Deterministic facies model using lithotype proportion mapping and plurigaussian simulation guided by seismic attribute.

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Summary

Modelers are faced with a variety of challenges when building geocellular models. One significant challenge centers on facies modeling. Practitioners are driven by the depositional models they understand, but all too often the mathematical methods they use are less understood. The selection of a simulation algorithm and the methods used to introduce trends and conceptual geologic information are two potentially significant areas in whichproblems canarise. To address these issues, the authorspropose common facies simulations algorithms be combined with the use of a lithotype proportion matrix (LPM).

LPM allows the geomodellers to map the reservoir both vertically and laterally using well proportion data. Acoustic impedance(AI)data will be treated as guidance to the trend of the reservoir interval. AIdata will be blocking to the 3D geocellular grid and used as the calibration to the model. By using the combination of seismic blocking, LPM, and plurigaussian simulation (PGS), themodeler will have objects control (facies) in their pixel-based model sequence model.

The implementation of a LPM and seismic attribute in combination with pixel-based methods,such as PGS provides a workflow that is both powerful and easy to use.

Introduction

Geostatistical methods have their limitation when applied in complex geological settings. In some cases, the reservoir architecture presents complex facies transitions, which cannot be simulated with mono-Gaussian techniques. However, modelers are presented with a plethora of challenges when attempting to produce models based on real data, including honoring depositional facies boundary conditions and their proportions, honoring the data in presence of numerous or closely spaced wells.

The simplest and frequently used method for facies modeling is sequential indicator simulation (SIS). This algorithm is very straightforward and able to handle anisotropy of maximum continuity direction. However, the algorithm cannot regulate the transitional rule between lithology laterally.

On the other hand, object-based modeling solves this major problem faced by SIS because it can rule the lithology transition laterally. This algorithm can produce a deterministic model. This means this specified algorithm is lack of randomness (stochastic). It usually fails for the very large well counts. Because it usually preserves the object model, it cannot preserve the probability distribution function of input wells in the process.

The plurigaussianapproach has the ability to handle complex facies relationship both vertically and laterally in a pixel simulation. The one powerful combination of methodologies is the use of LPM with plurigaussian algorithm. TheLPM counts for nonstationary casesfor each facies with every layer and interval.

Lithotype Proportion Matrix

The LPM consists of lithology curves representing the facies proportions lithotypes (grouped facies) locally for every blocked layer throughout the model. For the stationarity case (Figure 1A), a single proportion curve is calculated from the pooled set of well control. In nonstationary cases, local proportion curves are created from grouped wells (Figure 1B) located near one another that share similar facies relationships. These are referred to as grouped proportion curves. The LPM (Figure 1C) is computed by interpolating the grouped proportion curves to the geocellular grid. The result is essentially a suite of hundreds of trend maps; one for each lithotype in each layer throughout all layers and all intervals.

The purpose of the LPM is to introduce secondary information, minimally, the various trends in the data.

For example, Figure 1C shows the evaporite facies (blue) increasing in proportion to the east (right) and the siltstone facies (yellow) increasing to the north (up). If a practitioner chooses to modify these trends or insert a geometric pattern of facies related to the conceptual geologic model, the grouped proportion curves canbe edited and copied to desired locations as "pseudo" proportion curves. Thus, when the LPM is recreated, this updated secondary information is captured and ready to be used in subsequent simulations. Figure 2 illustrates a modified LPM, which captures a high permeability feature by modifying the proportions to include better quality reservoir in a channel-like feature.

Seismic Attribute Blocking and Seismic Calibration

Calibrating seismic properties, such as AI to lithologies is not a clear-cut process. Ideally, each lithology would correspond to a different range of AI values; unfortunately, this rarely occurs and there is more often an overlap between the lithologies and the range in AI (Figure 3).

The calibration involves the use of the crossplot, where the seismic attribute value lies on X-axis with the Y-axis as probability (Figure 4).

