A Geomorphology-centric ranking scheme for stochastic seismic inversion realizations

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SUMMARY

Advances in the acquisition and processing of 3D seismic data have led to significant improvements in our ability to image subsurface reservoirs. The limitations of conventional 3D seismic measurements for reservoir characterization include its band-limited vertical resolution as well as the non-uniqueness of inverting seismic amplitudes for reservoir properties. These limitations have an impact on our ability to accurately model thin reservoirs for volumetric computations. Stochastic seismic inversion addresses these concerns by producing multiple, equally likely realizations, consistent with the available well and seismic data, at the fine-scale vertical resolution required for such reservoirs. The nature of the algorithm results in a large number of realizations (typically in excess of 200). We, therefore, require a methodology to rank the realizations in a way that is meaningful for the problem at hand and identify models corresponding to the P10th, P50th, and P90th percentiles.

In the example presented here a feature recognized on a 3D deterministic seismic inversion result was interpreted as a mitten-shaped tidal bar using well-log data. The stochastic seismic inversion process generated realizations that showed a wide variation in the extent and geometry of the tidal bar. In this work we present an innovative ranking method used to classify the broad range of stochastic inversion results targeted at approximating this tidal bar geomorphological feature. From these results we were successful in identifying the various percentile models required for further analysis including input to reservoir simulation modeling.

Key words: Stochastic seismic simultaneous inversion, realizations, geomorphological ranking, threshold conditions.

INTRODUCTION

3D seismic data can be considered to be a fairly accurate snapshot of the subsurface, as accurate as the acquisition and processing allows. The constraint of the time sampling of conventional seismic data and its equivalent depth resolution are often insufficient to accurately model thin reservoirs for volumetric computations. This constraint can be overcome using stochastic seismic inversion (SSI), a form of sequential Gaussian collocated co-simulation, which produces models at the higher vertical resolution required.

The output of the SSI process is a large number of equally likely results or 'realizations' (typically in excess of 200). We therefore require a methodology to order the realizations to identify, for example, the percentile models (e.g. P10, P50, and P90) for further reservoir simulation modeling work. Suleiman et al (2012) proposed a methodology to rank the realizations using gates and transforms. We propose an alternate approach based on the identification of a specific geomorphological feature of the target reservoir.

The example described in this paper involves a geomorphological feature interpreted as a tidal bar from the 3D seismic deterministic seismic inversion results in combination with well logs and core data (**Figure 1 left**). Despite being calibrated to the wells, the SSI process generated realizations that showed wide variation in the extent and distribution of the bar. In this work we present an innovative ranking method used to classify such a broad range of inversion results.

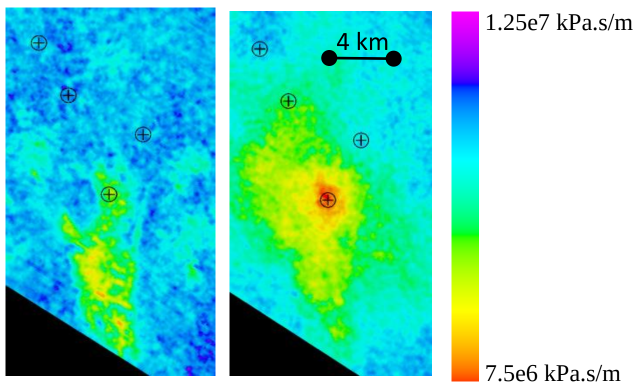

Figure 1 Left: Acoustic impedance slice from the deterministic seismic inversion showing the mitten-shaped target tidal bar feature. Right: Acoustic impedance slice from the stochastic seismic inversion mean of 256 realizations showing the same tidal bar feature.

METHOD AND RESULTS

Comparison of deterministic and stochastic seismic inversion results

The tidal bar geomorphology is clearly visible on the acoustic impedance horizontal slice of the survey area as seen in **Figure 1 left**, but the vertical sample of this data is limited to a time interval of 4 ms, equivalent to a depth interval of between 8 and 9 m. The reservoir units in this area are generally less than 15 m thick, therefore we must apply SSI to improve the vertical sampling to 1 ms, i.e. about 2 m. However, as already described, the stochastic process outputs many realizations, with each realization being equally valid. For example, **Figure 2** shows two separate realizations from the SSI process, the distribution of the amplitudes being significantly different.

