Function-Based Training Image Construction of Fluvial Point Bars: A Modern Analog Example from the Brazos River, Texas*

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Abstract

Point bars are difficult to model due to complex lateral and vertical heterogeneities at multiple scales. The Multi-Point Statistics (MPS) algorithm can create complex facies geometries while honoring seismic and well conditioning, but MPS requires the user to first provide a Training Image (TI), a three-dimensional conceptual model of the depositional facies that captures the complex lateral and vertical relationships between facies. This paper discusses a technique to build a TI for a fluvial point bar that combines a conceptual model of point bars with data from closely spaced wells in a modern analog. This TI was then used in MPS to populate point bar facies in a 3D framework built with layers inclined parallel to bedding. The fluvial point bar TI was constructed in a horizontally layered "sugar cube" framework where each TI layer represents a single time slice. To populate the TI, we used mathematical functions to describe a fining upward character, an upstream to downstream fining component, and vertical cyclicity with the thickest beds at the base and thinner beds at the top. Cores and LPSA data were used to define majority facies codes at different positions within the system from upstream to downstream, from bar top to bar base. To capture the trends observed in the system, these majority facies codes were used as targets for optimizing a linear equation with cell indices I, J, and K as independent variables. These equations were used to assign facies code trends across all grid cells of the TI. Four vertical fining upward cycles observed in the cores were placed into the TI using look-up functions with cell index K as the independent variable. This piece-wise linear function was developed to describe the locations of discontinuities at the boundaries of each major cycle. A correlated Gaussian noise function was used to add realistic variability to the TI. These trend functions were combined to create the lateral and vertical trends and cycle discontinuities in the TI. A rank transform function was used to impose the correct facies proportions as measured from core and wireline log data. The function-based TI was used in MPS for facies modeling in an inclined 3D layer framework. Bed and lateral accretion package geometries were informed by closely spaced lines of electrical resistivity tomography (ERT) and Ground Penetrating Radar (GPR) data. With this TI, MPS captured the trends and cyclicity accurately, although it was computationally expensive.

Introduction

This paper discusses a technique to build a Multi-Point Statistics (MPS) Training Image (TI) for a fluvial point bar that combines a conceptual model of a generic point bar point bar with gamma ray logs and laser particle size analysis (LPSA) data from closely spaced boreholes in a modern Brazos River (Texas) analog.

In Steam Assisted Gravity Drainage (SAGD) heavy oil recovery schemes, the expansion of steam chambers and resulting oil drainage is very sensitive to continuous mud bed barriers and the connectivity of high-quality sands. Accurate placement of potential steam barriers is critical to optimizing SAGD well pair placement. To maintain the continuity of mud beds, it is vital to build the static model with framework layers parallel to bed orientations following the pattern of lateral accretion (Figure 1).

Reservoirs composed of point bar deposits are challenging to model because difficult-to-predict lateral and vertical heterogeneities occur over a wide range of length scales. The high probability of variations in rock properties at scales shorter than well spacing creates great uncertainty when attempting to build accurate reservoir facies models. Unfortunately, seismic resolution is typically too low to provide complete confidence in the placement of SAGD-critical thin mud facies in the subsurface model.

Discussion

The MPS modeling algorithm can create realistic, complex facies geometries while honoring seismic and well conditioning, but MPS requires the user to first provide a Training Image. Training Images are three-dimensional conceptual models of the depositional facies that capture their complex lateral and vertical relationships. Geologists typically use combinations of conceptual models, core, wireline data, subsurface geophysical images, plus outcrop and other analog information for creating these idealized, three-dimensional characterizations.

To populate the basic facies trends in the TI, we used mathematical functions to describe a fining upward character, an upstream to downstream fining component, and vertical cyclicity with the thickest beds at the base and thinner beds at the top of the fluvial interval. Our point bar TI was constructed in a horizontally layered “sugar cube” framework where each horizontal TI layer represents a single time slice that is actually inclined in the subsurface. Cores and LPSA data from a modern Brazos point bar analog were used to define majority facies codes at different positions within the deposit from upstream to downstream, from bar top to bar base. To capture the trends observed in the system, these majority facies codes were used as targets for optimizing a multivariate linear equation using the cell indices I, J, and K as independent variables (Figure 2B). Then, these equations were used to assign facies code trends across all grid cells of the Training Image (Figure 3).

On average, four fining-upward cycles were observed in the cores in the 15 m thick bar, so four fining upward cycles were designed into the equation-based TI using look-up functions with vertical cell index K as the independent variable (Figure 4). This idealized piece-wise linear function was designed to describe the locations and magnitudes of discontinuities (missing facies tracts) across the boundaries of each depositional cycle. The broad trend and vertical cycle trend functions were combined to capture the idealized lateral and vertical trends and cycle boundary facies discontinuities in the TI.

To add geologically realistic variation to the TI, Sequential Gaussian Simulation was used to make a correlated Gaussian noise functions (Figure 5, Figure 6, Figure 7, and Figure 8). The amplitude of the noise function was modified so that the highest scatter occurs at the base of each vertical cycle and decays to zero amplitude at the top of each cycle.

A final rank-preserving transform step was used to impose the correct facies proportions as measured from core and wireline log data (Figure 9). Then, in an effort to adapt the analogue to the subsurface cases of interest, a conglomerate sub facies was created within the coarsest sand facies using a second correlated Gaussian noise function (Figure 10).

Conclusions

The function-based TI generated from the above steps was used in MPS for facies modeling in an inclined 3D layered framework geomodel (Figure 11). Modelling experiments show that MPS using this TI is able to capture realistic stratigraphic trends and cyclicity. However, MPS is a computationally expensive algorithm, especially when using a locally varying azimuth as is necessary when applying a semi-stationary Training Image to a curved point par depositional environment.

Reference Cited

Fustic, M., S.M. Hubbard, R. Spencer, D.G. Smith, D.A. Leckie, B. Bennett, and S. Larter, 2012. Recognition of down-valley translation in tidally influenced meandering fluvial deposits, Athabasca Oil Sands (Cretaceous), Alberta, Canada: Marine and Petroleum Geology, v. 29, p. 219-232.

