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Quantitative time-lapse interpretation - Reducing uncertainty with multiple attributes

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Summary

Quantitative interpretation of time-lapse seismic is a critical step in characterizing reservoir changes. While amplitude variation and time delays can indicate where general changes occur, inversion of baseline and monitor data for the change in elastic properties allows for changes in saturation, temperature, or pressure to be interpreted in terms of magnitude and vertical and lateral position.

As with all measurements, the calculated elastic properties have uncertainty from noise affecting the amplitudes of the data and other sources of non-repeatability. For a single attribute, the larger values in this uncertainty can change how the reservoir properties are interpreted. However, an interesting behaviour is seen when two moderately correlated attributes are considered. Because of their correlation, more subtle shifts in elastic properties can be interpreted when multiple attributes are considered. Examples from different time lapse surveys are shown. While the demonstration here is for monitoring steam injection in the McMurray Formation of the Alberta oil sands, the broader conclusions are applicable to any monitoring situation.

Modelling

A rock-physics model is a valuable tool to test variations in reservoir properties. In this example, the McMurray is modelled as an unconsolidated sand with mineralogy matching available XRD data and reservoir parameters from engineering data. The overburden pressure is calculated from the integration of a representative density log with shallow coverage. Because of the rigid nature of the saturating bitumen, a fluid shear modulus is applied, along with an appropriate fluid/solid substitution approach (Ciz & Shapiro, 2007). Changes to the model are made to account for variations in clay content and porosity of the different facies present.

To investigate the effects of steam injection on the model, a number of staged effects are considered. First, an increase in pressure from initial conditions to the downhole injection pressure affects the fluid properties and reduces the effective pressure on the rock. Second, temperature is increased in increments to that of the injected steam. The temperature has a significant influence on the bitumen properties, which are modelled here based on the relationships of Javanbakhti (2018). Finally, the fluid saturation is changed from predominantly bitumen to steam or hot water. Steam, in particular, has a significant effect on the density; however, it is the temperature changes prior to the saturation change that is the focus of this analysis.

Figure 1 shows the changes in elastic properties for the pressure and temperature changes modelled for high-porosity sandstone. At the maximum temperature considered, the expected change in P-impedance I_P shows a decrease of 32% from baseline conditions. This indicates that I_P is a key attribute for interpreting temperature changes. Simultaneously, the expected change in density for the same range is only 3% from baseline conditions. While density is a critical

