[PS]Application of a Training-Image Library to Fluvial Meandering Facies Models Using Multi-Point Statistics Conditioned on Analog-Based Forward Models*

Jose M. Montero[1], Nigel P. Mountney[1], Luca Colombera[1], and Na Yan[1]

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[1]University of Leeds, Leeds, United Kingdom (eejmm@leeds.ac.uk)

Abstract

Meandering fluvial systems form highly compartmentalized hydrocarbon reservoirs. Variogram- and object-based modeling techniques commonly fail to reproduce the geometry, distribution and lithological heterogeneity of major geobodies (e.g., point-bar elements and sinuous channel-fill deposits, mud drapes). A novel workflow for the generation of training images of fluvial meandering systems using Multi-Point Statistical techniques (MPS) has been developed. The aim is to produce a suite of models with higher geologic realism compared to outputs of traditional methods. The workflow includes the use of a library of training images in combination with tailor-made auxiliary-variable maps designed to handle non-stationarity. Training images with different levels of stationarity have been tested and included in a library to enable geomodelers to select the most suitable reservoir representation.

The training images are created using quantitative information derived from a relational database of geologic analogs (Fluvial Architecture Knowledge Transfer System; FAKTS), and a forward stratigraphic modeling tool which simulates fluvial meander-bend evolution and resulting point-bar facies organization (Point-Bar Sedimentary Architecture Numerical Deduction; PB-SAND). The devised training images incorporate fundamental features of the facies architecture of fluvial point-bar elements and larger meander belts composed of these and related elements.

The application of training images has been optimized to two MPS algorithms: SNESIM and DEESSE. To best model particular fluvial meandering successions, realizations have been performed whereby optimal reproduction of facies proportions, facies relationships, and architectural geometries is achieved, in part through incorporation of stationarity in the training images. The sensitivity of input parameters has been analyzed with multiple simulations across parameter space to define optimized modeling recipes for different fluvial systems, i.e., pairings of training images with sets of input parameters and auxiliary maps, and selections of appropriate MPS modeling algorithms. Modeling outcomes are compared quantitatively and qualitatively against corresponding facies models generated using variogram-based techniques. Results show that MPS techniques benefit from training images based on forward modeling to deliver realistic realizations better able to incorporate the fundamental heterogeneities of fluvial meandering systems.

Selected References

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Fluvial & Eolian Research Group, University of Leeds, UK
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Application of a training-image library to fluvial meandering facies models using Multi-Point Statistics conditioned on analogue-based forward models

Jose M. Montero*[1], Nigel P. Mountney[1], Luca Colombera[1] and Na Yan[1]

*) Corresponding author: eejmm@leeds.ac.uk
1) Fluvial & Eolian Research Group, University of Leeds, UK
School of Earth and Environment, University of Leeds, Leeds, United Kingdom Ls2 9JT

1. Introduction

Hydrocarbon recovery and groundwater management require detailed knowledge of the petrophysical properties and the connectivity of sedimentary bodies that form reservoirs and aquifers. Facies modelling seeks to reproduce the geometry and distribution of these bodies in the 3D space, to provide a framework for the construction of property and flow models. However, facies modelling is commonly based on indicator variograms and object-based simulations that fail to adequately reproduce complex geological shapes (e.g., highly sinuous fluvial channel bodies) or to honour conditioning data (e.g., well data), respectively.

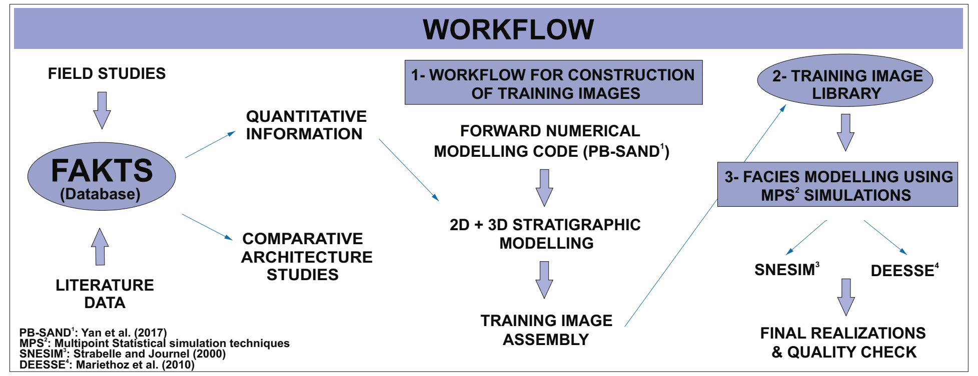
This project is developing new workflows that enable the generation of model outputs with improved geological realism compared to outputs commonly obtained through conventional methods. Results are being applied to model reservoirs that comprise fluvial meander-belt deposits. Simulation techniques based on multi-point statistics (MPS) are used to integrate complex geological patterns and to honour both soft and hard data. A library of training images — from which MPS modelling algorithms replicate geologic patterns — is being developed by using a forward stratigraphic modelling approach, PB-SAND (Yan et al. 2017).

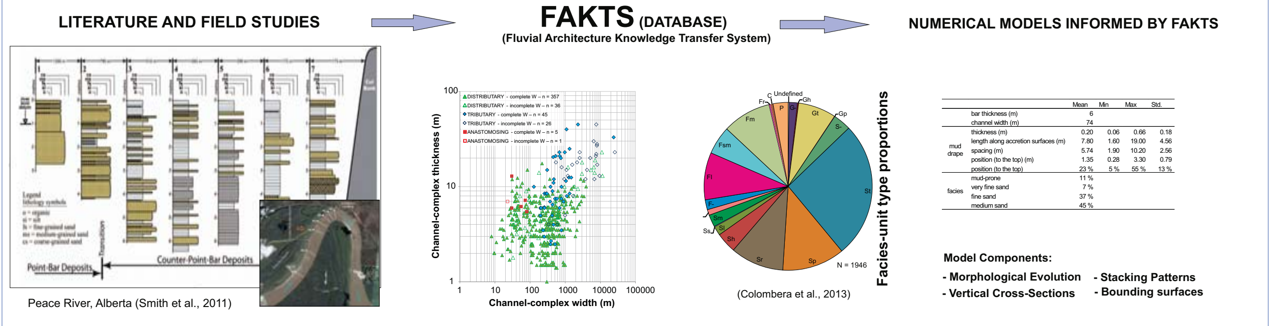
These training images incorporate fundamental features of the facies architecture of fluvial point bars and meander belts, expressed as facies models generated through mixed process-, geometric- and stochastic-based numerical simulations that are informed by quantitative architectural information drawn from a database of geological analogues, the Fluvial Architecture Knowledge Transfer System (FAKTS). The application of training images to different MPS algorithms (SNESIM, FILTERSIM, IMPALA, DEESSE) is being optimized. Common issues encountered in MPS modelling workflows are being addressed, including training-image preparation, selection of ideal modelling parameters (e.g., search-mask size, multigrids) and excessive runtime performance.

A workflow has been developed for the application of the training-image library to DEESSE and SNESIM modelling codes to simulate a channel-belt fluvial succession. Their functioning differences (ability to handle non-stationarity, runtime, etc) and the delivered results have been evaluated quantitatively and qualitatively in order to test the suitability of different workflows for incorporating different training images with variable levels of non-stationarity.