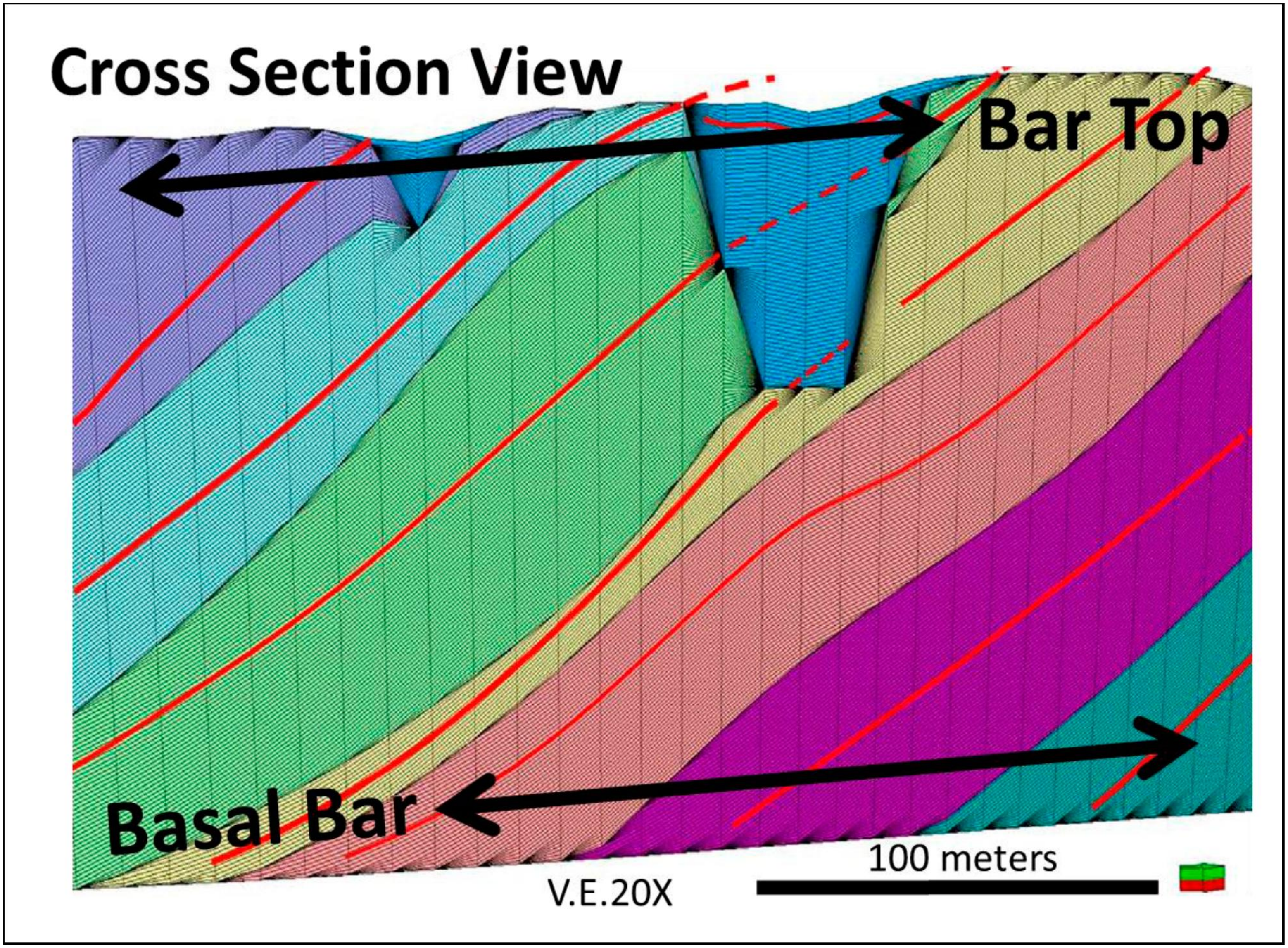

Figure 1. The analog model framework was designed with inclined layers oriented parallel to observed bedding surfaces. Therefore, each layer represents a single timeline that covers all coeval depositional sub-environments, from upstream lower point bar to downstream upper point bar. A properly designed Training Image (TI) must take into account the intended model framework and consider the fact that MPS operates in an I-J-K "simbox" space, not real world coordinates. Red lines represent the layering orientation "guide" surfaces, which are neither parallel to the zone tops nor the zone bases.

