Case Studies on the Spatial Distance Calculation in Facies Modelling

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One conceptual heterogeneity prototype is proposed to integrate the geological information in geostatistical modelling. In this prototype, three major heterogeneity axes are defined as: sedimentary dip, sedimentary strike and the vertical direction. In this paper, one case study is presented to illustrate the the dip and strike direction detection from the real data set. It is shown that the geological analysis to the data set will aid to set up a correct conceptual model for the spatial anisotropy based distance calculation. In the estimation and simulation, the new proposed anisotropy based spatial distance calculation and the direct multivariate probability estimation is implemented.

Methodology and Workflow

For the heterogeneity spatial variability characterization, the bivariate probability diagram proposed in this research characterizes the facies spatial variations. Using the bivariate probability diagram instead of the variogram will make it possible to integrate more geological constraints such as the facies stacking pattern into the model.

Practically, there is a need to estimate the bivariate probability along any spatial directions to reflect the spatial anisotropy. Interpreting the lateral heterogeneity is always a challenge in geostatistics. In the proposed methodology [1], a heterogeneity prototype is used to instruct the transformation of an effective spatial distance in the vertical direction. It provides a new approach to infer the lateral spatial statistics from available data. In this prototype, the vertical, strike and dip direction, are defined to reflect the different character of variation. The vertical direction will be the main facies stacking direction and usually reflects the sediments deposit history. Along the strike direction, the sediments will show a kind of source shifting which is normal in clastic sediments environments. The dip direction will be the direction from sediment source to the deposition locations. Recognizing these three axes is possible in most sedimentary deposits.

When the spatial variation information is characterized by the bivariate probability, the maximum entropy principle is used to combine all of them together to construct a multivariate probability distribution [2]. In this approach, the bivariate probability between each data pair is considered as a marginal probability of the target multivariate probability which will characterize the facies outcomes probability at these locations taken all together.

Finding the solution of the maximum entropy equation using the traditional Lagrange multiplier approach is a challenge to this multivariate probability estimation. Instead, an iterative scaling approach is used. It is based on the minimum Kullback-Leibler distance principle which is a more general maximum entropy approach. After the multivariate probability is constructed, conditional probability can be calculated directly from its definition. This approach is theoretically correct without any other assumptions.

These form the bases of the proposed spatial probability interpolation methodology named Direct Multivariate Probability Estimation(DMPE). The whole procedure of sequential simulation using the DMPE will include the following steps:

1. Defining the facies. The facies constituting the reservoir have to be defined from the available data: core samples, well logs and seismic data. They have to honour the geological information. Considering the multivariate data event space constraints, there should be no more than four categories in order to use the DMPE within reasonable computing time.

2. Geological analysis and bivariate probability modelling. From the vertical log analysis, obtain a pattern for the sedimentary units that may be defined by a sequence stratigraphic surface. Geological analysis of the data set will correctly define the dip and strike direction of the heterogeneity prototype. The anisotropy ratios for the prototype will also aid in geologically realistic modelling. The axes directions and anisotropy ratios will reflect the geologic understanding about the study area.

3. Define the simulation grid. Generally, a regular orthogonal simulation grid is adopted in most geological algorithm design. In this research, as the bivariate statistics constrained by the sequence stratigraphic surface, it is expected that the grid of x-y plane is aligned to the interpreted equal time surface. The reference level for the simulation is a specific geological layer which is used to restore the geometry of the reservoir at the time of deposition. The level have been deposited horizontally during sedimentation and should, if possible, correspond to a time line.

4. Implement traditional sequential simulation for each unsampled location. For each unsampled location, the spatial distance is expressed as an effective distance calculated from the dip and strike separation distance constrained from the heterogeneity prototype. The bivariate probability of each data pair is retried from the bivariate probability calculated from the vertical direction. The conditional probability is calculated using the DMPE. After each cell is simulated, it will be used as a hard data for later cells simulation.

Comparing with the traditional facies modelling, such as indicator kriging based approach, the new proposed methodology introduced above will integrate more information into the final facies model. The above procedure will be illustrated with a case study below.

Data Set

The data set in this case study is from the Production forecasting with Uncertainty Quantification project [3]. The well data have values of permeability, porosity and shale proportion. A total of 23 wells are available, see Figure 1.

The wells represent the Brent group from the North Sea basin. The upper part of the well data represents the Tarbert formation which is a prograding near shore sedimentary environment. The bottom part represents the upper Ness formation which has fluvial sediments. A short review of the Brent group is given below.

The Brent group comprises five lithostratigraphic units: the Broom, Rannoch, Etive, Ness and Tarbert formations [4]. It is generally interpreted to record the progradation and subsequent transgression of a wavedominated delta [5, 6]. The Rannoch and Etive formations record progradation of the wave-dominated delta front and coeval coastal barrier, while the Ness formation comprises delta plain deposits. The Tarbert formation comprises transgressive shallow marine sandstones, see Figure 2.

The Brent group has formed a major exploration target in the North Sea since the discovery of the giant Brent and Ninian fields in the early seventies. As such, its stratigraphy and sedimentology have been the focus of continuous interest and analysis by a large number of geoscientists [7, 8, 9].

Prototype Definition

In the proposed spatial anisotropy based distance calculation, building the geological prototype is a crucial step to ensure that the final facies model is reasonable and geologically realistic. It is built through geological exploration works based on the available data. In this case study, it will include the conceptual sedimentary model analysis, the facies definition and the modelling prototype coordinate definition.

Conceptual geological model

Based on the available data set, the Tarbert formation in the upper part of the Brent group will be modelled in this case study. The Tarbert formation is recognized by the first appearance of shoreline sediments (delta front or shoreface foreshore) in the upper part of the Brent group, above the continental deposits of the Ness formation.

Generally, the Tarbert formation has an average thickness of 30 to 50 meters and comprises several upward-shallowing, weakly wave-influenced shoreface sandstone successions that are stacked vertically and contain evidence for tidal current activity. The base of the formation therefore represents a sequence boundary that has been transgressively reworked with little preservation of intervening lowstand deposits. Moreover, the formation underlies, sometimes unconformably, the marine shales which belongs to the Heather formation [9].

Thus, the final geological model for the Tarbert formation is illustrated in Figure 3. In this conceptual model, each sand body of Tarbert formation would have an upcoarsing trend in the transgressive process. The bottom could be the sand from the Ness formation or the marine shale.

Facies definition

Before facies modelling, the facies types should be defined based on the geological background, well log data and other available data sources. If the DMPE method is used, the cell number in the model and the available CPU time should also be taking into consideration. Usually, three facies type is enough [10].

In this data set, there are three properties for each well: porosity, permeability and volume of shale. From the cross-plot between the volume of shale with the porosity and permeability shown in Figure 4, it can be seen they have a very high correlation coefficient. This is expected in such clastic reservoirs where the sand with a small percent of shale will have a higher porosity and permeability.

