A comparative study of reservoir modeling techniques and their impact on predicted performance of fluvial-dominated deltaic reservoirs: Discussion

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ABSTRACT

We found Deveugle et al.'s comparison of several techniques for modeling the facies of fluvial-dominated deltaic reservoirs particularly interesting. The paper's main finding confirms the importance of integrating geological concepts into geostatistical modeling to generate realistic reservoir models. Although we think that the paper is quite thorough in its investigation into several geological themes and multidisciplinary integrations, we want to comment on the following two issues.

- How the statistics of well data should be used in three-dimensional modeling.
- How to properly calculate and use facies probability.

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HOW THE STATISTICS OF WELL DATA SHOULD BE USED IN THREE-DIMENSIONAL MODELING

Should Models Honor the Statistics of Well Data?

Though it is generally recommended that well data be honored in a reservoir model, which Deveugle et al. (2014) adhere to in their paper, should the statistics of well data be honored in the model? This is a tricky question because the answer depends on several factors. Generally, when well data are representative of the reservoir condition, their statistics should be honored in the model. However, if they are not, their statistics may not be honored.

Deveugle et al. (2014) summarized their paper as follows: "Models constructed using all four algorithms fail to match the facies-association proportions of the reference model because they are conditioned to well data that sample a small unrepresentative volume of the reservoir" (p. 729). Clearly, the authors recognized the "unrepresentativeness of the well data," but the facies models constructed in their study still honor the statistics of their well data.

Well data sampling a small unrepresentative reservoir volume is a common problem in exploration and production because wells are not only drilled for collecting data, but also for the overall optimization of field development (Ma, 2011, p. 6). A facies model that honors unrepresentative well data is generally biased because it does not capture the correct target facies proportions. In such a situation, it is difficult to test the impact of different modeling techniques on describing geologic heterogeneity, a main objective of the study by Deveugle et al. (2014), because the accurate capture of facies proportions, as a set of first-order statistical moments, has a stronger influence on model performance than the heterogeneities represented by second- or higher-order statistics. We think that this is why the impact of different modeling algorithms on facies reconstruction was found insignificant in their study. Had the models been constructed with unbiased facies proportions similar to those of the reference model, the impact of different modeling methods should have been more pronounced. Deveugle et al. (2014) seem to support our assessment because they also noted that "In-place hydrocarbon volume is controlled by the facies proportions of the models" (p. 761). We understand that facies proportions may be uncertain in practice because of limited data, but debiasing facies proportions from unrepresentative well data should be an important step before a realistic facies model can be built.

Is It Possible to Debias Unrepresentative Well Data?

Facies modeling, when conditioned to well data that sample a small unrepresentative volume of the reservoir, does not have to produce a biased model. Debiasing well data or verification of unbiased sampling is one of the most important tasks in reservoir modeling, and this task should be done before constructing a model (Ma, 2009, p. 753–755).

To mitigate bias in well data, nearly all commercial reservoir modeling software provides the option of using target facies proportions in their facies modeling workflow, that is, the user has the choice of entering (presumably debiased) facies fractions. The five software platforms that we have used in the last two decades all provide this option (debiasing algorithms are explained in the next paragraph). Deveugle et al. (2014) indicated that Petrel was used for their facies modeling except for spectral component geologic modeling (SCGM; not commercially available), which is not a part of Petrel (the five software platforms include Schlumberger's Petrel, Paradigm's GOCAD, Roxar's RMS, and two other software platforms that are no longer commercially available). Petrel has the option of allowing users to set target facies proportions (Petrel, 2014a, b). Based on the authors' statement, SCGM "always exactly reproduces the target facies proportion in the well data" (p. 761). It should be noted that when well data conveys a sampling bias, using facies proportions from such data as target proportions will lead to a bias in the model. Only when sampling bias is deemed unimportant should well facies proportions be used as target proportions for the model to be unbiased (see Coupling Spatial and Frequency Characteristics in Reservoir Modeling section in Ma et al., 2011, p. 163). More commonly, reservoir modelers should avoid reproducing well facies proportions when sampling bias is observed (Ma, 2009, p. 753–755; Ma, 2010, p. 295, see section 3.7 Inference Errors Related to a Sampling Bias).

To debias well data in reservoir modeling, several methods have been developed, including the cell-declustering method (Journel, 1983; Pyrcz and Deutsch, 2003), Voronoi polygon tessellation (Isaaks and Srivastava, 1989, p. 238–241; Cressie, 1991, p. 374–376), and propensity zoning declustering (Ma, 2009, p. 753–755). For the data used in Deveugle et al. (2014), both Voronoi polygon tessellation and propensity zoning declustering could mitigate the unrepresentativeness of the pseudowells, that is, the inconsistency between facies proportions from pseudowells and those of the reference model. In fact, facies proportions presented in their indicator probability cube (their figure 7) are basically equivalent to those produced by propensity zoning declustering. This technique, which relies on geological interpretation, can yield similar facies proportions as those of the reference model (see column 6 and column 9 in their figure 11, where sequential indicator simulation and multiple-point statistics both derived facies proportions using the probability cube as a constraint). Alternatively, propensity zoning declustering using the geologic interpretations (such as their figure 8 or their figures 12 and 13) can also yield similar target facies proportions.

