

Capturing Depositional Processes Using MPS Simulation with Multiple Training Images*

Prasenjit Roy¹ and Sebastien Strebelle²

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¹Earth Science R&E, Chevron ETC, Houston, TX (prex@chevron.com)

²Earth Science R&E, Chevron ETC, San Ramon, CA

Abstract

Multiple-Point Statistics (MPS) simulation has emerged recently as a practical geostatistical modeling technique to simulate complex depositional facies patterns, such as sinuous channels, that cannot be modeled using conventional (two-point statistics) variogram-based techniques. MPS simulation consists of first extracting patterns from a 3D numerical training image describing the type of geological elements expected in the reservoir under study, and then reproducing similar patterns conditional to well and seismic data in the simulation grid.

However, hydrocarbon fields are very often characterized by multiple depositional processes, resulting in the juxtaposition of various types of facies architectures; for example, slope valley channels becoming unconfined lobes when reaching the basin floor in deepwater turbidite environments. To capture that spatial variety, a novel extension of the MPS simulation approach is proposed to enable the use of multiple training images representative of different depositional processes. This paper also demonstrates how additional modeling constraints, such as facies proportion maps and curves, as well as variable azimuth fields, help build MPS facies models, providing a more accurate representation of the underlying geological heterogeneity.



Capturing depositional processes using MPS simulation with multiple training images

Prasenjit Roy & Sebastien Strebelle

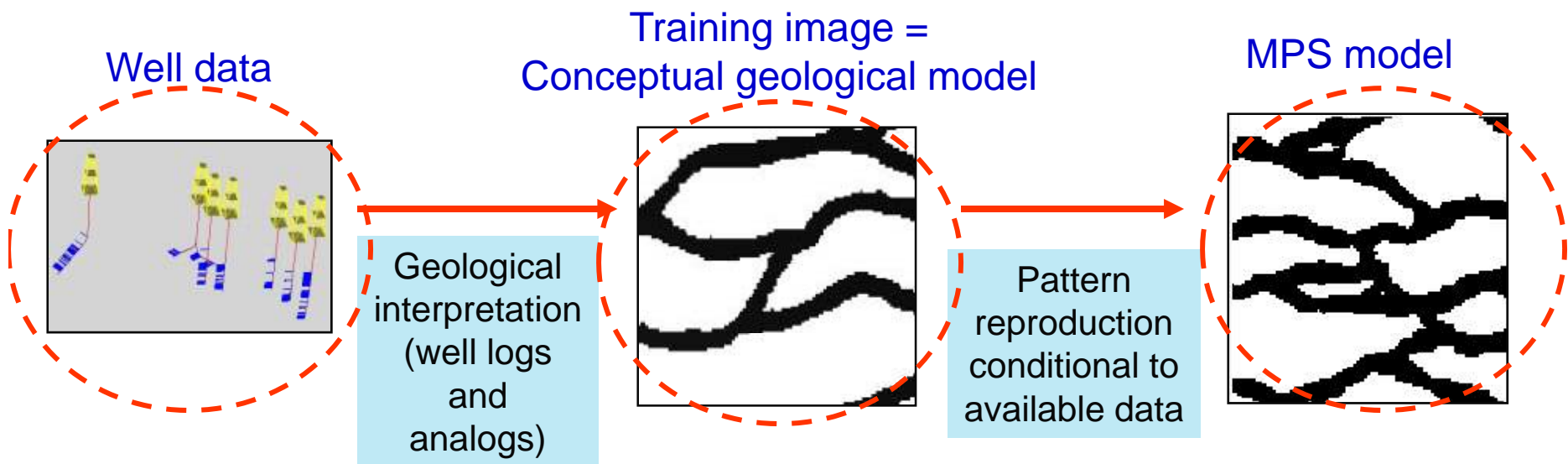
Chevron Energy Technology Company

April 23, 2008

MPS Background:

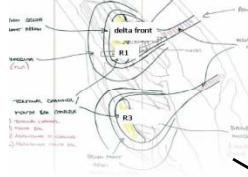
- MPS is a geostatistical approach that combines
 - Ability to reproduce “shapes”
 - Speed, flexibility and easy data conditioning

Excellent geological
modeling of
depositional facies

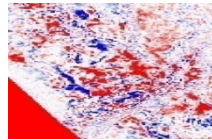


Training Image: geological model

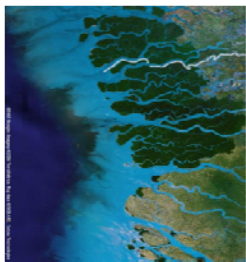
Hand drawn sketches of depositional model from expert geologist



Seismic data

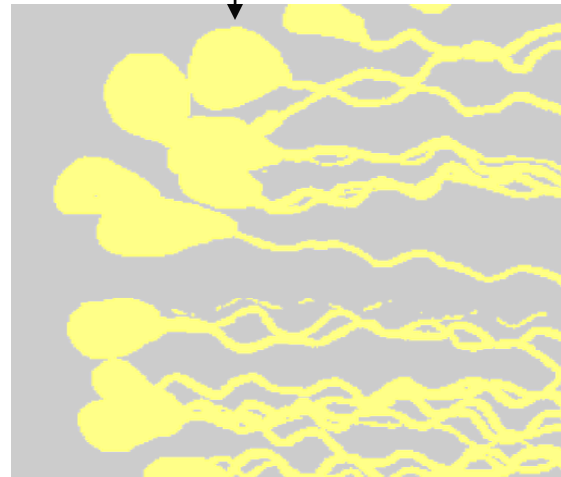
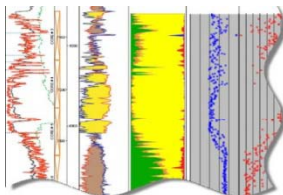


Analogues



Modified after Google map displaying Ganges delta

Core descriptions and other internal & external publications



Integrate geological & geophysical knowledge to create training image

■ Training image provides conceptual model which is used to **infer multiple point statistics**

■ Assumptions:

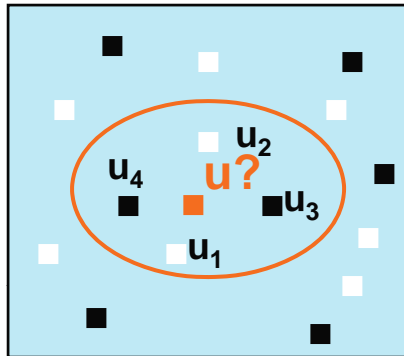
■ **Stationarity:** Similar shaped geobodies should be evenly distributed in the Training Image

■ **Conditional independence** between the data events (Journal, 2002)

Journal, A.G., 2002. Combining knowledge from diverse sources: An alternative to traditional data independence hypothesis. Mathematical Geology., v. 34, no. 5, 573-596.