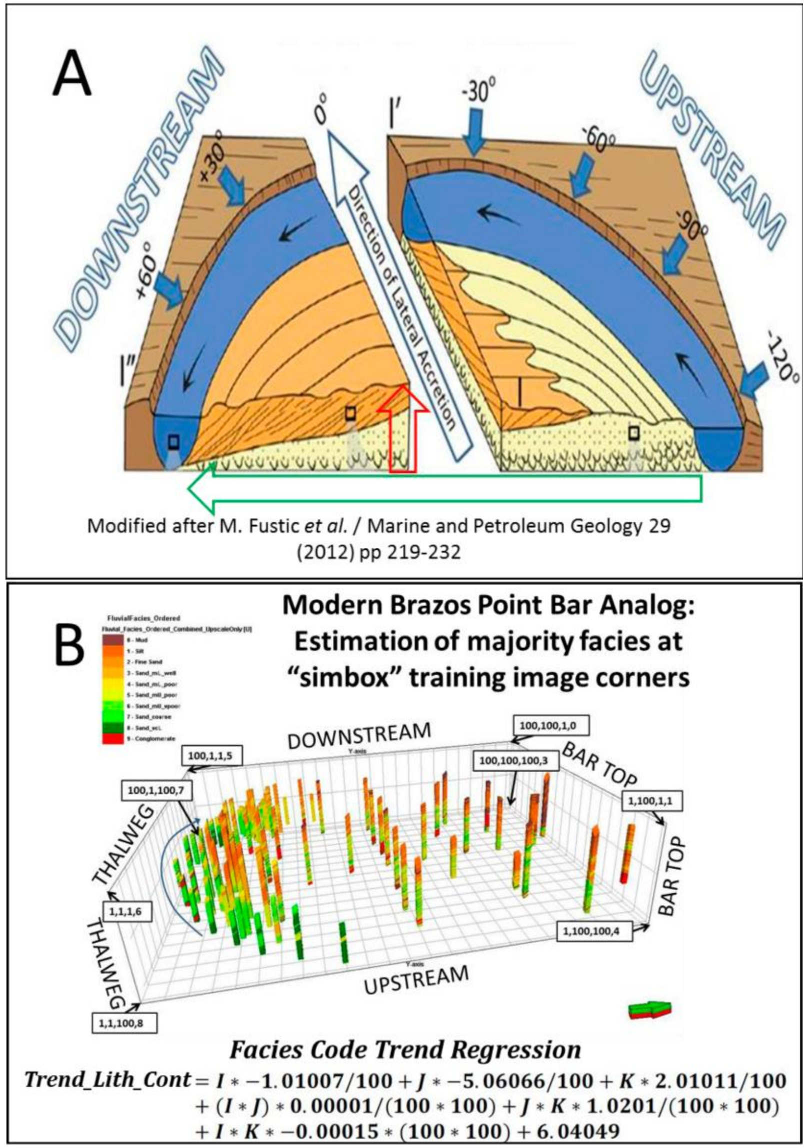

Figure 2. A) Fustic et al (2012) describe three depofacies trends within a single point bar: 1) Fining Upward – red arrow, 2) Fining Downstream – green arrow, and 3) Fining with increased Radius of Curvature – blue arrow. B) Logs, cores and Laser Particle Size Analysis (LPSA) data were used to estimate the majority facies codes at each corner of this Training Image "simbox" 3-D model. Numbers in boxes at the corners of the modeled cube are [I, J, K, Majority Facies]. Multivariate linear equations using cell I, J, and K indices as independent variables were optimized to mathematically describe these facies trends.

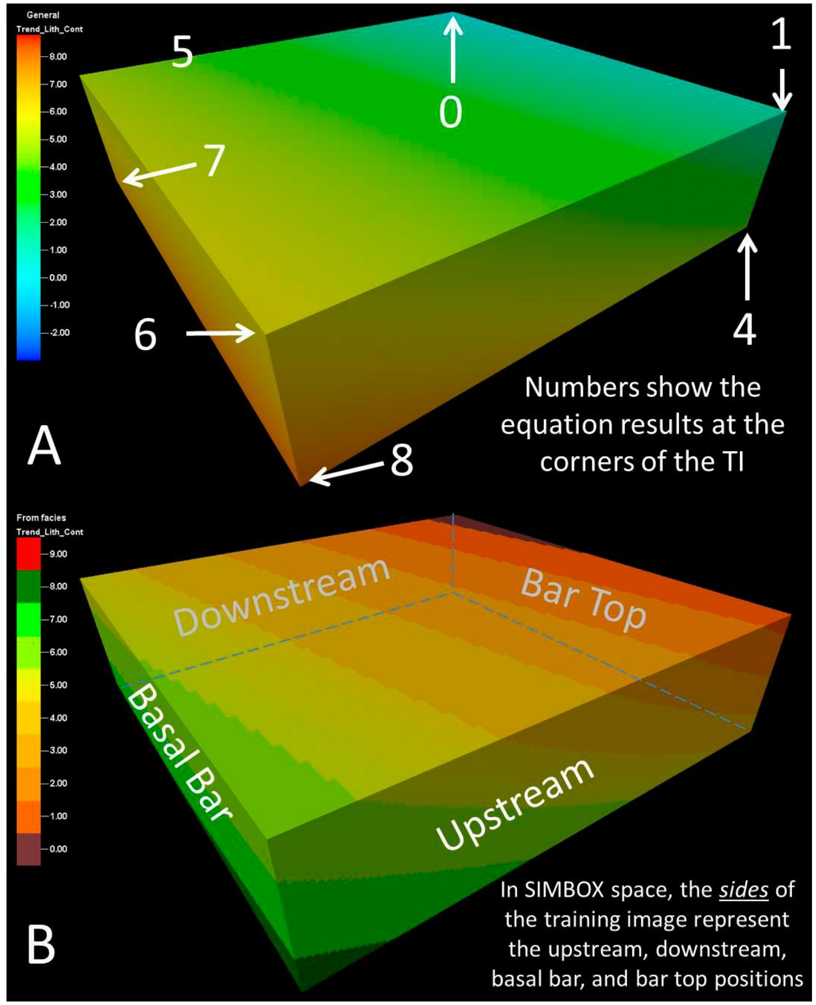

Figure 3. A) A training image framework was constructed with 100 cells in each direction. The Facies Code Trend regression of Figure 2 was applied using the I, J, and K indices as independent variables. Colors represent the interpolation of corner values through the Training Image volume. The calculator command is:

Trend_Lith_Cont=((-1.01007) *I/100 + (-5.06066) *J/100 + (2.01011)*K/100 + (0.00001)*(I*J)/(100*100) + (1.0201)*(J*K)/(100*100) + (-0.00015)*(I*K)/(100*100) + (6.04049))

B) Using a color table with boundaries halfway between the integer values shows the generalized trend of facies from the regression equation. Colors are integerized values from image A.

