



**HAL**  
open science

## Probability maps of reservoir presence and sensitivity analysis in stratigraphic forward modeling

Véronique Gervais, Mathieu Ducros, Didier Granjeon

► **To cite this version:**

Véronique Gervais, Mathieu Ducros, Didier Granjeon. Probability maps of reservoir presence and sensitivity analysis in stratigraphic forward modeling. AAPG Bulletin, 2018, 102 (04), pp.613 - 628. 10.1306/0913171611517242 . hal-01883765

**HAL Id: hal-01883765**

**<https://ifp.hal.science/hal-01883765v1>**

Submitted on 28 Sep 2018

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



## Probability maps of reservoir presence and sensitivity analysis in stratigraphic forward modeling

Véronique Gervais, Mathieu Ducros, and Didier Granjeon

AAPG Bulletin published online 08 November 2017

doi: 10.1306/0913171611517242

---

Disclaimer: The AAPG Bulletin Ahead of Print program provides readers with the earliest possible access to articles that have been peer-reviewed and accepted for publication. These articles have not been copyedited and are posted “as is,” and do not reflect AAPG editorial changes. Once the accepted manuscript appears in the Ahead of Print area, it will be prepared for print and online publication, which includes copyediting, typesetting, proofreading, and author review. ***This process will likely lead to differences between the accepted manuscript and the final, printed version.*** Manuscripts will remain in the Ahead of Print area until the final, typeset articles are printed. Supplemental material intended, and accepted, for publication is not posted until publication of the final, typeset article.

---

---

Cite as: Gervais, V., M. Ducros, and D. Granjeon, Probability maps of reservoir presence and sensitivity analysis in stratigraphic forward modeling, (*in press; preliminary version published online Ahead of Print 08 November 2017*): AAPG Bulletin, doi: 10.1306/0913171611517242.

---

1 **Probability maps of reservoir presence and sensitivity analysis in**  
2 **stratigraphic forward modeling**

3

4 Véronique Gervais\*, Mathieu Ducros and Didier Granjeon

5

6 *IFP Énergies nouvelles, 1 et 4 avenue de Bois-Préau, 92852 Rueil-Malmaison Cedex -*  
7 *France.*

8 *\* Corresponding author.*

9 *E-mail address: veronique.gervais@ifpen.fr (V. Gervais)*

10 **Acknowledgments**

11 The authors would like to thank Colin North, Allegra Hosford Scheirer and an anonymous  
12 reviewer for their suggestions to improve this manuscript. Part of this work was performed  
13 using the CougarOpt prototype software developed within the framework of IFPEN's joint  
14 industry project Cougar. The authors thank the participating companies for their support: BHP  
15 Billiton, ConocoPhillips, Engie, Petrobras, Repsol and Saudi Aramco.

16 **Abstract**

17 One of the main objectives of petroleum exploration consists of predicting reservoir location.  
18 Data collected in the basin are used to better understand the sedimentary architecture, but are  
19 usually insufficient to accurately characterize this architecture. Three-dimensional  
20 stratigraphic forward modeling has brought new insights in the understanding of sediment  
21 distribution. It gives the opportunity to investigate several geological models and to tackle  
22 reservoir presence probability. However, simulation time is a strong limitation to properly  
23 taking the uncertainties into account during operational studies. Here, we propose a  
24 methodology based on metamodels (or surrogate models) to perform sensitivity and risk  
25 analyses. The objective is to reduce the simulation time necessary to quantify the regional

26 impact of the input parameters and to estimate probability maps of reservoir presence. The  
27 approach consists of building functions that approximate the spatial outputs of the simulator  
28 (such as sediment thickness or net-to-gross distributions in the basin) and that are fast to  
29 evaluate. These functions are then called instead of the stratigraphic forward simulator for  
30 uncertainty quantification. The proposed methodology is applied to a three-dimensional  
31 synthetic case study, considering uncertainty on input parameters related to sediment  
32 transport, accommodation space and sediment supply. The sensitivity analysis quantifies in  
33 each location the influence of the parameters on the sediment distribution, which can help to  
34 better understand the role of each uncertain process on the basin architecture. In addition,  
35 probability maps of reservoir presence are estimated. The proposed approach is a promising  
36 trade-off between simulation time and information that can be inferred.

37

38 Keywords: process-based stratigraphic simulation, uncertainty, basin modeling, basin  
39 analysis, surrogate models, metamodeling, risk analysis, potential reservoir location.

## 40 **Introduction**

41 Predicting as accurately as possible the sediment and facies distributions in a basin is critical  
42 in petroleum exploration to get robust estimations of potential reservoir location. This process  
43 is driven by the data collected in the basin. However, they are usually insufficient to  
44 accurately characterize the sediment architecture; different geological scenarios can be  
45 consistent with a single dataset. For a couple of decades, numerical stratigraphic forward  
46 models have brought a new insight on sedimentology as they make it possible to simulate  
47 physical processes related to sediment transport and deposition (e.g. Lawrence et al., 1990;  
48 Flemings and Grotzinger, 1996; Bowman and Vail, 1999; Granjeon and Joseph, 1999). They  
49 can help to better understand the effect of each process alone, or their interactions with one

50 another. Parameters affecting the resultant sedimentary rock record include eustasy, grain size  
51 distribution, fluvial discharge, wave effect or sediment supply (e.g. Bonham-Carter and  
52 Sutherland, 1968; Cross, 1989; Tetzlaff and Harbaugh, 1989; Harbaugh et al., 1999; Paola;  
53 2000; Csato et al., 2014; Granjeon, 2014). More detailed studies of the uncertainty related to  
54 the parameters describing physical processes can also be performed. Sensitivity studies make  
55 it possible to identify how these input parameters influence the simulator outputs (e.g.  
56 Bagirov and Lerche, 1999; Burgess et al., 2006; Csato et al., 2013). Calibration processes can  
57 also be considered, using either trial and error or inversion algorithms (e.g. Cross and  
58 Lessenger, 1999; Charvin et al., 2009; Falivene et al., 2014). Many stratigraphic forward  
59 simulations are usually needed to properly take uncertainty into account. For instance, the use  
60 of Monte Carlo methods to estimate the distribution of a given output property due to the  
61 uncertainty on the input parameters requires a large number of calls to the simulator.  
62 However, the number of stratigraphic models that can be investigated during a study is  
63 usually limited by the simulation time. As a result, some authors study the uncertainty related  
64 to a limited number of input parameters only, or consider a reduced sample of the parameter  
65 space, even if it narrows the information that can be retained.

66

67 In this paper, we propose an alternative approach to derive robust interpretations for  
68 petroleum exploration within a limited simulation time. We focus here on quantitative  
69 sensitivity analysis and probability of reservoir presence in each location of the basin. Our  
70 objective is to define a workflow that can be run in practice during an operational study and  
71 provide information related to uncertainty in an exploration context. To that purpose, we  
72 propose to use a methodology already applied for reservoir simulations, called metamodeling  
73 (e.g. Feraille and Marrel, 2012). We assume that the geologist has identified a set of  
74 parameters given as input to the simulator and whose values are uncertain. They will be

75 referred to as “input parameters” in what follows. The proposed approach then consists in  
76 building functions computationally fast to evaluate that approximate the relationship between  
77 the input parameters and the simulator output properties. If these metamodels, also called  
78 surrogate models, predict accurately the outputs for any possible value of the input  
79 parameters, they can be used instead of the simulator for uncertainty quantification. In the  
80 context of stratigraphic forward modeling, the simulated properties can vary with the spatial  
81 location (distribution of sediment thickness or net-to-gross in the basin for instance). An  
82 extension of the metamodeling approach based on a reduced basis decomposition is then  
83 applied (Marrel and Perrot, 2012; Douarche et al., 2014; Marrel et al., 2015).

