Geostatistical reservoir modeling necessitates assumptions that often over-simplify heterogeneity, causing realizations to belie complex geologic reality. Outcrop studies provide robust suites of subseismic-scale (bed- to geobody-scale) statistics that characterize internal geobody architecture (e.g., bed thicknesses and lengths, grain size distributions). However, direct integration of such data into subsurface modeling workflows that capture geological complexity, remains challenging. This study: (1) presents bed-scale statistics from Late Cretaceous Horseshoe Canyon Formation fluvial point bar deposits that outcrop in southeastern Alberta, (2) investigates multiple modeling methodologies to test how different algorithms can integrate such statistics into reservoir modeling workflows, and (3) generates models that retain the geological essence of the outcrop deposits.

Stratigraphic sections (n = 40) record grain size, sedimentary structures, and bedding characteristics, providing the basis for reservoir model facies classification. Differential GPS surveys delineate individual lateral accretion packages (LAPs), capturing the stratigraphic framework for modeling outcrop architecture. Vertical and horizontal facies proportions and transition probabilities are calculated from measured sections, and constrain the probability that a facies is present at specific stratigraphic positions within each LAP. Bed-scale correlations are crucial for robust characterization of outcrop heterogeneity with such statistics. Probability cubes derived from these outcrop statistics guide simulations. Nested Truncated Gaussian Simulation (nTGS) is compared with Plurigaussian Simulation (PGS). nTGS realizations produce geologically-realistic outcomes with a small loss of fidelity to input facies proportions. PGS realizations produce less-geologically-realistic realizations, but better-preserve global facies proportions. Neither reproduces the LAP internal architecture observed in outcrop. Training images derived from outcrop statistics for multiple-point simulation achieve what nTGS and PGS could not, generating models with a better visual match to the outcrop that honors input statistics. This study presents a pathway to directly constrain models to measured outcrop statistics while also reproducing visual outcrop heterogeneity. As such, flow simulations on such models will test the flow-impacts of outcrop-derived architecture rather than purely stochastic heterogeneity.
1. Objectives

Build bed-scale models that:

1) Honor bed-scale outcrop statistics
   - Global Proportions and NTG Trends
   - Vertical Facies Proportion Curves
   - Facies Transitions
   - Bed thicknesses and lengths (indirectly)

2) Employ readily available, “off the shelf” algorithms:
   - Sequential Indicator (SIS)
   - Co-Sequential Indicator (COSIS)
   - Truncated Gaussian (TGS)
   - Plurigaussian (PGS)
   - Multiple-Point (MPS)

3) Reproduce a given geologic conceptual model (visual essence of the outcrop)

4) Produce realizations that can test impact of bed-scale detail on inter- and intra-point bar connectivity and flow.

2. Geologic Background

Horseshoe Canyon Formation outcrops exposed at Red Deer river valley in central Alberta comprise a 12-16 m thick fluvial meander belt deposit, which unconformably overlies shorefaces sands, and is capped by a laterally extensive coal (Ainsworth et al., 2015). Sediments shed off a NW-SE orogenic front were transported by rivers east and south until they were deposited at the margin of the Cretaceous Western Interior Seaway as part of Western Canada Sedimentary Basin (WCSB) fill. Outcrops are well-exposed due to “badlands” style topography 12 km southeast of Drumheller, AB. A 3 km NW-SE (“Red Deer River”) exposes successions roughly parallel to flow direction, and a 1 km NE-SW transect (“Willow Creek”) exposes successions roughly orthogonal to flow direction.

3. Stratigraphy and Zone Architecture

Steeply dipping intra-point bar erosion surfaces that truncate underlying strata characterize the stratigraphic architecture of the deposits. Sigmoidal erosion surfaces bound concordantly-bedded lateral accretion packages (LAP) of consistent dip direction and magnitude. The stratigraphic framework and facies of Durkin et al. (2015) are used as the basis for this study. High-energy facies include sandstone (F1), siltstone-clast breccia (F2), and sandstone with siltstone and organic interbeds (SIHS; F3). Moderate-energy facies include siltstone with sandstone and organic interbeds (MIHS; F4) and very fine to fine-grained sandstone with ripples (F5). Siltstone (F6) records low-energy suspension settling of sediment. Planform reconstructions of the meander bend architecture reveal a complex history of point bar accretion with punctuated rotation events and ultimate channel abandonment.

