### Abstract

When ensemble-based methods are applied to a facies reservoir field in a truncated plurigaussian framework, the problem prior to data assimilation is to exactly reproduce a given faices field by means of a pair of Gaussian random field realizations and mapping based on a truncation map.

Intermediate problem includes the model parameter estimation: Gaussian random fields probability distribution and the truncation map.

Evaluation of the pairwise facies likelihood is the key to the entire parameter estimation method.

### 1. Problem

### Abbreviation GRF: Gaussian random field TPG model: truncated plurigaussian model TM: truncation map

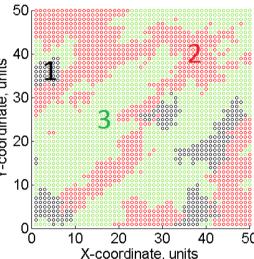


Fig. 1: Facies field

Problem is set to **exactly** reproduce a facies field  $F(x), x \in X$ , Fig. 1 by means of a TPG model.

First sub-problem is to estimate the probability distribution of a pair of stationary GRFs  $Y_1(x), Y_2(x)$ , and the TM, which maps a pair of GRFs into one facies random field.

The GRF distribution is specified by **covariance** function  $C_i(h) = Cov(Y_i(x+h), Y_i(x)), i = 1, 2,$ 

or **variogram** functions  $\gamma_i(h)$  (see Fig. 2 for relation).

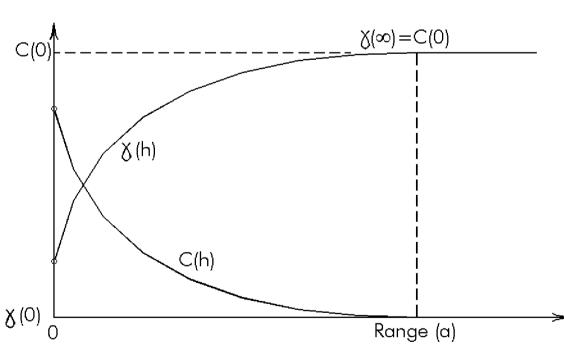


Fig. 2: Relation between covariance and (http://www.minetechint.com/papers/droy-thesis/)

variogram

The TM can have different complexity depending on parametrization (e.g., Fig. 3).