84 Metamodels are built from a set of simulated values, and a sufficient number of simulations is  
85 required to get accurate predictions. However, once an accurate surrogate model is obtained,  
86 different applications can be envisioned without any additional simulation. In particular, the  
87 influence of the input parameters on the output properties can be estimated at each location of  
88 the basin through a quantitative sensitivity study. Risk analysis can also be considered to  
89 estimate potential sweet spot locations for instance. In this paper, we propose to show the  
90 benefits of the approach in terms of simulation time and information inferred on the basin for  
91 exploration.

92  
93 The paper outline is as follows. First, we briefly describe the stratigraphic forward model used  
94 for the simulations. Then, the metamodeling approach is presented, along with the tools used  
95 to assess the quality of the surrogate models. Finally, the potential of the proposed  
96 methodology is demonstrated for sensitivity and risk analyses on a 3D synthetic case study  
97 representative of a passive margin, based on data from the Gulf of Mexico. More precisely,  
98 the distribution of the parameter influence in the basin is obtained for accumulated sediment  
99 thickness and sand proportion. A risk analysis is also conducted following the work of

100 Burgess et al. (2006), in which the presence of a reservoir is characterized by sufficiently  
101 large sediment thickness and sand proportion. The metamodeling approach makes it possible  
102 to estimate probability maps of reservoir presence.

### 103 **Stratigraphic forward simulation**

104 Stratigraphic forward simulators are increasingly used in exploration and production  
105 companies to improve predictions of reservoir and facies distributions. Several numerical  
106 models are now available, such as Delft3D (Hoogendoorn et al., 2008), SedSim (Tetzlaff and  
107 Harbaugh, 1989) and Dionisos (Granjeon and Joseph, 1999; Granjeon, 2014). They differ in  
108 their assumptions, objectives and scales of applications. In this study, we use the Dionisos  
109 software, available as a research and commercial product (DionisosFlow™). However, the  
110 workflow could be applied with any other stratigraphic forward simulator.

111 The objective of Dionisos is to simulate transport, deposition and erosion of sediments in a  
112 wide range of depositional environments at the basin scale (10's km x 10's km during 10's  
113 k.y.). The underlying forward model is based on multi grain size diffusional transport laws  
114 with gravity and water driven contributions. Erosion and deposition are controlled by  
115 sediment mass conservation and sediment transport processes. Accommodation is accounted  
116 for through subsidence and eustatic variations. Dionisos is also able to simulate carbonate  
117 deposition using environmental laws of production such as wave effects or bathymetry (Seard  
118 et al., 2013).

### 119 **Methodology for uncertainty quantification**

120 In what follows, we consider that input parameters are modeled as independent random  
121 variables with given probability distributions. These distributions can be uniform or normal  
122 for instance, and are defined according to the knowledge of the geologist. The objective of the

123 proposed workflow is to study the impact of this uncertainty on the sedimentary architecture  
124 of the basin. In this paper, we focus on spatial output properties such as the sediment  
125 distribution in the basin. However, other outputs such as properties along wells could also be  
126 considered. Many forward simulations are usually required to properly take uncertainty into  
127 account. A way to limit their number consists in building functions that approximate the  
128 relationship between the input parameters and the simulator outputs. If these functions  
129 provide accurate predictions for any values of the parameters within their uncertainty range,  
130 they can be used instead of the simulator for sensitivity and risk analysis for instance. The  
131 proposed workflow is summarized in Figure 1. The main steps are available in the  
132 CougarOpt research software, dedicated to uncertainty management and developed within the  
133 framework of joint industry projects (see e.g. Feraille and Marrel (2012) for more details).

#### 134 **Metamodeling approach**

135 Metamodels, also referred to as surrogate models or response surfaces, can be used to  
136 approximate scalar outputs of a simulator. They are built from a set of values of the output –  
137 the training set – simulated for a sample of the input parameter space, called design of  
138 experiments. The metamodels then only require a small computation time to provide an  
139 estimation of the output for any other parameter value. Several methods can be considered to  
140 build metamodels: polynomial regression, regression splines, neural network or Gaussian  
141 processes for example. Here, we refer to the last approach: estimations are obtained by  
142 kriging interpolation of the simulated values. More details can be found in Sacks et al. (1989)  
143 or Forrester and Keane (2009), for example.

144 In practice, the choice of the design of experiments is a key issue to optimize the simulation  
145 time necessary to build accurate metamodels. The number of simulations needed to get  
146 predictive estimations is unknown a priori. It depends on the number of parameters, the  
147 complexity of the relationship between these parameters and the output. If selecting a small



148 design, the metamodel may lack accuracy in some parts of the parameter space. Considering  
149 larger designs should improve the predictivity of the metamodel, but at the cost of longer  
150 simulation times. Designs of experiments are generated here following the Latin hypercube  
151 sampling (LHS) method (McKay et al., 1979). This approach takes the input parameter  
152 distribution into account and provides space-filling designs. In addition, all the parameters  
153 vary simultaneously and the size of the sample is chosen by the user.

154 Many outputs of stratigraphic forward models vary with location in the basin (e.g. the  
155 distribution of the sediment thickness). These spatial properties can be decomposed as a set of  
156 scalar outputs in each grid block. As a result, they can be approximated by a set of  
157 metamodels, one per scalar output. However, the induced computation time can be significant  
158 for a large number of grid blocks. The methodology described in Marrel et al. (2015) and  
159 Douarache et al. (2014) can be considered to overcome this limitation. It extends the kriging  
160 approach to functional outputs and encompasses the following steps:

161 1. Principal component analysis decomposition

162 First, we refer to the Karhunen-Loève decomposition (Loève, 1978). The functional  
163 output  $y(x, \theta)$  can be viewed as an infinite linear combination of orthonormal basis  
164 functions  $\phi_k$ :

$$y(x, \theta) = m(x) + \sum_{k=1}^{\infty} \alpha_k(\theta) \phi_k(x). \quad (1)$$

165 In this decomposition,  $x$  represents the spatial location,  $\theta$  the input parameters,  $m$  the  
166 mean and  $\alpha_k$  the projection coefficient on the basis function  $\phi_k$ . The parameters only  
167 influence the projection coefficients  $\alpha$ . With this formulation, the dependences on the  
168 input parameters and spatial location are thus decoupled.

169

170 In practice, estimating such decomposition boils down to perform a principal  
 171 component analysis on the training set  $y(x, \theta_i)_{i=1..n}$ :

$$y(x, \theta_i) = \hat{m}(x) + \sum_{k=1}^M \hat{\alpha}_k(\theta_i) \hat{\phi}_k(x) \text{ for } i = 1 \dots n. \quad (2)$$

172 The basis functions  $\hat{\phi}_k$  are the principal components. They are sorted in descending  
 173 order with respect to the explained variance of the output. If the number of grid blocks  
 174 is larger than the size of the training set, then  $M = n$ . In practice, an accurate  
 175 reconstruction can be obtained considering just some of these functions in linear  
 176 combination:

$$y(x, \theta_i) \simeq \hat{m}(x) + \sum_{k=1}^L \hat{\alpha}_k(\theta_i) \hat{\phi}_k(x). \quad (3)$$

177  $L$  should be chosen such that the resulting combination corresponds to a sufficiently  
 178 large proportion of explained variance. For instance, it was set to explain at least 99%  
 179 of the output variance in Douarche et al. (2014) and 95% in Marrel et al. (2015).