Seismic attribute blocking is used to block a 3D seismic attribute volume onto a grid. The purpose of seismic blocking is to calibrate the attribute value to identify which facies are associated with a particular range value of amplitude. This process will average the value of the seismic attribute and assign the value to every cell in3D geocellular. The preferred method is using the same number of samples to calibrate the relationship between the seismic attribute and the facies. This method will give the result of probability of seismic attribute class in relationship with facies. Seismic attribute blocking and calibration can be used to quality control (QC) the facies changing laterally and vertically.

Seismic data will help the geomodeller define the continuity of the facies because of lack of well data. With the combination of LPMand seismic attribute, the geomodeller can easily interpret the distribution of particular facies for particular layering of the model.

Sequential Indicator Simulation

Sequential simulation techniques explicitly calculate the conditional distribution at each point and sample from this distribution. SIS will require an indicatorfor each modeled interval. By constraining the randomness, spatial distributions vary from realization to realization;yet, always honor the data and variogram.

Plurigaussian Simulation

Plurigaussian method assumes a logical ordering or transition between lithologies controlledby LPM, the data, and variogram.The results also show the same ordering in the lithologies. PGS can use two variograms; one for each of the two lithology sets.

Case Studies

In a West Texas field located on the eastern edge of the Central Basin platform in the West Texas Permian Basin (Figure 5), production is from the Grayburg Formation (Permian,Guadalupian), which is transitional between the previously more open marine conditions of the San Andres Formation and the more arid sabkha and siliciclastic eolian dune field environment of the younger Queen Formation.

Lithologically, the Grayburg Formationis composed of alternating dolomite and siltstone for a total thickness of 140 m. Dolomites range from anhydritic skeletal wackestones tomudstones. Porosity is moldic or vuggy and can be extensively plugged by anhydrite. The siltstones are dominantly angular to subrounded quartz grains with angular feldspathic grains, which commonly alter to clay often plugging pore throats. Siltstone porosity is intergranular. This formation has a characteristic shoaling-upward, prograding sedimentary motif, ranging from shallow openmarine to tidal flat/sabkha sediments. The silt is believed to be of eolian origin, reworked by strandline processes into a series of thin, offlapping shoals. Progradation of the carbonate shelf was approximately from west to east. Structurally, the reservoir is a north-south-trending asymmetrical anticline, dipping gently eastward into the Midland Basin. The Permian climatic regime was similar to the Plio-Pleistocene with major periods of glaciation. The carbonates formed during interglacial periods of relative high sealevel, whereas the eolian siltstones were most likely deposited during low sea level glacial periods with a source from the present day southeast New Mexico.

Results and Discussion

Two different LPMs were created: one allowing the grouped proportion curves to be interpolated with no modification or introduction of pseudo-proportion curves, and one with modifications to introduce a continuous geometric zone of better reservoir quality (siltstone, thief zone) known to be present. Each LPM was used with two different modeling methods: SIS and PGS respectively. For SIS, a simulation is shown with no introduction of secondary information to demonstrate the general effect LPM has on this particular method. The results are shown below.

Sequential Indicator Simulation

If the modeler is SIS without a secondary constraint, such as LPM (Figure 6A),the results are noisy, there is no control over facies boundary conditions, and facies occur in areas where they do not belong. Figure 6B illustrates the improvement of the model with the introduction of the LPM. With the pseudo-proportion curve, themodeler can introduce amore geological concept and generate a cleaner facies model (Figure 6C).

AI calibration wasused as a background to the simulation. Based on the seismic blocking and calibration, the value AI ranges between 3.89 and 0.61 will result ineolian facies in the model (Figure 7).

Plurigaussian Simulation

PGSmethod assumes a logical ordering or transition between lithologies controlled by LPM, the data, and variogram. The results also show the same ordering in the lithologies. PGS can use two variograms: one for each of the two lithology sets (Figure 8). In this study, one variogram controls the geometry of two siltstone facies, and the other variogram controlsgeometry of carbonate facies. Figure 9A shows a model using unedited LPM generates highlyoptimistically simulated connectivity of high-permeability zone (red). Whereas, Figure 9B introduces the pseudo-proportion map to the model and generates a more geologically reliable model.

The PGS results model fits with the AI calibration better and also provides more reliable lithology contact vertically (Figure 10).