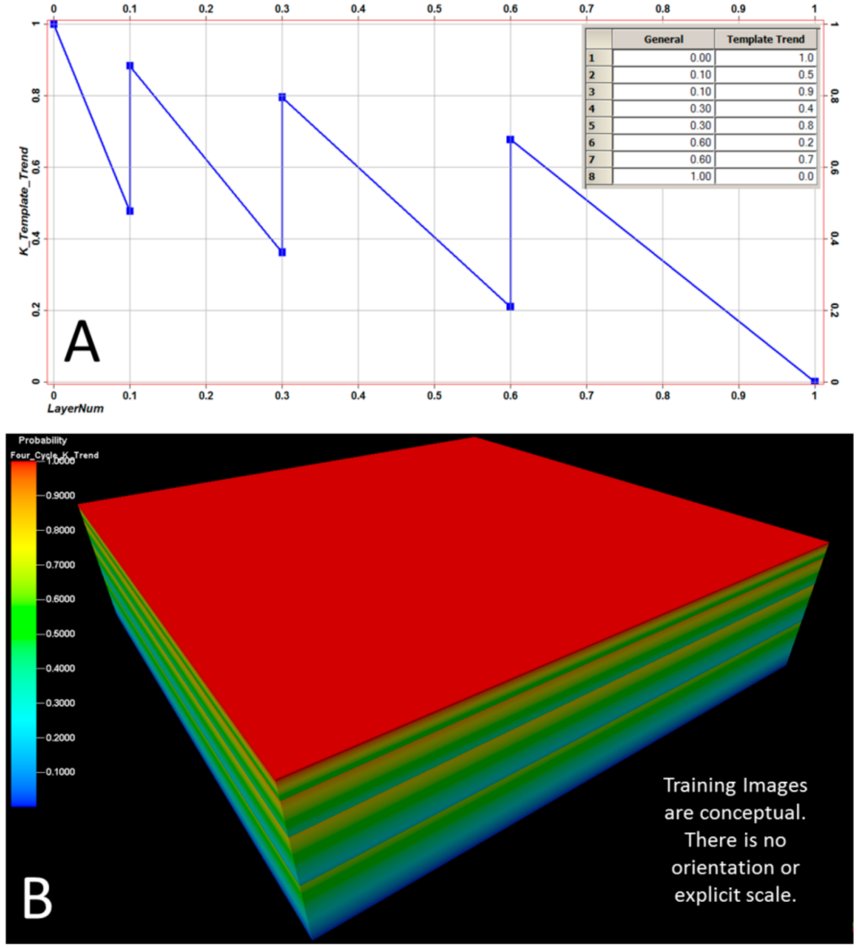

Figure 4. A) Lookup function was designed to impose four thinning-upward depositional cycles onto the general facies trend. The horizontal axis represents the normalized layer number and the vertical axis represents a scalar to be applied to the general facies trend. The sloped portions describe fining upward trends within each cycle. The vertical segments create facies omissions (discontinuities) at the cycle boundaries with the number of missing facies being proportional to the line length. The calculator command is:

Four_Cycle_K_Trend=Four_Cycle_Trend_vs_LayerNum((K-1)/100)

B) Volume displaying the resulting cyclicity scalar. Note the depositional cycles thin upward, with the bottom cycle occupying 40% of the vertical range, the next occupying 30%, then 20%, and then 10% in the uppermost cycle. When applied, the scalar was multiplied by -3, meaning a unit shift produces a lateral facies shift across the cycle boundary of three facies tracts.

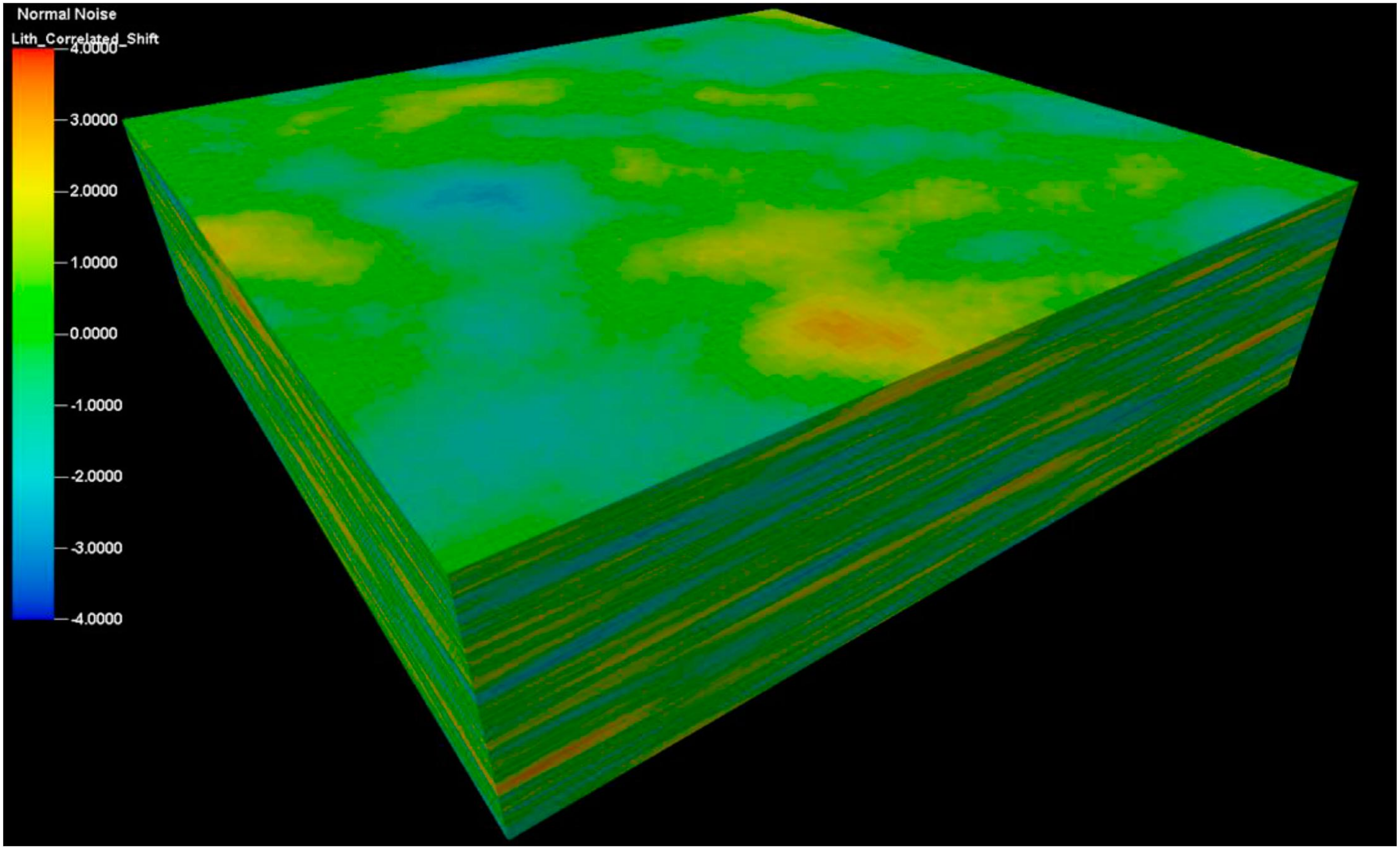

Figure 5. Volume containing a normalized Gaussian correlated random field with a mean of zero and a standard deviation of one to impose realistic lateral and vertical facies variations on the TI.

