Global sensitivity analysis on a hybrid geostatistical model using a distance-based approach

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Abstract

Hybrid geostatistical models aim at mimicking depositional events. The resulting models have the capability to simulate realistic stratigraphic structures for a variety of environments. However, this family of algorithms requires a high degree of parameterization. Therefore, having a good knowledge of the model parameters sensitivity is vital for understanding the behavior of such models. In this study, a distance-based approach using kernel Multidimensional Scaling (MDS) is used to investigate the effect of parameters variability on the outputs of a turbidite model. This study is conducted on realistic seafloor topography and evaluates the relative influence of the size of the turbiditic lobes, the sediment source location, the deposition model and the noise used to randomize the lobe thickness. The findings of this analysis have important implications for understanding, conditioning and uncertainty analysis of these newly developed hybrid geostatistical models.

1. Introduction

Flow in the reservoirs is controlled by subsurface discontinuities and heterogeneities. The implementation of algorithms to model these structures has therefore always been a focus of petroleum engineers and hydrogeologists. Recent approaches have been developed that account for depositional processes. These methods, called stochastic surface model (Pyrcz and Deutsch, 2004), random genetic (Biver, 2008) or hybrid geostatistical model (Michael et al., 2010; Leiva, 2009), produce geologically consistent subsurface discontinuities by mimicking the physics of sedimentation. Their overall concept is to stack unitary geological objects using deposition and erosion rules. These models are simpler than process-based methods because they approximate the result of erosion and deposition by moving pre-defined geometrical patterns. As a result the simulation time is dramatically faster than physics based models (days vs. seconds).

Because of their geological realism and their CPU efficiency, these algorithms are good candidates for integration in traditional geomodeling workflows. However several challenges remain in terms of inverse modeling and conditioning. Fitting to data is strenuous because direct conditioning as performed in most geostatistical algorithms is not feasible. Instead, an iterative and possibly CPU-demanding approach is required (Kersenberg et al., 2001). Some research has focused on developing a direct conditioning but requires log interpretation (Michaels et al., 2010) or a large amount of wells (Zhang, 2009). In addition, those methods neglect seismic data. For this reason, we believe that an inverse approach is the most
appropriate for conditioning. This requires the perturbation of input parameters in order to match data. However, those input parameters are numerous, and subject to uncertainty which makes the problem difficult to solve. Performing a sensitivity analysis can then help determine which parameters are most impacting the data fit and hence focusing on those few parameters to solve the inverse problem through optimization.

The overall aim of this paper is to present an example of the application of sensitivity analysis to determine the parameters controlling the behavior of hybrid models. We first present the workflow of hybrid geostatistical modeling and the issue of conditioning. Then we will propose a methodology for sensitivity analysis tailored to tackle the complexity of such systems, applied to a realistic turbidite model.

2. **Motivation for a sensitivity analysis**

   a) **Review of hybrid geostatistical modeling**

   This family of modeling techniques mimics, in time, a sequence of depositional events. For this reason, hybrid geostatistical algorithms belong to the family of forward stratigraphic models. This approach is tailored to include concepts about the deposition mechanisms, similarly to processed-based methods, but in a computationally efficient way. This work focuses on algorithms modeling turbidite systems, as presented by Pyrcz (2004), Michaels et al (2010), Leiva (2009) and Zhang (2009). The general methodology of hybrid modeling can be divided in four main steps depicted in fig. 1:

   ![Figure 1: basic methodology for hybrid geostatistical modeling.](image-url)
1. **Interpretation of the depositional environment.** This step aims at understanding the sedimentation mechanisms occurring in the depositional environment and identifying the resulting geological structures (often called geobodies). This can be accomplished by analyzing process based models results, outcrops or analog data.

2. **Definition of the deposition rules.** By understanding the processes and quantifying the geobodies present in the depositional environment, it become possible to model them numerically. However, quantifying numerically the geological knowledge is a critical task resulting in simplification and modeling errors. The goal is to represent the geological system only as accurate as required for modeling purposes such as flow performance or reserve calculation.