2. Workflow

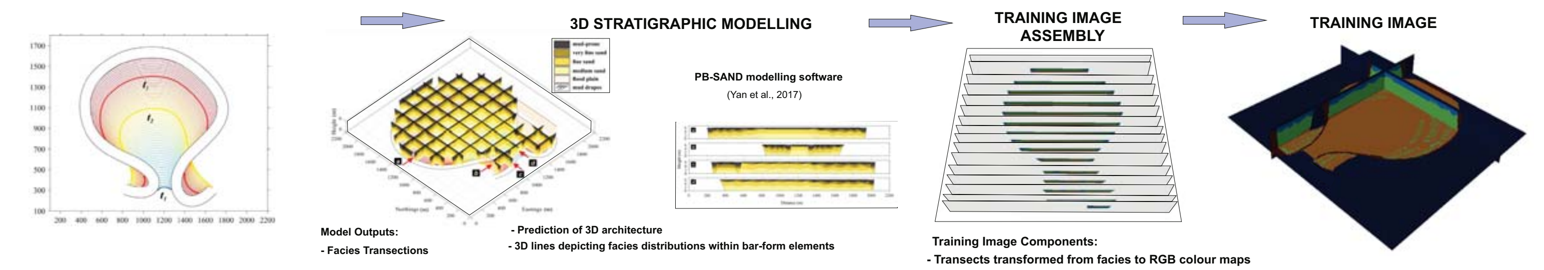
MPS methods require from a training image, the digital representation of the heterogeneities of our reservoir rock. Queries to the FAKTS database are performed to obtain the appropiated quantitative information to assemble the training image (e.g. facies proportions and element dimensions and arrangements). Afterwards, PB-SAND forward stratigraphic modelling software will create the training images which are themselves added to the training image library. An MPS method is selected then, SNESIM or DEESE, and a process of parametization is undertaken to optimize the quality and speed of the realizations. Finally a quality check is performed to accept or reject the different realizations.





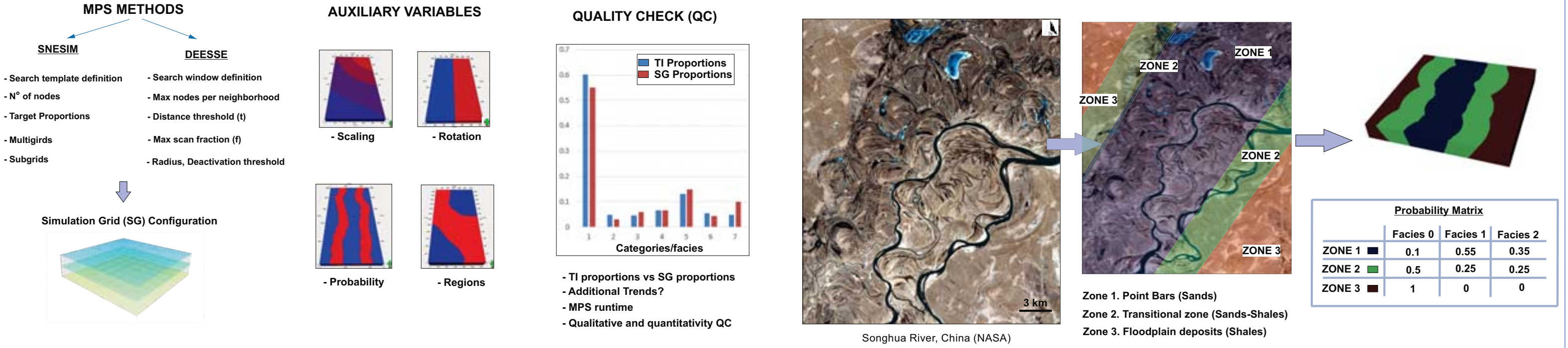
3. Using PB-SAND software to build training images

PB-SAND (Yan et al. 2017) is a forward stratigraphic modelling software used to build 3D stratigraphic models. The software allows customized simulations of fluvial point-bar evolution by varying parameters such as channel width, migration trajectory, and facies distribution including the presence and extent of mud drapes on developing bar fronts. Images of the architectural simulations are transformed to a digital representation in a form that allows them to be employed as training images for MPS modelling algorithm.



4. Grid configuration and construction of auxiliary-variable maps

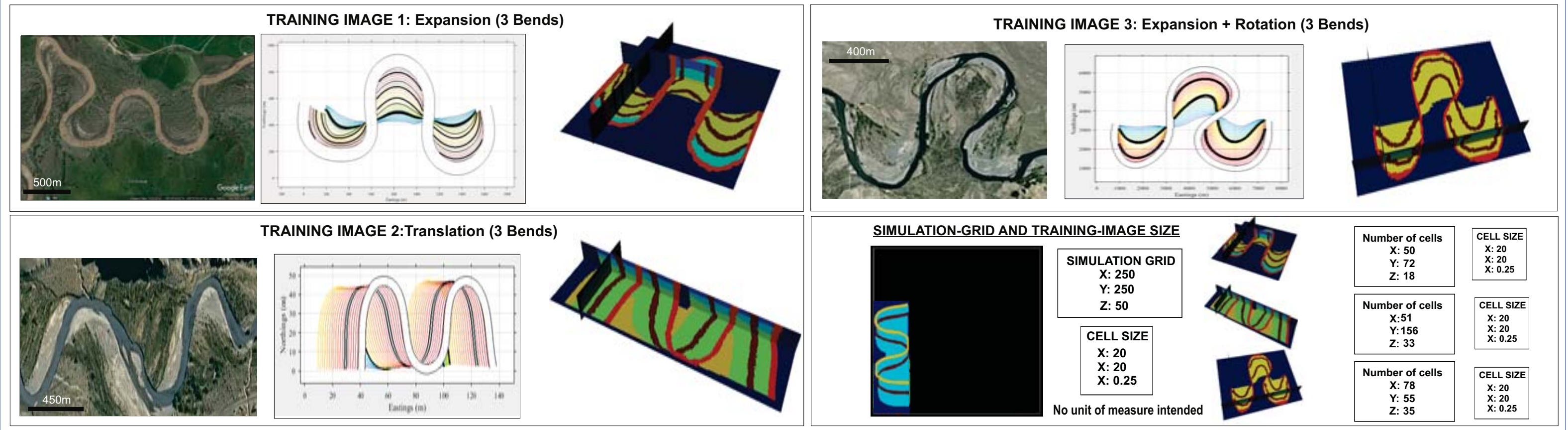
An MPS method is chosen (SNESIM or DEESSE). These two modelling algorithms employ different parameters, suitable values for which need to be assigned. A parametization process then is required to understand which parameters sets work better for a given training image. Auxiliary-variable maps are used to control different aspects of the simulation. See the example of a facies-probability map in the image below.