The volume of shale characterizes the sediments. It could be modelled directly as a continuous variable. While in this research, the facies will be constructed from the volume of shale first and used to build the facies model. The final permeability and porosity model will be constrained by the facies model.

Generally, for a shoreface sedimentary environment, it is divided into upper shoreface, lower shoreface [11, 12]. Upper Shoreface refers to the portion of the seafloor that is shallow enough to be agitated by everyday wave action (wave base). The continuous agitation of the sea floor in the upper shoreface environment filters the smallest grains leaving those grains heavy enough that the water cannot keep them suspended.

Lower Shoreface refers to the portion of the seafloor or sedimentary depositional environment that lies below everyday wave base. In this portion of the coastal environment, only the larger waves produced during storms have the power to agitate the sea bottom. Between storms, finer grained sediments accumulate on the seafloor.

Well logs such as spontaneous potential or gamma ray are usually used to define the facies. If core is available, it is important to understand the relationships between core, log facies and the nature of the depositional environments. Based on the above shoreface sedimentary characteristics, three facies types are defined from shale volume log using two arbitrary thresholds. As the Tarbert formation is a part of vertically stacked shoreface sandstone, the litho-facies type one which has a small proportion of shale (15%) can be interpreted as upper shoreface. While the one with volume of shale more than 45%, will be classified as shale. The value of between these two threshold will be lower shoreface as shown in Figure 6. Those two thresholds are used just for this study and are chosen based on the limited log data. One example of the facies vertical profile from shale volume log is shown in Figure 6.

Model grid definition

In the proposed spatial distance calculation approach, the dip and strike direction in the simulation domain will have a large impact on the final facies distribution. Thus, detecting and defining the dip and strike direction from the data set for subsequent geological facies simulation is an important step. The best way to do this is to construct well correlations across the study area. In this research, a total of 6 well correlation sections are built from the well log data as shown in Figure 7.

As can be seen from two well correlation lines along the North-to-South direction in Figure 8, and from bottom to top, the facies stacking is in a pattern of Shale → Lower shoreface → Uppor shoreface. Although the proportion of each facies changes, the upwarding stacking pattern doesn't change. Based on the shoreline sedimentary model and the conceptual geological model in Figure 3, the direction along North-to-South will be the direction from proximal to distal axis in heterogeneity prototype.

Four vertical well correlation sections perpendicular to the dip direction are shown in Figure 9. Although, the well stacking pattern along East-to-West direction will not change much along each line, their stacking patterns are different. Thus, the strike direction will be from East-to-West direction for this data set.

Based on these well correlations and the geological background of the Tarbert formation shown in Figure 3, the dip and the strike directions of the prototype of the model will be from North-to-South and East-to-West respectively, as shown in Figure 10.

Another aspect of the conceptual model is the anisotropy ratio between the vertical and dip direction. For the Brent formation, the vertical-to-horizontal ratio will be close to 1:600 along dip direction and 1:5000 along the strike direction based on some studies on the North Sea basin [5]. For the final geological model, the model dimensions are $1200 \times 2200 \times 35$ meter. The fine scale cell size is $20 \times 10 \times 1$ meters. Thus, the number of cells in each direction will be: $60 \times 220 \times 35$. The total number of cells for this model would be 462,000.

Facies Modelling

It has become a standard approach to split reservoir modelling into two steps: First generate the geometry of the facies and second, populate each facies with petrophysical properties such as porosity and permeability [13, 10].

Vertical bivariate probability diagram inference

Traditionally, the spatial variability is characterized by the indicator variogram for each facies. For the proposed DMPE approach, the spatial heterogeneity variability is characterized by the bivariate probability diagram. Using the well log data from these 23 wells, the vertical bivariate probability diagram is calculated as shown in Figure 11.

These bivariate probability diagrams in Figure 11 reveal some geological information. For example, the mean lengths can be read from the direct bivariate probability for each facies. Upper shoreface facies have a mean length of 20 meters which is the longest length along vertical direction. While for shale, the mean length is around 16. The lower shoreface has the shortest length of 8 meters.

By looking at the cross bivariate probability diagram, it also can be found that the upper shoreface to shale transitions are less frequent than the transition from upper shoreface to lower shoreface. This facies transition pattern is also supported from the well correlation sections as shown in Figure 8.

Spatial probability mapping

Although the results from the spatial probability mapping (estimation) will not be used in the final reservoir modelling, it is usful to check the computing environment for later stochastic simulation.

In this model, all 23 wells will be used as hard data for estimation. For each unsampled location, 8 conditioning data will be used as conditioning data.

In Figure 12 shows one slice along the dip and vertical direction from the estimation result. While along the strike and dip lateral direction, the estimation results are shown in Figure 13. Instead of using the traditional geometric distance calculation approach, the spatial distance is calculated from the proposed anisotropy distance calculation approach introduced in paper 102 of this volume. The random switching function along the strike direction is assumed follow a sine wave function that is clearly reproduced in the estimation results as shown in Figure 13.

Of course, any other kind of strike switching function can be used. For example, a simple changing to its amplitude and angular frequency of the sine function along the strike direction will produce different estimation probability maps as shown in Figure 14.

Stochastic simulation

The sequential simulation algorithm is used to address the joint uncertainty of facies outcomes in the study area.

As shown in Figure 15, there are some small scale noise in the simulation results. Part of the reason is the small number of conditioning data. Only 8 conditioning data are used. In this case, the actual conditioning data used may change greatly for two very close locations.

As can be seen from some 2D slices along the XY direction in the model, shown in Figure 16, the facies distribution shows a kind of wave along the strike direction which is integrated into the model through the spatial distance calculation.

Conclusion

Strike and dip direction can be discerned from most of the real data set. The stacking pattern for the vertical direction is dependent on the geological analysis to the research domain. A detailed well correlation and the relative sequence stratigraphy research will aid a correct direction detecting for the later modelling work. The geological understanding will be integrated into the model through the proposed spatial distance calculation approach.

