Statistical Uncertainty of Seismic Net Pay Estimations

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The companion article "A simple, robust algorithm for seismic net pay estimation" (Connolly, 2007, hereafter referred to as Net Pay 07) outlines a method to estimate net pay from band-limited impedance seismic data. The objective of this second article is to describe a procedure to estimate the uncertainty of these net pay predictions.

Errors in net pay estimation can arise from many sources; seismic noise, inaccurate wavelet estimation, rock property variations, picking error, calibration error and non-validity of the assumptions of the algorithm. Our approach estimates these uncertainties from a statistical process using a large number of pseudo wells. We'll show that variation of the internal layering within the reservoir is one of the most important sources of uncertainty so we ensure that the pseudo wells have geologically realistic layering patterns. From the pseudo wells, we generate synthetics having bandwidth, noise and AVO attributes consistent with the seismic data used for the net pay estimation. We obtain seismic net-to-gross estimates from the synthetics following the method described in Net Pay 07 and, from a comparison with the known seismic net-to-gross values from the pseudo wells, we obtain an estimate of seismic net-to-gross standard deviations as a function of apparent thickness and seismic net-to-gross.

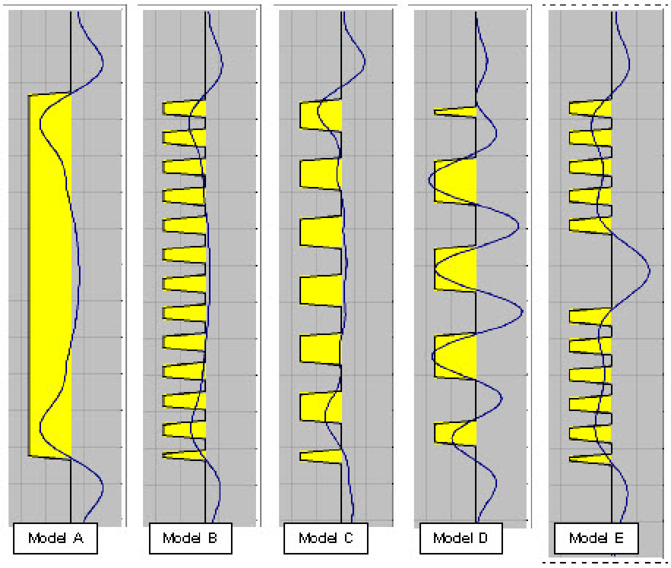
Although described for a specific algorithm this uncertainty estimation method is general and could be adapted to obtain uncertainty estimates for a wide range of seismic reservoir characterisation algorithms.

Internal Layering

The main assumption of the Net Pay 07 method is that, for constant apparent thickness, average band-limited impedance is proportional to *seismic* net-to-gross (true net divided by apparent thickness). However, the accuracy of this relationship decreases as the gross interval increases. Departures from proportionality are largely caused by variations of the internal layering within the reservoir. We'll illustrate this by considering a number of simple models.

Figure 1 shows impedance logs for five reservoir models, each having a gross interval of 100ms and with pay corresponding to the low impedance values. Superimposed are the corresponding band-limited impedance traces (6-10-40-60Hz Butterworth filter). Net Pay 07 stated that the approximate upper gross interval limit for this algorithm is half the wavelength of the lowest frequency, which for this wavelet is about 80ms, so these models exceed that upper limit.

The table shows the model parameters and average band-limited impedance values measured between the nearest positive-to-negative zero crossing at the top of the reservoir and the nearest negative-to-positive at the base. We can see that the ratio between average band-limited impedance and seismic net-to-gross is constant for models A, B and C, such that if we calibrated on model A we'd correctly predict the seismic net-to-gross of the other two. (Because the models have the same apparent thickness we don't need to worry about the detuning step described in Net Pay 07.) However, as the pay distribution becomes more blocky (model D) or less evenly distributed (model E) the relationship breaks down; for model D the predicted seismic net-to-gross is 32% but should be 44% and for model E it would be predicted as 58% but should be 42%. So we can see that layering variations alone, with no rock property variability and no seismic noise, can cause the algorithm to fail.



