Geologic Modeling of Eagle Ford Facies Continuity Based on Outcrop Images and Depositional Processes

Pejman Tahmasebi, (currently with the University of Wyoming), Farzam Javadpour, and Gregory Frébourg (currently with Thermal Energy Partners), University of Texas at Austin

Summary

Geologic modeling of mudrock reservoirs is complicated by the presence of multiscale heterogeneities and lithofacies lateral discontinuity. The resolution of wireline logs is also too low to capture many small-scale heterogeneities that affect fluid flow. In addition, the large distance between logged wells results in uncertain long-range correlations. Supplementary to wireline log data, high-resolution outcrop images offer a direct representation of detailed heterogeneities and lithofacies connectivity. We used high-resolution panoramic outcrop images to collect data on lithofacies heterogeneity and the role that depositional processes play in this heterogeneity. We then used these data in different classes of reservoir algorithms—two-point-based, object-based, and higher-order statistics—to build a geologic model. To present our methodology, we used data collected from Eagle Ford outcrops in west Texas. We found the higher-order-statistics method to be especially efficient, capable of reproducing details of heterogeneity and lithofacies connectivity.

Introduction

Mudrock depositional systems are a controlling factor in the development of major reservoir properties such as porosity and permeability. These data are generally extracted from well data (e.g., wireline logs, core samples, and drill cuttings) limited to the near-wellbore space domain and therefore do not contain sufficient information regarding the long-range connectivity and spatial correlations of facies (Sahimi 2011). On the other hand, outcrop images provide a unique and direct representation of geologic features, offering a clear illustration of the geometry and spatial continuity that allows visual inspection of the existing structures. However, because most outcrop data are limited to 2D sections, information from the third dimension is therefore needed to build 3D models with true spatial continuity. In this study, we used sedimentation-process theories to extract information for the third dimension of an outcrop. We used two Eagle Ford outcrops in west Texas to develop our methodology (Frébourg et al. 2016).

For outcrop images, we used different scales. From large-scale images, we extracted information about lateral lithofacies continuity and determined the statistical properties of stratigraphic horizons such as lens length and thickness. From small-scale images, we extracted vertical information such as ash-bed thickness and spacing. Although 2D outcrop images are an important source of data, extending such information to 3D modeling is not straightforward. Because we needed additional information about the distribution of facies in the third dimension, we used our understanding of the early compaction history of pelagic carbonate sand bodies for our Eagle Ford example (Frébourg et al. 2016). In this paper, we present a novel framework that is based on a combination of outcrop-data and sedimentation-process theories in reservoir algorithms to generate 3D geologic models.

Uncertainty in facies-distribution study is considerable, particularly for mudrock reservoirs. In statistics, problems with limited information are known as ill-posed problems. Among different models that use all existing data, stochastic techniques have been found to provide efficient and reliable solutions by using extracted data and producing various equiprobable realizations (Journel and Huijbregts 1978).

Available methods for facies modeling can be divided into two groups: pixel-based and object-based. In pixel-based methods, for each loop in a simulation, only one cell of the geomodel is constructed; therefore, each single cell needs to be visited separately. These algorithms account for short-range connectivity because they consider pixels (Deutsch and Journel 1998). On the other hand, object-based methods require the direct use and assembly of some predefined objects (e.g., channel, ellipses) in building a stochastic model (Deutsch and Wang 1996; Holden et al. 1998). Pixel-based algorithms honor the well data when dense wells or any conditioning data are being considered. These methods, however, produce models that are different from actual structures (e.g., disconnected structures).

Object-based modeling can compensate for the issue of disconnected structures in geomodels, but such modeling requires extra work to match the conditioning data. An approach that alleviates such issues and produces both long-range connectivity and conditioning data is multiple-point statistics (MPS). In our study, various stochastic-modeling approaches were used, and their performances were compared with those of an outcrop data set from an Eagle Ford mudrock formation.