180

## 181 2. Metamodeling

182 In decomposition equation (3), the input parameters only impact the projection  
 183 coefficients  $\hat{\alpha}_k(\theta)$ . Each of these coefficients can be approximated by a classical  
 184 kriging-based metamodel  $\hat{\alpha}_k^*(\theta)$  using the training set  $\hat{\alpha}_k(\theta_i)_{i=1..n}$ . The predictor of  
 185 property  $y(x, \theta)$  is then, for any value of the parameters:

$$y^*(x, \theta) = \hat{m}(x) + \sum_{k=1}^L \hat{\alpha}_k^*(\theta) \hat{\phi}_k(x). \quad (4)$$

186 We refer to this approach in what follows.

## 187 **Quality assessment**

188 To assess the quality of the predictor  $y^*(x, \theta)$ , we introduce an additional sample of the input  
189 parameter space – the test sample. The values simulated for the corresponding stratigraphic  
190 forward models are compared to the ones given by the predictor. This provides a quantitative  
191 estimation of the predictor quality, the so-called Q2 coefficient. It is defined at each location  
192  $x$  by:

$$Q2(x) = 1 - \frac{\sum_{j=1}^{nt} (y(x, \theta_j) - y^*(x, \theta_j))^2}{\sum_{j=1}^{nt} (y(x, \theta_j) - \bar{y}(x))^2}. \quad (5)$$

193  $(\theta_j)_{j=1..nt}$  represents the test sample and  $\bar{y}(x)$  the mean of the corresponding simulated values  
194  $y(x, \theta_j)_{j=1..nt}$  at location  $x$ . The numerator is the sum of the least-square errors between the  
195 predicted and simulated output values for the test sample. The denominator introduces a  
196 normalization by the output variance. The Q2 coefficient is less than 1 and decreases when  
197 the error increases. In the case of the reduced basis decomposition considered here (equation  
198 3), the Q2 coefficient reflects both the truncation and metamodeling errors.

## 199 **Uncertainty quantification**

200 Once an accurate predictor is obtained for the output property of interest, it can replace the  
201 simulator to perform sensitivity analysis and uncertainty propagation. No additional  
202 simulation is required.

203 The sensitivity analysis consists of estimating the influence of the input parameters on the  
204 output property of interest. It can help to better understand the processes at work in the  
205 different parts of the basin, or to discard the less influential parameters in a calibration  
206 process. Here, we propose to perform a quantitative sensitivity analysis based on Sobol'  
207 indices (Sobol', 1990). These indices measure the part of the output variance due to the

208 parameters or their interactions. The first order index, or primary effect, quantifies the part of  
209 the output variance explained by a parameter alone. Higher order indices are related to  
210 parameter interaction effects that are not included in first order indices. The Sobol' indices  
211 vary between 0 and 1. They get closer to one when the part of the output variance explained  
212 by the parameters increases. The sum of all the Sobol' indices involving a given parameter is  
213 called the total effect (Homma and Saltelli, 1996). It estimates the global sensitivity of the  
214 output to the parameter.

215 Sobol' indices are associated with a given scalar output. For spatial properties, these indices  
216 can be estimated in each grid block, which then provides the distribution of the parameter  
217 influence in the basin.

218

219 Finally, the uncertainty on the input parameters can be propagated to the output property of  
220 interest. To that purpose, the parameters are sampled according to their distributions (Monte-  
221 Carlo method for instance), and the corresponding values of the output are estimated from the  
222 surrogate models. To analyze the resulting output sample, percentiles can be computed in  
223 each grid block. Probabilities to meet some criteria, defining for instance a potential reservoir,  
224 can also be estimated at each location.

## 225 **Application to a geological case study**

### 226 **Case study**

227 The potential of the proposed workflow is illustrated on a 3D synthetic case study based on  
228 data from the Gulf of Mexico (Burgess et al., 2006). The model represents a clastic passive  
229 margin of 1000 km × 1000 km (621 mi × 621 mi) which consists of a continental shelf,  
230 margin slopes, a basin floor with some relief and a submarine canyon. The initial bathymetry  
231 is given in Figure 2.

232 The basin is discretized into  $50 \times 50$  grid blocks with a resolution of 20 km (12.4 mi). This  
233 resolution is larger than the one are generally considered (1 to 10 km (0.6 to 6.2 mi) for clastic  
234 environments for instance). However, our objective was to illustrate the potential of the  
235 proposed approach, which applies in the same way whatever the size of the grid blocks. The  
236 basin infill is simulated with Dionisos during a period of 3 m.y. with time steps of 0.2 m.y.. A  
237 sediment source of 3 cells wide is assumed on the western margin (Figure 2). The sediment  
238 input is composed of a constant supply of mud and sand. The sediments are distributed in the  
239 basin according to gravity-driven and water-driven diffusional processes. Eustatic oscillations  
240 are represented by a sinusoid. Basin deformation is related to subsidence rate and flexural  
241 isostasy defined by an elastic plate thickness of 30 km (18.6 mi). Finally, mechanical  
242 compaction applies to the deposited sediments with respect to the sand/mud ratio.

243  
244 The uncertainty considered in this study is related to the three major processes that affect the  
245 sedimentary architecture of the basin: accommodation, sediment and water supplies, and  
246 sediment transport. Uncertainty on accommodation is accounted for through a uniform  
247 subsidence rate and the amplitude and period of eustatic variations. Uncertainty on supplies is  
248 characterized by the variations in total sediment volume inflow, sand/mud proportion and  
249 water discharge. Last, a reference transport coefficient is introduced to take the uncertainty on  
250 the diffusional processes and water discharge into account. This reference coefficient  
251 characterizes the water-driven diffusion of sand in the marine environment and drives the  
252 perturbation of all other water-driven transport coefficients together with two additional  
253 parameters: the ratio between the mud and sand diffusion coefficients, and the ratio between  
254 the continental and marine diffusion coefficients. This parameterization reduces the number  
255 of unknowns and prevents the simulation of inconsistent scenarios (e.g. better transport of

256 sand than mud). Also, the parameters are related to a physical process, so that the results are  
257 more easily related to the physics of the problem.

258 Input parameters are assigned uniform distributions and the ranges of variation given in Table  
259 1. These intervals were deduced from the values considered in Burgess et al. (2006). The  
260 gravity diffusion coefficients are held constant at  $0.01 \text{ km}^2/\text{k.y.}$  ( $0.0038 \text{ mi}^2/\text{k.y.}$ ). The  
261 uncertainty on compaction is not considered here as it was expected to have a much lower  
262 impact on accommodation compared to eustatic variations.

263

## 264 **Metamodeling**

265 A set of simulations is required to build metamodels. In this study, four training sets of size  
266 30, 60, 90 and 120 are generated following the Latin hypercube sampling (LHS) method. An  
267 additional LHS of 50 simulations – the test sample – is also generated to assess the quality of  
268 the metamodels.

269

270 Two output properties are considered: a map of sediment thickness defined as the  
271 accumulated thickness of deposited sediments in each column of the grid, and a map of sand  
272 proportion defined as the total proportion of sand in each column of the grid. These property  
273 maps are used to characterize potential reservoirs in the basin. Their mean and standard  
274 deviation in the test sample after a simulation period of 0.4 and 3 m.y. are given in Figure 3.