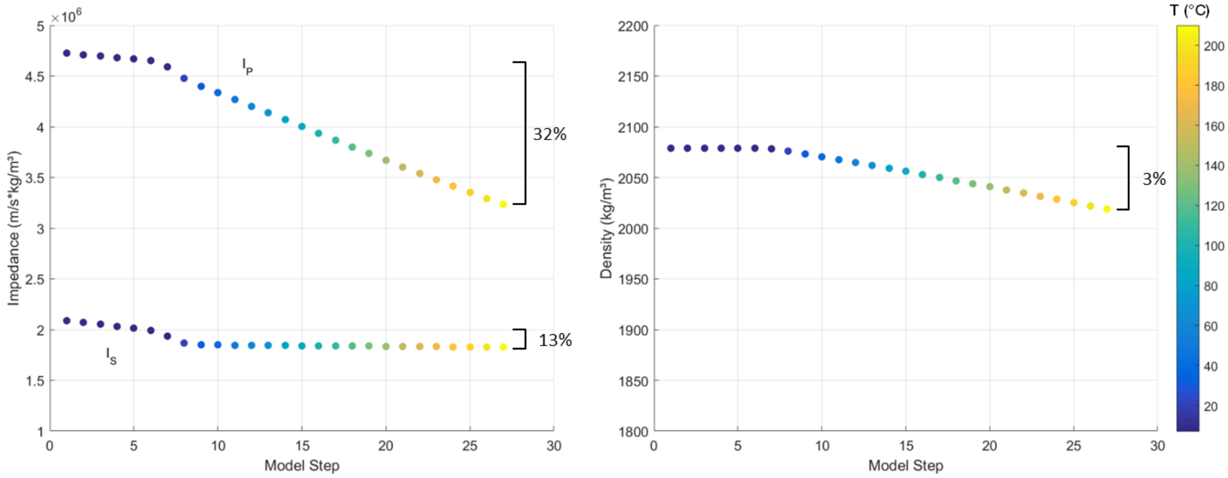

***Figure 1**. Rock-physics model results for steam injection progression steps. With increasing temperature, I_S has an immediate drop in value, while I_P decreases gradually (left). The large drop in I_P makes it a useful property for quantifying temperature changes, compared to the small changes in I_S and density (right).*

attribute for facies interpretation in the McMurray (Gray et al., 2004; Weston Bellman, 2007) and distinguishing gas-phase steam, this small change appears to rule it out as an important attribute for interpreting temperature changes. The S-impedance I_S changes by 13%, however all of this change occurs in the first 10 °C, with no changes beyond that point. Nevertheless, as shown in the next section, attributes such as density and I_S that have a small change in value are still valuable for interpreting the temperature effects.

Seismic Analysis

The data used for the first example is a mature steam flood consisting of a baseline and monitor survey with 15 years of separation. The data were properly processed, calibrated, and inverted,

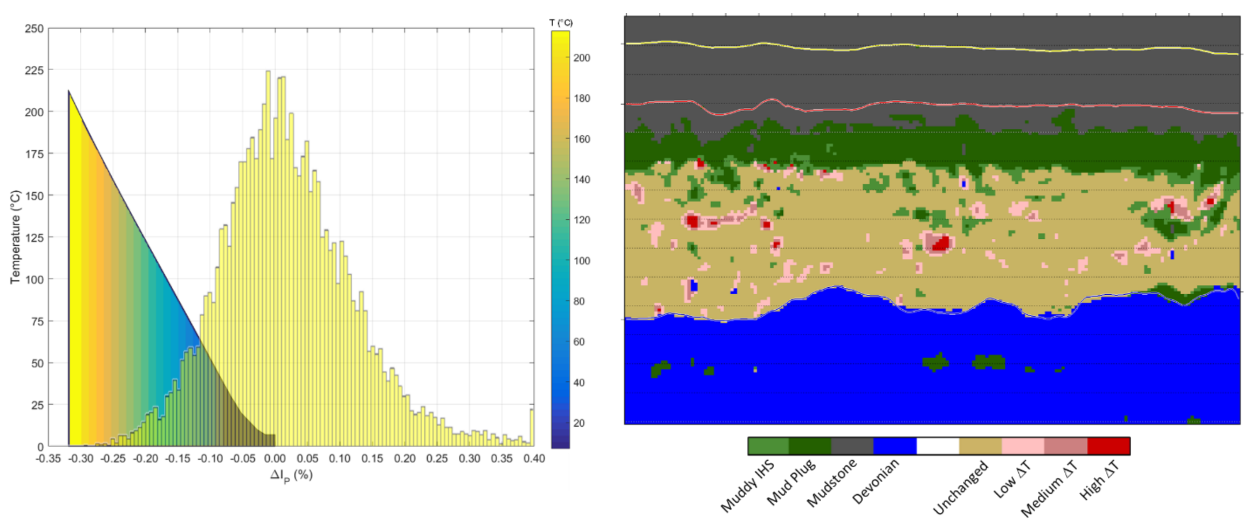

***Figure 2**. Histogram of the percentage change in I_P for an unchanged portion of reservoir overlain with the rock-physics template for temperature. The larger apparent decreases in I_P are erroneously attributed to temperature changes on the classification.*

