Title:

A COMPARATIVE STUDY OF RESERVOIR MODELING TECHNIQUES AND THEIR IMPACT ON PREDICTED PERFORMANCE OF FLUVIAL-DOMINATED DELTAIC RESERVOIRS: REPLY

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INTRODUCTION

We thank Ma et al. (2018) for their discussion of our paper (Deveugle et al., 2014), which assessed the impact of using different stochastic reservoir modeling techniques to capture geologic heterogeneity and fluid-flow behavior, via comparison with a reference model constructed from a fluvial-dominated deltaic reservoir outcrop analog (Deveugle et al., 2011). The stochastic models in Deveugle et al. (2014) were constructed using a sparse dataset of pseudowells, synthetic 3D seismic data, and geologic interpretations, in order to mimic a reservoir modelling project to support early field development. The first part of Ma et al.'s (2018) discussion raises the interesting issue of how to deal with bias in well data, and provides us with the opportunity to clarify some misconceptions regarding the recognition and handling of unrepresentative well data in reservoir modelling studies. The second part of their discussion seeks fuller explanation of our calculation of facies probabilities, and their implementation in generating facies proportions in the models of Deveugle et al. (2014). In this reply, we address each part of Ma et al.'s (2018) discussion in turn, and then conclude with an assessment of how their discussion points impact the main findings of our original paper (Deveugle et al., 2014).

RECOGNITION AND HANDLING OF BIAS IN WELL DATA

Wells sample a tiny proportion of any reservoir (e.g., 8 pseudowells sample 0.00001% of the volume of the reservoir models presented in Deveugle et al., 2014). The problem of small sample size is compounded by the non-periodic and non-stationary character of facies distributions in many reservoirs (e.g. “jigsaw puzzle” and “labyrinth” reservoir types of Weber and Van Guens, 1990), with the result that wells are highly unlikely to sample representatively the facies proportions and distributions within the reservoir. Thus, there is commonly some bias in the facies proportions and distributions sampled by wells (e.g. Pyrcz et al., 2006).

As outlined by Ma et al. (2018), there are several established techniques to decluster or debias well data. Declustering methods rely on weighting the data sampled by the wells to account for spatial representativeness, but assume that the entire range of the true data distribution (i.e., all facies types) has been sampled (e.g., Journel, 1983; Isaaks and Srivastava, 1989). In the absence of a clear and persistent spatial trend in facies between wells, debiasing of well data is achieved by using secondary data, such as a conceptual geologic model, to adjust the primary data distribution of the well samples (e.g., Frykman and Deutsch, 1998; Pyrcz et al., 2006; Ma, 2009). However, the reservoir geoscientist does not know *a priori* the “correct” conceptual geologic model or concept-derived scenario that pertains to any given reservoir. She or he should instead investigate “several diverse scenarios … perhaps based on a range of appropriate ancient, modern, and experimental analogs. In fluviodeltaic reservoirs, the scenarios should capture uncertainty in facies proportions … [which is one of several] critical aspects of facies architecture that control sweep efficiency” (p. 760 in Deveugle et al., 2014). Figure 8 in Deveugle et al. (2014) shows a series of maps for specific stratigraphic horizons in two such scenarios (in columns labelled “interpretation 1” and “interpretation 2”) that are consistent with available well data (Fig. 5 in Deveugle et al., 2014) and an appropriate conceptual geologic model (Fig. 4 in Deveugle et al., 2014). It should be noted that the map-view facies proportions in both interpreted scenarios differ from the map-view facies proportions in the reference model (in column labelled “reference” of Fig. 8 in Deveugle et al., 2014). Declustering and debiasing methods, including the propensity zoning declustering method (Ma, 2009) advocated by Ma et al. (2018), would be useful tools in assessing the range of uncertain facies proportions implied by the maps for the two interpreted scenarios, but they would not be sufficient to obtain the same facies proportions as those in the corresponding maps for the reference model. Although Deveugle et al. (2014) could have included debiasing of well data as one of the steps in the construction of their models, this would not have removed the differences in static and dynamic performance between reservoir models of different geologic scenarios. It is thus misleading to claim that it is possible to correct for a bias in well data using declustering and debiasing methods alone. Facies proportions should be treated as a “known unknown” in most reservoir modelling projects.

