Math Geosci
DOI 10.1007/s11004-013-9455-4

Conditioning Surface-Based Geological Models to Well and Thickness Data

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Received: 17 August 2012 / Accepted: 9 March 2013

Abstract Geostatistical simulation methods aim to represent spatial uncertainty through realizations that reflect a certain geological concept by means of a spatial continuity model. Most common spatial continuity models are either variogram, training image, or Boolean based. In this paper, a more recent spatial model of geological continuity is developed, termed the event, or surface-based model, which is specifically applicable to modeling cases with complex stratigraphy, such as in sedimentary systems. These methods rely on a rule-based stacking of events, which are mathematically represented by two-dimensional thickness variations over the domain, where positive thickness is associated with deposition and negative thickness with erosion. Although it has been demonstrated that the surface-based models accurately represent the geological variation present in complex layered systems, they are more difficult to constrain to hard and soft data as is typically required of practical geostatistical techniques. In this paper, we develop a practical methodology for constraining such models to hard data from wells and thickness data interpreted from geophysics, such as seismic data. Our iterative methodology relies on a decomposition of the parameter optimization problem into smaller, manageable problems that

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Published online: 05 April 2013

are solved sequentially. We demonstrate this method on a real case study of a turbidite sedimentary basin.

Keywords Geostatistics · Event-based models · Quantitative stratigraphy · Turbidite

1 Introduction

The goal of most geostatistical simulation methods is to represent spatial variability as realistically as possible while constraining generated realizations to data. A wide variety of geostatistical methodologies have been developed to achieve this dual goal. Such methods can be classified based on how the spatial variability is quantitatively modeled, using variograms, training images (multiple-point statistics or MPS), Boolean models, surfaces or events, or physical processes. The last case is in fact not a geostatistical method per se; rather the goal of process models is to use physical equations in order to simulate the process by which the spatial structures were generated. In this paper, we consider the so-called surface-based or event-based geostatistical models (Xie and Deutsch 2000; Cojan et al. 2005; Pyrcz and Deutsch 2004; Pyrcz et al. 2005, 2006, 2009; Pyrcz and Strebelle 2006; Stright 2006; Abrahamsen et al. 2007; Biver et al. 2008; Miller et al. 2008; Michael et al. 2010; Sylvester et al. 2011). Such models are of particular relevance when the spatial structures have been created by a geological process in which the individual depositional or erosional events are easily identifiable, resulting in a complex layered structure, whether carbonate, clastic or magmatic in composition. At the same time, surface-based models do not aim to be physically realistic, which is the aim of the process model, but remain realistic in terms of the geometries generated by such processes. In this way, surface-based models aim to mimic the end result created by process models but at a fraction of the computational time. Excellent candidate applications for event-based models include sedimentological systems, particularly those in which depositional energy dominates the erosion processes, for example, lobe systems in turbidite reservoirs.

Variogram-based methods offer direct as well as consistent ways to constrain geostatistical models to a variety of data (i.e., without creating artifacts near data). In the reservoir context, they allow straightforward conditioning to wells and seismic data. As the spatial model becomes more complex, conditioning becomes more problematic. For example, variogram-based models are easier to condition than training image-based models, which are in turn less problematic to condition than process models. Direct conditioning in process models remains an outstanding challenge, and only methods for one-dimensional models have been proposed (Lesshafft et al. 2011). In this paper, the problem of conditioning surface-based models to well and thickness data interpreted from seismic surveys is treated. Concerning the current state of the art, Pyrcz et al. (2005) proposed a method based on a local adjustment to fit the neighboring well data. If the surface geometry contradicts data outside a tolerance, the geometry is rejected. The main limitation of such an approach is the computational time associated with the rejection method. The approach based on direct interpolation between logs used by Zhang et al. (2009) necessitates a large

amount of wells, which is unrealistic in certain reservoir development environments, such as those offshore. Michael et al. (2010) proposed a method for conditioning using well correlation, whereby each of the depositional units needs to be identified in the well data and ordered according to the different depositional periods. A possible solution for conditioning is to use an iterative approach, in which the output model is compared with the data and the input parameters updated in accordance to the mismatch. Solutions to such inverse problems have been extensively studied in two-dimensional stratigraphy modeling for basin models (Charvin et al. 2009), but the developed methods are not tailored to efficiently fit reservoir-type data.

In this paper, an effective and efficient sequential method for conditioning surface-based models to well-log and thickness data is proposed, based on an optimization of the parameters controlling the model global and local spatial characteristics. The actual surface-based model, also termed the forward model, is based on Michael et al. (2010), and consists of the stacking of lobe-shaped events by first parameterizing the lobe shape through a Boolean model of event thickness and then sequentially stacking the events using rules that are a function of topography and the statistics of progradation/migration inferred from analogs. The main contribution of this paper, however, lies in the conditioning. A full conditioning by minimization of the misfit function through forward model parameter perturbation is simply impossible because of the large number of parameters and the differences in the nature of the various parameters involved (continuous as well as discrete). Instead, we investigate a sequential optimization of subsets of parameters in which such subsets are created based on the logical supposition of these events. We apply the methodology to a real-field case study of a deep-water turbidite lobe system.

2 Review of the Surface-Based Model Used

2.1 Main Concept

Our model is based on the work of Michael et al. (2010), which considers the specific case of deposition of lobes in a turbidite reservoir, an environment particularly suited for the surface-based method. However any other surface-based model can fit within our conditioning framework. The main idea of the surface-based model is to start from a given base topography and stack events (or thicknesses) to create a new surface from that base. This process is then repeated by taking the new surface as the base surface on which the next event is stacked (Fig. 1). Depositional events have positive thickness, whereas erosional events have negative thickness. The event itself can be modeled in various ways, and the rules of stacking can be adapted to the particular geological environment; however, these two elements are the main modeling components of the model described in more detail below.

2.2 Thickness Modeling

A geological event can be represented by a two-dimensional thickness map creating a new surface on top of an existing surface (or eroding in the case of negative thickness). In this paper, and for the specific case study, we model lobe shapes, which

