# Common Uncertainty Research Explorer
# Uncertainty Estimation in Geological 3D Modelling

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## SUMMARY

Three-dimensional (3D) geological models describe geological information in a 3D space using structural data and topological rules as inputs. They are necessary in any project focused on / studying the properties of the subsurface as they express our understanding of geometries at depth. These models, however, are fraught with uncertainties originating from the inherent flaws of the modelling engines combined with input uncertainty. Because 3D geological models are often used for impactful decision making it is critical that all 3D geological models provide reliable estimates of uncertainty.
This research focusses on the effect of various structural input data uncertainty propagation in 3D geological modelling. This aim is achieved using Monte Carlo simulation uncertainty estimation (MCUE), a stochastic method which samples from predefined probability distributions that are estimates of the uncertainty of the original input data set.
MCUE is used to produce a series of altered unique data sets. The altered data sets are used as inputs to produce a range of plausible 3D models. These models are then combined into a series of probabilistic models to propagate uncertainty from the input data to a probabilistic model.
The present paper presents an innovative way to improve MCUE by using model clustering based on topological signatures and sensitivity analysis.

**Key words: Uncertainty, 3D modelling, Monte-Carlo simulations**.

## INTRODUCTION

Three-dimensional (3D) geological models are important tools for decision making in geoscience as they represent the current state of our knowledge regarding the architecture of the subsurface. As such they are used in various domains of application such as mining (Cammack, 2016; Dominy, 2002), oil and gas (Nordahl & Ringrose, 2008), infrastructure engineering (Aldiss, Black, Entwisle, Page, & R.L., 2012), water supply management (Prada, Cruz, & Figueira, 2016), geothermal power plants (Moeck, 2014), waste disposal (Ennis-King & Paterson, 2002), natural hazard management (Delgado Marchal et al., 2015), hydrogeology (Jairo, 2013) and archaeology (Vos, Bunnik, Cohen, & Cremer, 2015). By definition, all models are uncertain as they are approximations of the natural world (Bardossy & Fodor, 2001). A geological 3D model uncertainty is linked to errors about its inputs (Novakova & Pavlis, 2017), its processing (model building) and its output formatting (discretization, simplification).

Nearly all the methods proposed in the past few years (de la Varga & Wellmann, 2016; Jessell et al., 2014; Lindsay, Aillères, Jessell, de Kemp, & Betts, 2012; Wellmann & Regenauer-Lieb, 2012) are based on Monte Carlo simulation uncertainty estimation (MCUE). This approach was introduced in geoscience with the Generalized Likelihood Uncertainty Estimation (GLUE) (Beven & Binley, 1992) which is a non-predictive implementation of Bayesian Monte Carlo (BMC) (Camacho et al., 2015). Instead of estimating uncertainty from a single best-guess model, MCUE (Figure. 1) simulates it by producing a series of potential models through perturbation of the initial input data. The output models are then merged to estimate uncertainty.

This is achieved by replacing each original data input with a probability distribution function (PDF) thought to best represent its uncertainty called a disturbance distribution. The disturbance distributions are then sampled to generate many plausible models. In that sense, MCUE can be defined as a form of heuristic BMC that is focused on uncertainty propagation. In the present work, GeoModeller is the modelling engine used for MCUE.
Several metrics have been used to express the final uncertainty, including information entropy (Shannon, 1948; Wellmann, 2013; Wellmann & Regenauer-Lieb, 2012) and stratigraphic variability (Lindsay et al., 2012). The case for reliable uncertainty estimation in 3D geological modeling has been made repeatedly and the work presented here aims to further improve several points of MCUE methods at the post-processing steps (Figure 1).