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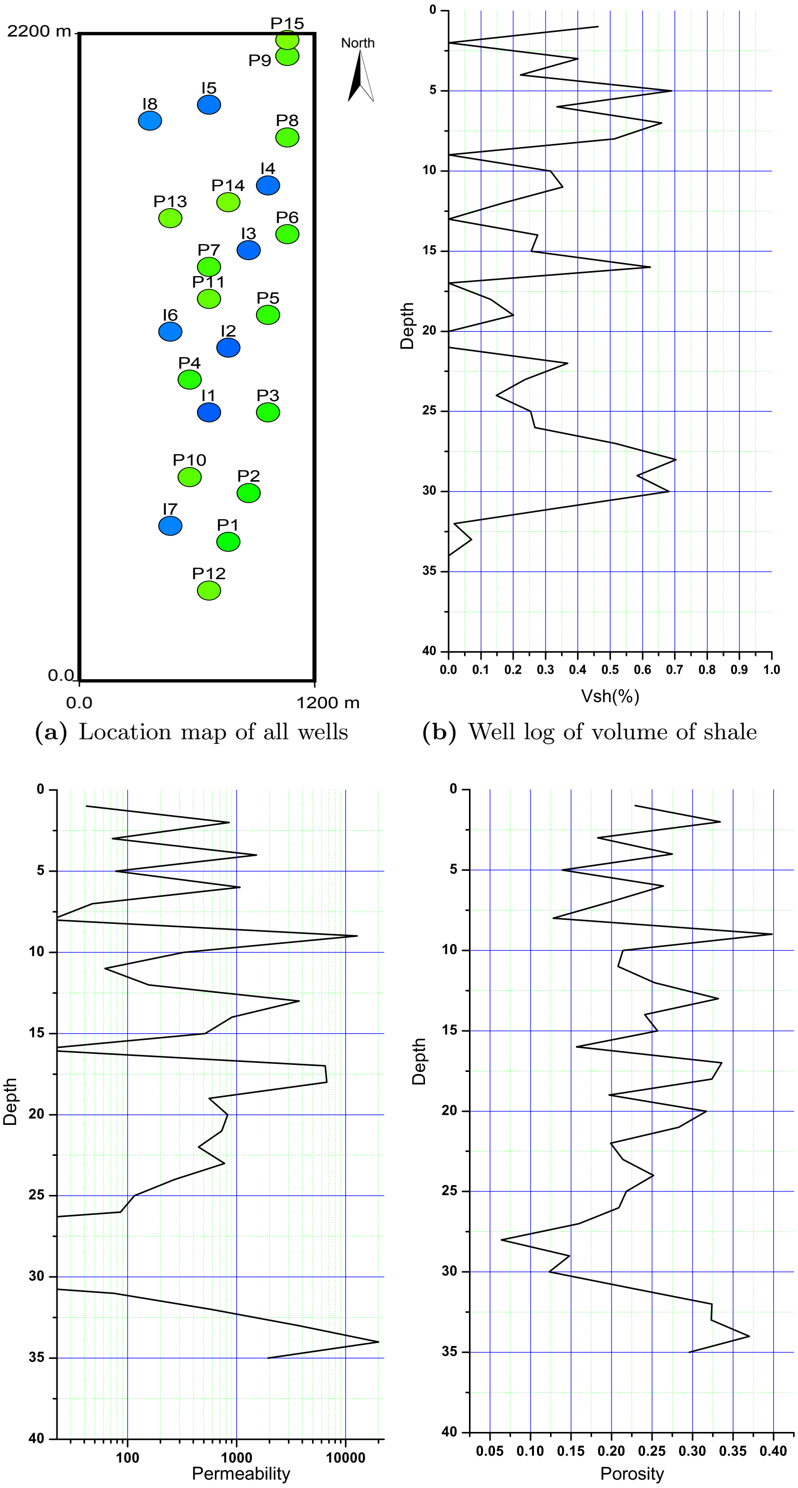


(a) Location map of all wells

(b) Well log of volume of shale

(c) Well log of permeability

(d) Well log of porosity

Figure 1: All available wells location map and the well logs from the well P9

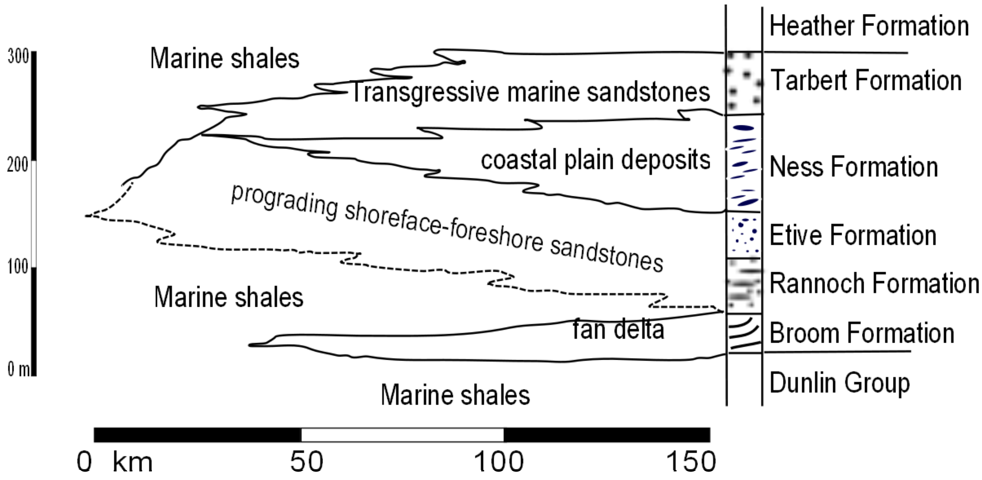


Figure 2: Schematic sequence stacking pattern of the Brent group in the North Sea basin [4]