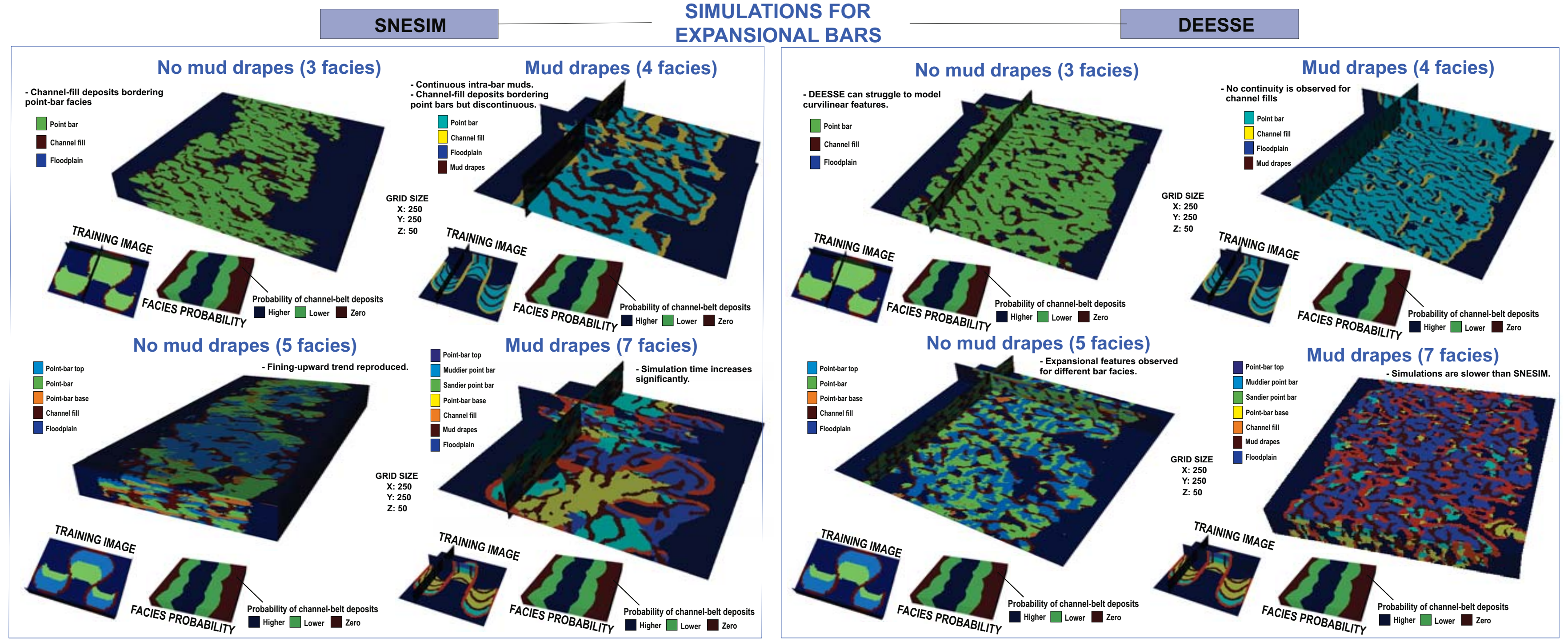


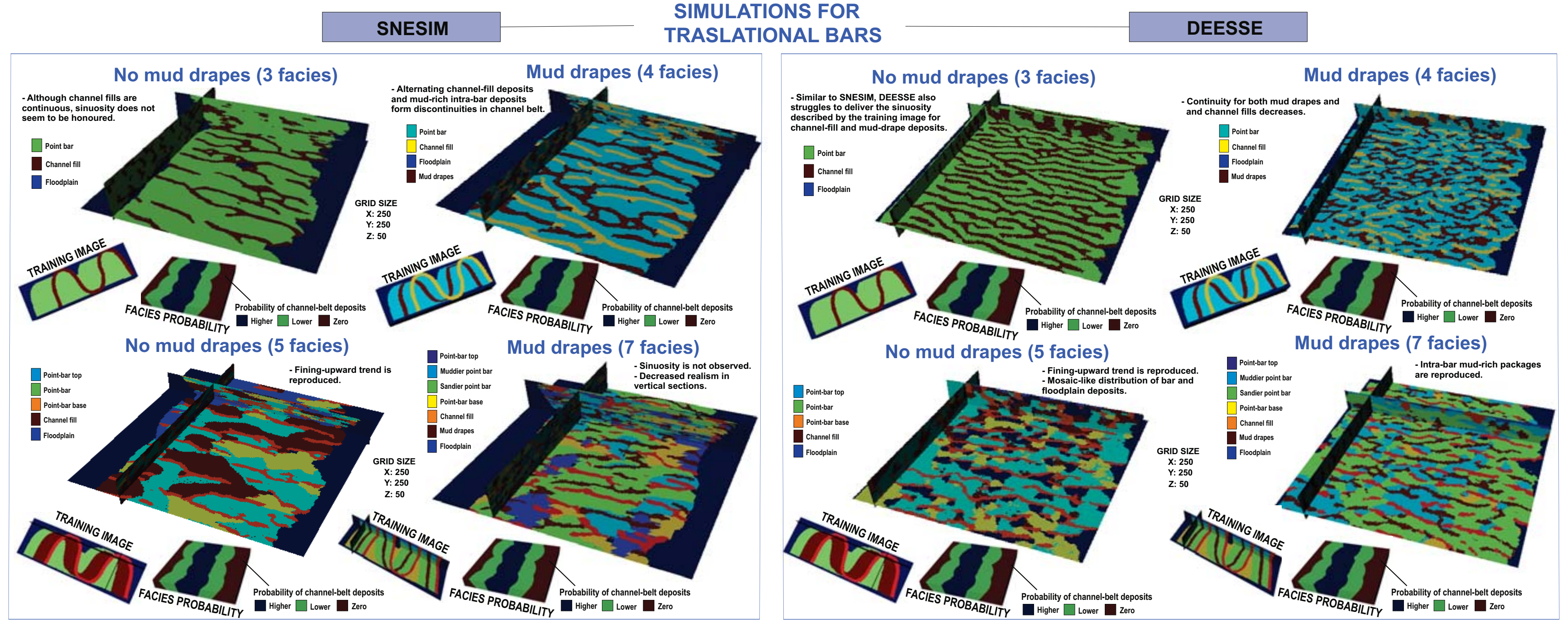
	Facies 0	Facies 1	Facies 2
ZONE 1	0.1	0.55	0.35
ZONE 2	0.5	0.25	0.25
ZONE 3	1	0	0

5. Training images selected for this study

Three different training images have been selected for this study. A three-bend expansional point-bar model from the Powder River (USA), a training image of a point-bar that developed via translation from the Chubut River (Argentina) and a training image of a point bar that developed via combined expansion and rotation also from the Powder River. Satelite images were treated as inputs in PB-SAND to build the final training images.







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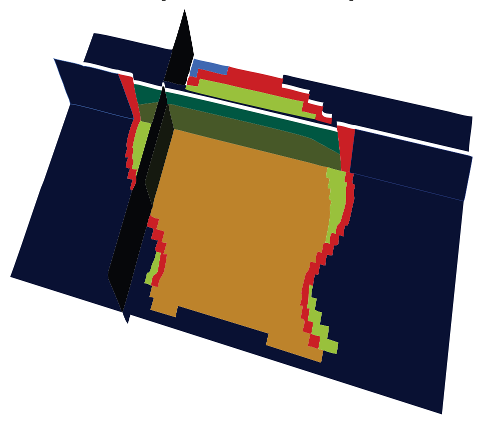
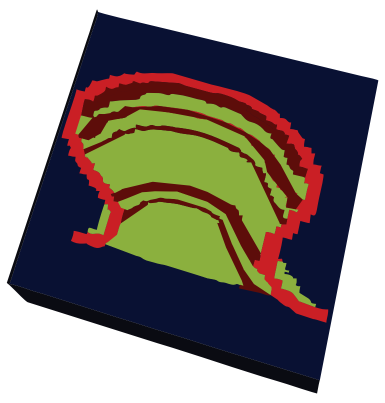
Fluvial point-bar architectural-element training-image library

TRAINING IMAGES FOR EXPANSIONAL POINT-BAR ELEMENTS

EXPANSIONAL
(One bend)