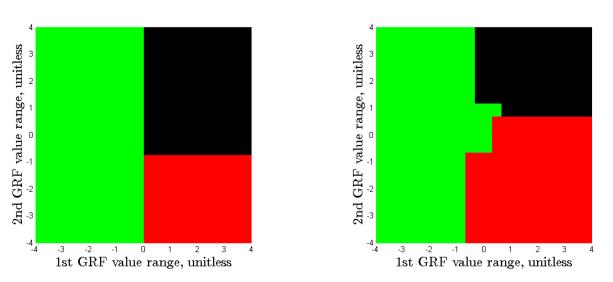


Fig. 3: TM examples with same proportion set

# Duplicating initial facies realizations using the truncated plurigaussian model

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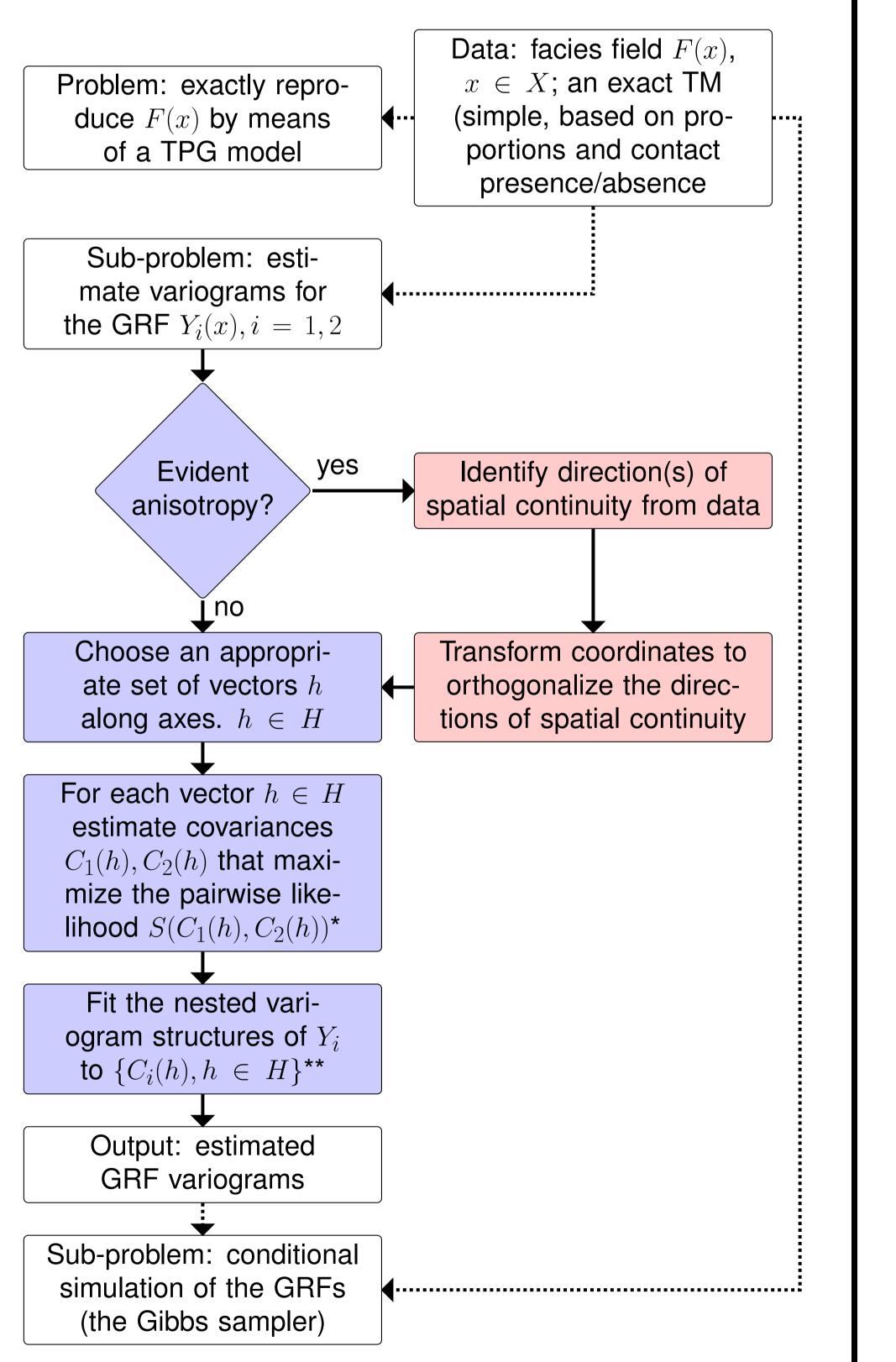
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More complex parametrization can be subject to an estimation and may result in a better data fit.

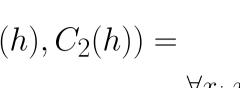
Second sub-problem is the conditional TPG simulation of Gaussian variables by means of the Gibbs sampler, given observations of facies in every grid.

### 2. Existing method

The existing method by N. Desassis & D. Renards (in print) allows to reproduce the exact field given a TM. The TM choice prior to any GRF parameter estimation is rather simple: based on proportions and contact presence/absence (Armstrong et al., 2011).



\*For each given vector h, estimate  $C_1(h), C_2(h)$  that maximize the data pairwise likelihood



 $S(C_1(h), C_2(h)) = \prod_{\forall x_i, x_j \in X | x_j - x_i \approx h} P\Big(\Big[\big(Y_1(x), Y_2(x)\big) \in I(x_i)\Big]$ 

 $\cap \Big[ \big( Y_1(x+h), Y_2(x+h) \big) \in I(x_j) \Big] \Big],$ 

where  $I(x_i)$  is the area on the TM associated to the facies observed at  $x_i$ .

\*\*Based on Desassis and Renard (2013).