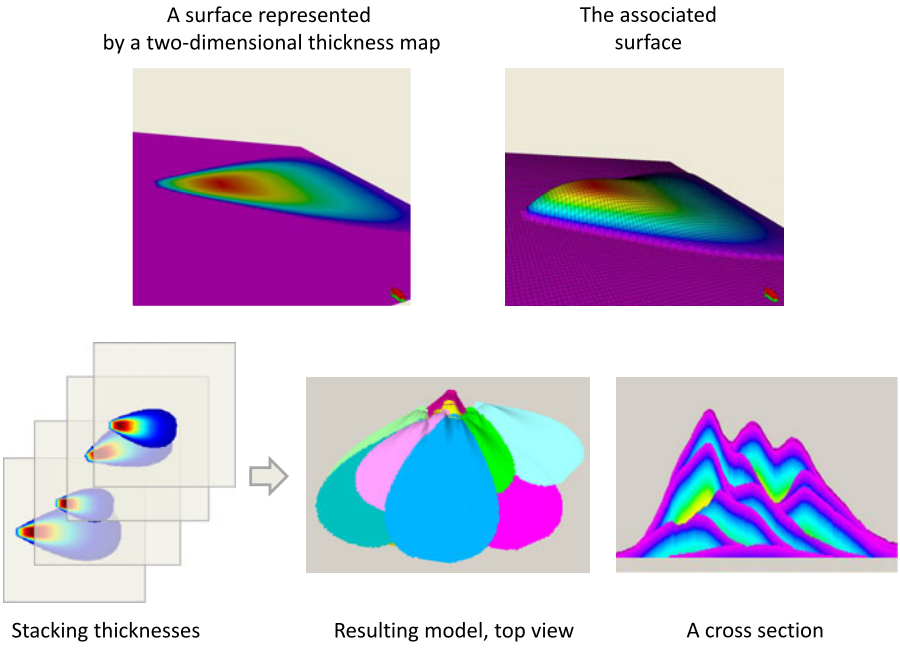

Fig. 1 Overview of the surface-based model, also termed the forward model

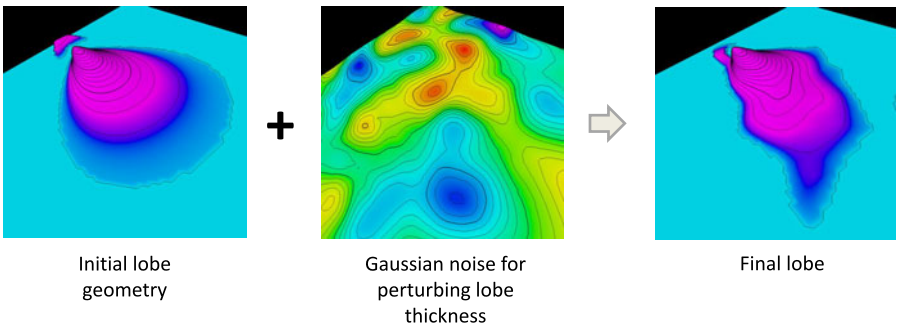

Fig. 2 Initial lobe geometry is perturbed by means of correlated Gaussian noise to provide a geologically realistic lobe shape

are represented by a simple Boolean shape (Fig. 2). Because the Boolean shape is too idealized, and also to provide some more flexibility in the conditioning, we add a two-dimensional stochastic component modeled as correlated Gaussian noise. The covariance structure, more specifically the correlation length and variance, are then additional model parameters. Other parameters relate to the Boolean shape, namely, the event maximum height, width and thickness. Table 1 summarizes the various model parameters. The noise component has an important role in allowing conditioning without creating artifacts. Because conditioning will be sequential (from bottom to top), the adding of a stochastic component to the Boolean shapes prevents the issue

Table 1 Summary of the various model parameters

Type	Parameters	Uncertainty representation	Source of uncertainty
Event geometry	Boolean shape	fixed	Statistics are inferred from analog data; shapes are idealized; erosion processes are not fully understood
	Width	cdf	
	Length	cdf	
	Thickness	cdf	
	Variance of added Gaussian field	cdf	
	Correlation length of the covariance	cdf	
Geological rules related to process	Progradation intensity	cdf	Abstraction of complex physical processes into simplified statistics are inferred from analogs process-based model analysis
	Migration intensity	cdf	
	τ-value	cdf	
	Erosion intensity	Fixed rule	
	Number of lobes	cdf	
	Coordinates (x_s, y_s) of sediment source	cdf	

of unrealistic upward propagation of any conditioning artifacts (e.g., thinner objects at the top and thicker ones at the bottom).

2.3 Event Placement

To place the event in two-dimensional space, an inhomogeneous Poisson point process model is used. The input to such a model is a locally varying intensity map based on two physical/geological constraints on the placement of events/lobes: (1) events tend to fill topographic lows and 2) distances between successive lobes are constrained by statistical knowledge of progradation and migration either from real systems, process models, or analog outcrop information. To model the placement of lobes, we translate each constraint into an intensity map that is scaled to $[0, 1]$ (hence, it is a probability map, Fig. 3). The information provided by these two maps is combined into a single map from which the location of a single event can be drawn. In the model, we parameterize the manner by which these two maps are combined by using the τ-model probability aggregation method (Journel 2002; Mariethoz et al. 2009). Hence, this single intensity map is parameterized by one single parameter, the τ-parameter, which determines how much the placement is driven by topography and how much it is driven by geological considerations from analogs.

2.4 Stacking and Erosion

With each depositional event, there is a possibility that some of the previous events will be eroded. Erosion is represented by a reduction of the thickness of the underlying layers. A fairly simple erosion model based on the curvature and gradient of

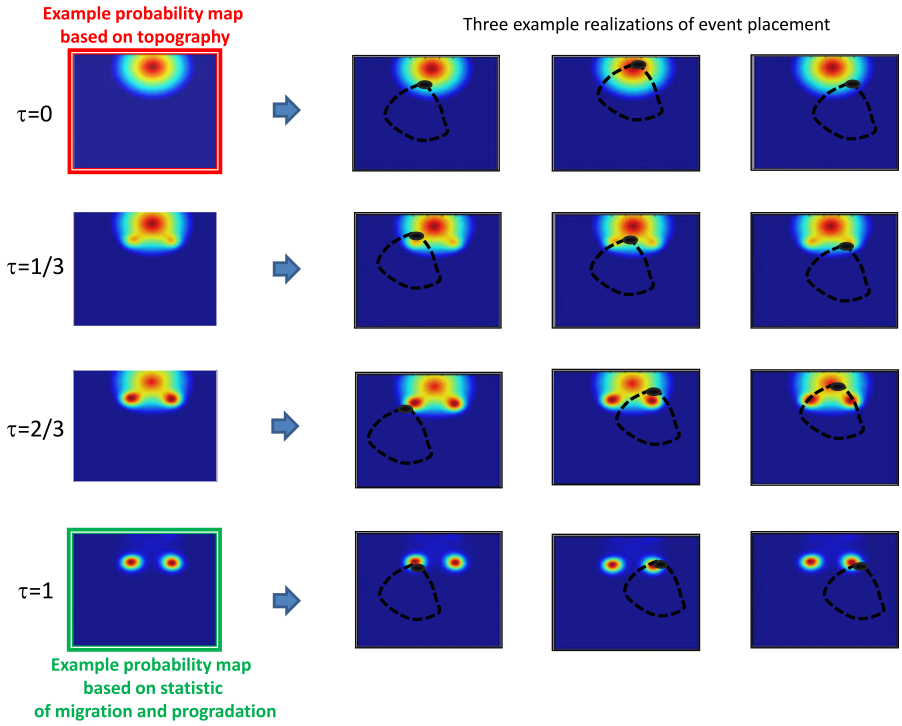

Fig. 3 Placing an event based on an inhomogeneous Poisson process with given local intensity map. The intensity map is based on two sources of information: topography and statistics of placement (progradation/migration). A single parameter τ determines how much each source of information influences the event placement

the deposition surface is used here. Locations with a high gradient will be eroded more than those with a low gradient because the flow energy is assumed to be lower in regions with a lower gradient. Erosion is more important at locations where the flow direction coincides with a high-magnitude gradient (high energy flow) and positive curvature (topographic relief). When computing the erosion intensity, maps of gradient and curvature are computed first. Then a flow direction map is estimated using the model of Jenson and Domingue (1988), which determines the direction of the steepest descent from any given location. The three maps (gradient, curvature, flow direction) are then normalized and combined. The result is a map that yields the erosion intensity at any given location underneath the new event. This erosion is evidently a simplification of actual erosion, which also depends on fluid and sediment properties such as grain concentration, viscosity, and flow thickness. In this study, an adjustment coefficient is used to estimate the thickness of eroded sediments from the relative erosion intensity. The model allows for the possibility of adding an additional intermediate shale layer between two events, reflective of a period with low energy. In many reservoir systems, the presence (or absence due to erosion) of this shale layer is important in terms of modeling reservoir connectivity.