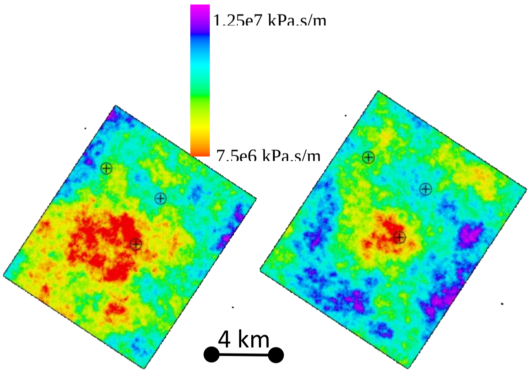

Figure 2. Two different acoustic impedance realizations, showing the outcome variability of the stochastic process.

Nevertheless, the arithmetic mean of a large number of realizations should converge to that obtained by the deterministic method as seen in **Figure 1 left**, albeit retaining the fine vertical sampling of 1 ms. Unfortunately the mean of all the realizations is not, in itself, an actual stochastic inversion realization, and we need to directly identify the different percentile results.

Determining a threshold test level

As we are primarily interested in delineating the extent of the mitten-shaped geomorphology of the target reservoir unit, we must rank the realizations in relation to their conformance to the mean extent. Unlike other ranking criteria that could have be applied (Suleiman et al. 2012; Moyen and Doyen 2009), our approach is to use an unbiased deterministic seismic inversion result as the target geometry for ranking. The method we have adopted is as follows:

From each result we identify a cut-off threshold boundary value of the property and identify all the cells that are below this value, the pass/fail slice as illustrated in **Figure 3**.

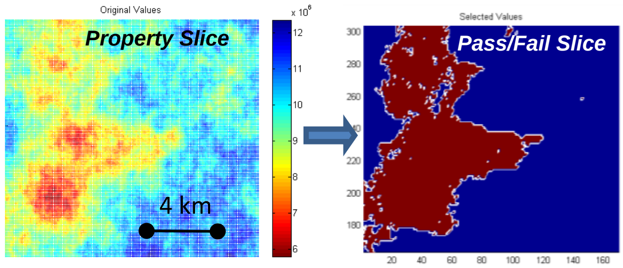

Figure 3. Applying the threshold condition to the property slice to get the pass/fail slice.

We repeat this process for each realization and obtain a map that shows the percentage of the total number of results for which that cell is below the threshold, as shown in **Figure 4 Top**. This map is very similar to the arithmetic mean calculated from the entire set of realizations (**Figure 4 Bottom**).

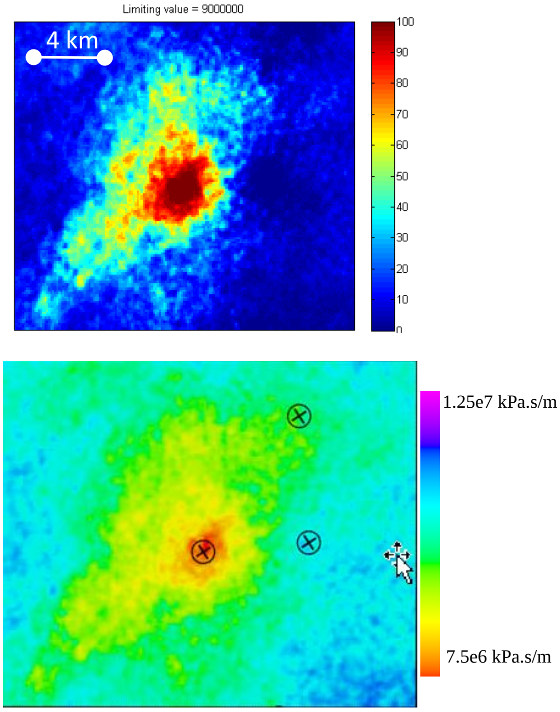

Figure 4. Top: The map of the percentage of total number of results for which that cell is within the threshold. The colour is the percentage of realisations for which that cell has a value above the threshold value. Bottom: The arithmetic mean of 256 realizations of the property.

