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Stochastic simulation of microseismic events not recovered from monitoring records

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Summary

Events estimated in microseismic data processing account for only a fraction of the microseismicity generated during a hydraulic fracturing experiment. Therefore, an uncertainty analysis of microseismicity-derived attributes is necessary to evaluate the impact of our limited knowledge of the microseismic information into the characterization of induced fractures. This study highlights the importance of incorporating tools from Geostatistics into the analysis of microseismic information. In the current application, I use Sequential Gaussian Simulation to estimate maps of location and probability of magnitude of microseismic events not recovered from the monitoring records. The simulation is performed using the observed microseismic event locations and their magnitudes as conditioning points. Spatial continuity of event magnitudes expressed in the form of variogram models and an assumed distribution of magnitudes, serve to constrain the simulation process. The result from the simulation is a map of microseismic event locations where every point in the map presents an associated magnitude distribution of probability. By thresholding the events with smaller magnitude an estimation of the location of events not recovered from the microseismicity records is obtained.

Introduction

Microseismic monitoring involves the passive recording of microseismic events produced during the injection of fluids at high pressure into rock formations (Maxwell et al., 2010). Depending on the prevalent signal to noise ratio (SNR), and the distance and orientation of the recording stations, only a fraction of the microseismicity generated during the injection process is recovered from monitoring records (e.g., Haney et al., 2011). Moreover, assuming a Gutenberg-Richter distribution of magnitudes (Gutenberg and Richter, 1944) it is possible that the fraction of induced microseismic events not represented in the processing results is larger than those identified during data processing. The attributes of observed microseismic events are used for the interpretation of different aspects of the fracture produced during the injection process (Maxwell, 2010). Therefore, an assessment of the uncertainty introduced due to our limited knowledge of the complete set of generated microseismic events is desirable for a better evaluation of the interpreted fracture's properties. In this study, such evaluation is accomplished through the use of Geostatistics.

Geostatistics involves the application of statistical concepts to geological variables. Simulation techniques are a part of Geostatistics that aim at providing numerical models to assess the uncertainty of geological variables (Deutsch, 2002). Uncertainty assessment through the use of simulated models has been applied into the estimation of connected pore volume (Srivastava, 1990), determination of velocity distributions (Lo, 1994), estimation of reserves (Derakhshan and Deutsch, 2008), and a broad amount of other applications of reservoir characterization (e.g., Strebelle and Journel, 2001; Ren et al., 2007; Deutsch, 2010; Le Ravalec-Dupin et al., 2011). Sequential Gaussian Simulation (SGS) is a simulation technique that involves the transformation of all the variables of interest into a Gaussian space (Deutsch, 2002). Using SGS, I obtain a numerical model where every point in a grid is a microseismic event with a magnitude distribution of probability. By thresholding the magnitude of the simulated events a map of new probable microseismic locations is generated.

Method

The simulation method is described using an example with a synthetic cloud of 130 microseismic event locations (Figure 1). The synthetic event locations are generated assuming a homogeneous Poisson point process (Lantuejoul, 2002). Event magnitudes are assigned randomly following a Gutenberg-Richter relationship with b = 0.75 (Figure 2a). Assuming that the synthetic events (observations) correspond to the larger magnitude events produced during the injection process, only magnitudes from the lower part of the distribution are assigned. The simulation steps are summarized as:

- Debiasing of the experimental distribution of magnitudes. Using the observed event magnitudes a probability function model is fitted. In this synthetic example, the model is known and directly assigned (Figure 2a).

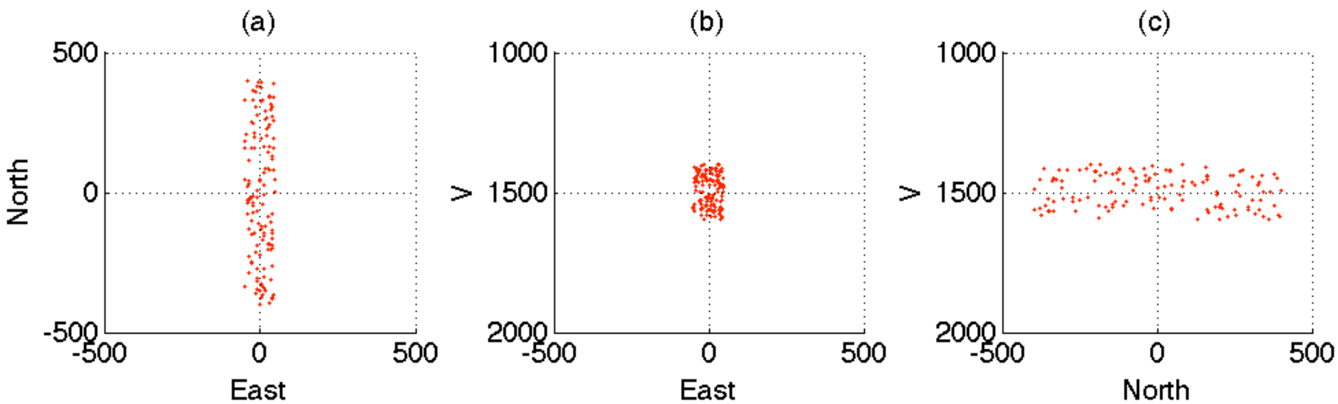

Figure 1: Synthetic locations of microseismic events.