The work flow used in this paper follows this hierarchical scheme:

1. First, geologic data from outcrop images are extracted.
2. Next, morphologic properties of objects, such as length and thickness, are carefully extracted and described in terms of mean and variance.
3. Then, because they only work with numerical information, variogram- and object-based methods are fed with statistical data extracted from outcrop images. The MPS model, however, is used directly on the available outcrop images.
4. Then, the modeling is extended to 3D space, which is challenging for the implemented methods. In 2D modeling, a strategy similar to the previous Step 3 is used for variogram- and object-based methods. The model generated by the object-based method is also used for the MPS method because outcrop data are not available in 3D form.
5. Finally, a set of synthetic acoustic impedance (i.e., seismic data) is synthesized and integrated within the MPS method, and the results are compared quantitatively.

In the Stochastic Modeling Techniques section, we describe the stochastic modeling used. Available 2D outcrop images and extracted information are discussed in the Data From Eagle Ford Outcrops section. In the Results and Discussion section, we...
demonstrate the performance of various stochastic algorithms and compare results quantitatively with those of the proposed method in this paper. Next, we use synthetic acoustic impedance (equivalent to 3D-seismic data) to demonstrate multivariable data integration. The paper is summarized in the Conclusions section, which lists some of the advantages of the proposed work flow.

Stochastic-Modeling Techniques

Two-Point-Based Statistics. Two-point-based statistical methods, also known as variogram-based techniques, consider only correlations between two points. Basically, a variogram measures the average dissimilarity between data that are separated by a vector, \( h \), and calculates half the average squared difference between each data pair (Goovaerts 1997; Deutsch and Journel 1998; Pyrcz and Deutsch 2014). A variogram, as a two-point descriptor, is used for measuring spatial continuity and variability, and is therefore unable to realistically model the geologic features; final models often appear too heterogeneous. Another disadvantage is that linking variogram models to complex geologic features such as curvilinearity, sinuosity, and outcrop data is difficult.

Indicator Kriging, one facies-modeling method used in this study, is a two-point-based algorithm that provides an efficient framework for facies modeling and conditional simulation. As explored in this paper, conditional simulation occurs when a geologic model is built using information such as well and seismic data, into which conditioning data also can easily be integrated. An algorithm starts with a single pixel and simulates the visiting point according to a Monte Carlo approach, drawing a random value that is based on a probability-distribution function. This probability function is constructed on the basis of previously simulated points—available well data and secondary (e.g., seismic) information.

Object-Based Modeling. Object-based algorithms are preferred when more-realistic models are required. In object-based algorithms, geologic structures are replaced with predefined objects based on available data on size, orientation, thickness, and other morphologic properties. Then, various stochastic models can be generated with given distributions in each of these mentioned parameters. Object-based methods can also be conditioned to other data, such as well, seismic, and proportional maps. For example, a global proportion can be defined for each object (e.g., populating the simulation grid until a set of conditions is met). Results of object-based algorithms are satisfying in terms of reproducing many realistic geodels. Object-based techniques, however, require extensive iterations when dense, hard, or additional secondary data are considered, and even then, convergence is not guaranteed.

Multiple-Point Statistics. Development of realistic geostatistical approaches for simulating large-scale porous media has been motivated partly by a current challenge in such modeling—namely, the question of how to include complex patterns and data in the models. Most of the geostatistical models in the past, as already discussed, relied on traditional two-point geostatistics, which have been demonstrated to be inadequate descriptors of structures that contain complex features and variability. Therefore, MPS methods were developed to address the limitations of traditional methods. MPS methods are based partly on the use of a training image (TI), representing a conceptual framework for the most important features of a system and the given prior geologic information. It is worth mentioning that no conditional data (e.g., secondary and well data) should be used for building the TI.

MPS methods were first introduced approximately 2 decades ago (Journel 1992; Guarino and Srivastava 1993; Srivastava 1994). Original methods were not, however, computationally feasible. The first practical method, the single-normal equation simulation (SNESIM) algorithm, which used a search-tree structure, was introduced by Strebe (2002). This method, because the computational time was dramatically lower than for that of the original MPS algorithm, helped in the investigation of further applications of MPS to practical problems. Since that breakthrough, several other MPS algorithms have been proposed (for a comprehensive review, see Tahmasebi and Sahimi 2016a, b). For example, Arpat and Caers (2007) introduced a pattern-based simulation (SIMPAT) algorithm that was based on patterns of heterogeneities and a distance function measuring differences between model and data. This method, however, requires highly intensive computations. To make the model computationally efficient, Zhang et al. (2006) proposed a method that simulated patterns with filters (FILTERSIM) that were predefined and fast-searching; they used a classification method to reduce the number of patterns. However, this technique suffers from extreme pattern reduction, which we refer to as pattern smoothing. Meanwhile, a direct-sampling algorithm was introduced—essentially identical to the SIMPAT, differing only in that it does not require extensive scanning of the TI—based on adding one pixel at a time to the model instead of to a pattern (Mariethoz et al. 2010). This algorithm uses only a fraction of the patterns in the TI and ignores the rest. However, using only a small part of the TI produces the realization of a system without many specific features such that many details may be neglected complexities.