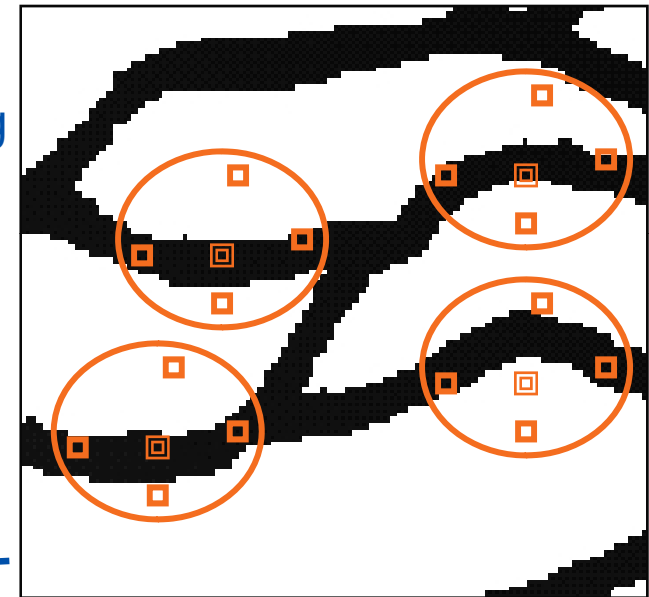
Pixel-based Sequential MPS Simulation Program (Guardiano and Srivastava, 1993)

Simulation grid

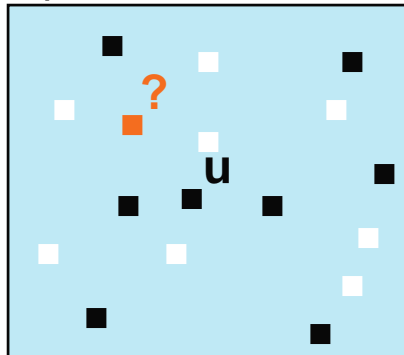


Look for patterns matching conditioning data

Training image



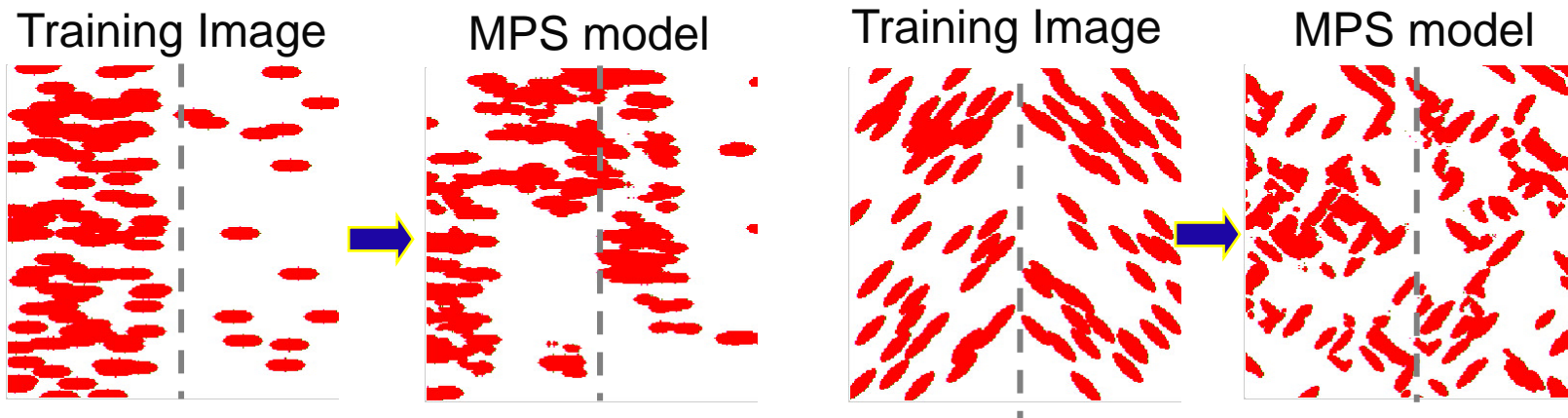
Updated simulation



Compute Probabilities
 $\text{prob}(\mathbf{u} \text{ in sand} | d_n) = 3/4$
 $\text{prob}(\mathbf{u} \text{ in shale} | d_n) = 1/4$
 Draw simulated value

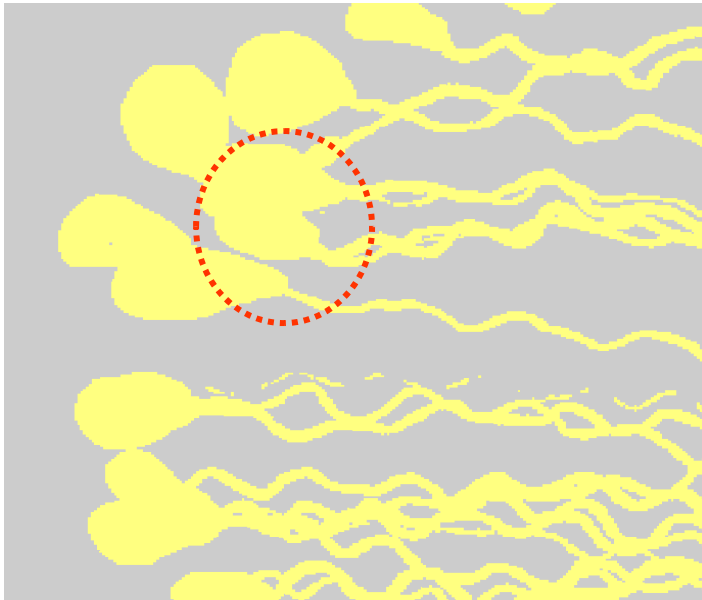
Go to next grid node...
(random walk)