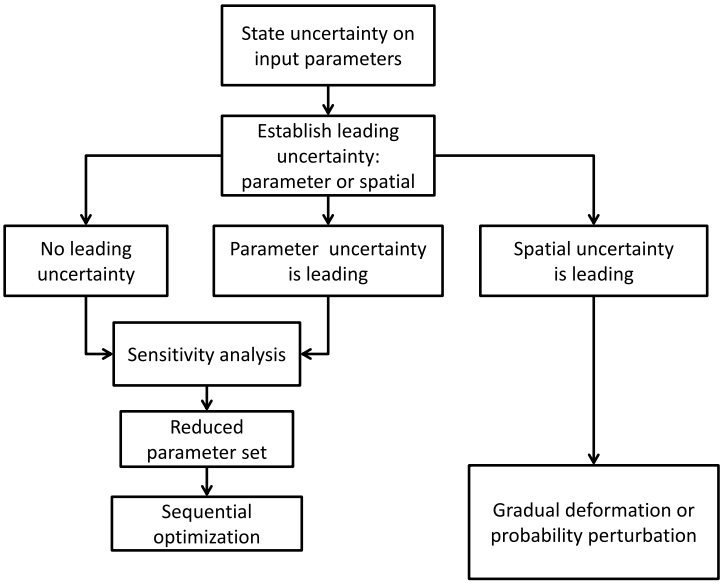

Fig. 4 Overview of the strategy for conditioning surface models

3 Methodology for Constraining to Data

3.1 Overview

The rationale for an iterative method for data conditioning is that it constitutes the most general way of conditioning the above-described surface-based model. Given the large number of parameters (Table 1) as well as the diverse nature of the parameters, a custom optimization scheme for solving the inverse problem of data conditioning is implemented. An overview of the strategy is given in Fig. 4. This strategy aims at making the ultimate optimization as simple as possible (a small number of parameters and divide/conquer approach). The three main steps of the approach consist in first establishing the leading source of uncertainty, then performing a sensitivity analysis on the corresponding parameters, and finally in performing a sequential optimization.

3.2 Establish Leading Uncertainty: Parameter Versus Spatial Uncertainty

In terms of the forward model (the unconditional simulation in geostatistical jargon), we can identify two sources of variation:

(1) Parameter uncertainty, considering the various parameters in Table 1.
(2) Spatial uncertainty, which is the uncertainty induced by the inhomogeneous Poisson process for a given fixed set of input parameters drawn from their respective CDFs (Table 1).

To aid the parameter optimization for data conditioning, it is proposed that the leading uncertainty (parameter vs. spatial) is identified first and, in the case that the leading

uncertainty is related to the input parameters, the most sensitive parameters towards matching the data is also indentified. Indeed, why perturb parameters that have little or no effect in better matching the data? To determine the leading uncertainty, two separate sets of runs are performed:

- **Set 1**: Various input parameters are randomly drawn, but the random seed for selecting the event locations is fixed. As a consequence, only parameter uncertainty is considered in the unconditional simulations.
- **Set 2**: The same input parameters are used for all the unconditional simulations, but the random seed to select lobe locations is changed. As a consequence, only spatial uncertainty is considered.

Date misfit is defined as the simple squared deviation between the simulated data and field data. The value of this misfit for all generated models is calculated. Then, for each set (set 1 and set 2), the variance in the data misfit values is computed. A high variance for a set means that the corresponding uncertainty strongly impacts the model variability in term of data fitting. Based on the two values, we can evaluate the relative importance of each type of uncertainty.

3.3 Sensitivity Analysis

Performing a sensitivity analysis of the input parameters can help determine which ones most impact the data misfit. The analysis can also help in validating the various modeling elements and determining whether the specified rules are consistent with the available data. The latter is an important tool because in surface-based modeling, some parameters are specified independently of the data (much like in Boolean modeling); hence, any inconsistency between the model and data would lead to the suboptimal constraining of such data. Because of the stochastic nature of events placement (spatial uncertainty), the relationship between input parameters and data misfit is also stochastic, possibly confounding the sensitivity analysis. A commonly used method for sensitivity analysis is experimental design combined with response surface analysis. To be efficient, such methods require models whose responses (the data misfit in this case) vary relatively smoothly with regard to the input parameters. Such is not the case for surface-based models; therefore, a distance-based model selection and sensitivity analysis is applied (Scheidt and Caers 2009; Caers 2011). The key idea behind this method is to define a dissimilarity distance between the simulated models. This distance indicates how similar two models are in terms of response (in our case, the data misfit). Based on these dissimilarities, the models are mapped in a low-dimensional space in which clustering is applied. Such mapping enables extraction of the underlying structure and the relations between models. Each cluster consists of models with similar characteristics. For each cluster, one can define the subset of parameter values used to generate the models. We identify the most influential parameters by studying how these subsets compare to each other.

3.4 Sequential Optimization

After the sensitivity analysis, the number of parameters to optimize may still remain significant. In some cases, the sensitivity analysis may not identify any leading

parameters. In such cases, we propose to solve the optimization problem sequentially. The idea is to divide the optimization problem into smaller parts that are easier to solve. These smaller sets of parameters are established as follows. First, the total set of parameters is divided into two subsets:

- **Subset 1**: Event-specific parameters, such as width, length, thickness, Gaussian noise, and location in space. Because these parameters can vary for each event, the number of parameters in this subset is a function of the number of events simulated. The Gaussian noise is represented by three parameters: the range, variance, and a gradual perturbation parameter r representing the amount of perturbation from a base noise realization. The latter is achieved using the gradual deformation method (Hu 2000). The basic idea behind the gradual deformation is to modify the stochastic simulation with a continuous parameter r. A small variation of this parameter r induces a small, gradual deformation of the noise.
- **Subset 2**: Global parameters, such as progradation/migration intensity, erosion (τ-value), and the location of the source.

The main idea is to first optimize subset 2 and then only optimize the parameters for each individual event sequentially, starting with the first event (the bottommost event) and ending with the last event (topmost). The following steps describe this sequential procedure in greater detail:

Step 0: In this step, parameter subset 2 is optimized using the polytope method (Nelder and Mead 1965). The input parameters associated with the individual events remain the same. Depending on the sensitivity analysis results, the inverse problem can be limited to the most sensitive parameters. Because only a few parameters need to be optimized, the problem can be solved relatively quickly in this way.