More recently, patch-based algorithms capable of efficient pattern reproduction have become more popular. One of the most recent of such methods is a cross-correlation-based simulation—by which the TI is reconstructed and is denoted by \( T \). The patch-based algorithms change the algorithm's progresses. Finally, \( OL \) represents the overlap region between neighboring templates. We can describe the cross-correlation function (CCF) and the reconstruction algorithm for 2D systems, after which the extension to 3D media will be clear.

Suppose that \( T \) (\( x, y \)) represents the data at point \( T \) (\( x, y \)) of a TI of size \( T_x \times T_y \), with \( x \in \{ 0, ..., T_x - 1 \} \) and \( y \in \{ 0, ..., T_y - 1 \} \). When the TI is examined, a portion \( D_T(u) \) is focused on, with size \( OL_x \times OL_y \); it is regenerated based on the data, such that it matches the corresponding part in the TI. Euclidean distance between a TI and \( D_T(u) \) is calculated as

\[
E_{T,D_T}(i, j) = \sum_{x=0}^{OL_x-1} \sum_{y=0}^{OL_y-1} [TD(x + i, y + j) - DT(x, y)]^2, \quad \sum \quad \sum
\]  

with \( i \in [0 \ up to \ T_x + OL_x - 1] \) and \( j \in [0 \ up to \ T_y + OL_y - 1] \) and \( i, j \in Z \). The \( i \) and \( j \) represent shift steps in the \( x \)- and \( y \)-direction. Therefore, the acceptable candidates (cand) can be expressed as

\[
(i_{cand}, j_{cand}) = \min_{cand} [E_{T,D_T}(i, j)]. \quad \sum \quad \sum \quad \sum
\]  

Eq. 1 can be rewritten and expanded as

\[
E_{T,D_T}(i, j) = \sum_{x=0}^{OL_x-1} \sum_{y=0}^{OL_y-1} [TD(x + i, y + j)^2 + DT(x, y)^2 - 2TD(x + i, y + j)DT(x, y)]
\]

\[
= C_{TD} + C_{DT} - 2C_{TD,DT} \quad \sum \quad \sum \quad \sum \quad \sum \quad \sum
\]  

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Because \( C_{Ox} \) and \( C_{Oy} \) are not dependent on any data event or TI, they are therefore constant. A CCF to quantify the similarity between the TI and DT is thus introduced as

\[
C(i, j) = \sum_{x=0}^{OL_x-1} \sum_{y=0}^{OL_y-1} TD(x+i, y+j)DT(x, y). \]  

(4)

Eq. 4 indicates that the desired position of \((i, j)\)—the best match with the TI—is one that maximizes \( C(i, j) \). If the size of the TI is not too large, all computations are conducted in the spatial domain. When the TI is large, calculations in the Fourier space can greatly reduce central-processing-unit time (Tahmasebi et al. 2017).

Ways of creating the TI include (1) sketches that are based on physical facts that explain the geologic character of the outcrop; (2) remote-sensing data for identifying spatial relationships and topology in a depositional model; and (3) core description and seismic data to infer fine/large-scale relationships between different layers and structures. In addition, unconditional, object-based methods and those that are based on physical processes that occur in an outcrop can provide high-quality TIs that contain more-realistic, more-complex patterns.