- Using the fitted probability model, the observed magnitudes are transformed to a Gaussian space (Figure 2b).
- Variogram modeling. In this step, the main directions of continuity are found by analyzing the geometrical distribution of the microseismic cloud. Presumably, these directions are also linked to the geomechanical properties of the medium (Maxwell, 2011).

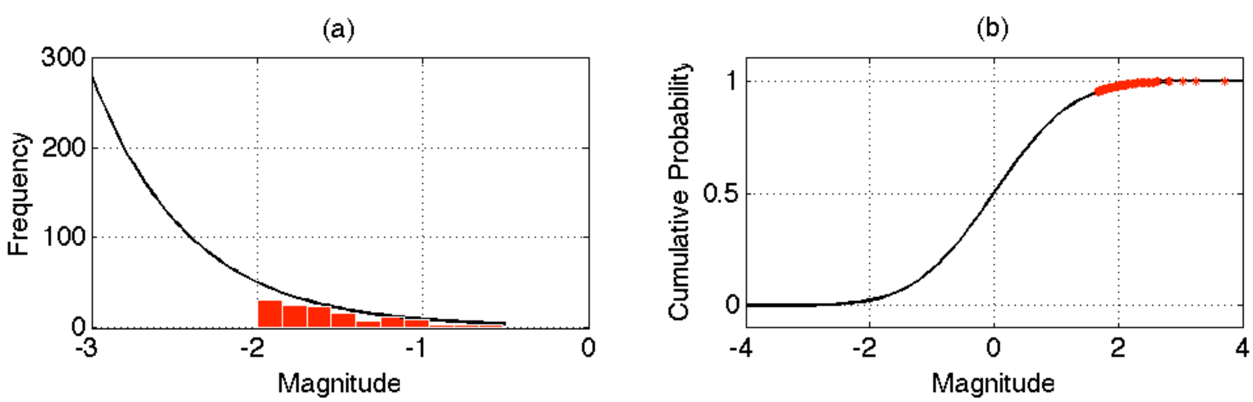

Figure 2: (a) Histogram of synthetic event magnitudes (red bars) and Gutenberg-Richter model that fits the synthetic observations (black line). (b) Experimental magnitudes transformed into a Gaussian space (red dots). The black line corresponds to a Normal CDF.

- Sequential Gaussian Simulation (Figure 3a).
- Transformation of simulation results back to original units (Figure 3b).
- Estimate statistical properties of the simulated values (Figures 4 and 5).

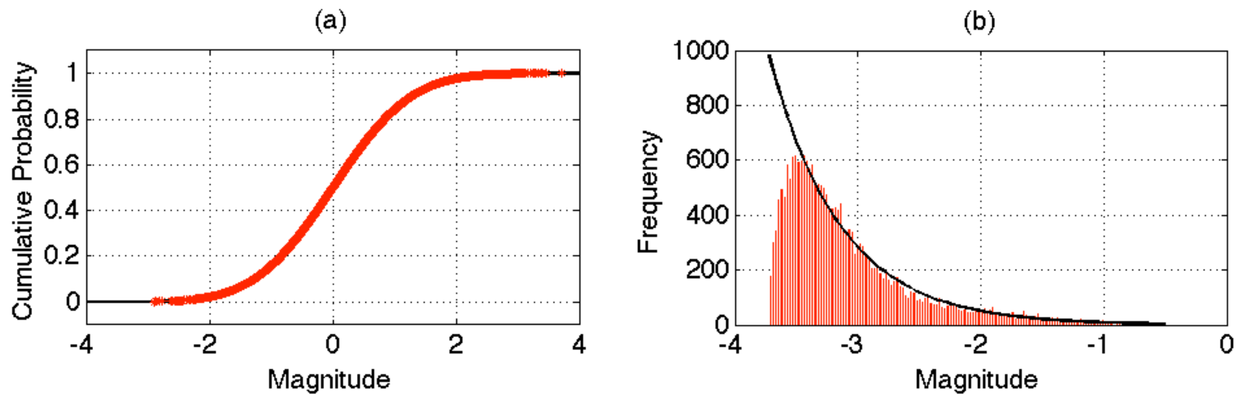

Figure 3: (a) Cumulative probability distribution of magnitudes of one realization of SGS (red dots). (b) Histogram of magnitudes of simulation results transformed back to the original magnitude units (red bars). Overlying the histogram is the assumed Gutenberg-Richter model (black line).