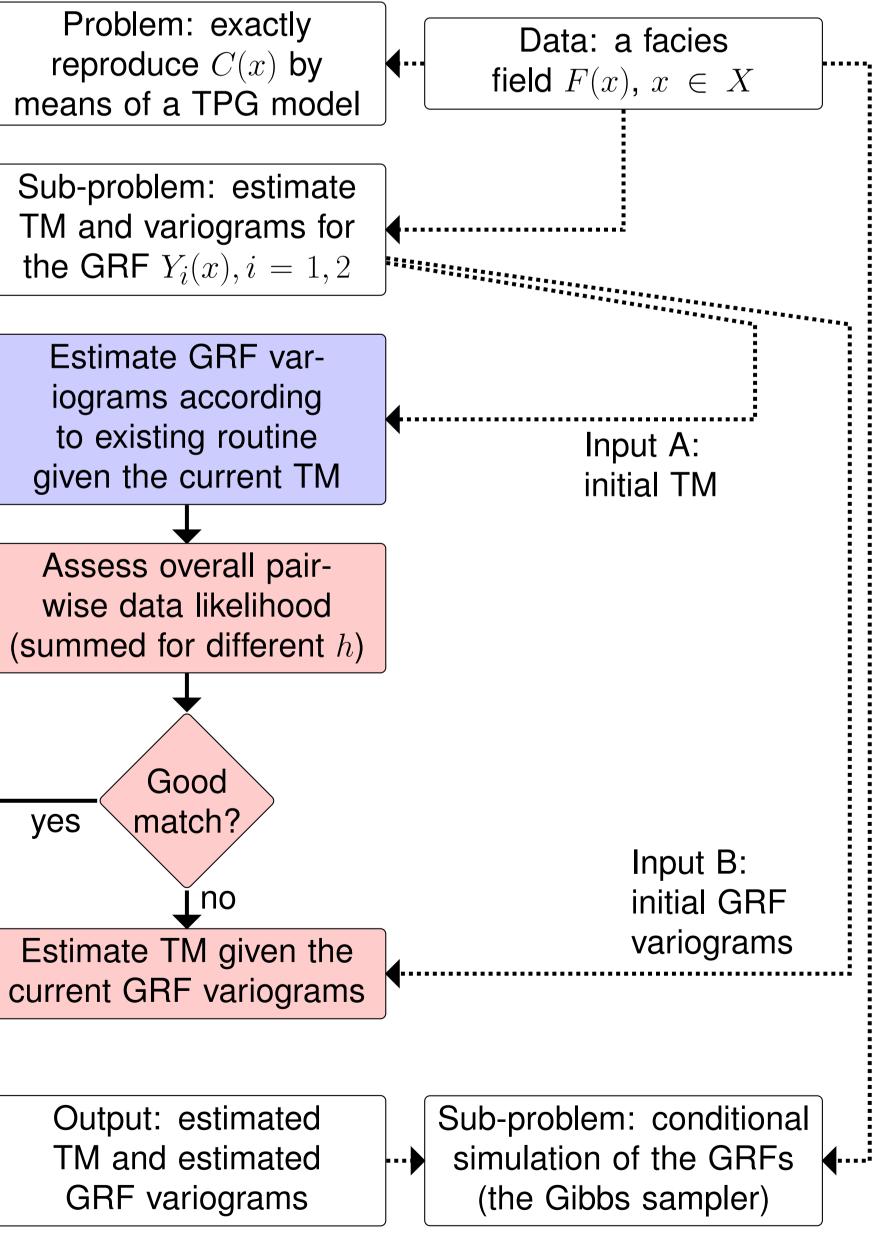
## 3. New workflow

An initial assumption might include a TM estimate (input A),

or an initial assumption might give the GRF distribution (input B). Both sets of parameters (TM and GRF variograms) can be reestimated conditional to each others based on the maximum pairwise likelihood.

The TM estimation uses a product of pairwise likelihood functions for different h.

Only terms corresponding to shorter correlations are multiplied to achieve reasonable computational time.



It is better to finish the estimation loop with GRF variogram estimation which is much faster computationally.

One cycle is usually sufficient to provide a useful estimate of a TM and the GRF variograms whether we start with input A or B.

0.08 0.07-0.06-Fig. 4: Auto-variograms and **GRF** N ВF one is unconditonal simulation? Acknowledgments

Entire problem solution is a pair of GRF realizations conditional to the facies field throughout the TM mapping.