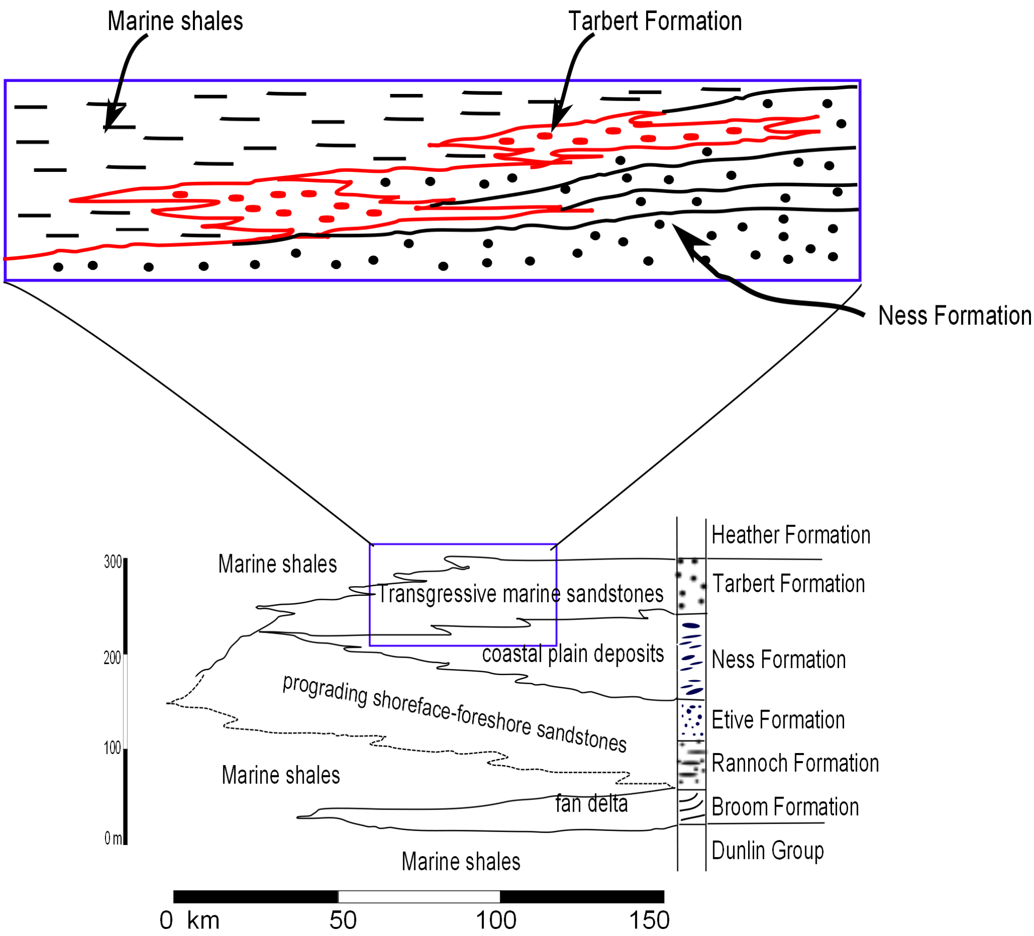


Figure 3: Conceptual geological model of Tarbert formation (Modified from Richards, 1992)

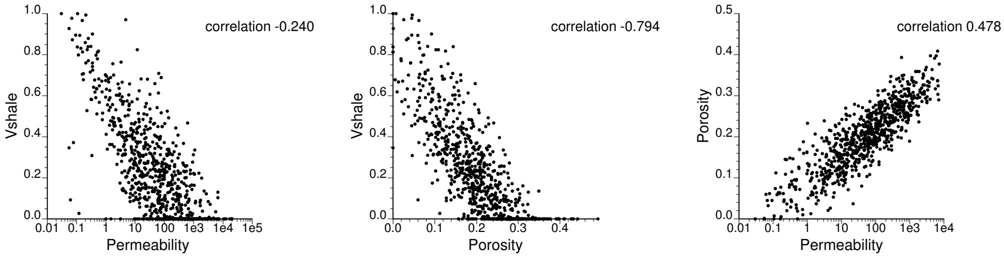


Figure 4: The correlation between of the volume of shale with the permeability and porosity

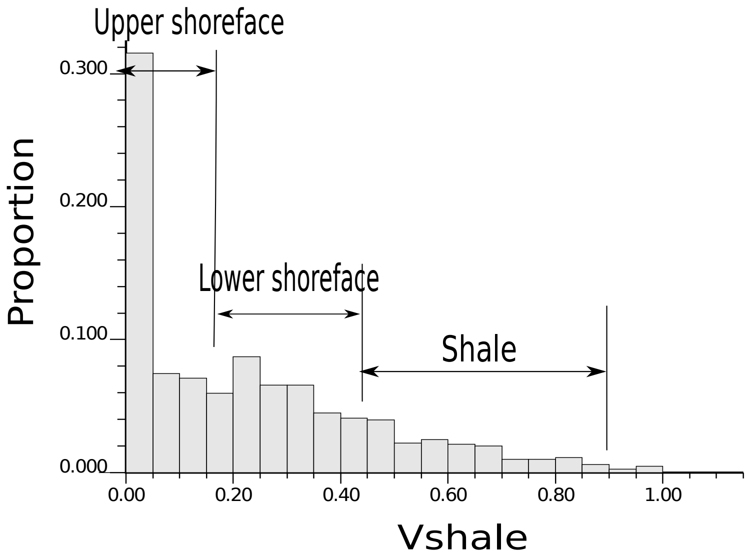


Figure 5: Shale volume histogram and the thresholds used to construct the facies

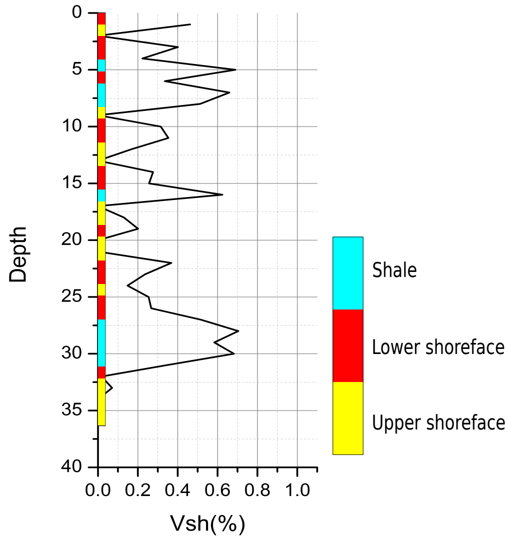


Figure 6: One example of vertical facies profile constructed from shale volume log