275 For this figure and the following ones, the values are mapped on the average topography  
276 computed on the test sample after 0.4 and 3 m.y., respectively. In addition, unfilled grid  
277 blocks indicate areas with no deposition. At the beginning of the simulation period (0.4 m.y.),  
278 sediments are mainly deposited in the delta near the input source (indicated by the white  
279 arrow), the submarine canyon and the western margin toe-of-slope (Figure 3A). These regions  
280 also correspond to the highest sand proportion (Figure 3E). At this time, no deposition has

281 occurred on the relief of the basin floor (Figure 3A). After 3 m.y., the submarine canyon has  
282 generally been filled and the topography of the western margin is globally symmetrical with  
283 respect to the input source (Figure 3C). The sediment deposition has spread around the entry  
284 point, and the basin relief is covered with sediments for some simulations. Sand is still mainly  
285 located near the source and on the western margin (Figure 3G).

286

287 To approximate the sediment thickness and sand proportion, a principal component analysis is  
288 performed on each training set (equation 2). Only the components necessary to explain 98%  
289 of the output variance are retained. Then, kriging-based surrogate models are computed for  
290 the projection coefficients associated to the reduced bases (equation 4). The metamodeling  
291 approach is applied to the values simulated after 0.4 and 3 m.y.. The quality of the resulting  
292 predictors for the sediment thickness and sand proportion is estimated from the 50 simulations  
293 of the test sample. The resulting values of the Q2 coefficients (equation 5) are given in Figure  
294 4. The Q2 coefficient cannot be computed in the grid blocks where deposition never occurs in  
295 the test sample, so that no values are displayed (unfilled grid blocks).

296

297 Globally, the two properties are better predicted when the size of the training set increases  
298 (larger values of the Q2 coefficient). The regions with less accuracy are located on the  
299 boundary of the deposition area and in distal parts of the basin, where sediments are deposited  
300 in a few simulations only. The predictions are globally more accurate for sediment thickness  
301 than for sand proportion, with larger values of the Q2 coefficient. With the proposed  
302 approach, sand proportion thus appears more difficult to estimate than sediment thickness for  
303 the same LHS. However, the predictions obtained with the largest training set are globally  
304 accurate in the regions with a significant deposition of sand (Figures 3B, 3D, 3F, 3G and 4D,  
305 4H, 4L, 4P).

306

307 The quality of the metamodels is also illustrated in Figure 5, which shows the distribution of  
308 the true and predicted values of sand proportion after 0.4 and 3 m.y. for two models of the test  
309 sample. The general trends are captured with only 30 models. However, considering a larger  
310 training set makes it possible to predict more accurately the distribution.

311

312

### 313 **Sensitivity analysis**

314 A variance-based sensitivity study was performed on the spatial distribution of sediment  
315 thickness and sand proportion, using the training set of 120 models. Figure 6 shows the total  
316 effect on these properties for the most influential parameters.

317

318 The sediment supply, water discharge and reference diffusion coefficient have a significant  
319 influence on both the sediment thickness and sand proportion distribution (large total effect,  
320 see Figures 6A to 6L). The sediment supply is globally the most influential parameter for the  
321 sediment thickness, with a dominant impact on the outer part of the delta (at 0.4 m.y.) and the  
322 western margin (Figures 6A and 6B). The sand proportion deposited in the delta and the  
323 western margin is mainly influenced by the sand proportion in the input source (Figures 6O  
324 and 6P), whereas the values in the more distal part of the basin appear driven by the mud/sand  
325 diffusion coefficient ratio (Figures 6S and 6T). The water discharge and reference diffusion  
326 coefficient have an equivalent impact, which is spatially distributed where the three above  
327 parameters have a lower influence (Figures 6E to 6L). Finally, the eustasy amplitude has an  
328 impact on the sediment thickness around the sediment entry point at the beginning of the  
329 simulation period (Figure 6M), but this effect disappears after some time (Figure 6N). On the



330 contrary, the subsidence rate becomes more influential through time in this area (Figures 6Q  
331 and 6R).

332

333 The information provided by sensitivity analyses can help to better choose the parameters to  
334 be tuned in the calibration step. For instance, if well data are available, these parameters may  
335 be different depending on the location of the well.

336

### 337 **Risk analysis**

338 The predictors for sediment thickness and sand proportion can also be used to perform risk  
339 analysis, for instance to study the location of potential reservoirs. Indeed, the probability  
340 distribution of these outputs due to the uncertainty on the input parameters can be estimated  
341 by sampling the distribution assigned to each input parameter and computing the  
342 corresponding values predicted by the surrogate models.

343

344 We consider here a Monte Carlo sample of the parameter space. The metamodels built with  
345 the training set of size 120 are used to estimate the corresponding sample of the sediment  
346 thickness and sand proportion distributions in the basin. Various analyses can then be  
347 performed on this sample.

348

349 First, percentiles can be estimated in each grid block. For instance, the maps of P5 and P95  
350 percentiles for the sediment thickness at 3 m.y. are given in Figure 7. As evidenced in Figure  
351 7B, at least 300 m (984 ft) of sediments are deposited in the delta and the submarine canyon  
352 for 95% of the sample. In addition, the probability to reach a sediment thickness of at least  
353 1000 m (3281 ft) on the western margin is about 5% (Figure 7D).

354

355 The Monte Carlo sample can also be used to estimate in each grid block the probability to  
356 meet some physical criteria. Following Burgess et al. (2006), we can identify potential  
357 reservoir zones characterized by sufficiently large sediment thickness and sand proportion.  
358 We consider here the probability to obtain a sediment thickness larger than 60 m (197 ft) and  
359 a sand proportion greater than 25% after 3 m.y.. The resulting maps are given in Figures 8A  
360 and 8B, together with the probability to meet the two criteria (Figure 8C). The region with a  
361 probability larger than 50% to be a reservoir zone is displayed in black in Figure 8D. It  
362 consists of the delta, the submarine canyon and the western margin toe-of-slope.  
363  
364 Finally, the parameter distribution corresponding to the sub-sample that meets the above  
365 criteria provides additional information on the dynamic system. It complements the sensitivity  
366 analysis by providing trends for parameter values that result in potential reservoir zones. For  
367 instance, we consider here three points A, B and C located in the delta, the submarine canyon  
368 and the western margin toe-of-slope, respectively (Figure 8C). The values of the input  
369 parameters for which the sediment thickness exceeds 60 m and the sand proportion exceeds  
370 25% at these locations are given in Figure 9 to Figure 11. The potential reservoirs in grid  
371 block A correspond to sufficiently large values for the source sand proportion, and more often  
372 to a large sediment supply. The reservoirs in grid block B (submarine canyon) are mainly  
373 characterized by a sufficiently large sand proportion in the input source. Finally, the reservoirs  
374 in grid block C, located on the western margin toe-of-slope, correspond to sufficiently large  
375 values for the source sand proportion, and more often to large values of the sediment supply,  
376 water discharge and reference diffusion coefficient. The results obtained here are consistent  
377 with the quantitative sensitivity analysis (Figure 6). Indeed, the subsample of the parameters  
378 that were not identified as influential at locations A, B and C remain close to uniform. On the  
379 contrary, the distributions of the most influential parameters are completely different from the

380 initial ones. The analysis presented here also provides information that could help for the  
381 calibration process. For instance, if data were available at location A stating the presence of a  
382 reservoir (as defined with the above criteria), the uncertainty range of the sand proportion  
383 could be reduced for calibration.