For the sake of simplification, we considered unconditional simulation—a simulation in which the algorithm does not have to honor any specific hard (quantitative) data (HD) exactly in the TI. G is partitioned into (square) blocks of size \( T_x \times T_y \) (in three dimensions, \( G \) is partitioned into cubes). Between every two neighboring blocks is an \( OL \) region of size \( \ell_x \times \ell_y \) representing \( DT \), in which \( OL_x(OL_y) = T_x(T_y) \) and \( OL_x(OL_y) \ll T_x(T_y) \), where the \( OL \) region is between two templates that are neighbors in the \((x, y)\) direction (Fig. 1). Suppose, for example, that the 1D raster path is along the vertical \((y)\) direction. The algorithm begins at the origin of the path in \( G \)—for example, the leftmost bottom template in \( G \)—and moves along the path. A realization of the disorder in the TI, equal in size to \( T \), is generated and inserted into the first block of \( G \) along the path, part of which represents the \( OL \) region with the next block.

The purpose of the \( OL \) region is to preserve the continuity near the common boundary between the two blocks. The aim is then to generate a suitable realization of the disorder for the next neighboring block along the path with a bottom section—the \( OL \) region—that makes a seamless transition between the two. If, however, several realizations of the disorder have the same degree of similarity to \( OL \), one of them is selected at random. The procedure continues until inspection of the first vertical column of the raster path is finished. The algorithm then moves forward, beginning with the bottom block of the next vertical column of \( G \), and uses the same procedure, considering its \( OL \) region with the neighboring block on the left. The next block is more complex because it has two \( OL \) regions—at the bottom and on the left. More details about the CCSIM algorithm can be found in Tahmasebi and Sahimi (2016a, b).

**Data From Eagle Ford Outcrops**

The Eagle Ford Group (Boquillas Formation west of the Pecos River) crops out along Highway 90 in Val Verde and Terrell Counties (Fig. 2). The middle Boquillas Member (Lock and Peschier 2006) is the outcrop equivalent of producing Eagle Ford strata in the subsurface. Three main lithologies are observed: organic-matter-rich, globigerinid wackestones; pelagic grainstone beds and lenses; and ash beds. The succession represents a low-productivity, low-accumulation-rate system, in which the globigerinid wackestones represent average conditions. After deposition of ash beds and subsequent release of iron in the water, blooms of planktonic productivity increase trophic levels, and result in an increase of coarse-grained, planktonic, skeletal sediment (Frébourg et al. 2016). Deposition and reworking by bottom currents below the storm wave base are responsible for the lateral discontinuity of pelagic grainstone beds and lenses and ash beds (Frébourg et al. 2016).

Several outcrops, even though intensely weathered, provide the opportunity to observe and measure the vertical and lateral variations of the exposed strata. However, because of the orientation of these outcrop sections, observation of the sedimentary bodies in three dimensions is not possible. Outcrops of the Boquillas Formation in the Ernst Tinaja, Big Bend National Park, Brewster County (Fig. 3), on the other hand, provide a unique opportunity for observation of the lateral continuity of the lithologies in three dimensions.

Using this set of exposures, we measured the lateral and vertical variation and stratigraphic relationships of the lithofacies of the Eagle Ford/Boquillas succession and extracted statistics to serve as input and control data for the model. The main issue encountered during this process resulted from the irregular surface of some of the outcrops. Although uneven surfaces helped provide 3D information at the Ernst Tinaja outcrops, irregular surfaces can create artifacts when mixed with the perspective associated with photographs. Data-set acquisition and processing had to be adapted to minimize artifacts and ensure correct measurements.

**Coarse-Scale Data Set of Outcrops.** This study provides parameters extracted from a data set presented in Frébourg et al. (2016)—a 220-m-long (722-ft) exposure at outcrop Section 13 (Fig. 2). This data set was generated from a combination of nine high-resolution...
GigaPans (with resolution ranges from 1 to 0.25 mm per pixel) and a lidar mosaic acquired through a focus on the geometry of laterally discontinuous pelagic grainstone beds and lenses. On the basis of these high-resolution photographs and controlled by field observations, eight lithological logs were traced. Using lidar mosaics supplemented by the high-resolution pictures, we measured the thickness and length of the pelagic grainstone beds and lenses with JMicroVision image-analysis software (Roduit 2008). The precision of the lidar mosaic is within 1 cm (0.39 in.). The high resolution provided by these data sets allowed some of the thicker ash beds (>1 cm) and other stratigraphic horizons to be traced. Thinner ash beds required a finer-scale data set. Detailed measurements made on the pelagic grainstone lenses at Section 13 (Fig. 2) provided the statistical variability in thickness and length of these sediment bodies. Statistical properties of their occurrence along the stratigraphic horizons are summarized in Table 1.