Non-Stationary Training Images

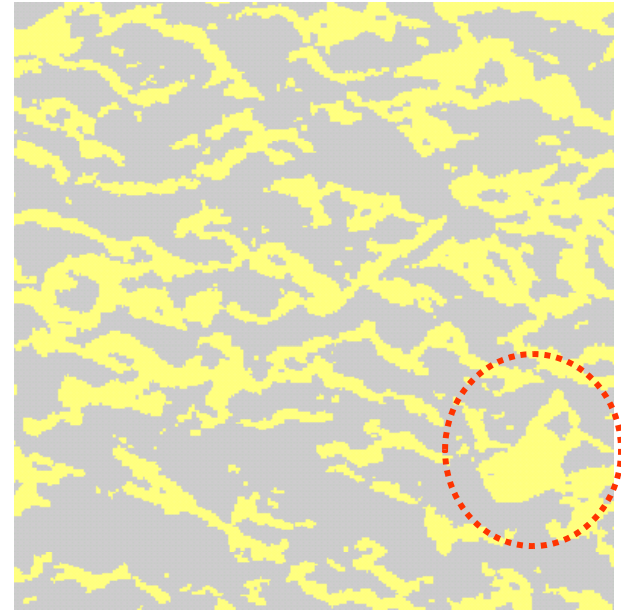


Training non-stationary features not reproduced in MPS models

Problem of Stationarity



Training Image



MPS model

- **MPS model result did not honor depositional regions**



Training Image: Issues of stationarity

■ Possible solutions:

- Apply variable azimuth and range with additional soft data constraint (Strebbelle, 2002, Levy et al., 2006)
- Using very large training image so that complex spatial patterns have atleast some replicates (Liu, Y., 2006)
- Using conditional Simulation with patterns which is a direct pattern recognition technique unlike more conventional probabilistic approach (Arpat & Caers, 2007)

Arpat, G.B. and Caers, J., 2007. Conditional Simulation with Patterns. Mathematical Geology, v. 39, no. 2, 177-203.

Levy, M., Harris, P., and Strebbelle, S., 2006. Multiple-Point Statistics (MPS)/Facies Distribution Modeling (FDM) of Carbonates – an Isolated Platform Example at 2006 AAPG International Conference and Exhibition, (November 5-8, 2006) Technical Program

Liu, Y., 2006. Using the Snesim program for multiple-point statistical simulation. Computers & Geosciences, v.32, 1544-1563.

Strebbelle, S., 2002. Conditional simulation of complex geological structures using multiple-point statistics. Mathematical Geology, v. 34, no. 7, 1161-1168



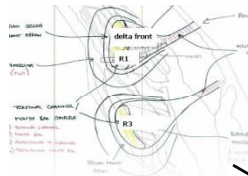
Training Image: Issues of stationarity

- Complex spatial patterns are sometime difficult to reproduce using trend and residual or due to lack of data
- Very large training image may require very large RAM
- Lower variability between realizations with pattern based techniques

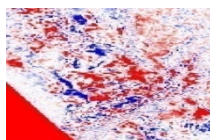
So what is NEW?

Conceptual depositional model

Hand drawn sketches of depositional model from expert geologist



Seismic data

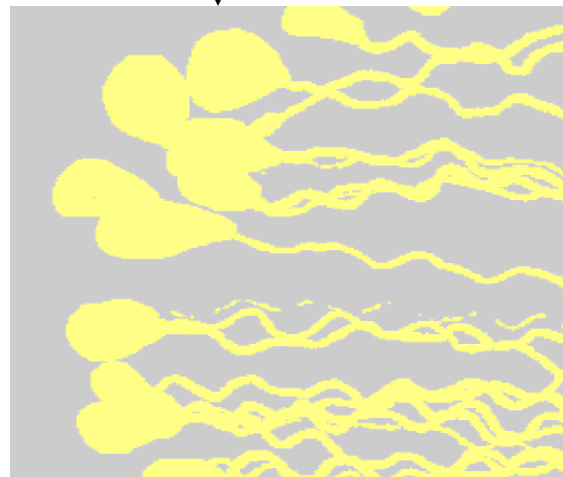
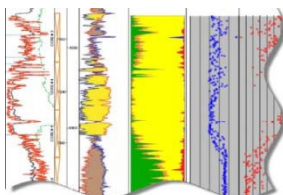


Analogues



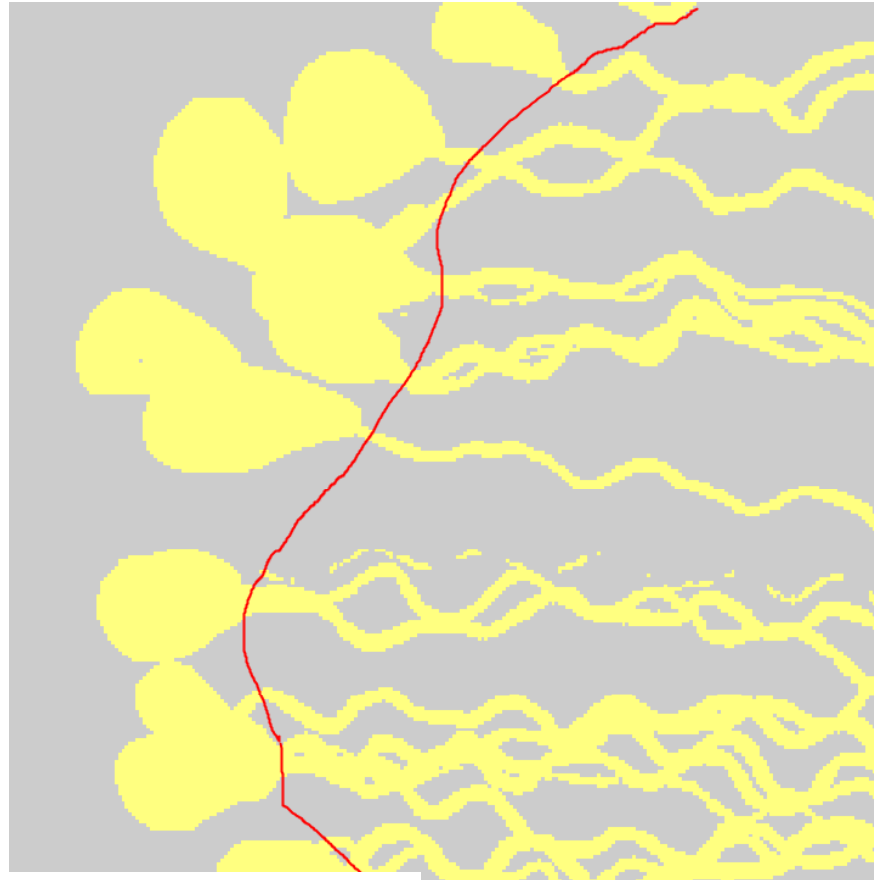
Modified after Google map displaying Ganges delta