To rank the individual realization in terms of their adherence to the mean result, we take each realization and calculate the pass/fail slice (**Figure 5a**). We then select the values of the average realization (**Figure 5b**) from the corresponding cells and calculate their mean (**Figure 5c**). This gives us a single value that is a measurement of the adherence of this realization to the morphology of the average of all the realizations.

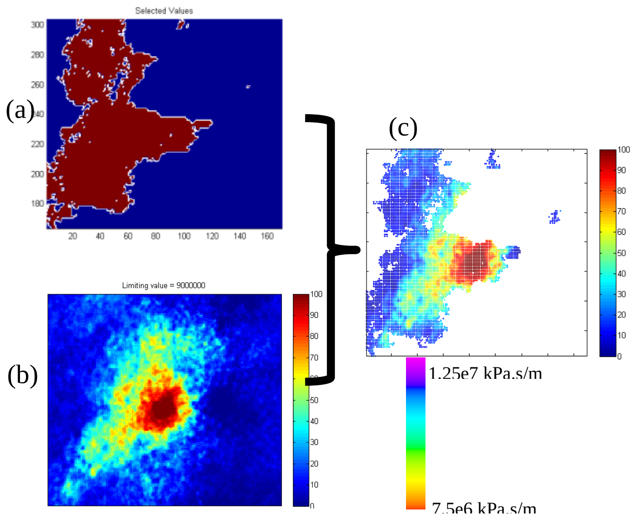

Figure 5. (a) The pass/fail slice. (b) The map of the percentage of total number of results within the threshold. (c) The selected cell values.

For a ranking scheme based on the normal distribution (i.e. one that identifies percentile values), it is essential that the ranking values we use adhere to that distribution (Rubin 2009). As can be seen from the histogram of the mean values shown in **Figure 6**, our ranking values meet this criterion. From this distribution we can then extract the required P10th, P50th, and P90th results from the input realization datasets as shown in **Figures 7a, 7b, and 7c**.

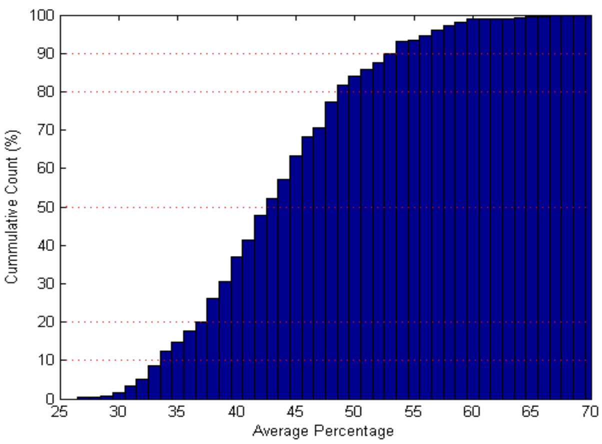

Figure 6. The cumulative distribution of the average percentage of the cells included from the mean inversion result.

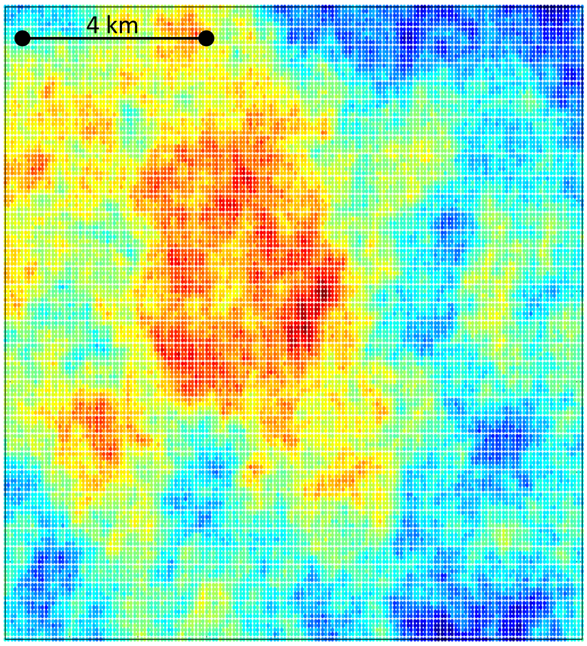

Figure 7a. The P10th realization.

