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Facies Modeling Described by Probabilistic Patterns Using Multi-Point Statistics: An Application to the K-Field, Libya*

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Summary

The main objective of this study is to illustrate the stochastic modeling of facies bodies using a multi-point statistical methodology (MPS) based on probability patterns derived from the integration of facies interpretation at well locations, seismic data, and the conceptual geological model. The proposed methodology was applied to real data in the K-Field of Libya. The reservoir unit, the Mamuniyat Formation of Ordovician age, is interpreted as a glacially influenced setting ranging from shoreface to base of slope fan-channel environments.

The input data was classified in two main groups: 1) hard data corresponding to facies description, derived from core, conventional logs, and especially image logs (FMI), from wellbores, and 2) soft data used as conditioning, derived from a scaled conceptual model constructed on the basis of seismic horizon-slice interpretation and analogues. The final results illustrate the benefits of using multi-point statistics for facies distribution in complex settings. The resulting model reproduces the facies heterogeneity and, to a significant degree, the conceptual model, leading to the conclusion that multi-point statistics offer a significantly improved representation of the geological heterogeneity.

Introduction

Facies modeling is one of the most important tasks in reservoir characterization. This is becoming more challenging as new discoveries are located in either geologically complex or poorly understood areas. Geoscientists are increasingly aware of the importance of managing

reservoir heterogeneities whilst modeling facies distributions. In order to deal with these issues, it is important to use stochastic methods for modeling, using, for example, soft data conditioned to hard data.

Typically, facies modeling of a reservoir is carried out using abundant hard data (cores and logs), but where such data is limited in scope or quality, the task becomes more difficult, as typically occurs in the exploration phase. In such cases, additional soft data is useful as a constraint on facies distribution, based on conceptual models, regional geology, analogues, and paleogeography, etc. Both kinds of input data, hard and soft, are essential for geological modeling and contribute to understanding the conceptual depositional model, notably in terms of the shape, size, and orientation of the different sediment bodies. Needless to say, the output geological model should always honor all input data.

Whereas outcrop models and seismic interpretation provide important information on reservoir architecture, heterogeneity, and spatial distribution, it is not fully clear how such information can be used in geostatistical reservoir modelling.

Multi-point simulation (MPS) methods allow the combination of conceptual models in training images (Strebelle and Cavelius, 2013). After creation of the training image, MPS generates patterns, then anchors them to subsurface well logs and seismic. In this way, complex and heterogeneous facies can be distributed in a reliable and more realistic model (Caers and Zhang, 2004).

The scope of this study was to work with the MPS method characterizing the relationship between multiple, spatially positioned points to capture heterogeneity patterns and ordering relationships, reproducing depositional conceptual models with well-defined shapes (Strebelle and Cavelius, 2013). The result was that each simulation was constrained by the input facies statistics, from well log analysis and FMI interpretation (hard data), and the probability patterns (soft data).

The methodology followed involved the construction of the conceptual model, definition of layering in the previously created 3D grid, definition of a training image based on geobody shapes, geometries, heterogeneities, and facies associations, the creation of probability patterns, and finally the facies distribution using MPS.

Field Description

The K- Field is located in the central Murzuq Basin, SW Libya. Discovered in 2005, this field produces from the Upper Ordovician (Hirnantian) Mamuniyat Formation.

The Mamuniyat Formation is the main reservoir unit in the area. It is underlain by the mud-prone Upper Ordovician Melaz Shugran Formation (Deschamps et al., 2013; McDougall and Martin, 2000) and overlain by the discontinuous and generally argillaceous Bir Tlacin Formation ([Figure 1](#)).

In addition, this Upper Ordovician column, as seen in outcrop, is also characterized by abrupt lateral changes of the facies and sequences, often reflecting significant glacial down-cutting and merging of unconformities to form nested paleovalleys (McDougall and Martin, 2000; McDougall et al., 2004).

There are six wells drilled in K-Field. Three of these (Wells K1, K2, and K4) are producers, whilst two (Wells K5 and K6) have not yet been tested. Finally, a well was drilled in the northern part of the field but tested dry (Well K3). The model described here was born from the need to understand the different performance of the drilled wells, and also to plan the drilling of future wells

MPS Model Methodology

Definition of Conceptual Geological Model

In order to build the conceptual model, it was necessary to interpret depositional environments throughout the entire stratigraphic column using cores and image logs; paleocurrents and fracture orientations were also interpreted from FMI. All these elements were used to summarize geometries, spatial distribution and dimensions of the key facies types ([Figure 2](#)).

The high-resolution well correlation for the Mamuniyat Formation is fully consistent with the seismic interpretation and gives the basic framework to interpret the depositional environments, stacking patterns, geometries, and architectural relationships of the major sand-body types ([Figure 3](#)).

A simplified scheme of six key facies associations (FA1 - FA6) was generated from the initial sedimentological facies breakdowns that were integrated into the conceptual model. The Mamuniyat section is dominated by Outwash fan (FA2) and Submarine channel (FA4) deposits; however, locally, more argillaceous Distal Outwash fan (FA3) or Proglacial Muds (FA6) may be important. Key statistics were computed for each of the reservoir zones to be applied to the model.

The pre-existing (McDougall and Martin, 2000) zonation (Lower, Middle and Upper Mamuniyat) was found, after seismic integration, to be highly diachronous and unsuitable for modeling of K-Field. A new genetically based; sequence stratigraphic, rather than purely lithostratigraphic, seven-layer zonation (A to G) scheme for the Mamuniyat Formation was generated by using azimuth tracking attributes and the integration of stratigraphy, sedimentology, and seismic. This study is focused on the distribution of glacial-marine facies of Zone A (Mamuniyat productive sandstones) ([Figure 4](#)).

After building the conceptual model, it was used to define the training image, based on geobody shapes, geometries, heterogeneities, and facies associations defined in the conceptual model and honoring the statistics from the well analysis.

Definition of Structural Model Layering

Before starting the facies modeling, the structural model was built using faults, horizons, and zones. The layering of the model was defined after conceptual model construction in order to take into account the stratigraphic resolution needed for the facies modeling ([Figure 5](#)). Good quality control is absolutely necessary at this stage, in order to avoid distorted cells, ensuring the development of a static model which can be used later in dynamic simulations.

The geometry of the model layers (discordance, concordance, truncations, etc.) should reflect the stratigraphy as precisely as possible ([Figure 6](#)). The total number of cells in the model will result from a compromise between reality and the practical limitations of the software whilst also seeking to avoid excessive upscaling (Strebel and Cavelius, 2013).