## 384 **Conclusions and perspectives**

385 In this work, we propose an approach to take into account the uncertainty on the stratigraphic  
386 model input parameters from a limited number of stratigraphic forward simulations. It  
387 consists in building metamodels that approximate the relationship between the input  
388 parameters and the outputs of the simulator. These metamodels are built by kriging  
389 interpolation of the output values simulated for a sample of the input parameter space. They  
390 provide estimations of the output for all other values of the parameters. If these estimations  
391 are close to the true (simulated) values, they can be used for uncertainty quantification. In  
392 particular, they make it possible to apply quantitative sensitivity analysis algorithms and  
393 Monte Carlo methods without additional simulation.

394  
395 The method is illustrated on a 3D synthetic case representative of a passive margin. It  
396 provides globally accurate predictions of the accumulated sediment thickness and sand  
397 proportion deposited in the basin from a limited simulation time. Using these metamodels, we  
398 estimate the influence of the input parameters at all locations. This information can help to  
399 discriminate among the various geological processes occurring in the formation of the  
400 sedimentary architecture. It also paves the way for new interpretations related to basin  
401 physiography and geological processes that provide guidelines for the model calibration.  
402 Finally, the metamodels are used to estimate probability maps of reservoir presence. In  
403 practice, the proposed workflow can be run automatically except for the size of the

404 experimental design. In the future, it would be interesting to introduce an automatic definition  
405 of this design, using for instance sequential approaches. They consist in complementing  
406 iteratively an initial sample with new simulations judiciously chosen.

407  
408 Interpretations of the results should be related to the assumptions and formulations of the  
409 stratigraphic forward model and to the choice of the uncertainty (parameters and range of  
410 variation). In the test case considered here, the choice of the input parameters was driven by a  
411 previous study. In practice, many parameters are potentially unknown. In that case, it is  
412 recommended to discard first the non-influential ones before running the proposed workflow.  
413 This can be achieved from a limited number of simulations using for instance screening  
414 methods.

415  
416 The results of our approach can be easily integrated in a study and should be seen as  
417 complementary to other kinds of studies (seismic interpretations, well correlation, sequence-  
418 stratigraphy). They can help petroleum geologists to prospect their basin and determine the  
419 most probable locations of adequate reservoir rock in the context of relatively unknown basin  
420 architectures. In particular, the proposed approach can help to identify a few geological  
421 scenarios representing the model uncertainty. These scenarios can then be used to initialize  
422 basin models with sedimentary facies maps, obtained from a classification of the stratigraphic  
423 model continuous outputs (sand proportion, bathymetry for instance) into basin model  
424 lithologies.

425

## 426 **References**

- 427 Bagirov, E., and I. Lerche, 1999, Probability and sensitivity analysis of two-dimensional basin  
428 modeling results, *in* J. W. Harbaugh, W. L. Watney, E. C. Rankey, R. Slingerland and  
429 R. H. Goldstein, eds., Numerical experiments in stratigraphy: Recent advances in  
430 stratigraphic and sedimentologic computer simulations: SEPM Special Publication 62,  
431 p. 35– 68.
- 432 Bonham-Carter, G., and A. J. Sutherland, 1968, Mathematical model and FORTRAN IV  
433 program for computer simulation of deltaic sedimentation: Computer Contribution, 24,  
434 Kansas Geological Survey, Lawrence, Kansas, 56 p.
- 435 Bowman, S. A., and P. R. Vail, 1999, Interpreting the stratigraphy of the Baltimore canyon  
436 Section, offshore New Jersey with PHIL, a stratigraphic simulator, *in* J. W. Harbaugh,  
437 W. L. Watney, E. C. Rankey, R. Slingerland and R. H. Goldstein, eds., Numerical  
438 Experiments in Stratigraphy: recent advances in stratigraphic and sedimentologic  
439 computer simulations, SEPM Special Publication 62, p. 117-138.
- 440 Burgess, P. M., H. Lammers, C. van Oosterhout, and D. Granjeon, 2006, Multivariate  
441 sequence stratigraphy: Tackling complexity and uncertainty with stratigraphic forward  
442 modeling, multiple scenarios and conditional frequency map: AAPG Bulletin, v. 90, no.  
443 12, p. 1883-1901.
- 444 Charvin, K., G. J. Hampson, K. Gallagher, and R. Labourdette, 2009, A Bayesian approach to  
445 inverse modeling of stratigraphy, part 1: method: Basin Research, v. 21, p. 5-25.
- 446 Cross, T. A., 1989, Quantitative Dynamic Stratigraphy, Englewoods Cliff, NJ, Prentice Hall,  
447 624 p.
- 448 Cross, T. A. and M. Lessenger, 1999, Construction and application of stratigraphic inverse  
449 model. In: Numerical Experiments in Stratigraphy: Recent Advances in Stratigraphic  
450 and Sedimentologic Computer Simulations, *in* J. W. Harbaugh, W. L. Watney, E. C.

451 Rankey, R. Slingerland, and R. H. Goldstein, eds, Numerical Experiments in  
452 Stratigraphy: recent advances in stratigraphic and sedimentologic computer simulations,  
453 SEPM Special Publication 62, p. 69-83.

454 Csato, I., D. Granjeon, O. Catuneanu, and G. R. Baum, 2013, A three-dimensional  
455 stratigraphic model for the Messinian crisis in the Pannonian Basin, eastern Hungary':  
456 Basin Research, v. 25, no. 2, p. 121-148.

457 Csato, I., O. Catuneanu, and D. Granjeon, 2014, Millennial-scale sequence stratigraphy:  
458 numerical simulation with Dionisos: Journal of Sedimentary Research, v. 84, no. 5, p.  
459 394-406.

460 Douarache, F., S. Da Veiga, M. Feraille, G. Enchéry, S. Touzani, and R. Barsalou, 2014,  
461 Sensitivity Analysis and Optimization of Surfactant-Polymer Flooding under  
462 Uncertainties: Oil & Gas Science and Technology – Rev. IFP Energies nouvelles, v. 69,  
463 no. 4, p. 603-617.

464 Falivene, O., A. Frascati, S. Gesbert, J. Pickens, Y. Hsu, and A. Rovira, 2014, Automatic  
465 calibration of stratigraphic forward models for predicting reservoir presence in  
466 exploration: AAPG Bulletin, v. 98, no. 9, p. 1811–1835.

467 Feraille, M., and A. Marrel, 2012, Prediction under Uncertainty on a Mature Field: Oil & Gas  
468 Science and Technology – Revue d'IFP Energies Nouvelles, v. 67, no. 12, p. 193–206.

469 Flemings, P. B., and J. P. Grotzinger, 1996, STRATA: Freeware for analyzing classic  
470 stratigraphy problems: GSA Today, v. 6, no. 12, p. 1-7.

471 Forrester, A. I. J., and A. J. Keane, 2009, Recent advances in surrogate-based optimization:  
472 Progress in Aerospace Sciences, vol. 45, no. 1-3, p. 50-79.

473 Granjeon, D. and P. Joseph, 1999, Concepts and applications of a 3-D multiple lithology,  
474 diffusive model in stratigraphic modeling, *in* J. W. Harbaugh, W. L. Watney, E. C.  
475 Rankey, R. Slingerland, and R. H. Goldstein, eds, Numerical Experiments in

476 Stratigraphy: recent advances in stratigraphic and sedimentologic computer simulations,  
477 SEPM Special Publication 62, p. 197-210.

478 Granjeon, D., 2014, 3D forward modelling of the impact of sediment transport and base level  
479 cycles on continental margins and incised valleys, in A.W. Martinius, R. Ravnas, J.A.  
480 Howell, R.J. Steel and J.P. Wonham, eds, From Depositional Systems to Sedimentary  
481 Successions on the Norwegian Continental Margin, International Association of  
482 Sedimentologists, Spec. Publ., v. 46, p. 453-472.