3. **Simulation of the geobodies.** Simulating the full sedimentation of a geobodies using process-based models is complex and computationally expensive. In a hybrid approach, the object is simulated by using a predefined geometry. The parameterization of the geobodies consists of defining a template shape and size. In our case, a two dimensional shape is created by using a mathematical function (equation 1, Leiva 2009). Based on this shape, a thickness property is interpolated such that the center of the lobe reaches a predefined maximum thickness, creating a 3D structure of the lobe (Leiva, 2009). This thickness is stochastically perturbed by adding a Gaussian correlated noise (generated with a sequential Gaussian simulation, Goovaerts 1997). The noise aims at reproducing the small scale variability of the lobe’s structures, making them more realistic. Figure 2 summarizes the simulation of one turbiditic lobe. Note that geobodies of increased complexity can be generated. For example, one can link a channel to each geobody to produce more realistic features.

4. **Construction of the 3D model**
   a. **Deposition.** This step consists in finding a computationally efficient way to control the spatial placement and interactions between geobodies. For turbiditic lobes, the rules of deposition are often controlled by the underlying topography and the previously deposited geobodies. In general, those rules aim at reproducing the compensational stacking patterns that have a tendency to fill topographic depressions. For example, Leiva (2009) uses the D8 algorithm (O’Callaghan et al, 1984) to model the sediment flow and deposition to find the lobe location in accordance to the topography. Michaels et al. (2010) adopt a different approach where statistics defining the migration and progradation of the lobes are inferred from a process based model. These statistics are then used during the simulation to draw the parameters of each lobe conditionally to the previously simulated lobes.
   b. **Erosion rules.** Erosion is an important mechanism to consider since it can create some connectivity paths by eroding flow barriers. In Leiva (2009), the process is simulated accounting for flow direction. Topographic gradient and curvature are used to give erosion values at a given point in the topography under a lobe deposition. This erosion modifies the thickness of the underlying lobes. The intensity of erosion is more important in high gradient region. In Michaels et al (2010), the geometry of the removed materials is directly associated with each geobody.
   c. **Stacking.** Following the previously defined rules, the geometry, thickness and location of each lobe is sequentially computed. It is represented as 2D property maps (figure 1). The simulation time is approximately 1 second per lobe.
Equation 1 Definition of the 2D shape a lobe

\[ r = a \cos \theta, x = r \cos \theta, y = b \cdot r \sin \theta \]

where \( a = L, b = 1.8 \frac{W}{a}, L \) lobe length and \( W \) lobe width and \( \theta \in [-\pi, \pi] \)

Figure 2 Methodology to define the geometry of a lobe. The first step determines the 2D shape of the object (equation 1). Then, using \( a \), the thickness profile is interpolated. The last step is to add a gaussian noise to perturb the thickness of the lobe.

The result of the simulated lobes is a set of 2D thickness maps. For each of the 2D map, we can create the boundaries surface of the lobe. The final 3D model is produced by stacking those lobes on top of each other. Therefore it is not a grid but a purely geometric object composed of surfaces. Faulting and folding needs to be considered before gridding those structures for flow simulation.

b) Challenge of conditioning

Turbidite systems characterization has gained importance as off-shore exploration becomes more strategic and feasible. However, reproducing these complex features tends to be difficult with traditional geostatistics. The hybrid approaches would improve the quality of such models but their use is limited due to issues of conditioning to well and seismic data. The key problem is due to the use of a forward stratigraphic model.