Definition of Training Image

Training images are representations of the geological conceptual model, showing the relationship between the facies that should be represented in the model. Training images may be hand-drawn images, resampled seismic attributes, aerial images, and/or outcrop analogs. Basic requisites for a training image include: the image should be simple, stationary, large enough to cover facies characteristics (connectivity, cyclicity, etc.), but small enough to run within an acceptable time frame; they may include facies shape and associations (i.e., relative positions and stacking), and the number must be limited (no more than eight facies are recommended). In the training image of the case study, six facies were defined representing the geometry, shape, orientation, and size of the main geological features present in the field area ([Figure 7](#)).

Definition of Probability Patterns

Multi-point facies modeling is a stochastic method that will ultimately convert a training image –extracted from a geological conceptual model- into a 3D reservoir model ([Figure 8](#)).

Two concepts implied in this methodology are:

- a) Multi-point means exploring the relationship between one-to-many points at the same time;
- b) In multi-point facies modeling, the traditional variogram from 2-point statistics is replaced by a training image and a facies pattern ([Figure 9](#)).

For the case study a training image with six facies defined was used to create a probability pattern adjusted to the facies statistics interpreted from the well data ([Figure 9](#)). The resulting pattern represents the conceptual model of K-Field area and honors the hard data from the wells.

Facies Modeling

The last step in this process is the facies modeling itself. Many possible solutions are generated, all of them anchored to the facies distribution in the wells ([Figure 10](#)); so upscaling of properties must first be carried out. Far from well locations, facies are propagated by using training images and optional soft data, such as trends (e.g., for channel orientation) and regions (e.g., to constrain facies propagation), with the additional possibility of adjusting to field statistics (this alternative is very useful in exploration, or in an appraisal phase with few control-point data).

The facies modeling workflow applied to the model can be summarized in the following steps ([Figure 11](#)):

- 1) Select the upscaled facies property;
- 2) Choose the zone defined in the structural model;
- 3) Select the facies modeling method (MPS);
- 4) Trust fraction strength;
- 5) Drop the pattern created before from training image;
- 6) (Optional) In some cases, it is useful to adjust manually the facies proportion on the basis of analogue data. If not, the fraction will be calculated automatically from the patterns.

Discussion of Results

Final model results illustrate the benefits of using multi-point statistics for facies distribution in complex settings. Facies modeling is driven by integration of the conceptual model, converted to a probability pattern, and constrained by hard data, which in this case included facies interpretation from well data.

The resulting model successfully reproduces the facies heterogeneity and, to a significant degree, the conceptual model, leading to the conclusion that multi-point statistics (MPS) offer a significantly improved representation of the geological heterogeneity ([Figure 12](#)).

The manual adjustment of the facies statistics when using the probability pattern allows control of the percentages derived from petrophysics, whilst simultaneously representing the shape, geometry, and size of the geological features generated from the training image.

Output model results show simulated architectural elements that match observed outcrop parameters and stacking pattern proportions, honor well data, and provide enhanced facies distribution predictions. Outcomes illustrate the importance of integrating sub-seismic-scale data into reservoir models using both outcrop and subsurface data.

Conclusions

Multi-point simulation is a powerful tool for generating more realistic 3D models, producing predictive facies distributions in a consistent static geological subsurface model.

MPS methodology allows the integration of outcrop and subsurface sedimentology, sequence stratigraphy, seismic interpretation and special attributes, to reproduce successfully the depositional complexity of the glacially influenced Mamuniyat Formation reservoir in the K-Field of Libya.

The modeling workflow illustrated here should improve petrophysical property distribution, volumetric calculations, and ultimately, the final model will contribute to a more robust dynamic flow model.

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References Cited

Caers, J., and T. Zhang, 2004, Multiple-point geostatistics: A quantitative vehicle for integrating geologic analogs into multiple reservoir models, *in* Integration of Outcrop and Modern Analogs in Reservoir Modeling: AAPG Memoir, v. 80, p. 383-394.

Deschampes, R., R. Eschard, R. and S. Rousseé, 2013, Architecture of late Ordovician glacial valleys in the Tassili N Ajjer area (Algeria): Sedimentary Geology, v. 289, p. 124-147.

McDougall, N.D., and M. Martin, 2000, Facies models and sequence stratigraphy of Upper Ordovician outcrops in the Murzuq Basin, SW Libya, *in* M.A. Sola and D. Worsley, editors, Geological Exploration in Murzuq Basin: Elsevier, p. 223-226.

McDougall, N.D., J.G. Quin, J. Vila, and K. Tawengi, 2004, Sedimentology, sequence stratigraphy and large-scale architecture of the Upper Ordovician Mamuniyat and Melaz Shugran Formations based on outcrop studies of the Ghat area: Repsol Exploración (for REMSA) internal report.

Strebel, S. and C. Cavelius, 2013, Solving speed and memory issues in multiple-point statistics simulation program SNESIM: Mathematical Geosciences special issue 2014, v. 46, p.171-186.

Villarreal, V., 2013. Multipoint facies simulation basic guidelines Petrel 2011.X.X: Schlumberger Internal Report, 1-22p.