483 Harbaugh, J. W., L. W. Whatney, E. Rankay, R. Slingerland, R. Goldstein, and E. Franseen,  
484 1999, Numerical experiments in stratigraphy: recent advances in stratigraphic and  
485 computer simulations. SEPM special publication, v. 62, 362 p.

486 Homma T., and A. Saltelli, 1996, Importance measures in global sensitivity analysis of model  
487 output: Reliability Engineering and System Safety, v. 52, no. 1, p. 1-17.

488 Hoogendoorn, R. M., I. Overeem, and J. E. A. Storms, 2008, Process-response modelling of  
489 fluvio-deltaic stratigraphy: Computers & Geosciences, vol. 34, no. 10, p. 1394-1416.

490 Lawrence, D. T., M. Doyle, and T. Aigner, 1990, Stratigraphic simulation of sedimentary  
491 basins: concepts and calibration: AAPG Bulletin, v. 74, no. 3, p. 273-295.

492 Loève, M., 1978, Probability Theory, vols. I-II.: New York, Springer, 416 p.

493 Marrel, A. and N. Perot, 2012, Development of a surrogate model and sensitivity analysis for  
494 an atmospheric dispersion computer code: Proceedings of PSAM 11 & ESREL 2012  
495 Conference, Helsinki, Finland, June 2012.

496 Marrel, A., N. Perot, and C. Mottet, 2015, Development of a surrogate model and sensitivity  
497 analysis for spatio-temporal numerical simulators: Stochastic Environment Research and  
498 Risk Assessment, vol. 29, no. 3, p. 959-974.

499 McKay, M. D., R. J. Beckman, and W. J. Conover, 1979, Comparison of Three Methods for  
500 Selecting Values of Input Variables in the Analysis of Output from a Computer Code:  
501 Technometrics, vol. 21, no. 2, p. 239-245.

502 Morris, M. D., 1991, Factorial sampling plans for preliminary computational experiments:  
503 Technometrics, vol. 33, no. 2, p. 161-174. Paola, C., 2000, Quantitative models of  
504 sedimentary basin filling: Sedimentology, v. 47, Issue s1, p. 121– 178.

505 Paola, C., 2000, Quantitative models of sedimentary basin filling: Sedimentology, v. 47, Issue  
506 s1, p. 121– 178.

507 Sacks, J., W. J. Welch, T. J. Mitchell, and H. P. Wynn, 1989, Design and Analysis of  
508 Computer Experiments: Statistical Science, vol. 4, no. 4, p. 409–423.

509 Seard, C., J. Borgomano, D. Granjeon, and G. Camoin, 2013, Impact of environmental  
510 parameters on coral reef development and drowning: Forward modelling of the last  
511 deglacial reefs from Tahiti (French Polynesia; IODP Expedition #310): Sedimentology,  
512 vol. 60, no. 6, p. 1357-1388.

513 Sobol', I. M., 1990, On sensitivity estimation for nonlinear mathematical models:  
514 Mathematical Modeling & Computational Experiment, vol. 1, no. 4, p. 407-414.

515 Tetzlaff, D. M. and J. W. Harbaugh, 1989, Simulating clastic sedimentation: New York,  
516 Springer US, 202 p.

517

## 518 **Authors**

519 Véronique Gervais joined the Geosciences division of IFP Energies Nouvelles in 2005. She  
520 received her Ph.D. in applied mathematics from the University of Aix-Marseille in 2004. She  
521 is involved in projects on uncertainty quantification and assisted history-matching in  
522 Geosciences.



523 Mathieu Ducros is a geologist with 10 years of experience in petroleum exploration. He  
524 obtained a M.Sc. degree from the École des Mines de Saint-Etienne in 2007. He started his  
525 career in Beicip-Franlab before joining IFPEN in 2010. Since then he works on improving  
526 basin modeling tools for better assessment of exploration risks.

527 Didier Granjeon joined the Sedimentology Group at IFP Energies Nouvelles in 1992. He  
528 received his Ph.D. in geology from the University of Rennes in 1996. He has been involved in  
529 basin studies from seismic and outcrop interpretation to numerical modeling. His work has  
530 been focused on the research and development of a three-dimensional stratigraphic forward  
531 model.

## 532 **Figure captions**

533 Figure 1 – Workflow for uncertainty quantification.

534 Figure 2 – Initial bathymetry, with a vertical exaggeration of 200. The location of the  
535 sediment input source on the western margin is indicated by the large white arrow.

536 Table 1 – Uncertainty range for the input parameters.

537 Figure 3 - Average (top) and standard deviation (bottom) computed on the test sample (50  
538 models) for the accumulated sediment thickness (left) and sand proportion (right) deposited  
539 after 0.4 and 3 m.y.. In this figure and all subsequent ones, the results presented at 0.4 and 3  
540 m.y. are mapped on the average topography computed on the test sample at 0.4 and 3 m.y.,  
541 respectively, with a vertical exaggeration of 200. Sedimentation never occurs in the unfilled  
542 grid blocks. The white arrow indicates the sediment input source location.

543 Figure 4 - Q2 coefficient computed with the training sets of size 30, 60, 90 and 120 for the  
544 accumulated sediment thickness and sand proportion deposited after 0.4 and 3 m.y.. The  
545 values are not displayed in the grid blocks where sediment deposition never occurs in the test  
546 sample (unfilled grid blocks).

547 Figure 5 - Sand proportion simulated (first column) and predicted for two models of the test  
548 sample after 0.4 and 3 m.y., considering metamodells built from the training sets of size 30  
549 (second column) and 120 (third column).

550 Figure 6 –Total effect computed for the input parameters that have a significant influence on  
551 the accumulated sediment thickness (left) and sand proportion (right) in the basin after 0.4 and  
552 3 m.y.. The training set of size 120 is used to predict the properties. The values are not  
553 displayed in the grid blocks where sediment deposition never occurs in the training set  
554 (unfilled grid blocks).

555 Figure 7 – P5 (top) and P95 (bottom) percentiles estimated for the sediment thickness after 3  
556 m.y.. The maximum value of the color scale is limited to 300 m and 1000 m in figures (b) and  
557 (d) for the P5 and P95 percentiles, respectively. The values are not displayed in the grid  
558 blocks where sediment deposition never occurs in the training set (unfilled grid blocks).

559 Figure 8 - Estimated probability of meeting various criteria after 3 m.y. The values are not  
560 displayed in the grid blocks where sediment deposition never occurs in the training sample  
561 (unfilled grid blocks).

562 Figure 9 – Parameter distribution in the set of models for which the sediment thickness is  
563 larger than 60 m and the sand proportion greater than 25% in grid block A.

564 Figure 10 – Parameter distribution in the set of models for which the sediment thickness is  
565 larger than 60 m and the sand proportion greater than 25% in grid block B.

566 Figure 11 – Parameter distribution in the set of models for which the sediment thickness is  
567 larger than 60 m and the sand proportion greater than 25% in grid block C.