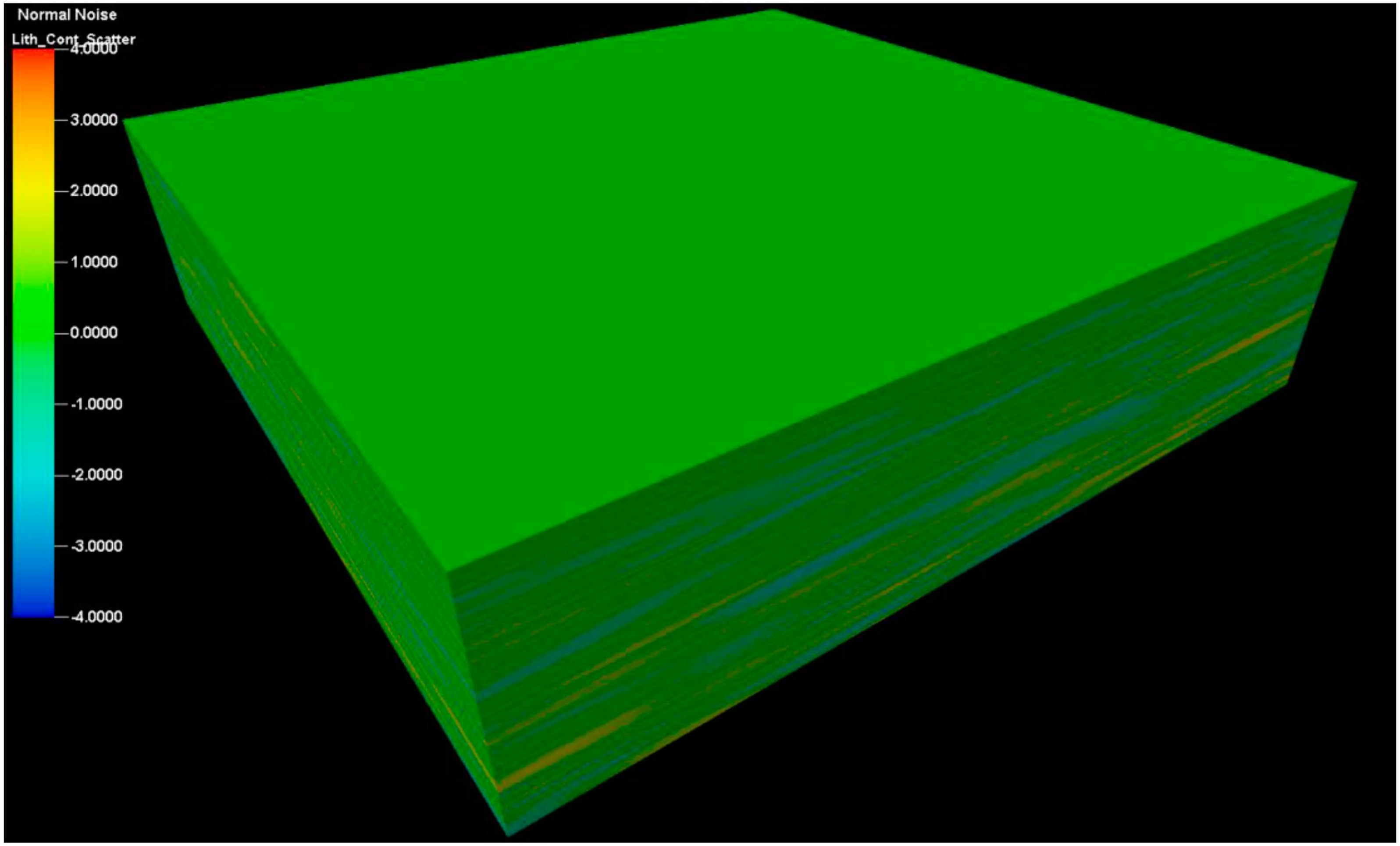

Figure 6. Observations of the modern analog indicate the largest facies variations are found near the bottom of the point bar, with smaller variation at the top. Similarly, within cycles the variation in facies is greater near the base and smaller at the top. To create this effect, we used a scalar that is the complement of the four-cycle trend (1-Four_Cycle_K_Trend). This produces an overall upward decrease in variability, with superimposed decreases in variability in each of the four cycles. The image shows the result of multiplying the correlated random field (Figure 5) by the complement of the four-cycle K trend (Figure 4B) to impose upward-decreasing facies variation, both overall and within each cycle. The calculator command is:

Lith_Cont_Scatter=(1-Four_Cycle_K_Trend) * Lith_Correlated_Shift

It was later decided that this resulted in variations of too great a magnitude. It was further modified by a 0.5 factor in the final application.