**Conditioning lobe thickness from well data**

Log data gives information about lobe thicknesses at a specific location. From a sedimentological standpoint, the thickness of a lobe is determined by two factors: the amount of sediments added during the deposition process and the amount of sediment removed by a possible erosion event. If erosion is not accounted for, conditioning of the model requires that the algorithm simulates a precise thickness at the
data location. This is challenging since thickness is determined not only by the deposition rules but also by the initial paleo-topography and the previously simulated geobodies. Honoring lobes interfaces observed in the well data cannot be ensured (fig. 3). Modifying the thickness around the well to ensure a match is not a solution because it does not preserve the geological consistency of lobe geometries. Erosion adds complexity in the conditioning because it requires considering how much material has been removed. How much a lobe is eroded depends on the nature and location of the geobodies simulated on top of it, and there is no direct ways to forecast this except by simulating the entire process. Some work has been done for well conditioning. Michaels et al. (2010) propose a method for conditioning using well interpretation. Each of the depositional units needs to be identified in well data and ordered according to the different depositional periods. However, interpreting wells is time consuming and very uncertain. In addition, the correlation needs to be consistent with the forward stratigraphic model. The approach based on interpolation between logs used by Zhang (2009) necessitates a large amount of wells, which is unrealistic in deep offshore development, where only a couple of them are in general drilled.

Figure 3 Issue of thickness well conditioning. 1) A new lobe needs to be deposited and its thickness has to fit well data. 2) The geometry of the lobe is parameterized using statistics on the length, width etc… 3) the location of the maximum thickness point is chosen according to the depositional rules and the topography. 4) All previous steps have been performed neglecting the data. The match with the well data is then not ensured.

**Seismic data**

Seismic data is another important data source in turbidite reservoir development, especially since it contains thickness information. However, conditioning to such data is difficult because it requires controlling the algorithms such that the total thickness of the simulated geobodies match a thickness defined all over the field. Contrary to wells, those data don’t give information about the exact locations of some lobes. In addition, they don’t provide information about the sequence of deposition in time (stacking of the lobes along the well does). Conditioning with the method of Michaels et al. (2010) is then inefficient because it controls the placement of the lobes at a specific location and not all over the domain. Another method would be to use a servo-system in order to control the placement of the lobes according to the remaining depositional space. This approach is not effective because the constraint on the lobes placement is ineffective until the lobes start to reach the reservoir. At this point, it is too late to perform an efficient match. The sequential simulation can indeed be seen as a Markov process, the location and shapes of the first lobes can have an influence on the final thickness of sediments.

c) Usefulness of a sensitivity analysis

A solution for conditioning is to find the right set of input parameters that produce a conditioned model. In basin modeling, the inference of input parameters (posterior) matching observation has extensively
been studied. However, those methods don’t focus on fitting efficiently data at the reservoir scale. In our case, an efficient approach requires an optimization algorithm. This algorithm has to perturb the parameters needed to run a hybrid simulation. In Tab. 1, all the inputs needed to perform a simulation are listed and associated to the cause of their uncertainties. Those parameters are all highly uncertain parameters. As a consequence, all of them should theoretically be the object of a stochastic optimization. Since such an analysis is computationally impractical, we propose sensitivity analysis as an efficient way to determine the important parameters influencing the behavior of the algorithm. Insensitive parameters can be frozen to a constant value reducing the dimension of the inverse problem. The sensitivity analysis is also a useful tool to study the behavior of an algorithm.

### Table 1: Input parameters needed to run a simulation and associated uncertainties. The parameters in red are the ones included in the sensitivity analysis.