Conclusion

There is no stochastic modeling method that is universally best for all possible petroleum reservoir problems. As stochastic modeling becomes more accepted in the petroleum industry, and as more stochastic modeling techniques are developed, the most successful case studies will be those that view the growing assortment of methods as a tool kit rather than as a set of competing methods.The seismic attribute can provide guidance becausethe well gap in between the well allows the model to makemore geological sense. PGS as the algorithm has the flexibility to give two variograms in one interval each for every lithology set.

The implementation of a LPM and seismic attribute in combination with pixel-based modeling,such as plurigaussian simulation provides a workflow that generates a more geologically reliable model.

References

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Yarus J.M., and Chambers R.L., 1994, Stochastic Modeling and Geostatistics; Tulsa, Oklahoma, AAPG.

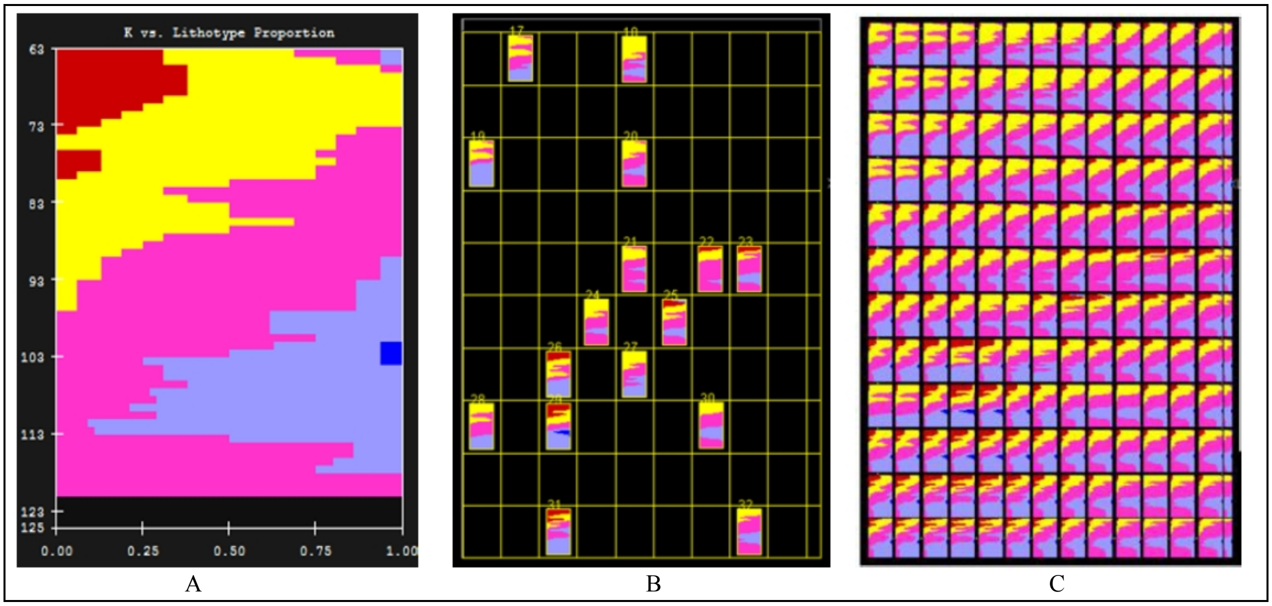


Figure 1: Interval 2 proportion curves and matrix:(A)vertical proportion curve, stationary case; (B)grouped proportion curves;(C)lithotype proportion matrix, nonstationary case (Yarus, et. al, 2012).