Similarly, polygonal tessellation can be used to identify potential bias in well data and to correct it if it is present. Although it may not accurately debias the data, this method can often significantly mitigate the bias. For example, channel-fill sandstones (CHs) represent about 10% of the rock volume sampled in the eight pseudowells in the upper parasequence PSS2. Although Deveugle et al. (2014) noticed that "the well data contain a higher proportion of channelized sand bodies (CH facies association; Table 1) than the reservoir volume (Figure 11)" (p. 759), they did not debias the data. How polygonal tessellation can be applied to debiasing the same data is illustrated in Figure 1, which will lead to a declustered CH facies proportion of 5% or less (the above is an estimate, as we do not have the actual well data required for accurate debiasing. However, comparing their figure 5 and our Figure 1, it is obvious that debiasing will significantly reduce the biased proportion of the CH facies from the pseudowells). More details on debiasing can be found in Pyrcz and Deutsch (2003, 2014, see p. 53–63).

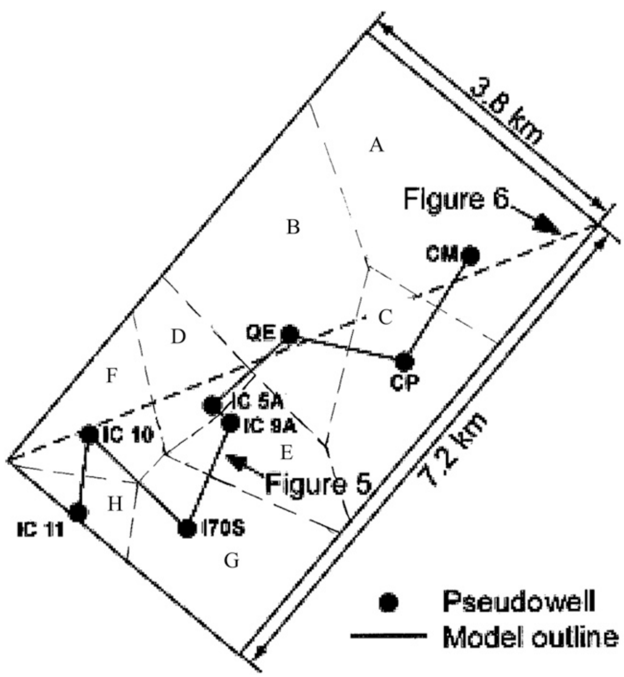

Figure 1. An example of Voronoi polygon tessellation (VPT) using Euclidean distance on declustering facies proportions for the problem in Deveugle et al. (2014) (modified from their paper). Notice that the polygonal areas (A-H) for the wells are very different, and thus a sampling bias is evident. For example, polygonal area A for pseudowell CM is nearly 10 times the size of the polygonal area H for pseudowell IC11. Regarding VPT, the most common VPT technique uses the Euclidean distance. Given a finite set of points (such as wells projected on a surface) in the Euclidean plane, a Voronoi polygonal cell consists of every point p_j, whose distance to the point p_j, is less than or equal to its distance to any other point p_k. Each polygonal cell is obtained from the intersection of these half distances. Hence, the line segments of the Voronoi diagram are all the points in the Euclidean plane that are equidistant to the two nearest sites (i.e., well locations), and the Voronoi nodes are equidistant to three or more sites. For declustering the facies data, a weight is assigned to each site and the weight is proportional to its relative areal fraction, that is, weight for site, *j* is equal to the area of site, *j*, divided by the total area of the field (Pyrcz and Deutsch, 2003, 2014).

FACIES PROBABILITY

Reconciliation of Different Facies Probability Entities

We noticed inconsistencies in the facies proportions from the pseudowells in Deveugle et al. (2014), for example, comparing their figures 5 (p. 738) and 11 (p. 749). The pseudowells in their figure 5 contain no CH facies in PSS1 whereas the same wells in their figure 11 contain approximately 3% CH facies. In their Facies Probability Maps and Vertical Trends … subsection (p. 741–744), geological interpretation maps were presented without the corresponding facies probability maps. Yet later on, the same probability maps were referred to repeatedly, and, under different names, for example, "interpretation facies distributions" (p. 745, 746), "facies-association maps" (p. 745), "facies probability maps" (p. 751), or "the model" (p. 755). This is confusing. From the subsection's title, the authors apparently wanted to derive facies probability maps from the geological interpretation maps, but no probability maps were ever presented. Furthermore, facies probability maps can only be created after reconciling inconsistencies between the interpretation maps and vertical facies proportions at wells. This was apparently not done in the Deveugle et al. (2014) paper. As a result, some of the facies maps (their figure 8; p. 742) and vertical trends are inconsistent with the facies data at wells (their figure 5; p. 738). Below, we list examples of such inconsistencies.