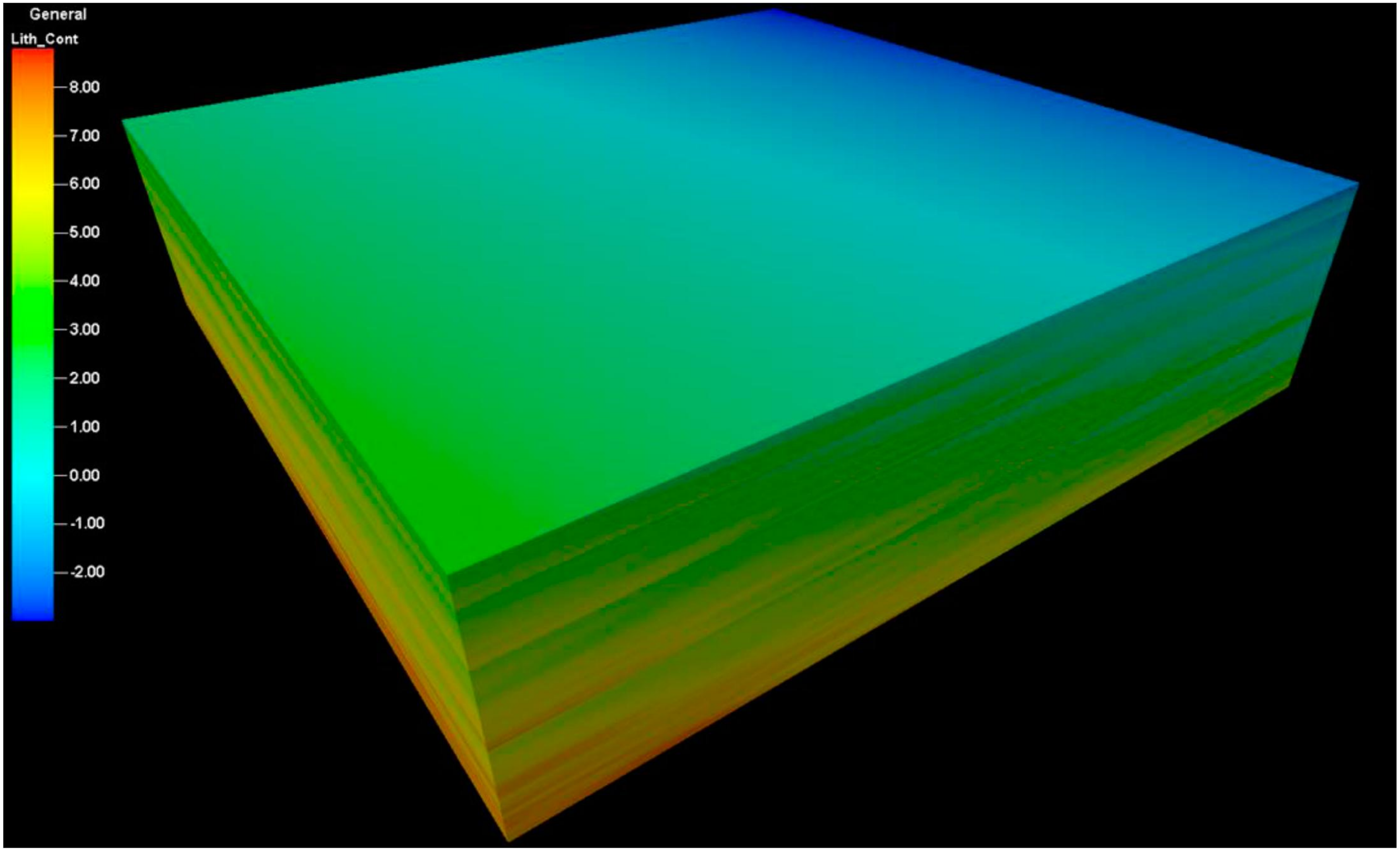

Figure 7. The general lithology trend (Trend_Lith_Cont, Figure 3), the four-cycle K trend (Four_Cycle_K_Trend, Figure 4), and the correlated random facies scatter (Lith_Cont_Scatter, Figure 6) were added together to create a continuous property (Lith_Cont). The calculator command is:

Lith_Cont = Trend_Lith_Cont - 3 * Four_Cycle_K_Trend + 0.5 * Lith_Cont_Scatter

Note that the resulting values (-3 to 9) are not in the desired range of facies codes (0 to 9) and must be rescaled for use.

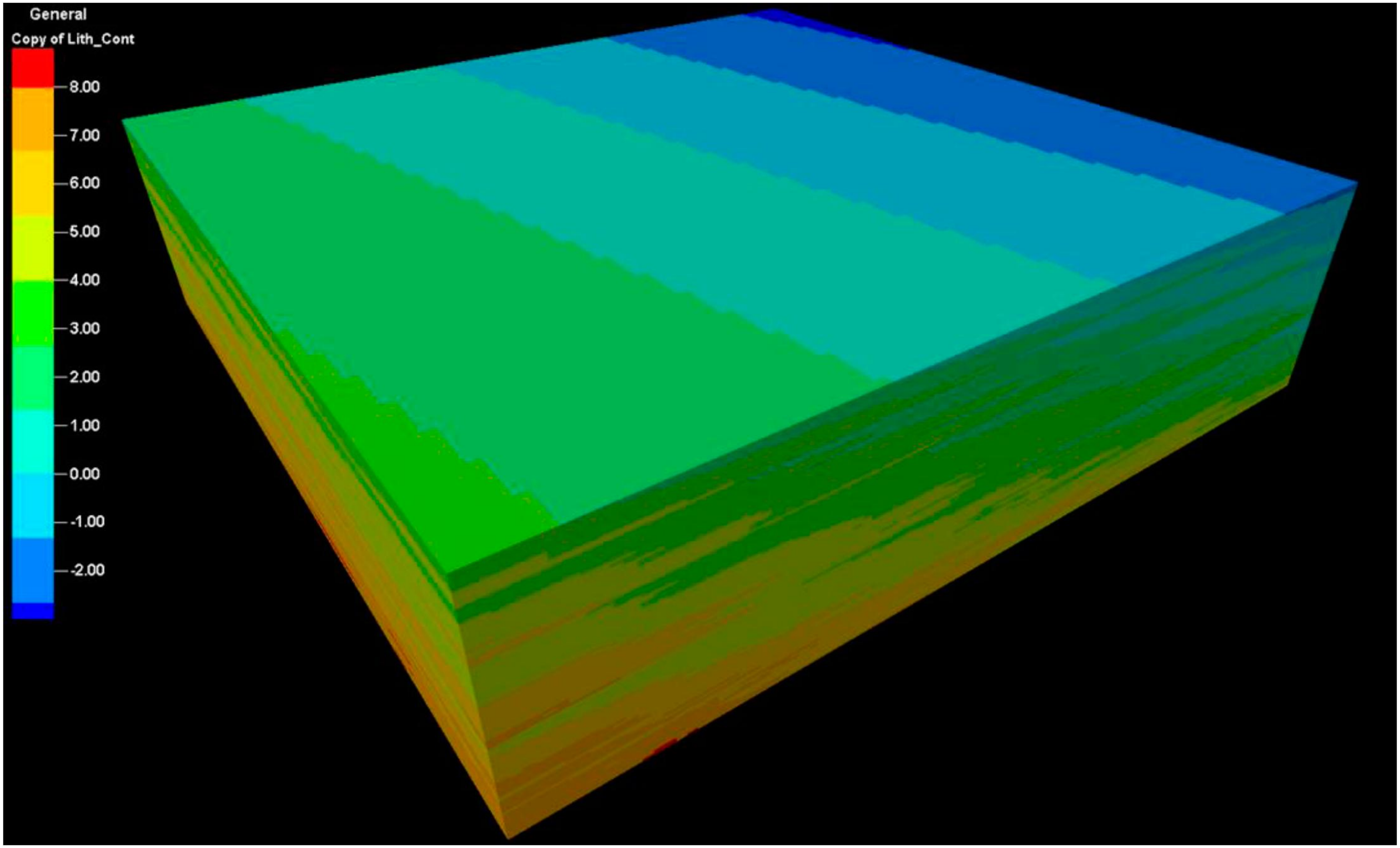

Figure 8. The resulting continuous property from Figure 7 can be transformed into discrete value ranges for a preview of the training image. At this point, the facies proportions do not yet match our analog targets.