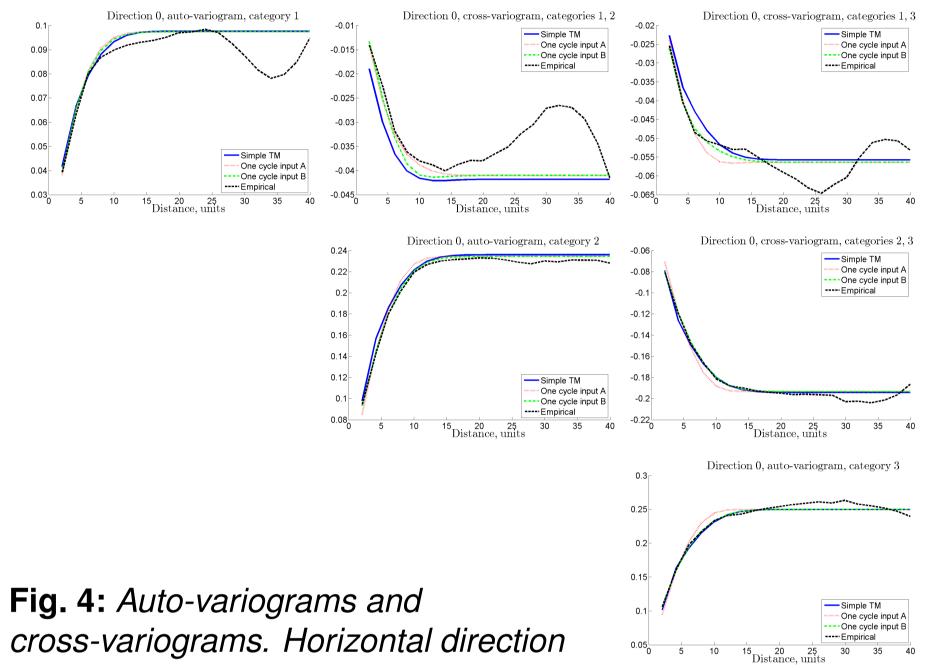
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References

Armstrong, M., Galli, A., Beucher, H., Le Loch, G., Renard, D., Doligez, B., Eschard, R., and Geffroy, F. (2011). Plurigaussian Sim. in Geosci.. Springer Berlin Heidelberg, 2nd revis. edn. Desassis, N. and Renard, D. (2013). Automatic variogram modeling by iterative least squares: Univariate and multivariate cases. Math. Geosci., 45(4):453-470.

### 4. Results

Increase in the likelihood function is reflected in an improvement in indicator variograms fit. We plot the empirical indicator auto-variograms and cross-variograms, Fig.4 and their theoretical equivalents from the estimated TPG models. We show the horizontal direction where the improvement was more significant.



The model fits the data well if the conditional GRF realizations 'look like' unconditional GRF realizations.

In Figure 5 one pair of realizations is a result of unconditional simulation and another pair is conditional to the facies field from Fig. 1 given the TM from Fig. 3 (second example).

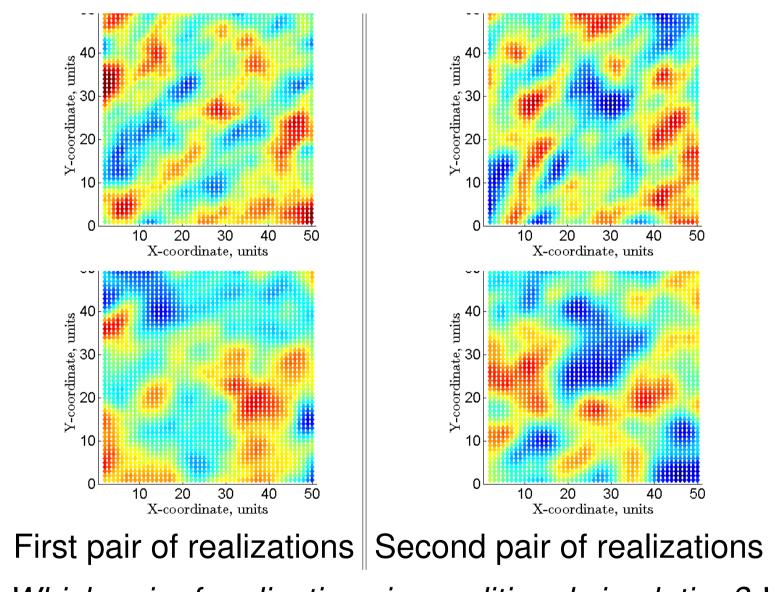


Fig. 5: Which pair of realizations is conditional simulation? Which