



## **A Bayesian 3D data fusion and unsupervised joint segmentation approach for stochastic geological modelling using Hidden Markov random fields**

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It is generally accepted that 3D geological models inferred from observed data will contain a certain amount of uncertainties. The uncertainty quantification and stochastic sampling methods are essential for gaining the insight into the geological variability of subsurface structures. In the community of deterministic or traditional modelling techniques, classical geo-statistical methods using boreholes (hard data sets) are still most widely accepted although suffering certain drawbacks. Modern geophysical measurements provide us regional data sets in 2D or 3D spaces either directly from sensors or indirectly from inverse problem solving using observed signal (soft data sets). We propose a stochastic modelling framework to extract subsurface heterogeneity from multiple and complementary types of data. In the presented work, subsurface heterogeneity is considered as the “hidden link” among multiple spatial data sets as well as inversion results. Hidden Markov random field models are employed to perform 3D segmentation which is the representation of the “hidden link”. Finite Gaussian mixture models are adopted to characterize the statistical parameters of the multiple data sets. The uncertainties are quantified via a Gibbs sampling process under the Bayesian inferential framework. The proposed modelling framework is validated using two numerical examples. The model behavior and convergence are also well examined. It is shown that the presented stochastic modelling framework is a promising tool for the 3D data fusion in the communities of geological modelling and geophysics.