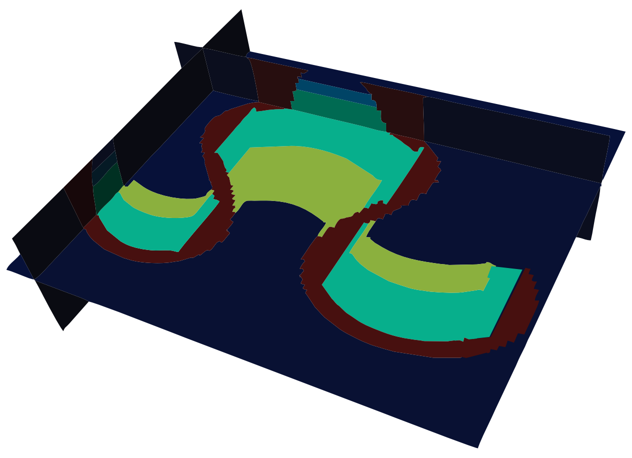


EXPANSIONAL (One bend)
Continuous mud drapes

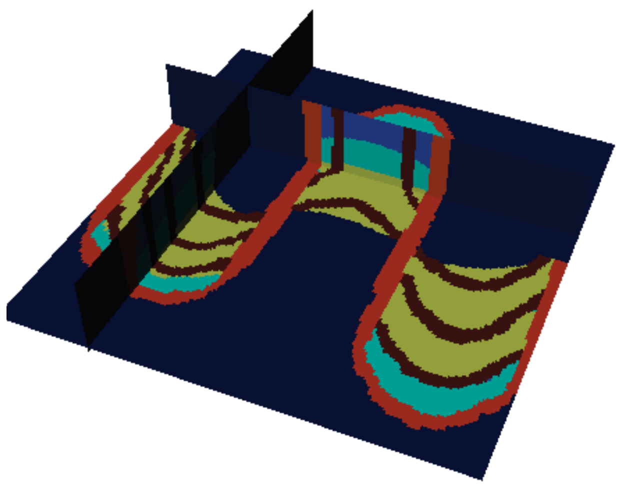


EXPANSIONAL (One bend)
Discontinuous mud drapes

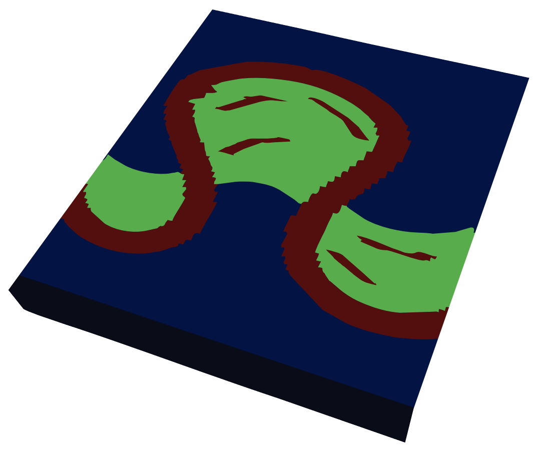
EXPANSIONAL
(Three bends)



EXPANSIONAL (Three bends)
Continuous mud drapes

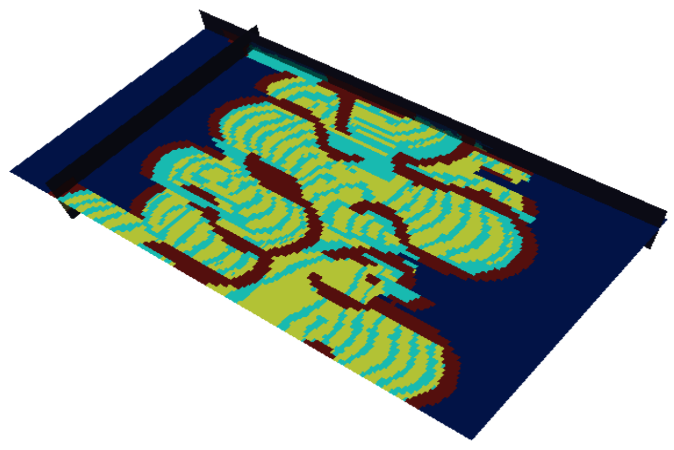


EXPANSIONAL (Three bends)
Discontinuos mud drapes

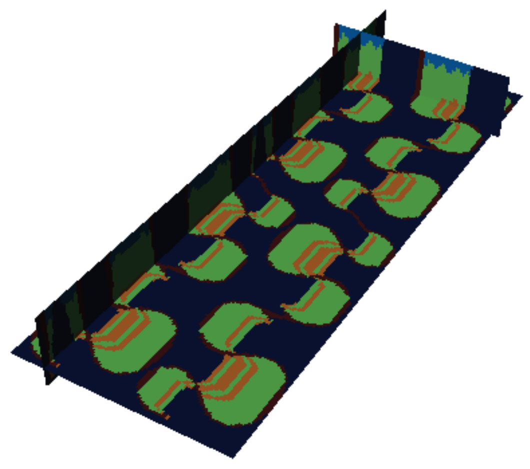


*No scale intended.

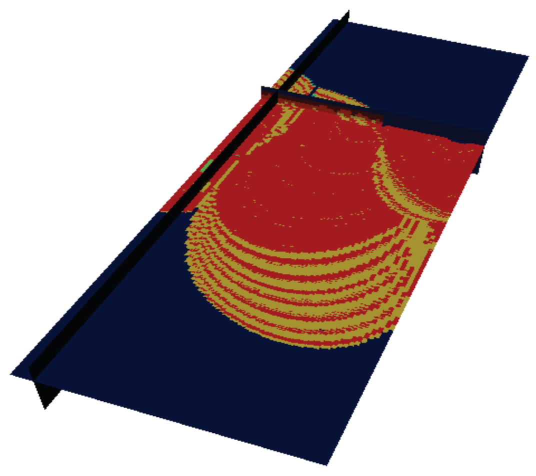
EXPANSIONAL
Point-bar elements



EXPANSIONAL
Continuous channels

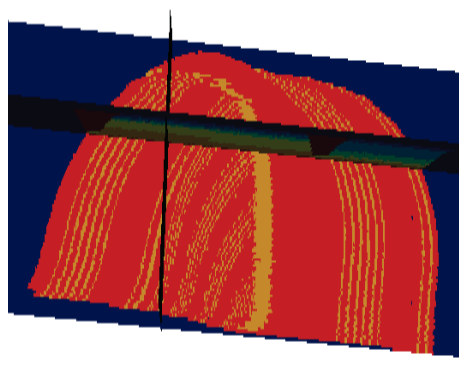


EXPANSIONAL
Point-bar elements

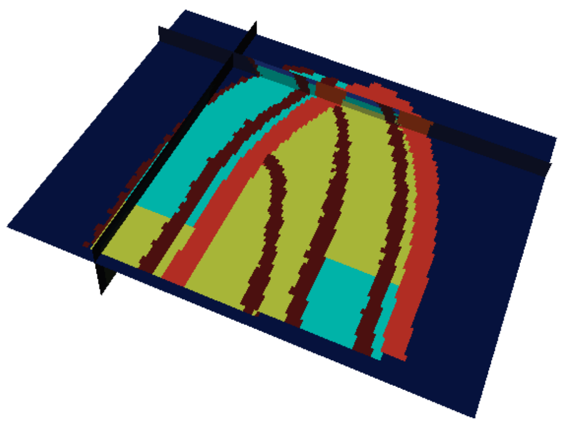


TRAINING IMAGES FOR TRANSLATIONAL POINT-BAR ELEMENTS

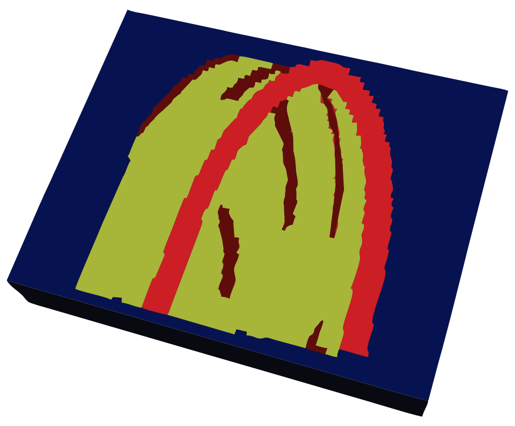
TRANSLATIONAL
(One bend)