	Model A	Model B	Model C	Model D	Model E
net	100	50	51	44	42
gross	100	98	99	92	98
net-to-gross	1.00	0.51	0.52	0.48	0.43
apparent thickness	100	100	99	101	101
seismic net-to-gross	1.00	0.50	0.52	0.44	0.42
average BLI*	-113	-56	-59	-37	-65
predicted seismic ntg		0.50	0.52	0.32	0.58
RMS BLI*	232	116	133	424	252

* *band-limited impedance*
measurements in milliseconds
predicted seismic net-to-gross based on calibrating to model A

Figure 1. Five reservoir models showing both the broad-band impedance logs and associated band-limited impedance traces. The broad-band models have been filtered with a 6-10-40-60Hz wavelet. The table lists the key reservoir properties and attributes measured from the band-limited traces.

We've seen that errors are likely to increase with increasing gross thickness and intuitively we might also expect errors to be largest for mid range values of net-to-gross, as there are more ways to rearrange a 50% net-to-gross reservoir than a 90% net-to-gross reservoir. Seismic net-to-gross uncertainty is therefore likely to be a function of rock property variability, seismic noise, apparent thickness and seismic net-to-gross (which are proxies for gross thickness and net-to-gross) as well as internal layering.

We propose a statistical approach to error estimation based on multiple pseudo wells that incorporate variations in all the above properties. Variations are constrained using data from appropriate well logs in the area of interest. We assume that internal layering patterns are essentially unknown but we constrain the realisations using bed-thickness distribution statistics to ensure the pseudo wells have geologically realistic layering patterns (which models A-E clearly don't).

Power-Law Geology

There has been some discussion in the sedimentology literature about the nature of bed-thickness distributions, mostly with respect to turbidite systems. A number of models have been proposed; log-normal, power-law cumulative and segmented power-law cumulative frequency distributions being the most favoured (Talling, 2001). We propose to generate layering patterns for pseudo wells by calibrating one of these models using well log data and then randomly selecting bed thicknesses from the probability distributions. The resultant pseudo wells will have random layering but will be constrained to have the same bed distribution statistics as the calibration wells.

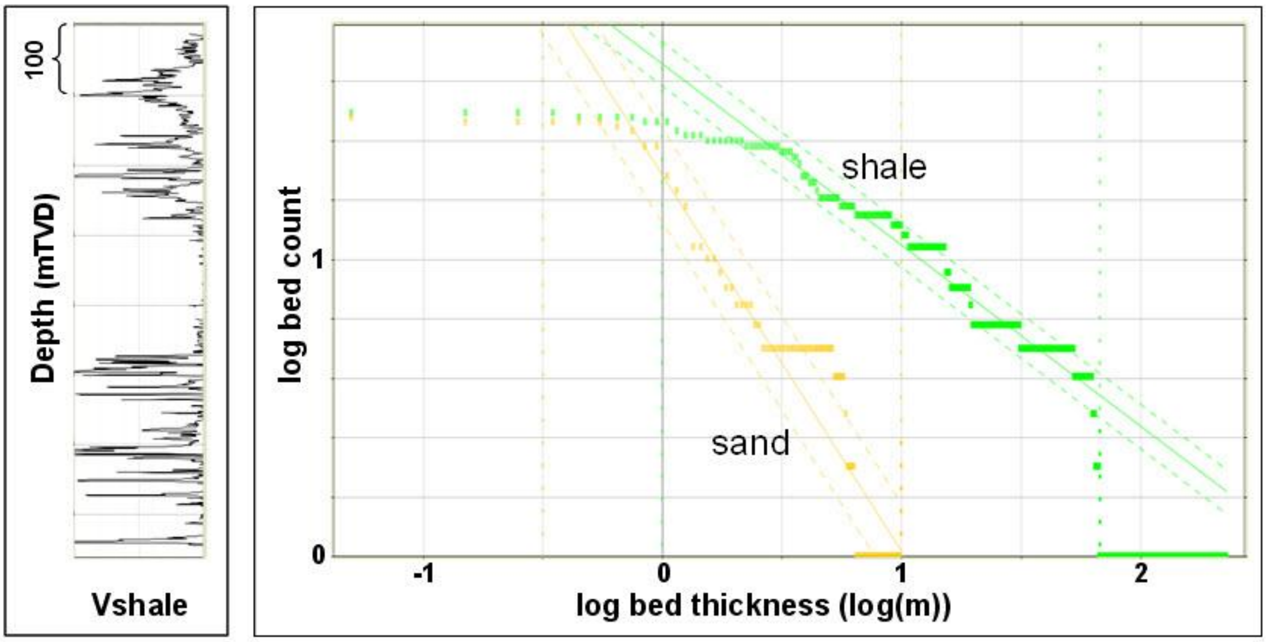


Figure 2. Vshale curve and associated cumulative bed-thickness distributions for sands and shales