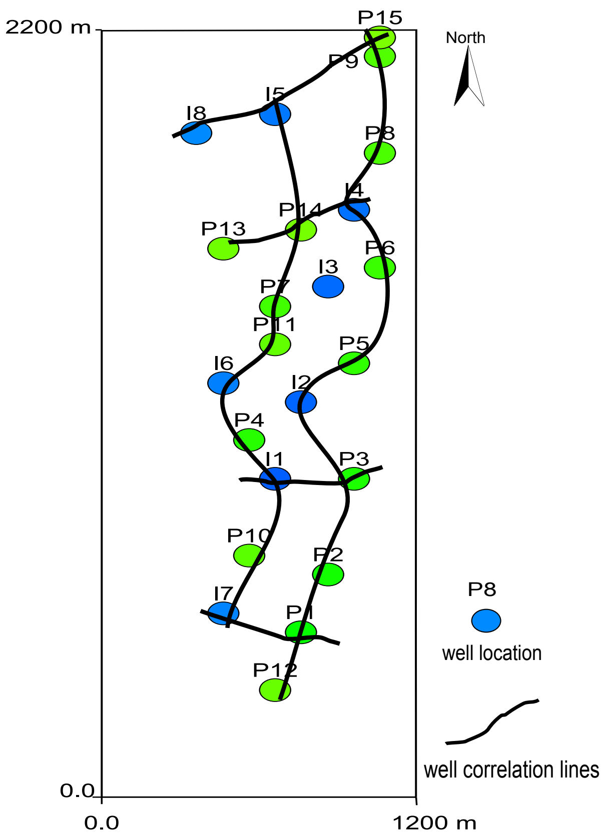


Figure 7: Well correlation sections

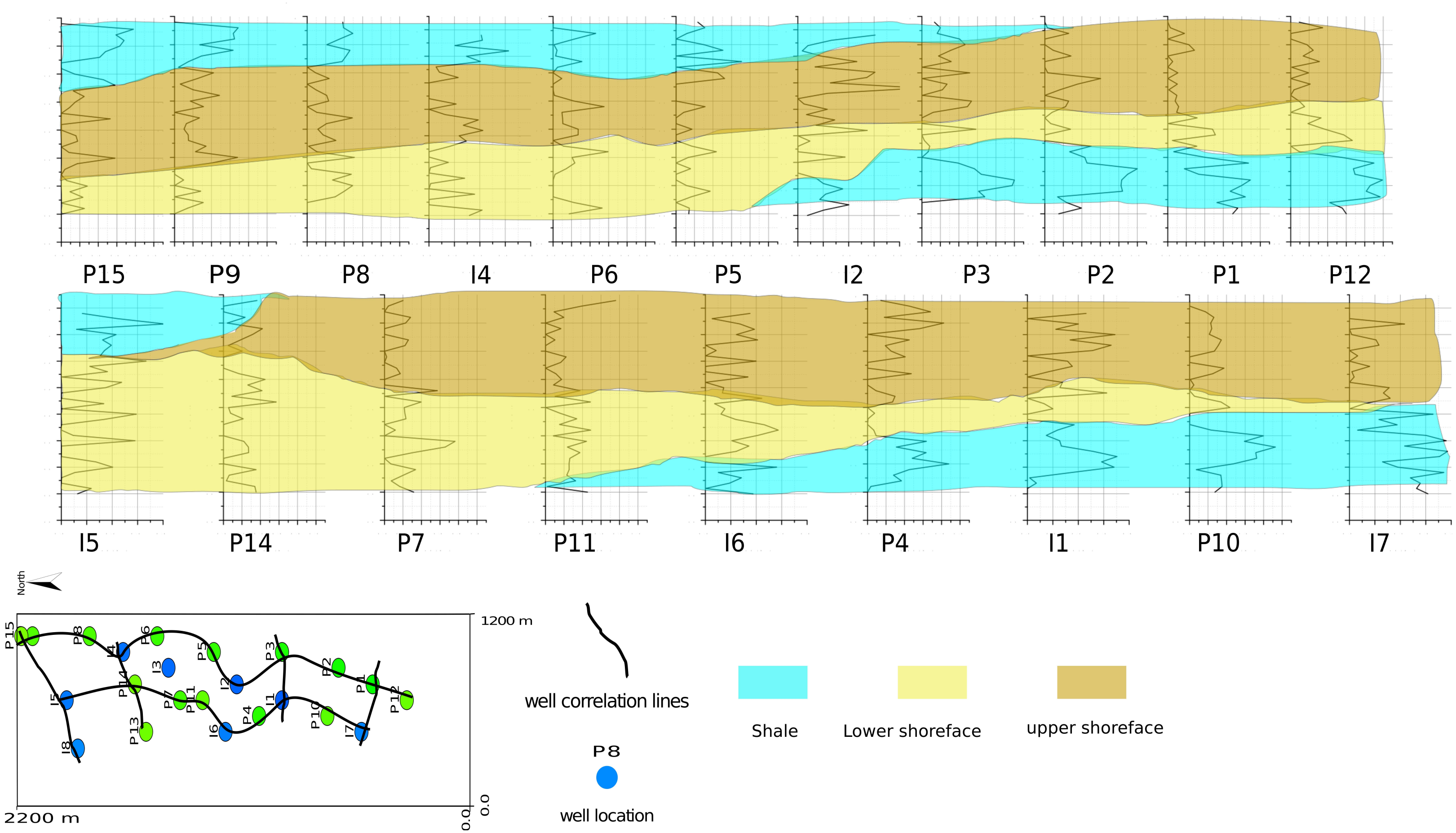


Figure 8: The well correlation along dip direction from the well data set