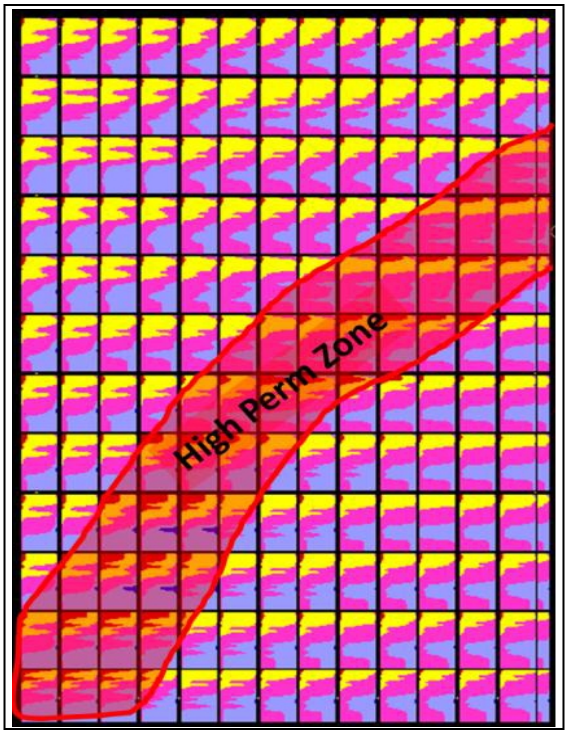
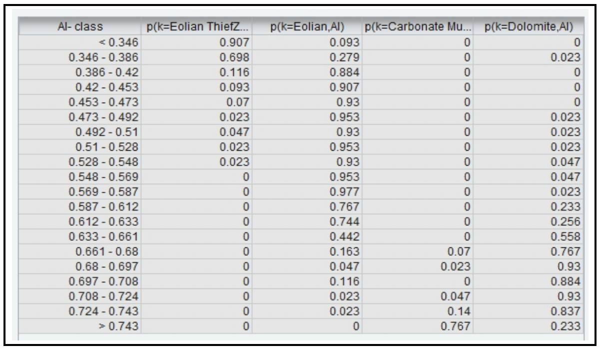


Figure 2: LPM showing a user-defined region of better quality reservoir relating to high permeability (Yaruset al. 2012).



AI- class	p(k=Eolian ThiefZ...	p(k=Eolian,AI)	p(k=Carbonate Mu...	p(k=Dolomite,AI)
< 0.346	0.907	0.093	0	0
0.346 - 0.386	0.698	0.279	0	0.023
0.386 - 0.42	0.116	0.884	0	0
0.42 - 0.453	0.093	0.907	0	0
0.453 - 0.473	0.07	0.93	0	0
0.473 - 0.492	0.023	0.953	0	0.023
0.492 - 0.51	0.047	0.93	0	0.023
0.51 - 0.528	0.023	0.953	0	0.023
0.528 - 0.548	0.023	0.93	0	0.047
0.548 - 0.569	0	0.953	0	0.047
0.569 - 0.587	0	0.977	0	0.023
0.587 - 0.612	0	0.767	0	0.233
0.612 - 0.633	0	0.744	0	0.256
0.633 - 0.661	0	0.442	0	0.558
0.661 - 0.68	0	0.163	0.07	0.767
0.68 - 0.697	0	0.047	0.023	0.93
0.697 - 0.708	0	0.116	0	0.884
0.708 - 0.724	0	0.023	0.047	0.93
0.724 - 0.743	0	0.023	0.14	0.837
> 0.743	0	0	0.767	0.233

Figure 3: AI probability value.

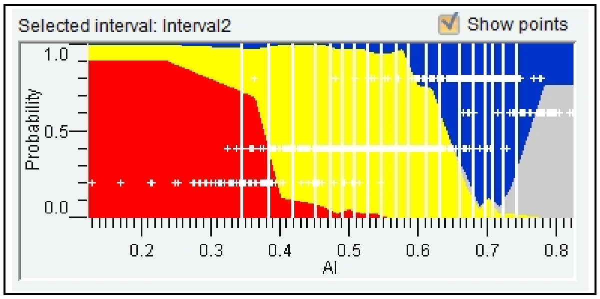


Figure 4: Crossplot diagram showing AI value (X-axis) and probability (Y-axis).

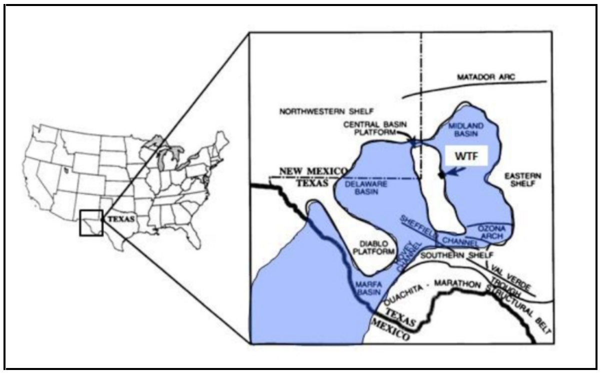


Figure 5: Study data location.