Notwithstanding that there is generally irreducible uncertainty in facies proportions, assessment of bias in well data is an important early step in any reservoir modelling project (e.g., Pyrcz et al., 2006). Applying declustering or debiasing would remove some of this bias. In practice, however, bias such as that present in the 8 wells used by Deveugle et al. (2014) often goes unnoticed, and may be propagated into well conditioning of seismic data and subsequent probability cube derivation. Deveugle et al. (2014) demonstrate in their parasequence-set-scale models that some modelling algorithms are compromised by an inability to resolve the discrepancy between biased well data and unbiased seismic data (e.g., spectral component geologic modeling, SCGM, and to a lesser extent sequential indicator simulation, SISIM). The resulting reservoir models contain facies distributions that are inconsistent with well data, seismic data and/or the underlying conceptual geologic model (e.g. Fig. 12 in Deveugle et al., 2014). These anomalous facies distributions are diagnostic of bias in well or seismic data (or both), and allow such bias to be recognized. This in turn should prompt the reservoir geoscientist to undertake data declustering or debiasing, and to carry out an uncertainty assessment that includes variability in facies proportions. Indeed, as part of such an assessment, the reservoir geoscientist may explicitly design scenarios that contain different ranges of facies proportions, in order to investigate the impact of uncertainty in geologic interpretation on predicted reservoir performance (e.g., Bentley and Smith, 2008).

CALCULATION AND IMPLEMENTATION OF FACIES PROBABILITIES

Reconciliation of different facies probability entities

Ma et al. (2018) point out several apparent inconsistencies in the parasequence-scale models of Deveugle et al. (2014) between vertical facies successions in a parasequence (in specific pseudowells; Fig. 5 in Deveugle et al., 2014) and areal facies distributions in maps that are explicitly drawn for the top of each parasequence (Fig. 8 in Deveugle et al., 2014). In fact, there are no inconsistencies between these two types of input data, because the areal facies distributions shown in the parasequence-top maps were not used to generate probabilities for facies distributions over the full thickness of the parasequence (as implied in the comments of Ma et al., 2018). Instead, facies distributions in each parasequence were conditioned to an areal trend and a vertical trend. This approach was adopted because the implementation of the object-based modelling (OBM) algorithm used by Deveugle et al. (2014) was not capable of incorporating three-dimensional probability cubes. For consistency, the same approach was followed for parasequence-scale models generated with the SISIM algorithm. The areal and vertical trends were incorporated as the probability of insertion for the centre of an object

(OBM algorithm) and as weighting factors for kriging (SISIM algorithm). The areal trends were a series of binary facies probability maps, one for each facies, for the top of each parasequence. For each facies, the map was assigned a probability of one where that facies is present in the facies-distribution map for a given geological scenario, and a probability of zero everywhere else. This approach ensured that the facies realisations express the general aspects of the interpreted scenarios. The vertical trend is a facies probability curve for each parasequence, which was taken initially from the facies proportions in the pseudowells, upscaled to match the resolution of the model grid. Since individual pseudowells may not sample a particular facies, or may grossly underestimate or overestimate its presence at certain depths, the resulting three-dimensional facies model may not preserve the proximal-to-distal and axial-to-marginal facies trends within an individual delta lobe, as described in the underlying conceptual geologic model (Fig. 4 in Deveugle et al., 2014). Consequently, the initial vertical facies probability curves were iteratively modified, together with facies proportions, to give the closest visual match to the position of facies-association boundaries in the pseudowells and to honor the facies architecture of the conceptual geologic model. This procedure follows reservoir modeling workflows that are commonly implemented in the subsurface (e.g., Hirsche et al., 1998; Caers, 2005), while reconciling the various input data used to generate facies probability distributions.