Table 1

Input parameters		Minimum value	Maximum value
Accommodation	Eustasy–Period (m.y.)	0.5	2
	Eustasy–Amplitude (m)	5 (16.4 ft)	50 (164 ft)
	Subsidence rate	25 (82 ft/m.y.)	75 (246 ft/m.y.)
Sediment supply	Source - supply (km <sup>3</sup> /m.y.)	20000 (4800 mi <sup>3</sup> /m.y.)	80000 (19200 mi <sup>3</sup> /m.y.)
	Source - sand proportion	10	40
	Water discharge (%)	50	200
Sediment transport	Sand marine diffusion coefficient - reference coefficient (km <sup>2</sup> /k.y.)	0.5 (0.19 mi <sup>2</sup> /k.y.)	2 (0.77 mi <sup>2</sup> /k.y.)
	Continental/marine diffusion coefficient ration (-)	50	100
	Mud/sand diffusion coefficient ration (-)	1.5	4.5

Identify model parameters with uncertain values (input parameters) and assign them a probability distribution

***Input probability distributions***

Generate a sample of the input parameter space (design of experiments)

***Design of experiments***

Perform stratigraphic forward simulations for the models of the design of experiments to form the training set

***Training set***

Compute metamodels approximating the outputs of interest of the simulator

***Metamodels***

Use the predictions provided by the metamodels to perform sensitivity and risk analyses

Sediment input source

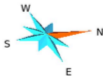
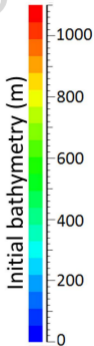


1000 km

1000 km

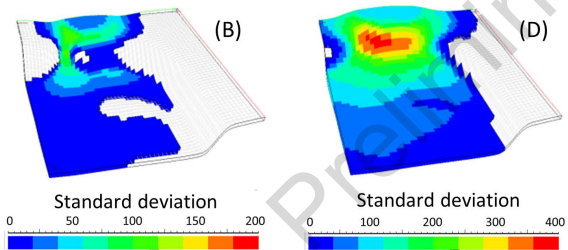
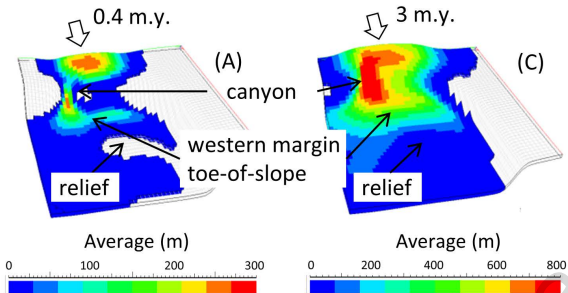
Submarine  
canyon

Relief

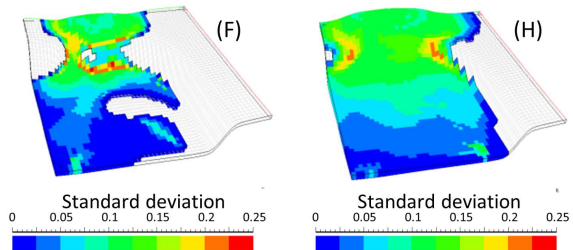
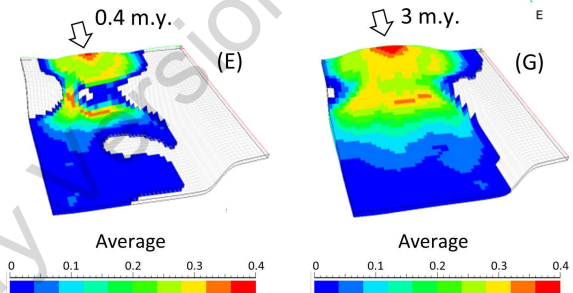


VE=200

### Sediment thickness

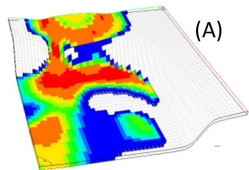


### Sand proportion

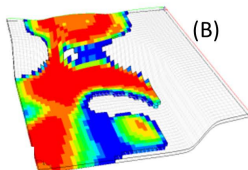


0.4 m.y.

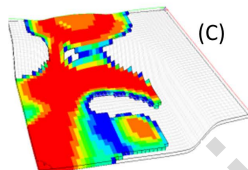
Sediment  
thickness



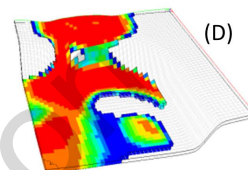
(A)



(B)

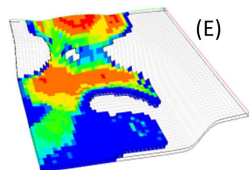


(C)

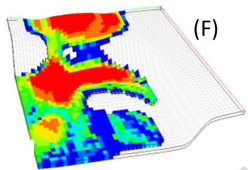


(D)

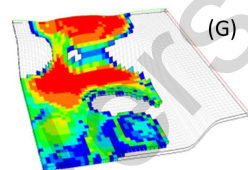
Sand  
proportion



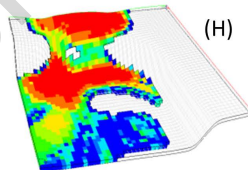
(E)



(F)



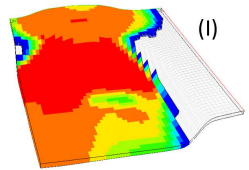
(G)



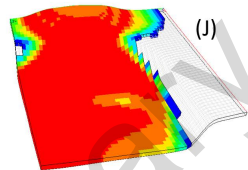
(H)

3 m.y.

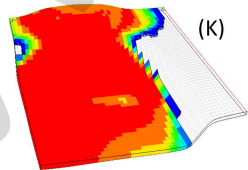
Sediment  
thickness



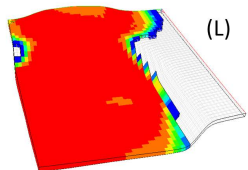
(I)



(J)

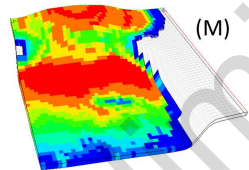


(K)

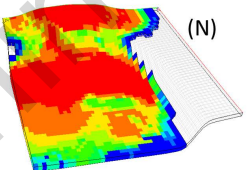


(L)

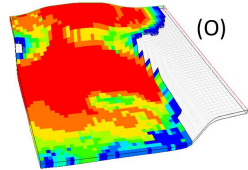
Sand  
proportion



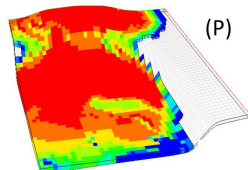
(M)



(N)



(O)



(P)

30 models

60 models

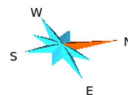
90 models

120 models

0 0.2 0.4 0.6 0.8 1



Q2 coefficient

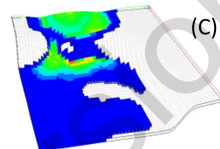
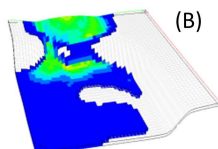
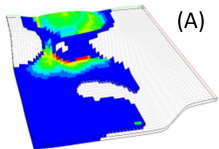


Simulations

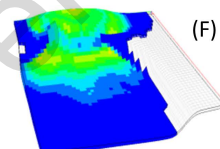
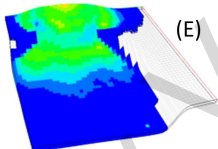
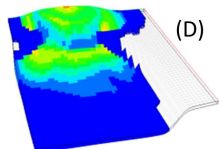
Predictions from 30  
models

Predictions from 120  
models

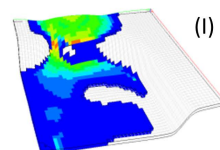
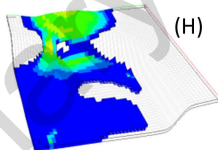
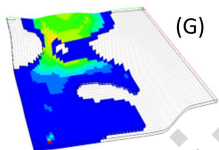
Model 1  
0.4 m.y.