<table>
<thead>
<tr>
<th>Input parameters</th>
<th>Cause of Uncertainties</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Initial Paleotopography</strong></td>
<td>This topography is difficult to infer, especially with complicated tectonic history. Basin modeling and structural restoration are required but these processes are very uncertain.</td>
</tr>
<tr>
<td><em>The surface representing the sea floor before deposition</em></td>
<td></td>
</tr>
<tr>
<td><strong>Objects geometry</strong></td>
<td>Simplified parametric shapes are an approximation of geological produced by depositional processes.</td>
</tr>
<tr>
<td><em>It describes the geometry of the lobes.</em></td>
<td></td>
</tr>
<tr>
<td><strong>Size of the objects</strong></td>
<td>Uncertain because inferred from analog models with only partially similar characteristics. The thickness is particularly uncertain because it is often modified by an erosion process difficult to quantify.</td>
</tr>
<tr>
<td><strong>Source location</strong></td>
<td>Very uncertain because this location is not recorded in any geological structures. Moreover, sources can be multiple and possibly outside the domain</td>
</tr>
<tr>
<td><em>Provenance of the sediments. It controls the global location of the sediments in the simulation field</em></td>
<td></td>
</tr>
<tr>
<td><strong>Model of deposition</strong></td>
<td>Uncertainties related to the abstraction of complex physical processes into simplified rules.</td>
</tr>
<tr>
<td><em>It controls the stacking of the objects</em></td>
<td></td>
</tr>
<tr>
<td><strong>Model of erosion</strong></td>
<td>This is the same uncertainties than deposition</td>
</tr>
<tr>
<td><em>It modifies the shape of already deposit objects</em></td>
<td></td>
</tr>
<tr>
<td><strong>Variance and Covariance of the noise</strong></td>
<td>These parameters are very difficult to infer because it would require a variography of the surface of real lobes.</td>
</tr>
<tr>
<td><em>This component is added to randomize the thickness of the lobes.</em></td>
<td></td>
</tr>
<tr>
<td><strong>Presence of intermediate shale</strong></td>
<td>The vertical resolution of seismic survey is too coarse to identify it and sparse well data cannot provide enough spatial information</td>
</tr>
<tr>
<td><em>This shale is deposited between the objects and creates flow barriers</em></td>
<td></td>
</tr>
<tr>
<td><strong>Volume of the structure</strong></td>
<td>Uncertain because based on estimations computed from seismic data and structural restoration</td>
</tr>
<tr>
<td><em>This criteria controls when to stop the simulation</em></td>
<td></td>
</tr>
</tbody>
</table>
3. Sensitivity analysis for surface model

a) Presentation of the problem

Sensitivity analysis aims at studying the variation of an algorithm’s output with respect to changes in the input parameters. In the case of models representing physical and geological processes, two main issues complicate the task. First, the way that the model responds to changes in its inputs is not transparent since input parameters may interact in a nonlinear way. Secondly, the stochastic nature of the model makes the output results non-unique (one set of inputs can give different results if the seed of the random number generator is modified). This variability is not linked to the input parameters uncertainties (fig 4). It adds variation to the output models and makes the interpretation more difficult. To tackle these two problems, an approach based on kernel MDS is chosen. Kernel MDS (Tanaka, 1994) is a useful method that investigates non-linear structures in the data and removes noise effects. It allows extracting major features from complex data.

![Sensitivity analysis](image)

Figure 4: Sensitivity analysis studies how the variation of the input parameters influences the model outputs. When the model is stochastic (different realizations can be generated with the same set of inputs just by changing the seed), it introduces adds spatial uncertainty in the results. This variability is not linked to the input parameters.

b) Sensitivity analysis methodology

We use global sensitivity analysis to study the output when the input parameters are varied over their entire allowable range. The method has been successfully applied by Scheidt and Caers (2009) to study the sensitivity of a reservoir flow behavior in term channel characteristics (fig. 5).

Starting with multiple reservoirs generated with the hybrid model, a dissimilarity distance matrix is computed. Depending on the distance chosen (for example Euclidean or Hausdorff distance), this matrix describes how similar the models in term of structural features, geophysical response or flow properties (Suzuki, 2008). The distance measure should be chosen such that it is correlated with the response of interest. For example, a distance based on water breakthrough is relevant to study the connectivity between two wells but it is not appropriate to study the total volume of the reservoir.
The distance matrix is then used to map all realizations into a Euclidian Space $R$, using the MDS (multidimensional scaling) method. The result is a set of points in $n$-dimensional space, where each point represents a stratigraphic model. The spatial arrangement of the points corresponds as much as possible to the dissimilarity between models with the distance defined.

The spatial structure of the points is often non-linear, making their analysis difficult. Kernel methods to transform an Euclidian space $R$ into a new space $F$, called the feature space where the relationship between points is more linear. Linear tools for clustering and pattern detection can then be used in $F$ more successfully.