Definitions of facies probability

Ma et al. (2018) also query the third and fifth steps of the workflow that was used to define facies probability volumes to condition the parasequence-set-scale models of Deveugle et al. (2014, p. 739-741). These two steps are described below in greater detail than in our original paper.

The third step of the workflow is the combination of five probability volumes, each for a different facies, into a single probability volume. The five probability volumes were derived from the reference model, which was cross-scaled to the same grid as the parasequence-set-scale models (workflow step 1). Cells occupied by a particular facies in the cross-scaled reference model were initially assigned a value of one in the probability volume for that facies, with all other cells assigned a value of zero (IND probability volume; Fig. 7B in Deveugle et al., 2014). To represent the effects of random noise and potential errors in facies assignment, a second set of probability volumes was generated for each facies by assigning a cell a value of 0.8 if it was occupied by that facies, and 0.05 if it was not (workflow step 2). When the five facies probability volumes were combined into a single probability volume (workflow step 3), his method ensured that the sum of all probability volumes equalled one in each cell ($0.8*1 + 0.05*4 = 1$), hence creating a probability density function in each cell that satisfies the three basic probability axioms (e.g., p. 22 in Billingsley, 1995, quoted by Ma et al., 2018). The facies-proportion estimates for the single, combined-facies probability volume were not significantly different from the facies proportions in the reference model, with the noticeable exception of the channel-fill sandstone (CH) facies. This is because the proportion of CH facies in the reference model (3% and 4% in different parasequence sets) was close to the level of added noise (5%); thus, adding even a small amount of probability to recognize CH facies in individual cells could result in a significant increase in CH facies proportion estimates when applied over the entire model volume.

The apparent inconsistency in the fifth workflow step noted by Ma et a. (2018) originates from the low-pass bandwidth filter (0-30 Hz or 0-60 Hz) that was applied to the probability volumes in step 4. First, this filter was applied to each of the five probability volumes that had been generated for different facies in workflow step 2. Since the probability volumes for each facies type were filtered independently from each other, the resulting volumes no longer combined to give a valid probability density function in every cell. Therefore, the probability volumes were then normalized by dividing the values of all five individual probability volumes in a given cell by their sum in that cell, to give a normalized filtered probability volume, in the fifth step of the workflow. The bandwidth filtering and normalisation procedures did not significantly affect the facies-proportion estimates.

CONCLUSIONS

Well data are inherently likely to contain a bias in facies proportions, since wells sparsely sample facies distributions that are non-periodic and non-stationary in most reservoirs. Although declustering and debiasing methods may reduce this bias, they cannot completely remove it without reference to additional data, such as conceptual geologic models. Many aspects of such conceptual models, including facies proportions, are not known *a priori* with a high degree of certainty. It is therefore naive to claim (as do Ma et al., 2018) that facies proportions from a reference model can be used to remove all bias in well data, because this assumes complete certainty and accuracy in this aspect of the reference model. Further, using facies proportions from such a reference model to inform a comparison of models constructed using different stochastic modelling algorithms and sparse, subsurface-mimicking data (as in Deveugle et al., 2014) is unrealistic and self-defeating. Although assessment of bias in well data is an important early step in any reservoir modeling project, the impact of irreducible uncertainty in facies proportions, together with the impact of other facies-architectural parameters, should be investigated by a scenario-based modelling approach.

Although the study of Deveugle et al. (2014) could have been extended to test a range of different facies proportions, the two main findings of the study are not affected by the omission of such work. These two findings are similarly unaffected by our fuller explanation of how facies probabilities were calculated and implemented to generate facies proportions in the models. First, the choice of stochastic modeling algorithm is less important than the robust application of underlying geologic concepts in constructing a reservoir model. Second, the use of appropriate conditioning data, which differ for various stochastic modeling algorithms, is also more important than the choice of modeling algorithm.

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