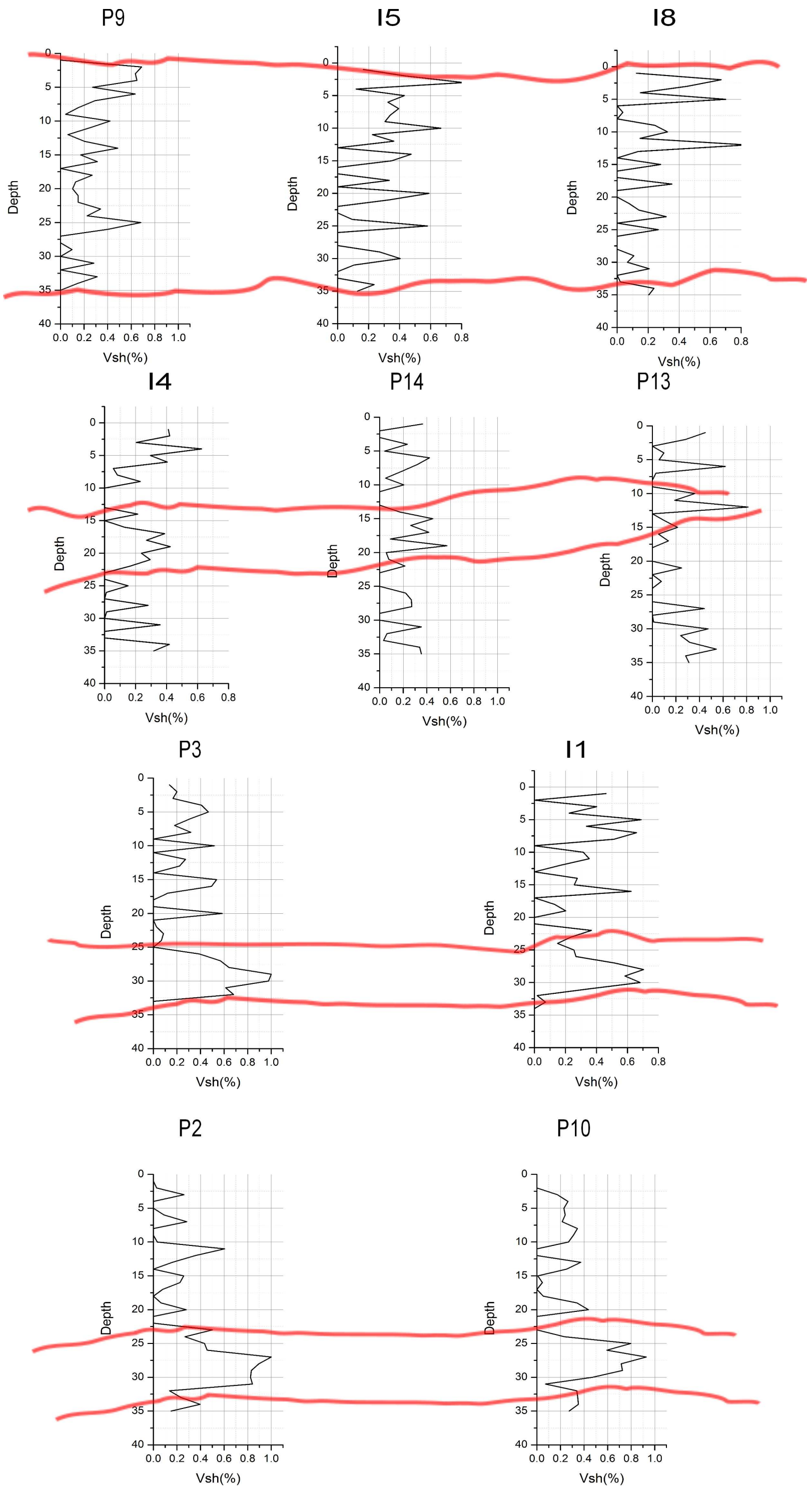


Figure 9: Three cross line along strike direction

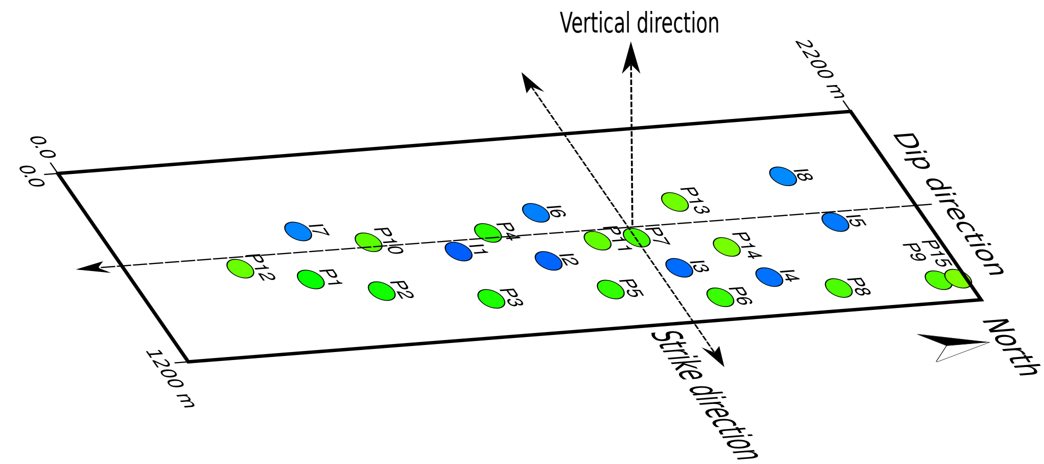
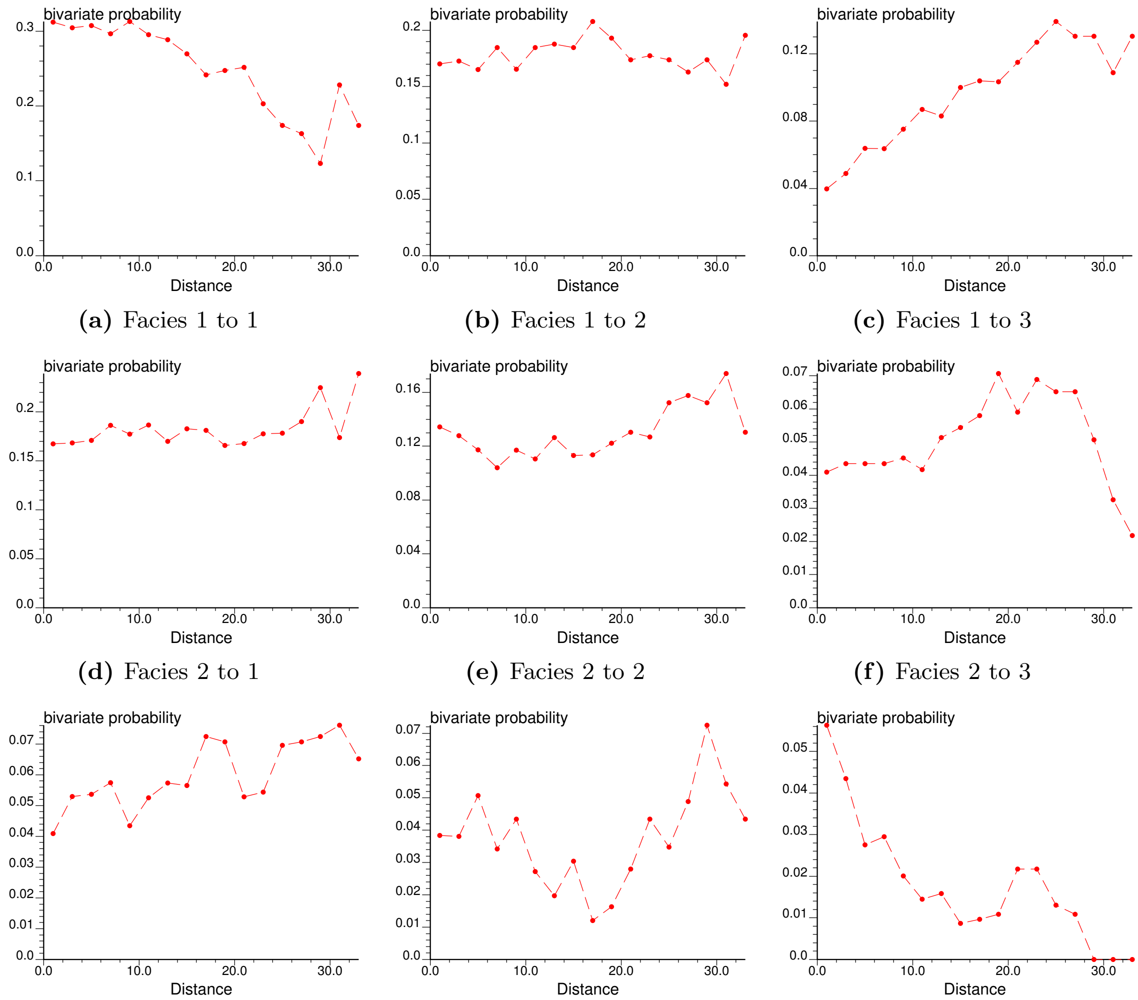