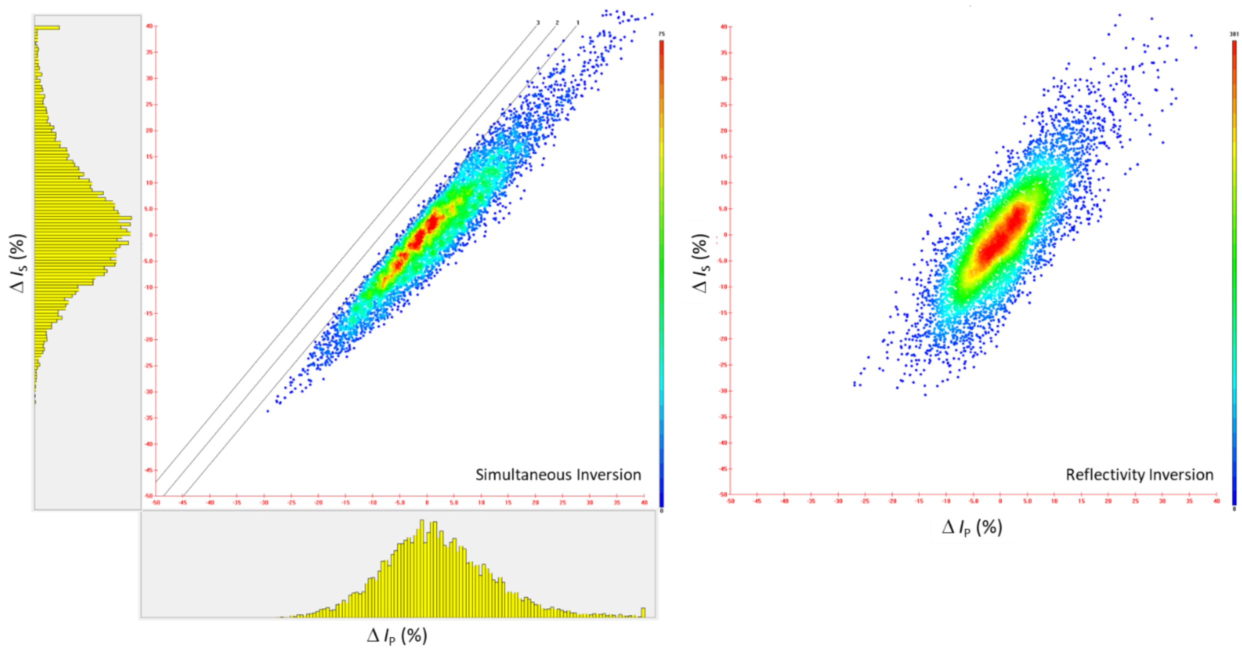

***Figure 3**. Crossplot of the percentage changes in I_S versus I_P for an unchanged portion of reservoir. The uncertainty in the measurements is correlated, allowing for more accurate isolation and classification of temperature changes. The same attributes derived from independent inversions of the reflectivity (right) show the same relationship, despite the absence of a stabilizing I_S-I_P trend in the inversion.*

to calculate the change in elastic properties. As I_P is expected to show the largest effect from temperature changes, the first examination is how temperature change would be interpreted using this attribute alone. Figure 2 shows a histogram of the calculated change in I_P for a given inline, superimposed on the rock-physics model relating temperature change and I_P change. By applying cutoffs corresponding to I_P changes of 10, 15, and 20% (approx. 50, 90, 125°C), the resulting classified section is shown. While a few areas of apparent temperature change are identified, the line is actually from an area of the survey in which no steam injection has occurred, and no temperature changes are present as confirmed by observation wells. These apparent changes are therefore a result of misclassification due to the non-repeatability of the surveys.

Figure 3 shows crossplots of the percentage changes in I_S versus I_P. For this un-steamed portion of reservoir, the I_S is expected to be unchanged. However, as with the I_P, the non-repeatability of the surveys results in some uncertainty in the measured I_S change. Critically, the random changes in I_S are not independent from the random changes in I_P, and the resulting point cloud shows a correlation. This is important because the points with a strong decrease in both I_P and I_S can be identified as falling on this uncertainty trend and therefore distinguished from points that have a strong decrease in I_P due to temperature change than don't have associated I_S changes. It should be noted that this correlation in uncertainty is not due to the stabilizing relationships between I_P and I_S in the inversion algorithm. Figure 3 shows the same crossplot and behaviour for independent inversions of the P-reflectivity and S-reflectivity in which this stabilizing relationship does not exist.