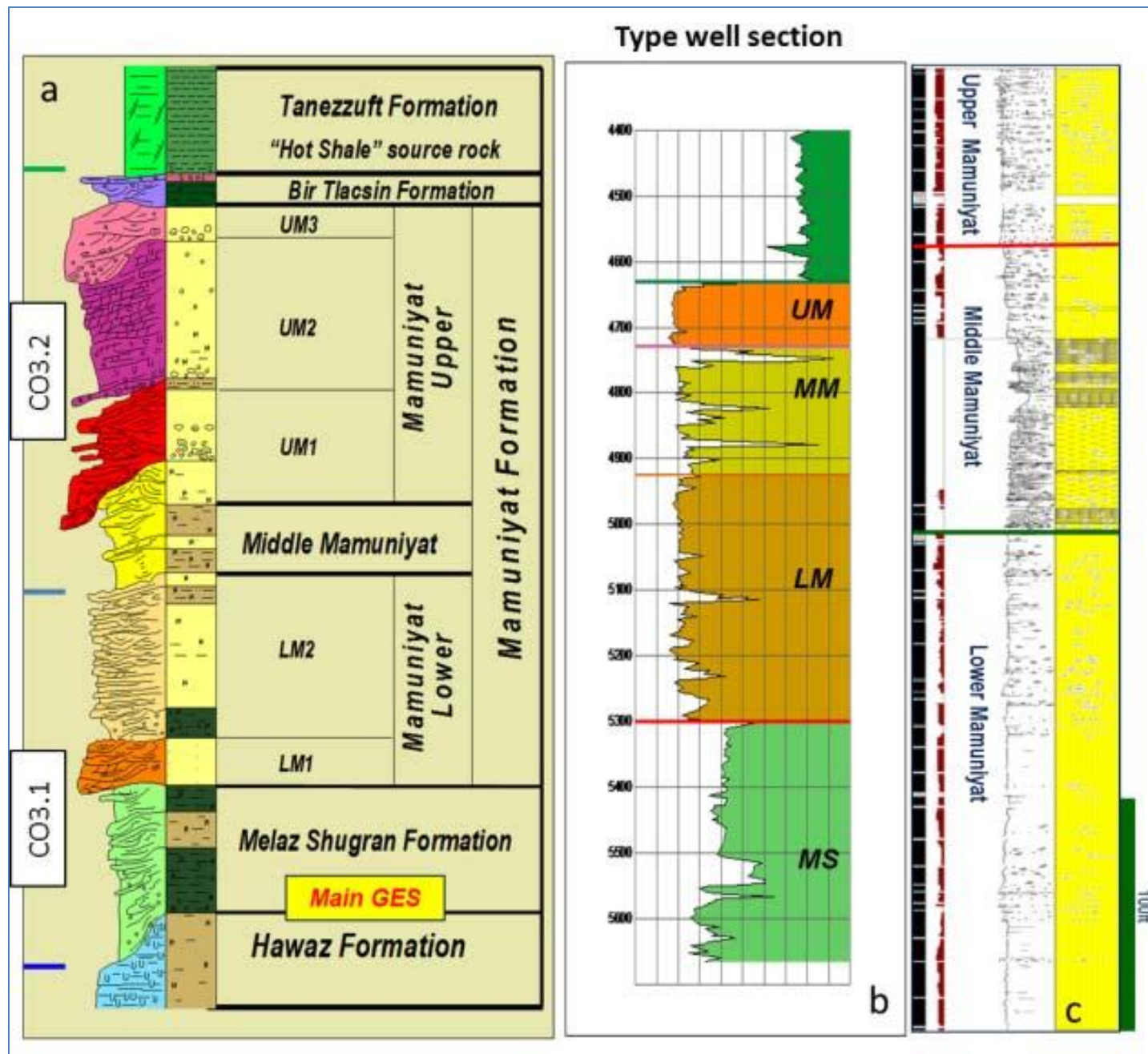


Figure 1. Stratigraphic column of Upper Ordovician after integration of outcrops, well logs, and cores (modified from McDougall et al., 2004).

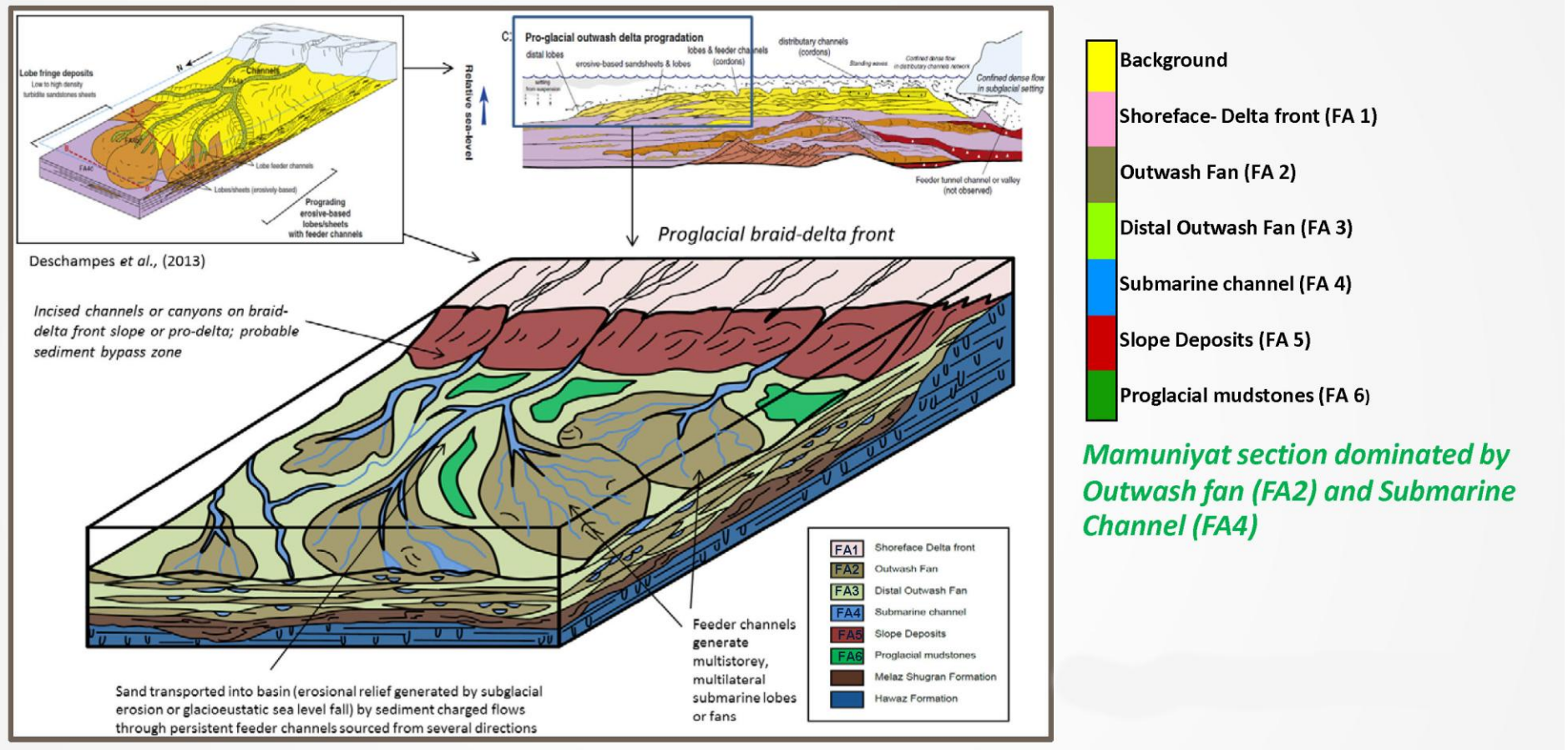


Figure 2. K-Field facies distribution. Conceptual depositional model for Mamuniyat Formation (modified from Deschampes et al.; 2013).