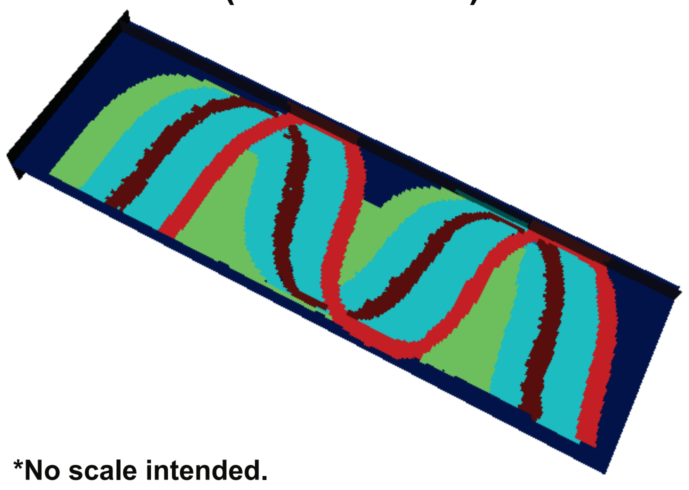
TRANSLATIONAL
Continuous mud drapes



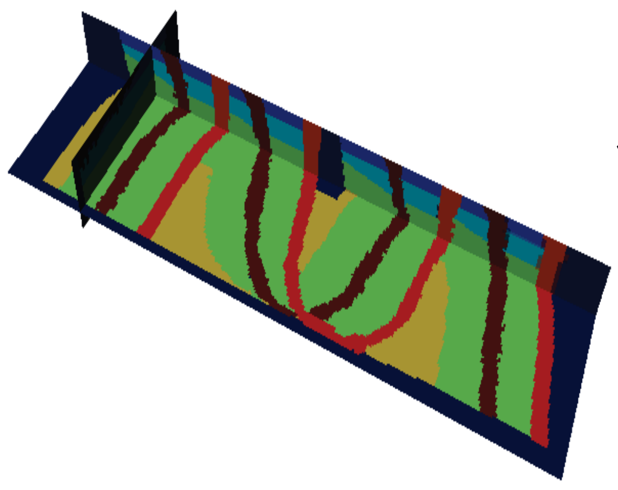
TRANSLATIONAL
Discontinuous mud drapes



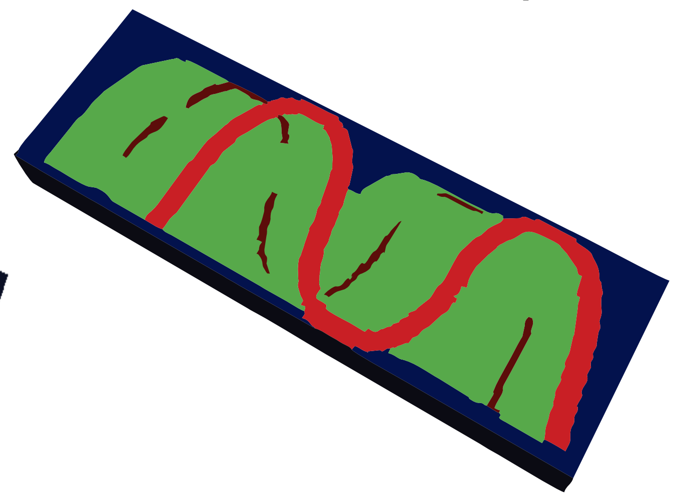
TRANSLATIONAL
(Three bends)



TRANSLATION
Continuous mud drapes

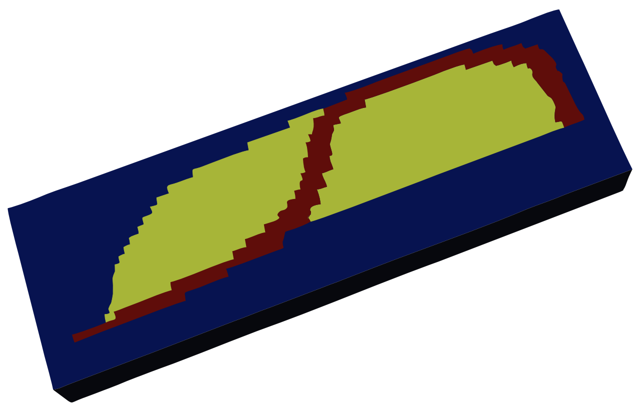


TRANSLATION
Discontinuous mud drapes

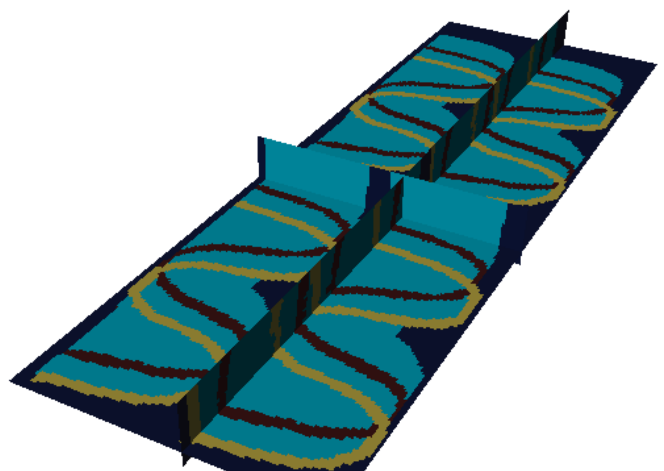


*No scale intended.

TRANSLATION (Example 2)

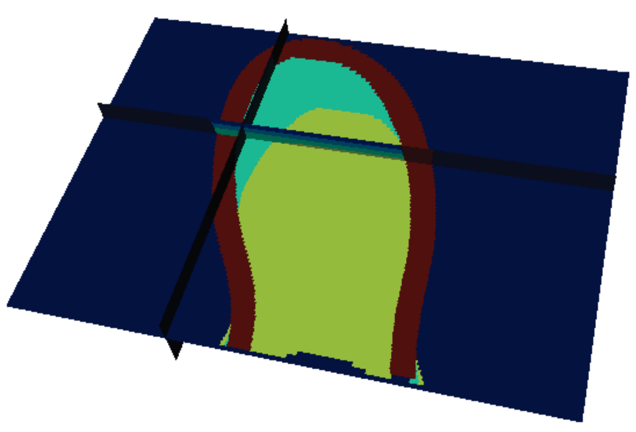


TRANSLATION
Two continuous translational channel belts

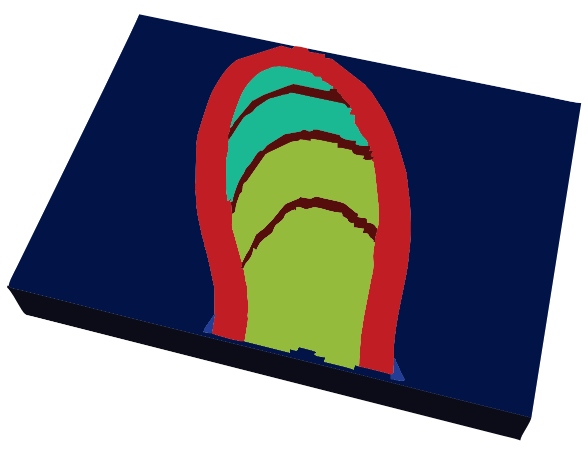


TRAINING IMAGES FOR EXPANSIONAL AND ROTATIONAL POINT-BAR ELEMENTS

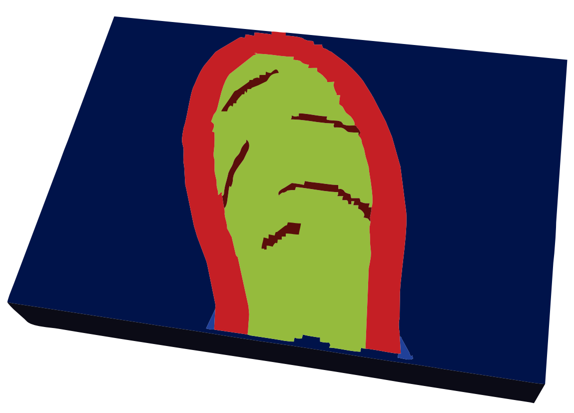
EXPANSION + ROTATION
(One bend)