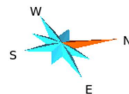
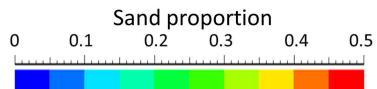
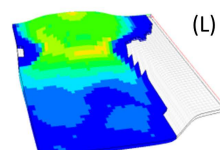
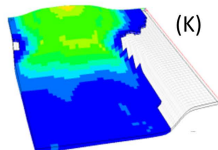
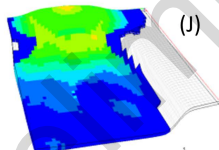
Model 1  
3 m.y.



Model 2  
0.4 m.y.



Model 2  
3 m.y.

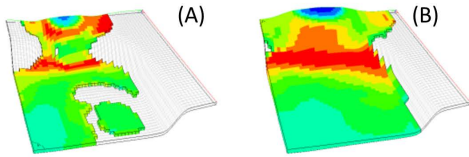




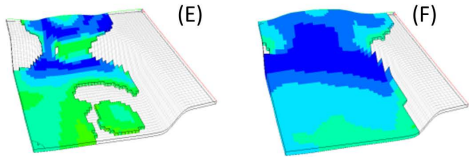
Sediment thickness

0.4 m.y.

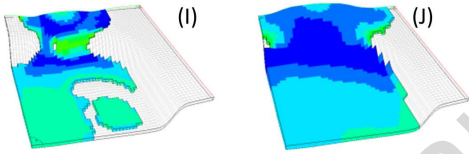
3 m.y.



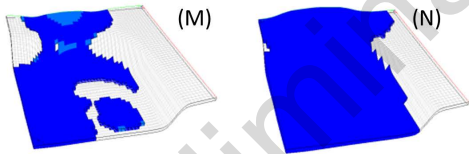
Sediment supply



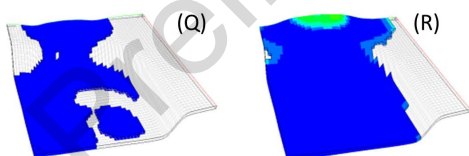
Water discharge



Reference diffusion coef.



Eustasy - amplitude



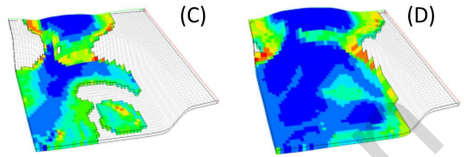
Subsidence rate



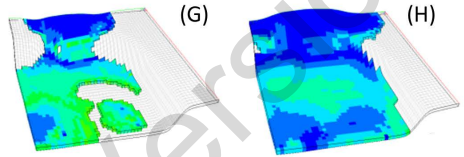
Sand proportion

0.4 m.y.

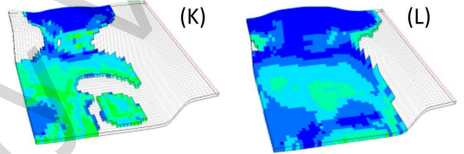
3 m.y.



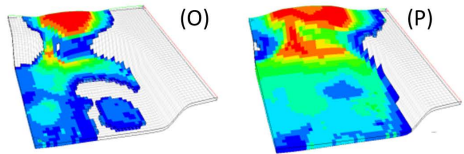
Sediment supply



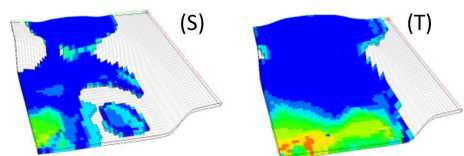
Water discharge



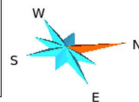
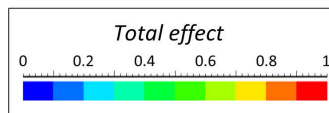
Reference diffusion coef.



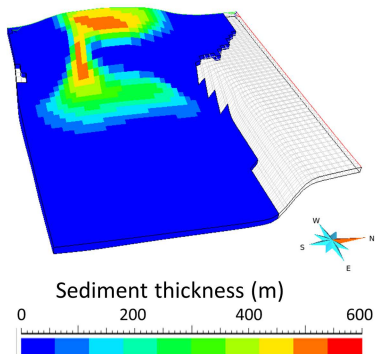
Source - sand proportion



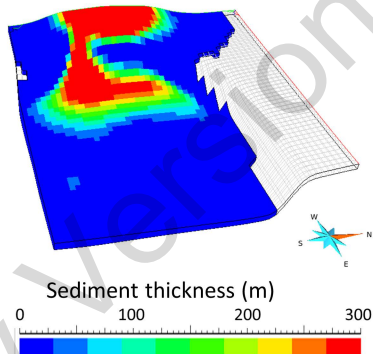
Shale/sand diffusion coef. ratio



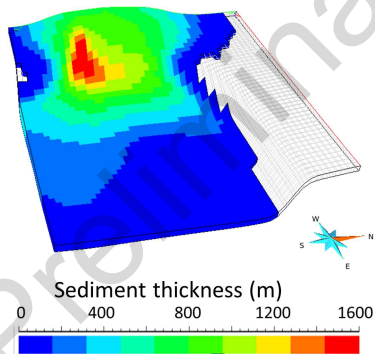
(A) Percentile P5



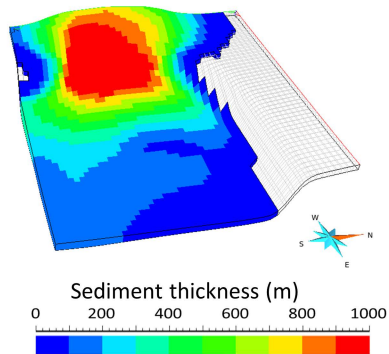
(B) Percentile P5 – truncated colorscale



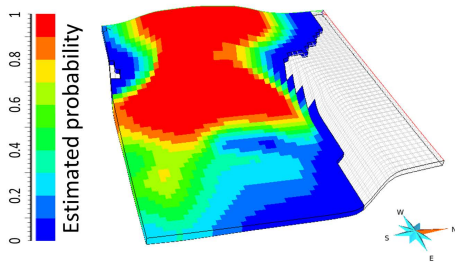
(C) Percentile P95



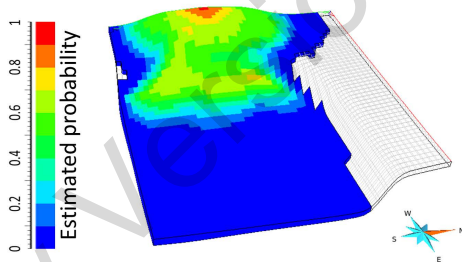
(D) Percentile P95 – truncated colorscale



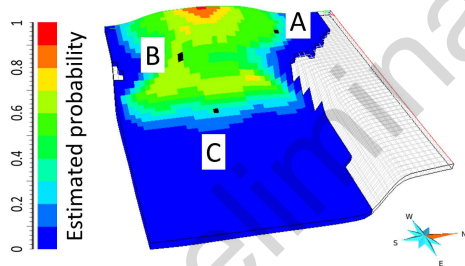
(A) Sediment thickness > 60m



(B) Sand proportion > 25%



(C) Sediment thickness > 60m  
and sand proportion > 25%



(D) Region with a probability larger than  
50% to meet the two criteria