Figure 10: The heterogeneity prototype definition for the case study



(a) Facies 1 to 1 **(b)** Facies 1 to 2 **(c)** Facies 1 to 3

(d) Facies 2 to 1 **(e)** Facies 2 to 2 **(f)** Facies 2 to 3

(g) Facies 3 to 1 **(h)** Facies 3 to 2 **(i)** Facies 3 to 3

Figure 11: Vertical bivariate probability diagram in the case study

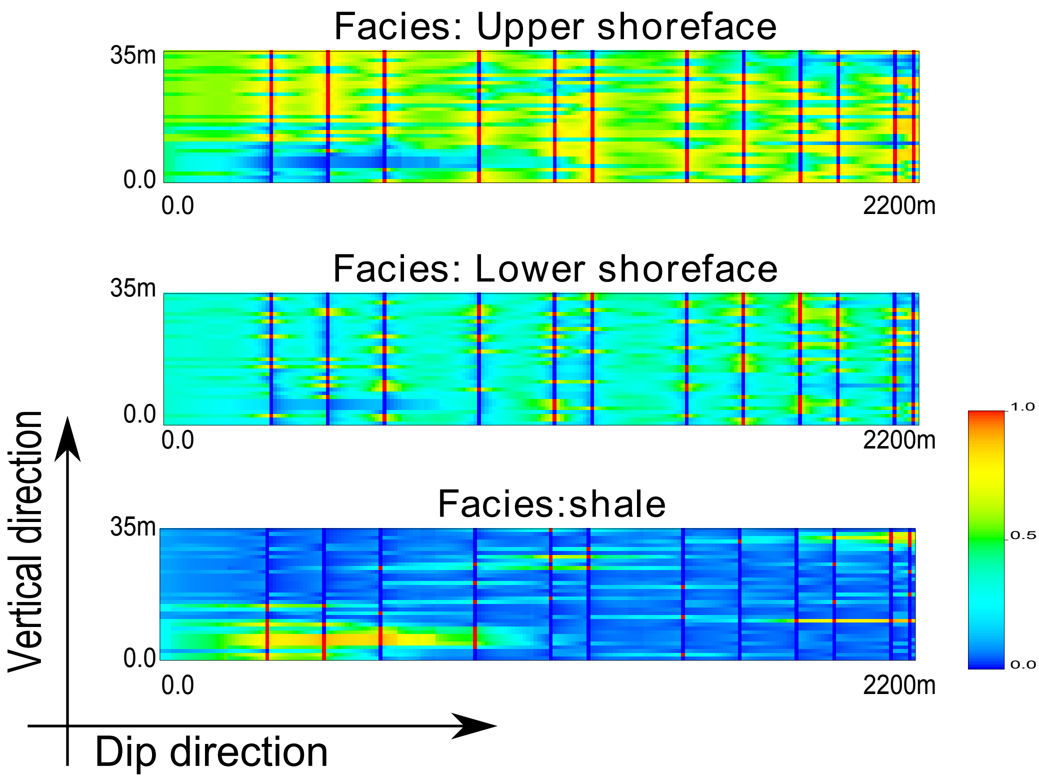


Figure 12: One slice along the vertical and dip direction of the estimation model for three facies using DMPE

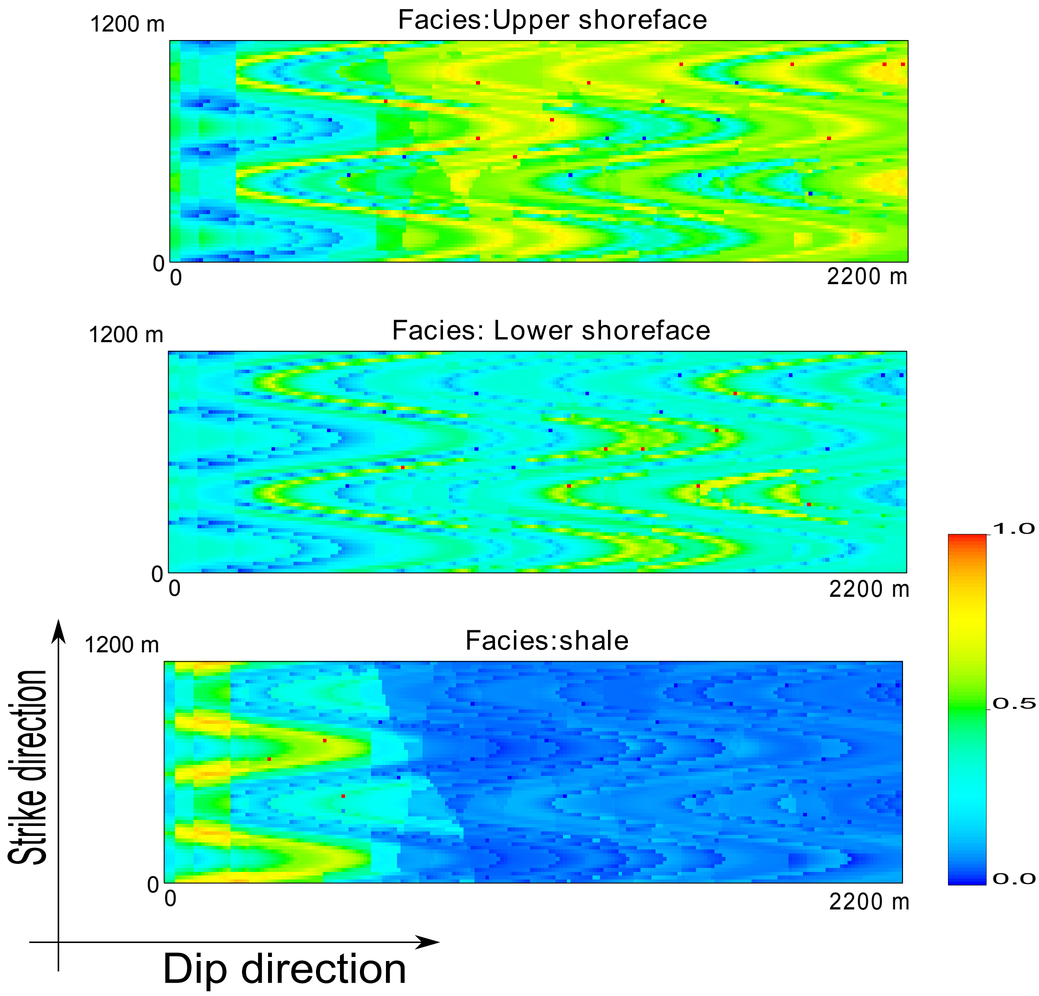


Figure 13: One slice along the strike and dip direction of the estimation model for three facies using DMPE