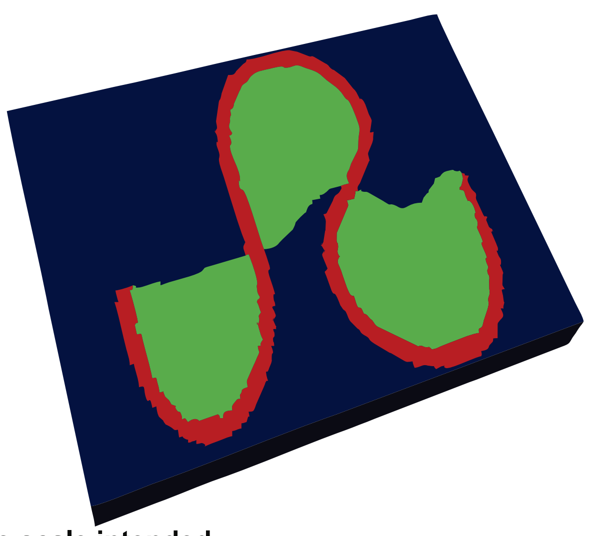
EXPANSION + ROTATION
(Mud drapes)



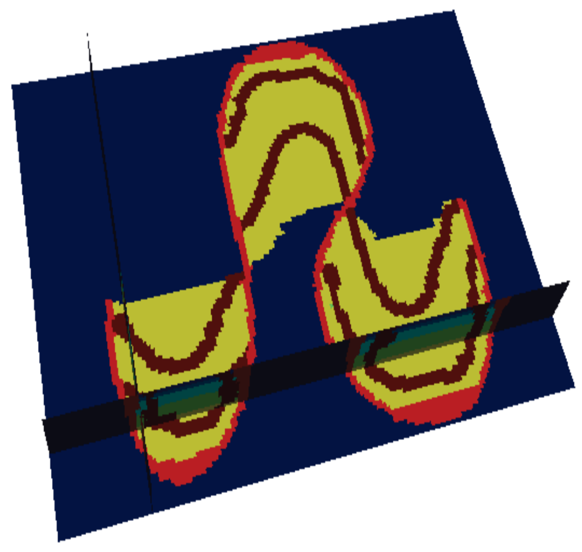
EXPANSION + ROTATION
(Discontinuous mud drapes)



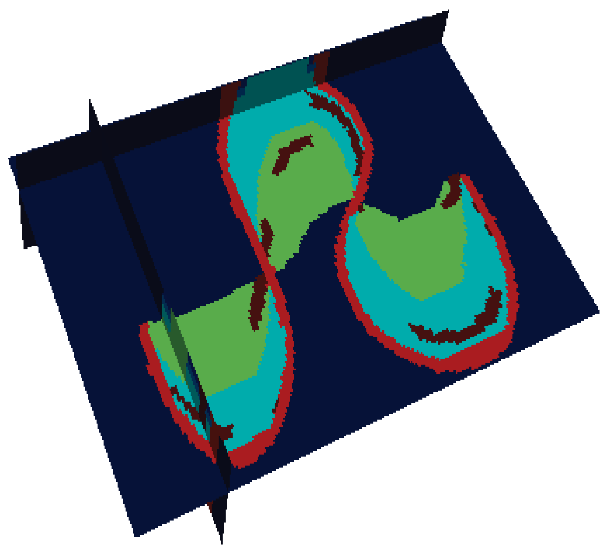
EXPANSION + ROTATION
(Three bends)



EXPANSION + ROTATION
(Mud drapes)

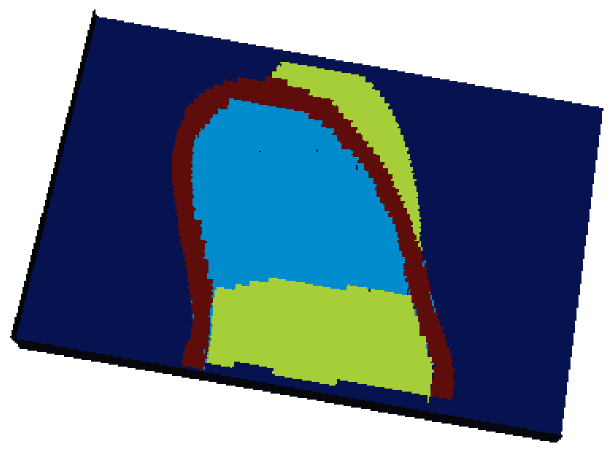


EXPANSION + ROTATION
(Discontinuous mud drapes)



*No scale intended.

EXPANSION + ROTATION
(Example 2)



COLOUR CODE

3 FACIES	4 FACIES	5 FACIES	7 FACIES
Point bar	Point bar	Point-bar top	Point-bar top
Channel fill	Channel fill	Point-bar	Muddier point bar
Floodplain	Floodplain	Point-bar base	Sandier point bar
	Mud drapes	Channel fill	Point-bar base
		Floodplain	Channel fill
			Mud drapes
			Floodplain

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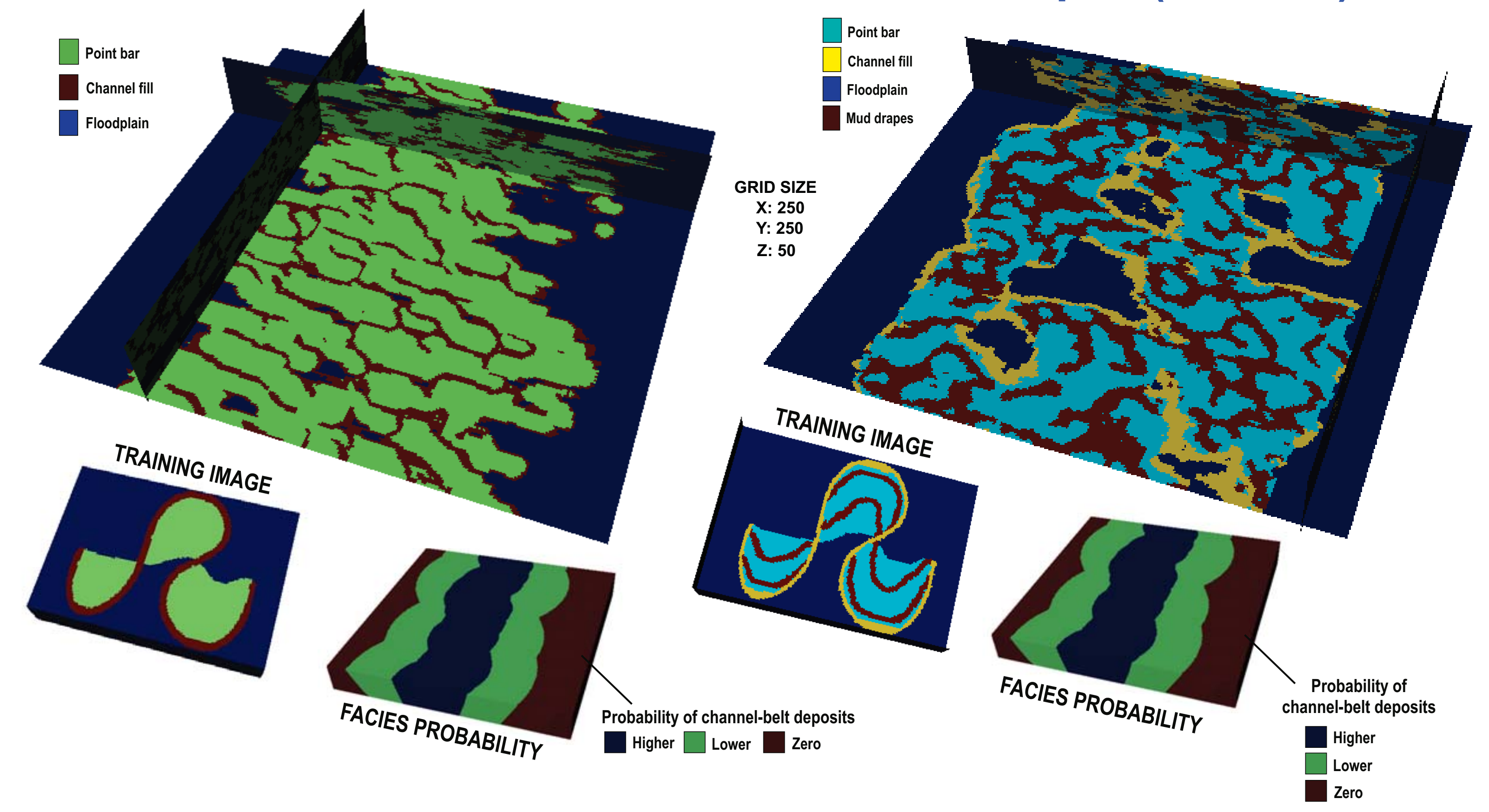
Fluvial meander-belt reservoir modelling using multi-point statistics conditioned on analogue-based forward stratigraphic models