We restrict our modelling to simple clastic binary systems such as sand-shale turbidite successions. We find that sands and shales generally have different bed thickness distributions so we determine their pdf's independently. Figure 2 shows a Vshale curve from a West African deep marine oil field and, to the right, the corresponding cumulative bed-thickness analysis on a log/log plot. Sands and shales are distinguished using a simple Vshale threshold treating amalgamated or eroded beds as single intervals. The bed thickness distributions, which are distinctly different for the two lithologies, are broadly linear over most of the scale range although showing deviation from linearity below about three metres for the shales and below about one metre for the sands. Others have noticed this non-linearity may which may be caused by the decreased probability of a well hitting a thin bed owing to their reduced spatial extent (Malinverno 1997) or, for thinner beds, limited logging tool resolution. The trends also often diverge for large bed thickness because the scarce sampling of thick beds results in less robust statistics.

We fit power-law trends over the linear portion of the distribution. For our purposes a power-law cumulative distribution appears to be adequate and is also consistent with the assumptions behind coloured inversion. This is because power-law bed distributions result in fractal layering patterns that have power-law power spectra (Lancaster & Connolly, 2007). The power-law fits are recast as pdf's for sand and shale bed thicknesses and used in the simulation of the pseudo wells.

We include rock property variability by measuring the means and standard deviations of Vp, Vs, Rho, porosity and Vshale for the sand and shale beds identified by the Vshale threshold as well as the correlations between these properties. Then, for each depth sample, we assign Vp, Vs and Rho values dependent upon the lithology but incorporating random variation consistent with the rock property statistics whilst also ensuring that the property correlations are retained.

Uncertainty Estimation

Let's assume we have carried out a seismic net pay estimation procedure as described in Net Pay 07 and we wish to obtain a map of the standard deviations of the seismic net-to-gross estimates. The inputs were an appropriate seismic dataset, including top and base picked horizons, together with a number of calibration wells. The outputs were a seismic net-to-gross and corresponding net pay map.

The method described in the preceding section generates pseudo wells with statistics that match the calibration wells. To obtain robust statistics of the correlation between seismic net-to-gross and average band-limited impedance we need to generate thousands of such pseudo wells with a range of gross interval to span that of the reservoir and a wide range of net-to-gross. From each realisation we construct an extended elastic impedance log having a chi angle to match the seismic data that was used to make the net pay estimation. We add noise and convolve with a wavelet again to match the target seismic dataset and then pick the zero crossings at the top and base of the reservoir in preparation for estimating the apparent thickness and average impedance values.