Core descriptions and other internal & external publications



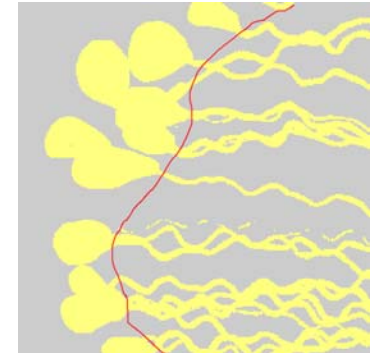
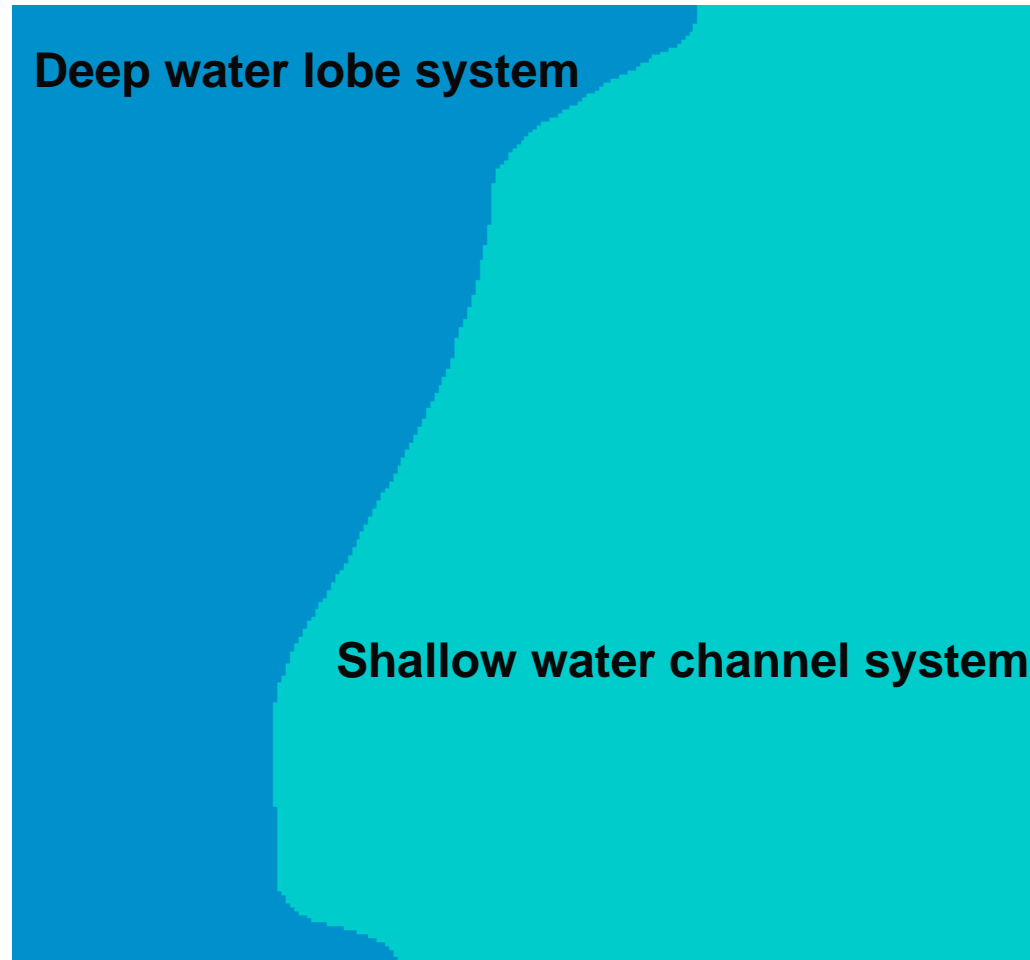
Conceptual depositional model