Once optimized, these parameter values are kept constant in the following steps:

Step 1 (event 1): The location and shape parameters of the first event are optimized, which requires finding the values of eight parameters: two parameters controlling the location (x_s and y_s, the location of the sediment source), three for the overall shape (width, length, and thickness), and three for the Gaussian noise (range, variance, r). In general, perturbing the first event of the sequence of deposition would induce possibly large changes in the model because it would impact all the following events. At the end of this step, the parameters of the first event are frozen, and its geometry is added to the initial paleotopography.

Step 2 to N_{events} (each step corresponding to event i): Starting from an initial guess, the location and geometry (subset 1) of event i is optimized. Because the first $i-1$ events are frozen, the forward model requires simulation of the deposition sequence from event i to the last event, which means there are $N_{\text{events}} - i + 1$ events to generate.

This sequential approach simplifies the parameter optimization problem by dividing it into similar steps. For each step, the optimization problem can be solved quicker because only one subset of parameters is being considered. This approach, termed a greedy approach, reduces the computational time taken by the forward simulations.

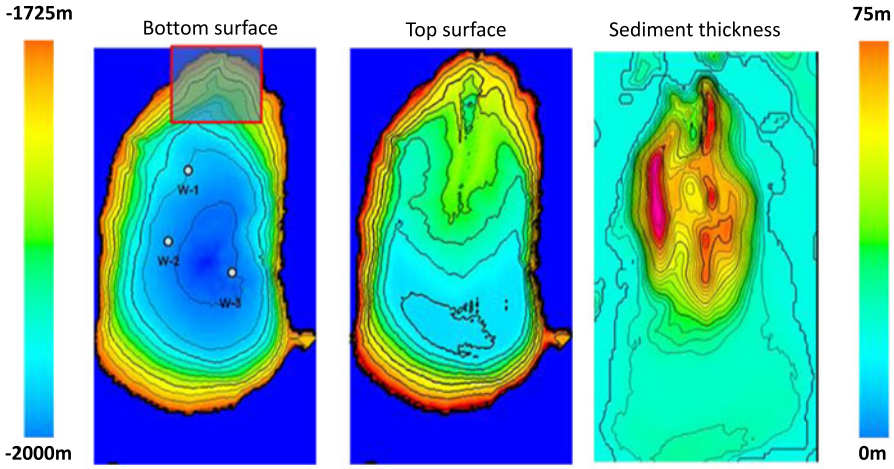

Fig. 5 Bottom and top surfaces interpreted from seismic data. The thickness is a result of subtracting these two surfaces. Sedimentation occurs mainly around the sediments source, which is assumed to be a single source and located inside the red window

4 Case Study

4.1 Description

The workflow is applied to a real data set originating from a Pleistocene turbidite system in the East Breaks mini-basin, western Gulf of Mexico (Miller et al. 2008). This basin is the fourth mini-basin in a chain of four that show less erosion and more lobate-like geobodies. The basin is 8 km wide and 16 km long (Fig. 5). The lobes in this case study are at storey set scale and recognized by a break in the stacking pattern, a rapid facies change and widespread low net package with < 1 m thick. The data consists of 3 well logs and 2 surfaces (the bottom and top surfaces of the mini-basin) interpreted from seismic surveys. The log data provides information about the thicknesses of individual lobes at the well locations. Because the mini-basin is very shallow, we assume that the morphology of the surfaces does not need any restoration. As a consequence, the bottom surface is used directly as the paleo-seafloor on which the simulated lobes are deposited. The top surface is then used to compute the thickness map of the sediments. The log data and thickness map are consistent with each other in the sense that the sum of all the lobe thicknesses recorded in the wells match the corresponding thicknesses defined in the map. In a traditional reservoir study, surfaces, also called horizons, are derived from seismic surveys, and individual lobes thicknesses are deduced from well-logging measurements. The data used in the case study are not raw seismic data but rather have been processed and interpreted; they are therefore subject to uncertainty. Data uncertainty plays a critical role in problems in which risks in the exploration, development or production of reservoirs have to be assessed (Thore et al. 2002). In general, such uncertainty is handled by working on alternative data sets. In other words, considering data uncertainty in our particular optimization scheme would require generating top surface models for each of the alternative data sets. In this study, it is assumed that only one such top surface is being

dealt with. The main challenge of the East Breaks lies in the different types of data. On one hand, matching the thickness map means reproducing the overall shape of the sediments package. Alternately, matching log data requires reproducing a precise internal layering at the well locations.

4.2 Forward Model Parameterization

The events have lobe shapes as described by Fig. 2. The well and thickness maps do not provide enough information to infer the prior distribution of the input parameters, such as lobe-specific parameters or global parameters. Global parameters, such as the source location, progradation, and migration intensity, are borrowed from the information provided by Miller et al. (2008). Because no data are available on the lobe geometry in Miller's paper, the distributions of the lobe sizes are based on the work of Saller et al. (2008), who presents an extensive study of similar deep-water fan lobes. Note that in our model, the thickness variable is used to build the initial geometry of a lobe, before any erosion occurs. The lobes observed by Seller et al. have already been eroded, therefore, the observed thickness does not equal the initial one. To circumvent this problem, the thickness distribution entered in our model is tuned such that the generated simulations display lobe thicknesses after erosion similar to those observed by Saller et al. (2008).

The parameters used to generate the Gaussian noise for each lobe should be chosen such that the perturbed lobe geometries are geologically realistic. However, defining a criterion that automatically evaluates the geological consistency of a lobe is difficult and evidently subjective. Therefore, a simple visual appreciation is made to define a priori parameter values. Various generated lobes are perturbed with different noise realizations, each with different variance and covariance structures. The geometry is either accepted or rejected based on the overall shape of the lobe. As a result, we estimate that the correlation length should be between 1000 m and 7000 m for all lobes. The variance is more critical because it defines the intensity of the variation and has a larger impact on the overall lobe geometry, and consequently, geological realism. The variance is defined such that the created perturbation cannot exceed (in thickness units) one-third of the maximum lobe thickness. Running the above-defined forward model also requires the definition of a stopping criterion. One possible choice is the number of lobes present in the system. In such a case, the forward simulation would end when the specified number of deposited lobes is reached. In our case study, however, the thickness map provides information on the volume of the deposited sediments, not the number of lobes. Therefore, we define that the forward simulation stops when the volume of the deposited lobes matches the reference volume. The advantage of this approach is that it does not require defining the number of lobes in advance. Table 2 summarizes the input parameters of the model.

4.3 Objective Function

An objective function determines how good a model is in terms of fitting the data. A matched model should fit the thickness map and the log data at the same time.