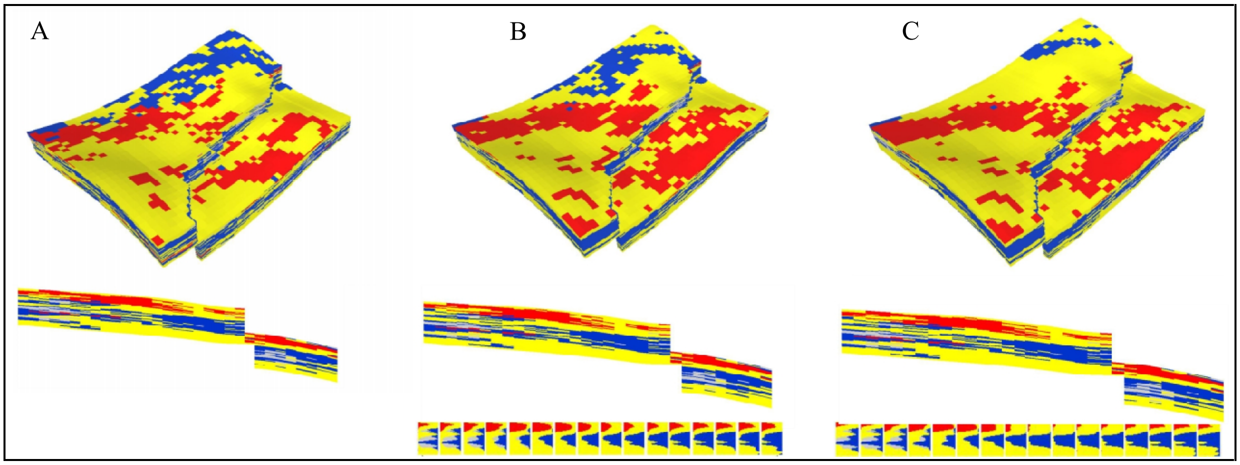


Figure 6: (A) SIS result with no LPM model; (B) raw LPM model; and (C) using the pseudo-proportion curve model.

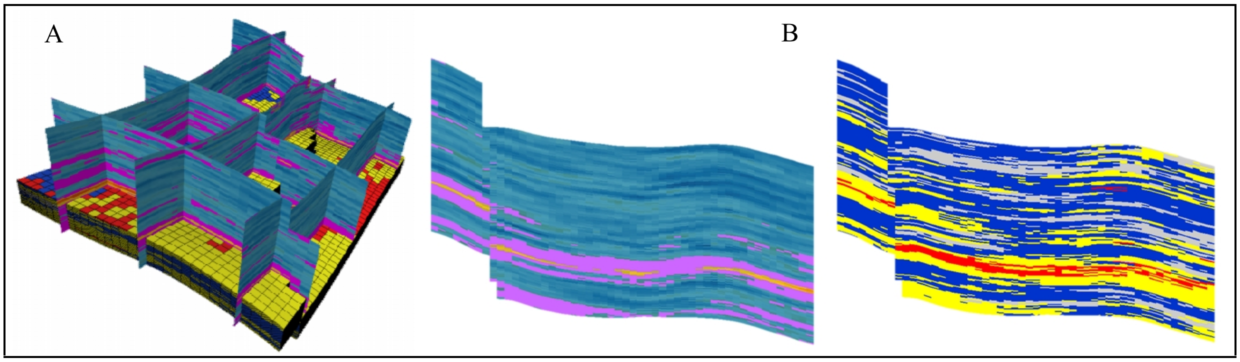


Figure 7: (A) 3D view of SIS QC model with AI calibration (purple marked AI range value 0.38 to 0.61) showing the distribution of eolian facies through the model;(B) Crosssection comparison between AI (left) and SIS facies model (right).