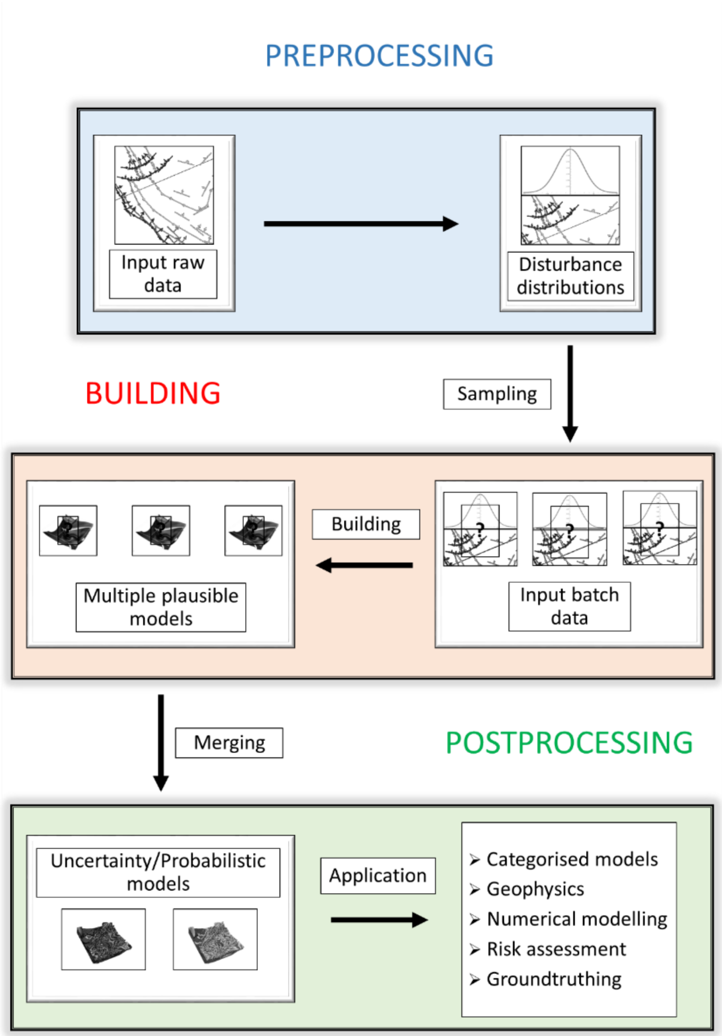


**Figure 1: MCUE procedure workflow.**

## PROPOSED METHOD AND RATIONALE

In the MCUE procedure, many plausible models (Figure 2) are generated and subsequently merged to derive a frequency model. The frequency model is interpreted as a probabilistic model and contains probability values associated to each lithological unit of the model in every model cell. Here, it could be argued that analytical solutions (where input uncertainties are analytically propagated through calculus) should asymptotically produce the same result as the MCUE procedure, therefore questioning its inherent value. Some arguments of cost vs efficiency can be put forth but they are by essence very case-dependent and cannot supply a sufficient case to the critic.

Although, a strong argument is found when turning the focus of uncertainty propagation as an exercise of statistical style to the relevance of such work. Here, the relevance is about the geological meaning of the displayed uncertainty, be it through MCUE or analytical methods.

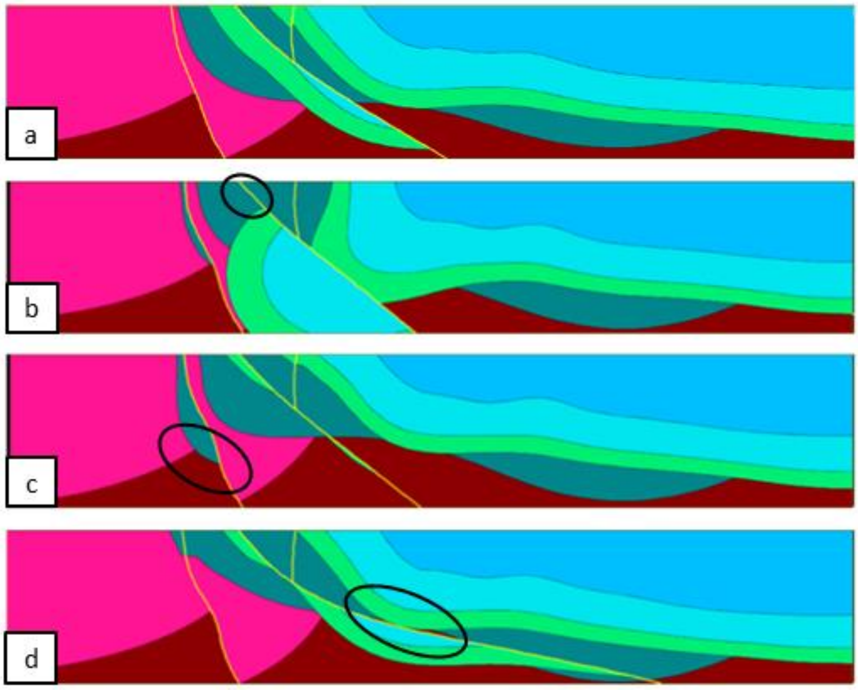


**Figure 2: Several cross sections of plausible models with noticeable topological differences (circled). Sub-Figure a is the initial static model. Each color corresponds to a separate geological unit.**

Because the MCUE method produces many models (before the merging step), it is possible to analyse each one separately to extract meaningful information such as their basic topological signatures. A topological signature is a record of the contact relationships of geological units. This kind of data is critical to geological problems as topology is key to many subsequent analyses and simulations that are run using geological models, such as fluid flow simulations, geophysical inversion, monitoring, thermal flow simulation, and engineering (Thiele et al., 2016; Thiele et al., 2016). Given that basic topological signatures are discrete, there is no universal continuity in the models generated through MCUE (Figure 2). Because of this, models may be topologically different at any possible degree. The implication is that a probabilistic or uncertainty model that merges all the plausible models indiscriminately (Figure 3) is, in fact, destroying information by operating a multi-convolution of likely yet incompatible outcomes. Deconvolution of such complex signals is an ill-posed problem because of its high non-uniqueness, and can be entirely avoided with appropriate analysis of the model suite prior the merging step.