Table 2 Summary the input parameters of the model

Type	Parameters	Uncertainty representation
Event geometry	Width	Uniform [1000 m 3000 m]
	Length	Uniform [2000 m 7000 m]
	Thickness	Uniform [5 m 35 m]
	Variance of added Gaussian field	Uniform [0 y] y depending on the maximum lobe thickness
	Correlation length of the covariance	Uniform [1000 m 7000 m]
Geological rules related to process	Progradation intensity	Uniform [500 m 1000 m]
	Migration intensity	Uniform [200 m 700 m]
	τ-value	Uniform [0 1]
	Coordinates (x_s, y_s) of sediment source	Uniform in red box (Fig. 4)

Matching the log data requires matching the lobe thicknesses recorded in each of the three logs

$$E_{\text{well } i} = \frac{1}{N_{\text{lobes\_in\_data}}} \times \sum_{1}^{N_{\text{lobes\_in\_data}}} (\text{lobe observed thickness}_i - \text{lobe simulated thickness}_i)^2.$$

The errors associated with each well are then averaged to obtain a combined well error $E_{\text{well total}}$

$$E_{\text{well total}} = \frac{1}{3} \sum_{i=1}^{3} E_{\text{well } i},$$

in the case of 3 wells. The mismatch between the two thickness maps, E_{seismic}, is computed as the mean square error of both surfaces discretized on a two-dimensional grid. The final objective function is then defined as follows

$$E_{\text{total}} = \frac{E_{\text{total wells}}}{E_{\text{wells\_initial}}} + \frac{E_{\text{seismic}}}{E_{\text{seismic\_initial}}},$$

where $E_{\text{wells\_initial}}$ and $E_{\text{seismic\_initial}}$ are the mismatch values of the initial guess.

4.4 Establishing the Leading Uncertainty

Two sets of model realizations (200 realizations each) are generated, one with constant parameter input and varying random seed for lobe location selection, and one with varying parameter inputs and a constant random seed. As a criterion for deciding the number of realizations to generate, we use the histogram of the misfit with the data calculated for each set of models. After 200 realizations, the two histograms

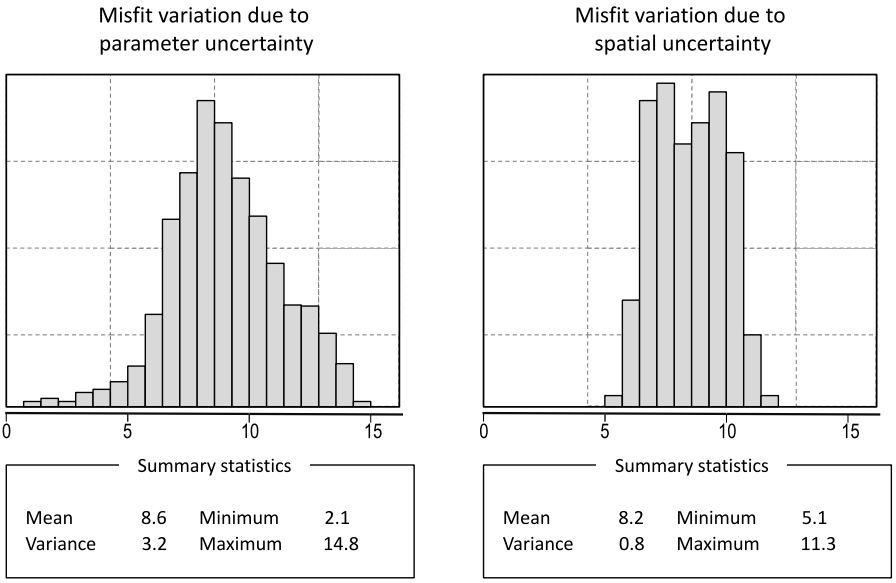

Fig. 6 Variation of data misfit with (*left*) input parameter uncertainty and (*right*) spatial uncertainty. The data misfit is a simple square deviation between simulated data and field data

remain stable when new realizations are added. Hence, we assume that a set of 200 models is sufficient to compare both uncertainties. The two series of runs show that parameter uncertainty is in this case the leading uncertainty since the corresponding histograms of misfit have the largest variance (Fig. 6). This makes sense in the East Breaks case because the lack of available prior geological knowledge to characterize the system results in high uncertainty of the input parameters. It strongly impacts the model output variability in terms of data fitting, meaning that it is possible to fit the well and seismic data with a wide range of structural parameters.

4.5 Sensitivity Analysis

The sensitivity analysis of the parameters on data misfit is based on 300 realizations. Linear interactions are considered. Figure 7 shows the sensitivity of the misfit toward each parameter in a traditional Pareto plot. The red line corresponds to the significance level, meaning that the parameter values that cross the line are statistically influential on the data misfit. The results show that the τ parameter, the variance and the covariance of the noise are the most influential parameters in terms of data fitting. The τ parameter is important because it modifies the probability maps used to draw lobe locations and, therefore, directly impacts the lobe stacking patterns. There are two explanations for the importance of the Gaussian noise. The first one is that perturbing the geometry of the lobes affects the internal layering of the model. The second reason is related to the shape of the deposition surfaces. Since the placement of the lobes is mainly controlled by the topography, the added noise modifies this topography and influences the placement of the lobes (Fig. 8).

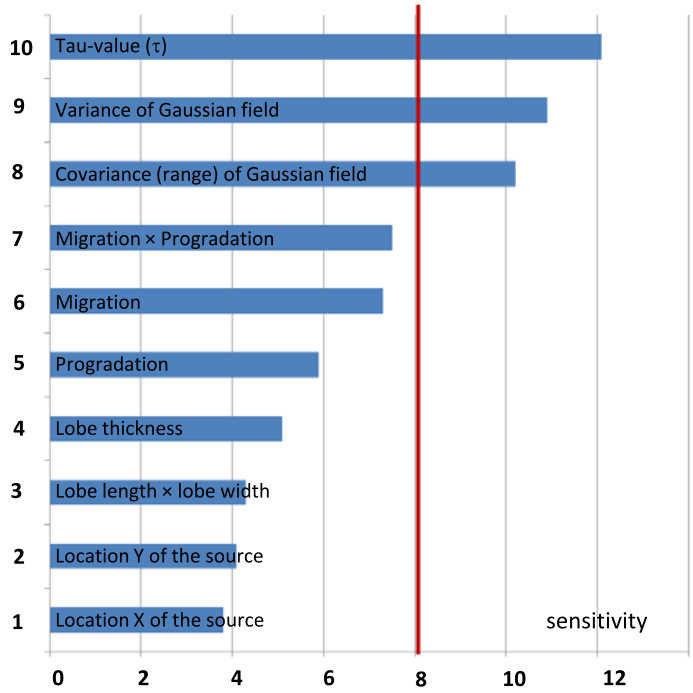

Fig. 7 Pareto plot showing the sensitivity of each input parameter on the data misfit. Interaction terms are denoted with "×"

4.6 Optimization

The τ value and the Gaussian noises added on top of the lobes are optimized using the sequential (step-by-step) optimization. To validate the efficiency of this approach, we need to ensure that the computational time taken by the optimization process is not too large. It is especially critical in our case because the analysis of the model spatial uncertainty and the parameter sensitivity already requires considerable CPU time. We observe during the runs performed in the sensitivity analysis that the number of lobes in the models varies from 10 to 15. Therefore, each optimization sequence of the conditioning approach is stopped after 50 iterations in order to control the total CPU time. The associated computational time for the full optimization scheme (around 1.5 h with a nonoptimized Matlab code) is assumed to be reasonable enough for the method to be integrated in a real modeling workflow. However, better matches (if desired, depending on the quality of the data) could be obtained with longer optimization runs.