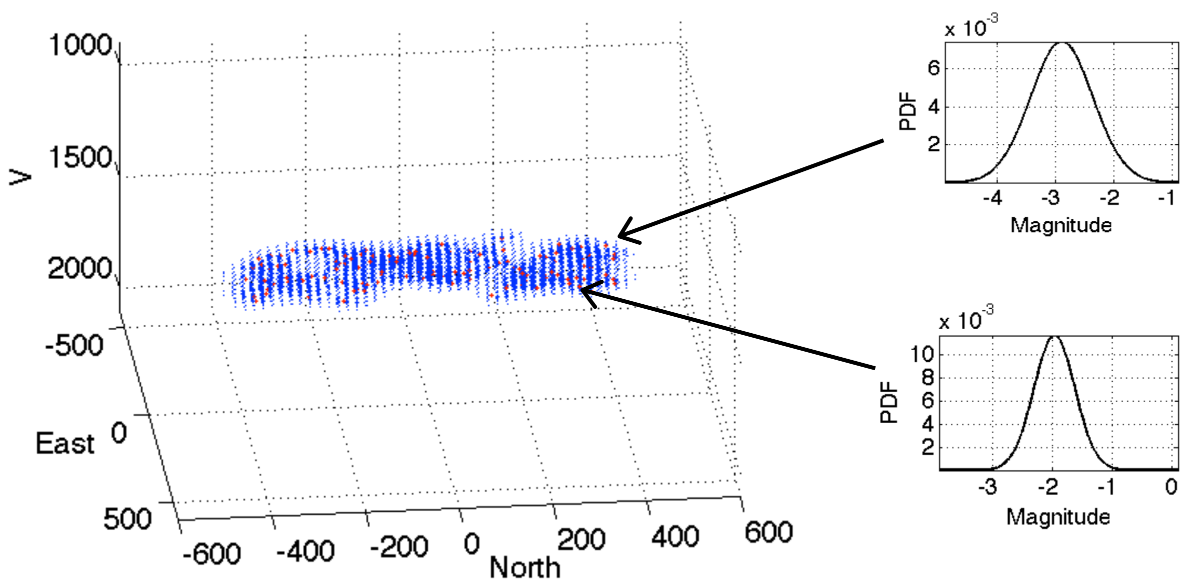

Figure 4: Map of simulated locations of microseismic events with average magnitude above -2.9 after 1000 SGS realizations (blue dots). Every dot has an associated magnitude distribution of probability (small boxes on the right). In this image the size of the dots are proportional to the average magnitude in each distribution. The synthetic (observations) conditioning events are plotted with red dots.

Each realization of SGS provides a map of magnitude distribution that is consistent with the assumed Gutenberg-Richter relationship, the variogram models and the conditioning information (observations). After an adequate number of realizations, statistical analysis of the simulation results allows uncertainty assessments of microseismicity attributes such as fracture density (number of simulated events above a magnitude threshold over the total of grid nodes, Figure 5), amount of energy involved in the generation of microseismic events, size of the stimulated volume. Considering that the magnitude of a seismic event is related to the fault plane dimensions, attributes like connectivity between events above a certain magnitude can be of significant interest to interpret the volume of the fracture contributing to the well's productivity.

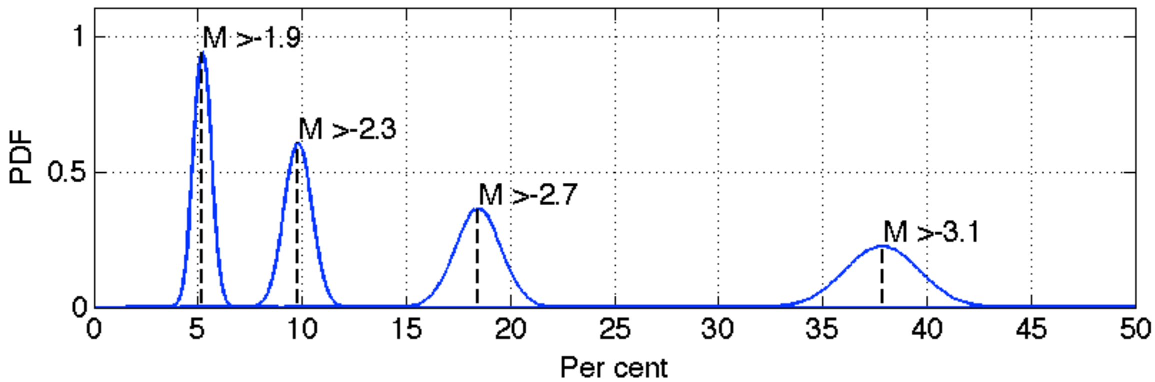

Figure 5: Probability distributions of percentage of nodes in the grid domain with simulated magnitudes above a specified value.

Conclusions

Practical limitations imposed by the positioning of monitoring stations and the prevalent SNR make impossible to recover the locations and attributes of all microseismic events generated during a hydraulic injection experiment. Consequently, it is important to establish methodologies that allow the assessment of the uncertainty introduced by our limited knowledge of microseismic information. In this study, I exemplified a methodology for such evaluation through the use of Sequential Gaussian Simulation. An important advantage of this methodology is that additional information can always be incorporated during the simulation process to obtain realizations consistent with all available knowledge about the medium. Main disadvantages rest on the susceptibility of introducing errors into the simulation results if the assumptions made are not valid. Potential applications of the methodology lie in the evaluation of all microseismicity-derived attributes in terms of the uncertainty associated to a limited knowledge of the total number of events produced during the injection process. This work highlights the importance of incorporating geostatistical tools into the analysis of microseismic data.

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