Fig. 2—Geologic map showing outcrop study area in west Texas (modified from Ruppel et al. 2012).

Fig. 3—Geologic map showing study area in Big Bend National Park (Brewster County) (modified from Turner et al. 2011). Location of measured section noted by black circle.
Study of these geometrical sedimentary bodies began at the Ernst Tinaja location (Fig. 3). Observations made at the Ernst Tinaja (Fig. 2 and Fig. 4) show that the morphology observed on the vertical faces of the roadcuts (X, Z plane) could be propagated in depth along the Y-plane. At this location, a creek has eroded through inclined layers of the Boquillas Formation, allowing observation of the bedding geometry (Fig. 5a).

<table>
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<tr>
<th>Elevation (m)</th>
<th>Number of Lenses</th>
<th>Average Lens Length (m)</th>
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<th>Average Lens Thickness (m)</th>
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Table 1—Statistical properties of stratigraphic horizons in this study. STD DV = standard deviation.

Study of these geometrical sedimentary bodies began at the Ernst Tinaja location (Fig. 3). Observations made at the Ernst Tinaja (Fig. 2 and Fig. 4) show that the morphology observed on the vertical faces of the roadcuts (X, Z plane) could be propagated in depth along the Y-plane. At this location, a creek has eroded through inclined layers of the Boquillas Formation, allowing observation of the bedding geometry (Fig. 5a).

**Fine-Scale Data Set of Outcrops.** A finer-scale data set was used to provide high-resolution and detailed TI for the model. Roadcut 54 (Fig. 2) along Highway 90 was chosen for this purpose because it has one of the least irregular surfaces of all the outcrops. Still, the irregularity of the outcrop surface did not allow tracing of contours of the different lithologies directly without artifacts being created that would have had a significant and negative impact on the model. This issue was resolved by our tracing 20 regularly spaced vertical sections on an image corrected for perspective and correlating them with a high-resolution image background (Fig. 4). This image was spatially calibrated, yielding a 4.7-m-wide (15.4-ft-wide) data set. The resulting TI (Fig. 4b), at a resolution of 1,200 dpi, corresponds to a resolution of 0.47 mm (0.0185 in.).

**Results and Discussion**

The three stochastic methods described were used to build a 3D model from an Eagle Ford outcrop data set. A comparison of results from the different methods is presented. The fine-grained character of mudrocks and associated weathering commonly result in poor outcrop expression, making lithological contrast for observing stratal relationships and architecture for building geologic models hard to perceive. The goal of this study was to provide morphologic data, including vertical- and lateral-variability statistics, for the three main lithologies found in the Eagle Ford Formation, as a framework for building a 3D geologic model that is based on 2D outcrop images.

As previously described, the collected outcrop data are restricted to 2D outcrop images. However, these images were acquired from several different sections and at different scales, thus providing useful statistical information about bedding and facies features in the third dimension. Such spatial morphologic information can be used in the first two described methods, the variogram-based and object-based methods. Using the extracted information, we constructed various 2D and 3D models. Because the MPS method requires a
physical representation of the input geologic model, however, this method could be applied only in 2D modeling because of the availability of the outcrop data in two dimensions. Some attempts have nevertheless been made to use the 2D images to reconstruct 3D models that were mostly limited to fine-scale porous media (Tahmasebi et al. 2015, 2016a,b, 2017). Variogram-based, object-based, and MPS-method models are presented in Figs. 6, 7, and 8, respectively. These models are generated on the basis of the data provided in Table 1 and the outcrop image in Fig. 4.

Fig. 5—Photos of Ernst Member of Bequillas Formation at Ernst Tinaja site (Big Bend National Park, Brewster County) showing bedding styles. (a) View of southern wall of Ernst Tinaja Canyon showing good lateral continuity of pelagic grainstone (competent beds) along cut axis. (b) Straight sand ridge. Red lines frame upcurrent and downcurrent boundaries of sand ridge, red dotted lines underline internal stratification, and white arrow points at inflection between stoss and lee sides (crest). Direction of progradation from bottom-right corner toward top-left corner. (c) Sand ridge. Red lines frame upcurrent and downcurrent boundaries of sand ridge; red dotted lines underline internal stratification. Direction of progradation from bottom-left corner toward top-right corner. (d) Crescentic (barchanoid) dune. Red dotted line follows top surface at middle of dune, showing progradation direction, from bottom-right corner toward top-left corner. All photos: Phone is 10 cm (4 in.) long.