Shallow water channel system



Deep water lobe system

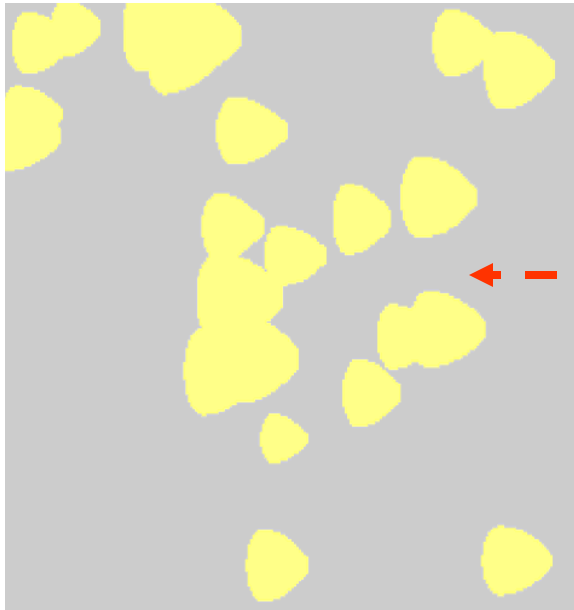
Conceptual model



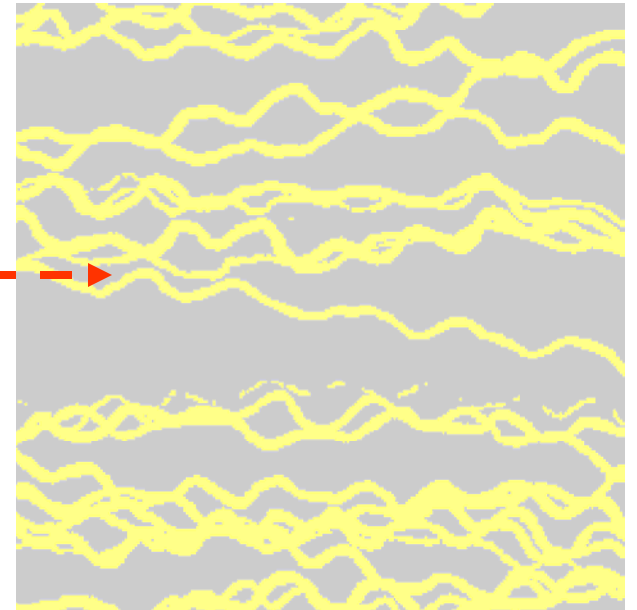
Define depositional regions based on conceptual model