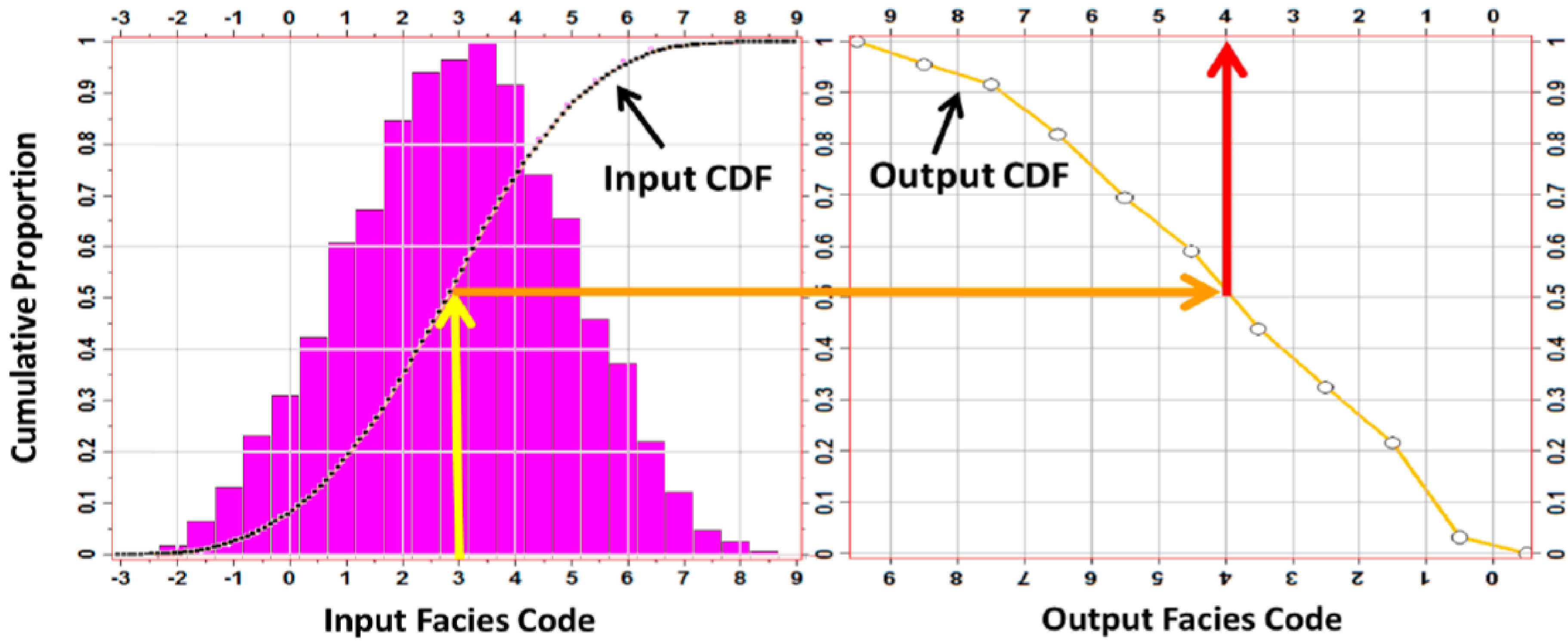

Figure 9. The combined lithology property (Lith_Cont) is put through a rank-preserving transform in order to honor the target facies proportions observed in the modern analog. The steps are as follows:

1) Create a Cumulative Distribution Function (CDF) of the property to be transformed. The independent variable (Input Facies) vertex coordinates of the transform function represent facies codes. The dependent variable (Cumulative Proportion) coordinates are the normalized running sum of the input facies counts.
2) Create an output (target) CDF. The dependent variable (Output Facies) vertex coordinates of the transform function are at the halfway points between integers. The independent variable (Cumulative Proportion) vertices are separated by the desired output proportions.
3) The input facies code of each cell is assigned a Cumulative Proportion using the Input Facies CDF as a lookup function (yellow arrow). Then the Cumulative Proportion (orange arrow) is used in the Output CDF lookup function, producing an output facies code (red arrow).

The calculator commands are:

Lith_CDF=Lith_Cont_CDF(Lith_Cont)
CDF_FaciesCodes=CDF_to_Facies(Lith_CDF)