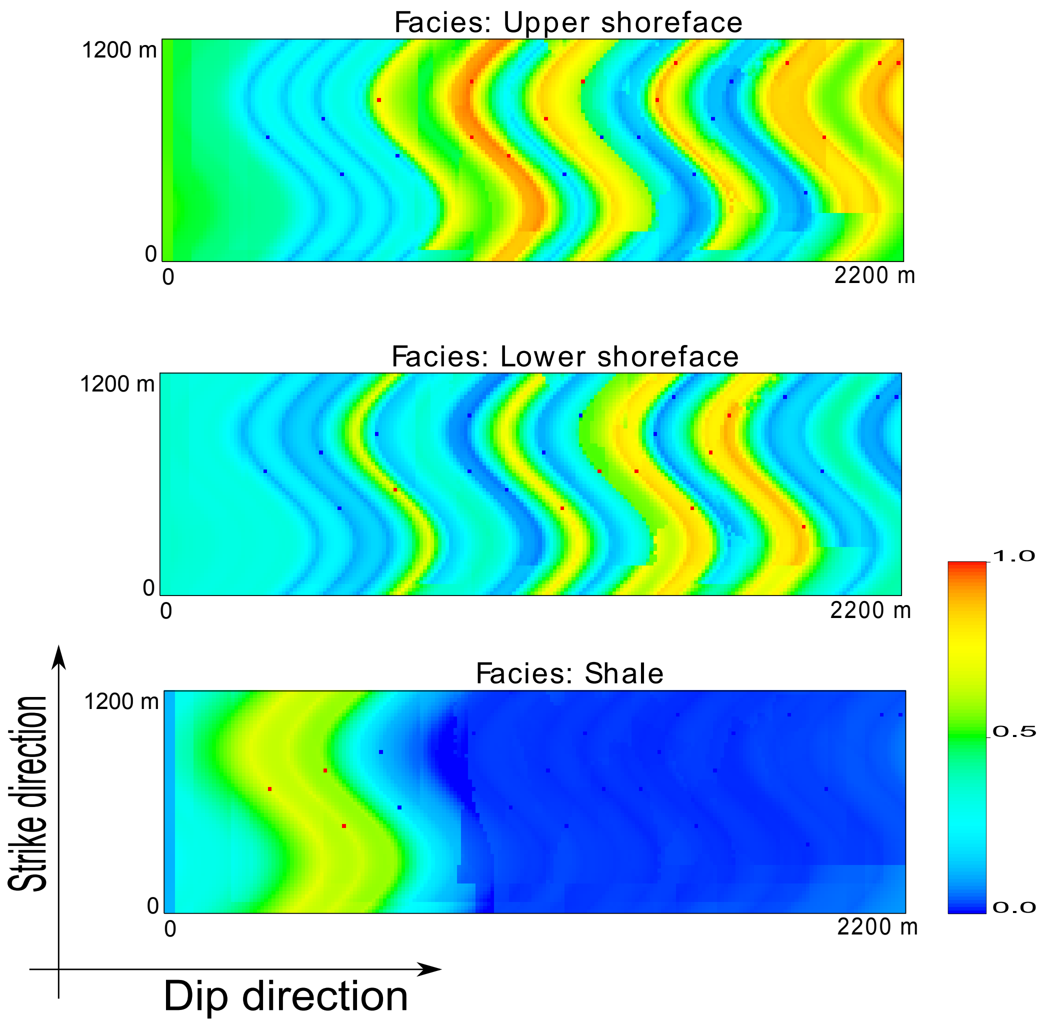


Figure 14: One slice of the estimation model with different random setting along strike direction

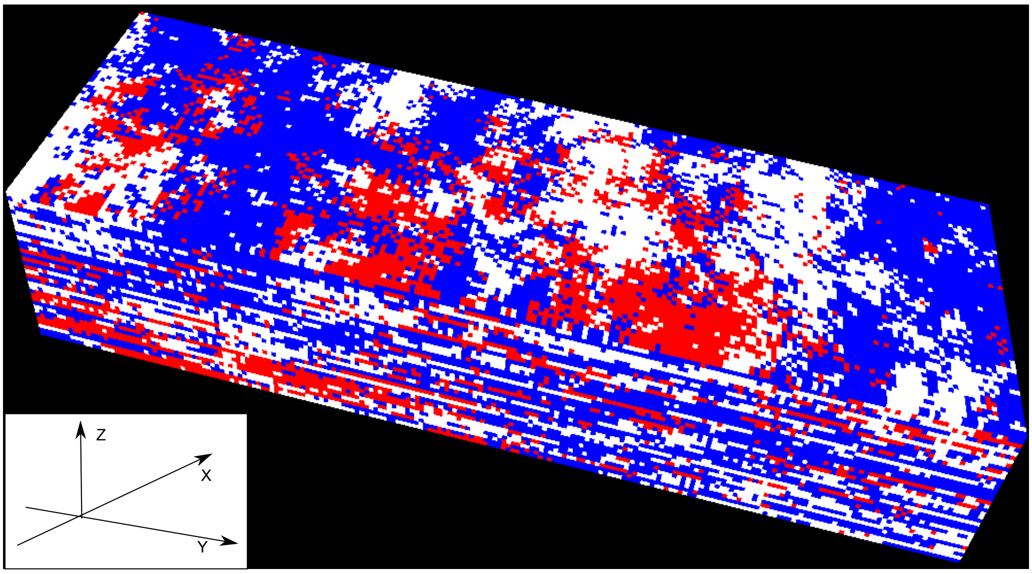


Figure 15: One 3D simulation output using the DMPE

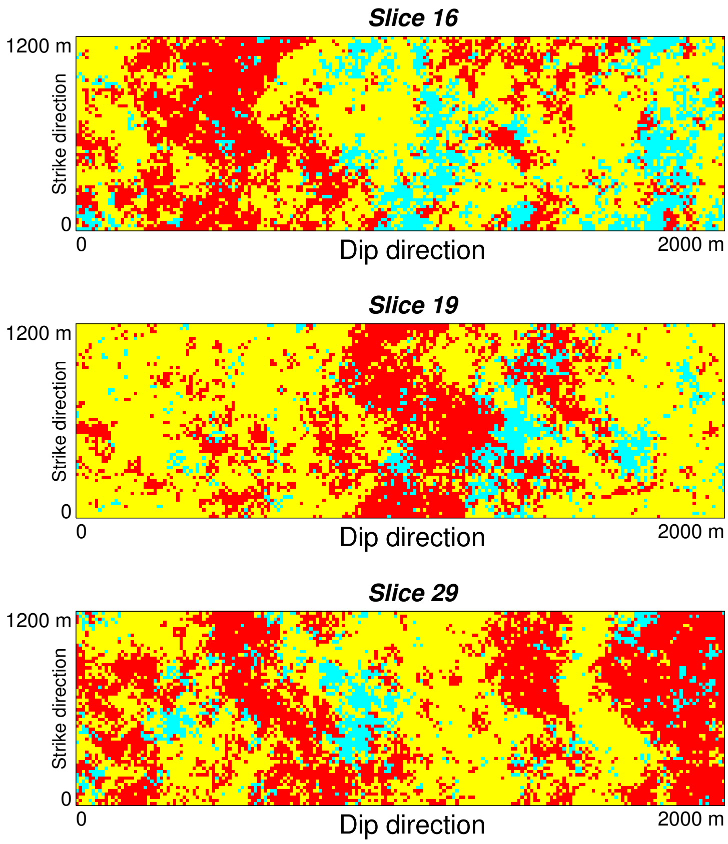


Figure 16: Three slices from the 3D simulation in the case study