MPS Simulation- use multiple training images

Deep water Training Image



Channel Training Image

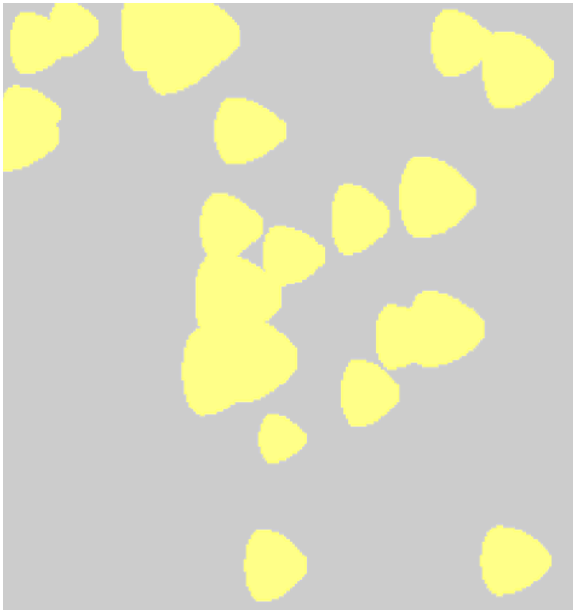


For 2 depositional regimes 2 training images are used

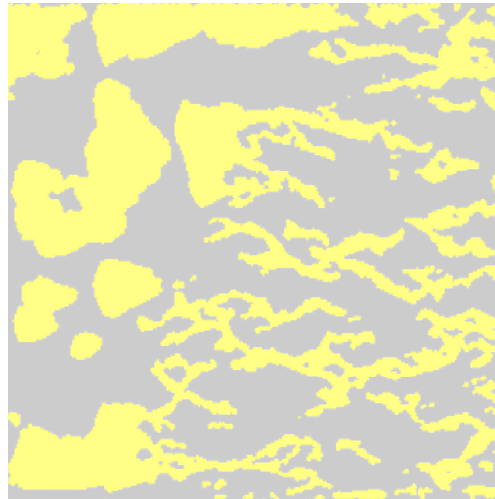


MPS Simulation- use multiple training images

Deep water Training Image



MPS Model

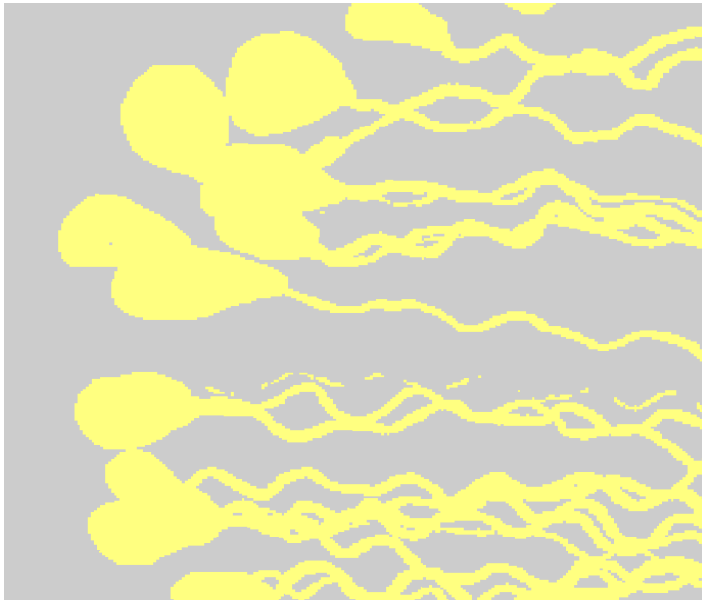


Channel Training Image

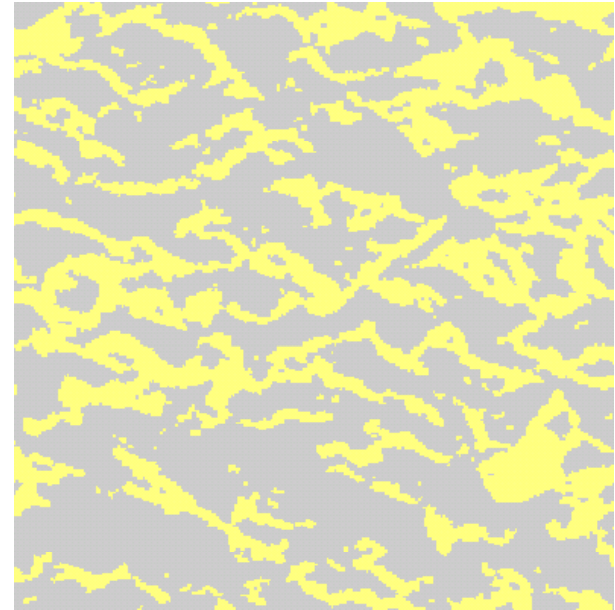


MPS model reflecting spatial geological heterogeneity

Problem of Stationarity



Training Image



MPS model

- **MPS model result did not honor depositional regions**



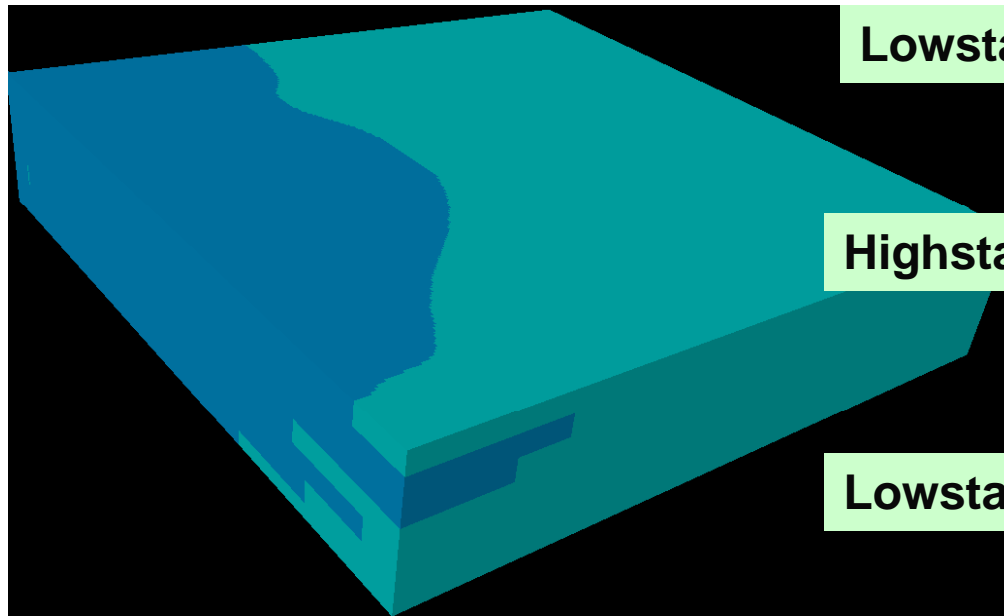
- **We propose to use multiple training images**
 - **Reservoirs can be categorized into separate depositional regimes**
 - **Each distinct depositional regime can be modeled by a unique conceptual model or training image**
 - **Follow conventional MPS technique to simulate each depositional regimes with different training images**
 - **Apply additional constraints to model vertical and spatial heterogeneities**

Here we propose to take advantage of the proven technique of probabilistic MPS simulation to model complex reservoirs by addressing the issue of stationarity using multiple training images

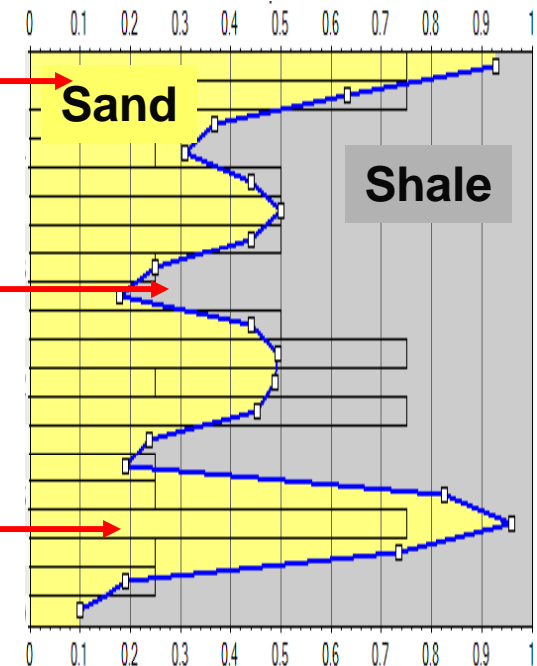
MPS Simulation- Variable net to gross by change in Sea level



Depositional model



Target: Vertical facies proportion

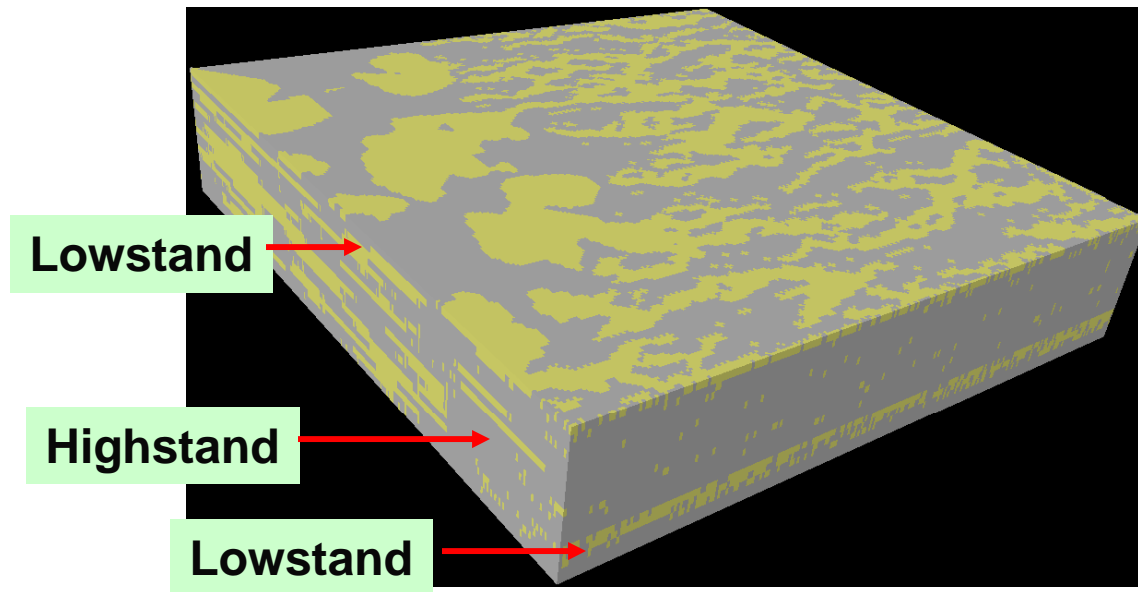


Depositional model reflecting vertical facies distribution with changes in sea level