☑ Show wells

Lithotype Contacts From Well Data

- 🟨 Eolian — contacts
- 🟦 Dolomite — contacts
- 🟥 Eolian ThiefZone — contacts
- ⬜ Carbonate Mud — contacts

Lithotype sets: ● Set 1 ○ Set 2

- Eolian (55.6%) ☑
- Dolomite (29.2%) ☑
- Eolian ThiefZone (10%) ☑
- Carbonate Mud (5.2%) ☑

Interval: Interval2

	Lithotype Set 1		Lithotype Set 2	
Model type:	Cubic		Cubic	
Major direction azimuth:	40	deg	75	deg
Major scale:	2100	meters	600	meters
Minor scale:	700	meters	400	meters
Vertical scale:	3.7	meters	4	meters

☐ Change correlation coefficient between lithotype sets

Repel Attract 0

☐ Conditional simulation (slow)

K plane: 123

Seed number: 423,141

Variogram model: Interval2_LPM_TD_EDITED_Variogram_1

Figure 8: Two variograms model for plurigaussian facies simulation.

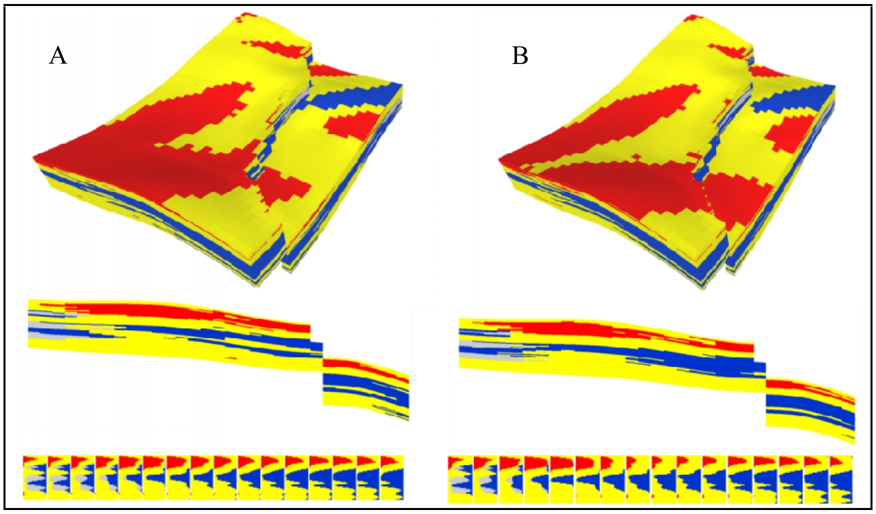


Figure 9: (A)PGS result with no LPM model;(B)raw LPM model.

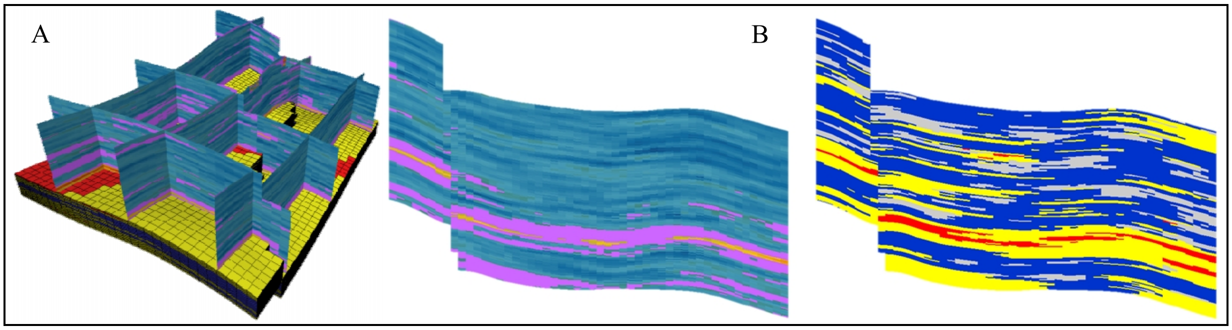


Figure 10: (A) 3D view PGS QC model with AI calibration (purple marks AI range value 0.38 to 0.61) showing the distribution of eolian facies through the model;(B) crosssection comparison between AI (left) and PGS facies model (right).