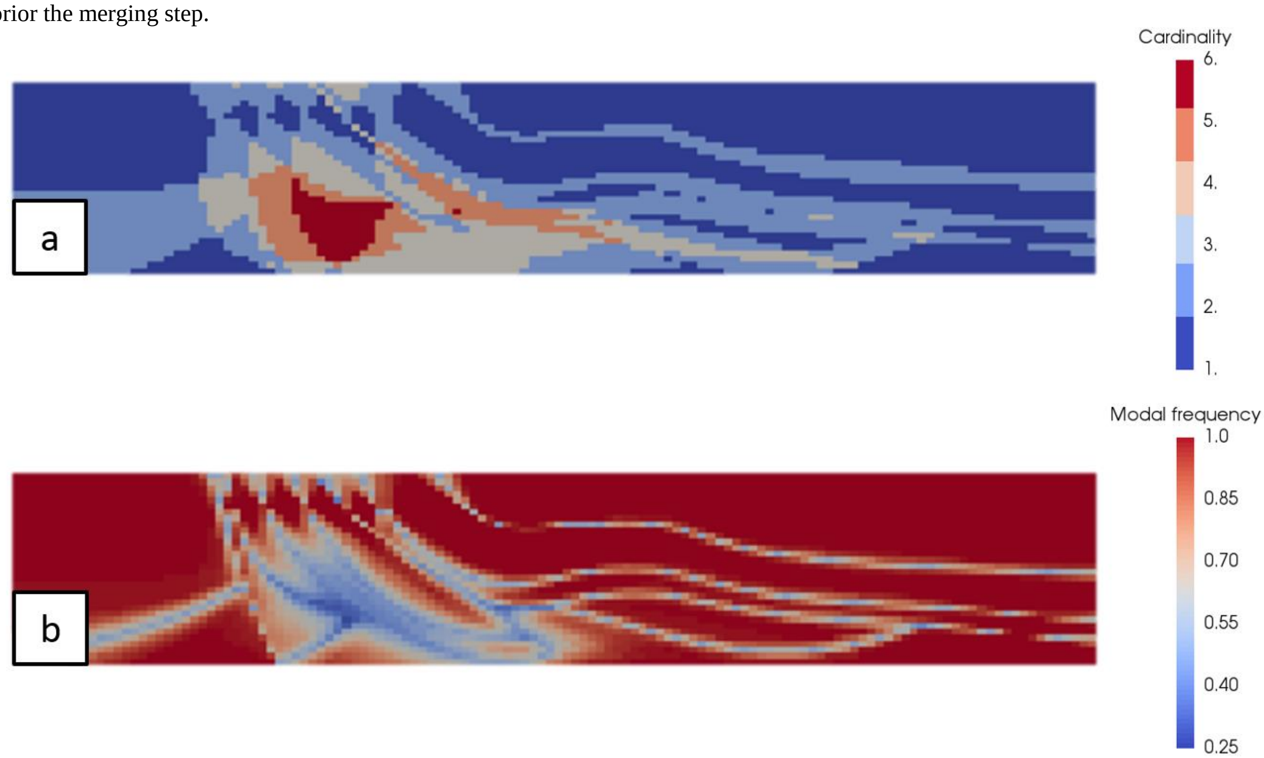

**Figure 3: Cardinality (number of observed units), indicating variability (a) and modal frequency (b), obtained from a complete merge.**

The proposed method involves the use of the clustering algorithm DBSCAN (Ester et al., 1996) on the individual topological signatures to produce probabilistic sub-models that incorporate plausible models with similar topological signatures. The sub-models can then be compared to one another or fed concurrently to other modeling/simulation engines for validation and/or further processing.

## RESULTS

Preliminary results show that clustering allows for varied outputs in terms of uncertainty propagation (Figure 4). The clusters are split about specific topological shifts where intercalary units are “squeezed” or “pushed out” and therefore modify the topological signature. Although the overall uncertainty remains unchanged, each sub-model shows reduced uncertainty and better topological consistency. This is of importance when MCUE results are used as geological constraints for geophysical inversion because topology impacts contrast models heavily.