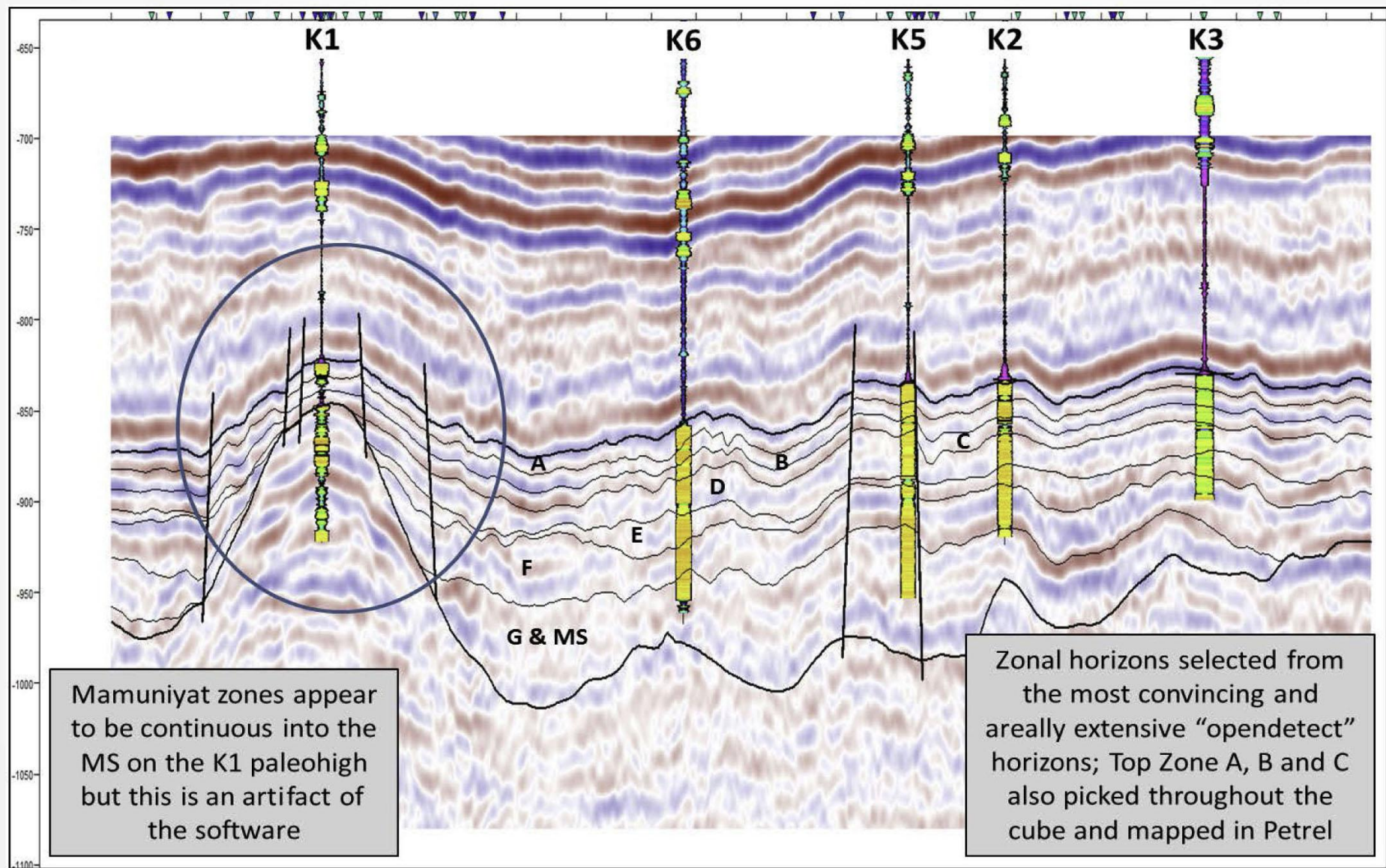
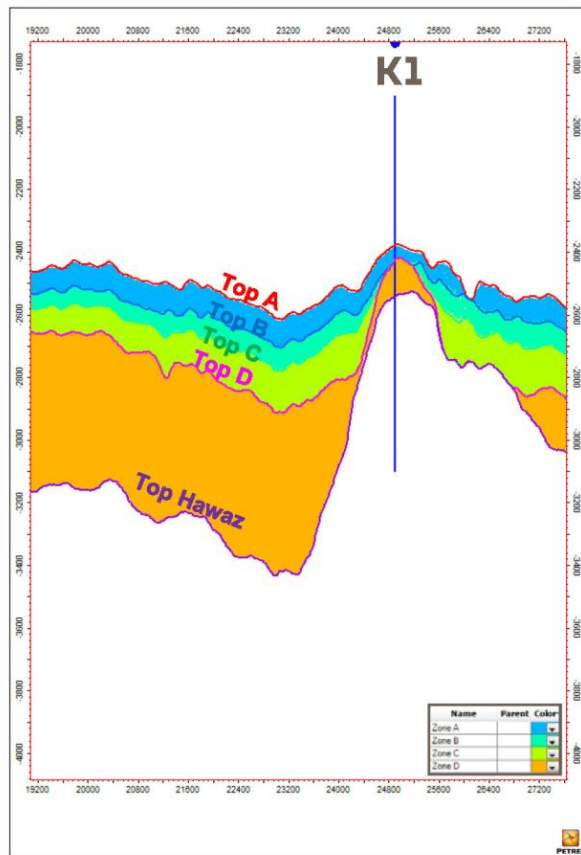
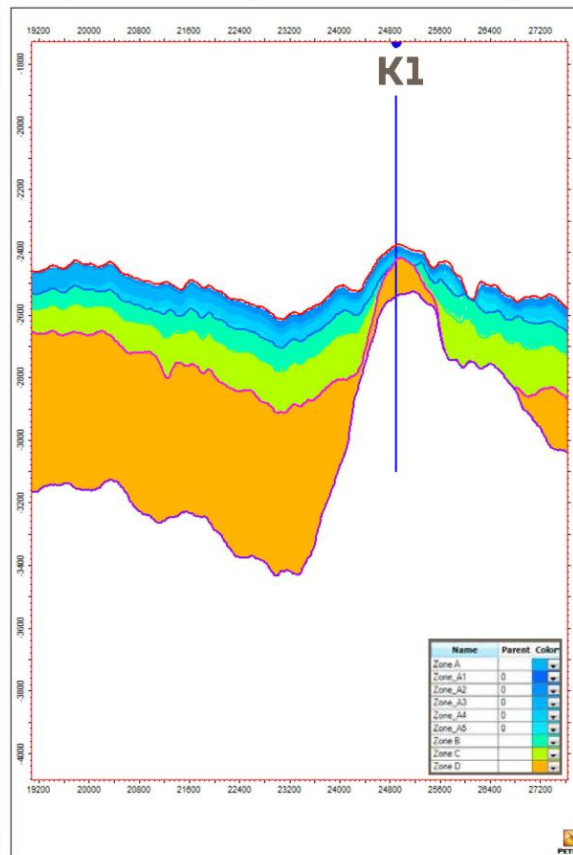


Figure 4. Interpreted zonal horizons A to G (derived from dip steering).