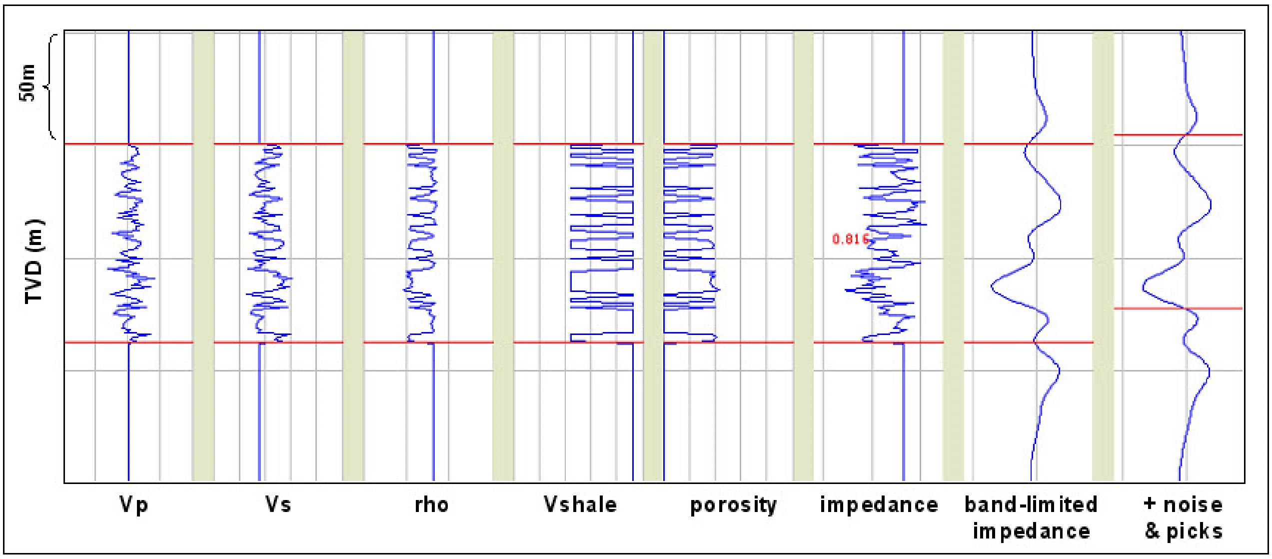


Figure 3. Example pseudo well and associated band-limited impedance traces.

Figure 3 shows a typical pseudo well realisation representing a single isolated reservoir package. The EEI log has a chi=20^{o}, chosen to match the seismic dataset that was used for the net pay estimation. This chi angle gives a good correlation between the EEI log and the Vshale curve. The right-most track of figure 3 shows the zero-crossing picks which define the range over which the procedure will measure the average band-limited impedance. Note that this selected realisation contains a picking error at the base of the reservoir; the lower-most sand has been missed as the seismic response is too weak to be picked as the base of the reservoir. This merely mirrors the type of picking error that an interpreter might make.

The next step measures apparent thicknesses and average band-limited impedances for each of the pseudo wells. The seismic net-to-gross of the synthetic data is then determined by dividing the ‘true’ net (as defined by the Vshale log) by the apparent thickness. Figure 4 shows crossplots of seismic net-to-gross against average band-limited impedance, each for a narrow range of apparent thickness, for a large number of realisations.

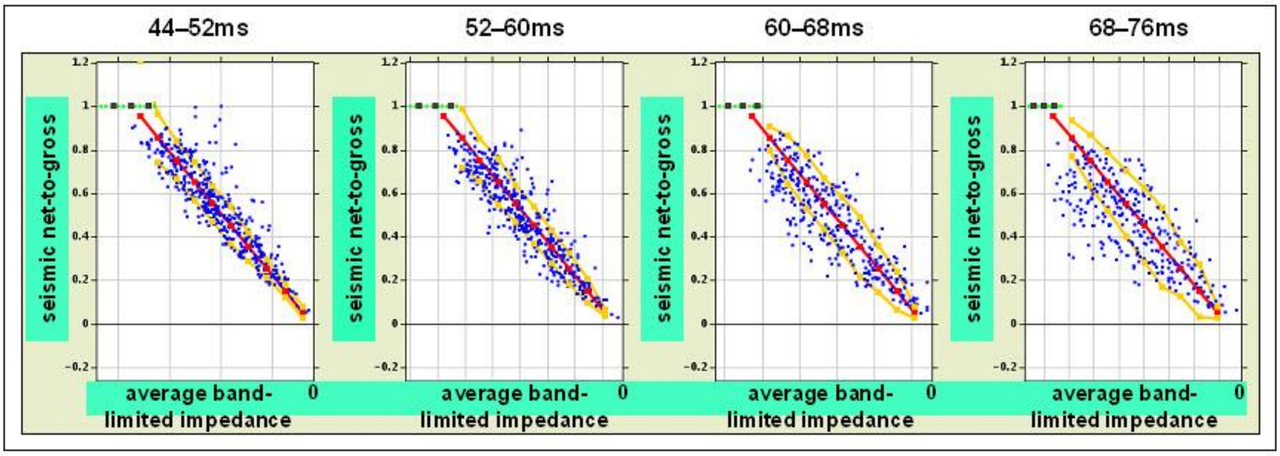


Figure 4. Crossplots of seismic net to gross against band-limited impedance, filtered to 8-12-80-100Hz, for a large number of pseudo wells displayed for restricted apparent thickness ranges. The orange lines are an estimate of the standard deviation of the data points.