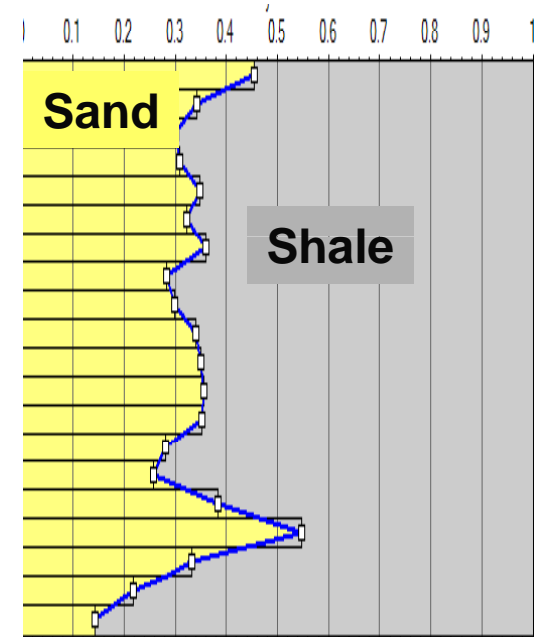
MPS Simulation constrained by vertical facies distribution



MPS model

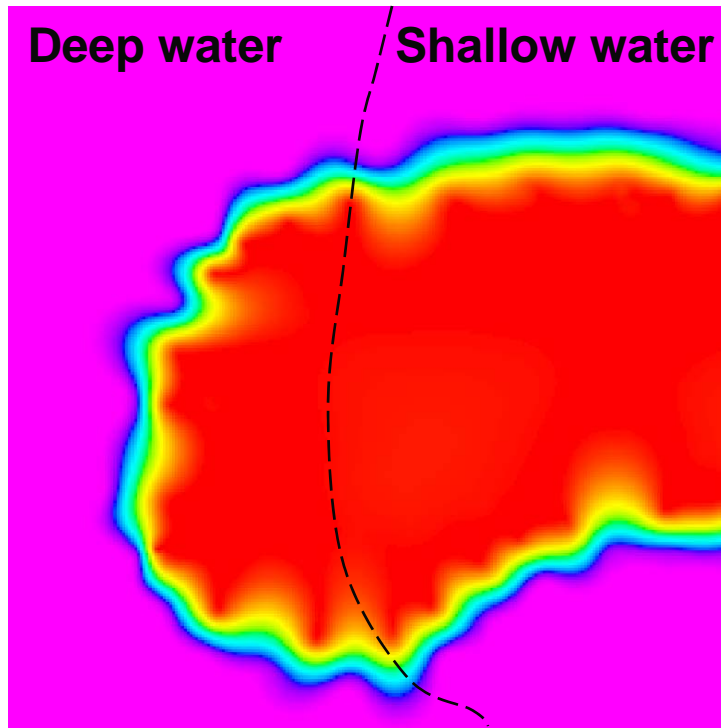


Result: vertical facies proportion

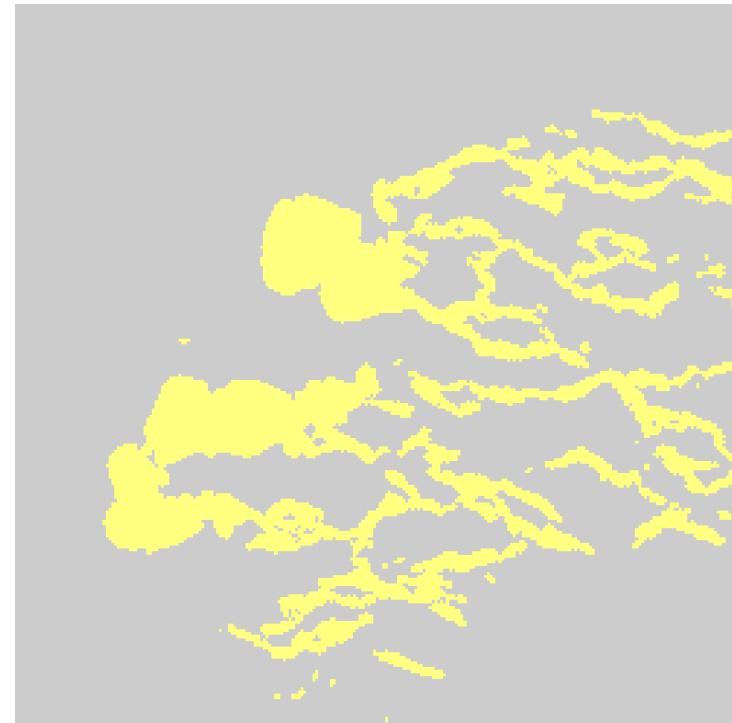


MPS model reflecting vertical facies distribution with changes in sea level

MPS Simulation constrained by facies proportion map



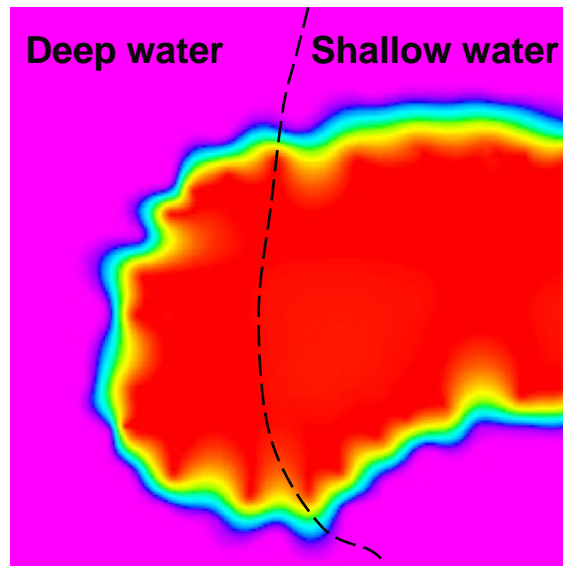
Sand proportion map



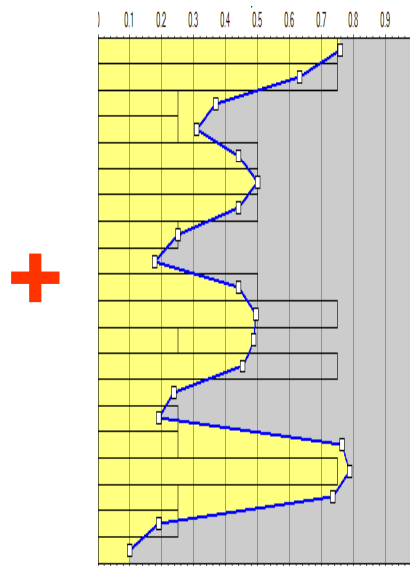
MPS model

Sand proportion map reflecting areal facies distribution

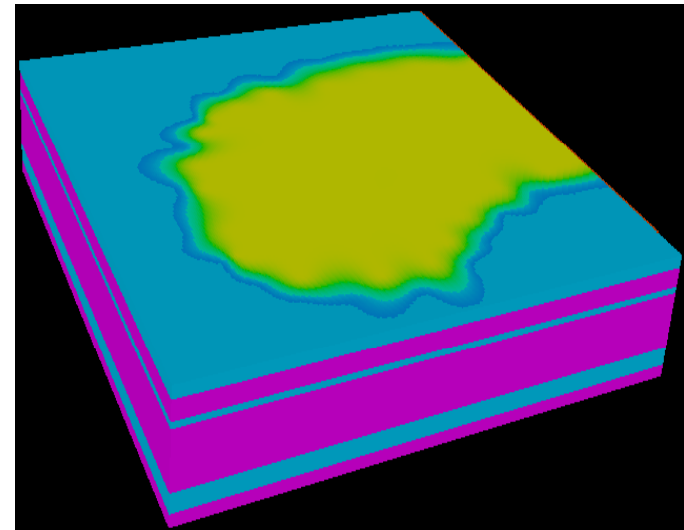
MPS Simulation constrained by facies probability cube



Sand proportion map



Sand proportion curve

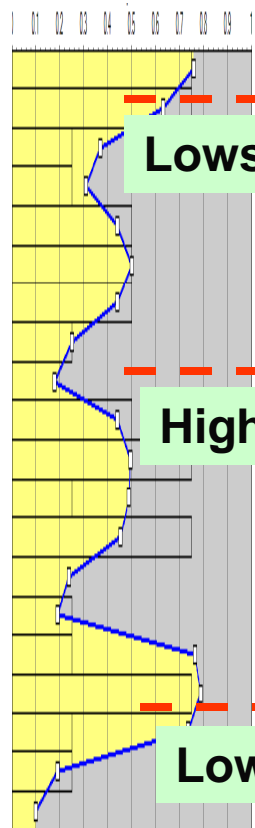


Sand probability cube

Combine sand proportion map & vertical proportion curve to create sand probability cube

MPS Simulation constrained by facies probability cube

Target vertical facies proportion curve

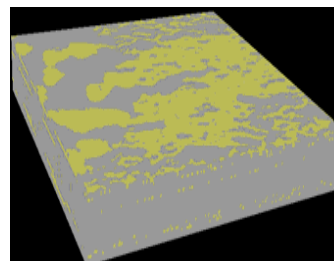
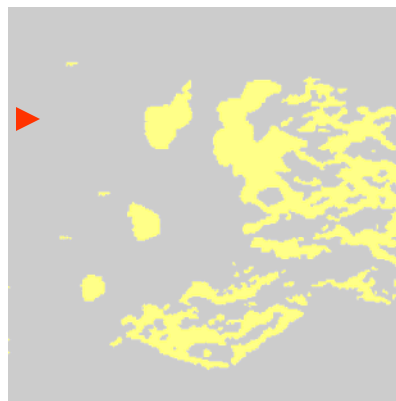
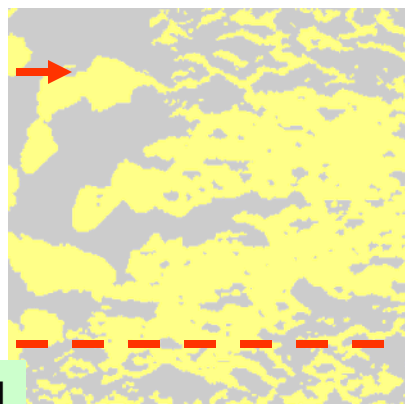


Lowstand

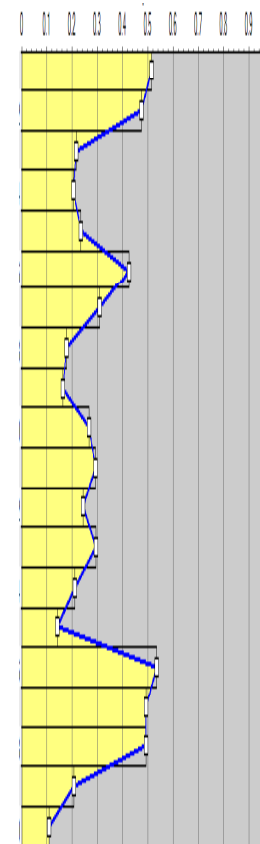
Highstand

Lowstand

MPS model



MPS generated vertical facies proportion curve





Conclusions

- **Using multiple training images**
 - **Complex reservoirs with multiple depositional regimes can be simulated honoring multiple hard and soft data constraints**