SNESIM

SIMULATIONS FOR EXPANSION+TRANSLATION BARS

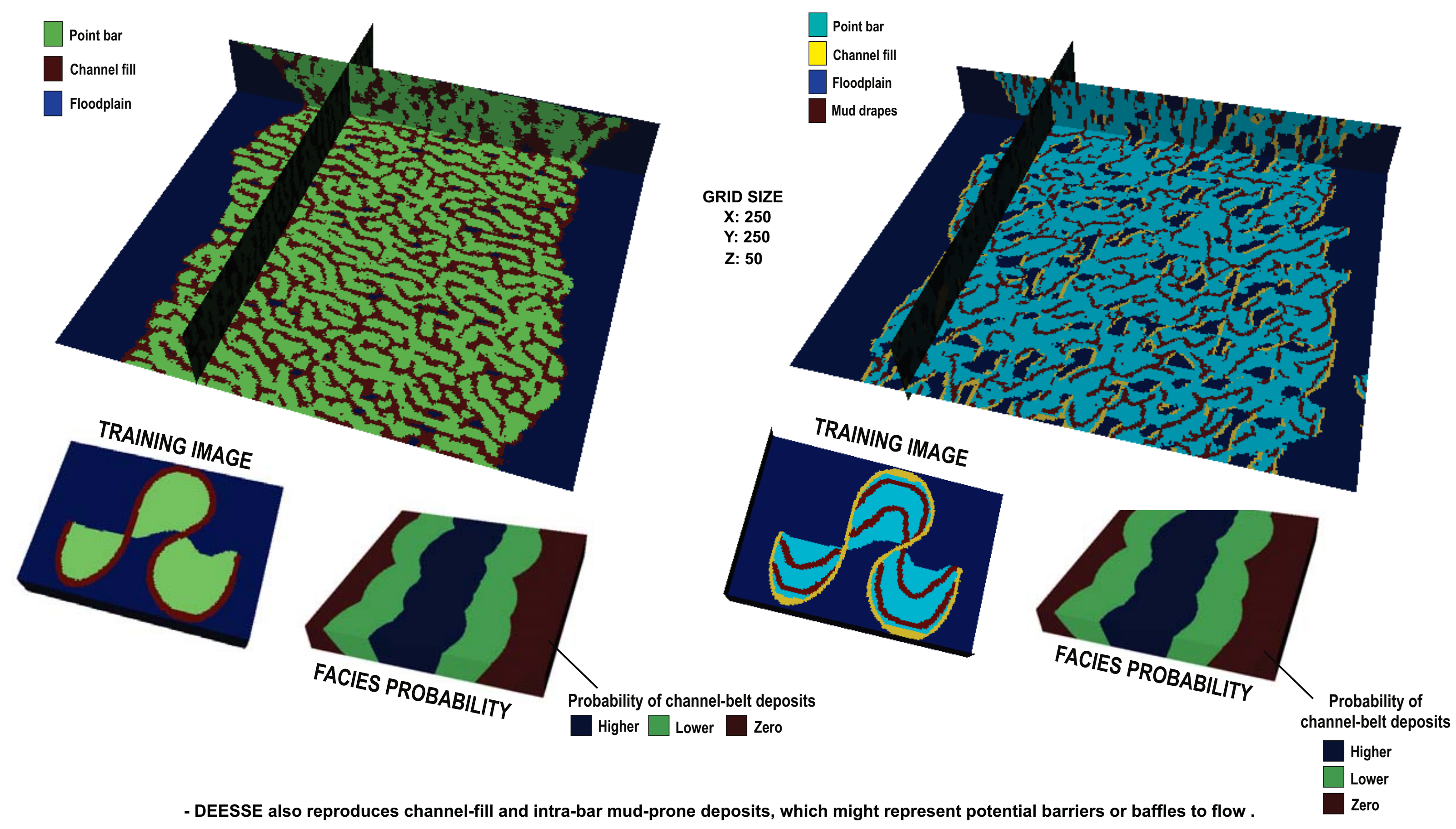
DEESSE

No mud drapes (3 facies) / Mud drapes (4 facies)



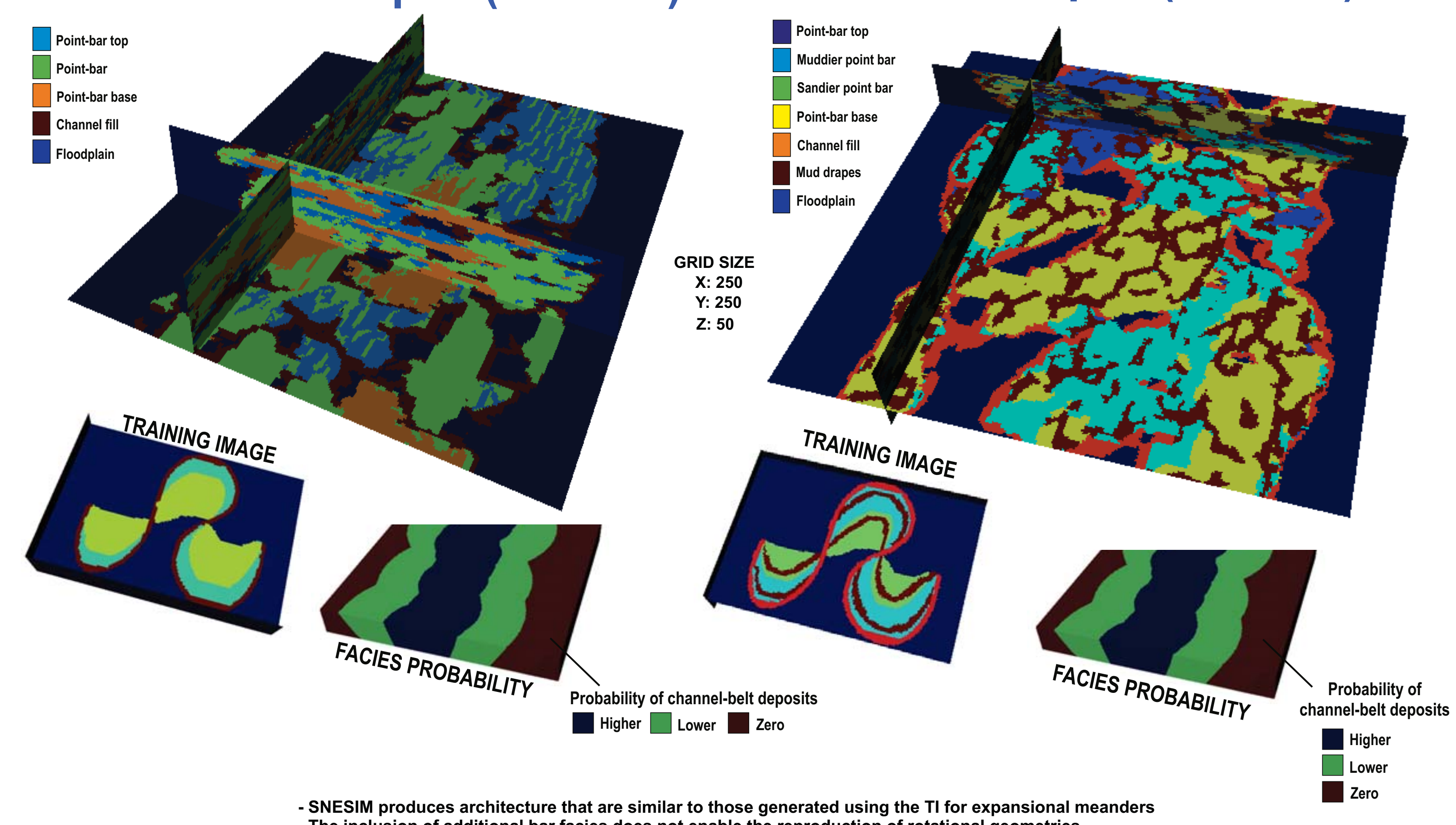
- No geometries that necessarily relate to meander rotation are observed.
- Realizations are similar to those obtained with training images for expansional meanders.