Net Pay 07 describes how to detune a 100% net-to-gross band-limited impedance wedge model and then concluded that the resultant attribute would be linearly proportional to seismic net-to-gross. Therefore the points on a crossplot of seismic net-to-gross against average band-limited impedance for a narrow apparent thickness range should all lie on a straight line between the origin (zero amplitude for zero net pay) and band-limited impedance value for the 100% seismic net-to-gross case at that thickness for a seismic net-to-gross of one.

Figure 4 shows this to be approximately true; there is a strong linear trend but with some scatter. The scatter is caused by a number of factors; the variable layering, the seismic noise, the uncertainty in the relationship between elastic parameters and Vshale and the picking error. The plots confirm the trends we'd previously suspected; that uncertainty increases with increasing apparent thickness and tends to be largest for mid range values for net-to-gross.

Net Pay 07 provided a rule-of-thumb that the upper limit of applicability of the algorithm occurs at an apparent thickness equivalent to a half-cycle of the minimum frequency. In the case shown in figure 4 this will be at about 60ms and there does indeed appear to be a marked decrease in linearity between the second and third crossplots. (The outliers mostly correspond to mis-picks such as the one shown in figure 3).

Sensitivities can be easily investigated; figure 5 shows crossplots for different wavelets over a narrow range of apparent thickness and clearly demonstrates uncertainty increasing as the low frequency content of the data is reduced as discussed in Net Pay 07. For this particular example, the pseudo wells had standard deviations for the elastic parameters set to zero and no noise was added. There was therefore perfect correlation between the pseudo wells' impedance and the Vshale curves so the uncertainty has arisen purely because of the effect of the layering.

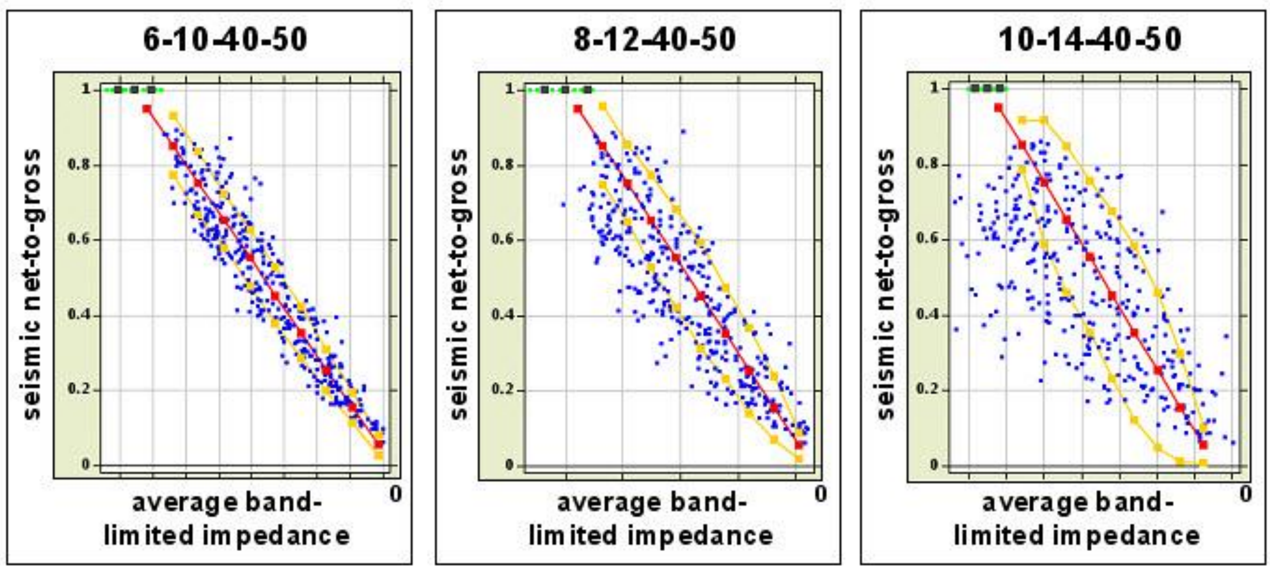


Figure 5. Crossplots of seismic net-to-gross against average band-limited impedance for different wavelets. All displays are for an apparent thickness range of 60-68ms. Impedance functions are set to have 100% correlation with Vshale curves and no additional noise was added.