Making of horizons



Making of zones



Layering

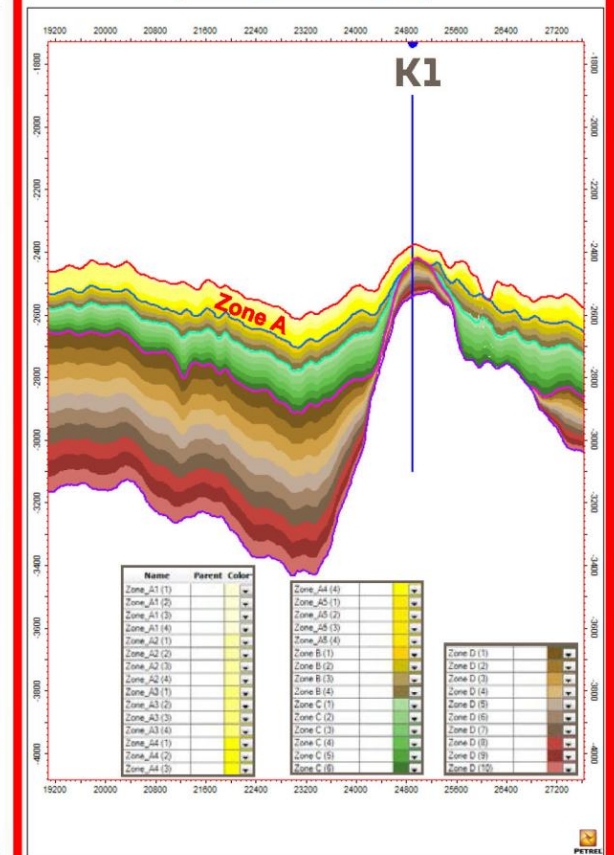


Figure 5. Structural model workflow applied to the K-Field study, showing the defined zones and layering.

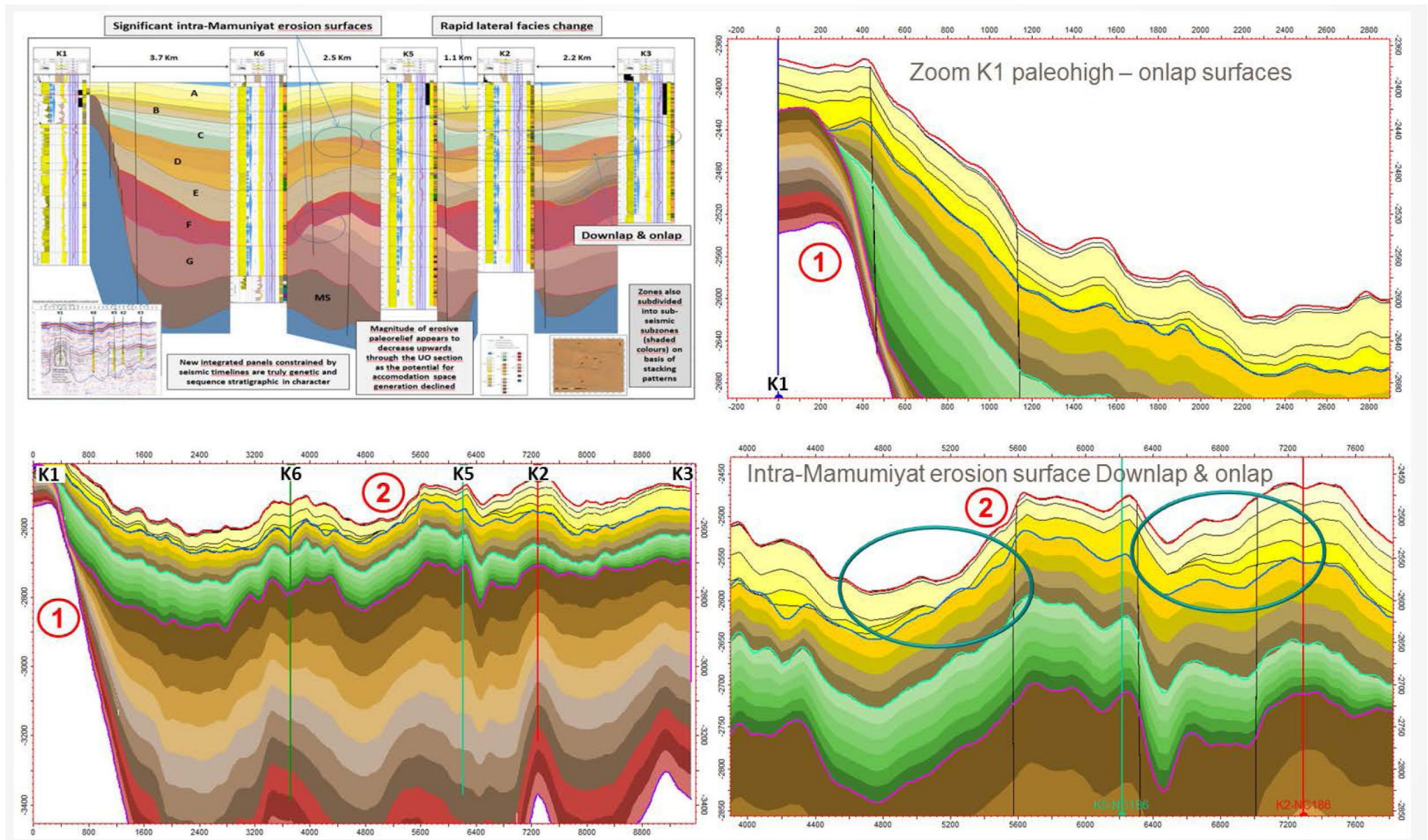


Figure 6. The structural model aligned to the stratigraphic framework. Note discordances and truncations reflected in the layers.