No mud drapes (3 facies) / Mud drapes (4 facies)



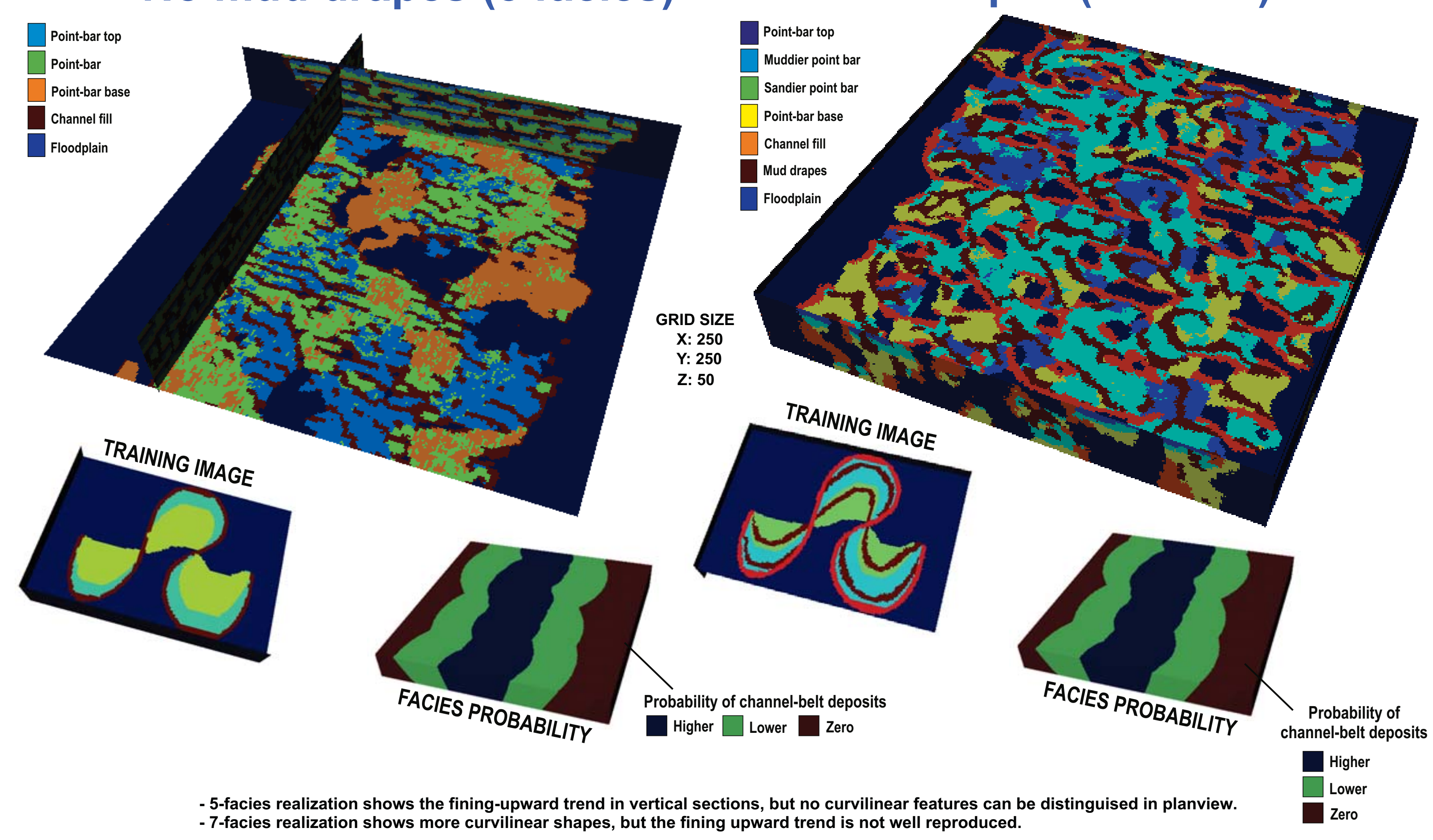
- DEESSE also reproduces channel-fill and intra-bar mud-prone deposits, which might represent potential barriers or baffles to flow .

No mud drapes (5 facies) / Mud drapes (7 facies)



- SNESIM produces architecture that are similar to those generated using the TI for expansional meanders
- The inclusion of additional bar facies does not enable the reproduction of rotational geometries.

No mud drapes (5 facies) / Mud drapes (7 facies)



- 5-facies realization shows the fining-upward trend in vertical sections, but no curvilinear features can be distinguised in planview.
- 7-facies realization shows more curvilinear shapes, but the fining upward trend is not well reproduced.

CONCLUSIONS

- The workflows that are being developed as a part of this research are applicable to different MPS algorithms (SNESIM, DEESSE) through a hierarchical approach to facies modelling. The comparison between the different MPS algorithms considered in this study enables quantification of their performance in modelling different types of fluvial successions.
- Simulations performed indicate that higher geological realism can be achieved with respect to the reproduction of features that cause compartmentalization in reservoirs hosted in meandering fluvial successions than those performed by conventional methods (Objects based, SIS, etc.). Realizations show the following features:

1) Simulations reproduce curvilinear shapes, features that are very common meandering systems and that SIS and other conventional methodologies fail to achieve.

2) Successful modelling of fining-upward trends in the vertical layers in a manner commonly observed in nature.

- It is desirable to use training images that incorporate repeated and reasonably homogeneous patterns that are not located to specific places within the training images. Although MPS methods are commonly believed to require stationarity to perform adequately, this study demonstrates that the incorporation of certain levels of non-stationarity in the training images can deliver realistic simulation results. This is for two reasons:

1) The training images used in this exercise include a sufficiently high proportion of patterns that can be captured by the algorithm.

2) The use of appropiate auxiliary-variable maps which succesfully adjust the population of categories/facies in the simulation grid for a given training image.

- The hierarchical approach involves the use of different auxiliary variables (probability maps and rotation maps). Special attention should be given to the probabilities assigned to each category and depending on the selected method (SNESIM or DEESSE) the parametization process can differ.
- Realizations have been assessed both qualitatively and quantitatively against 1) the training images themselves, and 2) known examples of high-sinuosity river architecture.
- Both SNESIM and DEESSE algorithms are able to reproduce curvilinear shapes, channelized shapes and fining-upward trends.
- However SNESIM and DEESSE fail to incorporate horizontal trends (expansion-related-fining-outward, counter-point-bar fining) that exist in the training images although application of auxiliary variables and multiscale modelling approaches were attempted to reproduce some of these features.
- In addition, difficulties have emerged in setting up the most appropriate simulations parameters in both SNESIM and DEESSE. Therefore, it is desirable to establish modelling recipes that facilitate simulation set-up; this can be achieved by pairing parameter sets with each training image used in the simulations.
- As is the case for the construction of the auxiliary-variable maps, the building of the training image is a crucial step: the difficulty in sourcing appropriate training images is a perceived barrier in the uptake and use of MPS methods for reservoir modelling.
- This research offers to the user the selection of different training images with varying levels of sedimentary heterogeneity at multiple scales and with regards to their distribution in meandering river systems that have different behaviours.

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