Fig. 6—Results of variogram-point-based statistics for (a) 2D (160 × 160 cells = 40 × 40 ft²), and (b) 3D (160 × 160 × 80 cells = 40 × 40 × 10 ft³) models of Eagle Ford Formation. Some inconsistencies of facies distributions in terms of their similarity with structures in Fig. 4b shown with yellow arrows.
The variogram-based model (Fig. 6) does not show geologic features in the outcrop. In fact, reproducing a similar distribution of horizontal layers and ellipses is not achievable with this method. Note that unrealistic distribution of facies is also observed.

Results from object-based techniques produce a slightly more realistic distribution of morphologic properties compared with that of the outcrop. Not all complexities or spatial information is expressed in simulated models; considerable simplification can be observed by comparing Fig. 4b and Fig. 6a.

On the other hand, results from the MPS method seem more realistic and similar to spatial features observed in the outcrop image. One reason for this significant similarity is the direct use of outcrop data. The other two methods require the extraction of necessary information to build the 2D/3D model. Clearly, inference of all complexities and spatial information from the outcrop elements is impossible. The MPS method, however, does not extract any of this information and instead directly uses outcrop data.

Our conceptual understanding of the geometry of the pelagic grainstone sedimentary bodies in three dimensions was based on field measurements and observations made along Highway 90 (Fig. 2) and the Ernst Tinaja location (Fig. 3). The length and thickness of the vertical section of 409 pelagic grainstone sedimentary bodies were measured at Section 13 of Fig. 2 (Fig. 9; see Frébourg et al. 2016 for methods and details). These measurements were used to define the vertical and lateral extent of the pelagic grainstone sedimentary bodies along their progradation axis, along with the amount of variation of these two dimensions. The width of the pelagic grainstone sedimentary bodies perpendicular to the progradation axis was derived from observations collected at the Ernst Tinaja location (Fig. 3). At this outcrop, note that, with the exception of the barchanoid morphology of isolated hydraulic dunes (Fig. 5d), the pelagic grainstone sedimentary bodies are laterally elongated perpendicular to their progradation axis (Figs. 5b and 5c).

The biconvex shape of the pelagic grainstone sedimentary bodies is associated with compaction phenomena linked to the slowing down and stopping of the prograding pelagic sand body (Fig. 10). As this process ends, underlying pelagic mud dewaterers under the pelagic sand body’s weight, and the latter sinks into the mud, changing its shape into the lenticular or biconvex appearance observed in cores and in outcrop (Figs. 10a, 10b). This lenticular or biconvex shape can appear on all cuts through the barchanoid hydraulic dune sediment bodies and all cuts of sand ridges, but along the axis perpendicular to the progradation (Fig. 11). Using field observations, we interpreted the pelagic grainstone sedimentary bodies to consist of either barchanoid hydraulic dunes or sand ridges with varying degree of sinuosity, with a possibility of the sand ridges coalescing.

We generated a new facies-distribution model with outcrop descriptions in the object-based method (Fig. 12). Note the three distinct regions in the model. For example, the upper part of the model, as expected, represents disconnected barchans that are found only in the region. Similarly, the channels in the middle and lower parts of the model represent two different structures in terms of their morphologic properties.
The model shown in Fig. 12 indicates a nonstationary distribution of the objects. The models that used 2D outcrop data in the previous section can be categorized as stationary models because the statistical properties of a region do not change much and the entire model displays similar distribution. The model based on 3D data, however, does not show a stationary distribution of objects. For instance, the statistical properties in the upper region differ completely from those of the lower one. Such behavior, called nonstationarity, requires a different treatment. To add more complexity to this example, the initial model (Fig. 12) was used. This model is an unconditional model that we consider the reference model for generating the necessary data. For example, a synthetic acoustic impedance image using a moving average method was constructed with the model shown in Fig. 12. To mimic the noise associated with the actual seismic data, we added a random noise to the acoustic impedance data. Likewise, well data were extracted along a vertical direction at random locations in the models shown in Fig. 12. In other words, the facies values in these random locations are selected and considered well data for the next steps. The produced well and acoustic impedance data are shown in Fig. 13.