These crossplots are telling us the most likely value of seismic net-to-gross for a given apparent thickness and average band-limited impedance (the inputs into the Net Pay 07 algorithm). If the detuning and calibration steps in Net Pay 07 had been correctly applied then the most likely values are already known; what we're interested in is the variance. By dividing the crossplot into a number of vertical bins we can measure the standard deviation as a function of seismic net-to-gross and from a full suite of crossplots we can build up a table of standard deviations as a function of apparent thickness and seismic net-to-gross. Therefore, given maps of each of these, we can generate a map of the standard deviation of our seismic net-to-gross estimates. Figure 6 illustrates this method.

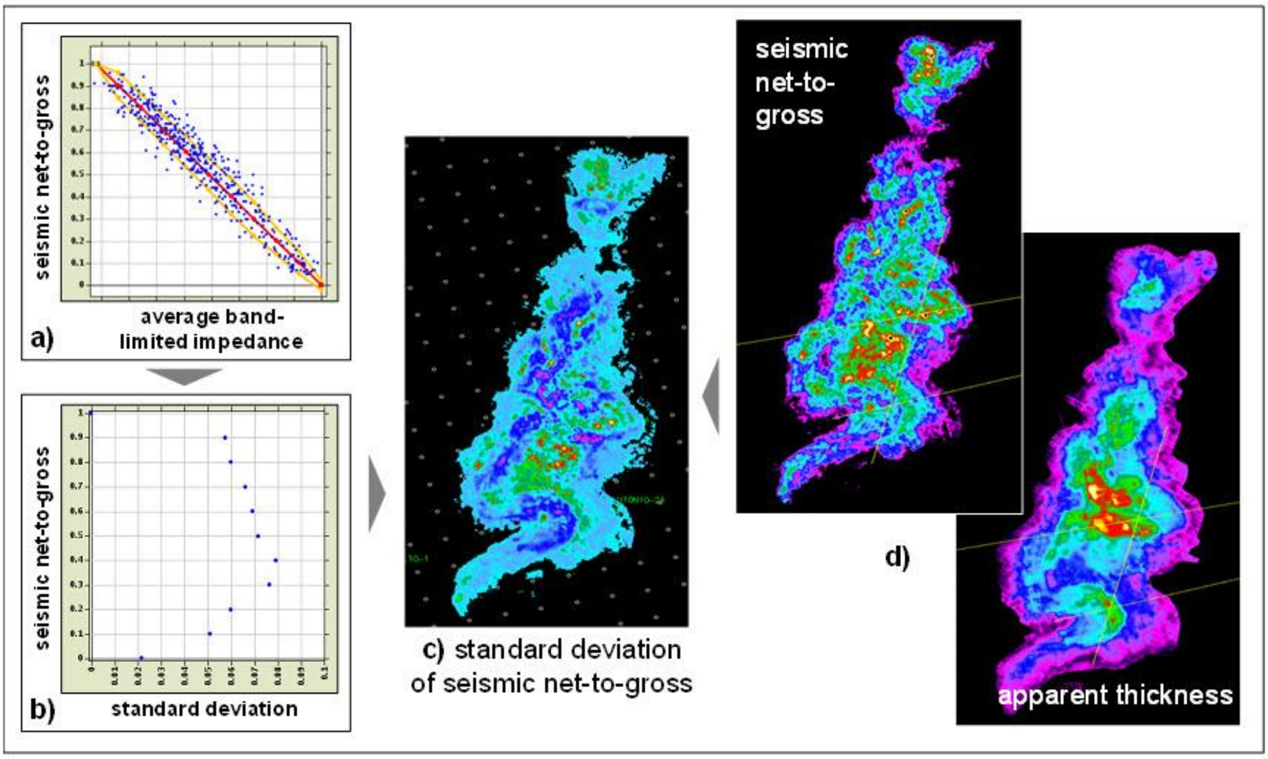


Figure 6. Workflow illustration a) crossplot of seismic net-to-gross vs. average band-limited impedance for a small range of apparent thickness (one of many), b) standard deviation values estimated from crossplot, c) map of seismic net-to-gross standard deviations derived from the c) and d) seismic net-to-gross and apparent thickness maps.