4.7 Results

The optimized model is composed of 12 lobes. Figure 9 displays the main features present in the East Breaks data. Most of the deposited lobes are gathered around the proximal part of the basin (near the source), and no deposition occurs in the distal

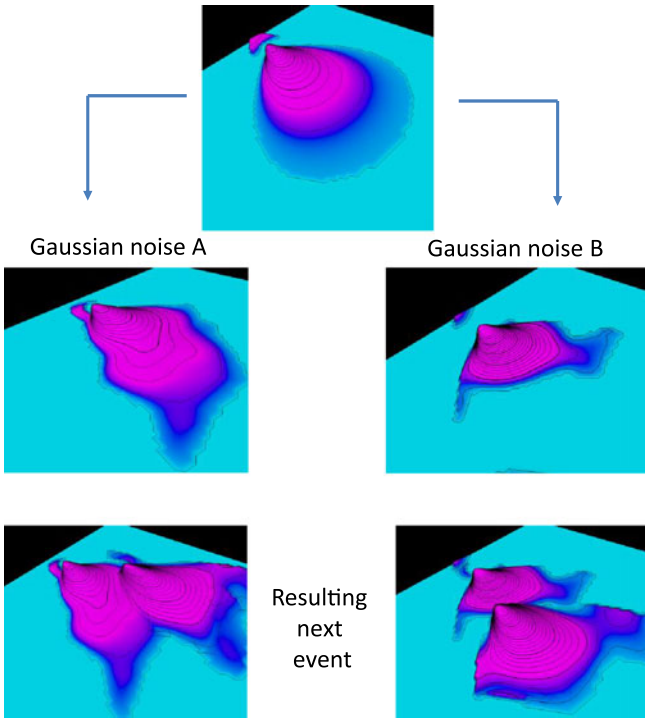

Fig. 8 Illustration of the impact of varying the Gaussian noise on the stacking of the next event/lobe

part. The high and low sedimentation areas are therefore accurately reproduced. The similarity of both measured and modeled thickness maps also confirm the performance of the conditioning. From the error map, we can see that most of the mismatch is located near the sediment source area. At this location, the environment of deposition is, in general, associated with high energy, and the associated erosion processes are intense. A source of residual misfit might be the model of erosion, which may not fully represent the physical processes at play.

The simulated lobes compare well with those recorded in the log data (Fig. 10). However, the surface-based model produces slightly less variability in terms of the lobe thicknesses, which is probably due to the use of statistics that only approximate the actual thickness variability. Another reason could again be the erosion model, which may be too simplistic. High variability in the recorded thicknesses can indeed mean high variability in the erosion intensities. Figure 11 displays the internal layering of the geological model at different stages of the optimization process. The initial guess presents a poor match with the data. At the end of step 5 (250 iterations), the model starts to fit the log data and thickness map (represented by the location of the top surface) with increased accuracy. The fit with the log data is especially good at the bottom part of the reservoir. Indeed, at the end of step 5, the first four lobes of the deposition sequence have already been perturbed and combined with the topography. Three of them are recorded in the cross-section (the three bottom ones). The final model reproduces the thickness of the reservoir observed at the cross-section

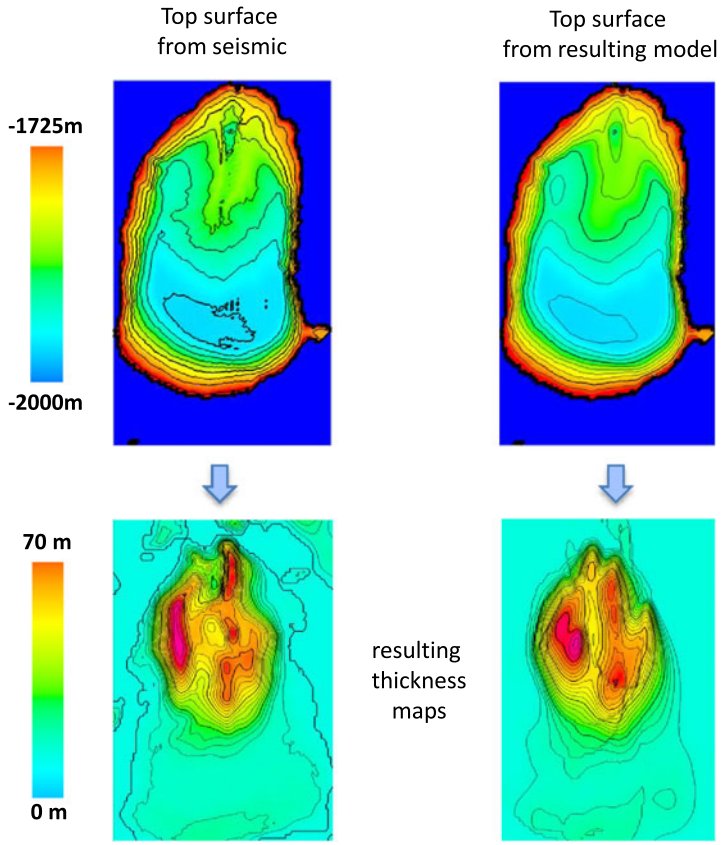

Fig. 9 Resulting optimized model vs. data

location and accurately fits the log data. Figure 12 shows three models generated from different initial guesses.

5 Acceleration by Reducing the Dimensionality of the Optimization Problem

The results of the case study outlined above show the possibility of fitting surface-based models to real data. The efficiency in matching data is important because it determines the applicability of such methods in real field cases. Here, we present some more analysis on the computational performance of the method. In the forward model, the geometry of the lobes and rules are defined by seven parameters. In addition, each lobe is controlled by eight lobe-specific parameters: two for the lobe coordinates in the domain (location), three to generate the Gaussian noise and three for the lobe thickness, width, and length. Because twelve lobes are present in the model, fitting the East Breaks data by solving the full inverse problem would require optimizing 103 parameters ($7 + 8 * 12$). The parameter uncertainty has been shown to be dominant and optimization of the lobe locations is therefore not necessary. As

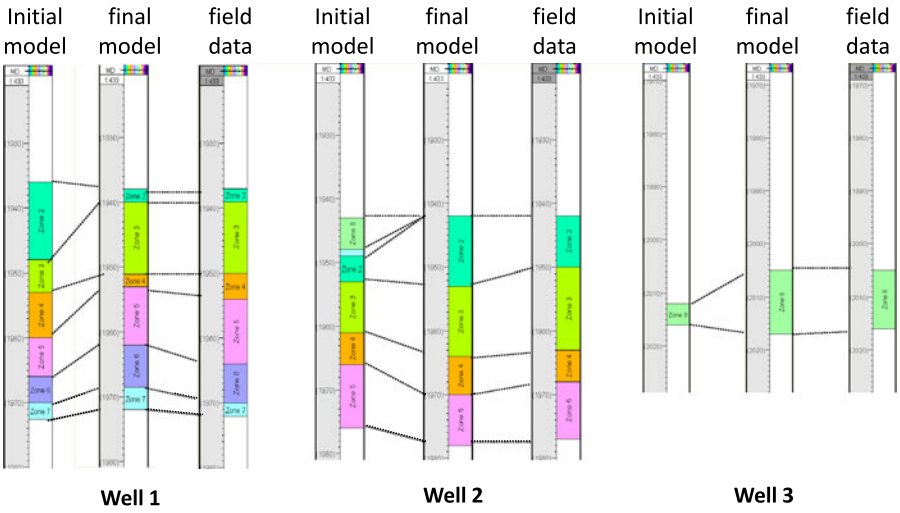

Fig. 10 Comparing simulated log and well-log data. The color in the well log indicates different lobes (not facies)