The size of this system was considered $160 \times 160 \times 80$ cells ($40 \times 40 \times 10$ ft$^3$). Note that we used synthetic acoustic impedance because of the lack of actual seismic data. All the following simulations are performed on a similar size.

Because two-point-based statistical methods cannot reproduce the complex morphologies of channels and barchans, not one has been used for our case. And, although object-based methods can provide a realistic representation of the geology, a simultaneous conditioning to well and seismic data in these methods is not practical. For example, they cannot reproduce well data completely. In this paper, $45\%$ of well data was not reproduced with the object-based method. Furthermore, considering seismic data for each facies is not straightforward. Such limitations have been extensively discussed in previous literature (Shmaryan and Journel 1999; Journel 2002; Gringarten et al. 2005; Hauge et al. 2007; Guo and Deutsch 2010; Pyrcz and Deutsch 2014; Tahmasebi 2017a). The higher-order statistics method, however, can incorporate well and seismic data into a single model. This method can reproduce the entire complexity of the outcrop-defined facies, even in the presence of various conditioning data (Fig. 8). An unconditional model generated by the object-based method, similar to the one shown in Fig. 12, was therefore considered as the TI (Fig. 14).

Dealing with a geologic system that contains multiple facies requires extraction of different probability maps from the seismic data. In other words, the probability of having any of the existing facies should be extracted from the seismic data. For this to happen, the Bayesian rule was used, by which the probability of each of the facies, given well and impedance data, was calculated (Doyen et al. 1994):
where \( P(f_n) \) represents the probability of facies \( f \) and \( P(I) \) is the probability of impedance values.
Three probability maps were extracted from the seismic data (synthetic acoustic impedance in Fig. 13) with the Bayesian equation, and results are shown in Fig. 15.

Probability maps indirectly divide the geologic system into three stationary regions. The simulation grid was divided into three separate regions based on the available facies, and another set of data, called auxiliary region data, was also added to the input data. The TI, well data, extracted probability maps, and auxiliary region data were all used stochastically to generate different realizations (Tahmasebi and Sahimi 2015). Using the described algorithm, we generated 50 realizations; two are shown in Fig. 16. An ensemble average map over the generated realizations was also created for checking the quality of well-data reproduction (Fig. 16). It should be noted that all the used well data are reproduced in this simulation.

Finally, the accuracy of the generated realizations was compared with the TI. For this purpose, variograms and multiple-point connectivity were calculated for realizations and the TI (Krishnan and Journel 2003). The multiple-point connectivity quantifies the probability $p(h; n)$ of having a sequence of connected $n$ facies/pixels in a specific direction $h$:

$$p(h; n) = \text{Prob}[I(u) = 1, I(u + h) = 1, \ldots, I(u + nh) = 1],$$

where indicator function $I(u)$ is defined by

$$I(u) = \begin{cases} 1, & u \in \text{facies } i \\ 0, & \text{otherwise} \end{cases}$$

Results show good agreement with the TI (Fig. 17).
Conclusions

The Eagle Ford Group is one of the most important and extensively studied energy resources in Texas. Statistical properties of the outcrop data have generally been extracted from collected images that are used to build similar models. Such statistical properties, however, are insufficient to include all complexities. In this paper, three different methods were used to generate 2D and 3D geologic models from Eagle Ford outcrop data. Two-point-based (variogram-based) techniques were unable to capture the complexity and long-range connectivity of data because of their high level of heterogeneity and layering; thus, they were poor choices for studying Eagle Ford outcrop data. Results from object-based techniques were more realistic and reproduced spatial continuity, but the method can hardly produce shapes such as those in Fig. 4. In general, this class of facies modeling can be used for specific and simple geometries such as circles, ellipses, and channels. Conditioning object-based techniques to well and secondary data is not straightforward. In contrast, when outcrop images are used directly, the MPS (higher-order statistics) method produces high-quality and realistic realizations. The MPS method used can produce high-quality models while it assimilates all available conditioning data.