After performing the kernel transform, we cluster the models by applying a K-means algorithms in the $F$ space. The clustering reflects the dissimilarity distance. As a consequence, each cluster contains models with similar properties: it can be same architecture, same flow behavior or same stratigraphic response depending on the distance chosen. The number of clusters is automatically chosen by the silhouette method (Kaufmann, 1990).

A realization is associated with a set of input parameters, a set of output results (thickness, length of sediments package…) and the cluster it belongs to. For each cluster, it is possible to compute a standardized average value of input and output parameters of all realizations within each cluster. A cluster is then summarized by a set of input and output average values and can be seen as a point in $N_i + N_o$ dimensions ($N_i$ being the number of different input parameters and $N_o$ the number of different outputs).

For all combinations of input and output parameters, a linear regression is performed. The slope of the line obtained is used to plot a tornado chart. For each combination input-output, the length of the bar is defined by the computed slope. The higher the slope, the more influence input parameters have on the output results. This analysis relies on a linear relationship between.

### 4. Applications to a realistic system

#### a) General description of study

In this study we use the algorithm developed by Michaels et al. (2010) and modified by Leiva (2009). An extra step has been implemented to add a Gaussian noise to lobe thickness. The sensitivity analysis will focus on the following selected parameters: the location of the source, the thickness of the lobes, the parameters of the deposition model, the variance and the covariance of the added noise. The other input parameters are kept constant. The paleotopography is obtained from a realistic field termed Exxon II (fig. 6). The stopping criterion is either a target volume to reach or a predefined number of lobes. There are no intermediate layers of shale and the erosion is computed as presented by Leiva (2009). In order to study the full variability of the model, the seed of the random numbers generator is changed for each the realization.
Figure 5 Methodology of the sensitivity analysis. The aim of this workflow is to account for the non-linearity of the response while removing noise effect due to the spatial uncertainty.

b) Input parameters uncertainty

Source Location
Location of the source is uniformly distributed in a window of 3kms by 3kms situated at the top of the domain (fig. 6).
Possible source location

Base Surface

Figure 6 Uncertainty on the source location. The map represents the elevation of the initial topography.

Model of deposition

Two different depositional models are used by the algorithm, (fig. 7). The first one computed a probability map based on migration (lateral stacking pattern) and progradation (longitudinal stacking pattern) statistics and elevation. These statistics are inferred from the Exxon model (Michael et al., 2010). The second model is based only on topographic features. The two maps are then combined using the tau models (Journel, 2002). The resulting probability map is used to simulate the location of the lobes. The variation between 0 and 1 of the tau values emphasizes more or less on one of the models. With the statistics approach, the distance between a new lobe and the previously simulated ones is partly controlled by the statistics and they tend gather closely. With the second model, the distance between the two lobes is only function of the topography leading to a higher degree of freedom in the lobe placement.

Figure 7. Each of the deposition models produces different probability map of lobe location. Using the Tau model, it is possible to combine them. Depending on the value of the tau, one the model is more or less considered.
Size of the lobes
The size of the lobes varies in thickness before erosion but not in width and length. The length is set to 4000 meters and width to 2000 meters. The thickness is uniformly varying from 5 to 35 meters. The reason for varying thickness only is due to the high uncertainty of this component, knowing that most of the observed lobes have been eroded at the top. The original thickness is indeed not visible anymore and the intensity of the erosion very difficult to quantify.

Added Gaussian noise
The noise is simulated with Sequential Gaussian Simulation (Goovaerts, 1997). The two controlling parameters are the variance (intensity of the perturbation fig. 8) and the range of an isotropic covariance (spatial correlation of the perturbation). The Gaussian noise is generated with a range varying between 1000 to 7000 m. The variance is chosen such that the thickness perturbation varies between 0 and 10 meters. A higher variance would cause large changes in the shape of the lobes and make them geologically unrealistic. The spatial uncertainty then refers to the several alternative realizations generated with a given variance and co-variance model (fig. 4).