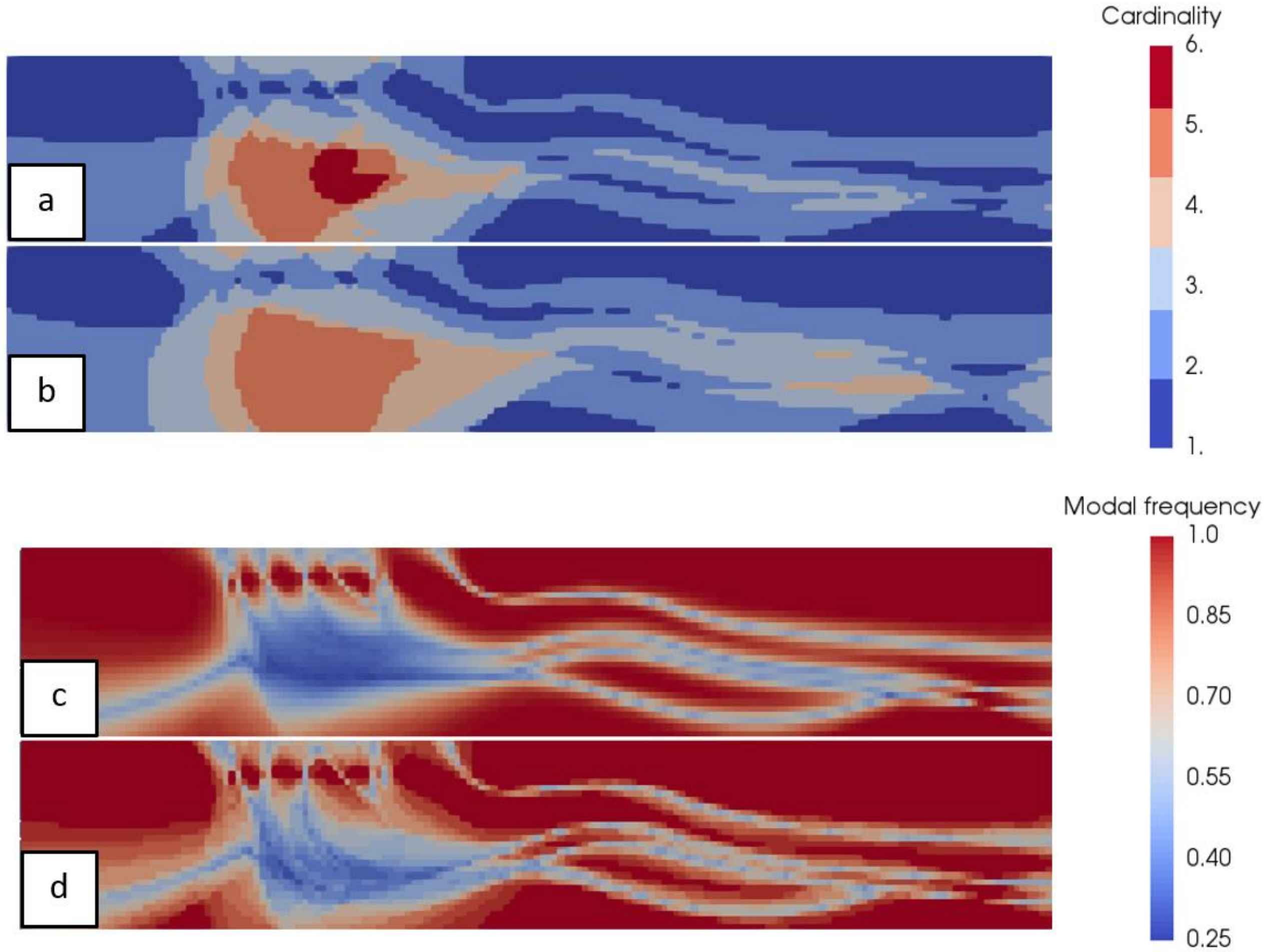


**Figure 4: Cardinality (a,b) and modal frequency (c,d) uncertainty models for two DBSCAN cluster merges.**

## CONCLUSION

By classifying the suite of plausible models into topologically coherent clusters, the proposed clustering procedure improves the post-processing steps in MCUE greatly and enhances the applicability of its results to other simulation tools. For instance, this work opens new possibilities for scenario testing. It also finds potential applications in dynamic/static, physical simulations, and is currently applied with success to probabilistic geophysical inversion (Giraud et al., 2017).

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