncertainty in the net-to-gross of the sand, and seismic noise. To answer this question, the new rock physics model was added to a stochastic model based inversion (Gunning and Glinsky, 2004, 2007). This inversion takes into account all the uncertainties, complexity and noise. The result is an ensemble of models that are consistent with all the rock physics and the seismic data (with AVO) to within the noise level. This is demonstrated in Fig. 7.

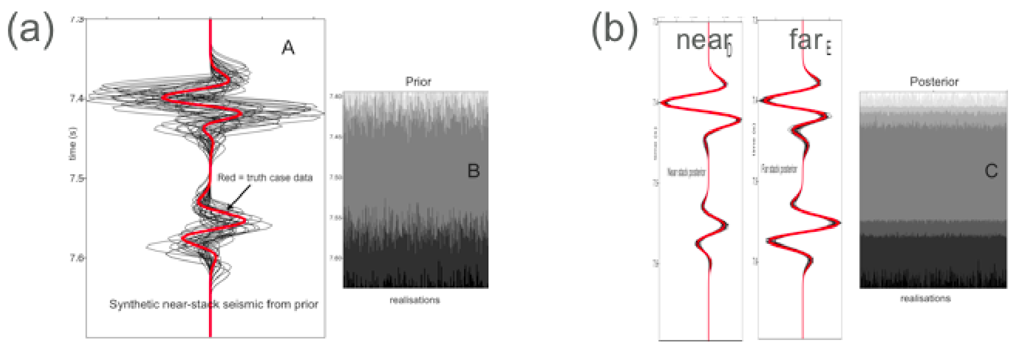

Figure 7 *(a) Near synthetic seismic of the ensemble of models before the inversion are shown in black, compared to the actual seismic in red. The ensemble of models are shown to the right. They are coloured according to layer number. Notice the large scatter. (b) After inversion. Both the near and the far stack seismic is shown.*

The six-layer model was constructed according to the seismically resolvable blocking of the wells. The seismic data used was the actual seismic data at well #2. The seismic noise level was estimated from a Bayesian wavelet derivation (Gunning and Glinsky, 2006).

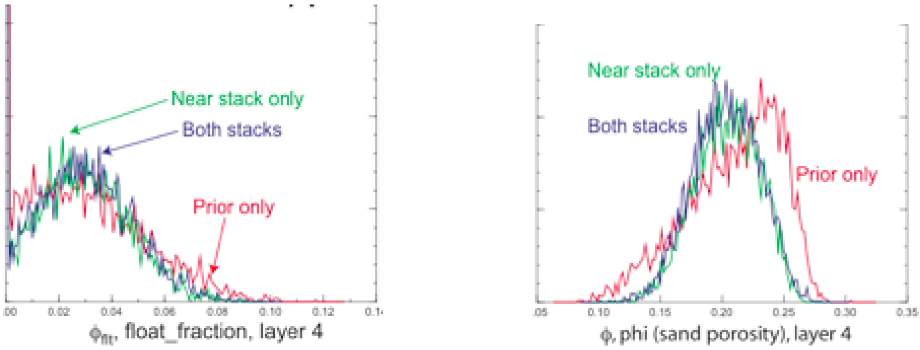

Figure 8 *Distributions of floating grain fraction and porosity, before (prior, red) and after the inversion (near stack only, green; both stacks, blue).*

Note that both the float fraction and the porosity are significantly influenced by the seismic data. The distributions after inversion are in good agreement with the actual values of 3.5% and 20% observed in the well. There was no additional value in using the AVO. Although it is not shown, the net-to-gross estimate was not changed by the inversion.

Conclusions

Using the new rock physics model, the permeability can be estimated from the seismic data for the deepwater turbidite area that was studied. Further analysis is currently being done on the core including 3D CAT scans, SEM, QEMSCANs, vp, vs, rho, and differential microscopic speckle interferometry (locally measuring the strain field). These are being done to verify the microscopic implications (floating grains and capture fraction) predicted by this mesoscale model.

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