Figure 8. Gaussian noises generated with different variogram sills and ranges.

Input uncertainty vs. spatial uncertainty.
Before performing sensitivity analysis, it is important to quantify how much variability in the results is due to the input parameter uncertainty (size of the lobes for example) and how much is related to spatial uncertainty (location of the lobes). In the case of a dominant spatial uncertainty, a sensitivity analysis on the input parameters may be irrelevant. To quantify these different uncertainties, three series of runs are performed, as showed in fig 9:
1. Randomization of both parameters and spatial attributes (each run uses a different random seed to generate the parameters and a net random seed for the simulation).
2. The second series considers only input uncertainty (randomly drawing the inputs parameters for each simulation but keeping the seed of the stochastic algorithm constant).
3. The third series uses always the same input parameters but with different seeds for the stochastic algorithms.

For each series of runs, we compute the variance and the average thickness of 15 simulated lobes. In the first series, the average thickness is 2.4 meters with a variance is 3.1. For the second series, the average thickness stays almost the same but the variance decreases to 2.7 (23 % decrease). In the third series, the the values of the variance is 1.6 (>50% decrease). These results show that in this example, the variation of the outputs is due mainly to the uncertainty in the input parameters. As a consequence, a sensitivity analysis on the input parameters is relevant.

Figure 9. Sensitivity analysis is relevant if the output variance is mostly controlled by the input variability. Freezing the spatial uncertainty by choosing a constant simulation seed produces high variability outputs (2.7 vs. 3.1). Conversely, the output variability is low (1.6 vs. 3.1) when only spatial uncertainty is considered.

a) Result of the sensitivity analysis

Output: ratio length/width

3000 realizations of 15 lobes each are generated. For each of the realizations, the maximum length and width of the deposited sedimentological bodies is computed. The output parameters are the ratio between those two values, and provide information on the global shape of the sediments. To build the dissimilarity matrix, an euclidian distance is computed between the top of the reservoirs (pixel by pixel difference). The K-MDS algorithm maps then the matrix in the feature space.
The main influencing parameters are the distal location of the source (fig. 10). The location of the source influences the shape because when situated relatively onshore, the slope of the topography forces the lobes to expand longitudinally (progradation). When the source location is more offshore, the slope of the topography is almost flat and does not force the lobes to be deposited in a particular direction. The stacking patterns are “isotropic” (fig.11). The second most important input is the depositional model parameters because it controls how the algorithm behaves with different gradient in the topography.

Output: Average thickness of the package

With the same 3000 realizations and using the same distance, the average thickness of the sediments is computed. This parameter controls how the lobes distribute spatially. In a reservoir, the average thickness is important because it gives information on the total reservoir volume. The results show that three main
parameters control the thickness of the model (fig. 12). The most important is the depositional model because it controls how much the lobes are spread. The two others are the variance and the size of the lobes. It also makes sense because these two parameters control the thickness of the lobes: thicker lobes mean thicker depositional packages.

Figure 12. Results of the sensitivity analysis on the average thickness of the sediment package. Ys stands for the longitudinal location of the source, Xs for the lateral location.

**Single well mismatch**

For each of the 3000 realizations, synthetic wells are drilled inside the domain. The intersections with the lobes are recorded to define geological markers. The dissimilarity between two realizations is defined by the difference between the markers locations. A realization is also selected as a reference (base case). In order to select a representative one, all of the computed realizations are mapped in the Euclidian space with MDS using the previously defined distance. The selected realization is picked at the center of the cloud of points. The output parameter considered is the average error between the synthetic and reference wells. This study aims at determining which parameters controls the vertical spread of the lobes. The information could be useful when well data needs to be fitted.