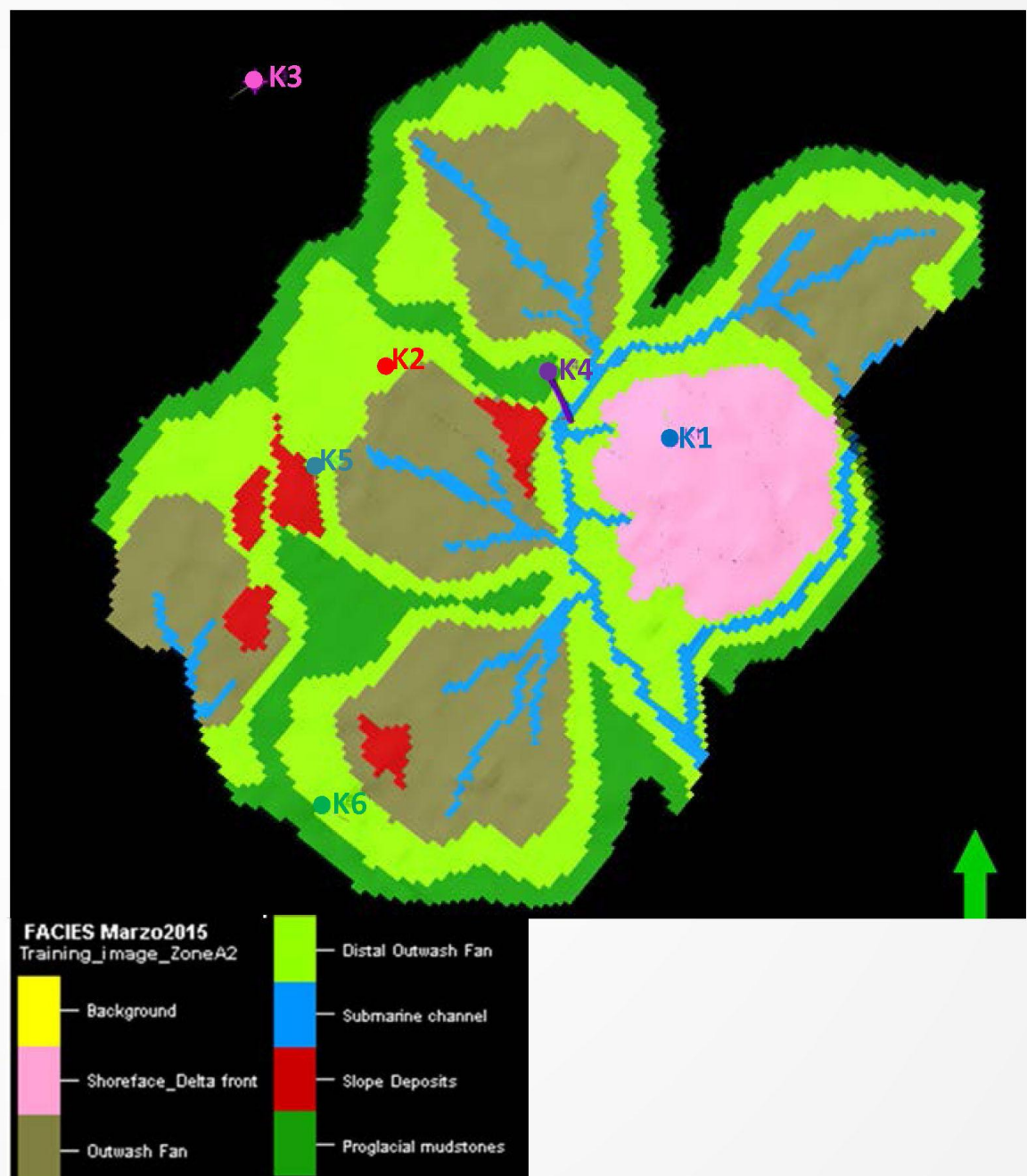


Figure 7. Example of a training image with 6 facies and background.

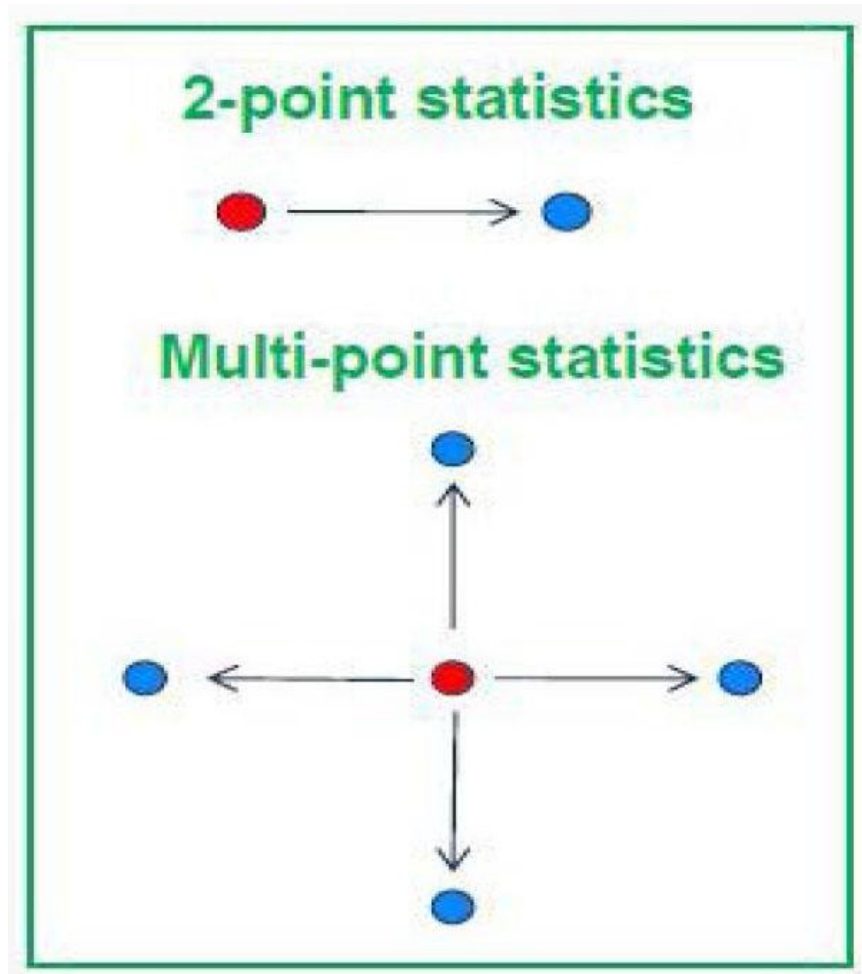
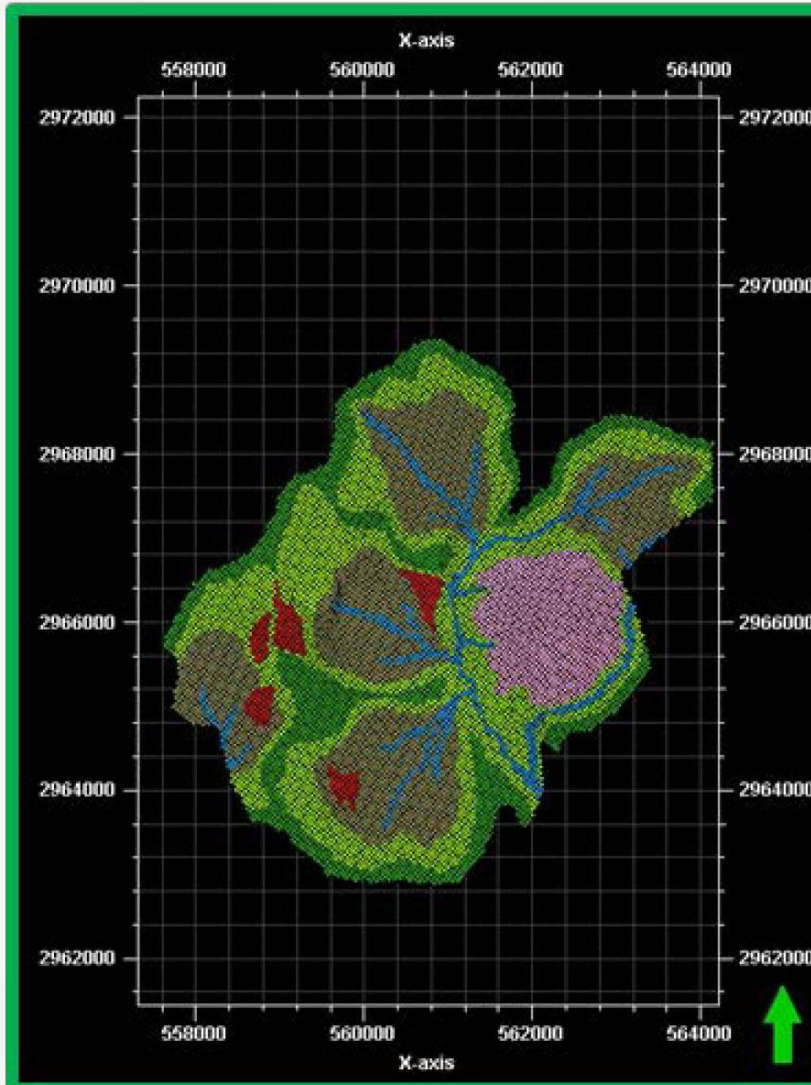