 - **Discretizing one large & complicated training image into multiple smaller pieces should decrease total RAM usage and improves performance**



ACKNOWLEDGEMENTS

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References

Arpat, G.B., and J. Caers, 2007, Conditional simulation with patterns: *Mathematical Geology*, v. 39/2, p. 177-203.

Guardiano, F.B., and R.M. Srivastava, 1993, Multivariate geostatistics; beyond bivariate moments: *Quantitative Geology and Geostatistics*, v. 5, p. 133-144.

Journal, A.G., 2002, Combining knowledge from diverse sources; an alternative to traditional data independence hypothesis: *Mathematical Geology*, v. 34/5, p. 573-596.

Levy, M., P.M. Harris, and S. Strebelle, 2006, Multiple-Point Statistics (MPS)/Facies Distribution Modeling (FDM) of Carbonates – an Isolated Platform Example (abstract): 2006 AAPG International Conference and Exhibition: Search and Discovery Article #40292 (2008) web accessed 30 October 2008 (<http://searchanddiscovery.com/documents/2008/08059levy/index.htm>)

Liu, Y., 2006, Using the Snesim program for multiple-point statistical simulation: *Computers & Geosciences*, v. 32, p. 1544-1563.

Strebelle, S., 2002, Conditional simulation of complex geological structures using multiple-point statistics: *Mathematical Geology*, v. 34/7, p. 1161-1168.