The current MPS methods are limited to perform a direct modeling, meaning that adding the third dimension to 2D outcrop images is challenging. Although this has been performed in the fine-scale porous-media modeling with isotropic assumption (Tahmasebi et al. 2015, 2016a,b), repeating a similar exercise for large-scale reservoir modeling can be challenging. Thus, as future work, one can consider using outcrop data at different directions and establish a meaningful 3D correlation between the 2D data. Another issue in the current pattern-based MPS method is reproducing the conditioning point data (i.e., well information). Recently, a new hybrid method that is based on a combination of pixel- and pattern-based methods has been proposed (Tahmasebi 2017b), but this new direction requires further research.

Nomenclature

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
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<tbody>
<tr>
<td>$C$</td>
<td>cross-correlation</td>
</tr>
<tr>
<td>cand</td>
<td>candidate number</td>
</tr>
<tr>
<td>$D_f$</td>
<td>data event</td>
</tr>
<tr>
<td>$E_{TI, D_f}$</td>
<td>Euclidean distance between TI and $D_f$</td>
</tr>
<tr>
<td>$G$</td>
<td>simulation gridblock</td>
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Fig. 17—Comparison between TI (red curve) and generated realizations (gray curves) in terms of variogram and multiple-point connectivity. Representations of behavior of facies (a, b) at bottom; (c, d) at middle; and (e, f) at upper part of realizations. a, c, and e represent variogram; b, d, and f represent multiple-point connectivity. $p(r)$ represents probability of multiple-point connectivity function. Both Lag and $r$ indicate sequence of points/pixels.
\[ h = \text{lag distance} \]

\[ I(u) = \text{indicator value at location } u \]

\[ OL = \text{overlap region} \]

\[ TI = \text{training image} \]

\[ T_x = \text{template size in } x\text{-direction} \]

\[ u = \text{visiting cell} \]

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References


Pejman Tahmasebi is in the Department of Petroleum Engineering at the University of Wyoming. Previously, he was a research scientist at Stanford University, the University of Texas at Austin, and the California Institute of Technology, working on porous media/materials reconstruction, granular materials and advanced computational methods. Tahmasebi’s current interests include computational geomechanics, coupled and multiphysics modeling, subsurface characterization, inverse problems, and data mining. He has authored or coauthored more than 45 technical papers. Tahmasebi holds BSc and MSc degrees from Amirkabir University of Technology and a PhD degree in modeling of subsurface reservoirs and porous media from the University of Southern California. He is an SPE member and is the recipient of the 2017 Vistelius Research Award from the International Association for Mathematical Geosciences.

Farzam Javadpour has worked as a reservoir engineer in industry and is currently working as a research scientist at the Bureau of Economic Geology (Jackson School of Geosciences, University of Texas at Austin). He is the coprincipal investigator of an industrial consortium and leads research works on novel techniques of reserves and permeability estimations as well as oil and gas production in shale systems. Javadpour is also studying the fundamentals of nanoparticle transport in porous media for EOR and reservoir-engineering applications. He teaches shale-gas characterization and production at the University of Texas at Austin. Javadpour has authored or coauthored more than 50 peer-reviewed journal papers and 25 SPE conference proceedings on topics related to shale gas, CO₂ injection, and transport in porous media. He holds a BS degree with distinction in petroleum engineering and MS and PhD degrees in chemical and petroleum engineering, respectively, from the University of Calgary. Javadpour’s work on the development of apparent permeability formulation for shale-gas systems appeared as a Distinguished Author publication in Journal of Canadian Petroleum Technology (JCPT) in 2009. He served as an associate editor for JCPT and was the recipient of the award for the best paper published in JCPT in 2008, the SPE Outstanding Service Award in 2010, and the SPE A Peer Apart Award in 2014.

Gregory Frébourg is a partner and the chief geologist of Thermal Energy Partners, where he focuses on geothermal exploration, research and development, and reservoir characterization. Previously, Frébourg worked as a research associate at the Bureau of Economic Geology, the University of Texas at Austin, for 6 years, during which he also lectured. Frébourg holds a BS degree, an MS degree, and a PhD degree, all in sedimentology, from the Department of Earth Sciences and Environment at the University of Geneva, Switzerland.