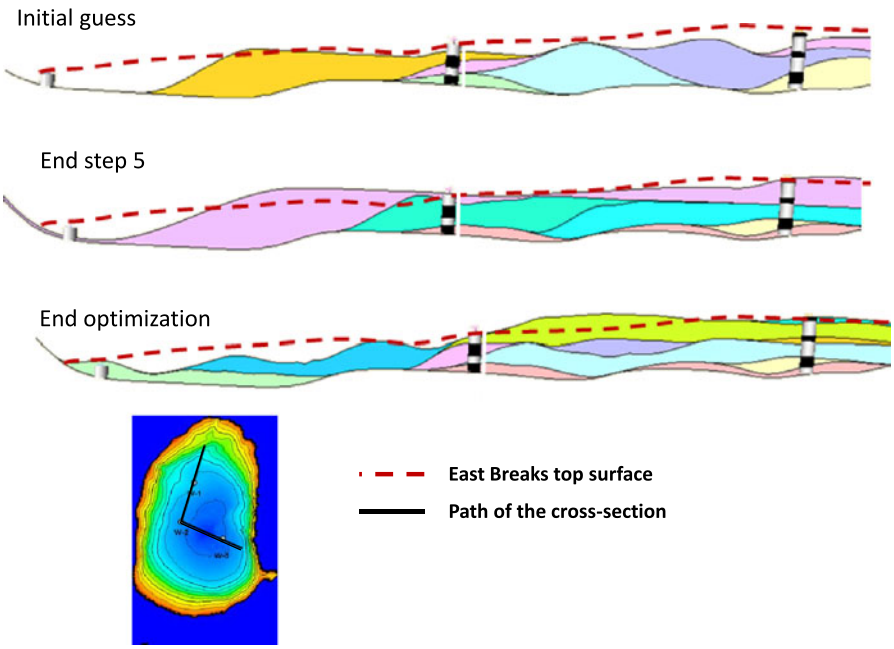

Fig. 11 Cross-section of the model at different steps of the optimization process. Each lobe is represented by a different colored zone

a consequence, the number of parameters to optimize is reduced to $79(7 + 6 * 12)$. The sensitivity analysis shows that the τ parameter and the parameters generating

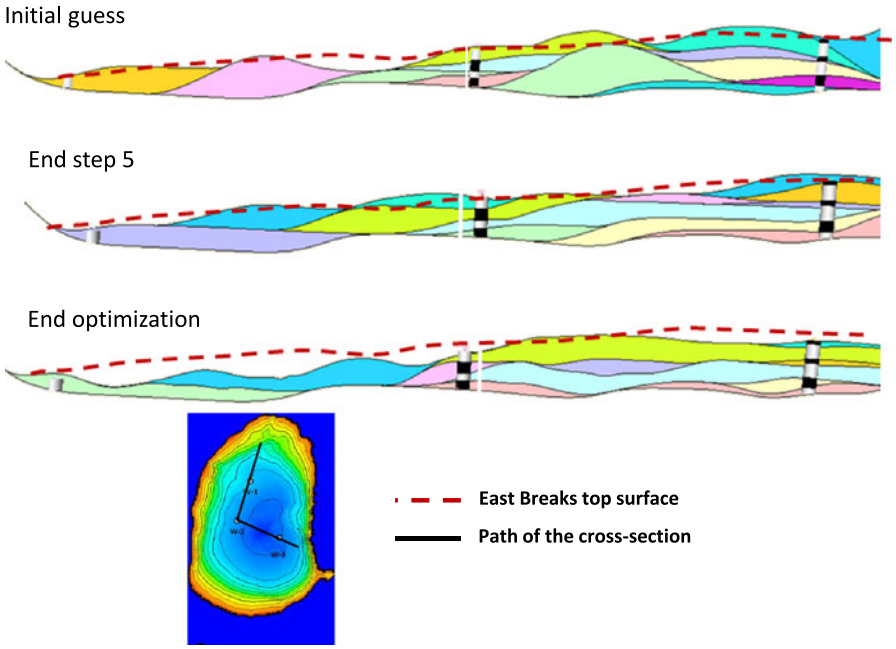

Fig. 12 Three matching models generated from different initial guesses. Notice the considerable variation between the models

the Gaussian noise are the most influential. Retaining only these influential parameters results in a set of 37 parameters ($1 + 3 * 12$). By using the proposed sequential optimization, the problem is then divided into 13 different steps: an initial step to optimize the τ value and one for each lobe noise optimization. As a consequence, the initial 103-dimensional problem is reduced to one one-dimensional problem and twelve three-dimensional problems.

To evaluate the efficiency of the method, what entails a good fit is first determined. To that end, 103 parameters are randomly sampled, and 10,000 realizations are generated. The minimal mismatch is set as a reference of good fit. Our conditioning workflow achieves a better match than this random sampling of 10,000 iterations (Fig. 13, left panel). It also outperforms the traditional optimization approach (i.e., full optimization by considering all parameters simultaneously) in terms of the speed of convergence and quality of fit. The efficiency of the method is even more evident when its evaluation is based on computational time and not on the number of iterations. Indeed, the simulation time of a single realization decreases during the step-by-step optimization; less and less lobes have to be simulated because the lobes of the previous iterations are combined with the topography. This improvement is illustrated in Fig. 12 (right panel). 650 iterations (12 lobes) of the full method take 2.7 hours. The computational time of a forward simulation is 14.9 seconds for 12 lobes. With our conditioning workflow, the same 650 iterations take 1.38 hours and obtain a far better match. The average computational time of a forward simulation is 7.6 seconds for 12 lobes.