Workflow Summary

This workflow produces a map of standard deviations of seismic net pay estimates created by the Net Pay 07's method.

1. Estimate power-law exponentials for cumulative sand and shale bed thickness distributions from Vshale logs.
2. Measure Vp, Vs, Rho, porosity and Vshale averages and standard deviations for sands and shales.
3. Measure cross-correlations between these properties (for sand and shale independently).
4. Define ranges of gross thickness and net-to-gross.
5. Generate multiple (thousands of) pseudo well logs (Vp, Vs, rho, Por, Vsh).
6. Generate required impedance logs (AI, EI or EEI).
7. Add noise.
8. Convolve impedance logs with appropriate wavelet.
9. Measure apparent thickness by picking zero crossings at top and base of reservoir interval.
10. Measure average band-limited impedance between zero crossings.
11. Measure total net from Vsh log and divide by apparent thickness to give seismic net-to-gross.
12. Crossplot average band-limited impedance against seismic net-to-gross for narrow ranges of apparent thickness.
13. Measure standard deviations of seismic net-to-gross as a function of apparent thickness and seismic net-to-gross.
14. From these and maps of apparent thickness and seismic net-to-gross generate a seismic net-to-gross standard deviation map.
15. Multiply by depth converted apparent thickness to obtain net pay uncertainty.

Top and base reservoir picking error is not explicitly included above but in practice the automated picker will produce errors similar to any real-data interpretation process.

Wells
Common practice is to estimate the uncertainty of seismic net pay predictions by measuring the accuracy of predictions at well locations – usually this means withholding some 'blind' wells from the calibration step. While useful in providing an indication of the validity of the process, it clearly will not result in a full description of the spatial net pay uncertainty which, as we've seen, is dependent on the local apparent thickness and estimated net-to-gross. Well ties also have their own inherent uncertainties, as discussed in Net Pay 07, unrelated to the uncertainties of the reservoir characterisation process.

The analysis presented in this article has further implications. Figure 5 shows crossplots based on pseudo wells with no rock property variability and zero seismic noise; the equivalent of perfect well ties. And yet there is significant scatter. Any one of these many pseudo well realisations could be a real well. So, if we have a real well that happens to have a layering pattern resulting in an average band-limited impedance that lies away from the optimum regression line then the seismically predicted net pay would not match the well. The implication being that an inaccurate well prediction does not necessarily mean a non-optimum average net pay estimation! Conversely, if we forced a tie at this well it would cause the overall result to be biased. In principle, we could compensate for this by including the real well's suite of logs as one of the realisations within the modelling and then measure and correct for this calibration bias.

Discussion
This article highlights the sensitivity of a specific net pay prediction algorithm to layering patterns. Probably any net pay estimation algorithm will exhibit some degree of such sensitivity implying that geologically reasonable layering patterns should always be included when testing these processes. The use of multiple pseudo wells could easily be applied more generally to estimate uncertainty from a broad range reservoir characterisation algorithms.

The method described here to generate the pseudo wells assumes that the power-law distributions are known but information about stacking order is not. The procedure therefore generates a large range of possible layer stacking patterns constrained only by the bed thickness distributions. However, it should be possible to improve the uncertainty estimation by introducing additional constraints on the range of stacking patterns. These could be based either on further well log analysis or on geological insights. For example, fixed layers could be included or higher order statistics used to give a bias to specific stacking order, such as coarsening upward cycles (although measuring such statistics is by no means easy). Further extensions to this method can easily be envisaged. For example, we could add the ability to model saturation and pressure changes to provide a tool for modelling DHI detectability or 4D sensitivities.

Conclusion
We have described a method that uses a large number of pseudo wells to determine the spatial uncertainty of seismic net pay estimations that were obtained from a specific algorithm described in the companion paper. We showed that variations in internal layering patterns are a significant contributor to the overall uncertainty from which it followed that forcing well ties could bias the overall net pay estimation. We described a procedure to generate pseudo wells having property variations consistent with calibration wells and, in particular, having realistic layering patterns achieved by using cumulative power-law bed-thickness distributions based on measurements from the calibration wells. The principle of this uncertainty estimation method is general and so could be applied to a wide range of seismic reservoir characterisation processes.

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