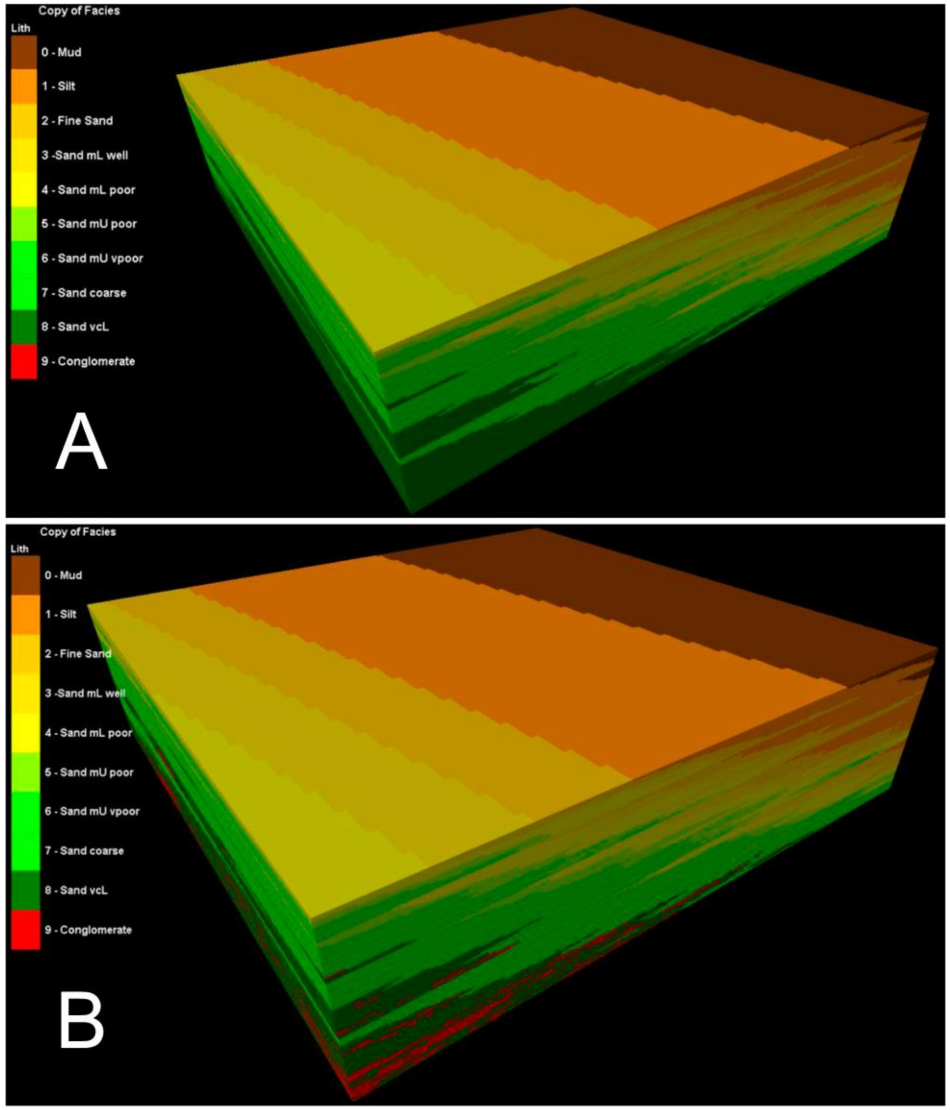

Figure 10. (A) The integerized continuous facies code volume resulting from operations shown in Figure 9. (B) Final MPS Training Image showing integerized facies codes with facies 9 (conglomerate) locally replacing facies 8 using another Gaussian correlated random noise field (Conglomerate_Shift). The calculator commands are:

Lith=min(8, round(CDF_FaciesCodes))
Lith=if((1-Four_Cycle_K_Trend) * Conglomerate_Shift > 0.5 and Lith = 8, 9, Lith)

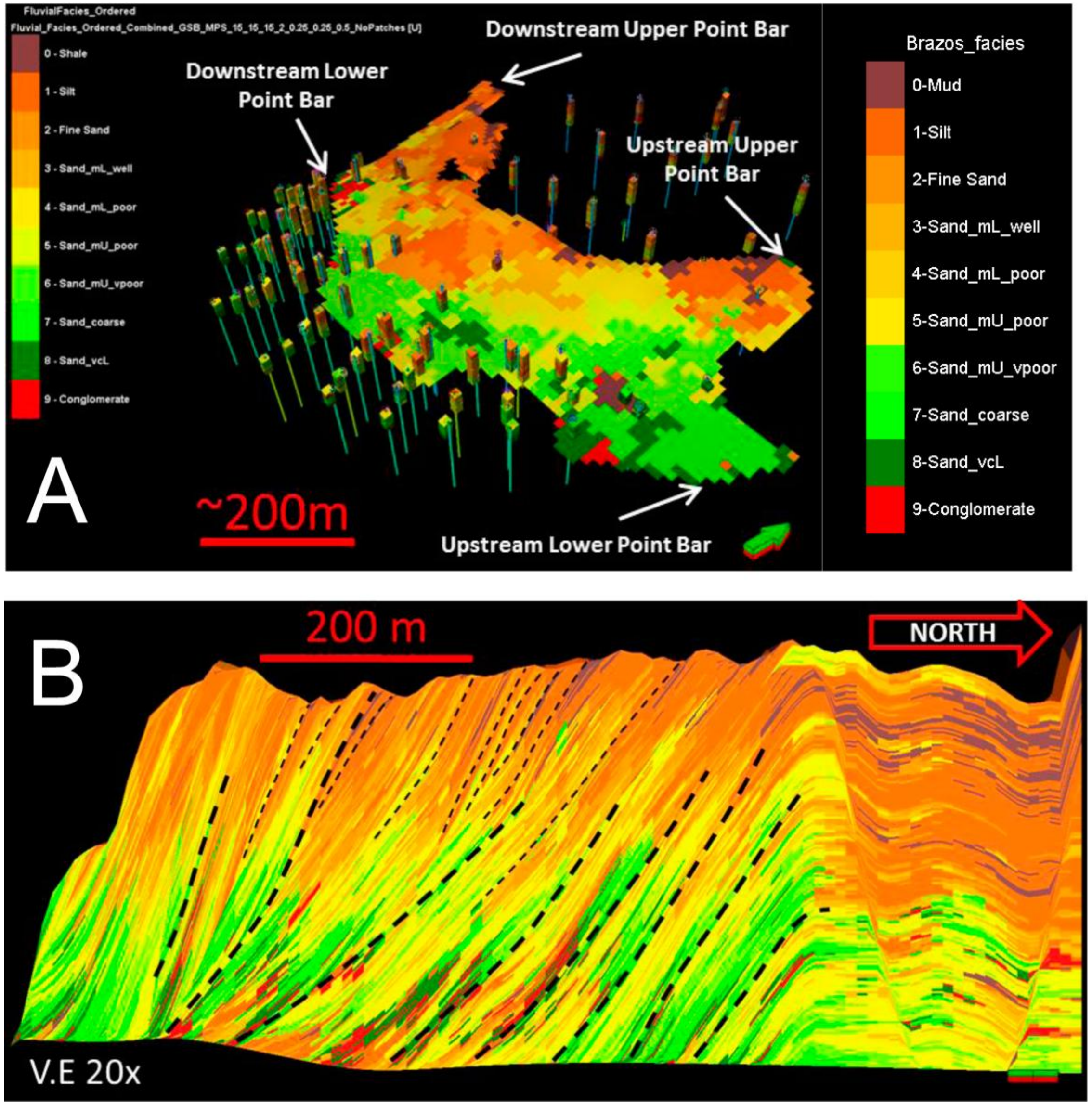

Figure 11. The function-based TI was used in MPS to create a facies realization. In addition to hard conditioning with upscaled well data, position-based locally varying facies probabilities were used for soft conditioning. A) An inclined K layer showing realistic, map view lateral facies trends with coarse-grained facies in the upstream lower point bar (greens) and fine grained facies in the downstream upper point bar (oranges). Vertical columns represent boreholes used for conditioning. B) North-South cross section showing realistic vertical facies transitions, including abrupt cycle breaks (black dashed lines).