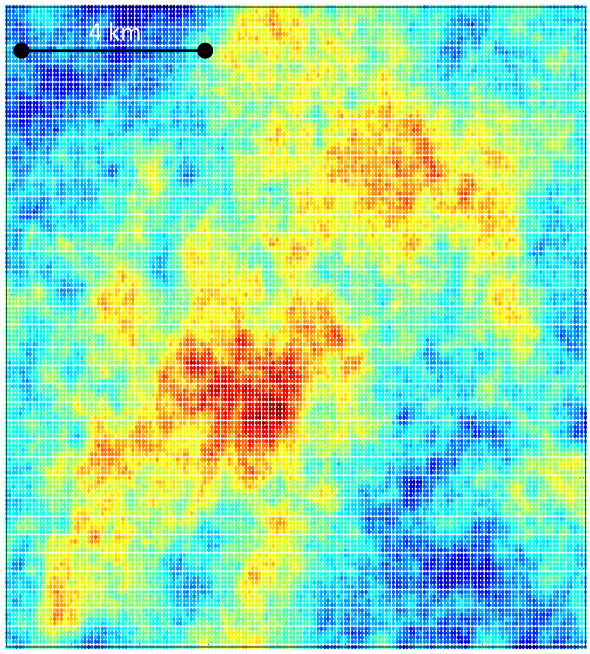

Figure 7b. The P50th realization.

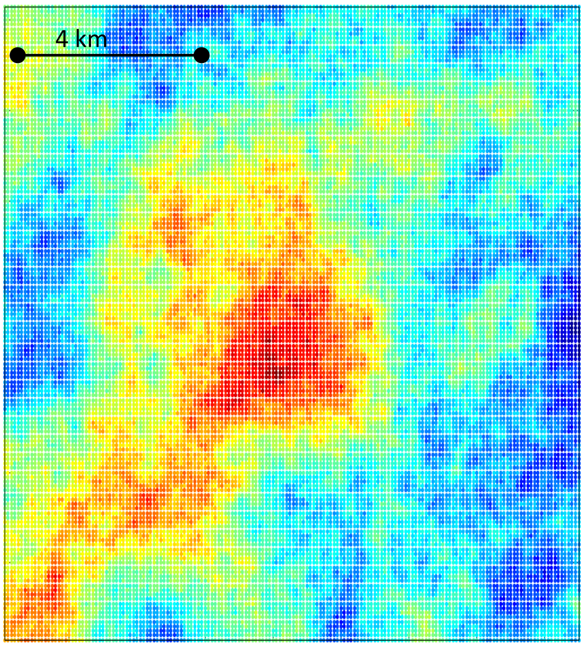

Figure 7c. The P90th realization.

CONCLUSIONS

Generating a wide variety of inversion results is not advantageous unless they can be ranked in terms of their relative likelihood. Although we can combine the results, by taking the mean for example, this is not a true stochastic inversion result. Other suggested ranking methods are based on transforms (porosity or other derived properties) that add an additional level of interpretive complexity and, more importantly, uncertainty.

The ranking methodology presented here is used to rank the realizations depending on their adherence to a geomorphological feature (in this example, a mitten-shaped tidal bar) that was recognised from the deterministic unbiased seismic inversion and confirmed by well logs and cores. This method is applicable wherever one or more major distinctive geomorphological features can be recognised.

Using this method we were successful in ranking the stochastic realization and identifying, for example, the P10th, the P50th, and the P90th realizations over this area of interest which could then be used for further reservoir simulation modelling work.

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