- Well IC11 contains approximately 50% stream–mouth–bar sandstones (SMBs) in the FS2.1 stratigraphic interval (i.e., the interval below the surface FS2.1 in their figure 5), but 100% SMBs are shown in the interpretation maps for the same stratigraphic interval (their figure 8). Similarly, IC11 has less than 40% SMBs for FS1.7, but 100% SMBs are shown in the facies maps for FS1.7.
- Well IC9A contains less than 50% of proximal delta-front sandstones (pDFs) in the stratigraphic

interval FS1.6 (their figure 5), but 100% pDFs are shown in the interpretation maps (their figure 8). A similar inconsistency is observed for FS2.2.

Although inconsistencies are common in facies interpretations, it should be reconciled for the consistency of the inputs and integrity of the modeling process. In Deveugle et al. (2014), such inconsistencies were not reconciled before these maps were used as probability maps to constrain the facies models. Methods and workflows for reconciling geological interpretations and well data to generate probability maps have been discussed in the literature (e.g., Ma et al., 2009, see p. 1244–1248, Probability Maps Integrating Facies Propensity and Frequency Data section; Ma, 2009, see p. 746–747, Section 4: Probability Maps Coupling Facies Frequencies and Spatial Propensities).

Definitions of Facies Probability

Regarding the creation of facies probability volumes in the third to fifth steps of their five-step workflow, Deveugle et al. (2014) stated that "(3) The five probability volumes for each facies association were combined into a single probability volume. … (4) A low-pass bandwidth filter was applied to the combined probability volume. … (5) Probabilities in the filtered probability volume were normalized. …" (p. 740). However, it is not clear how the probability volumes of the five facies can be combined into one volume while preserving the probabilities of each facies. Additionally, it is not clear how the probabilities were normalized in their step 5, especially after the combination in step 3. Recall the three basic probability axioms: (1) nonnegativity; (2) normalization (all probabilities lie between 0 and 1, and the sum of all probabilities equal to 1), and (3) finite additivity (Billingsley, 1995, p. 22; Hajek, 2007; Ma, 2009). Does the authors' normalization adhere to these axioms?

Furthermore, the statement "even a slight increase in the probability of allocating the channel facies to individual grid cells results in a significant increase of the *cumulative estimated proportion of the channel facies association over the entire model* volume" (p. 741, our italic emphasis) is confusing. An increase of probability (or proportion) of any facies over the entire model should equal an average increase in the same facies' probability for all grid cells. Given that each cell is assigned only one facies code in the model, the meaning of "cumulative estimated proportion" is unclear. Facies proportion or probability can be cumulative in the frequency domain, such as in a histogram or probability distribution, but cannot be cumulative over different cells in a model. If the probability was cumulative over different cells in a model, then it could easily become greater than 1, which violates the second probability axiom previously stated. We suspect that the authors tried to express the sensitivity of modeling algorithms to the input parameters because understanding such sensitivity is their main objective. However, such sensitivity analysis was not discussed within the context of their problem (no modeling algorithm was mentioned in that subsection).

CONCLUDING REMARKS

Most of the conclusions from Deveugle et al. (2014) may be valid, and the study is useful to a general geoscience audience. Many of the concepts that have been known to geomodelers and simulation engineers are confirmed by the studied fluvial-dominated deltaic reservoir, which is interesting to see. Nevertheless, we think that for a study to fully achieve its stated aims, the design should test appropriate statistical moments in relation to geological characteristics. Specifically, when testing the impact of different modeling algorithms on generating facies heterogeneities and the resultant flow behaviors, facies proportions from the reference model should be recognized as a set of first-order statistics to match. The constructed facies models honoring these statistics will then become unbiased. From general statistical theory, this is achievable even without a reference model, and is easily achievable when a reference model is available. Otherwise, large differences in facies proportions between the constructed models and the reference model overwhelm the sensitivities of different modeling algorithms. Because of nonnegligible bias in the modeled facies proportions, the second- and higher-order statistics (heterogeneities) became less important for predicting flow, and the sensitivities of facies modeling to the different algorithms became subdued. Although Deveugle et al. (2014) acknowledged the importance of facies proportions, they did not perform this important test, which resulted in biased models that do not reproduce the facies proportions of the reference model. However, generating unbiased facies proportions is important for justifying some of their key conclusions. We also noted some inconsistencies and confusing statements in the authors' discussion on facies probabilities.

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