Figure 8. Multi-point statistic concept – Petrel software (Villarroel, 2013).

TRAINING IMAGE

- Training_image_ZoneA2



PATTERN CREATION

- TI 5x7x3_Zone_A2

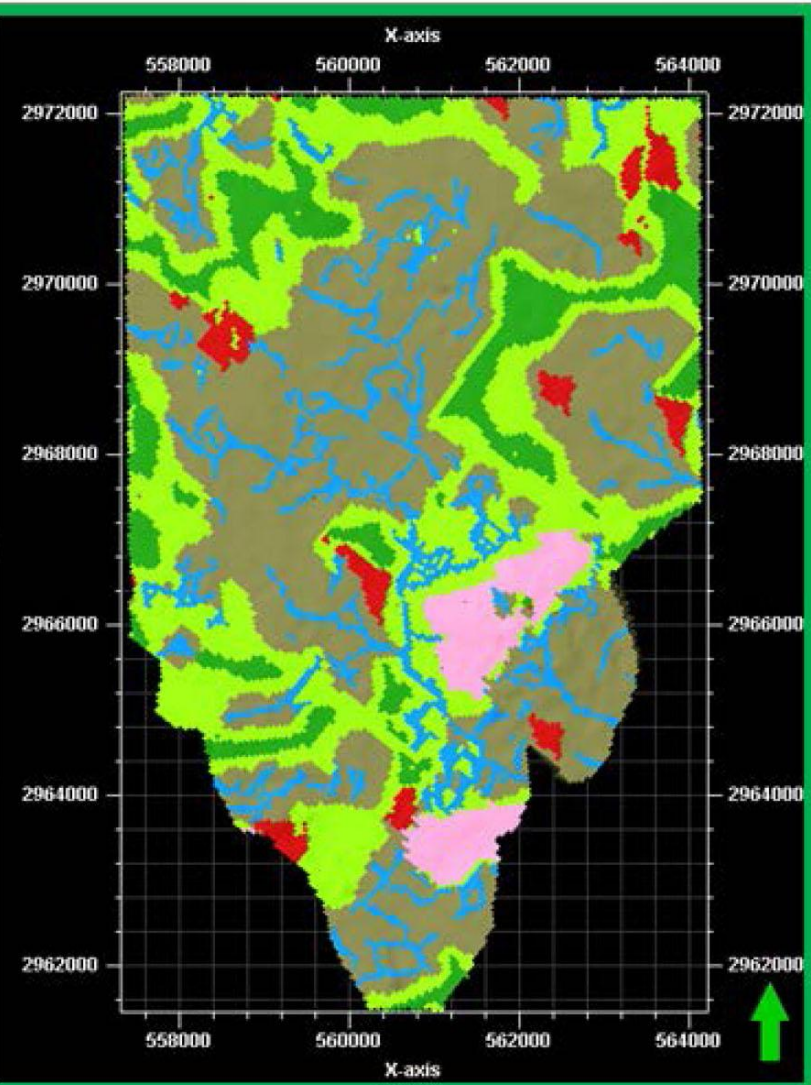


Figure 9. Pattern creation from a training image.