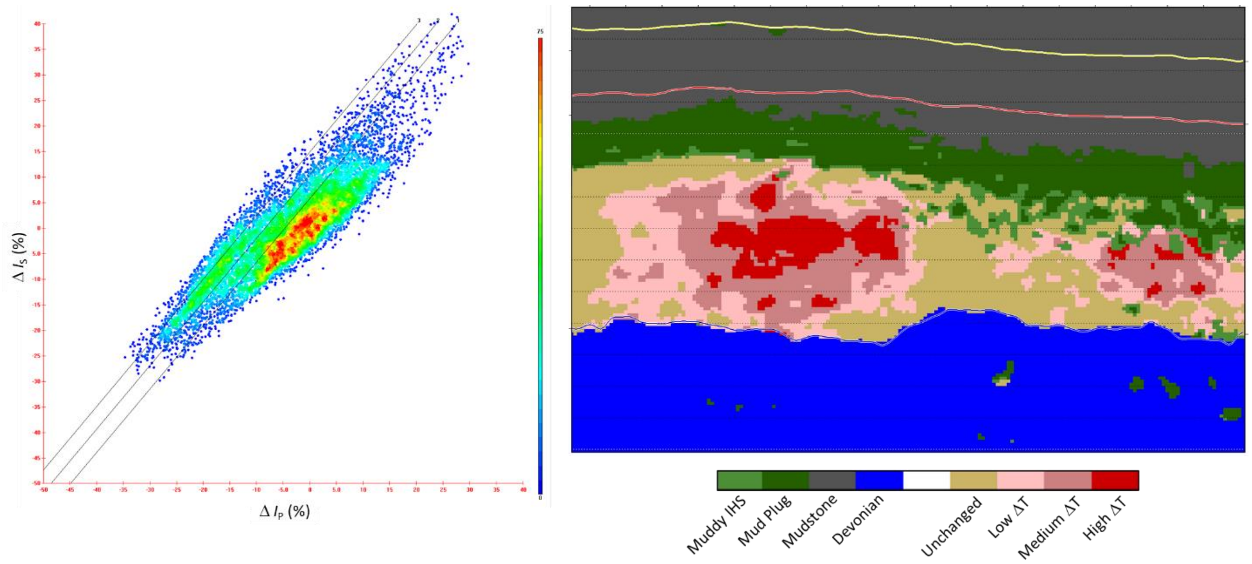

***Figure 4**. Crossplot of the percentage changes in I_S versus I_P for a heated portion of reservoir. The point cloud has spread out in the ΔI_P direction but the orientation of the data cloud remains parallel to the unaffected reservoir. By rotating the interpreted temperature cutoffs, an accurate classification of temperature changes is achieved.*

To identify the temperature changes associated with the 4D response, the cutoffs applied previously to the single I_P attribute were modified to the crossplot data. The changes in I_P of 10, 15, and 20% were preserved; however, the cutoffs were aligned obliquely with the uncertainty trend and the changes represented the lateral shift on the ΔI_P axis. It can be seen that there are no longer any points above the line classifying temperature changes, and the classified section therefore shows no erroneously interpreted temperature changes.

Figure 4 shows the crossplot and classified section for a line through the middle of the steam-affected reservoir. The crossplot point cloud is seen to spread laterally in the ΔI_P direction. The centroid of the portions of the cloud outside of the unchanged reservoir is also seen to decrease in the ΔI_S direction, as predicted. The oblique trend of the data is preserved for all temperature classes. The associated classification shows a distribution of temperatures that is consistent with expectations and matches the available temperature logs.

Conclusions

Interpreting reservoir changes on 4D seismic should consider the effects of all available elastic properties rather than one in isolation. This is true not only to investigate the different physical effects on different properties, but also due to the uncertainty present in the measurements. By using attributes with correlated uncertainty, the physical effects may be more easily distinguished in a manner that is still consistent with theoretical expectations.

References

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