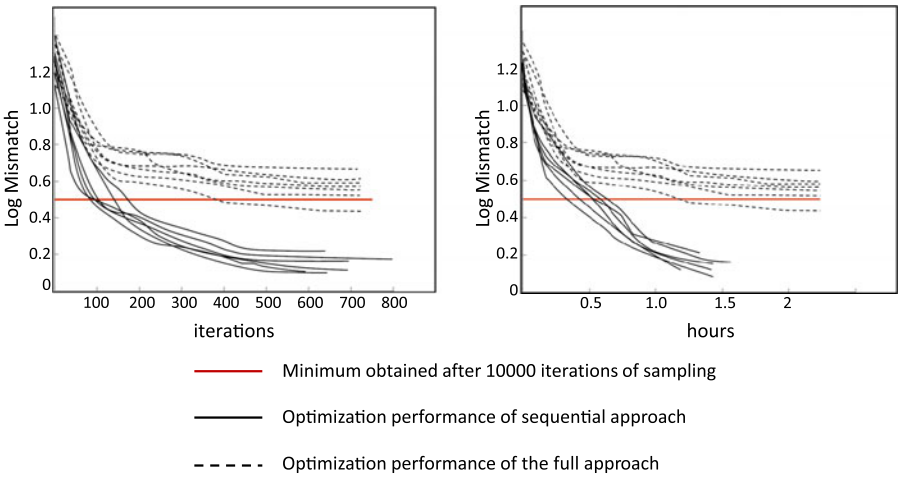

Fig. 13 Performance results of the different optimization approaches. On the *left*, the evaluation is based on the number of iterations. On the *right*, the evaluation is based on the computational time (hours)

6 Conclusions

A workflow is developed for conditioning surface-based models to well-log and seismic data. Solving the parameter optimization problem of these models is time-consuming and challenging due to the various types of parameters (discrete as well as continuous). The key idea behind the method is to decrease the dimensionality of the problem. To this end, three complementary approaches are developed. The first one identifies the leading uncertainty. The second one is a sensitivity analysis on the input parameters. The third one is a reformulation of the optimization problem into smaller problems to which the polytope method can be applied sequentially. The workflow is applied successfully to a turbidite data set composed of a thickness map and three well logs. The surface-based model used in the study reproduces the lobes structures. The workflow is general in the sense that it could be applied to any kind of data and environments of deposition. Although the approach is general in fashion and works well in the presented example, it is important to state some of its limitations. First, the variability between the generated matched models is not researched in this paper. In our case, this variability is supposed to represent the remaining uncertainty of the reservoir geometry given the available data and our model. This uncertainty is important because most of the decisions in reservoir exploration and management are based on it. In such cases, one wants to make sure that the full variability of the model is captured so that all the high pay zones are considered (in drilling, for example) or all unsuited events are hedged (in reservoir production). However, our approach perturbs a small subset of parameters, and solves the inverse problem sequentially using optimization; we do not use sampling or drawing from posterior distributions. As a consequence, the full variability of the model may not be entirely captured in the generated realizations. Future research will therefore need to focus on integrating this optimization method in an uncertainty assessment workflow.

Secondly, the proposed method would work best for field cases with lower amounts of data (exploration to appraisal) and with a high degree of uncertainty in the geological model (early development). Indeed, the method has the ability to drastically modify the geometry of the model, for example by changing the locations of the lobes and the thickness of the reservoir.

Acknowledgements We would like to acknowledge the donation of data by ExxonMobil.

References

Abrahamsen P, Fjellvoll B, Hauge R, Aas T (2007) Process based stochastic modeling of deep marine reservoirs. Paper presented at EAGE petroleum geostatistics, Cascias, Portugal

Biver P, D'Or D, Walgenwitz A (2008) Random genetic simulation of lobes: internal architecture construction and gridding. Paper presented at AAPG international conference and exhibition, Cape Town

Caers J (2011) Modeling uncertainty in the Earth sciences. Wiley, New York

Charvin K, Gallagher K, Hampson GL, Labourdette R (2009) A Bayesian approach to inverse modelling of stratigraphy, part 1: Method. Basin Res. 21(1):5–25

Cojan I, Fouche O, Lopez S, Rivoirard J (2005) Process-based reservoir modelling in the example of meandering channel, In: Leuangthong O, Deutsch C (eds) Geostatistics Banff. Springer, Berlin, pp 611–619

Hu L (2000) Gradual deformation and iterative calibration of Gaussian-related stochastic models. Math Geol 32(1):87–108

Jenson SK, Domingue JO (1988) Extracting topographic structure from digital elevation data for geographic information system analysis. Photogramm Eng Remote Sens 54(11):1593–1600

Journel A (2002) Combining knowledge from diverse sources: an alternative to traditional data independence hypotheses. Math Geol 34(5):573–596

Lesshafft L, Meiburg E, Kneller B, Marsden A (2011) Towards inverse modeling of turbidity currents: the inverse lock-exchange problem. Comput Geosci 37(4):521–529

Mariethoz G, Renard P, Froidevaux R (2009) Integrating collocated auxiliary parameters in geostatistical simulations using joint probability distributions and probability aggregation. Water Resour Res 45(8):1–13

Michael H, Boucher A, Sun T, Caers J, Gorelick S (2010) Combining geologic-process models and geostatistics for conditional simulation of 3-D subsurface heterogeneity. Water Resour Res 46 (W05527)

Miller J, Sun H, Stewart C, Genty D, Li D, Lyttle C (2008) Direct modeling of reservoirs through forward process based models: can we get there? Paper presented at international petroleum technology conference, Kuala Lumpur, Malaysia

Nelder A, Mead R (1965) A simplex method for function minimization. Comput J 7(4):308–313

Pyrcz M, Deutsch C (2004) Stochastic modeling of inclined heterolithic stratification with the bank retreat model. Paper presented at CSPG/CWLS/CHOA joint convention, Calgary, Alberta

Pyrcz M, Strebelle S (2006) Event-based geostatistical modeling of deepwater systems. Paper presented at 26th annual Gulf Coast section SEPM conference, Houston

Pyrcz M, Boisvert J, Deutsch C (2009) ALLUVSIM: a program for event-based stochastic modeling of fluvial depositional systems. Comput Geosci 35(8):1671–1685

Pyrcz MJ, Catuneanu O, Deutsch CV (2005) Stochastic surface-based modeling of turbidite lobes. Am Assoc Pet Geol Bull 89(2):177–191

Pyrcz M, Clark J, Drinkwater N, Sullivan M, Fildani A, McHargue T (2006) Event-based models as a quantitative laboratory for testing quantitative rules associated with deepwater distributary lobes. Paper presented at reservoir characterization: integrating technology and business practices: Gulf Coast section-SEPM twenty-sixth annual research conference

Saller A, Werner K, Sugiaman F, Cebastiant A, May R, Glenn D, Barker C (2008) Characteristics of Pleistocene deep-water fan lobes and their application to an upper Miocene reservoir model, offshore East Kalimantan, Indonesia. Am Assoc Pet Geol Bull 92(7):919–949

Scheidt C, Caers J (2009) Uncertainty quantification in reservoir performance using distances and kernel methods—application to a West Africa deepwater turbidite reservoir. SPE J 14(4):680–692

Stright L (2006) Modeling, upscaling, and history matching thin, irregularly-shaped flow barriers: a comprehensive approach for predicting reservoir connectivity

Sylvester Z, Pirmez C, Cantelli A (2011) A model of submarine channel-levee evolution based on channel trajectories: implications for stratigraphic architecture. Mar Petroleum Geol 28(3):716–727

Thore P, Shtuka A, Lecour M, Ait-Ettajer T, Cognot R (2002) Structural uncertainties: determination, management, and applications. Geophysics 67(3):840–852

Xie Y, Deutsch C (2000) Surface geometry and trend modeling for integration of stratigraphic data in reservoir models. Paper presented at sixth international geostatistics congress, Cape Town

Zhang X, Pyrcz MJ, Deutsch CV (2009) Stochastic surface modeling of deepwater depositional systems for improved reservoir models. J Pet Sci Eng 68(1–2):118–134