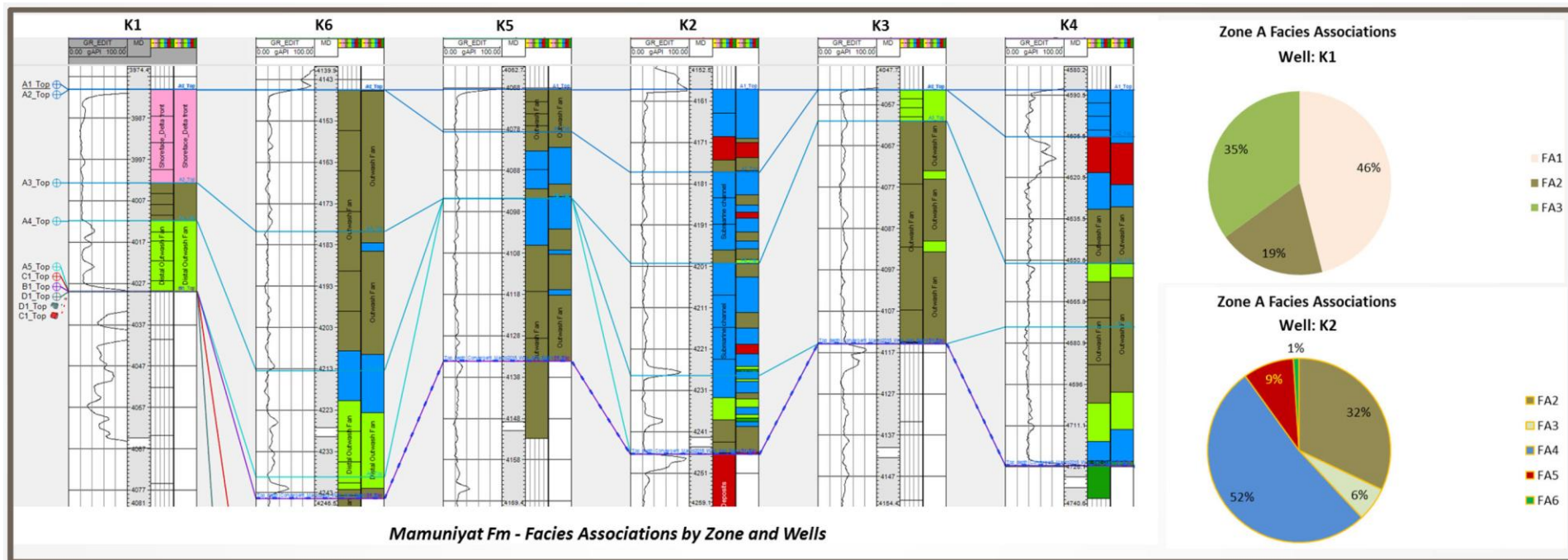


Figure 10. Upscaled well-log facies distribution for the Zone A of the Mamuniyat Formation.

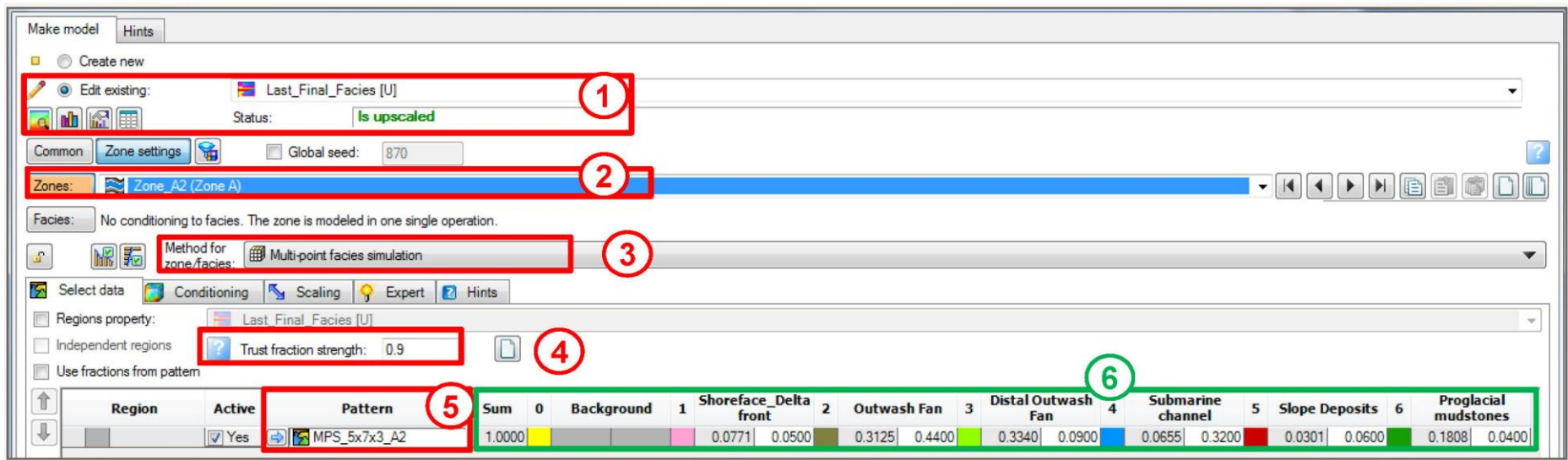


Figure 11. Facies modeling workflow.

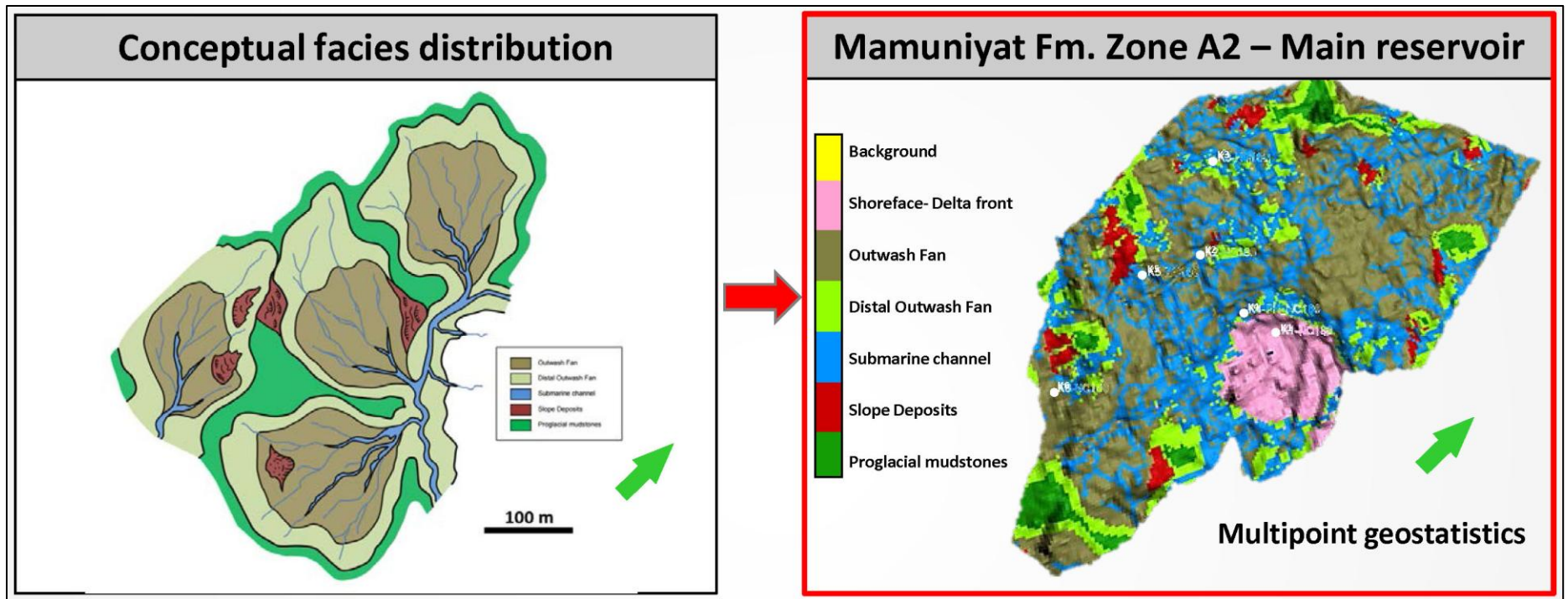


Figure 12. Facies distribution in Zone A2 – Main Reservoir.