The constructed 3D geocellular model has a grid cell size of 5 m x 5 m x 0.3 m (x, y, z) to represent fine-scale heterogeneity. Zones were defined by intra-point bar erosion surfaces that demarcate LAPs. Zone layers (parallel to sigmoidal surfaces) are 0.3 m thick so as to capture outcrop detail without compromising computational ability. Measured sections were integrated as hard-data for simulation as “pseudo” wellbores. TGS facies simulations were run on this grid. A sector model was taken out of the original grid to assess other simulation methods. Trends within packages and across zones make this an ideal dataset to test fine-scale facies simulation.
4. Statistical Methods & Probability Volume

2 Facies: Sequential Indicator Soft Data Experiment

A 3: Characterizing Horseshoe Canyon Data

3 Facies: Characterizing Horseshoe Canyon Data

6. Results & Problems: TGS & PGS

Co-Sequential Indicator Summary

Truncated Gaussian Summary

Plurigaussian Summary

- Employing soft data with a low Bz (i.e., week soft data conditioning) produces similar results to unconditional SIS.
- Probability of misclassification decreases significantly as a function of Bz, but varies whether simple or ordinary kriging is employed.

- High Sand Probability (60% sand / 40% shale)
- Homogenous Facies
- Probability of Misclassification decreases significantly as a function of Bz, but varies whether simple or ordinary kriging is employed.

- Low Sand Probability (40% sand / 60% shale)
- Moderately informs input variography and proportions.
- Probability of Misclassification increases slightly as a function of Bz, but varies whether simple or ordinary kriging is employed.

- Complex transition probabilities (HTP) were calculated using a horizontal transition probability (HTP) approach. Weighted transition probabilities from the various proportions of input soft data (i.e., sand, shale, breccia) were calculated for each facies in order to honor input variography.

- The implications is that you are creating more facies than there are real facies in the Horseshoe Canyon data.

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7. Problems with Variogram-based Modeling

Figure 7.1: A) Vertical and B) Horizontal transition probabilities visualized as Circos diagrams (Circos Table Viewer, 2017) where colored bands represent probability of transition between given facies. C) For PGS, these complex facies-transition relationships must be simplified into Lithotype Rules (LTR) that enforce order of occurrence and transition between facies (e.g. in LTR B, Breccia must lie adjacent to Sand or MIHS). These LTR examples are symbolic of the mean probability of each facies’ probability volume and D) corresponds to the true measured facies proportions.

- Variogram-based modeling sometimes under-represents low-proportion facies.
- PGS and nested, hierarchical TGS adequately reproduce low-proportion facies in realizations.
- Low-proportion facies are baffles and barriers to flow that are important to represent correctly.
- PGS and TGS do not appear to adequately reproduce architecture of low-proportion facies. While we hypothesized that transition statistics could enforce architectural outcomes, Lithotype Rules oversimplify transition probabilities when facies are numerous, and/or given facies are low-proportion, resulting in sub-optimal realizations.

8. Training Image-Based Modeling

Given the limits of variogram-based modeling, pattern-based modeling may hold the key to bed-scale architecture reproduction through training images development via outcrop statistics.

Candidates Include:

- Deterministic training images derived from outcrop photopans (see Figure 3.1).
- SNESIM: Widely deployed MPS algorithm.
- FILTERSIM: FILTERSIM can utilize conventional categorical training images, but because FLITERSIM can utilize continuous training images, there is space to experiment with the probability volumes directly.

Figure 8.1: Statistically-infused Training Image Generation Concept: 1) Measured section data is broken into subzones based on position in each LAP; 2) The VPC for each subzone breaks out facies proportions by layer; 3) SSIM constrained to layer facies proportions can be stacked into a single simulated volume representing the subzone statistics; 4) The composite of many realized volumes could be chained to comparable composites from each other subzone to build a TI.

9. Conclusions

- COSIS, even with strong soft conditioning, may have difficulty reproducing proportions of facies where the target-proportion is low.
- TGS and PGS reproduce facies proportions correctly, but do not appear to reproduce architecture adequately.
- Pattern-based modeling algorithms will be explored as an option to reproduce bed-scale facies architecture.

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11. References