The main controlling parameters are the depositional model and the noise variance (fig 13). The importance of the model is due to the fact that it controls the stacking of the lobes. For example, in cases where the model reproduces progradation patterns, a well situated offshore will only record a thin layer of sediments when the first few lobes are being deposited. The following lobes then move progressively towards the sea, closer to the wells. This leads to an increase in the amount of recorded sediments at the well location. As a result, the patterns observed in the log data are very specific, consisting of coarsening upward sequences, with lobe thicknesses increasing along the well. The noise variance is also important because it perturbs the thickness of the lobes. It is however more difficult to explain why the thickness of the lobe is not more influencing.

In general, several wells are drilled in a field and a very important feature to consider is the correlations between wells. This correlation controls the connectivity between them. This is a critical factor in history matching workflows.
Figure 13. Results of the sensitivity analysis on well mismatch. Ys stands for longitudinal location of the source, Xs for the lateral location.

Degree of correlation between wells
Two synthetic wells are drilled in the middle of the field, 2 km away. There are fairly close at the scale of the geological processes (one lobe is about 4 km long). The output parameter considered is the computed mismatch between the two wells. The dissimilarity matrix is the difference in the markers locations between two realizations. We study the parameters controlling the degree of correlation between two close wells. The results show that the covariance is the most important feature influencing the well correlations (fig 14). Indeed, if the range of the noise is smaller than the distance between the two wells, fluctuations in the lobes thickness will produce uncorrelated wells.

Figure 14. Results of the sensitivity analysis on the wells correlation. Ys stands for longitudinal location of the source, Xs for the lateral location.

Seismic mismatch
For each of the 3000 realizations, synthetic seismic data are computed using a geophysical forward model. The dissimilarity between two realizations is defined by the difference between their respective seismic responses. A representative realization is selected as a reference. The output values are the average error between the synthetic and reference seismic. Two different seismic responses are computed:
one at 25Hz for high quality response and one at 10Hz for a coarser response. This study aims at identifying what is controlling the structure of the reservoir.

For a high quality seismic, the most influencing parameters are the deposition model, the covariance, the variance and the source location. The reason why the size of the lobes does not influence the seismic response is probably due to the fact that only the thickness is varying, not the width and length. For the low quality one, there are no real predominant parameters because the data are not constraining enough.

![2D Slice 25 Hz forward seismic](image)
![2D Slice 10 Hz forward seismic](image)

**Figure 15. Results of the sensitivity analysis on seismic response.**

**True reference mismatch**

This example is a realistic application. The purpose is to determine the parameters that influence the match with the true top surface of Exxon II. 3000 realizations are performed. The stopping criterion is a target volume of sediments (the same amount as the one present in Exxon II) and not a predefined number of lobes. The results emphasize that the depositional model and the noise are controlling the mismatch.

![Reference top surface](image)

**Figure 16. Results of the sensitivity analysis on the top surface mismatch.**
5. Discussion and conclusion

A methodology for sensitivity analysis of hybrid geostatistical models has been presented. Based on Kernel Multidimensional Scaling, the approach enables to account for the interaction between parameters and the additional variability coming from the spatial uncertainties. The results outlined above show that the choice of the deposition model, the variance and covariance of the added noise are generally the most influencing parameters. Importance of the depositional model is because it determines the essence of the algorithm. The reason why the noise is so important is related to the shape of the deposition surfaces. The placement of the lobes is mainly controlled by the topography. The added noise modifies this topography; hence influence directly the placement of the lobes (fig. 17).

Figure 17. The lobe \( n \) is perturbed with two different noises. The first noise creates a low topography on the right of the lobe. The following lobe is logically filling it (left pictures). The opposite happened in the other case (right). This example shows the importance of the noise in the placement of the lobes.

These preliminary results are encouraging in term of applications to real data set and conditioning. Indeed, the model behaviors are dominated by those three parameters. To fit data, the dimension of the inverse problem can then be decreased to three parameters, which makes the process more feasible in term of CPU cost. The future work is now to develop an efficient way to modify these parameters in order to create conditional models. In addition, a sensitivity analysis based on the flow behavior would be interesting in order to determine which parameters needs to be perturbed in history matching workflows.
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